Databases and Information Systems VIII
H.-M. Haav et al. (Eds.)

doi:10.3233/978-1-61499-458-9-189

Learner Group Creation and Utilization in Adaptive E-Learning Systems

Vija VAGALE[a,1] and Laila NIEDRITE[a]
[a]University of Latvia, Raina boulv. 19, Riga, Latvia

Abstract. The adaptivity provision in the web based e-learning systems nowadays is actual topic. Adaptivity organization can be done by grouping users into previously defined learner groups and by offering these group delegates the appropriate learning scenario. In this article a detailed description of group creation algorithm is presented. A learner group module is made based on the creation algorithm and implemented in Moodle system. It creates course learning groups and classifies learners into already existing groups. Group creation is done by using feature tree. Learner grouping helps to ensure fast system adaptive reaction according to learner characteristics and learning course features. The system offers each learner group their own course learning scenario appropriate to created groups. The created learner group module can be used both in the whole adaptive learning system knowledge area and in individual courses and course categories.

Keywords. Adaptive e-learning system, learner model, learner groups, content model, learner group module

Introduction

Adaptivity improvement in adaptive learning systems (ALS) is important to acquire knowledge. One of the ways of how to organize adaptivity is learner group creation and utilization in the learning process organization. In the ALS learner classification is used that is common for the all courses offered by the system and that is ensured with the help of system administrator [20].

In this article possible ways of how to create groups in the course are described, parallel to already existing learning groups that in the system are defined by administrator (for example, Moodle cohorts) or in a course – by teacher (for example, by dividing users into subgroups) that are based on learner characteristics and that are used for learning course content adaptation. Further in the paper the concept learner group (LG) describes the group, which has learners that are grouped by similar feature values and is used to ensure adaptivity in the system. The offered adaptation provision type essence is the following: course teacher chooses the system-offered features and their values to be used for group creation. Learner classification in group creation process is done by using learner feature tree (FT), so that all possible combinations from features and their values are created. The list of groups is saved in the system database table. When a new learner has come to the course, he/she is classified into already created group by features that describe this learner. The system offers him/her

[1] Corresponding Author: E-mail: vija.vagale@gmail.com

appropriate course acquisition scenario based on a group that the learner was classified into.

Learner group utilization (a) gives an opportunity to predict student achievements [25]; (b) identifies learners with a small motivation and offer them correct actions [1, 10]; (c) gives an opportunity to predict what the learner knows and what doesn't [9]; (d) gives fast adaptive reaction for new learners based on his/her group identificator to offer appropriate learning scenario for him/her. The system-offered scenario is not enforced. At any moment learner can manage his/her learning process by oneself, by choosing the best learning type from the system-offered activities and resources.

The learning system basically consists of three main components: learner model, domain model and adaptive model [32]. Learner characteristic data are described in the learner model (LM) of the adaptive system. Learner knowledge structure is described in domain model. For more accurate use, in the paper domain model concept was replaced with the content model (CM) concept. In the adaptation model (AM) conditions that cause adaptive actions in the system are described.

The paper is organized as follows. Section 1 describes learner model. Section 2 presents content model logical structure. Section 3 describes the method of learner group creation that uses feature tree. Section 4 demonstrates learner group module that ensures learner group creation and learner classification into LG. Section 5 describes creation and utilization of the adaptation scenario. An experiment is described in Section 6, in which the learner grouping method was applied. Related work is presented in Section 7. Finally, conclusions and plans for future research are given in Section 8.

1. Learner Model

Data about learner are important for group creation. Data of this type are described in the learner model and are used to ensure adaptivity. In this paper LM data are important also to classify learners into created learner groups.

1.1. Data Types

The task of the learner model data is to describe a learner in a certain moment of time more precisely. LM data are connected with time dimension, in which data are actual. Based on the research [32] about the most often used data categories in the learner model and the research [30] about learner model data lifetime, in this paper the learner model illustrated in Figure 1 is used. The learner model data are divided into three classes according to its lifecycle or update frequency: BasicData, AdditionalData, LearningProcessData. The BasicData class contains constant or static data, values of which do not change over time or change very rarely. These data characterize LM PersonalData class and contain personal information about learner (for instance, login, password, name, surname, email, gender, date of birth, language, city, and country). To ensure system adaptivity, learner gender, language, and date of birth can be taken from the BasicData.

