

# Will Alderton

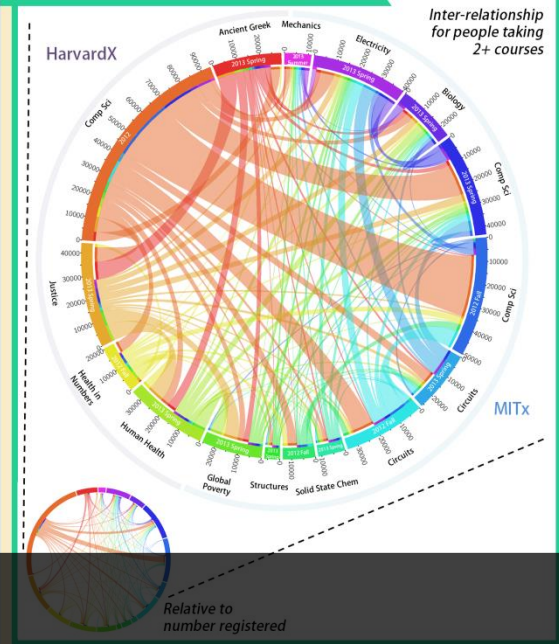
## Manager, Connect for Success

- Student success and retention program, monitoring 5000+ sts/sem
- Currently using Blackboard tools to monitor at-risk students
- Reactive approach → Proactive approach
- Academic analytics to identify at-risk cohorts on entry
- Learning analytics - What behaviour promotes strong performance?
- Keen to see what others are doing in this area

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# Erika Beljaars-Harris (RMIT)

- Academic perspective:
  - Role of academics in using analytics
- Ethics
- Roll out of learning analytics in higher education institutions

