Proposed Approach to Build Semantic Learner Model in Adaptive E-Learning

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ABSTRACT

In the context of E-learning, adaptive systems are more specialized and focus on the adaptation of learning content and the presentation of this content. The adaptive E-learning 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. The system controls the process of collecting data about the learner, the process of acquiring the learner profile and during the adaptation process.

The Semantic Web 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. The semantic web-based educational systems need to interoperate, collaborate and exchange content or re-use functionality.

In this paper, the proposed approach aims at improving representation of a learner model during acquiring leaner profile, which is based on learner interest and learning style, in content-based approaches by performing the next steps. First step is domain concept filtering in which concepts and items of interests are compared to the domain ontology to check the relevant items to the selected learning domain using ontology based semantic similarity. Second step is incorporating semantic content into the term vectors. Term definitions and relations are used, provided by WordNet ontology, to perform domain-specific concepts as category labels for the semantic learner models. The Learning style of the learner can be acquired by using the learner behavior during utilizing the E-learning system.

General Terms

Semantic Web, WordNet. E-Learning.

Keywords

Learner Model, Learner Interest, Learning Style, Ontology, Domain Concept Filtering, Semantic Similarity, Semantic Learner Model.

1. 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 [4] is shown. The system intervenes at three stages during the process of adaptation. It controls the process of collecting data about the learner, the process of building up the learner model (user modeling) and during the adaptation process.

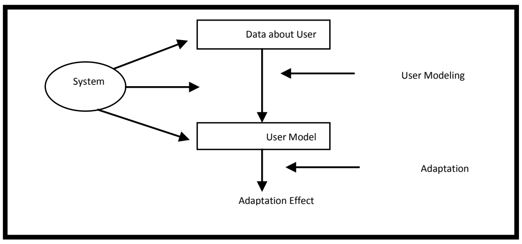

Figure 1: The Structure of an Adaptive System [4].

An advanced e-learning system has to comply with the following requirements [5]:

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.

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 [6] 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. Table 1 shows the comparative study of existing approaches of the proposed scheme.

Table 1. Comparative study of number of existing systems and approaches

Systems and approaches	Details
Protus 2.0 [40]	Architecture for adaptive and personalized tutoring system that completely relies on Semantic web standards and technologies. Ontology-based approach is presented
Automation of Learning Object Management System [41]	It uses of ontologies as knowledge representation formalism for learning object management has been analyzed, focusing on their realistic integration with existing standards.
CIBACO [42]	Authoring tool that allows a high school for web-based intelligent tutoring systems classroom for competency-based teaching. It allows a fast creation of web-classroom applications.
Ontology based web education System [43]	It uses XML and RDF to describe data in system, and uses ontology to describe grammar and relation of data.
LOTTI [44]	It offers support to the author in creating fully inclusive materials by suggesting correct behavior and place pedagogical emphasis on the design and development of the learning objects.
Agent based intelligent learning objects [45]	It is intelligent learning environments. It is useful to improve modularity, discoverability, and interoperability. The agent enables to promote learning experiences playing the role of learning objects.
Adaptivity and Interoperability in e-Learning Using Ontologies [46]	This is the design and development of an adaptive system based on ontology that takes into account information generally present into the e-learning environment, but mainly information about the learning styles and metadata a in order to propose the adaptation rules.

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.

This paper aims at proposing an approach to improve the representation of a learner model; that is based on learner interest and learning style of the learner, during acquiring leaner profile by performing the next steps. First step is the domain concept filtering in which concepts and items of interests are compared to the domain ontology to check the relevant items to the learning domain using ontology based semantic similarity. Second step is incorporating semantic content into the term vectors. Term definitions and relations are used, provided by WordNet, to perform domain-specific concepts as category labels for the semantically enhanced learner models. The Learning style of the learner can be acquired by using the learner behavior during utilizing the E-learning system.

2. RELATED WORKS

The authors in [9] 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.

The personalized e-learning method was proposed in [10]. The e-learning method is 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.

