COMPARATIVE ANALYSIS OF LEARNING ANALYTICS TOOLS TO IMPROVE LEARNING USED IN DIFFERENT LEARNING PLATFORMS

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Abstract

The aim of the paper is to present Go-Lab and Moodle learning platforms as tools suitable for applying Learning Analytics to improve learning. Moodle is one of the most popular open source learning platforms used both in schools and Universities, and Go-Lab is learning platform for Inquiry-Based Science Education in schools developed in Go-Lab project funded by EU 7FP programme and continued to be developed in new Next-Lab project funded by Horizon 2020. Learning Analytics aims to collect and analyse user activities to make learning and learning environments more effective and efficient. Go-Lab Learning Analytics services provide means to track user activities and analyse this tracked data. This provides the foundation for guidance mechanisms for students through scaffolding, as well as intelligent decision support for teachers and lab owners. More specifically, Learning Analytics services provide support for recommendations, intelligent feedback for students, and analytical reports that help to design better Inquiry-Based Learning scenarios and spaces. The add-on services consist of the bartering platform and the lab booking system to support Go-Lab Portal in different aspects. The bartering platform offers teachers peer assistance through a tutor social platform for expertise sharing related to online labs and inquiry learning spaces. Teachers are motivated to help other teachers and share their skills and knowledge about online labs on the bartering platform. On the other hand, there are the number of reports, blocks and other plugins for Moodle that provide Learning Analytics in this platform such as logs, activity, statistics etc. which are useful for students, teachers, administrators and decision-makers. A number of systems can be integrated with Moodle to provide Learning Analytics information. The paper is organised as follows: (1) systematic review on research topic, (2) analysis of Learning Analytics / educational data mining tools used in both platforms, (3) comparative analysis of possibilities provided by Learning Analytics tools in both platforms to improve learning, and (4) discussion and conclusion. The work presented in this paper is partially supported by the European Commission under Horizon 2020 research and innovation programme – as part of the Next-Lab project (Grant Agreement Number No 731685).

Keywords: Go-Lab, Moodle, Learning Analytics, Inquiry-Based Science Education, learning scenarios, bartering platform.

1 INTRODUCTION

The aim of the paper is to present Learning Analytics (LA) / Educational Data Mining (EDM) tools applied in Go-Lab and Moodle learning platforms to improve learning.

According to numerous researches, one of the most promising approaches to improve learning is its personalisation supported by application of intelligent technologies [1], [2], [3], [4], [5], [6], [7], [8].

Personalisation can be seen from two different perspectives, namely, while only one learning object (LO) [9], [10], [11], [12], [13], [14], [15] or a learning unit / scenario [16], [17], [18], [19], [20], [21], [22] is selected, and while a set of them is composed, i.e. personalisation of a learning unit / scenario by finding a learning path.

The reminder of the paper is organised as follows: systematic review results on research topic are presented in Section 2, analysis of LA / EDM tools used in Go-Lab platform is provided in Section 3, in Moodle platform – in Section 4, comparative analysis of possibilities provided by Learning Analytics tools in both platforms to improve learning is provided in Section 5, and discussion and conclusion finish the paper.

2 SYSTEMATIC REVIEW RESULTS

Systematic review according to methodology proposed by [23] was previously performed by the author in [24] and expanded in [25].

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According to [24], during XXI century (2001-2017), 82 publications (from which – 35 articles) in English were found on March 26, 2017, in Clarivate Analytics Web of Science database on the topic “TS=(virtual learning environment* AND learning analytics)”, and 604 publications (from which – 264 articles) – on the topic “TS=(learning management system* AND data mining)”.

After applying systematic review methodology [23], on the last stage 9 newest most suitable articles [26], [27], [28], [29], [30], [31], [32], [33], [34] were identified to further detailed analysis on possible application of LA / EDM to support learning in learning platforms / Virtual Learning Environments (VLEs).

This systematic review has shown that LA / EDM are already quite actively used in VLEs e.g. Moodle to solve different problems e.g. academic assessment, predicting students’ success and dropout, predicting instructional effectiveness of VLEs, etc. At the same time, LA / EDM are still rarely used to personalise learning in VLEs according to students’ needs, and future research is needed in the area.

As it was mentioned before, this systematic review was further expanded by the author in [25]. A number of papers on LA / EDM usage in VLEs were presented there, e.g. [35], [36], [37] to mention some of them.

