Learning Analytics: Research Informed Institutional Practice

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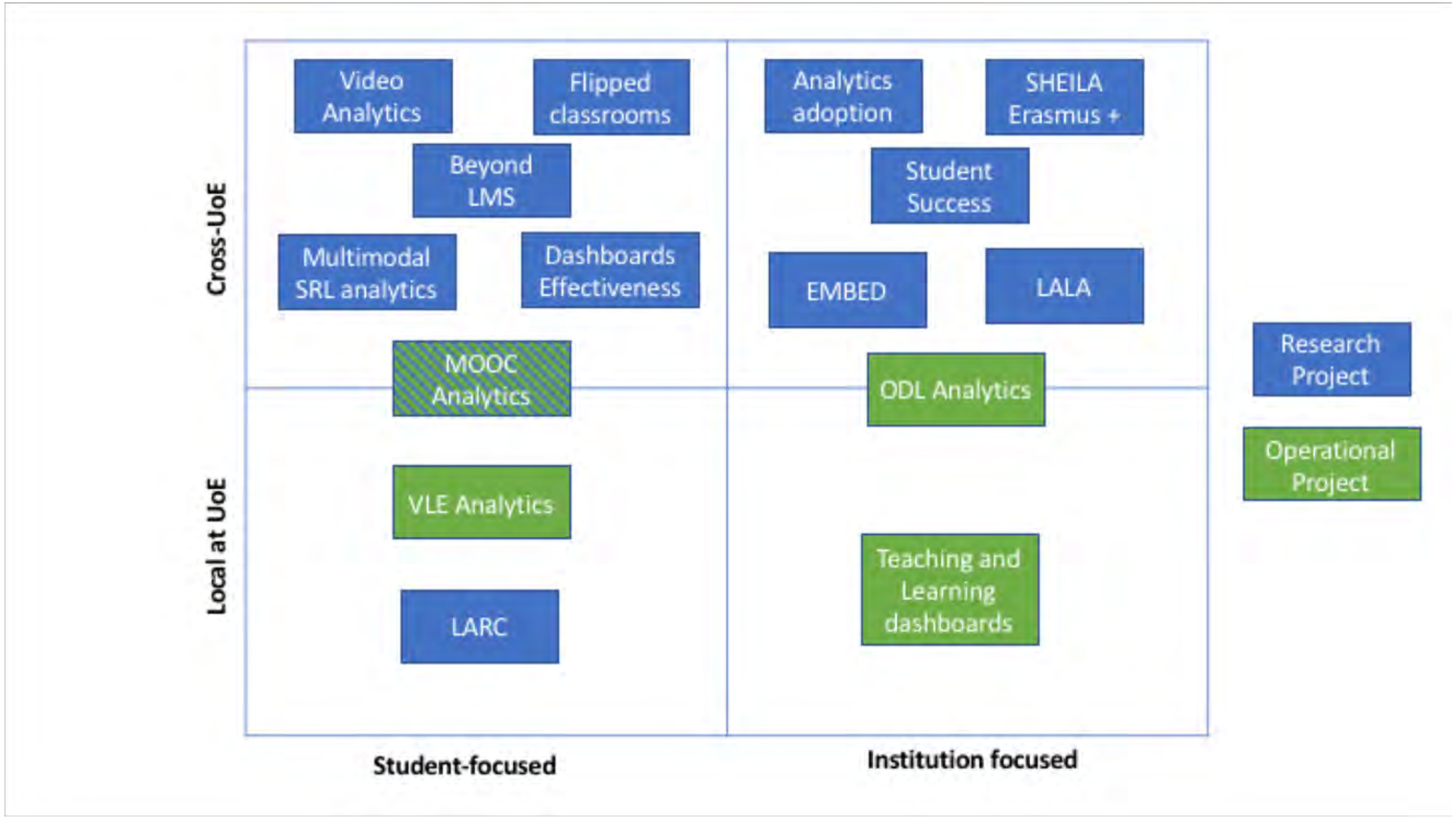
Yi-Shan Tsai

22 March 2019

Learning Analytics Map of Activities, Research and Roll-out (LAMARR)



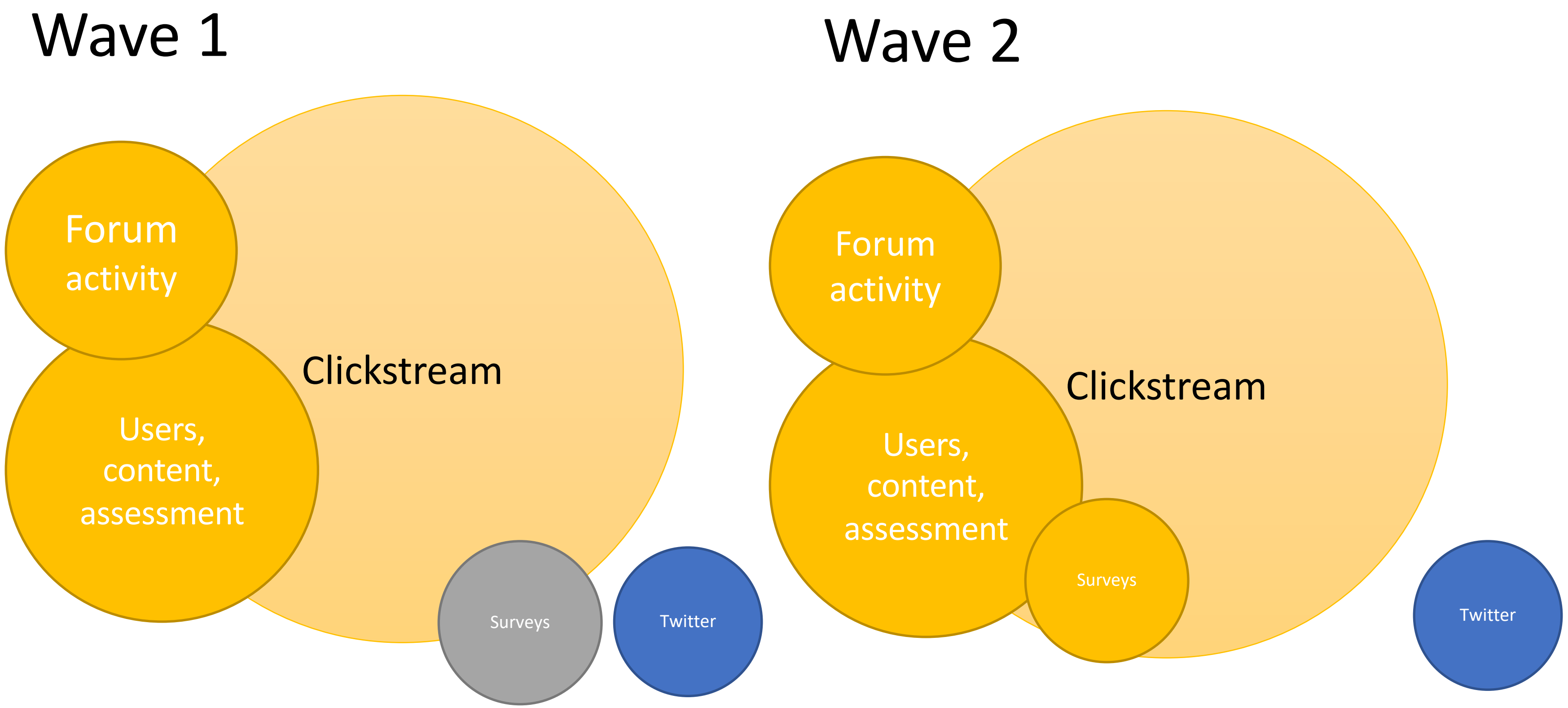
http://www.ed.ac.uk/information-services/learning-technology/learning-analytics

Early MOOC Analytics

- 6 courses:
  - Artificial Intelligence Planning
  - Astrobiology
  - Critical Thinking in Global Challenges
  - E-Learning and Digital Cultures
  - Equine Nutrition
  - Introduction to Philosophy
- 2 iterations analysed (more or less)
- August 2013 – April 2014
- Team drawn from UoE and CETIS

Detail on course design: MOOCs @ Edinburgh 2013: Report #1 (http://hdl.handle.net/1842/6683)

The Data


Wave 1
Forum activity
Clickstream
Users, content, assessment
Surveys
Twitter
Wave 2
Forum activity
Clickstream
Users, content, assessment
Surveys
Twitter

