A Multiagent Platform for Educational Resources Retrieval driven by Cultural Aspects

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Abstract

In this work we propose a multiagent architecture for web educational resources retrieval that helps users to find courses according to their personal and cultural aspects. 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 users from different regions. 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. We outline the overall multiagent system and present an example illustrating the searching process.

Keywords: Educational resources retrieval, Multiagent systems

1. Introduction

The web has become one of the biggest repositories of knowledge, easily accessible for everyone. Moreover, 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, including Cultural Aspects. This is usually a big task because of the great amount of existing electronic educational resources in the web, the difficulty to automatically manage different cultural aspects since some of them may be uncertain or imprecise, and the difficulty for the user to correctly specify his/her search. These problems are concerns of the information retrieval area. Information Retrieval deals with the representation, storage, organization of, and access to information items. The representation and organization of the information items should provide the user with easy access to the information in which he/she is interested [1]. Given a collection of documents and a query, the objective of a search strategy is to retrieve all the relevant documents to a user query while retrieving as few non-relevant documents as possible. Unfortunately, characterization of a user's information need is not a simple problem. It is not simple due to the semantic complexity of vocabulary. Information Retrieval faces with several problems. On one hand, authors and users frequently use different words or expressions when they refer to the same concept. For example, in mathematics, "matrix" can also be expressed as "array"; and if in a document appears "array" instead of "matrix" this document would not be retrieved. This problem can be solved making use of synonyms. On the other hand, some words can have different meanings. For example, the word "matrix" can refer to a rectangular array of elements set out by rows and columns, or to a container into which liquid is poured to create a given shape when it hardens. This is solved disambiguating the sense of the word. Some statistics [2] indicate that the great majority of users do not know search techniques, and they have difficulty of clearly expressing their information needs, and therefore, they do not obtain the wanted results.

In this work we describe how these problems may be solved with a multiagent educational resources retrieval platform driven by cultural aspects. In this framework, to improve the retrieval process, we present an Educational Resource Finder Agent specified as a Graded BDI agent model based on multi-context systems. We also propose a User Profile Agent to build the student profile using ontologies. The user profile involves personal and cultural aspects. Personal aspects include characteristics of each particular student such as age, foreign languages, learning style and professional background. Cultural aspects are preferences and ways of behavior determined by a person's culture. In this work, cultural aspects are just the features that distinguish between students' preferences from different regions. We decided to work over a set of characteristics, which were identified in research about a person's preferences in learning activities.

The remainder of the paper is organized as follows. Section 2 presents the use of ontologies for modeling cultural aspects. In Section 3, the Graded BDI agent model is introduced. In Section 4 we specify the Educational Resources Finder Agent. Finally, some conclusions and future work are presented.

2. Modeling Cultural Aspects

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. These cultural aspects are called *student profile*, and will determine the retrieval of educational material.

Cultural Aspects

The cultural aspects we consider at the moment are:

Country or Region. The history, climate, religion, economy, etc. are elements of each country that determinate the habits of its people, which can be different among different regions of the same country.

Language. The best way to communicate with a person is by using her/his mother language. Moreover, it.is better to use the idiomatic expressions and common usage verb tenses of her/his culture.

Attitude. 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.

Learning Styles. The learning style is one of the most important aspects considered in this work. The learning style and the preferred activities are important elements in the quality process of the adaptation of a course. Various studies about this area agree to consider that 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 organise and represent the information to the student for his/her better comprehension and fast knowledge acquisition. In this work we use 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, organised in small paragraphs, each one with one idea, whereas Analytic Visual prefer images or diagrams.

Activities Affinity. The preference degree of a student to an activity is established by the interaction with the system and with other students in the same activity. Activities can be classified according to the level of reaction and interaction that they require. Some activities require the student to implement a solution. Other requires less degree of reaction like the selection of a solution. And there are others that can be named "passive" activities like listening, read or see some material. Moreover, there may be activities that require interaction between students. Also, activities can require the use of different tools like: forum, chat, additional software like a simulation, among others. This aspect is associated with the degree of interaction that students are required within the system. Other important aspect is the material or resources used to present an activity (text documents, diagrams, figures, etc.) which are called resources. The preference degree of a student may be high or low according to the kind of resources and the characteristics presented by the activities.

