MOBILE LEARNING ANALYTICS APPLICATION: USING STUDENTS' BIG DATA TO IMPROVE STUDENT SUCCESS

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Abstract: Nowadays, the big data is becoming more and more important in the field of education. The huge amounts of data generated by the participants in the learning processes led to increased interest in the collection and analysis of student data to support and obtain insight into the students' learning activities. This formed a new research field, known as Learning Analytics. The paper focuses on solutions of some problems related to technological considerations in Learning Analytics. It propose a set of indicators that Learning Analytics should provide to help students to meet their learning goals and to improve their success. The mobile application Mobile LAP that allows students to trace out the values of the indicators during training is developed. Using Mobile LAP students are able to keep track on their own activity, success rate, adherence to the learning schedule.

Key words: Learning Analytics, Big Data, Mobile Application, Student Success, Moodle

1. INTRODUCTION

Nowadays, higher education institutions use a large number of software systems to automate their activities for different user groups (librarians, faculty, students, local and global communities, researchers, administrative staff, etc.) – student information systems, library systems, digital archives, planning and management systems, human resources, learning management systems, etc. When users use these systems, they leave a "digital footprint" and generate a huge amount of data every day, e.g. students generate data about their learning and experience at the university. For example, when conducting online courses vital pieces of data for students are stored in the learning management system (LMS) database, such as students' grades on a particular test/assignment or a whole course, duration of students' participation in learning activities and throughout the course, how many times students have accessed learning resources and activities, how many times students have participated in communication, etc.

In recent years, big data is becoming more and more important in the field of education. Many researchers have begun to explore how the new data sources on students and their learning, together with predictive analytics techniques, can be used to support and obtain insight into the students' learning activities [2] and to improve many aspects of the educational experience [1]. Learning Analytics represents the application of "big data" (extremely large data sets that may be analysed computationally to reveal patterns, trends, and associations, especially relating to human behaviour and interactions [3]) in education. In literature can be found a number of definitions for Learning Analytics. According to some authors Learning Analytics refers to the process of collecting, evaluating, analysing, and reporting organizational data for decision making [4] and for purpose of improving learning processes [5]. Other authors define Learning Analytics as "the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimising learning and the environments in which it occurs" [6]. Siemens [2] defines Learning Analytics as "the use of intelligent data, learner produced data, and analysis models to discover information and social connections for predicting and advising people's learning".

Learning Analytics is a promising emerging field, but higher education institutions need to become further familiar with methods (visual data analysis, social network analysis, semantic analysis, and educational data mining), benefits and challenges (tracking, collection, evaluation and analysis of data, the need for learning environment optimization, issues concerning ethics and privacy, etc.) related to its application [7]. Learning Analytics provides benefits for all levels of stakeholders: mega-level (governance), macro-level (institution), meso-level (teacher), and micro-level (student) [8]. By using Learning Analytics stakeholders can improve the quality of learning and digital learning resources, improve course outcomes, improve student retention, support informed decision making, track and predict students' performance, identify potential issues and students at risk, understand students' learning behaviours and develop more engaging and effective teaching and learning techniques. The development of tools for Learning Analytics requires the solution of some problems related to the following main technological considerations [9]:

- Data collection - how the organization obtains original data for storage, processing and reporting in the analytics tool;
- Data storage - the environment used to maintain an organization's learning analytics data;
- Data processing - the actions taken on stored data to transform them into business intelligence for analysis;
- Data reporting - the formal presentation of the results of a processed request.

An increasing number of case studies relevant to the implementation of Learning Analytics in higher education institutions have been published [10, 11]. Many higher education institutions worldwide have already used Learning Analytics to improve the quality of learning, student success and retention, to delivery automatic and immediate feedback, and to provide a personalised experience for students [4]. Many of these institutions have used or designed their own Learning Analytics tools that provide a "dashboard" to all stakeholders (students, faculty, administrative staff, etc.) [12, 13]. Data

comes from LMS, Student Information System and other systems. The level of development of modern technologies allows students to experience the benefits of Learning Analytics through the use of mobile and online applications that track data about their performance in the learning process and raise awareness on the learning process [14]. These applications allow students to get notifications, to foster their self-regulated learning and to track and monitor their learning time using mobile devices anywhere.

