A Multiagent Approach to Educational Resources Retrieval

Ana Casali[1], Claudia Deco[2], Cristina Bender[2] and Regina Motz[3]

[1] Departamento de Sistemas e Informática, Facultad de Ciencias Exactas, Ingeniería y Agrimensura, Universidad Nacional de Rosario. Pellegrini 250, 2000, Rosario, Argentina
acasali@fceia.unr.edu.ar
[2] Departamento de Investigación Institucional, Facultad de Química e Ingeniería, Universidad Católica Argentina. Mendoza 4197, 2000, Rosario, Argentina
{deco, bender}@fceia.unr.edu.ar
[3] Instituto de Computación, Facultad de Ingeniería, Universidad de la República, Julio Herrera y Reissig 565, 11300, Montevideo, Uruguay
rmotz@fing.edu.uy

Abstract. This work presents a multiagent architecture for web educational resources retrieval that may help users to find courses according to their personal and cultural aspects. This multiagent platform includes several kinds of agents with different functionalities. We particularly model the Educational Resources Finder Agent as a Graded BDI Agent, which is in charge of a flexible retrieval of the best courses according to the student profile.

1 Introduction

The use of electronic Educational Resources is increasing since e-learning became popular. Nowadays, students and professors are faced with the necessity of finding electronic educational resources that are more qualified according to their needs and characteristics, known as Cultural Aspects. This is usually a big task because of the following basic reasons: a) the great amount of existing electronic educational resources in the web; b) the difficulty to automatically manage different cultural aspects since some of them may be uncertain or imprecise; and c) the difficulty for the user to correctly specify his/her search.
Cultural Aspects are preferences and ways of behavior determined by the person's culture. In this work, the cultural aspects are just the features that distinguish between the preferences of students from different regions and they will help in the retrieval of educational material. Some cultural aspects are: country, language, attitude, and learning style. The history, climate, religion, economy, etc., are elements related to each *country* that determinate the habits of its people, which can be different among different regions of the same country. Concerning to the *language*, the best way to communicate with a person is by using her/his mother language, and idiomatic expressions and common usage verb tenses of her/his culture. The level of interaction preferred is related with the *attitude* of the student: active, passive or reactive. For example if the student is a reactive person, the course should offer dynamic activities. The *learning style* is one of the most important characteristics in the form that a person resolves a situation related with learning tasks. The learning style determines, in an indirect way, how to organize and represent the information to the student for his/her better comprehension and fast knowledge acquisition. We consider the following styles: Holistic Visual, Holistic Verbal, Analytic Visual, and Analytic

Verbal. The Holistic style is associated with the parallel process of the information. The student adopts a global boarding, exploring the different topics without a predefined order. They prefer to see real applications or examples as soon as possible. In this style one can find students, called Holistic Verbal, that prefer the information presented with declarative text, and others, called Holistic Visual, that prefer the information presented with graphics, images, etc. The Analytic style is associated with a linear or sequential process of the information. The students adopt a focal boarding, studying topics, one per time, in sequential order. This is a kind of student that does not prefer to see real examples. In this style one can find students, called Analytic Verbal, that prefer information in plain text, organized in small paragraphs, each one with one idea, whereas Analytic Visual prefer images or diagrams.

This work describes how problems related with finding electronic educational resources that are more qualified according to the user's needs and characteristics may be solved proposing a multiagent architecture for educational resources retrieval driven by cultural aspects. In this framework, to improve the retrieval process, the Educational Resources Finder Agent is modeled as a Graded BDI agent specified using a multi-context system.

This paper is organized as follows. In Section 2, the Graded BDI agent model is introduced. In Section 3 we specify the Educational Resources Finder Agent and its contexts and some of the main bridge rules are described. Finally, some conclusions and future work are presented.

