Development of an Intellectual Model of Personalized Learning

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Abstract: Digitalisation plays a big role in the educational process. One of the main trends in the development of education today is the transition to personalized education and adaptability to the level of competences of each student in university. Higher educational institutions in Kazakhstan in the last two years transitioned to the state to per capita credit financial and there is an urgent need to improve information systems for educational programs. The article discloses intellectual model of personalized learning for educational programs in universities based on the matrix of student's competencies and fuzzy logic. The work results will be used in educational organizations applications, as well as on online learning platforms.

Keywords: e-learning, artificial intelligence, recommendation system, course recommendation, information retrieval, recommender methodology, personalized learning.

I. Introduction

The curriculum system in the Universities of Kazakhstan consists of compulsory courses and elective once. Most university students are uncertain of which courses to choose from educational program as there is a lack of information about the objective and the content of the course. Moreover, the process of making a decision is complicated and students look for guidance and support from their academic advisors. Although some experts' opinion can be subjective to their own experience and do not take into consideration the preferences of each student. Hence, to ensure a high-quality level of education the implementation of educational programs in universities involves taking into account the principles of personalized learning, to tailor learning processes to students. The education system in Kazakhstan opens up new horizons for the development of students' competencies. In this regard, new models of personalized learning are needed, which will be adaptive to the level of competences of each student. The primary focus of this article is to investigate different approaches used to develop and assist students to select the most appropriate courses in University which suit their preferences, analysis of systems that support and advise students to select needed courses, models and methods of data analysis in the personalized learning field. The paper is structured as follows: In section 2, related works for personalized recommendation systems are presented. Followed by how individual educational trajectories are created. Before the conclusion the personalization within the discipline is considered.

II. Related Works

The theoretical and methodological basis of this study consists of scientific works of domestic and foreign authors exploring the field of personalized learning. In general, personalized recommendation systems play an important role in education. One of these systems is a collaborative filtering method [1-5]. This method predicts user preferences, taking into account the interests of other visitors who have very similar preferences with current users. There are also, number of studies that have addressed content-based filtering method based on functions previously provided by the user, which then is used to filter all elements in the system [6-8]. Another recommendation is to use the knowledge-based filtering method that offers elements to the user according to his knowledge of them and their connections to generate recommendations which meet user preferences [9-10]. The main drawbacks of this method are difficulty of acquisition and representing the domain knowledge in a machine-readable structure and it needs extensive efforts to extract the knowledge. However, it is more appropriate for designing course recommendation system which needs complex knowledge domain to make recommendations [11]. Hybrid filtering method is the combination of two or more methods from the previously described approaches used to improve the effectiveness and overcome limitations in order to improve the quality of the final result. Madadipouya and Chelliah [13] proposed four ways to create hybrid approaches by combining collaborative filtering and content-based filtering. Hybrid systems have emerged as means to overcome any problems that may emerge via the use of the different techniques.

In recent years, artificial intelligence techniques have been introduced and are implemented in personalized learning [14].

Research [15] incorporates computational intelligence-based recommendations into a classification that includes Bayesian methods that adapt existing probabilities to newly obtained experimental data. Moreover, artificial neural networks used for processing complex data using a variety of interconnected processors and computational paths. According to [16] Machine learning methods are used when it is necessary to learn by applying solutions to many similar problems. Genetic algorithms used to solve optimization and modeling problems by randomly selecting, combining and varying the desired parameters. Fuzzy set methods based on a generalization of classical logic and fuzzy set theory are applicable. The paper [17] presents that the use of these methods is a promising solution for system design in the era of Big Data. Personalized learning system can help students to find, organize, and use resources that match their individual goals, interests, and current knowledge.

III. PERSONALIZED LEARNING MODEL

Nowadays, it is very important for the education system to use knowledge-based learning approach. Educational programs in Kazakhstan today follow the traditional learning system where all students follow the same sequence of learning and current system need to be stimulated, supported and expanded to targeted use of digital and innovative practices. Students when entering the University have different background of knowledge, learning goals and preferences. In this regard, personalized education in modern conditions should continue moving toward the maximum disclosure of the abilities, skills and interests of students. Intelligent learning systems should have personalized learning paths that consider learner's needs and behaviors. Services that create individual trajectories are becoming the main way of personalization.

The personalized learning model for organizing learning courses was proposed [18] as an ontological model based on an individual learning trajectory. The described model meets three basic criteria. The first one is the personalization of learning, where the input level of knowledge is considered taking into account the individual pace of learning, without reference to time and place. The second one is a standardized content organization where certain requirements are imposed on the structure and content. The structure of the content should be detailed and consists from next elements: online lecture, assignments, online discussion, tests and exam. The intelligence of the system is the third criteria. The system should assess knowledge of students independently without human intervention [19].

Model of the learning process aims at following and guiding the learning process. The ontological model consists of advanced learning modules and tests and is described in [18]. Some of the modules are mandatory and end with a test, others are optional and start with a test then can be skipped if the test is passed. The described ontological model should minimize the inevitable repetitions that occur when studying the course, and give opportunity to students and teachers to form personalized educational trajectories.

