BROAD-RS: agent based architecture for educational context-aware recommendation

Paulo Alceu d´Almeida Rezende[1], Fernanda Claudia Campos[2]

Abstract

Educational resources have great potential to increase the design and composition of online classes. Educational recommendation system aims to identify student's profile and context to suggest suitable resources to his/her preferences and enrich, flexibilize and dynamize class contents. This work presents BROAD-RS (BROAD Recommendation System) architecture. It is capable of recommendation of Learning Objects, based on ontologies for modeling student profile and context in an e-learning environment. It was implemented in a multiagent system and the evaluation was performed in a real Software Engineering class, for students of higher education in Computing area. The main steps were: the teacher made the class plan and registered the Learning Objects, the student used the application in different contexts and the recommendation Learning Objects was executed at different moments. Considering the case study the results pointed to the feasibility of the architecture.

Keywords: Recommendation Systems, Context-aware, Agents, Ontology.

Resumo

Os recursos educacionais têm grande potencial para aumentar o projeto e criação de aulas online. Um Sistema de Recomendação Educacional visa identificar o perfil e contexto do aluno para recomendar recursos adequados às suas preferências a fim de enriquecer, flexibilizar e dinamizar os conteúdos educacionais. Este trabalho apresenta a arquitetura BROAD-RS (BROAD Recommendation System) que é capaz fazer recomendações de Objetos de Aprendizagem, com base em ontologias que modelam o perfil e o contexto do aluno. A arquitetura foi implementada em um sistema multiagente a avaliação foi feita em uma disciplina de Engenharia de Software, de alunos do ensino superior da área de Ciência da Computação. Os principais passos foram: o professor elaborou o plano didático e registrou os Objetos de Aprendizagem, o aluno utilizou o aplicativo em diferentes contextos e a recomendação dos Objetos de Aprendizagem foi realizada em momentos distintos. Considerando o estudo de caso, os resultados apontaram para a viabilidade da arquitetura.

Palavras-chave: Sistemas de Recomendação, Sensibilidade ao Contexto, Agentes, Ontologia.

1 Docente da Universidade Salgado de Oliveira de Juiz de Fora – UNIVERSO - JF / Técnico do Programa de Pós-graduação em Ciência da Computação (Universidade Federal de Juiz de Fora), E-mail: paulo.rezende@ufjf.edu.br

2 Docente do Departamento de Ciência da Computação e do Programa de Pós-graduação em Ciência da Computação (Universidade Federal de Juiz de Fora), E-mail: fernanda.campos@ufjf.edu.br

1. Introduction

Education is offering opportunities with a minimum of students and teachers' physical presences. Interactions are being mediated by information technologies. Specially, in higher education, e-learning has played an important role, considering virtual universities, online courses and training. According to Belizário Júnior et al. (2018) the e-learning is an electronic teaching model that can be adapted to student's learning styles.

One of the challenges of Web-based education is the adequacy of content to the student's profile. This is a difficult task, since teacher must know the needs and competences of each student. Another challenge is to design, develop and distribute educational resources for students with different profiles (Perreira et al. 2018). Learning Objects (LO) have proven to be suitable, practical and economical due to their potential for reusability, generality, adaptability and scalability.

The suggestion of content diversification in different contexts has been treated with the use of Recommendation Systems (RS) (Cazella et al., 2010). Bezerra et al. (2018) said that they have the purpose of analyzing a set of items and check which of them are the most relevant to a consumer. The question is how, when, and in which way we can recommend Learning Objects that enable students to: increase knowledge related to a particular subject, develop accurate skills related to a specific content and develop a critical awareness of this competence so that they understand how and when to use it.

The curriculum of the Engineering area (ACM, 2004) highlights the necessity to go forward the traditional expositive classes, and also consider the diversity of student and professional profiles. In this context, this project is dedicated to enhance graduate classes, considering the availability of Learning Objects in local repositories and linked data, in a variety of media It assures flexibility and dynamicity in formal and continuous education.

Subjects such as Software Engineering are offered both in formal higher education (undergraduate, graduate, master and doctorate degrees) as well as non-traditional education. In fact, Software Engineering keeps track of Computer professionals throughout their careers. Methods, techniques, tools, procedures and models are constantly updated, which require empowerment by developers, software engineers, quality, tests and requirements professionals, among others. The challenge imposed, according to Souza et al. (2016), is to discuss these issues by associating theory with practice in order to build a solid and critical knowledge.

The main goal of this paper is to propose BROAD-RS architecture, which automatically recommends LO according to a didactic plan, specified by a teacher, and adherent to the student's profile and context. Specific objectives include: (i) define an agent-based architecture to assure the necessary system autonomy; (ii) develop and make available the BROAD-RS assuring the modularity, flexibility and scalability of the virtual learning environment and allowing the reuse of Learning Objects.

To reach the goals, the research, reported in this paper, was carried out in 4 main stages: (i) literature review; (ii) architecture definition; (iii) implementation and availability of the recommendation system; and (iv) evaluation of the proposal through a case study.

The methodologies included the literature review, the proposal of architecture capable of making context-aware recommendation of Learning Objects, based on an ontology for modeling the profile and context of the student in an e-learning environment and implemented in a multiagent system. The teacher has a fundamental role in the recommendation model when identifying the Learning Objects metadata that will compose the didactic plan and the tasks, goals and competences to be achieved.

This paper is part of BROAD Project (Pereira et al. 2018) (Almeida et al. 2016) (Rezende et. al 2013) (Rezende et al. 2017) (Simões et al. 2017) belonging to the Knowledge Engineering Research Center (NENC) of the Post-Graduation Program in Computer Science at the Federal University of Juiz de Fora. (Pereira et al., 2018) presented a proposal in which the user's profile and context were extracted from a social network, while in (Almeida et al., 2016) features of groups of users in social networks were used to perform the search and selection of educational resources. Other works deal with recommendation system Ecosystems (Simões et al. 2017) (Veiga et al. 2016).

This article is organized as follows: section 2 presents the theoretical foundation. In section 3 we describe, analyze and compare the related works. Section 4 presents the BROAD-RS architecture, its recommendation model, agent modeling and the ontology. In section 5 we describe the evaluation in a real learning scenario. Final remarks and future works are presented in section 6.

2. Theoretical foundation

Recommender Systems are programs that present a set of resources (items, videos, articles, services, among others) considering their interests (Hernando et al., 2013). Users who consume the available resources are an important part of the RS because, through the information of their profile and context, it is possible to recommend resources as closely as possible to their interests.

The profile can be extracted in two ways: explicitly and/or implicitly. Explicit extraction occurs when users fill in their own information, promoting the definition of initial profile, and this can be updated over time. Implicit extraction occurs when the information is obtained passively, usually reflecting the behavior in an environment. Considering the context, any information that can be retrieved should be considered by the system (historical information, behavior when using the system, sensors, among others). It is worth emphasizing that both users' profile and context vary according to the situation and time.

A context-aware system can understand the context of a given situation and even share it with other systems for their response or respond by itself. For context-aware in recommender systems the system should rely only on relating the items and users based on the contextual information (Seyednezhad et al., 2018).

The use of information technologies in knowledge construction process is in a continuous expansion. It enables schools to carry out experiments beyond the classroom. A Learning Object can be planned to ensure the gradual development of the student's skills and abilities. LO provide interoperability between different computing environments, as well as ensure their easy access and usability. "The lack of Learning Objects (LOs) that can be recommended is an open problem. Another challenge is the personalized recommendation of LO" (Belizário Júnior et al. (2018).

The focus on Learning Objects recommendation aims at the development of skills that require new educational paradigms more flexible pedagogical models, respecting different social features, interests, needs and limitations of each student (Cazella et al., 2009). Recommendation Systems researches seek to suggest, among different possibilities, contents based on users' preferences, and that fit their expectations (Cazella et al., 2010).

