Multi-Agent System for Recommending Learning Objects in E-Learning Environments

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***Abstract*—This full paper of innovate-to-practice category presents a Multiagent System for recommending learning objects in Virtual Learning Environments (VLE), aiming to improve the customization of instructional guidance on educational content according to the student's profile. The methodology was initially research aimed at identifying the motivators of the students' performance and their weaknesses, adopting a personalized student model based on the level of knowledge, and providing predictive models to monitor the student's progress in the curriculum. This framework provides a distributed architecture, and consists of three layers: 1) Administrative layer; 2) Storage layer; 3) Pedagogical layer. For the recommendation of learning objects, a collaborative filter was used, which constitutes a successful technique in several recommendation applications, seeking similarities in users' habits to predict their future decisions.**

Keywords—multiagent system, virtual learning environment, recommendation.

I. Introduction

Considering the diversity of the student population, e-learning must recognize differences in students' personalities to make the learning process more individualized and help to overcome the unique learning model, in which the same learning resources are provided to all students. With the exponential growth in the areas of Artificial Intelligence (AI), several promising solutions for the recommendation of learning objects have been developed. Education 4.0 requires technological commitment, and the learning processes are focused on students and not on the teacher, with this, there is an increasing demand for personalized education.

A recent trend in the field of e-learning systems is to use personalized intelligent agents and recommendation systems that have been widely accepted as solutions to overcome the challenges of information retrieval by students due to information overload [1]. According to the IEEE, a Learning Object (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.

The ability of interactive learning agents to make optimal decisions in dynamic environments is proven and highly regarded. Personalized and intelligent educational systems are interesting resources to support teaching and learning activities. These environments make use of intelligent techniques to recommend educational content to the real needs of students.

Multi-Agent Systems (MAS) form a sub-area of Distributed Artificial Intelligence and focus on the study of autonomous agents in a multi-agent universe. For MAS, the term autonomous designates the fact that agents have an existence of their own, regardless of the existence of other agents. This technology overcomes some limitations of the well-known client-server model. Software agents, or simply agents, are generally defined as autonomous software entities, with varying degrees of intelligence, capable of exhibiting reactive and proactive behavior in order to satisfy their design goals.

The methodology used in this work, initially, was a research aiming to identify the motivators of the students' performance and their weaknesses, adopting a personalized student model based on the level of knowledge and providing predictive models to monitor the student's progress in the curriculum.

To explain the research developed, the article is organized as follows: the present section presented the introduction. Section II presents the background and related works. Section III describes the multiagent system developed, the tests performed are detailed in Section IV, and to conclude Section V presents the conclusion and future work.

II. Background and Related Studies

Multiagent Systems represent an area of major research and development within Agent-Oriented Software Engineering. Software agents with the ability to reason have come to be used in a variety of applications. Usually, each agent has a set of behavioral capabilities that define their competence, a set of goals, and the autonomy necessary to use their behavioral capabilities in order to achieve their goals.

There are many definitions for an agent. According with FIPA (The Foundation for Intelligent Physical Agents) the agent is an entity that resists in a environment where they interpret data through sensors, reflect events in the environment and perform actions that produce effects on the environment.

Agents have very important characteristics such as:

- Autonomy, where decision making is elaborated based more on past experiences than on the knowledge previously inserted by the design of the artificial intelligence; Temporality, where the agent chooses to remain in the environment or not;
- Communicability, when it exchanges information from the environment or other agents;
- Reactivity, which is the ability to react to changes in the environment; Mobility, which brings the ability to shift to environments other than the original;
- Flexibility, as it can accept the intervention of other agents; Proactive, where he is able to go beyond to respond to environmental stimuli, display a goal-oriented behavior.

Multiagent System (MAS) is a system formed by a set of agents that interact with each other through the exchange of messages. In a system of this type, the achievement of global goals is dependent on cooperation between agents, as each one is autonomous and cannot be forced by another to perform tasks or have its internal state directly altered [8].

