A Framework of Semantic Recommender System for e-Learning

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Abstract: With the rapid increasing of learning objects (LOs) in a variety of media formats, it becomes quite difficult and complicated task for learners to find suitable LOs based on their needs and preferences. To support personalization, recommender systems can be used to assist learners in finding the appropriate LOs which will be needed for their learning. In this paper, we propose a framework of a semantic recommender system for e-learning in which it will assist learners to find and select the relevant LOs to their field of interest. The proposed framework utilizes the intra and extra semantic relationships between LOs and the learner's needs to provide personalized recommendations for learners. The semantic recommendation algorithm is based on the extension of the query keywords by using the semantic relations, concepts and reasoning means in the domain ontology. The proposed system can be used to reduce the time and effort involved in finding suitable LOs, and thus, improves the quality of learning.

Key words: E-learning, learning object, personalization, recommender system, semantic web, semantic indexing system, ontology modeling, semantic query processing.

1. Introduction

With the rapid growth of Web-based learning applications, e-learning is becoming more and more popular than the traditional educational approaches. Learning management systems (LMSs) are typically employed in large-scale educational institutions to facilitate the delivery and organization of e-learning [1]. LMS can be defined as "the infrastructure that delivers and manages instructional content, identifies and assesses individual and organizational learning or training goals, tracks the progress towards meeting those goals, and collects and presents data for supervising the learning process of an organization as a whole" [2].

In general, courses in LMSs consist of LOs. LO can be defined as a digital and reusable piece of content used to achieve a learning objective. LO can be a text document, an audio file, a video, a picture, or a complete website [3]. Commonly, LMSs are considered as one-size-fits-all systems as they deliver the same kind of course structure and LOs to each learner [1], [4]. However, each learner has different characteristics such as levels of expertise, learning styles, prior knowledge, cognitive abilities and interests, and therefore, a one-size-fits-all systems do not support most learners.

Personalization is a promising way to deal with this problem by supporting each learner independently based on his/her characteristics. Personalization in LMSs occurs when such systems uniquely address a learner's needs and characteristics. This will help in improving the learner's satisfaction and in overall the quality of learning. To support personalization, recommender systems can be employed to overcome current limitations of LMSs in providing personalization through recommending suitable LOs to learners based on their individual needs and characteristics [1], [5].

The main goal of recommender systems is to assist users to deal with the information overload problem by providing personalized recommendations, content and services [6], [7]. Recommender systems are increasingly being adopted in E-commerce for recommending books, music, movies, TV shows or different types of items [8]. Such successful implementation of recommender systems in the e-commerce domain has encouraged researchers to explore similar benefits in the e-learning domain since the implementation of recommender systems in e-learning has high potential for achieving advanced personalization [1], [5], [9]-[11].

The semantic web is realized by adding semantics to the web in which it gives information a well-defined semantic meaning, so it makes it possible to facilitate information representing, interpreting, searching, sharing and reusing. Using semantic web technologies in the e-learning domain aims to improve the process of searching and finding LOs. In addition, it has been proven that the use of semantic web technologies in recommender systems can effectively enhance the quality of recommendations and provide explanations about why the recommendation list contains such particular items [12]-[16].

To this end, this paper presents a novel framework of a semantic recommender system for e-learning in which it will assist learners to find and select the relevant LOs to their field of interest. The proposed framework utilizes the intra and extra semantic relationships between LOs and the learner's needs to provide personalized recommendations. The semantic recommendation algorithm is based on the extension of the query keywords by using the semantic relations, concepts and reasoning means in the domain ontology. The rest of this paper is organized as follows: In Section 2, a brief overview of the research background and related works is presented. Section 3 shows the proposed framework with the semantic recommendation algorithm. Finally, conclusions and directions for future study are illustrated in Section 4.

2. Background and Literature Review

2.1. E-Learning

According to Tavangarian *et al*. [17], e-learning can be defined as "all forms of electronic supported learning and teaching, which are procedural in character and aim to effect the construction of knowledge with reference to individual experience, practice and knowledge of the learner. Information and communication systems, whether networked or not, serve as specific media to implement the learning process". E-learning has broad synonymous such as distance learning, technology-enhanced learning (TEL), computer-based training (CBT), internet-based training (IBT), online education, virtual education, and digital education. E-Learning is an effective tool for the learning process and it gives opportunity for learners to learn anywhere and anytime without restricting them to any physical boundaries. E-Learning is classified into formal and informal learning [18].

