Multi-agent system for Knowledge-based recommendation of Learning Objects

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KEYWORD

Clustering techniques, learning objects, metadata, multi-agent systems, and recommendation systems

ABSTRACT

Learning Object (LO) is a content unit being used within virtual learning environments, which -once found and retrieved- may assist students in the teaching - learning process. Such LO search and retrieval are recently supported and enhanced by data mining techniques. In this sense, clustering can be used to find groups holding similar LOs so that from obtained groups, knowledge-based recommender systems (KRS) can recommend more adapted and relevant LOs. In particular, prior knowledge come from LOs previously selected, liked and ranked by the student to whom the recommendation will be performed. In this paper, we present a KRS for LOs, which uses a conventional clustering technique, namely K-means, aimed at finding similar LOs and delivering resources adapted to a specific student. Obtained promising results show that proposed KRS is able to both retrieve relevant LO and improve the recommendation precision.

1. Introduction

The Learning Objects (LOs) differ from the traditional learning resources because of its immediate availability at Web-based repositories. LO can be located and accessed through their own metadata for educational purposes on virtual learning (Gil & García, 2007). Generally, LO are stored on Learning Objects Repositories (LOR), which in turn are joined to form a repository federation for sharing and accessing the resources from each other (Li, 2010).
Likewise, a Recommendation System (RS) is defined as a piece of software that facilitates users to discern more relevant and interesting learning information from LORs (Sikka, Dhankhar, & Rana, 2012).
Multi-agent Systems (MAS) -being emergent computing approaches- are widely spread in several e-learning areas providing solutions for complex and restrictive systems. In contrast with conventional computing approaches, MAS has special features such as customization, intelligence, accessibility, safety, task distribution, decision making, among others (Ahmad & Bokhari, 2012).

Currently, data mining techniques classifying or clustering data have shown to be useful for the process of retrieving high-quality information, that is delivering relevant items to a specific user (Sabitha, Mehrotra, & Bansal, 2012). In particular, clustering aims to divide data into subsets of similar instances (Jain, 2010), having the ad-vantage of not requiring a prior supervised knowledge on the underlying classes or groups to carry out the clustering or classification task. Instead, only the number of resultant groups and few initial parameters are required. Formally, clustering is the process is grouping homogeneous patterns using no any information about the nature of clusters contained in the data set (Peluffo Ordóñez, 2009). Within the recommendation systems (RS) context, clustering can be used to find similar learning objects so that RS delivers learning-supporting and high-quality educational material to users.

Recent works (Rodríguez, Duque, & Ovalle, 2013) (Rodríguez M, Salazar, Duque, Ovalle, & Moreno, 2014), introduced a model of a hybrid recommendation system for LO, which is based on a MAS having 8 agents, namely three of them are respon-sible for individually running a recommendation technique (Content-based, Collabo-ration-based and knowledge-based recommendation).The fourth agent is deliberative that is in charge of applying the hybridization technique. The fifth one is an ontologic agent that infers knowledge from the ontology. Other three agents are employed for communication purposes regarding user and federation of LO repository as well as a web service bridging between MAS and web application. Within this framework, this work proposes an improvement of the behavior of the knowledge-based recommendation agent incorporating the k-means algorithm as a clustering technique aimed at finding subsets of similar LOs previously ranked by students. To do so, a new cluster-ing agent is introduced. Such an agent performs the clustering process over the LO metadata when adding a new LO to the LOR federation. Then, this work constitutes a first model approach for a MAS for knowledge-based recommendation agent using data clustering. Experiments are done using Repository Federation of Learning Ob-jects Colombia - FROAC (available at: http:/froac.manizales.unal.edu.co/froac/). For quantifying the retrieval quality, a precision metric is used.
This work proposes a multi-agent Knowledge-based recommendation model for adaptive LO, according to the student's profile and prior knowledge, using metadata clustering. Which uses a conventional clustering technique, namely K-means, aimed at finding similar LOs and delivering resources adapted to a specific student, and we propose an improvement of the behavior of the knowledge-based recommendation agent incorporating the k-means algorithm as a clustering technique aimed at finding subsets of similar LOs previously ranked by students.

The rest of the paper is organized as follows: Section 2 presents the conceptual framework of this research. Section 3 reviews some related works analysis. Section 4 describes the proposed model integrating the clustering techniques and the proposed MAS. Section 5 explains the model validation and the results of the proposed model. Finally, the main conclusions and future research directions are shown in Section 6.

2. Basic Concepts

Following are the main concepts related to the LO recommendation using clustering techniques for knowledge-based recommendation.

