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ERSDO: E-learning Recommender System based on Dynamic Ontology

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Abstract
In distance learning, recommendation system (RS) aims to generate personalized recommendations to learners, which allows them an easy access to various contents at any time. This paper discusses the main RSs employed in E-learning and identifies new research directions to overcome their weaknesses. Existing RSs such as content-based, collaborative filtering-based and knowledge-based recommendations reveal significant softness due to their incapacity to collect accurate information about learners, especially new ones which is identified as cold start problem. In this paper, we are working on both, the new user cold start problem, which is considered as a big issue in E-learning system, and the recommendation based on updating information. This complication can be reduced by including other learners' information in the process of recommendation. The objective of this study is to propose an E-learning Recommender System based on Dynamic Ontology. Our recommended approach describes semantically course and learner, which will be integrated into Collaborative and content-based filtering techniques to generate the top N recommendations using clustering methods. The experiments measures are done using the famous "COURSERA" dataset mixed to our university USMBA dataset. The results obtained demonstrate the effectiveness of our proposed method in the process of recommendation compared to content-based method.

Keywords E-learning · Recommender systems · Dynamic ontology · Collaborative filtering · Content-based filtering · Hybrid recommender system

1 Introduction

In the last few years, recommender systems have been extensively considered as a solution to data overloading, as it plays an important role for users to provide

Extended author information available on the last page of the article the most relevant information. In the same way, E-learning recommender system is designed as a great tool that provides suitable and adapted subjects to learners. Recommender systems are initially implemented in commercial websites to predict user preferences. The main role of a recommender system is to analyze users' data that can be useful for other predictions. Hence, a recommender system is software that helps users identify the most interesting and relevant learning objects. Compared to classical e-commerce recommendation, RSs in E-learning context have a huge amount of information about learners, learner object and learning activities. Furthermore, one learning object can be part of different categories, and this is not the case in e-commerce system. In this regard, the recommender system becomes an essential element in any E-learning system. However, the vast majority of the current E-learning systems are structured to cover request-learners with static databases and not for dynamic environments. For this reason, dynamic ontology can be an effective method to improve the performance of recommendations(Fudholi et al., 2013).

Developing an E-learning Recommender System with Dynamic Ontology (ERSDO) is a great challenge due to the difficulty involved in the personalization of dynamic content and the creation of dynamic user profiles based on the learning behaviors of each learner. As described by Devedziu and al (Cakula & Sedleniece, 2013) in 2006, personalization is the process of adapting the learning experience to different learners by analyzing their knowledge, personal skills and their learning preferences. In the learning environment, a student's character (learning style), structure of information (ontology) and technological approach (recommender system) are identified as the cornerstones for the development of efficient E-learning systems.

Learning style, as a concept, describes different approaches to understanding information, and the way in which learners discover, take in, and remember information(*Effective Trust-Aware E-learning Recommender System Based on Learning Styles and Knowledge Levels*, s. d.). In literature, learning style theories explain how learners can be categorized according to their style of learning (Visual, Auditory, and Kinesthetic…). Although there are more than seventy learning styles models in literature review, only seven models are usually used in E-learning system. These models are ascribed to David Kolb (Raschick et al., 1998), Peter Honey and Alan Mumford, Neil Fleming with his famous VAK/VARK, Anthony Gregorc's NASSP and that of Felder Silverman [4].

Ontology by definition is a formal representation of classes, properties and relations between the concepts, data and entities, which can improve the definition of the learning domain. This study proposes a generic approach. It takes into consideration rapid and dynamic change in learner's behaviors due to the use of dynamic ontology, dynamic learning style and recommendation based on dynamic content. This approach identifies recommended courses to learners based on combining learner's ontology and content's ontology by using clustering algorithms. The objective of this article is twofold. First, it seeks to investigate the ability of constructing dynamic ontologies for learners and contents. Second, it aims to suggest an enhanced recommendation that best fits the learner needs.