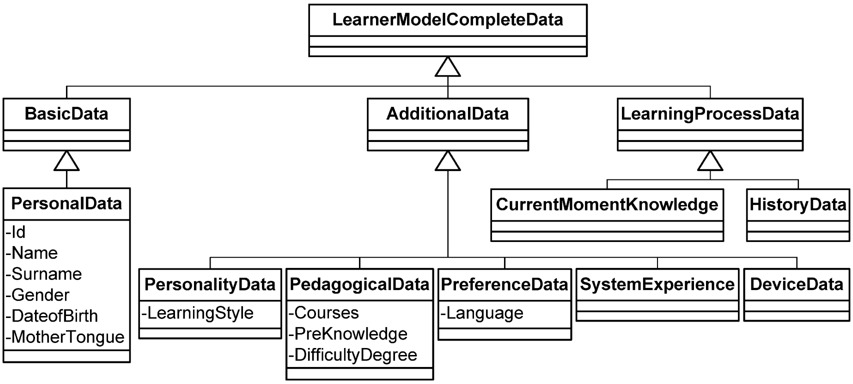

Figure 1. A class diagram of the learner model structure that is based on data lifecycle in the learner model

The AdditionalData class shows learner individuality that is really essential in the adaptive learning system. This class contains such LM subclasses as PersonalityData, PedagogicalData, PreferenceData, DeviceData, and SystemExperience. The AdditionalData examples are: learner concentration skills, personality type, learning style, cognition types (PersonalityData), learning process organization data, for instance, study course, course topic sequence, course difficulty level, course grounding (PedagogicalData), course language and learning environment preferences (PreferenceData), and experience in utilization of the learning system (SystemExperience). In particular, AdditionalData are used to ensure system adaptivity functions. The more AdditionalData the adaptive system is able to collect, the more adaptivity it can ensure for the system user. Additional data are dynamic data. These data tend to change over time. User can change course difficulty level multiple times during one course depending on ALS implementation.

The LearningProcessData class contains data about learner knowledge at the particular moment in time (CurrentMomentKnowledge) and data about learning process (HistoryData). The lifecycle of these data is the shortest, because during the learning process they are being changed and supplemented continuously. In the long run, the system is able to obtain new data about learner that are more qualitative.

The LearnerModelCompleteData class contains all the information that the system "knows" about the learner at the particular moment in time. This class has been characterized by data from such subclasses as BasicData, AdditionalData, and LearningProcessData. In the case of adaptive system, learner model data actualization must be ensured [30].

1.2. Data Acquisition Types

For more precise and full system description of the learner, it must anticipate different learner data acquisition types. Learner model can obtain data from:

- The system user profile. This is a way to collect basic data that are not enough to ensure qualitative system adaptivity.
- Quiz and test results. In this case – additional data, precision of which depends on correctness of the question formulation, interpretation and user honest attitude to a test. For example, in paper [33] intelligent ability data acquisition with the help of tests is described.

- User individual choice, when user chooses what he/she wants to see or use on his/her own [5]. In this case additional data are obtained.
- Data export to external system. In this case, only data that the learning system understands and is able to use to ensure individual reaction are valuable. In case of export, additional data that describe user more precisely are acquired. For instance, data about learner acquisition from e-Portfolio system Mahara is described in the paper [30].
- The learner group existing in the system, which the learner was grouped into. When signing into the system for the first time, a user is grouped into one of the groups that are already described in the system by his/her features, for example, classification by knowledge: beginner, medium, expert. In this case, stereotype modeling method is often used [20]. Conclusions about the learner from group feature analysis can be done by obtaining additional data for the LM, which does not always contain precise information about the learner.
- System-collected data about learner obtained during the learning process. Using data mining algorithms for these data, additional data are obtained.

Table 1 shows data acquisition types for each learner data group depending on the described LM. From Table 1 one can conclude that there are a lot of additional data acquisition opportunities, which can be realized in adaptive learning systems.

Table 1. Data acquisition sources for learning model.

Data sources	Basic data	Additional data	Learning process data
User profile	+		
Surveys and questionnaires	+	+	
Individual choices		+	
Data export from other system	+	+	
Learner group		+	
System learning process data		+	+

2. Content Model

Content in adaptive systems is described by content models [4, 6, 16]. In this paper, the content model that is based on the learning objects and various resource format utilization is used (Figure 2). Learning materials are made of objects. Therefore, learning material is divided into parts - learning objects (LO). A learning object is a collection of content, practical and testing parts that combines elements based on the one learning goal [2]. A LO is a part of learning material, which is independent and of multiple use, necessary and sufficient to acquire demanded information.

A learning course of the used CM consists of one or more topics. Each topic is made of one or more learning objects. Each LO consists of the learning object description, theoretical, practical, and assessment parts. The description represents the essence of the specific LO, its tasks, and its place in the course structure. The theoretical part contains offered knowledge and its representation types. For example, if Theory class attribute ContentType=Basic, then the basic content knowledge is offered by activities and resources. If attribute ContentType=Explanation, then the expanded content is offered. In this case, in addition to basic content, links to definition explanations are shown. The practical part contains activities that are necessary to strengthen the knowledge. A theoretical course can exist without practical part. The assessment part of the LO is used for testing of the acquired knowledge. It offers activities to obtain the grade, for instance, a task or a quiz.