The BDI model was originally proposed by Bratman [2] as a philosophical theory about practical reasoning, where human behavior is modeled with the following attitudes: beliefs, desires and intentions. According to the BDI model, the actions are derived from the practical reasoning process, which consists of two steps. In the first step, called deliberation, a selection is made of a set of desires that must be achieved. In the second step, it is defined how these desires can be achieved. Practical reasoning weighs conflicting considerations for and against competitive alternatives, where the relevant considerations are determined by what the agent believes, imports and values [3].

It is necessary that this reconsideration activity is carried out in a way that does not hinder the agent's functioning, because if on the one hand it is necessary so that the agent does not work for an unnecessary intention, on the other it can prevent the agent from carrying out his intentions. Intentions are formed from a deliberation process and from the refinement of other intentions, but they can also contain the initial intentions entered by the user.

A Multi-Agent System for Recommending Accessible Learning Objects developed to attend students with disabilities and professors' computation area is presented in [5]. As a result of the research, authors present a recommendation system of accessible learning objects using intelligent agents and communities of practice through the recommendation mechanism based on trust.

A multi-agent system for adaptive LO recommendation is proposed in [6]. Authors use 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.

The first steps and ideas of a framework to address the problem of suggesting the most suitable recommendations for instructors (for teaching and assessing), by designing an intelligent multi-agent recommender system that uses data analysis methods is presented in [7]. The paper addresses the whole framework, specifically focusing on the assessment part. The framework proposed takes into consideration the heterogeneous personalities and teaching/assessing styles of different instructors to personalize and customize their experience. It provides immediate and customize instructions and feedback to help instructors improve their educational tasks.

Considering the importance of the reliability of the student model, [9] propose a framework based on the Fuzzy student model and the Optimized Theory of Response to Fuzzy Item in the form of a Fuzzy pedagogical module. Based on these simultaneous Fuzzy systems and the use of the Multi-Agent System for student monitoring, student ability estimation and student assessment were done with less uncertainty. When examining the capability of the proposed system in an e-learning engineering education, it indicated that the success rate of recommendations for student motivation is higher than before and is over 83%.

An adaptive Virtual Learning Environment model based on Intelligent Tutoring Systems (STIs) using multi-agent systems is described in [10], and a prototype based on this model was designed and built using AVA Moodle as a study of case. Agents interact with users by sending messages to them and manage knowledge by changing the sharing of available resources and activities. In this way, agents carry out the actions previously defined by the teacher, in a personalized and adaptable way, according to each user's personal learning mode.

Regarding the integration of adaptive interfaces in remote laboratories for educational purposes, Rivera & Petrie [11] propose a model and set of diagrams to improve the user experience. The authors claim that with the use of intelligent adaptive interfaces, experiments can gradually increase their complexity, taking into account variables that are identified as part of the learning processes, such as: topic difficulty level, students' knowledge and level of course, among others.

III. MULTIAGENT SYSTEM

The system presented in this paper was based on the BDI architecture, where human behavior is modeled with the following attitudes: beliefs, desires and intentions. Beliefs represent the agent's fundamental view of his environment. Desires represent the desirable states that the system can present, or the motivational state of the agent. The intentions represent the current chosen action plan, corresponding to the states of the world that the agent actually wants to provoke, that is, there is a commitment to carry them out.

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The three mental attitudes that make up the BDI model are explained below:

- Beliefs: represent the characteristics of the environment that are updated after the perception of each action. They represent the informational component.

- Desires: contains information about the objectives to be achieved. They represent the emotional state of the system.
- Intentions: contains the current chosen action plan. They represent the deliberative component of the system.