Formal learning is a highly structured planned learning that obtained from activities within a structured learning setting. Formal learning includes learning offers from universities or schools, and it is delivered by trained teachers in a systematic planned mode. It is a push activity in which teacher pushes whatever information he wants to the learners. Informal learning is referred to as learning by experience in which learning can be obtained through daily life activities related to work, family or leisure. In informal learning, learners make their own choices both about what they want to learn and what techniques and technologies they will use to support their learning process. Recently, it is estimated that 20% of learner knowledge is obtained throughout formal learning and 80% is obtained throughout informal learning [9], [18].

2.2. Recommender Systems

Recommender systems are information filtering systems that assist users in finding contents, products or services (such as web sites, books, digital products, movies, song, travel destinations and e-learning material) by implicitly or explicitly collecting and analyzing preferences from other users [8], [19]. Recently, recommender systems have been used in diverse areas and their implementations in the Internet have been increased [19]. In general, recommender systems are classified into collaborative filtering (CF), content-based filtering (CB), and hybrid filtering.

CF generates recommendations for each user based on ratings provided by most similar users. The k Nearest Neighbors (kNN) algorithm is the most widely used technique for CF. The kNN, first, determines k neighbors that are the most similar users for an active user a, then, it produces predictions based on an aggregation approach with neighborhood ratings in items not rated by the active user a, and finally, it select the top-N recommended items for the active user a [19].

CB generates recommendations based on an active user selections made in the past (e.g., in a movie recommender system, if the user viewed and liked some action movies in the past, the recommender system will most probably recommend a recent action movie that the user has not viewed yet). CB works by using items' contents in which specific contents like text and images can be analyzed to measure the similarity. Similarity is computed between potential items to be recommended with items that the active user has visited, viewed, bought and ranked positively. The most similar items are then recommended for the active user [19].

Hybrid filtering based on combining two or more filtering techniques to utilize merits of each one of these techniques and achieve high performance. Most common hybrid approaches are the integration of CF with CB and CF with demographic filtering techniques [19].

2.3. E-Learning Recommender Systems

The motivation of developing e-learning recommender systems is the information overload problem that is exist in the e-learning domain [5]. When developing recommender systems in the e-learning domain, two perspectives can be considered: 1) a top-down approach appropriate for formal e-learning, where the domain professionals maintain the structure, learning materials and learning plans; and 2) a bottom-up approach appropriate for non-formal e-learning, where learners interact with information sources shared in the network [5], [20]. There are a number of essential differences between general-purpose recommender systems and e-learning recommender systems [11]:

- The goal of e-learning recommender systems is to assist the learner to find appropriate resources and learning activities for a better achievement of the learning goal and the development of competences in a short time [9].
- The e-learning recommender systems are generally employed to: advice materials that the instructor can use for improving the course [21]; aid the instructor to identify common misconceptions and to recognize students who present difficulties [22]; assist students in selecting their courses [23]; and help with peer recommendations [24].
- The e-learning recommender systems have a pedagogical context in which context factors such as pre and post requisites, instructional design, timeframe, pedagogical scenarios, and social networks should be considered [25]-[27].
- The e-learning recommender systems are greatly influenced by pedagogical factors such as the learning history, processes, strategies, knowledge, preferences, styles, patterns, misconceptions, weaknesses, activities, feedback, progress, and expertise [9], [26], [28].
- According to the pedagogical context in e-learning recommender systems, users can be categorized according to the role of the user (student, teacher, courseware designer) or the knowledge level (beginner, intermediate, advanced), or learning styles [9], [21].