This paper is structured as follows: In Sect. 2, we provide related works. In Sect. 3, we present the background theories, which includes the existing recommendation approaches, as well as the techniques used in our proposed approach. In Sect. 4, we explain our proposed recommender system ERSDO, its architecture, and the recommendation algorithm used in the system. The experimental results are discussed in Sect. 5. Finally, Sect. 6 includes conclusion and future work.

2 Related works

E-learning Recommender systems play a vital role in providing relevant contents from the large information available on the internet. A variety of approaches has been used to develop recommender systems, such as content-based filtering, collaborative filtering and hybrid filtering which overcomes the drawbacks of an individual approach. Recently, many researchers have developed E-learning recommender systems based on ontology, which represents knowledge in the field of education. For instance, Mohammed Ibrahim et al. (Ibrahim et al., 2017) have developed a course recommender system for university students, which suggests the best courses that meet their needs based on the ontology. In this study, authors represent knowledge about students' profile, course content and learning domain with static ontologies. In (Tarus et al., 2017) authors propose a new knowledge-based recommender system using ontology to model domain knowledge of learner profile and learning resources, the system adopted in this work applied SPM (sequential pattern mining) with collaborative filtering method to generate the top N recommendations. Another hybrid approach of recommendation based ontology is proposed by authors in (Ibrahim et al., 2019), this approach combines collaborative filtering and content based filtering, supported by ontology similarity between item's profiles and user's profiles. In (Bouihi & Bahaj, 2019), Bouihi and Bahaj have used the ontology to represent knowledge of content and context, and explores the SWRL rules as recommendation technique based on learning object relevance and weighting. This method helps students get the suitable learning materials to have successful learning experience. Ontology can also be used in order to structure semantic representation of Mooc profile and provide personalized recommendations for each learner. In 2018, Kahina and Latifa (Rabahallah et al., 2018) proposed a Mooc recommender system based on combining collaborative filtering and ontology. In this work, the authors use ontological knowledge to alleviate the cold start problem and integrate the properties of learner and Mooc into the recommendation process. Authors in (Agbonifo & Akinsete, 2020) developed a personalized recommender system based on ontology and collaborative filtering to recommend suitable and useful learning contents to learners. This system overcomes the problem of personalization and suggests relevant items based on learner's skill, his level and knowledge. However, all the related works mentioned above suffer from the cold start and sparsity problems as the most notable drawbacks in recommendation system field, because they do not take into account the changes of learner's learning style and his level. For this reason, we have thought of the dynamic ontology in the context of recommendation. Additionally, in dynamic environment, all learners' information will be updated and stored in learner ontology. Hence, they will be integrated into our recommendation system for providing the most suitable learning materials to learners. Furthermore, with dynamic ontology, recommender system can alleviate the cold start and sparsity problems with the aid of the huge amount of information collected from multiple resources. In doing so, it can improve both the performance and the quality of recommendations, and produce better results compared to other approaches.

3 Background theories

In this section, we present the background of conventional approaches of recommender systems, including the related methods for our proposed approach. A brief introduction about them is provided.

3.1 Collaborative Filtering (CF)

It is one of recommendation techniques widely used in several fields. It depends on the presumption that "similar clients have the equivalent preferences“ (Wu et al., 2020). For instance, Amazon, the well-known e-commerce website, utilizes its own recommendation system. At the point when you select a product to purchase, Amazon suggests other products that different clients bought, depending on that original product (Melville & Sindhwani, 2010).

3.2 Content-Based Filtering (CBF)

This technique recommends an element to the user based on its description. In this vein, a user is recommended materials similar to those he has favored in the past. For example, we consider a recommender system that uses content-based method to recommend courses to learners. If the course is about Big Data technologies and a learner named "Karim" enrolls in it, the recommender system will recommend another course to Karim. Furthermore, these courses will include much more vocabulary related to the topic consulted (for example, "Hadoop", "HDFS", "MapReduce") (Alharbi et al., 2014). In the context of our experimental study, we take content-based filtering as an element of comparison and evaluation of our proposed approach, because ontology as a technique it is based on the content.