2. Multiagent systems and graded BDI agents

In the recent past, an increasing number of multiagent systems have been designed and implemented to engineer complex distributed systems. Lately, the Agent community has made a great effort in the development of recommender systems and intelligent agents to help users confronted with situations in which they have too many options to choose from. These systems assist users to explore and to filter out their preferences from a number of different possibilities, many of them coming from the Web. Between their potential applications, the educational domain seems to be a good candidate as the offers of educational resources are in constant growth. Several previous works have proposed theories and architectures to give agent-based systems a formal support. Among them, a well-known intentional formal approach is the BDI agent architecture proposed by Rao and George [1]. It is based on the explicit representation of the agent's beliefs (B), its desires (D) and its intentions (I). Indeed, this architecture has evolved over time and it has been applied, to some extent, in several of the most significant multiagent applications developed up to now. Actually, most of agent architectures proposed do not account for uncertain or gradual information. In order to make the BDI architecture more flexible, to design and develop agents potentially capable to have a better performance in uncertain and dynamic environments, Casali et al. [2] have proposed a general model for Graded BDI Agents. This model allows to specify architectures able to deal with the environment uncertainty and with graded mental attitudes. In this architecture, belief degrees represent to what extent the agent believes a formula is true. Degrees of positive or negative desires allow the agent to set different levels of preference or rejection respectively. Intention degrees give also a preference measure but, in this case, modeling the cost/benefit trade off of reaching an agent's goal. Then, agents having different kinds of behavior can be modeled on the basis of the representation and interaction of these three attitudes.

The graded BDI model developed is based on the notion of multi-context system. This frame-

work allows the definition of different formal components and their interrelation. In the graded BDI approach, it is used separate contexts to represent each mental attitude and each context is formalized with the most appropriate logic apparatus. The interactions between the components are specified using inter-unit rules, called bridge rules. This approach has been used previously to model agent architectures, as a framework where the different components of the architecture and their interactions can be neatly represented [3].
In this paper, we present a multiagent architecture for an educational resource retrieval that may help a student to choose courses according to his/her personal and cultural aspects. This multi-agent platform includes several kinds of agents according to different functionalities. We particularly model the Educational Resources Finder Agent as a Graded BDI Agent, which is in charge of flexible retrieval of the best courses according to the student profile.

3. Multiagent Architecture for Educational Resources Retrieval

The proposed multiagent architecture is basically made up of three fundamental agents: The Semantic Refiner Agent (SR-Agent), the User Profile Agent (UP-Agent), and the Educational Resources Finder Agent (EF-Agent). In the scope of this paper we give special attention to the Educational Resources Finder Agent, which is modeled as a graded BDI agent. Also, we assume that there exists a learning object (LO) repository with the educational resources enhanced with metadata that describes their characteristics (e.g.: subject, language, amount of images). The multiagent system with its different agents, repositories and ontologies, and their interactions are illustrated in Figure 1.

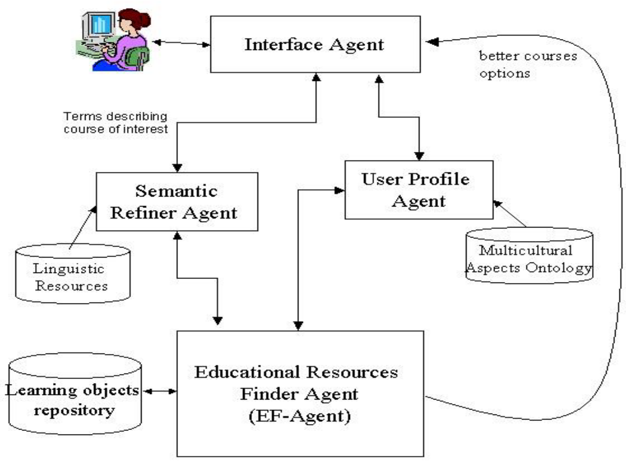

Fig. 1: Multiagent System Architecture

The **Semantic Refiner Agent (SR-Agent)** produces the search strategy associated to the user's interest. When a user asks a query, he/she gives as input a set of concepts that describes the subject of the course required. The result given by the SR-Agent is a search strategy associated to these concepts. A search strategy is a logical expression composed by different concepts combined with logical connectors, and it consists on the disjunction of the expansions of each concept, and then, the conjunction of these expansions. In this process, this agent uses linguistic resources such as: thesauruses, dictionaries, multilingual dictionaries and ontologies. The details of this process are described in [4].

The **User Profile Agent (UP-Agent)** extracts data from the user and from the ontology of multicultural aspects in order to build the user profile [5]. The personal data are obtained from the user by a set of queries driven by an appropriate ontology. The UP-Agent provides to the EF-Agent with the personal and cultural aspects characteristics, in order to retrieve only those courses that best satisfy his/her personal and cultural characteristics.