For an educational system to recommend Learning Objects, it is necessary to know the profile and context of the student, identifying his/her preferences, goals and learning styles. In addition, this information must be standardized in order to avoid semantic inconsistencies and easy interoperability between different modules and systems (Hinz et al.,2011).

Mobile learning (m-Learning) enables learning to take place anytime, anywhere. User's mobility due to mobile devices makes it even more important to consider a student's context, as his/her characteristics may change at any time. The student's context may change in a variety of ways (e.g. physical conditions, available physical resources or computational resources) (Jácome Júnior, Mendes Neto and Silva (2012).

An agent, according to (Russell and Norvig 2013 in Lima et al. 2017), is all that can be considered capable of perceiving the environment through sensors and acting on that environment. In this context, any computer program could be an agent, but one agent is expected to do something else: operate under autonomous control, perceive its environment, persist for an extended period of time, adapt to change, and be able to create and pursue goals. The use of agents, as autonomous systems, offers interesting solutions mainly in the development of distributed and complex applications. In addition, it supports domains with very heterogeneous components, and conflicted interests at the autonomous decision making (Elamy et al., 2005).

3. Related work

In this section we present models and proposals for the recommendation of educational resources, highlighting the types of systems, technologies, resources, methods and requirements. We also describe some proposals with agents in the recommendation strategy and ontologies to describe the student learning style.

Aguiar et al. (2018) proposed a Learning Objects recommendation strategy, a personalized approach based on student learning styles and tendencies. The solution is Based on Collaborative Filtering model combined with a Genetic Algorithm.

Bezerra et al. (2018) developed a Hybrid Recommender System integrated into an ontology that manages the learner profile information, and the contents of the YouTube and Wikipedia databases. For validation, the RS was implemented as a webservice and integrated to the architecture of ubiquitous learning environment (Edubi). It was tested by students of a higher education institution through the Edubi-Web and Edubi-Mobile applications.

Costa et al. (2018) work aimed to investigate how a Project-based Learning (PBL) activity, supported by a technological environment, can contribute to the development of projects by means of content recommendation resources and collaboration tools among peers.

Jácome Júnior et al. (2012) presented an environment named MobiLE capable of realizing the context-aware recommendation of Learning Objects, defined in a standard format, through the use of ontologies of a multiagent system and the application of a genetic algorithm.

Zaíne (2002) proposed an agent-based recommendation system, that uses collaborative filtering that models the profile of its users through the use of techniques of data mining on their access history. From this representation the agent makes recommendations based on what users with similar histories did in a specific activity.

The work of García et al. (2009) presents a framework for recommending alternatives to teachers to provide didactic ways that assist their students in solving tasks. To do so, it relies on collaborative filtering methods based on association rules, automatically extracted through data mining techniques from the history actions in the system.

Ferro et al. (2011) address the creation of a recommendation system model for teaching resources, to be used in VLE (Virtual Learning Environments), in order to suggest the teaching resources compatible with users' profiles.

The MILOS (Multiagent Infrastructure for Learning Object Support) is an infrastructure combining ontologies and agents, which implements the necessary functions for the processes of authorship, management, search and availability of LOs compatible with the Brazilian metadata standard OBAA (Agent-Based Learning Objects) (Vicari et al., 2009).

Lima (2017) presents a Systematic Review of Literature which aimed to identify the researches in Brazil that involve Intelligent Agents (IA) or Multiagent System (MAS) in the Educational context. Thus, the results of the Systematic Mapping focused on Brazilian informatics events in education. Many research groups were identified.

Belizário Junior et al. (2018) implemented an approach that uses Wikipedia content to create new educational resources considering ontology which models students and LOs. The problem of recommending LOs is formalized, and then a genetic algorithm (GA) is presented to solve it.

Primo, Vicari and Silva (2010) presented a model for the recommendation of educational contents described through metadata. This model deals with user profile, support for interoperability between educational applications, as well as cognitive aspects of learning. This work also presents how educational contents can be described through ontologies, which also facilitates the inference of appropriate contents to the users' profiles.

Pereira Júnior et al. (2018) present a Systematic Review of Literature (RSL) in order to verify the contribution of ontologies to Conversational Agents (CA) in the teaching-learning context. The results indicate that the use of ontologies in CAs is promising, since they allow actions in different domains, with different methods of interaction, inclusion of aspects of affectivity, and the need to meet non functional requirements such as usability and performance.

Hinz et al. (2011) propose the use of ontologies in modeling the student profile in an e- learning environment, in order to standardize information and facilitate the process of recommending Learning Objects.

Zhuhadar et al. (2009) carried out the process of recommendation based on searches of educational contents by users. The profile of its users considers knowledge areas in order to compare with educational content, thus enabling the recommendation process. For the description of these areas it is proposed the use of ontologies.

As Aguiar et al. (2018) our proposal considers the student´s Learning Style. Our architecture, as Bezerra et al. (2018), uses ontology and different contents, not specific YouTube and Wikipedia databases. We didn´t consider, at first, a Project-based Learning (PBL) activity (Costa et al. 2018), but we also support content recommendation, based on teacher's plan. Jácome Júnior et al. (2012) present a context-sensitive recommendation system of Learning Objects, which we consider a convergent solution, even if we didn´t adopt genetic algorithms. Zaíne (2002) proposed an agent-based recommendation system, but, different from our proposal the agent makes recommendations based on what users with similar histories did in a specific activity, and not based on the student's profile and context. Different from García et al. (2009) we assist teachers during the didactic plan and not to help students in solving tasks. Our proposal, as Ferro et al. (2011), addresses Virtual Learning Environments. Considering the use of ontologies in recommender systems, as our proposal, Primo et al. (2010) described Learning Objects through metadata, Belizário Junior et al. (2018) considered an ontology which models students and LOs, Hinz et al. (2011) modeled the student profile in an e-learning environment and Zhuhadar et al. (2009) considered the knowledge areas. The use of Agents and Multiagent System in the Educational context was described in Lima et al. (2017) Systematic Review of Literature, highlighting their use in Brazilian researches. Our evaluation process, as well as Bezerra et al. (2018), was with students of a higher education institution through a Moodle application.

4. BROAD-RS: Context-aware LO Recommendation System

The proposed architecture, named BROAD-RS (BROAD Recommendation System) (Rezende et al., 2013), recommends LOs adherent to the interests and needs of the student with the use of ontologies and agents.

The recommendation approach considers the teacher evaluation of the LO, the selection in a didactic plan, the student's context and tasks, objectives and skills to be achieved.

Using content-based filtering strategy, BROAD recommendation architecture is context-aware, adopting student current profile and context data. Context information is: external dimension (environment and location) and internal dimension (social groups, preferences, activities, goals and skills).

To assure the semantic representation of the student's profile and context we developed the PERSONNA ontology (Rezende et al, 2017). Some others ontologies complete the knowledge base including the domain organizations, knowledge areas, Learning Objects and metadata.

The agents implemented in BROAD-RS architecture are based on reactivity (autonomously acts to changes in its environment or messages received from other agents) with the ability to socialize in a multi-agent system. One of agents main ability is to check the interactions of teachers and students in the system, such as context and didactic plan updating. The agents also verify the interaction of the data with the ontologies and services of the architecture to make recommendations of LO in a more dynamic and agile way. The multi-agent system considers the didactic plan, defined by the teacher, and the context and profile of the student to recommend the most appropriate LOs.

The context is the physical environment or a set of situations (such as location and time), such as: students' geographical location, time of day, physical environment location, computer system characteristics, previous student's interactions, among others.

BROAD-RS architecture adopts some of the BROAD (Campos et al., 2011), LOM (IEEE et al., 2012) and OBAA (Vicari et al., 2009) standards to define its didactic plan.

