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Using Semantic Web to support Advanced Web-Based Environment

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Abstract—In the learning environments, users would be helpless without the assistance of powerful searching and browsing tools to find their way. Web-based e-learning systems are normally used by a wide variety of learners with different skills, background, preferences, and learning styles.

In this paper, we perform the personalized semantic search and recommendation of learning contents on the learning Web-based environments to enhance the learning environment. Semantic and personalized search of learning content is based on a comparison of the learner profile that is based on learning style, and the learning objects metadata. This approach needs to present both the learner profile and the learning object description as certain data structures. Personalized recommendation of learning objects uses an approach to determine a more suitable relationship between learning objects and learning profiles. Thus, it may advise a learner with most suitable learning objects. Semantic learning objects search is based on the query expansion of the user query and by using the semantic similarity to retrieve semantic matched learning objects.

Keywords- Semantic Web; Domain Ontology; Learner Profile; Adaptive Learning; Semantic Search; Recommendation.

I. INTRODUCTION

Learning environment allows learners to access electronic course contents through the network and study them in virtual classrooms. It brings many benefits in comparison with conventional learning paradigm, e.g. learning can be taken at any time and at any place. However, with the rapid increase of learning content on the Web, it will be time-consuming for learners to find contents they really want to and need to study. The challenge in an information-rich world is not only to make information available to people at any time, at any place, and in any form, but to offer the right thing to the right person in the right way [1].

In the context of e-learning [2], adaptive systems are more specialized and focus on the adaptation of learning content and the presentation of this content. According to [3], an adaptive system focuses on how the profile data is learned by the learner and pays attention to learning activities, cognitive structures and the context of the learning material.

In Figure 1, the structure of an adaptive system [5] is shown. The system intervenes at three stages during the process of adaptation. It controls the process of collecting data about the user, the process of building up the user model (user modeling) and during the adaptation process.

![Figure 1: The Structure of an Adaptive System [5]](Image)

An advanced e-learning system has to comply with the following requirements [6]:

**Personalization:** This requirement suggests that the learning process needs to take into account the user’s preferences and personal needs. This implies either that the user is in a position to specify explicitly these preferences or that the system has the ability to infer them through a monitoring process. The latter is far more convenient for the end-user and constitutes a highly desirable feature.

**Adaptivity:** The user’s preferences change over time and the system must be able to track them and properly adjust to them. By ‘properly’, it is implied that the whole history of the user’s learning behavior must be taken into consideration, and not just the user’s latest (most recent) actions.

**Extensibility:** An e-learning system has to be extensible in terms of the learning material it provides. The incorporation of new courses and resources must be an easy to accomplish the task.

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Interoperability: An e-learning system must be able to both access content from and provide content to digital libraries and other e-learning systems. In this way, the provision of enriched and updated content is feasible.

The semantic web [4] is a space understandable and navigable by both human and software agents. It adds structured meaning and organization to the navigational data of the current web, based on formalized ontologies and controlled vocabularies with semantic links to each other. From the E-Learning perspective, it aids learners in locating, accessing, querying, processing, and assessing learning resources across a distributed heterogeneous network; it also aids instructors in creating, locating, using, reusing, sharing and exchanging learning objects (data and components). The semantic web-based educational systems need to interoperate, collaborate and exchange content or re-use functionality.

Ontology [7] comprises a set of knowledge terms, including the vocabulary, the semantic interconnections, and some simple rules of inference and logic for some particular topic. Ontologies applied to the Web are creating the Semantic Web. Ontologies [8] facilitate knowledge sharing and reuse, i.e. a common understanding of various contents that reach across people and applications. Using ontology in learning environments aims to provide mechanisms to enhance the process of searching and finding learning resources and have the capability to organize and display information that make it easier for learners to draw connections, for instance, by visualizing relationships among concepts and ideas.

Learning environment should not only provide flexible content delivery, but support adaptive content search and recommendation. For better learning experience and effect, search and recommendation of learning content should take into account the contextual information of learners, e.g., prior knowledge, goal, learning style, available learning time, location and interests.

