It is with great pleasure that we invite you to participate in the 2019 Australian Learning Analytics Summer Institute (ALASI). This event is the main forum in Australia for advancing discussion, knowledge and innovation in the domain of learning analytics. It offers us the opportunity to bring researchers and practitioners together to demonstrate new work, workshop ideas and share expertise to collectively advance learning analytics.

**Website**: [uow.info/alasi2019](http://uow.info/alasi2019)

**Theme**

**Promoting cross-disciplinary collaborations, linking data, and building scale**

This year we seek to bridge disciplines and research communities within the learning sciences to bring a broad range of research questions, ideas, tools and prototypes together. The aim is to explore how the community can learn across disciplines by sharing application of learning analytics and artificial intelligence within education (primary, secondary and higher), organisations (workplace learning, teamwork and sharing knowledge) and ‘learning in the wild’.

The theme is all about promoting cross-disciplinary collaborations, linking data, and building scale to increase the validity and impact of learning analytics and artificial intelligence in the learning sciences.

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## Program

### Thursday, 28 November

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<th>Time</th>
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<td>8:30am</td>
<td>Registration opens</td>
<td>(Building 67 – Foyer)</td>
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<tr>
<td>9:30am</td>
<td><strong>Welcome</strong>&lt;br&gt;– Maarten de Laat, Sarah Howard, David Fulcher</td>
<td>(Building 67 – Room 107)</td>
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<td>9:45am</td>
<td><strong>Keynote:</strong>&lt;br&gt;<em>Bridging Education, Design, Learning Technology and Learning Analytics: Leveraging Multidisciplinarity in Striving for the Classroom of the Future</em>&lt;br&gt;– Bruce McLaren</td>
<td>(Building 67 – Room 107)</td>
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<tr>
<td>11:15am</td>
<td><strong>Break</strong></td>
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<td><strong>Adaptive Learning Meets Crowdsourcing: Introducing a Tool for Fostering Personalised and Higher Order Learning</strong></td>
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5:00pm  Reception  
*(Building 67, Level 1 – Hemingway Café)*

**Poster:**  
*Ethical perspectives of university students on consent for use of their data in higher education and research*  
– Rebecca Bosward, Jackie Street, Annette Braunack-Mayer

**Poster:**  
*Dark Data and Learning Analytics*  
– Joshua Burridge, Judy Kay

**Poster:**  
*Linguistic changes across different user roles in Online Learning Environment*  
– Lavendini Sivaneasharajah, Thushari Attapattu, Katrina Falkner

**Poster:**  
*Predictors of Student Satisfaction: A Large-scale Study of Human-Human Online Tutorial Dialogues*  
– Guanliang Chen, Dragan Gasevic

7:00pm  Reception finishes
## Friday, 29 November

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| 8:00am   | **Registration opens**  
       *(Building 67 – Foyer)*                                       |
| 8:30am   | **Plenary Panel:**  
**AI Research for the Learning Sciences**  
– Sarah Howard, Maarten de Laat, Kalina Yacef, Bruce McLaren, Paul Hutchings, Lina Markauskaite, Dragan Gasevic, Abelardo Pardo  
*(Building 67 – Room 107)* |
| 9:30am   | **Parallel Sessions**  
**Panel:**  
**User-centred AI and Learning Analytics: An interdisciplinary perspective**  
– Peter Reimann, Dragan Gasevic, Judy Kay, Abelardo Pardo, Kalina Yacef  
*(Building 67 – Room 107)*  
**Workshop:**  
**Blending Machine Learning, Graph Theory and Spectral Analysis to Better Understand Student Engagement and Regulation: Following the white rabbit of trace data**  
– Ben Hicks  
*(Building 21 – Room 114)*  
**Workshop:**  
**The Fifth Writing Analytics Workshop: Linking Reflective Writing Analytics to Learning Design**  
– Ming Liu, Rosalie Goldsmith, Sumati Ahuja, Xiaodi Huang  
*(Building 21 – Room 115)*  
**Demonstration:**  
**Ethical edgecases – a middle space bringing system builders into contact with ethicists**  
– Kirsty Kitto, Simon Knight, Linda Corrin  
*(Building 67 – Room 101)*  
**Demonstration:**  
**Evaluation of course design and learner behavior with Sankey Diagrams**  
– Rupa Vuthaluru, Simon Kerrigan, Dirk Ifenthaler, David Gibson  
*(Building 21 – Room G08)* |
<p>| 11:00am  | <strong>Break</strong>                                                            |</p>
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<td>– Vitomir Kovanovic, Sreko Joksimovic</td>
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<td><strong>Panel debate - The validity of using student evaluation surveys for performance based funding at Australian universities</strong></td>
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<td>4:45pm</td>
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Maps

Detailed maps for the Wollongong campus can be found on the Campus maps page: [uow.edu.au/about/locations/campus-map](http://uow.edu.au/about/locations/campus-map)

Building 21 and Building 67 highlighted

Wollongong campus, University of Wollongong with Building 21 and Building 67 highlighted
• **Bridging Education, Design, Learning Technology and Learning Analytics: Leveraging Multidisciplinarity in Striving for the Classroom of the Future**
  – Bruce McLaren

• **#C21LA: Tracking & Assessing 21st Century Competencies with Learning Analytics**
  – Simon Buckingham Shum, Darrall Thompson, Maimuna Musarrat, Zhonghua Zhang, Srecko Joksimovic

• **Scaling Personalised Student Communication. Current Initiatives and Future Directions**
  – Abelardo Pardo, Danny Liu, Lorenzo Vigentini, Marion Blumenstein

• **Learning Analytics in the Higher-Degree Research Setting – What's Possible?**
  – Kathryn Bartimote, Ross Coleman, Craig Napier, Jennifer Heath, David Fulcher

• **(Critical) Dreams of Open Practices as Researchers and Practitioners of Learning Analytics**
  – Sakinah Alhadad, Jason Lodge, Florence Gabriel

• **Learning Analytics Deployment Tactics: A meta-workshop**
  – Pablo Munguia

• **Adaptive Learning Meets Crowdsourcing: Introducing a Tool for Fostering Personalised and Higher Order Learning**
  – Hassan Khosravi, Dragan Gasevic

• **Measuring Soft Skills in Authentic Learning Environments**
  – Florence Gabriel, Fernando Marmolejo-Ramos, Sasha Poquet, Shane Dawson, George Siemens, Maarten de Laat

• **Educational research data: linking data for collaborative research about learning and teaching**
  – Kate Thompson, Simon Leonard, Dawn Adams, Maarten de Laat, Florence Gabriel, Sarah Howard, Simon Knight, Jason Lodge, Lina Markauskaite, Peter Reimann, Daniela Vasco

• **Ethical perspectives of university students on consent for use of their data in higher education and research**
  – Rebecca Bosward, Jackie Street, Annette Braunack-Mayer

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• **Panel debate - The validity of using student evaluation surveys for performance based funding at Australian universities**
  – Leonie Payne, Kirsty Kitto, Michael Pracy, Jason Lodge
Bridging Education, Design, Learning Technology and Learning Analytics: Leveraging Multidisciplinarity in Striving for the Classroom of the Future

Bruce McLaren (Carnegie Mellon University)

Abstract

In order to make strides in bringing technology to the classroom, scaling up its use, and creating the classroom of the future, myriad skills, techniques, and disciplines need to come together. For instance, we need to have a fundamental understanding of learning and education: how do people learn, how can we create the best conditions for learning? We also need to have structured and well-founded data capture and design techniques, in order to assess how teachers provide instruction and to design the best possible instructional approaches. Of course, we also need to know how to build robust and effective learning technology. Finally, we need to know how to leverage data to create useful learning analytics that support students, teachers, and administrators. In this talk I will discuss an example of the kind of multi-disciplinary research and development work that is key to creating the classroom of the future. In particular, I will present an overview of how Lumilo, a classroom orchestration system developed by Ken Holstein, a PhD student I co-advised, was created through bridging education, design, learning technology and learning analytics. Lumilo is in fact a glimpse of the future classroom: Teachers wear smart glasses that provide learning analytics to help them identify students to help; an empirical study has shown how Lumilo really does make a difference to student learning. I will conclude my talk by discussing possible future classroom scenarios that would benefit from a multidisciplinary approach, as well as some of the challenges the development of these scenarios will face.

Bio

Prof. Bruce M. McLaren is an Associate Research Professor at Carnegie Mellon University, USA, current Secretary and Treasurer and past President of the International Artificial Intelligence in Education Society (2017-2019). McLaren is passionate about how technology can support education and has dedicated his work and research to projects that explore how students can learn with digital learning games, intelligent tutoring systems, e-learning principles, collaborative learning, and classroom orchestration tools. McLaren's research with digital learning games, for instance, has shown that students can learn decimals better by playing a web-based
game than by using more conventional technology (e.g., McLaren, Adams, Mayer, and Forlizzi, 2017). His research with intelligent tutors has investigated how students learn when presented with erroneous examples in conjunction with intelligent tutors on the web (e.g., McLaren, van Gog, Ganoe, Karabinos, & Yaron, 2016). Finally, Prof. McLaren has researched and developed educational technology using AI techniques to help teachers moderate and orchestrate classroom activities. Prof. McLaren has over 160 publications (33 journal articles) spanning peer-reviewed journals, conferences, workshops, symposiums and book chapters (See http://www.cs.cmu.edu/~bmclaren/publications.html).
#C21LA: Tracking & Assessing 21st Century Competencies with Learning Analytics

Simon Buckingham Shum¹, Darrall Thompson², Maimuna Musarrat³, Zhonghua Zhang⁴, Srecko Joksimovic⁵

Abstract
In response to the changing demands on citizens and the workforce, educational institutions are starting to shift their teaching and learning towards equipping students with knowledge, skills and dispositions that prepare them for lifelong learning. These have been termed 21st Century skills/competencies, Core/Soft Skills, General Capabilities, Graduate Attributes, etc. There is now a lot of activity in the school and higher education sectors tackling the challenge of tracking and assessing these competencies in practical ways. Learning Analytics should in principle have important contributions to make, providing computational support for tracking learner processes (not just products), beyond the classroom in more authentic settings, visualizing patterns, and providing rapid feedback to educators and learners (Buckingham Shum & Crick, 2016). This workshop provides the chance to learn about ongoing efforts to develop and validate “C21LA”, and the nature of the challenges if these are to make a systemic impact, including the pedagogical, assessment, technological and political factors that together define educational infrastructures.

Keywords
Learning analytics, assessment, 21st century skills

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³ Email: maimuna.musarrat@uts.edu.au Address: Connected Intelligence Centre, University of Technology Sydney
⁴ Email: zhonghua.zhang@unimelb.edu.au Address: Assessment Research Centre, University of Melbourne
⁵ Email: srecko.joksimovic@unisa.edu.au Address: Teaching Innovation Unit, University of South Australia

1. Workshop Focus

21st century skills include the “Four Cs” (cf. Jefferson & Anderson, 2017) which are regularly referred to as creativity, critical reflection, communication and collaboration, Gardner’s “Five Minds” which also map to Thompson’s (2016) CAPRI model. However, there are many other lists that include other qualities such as learning dispositions, ethics and citizenship (e.g. Care, et al. 2018). While pedagogical shifts to equip students with these skills are certainly needed, that alone will not affect systemic change. A critical challenge is how these competencies can be tracked and assessed in meaningful ways, because assessment regimes drive educator and student behaviour. But since these skills are not easily quantifiable, need to be assessed over a period of time, and need to be displayed in interpersonal, societal and culturally valid contexts, traditional methods like observational or interview techniques are hard to apply at scale. Student self-report has an important place, but comes with obvious limitations. This has triggered significant educational research in the school and higher education sectors, but the potential of Learning Analytics is often not harnessed. Learning Analytics should in principle have important contributions to make (cf. Buckingham Shum & Crick, 2016), for instance: providing computational support for tracking learner processes (not just products); tracking activity not only inside the classroom but outside, in more authentic settings; tracking activity not only online and also face-to-face (via
multimodal sensors/analytics); providing rapid feedback to educators and learners to build metacognitive capabilities.

In recent years, learning analytics has been applied to develop more objective assessments for measuring some of the essential 21st century skills (e.g., ICT literacy – Learning in digital networks, Wilson, Gochyyev, & Scalise, 2016; Collaborative problem solving, Griffin & Care, 2015; Learning in online environment, Milligan & Griffin, 2016) which could not be objectively, reliably and validly assessed with traditional approaches. Researchers advocate that learning analytics and measurement science should be synthesized for facing the challenges of the assessment of the hard-to-measure 21st century skills (Wilson & Scalise, 2016).

This workshop provides the chance for participants to share, and learn about, ongoing efforts to develop “C21LA” tools, and critically, how we validate them (e.g. Milligan, 2018; Milligan & Griffin, 2016). The workshop will include some ‘show and tell’, but speakers will be asked to reflect critically on the challenges that remain for these to make a systemic impact, including the pedagogical, assessment, technological and political factors that together define educational infrastructures.

2. Proposed workshop structure

The workshop will run in 30-minute segments, each segment focusing on one tool. Each segment will have a presentation (15-20 minutes), followed by discussion (10-15 minutes). There will be a plenary discussion at the end.

3. Workshop Presenter Credentials

**Simon Buckingham Shum** is Professor of Learning Informatics at the University of Technology Sydney, where he is inaugural Director of the Connected Intelligence Centre. He has been active in shaping the field of Learning Analytics, and co-founded the Society for Learning Analytics Research.

**Darrall Thompson** is a Senior Lecturer and Learning Futures Fellow in the UTS Faculty of Design, Architecture and Building. His award-winning research and design thinking are embodied in the REVIEW platform, a criteria-based system used for enhancing assessment and evaluation capabilities among staff and students in universities and schools.

**Zhonghua Zhang** is a Research Fellow at the Melbourne Graduate School of Education in the The University of Melbourne. His research interests include assessment, educational measurement, and psychometrics. He has been leading a project which focuses on developing behavioral indicators from log stream data to measure students’ collaborative problem skill, which has been identified as one of the essential skills in the 21st century workplace.

**Srecko Joksimovic** is a Research Fellow at the School of Education and Data Scientist in Teaching Innovation Unit, University of South Australia. His research interests focus on exploring the symbiosis of human and artificial cognition to understand knowledge processes and their impact on society.

**Maimuna (Muna) Musarrat** is a Postdoctoral Research Associate at the UTS Connected Intelligence Centre, where she is working closely with the U@Uni Academy, researching the assessment of transferable skills in high school students using different tools.