4.1. BROAD-RS Architecture

BROAD-RS architecture recommends Learning Objects from semantic rules, which relate student's profile (explicit data) and context (explicit and implicit data), with the evaluation and selection of the LO made by the teacher from the didactic plan. The multi-agent layer automates the process and the knowledge base aids the recommendation process (Figure1).

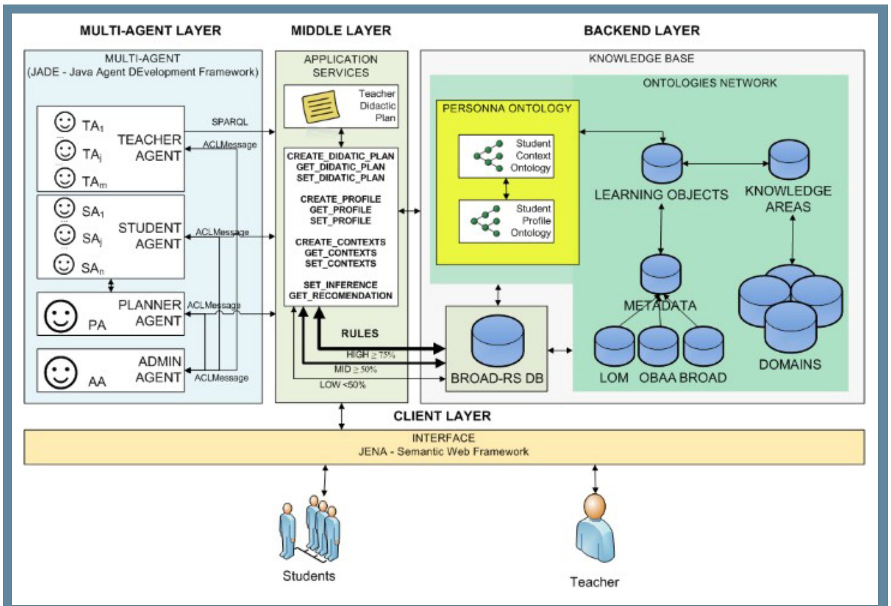

Figure 1: BROAD-RS architecture.

The architecture is structured in four layers:

1. Multi-agent layer: describes all agents, their roles and their interrelations and interactions in the application. The agents relate the context data and the student profile with the teacher didactic plan using the ontologies semantic rules. The agents have three basic characteristics: reactivity, proactively and, finally, the ability to socialize.
2. Middle layer: the service layer. It is responsible for the interaction of agents with the knowledge base. The main services are in this layer: didactic plan creation, context and profile recording and data recovery, and ontologies inferences to set recommendation step.
3. Backend layer: it is the knowledge layer, where the ontologies are stored. This is where we find PERSONNA Ontology, knowledge and domain ontologies, and Learning Object Ontology. It is in this layer that the application stores the LOs, the didactic plans and the previous recommendations.
4. Client layer: implements the registration of Learning Objects, students and teachers' registers and users' interface and screens in any language or framework.

The prototype was developed in JAVA language, using JADE technologies for agents and JENA to work with ontologies (OWL files). The Reasoner used was the Pellet and OWLAPI and SPARQL commands to work with the OWL files of the ontologies. We also used technologies such as Hibernate, ZK Boss Framework and MySQL database. Some tools that helped to develop the prototype were Protégé to work with OWL ontologies, NetBeans as JAVA IDE and Php MyAdmin for structuring the relational database.

4.2. Teacher's didactic plan

One of the architecture features is the teachers' support to define the didactic plan, detailing the procedures to reach an educational objective and skills to be achieved. The didactic plan includes a set of metadata that will allow the teacher to evaluate a LO. Through this evaluation, its relevance to the student can be identified, and then a qualified recommendation can be generated.

For the didactic plan educational metadata standards items from BROAD (Campos et al., 2011), LOM (IEEE et al., 2012) and OBAA (Vicari et al., 2009) were considered: Learning Resource Type, Interactivity Type, Interactivity Level, Semantic Density, Context, Typical Age Range, Difficulty, Language, Learning Content Type, Interaction, and Didactic Strategy.

4.3. Agents

The relationship between the students and the architecture is made through the use of agents, which recommend Learning Objects with the use of middle layer services. This approach favors the modularity, flexibility, and scalability of the learning environment. The multi-agent system has the following outline:

1. Teacher Agent (TA): responsible for all the activities developed by the teacher in the virtual environment and each one has its own instance. It is mainly responsible for verifying if there were changes in the didactic plan.
2. Student Agent (SA): its main objective is to identify students' preferences and profile, such as: contents of interest, preferred media and level of difficulty. It uses a database of previous recommendations and the PERSONNA ontology to structure the student's information. The student's information will be taken as a reference to search for more compatible Learning Objects to his/her context and profile. The SA represents the student her/himself in the virtual environment and each student has his/her instance.
3. Planner Agent (PA): indicates the Learning Objects to be displayed to a student. It receives the information from the other agents and evaluates if it is necessary to call the ontology inference machine. In the case of cold start, the PA recommends LO based on previous stored recommendations.
4. Administration Agent (AA): monitors the life cycle of all other agents, their services and also their interactions with the environment.

To illustrate the agents modeling we present diagrams from the INGENIAS methodology (Gômes-Sanz & Fuentes, 2002). A general-purpose case diagram includes the actors (teachers and students), and encompasses the management, use and recommendation of LO (Figure2).

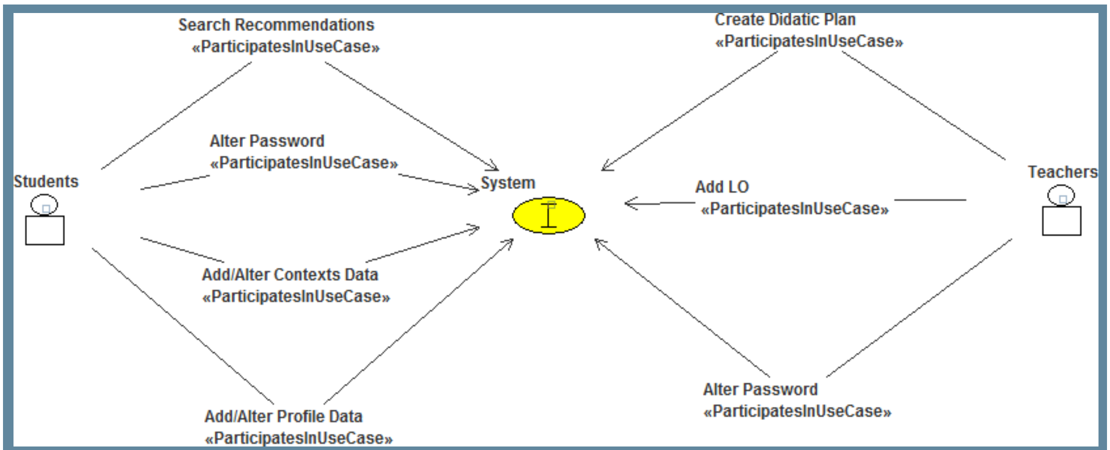

Figure 2: Use Case Diagram – General purpose.

The organization diagram is responsible for representing the different components of the system (agents, roles, resources and applications), the functionality of the system and possible restrictions on the interactions between the agents. In the organization of the system components, three groups were identified (Recomendation_Group, Student_Groupand Teacher_Group) (Figure3).

The task and goal diagrams represent the relationships in addition to their internal structures. They also indicate the inputs and outputs of each task and their effects both in the architecture, as well as in the state of each agent. Figure 4 represents the macro-level tasks and goals model.

