The Connected Learning Analytics Toolkit

Kirsty Kitto[#] Aneesha Bakharia [#] Mandy Lupton[#] Dann Mallet [#] John Banks[#]
Peter Bruza [#] Abelardo Pardo[*] Simon Buckingham Shum[⊙] Shane Dawson[†]
Dragan Gašević[†,▹] George Siemens[ϒ] Grace Lynch[⋄]
[#]Queensland University of Technology (QUT), Australia, [*]University of Sydney, Australia, [⊙]University of Technology Sydney, Australia, [†]University of South Australia, Australia, [▹]University of Edinburgh, Scotland, [ϒ]University of Texas (Arlington) USA, [⋄]Royal Melbourne Institute of Technology (RMIT), Australia.
kirsty.kitto@qut.edu.au

ABSTRACT

This demonstration introduces the Connected Learning Analytics (CLA) Toolkit. The CLA toolkit harvests data about student participation in specified learning activities across standard social media environments, and presents information about the nature and quality of the learning interactions.

Categories and Subject Descriptors

K.3.1 [**Computers and Education**]: Computer Uses in Education; H.5.2 [**Information Interfaces and Presentation**]: User Interfaces

Keywords

sensemaking, dashboards, social learning analytics

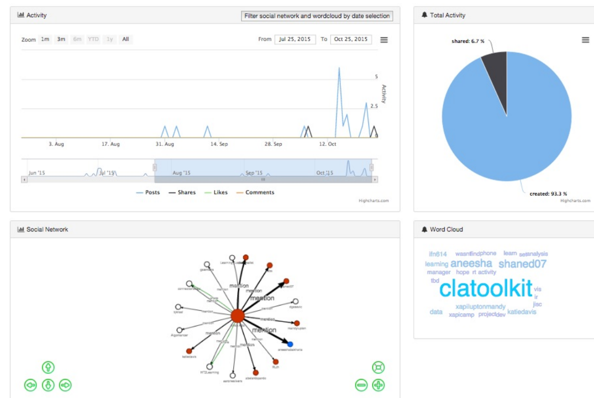

Figure 1: The student facing dashboard.

1. THE CONNECTED LEARNING ANALYTICS TOOLKIT

The Connected Learning Analytics Toolkit (CLA Toolkit) aims to improve the quality of student engagement and learning in collaborative online environments [8]. It does so by incorporating and analysing data from social media platforms that the majority of students already use in their personal lives, and increasingly make use of in education. The toolkit addresses prior challenges associated with teaching outside of the Learning management system (LMS) by allowing for data to be collated and visualised across a suite of education technologies and social media that any teacher could choose as fit for purpose. Students sign up to have their data collected for a series of pre-specified learning activities, a move that preserves student privacy [9], and goes some way towards a model of data ownership where the student controls access to their data [5]. Upon logging in, students are presented with a dashboard (see Fig. 1) that helps them to examine their participation in almost real time.

LAK '16 April 25-29, 2016, Edinburgh, United Kingdom

ACM ISBN 978-1-4503-4190-5/16/04.
DOI: http://dx.doi.org/10.1145/2883851.2883881

The CLA toolkit is Open Source (under a GPL3.0 license), with the current version available via GitHub [6]. Collected data is stored in the Experience API (xAPI) format, and so any analytics system making use of this format could extend the data capture functionality of the CLA toolkit to its specific purpose. The analytics functionality of the CLA toolkit is implemented by extracting xAPI statements in JSON form and storing them in a PostgreSQL database that can be queried as needed. This has allowed us to implement a number of standard analytics and dashboards. At present we have taken inspiration from SNAPP [2], LOCO-Analyst [1] and Social Learning Analytics [10], to develop a set of dashboards that help (i) students to explore the nature of their online social interactions, and (ii) instructors to find and interpret patterns of behaviour in a class.

The student facing dashboard (Fig. 1) currently includes an activity report that relates to their individual participation, a word cloud of concepts discussed by that student, and first degree social network analysis (higher order connections can be extracted, but are currently not reported to students to respect their privacy and current ethical approvals). This dashboard helps students to explore the nature of their online interactions using a number of filtering options, which allow them to examine particular time frames, or interactions with specific students.

Instructors currently see more analytics due to both privacy concerns, and the fact that the algorithms we are using require larger datasets than are normally available to individuals. Firstly, an aggregated Activity Dashboard (Fig. 2)

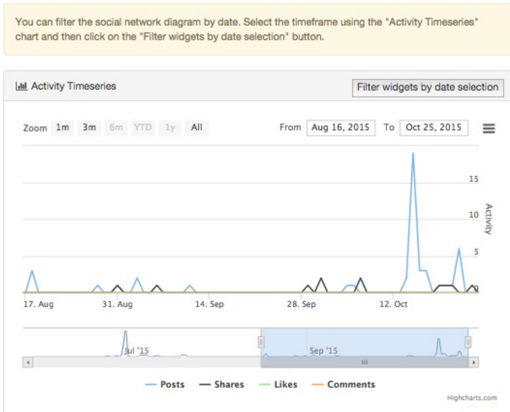

Figure 2: The Activity Dashboard.

