ADAPTIVITY IN ELEARNING LMS PLATFORM - APPROACHES AND SOLUTIONS

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Abstract: *Learning management systems (LMS) that are commonly used in e-learning provide low level of adaptivity. However, courses which have ability to adapt to the individual students' needs make learning easier and lead to better learning scores. Personalized courses (which adapt to individual needs of each learner) improve the learning progress. This paper presents personalized and adaptive eLearning approaches and solutions, which are implemented in contemporary eLearning systems. We establish a model for enhancing e-learning platforms by adaptivity. The solution model was presented by describing the structure of an adaptive course and illustrates different views for learners with different learning styles. In represented model, Moodle LMS was extended by an add-on and an experiment with students was performed in order to show the effectiveness of described approach. Special data mining clustering model was used for results analysis*

Keywords: *E-Learning, Adaptive eLearning, LMS, Cluster analysis*

1. INTRODUCTION

Adaptation is an important issue in e-learning systems, but commercial learning systems that incorporate adaptivity in today's e-education are rare. Numerous studies have been done dealing with developing adaptive systems which aim at providing courses that would be capable of adapting to individual needs and preferences of students.

Learning management systems (LMS) such as WebCT, Blackboard and Moodle are commonly and successfully used in e-learning. Those systems provide a variety of features and modules that support the creation and maintenance of online courses by the teachers. On the other hand, commonly used LMS provide only little or no adaptivity at all [5].

The possibility for adaptation of the learning content accordingly to the learner's performance and progress is a key issue for the learning process. The term "adaptive learning" means the capability to modify any individual student's learning experience as a function of information obtained through their performance on situated tasks or assessments.

The personalozed learning environments which are providing high level of adaptation according to students' preferences are future of e-learning systems. During the numerous studies, it shows that personalized learning environments give the best educational results [1]. In order to support individualized teaching and practice, it is often resorted to the development of specialized adaptive software for training [7].

This paper describes the combination of the LMS advantages and adaptive systems features, by introducing a concept for improvement of LMS with adaptivity based on learning styles and students' prior knowledge.

Taking into account the limitations of existing e-learning platform, we designed a model for adaptive course, which can be easily integrated into e-learning platforms to improve the adaptivity of the system.

Open-source LMS Moodle has been used as a prototype, and add-ons that allows automatic adjustment of Moodle based on students preferences have been developed. In order to verify the validity and efficiency of developed improvements, an experiment was carried out. Experiment included 160 students. Some of them used a customized (adaptive) version of Moodle, while some used ordinary (non-adaptive) Moodle course. Derived data set was used in design, training and testing of the clustering data mining model. The paper describes an experiment and discusses its results.

2. DEVELOPMENT AND DESIGN OF AN ADAPTIVE E-LEARNING MODEL

Improvement of the existing teaching model, developed in Moodle, must go in the direction of providing adaptive learning system. Where adaptivity will perform automated, independently of the conscious choices of students, but based on their preferences which were identified during learning and/or on the results of the questionnaire with which user profile formed.

The proposed model focuses on the adaptivity based on learning style [4] and prior knowledge of students. Model introduces the concept of improved LMS system. The point is to use open-source Moodle LMS as a prototype, and to develop widgets (add-on) that allow Moodle to provide an adaptive course.

At first level, the model is based on a precise separation between learner, content and adaptation model, while at second level each of these sub-model is divided into others sub-models [8].

The student model enables the system to provide individualised course contents and study guidance, to suggest optimal learning objectives, to determine students' profiles and the actual knowledge they have acquired, to dynamically assemble courses based on individual training needs and learning styles, and to join teachers able to provide support in terms of guidance and motivation and therefore to help the students with different backgrounds and knowledge levels to achieve their learning goals effectively on the Web [8].

