Educational Resources Recommendation System for a Heterogeneous Student Group

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KEYWORD

Educational resources; Metadata; Multi-agent systems; Recommendation systems; Student group; User profile

ABSTRACT

In a face-class, where the student group is heterogeneous, it is necessary to select the most appropriate educational resources that support learning for all. In this sense, multi-agent system (MAS) can be used to simulate the features of the students in the group, including their learning style, in order to help the professor find the best resources for your class. In this paper, we present MAS to educational resources recommendation for group students, simulating their profiles and selecting resources that best fit. Obtained promising results show that proposed MAS is able to delivered educational resources for a student group.

1. Introduction

In the traditional education classroom, the teacher is facing a heterogeneous group of students. This group there are students with different features, preferences and ways of learning (Kaššák, et al., 2015). UNESCO in 2011 defined educational resource how any type of resource (including curricula, course materials, textbooks, video, multimedia applications, streaming audio, and other material that is designed for use in the teaching and learning process) that are available for use by teachers and students, without the need for any payment for rights or licenses for use.
Likewise, a Recommendation Systems (RS) is defined as a piece of software that facilitates users to discern more relevant and interesting learning information (Sikka, et al., 2012). 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 educational resources, the system should be able to recommend resources adapted to one or more user's profile characteristics using metadata (Li, 2010).

Students and teachers need a starting place for thinking about, and understanding, how they learn. In addition, a learning style is a description of a process, or of preferences. Any inventory that encourages a

learner to think about the way that he or she learns is a useful step towards understanding and hence improving, learning (Fleming & Baume, 2006).
Besides, it is necessary that students "learn to learn" and teachers should recognize the individual differences of their students to customize their education. It is important highlights that teaching styles do not influence the learning styles of the students (Alonso, et al., 1997).
Similarly, teachers should give classes using teaching strategies that strengthen learning styles. That is teach the classes first with a style after another so that all students feel cared for according to their preferences in the way they learn (Othman & Amiruddin, 2010)

Currently, the group recommender systems have been extended and are increasingly popular. Some works make recommendations using hybrid approach combining content-based and collaborative strategies. It is used in cases where groups are heterogeneous and can only recommend a small amount of items in a given period (Kaššák et al., 2015)(Elahi, et al., 2014).
This type of recommendation is mainly applied in various contexts where people gather to perform a specific activity. These contexts are associated with the use of multimedia such as movies, TV content, music selections resources and educational resources (Boratto & Carta, 2010). Also, consider learning styles in the classroom to deliver tailored materials is increasing.
An alternative to the selection of the most suitable educational resources for each learning style is a mapping between metadata and every learning style. Several proposals have been made in this regard, using different models of learning styles and metadata standards (Duque, et al., 2015)(Peña, et al., 2002)(Rodriguez, et al., 2013).

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).

In this paper, we propose an educational resources recommender system for a heterogeneous student group, taking account the learning style of each student of the group. The aim is delivering, for the teacher, educational resources to supporting the face class.
Experiments are done using *Federación de Repositorios de Objetos de Aprendizaje Colombia* - FROAC (available at: http:/froac.manizales.unal.edu.co/froac/). For quantifying the retrieval quality, a precision metric is used.

The rest of the paper is organized as follows: Section 2 describes the proposed model the recommender for heterogeneous group student and the proposed MAS. Section 3 explains the model validation and the results of the proposed model, through a case study. Finally, the main conclusions and future research directions are shown in Section 4.

2. Proposed Model

This work proposes a multi-agent system for adaptive educational resources recommendation for a student group heterogeneous. The search resources are recommended according to learning style of each student. The learning style are built according to VARK model proposed by Fleming and Baume (Fleming & Baume, 2006). This model is an instrument to determine the preference of students to process information from the sensory point of view. This model is considered that people receive the information through the senses and the brain selects some of that information and ignores the rest. The model takes the name VARK by the acronym of sensory modalities identified.

The students answer the test to kwon the learning style own, this is the main input of the recommender system. Fleming and Mills suggested four modalities that seemed to reflect the experiences of the students and teachers (Visual, Aural, Read/write, and Kinesthetic). This is sensory modalities that are used for learning information (Fleming & Baume, 2006).