Aims & Research Questions

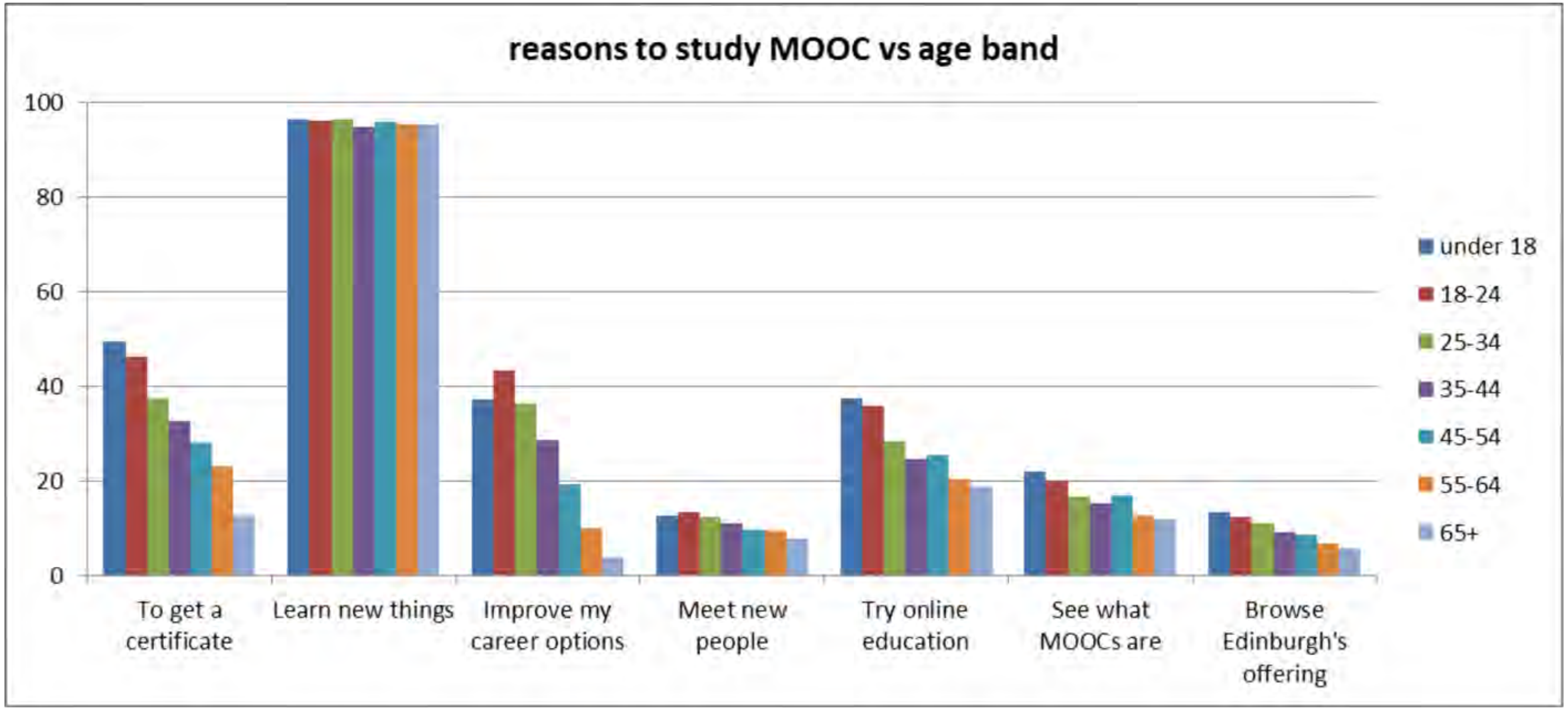
- Who are our participants?
- What data do we have?

- Can we identify patterns of participant behaviours such that participants could be categorised?
- How 'social' are participants?
- Are there patterns of in-platform behaviour which would predict retention / persistence in the course?

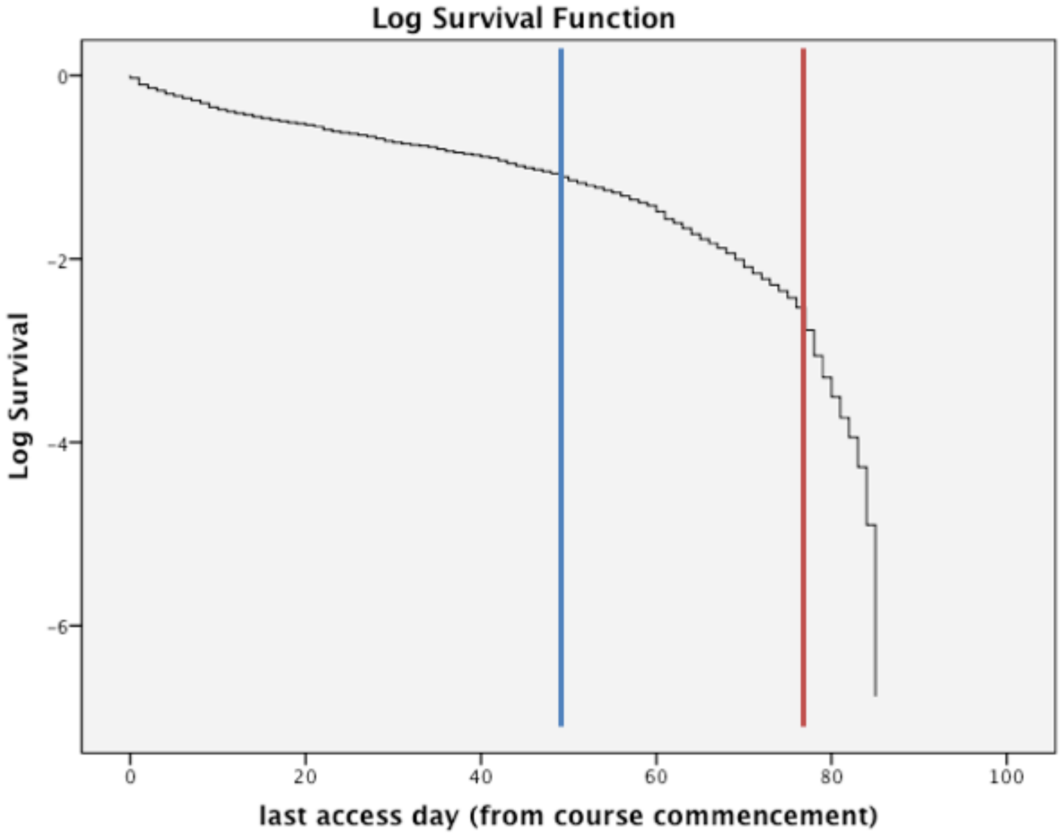
Techniques & Tools Used

- Standard course extract (mySQL)
- Survivor Analysis (SPSS)
- Social Network Analysis (R, Gephi, TAGS Explorer)
- Analysis of survey results (SPSS)
- Visualisations for exploring data (R, Gephi, Google charts, Excel)