3.3 Hybrid recommendation

This is another classification of recommendation system, which focuses on the advantages of two or more methods to increase efficiency and accuracy of recommendations. It is a mixture of at least two diverse recommendation techniques. The most common mainstream hybrid approaches are those of content-based and collaborative filtering. They utilize both the content of the element and the ratings of all users (Prasad, 2012).

3.4 Clustering technique and CF

In practice, Collaborative Filtering (CF) produces recommendations based on the entire user-item rating matrix by identifying the neighborhood of the intended user to which the recommendations will be made. The data sparsity is one of the most common problems of user-based CF, in which users give insufficient rating from a large database of items.

Furthermore, CF determines neighborhoods of each user on computing similarity between every pair of users. However, this will not be efficient with millions of users and items. To overcome these drawbacks, clustering techniques can be suggested as an effective solution. Clustering techniques regroup users or items into clusters with the same characters. Thus, they provide a new vision to identify the neighborhood. For example, Manh et al. study proposes the use of clustering techniques on the social network of users to derive the recommendations. They also noted that the clustering technique based CF performs better than the traditional CF algorithms (Pham et al., s. d.).

Furthermore, Ungar and Foster (Ungar & Foster, s. d.) present a model of collaborative filtering including variations of K-means clustering and Gibbs Sampling. In this study the authors compare different algorithms for estimating the model parameters. Xue et al. in (Xue et al., 2005) present clustering as an effectual solution of missing-value generating in recommendation process. In their research, authors integrate the advantages of memory and model-based collaborative filtering to provide higher accuracy in recommendation as well as solve the scalability and data sparsity problem.

3.5 Ontology method

Ontology is originally defined by Gruber (1992)(Gruber, 1993) as an "explicit specification of a conceptualization." It was later defined by Taniar and Rahayu (2006) as "a knowledge domain conceptualization into a computer processable format which models entities, attributes, and axioms." The goal of using ontologies in recommender system is modeling the information at the semantic level. As the ontology elements have been well checked before, reusing ontologies saves time and improves the quality of ontologies. In addition, ontology can be utilized to produce better performance with other methods and techniques, such as data mining and machine learning tools (Tarus et al., 2017). Due to the utility of ontology as a method for the interpretation of knowledge, developers in the fields of information processing and recommendation systems have broadly adopted it in their applications. In our proposed approach, we use ontology to model the knowledge about the user (student profile) and the course content (course profile), this two ontologies contain a set of entities, attributes and properties related to learning field. Different ontology representation languages like Web Ontology Language (OWL) and Resource Description Framework (RDF) are used to create ontology.

In the field of recommendation, ontology is used for knowledge representation. In this concern, we will delve into the role of ontology in enhancing the quality of recommendations. First, ontology has been used to infer user aims as well as enhance user profile in recommendation system. Ontology increases similarity matching, whereby coupling learner ratings with ontological domain knowledge. Since its inception, ontology in E-learning recommender system has made significant improvement by facilitating the process of personalization and providing effective recommendations.

What also makes ontology essential in recommendation is that it models characteristics of learners, learning style, knowledge level, learner history and other attributes in the personalization process.

4 Proposed approach

Our proposed E-learning ontology is designed as a set of homogenous ontological resources that have been identified for use in multiple learning environments (Fig. 1): This suggested approach is based on a constructivist-learning model, in which learners have the lead role in their learning process. Our proposal combine: Learner Profile Ontology (LPO) as a main source of learners' information, Material Resource Ontology (MRO) that will be used by the learners in the learning process and Learner-Course Relation Ontology (LCRO) to combine learners with course materials.

The Learner Profile Ontology (LPO) consists of the relevant information about learner which includes personal data (full name, gender, contact information, username, password…) and education data such as study level, field of study, languages preferences, and learning style. All these data are extracted from learner request and modified directly when the data source is changed.