The test alerts people to the variety of different approaches to learning. It supports those who have been having difficulties with their learning and has particular applications in business, relationship, sport, training and education.

In order to select the most suitable educational resources for each learning style is performed a mapping between metadata and every learning style. Similar to the proposal in (Duque et al., 2015), this paper presents a mapping between the scores in the VARK test for each simulated student and the metadata "Educational Resource Type" included in the LOM metadata standard.

Table 1 shows the mapping performed, where indicated with "1" if the Resource Type is relevant or not for each learning style. For example, if the Educational Resource Type of a LO is "Diagram", this will be convenient for a student with a 'Visual' learning style.

	V	A	R	K
Exercise				1
Simulation	1			1
Questionnaire				
Diagram	1			
Figure	1			
Graph	1			
Slide		1	1	
Table	1			
Narrative text		1	1	
Exam			1	1
Experiment				1
Problem statement			1	1
Self assessment	1			1
Lecture		1	1	

Table 1: LOM metadata vs. VARK learning styles.

Likewise, the agents of MAS can assume different roles within the system and can be created following a template. Each student is represented through an agent and it behaves autonomously, this ensure that the realized evaluation to each resource is independent. Once created the agents that representing students with their respective profiles, the evaluation process of educational resources begins.

The proposed model assisting teacher in the selecting educational resources for students group, because the system simulates the resource evaluation depending on their characteristics. After the evaluation, the scores assigned to educational resource for each simulated student are aggregated, and the educational resource with more points are best suited to the group average. This ensures greater efficiency and effectiveness against individual recommendation.

Figure 1 presents the architecture of the MAS proposed. Then explains the behavior and communication of each agents in this work.

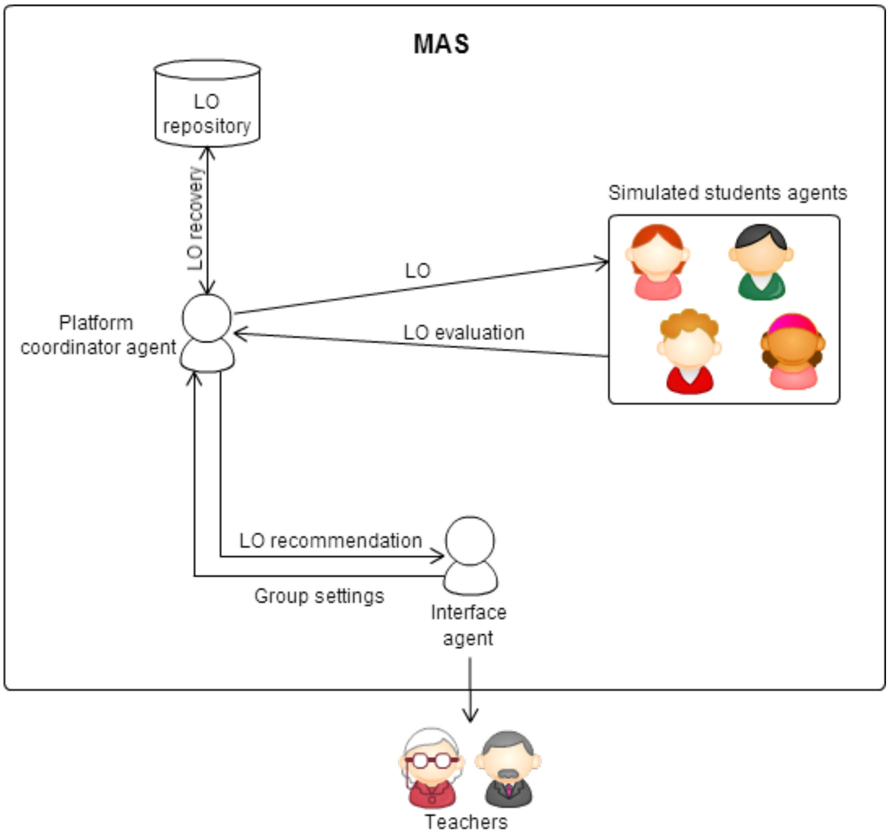

Figure 1: Proposed architecture.