This paper aims to perform the personalized semantic search and recommendation of learning contents on the learning Web-based environments. Semantic and personalized search of learning content is based on a comparison of the learner profile and the learning content description. This approach needs to present both the learner profile and the learning object description as certain data structures. Personalized recommendation of learning objects is based on ontological approach to guide what learning contents a learner should study, i.e. what learning objects a course should have according to learner preference and intention.

II. RELATED WORKS

Personalized search [9] is addressed by a number of systems. Persona [10] uses explicit relevant feedback to update user profiles that are represented by means of weighted open directory project taxonomy [11]. These profiles are used to filter search results. Personalized variants of PageRank, as found in Personalized Google or the Online Personalized Search System [12]. Authors in [13] re-rank the search results of queries for medical articles profiles keywords, associated concepts, and weights generated from an electronic patient record. In [14], it was filtered search results on the grounds of user profiles obtained from earlier queries. These profiles consist of a set of categories, and weighted terms associated with each category. In their work on personalizing search results, [15] they distinguish between long-term and short-term interests. While aiming at personalization in a broader sense, [16] use click-through data to increase the performance of search results.

In the paper [17], authors have proposed an approach to personalized query expansion based on a semantic user model. They discussed the representation and construction of the user model which represents individual user’s interests by semantic mining from user’s resource searching process, in order to perceive the semantic relationships between user’s interests which are barely considered in traditional user models and to satisfy the requirement of providing personalized service to users in e-Learning systems. They exploited the user model to provide semantic query expansion service in our e-Learning system.

Authors in [18] have shown that extracting the semantic interests of learner profiles can form a reasonable and simple way to represent the learning context, and that semantic learner profile, coupled with a semantic domain ontology that represents the learned content, enhance the retrieval results on a real e-learning platform.

This paper [19] proposed a new method for the personalized search, using click-through data as the personal data. Firstly, uses the semantic statistical of word frequency method to extract the query expansion terms and recommended to the user. Secondly, improves the Naïve Bayesian classifier and combines SVM to make users’ personalized learning models, then provides personalized re-sort results by user models. After experimental evaluation, it showed that this method has a significant effect, not only provides a meaningful query expansion terms, but also significantly improves the ranking of results.

The study in [20] authors proposed an ontological approach for semantic-aware learning object retrieval. The proposed ontological approach has two significant novelties: a fully automatic ontology query expansion algorithm for inferring and aggregating user intentions based on their short queries.

This paper [21] proposed a personalized e-learning method based on hybrid filtering. Two-level user profiles direct the recommendation process. Group profile reflects the users whose similar learning needs are similar with the current user. Topic profile describes the user’s interests with topics that the user has learned. Group profile and topic profile are bases of collaborative filtering recommendation and content-based filtering recommendation respectively.

In the paper [22], the authors introduced the principle and implementation steps of Collaborative Filtering (CF) algorithm. Then a novel CF recommendation algorithm was proposed on the combination of user profile weight and time weight. In this way, on one hand, the improved prediction can discover user’s latent demands more precisely. On the other hand, it also can sense the changes of user’s preference and then adjust the recommendation promptly.
III. THE PROPOSED SYSTEM

Personalized service is being paid close attention as a new method of intelligent information service to satisfy the increasing informational demands of the users in different systems. User model plays an important role in providing personalized service by representing the user's identity information and interests. There are many user models which have been adopted in various systems to acquire interests of users. In the e-Learning scenario, the learner model is exploited to represent the interests and background knowledge of individual learners [23]. The key technology of providing personalized learning services is to represent and acquire user's interests that are used in user modeling. User modeling is used to search and recommend content relevant to user interests.

In our proposed approach, personalized search of learning objects in e-learning is based on a comparison of the learner profile and the learning object (resource) description [24, 25]. Because such an approach needs to present both the learner profile and the learning object description as certain data structures, it requires the development of ontological models [26, 9] of the learner and learning object.

The proposed approach has two aspects, first for personalized search of learning objects is generally described in [24, 27], second for personalized recommendation suitable learning objects is proposed in [28, 29].

