Semantic Retrieval and Recommendation in Adaptive E-Learning System

Khaled M. Fouad Ibrahim
Computer Science Dept. , Community College,
Taif University,
Kingdom of Saudi Arabia (KSA)
kmfi25@yahoo.com

***Abstract*- The success of any e-learning system depends on the retrieval of relevant learning contents according to the requirement of the learner. This leads to the development of the adaptive e-learning system to offer learning materials considering the requirements and understanding ability of the learner.**

In this paper, the personalized retrieval and recommendation of the learning objects is performed. It is based on the learner profile. The learner profile is built by using the learning style of the learner that is acquired using the learner behavior during utilizing the e-learning system. Learning object recommendation is performed by the comparison between the learner profile and learning object metadata. Semantic and personalized retrieval of learning objects is based on semantic expansion of the query keywords. These expanded terms are used to perform the semantic similarity between the learning objects and the expanded terms to fetch the required learning objects to the learner that is matched with the learner profile and his requirements.

Keywords-component; Adaptive E-Learning; Learner Profile; Semantic Retrieval; Learneing Content Recommendation.

I. INTRODUCTION (HEADING 1)

In the context of e-learning [1], adaptive systems are more specialized and focus on the adaptation of learning content and the presentation of this content. According to [2], 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 [3] 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.

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.

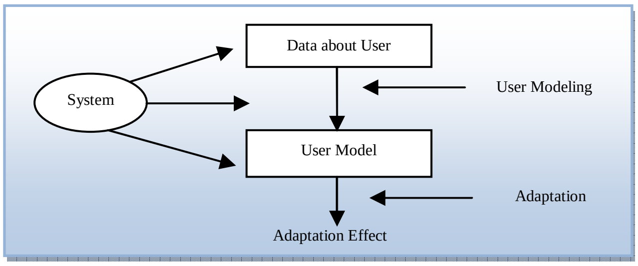

Figure 1: The Structure of an Adaptive System [3]

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 [5] 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 [6] 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.

This paper aims to propose the approach that performs the personalized semantic retrieval and recommendation of learning objects in the e-learning system. Semantic personalized retrieval and recommendation of learning object is based on a comparison of the learner profile; that is based on the learning style of the learner, and the learning object description. This approach needs to present both the learner profile and the learning object description as ontological data structures. Semantic retrieval of learning objects is based on the semantic query expansion of the learner query. It is also performed by the semantic similarity of the learning object and the expanded query.

II. RELATED WORK

Personalized search [7] is addressed by a number of systems. Persona [8] uses explicit relevant feedback to update user profiles that are represented by means of weighted open directory project taxonomy [9]. These profiles are used to filter search results. Personalized variants of PageRank, is found in Personalized Google or the Outride Personalized Search System [10]. Authors in [11] re-rank the search results of queries for medical articles profiles keywords, associated concepts, and weights generated from an electronic patient record. In [12], 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, [13] they distinguish between long-term and short-term interests. While aiming at personalization in a broader sense, [14] use click-through data to increase the performance of search results.

The study in [15] 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 [16] 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 [17], 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.

Personalized recommendation [18] is a widely used application of Web personalized services which alleviate the burden of information overload by collecting information which meets user's needs. An essential of Web recommendation is how to build user profile, which involves the information and preference of user and has great impact on the performance of Web personalized recommendation. For example, if a user profile provides information that can not represent user's recent interests; an e-Commerce system is unable to accurately recommend specific goods to the user.

The article [19] described the relevant technologies of personalized recommendation that is based on the domain ontology, for the intermediary in domain ontology, to construct user interest ontology modeling user interest, at last, recommendation based on KNNs algorithm. Systems take full account of the semantic factor, carry out excavation by ontology, and recommend resources to the user by domain ontology.

III. THE PROPOSED APPROACH

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 [20]. 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 retrieve and recommend content relevant to user interests.

