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SECTION 21. Pedagogy. Psychology. Innovations in the field of education.

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ADAPTIVE TECHNOLOGY FOR SUPPORT STUDENTS IN THE LEARNING PROCESS WITH USING THE MASSIVE ONLINE COURSES IN THE CLOUD INFRASTRUCTURE

Abstract: *In our investigation as results represent the developed model of the adaptive MOOC, which show its effectiveness, expressed in the growth of the motivation of course participants, the acquisition of planned learning outcomes by the trainees, their satisfaction with the learning process, the increase in the number of students successfully completing the course, increasing self-discipline, reducing the irrationally used time in the course. The developed model of adaptive MOOC improves the efficiency and quality of online education, providing students with the most opportunities for personalized learning.*

Key words: *mass open online courses, MOOC, BigData, adaptive learning, cloud computing.*

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Introduction

The appearance of MOOCs can be regarded as one of the ways to resolve the contradiction between the need for continuous professional self-improvement throughout life, the rapid renewal of the content of professional competencies in the era of the development of high technology and a rather long process of training and retraining in traditional universities. However, each student needs his own set of knowledge, skills, competencies, so we need to use such e-learning technologies that will ensure their receipt most quickly, qualitatively and effectively [1, 5, 9, 11, 16].

A serious disadvantage of MOOCs is the lack of an individual approach to each student due to the "hard" set by the author of the trajectory of training. The model of adaptive MOOC proposed by the authors allows each instructor to propose to move along an individual trajectory based on the dynamic collection, analysis and estimation of a big data. Such data include the level of preparedness of the student, information about learning content of the course and current academic achievements, personal characteristics of the student (gender, age, interests in the subject area, learning goals, memorization, preferences and achievements in studying other courses etc.).

Terminology

In our study, we will adhere to the following concepts [14]:

Individualization refers to instruction that is paced to the learning needs of different learners. Learning goals are the same for all students, but students can progress through the material at different speeds according to their learning needs. For example, students might take longer to progress through a given topic, skip topics that cover information they already know, or repeat topics they need more help on.

Differentiation refers to instruction that is tailored to the learning preferences of different learners. Learning goals are the same for all students, but the method or approach of instruction varies according to the preferences of each student or what research has found works best for students like them.

Personalization refers to instruction that is paced to learning needs, tailored to learning preferences, and tailored to the specific interests of different learners. In an environment that is fully personalized, the learning objectives and content as well as the method and pace may all vary.

Discussion

Various aspects of adaptive e-learning are highlighted in scientific publications. Thus, the authors of [2] L. de-Marcos, C. Pages, J.J. Martinez, J.A. Gutierrez (2007) explored how to implement dynamic selection of learning objects (LOs) to build the structure of the course depending on the input set of competences (formed by the learner) and the output (planned learning outcomes).

Alireza Kahaei (2014) [7] conducted a literary analysis of the parameters used to personalize e-learning. As a result, 17 parameters were summarized, in particular: 1. Information seeking task; 2. Level of knowledge; 3. Goals & plans; 4. Media preference or presentation styles; 5. Language preference; 6. Learning style; 7. Participation balance; 8. Progress on task; 9. Waiting for feedback; 10. Motivation level; 11. Navigation preference; 12. Cognitive traits; 13. Pedagogical approach; 14. Location; 15. Weather; 16. Date and time; 17. Patience. The selected parameters were used to evaluate how well-known MOOC platforms are personalized. The result revealed that most MOOC platforms at the present stage of development do not support the majority of personalization parameters.

Collective of authors Vytautas Stuikys, Renata Burbaite, Kristina Bespalova (2015) presented a model of the sequence of LOs [13] and its implementation using a meta-programming approach. The main personalization parameters in this model include the following: 1. Learner's level (Beginner, Intermediate, Advanced); 2. Learning style (Visual, Audial, Kinesthetic); 3. Learning activity (Reading, Case Study, Self-Assessment, Assessment); 4. Learning environments (Computer-based, Robot-based); 5. LO type (LO – Learning Object – a set of mandatory subfeatures, GLO – Generative Learning Object).