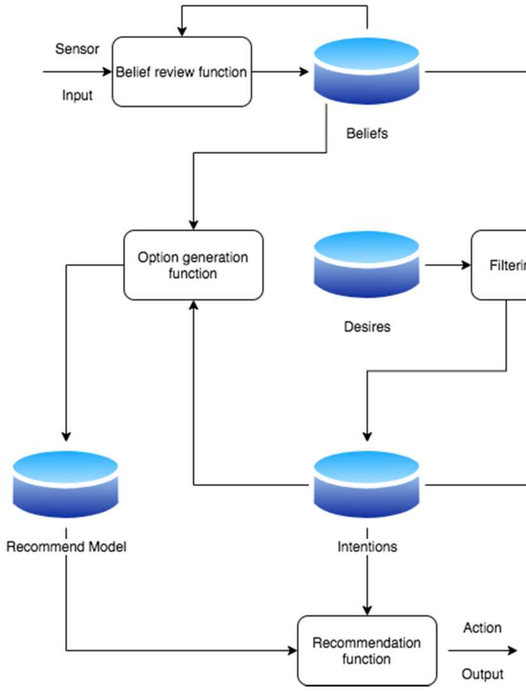

Fig. 1. Relationship between BDI Architecture Elements

Beliefs represent the agent's fundamental view of his environment. A belief is an intentional mental state fundamental to the interactions of agents with a notion identical to knowledge. An agent may have beliefs about the world he inhabits, about other agents, about interactions with other agents and beliefs about his own beliefs. Beliefs can even be contradictory. Since the world is dynamic, past events need to be remembered and are represented by beliefs. They can be seen as the informational component of the system.

Desires represent the desirable states that the system could present, or the motivational state of the agent. The agent chooses the wishes that are possible according to some criterion, encouraging him to carry out the tasks for which he was designed. In this way, desires motivate the agent to act to achieve his goals. In order for a desire to be fulfilled, it is necessary to have the inherent knowledge (the belief) and also the context favorable to its fulfillment. A desire may be in conflict with the agent's beliefs or with another desire.

The intentions represent the current chosen action plan, corresponding to the states of the world that the agent effectively wants to provoke, that is, there is a commitment to carry them out. They can be considered a subset of desires, but they must be consistent. If an agent decides to pursue a specific goal, then that goal becomes an intention. Intentions determine the practical reasoning process, as they determine the actions to be taken. Once an intention has been chosen, there will be a direction for the practical reasoning of the future, with the aim of realizing it. In practical reasoning theory, the process of deciding which goals are to be achieved is called deliberation, and what is done to achieve these goals is called the half-end process. The agent reconsiders his intentions from time to time to confirm the alignment of his intentions with his desires.

An agent is a computational entity with an autonomous behavior that allows it to decide its own actions. The decision of which action to carry out is determined by the agent, taking into account the changes that have taken place in the environment in which it operates and the desire to achieve its goals.

An agent's architecture specifies how it can be decomposed into a set of modules and its interactions describe how the data received from the environment and the agent's internal state determine its actions [4]. Thus, the architecture of an agent is the description of the internal processes that govern its interaction with its environment.

The Multi-Agent System (MAS) overcomes some limitations of the well-known client-server model. Our framework provides a distributed architecture compatible with the specifications of the Foundation for Intelligent Physical Agents (FIPA), a set of international standards maintained by the IEEE, and consists of three layers as specified in Figure 2.

1) Administrative layer: This layer is composed by the Administrator Agent who is responsible for allowing access to the system and controlling the registration of new users in Virtual Learning Environment. It allows access to the system and controls student activities.

2) Storage layer: responsible for storing information about the learning environment, student model and student history. In our system, a learning object is defined as <id, URL, name, type, topic, keywords, description>. These learning objects are referenced in the virtual learning environment by their URL. All learning objects are organized as a knowledge map to build a repository of learning objects.

3) Pedagogical layer: The pedagogical layer is composed by composed by the Profile Agent, Recommendation Agent and Tutor Agent, and must choose possible recommendations to help the student. It aims to suggest learning objects according to their profile. This layer allows to define the learning objects that will be recommended in order to assist students in the process of acquiring knowledge.