The key idea of the Semantic Web is to have data defined and linked in such a way that its meaning is explicitly interpretable by software processes rather than just being implicitly interpretable by humans. The Semantic Web can represent knowledge, including defining ontologies as metadata of resources. Ontology is a formal, semantic specification of a conceptualization of a domain of interest. Ontologies are used to describe the semantics of information exchange.

The metadata used in our work, data about data, is to provide structured information that describes, locates and explains information resources making it easier for resources to be retrieved. It is important to remember that data and metadata are different. Data is values, individual parts of information, whereas metadata describes the relationship between the parts and other data. Together data and metadata make information portable, because the relationships among the data values remain separate from their storage. Metadata is a key concept in developing the Semantic Web, to allow computers to share information automatically, data and metadata must be grouped together. Therefore, to ensure metadata can be automatically processed by machines, some metadata standard is needed [46].

The learner model is abstract expression to the learner characteristic. The learner model is not the expression of learner's all characteristics, but to describe and express partial learner characteristics according to the different learning system's needs.

The present research will describe details of building the learner and learning object ontological models to perform personalizes search in learning objects and recommendation suitable learning objects to learners.

In order to implement the proposed personalized search of learning objects according to the created ontological models of the learner and learning object, some IMS Learner Information Package Specification corresponding to some IEEE LOM [30] standard have been chosen, and the criteria to estimate conformity of LOM to the learner personal profile with the coefficients of importance. Our proposed system architecture is shown in figure 2.

Our system aims to perform these objectives:

1. Presenting a technical solution to an approach and methodology for personalized search of learning objects according to criteria that determine the learner’s interests.
2. Proposing an approach to adjust a learner’s interests. Because different attributes have different importance
to different learners, the system adjusts the weights in comparison to the learner’s interests and goals.

3. Proposing personalized learning objects search in E-learning, which is intended to allow a learner (user) to create a learner profile describing his/her personal interests using the IMS attributes [31], and then run a personalized search in a learning object repository on the Web to find relevant learning objects, which match that learner profile.

4. Ranking available learning objects by comparing values of corresponding attributes in the learner profile and learning object metadata (LOM).

5. Using specific ontology to infer what learning objects are needed for a course established for a specific learner requiring a specific subject and how to look for them on the Internet.

6. Recommending suitable learning objects according to a user’s preference and intention.

7. Referring to the experiences of similar users and adopting neighbor-interest to look for the learning objects that the user should be interested.

8. Providing adaptive, personalized recommendation for each user (learner).

A. Reusable Learning Objects (RLO) Creating

As mentioned in [32], authors have determined that the reusable learning objects is a reusable chunk of content with the following two fundamental properties: first is instructional sound content with the focused learning objectives. Second property is the facility that allows the learner to practice, learn, and receive assessment. Also, they define the sharable learning objects as RLO with the additional interoperability property that is the metadata or keywords that describe the object’s attributes and mechanisms for communicating with any e-learning system. The aim of this methodology is to select and extract as much of the existing raw content into RLO. The methodology is an iterative five step process to select appropriate content for the RLO with opportunities to refine and re-structure the extraction is taking place. The algorithm for building the RLO is shown in figure 3. A learning object must be modular, discoverable and interoperable, in order to be reused. To achieve these features and improve efficiency many people have dedicated long hours of hard work.

The majority of the efforts focus on the definition of standardization. Organizations such as IEEE [30] have contributed significantly by defining indexing standards called metadata (data about data). Metadata structures [33] contain information to explain what the leaning object is about, how to search, access, and identify it and how to retrieve educational content according to a specific demand.

The IEEE LOM standard specification specifies a standard for learning object metadata. It specifies a conceptual data schema that defines the structure of a metadata instance for a learning object. The IEEE LOM specification consists of nine categories, which includes 60 data elements. Each category has a specific purpose, such as describing general attributes of objects, and educational objectives. Table 1 shows the LOM categories adopted in our work.

