BRAIN. Broad Research in Artificial Intelligence and Neuroscience
ISSN: 2068-0473 | e-ISSN: 2067-3957
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2020, Volume 11, Issue 3, pages: 29-35 | https://doi.org/10.18662/brain/11.3/107

Intelligent Support System for Personalized Online Learning

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Abstract: *The current conditions of the COVID-19 pandemic have required universities to transfer educational processes in the online environment. eLearning systems provide educational institutions and students with the opportunity to effectively organize the educational process and share knowledge. They provide each student with freedom of access to information and flexibility of the learning process. The student can individually determine the duration and sequence of courses by changing the trajectory of the educational process following their needs. In the context of the pandemic, students and teachers have to optimize their work over the Internet. This requires more extended personalization of the learning process. Intelligent technologies allow you to construct personalized learning paths for each student, varying methods, forms, and speed of learning. This study presents the architecture of the e-learning support system for the selection of online resources and for including them in the student's learning path. The system developed as a set of personal agents and services that interact based on a set of interconnected ontological models. Ontologies provide a more adequate representation of online resources and compatibility of the user request format with descriptions of training resources from different developers. The system recommends training modules based on current requests and user characteristics that match their profile. The system dynamically updates the knowledge base user characteristics, thereby increasing the effectiveness of recommendations.*

Keywords: *Personalised eLearning; pandemic; learning paths; recommender system.*

How to cite: Shpolianskaya, I., & Seredkina, T. (2020). Intelligent Support System for Personalized Online Learning. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience, 11*(3), 29-35. https://doi.org/10.18662/brain/11.3/107

1. Introduction

eLearning systems present educational institutions and students the opportunity to effectively organize the educational process and to share knowledge. They provide each student with freedom of access to information and the flexibility of the learning process. Students can independently settle the duration and sequence of the courses and change the learning path, following their needs (Biletskiy et al., 2009). The need to implement intelligent online learning support systems is due to the requirements of an individual approach to each student. Intelligent technologies allow you to construct personalized learning paths for each student by choosing methods, forms, and speed of learning.

In recent years, there has been a huge increase in the number of learning resources available online (Odonnell et al., 2015). Large volumes of knowledge and a variety of alternative courses in the online environment require the construction of personal learning paths taking into account the capabilities, needs, and characteristics of students, their cognitive and personal characteristics.

The main problem is the difficulty for students to find the most appropriate courses that best suit their interests. Adaptive methods of managing educational resources help to personalize learning (Chrysoulas & Fasli, 2017). In personalized e-learning systems, the following tasks are solved: a) Construction of a learning path (Yang et al., 2010) and rational selection of a set of educational materials that meet the current needs of the student (Dharshini et al., 2015); b) determining the profile of the student (Kardan et al., 2013; Ognjanovic et al., 2016); c) development of ways to present knowledge about the educational process (Peylo, 2000; Tarus et al., 2017).

2. Methods

Construction of a learning path is a complex task due to the need for multiparametric analysis that takes into account the prerequisites and learning outcomes of the course program, current knowledge, individual characteristics, and learning styles of students (Dharshini et al., 2015). The composition of heterogeneous information resources and services in the learning path should be performed automatically. The procedures of learning object selection must perform quality analysis, taking into account their characteristics, their compliance with the user profile. The selection and sequence of knowledge fragments can be determined according to the student's characteristics, such as learning styles, preferences, abilities, initial requirements, and course duration.

Building a learning path involves discovering the best possible way to link each student to learning objects or pedagogical requirements. Some researchers consider the problem of creating an optimal learning path as a weighted directed graph where each node represents a course unit (Alshalabi et al., 2015). Many papers have proposed evolutionary algorithms, such as genetic algorithms, ant colony optimization algorithm, and the methods of Particle Swarm Optimization (Chu et al., 2009). Methods for finding the optimal learning path in the online environment are implemented in the form of recommender systems (Drachsler et al., 2015).

The purpose of developing and implementing recommendation systems in the e-learning environment is to optimize the selection of educational resources from a variety of available ones based on the analysis of the quality of educational resources and user perception (Sobecki & Tomczak, 2010). To make the LMS personalized, a recommender system can be integrated into the LMS to suggest training material based on information, relevant to a specific student (Dascalu et al., 2016).