Next, some particular works on the application of recommender systems in the e-learning domain are described. Most of the works are focused on the building of recommender systems for recommending LOs, learning courses, learning paths/activities, and learning goals. Al-Khalifa [3] introduced an Arabic LO repository with built-in recommender system (called Marifah), devoted for hosting Arabic LOs and serving the needs of the Arabic educational community. The repository has incorporated advanced features that cannot be satisfied using well-know search engines. The built-in recommender system will assist members of Marifah in selecting what LOs are appropriate for their interest. Hsu [29] proposed an ESL (English as a Second Language) recommender teaching and learning system that is able of generating, for ESL instructors, practical information about problems and questions of grammar which students come across. The proposed system supports teachers to recognize students' specific difficulties and weaknesses in learning; also it helps the student to realize his/her weak points in learning and offers enhancement recommendations. Masters, Madhyastha and Shakouri [30] developed a web-based hybrid recommender system (called ExplaNet). ExplaNet recommends a little subset of explanations to every student based on his/her characteristics and preferences. The hybrid recommendation algorithm effectively predicted, in two classroom trials, preferences for student explanations. Three classroom evaluations of ExplaNet demonstrated that students who used ExplaNet have improved comprehension and retention of difficult concepts. Romero *et al*. [22] proposed an advanced architecture for a personalized recommender system that utilizes web mining techniques for recommending a student with the most appropriate links/Web pages within an adaptable educational hypermedia system (AHA! system) to visit next. The authors developed a specific Web mining tool and integrated a recommender engine into the AHA! system to assist the instructor in accomplishing the entire Web mining process. Garcia *et al*. [21] proposed a personalized recommender system aims to find, share and recommend the most appropriate modifications to enhance the effectiveness of the course. The authors used association rule mining to find out interesting information through students' usage data in the form of IF-THEN recommendation rules. Also, they have used a collaborative recommender system to share and score the recommendation rules obtained by teachers with similar profiles together with other experts in education. Yang and Wu [28] proposed an attributes-based ant colony recommender system based on an ant colony optimization algorithm to help learners in finding adaptive LOs more effectively. Yang *et al*. [27] designed and implemented a curriculum resources personalized recommendation algorithm based on the semantic web technology as a personalized service in teaching system. Shishehchi, Banihashem and Zin [13] proposed a semantic recommender system for e-learning in which learners will be able to discover and choose the correct learning materials appropriate to their field of interest. The proposed system includes ontology and web ontology language (OWL) rules. Abramowicz, Małyszko and Węckowski [31] introduced a recommendation method that can enhance users' choices concerning their long–term learning goals. The proposed method works by analyzing time–variable user models to provide predictions that can expose potential changes in the fields of users' interests. Such predictions can be supportive in recommending learning goals. Santos and Boticario [5] identified the need for developing semantic educational recommender systems in order to extend existing LMSs with adaptive navigation support. The authors presented three requirements to be considered when developing semantic educational recommender systems. The requirements are: a recommendation model; an open standards-based service-oriented architecture; and a usable and accessible graphical user interface to deliver the recommendations. Leino [32] discussed design issues associated to employing recommenders in learning environments and how student perceptions of using rating and commenting can affect students in winnowing additional reading materials in a university course website. Positive student perceptions show that recommenders can improve the experience in virtual learning community. The rating feature was perceived to influence the selecting behavior, whereas commenting, was perceived to be less influential. Wang and Yang [33] examined the impact of collaborative filtering recommenders on college students' use of an online forum for English learning. The findings were as follows: 1) Students in the forum recommender group read online posts more frequently than the control group, and 2) students in the forum recommender group do better than their counterparts in their productive language test scores. Kumaran and Sankar [34] proposed a recommendation system using semantic net for e-learning. The proposed system helps the learners to search course content and get more personalized and contextual recommendation. Imran *et al*. [1] developed a framework to incorporate a recommender system approach into LMS. The developed framework can provide personalization by recommending LOs to learners based on their existing situation and learners with similar profiles who have successful learning experiences in a similar situation. The proposed framework can assist learners in reducing the learning time, enhancing the learning performance, and increasing the satisfaction level. Chen *et al*. [35] proposed a hybrid recommender system to recommend valuable learning items to assist users in their learning processes. Experiments performed on a centralized and a P2P online learning systems demonstrated a good performance of the system.

2.4. Benefits of E-Learning Recommender Systems

The benefits of introducing e-learning recommender systems go further than achievements of learning goals. Based on the literature, advantages of e-learning recommender systems can be to classified into three main points of view: (1) students' performance, (2) social learning enhancement, and (3) increased motivation [11].