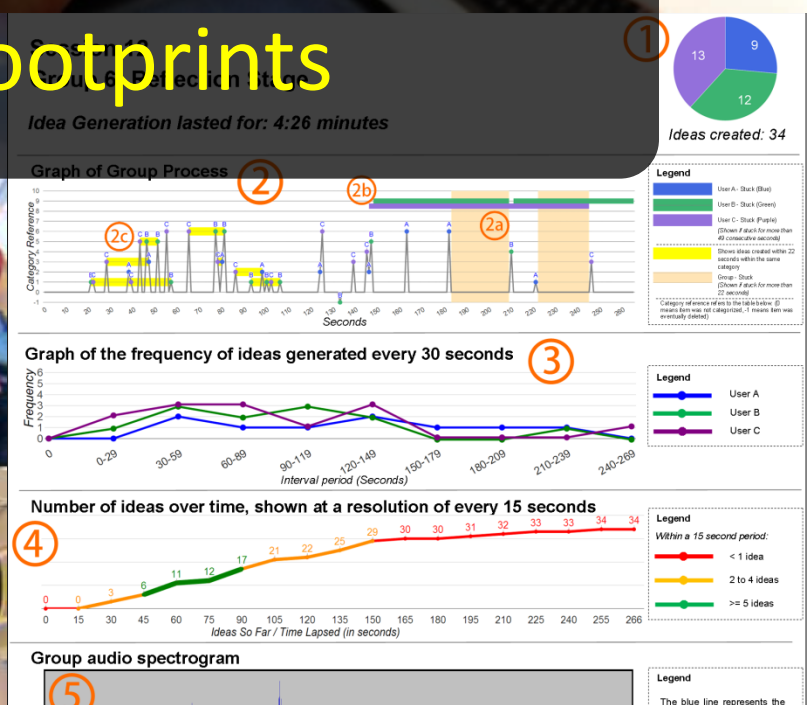


Reference

MOOC datasets and insights information

<http://www.coursera.org/mooc-datasets-and-insights-information>

# Understanding learners from their digital footprints



# Motivation and Self-regulation in Online Environments

Paula de Barba

Research Fellow | PhD Candidate



MELBOURNE SCHOOL OF  
PSYCHOLOGICAL SCIENCES



THE UNIVERSITY OF  
MELBOURNE

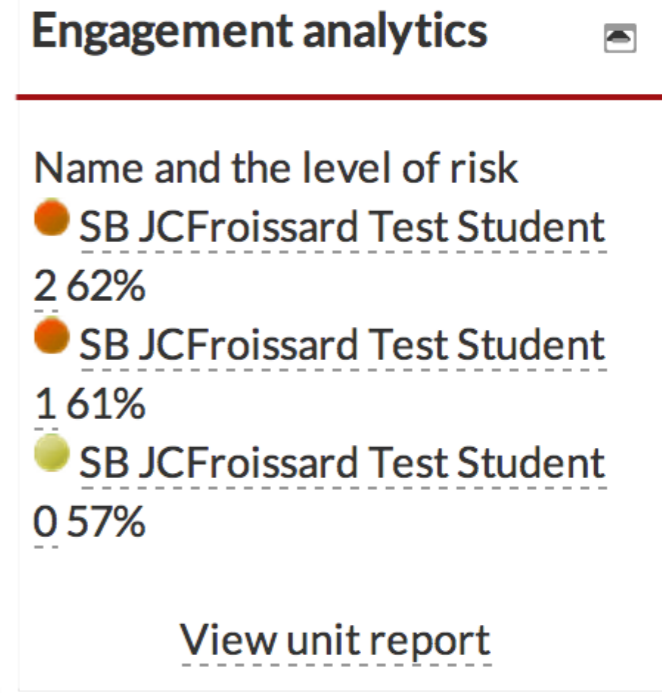


IBES  
Institute for a  
Broadband-Enabled Society



## Validating the effectiveness of the Moodle Engagement Block and piloting a student alert system to optimise retention

Macquarie University Teaching and Delivery grant 2015



Moodle Engagement Block

Project aims to:

- validate with historical data learning analytics tool
- survey convenors and students about attitudes and preferences to alerts
- trial use of manual alerts using tool
- develop pilot for automated alerts using tool



Chris.Froissard@mq.edu.au  
Educational designer

Username	Assessment Activity	Forum Activity	Login Activity	Total
<a href="#">SB JCFroissard Test Student 0</a>	1% (4%)	33% (100%)	23% (68%)	57%
<a href="#">SB JCFroissard Test Student 1</a>	1% (4%)	33% (100%)	27% (82%)	61%
<a href="#">SB JCFroissard Test Student 2</a>	2% (5%)	33% (100%)	27% (82%)	62%

Moodle Engagement Block: Report

## Eva Heinrich's Interests

### Supporting tertiary teachers to make sense of engagement data

By integrating data external to LMS and data provided by students

To acknowledge the widely differing student backgrounds

### Supporting tertiary teachers to use engagement data

By facilitating follow up with students inside the LMS

To improve student outcomes

To efficiently provide traceable interactions

Plan is to implement tools for Moodle and evaluate in real teaching settings





# Institute for Teaching and Learning Innovation Learning Analytics and Evaluations Units

*Doune Macdonald – Pro Vice Chancellor Teaching and Learning (Acting)*

*Marcel Lavrencic – Senior Learning Analyst*

- Refocused units following restructure
- Goals of the units are to provide relevant information to:
  - encourage innovation in teaching and learning practices
  - support student engagement
  - increase student academic achievement
  - support UQx
  - advise staff professional development
  - research





# Discovering Value in Data



DATA ABUNDANCE

DISCOVERING VALUE IN DATA? - [HTTP://WWW.NEWSCHOOL.EDU/VENTI/DETAIL.aspx?id=56252](http://www.newschool.edu/venti/detail.aspx?id=56252)

## Sandra Milligan

- measurement of complex higher order skills and capabilities (both domain-specific and for generic '21<sup>st</sup> C skills' )
- by developing new forms of digital assessment, calibration, certification and regulation
- using assessment evidence generated by students, peers (crowd), and machines