Table 1. The main categories of IEEE LOM

<table>
<thead>
<tr>
<th>Category</th>
<th>Category Fields</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>General</td>
<td>Identifier, Catalog, Entry, Title, Language, Description, Keyword, Coverage, Structure, Aggregation Level</td>
<td>general information that describes the learning object as a whole.</td>
</tr>
<tr>
<td>Technical</td>
<td>Format, Size, Location, Requirement, OrComposite, Type, Name, Minimum Version, Maximum Version, Installation Remarks, Other Platform Requirements, Duration</td>
<td>technical requirements and characteristics of the learning object.</td>
</tr>
<tr>
<td>Educational</td>
<td>Interactivity Type, Learning Resource Type, Interactivity Level, Semantic Density, Intended End User Role, Context, Typical Age Range, Difficulty, Typical Learning Time, Description, Language</td>
<td>key educational or pedagogic characteristics of the learning object.</td>
</tr>
</tbody>
</table>

One of the chartered activities of the IEEE LTSC is to develop an XML binding for LOM [34]. This activity is ongoing, but the standard XML binding has not yet been approved and published. While the LOM standard defines the structure of a metadata instance, it does not define how a learning technology system will represent or use a metadata instance for a learning object.

The XML Binding defines an exchange format for metadata. With XML, course developers may put semi-structured information, such as the course content or course structure, into a discrete relational field, and then work with this information as with structured blocks of data, not as with a string of bytes. In our research, we describe each Learning Object by means of the XML document validated against an XML Schema defined by the IEEE LOM standard. Figure 4 shows the used LOM category and its fields in our system as relationship diagram of database.

We choose the tags from the standard schema, so every tag in our schema is still meaningful to others. A third-party search engine that can handle the XML metadata documents conforming to the standard schema could also handle ours. Figure 5 shows the part of schema for learning objects metadata (generated by XML Editor [35]) and Figure 6 shows the part of DTD of the XML file of learning objects metadata.
Figure 4: The used LOM category and its fields in our system as relationship diagram of database

Figure 5: The part of schema for learning objects metadata
B. Learner Profile Acquiring using learning style

There are five popular and useful features when is viewing the learner as an individual, these are: the learner’s knowledge, interests, goals, background, and individual traits [36]. Learning styles are typically defined as the way people prefer to learn. We can represent the learning style in stereotype model according to the Felder-Silverman’s learning style categories. From the perception, input processing and understanding four dimensions, the Felder-Silverman’s learning style categories are shown in table 2 [37, 38].

The learner actions that can be used to identify learner cognitive traits in learning systems by learner behaviors that can enable to acquire the learning style. Number of these actions is shown in [39]. Example of the actions that can enable to acquire styles base on Felder-Silverman model (FSLSM) is found in table 3.

**TABLE III. THE RELATIONSHIP BETWEEN LEARNER ACTIONS AND (FSLSM) CATEGORY**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>FSLSM Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of visits/postings in forum/chat</td>
<td>High</td>
<td>Active, Verbal</td>
</tr>
<tr>
<td>No. of visits and time spent on exercises</td>
<td>High</td>
<td>Active, Intuitive</td>
</tr>
<tr>
<td>Amount of time dealt with reading material</td>
<td>High</td>
<td>Reflective</td>
</tr>
<tr>
<td>Performance on questions regarding theories</td>
<td>High</td>
<td>Intuitive</td>
</tr>
<tr>
<td>Performance on questions regarding facts</td>
<td>High</td>
<td>Sensing</td>
</tr>
<tr>
<td>Amount of time spent on a Test</td>
<td>High</td>
<td>Sensing</td>
</tr>
<tr>
<td>No. of revisions before handing in a test</td>
<td>High</td>
<td>Sensing</td>
</tr>
<tr>
<td>No. of performed tests</td>
<td>High</td>
<td>Sensing</td>
</tr>
<tr>
<td>No. of visits and time spent on examples</td>
<td>High</td>
<td>Sensing</td>
</tr>
<tr>
<td>Amount of time spent on contents with graphics</td>
<td>High</td>
<td>Visual</td>
</tr>
<tr>
<td>Performance in questions related to graphics</td>
<td>High</td>
<td>Visual</td>
</tr>
<tr>
<td>Performance on questions related to overview of concepts and connections between concepts</td>
<td>High</td>
<td>Global</td>
</tr>
<tr>
<td>Performance on questions related to details</td>
<td>High</td>
<td>Sequential</td>
</tr>
<tr>
<td>Performance on tests in General</td>
<td>High</td>
<td>Sequential</td>
</tr>
<tr>
<td>No. of visits and time spent on outlines</td>
<td>High</td>
<td>Global</td>
</tr>
</tbody>
</table>