The results of the review presented in [25] were as follows:

Due to increased usage of internet technologies, huge data is available in every sphere of life. The role of data mining has thus become very crucial to extract this hidden information from big data. The basic techniques in LA / EDM and their application examples are as follows:

- Classification: to classify each item in a set of data into one of a predefined set of learners group
- Clustering: to determine groups of students that need special course profiling
- Association rules: to discovering interesting relations between course elements which were used by student
- Prediction: to predict dependencies of using of Moodle activities and the final student grade

These techniques can be used together or one after the other, depending on the complexity of the task solved.

3 LEARNING ANALYTICS TOOLS IN GO-LAB

The Next-Lab Project (Next Generation Stakeholders and Next Level Ecosystem for Collaborative Science Education with Online Labs) [38] is a European research project focusing on the introduction of inquiry-based science education in schools. It has started on 1st of January 2017 and is the main sponsor of the Go-Lab Portal continuing the successful Go-Lab initiative.

The philosophy and technology of Next-Lab base on its previous project Go-Lab, and continues its mission of promoting innovative and interactive methods of teaching science in primary and secondary schools across Europe. Next-Lab expands its target group by also addressing younger students in primary education and by involving not only in-service but also pre-service teachers making efforts to align the project with teacher training programmes in different countries.

The Next-Lab portal as an environment for various kinds of inquiry-based learning activities generates many types of data, including traces of interaction with the system and results of the learning process. The LA services make use of such data to provide analytical information for the Next-Lab portal and add-on services in order to foster awareness, create individual scaffolds for students as well as information for teachers supporting the monitoring of learning activities and better informed decision making.

The focus of the analytics and scaffolding services in Next-Lab is on interaction and content analysis. For a better overview the LA services can be aligned to three aspects of the Next-Lab portal where different activities take place that can be supported.

One aspect is the portal as a whole. In the portal, the LA services can help teachers to find appropriate resources, for example through recommendations of apps, labs and inquiry learning spaces (ILS) templates.

The second aspect is to monitor the students' behaviour at the level of ILS in order to get a clear picture of their overall learning activities. This includes log protocols comprising of time stamped events like the access of a resource and app usage.

The analysis of the student actions when using particular apps and the thereby produced data is a third aspect which leads to tailored scaffolding and feedback mechanisms. Scaffolding mechanisms assist learners in tasks that they cannot solve alone without guidance. Based on previous analysis and modelling of learner behaviour it is possible to adapt the scaffolds to the needs of each particular learner. Typical scaffolding mechanisms are immediate feedback for example recommendations or the adaptation of an app according to the learner model.

Scaffolding services for learners rely on information about the labs, its users and their user activities as well as the subject domain of the lab. Therefore scaffolding apps are dependent on the lab metadata scheme developed in the project's WP5 as well as the smart device and gateway for remote labs.

For all types of LA it is beneficial that the results be accessible in the current learning context and not only in separate spaces [39]. This facilitates the usage of the LA results as they are offered in the context of the learning and teaching process and thus can also be connected more easily. This means there is not only the challenge to define and implement appropriate LA tools but also the challenge to integrate these with the learning and authoring platforms. One possible approach is to embed the results of external analysis tools (of possibly more general type) into the learning platforms to make the results of the analysis process directly accessible in the context of the platform. Technical solutions and architectural models for this approach have been developed in [40] and [41], the latter explicitly contextualised in the framework of Next-Lab.

The following user scenarios highlight how the stakeholders can benefit from the LA services within the Next-Lab portal and apps:

- LA for the lab repository- recommendations of resources in the Next-Lab Repository;
- LA on the ILS platform level – is focused on LA apps for supporting teachers in supervision, which is realised through a teacher dashboard;
- LA in apps – describes individual learner support through LA apps which are embedded in the ILS platform;
- Composition of micro-services to be embedded as an app – demonstrates how an analyst uses the analytics workbench in Next-Lab to create a micro-service to be deployed and published without any programming;
- Development of LA services and apps – describes the use case of the development of LA apps and services for project members and researchers in the field of LA.

Requirements:

The production of useful analysis processes is not an easy task, and it needs different methods and apps for each one of these different actors. There are at least four types of users who can benefit from analytics and scaffolding services.

Students: The main information need of students is awareness on the learning process and guidance. Thus, the LA services should enable self-reflection and recommend activities and resources to the learner individually.

Teachers: The teacher's perspective focuses on monitoring and instrumentation for classroom management, especially awareness of student behaviour in an ILS. In addition, Next-Lab supports teachers in finding and structuring learning material.

