A MULTI-AGENT ARCHITECTURE FOR LEARNING PATHS-BASED PERSONALIZED E-LEARNING SYSTEMS

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Abstract: The application of artificial intelligence and semantic models for increasing learning and tutoring quality by personalization is an emerging research area. Multi-agent frameworks facilitate the communication between the different components and ontological models can be used as knowledge sources for intelligent agents. In this research we analyse knowledge models and software architectures, outline trends in the personalized learning area and propose an agent-based architecture for e-learning systems that can conduct learning by generating and recommending personalized learning paths. Initial evaluation of prototype system is proposed and learning path generation scenarios are discussed.

Key words: multi-agent architecture, personalized e-learning, artificial intelligence, semantic models.

1.INTRODUCTION

Adapting and regulating the learning processes dynamically according to the learner preferences, knowledge, psychology, disabilities and performance by applying semantic models is a challenge. Appropriate content for each learner or group of learners is recommended after periodic evaluation of the level of knowledge and comprehension of the learners. Several adaptive learning system architectures for development of personalized E-learning environments have been proposed and evaluated, such as, intelligent tutoring systems, adaptive hypermedia systems, semantic web-based systems, cloud-based adaptive systems, recommender systems [1], etc. The most valuable factors for dynamic personalization of the learning are: learners' preferences; learners' knowledge; learners' psychological properties or learning disabilities [2]. Semantics-based models for representing the information for automated personalization are frequently used, as they can support application of intelligent algorithms. Many researchers use ontologies for semantical representation of metadata in e-learning systems [1, 3, 4, 5]. The applications were classified in [3] into curriculum ontology creation, ontology-based structuring of the learning content, and for retrieval of learning resources. An important approach for personalization of learning and tutoring is the development and dynamic selection of personalized learning pathways. Generation or selection of personalized learning paths are promising personalization approaches in adaptive e-learning. Ontology-based learning path recommendation solutions include an ontology-based learning path generation method, an ontology-based learning path selection, and update mechanism of the system ontologies.

In this research we propose an architecture and prototype of an integrated framework for personalized learning and tutoring aiming at optimizing the learning process by generating and recommending the best learning paths. Our aims are to propose flexible, easily extensible and adaptable to various learning contexts system architecture. The proposed architecture can support dynamic personalization, based on intelligent technologies and ensure high quality learning, based on adaptive learning paths. Ontology-based knowledge models are used for structured storing of all the needed knowledge.

2.SURVEY OF RESEARCH IN THE FIELD

There is a huge amount of research on the usage of intelligent technologies and semantic models for knowledge representation to increase quality of e-learning [2], [3, 6, 7]. We will propose brief analysis of the usage of ontologies for learning including path-based personalization. We will first analyse used knowledge models and intelligent technologies, and then discuss architectures for its organization.

2.1. Semantic models and intelligent technologies in e-learning

One or more ontologies have been used in many personalized learning research projects for modelling knowledge. An ontology-based e-learning system, supporting learners in building of adaptive learning paths is proposed in [3]. Participation of learners in path generation is useful for deeply understanding of the curriculum, syllabuses, and content of courses. The system using multiple aligned ontologies, organized on different layers is presented in [8]. It includes Curriculum ontology, Syllabus ontology and Subject ontology. Conceptual modelling of the domain of Learning Paths generation and selection in Higher Education is presented in [7]. An integrated framework for learning path -based personalization in Higher Education is proposed in [9]. Simulation modelling, machine learning and data clustering are used for learning path generation. A comprehensive survey of intelligent tutoring and adaptive hypermedia systems is proposed in [10]. Six of all the 15 discussed systems use personalization, based on learning paths. Authors conclude that majority of adaptive systems are based on some learner model, pedagogical resource model, learning model and adaptation model. Fuzzy logic can be used in many cases to model uncertainty in human thinking and interpretation. It is suitable and applicable for developing knowledge-based personalized advising systems in e-learning. A hybrid software infrastructure which integrates expert system, fuzzy reasoning, and ontology-based semantic knowledge models to provide dynamic personalized recommendations to students is presented in [11].