The paper presents solutions related to some of the main technological considerations in Learning Analytics listed above. On one hand, most of the students' data used for Learning Analytics comes from the LMSs. On the other hand, Learning Analytics should provide measurable indicators of students' behaviour. That is why an analysis of the big data generated in the learning process in one of the most used LMS Moodle is done. On the basis of this analysis, a set of Learning Analytics Indicators (LAI) that can help students to meet their learning goals and to improve their success are defined. A mobile application Mobile LAP is developed that allows students to trace out the values of LAI during training. Using the Mobile LAP students are able to keep track their own activity and success rate and to compare them with the average level of activity and success rate of the other students as well as to track whether they adhere to the learning schedule.

2. COLLECTING STUDENTS' BIG DATA IN MOODLE AND LEARNING ANALYTICS INDICATORS

The advancement of technology has provided the opportunity to track and store students' learning activities as big data sets within different systems [7]. These data can be automatically analysed, and combined with data about students' backgrounds, past academic performance or their career aspirations [1].

Much of the data that can help students to improve their success during training comes from the LMSs. Because of this, an analysis of data stored in the database of one of the most widely used LMS has been made. The database of Moodle has around 200 tables. When many students use the system they genera a huge amount of data that can be defined as big data. Data about courses, learning resources and activities, users and all activities that users perform within the system are stored in 75 tables [15]. The analysis of data stored in these 75 tables allow us to define which of the stored data can be useful for students to achieve better results. Part of these data are generated by students during their training (number of views of learning resources and activities, submissions, test results, etc.) and the rest - by teachers when they assess student activities (assignments, test, etc.).

There are a number of plugins for Moodle (Standard and Additional) that provide Learning Analytics. Most of these plugins provide information to faculty staff about students and their learning. Students have access to plugins that allow them to generate reports showing data about their completion of activities (Course completion status), progress in activities/resources of a course (Progress bar), results from graded or rated activities in a course (Activity results block), grades across activities (Gradebook), estimated dedication time to a course (Course Dedication), current level and progress towards next level (Level Up!) [16].

These plugins allow students to track their activity within the system, but do not allow them to compare their activity with the activity of the other students in the course. To improve their success students need information that helps them to track:

- what their active participation is compared to those of other students in the course;

- what their success rate is compared to those of other students in the course;

- whether they adhere to the learning schedule.

In order to allow students to track their activity and success rate during training and to compare them with the average level of activity and success rate of the other students as well as to track whether they adhere to the learning schedule additional reports have to be developed. For this purpose on the basis of the analysis of students' data stored in the Moodle database a hierarchical system of measurable indicators that can help students to meet their learning goals and to improve their success is defined. LAI are grouped in 4 levels. Level 1 contains three indicators – 1. Student Active Participation (Activity), 2. Student Success Rate and 3. Control of Scheduling. Each of these LAI contains one or more indicators of Level 2, every one of which groups LAI of Level 3. Each indicator of Level 3 groups indicators of Level 4, data for which are obtained through extraction and systematization of big data generated by students or/and teachers during training for each specific resource and activity (in the terms of Moodle) in the course or for the whole course.

The first indicator of Level 1 *1. Student Active Participation* (see Table 1) groups 3 LAI of Level 2 that allow students to track their active participation in the two types of Moodle activities (Learning activities for assessment and Learning activities for communication and collaborative work) and in the whole course and to compare their results with the average results of the other students in the course.

Table 1. Student Active Participation

Indicators of Level 2		
	Indicators of Level 3	
		Indicators of Level 4
Learning activities for assessment		
	SCORM Packages	
		Number of views of the SCORM package by the student
		Average number of views of the SCORM package by students in the course
		Number of attempts to perform the activity made by the student
		Average number of attempts to perform the activity made by students in the course
		Duration of student participation in the activity
		Average duration of students participation in the activity
	Database	
		Number of views of the Database by the student
		Average number of views of the Database by the students in the course
		Number of records added by the student during the current week
		Number of records added by the student during the previous week
		Number of records added by the student
		Average number of records added by students in the course