According to the IEEE, a LO can be defined as a digital entity involving educational design characteristics. Each LO can be used, reused or referenced during e-learning processes with the purpose of generating knowledge and competences based on student's needs. In addition, LO have metadata that describe the educational resources involved and facilitate their searching and retrieval. LOR (LO repositories) are specialized digital libraries for storing LO, i.e., several kinds of heterogeneous educational resources and their metadata. A federation of LOR allows the access of available educational contents from one access point (Tabares, Rodríguez, Duque, & Moreno, 2012).

Recommendation Systems (RS) are a tool aims at providing users with useful information results searched and recovered according to their needs, making predictions about matching them to their preferences and delivering those items that could be closer than expected (Mizhquero & Barrera, 2009). In the case of LO, the system should be able to recommend LO adapted to one or more user's profile characteristics using metadata (Li, 2010). There are several techniques of RS as follows (Burke, 2007):

Content – based RS:
In this kind of system the recommendations are made based on the user's profile created from the content analysis of the LOs that the user has already evaluated in the past. The content-based systems use "item by item" algorithms generated through the association of correlation rules among those items.

Collaborative RS:
These systems hold promise in education not only for their purposes of helping learners and educators to find useful resources, but also as a means of bringing together people with similar interests and beliefs, and possibly as an aid to the learning process itself.
In this case, the recommendations are based on the similarity degree among users. To achieve a good collaborative recommendation system that means that provides qualified recommendations, it is necessary to use good collaborative filtering algorithms aiming at suggesting new items or predicting the utility of a certain item for a particular user based on the choices of other similar users.

Knowledge- based RS:
Knowledge-based recommendation (KRS) attempts to suggest objects based on inferences about a user's needs and preferences. In some sense, all recommendation techniques could be described as doing some kind of inference. Knowledge-based approaches are distinguished in that they have functional knowledge: they have knowledge about how a particular item meets a particular user need, and can therefore reason about the relationship between a need and a possible recommendation. KRS is based on navigation history of a user and in previous elections (Vekariya & Kulkarni, 2012).

Hybrid Recommender Systems:
The hybrid approach seeks to combine the techniques ERS in order to complete their best features and thus make better recommendations. The proposed hybrid filtering approach transparently creates and maintains user's preferences.

In this paper we focus on recommendation systems based on knowledge.

Within the context of data mining, clustering techniques are part of the unsupervised methods aimed at data exploring, classifying and hierarchically ordering. These techniques are characterized by requiring no prior information on clusters contained into the data set, that is, they are discriminative type. By contrast, clustering only requires setting some initial parameters or any hint about the nature of data such as the sought number of groups. That said, the main purpose of clustering techniques is grouping homogeneous patterns from a clustering criterion, which is typically based on distances, dissimilarities or densities. Such grouping process is performed using no any supervised information about the underlying clusters (Jain, 2010) (Peluffo Ordóñez, 2009). Probably, the most popular clustering algorithm is the so-called K-means, which works as follows: Data are considered as geometrical points, which are grouped according to minimal distance between data points and some representative pre-established points named as centroids or centers. The geometrical location of centroids is iteratively updated and refined in such a way that an optimization criterion is fulfilled. For instance, in case of minimum-squares-based clustering, centroids are moved according to a mean square error cost function. Doing so, objects within a cluster are similar to each other, but different from the objects belonging to other groups. Mathematically, a cluster centroid is a central point whose calculation can be done by the arithmetic average as the simplest form. In this work, we use the standard K-means algorithm (Jain, 2010).

3. Related Works

Currently, there are studies on data mining techniques to support adaptive recommendations, although generally used for collaborative filtering-based recommendation and these studies do not use knowledge-based recommendation. Here are some work that are related to the proposal presented in this article.

The work of Park, 2013, aims to reduce error rates of recommendation when a large list of items and some have low scores, but are good elements to the user, are located in a very low place in the list of results; recommendation are applied in a pool of qualified items (popularities) are the scores that are given to items previously by users. To apply the clustering take the items with lower grades and joining elements with higher scores, calling adaptive clustering, in order to give the user elements with low scores (Park, 2013). In this paper used a clustering technique to items by popularities, however do not work in a virtual learning environment to deliver educational materials to support student learning based on its previous history. Sabitha et al., used quality metrics to retrieve LO through clustering techniques on student preferences and user profile. This study presents the indicators which measure the LO metadata to perform clustering, in order to recover the fittest through search similar LO groups. So, efficient and relevant provision of LO using data mining techniques can be achieved. Perform user grouping (Sabitha et al., 2012). The research of Anido et al., 2002 the authors say that to make an efficient search we need an efficient description of those resources to be located. This work show GESTALT the broker receives student queries, and tries to find the corresponding resources in other modules. When resources are located, the broker returns them to the user who made the query. The main limittion of this research is that not considered the user profile, therefore no recommendation system (Anido, Fernández, & Caeiro, 2002).