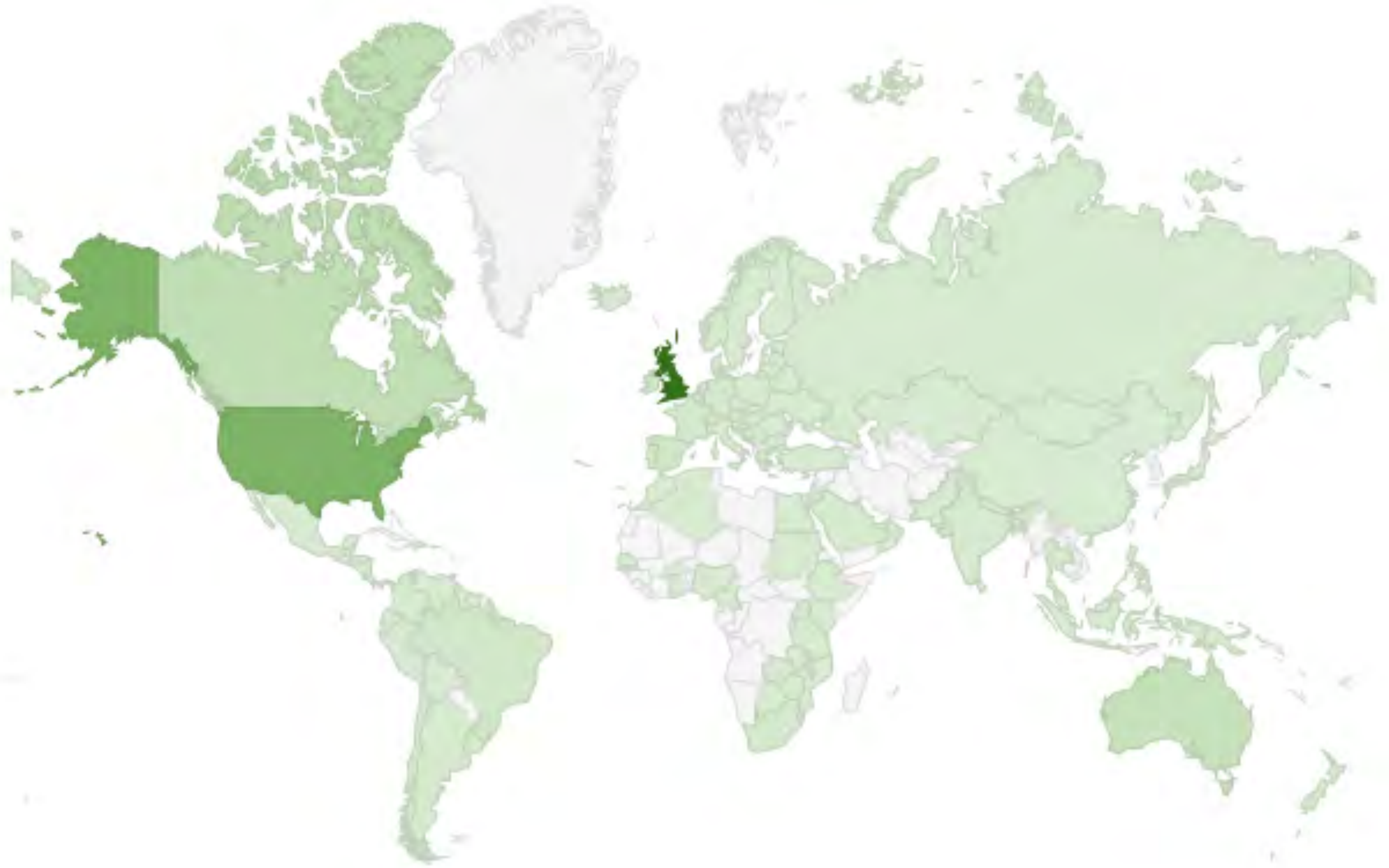
Analysis of survey data



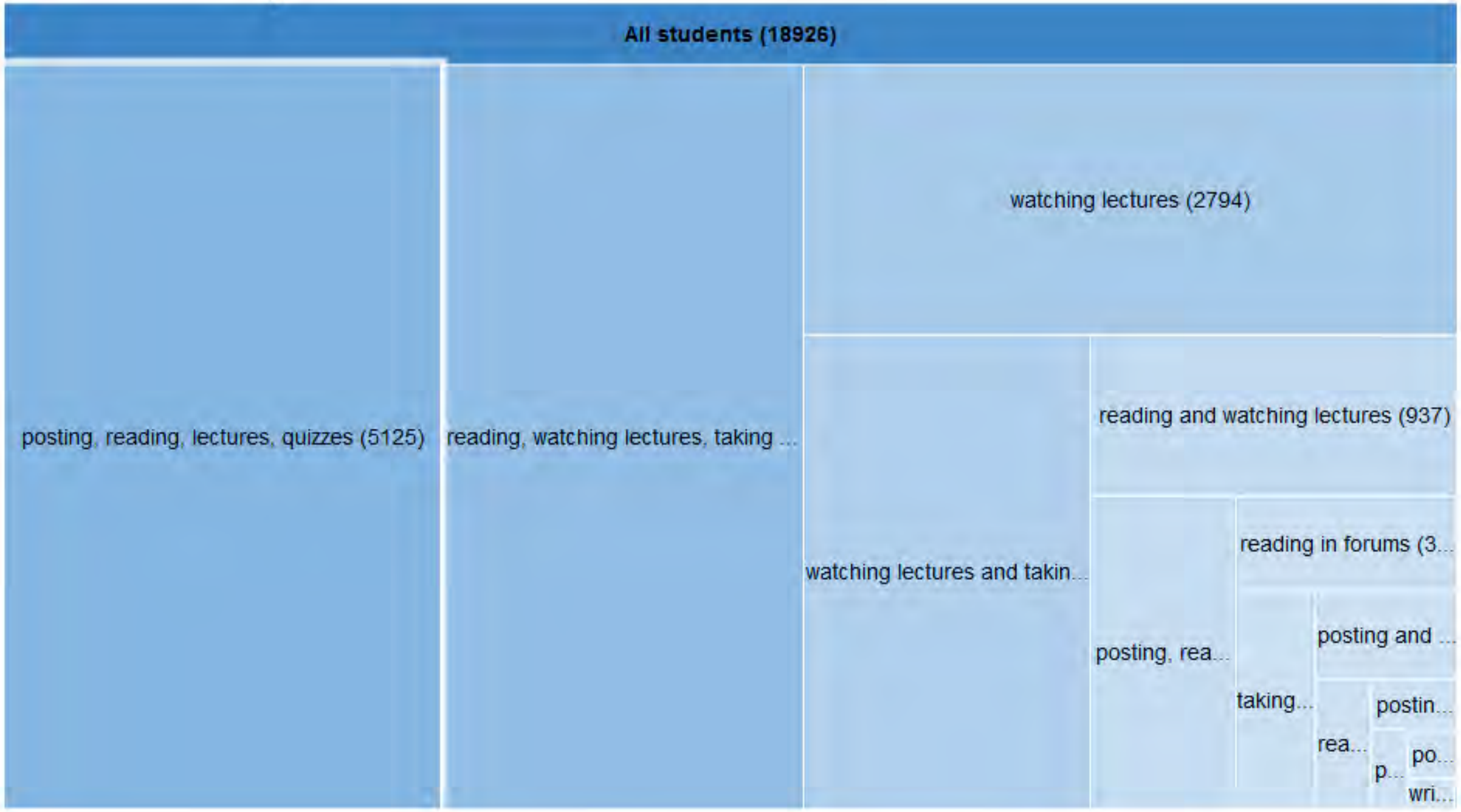
Introduction to Philosophy (wave 1) – survivor analysis