We analysed trends in the research on ontologies, agents and learning analytics in Scopus (see fig.1). Scopus analytics show increasing scientific interest of the usage of ontologies and agents in e-learning amid a declining number of scientific publications related to ontologies or intelligent agents during the last ten years. Combining technologies is important trend in personalized learning systems.

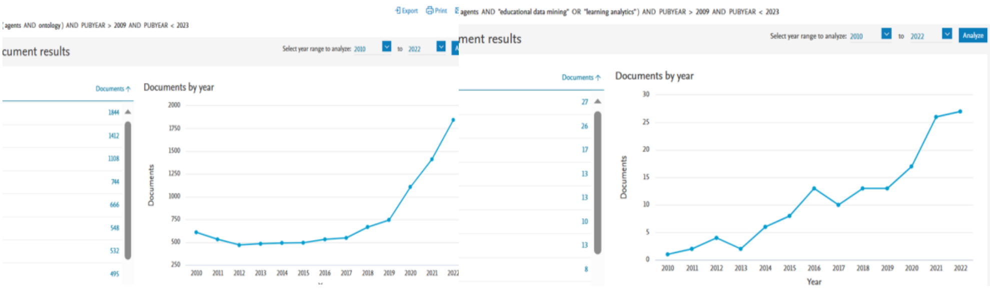

Fig.1 Scopus Analytics on research on ontologies, agents and learning analytics

2.2. Software architectures used in personalized e-learning systems

Software architectures used in e-learning can be classified in three main categories: traditional client-server architectures, service-oriented and agent-based.

Client-server architectures are used by almost all e-learning systems. These classical architectures also are in the base of most of personalized e-learning and recommender systems [1].

The usage of service-oriented architecture includes decomposition of the functionality of the e-learning system on components, each developed as a web service. Dynamic discovering of appropriate services and its linking are in the base of service-oriented architectures. The e-learning framework, proposed in [10] is service-oriented and uses machine learning for learning path generation and predictive evaluation of its quality.

Service-Oriented Cloud Computing Architecture (SOCCA) for personalized e-learning systems is proposed in [12]. It is designed to support maximum scalability and high service levels through virtualization and an optimized management and is very cost-effective modular solution. The cloud-based e-learning systems (like MoodleCloud) consist of cloud management system, hardware and software computing resources and services offered by the cloud. The drawback of cloud-based systems is restricted possibilities of modification by developers or tutors.

The main drawback of service-oriented architecture is that services are stateless, and this will make difficult implementation of complex algorithms, used in intelligent systems and modelling intelligent behaviour.

Agent – based architectures of personalized e-learning systems. Ontologies as knowledge bases for metadata in e-learning systems have collaborated well with other AI techniques, including software agents. The development and evaluation of ontology-based recommender systems were examined in [4, 13]. Several contexts of the usage of agents in ontology-based recommender systems were discussed in this research. Multiple agents were employed in [14, 15]. Most frequently used software agents are tutoring agents, which use information on learners, learning content and learning objectives represented semantically in the student model or domain model [16], and learner agents, which select and propose the personalized instructional design or recommend tutoring content, using ontologically represented metadata and set of rules [14].

Combining traditional client – server architectures and service-oriented or agent-based architectures is modern trend in development of complex software systems. Example is [18] which proposes a system consisting of intelligent and reflex agents located both in the two parts of the client-server architecture: A back-end component usually includes a knowledge base and assistant agents for gathering information about the client's needs. A front-end component includes an intelligent assistant that acts as a user interface and presents the selected learning path. Other example is a learning environment Moodle's extension. New versions of Moodle include REST servers and can send and accept GET/POST queries using XML/JSON technology. A multi-agent system called Observer [19] is integrated in Moodle e-learning systems to personalize tutoring and support students engaged in learning by monitoring their work. Modern architectures of the m-learning systems, supporting game-based learning [20], micro learning, inquiry learning also combine several architectural elements. We first will state important requirements to the architecture of complex e-learning system, supporting dynamic generation and selection of personalized learning paths, and then will describe our proposal.

