

Learning Analytics for Learners: Preface to Proceedings of First LAL Workshop at LAK'16

Susan BULL
University College London, UK

Blandine GINON
University of Birmingham, UK

Judy KAY
University of Sydney, Australia

Michael KICKMEIER-RUST
Technische Universität Graz, Austria

Matthew D. JOHNSON
University of Birmingham, UK

1. MOTIVATION

With the arrival of 'big data' in education, the potential was recognised for learning analytics to track students' learning, to reveal patterns in their learning, or to identify at-risk students, in addition to guiding reform and supporting educators in improving teaching and learning processes [1]. Learning Analytics dashboards have been used at all levels, including institutional, regional and national level [2]. In classroom use, while learning visualisations are often based on counts of activity data or interaction patterns, there is increasing recognition that learning analytics relate to *learning*, and should therefore provide *pedagogically useful* information [3]. While increasing numbers of technology-enhanced learning applications are embracing the potential of learning analytics at the classroom level, often these are aimed at teachers. However, learners can also benefit from learning analytics data (e.g. [4][5]).

Learner models hold data about an individual's understanding or skills, inferred during an interaction, and are at the core of educational systems that personalise the learning interaction to suit the needs of the learner [6]. Open learner models externalise the learner model to the user, and have long been showing learners information about their own learning, often with the aim of encouraging metacognitive behaviours such as reflection, planning, self-assessment and self-directed learning [7]. Benefits of showing learning data to learners for such purposes are now also being investigated in learning analytics (e.g. [8][9]). Nevertheless, despite a few exceptions (e.g. [9][10][11][12]), there is limited reference to both open learner models and learning analytics in the same publications. One of the aims of the Learning Analytics for Learners workshop, therefore, was to raise awareness of the overlap, as well as differences, in approaches to, and purposes of visualising and/or using learning data in these two fields.

2. SUBMISSION AND REVIEWING

Submissions were sought on any aspect of learning analytics aimed at learners. Submissions were reviewed by three members of the Program Committee, and papers and reviews were also scrutinised by members of the organising team. The papers were then discussed by the organisers, with particular attention given to cases where there was any disagreement amongst the reviewers. Of the ten submissions received, eight were accepted for presentation at the workshop.

We thank the members of the Learning Analytics for Learners Program Committee for their substantial efforts in making the workshop a success. Program Committee members were:

- Simon Buckingham Shum, University of Technology, Sydney, Australia
- Susan Bull, University College London, UK
- Eva Durall, Aalto University, Finland
- Albrecht Fortenbacher, HTW Berlin, Germany
- Alyssa Friend Wise, Simon Fraser University, Canada
- Dragan Gasevic, University of Edinburgh, UK
- Blandine Ginon, University of Birmingham, UK
- Dai Griffiths, University of Bolton, UK
- Sharon Hsiao, Arizona State University, USA.
- Stéphanie Jean-Daubias, University Claude Bernard of Lyon, France
- Matthew Johnson, University of Birmingham, UK
- Judy Kay, University of Sydney, Australia
- Michael Kickmeier-Rust, Technische Universität Graz, Austria
- Symeon Retalis, University of Piraeus, Greece
- Ravi Vatrapu, Copenhagen Business School, Denmark

The workshop sold out quickly at full capacity (40 participants), highlighting the timeliness of this topic in Learning Analytics.

3. WORKSHOP PAPERS

The main themes that were addressed in the workshop papers were *visualisation/dashboards*, *metacognition/awareness*, and *social learning*. Several papers considered more than one of these themes. Hatala et al.'s paper compares students' approaches to learning to learning analytics visualisations, and the quality of messages posted. Al-Shanfari et al.'s paper proposes ways to visualise uncertainty in data in an open learner model context. Marzouk et al.'s paper investigates facilitating self-monitoring and the type of analytics that may meaningfully prompt changes to learning, including social learning. Venant et al.'s paper also considers metacognition, awareness and deep learning, and social awareness; and Davis et al.'s demonstration paper explores self-regulation, and comparison to previous successful learners. Knight and Anderson take a theoretical perspective, arguing for participatory design for learning analytics for learners. Wasson et al.'s position paper argues for the need to address data literacy, and training learners in the new approaches and learning analytics and/or open learner model tools available to them. Finally, Martinez-Maldonado et al.'s paper also explores both learning analytics and open learner models, in their case to support behavioural change in a health context.

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