2.4.1. Student performance

From a student's viewpoint, the main advantages of e-learning recommender systems are:

- finding quality resources and to achieve the learning goal [31].
- detecting students with problems and weakness [29].
- identifying student's misconceptions [30].
- helping students to navigate in knowledge hyperspace in order to get a quality information feedback [36].
- monitoring students and adjusting the course content [37].
- helping promote personalized learning [28].

2.4.2. Social learning enhancement

In an educational context, the enclosure of social interaction and social navigation in collaborative e-learning recommender systems [38] can:

- facilitate the finding of like-minded student, thus, promoting student collaboration [39].
- propagate the ''word-of-mouth'' from trusted and high quality resources [40].
- improve virtual community experiences [32].

2.4.3. Increased motivation

By keeping students interested in the learning experience, e-learning recommender systems :

- have a positive feedback on student's motivation [39].
- improve the interaction in the learning environment [33].
- improve the atmosphere of the learning environment [41].

2.5. Semantic Web and Ontologies

As defined by Tim Berners-Lee (creator of W3C[1] standards): "The Semantic Web is what we will get if we perform the same globalization process to Knowledge Representation that the Web initially did to Hypertext" [14]. Semantic Web aims to improve our relationship with the Web by just making the information contained therein "understandable" by the machine as well as by human. Therefore, the semantic Web is related to the current Web, enhanced by semantic information. Current research on the Semantic Web is based on knowledge representation, ontologies, annotations and reasoning model, and also other areas such as databases. The idea of the semantic Web is not to make sure that computers can understand human language or operating in natural language, it is not artificial intelligence allowing the Web to think, but simply to group the information in a useful way, as a huge database, where everything is written in a structured manner. The semantic Web is an exchange space, which is still under construction with various promising features such as: it provides sufficient information on resources; and it describes content in meaningful and formal ways using ontologies to be interpreted by humans as well as machines [14], [42].

In Philosophy, ontology refers to the science describing the different kinds of entities in the world, and the relationships between these entities. In the Web domain, ontology defines the terms used to describe and represent an expertise area. The ontology is represented by schemas and knowledge to describe a domain by structured ways in a readable format by computers. Ontology allows establishing the interoperability and

[1] W3C : world wide web consortium www.w3c.org

sharing between different systems. We can imagine it as a database with a very large network of relationships between concepts. The ontology can provide us with several advantages such as [42], [43]:

- The enhancement of the web functioning by finding pages relating to a specific concept instead of those found using ambiguous keywords.
- Sharing the common knowledge of the information between people or software agents in a specific area.
- Enable the reuse of the field knowledge on reusing its ontology for different fields.
- Facilitate the field change suppositions in case our relating knowledge has to be changed.

The ontology should be constructed based on the following fundamental characteristics:

- It should precisely define the terms and their meanings so that the ontology can be used as a reference and provides a vocabulary that can be shared by communities in different areas.
- It should be based on rigorous and formal principles in which each concept, used for resources semantic markup, should has a shared signification and can be reused for different applications.
- It should be multi-use and has to be generic enough in order to be reusable for different uses, and different forms.

3. The Proposed Semantic Recommender System Framework

As shown on Fig. 1, the proposed semantic recommender system framework has three sub-systems: Repository services, Semantic Indexing services (SIS), and Users services.

3.1. Repository Services

The objective of using LOs repository system is to provide the e-learning system's users (Researcher, Teacher, Learner, ...etc) with the capability to store and maintain the LOs in more efficient way than that offered by a simple database.