3. SOFTWARE ARCHITECTURE FOR LEARNING PATH BASED PERSONALIZED E-LEARNING SYSTEM

3.1. Requirements to the personalized e-learning systems architecture

To ensure high quality tutoring, including learning paths-based personalization, the e-learning system should meet the following requirements:

- Compatibility with other e-learning systems;
- Modularity;
- Easy adapting to different learning contexts;
- Personalization and adaptation capabilities;
- Evaluation of its Recommendation quality. Evaluation measures should be defined and analysis of each recommendation should be performed using them towards the learning goals and results of learner or group of learners.
- Periodic and continuous assessments: Periodic assessments allow the system to assess attributes of adaptability and store learner's assessment results for future analysis of the personalization results.
- Selecting the best learning path and recommendations;
- Generating new learning paths in accordance with specified requirements;
- Continuous Data Collection, analysis, prediction, visualization;
- Monitoring and ensuring high level learners motivation;
- External resources retrieval, analysis, annotation and recommendation;
- Easy to develop and maintenance.

Our architecture describes a complete tool set for the personalization and optimization of learning and also the organization of the needed information for well working of these tools and main communication channels between tools.

3.2. Description of the proposed architecture

Learning paths-based personalization is one of the most complex personalization approaches in adaptive e-learning systems. It includes dynamic collection of complex data about learners, learning content, pedagogy, processing and organization of data in sophisticated models, and its use during conduction of goal-oriented tutoring and learning. Software agents are programs that act on behalf of human beings but having autonomous and intelligent behaviour. Intelligent agents are independent software entities that have internal state (knowledge), can process knowledge and communicate each other in native way. Intelligent agents are good software tools for supporting the learning process through collecting and processing data and knowledge, making predictions, interaction with students, lecturers and other participants, finding and integrating information from different sources, creating, selecting and recommending learning pathways. All these services agents can do in its native environment, in collaboration with other agents. Intelligent agents can use effectively and reason with semantically represented data in ontologies, and there are well-working multi-agent environments where agents can easily communicate and collaborate for achieving complex goals. Having in mind all these agent's properties, we found the multi-agent architecture as the most appropriate for development of complex personalized e-learning systems, having possibilities for personalized learning paths generation and recommendation.

Our multi-agent system collects student activity data, stores it in the ontology-based knowledge base analyses systematized data, extracts learning process indicators, creates predictions for the learning results for every student and on this base generates or selects and recommends personalized learning path for every learner. We have used a competency-based approach to offer a personalized learning path to the learners according to his competences. The multi-agent system also can participate in the evolution of knowledge base and learning resources.

We propose layered functional structuring of the MAS, on three levels: User interface level, Learning control agents and Resource evolution agent's level. Interface agent is responsible for proposing adequate interface for specific learner, tutor or developer. Tutoring agent, Learner agent, Assessment agent, External interoperability agent, learning pathway generation agent, Recommendation (or learning path selection) agent ensure organization and control of learning and tutoring. Resource searching and retrieval agent, Ontology mapping agent, Terminology extraction and ontology learning agent, learning resource evolution and Annotation agent are responsible for development and evolution of learning content and metadata. Coordination agent coordinates the system functionality and communication between agents (see fig.2).

Learning resource evolution and Annotation agent (LREAA). A personalized learning system should contain multimodal well – structured and semantically-annotated adaptable content for each learner. Semantic annotation is very important for automated selection, recommendation and sequencing. Most of the learning content can be developed and annotated at advance, using LREAA or not, but continuous evolution of the e-learning materials is crucial, and LREAA perform this tack.

