Dreaming of Electric Sheep: CSU's Vision for Analytics-Driven Adaptive Learning and Teaching

Simon Welsh
Adaptive Learning and Teaching
Services Charles Sturt University

Philip Uys
Learning Technologies
Charles Sturt University

Current institutional approaches to Learning Analytics which focus on student risk and engagement are problematic in terms of their ability to support improved student learning and success outside of retention. Charles Sturt University's (CSU's) deductive work on defining its institutional model of Learning Analytics has led it to reconfigure its Learning Analytics activities into an Adaptive Learning and Teaching program. Adaptive Learning and Teaching is defined as any educational approach that utilises feedback or analytics on student learning to adapt content, teaching, systems and/or design to enhance learning effectiveness. A key feature of the CSU vision is to focus analytic processes on students' representations of knowledge and integrate with the student "digital footprint" to provide real-time adaptation of online learning experiences and personalise online learning. Concurrently, CSU's Adaptive Learning and Teaching Services team is working to build capability in using Learning Analytics to inform adaptation in learning and teaching practices.

Keywords: Learning Analytics; Adaptive Learning; Deductive; Inductive; Analytics Strategy; Organisational Design; Student Success; Personalised Learning; Online Learning

A Brief History of Learning Analytics at Charles Sturt University

In 2013, Charles Sturt University (CSU) established a Learning Analytics Working Party (LAWP), a multidisciplinary body bringing together stakeholders from across faculties, technology, business intelligence, library, student support and administration. The second author of this paper is the founder and chair of LAWP. The LAWP then developed a Learning Analytics Strategy and CSU appointed a staff member, the first author of this paper, to drive the implementation of that strategy. An initial step in the implementation was to define how the institution wanted to apply Learning Analytics across CSU.

A Model of Learning Analytics was developed by the LAWP that identifies and defines the elements required for the implementation of Learning Analytics at CSU and how those elements interact (see Figure 1). The Model moves deductively from the definition of what the institution is trying to do with Learning Analytics (enhance student success), through a theoretical understanding of the drivers of student success to how Learning Analytics is to be embedded in the organisation to drive adaptation among students, staff and systems, and how impacts will be evaluated. The Model can be thought of as a map of all the areas of complexity that need to be resolved.
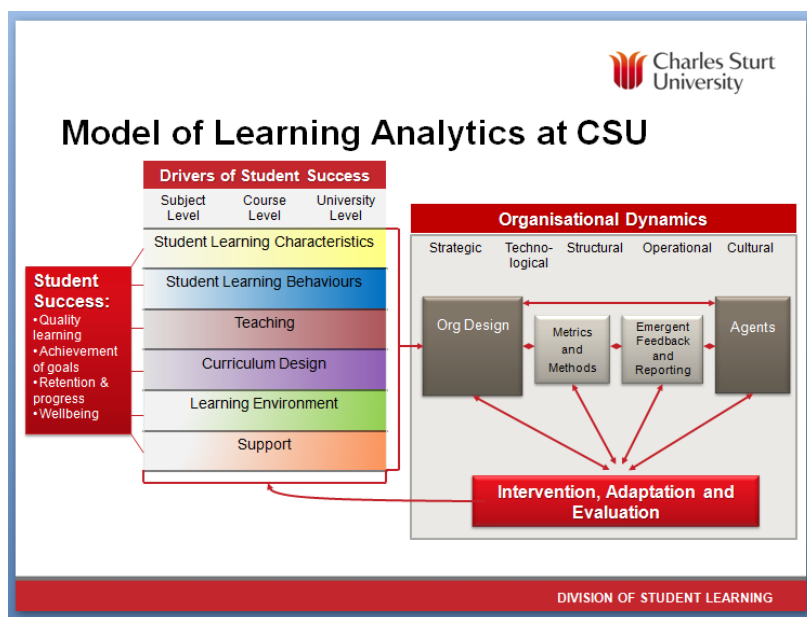
Figure 1: CSU Institutional Model of Learning Analytics