Unlike other approaches, in the student model we separate preferences and learning style from shown knowledge and performance. As the first sub-model (preferences and learning style) is static while the second one (knowledge and performance) is rather dynamic and takes a part in the event-driven storyboard monitoring. The first sub-model is that one of learning style and takes a central point within the student model[8]. For the learning style determination it was used ils (index of learning styles) questionnaire, which was developed by Felder and silverman [3]. The learning style is detached as separate sub-model and can be used for choosing best content for a learner possessing given mixture of learning styles as far as most of learners cannot be determined only by one style. Mentioned questionnaire (FS ILS) is added to moodle user registration form. In this way, the students' responses allow the determination of learning styles preferences, which are stored in a student model. According to the used model of learning styles, we highlight three groups of the students.

While the learning style can be determined in the very beginning of the learning explicitly by the learner or by appropriate pre-tests, other tests should be exercised during the e-learning process in order to assess prior or gained knowledge and performance results of each individual learner. Learner performance is used to control adaptive content selection. Extras (Moodle add-on) model developed to adapt the course according to students' previously acquired knowledge. An implementation principle in the existing system corresponds to the previously exposed technique of embedding add-on for adaptations to the learning style, in many ways. It is important to determine which category the user belongs to, according to the prior knowledge of the problem in question. Such adaptive course structures differentiate between categories of students: beginners (novice), average and gifted (advanced). During the application and registration to the course, students complete a questionnaire (pre-test). Student model follows the student's performance. Based on the demonstrated skills and knowledge in this pre-test, students are categorized as beginner, average or advanced. Meta-data that are used for sensing the level of student are stored in the student model.

The domain model is composed of content itself (granulized in learning objects (LOs) according to the SCORM standard), LO's metadata (LOM) and semantic ontologies organizing the content (LOs). There are supported various types of LOs – not only narrative content but also any learning activity such as task, topic for writing an essay, assessment question, game, etc. The semantic ontology should be specified by the course author at the beginning, in order to form a logical taxonomy for the knowledge domain (i.e., domain ontology) during the authoring process. Thus, the content LOs are developed by the author and next are placed by the course instructor on course pages.

For this purpose, when creating learning object, their contents indicate different levels (level 1 - beginners, Level 2 - average, level 3- advanced). According to a certain level of knowledge, certain levels of educational materials are available, and they are also categorized according to complexity (also in three levels: 1-beginner, 2-average and 3-advanced level). In order to ensure course adaptivity, it is necessary to create appropriate educational materials, which suit different levels of students. Educational materials are organized as a set of chapters. Each chapter is classified in its own set of subsections, and yet each sub-chapter is further divided into a set of subsections. Among the chapters and subsections, there are relationships that are mutually connected, and each level of educational content is assigned a certain weight (varying from 0 to 1). Weight of material awarded to student is appropriate for its factor (factor also varies from 0 to 1, depending on the level of knowledge). On this way, the student get only appropriate content, designed for that level of knowledge.

The fundamental concept of the proposed meta-model lies in creating an abundance of individual learning objects (LO). During the creation of educational materials, it is necessary to assign metadata to LO to indicate their complexity level. Learning objects that include only preliminary data on related topic (not going in the explanation of the same), are awarded to the first level, i.e. they are intended to present students-beginners. Educational materials which are having more fully issues' explain, are assigned to the second level. And they are presented to the average students. While the materials of the highest, third level, containing elements that are more advanced, point student to independent research and further learning, by linking with other subject matter, previously known and/or completely new concepts. Beside the assigned parameters which indicate the level education object belongs to, additional metadata that refer to the appropriate learning style are introduced.

In other words, each learning object also contains information about which learning style the LO suits best. LOs created in those way, contains the parameters of their complexity level and appropriate learning style it supports. All this suggests that it is necessary to create sufficient individual, learning objects, providing a choice of suitable LO, depending on the level of knowledge, also according to the preferred learning styles of students.

Content pages delivery is controlled by the adaptation engine (AE) for choosing most appropriate content (by adaptive content selection, link annotation and hiding, etc.) for presenting it to a learner with particular learning model (according to students' learning style, as well as to students' prior knowledge).

Proposed meta-model (with student model, domain/expert model and adaptation module) for adaptation of LMS is showed on figure 1. Extensions of the Moodle system are given in form of pre-test and FS ILS, in the section reserved for the registration on the course, and we can see that it leaves the possibility of further upgrading and improvement of the system (the empty box in the picture) in some other way, or in some other direction of adaptation.

