Journal of Universal Computer Science, vol. 21, no. 1 (2015), 1-6
submitted: 14/11/14, accepted: 28/11/14, appeared: 1/1/15 © J.UCS

Learning Analytics

J.UCS Special Issue

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1 Introduction

Already back in 2006 Retalis et al. [Retalis, 06] proposed their first thoughts on Learning Analytics (LA) and considered interaction analysis as a promising way to better understand the learner's behavior. A couple of years later, further activities were organized; especially Siemens and Long [Siemens, 11] predicted that the most important factor shaping the future of higher education would be big data and analytics. Just few months later, the Horizon Report [Horizon, 11] also described Learning Analytics as a big trend for the forthcoming years. Since then a number of conferences (for example LAK 11[1], LAK 12, …) have been organized and different projects have been started as well as the topic has been rising on Google trends[2]. The number of research publications has also increased arbitrarily in different directions; for instance to define the upcoming research field [Siemens, 12] [Duval, 11] [Elias,

[1] Learning Analytics and Knowledge Conference

[2] http://www.google.com/trends/explore#q=Learning%20Analytics (last visited October 2014)

11] [Drachsler, 12], to gather practical experiences [Schön, 12] [Ebner, 13] or simply to confine LA from other topics (especially from Educational Data Mining (EDM)) [Baker, 12].

2 Special Issue on Learning Analytics

As mentioned above, the analysis and discovery of relations between human learning and contextual factors that influence these relations have been one of the contemporary and critical global challenges facing researchers in a number of areas, particularly in education, psychology, sociology, information systems, and computing. Traditionally, these relations concern learner performance and the effectiveness of the learning context from a summative point of view. Be it the assessment marks distribution in a classroom context or the mined pattern of best practices in an apprenticeship context, analysis and discovery have always addressed the elusive causal question about the need to best serve learners' learning efficiency and the need to make informed choices on a learning context's instructional effectiveness.

Learning efficiency encompasses any and all aspects that concern "learning" of individual learners or groups of learners. Examples of learning efficiency aspects include learning style, metacognitive scaffolds, peer interactions, self-regulation, co-regulation, social networking, and other learning-oriented activities and characteristics associated with learners.

Instructional effectiveness encompasses any and all aspects that concern enhancement of targeted as well as inadvertent "support for learning". Examples of instructional effectiveness include pedagogy, andragogy, peer evaluation, software-agent-oriented guidance, lectures, content, presentation of content, instructional design, learning objects and other resources, assessment structures, open learning, and so on.

With the advent of new technologies such as eye-tracking, activities monitoring, video analysis, content analysis, sentiment analysis and interaction analysis, the world of learning analytics has emerged as a vast research area with strong potential in various forms of formal, informal and non-formal learning opportunities. This special issue focuses on these research dimensions and aims to foster discussion on both individual impacts of these dimensions and their interdependencies.

3 Contributions of the special issue

The special issue got huge attention due to the fact that Learning Analytics is a big topic in the field of Technology Enhanced Learning these days. Nevertheless a careful peer-review-process reduced the number of contributions to finally eight:

3.1 The Procrastination Related Indicators in e-Learning Platforms

This paper by Paule-Ruiz, Riestra-González, Sánchez-Santillán and Pérez-Pérez discusses the use of indicators in e-learning systems. By establishing the importance of providing visual support as feedback during learning process, the authors consider

indicators as tools to both help instructors and learners in planning and development of learning strategies, and help system in generating recommendations ad decisions. The analysis of the indicators and associated learning analytics in actual e-learning platforms led to better understanding of the effective use of indicators and the influence of academic procrastination in the learning performance.

3.2 Dropout prediction and reduction in Distance Education courses with the Learning Analytics Multitrail approach

Cambruzzi, Rigo and Barbosa look at dropout rates in distance education courses using learning analytics approaches. Authors developed a system to deal with dropout problem in such courses at university level; using Multitrail approach, which represents and manipulate data from several sources and formats. The system incorporates various tools for data visualization, dropout predictions, support to pedagogical actions and textual analysis. Experiments using the system demonstrated dropout prediction with 87% precision, which enabled implementation of specific pedagogical action resulting in 11% average reduction in dropout rates.