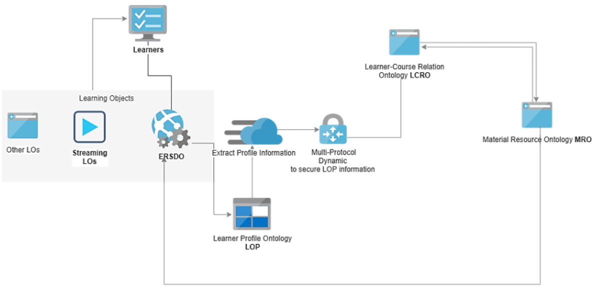

Fig. 1 Our proposed approach E-learning Recommender System with Dynamic Ontology (ERSDO)

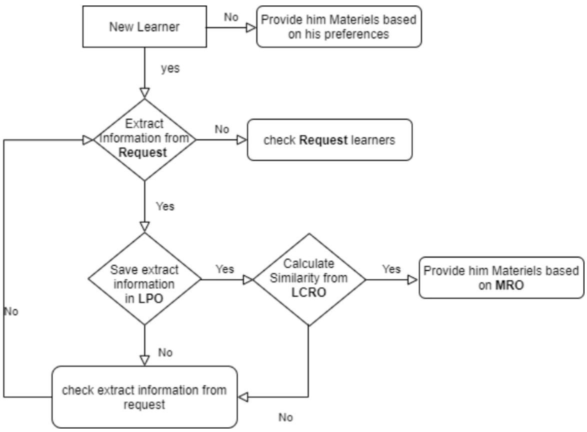

Fig. 2 The workflow of our proposed ontology recommender system

Material Resource Ontology (MRO) provides information about course material such as course information (course type, course name, course domain, course ID…), our system uses SKOS (simple knowledge organization system)(Miranda et al., 2016) to identify domain vocabulary and owl standard to represent pedagogical content.

Learner-Course Relation Ontology (LCRO) is the third component of our system. It contains the different combinations between courses and learners features based on log file (Figs. 1 and 2).

In our proposed approach, each learner sends requests demanding specific resource materials with particular properties. Each request transformed in subset features is divided into three groups, learner profile attributes and material resource attributes. If the learner demanding information is a new learner, E-learning Recommender System with Dynamic Ontology (ERSDO) supplies dynamically all extracted information from the sent request in the predefined ontologies LPO and securitizes this information with multi-protocol dynamic of security. Then it calculates similarity from LCRO between the new learner and other learners with similar profiles who have already consulted the learning platforms. Finally, ERSDO provides suitable recommendation to learner based on MRO information (see Figs. 1 and 3).

ERSDO in our architecture has mainly two functions: it updates continuously and systematically all information resources in E-learning platforms and provides recommended materials to learners. To store all information resources dynamically, ERSDO uses clustering technique to form sub-clusters with similar properties. In the step of recommendation, ERSDO computes similarities based on the learner and the course ontologies from LCRO, and matches the courses clusters and the learners clusters based on the request of active learner and his historical data.

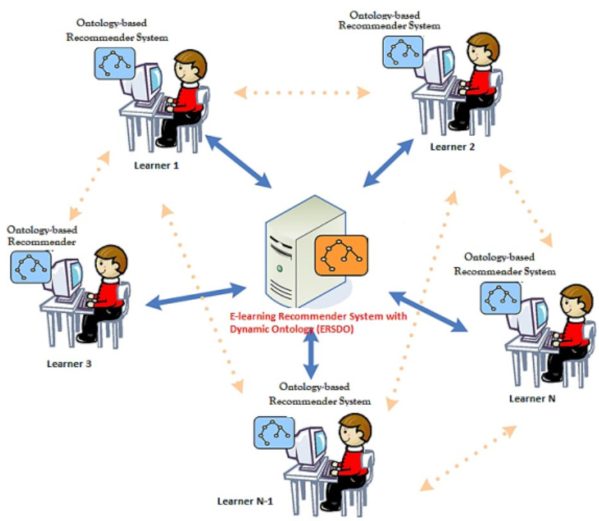

Fig. 3 ERSDO server web implementation

4.1 Similarity

For computing similarity between learner profiles and learning materials, there are many measures. The commonly used measurement is cosine similarity (Ghauth & Abdullah, 2010). We use cosine similarity equation to calculate similarity scores between two vectors. In our case, the first vector is taken from learners and the second vector is taken from the weight matrix of LCRO ontology:

$$\mathrm{Cos}\,(\overrightarrow{w_c}, \overrightarrow{w_s}) = \frac{\overrightarrow{w_c}.\overrightarrow{w_s}}{\|\overrightarrow{w_c}\| \,.\, \|\overrightarrow{w_s}\|} \tag{1}$$

4.2 Recommendation algorithm

The recommendation module includes the generation of the list of recommended courses to the target learner. We use the following algorithm based on the LCRO ontology and MRO ontology.

```
Algorithm 1: Top N Recommendations using ERESDO

Begin
Input
Set of courses objects CO = {i1, i2, i3,.., in} in MRO
Set of learners L= {L1, i2, i3,.., ik} in LCRO
Output
 top N recommendations
Method
   for each i є CO, k є L, do
1 : Identify domain vocabulary using SKOS
2 : Use clustering technique to form sub-clusters with
    similar properties FROM LCRO
3 : Compute ontological similarity for each sub-clus
    ters.
4 : Generate top N recommendation for target learner
    End for
End
```

5 Experimental results

This section presents the results of our proposed architecture, using Moodle as a platform of materiel courses and the students of the BA degree at USMBA University as a study group for our experiments.

5.1 Dataset analysis

In our experiment, we need data from many participants to validate our approach. That's why we have used Moodle (*Moodle*, s. d.) as a platform of our experiences process. Furthermore, for our experience, Moodle has certain advantages. First, it allows us to know the different information about the students 'interactions. This, for example, includes the course they visit, and how they carry out their quizzes and assignments etc. Second, in Moodle we can implement in its open source programme our algorithms. Our Moodle Dataset is created from three sources, which are Faculty of Arts and Humanities, Dhar El Mahraz, Faculty of Arts and Humanities, Sais-Fes, and Coursera (*Coursera*, s. d.) dataset. Faculty of Arts and Humanities, Dhar El Mahraz dataset has 11 departments each of which contains between 50 and 150 support courses. Each department has its own directory that includes all files belonging to this department. The documents in each class of Faculty of Arts and Humanities, Sais-Fes are considered in 7 departments. Each course has its own directory that includes all files belonging to these courses. Coursera contains mainly 890 course data (*Coursera*, s. d.; Table 1).

5.2 Experimental Process

In this work, our objective is to know the effectiveness of our algorithm in the recommendation phase of E-learning system, and to identify which kind of learning object is best preferred for our learners (students) between small, medium, and large sizes. The criterion on which we based our analysis is the number of students or learners who consult those learning objects. If the number of consultations is too high, it implies that our approach offers the right content to the target person. With is in mind,

Table 1 Datasets properties of BA degree, years 2020/2021

Sources	Number Of departments	Number Of courses	Departments
Faculty of Art and Human Sciences Dhar El Mahraz	11	2378	Department of: Arabic Language and Literature, French Language and Literature, English Language and Literature, Hispanic Language and Literature, German Language and Literature, Islamic Studies, History, Geography, Philosophy, Sociology, Psychology.
Faculty of Art and Human Sciences Sais	7	1569	Department of: Arabic Language and Literature, French Language and Literature, English Language and Literature, Hispanic Language and Literature, German Language and Literature, Islamic Studies, Geography.
Coursera	6 categories	890	A variety of courses

we have made progress in two experiments using the same dataset in two web servers. The objective behind the use of two web servers is the momentary evaluation of the number of consultations that reflect the importance of the recommendation. The experiment using ERSDO was validated in the first server while the second experiment using recommendations based on content-based filtering was implemented in the second server. The results from the two experiments were then compared.