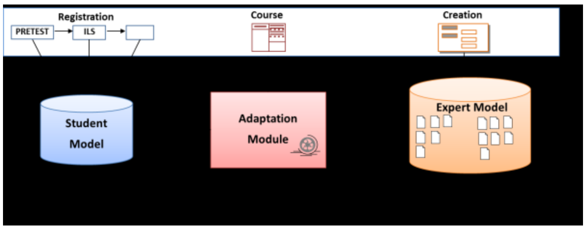

Image 1: LMS architecture with appropriate extensions for achievement of adaptability

3. IMPLEMENTATION

Implementation itself is analogous to the previously described cases of proposed solutions. The student during the registration for a course first completed pretest, which determines the level of his knowledge. Based on the demonstrated skills and knowledge in this pre-test, students are categorized as beginner, average or advanced. Meta-data that are used for sensing the level of student knowledge is stored in the model student. Then students complete a questionnaire to determine the preferred learning style [9]. In this way, the responses of students, allow the determination of characteristics of learning styles, which are then stored in a student model. Therefore, even through the course registration form the metadata on the category of students and his learning style are obtained.

Automated system response, in scope of forwarding the education course, which corresponds to the category of knowledge and the student's learning style allows the adaptation module, which is responsible for access to information about the student's learning style and category, through the student model. The adaptive module calculates the value of each adaptive features based on student's learning style preferences. Values of adaptability features indicate the way an individual course will be made. In addition to learning style preferences, adaptive module reads the metadata on the category of student. Then, using the expert model, access to appropriate elements of the course, which are presented to students through the LMS interface. Learning objects, which are elected in a personalized course, must be suitable to the learning style and the level of knowledge to which the student belongs.

The proposed adaptive model is applied to an existing LMS platform, and according to these principles IT course has created (which is taught to work in the Office software tools).

4. CONDUCT EXPERIMENT TO EVALUATE THE PROPOSED ADAPTIVE LMS META-MODEL

Experiment with students was performed in order to show the effectiveness of described approach. Data were collected on a sample of 160 students of the second year a group of teachers and first year of educators (pre-school teachers), undergraduate studies at the Teacher Training Faculty in Uzice, University of Kragujevac. Part of the data was collected by surveying the students before the course, and part of the processed data was obtained at the end of e-learning course.

As said before students were given an adjusted FSLSM survey questionnaire in order to determine the preferred learning style of each. Processing the survey data led to the classification of students into three clusters based on preferred learning styles of students. For model building clustering algorithm was used, which is used for the natural grouping of data based on their attributes, so that the values of attributes within a cluster are similar and significantly different between clusters. Each cluster comprises multiple learning styles defined FS ILS model, but they relate to the way of presenting educational content within a same group.

Table 1: Characteristics of defined students' groups

Group 1	Group 2	Group 3
Going through obligations sequentially and linear	Students choose topics for essays	Going through obligations sequentially and linear
Many specialized topics for discussing	Going through obligations sequentially and linear	Written materials
Multimedia materials	Practical work	Strict deadlines for finishing obligations
Team or group work	No strict deadlines for finishing exam obligation	Team or group work

Besides testing the student population according to features and preferences in learning and determining the associated learning styles, testing was done on existing prior knowledge. For this purpose, another poll was conducted to determine the level of students' knowledge. The survey showed that students could be grouped into one of three groups based on demonstrated knowledge: beginner student, a student of the average level of knowledge and advanced user. Thus, according to prior knowledge, students are classified into three groups (1 - novice, 2 - average knowledge, 3 - advanced knowledge).

A total of 160 students who participated in the experiment, were divided into three groups, according to level of knowledge. Each of groups is further divided into three sub-groups according to the learning style (at the end we have groups 1-1, 1-2, 1-3 ... 3-3). The polling determined a membership in a particular cluster, but in the experiment all students are not directed to the appropriate module of the course. Namely, by the random selection of students when applying for a course, half of them were referred to the adaptive course appropriate to their demonstrated characteristics, and the other half was sent to an existing, traditional e-learning course, that does not support adaptation.