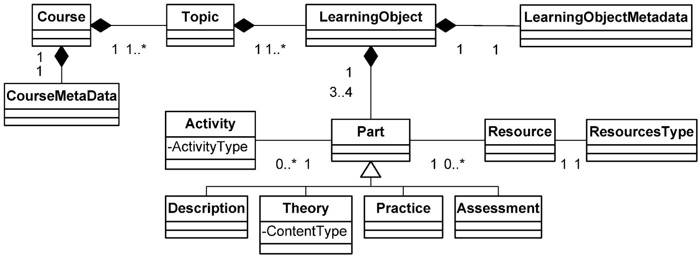

Figure 2. Adaptive e-learning system class diagram of content model

Each LO part contains different types of information resources and activities that a learner can use to acquire a LO. To strengthen and estimate knowledge, a learner is offered to accomplish certain activities such as exercise, task, or quiz. Resources are used to represent the offered knowledge. A wide variety of resource types is described in the content model, which is composed based on the learning style data of a person (Figure 3). For example, if a learner has Aural learning style, then resources with ResourceType=Listening are offered in the LO theoretical part. Such resources are audio recordings and audio conferences.

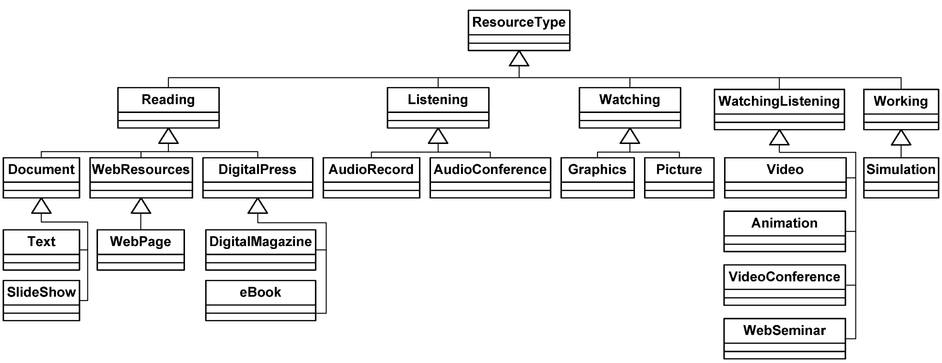

Figure 3. Resource types used in the theoretical part of the learning object and depending on the learning style of a person

3. Learner Group Creation

Web-based learning systems ensure access to a lot of people. To obtain fast system reaction, in many learning systems learner classification is implemented by means of previously-defined groups (stereotypes) [26, 29]. Each learner is described with a specific set of properties that are called features. Before the system classifies a user in a group, the described learner groups need to be defined in the system. Groups are created using grouping method. The grouping is a unification of researched values by their existing features and obtaining homogeneous groups. Classification is a mapping from the feature space X to a set of labels (or classes) Y [14]. The learner classification takes place when the system executes the classification algorithm, and grants each learner a group number (name). The learner data that are important to ensure system adaptivity are mapped in the previously defined feature sets. Classification is realized with classificators. The classificator is a coding model of criteria set that allows the data instance to grant a particular class according to some variable values [17]. There exist different methods for classificatory construction, for example, decision trees, nearest-neighbor classifiers, etc. [17, 25, 27].

3.1. The Method

In this paper a method to model LG in the ALS dynamically is used employing a feature tree for learner classification. Grouping features obtained by the offered method from conditions written in the AM that use characteristics of a learner. Either all obtained features or only part of them can be used for group creation. Knowing the features and the number of their possible values, all possible combinations from features and their values are calculated, thereby, obtaining different learner groups.

The creation of LG is based on four steps: (1) choosing the feature (only one) that will serve as a basis for creating groups; (2) determining the set of all possible values for each feature; (3) creation of FT to classify learners using chosen features and their sets of values (feature sequence does not affect the tree creation); (4) identification of learner groups that are obtained using lower level nodes of the tree structure.

More information about the proposed method and its utilization scenarios is given in paper [31]. Practical implementation of this method is described in the 4th Section of the paper.

3.2. Application of the Method

The offered method for creating groups can be used for different number of features and their values. A simple example is a group that is created based on three features. Out of all system-intended adaptation types in the paper only the ones that are used in a course learning object (in the simplest case - one topic) will appear. New learning groups will be created based on the above-described learner model. These groups will be made based on the data about basic knowledge in each individual learning course (PedagogicalData); course difficulty level (PedagogicalData) and learning styles from LM class PersonalityData.

Each course pre-knowledge (PK) is defined in the course description. Each learner PK can be found: (a) by analyzing external system data about the learner; (b) by learner testing; (c) by using learner’s individual choice. Course difficulty level (DL) is used to give a learner the opportunity to choose the maximum course grade that is acceptable for him. In the system, offered task, test difficulty level, and course final grade depend on the chosen DL. The user individual choice is used for DL value acquisition. Learning styles (LS) can be defined using testing and data mining algorithms. LS define system-offered resource types.

In the example, the “Pre-knowledge” feature has two possible values in the learner group classification. If the learner has any pre-knowledge in some course, then PK=1, but if he/she has no pre-knowledge, then PK=0. Course difficulty level can take the following values: DL=L (Low), DL=M (Medium), or DL=H (High), where DL=L is the lowest (easiest) course difficulty level, DL=M is the medium level and DL=H is the highest (toughest) level. The feature “Learning styles” can take values: V, A, R, K, VA. These values show what kind of information the learner prefers to perceive. V (Visual) means visual information, perceived by looking, A (Aural) – hearing, K (Kinesthetic) – by working and VA (VisualAural) – looking and hearing.

