Intelligent multi-agent learning system applying educational data mining

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In this paper, we present a methodology for personalizing learning in accordance with the needs of individual students by using an intelligent, multi-agent learning system and data mining. Learning personalization is implemented on the basis of several methods. The Felder and Silverman Learning Styles model is used to create student profiles, and the probabilistic suitability indexes are identified to interlink learning components (i.e., learning objects, learning activities and learning environments) with the learning styles of individual students. Other technologies, which were proposed for creating the learning system, are ontologies, recommender system, intelligent software agents and educational data mining/learning analytics. Personalized learning units are referred to here as learning units composed of the learning components that have the highest probabilistic suitability indexes for particular students. In the paper, first, a systematic review on the application of intelligent software agents in learning is performed using the Clarivate Analytics Web of Science database. Second, we present the methods for personalizing the intelligent technologies of learning application, which are used to create optimized learning units for individual students. The developed student profiles and personalized learning units are further corrected by applying the methods and tools of data mining. The model of an intelligent, multi-agent learning system, based on the application of the aforementioned technologies, is presented in more detail. The principal success factors of the proposed methodology are the pedagogically sound vocabularies of learning components, an expert evaluation of the learning components in terms of their suitability for particular students as well as the application of ontologies, recommender systems, intelligent software agents and data mining.

Keywords: *personalization, intelligent multi-agent learning system, learning styles, learning units, ontologies, recommender system, intelligent software agents, data mining.*

1. Introduction

The aim of this research is to analyze and propose a model of intelligent, personalized, multi-agent learning system by applying the methods and techniques of educational data mining. This system is modelled based on an original methodology to personalize learning by intelligent technology application.

The personalization of learning by applying intelligent technologies became a very popular topic in scientific literature during last few years (Arimoto et al. 2016; Jasute et al. 2016; Juskeviciene et al. 2016; Takala et al. 2016; Jevsikova et al. 2017). The core idea of adaptive personalization lies in achieving a common goal – to provide students with what they require without expecting them to ask for it explicitly. Because of the multi-faceted nature of the problem, which includes recommendation systems, customization, adaptive Web sites and artificial intelligence, a universal definition, one that would cover all its theoretical and technological areas, has so far not been proposed. From the educational viewpoint, personalization attempts to provide an individual with tailored products, services, information etc. A more technical standpoint regarding personalization is linked with the modelling of Web objects (products and pages) and subjects (users) as well as their categorization, organizing them to achieve the desired level of personalization.

Personalization can be seen from two different perspectives. The first being with only a single learning object (LO) (Kurilovas 2009; Kurilovas and Serikoviene 2013; Dorca et al. 2016), or a learning unit/scenario (Kurilovas et al. 2011; Kurilovas and Zilinskiene 2012) being selected; the second perspective is observed with a set of them being composed, i.e., the personalization of

a learning unit by finding a learning path. The former perspective formulates the LO selection problem (Kurilovas, Serikoviene and Vuorikari 2014), and the latter one solves the curriculum sequencing problem (Kurilovas et al. 2014).

In the paper, first of all, a systematic review on the application of intelligent software agents in education is performed. Second, presented are two methodologies, one regarding the personalization of learning by applying intelligent technologies and the other regarding how optimized learning units can be developed for particular learners using learning analytics/educational data mining (LA/EDM). Third, the novel model of a personalized, intelligent, multi-agent learning system is proposed.

The rest of the paper is organized as follows: the second section presents the systematic review, the third presents methods to personalize learning with intelligent technologies and to create optimized learning units for individual students with LA/EDM, the fourth section presents the model of a personalized, intelligent, multi-agent learning system, and the fifth section concludes the paper.

2. Systematic Review

In order to identify the latest results in the application of intelligent multi-agent systems in education, the basic systematic literature review method has been used (Kitchenham 2004). The intention of the scientific review was to answer the question: "What are the latest contributions to the application of intelligent agents in education?" The systematic literature review was performed in the Clarivate Analytics (former Thomson Reuters) Web of Science database. The search history can be seen in Figure No. 1. In the last two

years (2014–2016), thirty-four articles were published on the topic "intelligent multi-agent* system AND learning." The main factor for choosing papers for the review from the search results was their relevance to education, as multi-agent systems have a variety of applications. After applying a systematic review methodology, on the last stage, 10 suitable papers were identified for further analysis of the topic.

ing a dominant performance-approach, demonstrated a higher achievement rate in the prompt and feedback condition.