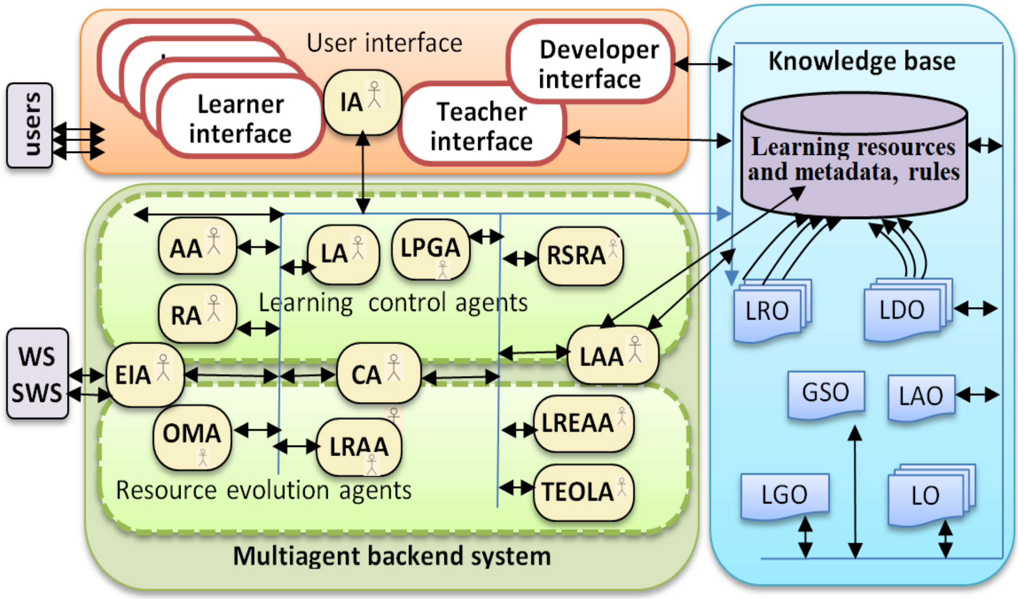

Fig. 2. The proposed architecture

Terminology extraction and ontology learning agent (TEOLA) implements linguistic and knowledge extraction algorithms. It is used so support ontology evolution when new learning content is added to the learning course.

Ontology mapping agent (OMA) can implement automatic or semi-automatic ontology mapping algorithms and is used when some changes are made in domain or learner ontologies or new ontology is added to the ontology network**.**

Resource searching and retrieval agent (RSRA) searches external resources in the internet or from other e-learning systems. It uses Natural Language Processing techniques and ontology-based semantic analysis to evaluate the correspondence of the found textual content to the learner's needs. It uses services, proposed from EIA when needed.

Good quality learning materials (Learning objects), annotated by metadata are stored in e-learning system's learning object repositories. For efficient retrieval and recommendation of learning materials according to the learner's needs, the learning materials are tagged with a set of metadata such as topic of the document, type of the document, learning goals, learner types, etc. etc. Annotation also facilitates the sharing and reuse of learning materials across different information repositories or learning management systems. **Learning resources annotation agent** (LRAA) is intended for e0learning resources annotation, using metadata standards and system ontologies. Coordinator agent usually asks LRAA to annotate new learning resources, added to the repository.

Learning pathway generation agent (LPGA) generates plans for achievement of the learning goals and then maps plans to annotate learning resources and in this way proposes learning pathways**.** Both traditional and deep knowledge tracing methods can be used. This agent also uses learner's data and knowledge, extracted by LAA and stored in ontological models to generate and recommend personalized learning paths based on the prediction of learner's success using indicators of engagement and machine learning algorithms.

Recommendation (or learning path selection) agent (RA) compares learning path annotations or learning resource annotations with learner's properties and apply rules for recommending suitable ones to the learner or group of learners. It also can ask RSRA, IA or CA about external resources when there are no suitable content in the system.

Coordinator agent (CA) knows all about the functionality of all the agents in the MAS and use clear rules for control the functionality of the system by asking appropriate agents for performing needed services and estimating achieved results.

Learning Analytics Agent (LAA) analyses data about learners and learning context extracting learner's behavioural signals from the data. Knowledge tracing is one of the main functionalities of LAA. It traces the learner knowledge and comprehension over time and uses models for predicting a learner performance and knowledge on future curriculum interactions. LAA implements statistical and machine learning (including clustering and classification) algorithms to group students based on their obtained score values.

External interoperability agent (EIA) acts as converter between e-learning standards or call web or Big Data services when some of the system components require external information or learning content. It is responsible for ensuring interoperability between systems in searching external learning content.

Assessment agent (AA) ensures analysis of assessment results, user logs, and modality dataset to evaluate the level of meeting the requirements of adaptive and adaptable learning. It also can be used for automatic test generation, including personalized ones.