References


Scaling Personalised Student Communication  
Current Initiatives and Future Directions

Australian Learning Analytics Summer Institute  
University of Wollongong 28 November 2019

Facilitators
Abelardo Pardo – University of South Australia  
Danny Liu – The University of Sydney  
Lorenzo Vigentini – UNSW, Sydney  
Marion Blumenstein – University of Auckland, New Zealand

Presenters
Jurgen Schulte – University of Technology Sydney  
Mark McConnell – University of Auckland  
Shane Wilkinson – The University of Sydney  
Markus Muellner – The University of Sydney  
Anthea Fudge – University of South Australia  
Nengye Liu – University of Adelaide  
Tania Bucic – UNSW, Sydney  
Steve Leichtweis – University of Auckland

Student engagement is one of the aspects that mediates the success of a learning experience. Fostering this engagement has always been present in the teaching practice and communication has been one of the elements used to promote it. The increasing presence of technology mediation is offering new possibilities in this space. Areas such as learning analytics and educational data mining are exploring how to combine multiple data sources and use this information to increase our understanding of how students learn, but also to improve their experience. The research activity in this space has increased significantly over the last decade, but there are still various challenges especially when it comes to institutional adoption, or translation of research results into practice.

One of the aspects of learning experiences that has drawn the attention of both researchers and practitioners is the possibility to personalise the communication for large number of students. It is assumed that a personal communication that takes into account the reality of the student is more effective than generic messages and suggestions. But at the same time, scaling this approach for large student cohorts while maintaining the quality has remained a challenge.

In the last few years there has been a set of tools and approaches that have emerged to translate or put into practice the findings produced by the research community in the space of scaling personalised student communication. Combining research in the areas of data mining, feedback, pedagogy, and learning design, practitioners have been using personalisation techniques to improve the way they communicate with large student cohorts.

The session has two aims. The first one is to disseminate a set of current initiatives in the area of personalized student communication describing their approach to design, deployment and impact. The presentations will include a succinct description of the scenario, the objectives, the techniques and tools used and the observed impact. The second is to identify which aspects of this area need further evolution, or which new ones could be explored in the future.
## Morning (Building 21 Room 115)

<table>
<thead>
<tr>
<th>Time</th>
<th>Title</th>
<th>Presenter/Facilitator</th>
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<tbody>
<tr>
<td>11:45am</td>
<td>Introduction</td>
<td>Lorenzo Vigentini, Marion Blumenstein, Danny Liu, Abelardo Pardo</td>
</tr>
<tr>
<td>12:00pm</td>
<td>Scalable personal learning support with OnTask</td>
<td>Jurgen Schulte, University of Technology Sydney</td>
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<tr>
<td>12:15pm</td>
<td>Using OnTask in a large first year Commercial Law course on a Bachelor of Commerce degree</td>
<td>Mark McConnell, University of Auckland</td>
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<tr>
<td>12:30pm</td>
<td>Student peer assessment in undergraduate chemistry laboratories using SRES</td>
<td>Shane Wilkinson and Markus Mueller, The University of Sydney</td>
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<tr>
<td>12:45pm</td>
<td>Using OnTask to support diverse student cohorts through personalised, data-informed feedback.</td>
<td>Anthea Fudge, University of South Australia</td>
</tr>
<tr>
<td>1.00pm</td>
<td>Disruptive innovation in the marketing classroom for a personalized learning journey</td>
<td>Tania Bucic, UNSW, Sydney</td>
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<td>1.15pm</td>
<td>Lunch</td>
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## Afternoon (Building 21 Room 115)

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<tr>
<th>Time</th>
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<tbody>
<tr>
<td>2.30pm</td>
<td>Using OnTask to Communicate with a Large Cohort of First Year Business Students</td>
<td>Nengye Liu, University of Adelaide</td>
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<tr>
<td>2:45pm</td>
<td>Initial themes for future directions in scaling personalised student communication</td>
<td>Steve Leichtweis</td>
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<tr>
<td>3:00pm</td>
<td>Group discussion: Unpack and prioritise themes for future direction. Propose 2-3 concrete avenues to increase uptake of approaches</td>
<td>Work in groups</td>
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<tr>
<td>3:30pm</td>
<td>Group presentation</td>
<td>One representative per group</td>
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<tr>
<td>3.45pm</td>
<td>Final remarks</td>
<td>Lorenzo Vigentini, Marion Blumenstein, Danny Liu, Abelardo Pardo</td>
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<tr>
<td>4.00pm</td>
<td>Finish</td>
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Learning Analytics in the Higher-Degree Research Setting – What’s Possible?

Kathryn Bartimote1, Ross Coleman2, Craig Napier3, Jennifer Heath4, David Fulcher5

Abstract
In this combined demonstration/roundtable session participants will explore the possibilities for learning analytics in higher-degree research (HDR) contexts. A dashboard developed to help predict and monitor student on-time completion will be introduced. The rationale, data modelling techniques, and approach to faculty roll out for this particular project will be described. Following this a series of stimulus questions will be put to participants, including highlighting the similarities and differences between coursework and higher degree research settings for learning analytics research and practice. This will include consideration of the different roles of student, teacher/supervisor, senior academic leaders and administrators and how learning analytics can play a part in the work each of these roles undertake to support research higher-degree education.

Keywords (not a research paper)
Doctoral students, HDR students, higher education, research education, academic analytics, learner analytics

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1. Background

Broad and proactive participation in research activities can have a positive effect on first year higher degree research candidates (Bertone, 2018; Kiley, 2018; Manidis, 2017). Apart from helping with the acquisition of disciplinary language and rhetoric, such interactions can also help reduce the isolation encountered when transitioning into being a research candidate. In a similar fashion, proactive supervisory practices help facilitate student transition. This includes bi-directional feedback as well as an development of disciplinary practice. University staff beyond the research supervisors also have a role to play here as they too contribute to the teaching and learning climate surrounding doctoral education. The inclusion of readily accessible dashboards presenting synthesised data pertaining to the HDR student journey, as with the specific example shared here, aims to support research and student success.

The research student journey contrasts to the well structured coursework journey in many ways and the session will explore some of these aspects and implications for learning analytics.

Questions posed will include:
• What can HDR analytics learn from coursework analytics? And where should we diverge?
• What are the unique challenges of using analytics to support candidature management in different contexts e.g. a large research group versus a whole institution?
• How can analytics be used to support HDR students and their study experience?
• How can analytics inform the research education strategy for an organisational unit or even the institution as a whole?
• What information is useful to HDR students, supervising academics, support and administrative staff in the HDR context?
2. The Session

This 1.5 hour combined demonstration/roundtable session will be largely discussion based, with the presentation of a dashboard providing a springboard for a wider discussion around the possibilities for HDR analytics.

It will be organised as follows:

1. (15 mins) Settle in, meet and greet, share plan for the session
2. (30 mins) Presentation & plenary discussion – HDR on-time completions dashboard
3. (30 mins) Open discussion around a series of stimulus questions posed by the facilitators
4. (15 mins) Closing thoughts, comments, and individual reflection on next steps

3. Presenter Credentials

Kathryn Bartimote is Head Quality and Analytics within the central Education Portfolio at the University of Sydney. She is leading the enablement of learning analytics across the institution. Her research is in the area of educational psychology.

Ross Coleman is Director Graduate Research within the Education Portfolio at the University of Sydney. He leads strategy for research education across the institution. His research is in the area of marine biology.

Craig Napier is Associate Director Institutional Analytics within the Strategy Portfolio at the University of Sydney. He leads business intelligence and advanced analytics initiatives at the institution, partnering with relevant business sponsors.

Jennifer Heath is Chief Operating Officer within the Australian Institute for Innovative Materials (AIIM). She has a focus on HDR student experience and has a background in data-driven student support at the whole-of-institution level, data privacy and higher education strategy.

David Fulcher is Manager Learning Analytics within the central Learning Teaching and Curriculum group at the University of Wollongong. He leads a team developing tools for teachers and others to identify students in need of support.

References


(Critical) Dreams of Open Practices as Researchers and Practitioners of Learning Analytics

Sakinah Alhadad1, Jason Lodge2, Florence Gabriel3

Abstract
As a field, learning analytics aim to support and improve educational practice, through expanding and deepening our understanding of learning and of its environments, as well as through embedded implementation in educational practice. In this round-table discussion, we interrogate one avenue to improve the potential of achieving our aims -- through open science practices. What is important for the field? What is feasible? What are the potential, and perhaps unique challenges for learning analytics? Through our collective wisdom, we look to evaluate how elements of open practices in learning analytics research might help us achieve important shared goals of learning analytics stakeholders. We welcome all stakeholders to join in the discussion -- whether out of sheer interest to learn about what is happening in the field, or to collectively forge pertinent ways forwards as aligned with shared values of openness.

Keywords (not a research paper)
open science, open practices, research-practice boundaries, interdisciplinarity, translation, credibility

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1. Round-table discussion: Paving feasible and productive ways forward for open learning analytics

The learning sciences and learning analytics community are diverse in their disciplinary and interdisciplinary origins and approaches. This richness in diversity and plurality ostensibly strengthens our capacity to better understand the wicked problem of learning in education. Central to scientific study is how we communicate and consume information about science. We do this with the intention to not only progress science itself, but also to affect positive change in practice, policy, and society, to a large extent. Much of the ideals of the sector are also what comes with greater challenges -- examples include:

- research-practice partnerships (Coburn & Penuel, 2016; Pincham et al., 2014)
- research-informed practice (i.e., translation from research to practice; Daniel, 2012; Mayer, 2012; Cain & Allan, 2017)
- practice-informed research (i.e., applied research/practice-embedded) (Penuel, Bell, Bevan, Buffington & Falk, 2016)
- interdisciplinary/transdisciplinary research (Lodge et al., 2017; Palghat, Horvath, & Lodge, 2017)

Openness could be one mechanism through which we could support some of these challenges. Arguably a core value in educational research and practice, openness has been explicitly discussed in the field for decades. Whether as researchers or practitioners, we all evaluate the quality of scientific and practice products -- and at any given time, we do this with limited information. Our evaluative capacity is not only limited to what is overtly available to us, but also within human information processing capacity limits (Alhadad, Searston, & Lodge, 2018; Bishop, 2019).
Key questions:

- How do we facilitate synthesis of knowledge creation in understanding of learning in the learning sciences? (Cross disciplinary communication) (from interdisciplinary work to intradisciplinary translation --e.g., LA work can also develop better understanding of learning and learning theory, how does this feed back to disciplinary literature)
- How do we facilitate translation from research to practice and policy, and vice versa (particularly when LA work often involves algorithms and coding that are not always open or shared)?

One of the biggest enablers to date for Open Science has been advances in technology. Several free and relatively easy to use online platforms have been created to support individuals in making their research-related content openly available, and to some specified extent as appropriate as per ethical and paradigmatic considerations. Figure 1 illustrates eight prototypical elements of the research process that can be made open and accessible for others. How this could be done is situated in different research paradigms and disciplines, however, is still underexplored -- this is the focus of the present roundtable discussion.

In this session, we will discuss, for each element, why they might be particularly important for our field compared to more explored fields (e.g. given more technical aspects of LA research), and how we might work productive (and feasible) ways forward to support critical evaluation for research and practice progress. We critically discuss what this means for the learning sciences, and what may need to be reconsidered or redesigned for complex applied research often conducted in our fields. We also consider what this means for translation across disciplinary and implementation or practice boundaries (including industry and policy).

Figure 1. Shareable elements of the research process in Open Science. Figure extracted from Alhadad, Searston, & Lodge (2018).

We welcome everyone to join in the discussion – whether out of sheer interest to learn about what is happening in the field, or to collaboratively and collectively forge pertinent ways forwards as aligned with shared values of openness.

2. Workshop Presenter Credentials

Sakinah Alhadad, PhD is a Lecturer in Learning Innovation at the Centre for Learning Futures at Griffith University. She is involved in institutional-level strategies related to the science of learning, and evidence-informed practice. Her research focuses on the processes of understanding, using, and generating research evidence and data in educational practice. She continues to explore and promote open science practices in applied educational research methodologies and contexts.

Jason Lodge, PhD is Associate Professor of Educational Psychology in the School of Education and Science of Learning Research Centre at The University of Queensland. Jason conducts research on the translation of the science of learning into practice in educational settings, particularly in digital learning environments and higher education. He has also been involved in exploring and promoting open science practices in education.

Florence Gabriel, PhD is a Research Fellow at the Centre for Change and Complexity in Learning at the University of South Australia. Her background is in cognitive psychology and educational neuroscience, and she recently gained experience in education policy through her work at the OECD. Her research focuses on student attitudes towards learning, STEM education and evidence-based practice in education.

References


Learning Analytics Deployment Tactics: A meta-workshop

Pablo Munguia

Abstract
Learning analytics is a young field and beyond the research space its uptake has been slow across academics and organisations. Often, top-down strategies are not easily adopted or focus on metrics that may not align across all disciplines in a university. Bottom-up approaches, while well focused, have difficulty increasing their reach and capacity. Ultimately, designing a professional development plan in a university is not enough at best, and incorrect at worst. This workshop is intended for participants who are interested in disseminating learning analytics tools across courses and disciplines, enabling cross-discipline collaboration and innovation. The intent is to workshop the first steps required to breach this barrier with a constructive approach. At the completion of the workshop, you will have explored: (a) components that rely on first principles to identify datasets and metrics generically useful, and how to identify more specific variables. (b) development of tactics for increasing engagement among academics and across units. This is a hands-on workshop that will incorporate insights from LASI 2019.

Keywords:
Learning analytics at scale, strategy, university policy, data connectivity

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1. BACKGROUND

Learning analytics is coming to town. Many universities have now adopted policies to ensure proper use and storage of student generated data (Tsai and Gasevic 2017), and research within the learning analytics field is maturing to scope mechanisms that improve the student experience beyond a single course into program and even school levels (Knight et al 2016, Deakin-Crick et al 2017). Practitioners of learning analytics have emphasized the importance of stakeholder engagement, whether teachers or services (Greller and Drachsler, 2012, Colvin et al., 2015, Arnold et al., 2014, Tsai et. al., 2018). The rationale is clear, the learning analytics field is not just research-focused but it provides a pathway to improve the teaching service and as such it requires willing customers.