In another study by Trevors, Duffy and Azevedo (2014)we examined how one such HLE---\\nMetaTutor, an intelligent, multi-agent tutoring system designed to scaffold cognitive and\\nmetacognitive self-regulated learning (SRL, the authors examined how the MetaTutor environ-

Set	Results	Save History / Create Alert Open Saved History
# 2	34	TS=(intelligent multi-agent* system AND learning)) *AND* DOCUMENT TYPES: (Article) *Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI Timespan=2014-2016*
# 1	97	TS=(intelligent multi-agent* system AND learning) *Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI Timespan=2014-2016*

Figure No. 1. **Search history in the Thomson Reuters Web of Science database.**

The purpose of a study by Duffy and Azevedo (2015) was to examine whether the pedagogical agents' scaffolding (instructional prompts and feedback) would impact the self-regulated learning processes and achievements of learners in the MetaTutor learning environment. The authors also aimed to better understand the interaction between agent scaffolding and learners' achievement goals: whether the dominant achievement goal, adopted by the learners, moderated the impact of agent scaffolding. This study demonstrates that agents' prompts and feedback within a computer-based learning environment foster learning behaviours, such as an increased use of self-regulated learning strategies and time spent viewing relevant material during the learning session. Results also revealed a significant interaction between achievement goals and the condition on achievement outcomes, such that learners, while adopt-

ment, an intelligent, multi-agent tutoring system designed to scaffold cognitive self-regulated learning processes, interacts with the prior knowledge of a student to affect their note-taking activities and subsequent learning outcomes. Note-taking is a prevalent strategy that offers students an opportunity to integrate information and build a coherent mental representation of the material. Sixty college students studied with MetaTutor and took notes. Learner-system interactions demonstrate that most of the note-taking were verbatim copies of the instructional content, which negatively related to the post-test measure of learning. There was a link between prior knowledge and pedagogical agent scaffolding, such that low prior knowledge students took a greater quantity of notes compared to their high prior knowledge counterparts, but this occurred only in the absence of the MetaTutor self-regulated learning scaffolding. When

the scaffolding was present, the note-taking activities of low prior knowledge students were statistically equivalent to the number of notes taken by their high prior knowledge counterparts.

Harley et al. (2015) presented the evaluation of the synchronization of three emotional measurement methods (automatic facial expression recognition, self-report, electrodermal activity) and their agreement regarding the emotions of students. Data were collected from 67 undergraduates who learned about a complex science topic while interacting with the MetaTutor learning environment. Videos of learners' facial expressions, captured with a webcam, were analyzed using the FaceReader facial recognition software. Learners' physiological arousal was recorded using the Affectiva's Q-Sensor electrodermal activity measurement bracelet. Students reported their experience of nineteen different emotional states on five different occasions during the learning session, which were used as markers to synchronize data from the FaceReader and the Q-Sensor. Authors found a 75.6% agreement between the facial and self-report data, but low levels of agreement between them and the Q-Sensor data, suggesting that a tightly coupled relationship does not always exist between emotional response components.

Harley et al. (2016) examined the predictive effects of learners' trait emotions and personality traits on agent-directed emotions. Overall, significant relationships between a subset of trait emotions and personality traits were found, though the relationships differed between pedagogical agents. These results demonstrate that some trait emotions and personality traits can be used to predict learners' agent-directed emotions toward specific pedagogical agents. Authors suggest that further research is required to draw conclusions regarding the relationship between agent-directed emotions, trait emotions, personality traits and learning.

According to Hooshyar et al. (2015), Computer Science minors possess misconceptions about what computer programming is. In their paper, the authors propose a Bayesian, flowchart-based, intelligent tutoring system. The aim of the system is to improve the problem-solving skills of students and introduce them to basic programming algorithms prior to learning the syntax required to write code in traditional manner. Using the text-to-flowchart system, students can program through a visualization-based flowchart design. The proposed flowchart, multi-agent system was assessed and received positive feedback; the experimental group was observed to have gains over a control group.