Interface agent: It is responsible for presenting two interfaces to the teachers. A first interface allows entry the characteristics of a group. The data can be entered to the platform using a plain text that contains the id of the students and the results of the scores for each learning style. In addition to the above, the teacher can enter keywords related to the central theme of the course and with these perform the initial search of the LO in the repository. Other data that help to refine the amount of resources to be evaluated are: the education level to which is this course, learning time than is available for the course and the age range of students.

Coordinator agent: responsible for creating agents that simulate each of the members of the student group, which are created with the profile of learning according to the VARK model, admitted by the teacher together with the configuration data of the group. This agent also makes consulting LO in the repository and sends these to each of the simulated students so that they make their respective evaluation. Finally received the assessments made during the simulation and totals the results for the overall rating for each LO and recommend the LO with the higher qualifications

Generic student agent: This generic agent is the basis for creating the simulation of each student. Each simulation must be different, receiving the configuration data of individually profile, where the complete classification of each learning style is present being as the profile contains not only data of the predominant style, but also takes the calcification obtained in the other styles available in the model. This allows a weighted score of each LO. Once completion the LO classification, these come back to the Coordinator agent who totalizes the obtained data.

3. Case Study

This section is divided in two parts, the first one show the description about implementation process, and the second is showing the validation and tests on the system.

3.1 Implementation

To validate the model proposed we make two different experiments apply to case study. We use the educational resources stored in *Federación de Repositorios de Objetos de Aprendizaje Colombia* - FROAC (available at: http:/froac.manizales.unal.edu.co/froac/), in the aim to delivered metadata resources to initialized process.

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

Figure 2 shows the configuration interface for the group, where the specifics of each student and the general characteristics of the group are entered.

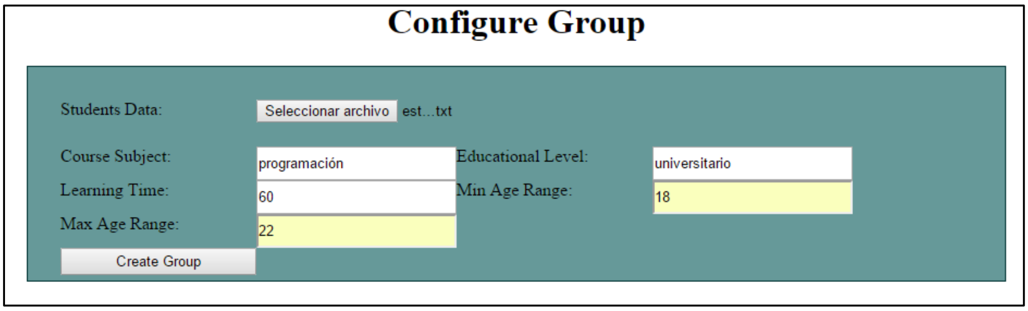

Figure 2: Configure Group Interface.

Following, we describe each one of the fields:

First, in Student data field is selected and loaded a plain text file where the first column represents a serial of the student, the second column corresponds to the score obtained for the student in the visual component of VARK test, in the next column the score for aural component, then the reader/writer component and finally in the fifth column value of kinesthetic component.

Second, Course Subject corresponds to the name of course.

Third, Educational Level is concern to the degree which it is addressed, such as primary, secondary, university degree, graduate.

Next, Learning Time corresponds to the maximum time spent for this specific class, the recovered set of LO should not exceed that time; this field is given in minutes.

Finally, as fifth and sixth maximum and minimum of age range correspond to the age limits of the group of students.

Figure 3 shows the interface to display LOs that are recommended to the teacher. When is presented the set of LO that accomplish the criteria established in the recommendation system configuration.

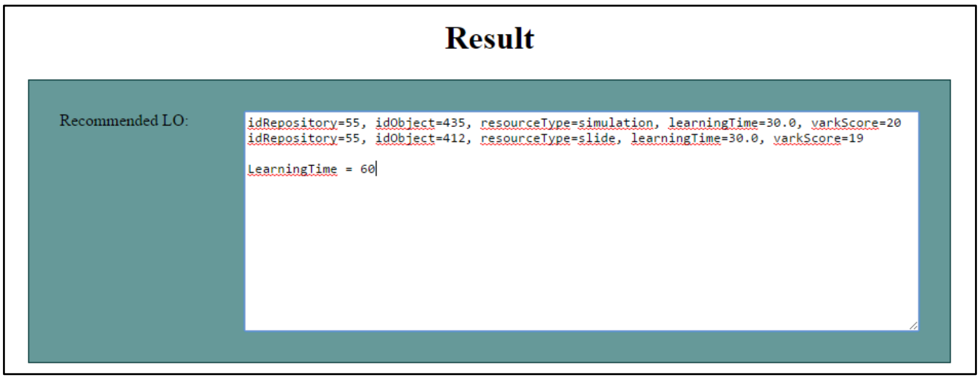

Figure 3: Results Interface.