Maria Luisa Sein-Echaluce1, Angel Fidalgo-Blanco, Francisco J. Garcia-Penalvo, Miguel Angel Conde (2016) [12] identified the following "adaptive pills": 1. Self-assessment training; 2. Adapted advance to the student's learning speed; 3. Adaptation of learning to different profiles/skills/interests; 4. Contributing and sharing resources among a set of users with a common interest/profile; 5. Adapted learning to the acquired knowledge (the results of the activities to be carried on); 6. Monitoring student's progress.

Soufiane Ardchir, Mohamed Amine Talhaoui, Mohamed Azzouazi (2017) [3] have proposed to collect and analyze the following data to provide personalization in the MOOCs:

1. Objective information, which incorporate data provided directly by the learner like: personal data, previous knowledge, preferences, etc. The learner edits this data during his/her registration on the system; 2. Learner's performance, which includes data about level of knowledge of the subject domain, his/her misconceptions, progress and the general performance for particular learner; 3. Learning history, which includes information about lessons and tests learner has already studied, his/her interaction with system, the assessments he/she went through, etc.

Maxim Skryabin (2017) studied the different types of students' behavior before they drop an adaptive MOOC. Student behavior was measured by the following variables: number of attempts for the last lesson, last three lessons solving rate, the logarithm of normed solving time, the percentage of easy and difficult lessons, the number of passed lessons, and total solving time [17]. The author proposed three types of dropout: «solved lessons», «evaluated lessons as hard», and «evaluated lessons as easy».

Dolores Leris, Maria Luisa Sein-Echaluce, Miguel Hernandez, Concepcion Bueno (2017) proposed six indicators that determine «Adaptivity in a MOOC» [8]:

Indicator 1. Course contents / activities are accessible depending on the choice of the participant or on the results in activities previously evaluated;

Indicator 2. Course content / activities are accessible depending on the working pace of participant. There is no fixed timetable for accessing contents nor are all contents offered at the same time;

Indicator 3. The participant can choose between different levels of difficulty in the contents / activities to reach different learning objectives;

Indicator 4. Participants are organized by same area of interest / same background / same level of experience, to debate in specific forums;

Indicator 5. Participants can choose between different methods of evaluation (self-evaluation, peer evaluation, etc.);

Indicator 6. The need for peer assessment is also organized according to area of interest / background / level of experience.

Thus, despite the depth of research in this area [4, 6, 10, 15], the tasks of developing an adaptive model of MOOC remains urgent and requires investigation and prepares new solutions.

The adaptive model of mass open online courses

The introduction of adaptive technologies in MOOC makes sense if the number of students studying it exceeds a thousand people a year. When analyzing a sample of a smaller size, it is difficult to build an appropriate model and develop a flexible algorithm for implementing MOOC adaptively. The next important condition for building the model is a clear structuring of the electronic educational content and the selection of LOs. Recall that in MOOC, a LO is considered as a separate structural element of electronic learning content, corresponding to a specific learning goal and contributing to the overall goal of the course. The number of possible routes for the implementation of adaptive educational technologies depends on the number of educational objects allocated. Further it is necessary to carry out measurements and collect analytical data on different parameters. Using the combination of various adaptive models of e-learning, as well as the means and methods of processing the received structured and unstructured data of huge volumes (BigData), you can get a variety of models of behavior of thousands of students and for each, respectively, determine the most optimal training route. Heuristic algorithms are used to construct individual trajectories of students' education. In order to correct the individual trajectory of learning, it is proposed to implement methods of data mining based on the trainee's personal characteristics. In the framework of the investigation, we developed an adaptive MOOC model (Fig. 1), each subsystem of which we describe in more detail.