Khamparia and Pandey (2015) particle swarm optimisation (PSO present a review of developments in the field of e-learning strategies from 1990 to 2014. The main focus of the study is the application and deployment of knowledge-based and intelligent computing methods in education. The survey of papers revealed that a single knowledge-based method is not used to solve any particular e-learning problem. Usually, methods are cross-applied to different problems. For example, genetic algorithms, multi-agent systems, ontologies, artificial neural networks and rule-based reasoning were widely used to address learning path generation, object recommendation and domain ontology construction problems in education. Rule-based reasoning and artificial neural networks are also deployed to address data mining challenges. Generally, artificial neural networks were

more widely applied than rule-based reasoning because of the inference efficiency problem, difficulty in the maintenance of a large rule base and the problem of interpretation. Artificial neural networks were most often deployed for the solution of problems where classification of data is necessary, but complex reasoning is less crucial.

Hammami and Mathkour (2015) suggest an improvement on educational multi-agent adaptive systems in the form of an additional distributed blackboard agent. The proposed intelligent agent ensures communication amongst the rest of the agents governing an educational system. The formal model for the operation of the agent is also described. A message exchange and the synchronization of agents using the object Petri Nets is also proposed. According to the authors, a major advantage provided by the use of the object Petri Net is the modelling of the internal behaviors of agents and intelligent blackboards, which can be used for better understanding of their collaboration. In addition, the object Petri Net can be is used to verify and validate the model before the implementation to ensure that the design meets the original specifications. An exploratory implementation of the system has been deployed and tested. The evaluation of the educational system was performed using an e-traceability system and an online questionnaire. Experimental results indicate that most students were pleased with the activities related to the e-content. However, data also indicated that only a few students communicate with their teacher and other students.

Hoppe (2016) deals with the evolution of a particular educational multi-agent system introduced in another study by Müehlenbrock et al (1998). The original article used multiple student modelling as a method to configure and inform group-learning situations based on individually assessed learner models in addition to suggesting methods for detecting collaboration patterns from group action logs. The commentary traces a line of development from the 1998 system to the current mobile and web-based learning architectures and approaches to action logging for interaction analysis. Authors describe how the move toward mobile devices led to a variety of programming platforms, which, in turn, required more flexible protocols and interfaces. Thus, new architecture solutions were applied, such as blackboard architecture, which is used to avoid direct agent-agent communication. Another issue, already addressed in their 1998 paper, has been action logging as a basis for interaction analysis. However, again, more general quasi standards have been established in connection with web-based technologies and social networking platforms. In the ongoing EU project f Go-Lab, this has led to authors abandoning the "common format" in favor of using Activity Streams. The review shows how themes and architectural solutions evolved during the last two decades to meet the changing technological landscape of e-learning.

Hameed et al. (2016) proposed a model of a multi-agent e-learning system. The system is based on the Agent-Group-Role method. It is a notation used for the organization of multi-agent systems in Aalaadin, a meta-model for multi-agent systems (Ferber and Gutknecht 1998). Special attention in the work is devoted to the verification of the system's exact adherence to requirements and specifications. Safety and liveness properties are taken into account, ensuring that the system avoids error states (safety) and performs its tasks (liveness). The formal

verification of the system was performed by means of a timed-automata-based model checker Uppaal with positive results.

En-Naimi and Zouhair (2016) present a novel approach toward case-based reasoning. The approach is based on the reuse of traces for dynamic online user classification and prediction of behavior. This can be accomplished by the use of a user's history, the chronology of interactions and the productions left by the user during his navigation process. This approach involves the use of incremental, dynamic case-based reasoning, which is able to study dynamic situations (recognition, prediction and learning). The proposed multi-agent architecture is based on three layers of agents with a pyramidal relation. The lower layer allows building a representation of the target case. The second layer implements a dynamic process: search for past situations similar to the current one. Finally, the prediction/decision layer captures the responses sent by the second layer to transform them into actions proposed either by a virtual or human supervisor. After the prediction of the situation, the supervisor suggests an appropriate solution. In this manner, the proposed system can keep a constant automated intelligent watch of the environment.

Based on the presented systematic review, one can summarize that the application of intelligent software agents and multi-agent systems in education has been actively evolving for the past two decades. In the two past years (2014–2016), software agents were studied and deployed to solve a wide array of educational challenges. This demonstrates that intelligent agents are a promising and powerful way to personalize learning. Intelligent agents can adapt learning materials to the different learning styles of students and leverage innate pre-dispositions for knowledge acquisition on intellectual, sensory and emotional levels.