*Out with the old...*



*...in with the new... to support commercially-sustainable, 21<sup>st</sup> C learning at scale*

# Negin Mirriahi – UNSW Australia

Academic Developer & Lecturer

## LA to inform pedagogical change:

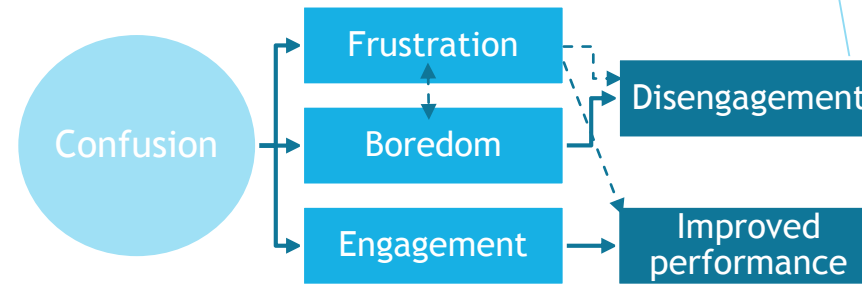
- What are students' learning behaviour patterns or learning profiles?
- How can we improve our course design to enhance students' learning experience?
- How can we enhance students' self-regulated learning and reflective practice skills?

**Videos**

**MOOCs**

# What learning analytics can tell us about confusion?

- ▶ Confusion is a part of the learning process



- ▶ Confusion can lead to engagement. Confusion during the training is a good thing “if it occurs on items designed to resolve this confusion” (Padros, Baker, San Pedro & Gowda, 2014) but not during the problem-solving.
- ▶ Frustration can be positively correlated to learning: on some occasions original frustration leads to engagement (Padros, et al., 2014) but often it also leads to boredom (D’Mello & Greasser, 2011) and disengagement (Greasser & D’Mello, 2012). Conditions under which frustration leads to engagement?
- ▶ Boredom was often found to be negatively correlated with learning outcomes, but some of the recent findings suggest that it’s bad only during the problem-solving and good during the training phase.
- ▶ Methods: machine-learning/data mining/decision trees, likelihood metric, extractions (PCA, cluster analysis)

# Associate Head of Teaching and Learning



Two courses  
Grad/Undergrad

Tech to empower  
individuals and  
communities

Active learning

Behavioral analytics

Use of technology

User validation

# Learning Analytics in Oz: What's happening now, what's planned, and where could it ( and should it) go?

*The choices are dizzying...*

...and there are plenty of vendors with things to sell...




...and there is the fear of ending up with black boxes that limit our options...



...while knowledge and expertise are scattered around the globe...



*...so where to start?*

it could all be very  expensive if we do something, or a high opportunity cost if we do nothing. How do we calibrate our institutional choices and see where we are at, where we might possibly go, and how we might want to get there?



*You are here*



**Academic Writing Analytics**  
Rapid formative feedback  
on draft texts to provoke reflection

One of the key innovations of the KSV was the use of flexible thresholds in the creation of network representations. This is what allowed us to create visualizations of LSA-based representations of texts. Rather than attempting to provide a two-dimensional layout based on the first few dimensions resulting from the matrix decomposition used in LSA, our approach has been to determine the similarities between documents based on the cosines between the vectors representing documents. A graph is then created in which the nodes correspond to the documents and the edges correspond to the LSA-based similarities between them. A force-directed layout **NOVELTY** then applied to the graph such that the positions of nodes **CONTRAST** dimensional representation minimize the distortion of the (very low dimensional) representation. This representation of a maximally connected graph typically lacks clarity, and in typical cases where there are tens or hundreds of nodes the graph is essentially unintelligible due to the large number of edges.

**Dispositional Learning Analytics**  
Rapid formative feedback  
to stimulate self-directed change