Staring at data or analyses of your own performance as a teacher can be confronting and challenging, and perhaps daunting if you are not numerically inclined. University-wide strategies such as initiating “professional development” courses may work, but often encounter obstacles. These challenges are scale-related, a solution needs to help different disciplines in a university, ensure the metrics are well understood, and allow for diverse feedback to help improve the analytical solution. Ultimately, designing a professional development plan is not enough at best, and incorrect at worst. The alternative approach stems from individual academics sharing their learning analytics practice with fellow teachers. Here, the challenges include the rate of adoption across the university, and the generation of support to help disseminate the uptake.

How can we equip academic staff with the right tools and increase their engagement (or design better tools)? This workshop will be run as a meta-workshop, where participants will be experiencing a simulation of how academics could engage with activities designed to equip academic staff with the knowledge(s) needed to engage with learning analytics. In turn, the insights by the workshop participants as subjects of the exercises will help generate strategies that can then be shared with their home institutions.

This workshop has also been conducted at the Learning Analytics Summer Institute in Vancouver, Canada in 2019 and the insights from that workshop will be also presented and incorporated.
2. ADVANCED PREPARATION FOR WORKSHOP
Read through the papers once signed into the workshop and conduct the pre-workshop survey. These resources will be available to participants a week before ALASI. Bring a laptop to the workshop.

3. PRE-REQUISITE SKILLS / EXPERIENCE
Basic understanding of learning analytics.

4. THE WORKSHOP SCHEDULE
15 min Introduction
30 min 1st group work
15 min Reflection
30 min 2nd group work
30 min Deployment & final reflection

As Director of Learning analytics and Associate Professor of Research and Quality at RMIT University, Pablo Munguia has been conducting research and running workshops on how to implement and deploy learning analytics at universities and engage with their leadership.

References


Adaptive Learning Meets Crowdsourcing: Introducing a Tool for Fostering Personalised and Higher Order Learning

Hassan Khosravi, Dragan Gasavic

Abstract
This 1.5 hour demonstration presents RiPPLE, which is an open and free-to-use adaptive learning system. RiPPLE recommends personalised learning activities to students based on their knowledge state from a pool of crowdsourced learning activities that are generated by educators and the students themselves. RiPPLE integrates insights from crowdsourcing, learning sciences and adaptive learning, aiming to narrow the gap between these large bodies of research, while providing a practical platform-based implementation that instructors can easily use in their courses. The aim of this demonstration is to provide a theoretical justification coupled with a hands-on illustration of the RiPPLE system to help participants make an informed decision on whether or not they would like to adopt RiPPLE.

Keywords
Adaptive learning, Crowdsourcing in Education,

1. Rationale
A growing body of knowledge provides evidence about the effectiveness of Adaptive Learning Systems (ALSs) in supporting student learning (VanLehn, 2011; Ma, Adesope, Nesbit, & Liu, 2014). The most successful adaptive platforms tend to focus on a specific domain and also require a tremendous investment of time by experts during the development of curriculum content, which makes it difficult to scale these approaches across many domains. As a viable alternative, we see great promise in trying to leverage ideas from crowdsourcing and learning science to create adaptive systems where students themselves could generate content that can be adaptively served. The benefits of engaging students in content creation are twofold. The first benefit is in transforming the role of students from passive recipients of content to active creators of course material. Previous studies have reported that placing the responsibility of content creation in the hands of students reinforces and deepens their understanding of the course content (Draper, 2009), highlights the significance of representing their work in a clear and logical fashion, encourages reflection on the course objectives (Purchase, Hamer, Denny, & Luxton-Reilly, 2010), and enhances their conceptual understanding (Bates, Galloway, & McBride, 2012). The second benefit comes from harnessing the creativity of students themselves towards the development of large repositories of learning resources. Previous studies have demonstrated that students indeed have the capacity to create high-quality learning resources that meet rigorous judgemental and statistical criteria (Walsh, Harris, Denny, & Smith, 2018).

This demonstration presents RiPPLE, which is a crowdsourced adaptive learning system. To date, over 3000 registered users from 15 courses have used RiPPLE to create over 7,000 learning resources and attempt or review over 200,000 learning resources. Many of the main features including creation of a RiPPLE offering, creation and moderation of content, visualisation of learner models, recommendation of learning resources, assessing student profiles and course reports are demonstrated using hands-on activities. Prototypes of RiPPLE demonstrating the student view and the instructor view are available here. The platform provides easily accessible data to support research on a number of topics that are of interest to the LA community, including empirical evaluation of the effect-size of engagement with (1) higher-order learning activities such as evaluative judgement (2) open learner models and (3) recommender systems on learning. An evaluation of the platform has been conducted based on a pilot in an introductory course with 486 students at The University of Queensland. Initial results suggest that the use of the
RIPPLE platform led to measurable learning gains and that students perceived the platform as beneficially supporting their learning.

Figure 1 illustrates one of the main pages of RIPPLE.

![Figure 1](image1)

**Figure 1.** Illustration of one of the main pages of RIPPLE

**Figure 2.** Overview of one of the main pages of RIPPLE

2. **Aim and Format**

The aim of this demonstration is to provide a theoretical justification coupled with a hands-on illustration of the RIPPLE system to help participants make an informed decision on whether or not they would like to adopt RIPPLE. The demonstration will have three parts that are **half an hour** each:

1. The first part will provide a rationale for developing RIPPLE (a crowdsourced adaptive learning system) and the gap it is trying to fill with reference to the related literature.
2. The second part will introduce the system through a series of hands-on demonstrations, taking the participants through the main features of RIPPLE. This part also includes discussions about the lessons learned and best practices for integrating RIPPLE into a course.
3. The third section invites an open discussion around the benefits and challenges of using RIPPLE (or more broadly crowdsourcing and adaptive learning) in higher education.

Technical support for the adoption of the system can be provided after the session for those that are interested in piloting RIPPLE.

**References**


Measuring Soft Skills in Authentic Learning Environments

Florence Gabriel1, Fernando Marmolejo-Ramos2, Sasha Poquet3, Shane Dawson4, George Siemens5, Maarten de Laat6

Abstract
Soft skills, such as critical and creative thinking, are recognised as increasingly important in the 21st century. They have been shown to predict academic achievement and are highly valued in modern workplaces. While teachers can help students foster soft skills in Authentic Learning Environments, there is no clear consensus as to how they should be developed, measured and assessed. In this round-table discussion, we will examine suitable data types and instruments to measure soft skills, and we will situate this discussion within the context of existing learning analytics research.

Keywords
Soft skills, Authentic Learning Environments, Team-based learning, Measurement, Assessment

1. Developing soft skills in Authentic Learning Environments
The term soft skills describes the set of knowledge, skills, attitudes and personal traits that are considered important to thrive in today’s world (Care, Griffin & Wilson, 2018). These skills predict academic achievement (Farrington et al., 2012) and are forecast to substantially contribute economically to organisations and society (Deming, 2017). Assessing, measuring, and developing soft skills, therefore, is becoming an important area of focus within the academy.

Soft skills include critical and creative thinking, collaborative skills, self-regulation, problem solving skills, communication skills, and empathy. Although, they are already widely implemented and included in school curricula around the world, questions remain about formally measuring them.

Authentic Learning Environments (ALE), such as project-based learning, can provide richer learning experiences for fostering soft skills than traditional learning environments thanks to their emphasis on active engagement with peers while solving realistic problems. ALEs focus on real-world, complex problems and their solutions, and are inherently multidisciplinary (Lombardi, 2007). Tasks in ALE are often ill-defined to allow for competing solutions and diversity of outcomes (Herrington, Reeves, Oliver & Woo, 2004).

Teaching in ALEs allows us to capture more valuable learning data going beyond what is traditionally viewed as a primary cognitive activity. They provide opportunities for students to collaborate, innovate and reflect on their own learning (Herrington & Herrington, 2008). One promising example is the Epic Challenges Program (ECP) developed by NASA (Camarda, de Weck & Do, 2013). ECP connects teams of students to experts to solve complex, open-ended, multidisciplinary problems (e.g. How can we sustain life on Mars?). These challenges promote phenomenon-based learning, teamwork and creativity. This program will be developed in the Adelaide region in 2020 in collaboration with the University of South Australia and will provide a good opportunity to collect data on soft skills.
2. Measuring soft skills with Learning Analytics

How can researchers get accurate, valid and reliable real-time insights on the development of soft skills? To assess the psychological attributes of student learning, log files are inadequate. Instead, researchers need to look at interactions between students while they are involved in activities that include solving complex problems. While this is an under-developed area of research, some proposals for methods to measure soft skills are being developed. D’Mello and colleagues (2017) introduced the Advanced, Analytic, and Automated (AAA) approach to measure students’ engagement during learning. They suggest measuring multimodal data (e.g. facial expressions, heart rate and skin conductance) to infer mental states associated with students’ engagement. However, this approach has been criticised, as facial expressions can denote more than one emotion and vary depending on culture (Barrett et al., 2019). A separate methodology to measure student behaviour and affective states in the classroom was developed by Ocumpaugh and colleagues (2015). For any particular computer-based task, researchers can combine these observations with log files to develop models to infer students’ emotions and engagement with the task.

There are a number of other ways to measure soft skills yet to be explored in depth. Eye-tracking, EEG, and electromyography could be used to measure non-cognitive abilities in addition to what is recorded in Learning Management Systems. Analysing interactions that a student has with other students, teachers, technology, etc. may provide a sophisticated, nuanced means of measuring soft skills.

3. Goal of this round-table discussion and questions to be discussed

This round-table will provide an opportunity for researchers to explore ways to measure soft skills in light of increased resistance, societally, to assessing psychological attributes. Questions around suitable data types and instruments to measure soft skills will be discussed. This session will explore soft skill assessment through real time social analytics based on participation (affective, cognitive and collaborative), dialogic and discourse analysis. The round-table will also focus on what, if any, promise is held in a range of new approaches and technologies such as EEG, HRV, pupil dilation, eye tracking, and emotion detection through facial expressions. Finally, the panel will situate soft skills assessment within the context of existing learning analytics research and suggest next steps in advancing both the measurement of skills and intervention strategies to improve learner development.

References


Educational research data: linking data for collaborative research about learning and teaching

Kate Thompson¹, Simon Leonard², Dawn Adams³, Maarten deLaat⁴, Florence Gabriel², Sarah Howard⁴, Simon Knight⁵, Jason Lodge⁶, Lina Markauskaite⁷, Peter Reimann⁷, Daniela Vasco³

Abstract
Educational research encompasses a broad range of data collection methods and disciplinary approaches including cognitive science, computer science, anthropology, sociology and neuroscience to name but a few. Some of the challenges facing educational researchers, teachers and learners are related to the availability and processing of educational data, the use of data to make decisions and complexity of relating local, individual and classroom level questions about learning to decisions about policy and practice. There is a need to develop a national network of education researchers who bring together a range of data collection and analysis procedures who are able to identify research agendas and train new researchers (as well as teachers) in the collection, analysis and interpretation of educational data. In this panel, research leaders will participate by providing an example of a case, and providing a chance for the other panel members to discuss the issues related to educational data.

Keywords
Educational data, analysis, research questions, research facilities

1. Panel Focus
Educational research encompasses a broad range of data collection methods and disciplinary approaches including cognitive science, computer science, anthropology, sociology and neuroscience to name but a few. Educational datasets can be broad, such as that collected from learning management systems, or standardised test results, or deep, such as rich, multimodal data collected from learning management systems, or standardised test results, or deep, such as rich, multimodal data to investigate specific learning situations. As methodological and analytic tools develop, discovering the relationships between teaching, learning, tools and space become possible, and is in fact necessary for transformative learning and teaching.

Some of the challenges currently facing educational researchers, as well as teachers and learners, are related to the availability and processing of data (collecting and storing video data, analytic techniques), the use of data to make decisions (about teaching, learning, design), and the complexity of relating local, individual and classroom level questions about learning to decisions about educational policy and practice. There is currently no standard approach to the presentation of this type of educational data. In addition, there are considerable ethical implications of sharing data about students collected during learning situations which prevent the collection of community data with high re-use value. There is therefore a need to develop a national network of education researchers who bring together a range of data collection and analysis procedures who are able to identify research agendas and train new researchers (as well as teachers) in the collection, analysis and interpretation of educational data. Many initiatives in the learning sciences aim to address these challenges with data, and journals such as the British Journal of Educational Technology (Rushby, 2015) as well as the Journal of Learning Analytics publish special issues comprised entirely of ‘data papers’ describing shareable datasets (Haelermans, Ghysels & Prince, 2015; Kadijevich, 2015).

Individual institutions have facilities that focus on the collection and analysis of educational data. Leadership and collaboration initiatives are needed to connect these researchers to create a research agenda and guidelines to support the transformation of education research in Australia. There is a lack of cross-institutional collaboration, and we propose to bring together a group of research leaders in education to enable the: identification of existing datasets; alignment of data collection with research challenges; mapping of the providers and consumers of educational data; creation of a research agenda; and creation of guidelines for collecting, storing, visualising, sharing and reporting on this type of educational data.
1.1. Institutional contexts

1.1.1. Creative Practice Lab and PACER (Griffith University)
The CPL was designed to support preservice teachers to develop the skills required to deliver research-informed teaching, as well as provide a space to enable opportunities for outreach, partnerships and connection with external education partners and stakeholders. In the CPL, a custom built recording system is used, generating video and audio data, as well as capturing interactions with digital devices. Multimodal data can be generated and displayed to teaching staff in close to real-time. PACER extends this to focus on research connected to autism, and including eye tracking infrastructure.

1.1.2. Samsung SmartSchool (University of South Australia)
The Samsung SMARTSchool serves primarily as a training facility for current teachers and teaching students, allowing them to review their performance through technology. The SMARTSchool is also used for research purposes and has a strong focus on STEM education. The facility was designed to be a flexible education space and includes a range of cutting edge technologies, such as giant screens, video walls, smart phones, tablets and virtual reality. It is equipped with an audio-visual recording systems to allow interactions between teachers, students and technology to be captured.

1.1.3. Educational Design Research Studio (University of Sydney)
The Educational Design Research Studio is a research facility for studies that aim to gain a rich understanding of collaborative complex knowledge co-creation and problem solving activities. It is equipped with high quality multi-stream audio-visual recording equipment, sufficient to capture interaction details, such as talk, gestures, expressions, drawing, note-taking and other important elements of written, verbal and embodied interaction. Video-based observational data will be connected with other kinds of behavioural data to develop our understanding of collaborative knowledge work processes.

1.1.4. Science of Learning Centre (University of Queensland)
The Educational Neuroscience Classroom at UQ is a state-of-the-art research facility. The classroom allows for precise measurement of brain activity, eye movements, and physiological responses that occur while individuals engage in learning. Together these measurements allow researchers to probe the brain processes that underlie learning and behaviour.