On the other hand, no research studies were found that would have analyzed personalized, intelligent, multi-agent systems based on developing learning style-based learner profiles that would create "optimal" (in terms of the suitability to a particular learner's profile) learning units. Therefore, this approach has to be analyzed, and an appropriate multi-agent system should be modelled to be designed and piloted in real pedagogical situations. Some appropriate solutions are proposed in the following sections.

3. The Methodology of Learning Personalization by Applying Intelligent Technologies

According to Kurilovas (2016), learning software and all learning processes should be personalized in accordance with the main characteristics/needs of the learners. Learners have different needs and characteristics, i.e., prior knowledge, intellectual level, interests, goals, cognitive traits (working memory capacity, inductive reasoning ability and associative learning skills), the learning behavioral type (according to the self-regulation level of the individual) and, finally, the learning styles.

Future education means personalization plus intelligence. According to Kurilovas (2016), learning personalization means creating and implementing personalized learning units/scenarios, which would be based on a recommender system suitable for particular learners in accordance with their personal needs. Educational intelligence supposes an application of intelligent technologies and methods to enable personalized learning for improving learning quality and efficiency.

In personalized learning, first of all, integrated learner profiles (models) should be implemented. In STEM (Science, Technology, Engineering and Math) education and e-learning, it should be based mainly on the Felder and Silverman Learning Styles Model (Felder and Silverman 1988), because this model is known as the most suitable for STEM education and e-learning. Dedicated psychological questionnaires, like the Soloman-Felder Index of Learning Styles Questionnaire, should be applied here.

After that, an open learning style model should be created, the implicit (dynamic) learning style modelling method should be used and, finally, the rest of the features in the student profile (knowledge, interests, cognitive traits, goals, learning behavioral types etc.) should be added to the profile.

A personalized, ontologies-based recommender system should be created to suggest learning components suitable to particular learners in accordance with their profiles. A recommender system should form the preference lists of the learning components according to the expert evaluation results.

Probabilistic suitability indexes should be identified for all learning components in terms of their suitability levels to particular learners. The probabilistic method for creating the whole personalized learning unit/scenario, consisting of suitable learning components that are optimal for particular students in accordance with their learning styles, is proposed by Kurilovas et al. (2016). The method is based on students' probabilistic learning styles and the expert evaluation of the suitability of different learning components to student learning styles. The probabilistic suitability indexes could be calculated for all the learning components and all the students as well if one would multiply the suitability ratings of learning components, these being obtained while the experts evaluate the suitability of the learning components to any particular learning styles by the probabilities of the learning styles of particular students.

All learning components in the recommender system should be linked to any particular students in accord with their probabilistic suitability indexes. The higher the suitability index, the better the learning component fits a particular student's needs. These suitability indexes should be included in the recommender system, and all learning components should be linked to students based on these suitability indexes.

The LA/EDM methods and techniques should be used to analyze the behavior of students in e-learning systems. Acquired this way, data may differ from the self-reported psychological evaluations from the questionnaires. Also, for a student, the potential for knowledge would constantly increase as they learn, do exercises, take tests and otherwise interact with the educational system. This constant stream of information should be used to continuously improve students' models and as consequence the service provided. Presently, researchers are addressing the questions of cognition, metacognition, motivation, affect, language, social discourse etc. by using data from virtual learning environments, intelligent tutoring systems, massive open online courses, educational games and simulations as well as discussion forums. The LA/EDM are also used to develop the assessment of learners' skills. Any additional information about the students increase the teachers' confidence to act, which, in turn, grants students more of the teacher's pedagogical presence. With students' permission LA/EDM could be also used to analyse data on students' informal

conversations on social media (e.g., Twitter, Facebook) concerning their educational experiences-opinions, feelings and concerns about the learning process. A hybrid learning style identification can cluster learning styles into three or four combinations based on learning performance, which suggests that the LA/EDM technique can identify multiple learning styles and problem-solving approaches. Such an incorporation of the LA/EDM agent would create new ways of understanding trends and behaviors in students, which can be used to improve learning design, strengthen student retention, provide early warning signals concerning individual students and help to further personalize the learner's experience.