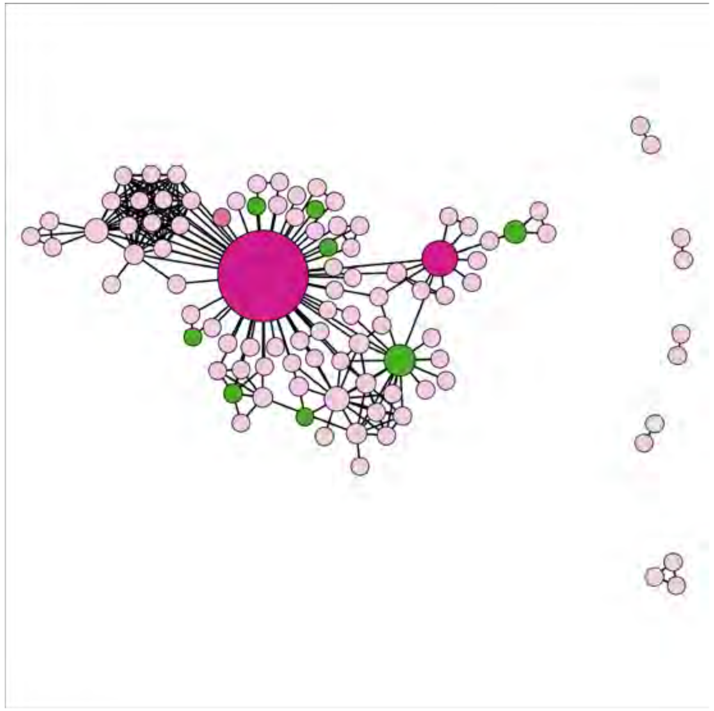


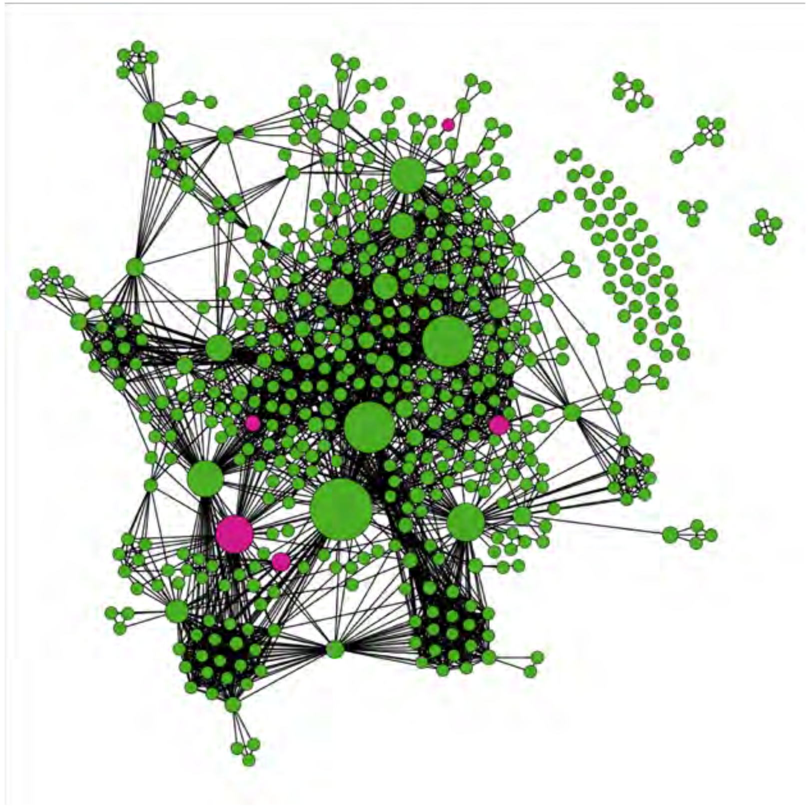
Equine Nutrition (wave 1) – learner location



Equine Nutrition (wave 1) – tool usage

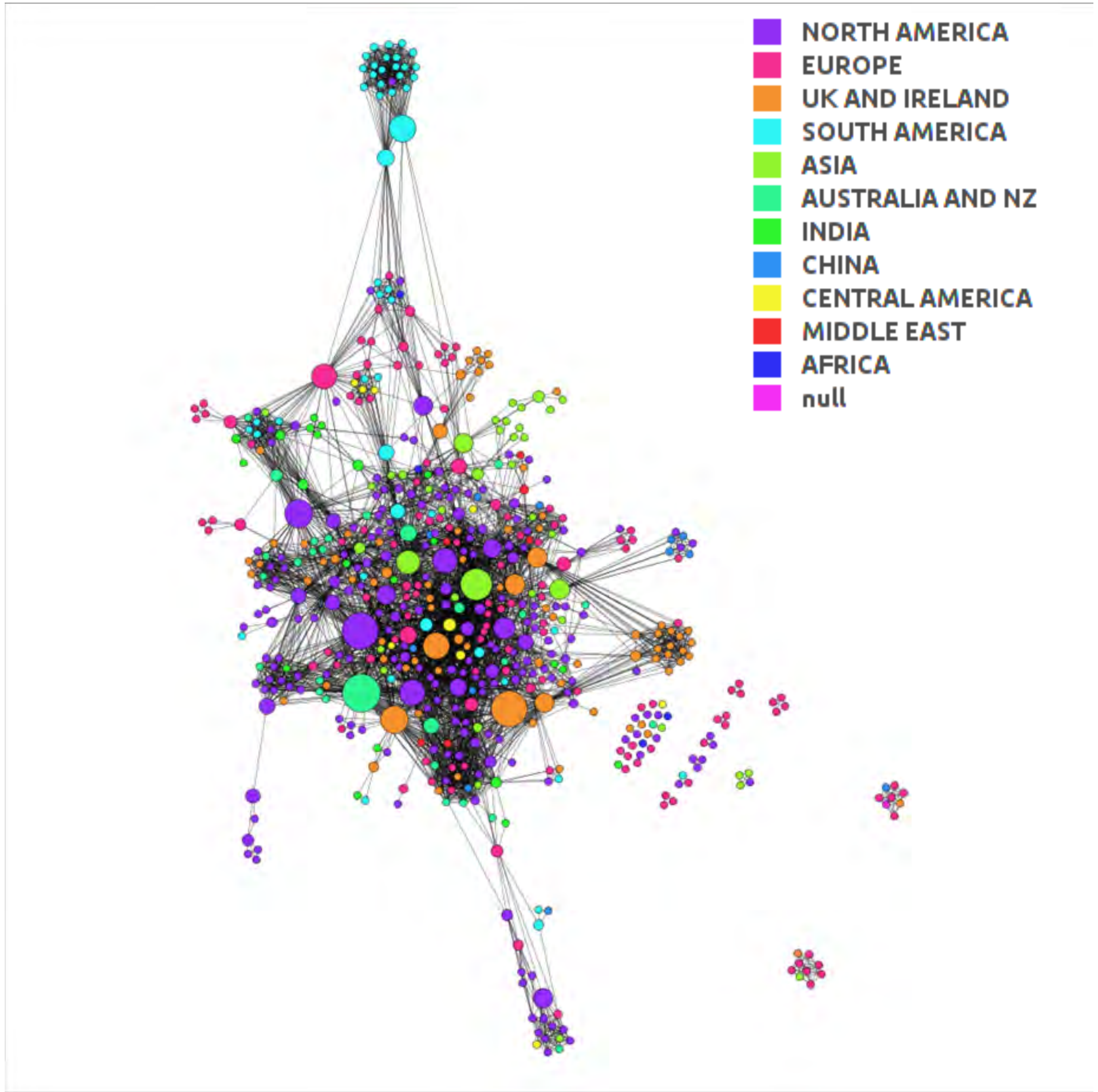






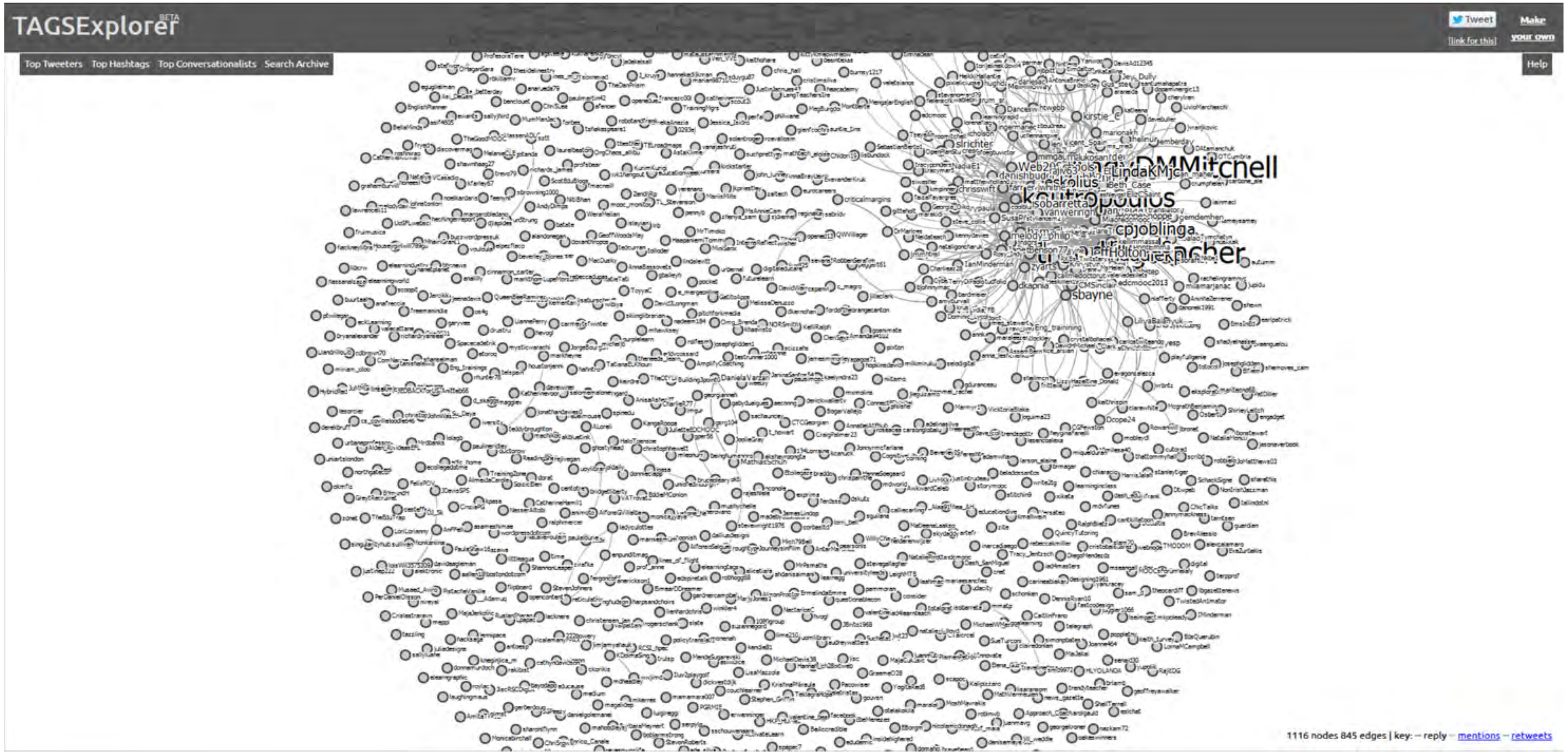
AI Planning and Equine Nutrition (wave 1)