Indicators of Level 2		
	Indicators of Level 3	
		Indicators of Level 4
	Workshop	
		Number of views of the Workshop by the student
		Average number of views of the Workshop by students in the course
		Number of works submitted by the student
		Average number of works submitted by students in the course
		Number of works graded by the student
		Average number of works graded by students in the course
		Number of attempts of the student to submit a work
		Average number of attempts of students in the course to submit a work
	Glossary	
		Number of views of definitions in the dictionary by the student
		Average number of views of definitions in dictionary by students in the course
		Number of definitions added to the dictionary by the student
		Average number of definitions added to the dictionary by students in the course
		Number of definitions added by the student that are approved by the teacher
		Average number of definitions added by students in the course that are approved the teacher
	Lesson	
		Number of views of the Lesson by the student
		Average number of views of the Lesson by students in the course
		Number of attempts of the student to perform the activity
		Average number of attempts of students in the course to perform the activity
		Number of pages of the lesson visited by the student
		Average number of pages of the lesson visited by students in the course
		Duration of participation of the student in the activity
		Average duration of participation of students in the course in the activity
	Quiz	
		Number of attempts that students have to solve the Quiz
		Number of attempts made by the student to solve the Quiz
		Average number of attempts made by students in the course to solve the Quiz
		Time for which the student has solved the Quiz
		Average time for which students in the course have solved the Quiz
	External Tool	
		Number of views of the External tool by the student
		Average number of views of the External tool by students in the course
		Number of activities carried out within the External tool
	Assignments	
		Number of views of the Assignment by the student
		Average number of views of the Assignment by students in the course
		Number of submissions added by the student
		Average number of submissions added by students in the course
		Number of attempts of the student to respond (submit assignment)
		Average number of attempts of students in the course to respond
Learning activities for communication and collaborative work		
	Forum	
		Number of views of discussions by the student during the current week
		Number of views of discussions by students in the course during the previous week
		Total number of views of discussions by the student

Indicators of Level 2		
Indicators of Level 3		
	Indicators of Level 4	
		Average number of views of discussions by students in the course
		Number of discussions added by the student during the current week
		Number of discussions added by the student during the previous week
		Total number of discussions added by the student
		Average number of discussions added by students in the course
		Number of comments read by the student during the current week
		Number of comments read by the student during the previous week
		Total number of comments read by the student
		Average number of comments read by students in the course
		Number of comments added by the student during the current week
		Number of comments added by the student during the previous week
		Total number of comments added by the student
		Average number of comments added by students in the course
	Chats	
		Number of messages sent by the student during the current week
		Number of messages sent by the student during the previous week
		Number of messages sent by the student
		Average number of messages sent by students in the course
		Number of sessions views by the student
		Average number of sessions views by students in the course
	Wiki	
		Number of views of the Wiki by the student during the current week
		Number of views of the Wiki by the student during the previous week
		Number of views of the Wiki by the student
		Average number of views of the Wiki by students in the course
		Number of wiki pages added by the student during the current week
		Number of wiki pages added by the student during the previous week
		Number of wiki pages added by the student
		Average number of wiki pages added by students in the course
		Number of views of wiki pages by the student during the current week
		Number of views of wiki pages by students during the previous week
		Number of views of wiki pages by the student
		Average number of wiki pages by students in the course
Course		
	Course Activity by Time Period	
		Number of course views by the student during the current week
		Number of course views by the student during the previous week
		Duration of participation of the student in the course during the current week
		Duration of participation of the student in the course during the previous week
	Course Activity by Weeks	
		Number of course views by the student (for each week)
		Duration of participation of the student in the course (for each week)
	Learning Activities and Resources	
		Number of views of learning activities and resources by the student during the current week
		Number of views of learning activities and resources by the student during the previous week
		Number of views of learning activities and resources by the student

Indicators of Level 2		
	Indicators of Level 3	
		Indicators of Level 4
		Average number of views of learning activities and resources by students in the course
		Number of student participations in learning activities during the current week
		Number of student participations in learning activities during the previous week
		Number of student participations in learning activities
		Average number of participations of students in the course in learning activities

The second indicator of Level 1 *2.Student Success Rate* (see Table 2) groups 2 LAI of Level 2 that allow students to track their success rate in each type of Moodle activities and in the whole course and to compare their results with the average results of the other students in the course.