From Learning Analytics to Adaptive Learning and Teaching

Current *institutional* approaches to Learning Analytics – as distinct from the work being done in Learning Analytics research or in innovative small-scale applications – are often focused on predicting student attrition risk and/or monitoring student engagement to inform interventions usually around enhancing retention. Purdue University's *Course Signals* program is an exemplar of such approaches. Australian institutions are also active in this space whether that be through the development of institutional approaches to the use of analytics tools embedded in Learning Management Systems (LMS) (eg Retention Centre in Blackboard) or the development of dedicated engagement/retention predictive engines which encompass a broader range of analytics sources. The University of New England, University of South Australia, UTS, Griffith University and CSU are just some examples of institutions with the latter (Siemens, Dawson and Lynch, 2013; Let's Talk Learning Analytics and Retention National Forum, 2015; Alexander, n.d.). Typically, these predictive engines and analytics tools use behavioural indicators (ie number of log-ins or clicks in an LMS) or learning outcomes (ie failed an assessment, failed to submit, GPA, etc) as their metrics. In a review of four American institutions' engagement/retention analytics models, Sharkey (2014) reports that most predictive models around student engagement/risk tend to use the same sorts of variable (behaviours or learning outcomes) in the same kinds of ways.

This paper argues that, as a direction for institutional Learning Analytics strategies, an over-emphasis on the kinds of engagement/retention approaches currently observed is limiting for a number of reasons:

- Where's the "learning" in Learning Analytics? Engagement is defined in behavioural terms (eg whether students accessed a site/resource), rather than in terms of actual learning quality. Lodge and Lewis (2012) discuss the issues associated with a behaviourally-focussed approach to the measurement of learning, concluding that: "strict behavioural data such as this lacks the power to contribute to the understanding of student learning in a complex social context such as higher education" (p.3). Such an approach places emphasis on the management of student behaviour, either micro (increasing clicks/activity) or macro (course completion), rather than enhancement of learning per se. This also begs the question of whether these approaches are truly *Learning* Analytics or more akin to Academic Analytics (see Ferguson, 2012, for a discussion of the distinction);

- Institutions can develop an over-reliance on inductive analytics processes, where analytics are gathered and analysed for predictive associations without integration into a deductive model with a clear focus on student success. This may be viable if the goal is to predict distinct outcomes, like withdrawal from a course or program, but learning is a process and inductive approaches alone may fail to support the complexities of enhancing the quality of

student learning. Furthermore, many metrics which are readily available for inductive analysis are simplistic, not context specific and lead to "counting clicks" rather than monitoring the effectiveness of learning. As Lodge and Lewis (2012) comment, taking a constructivist approach to learning, "the emphasis here is on "how" [students interact with knowledge] and not "how much" as appears to be the nature of the data collected using LA" (p.3). For example, the number of forum posts or LMS log-ins by a student does not tell us about the quality of those posts/sessions, or their relevance to the learning design. Without a deductive model to drive the development of analytics capabilities there can be too much weight placed upon on such simplistic metrics and we end up focusing on what we've got rather than asking: how do we get what we need? As Gasevic, Dawson and Siemens (2015) state:

"Learning analytics resources should be well aligned to established research on effective instructional practice. In so doing we can move from static prediction of a single academic outcome, to more sustainable and replicable insights into the learning process" (p.66);

- Learning Analytics systems that provide students (via dashboards or notifications) with general or summative indicators of behavioural engagement have little utility in improving learning as they fail to provide the kind of specific instructive feedback to the student on where their learning is ineffective and how to improve it that Hattie and Timperley (2007) argue is critical. Rather, all they indicate to the student is a need for more *activity* (e.g. more forum posts or library searches) … precipitating "The Boxer Response" (named for the horse in George Orwell's *Animal Farm*), where the student is asked to embrace the mantra "I will work harder" but with little guidance on what they need to work on or how. Feedback is needed at the point of learning and that feedback needs to be about the specific learning process/activity that is occurring (Hattie and Timperley, 2007). Furthermore, there is intractable complexity in attempting to predict the occurrence of quality learning at scale across students, across learning designs, across content and across disciplines. There is substantial variation in what quality learning looks like in different contexts and attempting to implement institutional-scale systems to address this may miss the point, even if it could be done. That is, any kind of system that provides students with a summative or lag indicator of the quality of their learning would still not meet the need for feedback at the point of learning about the specific learning process/activity that is occurring. The goal is to support *adaptation during learning*, not adaptation by re-learning;
- some learning designs problematise meaningful analytic measurement (eg work placements);
- there are serious ethical issues around a) the extent to which students would reasonably expect to be surveilled and b) the University's obligation to act once it has information about students at risk; and
- such Learning Analytics approaches are typically focused on "raising the floor" (supporting students at risk) and ignore opportunities to "raise the ceiling" (supporting high-achieving students to optimise their talents).