5. RESEARCH DATA

Data mining aims to discover patterns, groups, previously unknown relationships in data and also to make predictions. For this particular research we used the Cluster Analysis. Cluster analysis, as well as other data mining tools, is successfully applied in recent years in the learning domain. The application of data mining techniques in course management systems has proven to be successfully applied to the Moodle data [6]. Cluster analysis also showed useful for classifying the types of students by types according to different characteristics [2].

Cluster analysis contains the following views: the cluster diagram, the cluster profile, the characteristics of clusters and differences between clusters. The first step of cluster analysis is a model that set the variable. The model contains the following variables: the course, the number of hours spent on the course, number of logins to the course, prior knowledge, learning style, the associated cluster and mark. The tool itself optimizes the number of clusters, but it can be explicitly defined. The cluster diagram (figure 2) shows all the clusters that were identified by the algorithm, as well as their connections. The clusters with a large number of objects (types) are shown in darker shades on the diagram. There may be some common objects characteristics and they are shown as links. If common characteristics are stronger, insofar their links are more prominent on the diagram (darker lines).

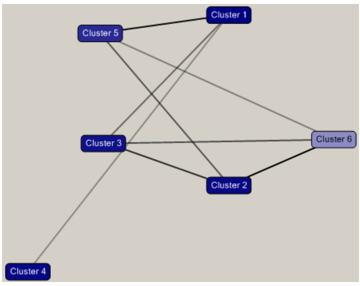

Image 2: Cluster diagram

The basic features of the entire population were:

- Equal representation of both the course
- Approximately the same number of students which spent the optimum time at course and more time than optimum; and nearly a quarter of the population are not spent enough time on course (less than optimum time)
- Maximum number of students is with the initial previous knowledge (beginners)
- The most common is the corresponding beginner/VAS group
- The most common is a style of verbal/active/sequential learning style (VAS)
- The dominant group is associated beginner/VAS

Cluster profiles allow different types of analysis. For example, if we are interested in student success, we see that the marks of 5, 6, 7, 8, 9 and 10 for the entire population are approximately equally represented. The best marks are in clusters 2, 3 and 6. Marks greater than 7 are represented in cluster 2 with a total of 86%, in cluster 3 with 48%, in cluster 6 with 68% probability. When referring only to marks 9 and 10 is dominated by cluster 2 with 56%, then cluster 6 with 33% and at the end of cluster 3 with 11% probability. It means that the students with excellent results are concentrated in clusters 2 and 6, and in cluster 3 are students with very good results, because in this cluster mark 7 is represented with 52% probability. Students with the weakest results are grouped in clusters 4, 1 and 5. Totally marks 5 and 6 are represented as follows: cluster 1 with 100%, cluster 4 with 88% and cluster 5 with 64% probability. In cluster 5 there are a significant number of students with mark 7 (with a probability of 32%). Total ranking of students according to success by clusters: 2, 6, 3, 5, 4 and 1. It is seen that the clusters 2 and 6 have the highest occurrence probability rating mark greater than 7, and for the optimal time spent on the course, the average level of pre-knowledge and participation in the course. In a similar way other parameters can be analyzed.

Table 2: Tabular view of clusters (a)

Variables	States	population	C1	C2	C3	C4	C5	C6
course	1	81	0%	48%	100%	4%	93%	79%
course	2	79	100%	52%	0%	96%	7%	21%
time	2	67	98%	0%	0%	85%	20%	35%
time	1	63	1%	0%	100%	15%	70%	0%
time	0	30	1%	100%	0%	0%	10%	65%
mark	5	38	33%	77%	0%	0%	26%	0%
mark	6	36	55%	23%	4%	0%	39%	6%
mark	7	35	12%	0%	12%	52%	32%	26%
mark	8	26	0%	0%	30%	37%	2%	35%
mark	9	16	0%	0%	37%	11%	0%	12%
mark	10	9	0%	0%	19%	0%	0%	21%

The main difference between cluster 2 and cluster 3 is the type of course that the students attended, as well as time spent on the course. Both parameters have the same degree of influence in both clusters. Cluster 2 maximum favors adaptive course, while cluster 3 maximum favors traditional e-learning course. The same percentage (76.43%) Cluster 2 favors the optimal time spent on the course, and cluster 3 favors ore than optimum time spent on the course. Cluster 2 favors marks 9 and 10, while cluster 3 favors mark 7. These differences should seek the causes of better students (better marks on final testing) in the cluster 2 compared to students who belong to the third cluster.

