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Personalized e-learning recommender system based on a hybrid approach

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Abstract—In recent years, the development of recommendation systems has aroused growing interest in many areas, especially in e-learning. However, the lack of support and personalization in this context leads the learners to lose their motivation to continue in the learning process. To overcome this problem, we focus on adapting learning resources to the needs of learners using a recommender system. Thus, most of the existing studies in this area don't take into account the differences in the characteristics of learners. This problem can be mitigated by incorporating additional learner information into the recommendation process. Additionally, many recommender techniques experience cold start and rating sparsity issues. This article presents our proposed recommendation system in order to provide learners with appropriate learning resources to follow the learning process and maintain their motivation. We propose hybrid recommender system that combines recommendation techniques to solve the problem of retrieving relevant learning resources for learners and that can alleviate both the cold-start and data sparsity problems. Using this hybridization between different techniques is useful in the personalization of the learner's profile. We consider different learner characteristics such as their preferences, their goal, and their level of knowledge, hence resulting in the generation of more accurate recommendations.

Keywords—Recommender system, Personalization, E-learning, Hybrid recommendation techniques

I. INTRODUCTION

The rapid progression of technology has affected many aspects of our lives, especially those related to education. The impact of the COVID-19 pandemic has resulted in the shift of learning from traditional school classrooms to online learning environments [1], [2]. E-learning environments are gaining popularity in higher education, particularly for distance learning. Ideally, they provide free access and open participation to learners around the world via the Internet and other technologies [3].

E-learning offers online courses and learning resources in various categories such as computer science, mathematics, engineering, etc. E-learning environments do not automatically detect the most suitable resources for each learner's real needs such as the type of learning objects (e.g. video, images, text, etc.), the language of teaching, what they want to learn, the need to work with peers or individually, etc. This is the common problem of search ability which corresponds to the difficulty of finding the right resources among a very large number without cognitively overloading the user [4]. In other words, recommendations must be personalized to meet the wide diversity of learners and target the most appropriate resources for the learning domain.

However, the lack of accompaniment and personalization in this context leads learners to lose their motivation and leave the learning process which can reduce their success rate in e-learning systems. Therefore, it is crucial to develop recommendation systems to help learners access the right e-learning resources. In recent years, many efficient and effective recommender techniques have been considered to solve the problem of retrieving relevant learning resources for learners. The various aspects of recommender techniques are discussed below. But not each technique has the capabilities to overcome the problems of cold start, scalability and sparsity.

To overcome these problems, our paper aims to improve the performance of recommender system in e-learning in order for learners to succeed in their learning experiences, by adapting learning resources to learners' needs that change as they progress in their studies, to improve learners' satisfaction and help them achieve their goals effectively in less time and at lower cost.

In order to improve the accuracy of recommendation, we propose a hybrid recommendation technique that generally combines the best features of several recommendation techniques such as content based [5], collaborative filtering [6], knowledge-based, context aware, group recommendation [7], skill-based, ontology-based [8], case based reasoning, fuzzy-based, and many others, to provide higher performance and overcome the disadvantages of each technique. We propose a model that consists of three layers, namely a user interface, a database server and a recommendation engine.

In the following section, we will present a brief review on recommendation techniques relevant to this work, and discusses related work about e-learning recommender systems. Section 3 presents the architecture of our proposed system. Subsequently, we will describe our hybrid recommendation approach step by step in section 4. Then, we will end our article with a conclusion and a presentation of our future research work.

II. RELATED WORK

This section offers a brief overview of the recommendation techniques that are pertinent to this study as well as some related e-learning recommender system research.

A. Recommendation techniques

Recommender systems are useful for recommending relevant items to users. For generating recommendations, several techniques have been proposed and used.

Content-Based: The system learns to recommend items that are similar in content characteristics to those the user liked

in the past. The principle of the content-based recommendation is based on the calculation of the similarity of the characteristics of the items associated with the compared objects [5]. Content based recommenders can be classified into attribute-based technique [9] and case-based reasoning [10]. Case-based reasoning techniques recommend items that have the highest correlation to previous items appreciated by the learner, whereas attribute-based techniques recommend items based on the correspondence of their attributes with the learner profile [11].

Collaborative filtering: This technique recommends to the active user the items that other users with similar preferences liked in the past [12]. Similarity in preference of two users is calculated based on the similarity of users rating history [13]. A rating measures the degree of interest in an item by a user. The calculation of similarity between users is the principle of collaborative filtering

Knowledge-based: This technique recommends items to users based on domain knowledge of how items meet user preferences [14]. In e-learning, knowledge-based technique aggregates knowledge about the learning resources and learners to apply them in the recommendation process [15].