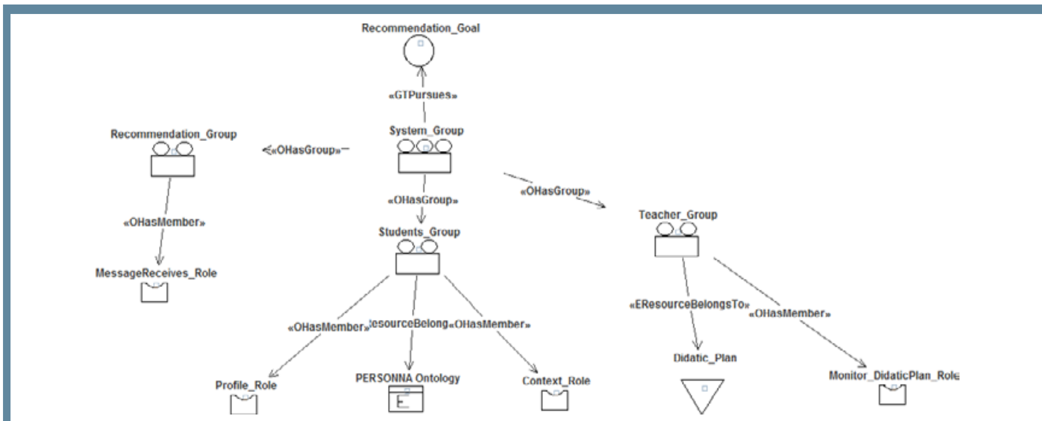

Figure 3: Organization Model –With main groups.

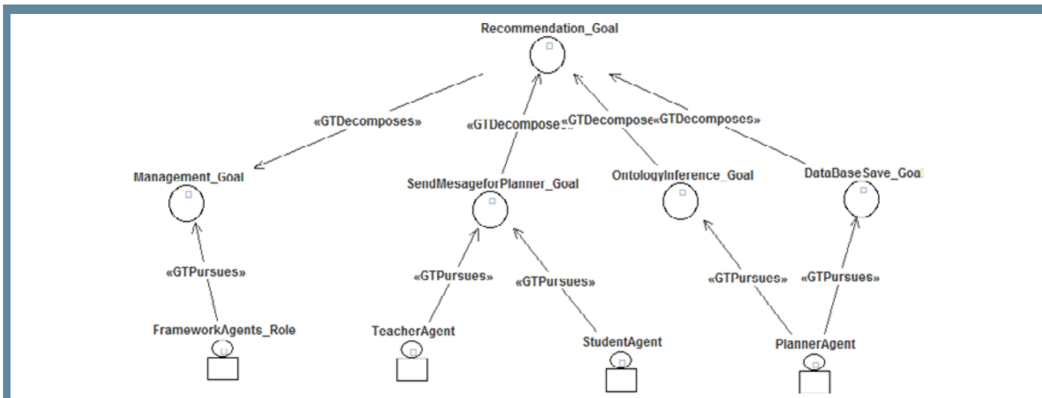

Figure 4: Tasks and Goals Model - Macro Level Diagram.

4.4. PERSONNA Ontology

One way of obtaining implicit information related to the student's learning profile and context is by monitoring his/her interactions in the virtual environment. The PERSONNA ontology models the profile and context of the student in an e-learning environment in order to standardize the information and ease the process of Learning Objects recommendation (Rezende et al., 2013), (Rezende et al., 2017). Figure 5 presents an overview of the PERSONNA ontology with its main classes and properties.

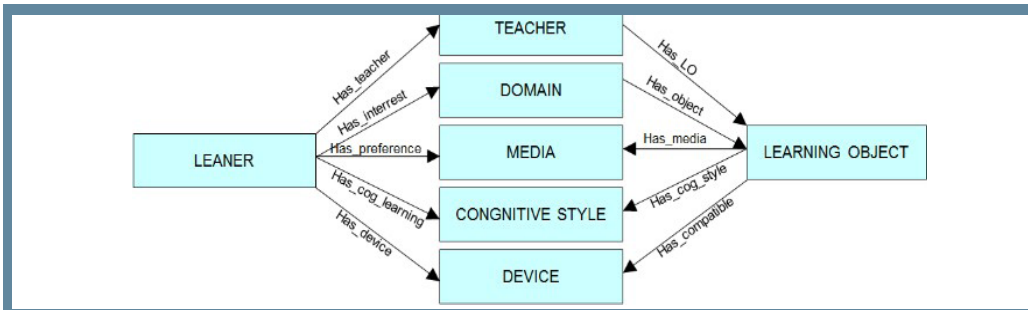

Figure 5: Overview of the PERSONNA ontology.

Figure 6 presents some SWRL rules of the PERSONNA ontology in the BROAD-RS architecture.

has_compatibled(?o, ?dv), has_device(?l, ?dv), has_interrest(?l, ?d), has_objects(?d, ?o) ->has_recomended_high(?o, ?l)
has_cognitive_style(?o, ?cs), has_interrest(?l, ?d), has_learner_cognitive_styles(?l, ?cs), has_objects(?d, ?o) ->has_recomended_high(?o, ?l)
learner(?p), integer[>= 18 , <= 65](?age), has_learner_age(?p, ?age) ->has_learner_driver_age(?p,true)
has_compatibled(?o, ?dv), has_device(?l, ?dv), has_objects(?d, ?o) ->has_recomended_mid(?o, ?l)
has_interrest(?l, ?d), has_objects(?d, ?o) ->has_recomended_low(?o, ?l)
has_compatibled(?o, ?dv), has_device(?l, ?dv) ->has_recomended_low(?o, ?l)
has_cognitive_style(?o, ?cs), has_learner_cognitive_styles(?l, ?cs) ->has_recomended_low(?o, ?l)
has_cognitive_style(?o, ?cs), has_learner_cognitive_styles(?l, ?cs), has_objects(?d, ?o) ->has_recomended_mid(?o, ?l)
has_learner_preferences_media(?l, ?me), has_media(?o, ?me), has_objects(?d, ?o) ->has_recomended_mid(?o,?l)
has_interrest(?l, ?d), has_learner_preferences_media(?l, ?me), has_media(?o, ?me), has_objects(?d, ?o) ->has_recomended_high(?o, ?l)

Figure 6: PERSONNA Ontology SWRL Rules.

The rules are used to infer the adherence level of the student learning style to a given learning object according to his/her profile and context and the didactic plan defined by the teacher. For this purpose, three levels of adherence were adopted:

- *High* ≥ 75% of the selected objects match a learning style - fully adherent to the student profile and context.
- *Mid* ≥ 50% and < 75% of the selected objects match a learning style - adherent to the student profile and context.
- *Low* < 50% of the selected objects match a learning style - student profile and context are not defined.

5. BROAD-RS In Use

The evaluation of the proposed recommendation system is descriptive, specified through a User Scenario, based on the formalization of Case Studies, in order to demonstrate the feasibility of the developed artifacts (Drescht et al., 2015). Scenarios, extensively explored in the demonstration of the practical operation of systems, were used in a real case of a high education class.

A scenario in the educational context consists of complete description of an activity, where the expected results are clearly defined from beginning to the end of an activity. A learning scenario consists of different situations initiated and finalized through events, the result of student's actions in the educational environment or comes from the environment itself.

The scenario consists of LO recommendations of a Software Engineering class for students of Computing courses (Computer Science, Information Systems and Computer Science Teaching). This scenario is environment sensitive to the student's learning situation, showing which contextual elements should be analyzed at each moment and the possible recommendations to be made.

The evaluation process included the following steps: definition, goal formulation, planning, execution/observation and presentation of the results. The objective is to evaluate teacher's registration, selection and evaluation of Learning Objects and the elaboration of a didactic plan for a Software Engineering class. The recommendation of these objects will be to a student, whose profile and context are adherent to the learning style identified by the agents. The actors of the evaluation are a teacher and a student.

The repository was available with 60 Software Engineering Learning Objects registered with the metadata standard to be used by the agents.