Ontology for Cultural Aspects

Ontologies are the descriptions of the entities, relations and restrictions of a domain, expressed in a formal language to enable machine understanding. Tom Gruber [3] has defined "an ontology is a formal, explicit specification of a shared conceptualization". Additionally, ontologies to be used on the web need to be supported by established web languages to facilitate interoperability and take advantage of existing tools. In order to make metadata understandable to the Web community, classification schemas defining vocabularies in an unambiguous way must be available on the web forming namespaces, which give well understood semantics for the terms used in metadata descriptions. In this section we present the cultural aspects implemented as an ontology encoded in OWL language [4], developed using Prótegé [5], and the reasoner Racer to check the model satisfability.

The ontology is modeled though three diagrams, one of them, which is presented in the Figure 1, gives a general vision of the ontology for cultural aspects. The other two diagrams depict in detail the characteristics of Preferred Activities, and the Learning Styles considered in this work. These diagrams are not showed because for size reasons, but you can find a complete description of the ontologies in http://www.fing.edu.uy/inco/proyectos/EduCa/Ontologies.html

We implement only those concepts or properties, which are not implemented by some standard. LOM [6] offers the implementation of some elements. Some others are implemented by Dublin Core [7]. The rest of elements are implemented by our cultural aspect ontology. We use a prefix in concept names for those concepts defined in another namespace and used here.

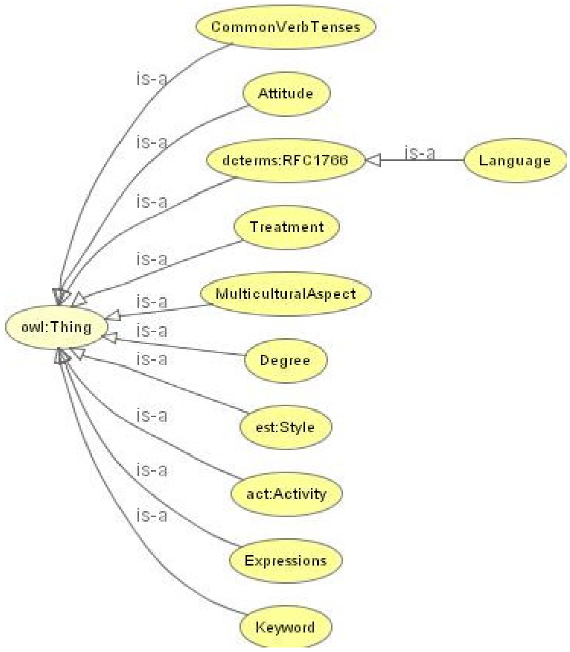

Figure 1: Ontology for Cultural Aspects

The *dcterms: RFC1766* is the language concept in LOM, but implemented by Dublin Core. It uses the standard RFC1766 that contains the list of idioms in the world. The prefix *est* is used to reference concepts that are defined, in our Learning Style Ontology. The prefix *act* is used to reference concepts that are defined in our Activities Ontology.

These different aspects are gathered in the user profile and are used by the multiagent system to improve the educational resources retrieval.

3. Multiagent systems and Graded BDI Agents

In the recent past, an increasing number of multiagent systems (MAS) 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 multiagent systems a formal support. Among them, a well-known intentional formal approach is the BDI architecture proposed by Rao and George [8]. This model 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. [9] have proposed a general model for Graded BDI Agents. This model allows 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 behaviors, 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 introduced by [10] in order to help in the design of complex logical systems. This framework allows the definition of different formal components and their interrelations. 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 in the tourism domain [9], as a framework where the different components of the architecture and their interactions can be neatly represented.

In this paper, we present a multiagent architecture for an educational resource retrieval that helps a student to choose courses according to his/her personal and cultural aspects. This multiagent 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.

4. Multiagent Architecture

The proposed multiagent architecture is basically made up of three fundamental agents: The Semantic Refiner Agent (SR-Agent) that produces the search strategy associated to the user's interest, the User Profile Agent (UP-Agent) that extracts data from user's behavior in order to build the user profile, 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, the repositories and ontologies they used and their interactions are illustrated in Figure 2.