5.3 Classifier accuracy

To evaluate the performance of our proposed system ERSDO in comparison with the common content-based filtering, we used F1 measure. F1 measure is a metric that combines precision and recall into a single value for comparison. F1 measure is accomplished with the following formula (Bogdan & Vladimir, 2020):

$$F1\_measure = \frac{2 \times precision \times recall}{precision + recall} \tag{2}$$

The following results displayed in Table 2 reveal that F1 measure is higher for ERSDO system recommendation compared to content based algorithm. This explains that our approach enhances the quality of recommendations (Table 3).

5.4 Discussion

Conventional recommendation methods consider only certain similarities between learners with the same interests without taking into account some technical problems

Table 2 Precision, Recall and F1 of ERESDO and CONTENT_BASED

Size of data by learning objects	Number of learners used objects based on ERSDO (Server 1)	Number of learners used objects based on CONTENT_BASED (Server 2)
Small size	8789	6457
Medium size	5687	4987
Large size	6192	2678

Table 3 Precision, Recall and F1 of ERESDO and CONTENT_BASED

Size of data by learning objects	ERSDO			CONTENT_BASED		
	P	R	F1	P	R	F1
[10–20]	0,439	0,391	0,41	0,357	0,389	0,371
[20–30]	0,481	0,318	0,382	0,297	0,341	0,318
[30–40]	0,452	0,395	0,421	0,317	0,429	0,369
[40–50]	0,39	0,43	0,409	0,26	0,394	0,313
[50–60]	0,58	0,42	0,487	0,31	0,47	0,379
[60–70]	0,61	0,567	0,597	0,411	0,393	0,401
[70–80]	0,691	0,68	0,687	0,599	0,549	0,582

like sparsity, cold start, and overspecialization…etc. ERSDO overcomes all these problems including data extraction from multiple data sources, by building dynamic connection between the user profiles and courses that will help to reduce information overloading, preparing the correct recommendation. Furthermore, it provides suitable courses that match the learner's needs. Figure 4 displays a comparison between ERSDO approach and the traditional Content-based approach using F1_measure metric; the experiments showed that our proposed approach gives better results in terms of performance and accuracy than the traditional content-based filtering, because this latter has many limitations in the mapping phase from multiple heterogenic resource. The integration of dynamic ontology into the recommendation process improves the quality of recommendations and alleviates the drawbacks of traditional methods. In addition, the use of ontology in our approach allowed us to incorporate learning style of learner and his knowledge level in the recommendation process, which helps provide more personalized recommendations to learners.

6 Conclusion and future work

In this article, we have proposed an E-learning recommender system based on dynamic ontology, which recommends relevant courses to online learners. Our proposed E-learning ontology is divided into two modules: learner ontology and course ontology. These two ontologies are updated dynamically when the data source is changed. Besides, they are incorporated in the recommendation process. This method can effectively alleviate the cold start problem and sparsity and enhance the quality of recommendations to learners in E-learning platforms. The experimental results of this study demonstrate that the proposed approach gives better performance and precision than traditional content-based approach. Additionally, the integration of dynamic ontology in the recommendation system plays an important role in providing the best recommended courses to learners that match their needs.

Our future work will focus on developing this proposed approach with machine learning techniques and intelligent tools and integrate the new recommendation system in LMS to provide better personalized recommendations to each learner.

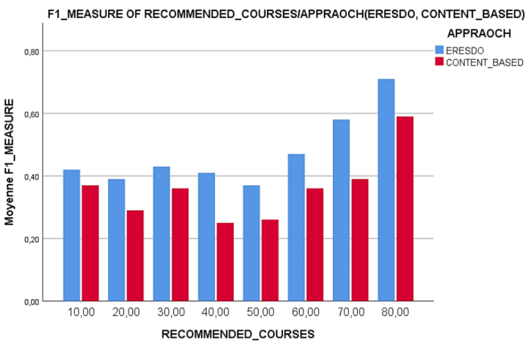

Fig. 4 F1-Measure of Recommended courses of ERSDO approach VS CONTENT-BASED approach

Conflict of interest None.

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