**Figure 6 The part of DTD of the XML file of learning objects metadata**

**TABLE II. CATEGORIES OF FELDER-SILVERMAN’S LEARNING STYLE**

<table>
<thead>
<tr>
<th>Learning Style Category</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensing vs. Intuitive</td>
<td>It represents the abstraction level of the learning material the learner prefers. A sensing learner likes learning facts and needs more practical case studies. An intuitive learner usually prefers innovation and dislikes repetition.</td>
</tr>
<tr>
<td>Visual vs. Verbal</td>
<td>It indicates whether the learner prefers auditory (textual) or visual documents.</td>
</tr>
<tr>
<td>Active vs. Reflective</td>
<td>It indicates how the learner prefers to process information: actively (through engagement in activities or discussions) or reflectively (through introspection)</td>
</tr>
<tr>
<td>Sequential vs. Global</td>
<td>It indicates how the learner progresses toward understanding. Sequential learners prefer sequential explanations while global learners usually prefer an initial overview of the involved topics which possibly shows them the most important steps and relations they are going to study</td>
</tr>
</tbody>
</table>
IF learner does not know the answer; 
THEN 
Show learner image/diagram;  

IF learner shown image/diagram AND learner gives correct answer;  
THEN 
Increase VISUAL;  

IF answer is given in the explanation text AND learner does not know the answer;  
THEN 
Increase INTUITOR AND Increase VISUAL;  

Figure 7 Example of rules used to adjust learner learning style

C. Learning Content Recommendation and Matching

Personalized recommendation is a widely used application of Web personalized services which alleviate the burden of information overload by collecting information which meets the user’s needs. An essential of Web recommendation is how to build user profile, which involves the information and preference of user and has a great impact on the performance of Web personalized recommendation. The Adaptive Systems and Recommender Systems [41] are focused in exploring a certain hypermedia structure in order to help user finding the best way for their interests, while the Recommender Systems are focused on a network of Web resources, bind by existing or virtual relations, aiming to provide users with individual views on Web data.

The Felder-Silverman Learning Style Model is described by the dimensions of Learning and Teaching Styles [42], creating a relationship to learning styles and teaching strategies that could be adopted to support the learner learning style [43].

Zaina and Bressan in [44, 45] proposed an alternative approach that splits the learner learning profile (preferences) into three categories: perception, presentation format and learner participation. Along the text, this altered model is referred to as preference categories; its goal is to detect clusters of preferences that reflect different data perspectives caught during the tracking of learning styles.

Each category has a teaching-method correspondence that defines the matching with the learners’ learning styles, as predicted in the Felder/Silverman proposal as found in [45]. According to Felder and Silverman, the teaching-learning style corresponds to the values of LOM category fields. The Example to show the relationship between LOM educational fields and the preferences category is shown in table 4.

By matching the learning objects metadata, that is stored in learning objects repository, with the learner profile in the system, the system can recommend the learning objects based on the learning styles.

D. The Domain Ontology

The main reason for ontology [47] is to enable communication between computer systems in a way that is independent of the individual system technologies, information architectures and application domain.

<table>
<thead>
<tr>
<th>Preference Categories</th>
<th>Features</th>
<th>Learning Styles</th>
<th>Teaching Methods</th>
<th>LOM – Educational Field</th>
<th>LOM – Educational Field Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perception</td>
<td>Intuitive</td>
<td>Intuitive</td>
<td>Intuitive</td>
<td>Intuitive</td>
<td>Intuitive</td>
</tr>
<tr>
<td>Presentation Format</td>
<td>Auditory</td>
<td>Auditory</td>
<td>Auditory</td>
<td>Auditory</td>
<td>Auditory</td>
</tr>
<tr>
<td>Learner Participation</td>
<td>Active</td>
<td>Active</td>
<td>Active</td>
<td>Active</td>
<td>Active</td>
</tr>
</tbody>
</table>

Table 4: The relationship between LOM educational fields and the preferences category

Ontology includes rich relationships between terms and each specific knowledge domain and organization will structure its own ontology which will be organized into mapped ontology. The domain of our learning content and the ontology we have developed within proposed system is that of computer science. The ontology covers topics like artificial intelligence, communications; computational theory, computer graphics, data structures, database, programming, etc. It is used mainly to index the relevant learning objects and to facilitate semantic search and re-usability of learning objects.