The feature tree structure is composed from the selected features and their value sets. In the node of the highest level it has an arbitrarily selected feature that is taken from the group creation features. The feature selection sequence has no essence. In the highest level, the observed example has the feature “Pre-knowledge” (Figure 4). Then, depending on the possible value number of the written feature (for pre-knowledge - 2), two sub-nodes are created. The transition is made according to „Pre-knowledge” values. The next arbitrarily chosen feature is written in the created nodes (in this case, it’s „Levels of difficulty”). Course difficulty level has three values, which is why three edges that have end points in “Learning styles” go out of this node. The possible value number of this feature is five, which is why five edges go out of each node. Since all the features are already used in the tree structure, the lowest level contains nodes with group names. In the example, groups are named „G1”, „G2”, ..., „G30”. The result is a feature tree that helps to identify learner’s affiliation to a specific learner group.

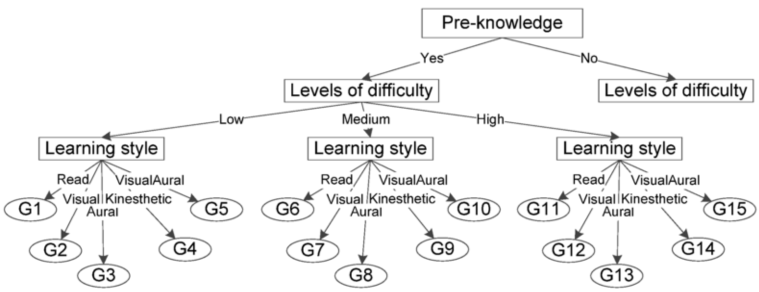

Figure 4. A feature tree where the feature hierarchy with all possible values and the obtained learner groups below is shown

Figure 4 shows only the left branch of FT that represents 15 groups. The same number of groups is obtained in the right branch. The observed examples provide 30 different groups according to learner pre-knowledge (2 values), course difficulty level (3 values) and learning style (5 values). Figure 4 shows that the group „G15” includes all learners who have some pre-knowledge in the course; they have chosen the highest difficulty level of the course and they all have visual-aural learning style.

The application of FT gives an opportunity to create learner groups based on different constant features and their values. For example, if adaptation is ensured only by age feature with three value ranges, then three learner groups will be defined. In this case, if learner age (3 values), learner pre-knowledge (2 values), course difficulty level (3 values), and learning styles (5 values) are used for adaptation, then adaptive system will be required to adapt to 90 learner groups.

4. Learner Group Module

LG module that was implemented in a free learning management system Moodle was made for learner group management. The main functions of LG module are: (a) learner group creation within one course and (b) group identificator allocation for new course users depending on specific learner characteristics.

LG module is available in Moodle course page for users with a course teacher role. Two new tables „clg" (course learner groups) and table „clg_members" were created in the system database as a result of module activities. Table „clg" stores descriptions of the created LGs. Table „clg_members" contains a list of course learners and their LG identificator. A module obtains data for LG creation from the AM. Data about specific learners are taken from that part of database responsible for LM. The created LG module interaction with the system components is shown in Figure 5. The grey figures show new components of the system. Bullets show the data flow directions.

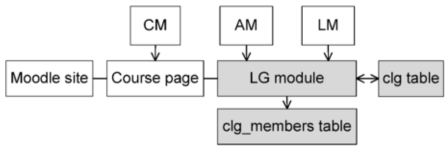

Figure 5. LG Module interaction with existing system components

4.1. Learner Group Creation

At the beginning of the course learner groups, which will be used later for a new learner classification, are defined. LG module collects learner features from adaptation model. In the AM system adaptive reactions, conditions of which contain data from LM, are described. A module creates LG from AM data and course teacher choices. The feature tree described in the 3rd Section is used for group creation. Created groups are saved in the system database table „clg" (Figure 5).

Working principle of the LG module for learner group creation is shown in Figure 6, where colored figures represent module communication with other components of system. LG module operates in accordance with the following algorithm:

1. All learner features, which are necessary for the system to ensure adaptive reaction, are obtained from AM.
2. Course teacher chooses a feature that will be used for group creation from the list of obtained features. Feature selection sequence is not important.
3. The AM gives a set of values for the chosen feature.
4. If a teacher wants to continue and there are still unused features, then a teacher returns to step 2. If all features are already used or teacher does not want to continue group creation, then a teacher proceeds with step 5.
5. Creation of different variations using chosen features (LG creation).
6. Created groups with their features are saved in table „clg".