Reformat and Koosha in [11] introduced a method for learning and updating a user profile automatically. The proposed method belongs to implicit techniques – it processes and analyzes behavioral patterns of user activities on the web, and modifies a user profile based on extracted information from user’s web-logs. The method relies on analysis of web-logs for discovering concepts and items representing user’s current and new interests. Those found concepts and items are compared with items from a user profile, and the most relevant ones are added to this profile. The mechanism used for identifying relevant items is built based on a newly introduced concept of ontology-based semantic similarity.

In [12], authors illustrated a novel design and development of an agent and ontology based service discovery and personalization framework. In particular, ontological user profiling was applied to capture users’ possibly changing information/service requirements, and probabilistic language modeling was exploited to develop an effective mechanism for user query contextualization based on both current and past search history. As user queries are usually short e.g., only 2.x words long on average, query personalization and contextualization is essential for effective Web service discovery. Their initial experiments had shown that the proposed ontological user profiling and probabilistic language modeling mechanisms were promising. Users interact with their agents who will in-turn looking up the most relevant Web services from the external service registries on behalf of their users.

3. THE ARCHITECTURE OF PROPOSED APPROACH

The proposed approach can provide adaptive learning support according to the learner's individual differences, promote learners to study initiatively, and achieve the knowledge construction. It can provide the adaptive learning content based on the learner's interest and learning style.

Based on these considerations, a new architecture of adaptive learning is proposed in the current paper. It is illustrated in figure 2. According to the proposed architecture, the proposed approach is mainly composed of three basic processes: acquiring Learner Interest, semantic learner interest representation, and acquiring learning style of the learner based on learner behavior in the system. The basic functionality of the proposed approach will be explained in the next sections.

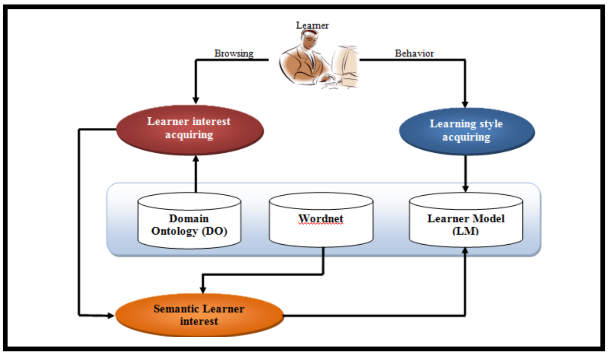

Figure 2: The architecture of the proposed approach

3.1 Learner interest acquiring

In this system, learner interest model's knowledge expression uses the thought which is based on the space vector model's expression method and the domain ontology [13]. The figure 3 shows certain steps to acquire learner interest.

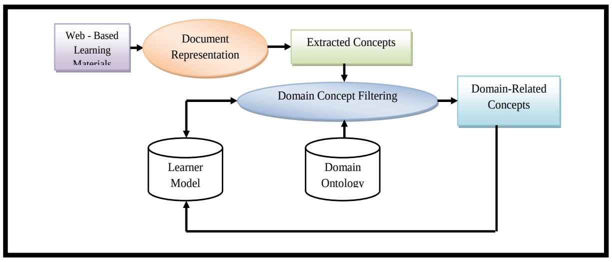

Figure 3: Acquiring E-learners interest Steps

3.1.1 User's Web Log Analysis

Web usage mining [37], the process of discovering patterns from web data using data mining methods, strives to find learner preferences based on the web-logs that reside on servers. Web log [38] records each transaction, which was executed by the browser at each web access. Each line in the log represents a record with the IP address, time and date of the visit, accessed object and referenced object. In such data we follow sequences in visiting individual pages by the learner, who is, under certain condition, identified by the IP address. In sequences we can look for learners behavior patterns.

The data from Web logs, in its raw form, is not suitable for the application of usage mining algorithms. The data needs to be cleaned and preprocessed. To perform log data analysis the data pre-processing process must be accomplished. The data pre-processing is the process of cleaning and transforming raw data sets into a form suitable for web mining. The task of the data pre-processing module is therefore to obtain usable datasets from raw web log files, which, in most cases, contain a considerable amount of incomplete and irrelevant information.

The overall data preparation process [39] is briefly described in figure 4.