3.3 Learning Analytics for the Academic: An Action Perspective

Dix and Leavesley sketch the big picture of the application of learning analytics in academic education. Their tour d'horizon starts with the quest for actionable analytics fitting into the pattern of requirements and necessities of academic life of students, academics and their institutional context. The authors identify the crucial role of (lack of) time in a task structure with multiple competing goals and analyze the conditions under which the availability of learning analytics can influence learning and teaching by triggering action. The presented framework based around academic timescales starting off with daily routines and ending with multi-year curricular development processes focuses on strategies for synchronizing the recognition of need with the potential for execution in teaching and learning interventions.

3.4 Learning Analytics at "Small" Scale: Exploring A Complexity-Grounded Model for Assessment Automation

Goggins, Xing, Chen, Chen and Wadholm argue that summative evaluation of learning in small collaborative groups neglects the quality of learning centered interaction in the group and does not assist in-time scaffolding and intervention by teachers. Hence they propose and explore an automatic assessment model for technology-mediated small group learning that takes into account a range of events: communication, tool selection, whiteboard actions and system events. These data are processed on the basis of a simple, theoretically sound rule set that focuses on the development of the learning process. By applying Tree Augmented Naïve Bayes Classifiers they are able to do fully automatic formative tracking of the interactive learning process that can easily be monitored and interpreted by teachers.

3.5 Towards a Learning-Aware Application Guided by Hierarchical Classification of Learner Profiles

Taraghi, Saranti, Ebner, Müller and Großmann describe the use of implicit feedback, based on learner's answering behavior in the Android application *UnlockYourBrain* for mathematics learning. An analytical approach is introduced in the paper for modeling a learner profile on the basis of such answering behavior. Similar learner's profiles are grouped together to construct learning behavior clusters using hierarchical clustering. Authors conclude that building awareness about learners' behaviors is critical for future learning-aware applications.

3.6 Development of the Learning Analytics Dashboard to Support Students' Learning Performance

Park and Jo present the *Learning Analytics Dashboard (LAD)* application that shows online behavior patterns of students in virtual learning environment. The application tracks students' log files to mine large amounts of data to find meaning and visualize the results. While a usability test on an early version of LAD did not find any significant impact on students' learning achievements, it did reveal that visualized information had impact on students' understanding level and the overall satisfaction with LAD contributed to both students' degree of understanding and their perceived change of behavior.

3.7 A Visual Analytics Method for Score Estimation in Learning Courses

In order to foster self-awareness of students, de-la-Fuente-Valentín, Pardo, López Hernández and Burgos describe a visual analytics technique that enables students to compare their learning performance to that of others. The presented method is based on similarity measures between students' behavior and the relation to their final grade, under the assumption that the students who behave similarly are graded similarly. The approach is validated then with an empirical evaluation.

3.8 Learning Analytics for English Language Teaching

In this work by Volk, Kellner and Wohlhart the collected data from an online language-learning platform is analyzed. The presented results comprise usage behavior over the whole school year as well as user activities in different school types among different Austrian provinces on a large scale. Furthermore the efficiency and effectiveness of different type of exercises are explored.

4 Program Committee

We express our gratitude to the program committee for their valuable work on reviewing all contributions and giving detailed feedback. Thank you for your expertise:

- Dietrich Albert (Graz University of Technology, Austria)
- Ulrike Cress (University Tübingen, Germany)

- Shane Dawson (University of South Australia, Australia)
- Michael Derntl (RWTH Aachen University, Germany)
- Margarete Grimus (Graz University of Technology, Austria)
- Andreas Holzinger (Medical University Graz, Austria)
- Michael Kickmeier-Rust (Graz University of Technology, Austria)
- Siu Cheung Kong (The Hong Kong Institute of Education, Hong Kong)
- Michael Kopp (University of Graz, Austria)
- Yanyan Li (Beijing Normal University, China)
- Felix Mödritscher (Vienna University of Economics and Business, Austria)
- Alexander Pohl (University of Munich, Germany)
- Mimi Recker (Utah State University, USA)
- Martin Schön (Graz University of Technology, Austria)
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- Patrick Schweighofer (University of Applied Sciences, Campus02, Austria)
- Philip Tsang (Caritas Institute of Higher Education Hong Kong, Hong Kong)
- Katrien Verbert (Eindhoven University of Technology, Belgium)

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November 2014

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