1.2. A research agenda
The working group has established common research interests and a process to guide cross-institutional collaboration and provide contexts for the discussion of issues around educational data. The first is to build robust, valuable case studies to review their performance through technology. The second is to investigate multimodality and multimodal data – beyond learning analytics, how are they connected? Making sense of measurement types and discussions of objective and subjective data.

1.3. Moving forward
The leadership team will establish national working parties to progress with identified priority areas. These may include infrastructure necessary to support the collection, analysis and sharing of big educational data, collaboration with teachers about research-informed instruction, or pushing a national policy agenda around the funding of educational research. This funding will ensure that the proposed activities move forward rapidly rather than suffering from further delays.

2. Panel Presenter Credentials
The workshop will be led by Dr Kate Thompson (Head of the Creative Practice Lab, Griffith University). She leads the educational research component of international projects about team science and has been leading research on multimodal data for learning for the last decade. Associate Professor Jason Lodge (The University of Queensland); Professors Lina Markauskaite and Peter Reimann (co-directors of the Centre for Research in Learning and Innovation, The University of Sydney), and Dr Florence Gabriel (University of South Australia) will participate in the panel discussion. Each researcher will provide an example of a case, highlighting one issue to be solved with respect to educational data.

References
Ethical perspectives of university students on consent for use of their data in higher education and research

Rebecca Bosward1, Jackie Street1, Annette Braunack-Mayer1

The study of learning analytics has enabled researchers to improve education and learning outcomes for students. However, university students have little awareness of learning analytics or knowledge of the ethical issues concerning use of their data.

We undertook a qualitative study to explore university students’ attitudes and beliefs towards consent for collection and use of their data. We found that age, gender, international or domestic status, and type of degree appeared to influence their attitudes to consent for use of their data. Overall, students want to be asked for consent to use their data and are only willing to support such usage if the data were anonymised, there was a clear benefit and they could see the outcomes that came from use. Transparency and openness were perceived to be most significant for consent and building trust. Students were particularly concerned about the possibility of discrimination.

The findings suggest students want to know what universities are doing with their data. Developing strategies to improve student engagement and increasing transparency and openness about the outcomes of research involving student data, will be a significant step forward in building trust and improving learning analytics acceptance and effectiveness.

Keywords
Learning analytics systems, empirical ethics, consent.

1. Presentation Focus
The focus of this presentation is to highlight the current ethical issues on consent surrounding learning analytics and collection and use of student data in higher education and research settings. It will present the outcomes of a series of focus groups that explored university student’s attitudes and beliefs on consent for use of their data in university and research. Recommendations will be made for applications of this research and for future research. “Ethical perspectives of university students on consent for use of their data in higher education and research” is part of a larger research project in ACHEEV which aims to investigate the potential for enhanced legal, ethical and policy guidance to ensure that big data are collected, held, managed, analysed and disseminated appropriately.

2. Poster Presenter Credentials
Rebecca Bosward has a bachelor’s degree from the University of Wollongong in Public Health – Health Promotion and Public Health Honour’s degree in progress. She is a research assistant for ACHEEV at UOW and Early Start Research UOW.
References
Dark Data and Learning Analytics

Joshua Burridge1, Judy Kay2

Keywords
Dark data, technology enhanced learning, e-learning, data lake, data analytics

Abstract
Data collection and storage has a cost regardless of whether the data is used, and approaches to data science in business recognise this un- or under-utilised data (so-called ‘dark data’). Dark data has been recognised as an important problem in the business world because of this cost without benefit, as well as potentially serious risks associated with privacy and security.

Dark data in the general sense may be defined as data that exists but is not being/has not been analysed and acted upon. Different fields have more specific definitions; in business, this has been described as “the information assets organizations collect, process and store during regular business activities, but generally fail to use for other purposes” (Gartner Inc, n.d.) and in library science as “any data that is not easily found by potential users” (P. Bryan Heidorn, 2008).

We explore this notion in relation to learning analytics. We see two key and very different aspects. In spite of the fact that learning analytics work has not been previously linked to the business concept of dark data, it has, nonetheless, a long track record of bringing dark data into the light. For example, it has harnessed digital records of student data to identify at risk students, and LMS data to enable teachers to gain insights about their classes. However, a second aspect of dark data is assuming growing importance for learning analytics; this is the creation of large data lakes of diverse and long-term data. This paper aims to introduce the notion of dark data to learning analytics as a foundation for building better processes and tools to address the challenges of dark data and to harness it effectively.

Data science in general can be seen as an iterative process of purpose or problem identification, data collection, storage, collation, exploration, analysis, reporting, and finally use in service to the identified purpose or problem. The costs in data science, whether money, time, or otherwise occur at each stage in this lifecycle – but the benefits are typically only realised when the results are leveraged at the end. This may take the form of a direct change in policy, an active system showing results to teachers or students, or it may feed the results in to new studies. Dark data is created when data does not go through each of these stages and ‘hangs’ partway along – and thus fails to yield its potential benefits.

A key motivator for leveraging dark data rather than simply recording new data is that data acquisition is difficult and costly – and this is especially true in the context of education. The sources of data that learning analytics is most interested in are people, and people are notoriously difficult to study. Time requirements, an increased desire for privacy in a world of digital surveillance, and the requirements of ethical research mean that each piece of data obtained represents significant cost – likely to be more than the cost of any other activity in the life of that data from storage to analysis. While the sunk cost fallacy does still apply here and not all data will be worth extended analysis, determining this still requires the explicit acknowledgement of the dark data in the first place – and this may lead to data being disposed of, reducing the overall cost as well as risk.

The primary reported block causing dark data in business is the lack of analysis tools and skills for particular types of difficult-to-analyse data, such as social media data (Kimble & Milolidakis, 2015) – and learning analytics is also likely to encounter this issue. But easier to analyse data exists in educational settings that are not universally recognised as relevant data, from student interactions in computer laboratories, to the use of web-delivered learning content, to the interactions with other easy-to-measure interfaces such as email. Identifying where that data (and what data) gets ‘held up’ in the pipeline and becomes dark data may not be obvious – and since the people running these systems and the people who may be interested in analysing the data they record are often different there may not be an awareness of the data in the first place.

Consider the following scenario: a student undertakes an online quiz in a learning management system. This student ends up with a score for this quiz, let’s say 7.5/10. This score is recorded in the LMS and is later used both for assessment and for research on the efficacy of an intervention. On the surface the data appears follow the full process from collection to usage – and for the single piece of data being the 7.5/10 score this is correct. The dark data in this instance is the data that various systems collect, but do not pass on to the ‘next step’.

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One layer where this is likely to occur is in the LMS itself. Details about the quiz are likely to be recorded as a natural function of the LMS, such as the time the student took the quiz (both time of day and length of quiz), or the number of attempts the student made. Other data is likely to have been recorded by the browser or device the student used, but were not sent to the LMS or were not known to the researchers – for example the order the student answered the questions, the number of times and ways they replaced or changed their responses, or whether and when the student task switched (i.e. alt+tab) away from the quiz browser window.

So far each of these issues already has a corresponding solution from business analytics. The issue of data that is not being recorded is solved simply by identifying that the data exists and taking steps to make it explicit in the lifecycle for use or disposal. The more complex issue of data collation (and associated activities such as annotation and representation) is the driver of an innovation in data science known as the ‘data lake’, which unifies storage of data such that it can be analysed en masse (especially using AI/machine learning) (Stein & Morrison, 2014). These concepts have slowly begun making inroads into educational data science e.g. in (Villegas-Ch, Luján-Mora, Buenaño-Fernandez, & Palacios-Pacheco, 2018).

A potential issue with this trend lies in solving ‘part of the problem’ – that is, following the lead of data science in business will help solve the problems that business has solutions for, but will introduce or fail to solve problems that business is currently grappling with. A key issue with data lakes is they sit on the ‘collation’ stage of the overall data science process, and thus this approach to dark data will only push it to this collation stage – as identified in business analytics in (Cafarella, Ilyas, Kornacker, Kraska, & Re, 2016). Another way the ‘darkness’ of the data described in the earlier quiz example may cause issues may arise when later researchers use what has been recorded, but without an awareness of the original context of that data collection – a significant risk with data lakes promising long term storage for longitudinal analyses.

While this is still a very open problem to be solved in the business analytics domain, it may be that educational data science fields may be able to bring in their existing methods to address this issue. In some sense ‘dark data’ represents a bias in a data science process – a bias towards data a researcher was aware of, or an existing tool asked for or collected itself, or a bias towards familiarity with past projects or collection methods – and educational data science has identified methods for dealing with this.

For example, the idea that data collection and analysis in education is inherently ‘designed’ and thus embeds socio-political ideas and realities is the topic of (Williamson, 2019). The proposed solution here is to use dialogue with stakeholders to both identify what data is relevant, and to add a layer of translation to what numbers that would otherwise sit in isolation would represent. Applied to dark data, this would bring transparency to data sitting in a data lake by adding annotation descriptions or labels to data, explanatory notes to previously identified discrepancies, or by identifying links between data sources that were not yet apparent. These changes may increase the likelihood that such data would be made use of (and made use of properly) in later stages of the data science process potentially up to the usage stage.

Dark data is an untapped resource in educational data science that may yield new insights or add evidence for existing ideas. By investigating the circumstances of educational activities to identify potential sources of such data as well as managing this data through the data science process the overall performance of educational data sciences fields may be improved. This paper aims to introduce the notion of dark data to learning analytics as a foundation for building better processes and tools to address the challenges of dark data and to harness it effectively.

References


Linguistic changes across different user roles in Online Learning Environment

Lavendini Sivaneasharajah1, Thushari Atapattu 2, Katrina Falkner3

Abstract
In recent years, we have witnessed an increasing interest in online learning environments, particularly in Massive Open Online Courses (MOOCs). However, prevailing studies show that only five percentage of students complete their courses successfully in online learning environment. This raises a question ‘Are students really learning from MOOCs?’ The vast amount of student data available in MOOC platforms enables us to gain insight into student learning behaviours. In this paper, we explore the idea of ‘student roles’, identifying linguistic change associated with roles that will later help us to understand students’ learning process in MOOCs. As an initial stage of this research, the study aims to categorise student roles (e.g. information seeker, information giver) based solely on discourse analysis. Further analysing the linguistic change for each student roles with time. A classifier has been built to identify information-seeking/ information-giving/ other user role with the accuracy of 87.30%. Further, our linguistic experiments show that distinctive behaviours can be observed across different user roles.

Keywords
MOOCs, Discussion forums, Student Role, Natural Language Processing, Machine Learning

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1. Introduction
With the advent of MOOCs, there has been an eruption in online learning environment. Students are increasingly seeking alternative learning mediums, with MOOCs increasingly looked upon as a valuable source of learning. As many of the MOOCs are freely available for students, it draws interest of thousands of learners (Shah, 2017). However, studies show that only one in every twenty students who enrol in MOOCs complete their studies successfully (Koller, Ng, Do & Chen, 2013). This raises a question, Are students really learning from MOOC? The major problem this study aims to solve is whether discovering student role and tracking their linguistic changes help to understand student learning.

As this study demonstrates a proof of concept, our initial stage is to identify user roles that are associated with each student. Our end goal is to use these identified user roles and track their role changes with time. Further, tracking linguistic changes associated with each role. These roles tracking and associated linguistic changes will eventually result in a deeper understanding of student’s learning lifecycle.

2. Methodology

2.1. Data Set
We extracted a dataset from the AdelaideX ‘Introduction to Project Management’ and ‘Risk Management for Projects’ courses offered in 2016 and 2017 respectively. A total of 9497 user posts was extracted from 923 different users. We sampled 1119 posts from Risk Management for Projects for this pilot study. We extracted user posts of students who have posted a minimum of six posts during the entire semester. Posts were manually annotated into information seeker, information giver and other user roles by two independent human evaluators. According to Cohens kappa, the high inter-rater agreement (k= .0.926) in between the two annotators ensures the validity of the classification.

2.2. Experiments
A recent study by Hecking et al. (2016), categorize the user roles into three different classes: information-seeker (IS), information-giver (IG) and other (O). This user role identification is grounded by post classification methodologies (Arguello & Shaffer, 2015). However, these existing studies have used both the contextual (e.g. votes) and linguistic features for the classification. Our first experiment addresses role classification by eliminating the contextual and structural features. That is, we predict these classes solely based on linguistic features. In this multiclass classification, each user post is classified into one of the three previously defined labels (IS, IG, O) by using discourse features and linguistic features that were extracted.
Our second study is an ongoing experiment; here we conducted several linguistic experiments to understand the linguistic changes of each user role with time. The work of Dowell et al. (2017) is a linguistic study on MOOC data to identify the conversion in learner’s language and discourse characteristic with time. However, the study is limited to few linguistic experiments and the research fails to investigate the linguistic changes associated with each user role. To address this gap, we conducted several experiments using different linguistic features to discover discourse complexity, number of embedded information and lexical frequency profile etc. We implemented a language model that calculates the Flesch-Kincaid (Klare, 1974) reading level measure and measured the discourse complexity with time for each user. The number of embedded information in a user post built upon the theory of clause extraction (Bulté & Housen, 2012). We created a NLP parse tree for each user posts and used clause-level part-of-speech tags (e.g. SBAR, SBARQ etc.) to extract clauses from user posts. Subsequently implemented a rule-based program to calculate the number of clauses from user posts to measure number of information embedded in a post. Further, this clause extraction can also be used as an indicator for linguistic complexity. On the other hand, we have also analysed the lexical frequency profile for each user role by extracting n-grams from lecture slides and calculating the frequency of each n-gram within a user post.

3. Results, Discussion and Future work

In our first experiment, we implement multiclass classifiers with different set of classifiers using Weka. All these classifiers tested using 10 Fold Cross-Validation to assess the accuracy. Among these, Random Forest classification model performed best with 87.30 of accuracy (F1=87.30, k=78.34) comparing to other models (Hecking, Chounta & Hoppe, 2016). Further we also fine-tuned the parameters for Random Forest classifier using scikit-learn library (RandomizedSearchCV and GridSearchCV). The results show that Random Forest classifier performs at its best in the following parameter setting: n_estimators': 400, 'min_samples_split': 10, ‘min_samples_leaf’: 4 and max_depth': 70.

According to our second study, Figure 1 shows the reading level measures (complexity) of a sample of six users. The results indicates that if a particular use role can be seen in consecutive user posts the level of complexity increases/decreases with minimum change and when there is a role change(e.g. IS → IG or IG→ IS or O→IG ) there is a high dramatic change in linguistic complexity. This trend is observed across our data set.