The level of students' competences (i.e., knowledge/understanding, skills and attitudes/values) directly depends on the level of application of optimal learning units in real pedagogical practice. For this purpose, pedagogically and technologically sound vocabularies for learning components should be created and stored in the recommender system. Furthermore, the collective intelligence of experts and students should be used to evaluate the suitability of learning components to particular learner needs. Thus, a recommender system should form the preference lists of the learning components according to the expert evaluation results. The most suitable learning components for particular students should be put at the beginning of the list.

Probabilistic suitability indexes should be identified for all learning components in terms of their suitability level to any particular learners. Thus, personalized learning units could be created for particular learners. The optimal learning units (i.e., learning units of the highest suitability) for any particular students mean the methodological sequences

of learning components having the highest suitability indexes for particular students.

After that, the data on the practical use of recommended learning units in a learning environment (i.e., the data obtained by using LA/EDM) should be compared with learning units recommended to them based on probabilistic suitability indexes. In the case of any noticeable discrepancies, students' profiles and accompanied suitability indexes should be identified more precisely, and students' personalized learning units should be corrected according to new identified data. In this way, after several iterations, one could noticeably enhance the learning quality and effectiveness of students.

A number of intelligent technologies should be applied to implement this approach, e.g., ontologies, recommender systems, intelligent software agents, decision support systems to evaluate quality and suitability of the learning components, personal learning environments etc.

4. The Model of the Personalized, Intelligent, Multi-Agent Learning System

Intelligent software agents should be used to implement the personalized, intelligent learning system model. According to the systematic review (Section No. 2), researchers agree that intelligent pedagogical agents could help in personalizing learning, but there is no real agreement on what an agent is. Agents' abilities vary significantly, depending on its roles, capabilities and environments. In order to describe these abilities, different notions of agents have been introduced. Intelligent agents are introduced by most of the researchers with four major concepts defining their behavior: (1) autonomy, (2) responsiveness or reactiveness, (3) pro-activeness and (4) social ability.

There is also a strong notion on the characteristics of agents, which refer to adaptiveness, pro-activity and intentionality. There are also various taxonomies created for agents, e.g., collaborative, interface, mobile, information, reactive, hybrid and smart agents. In this context, intelligent agents have been associated with a variety of functions, e.g., personal assistants, information managers, information seekers, planning agents, coordination agents or collaborative schedules, user representatives and so forth. Their application in the educational field is mostly as personal assistants, user guides, alternative help systems, dynamic distributed system architectures, human-system mediators etc.

Because pedagogical agents are autonomous agents, they inherit many of the same concerns that autonomous agents must address in general. It has been argued that practical autonomous agents must generally manage complexity. They must exhibit robust behavior in rich, unpredictable environments; they must coordinate their behavior with that of other agents, and they must manage their own behavior in a coherent fashion, arbitrating between alternative actions and responding to a multitude of environmental stimuli. In the case of pedagogical agents, their environment includes both the students and the learning context in which the agents are situated. Student behavior is by nature unpredictable, since students may exhibit a variety of aptitudes, levels of proficiency and learning styles.

According to the systematic review, in order to create a conceptual model of a personalized, intelligent learning system, some kind of multi-agent system should be used. A conceptual model of a personalized, multi-agent, intelligent learning system, which is further discussed and presented,

is absolutely novel within the scientific literature. This model is the most suitable for STEM education and e-learning, since it is based on the Felder-Silverman Learning Styles Model, which is recognized as the most suitable for STEM and e-learning.

The proposed model, based on a consequent application of 5 intelligent software agents, is described below.

First of all, according to Kurilovas (2016), a dedicated psychological questionnaire, like the Soloman-Felder Index of Learning Styles Questionnaire, should be applied to obtain the probabilistic learning styles of the students. Thus, a learning styles identification software agent (1) should be developed to obtain these values of student learning styles. All probabilistic learning style combinations presented in an earlier study (Kurilovas et al. 2016) should be stored for each student in his/her profile (model).

Second, according to Kurilovas (2016), an open and dynamic learner profile development software agent (2) should be used to create learners' profiles (models) using the results obtained by the agent (1) and adding the other features of learners (knowledge, interests, goals, cognitive traits, learning behavioral type etc.).