Recommender systems use ontologies, artificial intelligence, and fuzzy logic, as well as other methods, to provide personalized recommendations (Chen et al., 2012). In (Lin, 2010) it is proposed to use expert methods and fuzzy logic to evaluate the quality and ranking of online resources. This approach provides a simple and convenient tool to support the online course selection process based on the preference assessment procedure. In recommendations of e-learning resources, ontologies are used to represent knowledge about the learner and the learning objects (George & Lal, 2019). Ontologies can be reusable, and they support inference mechanisms to provide more relevant recommendations. In (Sharma & Ahuja, 2016), the authors used ontology to support e-learning using a recommendation system. In Curlango-Rosas, Ponce & Lopez-Morteo (2011), a method for searching for learning objects is proposed, following a student's profile and the description of the learning objects. In Gulzar, Raj & Leema (2019), an approach to creating a recommender system is proposed where an ontology is used to model and represent knowledge about the student and educational resources. The sequential pattern analysis algorithm detects subsequent patterns of choosing didactic modules in the students learning process.

3. Results

The method of integral course quality assessment based on the fuzzy logic approach has been proposed to ensure the evaluation, selection, and integration of e-learning objects into the learning trajectory. We have proposed a new approach to the problem of e-learning courses quality evaluation, which we dene in terms of fuzzy preference relations and linguistic variables with a single integral indicator. This approach provides a simple and convenient tool to support the process of online course selection based on the quality assessment procedure and the learners' preferences. Evaluation of the functional characteristics of a learning object has been performed based on a comparison of the resource descriptions in the ontological model of training materials and the user model. Semantic proximity measures have been used to assess whether resources match the student's profile.

To enable the process of searching and composing learning resources into the learning path to be implemented dynamically automatically, resources are given a semantic description using the OWL language based on ontologies. The ontology includes a resource description model, a student model describing their requirements and characteristics, and an ontological model of curriculum competencies. Using the ontological approach provides the basis for creating an intelligent e-learning support system, when ontologies store data on the current state of the student's learning process, data on their requirements, and data on successful strategies for selecting and using resources by other users with similar characteristics. Based on this information, the system searches for resources and then integrates them into the structure of the learning path.

In the proposed e-learning support system, domain ontology classifies various areas of professional and scientific knowledge and binds to them the concepts (keywords) used in various online courses. The applied ontology holds information related to users and learning resources. The system uses the student's profile to recommend an e-course with appropriate characteristics. The student profile is continuously updated during the training process.

Ontologies are used as an integration platform for all processes. Information search based on personalized agents creates a dynamic environment integrated with all e-learning processes. Students, using personal agents, search for educational material according to their needs. Learning objects are associated with the corresponding ontologies, which makes it possible to build semantic queries on a given topic. Ontology becomes a link between the needs (requests) of the user and the characteristics of the educational material. The possibility of navigation through the portal can also be extended with semantically explicit links between pages of the portal.

The developed system to support personalized learning has a microservice architecture and includes online procedures for monitoring learning processes. The adaptive recommender system operates with the following services: service for online courses quality assessment, service for user behavior data collection, service for user behavior data collection. The system generates and evaluates alternative options for the synthesis of individual trajectories and selects the learning object that best corresponds to the current student profile. Each user has a personalized agent that connects to the online learning system services.

The software implementation of the system provides flexible support for the student, forming appropriate recommendations in the learning process.

4. Conclusions

This paper presents a new approach to solving the problem of personalization of learning in a dynamic electronic environment. Within this approach, a method of using OWL-ontology for integrating resources into an individual learning trajectory is proposed. The architecture of the e-learning support system for the selection of online resources for their further inclusion in the individual trajectory of student learning is defined. The developed system is implemented as a set of personal agents and services that interact based on a knowledge base represented as a set of interconnected ontological models. The system recommends a resource based on current requests and user characteristics following their profile. In the process, the system dynamically updates the knowledge base about the current characteristics of the user, thereby increasing the effectiveness of generated recommendations.

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