Learner agent (LA) is responsible for the actual state of learner's profiles and learner profile ontology. It receives data from LAA and IA and updates learner's profiles. It also controls actuality of the information about learner's preferences, performance and knowledge, using explicit and implicit data gathering techniques.

Tutoring agent (TA), also called **pedagogical agent** customizes tutoring according to the learner's mental model, tutor actions and learner's state in collaboration with the LA, AA, RA. Its main goal is to increase learner motivation and performance**.** It also can be used for personalized automatic selection of learning paths.

Interface agent (IA) proposes the adequate interface for learners or teachers. It uses learner's data and also can actualize information about learners, using machine learning techniques [17], heuristics and dynamic analysis of learner's behaviour.

Knowledge base. The main types of knowledge models, used in personalized education systems are [11]: learner model, pedagogical resource model, learning model, adaptation model, tutoring domain model. Relational or NoSQL databases can be used to store raw data, collected by LAA and also some of results from the application of learning analytics algorithms. Groups of similar competences can be formed based on the application of collaborative filtering, clustering, machine learning, rule-based or other type algorithms. Ontological models enclose the knowledge, and the information and rules are useful for supporting decisions and recommendations. Some results of data analysis (i.e. instances, extracted by text mining) are stored in ontologies and are used for conducting personalized learning. As a results of the rule-set execution concepts or relations can be extracted and stored in some of the ontologies as new knowledge.

A personalized educational system recommends learning content and its sequencing in learning pathways based on features. Identification of valuable and correct set of features and its systematization is one of the main challenges in personalized learning. We propose a model of mapped ontologies to organize all the knowledge, needed for personalization. Ontological modelling includes extraction of learner's and learning context characteristics in order to personalize learning based on learners' needs, performance, knowledge, learning style, psychological characteristics, and its semantic representation in machine-processable way. Modularization of knowledge and reusing of previously developed ontologies are very important during modelling. The modular approach allows usage of different set of mapped ontologies in different systems according to the specific learning contexts. The most frequently used ontologies are:

- Learning domain ontology (LDO);
- General subject ontology (GSO);
- Learner ontologies (LO);
- Learning resources ontology (LRO);
- Learning goal ontology (LGO);
- Learning Analytics Ontology (LAO);

The e-learning system should contain adequate well-organized and adaptable learning content of a particular topic presented in multiple modalities. The learning content can follow some e-learning standards, or not. Ontology-based annotation is one of the best approaches to support the dynamic selection and sequencing of learning objects. Domain ontologies, learning resource description ontologies and General subject ontologies can be good basis for learning resource annotation.

English language terminology is used in almost all freely available domain ontologies. Learning content is in Bulgarian, but in many courses English language terminology also is presented. We recommend development and usage of ontologies lexicalized both in Bulgarian and English languages (bilingual ontologies). This can simplify the ontology building process (as most of the available ontologies are developed in English language), ontology reuse, ontology evaluation, and also comparison of e-Learning resources, annotated by ontologies [21].

Learner ontologies include important learner's characteristics. Main widely used learner's properties were extracted and classified into six subcategories, namely cognitive, motivational, behavioural, emotional, metacognitive aspects, and combined domains [5]. These basically characteristics should be used in the main learners ontology in every personalized system, and other specific learner's properties, needed in specific system should be systematized in specific learners ontologies (for example dyslexia characteristics). Some of these specific learner ontologies have to be mapped to the main learner's ontology when needed.

Learning Analytics Ontology integrates all the dimensions and characteristics, of Learning analytics data and knowledge extracted by LAA agent. This ontology stores mainly dynamically extracted data about learner's progress and this information is very useful for dynamic selection or recommendation of learning paths.

One of the main advantages of the ontological representation of the knowledge, extracted from educational data by usage of leavening analytics is possibility to use this knowledge in the reasoning process by software agents for deducing new knowledge. Ontological representation of knowledge also makes easy to find contradictory information.