Networks coloured by role



Astrobiology

Network coloured by location



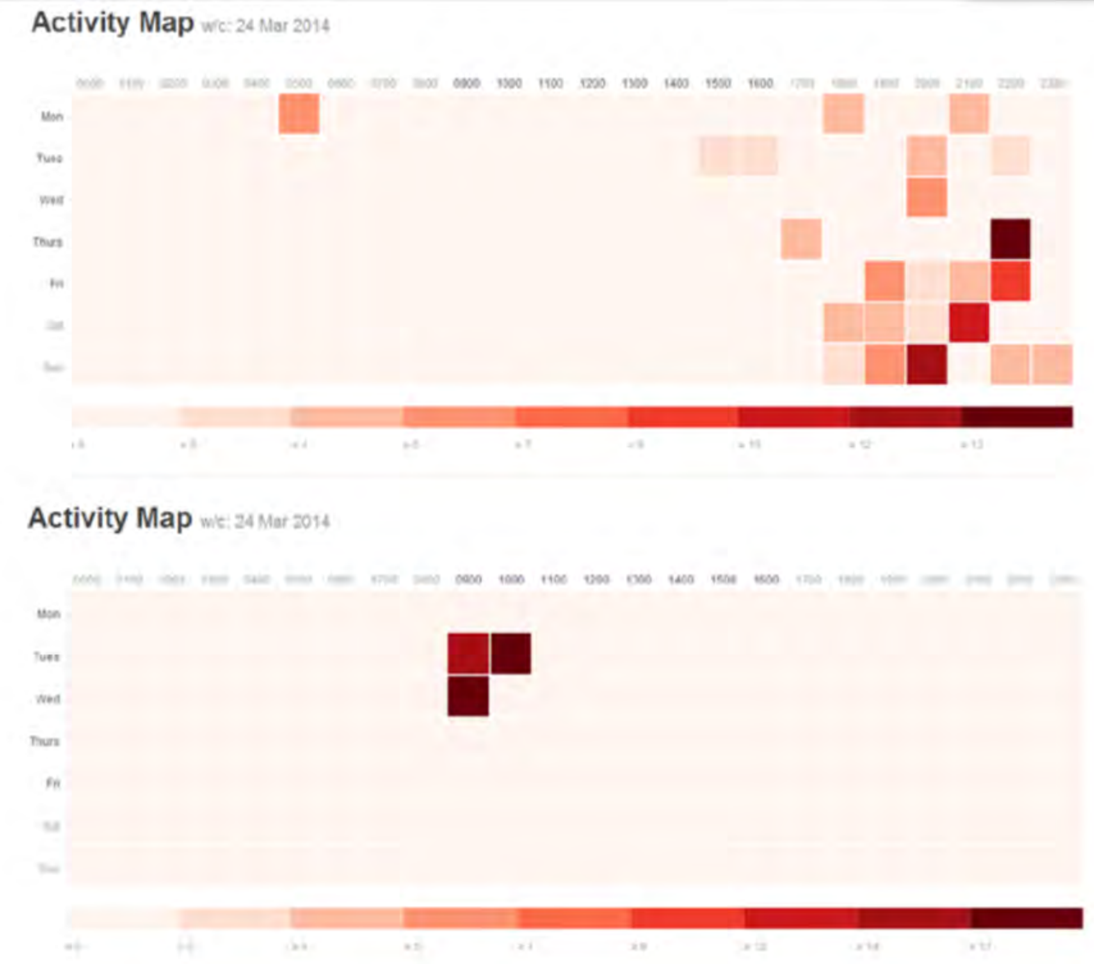
E-Learning and Digital Cultures (wave 2)