Ontology-based: This technique uses an ontology for knowledge representation [15]. In the context of e-learning domain, ontology is used to model knowledge about the learning resource and learner.

Hybrid recommender systems: This technique combines the characteristics of two or more recommendation techniques e.g. collaborative filtering and content-based filtering systems to benefit from the strengths of each technique and to improve performance [16].

Demographic-based recommender systems: This technique aims to categorize the user based on personal characteristics and give recommendations based on demographic classes such as gender, age, education, etc. [17]. Users with common or similar personal characteristics are likely to have similar item preferences.

Context aware-based recommender systems: This technique provides personalized services by adapting them to the user's specific contextual situation [18]. In E-learning, a learner's contextual information can be their learning style, learning goal, prerequisite, learning progress, available learning time, device, location, etc. [19].

Group recommender system: This technique recommends items to a group of users instead of an individual [20]. It analyses a group of students' behaviors and makes recommendations. Different characteristics of the learners are used to group them together.

Skill-based models observe the similarity of skills between learners and group them according to their abilities. Both skill-based and group-based systems use content-based or collaborative techniques to recommend the learning objects after initial grouping [7], [21].

Social network-based recommender systems: This technique uses information available in social networks to identify user preferences and generate recommendations based on information on user-profiles and relationships between users [22], [23]. Facebook and LinkedIn are examples of social media sites using social network recommendations.

B. E-learning recommender systems

Several recommendation systems have been implemented in e-learning, most of them focus on recommending learning materials and objects. Following are some related e-learning recommendation systems.

In [24], the authors proposed a multi-agent learning object recommendation system based on ontological modeling. In their system, the ontology was used to represent information about learning objects and the profile of the learner according to her/his characteristics. The recommendation used learning style as the main characteristic and applied rules of inference to generate learning objects suitable for learners.

In [25], the authors proposed a knowledge-based recommendation system supported by an ontological modeling approach to help educators design teaching-learning activities.

In [26], the authors proposed a personalized learning object recommendation system that supports learners with appropriate learning object recommendations in the course. Based on a collaborative filtering technique, the system provides learning objects that may be relevant to learners based on their previous experiences as well as learning objects visited by similar learners' profiles.

In [27], the authors proposed a rule-based recommendation system that allows learners to choose from a pool of learning activities with different levels of difficulty. The system provides learners with recommendations on which learning activities are suitable for them, given their previous performance, the performance of neighboring learners who have similar characteristics, and activities that learners initially selected. Since information about the learner's performance is essential to provide the appropriate recommendation, the system cannot provide recommendations for the target learner in the first learning unit.

In [28], the ontology was used in the Learning Object Recommendation (LORecommendNet), which can be utilized to allow machines to interpret and process learning objects in a recommendation system. The learner was mapped to a personalized learning object using the ontology.

Based on the work presented above, we propose to develop a new recommender system in an e-learning context that focuses on learning resources. The choice of recommending personalized resources is due to its importance in satisfying the needs of the learners and respecting their interests, in order to engage them in the learning process.

A review of the literature in this area of study revealed that although many studies on recommending e-learning resources have been conducted using a variety of techniques, a more precise recommendation approach remains to be performed. Many recommender systems depend on one recommendation technique, our system is based on a hybrid knowledge approach that combines several techniques at the same time. The main advantage of hybridizing techniques is to take advantage of each technique's strengths while overcoming the limitations of individual techniques [29]. Therefore, the hybrid approach can mitigate issues like sparsity and cold start issues that limit the performance of recommender systems. Our approach aggregates content-based, collaborative filtering, group-based, context aware-based, demographic-based, ontology-based for domain knowledge representation

of the target learner in the recommendation process. Using this hybridization between these different techniques is useful in the personalization of the learner's profile. We consider different learner characteristics such as their preferences, their goal, and their level of knowledge, hence resulting in generation of more accurate recommendations.

III. E-LEARNING ENVIRONMENT RECOMMENDER SYSTEM ARCHITECTURE

The primary goal of the proposed system is to recommend useful and interesting learning resources to learners based on their preference, their goal, and their level of knowledge in e-learning. The architecture of our proposed system includes 3 main layers namely Learner Interface, Database Server, and Recommendation as shown in Fig. 1.