4. Proposed Model

This work proposes a multi-agent system for adaptive LO recommendation as a hybrid recommendation, but the main interest of this article focuses on the knowledge recommendation. The search LO result are recommended according to learning style, evaluation by other users and students prior knowledge. Prior knowledge are LO evaluated by students in the past. The LO is retrieved from LOR accessible via web and have descriptive metadata of these objects.
Figure 1 shows the process for generating recommendations based on knowledge, which are the focus of this article.

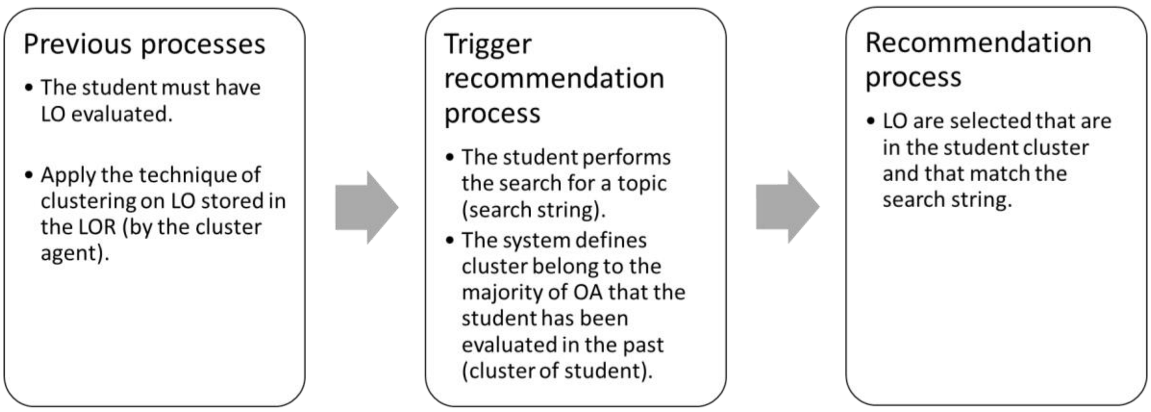

Fig 1. Knowledge-based recommendation process

The system was built under the MAS paradigm in order to exploit its advantages: the parallelism to perform simultaneously recommendation processes, the ability of deliberation to decide on which LOs recommend; cooperation, coordination, and distribution of tasks to clearly identify the problems that must resolve each agent and define their boundaries. GAIA and more-CommonKADS methodologies were used for the analysis and design of MAS. The GAIA methodology used the model of roles, which are associated with responsibilities, permissions, activities and protocols, and the services model (Wooldridge, Jennings, & Kinny, 1999). Of the methodology MAS-CommonKADS proposed by Iglesias in his doctoral thesis in 1998, used the seven proposed models (Iglesias Fernández, 1998).

Figure 2 presents the architecture of the MAS proposed, where there are agents presented in previous works and adds a new clustering agent, which is responsible for perform the k-means algorithm, and in this model improves the behavior of the Knowledge-based recommender agent, using the LOs cluster previously generated by the clustering agent.