Table 2. Students Success Rate

Indicators of Level 2		
	Indicators of Level 3	
		Indicators of Level 4
Activities		
	Workshop	
		Student's grade for submission
		Student's grade for assessment of student peers' submissions
		Average grade for submission
		Average grade for assessment of peers' submissions
	Glossary	
		Number of definitions added by the student that are approved by the teacher
		Average number of definition added by students in the course that are approved by the teacher
		Grade
		Average grade of students in the course
	Lesson	
		Max time for activity performing by the student
		Average time for activity performing by students in the course
		Grade
		Average grade of students in the course
	External Tool	
		Grade
		Average grade of students in the course
	Assignment	
		Grade
		Average grade of students in the course
	Quiz	
		Grade
		Average grade of students in the course
	Database	
		Grade
		Average grade of students in the course
Course		
	Student success rate by time periods	
		Average grade of the student during the current week
		Average grade of students in the course during the current week
		Average grade of the student during the previous week

		Average grade of students in the course during the previous week
	Student success rate compared to average grade	
		Average grade of the student
		Average grade of students in the course

The third indicator of Level 1 3. Control of Scheduling (see Table 3) contains 1 indicator of Level 2 (containing 1 indicator of Level 3) that allow students to track the learning schedule for each Moodle resource and activity in the course as well as deadlines for activity performing and their grades.

Table 3. Control of Scheduling

Indicators of Level 3
Indicators of Level 4
Control of Scheduling
Resource/Activity
Schedule (time period)
Date and time of first access
Date and time of last access
Deadline for activity performing
Date and time when the student performs the activity
Graded/ Not Graded Activity

3. MOBILE LEARNING ANALYTICS APPLICATION

On the basis of the analysis of data stored in the Moodle database that can help students to improve their success and defined hierarchical system of LAI for systematization of this data a special Learning Analytics mobile application, Mobile LAP, is designed and implemented. The Mobile LAP gathers big data that the university collect in the used software systems, analyses that data, and generates reports in order to help students to improve their success.
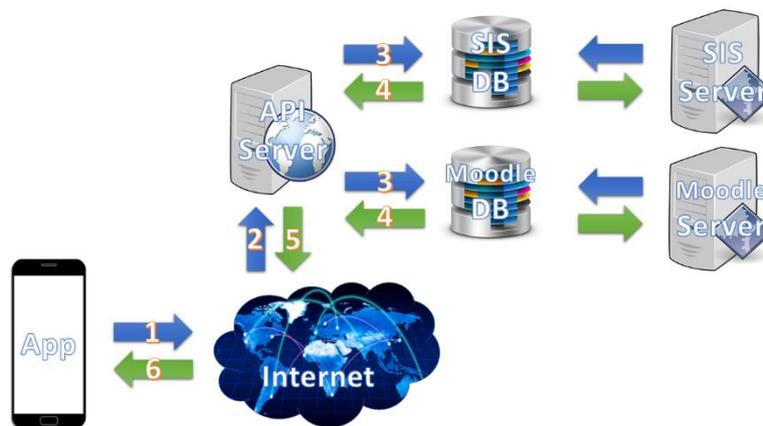

Figure 1. Architecture

The architecture of the Mobile LAP (see Figure 1) includes 7 components. The client application (App) sends requests to server application (API Server) that receives requests, processes requests and sends responses back to the App. Connection between

App and API server is provided through Internet. On the basis of the request type API server sends request for data to one of the used data sources – database of Student information system (SIS DB) or Moodle database (Moodle DB). Much of the data on which the mobile application depend comes from Moodle, including log-in information, courses, data for participation of student in specific activities, time students spend interacting with learning resources, activities or other students in the course, grades. The other part of data comes from the Student information system, including personal data for students and their grades obtained through the training. The database which has received the request, proceeds the request and sends data back to API server. API server process received data and send back response to App which processes the response from API server and visualises the response. The other two components are SIS Server (server running Student informational system software) and Moodle Server (server running Moodle).