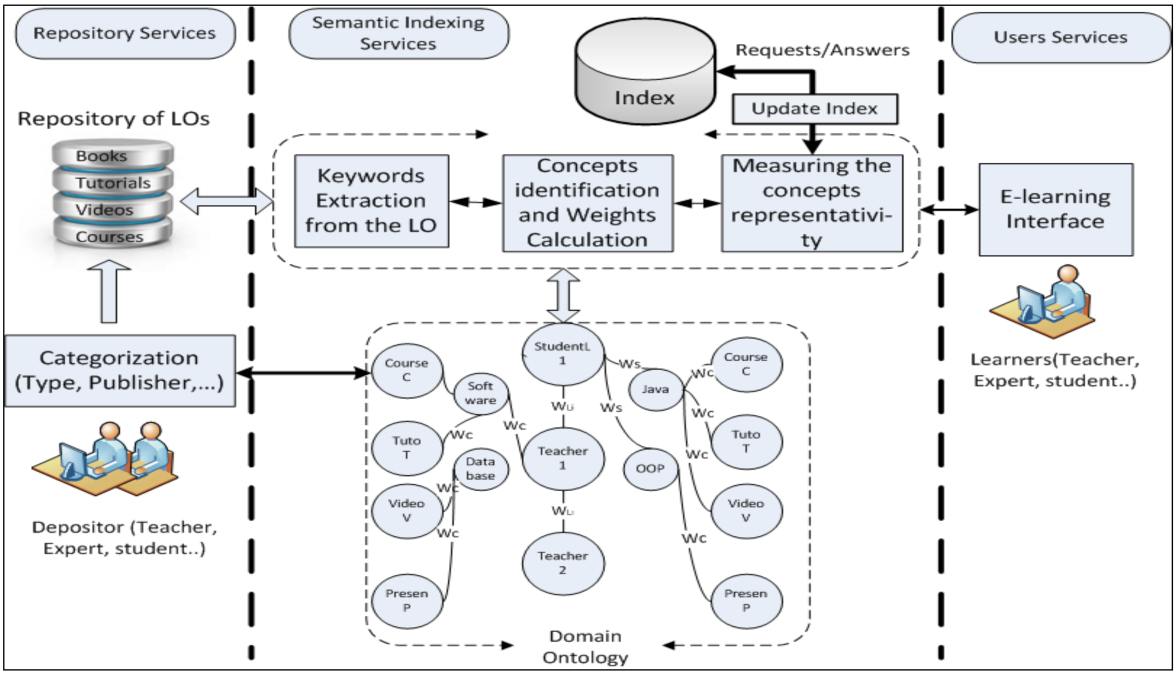

Fig. 1. Semantic recommender system framework.

The repository system is considered as a pre-categorization stage of the LOs. Because a user is best positioned to categorize its own LOs, the repository system contains an interface that allows the user to be involved in the categorization process. This will enforce the LOs to be properly categorized in the repository system. The interface allows the addition, deletion, modification, evaluation and retrieval of LOs.

In addition, there has been an increasing interest in making LOs more readily discoverable by using metadata standards to describe them. Metadata standards generally used to describe information resources, in order to facilitate their categorization, storage, search and retrieval [44], [45]. Consequently, in reference to the Dublin Core Metadata Element Set (DCMI, http://dublincore.org/), each LO is defined via the attributes: Title, Author, Depositor, Publisher, Date, Type, Topics, Description, Language, and Keywords. Most of values of these attributes are provided from the ontology (see Fig. 2). If an attribute value does not exist, the depositor can add it manually to the domain ontology.

3.2. Semantic Indexing Services

The main aim of Semantic Indexing services (SIS) is to classify LOs according to the concepts that each of LOs represent. A concept is represented by a set of instances or objects interconnected by common relationships. The SIS consists of three processes:

3.2.1. Initial indexing process

The initial indexing process, firstly, extracts from a LO the keywords that are most representative to the object and store them in an index. The index contains the ID of the LO with its representative weighted keywords. Then, it traverses the index to identify the most relevant keywords related to the user's query. This process is based on the presence or absence of a keyword in the LO, without exploiting the semantic level contained in the LO. The use of a domain ontology will allow the exploitation of the semantic contents of LOs to better index them and increase the precision and recall of the LO retrieval.

3.2.2. Domain ontology construction process

The literature contains several thesauruses, corpus, and ontologies in the e-learning domain, but none of them satisfy our needs in this study. For this reason we choose to construct a new domain ontology, that can be applied to different domains or sub-domains (IT, MIS, Law, Medicine, ...etc) in our system.