Results of clause extraction shows, that information embeddedness in a user post increases and decreases for information giver and information seeker respectively with time. Similarly, the lexical frequency profile of an information giver is higher than that of an information seeker. As our future work, we hope to do further experiments (e.g. sentiment analysis, level of informative information, newness of user posts) to analyse the associated behaviour of each user role in discussion forums.

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Predictors of Student Satisfaction: A Large-scale Study of Human-Human Online Tutorial Dialogues

Guanliang Chen¹, Dragan Gasevic²

Abstract
For the development of successful human-agent dialogue-based tutoring systems, it is essential to understand what makes a human-human tutorial dialogue successful. While there has been much research on dialogue-based intelligent tutoring systems, there have been comparatively fewer studies on analyzing large-scale datasets of human-human online tutoring dialogues. A critical indicator of success of a tutoring dialogue can be student satisfaction, which is the focus of the study reported in the paper. Specifically, we used a large-scale dataset, which consisted of over 15,000 tutorial dialogues generated by human tutors and students in a mobile app-based tutoring service. An extensive analysis of the dataset was performed to identify factors relevant to student satisfaction in online tutoring systems. The study also engineered a set of 325 features as input to a Gradient Tree Boosting model to predict tutoring success. Experimental results revealed that (i) in a tutorial dialogue, factors such as efforts spent by both tutors and students, utterance informativeness and tutor responsiveness were positively correlated with student satisfaction; and (ii) Gradient Tree Boosting model could effectively predict tutoring success, especially with utterances from the later period of a dialogue, but more research effort is needed to improve the prediction performance.

Keywords
Intelligent Tutoring Systems, Student Satisfaction, Educational Dialogue Analysis, Gradient Tree Boosting

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1. Introduction
Intelligent tutoring systems (ITS) are computer systems that are designed to act as human tutors and provide personalized instruction or feedback to students in online learning environments. A special class of ITS is dialogue-based intelligent tutoring systems such as AutoTutor and BEATLLE, which emphasize the use of human-agent dialogue in one-to-one tutoring. Such systems have been built on advances in psycho-/socio-linguistics, computational linguistics, and natural language processing to create productive learning experiences in human-agent dialogue tutoring. In line with (Vail & Boyer, 2014), we argue that the future development of dialogue-based systems can benefit greatly from the analysis of massive datasets collected in online tutoring. Specifically, we are interested in understanding what constitutes successful human-human online tutoring. In this paper, we report on the findings of a study that looked at factors that predict student satisfaction with human-human online tutoring. The analysis of human-human online tutoring requires consideration of factors that shape the entire tutorial process. To our knowledge, few studies have attempted to identify the crucial factors that are correlated with the success of a tutoring session. Thus, our work aimed at identifying factors that are correlated with the success of a dialogue-based tutoring session. Formally, our work was guided by the following research question: what factors are related to student satisfaction with online tutoring service? By investigating the research question, we expected to (i) help tutors in existing online tutoring systems to better direct their efforts in guiding students, and (ii) inform the design of future dialogue-based ITS.

2. Methods and Results
To this end, we first formulated a set of hypotheses about potential factors that were correlated with the success of a dialogue-based tutoring, which were grounded in previous research findings on online tutoring or relevant educational topics. Then, we conducted an extensive analysis of a large-scale dataset provided by a company offering online tutoring services to students, which contained transcripts of over 15,000 dialogue-based tutoring sessions generated by more than 5,000 students, to test the formulated hypotheses. In more details, we hypothesize that a tutorial dialogue will be more likely to success if: (1) a student/tutor spends more efforts (H1); (2) the utterances sent by a student/tutor are more informative (H2); (3) a student...
spends less time in waiting to receive a response from a tutor (H3); (4) the tutorial dialogue is of high lexical entrainment (H4); (5) the utterances sent by a student/tutor are less complex (H5); (6) a tutor/student asks more questions (H6); (7) the utterances sent by a student/tutor convey more positive sentiment (H7); (8) a student/tutor has more prior tutorial dialogues (H8).

To test the formulated hypotheses, we first classified tutorial dialogues receiving ratings of 4 or 5 from students as the Success group and those of ratings of 1 or 2 as the Failure group. Then, we defined a set of metrics to describe the factors investigated in each hypothesis and compared the two groups with Mann-Whitney test on the relevant metrics to test our hypotheses. The results are given in Table 1.

Based on Table 1, we concluded that H1, H2, H4, H6, and H7 was fully supported by our analysis, while there were some support for H3, H5, and H8. Take H3 as an example, we observed a significant difference between the two groups in terms of Avg. response time, i.e., compared to Failure students, Success students spent less time (about 5 seconds) in waiting for responses from tutors. In a different vein, when inspecting H5, we discovered that the utterances made by tutors in the Success group were slightly less complex than those in the Failure group (85.11 vs. 83.93). However, we did not observe a significant difference between the utterances made by students in the two groups.

### 3. Discussion and Conclusion

In this work, we demonstrated that student satisfaction is correlated with a set of dialogue features, which include (i) the efforts invested by tutors/students; (ii) the informativeness of tutor/student utterances; (iii) the readability level of tutor utterances; (iv) tutor responsiveness; (v) the number of questions asked by tutors/students; (vi) the entrainment level of a tutorial dialogue; (vii) the positive sentiment level of tutor/student utterances; and (viii) students’ experience in using the tutoring service. This may shed some light on how to better direct online tutors’ efforts in guiding students. For example, tutors may consider to provide prompt responses, use more words of positive sentiment and suitable readability level, and ask a suitable number of questions to assist students to solve problems.

### References

User-centred AI and Learning Analytics: An interdisciplinary perspective.

Peter Reimann¹, Dragan Gašević², Judy Kay³, Abelardo Pardo⁴, & Kalina Yacef⁵

Abstract
The goal of this panel is to (a) critically assess the state-of-the-art of explainable learner models in the fields of AIED and LA and (b) to discuss suggestions for the engineering of better explainable learner models. Taking an interdisciplinary and transdisciplinary perspective on learner modelling, new approaches will be introduced regarding the question how to make learner models explainable, building on research on open learner models in the field of AI in Education. The panellists will further explore the potential for a deeper involvement of the end-user in the design and engineering of learner models, reflecting the fact that what requires explanation and is accepted as explanation is deeply dependent on users' knowledge and information needs.

Keywords
Artificial Intelligence, end-user development, explainable AI, open learner models.

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Panel Focus
The currently most discussed relation between learner data and AI concerns the use of AI—mainly in form of Machine Learning (ML) methods—for analysing learning data (e.g., Lan et al, 2014). In doing so, the learning data analyst has a choice between a wide variety of methods (Robero et al., 2010). One dimension along with these methods can be distinguished is the extent to which they yield explanatory versus black box models (Rosé et al, 2019). This distinction is not so much about accessibility—if the model is hidden from or open to the user—but is essentially an epistemic one: the extent to which a model is explained (or explainable) to the user. (The user in the cases of educational systems are teachers, students, and sometimes other stakeholders, such as parents.) In the wider discussion on explanations in AI (e.g., Abdul et al., 2018), models with few parameters are considered better explainable than those with many parameters. Decision-tree models, for instance, are better explainable than, say, (deep) Neural Net models with potentially thousands of parameters. For explanatory learner models in education, Rosé et al. (2019) make the interesting suggestion to distinguish black box models from explanatory models in that the latter are (i) providing insights about learning and (ii) are explicitly engineered to be explainable by the end-user.

The goal of this panel is to (a) critically assess the state-of-the-art of explainable learner models in the fields of AIED and LA and (b) to discuss suggestions for the engineering of better explainable learner models. The panel will address these points from an interdisciplinary perspective, one that combines computer science with social and learning sciences. The panel will scrutinize, amongst other aspects, to what extent the conventional separation of design and engineering tasks from use tasks should be maintained for the engineering of explainable learner models. It will explore the potential for
connecting LA and AIED with End-User Development (EUD) research as conducted in the field of Human-Computer Interaction (Paterno & Wulf, 2017). EUD covers activities reaching from parametrization or customization to modification and extension of software (end-user programming). For the engineering of learner models, the EUD perspective affords the question to which extent learner models can or should be engineered by (teams of) expert engineers and to which extent the end-user will need to involved not only in the design phase (requirements analysis) but also have control over design aspects in the use phase. This suggest that research on explainable learner models may not only have to be interdisciplinary in nature, but transdisciplinary: it needs to consider new forms of collaboration between experts (engineers, computer scientists, learning designers) and end-users (teachers, instructional designers, students).

**Panel Presenter Credentials**

The panel is composed of five experts on Learning Analytics, Educational Data Mining, and AI in Education. It is organised and led by Peter Reimann, Professor for Education at the University of Sydney, who specialises in Learning Sciences. Dragan Gašević is Professor of Learning Analytics in the Faculty of Information Technologies. Judy Kay is an expert on HCI and AI in Education working as Professor in the School of Computer Science at Sydney University. Abelardo Pardo is Professor and Dean Academic at the Division of Information Technology, University Engineering and the Environment at the University of South Australia. Associate Professor Kalina Yacef is an expert on educational data mining in the School of Computer Science, Sydney University.

**References**


Blending Machine Learning, Graph Theory and Spectral Analysis to Better Understand Student Engagement and Regulation: Following the white rabbit of trace data

Ben Hicks

Abstract
We want students to be engaged and develop self-regulatority behaviour but identifying this through the narrow lense of online metrics can be challenging. This demonstration outlines a blended approach to examining online learning data (trace data); both in terms of layering different data using visualisation tools as well as linking various analytic tools; clustering, networks and a technique analogous to spectral analysis. Although a strong technical foundation underpins the methods there is a careful choice of visualisations to enable intuitive interpretation of the results.

Suggested format: 1.5 hour part demonstration / workshop. If you are interesting in trying some of the analysis in R or exploring some of the visualisations please bring a laptop along.

Keywords (not a research paper)
Learning analytics, social network analysis, clustering, machine learning, activity, engagement, learning design

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1. Workshop Focus
Examining the trace learning data expunged by the Virtual Learning Environment (VLE) can provide a way to understand Learning Design (LD) strengths and how student’s engage with their learning, and could possibly better than asking students themselves. This workshop will follow a year long journey in understanding the engagement of groups of students across two subjects, looking at both the VLE site activity and forum discussion.

1.1. Clustering by clicks
The first step in this journey is to group the students in some meaningful way from their VLE trace data. A key question arises: is a particular type of behaviour indicative of a successful student, or is the trace data more indicitive of other learner attributes? Are these different clusters influenced by LD, and do they interact the same with the site in a similar temporal manner, or not?

Figure 1. Site activity by cluster
1.2 The ‘harmonics’ of a cohort
Once the clusters of students have been formalised, we examine the trace data from another angle, that being a ‘spectrum’ of the clicks of a particular cluster. This allows to view a snapshot of the ‘signal’ of clicks coming from a group, and allows us to have a quick way to visualise and compare a stream of clicks, which can also then be filtered by content and cluster.

![Figure 2. Activity ‘spectrums’ by cluster](image)

1.3 Joining the dots
Using Social Network Analysis (SNA) is a natural fit for examining the discussion forum trace data and can have a strong impact on learning (Bruun & Brewe, 2013). We attempt to see what can be gleaned by layering other trace data with the network, such as academic performance and forum views. We also examine what can be understand about the social dynamics by performing a triadic census of the network and comparing this to randomly generated graphs with similar properties, and decide if the network is more hierarchical or egalitarian (Grunspan et al., 2017).

![Figure 3. Forum Network](image)

2. Workshop Presenter Credentials
Ben Hicks has a breadth of experience in education having taught mathematics in 3 continents and a variety of educational systems and cultures. In recent years he has helped develop and implement systems for tracking student effort and engagement in a high school context, and presented to school leaders on how best to disseminate data to teaching staff to foster dialogue about learning. Ben has moved away from the classroom to focus on Learning Analytics and works with the rich online learning dataset available at Charles Sturt University whilst developing open source tools in R for Learning Analytics published in the `lakit` package.

References
The Fifth Writing Analytics Workshop: Linking Reflective Writing Analytics to Learning Design

Ming Liu¹, Rosalie Goldsmith², Sumati Ahuja³, Xiaodi Huang⁴

Abstract
Reflective writing is a fundamental learning activity across learning contexts. With the recent advancement of natural language processing techniques, text analytics are able to identify salient textual features of students’ written assignments, such as academic reflective essays and reflective statements, and generate actionable feedback. However, how to best use reflective writing analytics tools, such as AcaWriter, in different learning contexts is a challenging and important issue. This workshop seeks to connect writing analytics and educators who work on linking the writing tool into learning design. We will demonstrate how AcaWriter can analyze writing from learning contexts, and how to integrate this tool in various learning contexts. Participants will have a hands-on experience of using AcaWriter, and be shown a few case studies of using acaWriter in different subjects at the University of Technology, Sydney, and finally we will discuss the challenges of linking writing analytics tools to learning design.

Keywords (not a research paper)
Writing analytics, AcaWriter, Automated Writing Feedback, Learning Design

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1. Workshop Focus

In recent years, the integration research of learning analytics to learning design has attracted a great attention in the learning analytics (LA) community (Lockyer & Dawson, 2011; Macfadyen, Lockyer and Rienties, 2019). With the advancement of natural language processing and machine learning, writing analytics has become an emerging field of LA and has shown its potential for students to revise their written assignments (Gibson et al., 2017), and for teachers to improve learning design with the evidence (Cherie, Gibson and Buckingham Shum, 2018). The proposed fifth workshop in the series will build on the previous ALASI writing analytics workshops to develop writing analytics literacy and learning design skills. The focus will be on the integration of AcaWriter with learning design by linking theory, pedagogy and assessment to close the feedback loop (Corrin, et al., 2018; Knight, Shum, & Littleton, 2014; Shibani, Knight, Buckingham Shum, & Ryan, 2017). This workshop will provide participants with hands-on experience in using AcaWriter (in the first session), and detailed use cases in authentic learning environments and discussion of how best to use AcaWriter in different learning contexts (in the second session). Thus, the fifth workshop is intended to:

- increase the participants’ knowledge of reflective writing analytics with using AcaWriter system;
- enhance conversation on writing analytics literacy development and learning design integration by bring together text analytics researchers and educators.
- move the field forward by creating a writing analytics research and application community in Australia.