The following five groups of contextual information were used:

1. Personal and Behavior Data - name, sex, courses, classes, spoken languages (fluency), knowledge, preferences in the use of the educational environment, and way of navigation through didactic contents.
2. Domain Data - LOs data available to the student (educational domain) and didactic plan created by the teacher.
3. Technological Data - Information about the computational device used to browse the didactic content.
4. Location Data - place where the student is located.
5. Time Data - time of access to the educational system.

To evaluate BROAD-RS in use, we will detail the following steps:

1. Teacher creation of the class didactic plan and registration of LO,
2. Student´s access to Moodle, expanding the profile and context in two locations and time and recommending the Learning Objects.

Due to the limitation of space only the performance of some agents is detailed.

5.1. Didactic plan and LO registration

A teacher uses BROAD-RS in his Software Engineering class and needs to make recommendation of Learning Objects that meet students' profiles and contexts. When accessing BROAD-RS, the first screen with "Menu" on the right is displayed with the options: Learning Objects (Learning Objects Registration) and My Didactic Plan (Teaching Plans Definition Screen) (Figure7).

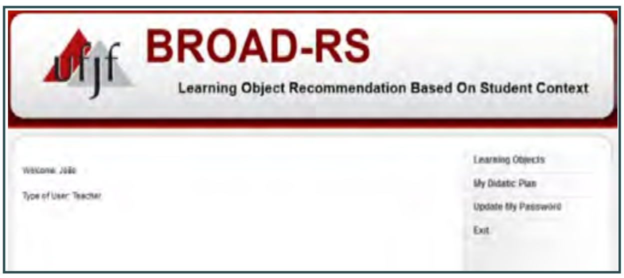

Figure 7: System input screen for teacher access.

BROAD-RS is also a repository of Learning Objects and the teacher registers 5 new LOs. They are: two scientific articles, a video lesson, an exercise and a presentation (Figure 8).

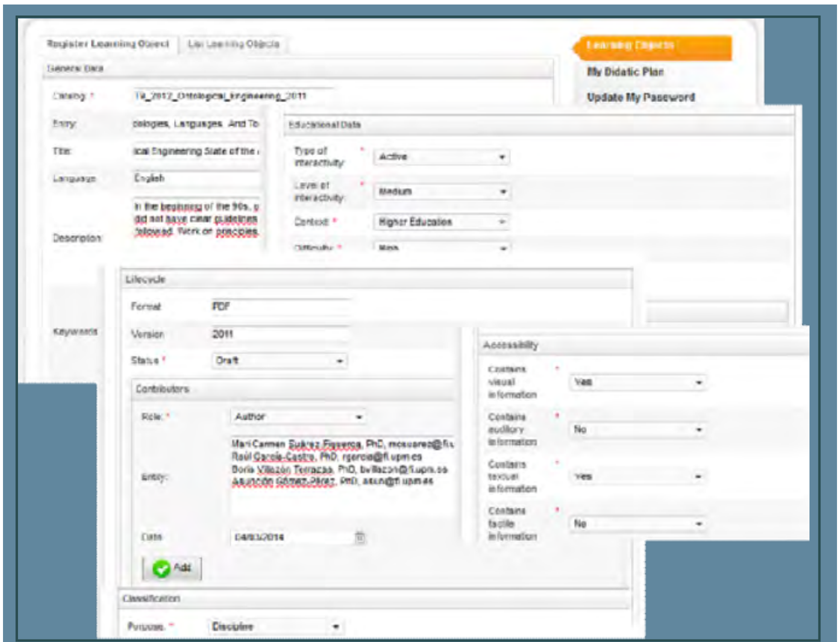

Figure 8: Learning Objects Registration.

The teacher defines the Learning Objects for his class and evaluates them according to the metadata. Figure 9 shows the teacher defining the selected LO "t9_2012_Ontological.pdf".

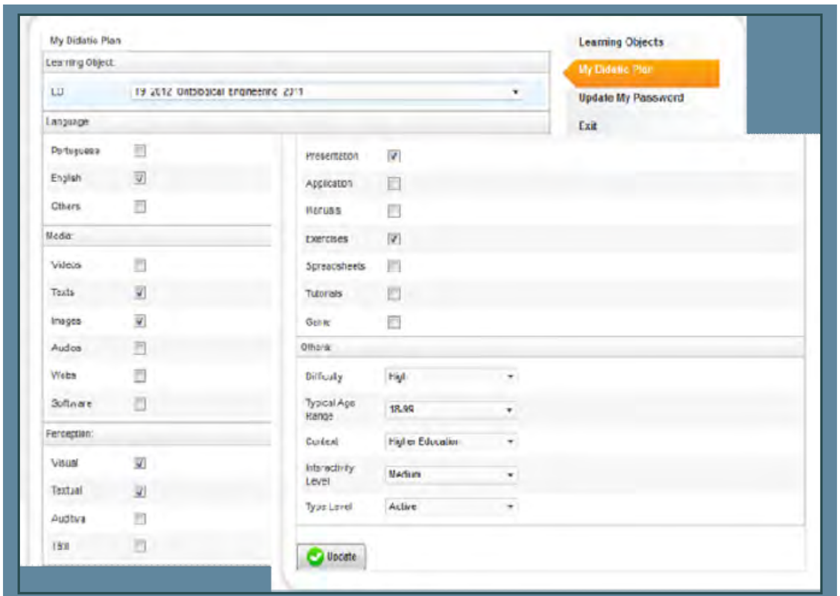

Figure 9: Teaching Plan Definition Screen.

Figure 10 shows the agents interaction when the teacher accesses the system and relates the didactic plan to the Learning Objects. The user accesses the system (1: Access). The teacher has the possibility to register Learning Objects and didactic plan (2: Change Didactic Plan or LO). The AA agent (ADMINISTRATION AGENT) checks whether the TA agent (TEACHER AGENT) and the PA Agent (PLANNER AGENT) are in active mode (3: Check Availability and 4: Check Availability). The TA agent checks if there is any update in the data (5: Verify Version). Since there was an update in the data, PA agent runs the inference machine of the ontology (6: Call Inference). Thus the inferred data is loaded into a relational database and displayed on interface (7: Return Inferred Data and 8: LO Recommendation).

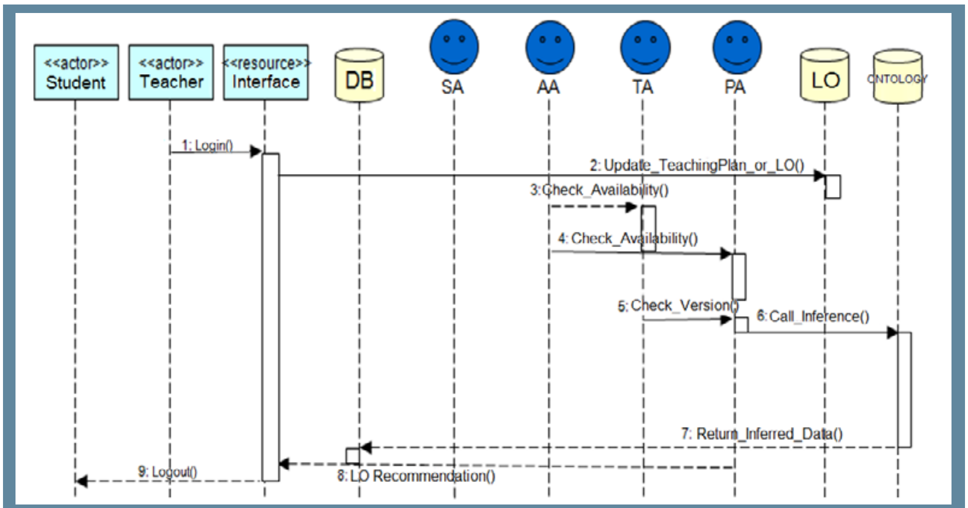

Figure 10: Sequence Diagram of a Teacher creating the didactic plan.