Twitter network

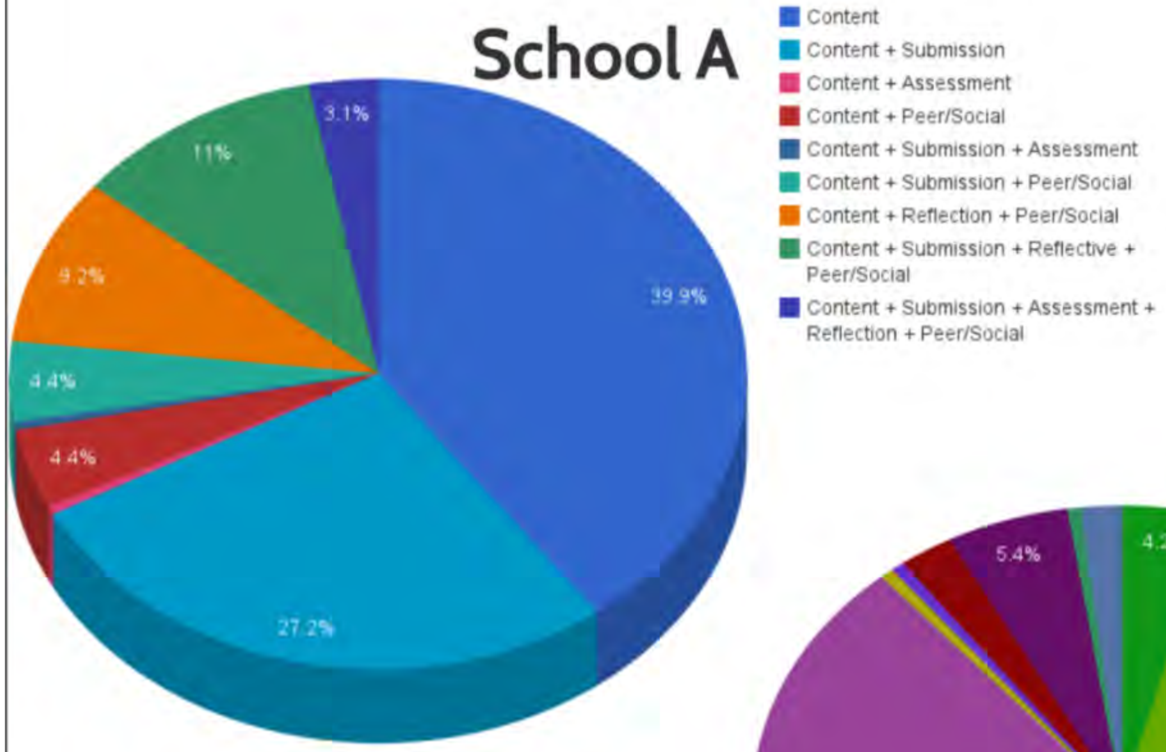
Lessons Learned

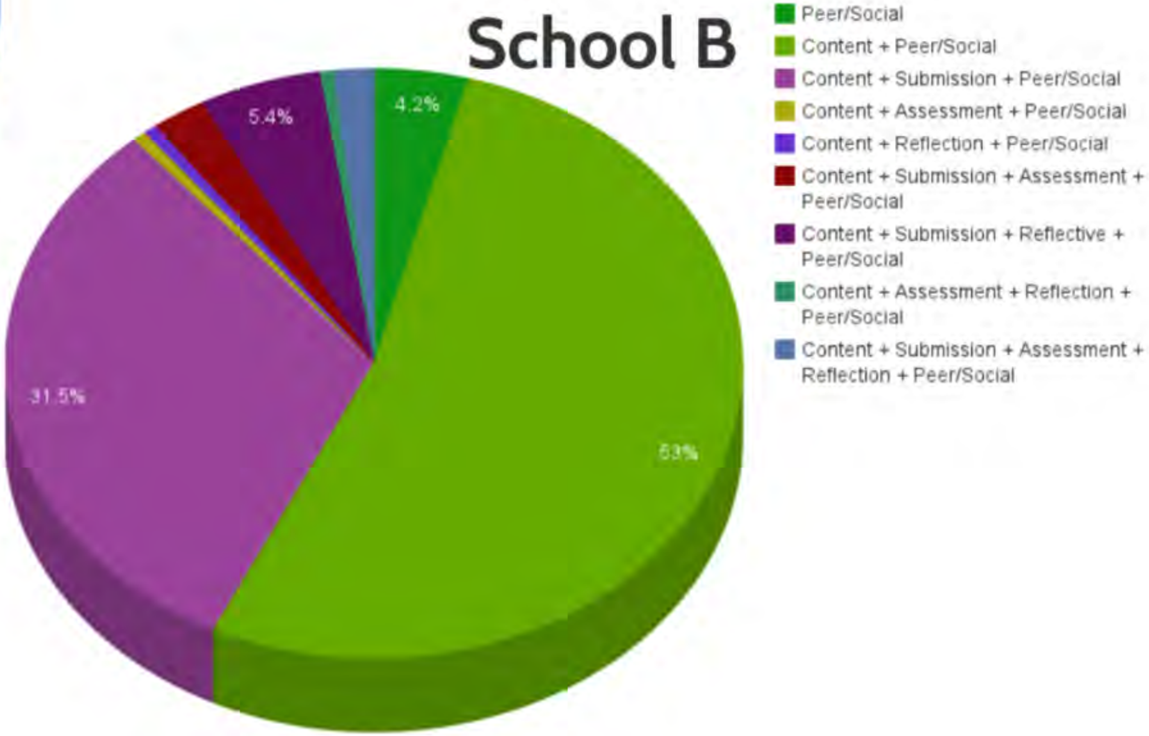
- Usability of data is low
  - Data is very ‘raw’ - requires a lot of processing
  - Invest up-front in quantifying and describing the data - use staff with some educational background
  - Make institutional reporting requirements turnkey
  - Consider whether a standardised data extract would work for a large number of purposes
- Effort and skills required can be significant
  - Define your questions
  - Make pragmatic decisions – quite a bit can be done with simple tools / existing skills
  - Foster an open / sharing culture to bring diverse skills together and pool resources
- Platforms are still maturing
  - Platforms are still evolving - be prepared for change and re-work
  - Not all platforms will give you the same data – comparisons could be hard
- Experience can re-used
  - Experience / approaches may be useful when considering work with on-campus platforms

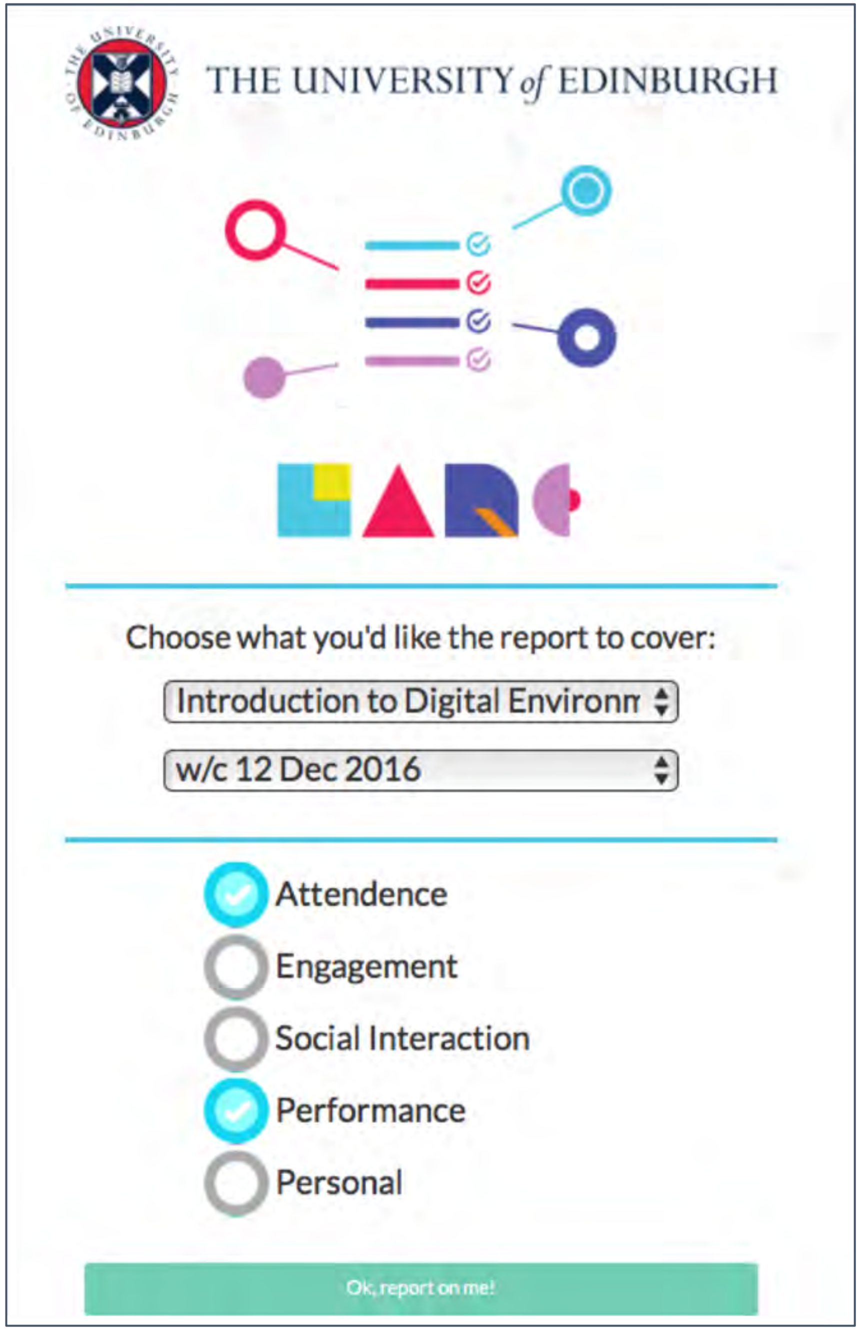
Early VLE Analytics



Heat Map examples from the MSc in Surgical Sciences online programme ESSQ


School A
Content
Content + Submission
Content + Assessment
Content + Peer/Social
Content + Submission + Assessment
Content + Submission + Peer/Social
Content + Reflection + Peer/Social
Content + Submission + Reflective + Peer/Social
Content + Submission + Assessment + Reflection + Peer/Social
39.9%
27.2%
4.4%
4.4%
9.2%
11%
3.1%


School B
Peer/Social
Content + Peer/Social
Content + Submission + Peer/Social
Content + Assessment + Peer/Social
Content + Reflection + Peer/Social
Content + Submission + Assessment + Peer/Social
Content + Submission + Reflective + Peer/Social
Content + Assessment + Reflection + Peer/Social
Content + Submission + Assessment + Reflection + Peer/Social
4.2%
5.4%
31.5%
53%



Learning Analytics Report Card (LARC)

http://larc-project.com

- How can University teaching teams develop critical and participatory approaches to educational data analysis?
- How can we develop ways of involving students as research partners and active participants in their own data collection and analysis, as well as foster critical understanding of the use of computational analysis in education?

Knox, J. (2017). Data Power in Education: exploring critical awareness with the 'Learning Analytics Report Card' (LARC). *Special Issue: Data Power in Material Contexts, Journal of Television and Media*. http://journals.sagepub.com/doi/full/10.1177/1527476417690029

Isard, A. and Knox, J. 2016. Automatic Generation of Student Report Cards. 9th International Natural Language Generation conference. Edinburgh, Sept 5-8 http://www.macs.hw.ac.uk/InteractionLab/INLG2016/proceedings/pdf/INLG33.pdf

Attendance ☑ Engagement ☑ Social ☑ Performance ☑ Personal ☑

Lenient Report

Your attendance has in general been good but this week you logged on less often than usual.

You have mostly been suitably engaged with the course content but this week you seemed a little less interested in the topic than usual.

You have usually been exceptionally social during the course and this week you seemed to interact more with others than usual. Many of your forum posts have been positive in tone, many have been neutral, and very few have been negative.

You are in the middle third of students for attendance and engagement, but the lowest third of students for social interaction.