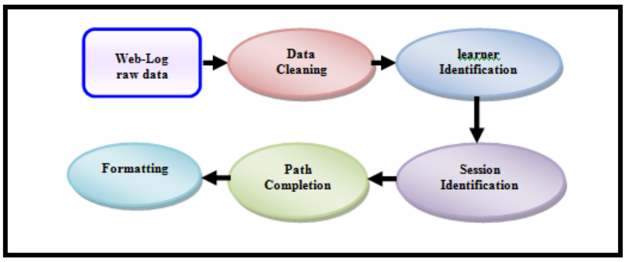

Figure 4: Data preparation process for web log

Data Cleaning: to remove accesses to irrelevant items (such as button images), accesses by Web crawlers (i.e. non-human accesses), and failed requests.

Learner Identification: Because web logs are recorded in a sequential manner as they arrive, therefore, records for a specific learner are not necessary recorded in consecutive order rather they could be separated by records from other learners.

Session Identification: To divide pages accessed by each learner into individual sessions. A session is a sequence of pages visited by a learner. We also call it as a usage sequence.

Path Completion: To determine if there are important accesses which are not recorded in the access log due to caching on several levels.

Formatting: Format the data to be readable by data mining systems.

Once web logs are preprocessed, useful web usage patterns may be generated by applying data mining techniques.

3.1.2 Document Representation

The data from Web logs, in its raw form, is not suitable for the application of usage mining algorithms. The data needs to be cleaned and preprocessed. To perform log data analysis the data pre-processing process must be accomplished. The data pre-processing is the process of cleaning and transforming raw data sets into a form suitable for web mining. The task of the data pre-processing module is therefore to obtain usable datasets from raw web log files, which, in most cases, contain a considerable amount of incomplete and irrelevant information [14].

The Vector Space Model [15, 16, 17] is adapted in the proposed approach to achieve effective representations of documents. Each document is identified by n-dimensional feature vector where each dimension corresponds to a distinct term. Each term in a given document vector has an associated weight. The weight is a function of the term frequency, collection frequency and normalization factors. Different weighting approaches may be applied by varying this function. Hence, a document j is represented by the document vector d_j:

$d_j = (w_{1j}, w_{2j}, \ldots, w_{nj})$ Where, w_{kj} is the weight of the kth term in the document j.

The term frequency reflects the importance of term k within a particular document j. The weighting factor may be global or local. The global weighting factor takes into account the importance of a term k within the entire collection of documents, whereas a local weighting factor considers the given document only. Document keywords were extracted by using a term-frequency-inverse-document-frequency (tf-idf) calculation [16; 17], which is a well-established technique in information retrieval. The weight of term k in document j is represented as:

$$w_{kj} = tf_{kj} \times (\log_2^{n} - \log_2^{df_k} + 1)$$

Where: tf_{kj} is the term k frequency in document j, df_k is number of documents in which term k occurs, n = total number of documents in collection.

The main purpose of this step [14] is to extract interested items in the web page, then get term frequency that reflects the importance of term, finally get the weight of terms in the selected page. The output of this step is the weight of terms in selected page that can be used to build learner interest profile.

3.1.3 Domain Concept Filtering

This process [14, 18] discovers concepts which represent the learner's interests. These concepts and items are compared to the domain ontology to check the relevant items to the learner profile. The most relevant ones update the learner profile. The items relevance is based on ontology-based semantic similarity where browsed items by a learner on the web are compared to the items from a domain ontology and learner profile. The importance is combined with the semantic similarity to obtain a level of relevance. The page items are processed to identify domain-related words to be added to the learner profile. A bag of browsed items is obtained via a simple word indexing of the page visited by the learner. The irrelevant words are filtered out using the list of concepts extracted from domain ontology. Once domain-related items are identified, their relevance is evaluated to learner's interests. The selected method was used in [11, 19] to compute semantic similarity function (S) based on a domain ontology. The similarity is estimated for each pair of items where one item is taken from a learner profile, while the other one from a set of browsed items. The functions S_w is the similarity between synonym sets, S_u is the similarity between features, and S_n is the similarity between semantic neighborhoods between entity classes of ontology p and b of ontology q, and W_w,W_u and W_n are the respective weights of the similarity of each specification component.

$$S(a^p, b^q) = W_w \times S_w(a^p, b^q) + W_u \times S_u(a^p, b^q) + W_n \times S_n(a^p, b^q) \quad \text{For } W_w;\ W_u;\ W_n \geq 0:$$

Weights assigned to S_w, S_u, and S_n depends on the characteristics of the ontologies.