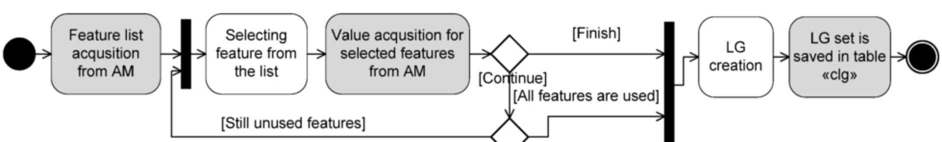

Figure 6. An algorithm of creation of the LG module learner group

4.2. Learner Group Identificator Assignment to Learner

If a course has already defined learner groups, then the LG module classifies learners into LGs. It happens only when a learner enters the course for the first time. Learner is assigned a group identificator based on the course-organized learner groups and learner characteristics. Two arrays are used to find LG identificator. One of them is a two-dimensional array „aclg" (*array course learner groups*) with values of course learner group features. The other one is a one-dimensional array „ald" (*array learner data*) with feature values belonging to the new learners of the course. The one-dimensional array is compared with each row from the two-dimensional array. As the result of row comparison, value coincidence checksum CSum is obtained. CSum value is saved in the one-dimensional „result" array. Learner group conformity for a specific learner is defined by the highest checksum value index of the „result" array.

A more precise new learner classification in already existing learner groups is shows in Figure 7. LG module does the following actions to execute this task:

1. The module checks whether a course has any already created groups.
2. The next step follows only if a course has learner groups, otherwise, the module ends its job.
3. „aclg" array is created using „clg" table data.
4. „ald" array is made; there the module stores data about the classified learner in a specific sequence that corresponds to „aclg" array feature sequence.
5. A not examined row of the „aclg" array is taken.
6. Zero is assigned to the checksum (CSum=0).
7. Comparison of the feature value in the taken row of the „aclg" array and the corresponding feature value in the „ald" array.
8. The checksum value is increased by one, if the feature values coincide, otherwise, CSum value does not change.
9. Returning to step 7, if uncompared features still remain, otherwise, the next step follows.
10. The obtained checksum is saved into „result" array.
11. Returning to step 5, if uncompared rows still remain in the „aclg" array, otherwise, the next step follows.
12. The highest value index of the „result" array is found.
13. A necessary group identificator is found by array value index (serial number).
14. The obtained LG identificator is assigned to a learner and the obtained conformity is saved in the „clg_members" table.

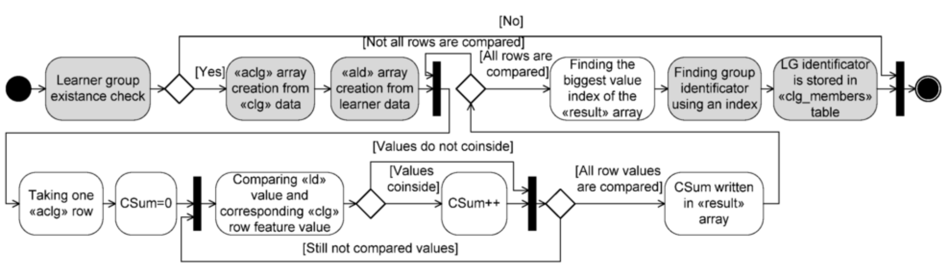

Figure 7. An LG module group identificator searching algorithm

5. Learner Group Utilization

After classifying the system user in a specific learner group the system offers an appropriate adaptation scenario depending on the group description. A scenario is a textual description of the typical sequence of activities that is produced by a system participant (actor) [21].

In section 3, 30 learner groups were obtained based on three learner features: course pre-knowledge, course difficulty level and learning style. System should offer an appropriate adaptation scenario to each obtained group. In the adaptation model described the learner and the content model element value match is used for scenario acquisition (Table 2). For example, if the learner has some pre-knowledge (PK=1), then E=0, thus, the basic concept definitions will not be shown when composing course topic (LO) content.

Table 2. Learner model feature and content model value mapping to ensure adaptive reaction of the system.

Learner characteristics	Values	Values	Adapted parts of the LO
Pre-knowledge (PK)	PK=1 (Yes)	E=0 (No)	Theory(contentType=Explanation)
	PK=0 (No)	E=1 (Yes)	
Levels of difficulty (DL)	DL=L (Low),	A=E (Easy)	Practice(activityType=Exercise), Assessment(activityType=Task), Assessment(activityType=Quiz)
	DL=M (Medium),	A=M (Medium)	
	DL=H (High)	A=H (Hard)	
Learning styles (LS)	LS=R (Read),	RT=R (Reading)	Theory(contentType=Basic)
	LS=V (Visual),	RT=W (Watching)	
	LS=A (Aural),	RT=L (Listening)	
	LS=K (Kinesthetic),	RT=D (Working)	
	LS=LW (VisualAural)	RT=WL (WatchingListening)	

Using the value mapping described in Table 2, there is a certain adaptation scenario generated for each group. The corresponding scenarios of the created learner groups are described in Table 3 using set S where S={Theory(BasicContent), Theory(Explanation), Practice(Exercise), Assessment(Task), Assessment(Quiz)}. For instance, S30={WL,1,H,H,H}.

Table 3. Scenarios for adaptation of course topic content of 30 learner groups, practical part, and evaluation part, obtained in the result of grouping.