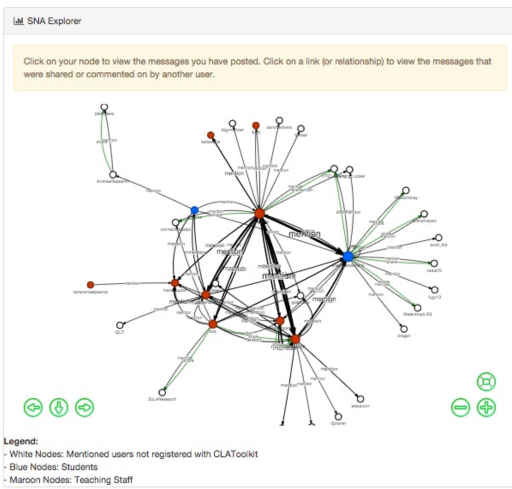

Figure 3: The Instructor facing SNA Dashboard.

can be used to both investigate behavioural patterns in a class, filter the other reports (i.e., SNA and Content Analysis), and to access the student dashboards for people in their class. The Instructor facing Social Network Analysis (Fig. 3) displays the type of connections occurring between people signed up to the system (description is unified using the Connected Learning Recipe [7]), and also allows for drill down examination of sub-connections and interactions. The Content Analysis dashboard shown to instructors (Fig. 4) currently includes a basic word cloud; Topic Modelling using the Latent Dirichlet Allocation algorithm; sentiment analysis [4]; and a Cognitive Presence classification from the Community of Inquiry model [3].

2. THE DEMONSTRATION

The current state of the dashboards available in the CLA toolkit can be explored by anyone in a trial account at:
`http://clatoolkit.beyondlms.org/`
`username: trialAccount`
`password: tryoutCLAtoolkit`
This Demonstration will exhibit current capabilities, as well as giving attendees assistance in registering for a 'LAK16' course which will help them track their engagement with the

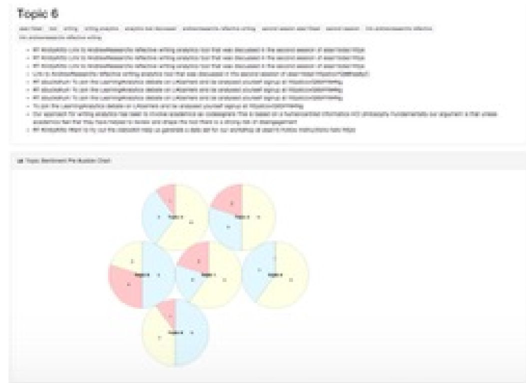

Figure 4: Content Analysis Dashboard

conference.

3. ACKNOWLEDGMENTS

Support for this project has been provided by the Australian Government's Office for Learning and Teaching (OLT). The views in this project do not necessarily reflect the views of the OLT.

4. REFERENCES

[1] L. Ali, M. Hatala, D. Gašević, and J. Jovanović. A qualitative evaluation of evolution of a learning analytics tool. *Computers & Education*, 58(1):470–489, 2012.

[2] S. Dawson, A. Bakharia, and E. Heathcote. SNAPP: Realising the affordances of real-time SNA within networked learning environments. In *Proceedings of the 7th International Conference on Networked Learning*, pages 125–133, Denmark, Aalborg, 2010.

[3] D. R. Garrison, T. Anderson, and W. Archer. Critical thinking, cognitive presence, and computer conferencing in distance education. *American Journal of distance education*, 15(1):7–23, 2001.

[4] C. Hutto and E. Gilbert. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Eighth International AAAI Conference on Weblogs and Social Media*, 2014.

[5] K. Kitto. Towards a manifesto for data ownership. http://www.laceproject.eu/blog/towards-a-manifesto-for-data-ownership/.

[6] K. Kitto and A. Bakharia. CLAToolkit, 2015. https://github.com/kirstykitto/CLAToolkit.

[7] K. Kitto and A. Bakharia. CLRecipe, 2015. https://github.com/kirstykitto/CLRecipe.

[8] K. Kitto, S. Cross, Z. Waters, and M. Lupton. Learning analytics beyond the lms: the connected learning analytics toolkit. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge*, pages 11–15. ACM, 2015.

[9] A. Pardo and G. Siemens. Ethical and privacy principles for learning analytics. *British Journal of Educational Technology*, 45(3):438–450, 2014.

[10] S. B. Shum and R. Ferguson. Social learning analytics. *Journal of educational technology & society*, 15(3):3–26, 2012.