5.2. Recommendation of Learning Objects

For the recommendation of Learning Objects it is necessary to define the profile and context of the student. In this Use Scenario, we considered a female student of the 4th year of the Computer Science course, attending the Software Engineering class, she speaks Portuguese and English and shows active behavior (learning through trials and experimentation) and she prefers visual materials, such as images, pictures, videos, diagrams, and data flows. As she accesses BROAD-RS, a "Menu" is displayed with the options: My Recommendations (Where LO Recommendations are displayed) and My Profile/Context (Student's Context and Profile Data). Figure 11 illustrates the student registering the profile and context information to answer a questionnaire about her characteristics.

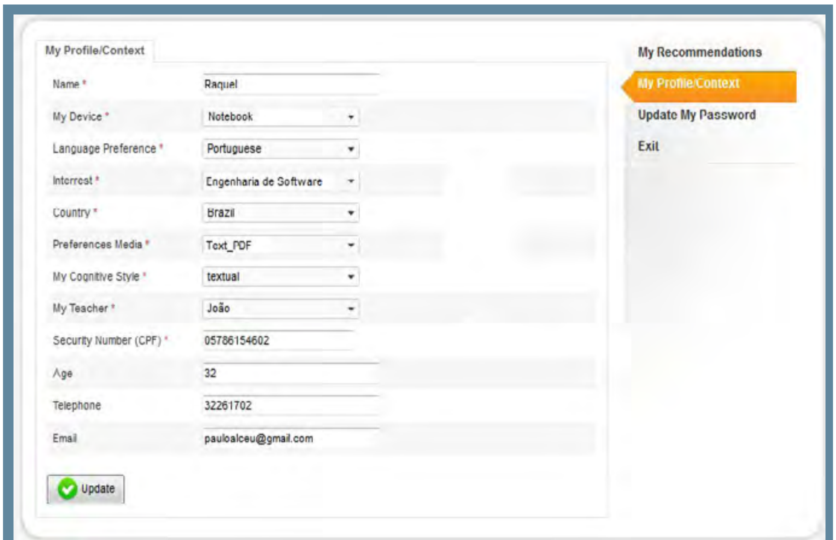

Figure 11: Student's profile and context screen (Profile 1).

At first, the student uses her Notebook, she is connected to the university network cable (context) and defines her learning style as "textual". At the moment, her favorite language is Portuguese and the type of file is PDF (Portable Document Format). Figure 12 presents the recommendations for this scenario in three levels of adherence (High, Mid and Low). The system recommends as High adherence an article and a book. The system also recommends as Mid a video and another article, and finally recommends as Low another article.

At a second moment, the same student uses her Smartphone to access the system via wireless network (context), and redefines her learning style to “visual”. At the moment, her favorite language is English and the type of file is MPEG (Moving Picture Experts Group) (Figure13).

Figure 12: BROAD-RS: Recommendation Screen (First recommendation).

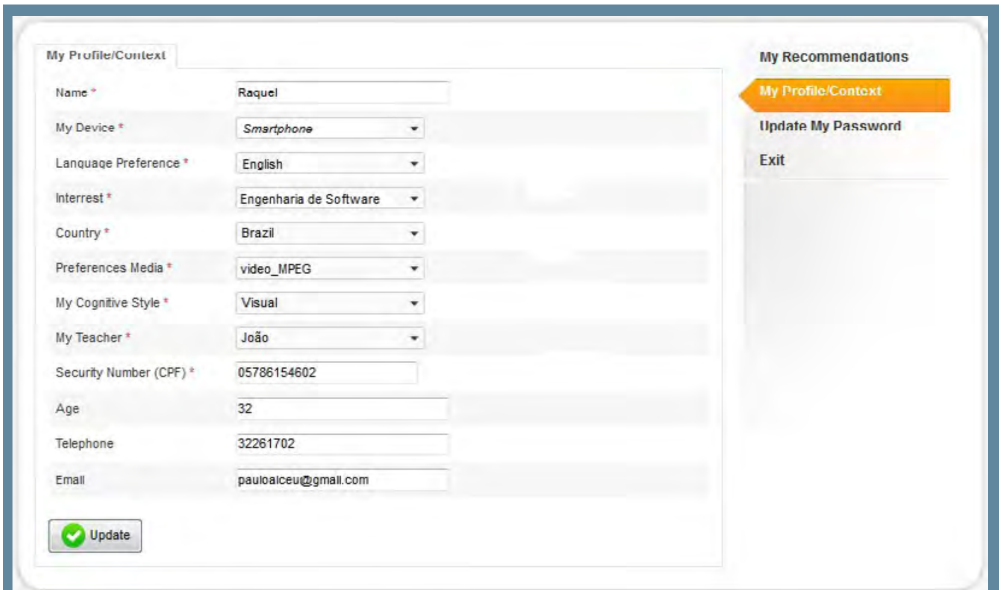

Figure 13: Student’s context and screen profile (Second Recommendation).

Figure 14 presents the way in which the agents interact when the student accesses, creates or changes her context and profile data.

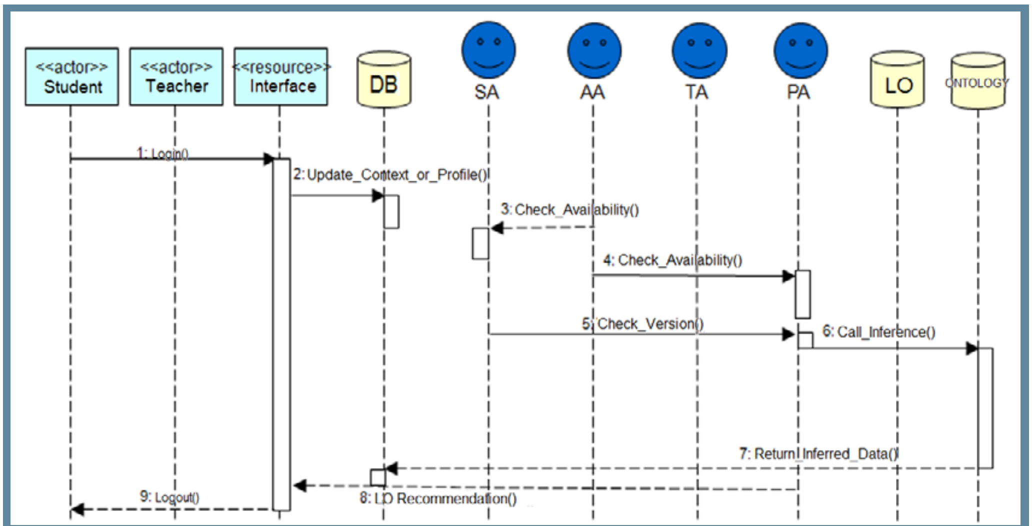

Figure 14: Sequence Diagram of a Student changing the profile and context.

Figure 15 illustrates the way in which several Learning Objects are recommended. At this moment, SA (STUDENT AGENT) and PA (PLANNER AGENT) agents act, due to the change in the data, executing the inference machine of the ontologies (Peller Reasoner). At the second moment, the system recommends (High) two videos in the MPEG format considering the context and profile data defined by the student. The System also recommends (Mid) a video in MP4 by its metadata characteristics and recommends (Low) one other article.