Group name	Scenario	Theory		Practice	Assessment	
		Basic (RT)	Explanation (E)	Exercise (A)	Task (A)	Quiz (A)
G1	S1	R	0	E	E	E
			…			
G15	S15	WL	0	H	H	H
			…			
G30	S30	WL	1	H	H	H

If a new user logs in the system and chooses a learning course entering it for the first time, then, the system obtains the data about his/her learning styles and the course pre-knowledge (tests, external system, user choice). After that user has to choose the course difficulty level that will affect his final grade in the course. Then, the system classifies the learner into one of the created groups. For example, if a user was classified into group G1, then he/she will experience the adaptation scenario “S1”, where S1={R,0,E,E,E}. This scenario implies that the representation of the course topic content will be provided using LO content resources from “Reading” category. These resources are „Documents”, „Websources”, and „DigitalPress” (Figure 3). In the topic content, definitions of the concepts will not be included automatically. Appropriate practical tasks will be selected in the practical part, difficulty level of which will be set to “Easy”. The task/test offered for topic grade acquisition will also have the difficulty level “Easy”. More information about LG utilization scenarios is given in paper [31].

6. An Experiment

LG creation and learner classification in existing groups was tested in terms of the experiment on 30 participants with bachelor degree in “Information technologies” study program from the Daugavpils University. LGs were created with the help of LG modules in “Basics of Programming” course by such features as: pre-knowledge in the course, course learning level, and learning styles. The data about the new learners of the course that were missing for LG creation were obtained using tests and user individual choices.

Learning style can be defined as a way of how a person obtains, processes, and organizes information [7]. Different learning style models such as Felder-Silverman Learning Style Model, model by Kolb, The Myers-Briggs Type Indicator, Herrmann Brain Dominance Instrument and others [19] exist. In the paper the VARK model was used for LS determination, because: (a) it is based on learner dominant sensor systems [18]; (b) this model is successfully implemented in the papers [13, 15]; (c) its realization is simple from technical view and the results can be easily interpreted.

The survey that was integrated into the system was taken from the official VARK site. Learning styles were identified with the help of this survey - Visual, Aural, Read/Write, and Kinesthetic. Learning styles with one or more equal values (two, three or four different combinations of learning styles) were obtained as a result of the test. In the described adaptive system, only style combination Visual-Aural has implied adaptive reaction by offering resources that can both involve listening and looking. All other learning style combinations were reduced to one style. Based on the research described in the papers [3, 24, 28], learning styles were ranked as follows by their frequency: Kinesthetic, Aural, Visual, and Read. That is why, if the obtained style combination has K in it, then this combination is reckoned in the Kinesthetic style, for example, VK, AK, RK, VAK. VAR style combination was added to VA, AR combination – to A, and VR – to the Visual style. Remaining combinations that contain style R were added to the Read style.

The results of testing showed that 20 out of 30 students (67%) prefer only one learning style: 11 students – Aural, 5 students – Read, 4 students – Visual, and no one – Kinesthetic style. 10 more combinations were obtained from two styles (33%): 1 student – AK, 3 students – VK, 2 students – VR, and 4 students – AR. Additional styles were obtained by reducing tested learner style combinations to one style: K 4 (from AK and VK), A 4 (from AR), V 2 (from VR). Testing results showed that A=16 (53%), V=6 (21%), R=4 (13%), and K=4 (13%) students. Only 11 out of 30 respondents (37%) had some pre-knowledge in the course. The Medium difficulty level was chosen by 13 students (43%), and High – by 17 students (57%). None of the students selected the lowest level.

Using LG module experiment participants were classified into 12 groups. The majority of the students (6) were grouped into group G28 (PK=0, DL=H, LS=A). Four learners were classified into groups G23 (PK=0, DL=M, LS=A) and G13 (PK=1, DL=H, LS=A). Relying on these data, it can be concluded that students had high motivation to learn this course. Then, each of the groups G12 (PK=1, DL=H, LS=V) and G24 (PK=0, DL=M, LS=K) had 3 students. Two students were classified into groups G11, G21, and G22. Only one student was classified into groups G6, G8, G27, and G29.

7. Related Work

In many adaptive learning systems learner knowledge is used as an adaptation source [5, 22]. Knowledge representation and actualization is done using models like stereotype, overlay, combination, differential, perturbation, plan, and other models [12, 23, 32]. For example, in the paper [20], a stereotype model is used to offer knowledge that is modeled using the learning pattern. Users are divided into the following categories: beginners, intermediate level, and expert level users. The system adapts their preferences based on the category that they are related to.

UNIX Consultant user modelling component KNOME uses double-stereotype system, where the user expertise and information difficulty level are represented. Expertise groups are: novice, beginner, intermediate, and expert. Information difficulty levels are: easy, medium, and complex. The relations between user stereotypes and knowledge difficulty levels are described based on the data about users or their activities in the system [9].