The following meta notations are introduced in Table 1.

Table 1. Meta notation

Designation	Description
Path	Set of trajectories
M_m	Set of Mandatory modules
M_o	Set of Optional modules
T_m	Set of Mandatory module tasks
T_o	Set of Optional module tasks
Q_m	Set of Mandatory module tests
Q_o	Set of Optional module tests
●	Concatenation
sert, P	Predicates

It is mandatory to pass two trajectories in order to get a certificate. It can be seen in the following ontological model as Path1, Path2 and
Path3.
In order to obtain a certificate, formula (1) for Path1 and Path2, or formula (2) for Path2 and Path3 should be successfully learned in the form of production rules:

$$\frac{Path_1 \in Path, Path_2 \in Path, Path_1 \bullet Path_2}{sert(Path_1 \bullet Path_2)=1} \quad (1)$$

$$\frac{Path_2 \in Path, Path_3 \in Path, Path_2 \bullet Path_3}{sert(Path_2 \bullet Path_3)=1} \quad (2)$$

Within each direction there is a subset of conceivable areas of study.

The $Path_l$ trajectory is considered to be effectively completed in case the student has effectively completed the instructions of the desired modules and successfully answered the tests of the required modules equation (3):

$$\frac{Path_1 \in Path, M_{m1} \in M_m, M_{o1} \in M_o, T_{m1} \in T_m, T_{m1}=1, T_{o1} \in T_o, Q_{m1} \in Q_m, Q_{m1}=1, Q_{o1} \in Q_o}{P(Path)=1} \quad (3)$$

The $Path_l$ trajectory is considered to be effectively passed if the student has effectively completed the tasks of the desired modules (4):

$$\frac{Path_1 \in Path, M_{m1} \in M_m, M_{o1} \in M_o, T_{m1} \in T_m, T_{m1}=1, T_{o1} \in T_o, Q_{m1} \in Q_m, Q_{o1} \in Q_o}{P(Path_1)=1} \quad (4)$$

The $Path_l$ direction is considered to be successful in case the understudy has effectively replied to the tests of the specified modules (5):

$$\frac{Path_1 \in Path, M_{m1} \in M_m, M_{o1} \in M_o, T_{m1} \in T_m, T_{o1} \in T_o, Q_{m1} \in Q_m, Q_{o1} \in Q_o, Q_{m1}=1}{P(Path_1)=1} \quad (5)$$

The $Path_l$ trajectory is considered to be effective if the understudy has effectively completed the tasks of the desired modules and successfully answered the tests of the specified modules and replied to the tests of the optional modules by equation (6):

$$\frac{Path_1 \in Path, M_{m1} \in M_m, M_{o1} \in M_o, T_{m1} \in T_m, T_{m1}=1, T_{o1} \in T_o, Q_{m1} \in Q_m, Q_{m1}=1, Q_{o1} \in Q_o, Q_{o1}=1}{P(Path_1)=1} \quad (6)$$

The $Path_l$ trajectory is considered to be effectively passed if the understudy has effectively completed the tasks of the desired modules and successfully answered the tests of the specified modules and replied the tests of the optional modules' equation (7):

$$\frac{Path_1 \in Path, M_{m1} \in M_m, M_{o1} \in M_o, T_{m1} \in T_m, T_{m1}=1, T_{o1} \in T_o, Q_{m1} \in Q_m, Q_{o1} \in Q_o, Q_{o1}=1}{P(Path_1)=1} \quad (7)$$

The $Path_l$ trajectory is considered to be effectively passed if the understudy has effectively completed the tasks of the desired modules and answered the tests of the optional modules by equation (8):

$$\frac{Path_1 \in Path, M_{m1} \in M_m, M_{o1} \in M_o, T_{m1} \in T_m, T_{m1}=1, T_{o1} \in T_o, Q_{m1} \in Q_m, Q_{o1} \in Q_o, Q_{o1}=1}{P(Path_1)=1} \quad (8)$$

The $Path_l$ is considered to be effectively completed if the understudy has effectively completed the tasks of the desired modules and completed the tasks of the optional modules' equation (9):

$$\frac{Path_1 \in Path, M_{m1} \in M_m, M_{o1} \in M_o, T_{m1} \in T_m, T_{m1}=1, T_{o1} \in T_o, T_{o1}=1, Q_{m1} \in Q_m, Q_{o1} \in Q_o}{P(Path_1)=1} \quad (9)$$

The $Path_l$ trajectory is considered to be effectively completed if the understudy has effectively completed the tasks of the desired modules and completed the tasks of the optional modules' equation (10):

$$\frac{Path_1 \in Path, M_{m1} \in M_m, M_{o1} \in M_o, T_{m1} \in T_m, T_{o1} \in T_o, Q_{m1} \in Q_m, Q_{m1}=1, Q_{o1} \in Q_o, Q_{o1}=1}{P(Path_1)=1} \quad (10)$$

The $Path_l$ trajectory is considered effective if the understudy has effectively completed the tasks of the desired modules and passed the tests of the optional modules' equation (11):

$$\frac{Path_1 \in Path, M_{m1} \in M_m, M_{o1} \in M_o, T_{m1} \in T_m, T_{o1} \in T_o, T_{o1}=1, Q_{m1} \in Q_m, Q_{m1}=1, Q_{o1} \in Q_o}{P(Path_1)=1} \quad (11)$$

The production rules for trajectories 2 and 3 are composed in a comparable way.