The mobile application is simple and easy-to-use for students. It allows them to generate dynamically reports for their active participation in a course and their success rate, containing values of the defined LAI (see Table 1, Table 2, Table 3) and to compare their results with the average values for active participation and success rate of the other students in the course. These comparisons are helpful because they allow students to view if they are below or up to the average level of students in the course and can help to take measures to increase their activity and success. The APP allow students to track their learning schedule. They can use the APP to view details of resources and activities already completed and grades obtained, and the dates of impending ones. Students have alerts sent to their device through the app if their active participation shows they are falling below an average level. Assessment events also can be transferred to student calendar with alerts.

To use the mobile app students need to log in with their faculty number and EGN (PIN, LCN). After login students have to select the course for which they want to generate reports with values of LAI for their active participation, success rate or control of learning schedule. The course names between the students can select are extracting from the data source (Moodle database). This limits the user choice and thus eliminates the possibility of introducing incorrect data (courses that no exist in Moodle or courses in which the student is not enrolled). Besides selecting the course name, students have to select report from which of the three main sections (see Figure 2, Screen 1) they want to generate:

- Control of Scheduling - allows students to view if they read learning resources/activities and submit the assignment on-time, late, or not at all.

- Activity - allow students to view what their active participation in learning activities and resources (page view, participations, assignments, etc.) is compared to the average level of active participation of other students in the course.

- Success Rate - allow students to view what their grades in learning activities are compared to the average grade of students in the course.
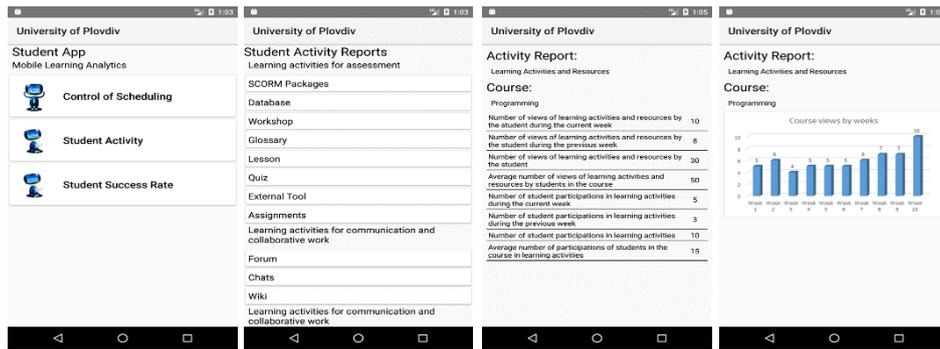
Figure 2. Screens of Mobile Learning Analytics Application

Each one of these three sections contains a list of reports with names corresponding to the indicators of Level 3 from Table 1, Table 2 and Table 3 (see Figure 2, Screen 2) between the students have to select. The generated report contains values of LAI of Level 4 presented in a variety of ways (including tables, charts, graphs of active participation over time compared with others, etc.) that students can use to improve their success. Screen 3 and Screen 4 present an examples of generated reports. The report from Screen 3 contains summarised data about student' activity in all learning resources and activities in Programming course. The analytic results show that the activity of the student is below the average level of the students in the course. These results can help student to take measures to increase him/her activity during the next week. The report from Screen 4 contains one chart that presents how many times the student has accessed Programming course during its time period – 10 weeks. The chart clearly shows that the student has participated most active in the course during the last four weeks.

4. CONCLUSION AND FUTURE WORK

Mobile LAP provides information to students about their learning activity. It allows students to track their activity and success rate during training and to compare them with the average level of activity and success rate of the other students in order to increase their success as well as to track whether they adhere to the learning schedule.

Mobile LAP will be expanded with functionalities allowing students to compare their active participation and success rate with these of excellent students from previous cohorts. The users' privacy [17] and data protection [18] will be improved in the next version. Other data sources containing data that can help students to improve their success (e.g. library system) will be added.

The developed mobile application will be tested over the next school year from full-time students. On the basis of the feedback from students the functionalities of the application will be expended.

extraction and aggregation of data for knowledge and processes in learning" of the Scientific Research Fund at the University of Plovdiv.

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