Lab owners: Analysis of lab usage can provide valuable information to lab owners. Hence, lab usage statistics can also be very useful in resource planning and lab booking. Insights into the usage patterns of labs helps to assess whether the lab is used as intended or modifications and user guidance are needed.

Researchers: LA can support Next-Lab researchers in decision making regarding the Next-Lab development. The large-scale data collection can foster new insights in the research field of technology-enhanced learning. Furthermore, the LA services will be exploited by the development of other services like personalisation and recommendation.

4 LEARNING ANALYTICS TOOLS IN MOODLE

Despite the fact that Moodle is one of the most popular VLEs it does not have any scenarios for personalised eLearning, which depend on users' needs, possibilities and etc. Creating personalised course content can result and increase engagement of any course in any VLE. To create such type of personalised course content in Moodle users need to use the FilterCodes plugin. The FilterCodes plugin gives the ability to create customised and personalised site and course content by using plain text tags. It is enough easily: insert the name of the students anywhere by simply adding plain text tags like {firstname} into the Moodle site or course content. It is also possible to show/hide any specific content in the course based on the user role. Even it can be used to fill in the user details automatically into Contact Forms. If the condition is not yet in the particular context, the specified tag and its content will be removed.

In order to personalise course content from the technical point of view all data which users/teachers/analytics can receive are accumulated in database tables (about 130). Despite of which method for course/student personalisation will be used, the entire tasks of Data Mining must be observed: extract, transform and load the data before choosing the right techniques. .

Application of LA to personalise learning in Moodle was previously analysed by the author in detailed way in [25]. In [25], first, existing Moodle-based learning activities and tools were interlinked with students' learning styles according to Felder-Silverman learning styles model [42] using expert evaluation method {13], [14], [18]. Second, a group of students was analysed to identify their individual learner profiles, and probabilistic suitability indexes [19] were calculated for each analysed student and each Moodle-based learning activity to identify which learning activities or tools are the most suitable for particular student. The higher is suitability index the better learning activity or tool fits particular student's needs [2], [19]. Third, using appropriate LA methods and techniques, we could analyse what particular learning activities or tools were practically used by these students in Moodle, and to what extent. Fourth, the data on practical use of Moodle-based learning activities or tools could be compared with students' probabilistic suitability indexes [19]. In the case of any noticeable discrepancies, students' profiles and accompanied suitability indexes should be identified more precisely, and (fifth) students' personal leaning paths in Moodle should be corrected according to new identified data. Thus, using LA, we could noticeably enhance students' learning quality and effectiveness.

5 COMPARATIVE ANALYSIS

According to [25], classification, clustering, association rules and prediction are the most suitable LA / EDM methods/techniques to be applied to personalise learning in learning platforms.

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2 The second aspect is to monitor the students' behaviour at the level of ILS in order to get a clear picture of their overall learning activities. This includes log protocols comprising of time stamped events like the access of a resource and app usage.

3 The analysis of the student actions when using particular apps and the thereby produced data is a third aspect which leads to tailored scaffolding and feedback mechanisms.

In [25], five-stage methodology is presented aimed at enhancing students' learning quality and effectiveness in Moodle. Felder-Silverman learning styles model [42] and appropriate learning styles questionnaire [43] were applied to identify particular students' learning styles, expert evaluation was applied to establish probabilistic suitability indexes of learning activities and particular students, and LA / EDM were be used to identify what particular learning activities were practically used by these students in Moodle, and to what extent. Finally, in the case of any discrepancies, students' personal learning styles and optimal learning units should be corrected appropriately.

6 DISCUSSION AND CONCLUSION

The advantages of personalizing eLearning with systems that provide smart adaptivity are:

- Educational planning becomes an active process based on objective data;
- The complexity level of training corresponds to the individual students needs
- The motivation becomes high

Nerveless such systems also have some difficulties disadvantages of personalisation as an eLearning scenario can be reduced to the following list:

- There is a risk of misinterpretation of training needs of students due to incorrect interpretation of data by LA systems;
- The costs of creating adaptive learning systems and the necessary LA systems are very high;
- As many as would be the classifications of trainees, to fully reflect the variety of personal characteristics of the user to date, no system is able to;
- A single style of personification – the use of mean values identified by LA and used to build typical learning paths (the style of personification of the educational experience "Decision tree") – contradicts the individual approach to the trainee;
- When using adaptive systems, the ability of the learner to self-organise student's progress in the learning process is reduced.

Regardless of the fact that personalisation is an open question in the scientific community and given the information provided, it can be said that the new generation of education system, such as Next-Lab includes all the necessary tools for increasing the quality of education, the level of knowledge obtained, etc.

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