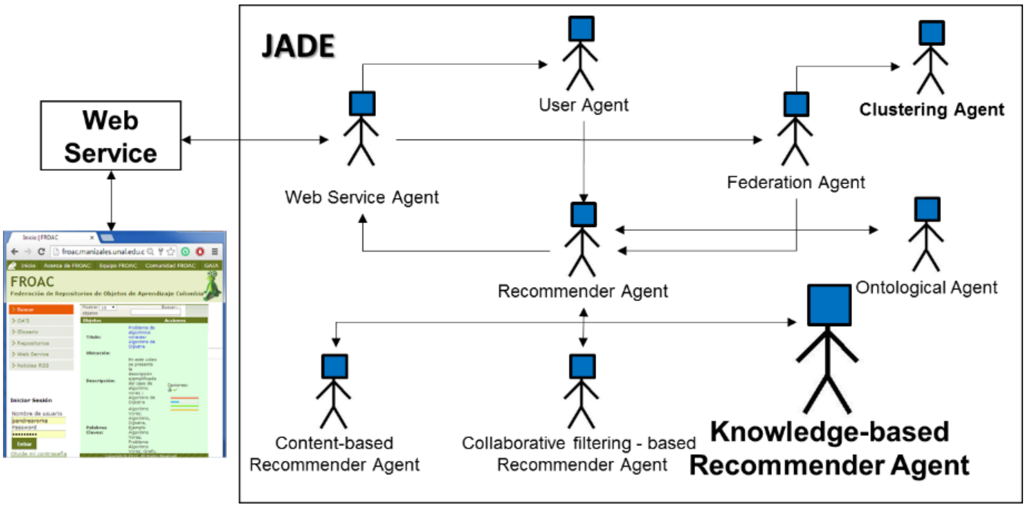

Fig. 2. Proposed architecture

Then explains the behavior of the agents that were modified in this work.

Clustering agent: This agent communicates with the federation agent to access the LO numeric metadata. When registering a new LO within the LOR federation, this agent perform the clustering technique, specifically the k-means algorithm generating five cluster and using Euclidean similarity metric. We work with the numeric metadata because we chose a technique that uses numerical values to find the clustering. Therefore the numerical metadata that are used are:
general_aggregationlevel, technical_duration, educational_interactivitytype, edu-cational_interactivitylevel, educational_semanticdensity, educational_difficulty, educational_typicallearningtime, the LO learning style provides (Visual, auditory, reader, kinesthetic), In addition format, educational_context, learn-ing_resource_type, min_edad y max_edad. At the end of the process, each LOs of repository federation is classified in one of the groups.

Knowledge-based recommender agent: When the student enters the system to search resource, this agent located LO ranked in the past with a score equal or greater than 4, scale of 1 to 5, where 5 indicates that LO like the student. Accordingly, LOs belonging to found clusters, which in turn satisfy the searching criteria is the result of the recommendation. Finally this result comes to the process of making hybrid recommendation in the deliberative recommendation agent to be delivered to the user.

The JADE (Java Agent Development Environment) framework was used to per-form the prototype implementation that offers a suite of resources to supply the development and implementation of MAS (Bellifemine, Poggi, & Rimassa, 1999). For this work, we have chosen JADE-LEAP (http://jade.tilab.com/), a FIPA-compliant agent platform that follows international agent communication standards.

5. Case study

For the case of study to the model proposed knowledge-based recommendation, we extract 10% of LO metadata from FROAC (Tabares, Rodríguez, Duque, & Moreno, 2012), which constitute the input of the MAS model. In addition students of Computer/ Management Information Systems, Universidad Nacional de Colombia, Manizales, belonging to the research group on adapted and intelligent environment -GAIA, were selected to rank the relevance of the recommendation outcomes. The relevance is understood as the importance of LO delivered for carrying out a learning process. Formula 1 is the metric of precision that is commonly used to measure the quality of information retrieval.

$$Precision = \frac{Relevant\ LOs}{Relevant\ LOs + Retrieved\ LOs} \quad (1)$$

Only the result of Knowledge-based recommendation, which is the objective of this work, was taken for this article. Previously students LOs ranked and which constitute prior knowledge. Then delivered them LO results we ask to evaluate if those LO were relevant. Figure 3 shows the result of the clustering technique. Applied the k-means algorithm and selected a *K=5*.