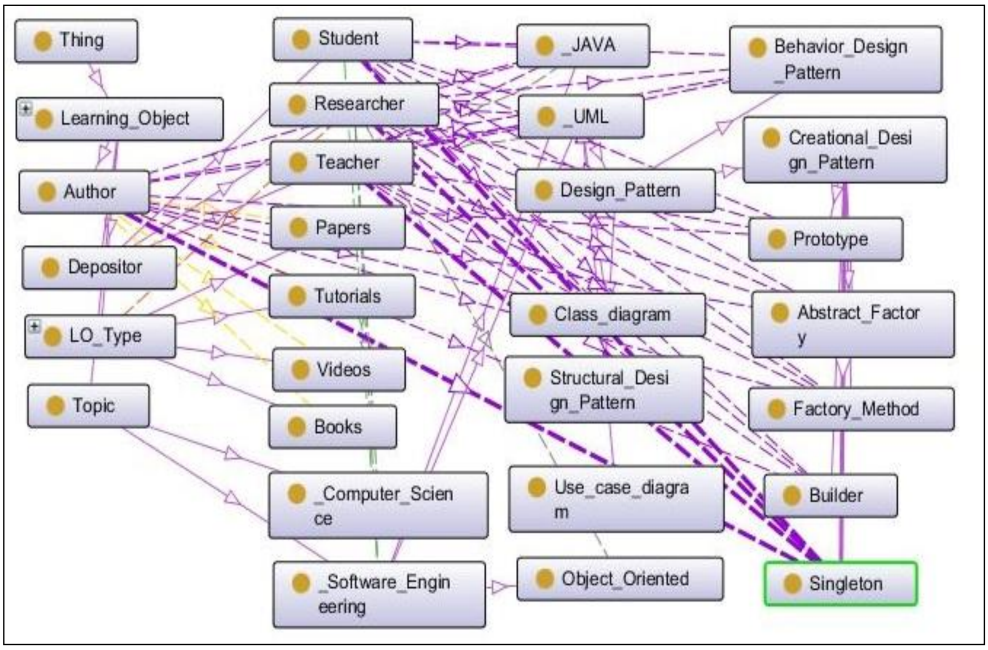

Fig. 2. An example of the proposed domain ontology. It represents the concept hierarchy of the e-learning system. This hierarchy represents the "part of" relationship.

Fig. 2 shows a part of the constructed e-learning domain ontology. It represents the entities hierarchy of the e-learning system, this hierarchy uses several relationships as “is part of”, “is a”, “is author of”, “is publisher of”, ...etc. We propose a dozen relationships between concepts to cover up most of the semantics that are supported by the concepts. New relationships can be added as needed. The OWL (Ontology Web Language) [46] and the ontology editor Protégé-2000 [47], [48] are used to implement our ontology. Protégé-2000 is used for several reasons:

- It is a free and open source editor.
- It can, via "plug ins", import and export ontologies in different implementation languages for ontology-schema such as RDF, OWL, DAML, OIL ... etc.
- Ontologies can be edited interactively within Protégé and accessed through a graphical user interface and Java API.
- Ontology editor for defining classes of concepts.
- Automated generation of tools for building knowledge bases that define instances of concepts.
- Knowledge-visualization systems.
- Lots of user-contributed "plug ins" and the availability of various "plug ins": JSave, Protégé Web Browser, XML Schema, Docgen, PROMT, OWL-S Editor.
- Ability to archive ontologies and knowledge bases in various formats.

To construct our ontology, we have adopted the seven-steps approach that is proposed by Noy and McGuinness [43] as follows:

Step 1. The domain definition and the domain scope

- The covered domain by our ontology is the e-learning domain.
- The ontology will be used by learners, researchers, and domain experts via an interface.
- The ontology maintenance must be ensured by specified domain experts.

Step 2. Considering the possibility of reusing the existing ontologies

In order to enrich our ontology, we can extract concepts from other ontologies according to our needs.

Step 3. Enumerate the most important keywords of Ontology

Due to the high number of keywords to be treated in our ontology, we cannot list them all in this paper. Furthermore, the keywords list will never be exhaustive, as new concepts will constantly be added to the ontology.

Step 4. Define classes and their hierarchy

In this step, we use the ontology model that we have developed to classify the collected keywords from the previous steps according to the following attributes: Title, Author, Depositor, Publisher, Date, Type, Topics, Description, Language and Keywords. This classification represents the first level of ontology construction. For each class of the first level, we use the top-down approach in order to define the keywords hierarchy of the class using the defined relationships network.

Step 5- Step 6. Define the classes' properties and their facets

The classes' properties and their facets are defined in the designed ontology model level. Each concept in the ontology gets the model class properties which it belongs to.

Step 7. Creating the instances

Our ontology concepts represent classes related to the e-learning domain. The instance (Object) is an instantiation of class, and can be considered as a keyword that belongs to a concept (Class). Example: the instance "Unified Modeling Language" belongs to the concept (Class) "Object Oriented paradigm". However, deciding whether a keyword is a concept of an instance depends on the application or the domain of the ontology.