To address the above, and informed by work on the Model of Learning Analytics, CSU moved from a Learning Analytics program to an Adaptive Learning and Teaching (ALT) program. Adaptive Learning and Teaching is defined as any educational approach that utilises feedback or analytics on student learning to adapt content, teaching, systems and/or design to enhance learning effectiveness. The focus is not only on monitoring and managing the student relationship, but on providing a "data engine" to enable adaptations across practice (by staff and students), systems (and the learning experiences they enable) and processes that support improved student learning.

The ALT approach incorporates traditional feedback mechanisms (eg student evaluations) and other data and analytics sources. However, it employs a reconfigured view of Learning Analytics as a learning *design* challenge, in the first instance. That is, rather than Learning Analytics being a capability that is applied to an extant learning design, it is something that needs to be designed into the learning activity such that by engaging in the activity the student intrinsically generates analytics about the learning process that are meaningful for both themselves and the teacher. For this occur, there is a need to re-direct Learning Analytics such that the point of focus for analyses is not, primarily, the student digital footprint but the *representations of knowledge* created through the interaction with analytics-enabled learning activities.

A key feature of the ALT approach is using learning technologies (designed to support specific

pedagogies) to create and capture representations (relevant to the pedagogy in question) of student thinking and knowledge, which can be coupled with other data and analyzed to provide insight on student learning. These insights are then used to enable adaptation at four levels:

1. Real-time adaptation of learning activities to personalise the student experience *and promote deep learning*;
2. Adaptation for students by supporting development of their meta-cognitive skills, learner dispositions and learning strategies;
3. Adaptation in teaching and learning design; and
4. Adaptation of learning technologies and systems.

A Pathway to Personalised Online Learning

For CSU, Adaptive Learning and Teaching is a pathway to delivering personalised online learning. The key to this is the real-time adaptation of online learning activities providing *adaptation during learning* that is responsive to:

- The knowledge of the student – as represented via the learning technology; and
- Their learning behaviours – as captured via a student's "digital footprint".

Multi-dimensional analytics are critical to paint a holistic picture of student learning and CSU is currently working on integrating data sources in a way consistent with "Phase 3" of the Learning Analytics Sophistication Model proposed by Siemens, Dawson and Lynch (2013). The ability to couple knowledge representations and cross-systems data on learning behaviours will enable the personalisation of a) the pathway within a specific learning activity (as done in many existing adaptive learning tools) and b) the feedback/interventions provided – where feedback is provided based on what the particular student has/has not done in their broader learning context. For example, if there are key resources associated with a learning activity, have they been reviewed? Have "lead up" or pre-requisite activities been completed satisfactorily? Where there are gaps, the student can be directed to address these specifically and/or provided with any additional support resources that are embedded in the activity. By using students' "digital footprints" to inform feedback/intervention the opportunity is created to also employ "big data style" recommender processes: students who also struggled with X, did Y and Z.

A critical challenge is developing technologies that can "read" a wider variety of knowledge representations. Current adaptive learning tools rely heavily on multiple choice or open numerical responses (Education Growth Advisors, 2013), which work well for questions with clear "right or wrong" answers. We need to broaden this – for example, employing capabilities like natural language processing – and deal with the challenge of content specificity. To address the latter challenge, new ALT technologies would focus more on what's happening in the learning process. That is, focus on the form of the knowledge representation more than its content. ALT technologies would look for *patterns* in the knowledge representation (and any changes therein) that suggest deep learning is occurring and feedback to the student would seek to promote deep learning. For example, in the analysis of free text, an ALT technology would look for evidence of deep learning in the patterns of language used – connection and critique of ideas, development of hypotheses, etc – and the feedback to the student guides deeper engagement (ie scaffolds deep learning).

Importantly, ALT technologies should be viewed (and used) as a complement to the teacher, not a replacement. Such technologies would deal with basic pedagogies (eg practice-mastery paradigms) and/or construct learning experiences to guide students toward patterns of (deep) engagement with content (as defined by the form of the knowledge representation), but the quality of students' ideas, analyses and conclusions remains the realm of the teacher. Indeed, the use of ALT technologies may create more space for teachers to focus on these higher-order dimensions with their students.