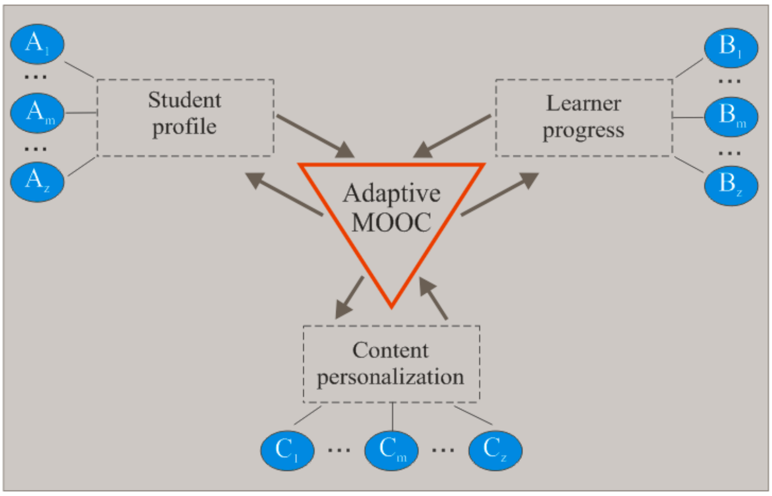

Figure 1 – The adaptive model of mass open online courses.

1. Subsystem «Student profile», which is responsible for the detailed collection of the following data:

A_1 – gender (male, female);

A_2 – age group (up to 20 years, 21-39 years, 40-59 years, more than 60 years);

A_3 – interests in the subject area (input questioning: learn new, pass a test/examination, broaden your horizons, personal development);

A_4 – the purpose of the training (low level - initial acquaintance with the subject area, medium - in-depth study of the discipline, high - retraining or advanced training);

A_5 – features of perception and memorization of information (visual, audial, kinesthetic, digital).

2. Subsystem «Learner progress», designed to collect constantly changing data about student's academic achievements:

B_1 – points for each evaluated educational object (in points, 50-70% - low, 71-89% - medium, 90-100% - high);

B_2 – achievements in the study of other courses (received scores on completion of the course, assessment for the final exam);

B_3 – level of preparedness of the student (entrance testing in points: low, medium, high);

B_4 – the number of attempts to complete the tasks;

B_5 – the time spent on the tasks;

B_6 – level of difficulty in completing the assignment according to the learner's feedback (easy, normal, hard);

B_7 – the level of complexity of the material according to the feedback of the learner (easy, normal, hard).

3. Subsystem «Content personalization», which on the basis of analysis, evaluation and generalization of the received data for each individual student forms an optimal learning strategy and provides a unique setting of parameters, in particular the presentation format and the level of complexity, of the proposed electronic educational content. The main idea underlying the development of this subsystem is the following: a quality training program in MOOC should be extremely individualized. Unlike the usual MOOC, the adaptive course lacks the usual menu for the students "Course content", it is impossible to move consistently at the rate, choosing educational objects at your discretion,

in the course of the student's progress, his success is noted, and not points are awarded.

Thus, this subsystem generates a set of personal learning paths $C_1 \dots C_z$.

Experimental development of adaptive MOOCs is carried out at courses in the field of information technology for students of technical areas of preparation at the university. Depending on the answers of students, we send them to different paths of the course: someone goes forward one way, someone else, and someone comes back and re-learns the material and performs assignments. Currently, the MOOC developed is being tested, the results are evaluated and the necessary adjustments are made.

Preliminary results of using the developed model of the adaptive MOOC in general show its effectiveness, expressed in the growth of the motivation of course participants, the acquisition of planned learning outcomes by the trainees, their satisfaction with the learning process, the increase in the number of students successfully completing the course, increasing self-discipline, reducing the irrationally used time in mastering the course.

Thus, the developed model of adaptive MOOC in real time mode allows to respond to the educational needs and capabilities of each individual student, as well as to his actions and learning progress in course development. It is this approach, in our opinion, that provides for the individualization of training, which, as a rule, is absent in most MOOC focused on mass use, and is their essential disadvantage. The proposed model of adaptive MOOC improves the efficiency and quality of online education, providing students with the most opportunities for personalized learning.

Conclusions

Thus, the developed model of adaptive MOOC in real time allows you to respond to the educational needs and capabilities of each individual student, his or her actions and learning progress in the study course. This approach, in our opinion, provides individualized of training, which, as a rule, missing in most MOOC focused on mass use, and is their essential disadvantage. The proposed model of adaptive MOOC improves the efficiency and quality of online education, providing students with the most opportunities for personalized learning.

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