3.2.3. Semantic indexing based on the domain ontology

Fig. 3 illustrates the indexing process of LOs using the e-learning ontology to improve the quality of indexing on the repository. The indexing process is a recursive process in which it is repeated for each LO added to the repository. The indexing process constitutes of four major phases:

Phase 1. keywords extraction from the LO.

This phase has two steps. Step 1: each LO has a number of attributes (Title, Publisher, Topics, Description,..etc) given by the depositor. A linguistic processing approach is applied on these attributes to extract a set of potential representative keywords of the LO. Step 2: different methods of automatic content extraction (ACE) [49] are applied on the LO contents based on its type (text, audio, image or video). The raw information included in the LO is processed to extract the keywords that represent at best the LO contents. The ACE methods provide a more representative and comprehensive keywords than that given by the depositor as they process the LO contents in neutral way. The union of these two steps enhances the classification and indexation of LOs.

Phase 2. Concepts identification.

In this phase, for each keyword, we explore the relationship network implemented in the domain ontology to find the closest concept to that keyword. For example, in case we have a concept C_j that is not existed in the LO but one of its instances (known as keywords) is presented in the LO, we consider that the concept C_j itself is also a representative concept of the LO. Another example, in case we have a concept C_j that is not existed in the LO but one of its related concepts (known as Cs) is presented as a keyword in the LO, we consider that the concept C_j is also a representative concept of the LO. The keywords that don't exist in the ontology are added to the enrichment ontology list (see Section 3.23).

Phase 3. Measuring the concepts representativity.

This phase explores the intra and extra semantic relationships between the existing concepts in the LO. Specifically, we explore the fact that the concepts appearance in the same LO has its benefits in enhancing the semantic representativity of the LO. This phase has two steps.

Step 1. Calculating intra semantic relationship between each concepts and its keywords (instances): for each concept, we calculate its weight in representing the LO according to the following factors: keyword location in the LO (title, LO contents), keyword appearance frequency in the LO, type of relationship between the keyword and the concept (is synonym of, is part of, has a ... etc), and the depositor rate (see Section 3.21).

Step 2. Calculating extra semantic relationship between each pair of concepts: the similarity between each concepts pair (Sim(C_j, C_k)) is calculated based on the shortest path (i.e, the number of arcs) between the two concepts in the ontology. Then, we calculate the sum of the similarities (SumSim) for each concept in the LO, as follows:

$$SumSim(C_j) = \sum_{k=2}^{m} Sim(C_j, C_k) \tag{1}$$

where, SumSim (C_j) is the sum of similarities between the concepts C_j and the other concepts that represent the LO. Sim(C_j, C_k) is the similarity between the concepts C_j and C_k. m is the number of concepts in the LO. The result calculated by (1) is then normalized by dividing it by the greater value found, in order to get a result between 0 and 1. The normalized representativity of concept C_j is calculated as follows:

$$Representativity(C_j) = \frac{SumSim(C_j)}{\max_{k \in [1,m]} SumSim(C_k)} \tag{2}$$

The concepts which have the highest representativity are selected to be the most representative concepts of the LO. Otherwise, the concepts which have the lowest representativity (semantically isolated) are ignored.

Phase 4. Index update.

In this phase, the most representative concepts of each LO are added to the index with their representativity values.

3.3. Users Services

The e-learning system interface concerns the interaction with the learners, passing information to and from the learners. Its main components can be listed as follows:

3.3.1. Depositor and learning object ratings

This component proposes a mechanism for rating the depositors and the LOs via the interface.
The calculation of the depositor rate is based on:

- The rate given by the evaluators to the depositor,
- The rate of evaluators themselves who give rate to the depositor,
- The confidence weights calculated by the distance (extracted from the ontology) between the evaluators and the depositors,
- The rates given by evaluators to the LOs which are added by the depositor.
- The calculation of the LO rate is based on:
- The depositor rate (calculated above),
- The rate given by the evaluators,
- The rate of the evaluators themselves who give rate to the LO.