Third, pedagogical suitability software agent should be created to implement recommender system. This agent should use high-quality vocabularies of learning components and results of the expert evaluation of suitability of particular learning components to students' learning styles. This pedagogical suitability software agent should link optimal learning components to particular students in accordance with probabilistic suitability indexes. As it was mentioned in Section No. 3, all learning components in the recommender system

should be linked to particular students based on their probabilistic suitability indexes. The higher probabilistic suitability index, the better the learning component fits a particular student's needs.

An optimal learning unit/scenario (i.e., a learning unit/scenario of the highest quality) for a particular student means a methodological sequence of learning components having the highest suitability indexes. Thus, the fourth agent for the composition of optimal learning units/scenarios should be designed for particular learners in accordance with their learning characteristics. These optimal learning units/scenarios should be created by an intelligent software agent by combining those learning components that are optimal for particular learners. The number of different combinations of learning components that are optimal for a particular student should be further analyzed by the teacher in order to create and use the learning unit/scenario as a pedagogically sound sequence of the learning components. For this purpose, an additional ontology linking learning components (learning objects, activities and environment) based on their mutual suitability should be created and implemented in the agent.

Last but not least, the data on real student behavior patterns within a learning environment, obtained by using the LA/EDM methods and tools, should be used to correct their profiles according to the data obtained. Thus, a LA/EDM software agent should be developed to correct student profiles based on their behavior in the learning environment, implementing recommended learning units. The wide range of data regarding the behavior of students should be used to generate good quality, real-time predictions about suitable material and activities and success in acquiring knowledge and skills.

Students, teachers, managers, policymakers and other agents all will have access to live and accurate information about students using the educational system. Students and teachers should be able to plan their work on the basis of reliable tools that can produce detailed and personalized recommendations about what should be done to achieve the best learning outcomes.

Students practically use some learning activities/tools in real learning practice within a learning environment before identifying the appropriate probabilistic suitability indexes and recommending suitable learning units. Here one could hypothesize that students preferred to practically use particular learning activities/tools that fit their learning needs mostly. Thus, by using the appropriate LA/EDM methods and techniques, it would be helpful to analyze which particular learning activities/tools were practically used by these students in the learning environment and to what extent.

After a thorough analysis of different studies (Romero et al. 2008; Baker and Yacef 2009; Baradwaj and Pal 2011; Verma et al. 2012; Srivasatava and Srivastava 2013; Milevski and Zdravev 2013; Romero et al. 2013; Campagni et al. 2015), the authors came to the conclusion that basic LA/EDM techniques, applicable in this case, should be (but not limited to) the following: (1) An attempt to classify each item in a set of data into one of the predefined sets of a learner group; (2) A clustering to determine the groups of students that need special course profiling; (3) Association rules to discover interesting relations between course elements that were used by particular students; (4) A prediction to foresee the dependencies of using a learning environment's activities/tools and the final learning outcomes of a student; (5) A
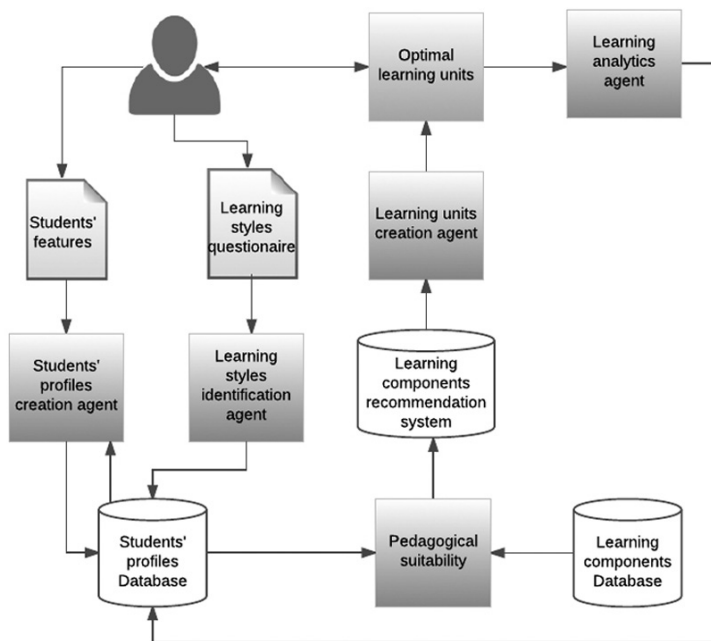
Figure No. 2. **The conceptual model of the personalized, multi-agent, intelligent learning system**

decision tree of student actions. To determine and to set the appropriate algorithm to a new data set is a difficult task, because there is no single classificatory that would be equally well-suited for all data sets. In practice, it is very important to choose the proper classification/clustering or other algorithm to a particular data set.