Building Capacity Not Just Apps

The CSU ALT program is not just about building "smart" learning technologies, a critical part is building capacity of staff and students in using Learning Analytics to inform practice and adaptation. The unit implementing the ALT program is Adaptive Learning and Teaching Services and was named to deliberately position it as a service provider to those using Learning Analytics at the university, primarily teaching staff and students. The objective is to avoid Learning Analytics being seen as

CP:249

something that is done by the "data geeks", to become something that is just part of everyday practice and experience. It is not about Adaptive Learning and Teaching Services doing Learning Analytics for the University, rather it's about this unit mainstreaming Learning Analytics.

The ALT program seeks to enhance organizational capability, whether that be through professional learning for academics or through developing innovative learning applications. Thus, the role of the Adaptive Learning and Teaching Services is to promote, enable and support the application of ALT approaches and technologies. The key functions of ALTS are shown in Figure 2.

1. Educational Intelligence Services	2. Innovation and Research Support	3. Organisational Engagement	4. ALT Systems Development and Support
• Provide L&T data, analysis and advisory services to enable a) increased responsiveness to students and b) improved decision-making and planning • Contribute to strategic development of L&T data reporting and use • Custodianship of relevant systems (eg SES, Blackboard Analytics)	• Strategic development of ALT technologies at CSU (incl review, planning and evaluation) • Seed, conduct and/or support research and experimentation in ALT across CSU • Work with uImagine to development and implement L&T innovations • External engagement • Source funding • Explore commercialisation opportunities	• Enhance organisational knowledge, capability and culture around the use of ALT, data/metrics and student-centred analytics • Maximise engagement with ALT, data and student-centred analytics • Internal stakeholder consultation	• Customisation of existing L&T technologies to enhance ALT and reporting capabilities • Customisation, configuration and integration of new ALT systems • Development of bespoke ALT systems and reporting tools (if required) • User support and system custodianship (incl vendor management) • Enhancement of reporting and analytics capabilities in conjunction with P&A, DIT, DSA, DLS and Smart Learning

Figure 2: Key Functions of Adaptive Learning and Teaching Services at CSU

We "background" Learning Analytics to talk about ALT because Learning Analytics informs adaptation in learning and teaching by people and systems, but it is not the outcome that drives the institution. Learning Analytics is a means to an end and that end is a rich and responsive student-centred learning experience that integrates analyses of student learning processes and learning behaviours to enhance student success.

References

Alexander, S. (n.d.). Student retention and learning analytics. In *Slideshare*. Retrieved from http://www.slideshare.net/ShereelAlex/olt-conference-learning-analytics?qid

Education Growth Advisors. (2013). *Learning to Adapt: Understanding the Adaptive Learning Supplier Landscape*. Retrieved from http://tytonpartners.com/library/understanding-the-adaptive-learning-supplier-landscape/

Ferguson, R. (2012). Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning, 4*(5/6) pp. 304–317.

Gasevic, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning Analytics are about learning. *TechTrends, 59*(1), 64-71. Retrieved from http://link.springer.com.ezproxy.csu.edu.au/article/10.1007/s11528-014-0822-x

Hattie, J., & Timperley, H. (2007). The Power of Feedback. *Review of Educational Research, 77*(1), 81–112. doi:10.3102/003465430298487

Let's Talk Learning Analytics and Retention OLT Project National Forum- Case Studies. (2015). Retrieved from http://www.letstalklearninganalytics.edu.au/national-forum/

Lodge, J., & Lewis, M. (2012). Pigeon pecks and mouse clicks: Putting the learning back into learning analytics. *Proc. ascilite Conference: Future Challenges/Sustainable Futures, (25 – 28 November, Wellington, NZ).* Retrieved from: http://www.ascilite.org/conferences/Wellington12/2012/images/custom/lodge%2c_jason_-_pigeon_pecks.pdf

Sharkey, M. (2014). Your Secret Sauce is not so Secret. In *Blue Canary Blog*. Retrieved from http://bluecanarydata.com/your-secret-sauce-is-not-so-secret/

Siemens, G., Dawson, S., & Lynch, G. (2013). Improving the Quality and Productivity of the Higher Education Sector – Policy and Strategy for Systems-Level Deployment of Learning Analytics. Society of Learning Analytics Research. Retrieved from: http://solaresearch.org/core/improving-the-quality-and-productivity-of-the-higher-education-sector/

Note: All published papers are refereed, having undergone a double-blind peer-review process.