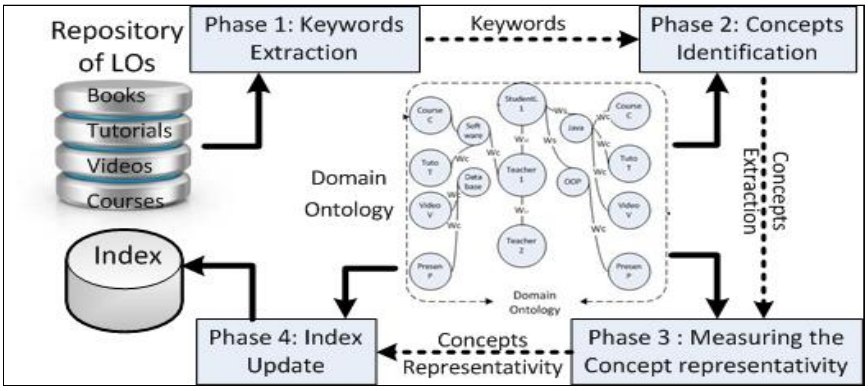

Fig. 3. Illustrate the indexing process using the domain ontology.

3.3.2. Semantic recommendations based on the domain ontology

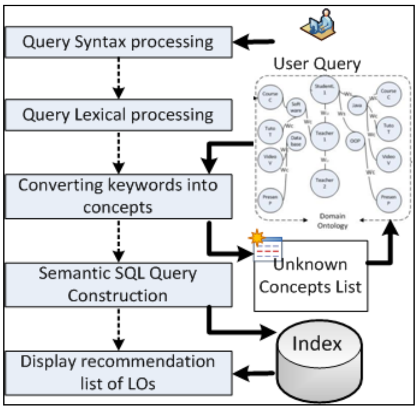

Fig. 4. General scheme of semantic recommendation process based on the domain ontology.

In this component, learners needs will be processed semantically to get proper recommendations of LOs. It consists of five steps as presented in Fig. 4.

Step 1. The learner expresses his need using his own keywords to form a request (query). The query is then analyzed to check the syntax in order to make sure that the query is well formed.

Step 2. The query is undergo in a lexical and lemmatization process, which consists of normalization and stop words removal processes.

Step 3. This is the most important step that distinguishes our recommendation approach from the other conventional search methods. This step converts the keywords (given by Step 2) into existing concepts in the domain ontology. Accordingly, in this step, a semantic query is formed by the extension of the learners keyword query. This step provides two different lists:

- A list that includes the recognized concepts (presented in the domain ontology).
- A list that includes the unrecognized concepts, which will be used to enrich the domain ontology (see Section 3.33).

The search will be done among all the related concepts (concepts recommended by the system) not just among the recognized ones. This allows the retrieving of all the LOs which are semantically related to the keywords used in the query.

In order to help the learner to express his needs, a visualization ontology tool will be implemented in the system interface. This tool will allow the learner to directly cross the domain ontology to select the existed concepts that best forms his/her request.

Step 4. The semantic query will be translated into SQL query which permits the interrogation of the index in order to get a list of recommended LOs for the learner.

Step 5. The recommended list of LOs is ordered and displayed based on their ratings (see Section 3.31).

3.3.3. Ontology enrichment tool

The proposed system provides an ontology enrichment tool in which it enriches the ontology with new concepts from two different sources:

- The list of unknown concepts encountered in LOs during their indexing (see Section 3.23).
- The list of the concepts that are requested by the learner but not included in the domain ontology (see Section 3.32).

4. Conclusion and Future Work

This paper proposes the use of semantic recommender system framework to provide personalized e-learning, in particular, providing recommendations to assist learners in finding and selecting the relevant LOs to their field of interest. This paper presents a semantic recommendation algorithm that utilizes the intra and extra semantic relationships between LOs and the learner's needs to provide recommendations for learners. The semantic recommendation algorithm is based on the extension of the query keywords by using the semantic relations and reasoning means in the domain ontology.

Furthermore, there are two significant implications of the proposed system. First, the proposed system can assist the learners in finding suitable LOs for a successful achievement of the learning process. Second, the proposed system can assist the instructor or the course designer in suggesting materials that can be used for enhancing the course syllabus. Future study will focus on validating the performance and quality of recommendations of the semantic recommendation algorithm, and implementing the proposed framework on a recommender system prototype.

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