The **Educational Resources Finder Agent** (EF-Agent) is in charge of looking for different learning objects in order to satisfy the student preferences. The output of this agent is an ordered list of educational resources supplied by a set of universities. This agent will decide the best order taking into account the student interests and cultural aspects, the expected satisfaction of preferences by the course, its cost (e.g. its estimated duration time) and the trust in the resource supplier. We have designed the EF-Agent as a recommender agent using the graded BDI agent model. On the one hand, we chose a BDI model because we consider this agent must decide an intention (e.g. the best course/better courses offered to the student) depending on different attitudes as the beliefs of the web environment (e.g. the learning objects with their characteristics), the preferences and restrictions of the student (e.g. the characteristics he prefers or rejects for the learning object), and the trust in the course supplier (e.g. university, institution). Using an intentional model as the BDI, allows us to specify an architecture where all these mental attitudes and their interactions can be neatly represented and weighted, in order to take more flexible decisions. On the other hand, we proposed a graded model because there are uncertain and imprecision involved in how a learning object with diverse characteristics, provides a student with different styles of learning (e.g. holistic visual). Also, the student's preferences and restrictions may be graded.

The EF-Agent is formalized using a multi-context system. This agent specification contains three basic components: contexts, logics, and bridge rules, which channel the propagation of consequences among theories. Thus, an agent is defined as a group of interconnected units:

$<\{C_i\}_{i \in I}, \Delta_{br}>$ where each context C_i is the tuple $C_i = (L_i, A_i, R_i)$ where L_i, A_i and R_i are the language, axioms, and inference rules respectively. When a theory (a needed set of formulae) is associated with each context, the specification of a particular agent is complete. The deduction mechanism of these systems is based on two kinds of inference rules, internal rules, and bridge rules, which allow to embed formulae into a context whenever the conditions of the bridge rule are satisfied. In the EF-Agent model, we have different context to represent the different mental attitudes. This allows us to use an adequate language and logic for each case. We have contexts to represent beliefs (BC), desires (DC), intentions (IC), and a social context (SC), which represents the trust in other provider agents. We also consider two functional contexts: Retrieving (RC) and Communication (CC). In summary, the BDI agent model is defined as:

$$\text{EF-Agent} = (\{BC, DC, IC, SC, RC, CC\}, \Delta_{br}).$$

The overall behavior of the system will depend of the logic representation of each intentional notion in the different contexts and the bridge rules. In order to represent and reason about graded notions of beliefs, desires and intentions, we use a modal many-valued approach [6] where uncertainty reasoning is dealt with by defining suitable modal theories over suitable many-valued logics. The formalization of the adequate logics for the different contexts in a general graded BDI agent is described in [2]. In the following we outline the particular characteristics of the different contexts for the EF-Agent's specification.

Belief Context: The purpose of this context is to model the EF-Agent's beliefs about the educational environment. These include the knowledge about the educational objects with metadata that represents different characteristics such as the subject, language, amount of practice, amount of figures and interactivity. The course suppliers provide this information and it is stored in a relational database. In this first approach we do not consider uncertainty involved in this information. Also, in this context we must evaluate how certain are that a learning goal (G) could be achieved through the different courses (O_i). We use a modal many-valued approach to represent this kind of uncertain knowledge.
The language for this context has formulae of a propositional dynamic language L_D like $[O_i]$ G, meaning, "After the execution of the course O_i, the goal G becomes true". Over this bi-valued language L_D we introduce the modality B and then, the modal formulae are many-valued. For instance, let us consider that the belief degrees are to be modeled as probabilities. Then, for each formula p, we consider a modal formula B_p, which is interpreted, as "p is probable". This modal formula B_p is then a fuzzy formula, and in particular, we can take as truth-value of B_p precisely the probability of p. Moreover, using a many-valued logic, we can express the governing axioms of probability theory (or other uncertainty model) as logical axioms involving modal formulae.
The EF-Agent in this context includes many-valued modal formulae as $B[O_i]$ G. This formula is graded and its degree represents the uncertain of how the learning object O_i satisfies G. The learning goals represent the conjunction of different learning preferences such as subject, language and learning characteristics.
Desire Context: In this context, we represent the EF-Agent's desires. In this application, the EF-Agent adopts as desires the student's preferences in the course's subject and different characteristics. Inspired by the works on bipolarity representation of preferences by Benferhat et al. [7], we suggest formalizing agent's desires also as positive and negative. Positive desires represent what the agent would like to be the case (e.g. subject: kinetics, style: holistic). Negative desires correspond to what the agent rejects or does not want to occur (e.g. language: Portuguese). Both, positive and negative desires can be graded. As for the BC language, the language DC is defined as an extension of a propositional language L by introducing two (fuzzy) modal operators D^+ and D^-. D^+ G reads as "G is positively desired" and its truth degree represents the agent's level of satisfaction would G become true. D^- G reads as "G is negatively desired" and its truth degree represents the agent's measure of disgust on G becoming true.
In this context the student's desires will be expressed by a theory containing quantitative expressions about positive and negative preferences. These formulae express in different degrees what the student desires from a learning object. Then, the EF-Agent, starting from these desires, begins a chain of intra and inter-context deductions in order to determine which the best courses to recommend to the user are.
Social Context: The aim of considering a Social Context (SC) in the EF-agent architecture is to model the social aspects of agency. To do so, a key issue is the modeling of the agent's trust on other agents. In an agent community different kinds of trust are needed and should be modeled [8]. Here, we consider the trust in the educational resources suppliers that interact with the EF-Agent in order to evaluate the risk of course plans. For this application, we consider that the trust depends only on the kind of course that the universities offer.