4.PRESENTATION OF THE RESULTS AND DISCUSSION

We used JavaScript programming language, HTML and CSS for graphical interface, and JADEX MAS software [22] for implementing the MAS system. JavaScript is the leading scripting language widely used for client-side programming and it is essential for the development of modern web applications. The MAS also can be integrated inside e-learning environments and used by large numbers of students. It also can connect multiple e-learning environments, using External interoperability agent. Using rule-based approach, we implement in Coordinator agent strategies for predicting performance of groups of learners (using LAA) and generating personalized learning paths by sending messages to LPGA. Then CA can require delivering content according to adequate learning pathways from Resource searching and retrieval agent.

Functional evaluation includes evaluation of how MAS works, including collaboration and communication between agents, and evaluation of quality of ontologies. We have used JADEX Control Centre to test communication functionalities of the MAS. The JADEX BDI kernel is a Belief-Desire-Intention (BDI). It provides communication infrastructure, reasoning capabilities and management facilities. Using the BDI reasoning mechanism is natural way for trying out different plans for achieving learning goals. Learning paths are generated as plans, which steps are learning resources. JADEX technology also includes integration with web services and publishing JADEX services can be made with minimal effort in the web.

The ontologies were developed using Protégé environment and were evaluated for logical inconsistencies using built-in reasoners as Pellet and HermiT. Evaluation by experts also was performed. We also test our prototype system in several typical working scenarios. Some of them are:

Scenario 1. Learning disability personalization**.** The MAS reports about possible dyslexia learners, attending the course. The tutor performs precise tests and confirm the proposed disability diagnose. As there are no specialized learning content and specific ontologies for dyslectics, course developer adds dyslexia ontology and in collaborating with ontology mapping agent align this ontology to learner ontology or resource description ontology. The course developer also can add some learning content for dyslexia learners. Then CA asks LPGA to annotate the added content. Using annotation metadata, domain ontology, and learner profile ontology, LPGA generates learning path for dyslexics, closely related to the standard learning path of the course, but containing resources for dyslexics, and recommend this path to the dyslexia learner. The generated learning path is stored as standard learning path for dyslexics and will be recommended by RA to every dyslexia learner, attending the course.

Scenario 2. Learning paths for students with gaps from previous courses. For typical knowledge gaps specific learning paths can be generated and stored at advance and adequate annotated resources can be added in the repository. For specific knowledge gaps external resources should be searched by RSRA in collaboration with LA, EIA and RA and recommended dynamically. Some of these resources can be stored in the repository after annotation by LREAA.

Scenario 3. Learning paths for students with low attendance and for dropout prevention. TA in collaboration with CA, LAA, LA and LPGA periodically make predictions about learners at dropout risk. For these learners RA can recommend learning paths, including interesting educational games, tests and learning activities to get students engaged. AA also should perform specific tests and LAA try to predict student's performance for future recommendation of suitable content.

Application-level evaluation is pending. 18 Students in the Technical College of Sofia took part in this evaluation, attending 3 programming courses. Evaluation of the results is performed both by comparison of final tutoring effect (based on test results) and student's satisfaction (both by questionnaires and by evaluating data about student's participation, extracted by the LA). The results are promising, but we need more experiments with more students.

5.CONCLUSION

Dynamic personalization, based on intelligent technologies and semantics-based knowledge models can ensure high quality learning, based on adaptive learning paths. Combining various types of logical models and intelligent technologies is important trend. The paper presents modular agent-based software architecture for personalized e-learning systems. We showed how semantic ontology-based models can be used for representation of knowledge, needed for the MAS. Implemented prototype system also is discussed. The multi-agent system can generate and recommend personalized learning paths, based on the prediction of learner's success, and in this way increases the efficiency of the learning process and supports students engaged in learning. A novelty of our architecture is the way of organization of complex multi-agent systems in e-learning to conduct intelligent teaching including generation and recommendation of personalized learning paths. This flexible and adaptable architecture can be in the base of systems, supporting the teacher in the tutoring or resource-development activities, as well as leading students in achieving their educational goals based on their performance, progress, motivation, disabilities, learning styles, preferences, etc. Integration of ontology-based technologies, rule-based approach and intelligent agent-based software architectures ensure easier and effective development of high-quality personalized e-learning systems. Integration of semantically represented knowledge, reasoning capabilities and goal-directed modular and flexible agent-based architectures gives natural way for using intelligent technologies to improve learning.

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