In this approach, personalized recommendation of learning contents in e-learning is based on a comparison of the learner profile and the learning objects metadata [21, 22]. 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 [23, 7] of the learner profile and learning object.

The metadata used in this 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 [24].

The present research will describe details of building the learner and learning objects ontological models to perform personalizes retrieval in learning objects and recommendation suitable learning objects to the learners. Our proposed approach architecture is shown in figure 2.

In order to implement the proposed personalized retrieval of learning objects according to the created ontological models of the learner profile and learning objects, some IMS Learner Information Package Specification corresponding to some IEEE LOM [25] standard have been chosen, and the criteria to estimate conformity of LOM to the learner personal profile with the coefficients of importance.

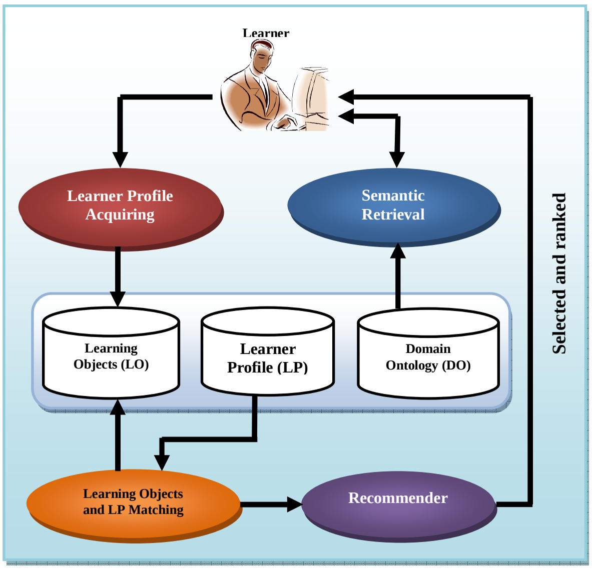

Figure 2: The Proposed System Architecture

A. *Learning Objects Metadata*

The majority of the efforts focus on the definition of standardization. Organizations such as IEEE [25] have contributed significantly by defining indexing standards called metadata (data about data). Metadata structures [26] 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 I shows the LOM categories is adapted to our work.

TABLE I. THE MAIN CATEGORIES OF IEEE LOM

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

One of the chartered activities of the IEEE LTSC is to develop an XML binding for LOM [27]. 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.

In this research, each Learning Object is described by means of the XML document validated against an XML Schema defined by the IEEE LOM standard. The tags from the standard schema are chosen, 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 3 shows the part of schema for learning objects metadata (generated by XML Editor [28]).

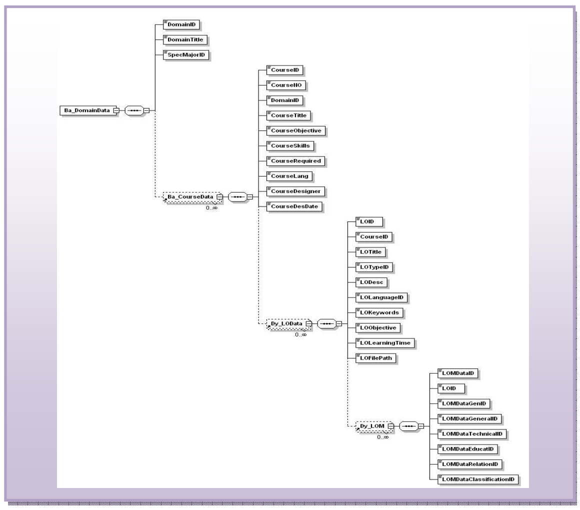

Figure 3: The part of schema for learning objects metadata

B. Learner Profile Acquiring

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 [29].

The learner profile based on the learning style can be acquired by analyzing the learner behaviors during utilizing the system. Learning styles are typically defined as the way people prefer to learn. It can be represented 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 II [30, 31].