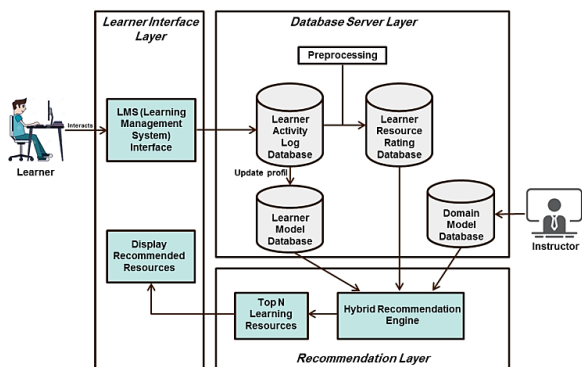


Fig. 1. Recommender system architecture of learning resources in the context of e-learning

A. Learner Interface Layer

It is the e-learning interface with which learners interact. It takes the inputs information like their behavior information, and sends it to the Learner Activity Log Database. It is also used to visualize the proposed personalized resources filtered after the recommendation process. The module Display Recommended Resources presents recommendations to the learner.

B. Database Server Layer

This includes four databases that store: Learner Activity Log, Learner Resource Rating, Learner Model, and Domain Model. It gathers data to be used by the recommendation engine.

Learner Activity Log creates a Learner Model from the learner characteristics and creates a Learner Resource Rating after preprocessing on the data. The primary questions to be addressed are: what the motivation of the learner is, what content they want to learn and how they want to learn. To answer these questions, we need to know specific learner characteristics such as their learning style, goal, and level of knowledge. The initial learner characteristics, such as learning style and goal of learning, have to be collected from the learners through questionnaires. The current level of knowledge of the learner is assessed by carrying out a pre-evaluation in the domain. Learning style will be initialized based on the Felder-Silverman Learning Style Model (FSLSM) [30].

The learner's preference data contain implicit feedback (e.g., viewing, clicking, time spent selecting resources, etc...) and explicit ratings (e.g., like/dislike, scores 1-5, comments)

on learning resources, which will be pre-treated from Learner Activity Log to perform Learner Resource Rating Database

The Learner Model Database represents these various characteristics (learning style, goal, and level of knowledge) of the learners that can be used to generate an individualized learning resources, it is a collection of static and dynamic data about each learner. From an assessment of the learner's knowledge and monitor his or her changing preferences, their profile will be updated.

The Domain Model contains all the knowledge for a particular discipline. Typically, the domain model gives a domain expert's view of domain. The whole course is divided into units or concepts, all consisting on several lessons. A learning unit holds one unit of knowledge and presents different aspects of it with different types of learning object which constitutes multiple external representations such presentations, questions activities, examples, exercises, glossary [31].

C. Recommendation Layer

It is the most important part in the learning process and constitutes the core of our proposed system. The Hybrid Recommendation Engine is the main component that generally combines the best features of several recommendation techniques to provide higher performance, which aims to generate suitable recommendations for a target learner based on learner model and domain model as well as the learner ratings on learning resources. Then, it is necessary to generate the list of the Top N Learning Resources recommendations for the target learner, and display them to the learner. The next section describes the proposed recommendation process step by step.

IV. A HYBRID RECOMMENDATION APPROACH IN E-LEARNING

Recommendation learning resources is fulfilled by following the steps which depicted in Fig. 2. Application of ontology is a key aspect for the success of our personalized recommender system. It can simplify the knowledge structuring by providing a standard based manner for knowledge representation. Ontology has some advantages encouraging us to use it in our knowledge approach. The most important advantage is usability and shareability [32]. Ontology is proposed in this case to describe learner profiles and learning resources. So, it is included in our system to represent learner profile, domain model and learning resources to achieve easier knowledge sharing and reuse.

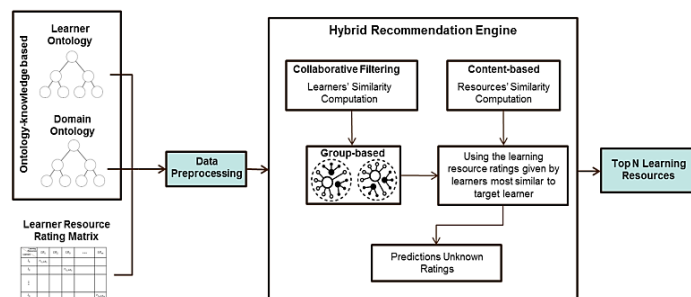


Fig. 2. Hybrid recommendation model for e-learning

Extract the knowledge about the learning resource and learner's knowledge, is the main task in knowledge based recommender system. We will use the ontology to represent all required knowledge.