You are not too concerned about what others in the class think about you, and that is absolutely fine.

attendance=13
engagement=13
social=1
performance=2
personal=0

Strict Report

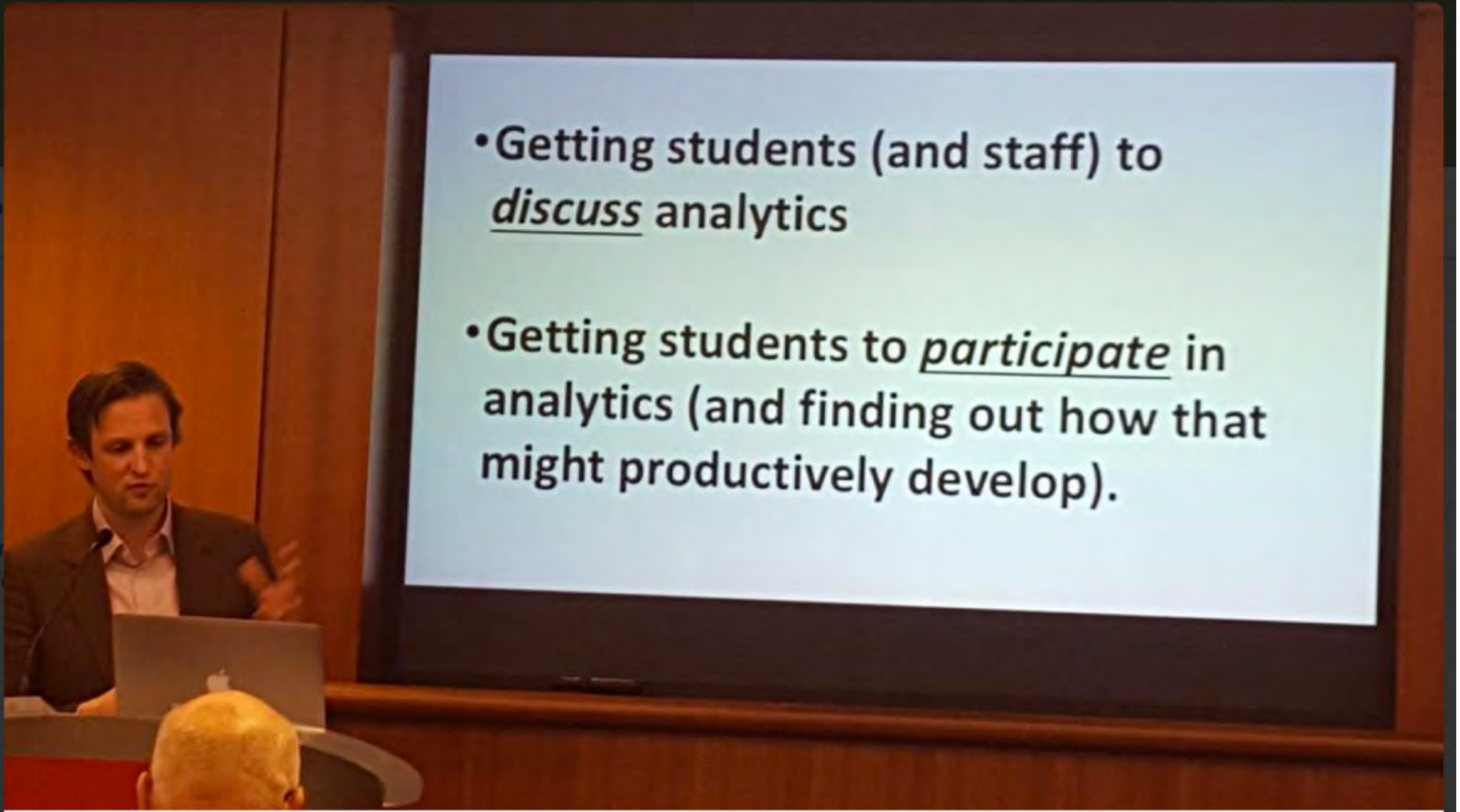
Your attendance has in general been good and this week you logged on less often than usual.

You have mostly been relatively engaged with the course content and this week you were noticeably less interested in the topic than usual.

You have usually been suitably social during the course but this week you noticeably interacted less with others than usual. Many of your forum posts have been positive in tone, many have been neutral, and none have been negative.

You are in the middle third of students for attendance, social interaction and engagement.

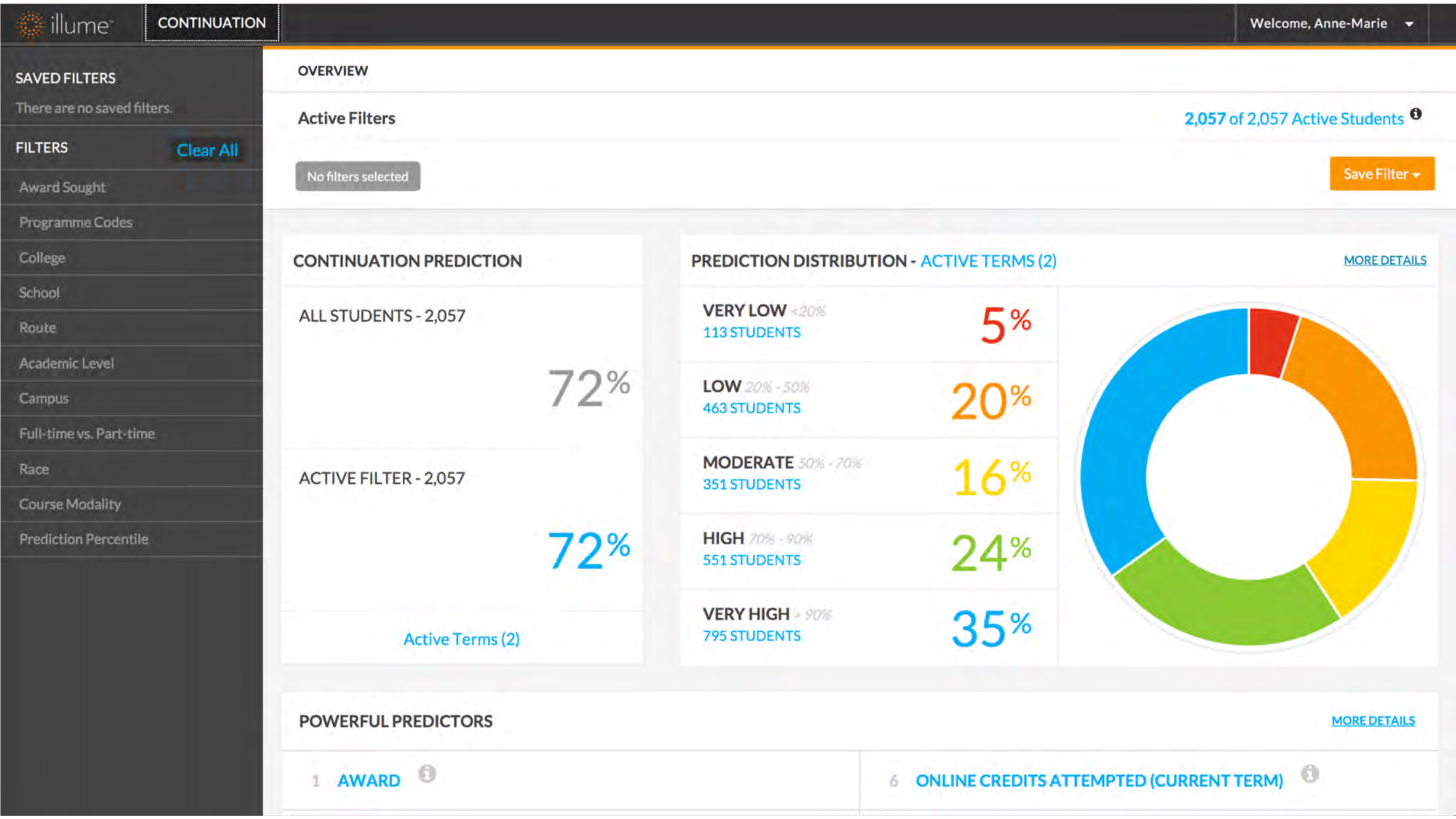
You are not interested in what others in the class think about you, and this seems to indicate a lack of interest in the group.