In the following we present an overview of the agents that cooperates in the multiagent system given special attention to the Educational Resource Finder Agent, which is modeled as a graded BDI agent.

The Semantic Refiner Agent: 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 to the refiner 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. The SR-Agent guides the user for sense disambiguation of the concepts submitted by him/her. Then, it allows the user to select concepts hierarchically related with the first one, in order to reduce the amount of documents to retrieve. Finally, it expands semantically concepts in order to increase the amount of courses to be retrieved. In this process, this agent uses linguistic resources such as: thesauruses, dictionaries, multilingual dictionaries and ontologies. Which resource or resources are used, depends on the knowledge area of the query and on available resources for that area. For more details see [11].

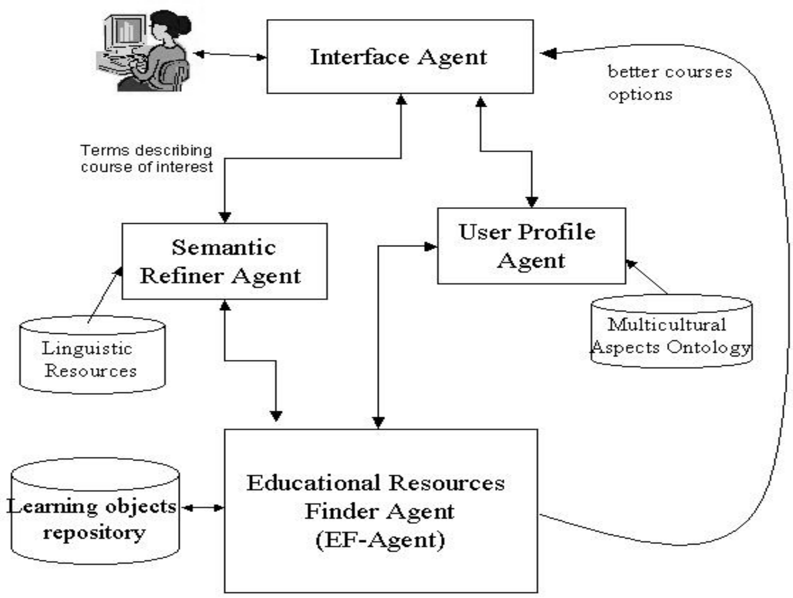

Figure 2: The proposed Multiagent System

The User Profile Agent: The User Profile Agent (UP-Agent) extracts data from the user and from the ontology of multicultural aspects [12] in order to build the user profile. The personal data are obtained from the user by a set of queries driven by an appropriate ontology. The UP-Agent provides to the Educational Resources Finder Agent with the personal and cultural aspects, in order to retrieve only those courses that best satisfy his/her personal and cultural characteristics.

The Educational Resource Finder Agent: The Educational Resources Finder Agent (EF-Agent) is in charge of looking for different learning objects in order to satisfy the preferences of a student. The output of the EF-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 interests and the cultural aspects of the student, the expected satisfaction of the 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 modeled as a graded BDI agent is formalized using multi-context systems. The multi-context system specification of an agent 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 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: for 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 [13] 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 [9]. In the following we outline the particular characteristics of the different contexts in a multi-context specification of the EF-Agent.

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 include 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 approach we consider that this information is certain. Also, in this context we must consider how certain is that a learning goal (G) could be achieve through the different courses (O_i). In this work we use modal many-valued approach to represent this kind of knowledge. For this context we choose an appropriate modal language to reason about the belief of formulae. The B modality is introduced to a propositional dynamic language L_D where we have formulae like $[O_i]\ G$, meaning, "After the execution of the course O_i, the goal G becomes true". 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. Then, the many-valued logic machinery can be used to reason about the modal formulae like $B[O_i]G$, representing that "After the execution of the course O_i, the goal G becomes true, is probable" and its degree may be considered the probability (or other uncertainty measure) of $[O_i]G$. The EF-Agent in this context includes multivalued 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, desires represent the student's preferences in the subject and also in some course characteristics. Inspired by the works on bipolarity representation of preferences by Benferhat et.al. [14], 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 do 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 modelling of the agent's trust on other agents. In an agent community different kinds of trust are needed and should be modelled [15]. 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. Moreover, when the execution of a plan involves the delegation of some actions to other agents, there is some risk that must be contemplated. A theory for IC in the EF-Agent represents those desires the user can intend by different feasible plans. 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 modelling user's needs.