A. Learner Ontology

In the proposed system, the ontological model tries to combine all the fundamental concepts between the interactive elements to provide a model that contains several parts; learner, knowledge level, personal data, learning style and domain. Learner profile is very important in adaptive e-learning system. Knowledge level identifies the learner knowledge in a specified domain by carrying out a pre-evaluation. Personal data include all the demographic data (name, age, gender, etc.). Knowing what the learner wants to learn (which domain, specialty, prerequisite, interest) through the questionnaire. Learning styles include any of the four dimensions of the FLSM namely visual/verbal, sequential/global, active/reflective, and sensing/intuitive [30] as shown in Table I. To obtain the learner’s learning style, an online questionnaire “Index of Learning Styles Questionnaire” [33] will be administered to the learner during account registration process. Fig. 3 shows knowledge about the learner.

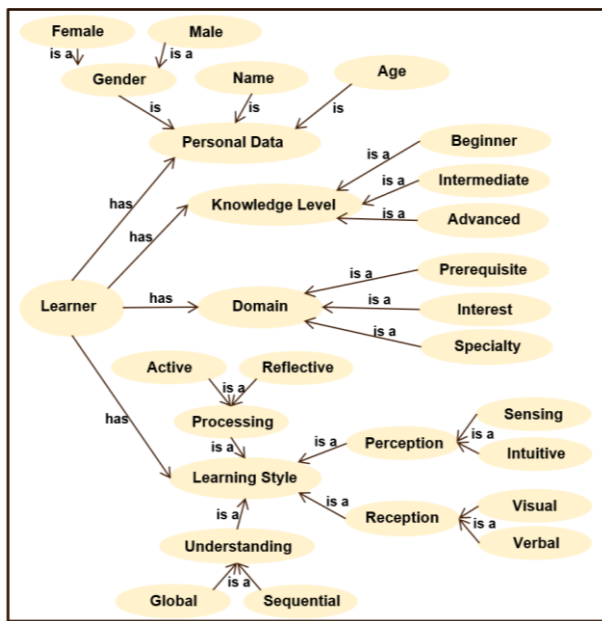


Fig. 3. The learner model ontology

B. Domain Ontology

A domain model presents and describes how the information content in the e-learning is structured. The whole course is divided into units, all consisting on several concepts. Every concept has one or more learning object(s) and contains learning resources and activities such presentations, examples, questions activities, exercises. Fig. 4 shows the structure of the domain model.

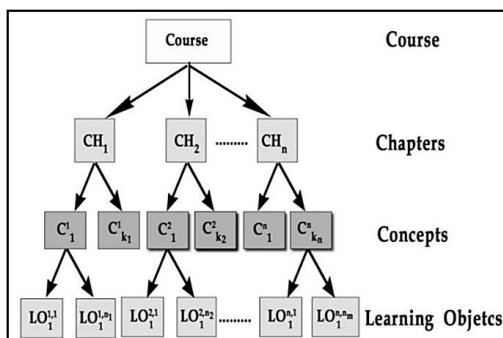


Fig. 4. Hierarchical organization of the domain model [6]

TABLE I. CHARACTERISTICS OF LEARNERS BASED ON FLSM

Dimension	Learning style	Characteristics
Processing	Active	-Works in groups -Prefers to try new material instantly -Handles practical stuff
	Reflective	-Works alone -Prefers to taking the time to think about a problem
Perception	Sensing	-Is patient with details -Prefers senses, facts and experimentation
	Intuitive	-Interested in overviews and a broad knowledge -Interested in innovations and accept complications -Preferring principles and theories
Reception	Visual	-Prefers to perceive materials as images, videos
	Verbal	-Prefers to perceive materials as text
Understanding	Global	-Prefers to get the big picture first -Assimilated and understands information in a linear and incremental step
	Sequential	-Preferring to process information sequentially

The learning resource ontology represents knowledge about the learning resources (see Fig. 5). Knowledge represented in this ontology include learning resource’s name, domain, language, the prerequisites required to access, knowledge level which may be: beginner, intermediate and advanced, as well as learning resource format which may be text, image, audio or video, and learning activity such as lecture notes, exams and assignments. In this model, ontology has been used for personalization of learner profile as well as modeling of the learning resource ontology.