The following model was created in order to analyze the success of students with the same level of knowledge. It was elected the average level of knowledge. This model includes the same variables as the previous one. The following cluster diagram is obtained (fig. 3).

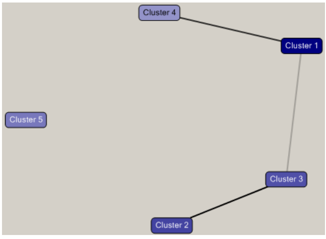

Image 3: Cluster diagram for average pre-knowledge level

The diagram shows that there is similarity (relationship) between cluster 2 and cluster 3, as well as among cluster 1 and cluster 4. Cluster 5 is significantly different from all other clusters of this model.

In this part of the total population there is about the same representation of adaptive course (33) and traditional e-learning course (31). In clusters 1, 2, 3 and 4 are students with grades higher than 6. In clusters 2 and 3 is the presence of adaptive course of nearly hundred percent and is 97% and 96% respectively. In clusters 1 and 4 is the presence of the traditional e-learning course dominant and is 97% and 100% respectively. In cluster 5 is greater, the presence of adaptive course and is 70%. Evidently, much better results are in clusters 2 and 3 compared to clusters 1 and 4. It means that students in adaptive e-learning course had significantly better results.

Table 3: Tabular view of clusters (b)

Variables	States	population	C1	C2	C3	C4	C5	C6
course	1	81	0%	48 %	100 %	4%	93 %	79 %
course	2	79	100%	52 %	0%	96 %	7%	21 %
pre-knowledge	1	90	98%	52 %	25 %	2%	100 %	66 %
pre-knowledge	2	64	2%	37 %	73 %	98 %	0%	20 %
pre-knowledge	3	6	0%	11 %	2%	0%	0%	14 %
mark	5	38	33%	77 %	0%	0%	26 %	0%
mark	6	36	55%	23 %	4%	0%	39 %	6%
mark	7	35	12%	0%	12 %	52 %	32 %	26 %
mark	8	26	0%	0%	30 %	37 %	2%	35 %
mark	9	16	0%	0%	37 %	11 %	0%	12 %
mark	10	9	0%	0%	19 %	0%	0%	21 %

The conducted data analysis clearly shows that the success of the students who participated in the adaptive e-learning course is significantly better than students who were in the traditional e-learning course. Also, students with certain levels of knowledge (not novices) were more successful than novice students. Participation in the adaptive e-learning course allowed the students to a certain level of knowledge to achieve even better results. Time spent on the course is a necessary condition for achieving satisfactory success. A significant number of students who participated in the traditional e-learning course and spent a significant amount of time on the course did not achieve good enough results.

5. CONCLUSION

This paper describes a model of adaptive learning in which the open-source LMS Moodle has been used as a foundation, and add-ons have been developed that allows automatic adjustment of Moodle based on students preferences (learning style and previous knowledge). Model has add-on which allows adaptation according to learning style and add-on which adapt learning process according to students' previous knowledge. The proposed system comprises student model and expert model, and also adaptation module. Student model gathers information about student learning preferences to which system approaches through adaptation module, and with the help of expert model produced personalized, adaptive e-learning course.

The designed model of adaptive learning is validated by experiment. Random half of the students involved in adaptive e-learning course, the other half in the traditional e-learning course. The following quantities were treated: the time spent on the course, number of logging, pre-knowledge, learning style and the combined size - the associated cluster, which involves a level of knowledge and learning style. For the purpose of data analysis data mining clustering algorithm was used.

Cluster analysis enabled us to obtain a rich set of information in forms of graphs and tables from which many relevant conclusions can be made. This clustering model can be used to learn more about students in order to target learning styles and course to specific groups. The results obtained fully confirm the validity of the concept of adaptive learning and the clustering model

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