2. Workshop Presenter Credentials

Dr. Ming Liu is a research fellow of text analytics at the Connected Intelligence Centre, UTS. His research work is focused on researching and developing automated feedback tools that support writing, reading and peer reviewing in the context of individual and collaborative learning using learning analytics and artificial intelligence. He has initiated and participated several Australian and Chinese government funded writing analytics research projects, including AcaWriter (https://acawriter.uts.edu.au) funded by UTS, Glosser (Comprehensive support for collaborative writing) funded by ARC, iWrite (http://iwrite.sydney.edu.au/iwrite.html) funded by OLT, Cooperpad (Collaborative Writing Analytics Tool) and VisualPeer (Formative Peer review Analytics tool) funded by NSFC. He has co-chaired the LAK19 and ALASI2018 Writing
Analytics workshops.
Dr Rosalie Goldsmith is an applied linguist who is a member of the Academic Language and Learning Team, University of Technology Sydney. Rosalie works with the faculty of Engineering & IT. Her main research areas are Engineering Education, Writing Practices, reflective writing and reflective writing analytics, Practice Architectures Theory, peer learning, WIL and developing professional identity.

Dr. Sumati is an academic with an impressive background of working in industry for over 25 years and teaching in both undergraduate and postgraduate programs for 10 years. She has held senior positions at internationally renowned architectural firms. Sumati moved to full time academic role in 2018 after completing her PhD in Management from UTS Business School. Her PhD focused on the changing nature of professional work and how professionals respond to changes in the way their services are procured and delivered. The future of work continues to be Sumati's research interest with a focus on how technologies are transforming the work of human experts.

Dr. Xiaodi Huang received his Bachelor of Science in Physics in 1989, M.Phil. degree in Computers in Education in 1992, and a PhD in 2004. He is a senior lecturer in the School of Computing and Mathematics at Charles Sturt University. His research areas include visualization, data mining, and web services. He has published over 100 scholar papers in international journals and conferences. Dr Huang is a regular reviewer for several international journals, and serves as the committee members of a number of international conferences. He is a senior member of IEEE Computer Society and member of the ACM.

References


Demonstration: Ethical edgecases – a middle space bringing system builders into contact with ethicists

Kirsty Kitto¹, Simon Knight¹, Linda Corrin²

Abstract
This demonstration will run in a workshop mode that explores the issues that arise in relying purely upon ethical frameworks and checklists to influence the behaviour of LA practitioners. It will introduce a newly proposed conception of “practical LA ethics” which places the burden of ethical behaviour upon practitioners. An enabling ethical edge cases database will be used by participants to bring system builders into dialogue with legal and ethics experts, so adding to the sophistication of discussions of this important topic in the Australian context.

Keywords
Learning Analytics, ethics, edge cases, scaling adoption

1. Introduction and Focus

Learning Analytics (LA) has, since its inception, had a strong emphasis upon ethics, with numerous checklists and frameworks proposed to ensure that student privacy is respected and potential harms avoided. However, they often contain contradictory instructions, and few practitioners appear to be following them when building LA solutions. Indeed, McNamara, Smith, and Murphy-Hill (2018) recently demonstrated that the ACM code of ethics (https://www.acm.org/code-of-ethics) had no discernible impact upon the decisions made by 63 software engineering students and 105 professional software developers in responding to a set of 11 ethical vignettes. It is likely that similar results would be found for the many checklists and best practice approaches that have been proposed in LA, although this is an area where well-grounded research is desperately required. This does not imply that practitioners do not want to be ethical. Indeed, Johanes and Thille (2019) recently demonstrated that practitioners often have a strong desire to “do the right thing” when building LA solutions.

It seems that an approach to ethics that is grounded in frameworks and checklists alone is not sufficient. One possibility is to provide a “middle space” (Knight, Buckingham Shum and Littleton, 2014), where LA practitioners can work with ethicists, legal experts, and other stakeholders to deliver solutions that meet the needs of society. A new approach (Kitto and Knight, 2019) argues that we should adopt approaches grounded in practical ethics, and presents a database of “ethical edge cases” which holds potential to provide this middle space.

This workshop will introduce the ethical edge case database, and provide participants with a forum to provide feedback on its format, enhance and extend it. The publicly served database can be accessed at www.ethicalEdges.com, and an open source instance is available for modification (at https://github.com/uts-cic/EdgeCaseDB). All input is welcome!

2. Workshop description

This demonstration will take the format of a short (1.5 hours) workshop which interactively brings participants together to work on the ethical edge case database, by adding edge cases and extending existing ones. Participants will be introduced to a number of key ethical and legal frameworks that could impact upon LA, and asked to
consider their influence on LA practitioners to date. They will then be introduced to the conception of an edge case and shown how these can drive the development of LA tools, before being guided through the construction of new edge cases and their entry into the LA edge case database.

2.1. Planned workshop schedule (1.5 hours)

<table>
<thead>
<tr>
<th>Time allocated</th>
<th>Focus</th>
</tr>
</thead>
<tbody>
<tr>
<td>15min</td>
<td>Introduction</td>
</tr>
<tr>
<td>15min</td>
<td>Ethical frameworks and checklists – an introduction</td>
</tr>
<tr>
<td>45min</td>
<td>Building ethical edge cases</td>
</tr>
<tr>
<td>15min</td>
<td>Discussion and wrap up</td>
</tr>
</tbody>
</table>

2.2. Upon completing this workshop participants will be

- Familiar with some of the major ethics frameworks that have been developed in LA
- Aware of some of the tensions that exist in these frameworks when applied by practitioners
- Familiar with the ethical edge case database and how it can be used to bring LA practitioners into contact with those who are working on the ethical and legal aspects of LA solutions.

2.3. You will need to bring

- An interest in building LA solutions, the ethical/legal aspects of those solutions, or both!
- A desire to participate in formulating ethical edge cases that can be used to seed the next generation of LA ethical practice.

3. Credentials of team

Dr Kirsty Kitto is a Senior Lecturer of Data Science at UTS’s Connected Intelligence Centre (CIC). She is working with the postgraduate futures team at UTS to extract Canvas data using the Live API and then pull it into student and staff facing LA dashboards.

Dr Simon Knight is a lecturer in the Faculty of Transdisciplinary Innovation. His research interests include learning design and educational technology, educator use of evidence in their practice and learning analytics (particularly writing analytics).

Associate Professor Linda Corrin is Academic Director, Transforming Learning at Swinburne University of Technology. Her interests in learning analytics range from how students and teachers interpret learning analytics data/visualisations to the ethical implications of the use of data in higher education. She is a co-ordinator of the ASCILITE Learning Analytics Special Interest Group and co-founder of the Victorian/Tasmanian Learning Analytics Network.

References


Evaluation of course design and learner behavior with Sankey Diagrams

Rupa Vuthaluru¹, Simon Kerrigan¹, Dirk Ifenthaler², David Gibson¹

Abstract
This demonstration will show how individual learner behaviours and learning paths can be visualized and explored using Sankey diagrams. Trace data from a collaborative problem solving digital learning environment, Curtin Challenge, were used to examine how learners are interacting with content as planned by learning designers. Behavioural differences of individual learners were visualized as learning paths, which provide evidence for validating course design as well as student learning outcomes. A series of research questions were addressed including: 1) Completion Paths – how do teams and individuals differ with respect to sequence of task completion, what variability do they exhibit in starting times and durations, 2) Evaluation of course design – impacts of learning design on student engagement patterns, and impacts of student behavioral patterns on achievement of learning aims. The long term aim of the research is to determine the challenges and potential of fine-gained time-sensitive analyses of individual and collaborative problem-solving tasks to inform an understanding of the structural, correlational and causal relationships of students achieving learning outcomes.

Keywords
Collaborative problem solving, Sankey diagrams, Learning Paths, Challenge Platform, Learner behaviours

1. Demonstration Focus
Curtin University’s Challenge Platform was created in response to two imperatives of educational technology in higher education - ubiquitous mobile computing and the transformation of problem-solving patterns, creativity and thinking required for the future of work. The idea of ‘learning by doing’ (Dewey, 1938) embodies a truism of learning theory: students learn by authentically interacting with the world and receiving rewards and feedback. When that world is a digital learning design, the learner interacts with planned affordances for learning and leaves a fine grained physical record that can serve as signature of their encounters with the intended learning opportunities (Ifenthaler, Gibson, & Doboz, 2017). The analysis of individual user experiences is an important aspect of course evaluation as the investigations play an important role in identifying if the course design has successfully achieved its aims. This study explored Sankey diagrams as a tool to visualise learners’ behaviour and paths through course content to represent and evaluate individual participation and contribution during collaborative problem solving, using the log files captured by Curtin Challenge, a learning experience platform for individual and group earning.

1.1. Methodology and Observations
Sankey diagrams are used to visualise flows of materials and energy in many applications (Lupton, 2017). A Sankey-like diagram was first used by Charles Joseph Minard in 1869 to visualise Napoleon’s Russian campaign of 1812 (Friendly, 2002). Sankey diagrams visualise flows from one state to another by using the width of the arrows to indicate the quantity of flow within the system. They have been used in education for overviews of video consumption within MOOCs (Lundqvist, Godinez, & Warburton, 2018). However, they have never before been used to study individual learner behaviours during collaborative problem solving. The flows recorded in this particular case involve the time, attention and actions of a learner who is interacting with a digital learning experience. We can think of the metaphor of ‘web pages’ acting as activity centers of an extended module or unit of digital learning, and interactive elements on those pages as sensors collecting the actions of learners. The Sankey diagrams can be interpreted as ‘time on task’ ‘indicators of level of engagement’ and ‘autonomous task sequence from learner choices.’ Each activity is noted as a node in a network and the links of the network are the in-paths and out-paths to each node over time. The Sankey diagram summarizes the navigation sequence and may represent several days of interactions by the learner. The Challenge platform developed at Curtin University sets the digital context for data collection (Gibson, Irving, & Scott, 2018). The platform enables individuals to build up a longitudinal record of digital engagement and to document change over time at the individual and team level while working alone or with others.
Data for the analyses were collected from log files of the interactions. The Plotly Python library was used as reference for creating the Sankey diagrams. Dynamic inline figures were created and explored as outputs in Jupyter notebook using Python code, but only a static diagram can be shown in print. Figure 1 depicts an individual learner behaviour aggregated to days while completing the tasks in the course. Students may navigate between tasks in any order (which allows and creates loops representing multiple exposures to content such as in re-teaching or self-review). The nodes (vertical bars) in the Figure 1 represent the main activities comprised of multiple tasks (detailed data on each subtask is available but not considered in this level of analysis), width of the node and the link thickness represent relative length of time spent on that task compared to other tasks. The process is from left to right where one task (flow) ends and another starts. When a researcher hovers over a bar or path of the online dynamic diagram (not shown), it highlights number of attempts of that task (as inputs) and number of times learner moved away from that task to attempt another task (as outputs). Several learner behaviours were observed and complexity of tasks were reviewed based on number of attempts made by learners, the sequence of choices made by the learner, and in combination with the design implications. In Figure 1 the number of interactions and time on task for research tasks were greater than other tasks. Of interest at this level of analysis is the role of this contribution to the team achieving a level of completion on the overall unit, project or assignment.

![Sankey Diagram](image)

Figure 1. Individual learner paths through resources and task completion data aggregated by days

**Presenter Credentials**

Dr Rupa Vuthaluru, is Physicist and Data and Learning Analyst from Curtin University, Learning Futures. Vuthaluru’s research focuses on mathematical modelling, simulations, three dimensional computational fluid dynamic modelling (CFD), designing undergraduate and postgraduate higher education curriculum courses including integration of Virtual Reality (VR) and Remote Laboratories (RL) technologies. She has over 33 publications on these topics. She coordinated courses in Engineering and Science faculties at Curtin University and created nexus between teaching and research in particular Heat Transfer and Fluid Mechanics fields with technology-enhanced pedagogical content knowledge

**References**


Exploring the power of using theory to develop learning analytics

Karl Maton¹, Sarah K. Howard², Yaegan Doran³, Joel Nothman⁴, Kathryn Bartimote⁵, Danny Liu⁶, James Tognolini⁷, Kalina Yacef⁸, Pablo Muguia⁹

Abstract
In this roundtable session, we invite participants to consider if, how, why and when researchers and practitioners should seek to integrate theory into their learning analytics work. From construct definition to statistical validation, from approach to interpretation, our assertion is that attendance to theory is essential for meaningful analytics in educational settings. The facilitators will provide an overview of the educational (and other) theories and frameworks appearing in recently published learning analytics literature. Two research teams will share examples from work in progress wherein theory is being applied in two different research stages (1) the definition and development of indicators of engagement and collaboration; and (2) automating the qualitative coding of knowledge building in teacher practice. Participants will be encouraged to share how their current work in planning or progress may or may not benefit from the application of theory. Further, together we will discuss working in multidisciplinary teams, and the challenges of riding the boundaries of multiple perspectives to create a valued and tenable analytics product. Participants will gain exposure to a range of useful educational theories, and generate practical ideas for their application in all phases of research.

Keywords
learning analytics, theory, framework, automated processes, user behaviour

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1. Roundtable Focus

1.1 Background
This Roundtable session will explore the use of theory to develop meaningful and relevant learning analytics. In recent years there has been considerable effort in the fields of learning analytics and data mining to engage with theory. This effort has been a clear rebuke to Anderson's (2008) claim that 'theory is dead' in the wake of Big Data research. Anderson claimed that volume would allow data to speak for themselves without theory. However, such empiricism often leads to the question of ‘So what?’ – patterns may emerge, but their meaningfulness is not necessarily self-evident. In the field of Learning Analytics, researchers are interested in the application of 'big data' approaches to better understand relationships and context (Knight & Buckingham-Shum, 2016), but also students and their learning (Bartimote, Pardo, Reimann, 2019). If a key objective of learning analytics is actionable information, then that information needs to be meaningful. To be meaningful requires some kind of theoretical framework.

Others agree that “learning analytics research should be explicit about the theory or conception of learning underlying the work and manifest this conception in the work presented” (Suthers & Verbert, 2013). Increasingly, researchers are heeding this call and are turning to theories such as social cognitive theory and self-efficacy beliefs, various self-regulated learning models, measurement theory, social-constructivism, human-computer interaction (HCI) and activity theory, Kolb’s experiential learning cycle, etc.
However, not all education theories are equally suited to learning analytics. In many cases data collections are not designed to support theoretical coding, making analysis markers difficult to identify. Often concepts are metaphorical and poorly defined in terms of their empirical referents, or too subjective to be translated into algorithms. What is required is the right kind of theory, able to offer explanatory power to match the descriptive power of big data. Ideally, the theory should: (1) explore relational practices, in order to make meaningful the patterns emergent from inductive analysis of big data; and (2) offer concepts with clear empirical referents that are capable of being transformed into algorithms. The first would add explanatory power to the descriptive power of inductive analyses; the second would enable explanatory power to be achieved at scale. Ultimately, these considerations are important if theoretically-informed analytics are to be meaningful in learning contexts.