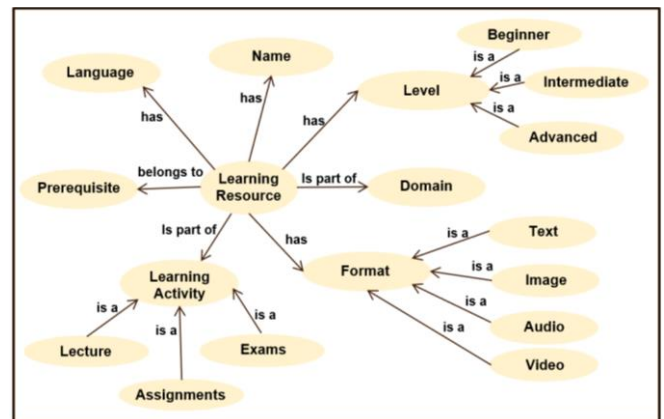


Fig. 5. The learning resource ontology

C. Learner Resource Rating Matrix

Each learner likes certain learning resources, and the rating value $r_{l,LR}$ is the data associated with each learner l and learning resource LR . $r_{l,LR}$ represents how much the learner l appreciates the learning resource LR . These rating values are collected automatically in the matrix, called Learner Resource Rating Matrix, in which each row l_i represents the list of rated learning resources for learner l_i , while each column LR_j lists all the learners who have rated the learning resource LR_j .

Fig. 6 indicates Learner-Resource rating Matrix with n rows and m columns, where n denotes the number of learners $L = \{l_1, l_2, \dots, l_n\}$, and m denotes the number of learning resources $LR = \{LR_1, LR_2, \dots, LR_m\}$.

Learning Resources \ Learners	LR_1	LR_2	LR_3	...	LR_m
l_1	r_{l_1, LR_1}				
l_2			r_{l_2, LR_3}		
\vdots					
l_n					r_{l_n, LR_m}

Fig. 6. Learner-Resource rating Matrix

This matrix uses a 0-to-5 rating scale where the score 0 indicates that the learning resource is not yet explicitly rated or used at all, 1 indicates that the learner is not at all satisfied with the learner resource, 3 indicates that the learner is not moderately satisfied, and finally, 5 means that the learner is strongly satisfied with the selected learning resource.

D. Computing Similarities and Predictions

Once ontology domain knowledge about the learner and learning resources as well as the learner ratings on learning resources has been preprocessed, the recommendation engine analyzes them, and the subsequent step is to group similar learners according to their learning styles, domain, and levels of knowledge in their chosen domain based on similarity computation (as shown in Fig. 7), and compute the similarities of learning resources as well as predictions for the target learner. In computing the similarities, the ratings and ontology domain knowledge are considered.

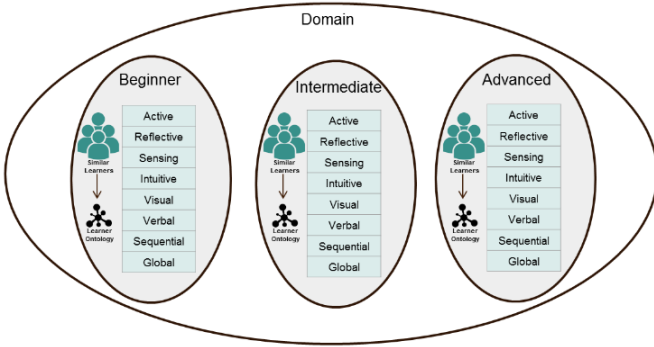


Fig. 7. Grouping of learners according to their preferred domain, their level of knowledge, and their learning style

1) Computing similarities

We will use Adjusted Cosine Similarity [34] to calculate ontological similarities. The following formula (1) will be used to calculate ontological similarity $sim(LR_i, LR_j)$ between two learning resources i and j :

$$sim(LR_i, LR_j) = \frac{\sum(r_{l, LR_i} - \bar{r}_i)(r_{l, LR_j} - \bar{r}_j)}{\sqrt{\sum(r_{l, LR_i} - \bar{r}_i)^2} \sqrt{\sum(r_{l, LR_j} - \bar{r}_j)^2}} \quad (1)$$

Where r_{l, LR_i} denotes the rating given to learning resource i by learner l , \bar{r}_i is the ontological mean rating of all the ratings provided by l . $i, j \in \{1, 2, \dots, m\}$, $i \neq j$. Ontological information is utilized in computing the mean rating \bar{r}_i in the proposed approach.