The conceptual model of a personalized, multi-agent, intelligent learning system is presented in Figure No. 2.

Conclusion

In order to create a personalized, multi-agent, intelligent learning system, first of all, students' learning styles should be identified using, for example, the Felder-Silverman Learning Styles Model, then creating full open dynamic learner profiles, identifying the probabilistic suitability indexes and recommending personalized learning units for particular students as well as verifying these learning units with learning analytics/educational data mining methods and techniques.

Personalized intelligent learning system should be based on a multi-agent approach. It should consist of at least five intelligent software agents: (1) a learning styles identification software agent, (2) a learner profile creation software agent, (3) a pedagogical suitability software agent, (4) an optimal learning units/scenarios creation software agent and (5) a learning analytics/educational data mining software agent.

Basic learning analytics/educational data mining techniques, applicable in this case, should be (but not limited to) the following: (1) An attempt to classify each item in a set of data into one of the predefined sets of a learner group; (2) A clustering to determine the groups of students that

need special course profiling; (3) Association rules to discover interesting relations between course elements that were used by particular students; (4) A prediction to foresee the dependencies of using a learning environment's activities/tools and the final learning outcomes of a student; (5) A decision tree of student actions.

Thus, optimized (i.e., the most suitable) learning units/scenarios could be developed for particular learners. A number of intelligent technologies should be applied to implement this approach, e.g., ontologies, recommender systems, intelligent agents, learning analytics, expert evaluation techniques to evaluate quality and suitability of the learning components etc.

The main success factors of this approach are pedagogically sound vocabularies of learning components, used to create personalized learning units/scenarios, and experts' collective intelligence.

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INTELEKTINĖ DAUGIAAGENTĖ MOKYMOSI SISTEMA, NAUDOJANTI EDUKACINIŲ DUOMENŲ TYRYBĄ

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S a n t r a u k a

Straipsnyje yra pristatyta mokymosi personalizavimo pagal besimokančiųjų poreikius metodologija, kurioje yra naudojamos intelektinė daugiaagentė mokymosi sistema ir duomenų tyryba. Mokymosi personalizavimas yra įgyvendinamas remiantis keliais metodais. Felderio ir Silverman mokymosi stilių modelis naudojamas besimokančiųjų profiliams kurti, o tikimybiniai tinkamumo rodikliai yra identifikuojami tam, kad būtų galima susieti mokomuosius komponentus (t. y. mokomuosius objektus, mokomąsias veiklas ir mokymosi aplinką) su konkrečių besimokančiųjų mokymosi stiliais. Kitos pasiūlytos mokymosi sistemos kūrimo technologijos yra ontologijos, rekomendavimo sistema, intelektiniai programiniai agentai ir edukacinių duomenų tyryba (mokymosi analitika). Personalizuotais mokomaisiais moduliais čia vadinami moduliai, sudaryti iš mokomųjų komponentų, kurie turi aukščiausius tikimybinius tinkamumo rodiklius konkrečių

besimokančiųjų atžvilgiu. Straipsnyje visų pirma yra atlikta intelektinių programinių agentų taikymo švietime sisteminė apžvalga „Clarivate Analytics Web of Science" duomenų bazėje. Antra, yra aprašyti mokymosi personalizavimo metodai, taikant intelektines technologijas mokomiesiems moduliams, optimizuotiems konkretiems besimokantiesiems, kurti. Sukurti besimokančiųjų profiliai ir personalizuoti mokomieji moduliai yra toliau koreguojami duomenų tyrybos metodais ir priemonėmis. Detaliau yra pristatomas intelektinės daugiaagentės mokymosi sistemos, grįstos minėtomis technologijomis, modelis. Esminiai pasiūlytos technologijos sėkmės veiksniai yra edukologijos atžvilgiu kokybiški mokomųjų komponentų žodynai, mokomųjų komponentų ekspertinis vertinimas jų tinkamumui konkretiems besimokantiesiems įvertinti, taip pat ontologijų, rekomendavimo sistemos, intelektinių programinių agentų ir duomenų tyrybos taikymas.

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