3.2 Validation

The aim the first experiment is to validate the discriminating among different groups. If two groups have the different predominant learning style, presumably the recommender result are different for these groups, although the search string are equals.

For this experiment, we have two student groups, in the figure 4 show learning style for each student in these groups.

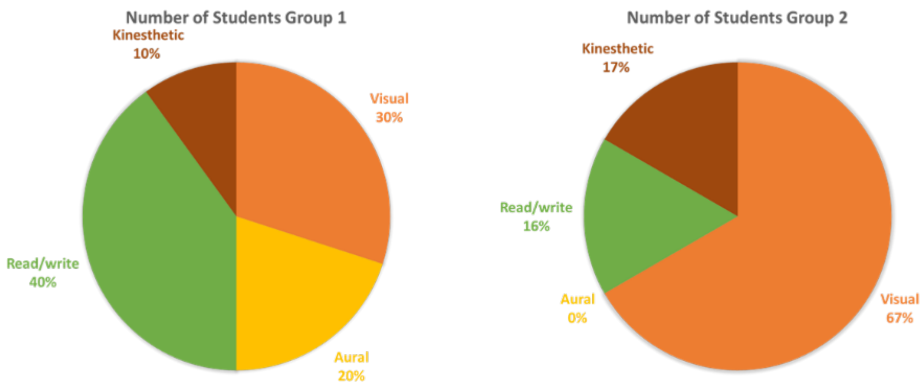

Figure 4: Distribution of groups in learning styles in experiment 1.

Students group 1, the learning style predominant is Reader/Write; this means that the preference for learning are the narrative text, slide, exam, problem statement, and lecture.
Students group 2, the learning style predominant is Visual; this means that the preference for learning are simulation, diagram, figure, graph, table, and self-assessment.

In the experiment, the results are different in both cases; the searching string is "*programación*". The table 2 show the educational type resources result.

Group 1	**Group 2**
Text	Simulation
Lecture	Graph
Lecture	

Table 2: Educational type results for each group.

With this experiment concludes that the proposed recommendation system discriminates and delivers different results for each group of students, according to the learning style of the majority.

The second experiment want to measure the level of satisfaction of the recommendation. Formula 1 is the metric of precision that is commonly used to measure the quality of information retrieval. The relevance is understood as the importance of LO delivered for carrying out a learning process. For that 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.

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

A precision metric was applied for performing the LO relevance evaluation. The table 3 and 4 show the results for precision metric for each group.

Group	Relevant LO	Recommended LO	Precision
Group 1	4	5	0,8
Group 2	2	3	0,67
Average	**3**	**4**	**0,75**

Table 3: Precision metric results with recommender.

Group	Relevant LO	Recommended LO	Precision
Group 1	1	7	0,14
Group 2	1	3	0,33
Average	**1**	**5**	**0,2**

Table 4: Precision metric results without recommender.

On average, recommendation system recovered around four LO for each student group and on average, three were relevant, therefore the result of precision was 0.75 on average for this experiment. If delivered to the student group random LO about theme (without recommender), the number of results are five LO, on average only 1 which is relevant LO, then precision is 0.2., and can be concluded that recommendations adapted to the student groups are delivered supports the teaching process on the face classroom.

4. Conclusions and future work

This paper proposes a model for recommendation of educational resources for a student group, which is based on the MAS paradigm using repository federations. Such a model takes advantage of simulating.

This proposal can support the teacher in the difficult task of selecting educational resources for use in the teaching of large groups of students. The suggestions are based on the characteristics of the students and how they learn best.

The results of the case study show that there is differentiation between the recommended educational resources for each group of students, who are relevant and can support the learning process.

Experiments are carried out over *Federación de Repositorios de Objetos de Aprendizaje 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 student characteristic and other recommendation techniques. 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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