Intention Context: This unit is used to represent the agent's intentions. Together with the desires, they represent the agent's preferences. However, we consider that intentions cannot depend just on the benefit of reaching a goal G, but also on the world's state and the cost of transforming it into one, where the formula is true. By allowing degrees in intentions we represent a measure of the cost/benefit relation involved in the agent's actions towards the goal. In this case, the agent's plan would be the choice of a particular course for the student to follow. A theory for IC in the EF-Agent represents those desires the user can intend by different feasible courses. Using this set of graded intentions, this agent derives the final intention and the best-recommended courses. This allows the agent to take more flexible decisions modeling user's needs.
Retrieving and Communication Contexts: The nature of these contexts is functional and they are essential components of our model. The Retrieving Context (RC) has to look for feasible courses in the repository of learning objects, offered by the different supplier agents. All the course plans offered are introduced in the RC via the Communication Context. The Communication unit (CC) makes it possible to encapsulate the agent's internal structure by having a unique and well-defined interface with the environment. The theory inside this context will take care of the sending and receiving of messages to and from other agents in the multi-agent society.
Bridge Rules: For our EF-Agent, we define a collection of basic bridge rules to set the interrelations between contexts. As already mentioned, there are bridge rules from BC and DC to RC that, from the positive and negative desires, the beliefs of the agent regarding what the user can or cannot achieve through a particular course, generate predicate instances in the RC unit that are used by the retrieving program to find the feasible learning objects. Regarding intentions, there is a bridge rule that infers the degree of I_{Oi} G for each feasible course O_i that allows to achieve the goal G (conjunction of the student preferences). The intention degree is thought as a trade-off among the benefit of reaching a goal, the normalized cost of the learning plan and the trust in its provider U. As for example, we show the following bridge rule that computes this value from the degree of D^+ G (d), the degree of belief $B[O_i]G$ (r), the cost of the course (c) and the trust t in the course supplier U (t):

$$\frac{DC: (D^{+} G, d),\ \ PC: fcourse(O_i, G, r, c),\ \ SC: (T_U[O_i]\,G, t)}{IC: (I_{Oi}\,G, f(d, r, c, t))}$$

Different functions f allow to model different agent behaviors. The learning plan O_b that allows getting the maximum intention degree i, will be set by the RC as the best course and will be recommended to the user.

4. Conclusions and future work

We have presented a multiagent architecture for educational resources retrieval that may help users to choose courses according to their personal and cultural aspects. This framework includes the EF-Agent specified using a graded BDI agent model. This model allows us to define an agent that explicitly represents the uncertainty of beliefs related to educational objects, and graded user's preferences and restrictions. The user's profile is incorporated in the EF-Agent by introducing his preferences (positive and negative) and the importance he/she gives to the different variables that weigh in the selection of the educational object. This profile together with the course information, constitute the knowledge base for the EF-Agent's reasoning.

This work is related to the EduCa Project (http://www.fing.edu.uy/inco/grupos/csi/esp/Proyectos/Educa.htm), where the development of the Learning Objects Repository, the SR-Agent and the UP-Agent are part of the ongoing work. As for future work, we plan to implement a prototype of the EF-Agent and the necessary interactions with the other agents in this multiagent system.

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