Individual learning styles are widely used to ensure ALE adaptivity. In the paper [11] 71 learning style models are identified and 13 out of them are declared as the main models. In the paper [19] a comparison of 5 learning styles is given: Kolb (experiential model), Gregorc (phenomenological model), VARK (sensory/perception model), Felder-Silverman (combines experiential, phenomenological and sensory models), Dunn and Dunn (combines elements from all four). The composite table of styles, where the classification of the most popular learning styles is represented and common style elements by general commonality of terminology and theoretical comparability can be observed, is described in this paper.

The author of the paper [22] categorizes learners by style (Felder-Silverman) and thinking style (Herrmann model), which divides the brain into a four-quadrant brain dominance model: Quadrant A, Quadrant B, Quadrant C, and Quadrant D. Online course supply that is based on VARK learning style is described in the paper [13].

Learner classification is widely provided using data mining methods. The decision tree classification algorithm C4.5 to classify students into different groups with equal final grades is used in the paper [27]. Student success is evaluated to foresee student achievements by the end of the semester with the purpose to determine which of the learners needs special attention based on the information about student visits, class tests, workshops, and grades, by means of the decision tree [1].

In the paper [7] the decision model is organized using Dynamic Bayesian Network that determines conformity between learning style (Felder-Silverman) and learning resource to decide, whether respective resource is interesting for student or is not. To determine style, students have an opportunity to accomplish a test. If it does not happen, the style is chosen according to the used learning resource from the described decision model.

The mechanism to classify learners that is based on k-nearest neighbor and genetic algorithms is offered in the paper [8]. Authors use data about elementary school students and determine student learning style for group classification. Students are divided into three groups: dilatorily type (students that spend more time looking at the learning units), transitory type (spend very short time for browsing), and persistent type (browsing depth is the highest).

8. Conclusions and Future Work

In this paper a method to create learner groups based on the feature tree is described. Features are selected according to adaptation conditions described in the adaptation model. The offered method is suitable for adaptive e-learning systems, which activity is based on learner group utilization.

Benefits from the offered LG organization type are the following: (a) Features and the number of values for LG creation can vary. This approach gives an opportunity for the organized adaptivity of a different type to exist in parallel in the system. (b) The LG module ensures the opportunity in each course to organize its own LGs that help to take into account course specificity. This approach was not found in any of related works. The offered LG organization type does not rule out an opportunity to organize LG in the bigger ALS knowledge area, for example, in some course category or united in the whole system. (c) The parallel existence of different LGs in the system gives an opportunity to organize adaptivity not only on the learner level, but also on the course level, when each course has its own LGs. (d) Fast adaptive reaction provision that is achieved for all learner groups by offering the system-created adaptation scenario.

The offered learner grouping method was experimentally tested having student classification organized into LGs by three features: pre-knowledge in the course, course learning difficulty level, and learning styles. Conclusions from the obtained learner data were: (a) in the course ”Basics of Programming” only 37% of the learners had pre-knowledge, (b) 43% of students were satisfied with course learning in the medium level, but 57% wanted to get the highest course evaluation. These two indicators show the high student motivation in learning the programming course.

The learner group and adaptation scenario conformity that is offered to a learner still needs to be tested. When collecting data about the course results in the long term, the system could offer to choose between pre-created LG adaptation scenario and “the best” adaptation scenario. “The best” adaptation scenario is the one that was used by a specific group of learners to achieve the highest grade in the course. A learner always has an opportunity to decline the offered adaptation scenario and organize the course learning on his/her own. The future research will be directed to: (a) test the correctness of learner classification into learning groups, (b) offer “the best” adaptation scenario, and (c) find out whether the style combination reduction used in this paper is correct.

References

[1] Baradwaj B.K., Pal S. Mining Educational Data to Analyze Students' Performance. *International Journal of Advanced Computer Science and Applications,* 2011, 2(6). 63-69.

[2] Barrit C., Lewis D., Wieseler W. Cisco systems reusable information object strategy version 3.0, 1999.

[3] Bernardes E., Hanna M. How do management students prefer to learn? Why should we care? *International Journal for the Scholarship of Teaching & Learning*, 2009, 3(1), 1-13.

[4] Brusilovsky P. Adaptive Hypermedia for Education and Training. In: *Adaptive Technologies for Training and Education*, Cambridge: Cambridge University Press, 2012. 46-65.

[5] Brusilovsky P. Methods and techniques of adaptive hypermedia. In: *User modeling and user-adapted interaction*, 1996, 6(2-3) 87-129.