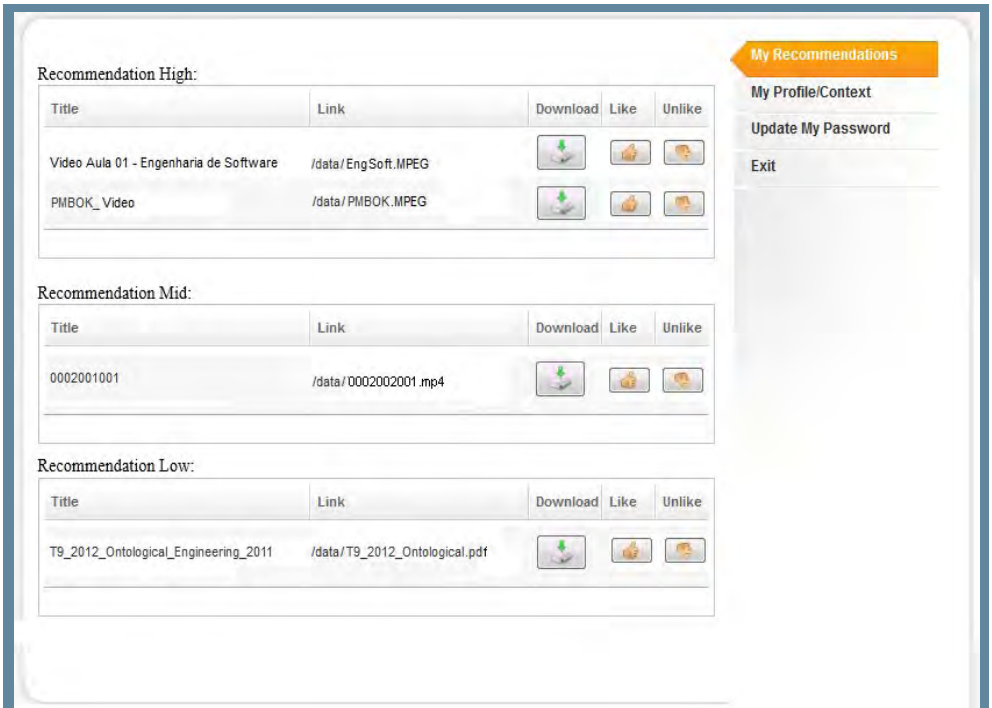

Figure 15: LO recommendation screen of the BROAD-RS.

Figure 16 presents the way in which the agents interact when the student accesses the system without changing her data.

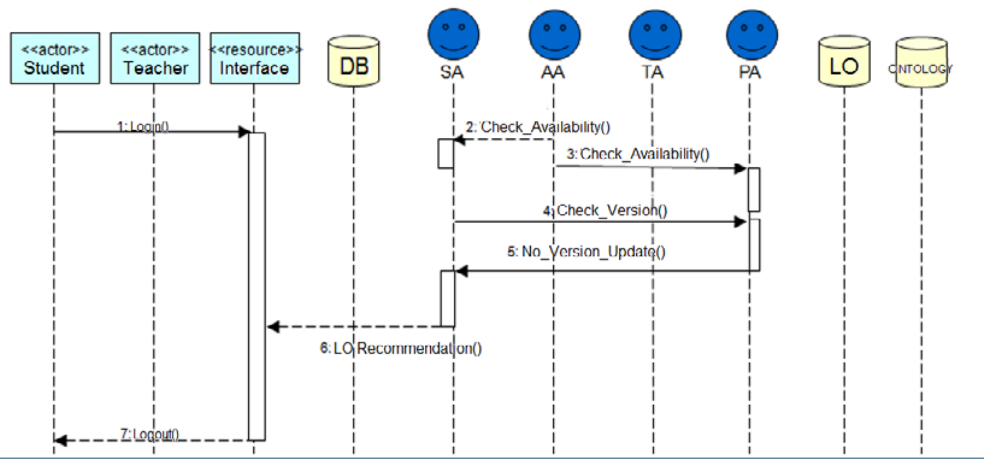

Figure 16: Sequence Diagram of Student accessing the system.

5.3. Use scenario conclusion

BROAD-RS architecture allows the automatic recommendation process, according to the didactic plan specified by the teacher and the profile and context of the student. Based on a multiagent implementation, the system autonomy has been validated.

The research consisted of a BROAD-RS analysis of the student's context, in order to investigate the possibility of modeling and implementing a LO recommendation system in order to improve the characteristics of adaptability to students' profiles. With the learning scenario the evaluation was carried out, and the student had the chance to change the context. It was the opportunity to evaluate the system performance, when, for example, different devises are used as notebook or Smartphone, and when the student wants LO with interfaces that fit the hardware.

It was, also, observed the automatic relationship of the agents with the ontologies. When students and teachers do not change the data, such as context and didactic plan, agents do not need to infer new recommendations. At this situation it uses the cold start recommendations stored in the database. However, in case of update agents automatically react to these modifications, and new recommendations can be displayed. This strategy ensures that recommendation process be carried out in a dynamic and agile way.

Teacher and student did not have difficulties in using the architecture for LO registration, LO evaluation for the didactic plan and/or profile and context registration. The student considered all recommended items adherent to her profile and context.

6. Final remarks

Considering the amount of LO and educational resources on the Web, and different approaches of the same concept, the use of recommendation systems is appropriated. It helps the process of searching and recovering of LO and presents the ones that best fit student's profile and context.

Context-aware emphases user's context analysis and the situations configured over time, trying to make the systems able to proactively perceive the best conditions according to this perception. This work addressed issues related to recommendation, in e-learning systems, more specifically, context-aware learning object recommendation systems.

This research will contribute to increase the use of Learning Objects through a process systematization of the recommendation of educational content adherent to a teacher's plan and students' profile. BROAD-RS architecture has the following requirements: it is based on student's context and profile and teacher evaluation (didactic plan), uses semantic enrichment (ontological rules), and all recommendations are stored in a database. Therefore, the aim of this approach is to improve the teaching-learning process in a way of motivating the student and avoiding drop out.

Software Engineering discipline presents a diversity of Learning Objects in the BROAD-RS repository and in linked data, which allowed the selection and evaluation of LO to compose the teacher class plan and match the students' profile.

The research question of this work was answered by the modeling and implementation of the BROAD-

RS architecture and with features of adaptability to student's context and profile. A formal scenario of a learning situation was presented. The identification of the relevant data to define the recommendation of Learning Objects was achieved by the proposal of the ontology of students' contexts and profile.

The development of context-aware environments demands the development of richer LO, since they need to predict different learning situations and find more suitable means to present the educational content. Therefore, tools to help authorship are necessary.

Some of our future works challenges are:

1. Consider more context characteristics to improve the recommendation approach.
2. Gather user profile and context information in social networks and virtual learning environments.
3. Prepare this architecture for mobile devices, including a new interface agent, for analyzing the environment to which LO is recommended.
4. Create an agent that gathers environmental context data, such as: GPS location, equipment type, operating system type, and more.

Future recommender systems move towards the development of richer, adaptive and flexible solutions, facing students' daily school activities.

Acknowledgements

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

7. References

ABDALLA, A. et al. **R. ECOS – Educational Recommender Ecosystem.** Ieee/acm joint 5th international workshop on software engineering for systems-of-systems and 11th workshop on distributed software development, software ecosystems and systems-of-systems. Anais, 2017.

ACM/IEEE. Software Engineering Curriculum. **Guidelines for Undergraduate Degree Programs in Software Engineering,** 2004.

AGUIAR, J., FECHINE, J., COSTA, E. **Recomendação de Objetos de Aprendizagem utilizando Filtragem Colaborativa baseada em Tendências e em Estilos de aprendizagem. In Brazilian Symposium On Computers In Education (Simpósio Brasileiro De Informática Na Educação-SBIE)** (Vol. 29, No. 1, p. 1423), 2018.

ALMEIDA, R. et al. **Recomendação de Recursos Educacionais para Grupos: buscando soluções em Redes Sociais**. Anais do XXVII SBIE 2016.7 nov. 2016 Disponível em: http://www.br-ie.org/pub/index.php/sbie/article/view/6785, 2016.

ALMEIDA, R. et al. **Sistemas de Recomendação de Recursos Educacionais para Grupos de Redes Sociais: um Mapeamento Sistemático.** SBIE, 1022–1031, 2014.