In our research, the recommendation is based on the learning by doing method, proposed by John Dewey, which defends education as a process of reconstructing and reorganizing acquired experiences that will influence future experiences. In this way, everything is experiences and possibilities in education through the movement of the student in action. In this method, the system is active and encourages the student to select information and deduce guidance on the domain model.

The pedagogical strategy related to the MAS proposed in this research allows teachers to view the suggested recommendations. Regarding the student's orientation, the strategy must take into account the student's profile and the characteristics of the environment. This layer determines that the teacher is responsible for inserting the learning objects, which will be stored in the same database as the VLE.

Our framework has four intelligent agents described below, to follow the students' actions in the VLE, and suggest the learning object recommendations.

- Administrator Agent: is responsible for controlling student access, as well as authorizing access to the virtual room for new users. This agent also assists with password reset if necessary.
- Profile Agent: is responsible for identifying the students' learning style, according to the data stored in the student model.
- Recommendation Agent: analyzes the student's history to recommend learning objects, and the students are responsible for evaluating the suggested recommendations.
- Tutor Agent: When verifying that a learning object was recommended, but has not yet been accessed, the Tutor Agent suggests help for students. This help is not a recommendation, but an attempt to bring those absent students closer to the VLE.

In addition, the pedagogical layer determines why it is necessary to carry out the recommendation. The objective can be to verify the knowledge acquired by the students, and guide them by recommending educational resources that are in accordance with their learning style.

IV. Conclusion

This paper presented a Multiagent System for recommending learning objects in Virtual Learning Environments (VLE). This framework provides a distributed architecture with three layers: Administrative layer; Storage layer; Pedagogical layer.

Our framework is composed by four intelligent agents, to recommend the learning objects: Administrator Agent (responsible for controlling student access); Profile Agent (responsible for identifying the students' learning style); Recommendation Agent (analyzes the student's history to recommend learning objects); Tutor Agent (suggests help for students). The agents are in the implementation phase, and as future work, we suggest applying them in virtual classes to validate the recommendation's effectiveness.

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References

[1] J. K. Tarus, Z. Niu, and G. Mustafa. (2018). “Knowledge-based recommendation: a review of ontology-based recommender systems for e-learning”. Artificial intelligence review, 50(1), 21-48.

[2] M. Bratman. (1987). "Intention, plans, and practical reason" (Vol. 10, p. 20). Cambridge, MA: Harvard University Press.

[3] M. Wooldridge. (2000). "Semantic issues in the verification of agent communication languages". *Autonomous agents and multi-agent systems*, *3*(1), 9-31.

[4] J. M. Wooldridge. (1995). "Selection corrections for panel data models under conditional mean independence assumptions". *Journal of econometrics*, *68*(1), 115-132.

[5] A. B. Mourão, and J. F. M. Netto. (2019). "SIMROAA Multi-Agent Recommendation System for Recommending Accessible Learning Objects". In *2019 IEEE Frontiers in Education Conference (FIE)* (pp. 1-9). IEEE.

[6] P. A. R. Marín, N. Duque, & D. Ovalle. (2015). "Multi-agent system for Knowledge-based recommendation of Learning Objects". *ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal*, *4*(1), 80-89.

[7] Y. El Geddawy, F. Mikic-Fonte, M. Llamas-Nistal, & M. Caeiro-Rodríguez, M. (2019). "Adaptive Multi-Agent Assisting Framework for a Personal Teaching Environment". In *2019 IEEE Frontiers in Education Conference (FIE)* (pp. 1-4). IEEE.

[8] S. Parsons, & M. Wooldridge. (2002). "Game theory and decision theory in multi-agent systems". *Autonomous Agents and Multi-Agent Systems*, *5*(3), 243-254.

[9] S. Nafiseh, & M. G. Ali. (2013). "Evaluation based on personalization using optimized firt and mas framework in engineering education in e-learning environment". In 4th International Conference on e-Learning and e-Teaching (ICELET 2013) (pp. 117-120). IEEE.

[10] C. E. G. PalominO, R. A. Silveira, & M. K. Nakayama. (2015). "Using agent-based adaptive learning environments for knowledge sharing management". International Journal of Knowledge and Learning, 10(3), 278-295.