Model of the learning process can be described in a formal way using logical rules mentioned above. First of all, it allows to implement model in software. Moreover, the flexibility of the model is increased by use of fuzzy logic when the system makes a decision.

IV. The Ontological Model of Discipline

In this section personalization within the discipline is considered. The ontological model of discipline can be applied in order to create structure and content. For instance, modeling on a specific discipline is suggested in paper [20]. The ontological model that is described is built in Protégé tool [21]. It was developed at Stanford University in collaboration with the University of Manchester. Ontology is widely used tool for modeling of relations between objects that belong to different subject areas. In computer and information science ontology is defined as a set of representative primitives that are used to model a domain of knowledge or discourse. A representational primitive is typically a class (or set), attributes (or properties), or relationships (or relations between members of a class). This formalism decides the "O" ontology as triple (V, R, K), where V – could be a set classes for the subject field, R – could be a set of relationships between the classes, and K – may be a set of attributes within the field [22, 23].

The ontological model comprises from the discipline topics and the glossary. Each of the discipline topics incorporates glossary's fundamental concepts, control questions are created on the topic linked to the glossary. Also, assignments are developed in order to confirm the accomplishment of result of each topic. A knowledge base of questions and answers by the ontology is made in human language, the system can self-learn within the framework of a set of discipline (see Fig.1).

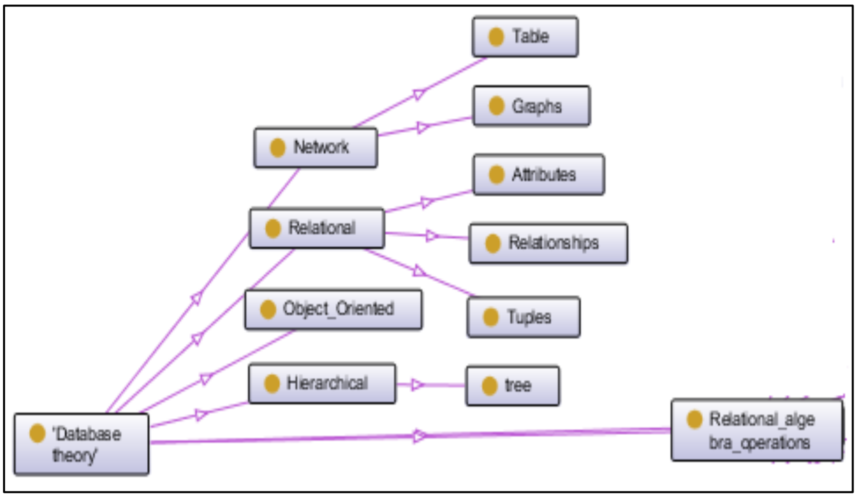

Fig. 1. "Databases theory" discipline's ontological model

The ontological model of a discipline provides possibility to create connections between discipline topics, glossary, assignments and questions. Hence, the intelligent search is becoming possible, in terms of questions and answers in human language in the learning process, checking the achievement of learning outcomes through assignments, as well as open responses of the students.

V. Conclusion

Finally, analyzing the purpose of these article, we observe that described methods, models and Artificial Intelligence techniques play a key role in realizing the idea of personalized learning - tailoring learning, its content and pace to the specific needs of each student. Regarding the individual educational trajectory for each student, we can highlight that it is important to take into account their strengths, weaknesses, abilities and tasks. When study trajectories are applied students get more selectivity and flexibility, which gives a more flexible assessment of knowledge. This will reduce the time for preparing for classes, develop creative and innovative methods to increase the level of assimilation of knowledge and select individual educational trajectories for students. Machine learning techniques also have significant potential for developing the social and emotional skills needed in learning, as they allow educators to personalize the learning process based on the analysis of both qualitative and quantitative data to help students master these skills. Artificial intelligence will play an important role in solving another major challenge facing educational technology professionals: the implementation of personalized knowledge assessment. The forms of assessment used today are rarely focused on the skills that students will need when they enter the labor market.

For the future work it is important to note that personalized education needs more study. It is important to ensure that the curricula of universities are up-to-date and adequately prepare students for the world they will face after graduation. The knowledge base in many subject areas is constantly changing and expanding, which makes it difficult to ensure the adequacy and relevance of the content of courses. The ability to use big data sets, analyze that data and draw conclusions, and communicate those findings through dashboards and visualizations tailored to the needs and responsibilities of those responsible for curriculum development can increase the relevance and accuracy of the information available and the level of preparedness of those involved in this important matter.

In a broader context, the stated topic is in the trend of global changes in the imperatives of the education system associated with an unprecedented expansion of the use of information technology and artificial intelligence as an effective assistant to the organization of personalized learning.

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