BELIZÁRIO Júnior, C., Dorça, F. **Uma Abordagem para a Criação e Recomendação de Objetos de Aprendizagem usando um Algoritmo Genético, Tecnologias da Web Semântica e uma Ontologia.** In Brazilian Symposium on Computers in Education (Simpósio Brasileiro de Informática na Educação-SBIE) (Vol. 29, No. 1, p. 1533), 2018.

BEZERRA, S. F. et al. **Um Sistema de Recomendação Híbrido Integrado a Ontologia em um Ambiente de Aprendizagem Ubíqua.** In **Brazilian Symposium on Computers in Education** (Simpósio Brasileiro de Informática na Educação-SBIE) (Vol. 29, No. 1, p. 1253), 2018

CAMPOS, F. C. A. et al. **Projeto BROAD: Busca semântica por objetos de aprendizagem. In: ESUD 2011 – VIII Congresso Brasileiro de Ensino Superior a Distância Ouro Preto - UNIREDE,** Ouro Preto, Brasil, p. 3–5, 2011.

CAZELLA, S. C. et al. **Recomendação de Objetos de Aprendizagem Empregando Filtragem Colaborativa e Competências In: Simpósio Brasileiro de Informática na Educação** - SBIE, Anais do XX Simpósio Brasileiro de Informática na Educação, Brasil. Vol. 1. No. 1, 2009.

CAZELLA, S. C.; NUNES, M. A. S. N.; REATEGUI, E. **A Ciência da Opinião: Estado da Arte em Sistemas**

de Recomendação. In: André Ponce de Leon F. de Carvalho; Tomas Kowaltowski. (Org.). **Jornada de Atualização de Informática** - JAI 2010- CSBC2010. v.1, p. 161-216, PUC-RIO, Rio de Janeiro, Brasil, 2010.

COSTA A, O., BERNI R, E., ALEJANDRA B, P. **Recomendação de Conteúdo em um Ambiente Colaborativo de Aprendizagem Baseada em Projetos. Revista Brasileira de Informática na Educação,** 26(1), 2018.

DRESCHT, A.; LACERDA, D.P.; ANTUNES, J.A.V. **Design Science Research: método de pesquisa para avanço da ciência e tecnologia.** Porto Alegre, Bookman, 204 p, 2015.

ELAMY, A. H. **Perspectives in agent-based technology**, In: Agent LinkNews, n.18, p.19- 22, 2005.

Elamy, A. H. 2005. Perspectives in agent-based technology, In: Agent LinkNews, n.18, p.19- 22.

FERRO, M. R. C. et al. Um **Modelo de Sistema de Recomendação de Materiais Didáticospara Ambientes Virtuais de Aprendizagem** In: **Simpósio Brasileiro de Informática na Educação - SBIE, Anais do XXII Simpósio Brasileiro de Informática na Educação,** Aracaju, Brasil. Vol. 1. No. 1, 2011.

GARCÍA, E. et al. **An architecture for making recommendations to courseware authors using association rule mining and collaborative filtering.** In: User Modeling and User-Adapted Interaction, 19(1-2), Córdoba, España, p. 99–132, 2009.

GÔMES-SANZ, J; J, FUENTES, R. **Agent Oriented Software Engineering with INGENIAS, Agented-Oriented Methodologies,** In: IDEA Group Publishing, Madrid, España, 2002.

HERNANDO, A. et al. **Incorporating reliability measurements into the predictions of a recommender system. Information Sciences,** v. 218, p. 1–16, 2013.

HINZ, V. T.; GASPARINI, I.; PIMENTA, M. S. **Em busca de recomendação de objetos de aprendizagem em um ambiente e-learning com uso de ontologias** - In: **laclo 2011 - sexto congresso latino americano de objetos de aprendizagem,** sexto congresso latino americano de objetos de aprendizagem, Montevidéu, Uruguai, 2011.

IEEE. LOM - **Learning Object Metadata Working Group** 12. 2012. Disponível em: http://www.ieeeltsc.org:8080/Plone/working-group/ Acesso em: 7 de setembro de 2012.

Jácome Júnior, L.; Mendes Neto, F. M.; Silva, L. C. N. 2012. **Uma Abordagem Baseada em Algoritmo Genético para Recomendação de Objetos de Aprendizagem Sensível ao Contexto do Estudante.** In: **Simpósio Brasileiro de Informática na Educação - SBIE, Anais doXXIII Simpósio Brasileiro de Informática na Educação**,Fortaleza,Brasil,p.4–8.

LIMA, D., NETTO, J. F., & de MENEZES, C. 2017. **Agentes Inteligentes e Sistemas Multiagente: Um Mapeamento Sistemático Focado nas Iniciativas Brasileiras. In Brazilian Symposium On Computers In Education** (Simpósio Brasileiro de Informática na Educação-SBIE) (Vol. 28, No. 1, p. 41).

PEREIRA, C. K. et al. BROAD-RSI – Educational recommender system using social networks interactions and linked data. **Journal of Internet Services and Applications,** v. 9, n. 1, p. 7, 2018.

PEREIRA Júnior et al. **Uso de Ontologias para Agentes Conversacionais no Contexto de Ensino-Aprendizagem: Uma Revisão Sistemática da Literatura. In brazilian symposium on computers in education** (Simpósio Brasileiro de Informática na Educação-SBIE) Vol. 28, No. 1, p. 183, 2017.

PRIMO, T. T., VICARI, R. M, SILVA, J. M. C. **Rumo ao Uso de Metadados Educacionais em Sistemas de Recomendação,** In: **anais do XXI simpósio brasileiro de informática na educação,** SBIE, João Pessoa, PB, 2010.

SIMÕES, L. et al. **Sistema de Recomendação de Serviços Baseado em uma Arquitetura Aberta para um Ecossistema de Software. Simpósio brasileiro de sistema de informação,** 2017. p. 340-347.

REZENDE, P. et al. **BROAD-RS: uma arquitetura para recomendação de objetos de aprendizagem**

sensível ao contexto usando agentes, In: anais do Esud 2013 - X congresso brasileiro de ensino superior, 2013.

REZENDE, P. et al. PERSONNA: a proposal of student`s context and profile ontology for learning objects recommendation. **Brazilian Journal of Computers in Education,** [S.l.], v. 23, n. 01, p. 70, 2017.

SEYEDNEZHAD, S.M. M. et al. **A Review on Recommendation Systems: Context-aware to Social-based.** Available in https://arxiv.org/pdf/1811.11866.pdf. Accessed at 11/11/2019, 2018.

SOUZA, S. S. R. et al. **Construção de Plataformas Digitais durante o Ensino de Engenharia de Software: um Relato de Experiência.** Anais do **IX Fórum de educação em engenharia de software (FEES 2016)**, Maringá, PR, Brasil,2016 Vol. 1. No. 1.

VEIGA, W. **BROAD-ECO: Ecossistema de e-Learning baseado em serviços educacionais.** Dissertação de Mestrado. p. 1–162, 2016

VICARI, R. M. et al. **Brazilian proposal for agent-based Learning Objects metadata standard - OBAA.** In: http://www.portalobaa.org, Universidade Federal do Rio Grande do Sul, Brasil, p.2–5, 2009.

ZAÍNE, O. R. **Building a recommender agent for e-learning systems, In: Computers In Education, Proceedings. International Conference On**, vol.1 Alberta, Canada, p. 55-59, 2002.

ZHUHADAR, L. et al. **Multi-model ontology-based hybrid recommender system in e-learning domain. In: Web Intelligence and Intelligent Agent Technologies**, WI-IAT ’09. **Ieee/wic/acm international joint conferences on, volume 3**, EUA, pp. 91–95, 2009.

Recebido em: 21/07/2021

Aceito em: 26/10/2021