It was proposed in [48] a knowledge engineering approach to build domain ontology. Figure 8 shows main steps of the ontology development process.

![Ontology Development Process](image)

Figure 8 Main steps of the ontology development process

We use protégé [49, 50] as our ontology tool. Since protégé is an open source ontology editor, developed by Stanford Center for Biomedical Informatics Research and coded by JAVA. Protégé interface style is similar to Windows applications’ general style, so it is easy to learn and use. Figure 9 shows part of our domain ontology and the extracted...
E. Semantic LO Search

According to keyword-based search present serious problems related to the quality of the search results. It often happens that relevant pages are not indexed by a traditional search; in this case important information can be reached only if its specific internet address is known. Moreover, searches based on keywords are very closely related to the spelling of the word and not to its meaning. One current problem of information search issues is that it is not really possible to automatically extract meaning from the relevant results of a query. One main reason for this is that the web was initially designed for direct human use and thus the documents do not provide machine readable semantic annotations. This work focuses on the first of these items, specifically in the formulation and the user’s query processing. We expect to prove that through linguistic processing, the use of dictionaries and domain ontologies, the instructional designer’s query terms become more specific.

The Semantic Search process includes the steps, that is appeared in the next algorithm, is shown in the figure 10.

**CONCLUSION**

The adaptive learning system provides support to the learner according to the individual characteristic. It can provide a learner view adapt to learner customization characteristic, which not only includes personalized resources, but also includes the personalized learning process and strategy. So we should establish a learner model for each learner, containing the information such as state-of-art of learner, the goal and interest and so on. The system reduces the information spaces for learner browsing according to the learner model in the application, and presents the most interesting information to the learner.

**Input:** Query of User.

**Output:** Retrieved Semantic Information

**Procedure:**
1. Tokenizing query keywords to number of terms.
2. Remove the stop words.
3. Stem the word.
4. Get POS (Part of Speech) of the word in the query.
5. Expand the words by the hypernym and hyponym concepts in the Wordnet.
6. Expand the words by the Domain Ontology (DO) as:
   a. Search the word in the DO.
   b. Check if the word is the root or not.
      i. If Yes
         1. Get the Hyponym, and Get the neighbor node.
         2. Add the two concepts to the expanded query.
      ii. If No and is not the Leaf.
         1. Get the Hyponyms Hypernyms, and neighbor.
         2. Add the two concepts to the expanded query.
      iii. If No and is the Leaf.
         1. Get Hypernyms, and neighbor.
         2. Add the two concepts to the expanded query.
   c. Compute the similarity between concepts, put N pre-expansion words that has high relativity as expansion words.
   d. Add Expanded Query to the original query.
7. Use Semantic Similarity between the expanded words and the terms in the LO.
8. Rank the LO based on the high semantic similarity weight.
9. Return the ranked LO from LOR.

**Figure 10 Algorithm of Semantic Search of LO**

This work presented a technical solution to an approach and methodology for personalized search and recommendation of learning objects according to the learner’s profile. Adaptive recommendation model is to retrieve and recommend for a learner suitable learning objects.

In this work, we have defined a methodology that links learning objects metadata and learning profiles for automatic content recommendation. To do so, we have used the Felder-Silverman Learning Style Model along with the IEEE LOM standard, a combination that, extending former works, can suitably relate learner profiles and learning objects, automatically, in different fields of learning, and consistently reflecting the intrinsic style of the learners.

The semantic search of the learning objects is based query expansion and using semantic similarity between the learning objects and the query keywords.
REFERENCES


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