[6] Brusilovsky P., Millán E. User models for adaptive hypermedia and adaptive educational systems. In: *The adaptive web.* Springer-Verlag, 2007. 3-53.
[7] Carmona C., Castillo G., Millán E. Discovering student preferences in e-learning. In: *Proceedings of the international workshop on applying data mining in e-learning*, 2007. 33-42.
[8] Chang Y.C., Kao W.Y., Chu C.P., Chiu C.H. A learning style classification mechanism for e-learning. *Computers & Education*, 2009, 53(2), 273-285.
[9] Chin D.N. KNOME: Modeling what the user knows in UC. In: *User models in dialog systems.* Springer Berlin Heidelberg, 1989. 74-107.
[10] Cocea M., Weibelzahl S. Can Log Files Analysis Estimate LearnersLevel of Motivation? In: Herder, E., Heckmann, D. (eds.) *Proceedings of 14th Workshop on Adaptivity and User Modeling in Interactive Systems*, ABIS. University of Hildesheim, 2006. 32-35.
[11] Coffield F.J., Moseley D.V., Hall E., Ecclestone K. Learning styles for post 16 learners: What do we know. London: Learning and Skills Research Centre/University of Newcastle upon Tyne, 2004.
[12] Dagger D., Wade V., Conlan O. Towards a standards-based approach to e-Learning personalization using reusable learning objects. In: *World Conference on E-Learning in Corporate*, *Government, Healthcare, and Higher Education.* 2002. 210-217.
[13] Drago W.A., Wagner R.J. Vark preferred learning styles and online education. *Management Research News*, 2004, 27(7), 1-13.
[14] Duda R.O., Hart P.E., Stork D.G. *Pattern classification*. John Wiley & Sons, 2012.
[15] Eom S.B., Wen H.J., Ashill N. The Determinants of Students' Perceived Learning Outcomes and Satisfaction in University Online Education: An Empirical Investigation*. *Decision Sciences Journal of Innovative Education*, 2006, 4(2), 215-235.
[16] Esichaikul V., Lamnoi S., Bechter C. Student Modelling in Adaptive E-Learning Systems. *Knowledge Management & E-Learning: An International Journal (KM&EL)*, 2011, 3(3), 342-355.
[17] Espejo P.G., Ventura S., Herrera F. A survey on the application of genetic programming to classification. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 2010, 40(2), 121-144.
[18] Fleming N.D. *Teaching and learning styles: VARK strategies*. Christchurch, New Zealand, 2001.
[19] Hawk T.F., Shah A.J. Using learning style instruments to enhance student learning. *Decision Sciences Journal of Innovative Education*, 2007, 5(1), 1-19.
[20] Hewagamage K.P., Lekamarachchi R.S. Learning Patterns: Towards the Personalization of E-Learning. *Towards an ICT enabled Society*, 2003.
[21] Koch N. *Hypermedia systems development based on the Unified Process*. Ludwig-Maximilians-University Munich, Institute of Computer Science, 2000.
[22] Mahnane L., Laskri M.T., Trigano P. A Model of Adaptive e-learning Hypermedia System based on Thinking and Learning Styles. *International Journal of Multimedia & Ubiquitous Engineering*, 2013, 8(3).
[23] Martins C., Faria L., de Carvalho C.V., Carrapatoso E. User Modeling in Adaptive Hypermedia Educational Systems. *Educational Technology & Society*, 2008, 11(1), 194-207.
[24] Miller P. *Learning styles: The multimedia of the mind*, 2001.
[25] Minaei-Bidgoli B., Punch W.F. Using genetic algorithms for data mining optimization in an educational web-based system. In: *Genetic and Evolutionary Computation.* 2003. 2252-2263.
[26] Rich E. User modeling via stereotypes. *Cognitive science*, 1979, 3(4), 329-354.
[27] Romero C., Ventura S., García E. Data mining in course management systems: Moodle case study and tutorial. *Computers & Education*,2008, 51(1), 368-384.
[28] Shah K., Ahmed J., Shenoy N. How different are students and their learning styles? *International Journal of Research in Medical Sciences*, 2013, 1(3), 212-215.
[29] Tsiriga V., Virvou M. Initializing the student model using stereotypes and machine learning. In: *IEEE International Conference on Systems, Man, and Cybernetics.* 2002.
[30] Vagale V. ePortfolio Data Utilization in LMS Learner Model. In: Hammoudi S., Maciaszek L., Cordeiro J., Dietz J. (eds.) *Proceedings of the 15th International Conference on Enterprise Information Systems, ICEIS2013*, *4-7 July, Angers, France*. Portugal: SCITEPRESS, 2013. 489-496.
[31] Vagale V., Niedrite L. Learner Classification for Providing Adaptability od E-Learning Systems. In: Haav H.-M., Kalja A., Robal T. (eds.) *Proceedings of the 11th International Baltic Conference, DB&IS 2014, 8-11 June, Estonia.* Tallin: Tallinn University of Technology Press, 2014. 181-192.
[32] Vagale V., Niedrite L. Learner Model's Utilization in the e-Learning Environments. In: Caplinskas A., Dzemyda G., Lupeikiene A., Vasilecas O. (eds.) *Proceedings of the 10th International Baltic Conference*, *DB&IS 2012*, 8-11 July, Vilnius, Lithuania. Vilnius: Žara, 2012. 162-174.
[33] Vagale V., Niedrite L. Intellectual Ability Data Obtaining and Processing for E-learning System Adaptation. In: Niedrite L., Strazdina R., Wangler B. (eds.) *Workshops on Business Informatics Research*, *BIR 2011*. Berlin Heidelberg:Springer, 2012. 117-129.