The similarity measures are defined in terms of a matching process [11, 19]:

$$S(a, b) = \frac{|A \cap B|}{|A \cap B| + \alpha(a,b)|A/B| + (1-\alpha(a,b))|B/A|}$$

where A and B are description sets of classes a and b, i.e., synonym sets, sets of distinguishing features and a set of classes in semantic neighborhood; (A∩B) and (A/B) represent intersection and difference respectively, || is the cardinality of a set; and α is a function that defines relative importance of non-common characteristics. A set of browsed items that are similar to items from the learner profile is considered as a set of items that can be added to this profile.

3.2 Semantic learner interest representation

To overcome these weaknesses of term-based representations, an ontology-based representation [20, 21, 22] using WordNet [23] will be performed. Moreover, by defining an ontology base, which is a set of independent concepts that covers the whole ontology, an ontology-based representation allows the system to use fixed-size document vectors, consisting of one component per base concept.

In the proposed system, the method based on WordNet [23] is used to improve traditional vector space model. WordNet is ontology of cross-lexical references whose design was inspired by the current theories of human linguistic memory. English names, verbs, adjectives and adverbs are organized in sets of synonyms (synsets), representing the underlying lexical concepts. Sets of synonyms are connected by relations. The basic semantic relation between the words in WordNet is synonymy [24]. Synsets are linked by relations such as specific/generic or hypernym /hyponym (is-a), and meronym/holonym (part-whole). The principal semantic relations supported by WordNet is synonymy: the synset (synonym set), represents a set of words which are interchangeable in a specific context. WordNet [24] consists of over 115,000 concepts (synsets in WordNet) and about 150,000 lexical entries (words in WordNet). This representation requires two more stages: a) the "mapping" of terms into concepts and the choice of the "merging" strategy, and b) the application of a disambiguation strategy.

The purpose of this step is to identify WordNet concepts that correspond to document words [25]. Concept identification is based on the overlap of the local context of the analyzed word with every corresponding WordNet entry. The entry which maximizes the overlap is selected as a possible sense of the analyzed word. The concept identification architecture for the terms in the initial learner model is given in figure 5.

WordNet categories [26] are used to map all the stemmed words in all documents into their lexical categories. For example, the word "dog" and "cat" both belong to the same category "noun.animal". Some words also has multiple categories like word "Washington" has 3 categories (noun.location, noun.group, noun.person) because it can be the name of the American president, the city place, or a group in the concept of capital. Some word disambiguation techniques are used to remove the resulting noise added by multiple categories mapping which are: disambiguation by context and concept map.

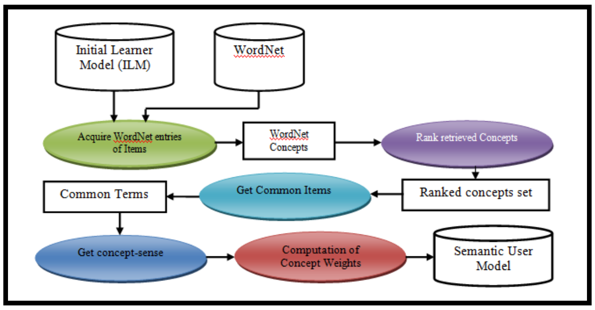

Figure 5: Semantic Learner Model using Concept Mapping

3.2.1 Concept Weight Computation

The concepts in documents are identified as a set of terms that have identified or synonym relationships, i.e., synsets in the Wordnet ontology. Then, the concept frequencies Cf_c are calculated based on term frequency tf_{tm} as follows:

$$Cf_c = \sum_{t_m \in r(c)} tf_{tm};$$

where r(c) is the set of different terms that belongs to concept C . Note that WordNet returns an ordered list of synsets based on a term. The ordering is supposed to reflect how common it is that the term is related to the concept in standard English language. More common term meanings are listed before less common ones. The authors in [20, 21] have showed that using the first synset as the identified concept for a term can improve the clustering performance more than that of using all the synsets to calculate concept frequencies.