[11] L. F. Z. Rivera, & M. M. L. Petrie. (2018). Models and smart adaptive interfaces for the improvement of the remote laboratories user experience in education. In *Online Engineering & Internet of Things* (pp. 416-423). Springer, Cham.

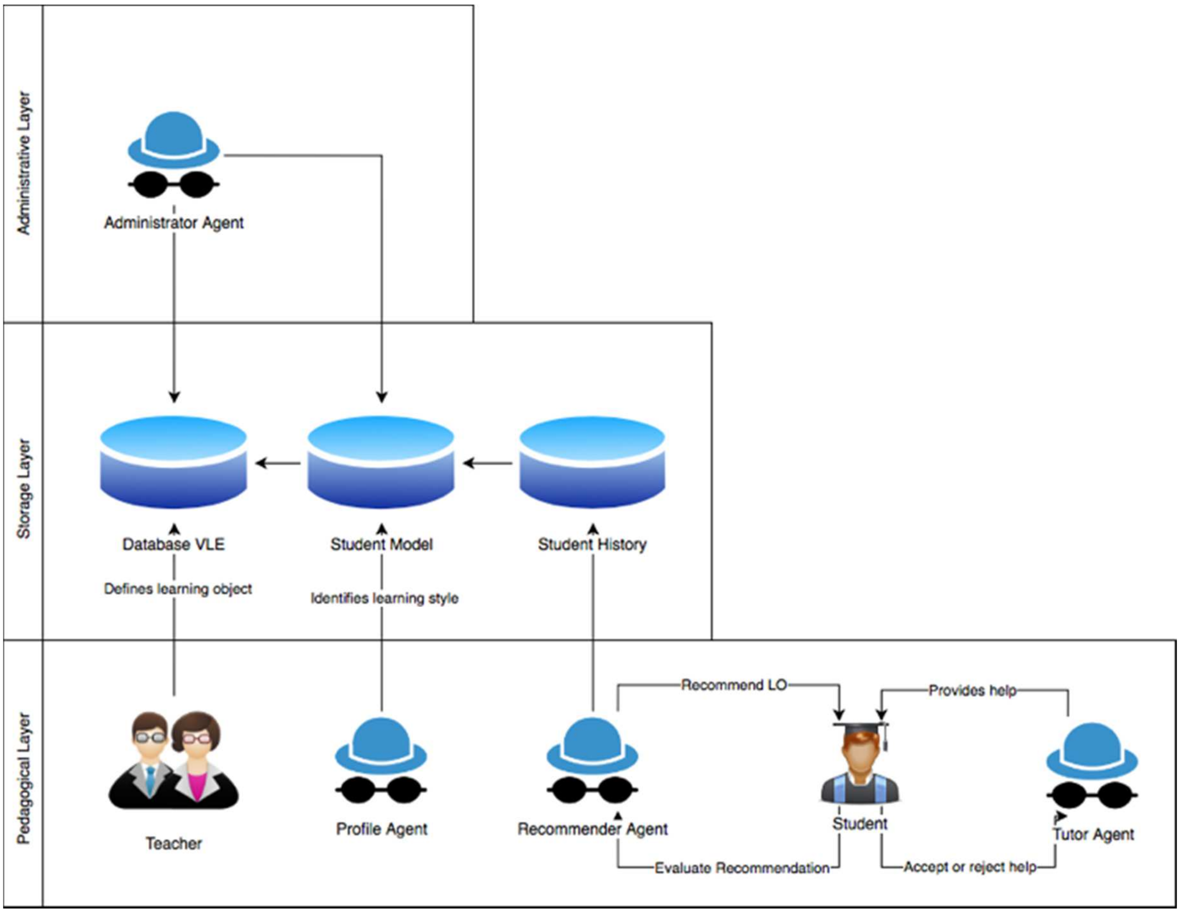

Fig. 2. Layers of Multiagent System