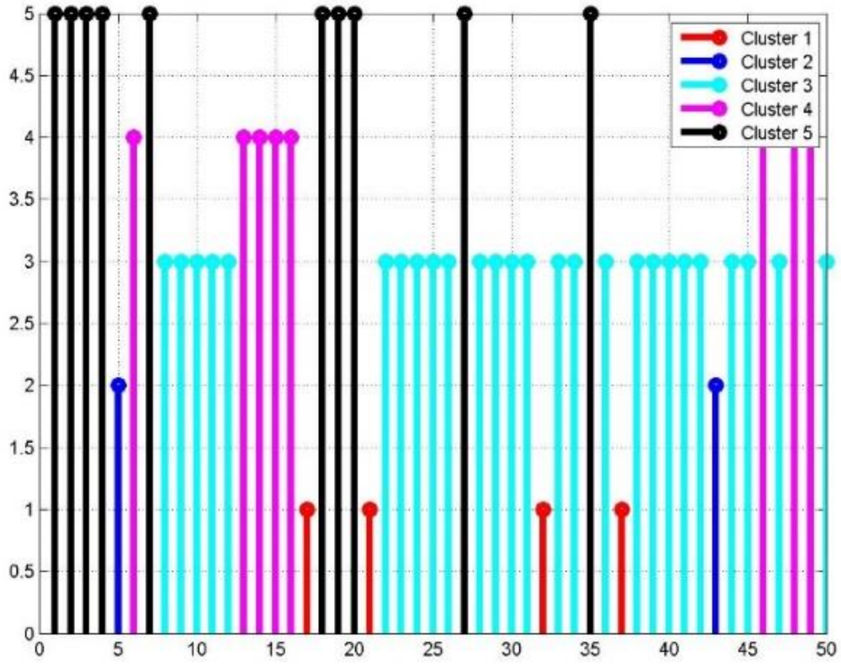

Fig 3. Result of the clustering technique for each LO

Figure 4 shows the average of the results of the ranked. And Figure 5 presents the comparison of precision metric using RS, against the choice the student delivered all the stored LO.

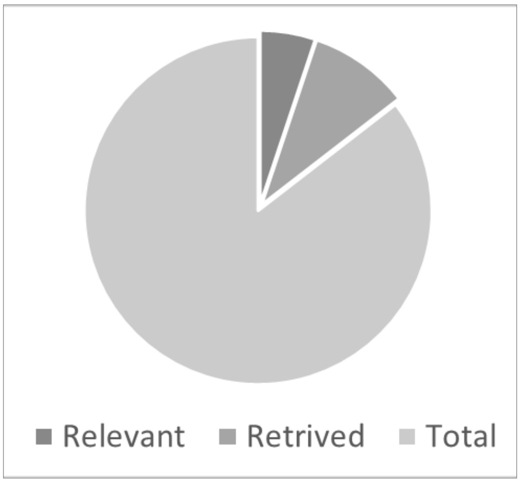

Fig. 4. Average of the LO recovered and LO relevant.

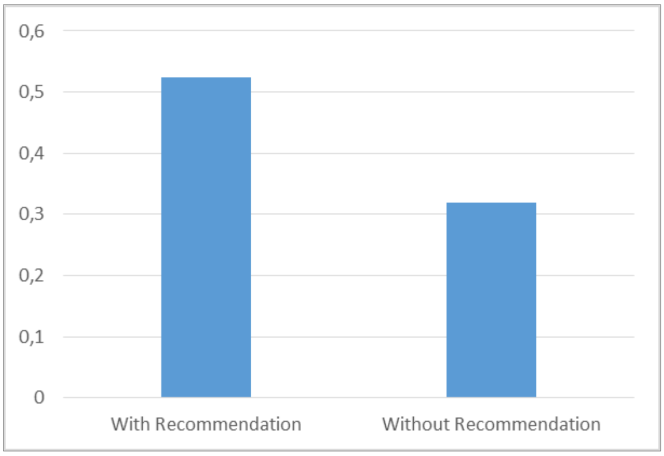

Fig. 5. Precision to use recommendation and without recommendation.

A precision metric was applied for performing the LO relevance evaluation. On average, Knowledge-based recommendation recovered around five LO for each student and on average three were relevant, therefore the result of precision was 0.54. If this result is compared, if delivered to the student all LO; i.e. 50 LO are recovered, on average 16 LO are relevant, then precision is 0.32., and can be concluded that recommendations adapted to the student are delivered as usage history and supports the process of teaching / learning.

Also compared the results of recommendation using clustering techniques, proposed in this work, with the implementation of the measure of similarity overlap, proposed in previous works. Precision measurement resulted in zero. It can be concluded that applying a clustering technique to the Knowledge-based recommendation improves the relevance of the LO delivered in the adaptation process.

6. Conclusions and future work

This paper proposes a model for recommendation of learning object, which is based on the MAS paradigm using repository federations. Such a model takes advantage of clustering techniques to perform recommendations according to the student’s prior knowledge.

Broadly speaking, the proposed model works as follows: Once grouped all available LOs regarding similar numerical metadata, we seek for the clusters that match to those LOs previously ranked by a student. Accordingly, LOs belonging to found clusters, which in turn satisfy the searching criteria, are delivered. This is done at the moment when a student fills a query form provided by the LOR federation. More specifically, when registering a new LO within the LOR federation, the clustering agent performs its behavior being the k-means procedure. It is important to mention that we use the conventional K-means algorithm, which employs the Euclidean distance as a metric. Experiments are carried out over Repository Federation of Learning Objects Colombia - FROAC (htp:/froac.manizales.unal.edu.co/froac/). Our model not only slightly improves the precision rate but optimizes the amount and quality of delivered LOs.

As a future work, we are aiming at exploring and incorporating more data mining techniques within MAS, also expand the validation of the system. As well, the model performance is to be improved from an adequate agent behavior configuration.

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