The ontological similarity $sim(l_v, l_u)$ between two learners l_v and l_u will be calculated using Pearson Correlation Coefficient (PCC), which outperforms other similarity measurements [35]. Equation (2) can be used to calculate the PCC between learners v and u :

$$sim(l_v, l_u) = \frac{\sum(r_{l_v, LR_i} - \bar{r}_{l_v})(r_{l_u, LR_i} - \bar{r}_{l_u})}{\sqrt{\sum(r_{l_v, LR_i} - \bar{r}_{l_v})^2} \sqrt{\sum(r_{l_u, LR_i} - \bar{r}_{l_u})^2}} \quad (2)$$

Where r_{l_v, LR_i} denote the rating given to LR_i by the learner l_v , \bar{r}_{l_v} is the mean rating of all the ratings provided by learner l_v , u and $v \in \{1, 2, \dots, n\}$, $u \neq v$.

2) Making Prediction

Once we obtain the set of k most similar learners (k -nearest neighbors) and the k most similar resources using respectively the PCC similarity and Adjusted Cosine Similarity, the next step is to compute predictions of unknown ratings for the target learner. In the case of insufficient ratings, the principle is to predict the rating r_{l_k, LR_h} providing by target learner l_k for a LR_h (k -nearest neighbors) using the rating given to LR_h by other similar learners (nearest neighbors) obtained by (2). The predicted ratings are computed from the k most similar resources (k -nearest neighbors) obtained by (1) that they are rating by similar learners to l_k (those who belong to the same group), and the ratings given on it by the target learner. To compute the predictions of ratings, we use the following prediction (3).

$$Pred_{l_k, LR_i} = \frac{\sum(sim(LR_i, LR_h) \times r_{l_k, LR_h})}{\sum(sim(LR_i, LR_h))} \quad (3)$$

Where $Pred_{l_k, LR_i}$ is the predicted rating for unrated resource LR_i by the target learner l_k , $sim(LR_i, LR_h)$ is the similarity between two resources LR_i and LR_h , and r_{l_k, LR_h} is the rating of resource LR_h (the neighbors) by the target learner l_k .

E. Generating list of recommended learning resources

After creating ontology to represent knowledge semantically about the learner and learning resources, and grouping together the learners using these ontologies (according to their preferred domain, their level of knowledge, and their learning style), and computing the similarities, and after predicting all unknown resources rating in a Learner-Resource matrix, it is necessary to generate recommendations list (top N) for the target learner. It consists of eliminating all resources that do not match the learner's preference and need, like language, knowledge level. The following algorithm shows how generate a list of the top N recommendations.

Algorithm: Generate a list of the top N recommendations

Input:

Set of learning resources

$$LR = \{LR_1, LR_2, \dots, LR_m\}$$

Set of learners

$$L = \{l_1, l_2, \dots, l_n\}$$

Ontological knowledge

$$O = \{Learner, Learning Resource\}$$

Learner-Resource Rating

$$R = \{r_{l_1, LR_1}, r_{l_1, LR_2}, \dots, r_{l_n, LR_m}\} \text{ Where } R \in \{1, 2, 3, 4, 5\}$$

Output:

Generate Top N recommendation List

Method:**foreach** $LR_i \in LR, o \in O$, **do:**

Calculate ontological similarity

 $sim(o_{LR_i}, o_{LR_j})$ using (1)**endfor****foreach** $l_k \in L, o \in O$, **do:**

Calculate ontological similarity

 $sim(o_{l_k}, o_{l_s})$ using (2)**endfor****foreach** unknown ratings of the target learner:Predict ratings $Pred_{l_k, LR_i}$ using (3)**endfor**

Filter learning resources according to learner profile

return top N recommendation list for target learner l_k

V. CONCLUSION AND FUTURE WORK

Recommender systems play an important role in today's e-learning field. In this article, we have presented the architecture of our proposed system which includes 3 main layers namely Learner Interface, Database Server, and Recommendation, and we have presented a hybrid recommendation technique that generally combines the best features of several recommendation techniques to recommend the most appropriate learning resources to learners based on their knowledge level, their preferred domain, and their learning style. The ultimate goal is to improve the performance of recommender system in e-learning in order for learners to succeed and to improve their learning experience, by adapting learning resources to learners' needs that change as they progress in their studies, to improve learners' satisfaction, maintain learner's motivation, and help them achieve their goals effectively in less time and at lower cost. For our future work, we will implement our recommender system and integrate it into a learning platform. Then, we will evaluate it as an adaptive application that personalizes resources for learners with different profiles who participate in e-learning systems to show that our proposed hybrid approach can obtain better performance and accuracy than the other.

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