TABLE II. CATEGORIES OF FELDER-SILVERMAN'S LEARNING STYLE

Learning Style Category	Description
Sensing vs. Intuitive	**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.**
Visual vs. Verbal	**It indicates whether the learner prefers auditory (textual) or visual documents.**
Active vs. Reflective	**It indicates how the learner prefers to process information: actively (through engagement in activities or discussions) or reflectively (through introspection)**
Sequential vs. Global	**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**

The learner actions can be used to identify learner cognitive traits in the learning systems. Learner behaviors can enable to acquire the learning style. Number of these actions is shown in [32]. Example of the actions that can enable to acquire learning styles base on Felder-Silverman model (FSLSM) is found in table III.

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

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

The Actions that are found in [33], are considered as the number of rules to describe learner learning style by recording the learner behavior in the system as found in figure 4.

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 INTUITIVE **AND** Increase VISUAL;

Figure 4: Example of rules used to adjust learning style of the learner

These actions can be used to acquire the learning style as shown in table III and figure 5.

C. Learning Objects Matching and Recommendation

The Felder-Silverman Learning Style Model is described by the dimensions of Learning and Teaching Styles [34], creating a relationship to learning styles and teaching strategies that could be adopted to support the learner learning style [35].

Zaina and Bressan in [36, 37] has 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 [37]. 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 IV.

By matching the learning object metadata, that is stored in learning objects repository, with the learner profile; that is based on learning style, in the system, the system can recommend the learning objects. This approach needs to present both the learner profile and the learning object metadata as ontological data structures as found in XML format.

TABLE IV. THE RELATIONSHIP BETWEEN LOM EDUCATIONAL FIELDS AND THE PREFERENCES CATEGORY

Preference Categories	Features	Learning Styles	Teaching Methods	LOM – Educational Field	LOM – Educationa l Field Value

Perception	The focus is in the best way through which the learner can obtain information: contents, exercise types, for instance.	Sensing	Concrete	Interactivity	Active
		Intuitive	Abstract		Expositive
Presentation Format	It is related to the input. Content preferences chosen by the learner such as media types.	Visual	Visual	Learning Resource Type	Figure, Video, Film, and others
		Auditory	Verbal		Text, Sound, and Format others
Learner Participation	It represents the learner preferences for the activities participation or observation.	Active	Active		Practical Exercise, Experiment, and others
		Reflective	Passive		Questionnaire and Readings

D. *Semantic LO Retrieval*

One main reason for this component 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 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 retrieval and re-usability of learning objects. We used protégée [38, 39] as our ontology tool. Since protégée 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 5 shows the part of our domain ontology that is built by Protégé.

The Semantic Retrieval process includes the steps, that is appeared in the next algorithm, is shown in the figure 6.

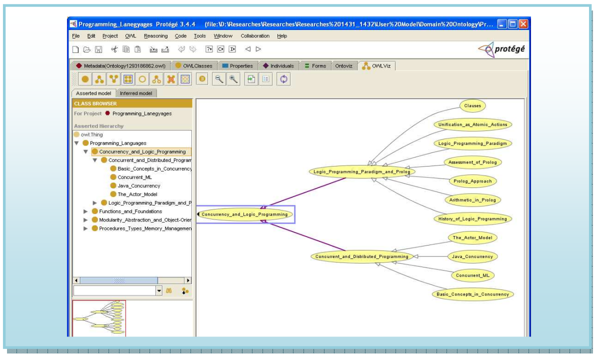

Figure 5: Part of generated Domain Ontology (DO) by Protégé

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 6 Algorithm of semantic retrieval for learning objects

CONCLUSION

The system reduces the information spaces for learner browsing according to the learner profile in the application, and presents the most interesting information to the learner matched with the learning style. In this work, I have introduced a methodology that links learning objects metadata and learner profiles for automatic content recommendation.

To do so, I 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 retrieval of the learning objects is based query expansion and using semantic similarity between the learning objects and the query keywords.

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