Hypernyms of concepts can represent such concepts up to a certain level of generality. The concept frequencies are updated as follows:

$hf_c = \sum_{b \in H(c,r)} Cf_b$;

where $H(c, r)$ is the set of concepts C_H , which are all the concepts within r levels of hypernym concepts of c.

In WordNet, it is obtained by gathering all the synsets that are hypernym concepts of synset c within r levels. In particular, $H(c, \infty)$ returns all the hypernym concepts of c and $H(c, 0)$ returns just c.

The weight of each concept c in document d is computed as follows:

$wh_c = hf_c \times idf_c$;

idf_c is the inverted document frequency of concept c by counting how many documents in which concept c appears as the weight of each term t in the document d.

3.3 Learning style 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 [27].

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 2 [28, 29].

Table 2. 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 [30, 31]. Example of the actions that can enable to acquire learning styles based on Felder-Silverman model (FSLSM) is found in table 3.

Table 3. 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 [32], are considered as the number of rules to describe learner learning style by recording the learner behavior in the system as found in figure 6.

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 6: 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 3 and figure 6.

3.4 Domain Ontology

The main reason for ontology [33] is to enable communication between computer systems in a way that is independent of the individual system technologies, information architectures and application domain. 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 the learning content and the ontology that have been 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.

The knowledge engineering approach was proposed in [34] to build domain ontology. Figure 7 shows main steps of the ontology development process.

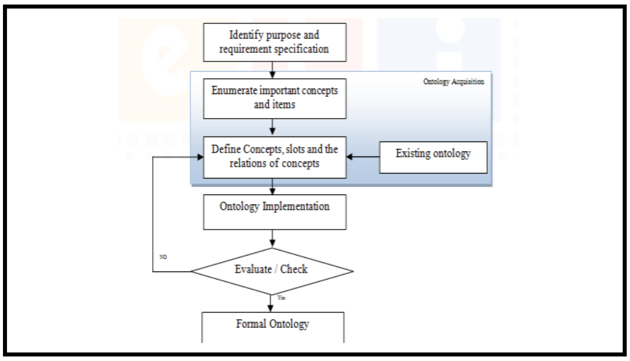

Figure 7: Main steps of the ontology development process

The ontology editor protégée [35, 36] is used to build the domain ontology in the proposed approach. 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 8 shows part of the implemented domain ontology.

Figure 8: Part of domain ontology

4. SUGGESTIONS AND RECOMMENDATIONS

The user profiles can maintain sophisticated representations of personal interest profiles. These representations can be utilized for effective information retrieval. Fuzzy clustering allows an entity to belong to more than one cluster with different degrees of accuracy, while hard clustering assigns each entity exactly to one of the clusters. Thus, fuzzy clustering is suitable in constructing the learner profiles representations such as (learner ontology). Such representation of learner profiles is useful because some information is not forced to fully belong to any one of the user profiles. Fuzzy clustering methods may allow some information to belong to several learner profiles simultaneously with different degrees of accuracy.

The proposed approach depends on using semantic web to extract the learner model. Fuzzy technique is used to cluster the extracted data of learner model to classifying the learners for their interests. Classifying the interests of learners enables learning systems to handle learner as groups to recommend them what they must teach corresponding to their interests in the learner profile clusters.

Using the clustering of learner profiles in e-learning system is useful, so it is recommended to represent the cluster of profiles on learner ontology to express sophisticated user profiles in order that a user may own several interests. A user profile may correspond to the several ontologies. Ontology-based learner profiles typically maintain sophisticated representations of personal interest profiles. These representations can be utilized for effective information retrieval in the e-learning systems.

5. CONCLUSION

The adaptive e-learning system provides support to the learner according to the individual characteristic. It can provide a learner view adapt to learner personalization characteristic, which not only includes personalized resources, but also includes the personalized learning process and strategy. So the learner model should be established 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.

This work presented a technical solution to an approach and methodology to enhance acquiring learner model and representation of the learner profile based on WordNet.

In this work, the most interesting information to the learner matched with the learning style is presented. To do so, we have used the Felder-Silverman Learning Style Model along with the IEEE LOM standard, a combination that, extending former works, in different fields of learning, and consistently reflecting the intrinsic style of the learners.

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