In this workshop, we would like to highlight the potential for theoretical perspectives in learning analytics research to expand the depth and breadth of the field. The two research in progress examples to be presented rely on (1) a sociological view of social connection, and (2) Legitimation Code Theory (LGT) which has deep roots in sociology.

1.2 The Workshop

The 3-hour workshop will be organised as follows:

1. (15 mins) Settle in, meet and greet, share plan for the session
2. (20 mins) Presentation & plenary discussion – Introduction to range of theories and their suitability to learning analytics
3. (30 mins) Presentation & plenary discussion – Research in progress Example 1: the definition and development of indicators of engagement and collaboration
4. (30 mins) Presentation & plenary discussion – Research in progress Example 2: automating the qualitative coding of teacher practice
5. (30 mins) Participant-led group discussion – Share applicability of theory to current work in planning or progress
6. (30 mins) Plenary discussion – Working in multidisciplinary teams: Should the marriage of multiple perspectives be attempted?
7. (25 mins) Closing thoughts, comments, and individual reflection on next steps

2. Workshop Presenter Credentials

All presenters are working in the area of theoretical development and the use of data to inform learning. Professor Karl Maton, A/Prof Sarah Howard and Dr Kathryn Bartimote will lead the plenary presentation and discussion examining the suitability of theory to learning analytics. Kathryn, Dr Dany Liu, Professor James Tongolini, A/Prof Kalina Yacef and A/Prof Pablo Muguia will present their work developing indicators of collaboration and engagement. Karl, Sarah, Drs Yaegan Doran and Joel Nothman will present their current work automating qualitative theoretical coding. Prof James Tongolini and A/Prof Kalina Yacef will lead the workshop extending the two presentations of work to discuss the applicability of theory in current work, identified by workshop participants. Working in multidisciplinary teams, Yaegan, Danny and A/Prof Pablo Muguia will facilitate small group discussions on the ‘marriage of multiple perspectives’, drawing on their experience working across disciplines.

References


Multimodal Analytics for Classroom Proxemics

Roberto Martinez-Maldonado and Gloria Fernandez Nieto

Abstract
We use the term Classroom Proxemics to refer to how teachers and students use the classroom space, and the impact of this and the spatial design on learning and teaching. The increasing progress in ubiquitous technology makes it easier and cheaper to track students’ and teacher’s physical actions unobtrusively, making it possible to consider such data for supporting research, educator interventions, and the provision of feedback regarding the use of the classroom space. This workshop is aimed at provoking reflection on potential ways in which teachers can effectively use positioning traces to gain insight into their classroom practice. The workshop will include hands-on ideation activities to explore potential ways in which positioning and other sources of proxemics data can support professional development and research in learning spaces. Indoor positioning sensors along other multimodal learning analytics technologies will be demonstrated during the workshop to facilitate understanding of the broader opportunities of such technologies for learning analytics.

Keywords
multimodal learning analytics, sensors, visualisation, positioning, teaching

1. Focus of the workshop
Previous research has found that teachers’ positioning and mobility strategies in the classroom can strongly influence students’ engagement, motivation, disruptive behaviour and self-efficacy (see review by O’Neill & Stephenson, 2014). Inspired by work on instructional proxemics (Chin et al., 2017; McArthur, 2015), the term Classroom Proxemics is proposed to refer to the research space targeted in this workshop. First, this term points at foundational work by Hall (1966) who defined proxemics as the study of culturally dependent ways in which people use interpersonal distance to mediate their interactions. This work has been widely used in architecture and interior design, including the design of learning spaces (Thompson, 2012). Using proxemics as a theoretical lens is highly relevant, because teachers and students make use of the space, furniture, objects and various kinds of technology to interact among themselves.

Second, inspired by work on orchestration (Dillenbourg et al., 2011), the classroom can be considered as the ecological unit of analysis. The classroom includes social, epistemic and physical aspects, that are quite intertwined (Goodyear et al., 2018) and teachers may have varied degrees of control over these aspects according to their pedagogical approach and the tasks unfolding in them.

Feedback and visual representation of movement and positioning traces captured in physical spaces has been studied in previous work. For instance, (Chin, Mei, and Taib 2017) presents the approach of instructional proxemics to generate personal and pedagogical understanding from how teachers of a second language use their spaces, body movement and positioning and its impact on learning and teaching by using human observations, video and audio. Other researchers, by using indoor localization (Bdiwi et al. 2019), and real case studies(Martinez-Maldonado 2019) explore visual representation of positioning data to explore its potential in spacial pedagogy.

The focus of this workshop is at the intersection between work that has used classroom observations to generate understanding of classroom dynamics (McArthur, 2015) and emerging work focused on creating interfaces to enhance teachers’ awareness, using automatic position tracking (An et al., 2018; Martinez-Maldonado, 2019). Much work needs to be done to identify the kind of reflections that teacher’s positioning data can provoke, and the metrics that may be useful for sensemaking.

2. Participants
The intended audience includes participants interested in developing adaptive and flexible ways to investigate how learners and teachers use the learning spaces. We expect to conduct a 3-hours workshop with at least 10 participants representing...
different research communities, including the learning sciences (LS)/education, technology-enhanced learning (TEL) and, also, more data intensive communities such as learning analytics and artificial intelligence in education (AIED). The participation of practitioners and educators will be also encouraged. Participants will gain first-hand experience in using wearable sensors to track their positioning and in interacting with the data generated from these sensors.

3. Workshop activities

The workshop will follow a JIGZAW collaboration pattern according to the following schedule:
1) **Introduction**, the workshop will start with short introductions by all the participants and a brief summary of the focus and scope of the workshop (20 minutes);
2) **Community Groups**, will be formed with the aim of scoping the problem and identifying gaps which will be shared with all the workshop participants (60 minutes);
3) **Design Groups**, members from the community groups will be re-grouped into design groups to define future scenarios (60 minutes);
4) **Consolidation and Reflection**, a lead debrief will be facilitated with the goal of consolidating a group of researchers and practitioners interested in the topic (20 minutes).

Breaks and transitions are already considered in this plan.

4. Organisers

Roberto Martinez-Maldonado is Senior Lecturer at Monash University, in Melbourne. His areas of research include Human-Computer Interaction, Learning Analytics, Artificial Intelligence in Education, and Collaborative Learning (CSCL). In the past years, his research has focused on applying artificial intelligence and visualisation techniques to help understand how people learn and collaborate in collocated environments. He currently is co-director of the CrossMMLA SIG, the special interest group on Multimodal Learning Analytics Across Spaces.

Gloria Fernandez Nieto is a second year PhD student at University of Technology Sydney in the Connected Intelligence Centre. She is currently supervised by Professor Simon Buckingham Shum, PhD Kirsty Kitto and PhD Roberto Martinez. Her current research focuses on exploring alternatives of feedback to understand traces from data collected in the CSCL classroom to prompt reflection in teaching and learning practices. She also has focused her previous research on Learning Analytics, Technology Enhance Learning and Knowledge Management.

References


Thompson, S. (2012). The applications of proxemics and territoriality in designing efficient layouts for interior design studios and a prototype design studio. Masters dissertation. California State University, Northridge, United States
Quantext in the classroom: lessons from tertiary teachers

Jenny McDonald¹, Adon Moskal, Cathy Gunn & Irina Elgort

Abstract
First presented as a proof of concept at ALASI 2017, Quantext, a text analysis tool for teachers, has developed substantially since then and has been used by a number of teachers and institutional support staff at three NZ universities, one Australian university and one polytechnic. In this 3-hour workshop, using fully anonymised data, we present three use cases derived from a NZ nationally-funded project to pilot Quantext, inform its development and evaluate its use in tertiary classrooms. Each use case demonstrates a distinct approach to analysing text to derive actionable insights. With the use cases serving as models, workshop participants will gain hands-on experience with Quantext using either their own data or our demonstration data sets. There will be ample time for discussion, reflection and feedback.

Keywords
Formative feedback, academic development, text analytics, student evaluations of teaching, discourse analytics.

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1. Quantext Workshop Focus

The pedagogical value of timely and relevant feedback is well established (e.g. Black & Wiliam, 2005). Feedback closes a critical loop between teachers and learners in Laurillard’s (1993) Conversational Framework and feedback is as important for teachers as it is for learners (e.g. Hattie, 2015; Hendry & Dean, 2002). Especially at undergraduate level, increased class sizes compromise the quality of learning conversations and teachers are challenged to find time to read and respond to students’ work. Opportunities to monitor and learn from discursive interactions between teacher and students throughout a course are minimal or non-existent. In worst possible cases, learners never receive feedback from teachers or receive feedback only when it is too late and teachers fail to respond to feedback implicit in the work their students produce (e.g. Hendry & Dean, 2002; Mason, 1992). However, there is potential for aggregated text to reveal learning challenges and (mis)conceptions, depth of understanding, and disciplinary literacy development (McDonald, Bird, Zouaq & Moskal, 2017). If flexible and reliable tools are available to support analysis of student text, the benefits to students and teachers should be immediate. The goal of the Quantext development team is to provide such a tool (McDonald & Moskal, 2017).

1.1. Classroom use cases

A range of use cases are emerging. The most common, and arguably the most useful, are often the simplest and perhaps the most obvious: identifying what students find hard, using opportunities to link student interests to coursework, and providing opportunities for teacher reflection. Each of these use cases is briefly described below. In addition, teachers and institutional researchers are evaluating Quantext as a tool to aggregate or summarise free text comments from Student Evaluations of Teaching (McDonald, Moskal, Goodchild, Stein & Terry, 2019) and there is considerable interest in developing Quantext as an accessible tool for qualitative educational research.

1.1.1. Identifying what students find hard

In two large undergraduate classes, each week, teachers asked their students what they found most challenging from the lecture material introduced during the week. Students responded to free text questions presented in the University LMS quiz tool. Student responses were then aggregated in Quantext. Quantext summarises content words that occur together more often than expected by chance. The concepts that most students find challenging are visualised as bar charts. This simple procedure allows teachers to be immediately alert to difficult areas. They know which material to revisit in following lectures and can provide additional examples for students to work through.
1.1.2. Linking student interests and experiences to course content
In some contexts, finding out about students’ interests at the start of a course presents an opportunity to relate these interests to course material. One example, a post-hoc concept demonstration, has previously been reported at LAK18 (Elgort, Lundqvist, McDonald, & Moskal, 2018). Subsequently, an in-class use case in a foundation level course at an Australian university demonstrated the benefit of adapting course content to student interests (Stokes & McDonald, 2018). Most recently, in an undergraduate education class, students were asked to relate their personal experiences to specific theoretical concepts. The teacher shared aggregated summaries of students’ responses with the class and reported that this was greeted positively by students; they could immediately see the value of their own experiences in relation to the course.

1.1.3. Promoting teacher reflection
Quantext allows teachers to group responses by length, keywords, key groups of words (ngrams) as well as by arbitrary search terms and common collocations (words which occur together more often than expected by chance). Responses can be viewed using either a keyword-in-context view or a wordtree view (Wattenberg & Viégas, 2008). This is especially useful where students use terms or expressions that seem unusual given the context. For example, aggregated summaries of foundation chemistry student responses to a question about chemical structure alerted the course teacher to a small group of students developing an erroneous conception of a ‘bent tetrahedron’.

2. Intended Learning Outcomes
These use cases are simple examples of deriving valuable teaching insight directly from students’ writing. None of them would be possible without the right tools to facilitate the process. By the end of this session, participants will: be able to describe basic approaches to analysing text at scale; be aware of classroom contexts where these approaches add value; be able to analyse their own or sample data; have an awareness of key cautions and caveats in relation to basic text analytic techniques.

3. Workshop Presenter Credentials
Jenny McDonald is lead investigator for the Quantext Pilot Project and co-developer of Quantext. She holds honorary/adjunct roles at the University of Auckland (CleaR) and Victoria University of Wellington (CAD).
Adon Moskal is a senior lecturer in IT at Otago Polytechnic, and lead developer for Quantext.
Cathy Gunn is an associate professor at the Centre for Learning and Research in Higher Education (CleaR), University of Auckland.
Irina Elgort is a senior lecturer at the Centre for Academic Development (CAD), Victoria University of Wellington.

References
Introduction to Quantitative Ethnography and Epistemic Network Analysis

Vitomir Kovanović1, Srećko Joksimović2

Abstract
With the broader adoption of educational technologies, there has been an abundance of data collected on students learning processes. While collected data provides important insights into the development of important skills and competencies, the captured data is for the most part being analysed with traditional quantitative or – to a lesser extent – qualitative methods or their combination. In this workshop, we will provide an overview of Quantitative Ethnography (QE) and Epistemic Network Analysis (ENA), a set of novel approaches for data analysis that combines aspects of qualitative and quantitative methods to provide richer insights than typically available with traditional research approaches. The workshop will specifically focus on ENA, the most widely used method for QE and provide participants with hands-on experience in applying ENA on real-world learning analytics data. Specifically, after the short overview of the basics of QE and ENA, participants will be guided through a sample analysis using ENA Web application. Finally, participants will conduct a full ENA analysis of the real-world data to test their knowledge and understanding of QE and ENA.

Keywords
Epistemic Network Analysis, Quantitative Ethnography, Learning Analytics Methodology, Text Analysis, Discourse Analysis

1. Introduction
The ability to teach and assess the development of complex thinking skills is crucial for 21st-century educational research. In the age of educational games and the Big Data they generate, we have more information than ever about what students are doing and how they are thinking. However, as the sheer volume of data available can overwhelm traditional qualitative and quantitative research methods, Quantitative Ethnography (QE) (Shaffer, 2017) is a set of research methods that weave the study of culture together with statistical tools to understand learning — a way to go beyond looking for arbitrary patterns in mountains of data that games and simulations generate and begin telling textured stories at scale. The foundational method under the umbrella of Quantitative Ethnography is Epistemic Network Analysis (ENA) (Shaffer, Collier, & Ruis, 2016), a network modelling technique for modelling learning in Big Datasets. The primary goal of ENA is to discover and quantify connections among elements in coded data and representing them using dynamic network models. The model has been increasingly used in Learning Analytics field for understanding how different aspects of learning relate to one another (Ferreira, Kovanović, Gašević, & Rolim, 2018; Fisher, Hirshfield, Siebert-Everstone, Arastoopour, & Koretsky, 2016; Knight, Arastoopour, Shaffer, Buckingham Shum, & Littleton, 2013; Phillips, Kovanović, Mitchell, & Gašević, 2018; Rolim, Ferreira, Kovanović, & Gašević, 2019; Tsai, Kovanović, & Gašević, 2019). However, despite the increased use of ENA in Learning Analytics, there have not been many workshops on the topic of ENA. The goal of this workshop is for each participant to develop a foundational understanding of QE and ENA and how they can be used for analysing educational data. Participants will also learn how to use ENA Web interface and conduct a small analysis on the real-world dataset provided by the workshop facilitators.