Planner and Communication Contexts: The nature of these contexts is functional and they are essential components of our model. The Planner Context (PC) has to look for feasible plans in a repository of the courses offered by the different supplier agents. All the course plans offered are introduced in the PC 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 where our graded BDI agent lives.

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 PC 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 PC unit that are used by the planner 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):

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

Different functions f allow to model different agent behaviours. The learning plan O_b that allows to get the maximum intention degree i to will be set by the PC unit as the best course and will be recommended to the user.

An example

We relate a short example to illustrate the different functionalities and interactions of the agents in the multiagent system. Let us suppose that María, a Argentinean physics student, wants to find courses about "dynamics" and she decides to ask, in English, for the more general concept "mechanics". In first place, the

SR-Agent is in charge of the semantic refinement. For this purpose this agent, takes “mechanics” and verifies that it is orthographically correct. If the user had written "mecanics", the agent would have suggested her the word "mechanics", which is orthographically correct. Then the agent shows different senses of that word, in order to help the user to disambiguate this word. In this case, it has two senses. Mechanics is the branch of physics concerned with the motion of bodies in a frame of reference; and mechanics are the technical aspects of doing something, e.g. mechanisms of communication. In this case, María chooses the first sense. After this, this agent expands this concept with its hyponyms using a linguistic resource (e.g. WordNet). María moves in the hierarchy and selects the term “dynamics”, because she is interested in the branch of mechanics concerned with the forces that cause motions of bodies. Also, the SR-Agent takes this phrase, expands it, and automatically incorporates the term “kinetics”, in order to incorporate a synonym. Finally, it takes this set of terms and automatically builds the following search strategy:

dynamics OR kinetics

If a search involves several concepts, the SR-Agent does the process described above with each concept and then it combines them. As a result, the search strategy associated with this search consists on the disjunction of each one of the expansions and then the conjunction of the resulting sets of expansions.

The User Profile Agent makes the Maria’s profile proposing a set of questions and using the Multicultural Aspects Ontology. For this example, the user profile for Maria could be: (Language = “Spanish”, 1), (Language = “English”, 0.7), (style 1 = holistic, 0.4), FigurePreference = “High”, (style 2 = visual, 0.8), ExercisePreference = “Low”

This information, representing all Maria’s preferences, including the subject of the course, her personal and cultural conditions, is sent to the EF-Agent. The EF-Agent models these preferences as positive and negative desires that the agent will try to satisfy through an appropriate course.

5. Conclusions and future work

We have presented a multiagent architecture for educational resources retrieval that helps users to choose courses according to their personal and cultural aspects.

The proposed multiagent architecture is basically made up of three fundamental agents. The Semantic Refiner Agent acts as a specialist in information sciences, and prepares an appropriate strategy, and it solves most of the problems related with search contingencies. It produces the search strategy associated to the user's interest. The User Profile Agent extracts data from user’s behavior and from the cultural aspects ontology, in order to build the user profile. The Educational Resources Finder Agent (EF-Agent) is in charge of looking for different learning object in order to satisfy the preferences of a student. Its output is an ordered list of educational resources.

The EF-Agent is specified using a graded BDI agent model. This model allows us to define architectures that explicitly represent the uncertainty of beliefs, graded desires and intentions. The user’s profile is incorporated in the EF-Agent by introducing his preferences (positive and negative) and the importance he 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 multiagent model takes advantage of ontologies, using them for the semantic improvement of the educational resources search process. Moreover, the user’s background, objectives, learning styles and cultural environment, are specified by ontologies and used in the retrieval process of the educational resources.

As for future work, we plan to implement a prototype of the EF-Agent in a multi thread version of prolog. We must also specify and implement the different interactions in this multiagent system.

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