2. Objectives and Target Group
Given the focus on practical skill-building, the main objectives of the proposed tutorial are:
1. Gain an understanding of the basics of QE and its underlying principles,
2. Understand the inner workings of ENA algorithm and how it fits QE paradigm,
3. Learn how to use ENA Web application to analyse educational data,
4. Gain skills in interpreting ENA results and their contextualisation within a given problem.

The primary audience for this workshop are learning analytics researchers and practitioners, with a background in engineering, sciences or humanities. The workshop would be beneficial not only to graduate students in learning analytics but also to
3. Format

A preliminary program for this three-hour workshop is as follows:

- **15 min:** Opening of the workshop, the introduction of the presenters and audience, and a short overview of the workshop structure, goals, and activities.
- **30 min:** Introduction to Quantitative Ethnography and how it is different from the popular qualitative and mixed methods approaches.
- **30 min:** An overview of ENA algorithm with a guided example that shows the workings of the algorithm.
- **15 min:** Coffee break.
- **30 min:** A short overview of the ENA Web interface and how it can be used to run ENA analysis. The participants will be guided through a step-by-step analysis of a sample dataset provided by the organisers.
- **45 min:** Analysis of real-world educational dataset using ENA Web interface and interpretation and discussion of the findings.
- **15 min:** Closing of the workshop, a final discussion of what has been covered and any final comments, remarks and questions.

As this will be a hands-on workshop, participants are expected to bring with them their own laptops computers, and attendance should be limited to 20-25 persons. The facilitators will provide a selection of educational datasets which will be used in the hands-on part of the workshop. A screen projector for presenters and tables for attendees are the only equipment requirements.

4. Workshop Facilitators

**Dr Vitomir Kovanovic** is a Research Fellow at the School of Education, University of South Australia and a Data Scientist at the Teaching Innovation Unit, University of South Australia. His research focuses on the development of novel learning analytics systems using learners' trace data records collected by learning management systems with the goal of understanding and improving student learning. Vitomir is particularly interested in students' self-regulation of learning and understanding how trace data can be used to gain a deeper understanding of learning processes. Vitomir is also an academic editor at PLOS One journal and currently serves as a secretary of the Society for Learning Analytics Research (SoLAR).

**Dr Srecko Joksimovic** is a Research Fellow at the University of South Australia, Adelaide, Australia, and a research associate at the Learning Innovation and Networked Knowledge Research Lab at University of Texas, Arlington, United States. With the background in computer science, his research focuses on the analysis of teaching and learning in networked learning environments. His efforts include developing theory-driven data-informed analytics models for assessing the quality of learning in computer-mediated context, generating insights into factors that promote effective collaborative learning and informing the design of digital environments in which collaborative learning occur.

References


Learning Analytics Growing Pains

Sociotechnical Infrastructure Changes as LA Tools Mature

Simon Buckingham Shum¹, Antonette Shibani²

Abstract
As Learning Analytics tools mature, there are often ‘growing pains’ in how the infrastructure adapts to the social and technical requirements of scaling up. Across institutions in Australia, there is increasing work being done in this transitional space, including moving from prototypes to products, institutional adoption of LA, engaging stakeholders, organisational leadership, long term impact, and invisible work in keeping everything going. This workshop aims to build common ground across institutional contexts by sharing stories and identifying insights, to inform the design of better sociotechnical infrastructures supporting this critical phase.

Keywords
learning analytics, infrastructure, tools, scaling up, adoption

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1. Workshop Focus
Learning Analytics (LA) as a field is reaching a new stage of maturity, as a growing number of tools transition from small scale pilots that have demonstrated promise, to larger scale services within an institution. Those pilots may have been a small scale deployment of a commercial product, or a prototype developed by in-house/external teams. This workshop aims to deepen the conversation between LA researchers and practitioners who are working in this transitional space, since as the scale of the system grows, technologies, roles and stakeholders change — and there are often “growing pains” as the infrastructure, social and technical, adjusts. By sharing our stories, it is hoped that the workshop will build common ground across institutional and LA contexts, and identify insights to inform the design of better sociotechnical infrastructures to support this critical phase.

Topics include but are not limited to:
- **From prototypes to products.** Can we expect the same platform to serve both rapid prototyping and production services? How do we design with future evolution in mind?
- **Scaling up for institutional adoption.** For adoption and embedding of LA at scale, a transition from technical to social systems is required (Gasevic, Tsai, Dawson & Pardo, 2019). What strategies are useful, and why? How do we handle resource management?
- **Stakeholder engagement.** Who needs to be in the loop, and when? What obstacles are there to effective communication between specific stakeholder groups? Who purchases, invents, develops, maintains, and evaluates LA tools? What design processes assist this process? Who supports educators and students once deployed?
- **Invisible work.** No matter how good the technology, embedding it into daily practice invariably brings “invisible work” that’s required to oil the wheels and keep everything going. What examples/stories do you have about what this looked like in your case study?
- **Organisational leadership.** Institutions need strategy to build mindsets, capabilities, and capacity for LA, and this requires an alignment to their institutional vision and goals (Tsai, Moreno-Marcos, Jivet, Scheffel, Tammets, Kollom & Gašević, 2018). How can the organisation facilitate or obstruct this process? Who are the key stakeholders in this scaling up process?
- **Long term impact.** For sustainable use and implementation of LA, the development and evaluation of tools can no longer be supported by short term goals or one-off studies. What pedagogical grounding is required for long term impact? How do we balance scalability and catering for specific contexts (contextualization) for maximum impact? (Shibani, Knight & Buckingham Shum, 2019) How do we map supply and demand to truly embed LA in classrooms?
2. Confirmed Speakers

The following confirmed speakers will share their institutional insights during the workshop:

- **Promoting institutional adoption of a personalised feedback tool. The OnTask experience**
  Aberlado Pardo, Professor and Dean Academic at the Division of Information Technology, University of South Australia

- **Co-creation - How human-centred LA at Sydney has co-evolved with 2 to 1100 educators**
  Natasha Arthars, Postgraduate Research Fellow, DVC Education Portfolio, The University of Sydney
  Danny Liu, Senior Lecturer, DVC Education Portfolio, The University of Sydney

- **Development and Dissemination of an Adaptive Learning System: Reflections and Lessons Learned**
  Hassan Khosravi, Senior Lecturer in Learning Analytics, The University of Queensland

- **A sustainable deployment of textbook smart e-resources in University courses: building a partnership with a publisher for effective learning design**
  Dr Lorenzo Vigentini, Academic Lead Educational Intelligence & analytics, UNSW Sydney
  Dr Happy Novanda, Learning Design Manager, McGraw Hill International
  Simon Banks, National Enterprise Manager, McGraw Hill International

- **How research and practice in LA co-evolve: Insights from the Writing Analytics tool AcaWriter**
  Antonette Shibani, Lecturer at the Faculty of Transdisciplinary Innovation, University of Technology Sydney
  Simon Buckingham Shum, Professor of Learning Informatics and Director of the Connected Intelligence Centre, University of Technology Sydney

- **Stakeholder engagement in scaling up LA**
  Bruce McLaren, Associate Research Professor at the Human-Computer Interaction Institute, Carnegie Mellon University, USA

3. Workshop Presenter Credentials

Simon Buckingham Shum is Professor of Learning Informatics at the University of Technology Sydney, which he joined in August 2014 as inaugural director of the Connected Intelligence Centre. Developing approaches to helping UTS both innovate and achieve impact with LA infrastructure is central to CIC’s mission. Simon has been active in shaping the field of Learning Analytics since the inaugural LAK 2011 conference, serving as a Program Chair (2012/2018), convening many workshops, and a regular keynote speaker. He co-founded the Society for Learning Analytics Research, serving as a V-P and continuing on the Executive.

Antonette Shibani is a Lecturer in the Faculty of Transdisciplinary Innovation at the University of Technology Sydney, Australia. In her doctoral research, she explored the co-design and implementation of a writing analytics tool called ‘AcaWriter’ in higher education, enabling its move from research to classroom practice. Shibani has been involved in the international Learning Analytics community by presenting her work in a number of LAK conferences, and Australian Learning Analytics Summer Institutes (A-LASI). She has chaired/co-chaired five workshops in LAK and A-LASI to build writing analytics literacy within the LA community. She is currently an executive member of the Society for Learning Analytics Research.

References


Panel debate - the validity of using student evaluation surveys for performance based funding at Australian universities

Leonie Payne¹, Kirsty Kitto¹, Michael Pracy¹, Jason Lodge², Abelardo Pardo³

Abstract
The Australian Federal Government announced in August 2019 that aspects of the Quality Indicators for Learning and Teaching (QILT) Student Experience and Graduate Outcomes surveys will form two of the four key metrics for performance based funding of Australian Universities from 2020. Given the lack of consensus on the validity and appropriate use of student evaluations of teaching, it is time to explore the ramifications of this decision. And who better but the Learning Analytics community to do so? We propose a plenary panel debate on the provocation “Student evaluations of teaching are the worst form of evaluation, except for all of the others”.

Keywords
Performance based funding, QILT, Student evaluation surveys, teaching quality, higher education

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1. Panel Debate Background - Performance Based Funding
The Performance-Based Funding for the Commonwealth Grant Scheme: Report for the Minister for Education was released in August 2019. This report outlines the proposed measures for performance-based university funding to be implemented in 2020, with the inclusion of the Student Experience and Graduate Outcomes QILT (Quality Indicators for Learning and Teaching) surveys. The metrics to be included are student satisfaction with teaching quality (Student Experience survey) and graduate employment rates (Graduate Outcomes Survey) for domestic bachelor students. The stated aims of the scheme include to create more “accountability” for public investment on higher education priorities and to provide financial incentives to encourage improved university performance, with the identified key principles of “fitness-for-purpose, fairness, robustness and feasibility” (Commonwealth of Australia, 2019).

Given the implications that these decisions will have for university funding, and the diverse conflicting perspectives on the validity of student surveys as a form of teaching quality evaluation, we propose a panel debate for ALASI 2019. The topic will be: “Student evaluations of teaching are the worst form of evaluation, except for all of the others”. We envisage the debate would provide a highly interactive, entertaining and potentially controversial event, that would help to advance discussion about this important topic which will have high impact upon the Australian university sector.

1.1. Quality Indicators for Learning and Teaching (QILT)
The Quality Indicators for Learning and Teaching (QILT) is an annually published survey that allows comparison of Australian higher education institutions and study areas on measures of student experience (QILT 2018). It is an example of Student Evaluations of Teaching (SET) (Marsh 2007). The QILT survey provides an opportunity for students to make comparisons of universities based on surveyed student experience and graduate employment outcomes (QILT 2015).

1.2. Arguments for and against the Validity of Student Evaluations of Teaching
The Marsh (2007) review discusses a wide range of research which has demonstrated that there is validity in using Student Evaluations of Teaching as a measure of teaching performance. For example, there is a well-established relationship between student ratings and learning with SETs having good internal consistency and stability (Abrami 2001). In addition, Sporen, Brockx, & Mortelmans (2013) found that SETs are also correlated with teachers’ self-evaluations, alumni ratings and evaluations by trained observers. Aleamoni (1999) dispels the myth that student ratings are merely a “popularity contest”, finding students rated educators on their preparation and organisation, stimulation of interest, motivation, answering of questions, and courteous treatment of students. In contrast, a wide body of research questions the validity and appropriate application of student surveys for evaluating teaching quality. For example, Johnson (2000) cautions against the use of student
evaluation questionnaires as a bureaucratic tool driven by market ideologies, arguing that while student evaluations may be useful as formative diagnostics they are not appropriate tools for summative judgement for employment decisions and tenure. Similarly, a study by Boysen et al (2014) demonstrates that teaching evaluations are interpreted by administrators and teaching faculty as possessing higher levels of precision than are warranted given the statistical methodologies used. Shevlin et al. (2000) argues that a ‘halo’ effect limits their ability to measure the multi-faceted, multi-dimensional nature of teaching effectiveness, and Macfadyen et al (2016) posit bias in what type of students even respond to SETs, arguing that this sample does not reflect the individual and course characteristics of the total student population. Thus, the cases for and against SETs are extensive, and conflicting, which sets the scene for a lively forum.

2. Panel Format

This panel would take the format of a plenary session debate, with 6 speakers allocated to one of 2 teams, for, and against the proposition. Team captains will be Jason Lodge and Kirsty Kitto with the remainder of the participants to be determined once ALASI attendees are known. We will endeavor to bring a QILT member, and the VC of Woollongong (who chaired the performance based funding review) into the panel as team participants. Abelardo Pardo will play the role of MC.

3. Organiser Credentials

- Leonie Payne is a PhD Student at the Connected Intelligence Centre, UTS, where she is working on a thesis that aims to bring rigour to the evaluation of quality in Higher Education by accounting for bias in student response rates.
- Kirsty Kitto is a Senior Lecturer at the Connected Intelligence Centre, UTS, where she leads a number of LA projects. She was formerly seconded to the QUT Quality and Evaluation unit where she worked on analysing 4 years of SET data to derive performance metrics for teaching.
- Michael Pracy works as a data scientist at the Connected Intelligence Centre, UTS. His background is in astrophysics, where he performed extensive work on controlling for bias in data obtained from astrophysical phenomena.
- Jason Lodge is an Associate Professor at the University of Queensland where he concentrates on the application of the learning sciences to higher education. Specifically, he is interested in the cognitive and emotional factors that influence learning and behaviour and how research findings from the learning sciences can be better used to enhance design for learning, teaching practice and education policy.
- Abelardo Pardo is Professor and Dean Academic at the University of South Australia and the Environment at the University of South Australia. His research interests include the design and deployment of technology to increase the understanding and improve digital learning experiences. He is the current president of SoLAR.

References

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