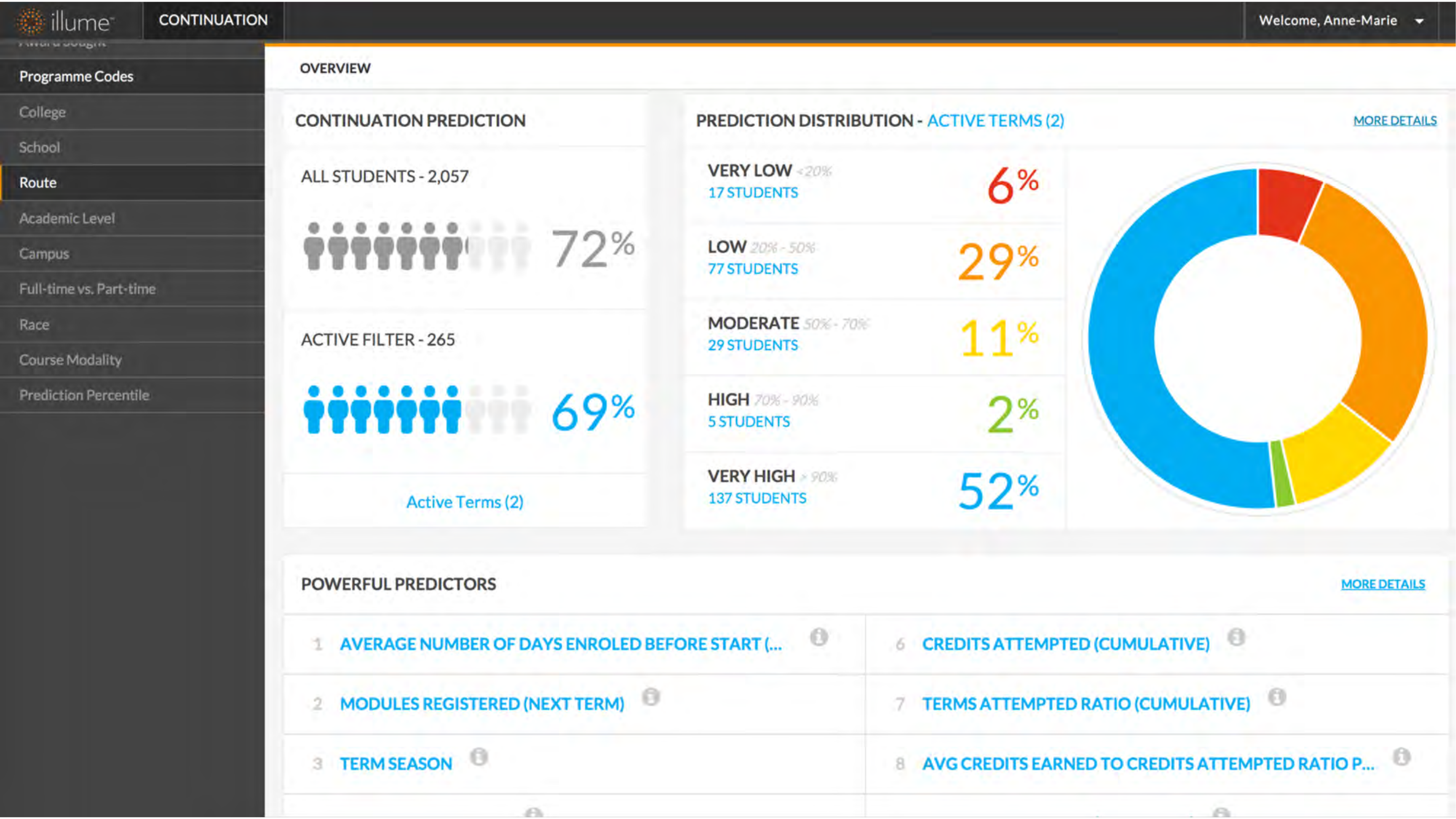


Paul Prinsloo @14prinsp · 11h

Yes. Student centred learning analytics as discursive space @j_k_knox #lak17 pic.twitter.com/WxrrMj4OsM

3


illume
CONTINUATION
Welcome, Anne-Marie
SAVED FILTERS
There are no saved filters.
FILTERS
Clear All
Award Sought
Programme Codes
College
School
Route
Academic Level
Campus
Full-time vs. Part-time
Race
Course Modality
Prediction Percentile
OVERVIEW
Active Filters
2,057 of 2,057 Active Students
No filters selected
Save Filter
CONTINUATION PREDICTION
ALL STUDENTS - 2,057
72%
ACTIVE FILTER - 2,057
72%
Active Terms (2)
PREDICTION DISTRIBUTION - ACTIVE TERMS (2)
MORE DETAILS
VERY LOW <20%
113 STUDENTS
5%
LOW 20% - 50%
463 STUDENTS
20%
MODERATE 50% - 70%
351 STUDENTS
16%
HIGH 70% - 90%
551 STUDENTS
24%
VERY HIGH > 90%
795 STUDENTS
35%
POWERFUL PREDICTORS
MORE DETAILS
1 AWARD
6 ONLINE CREDITS ATTEMPTED (CURRENT TERM)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CONTINUATION
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Programme Codes
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Full-time vs. Part-time
Race
Course Modality
Prediction Percentile
OVERVIEW
CONTINUATION PREDICTION
ALL STUDENTS - 2,057
72%
ACTIVE FILTER - 265
69%
Active Terms (2)
PREDICTION DISTRIBUTION - ACTIVE TERMS (2)
MORE DETAILS
VERY LOW <20%
17 STUDENTS
6%
LOW 20% - 50%
77 STUDENTS
29%
MODERATE 50% - 70%
29 STUDENTS
11%
HIGH 70% - 90%
5 STUDENTS
2%
VERY HIGH > 90%
137 STUDENTS
52%
POWERFUL PREDICTORS
MORE DETAILS
1 AVERAGE NUMBER OF DAYS ENROLED BEFORE START (...
2 MODULES REGISTERED (NEXT TERM)
3 TERM SEASON
6 CREDITS ATTEMPTED (CUMULATIVE)
7 TERMS ATTEMPTED RATIO (CUMULATIVE)
8 AVG CREDITS EARNED TO CREDITS ATTEMPTED RATIO P...

illume | CONTINUATION | Welcome, Anne-Marie

SAVED FILTERS

There are no saved filters.

FILTERS Clear All

- Award Sought
- Programme Codes
- College
- School
- Route
- Academic Level
- Campus
- Full-time vs. Part-time
- Race
- Course Modality
- Prediction Percentile

« OVERVIEW / STUDENT LIST

Active Filters — 265 of 2,057 Active Students

Route: PTMSCSUGSC1P-Surgical Sciences (Online Distance Learning) (MSc) (Part-time) ✖ | Hide Filters | Save Filter

STUDENT LIST

Add Columns | Export Student List

STUDENTS PER PAGE: 10

STUDENT ID	FIRST NAME	LAST NAME	EMAIL	CONTINUATION PREDICTION
104940180972				Low
128013779454				Low
133994700213				Low
135679679454				Low
14315578695				Low
166115577177				Low
173629678695				Low

Leif Nelson
@leifnelson

Follow

Analytics not needed in "artisinal" courses, but needed in large "industrial" courses. #lak17

Learning Analytics Policy and Governance

- Task Group (reporting to Senate Learning and Teaching, and Knowledge Strategy Committees)
- Governance group:
  - Convenor - a senior academic member of staff with expertise in Learning Analytics
  - The Assistant Principal with strategic responsibility for Learning Analytics
  - A student representative
  - The University's Data Protection Officer
  - Representatives from relevant service units (Universities Secretaries Group and Information Services Group)
  - A member of academic staff with expertise in research ethics.

Statement of Principles

1. LA will not be used to inform significant action at an individual level without human intervention.
2. We will use LA to benefit all students in reaching their full academic potential.
3. We will be transparent about data collection, sharing, consent and responsibilities.
4. We will actively work to recognise and minimise any potential negative impacts from LA.
5. We will abide with ethical principles and align with organisational strategy, policy and values.
6. LA will be supported by focused staff and student development activities.
7. LA will not be used to monitor staff performance.

https://www.ed.ac.uk/files/atoms/files/learninganalyticsprinciples.pdf

Statement of Purposes

1. Quality
2. Equity
3. Personalised feedback
4. Coping with scale
5. Student Experience
6. Skills
7. Efficiency

https://www.ed.ac.uk/files/atoms/files/learninganalyticsprinciples.pdf

Edinburgh: Purposes

- **Skills** – Interactions with analytics as part of the University learning experience can help our students build 'digital savviness' and prompt more critical reflection on how data about them is being used more generally, what consent might actually mean and how algorithms work across datasets to define and profile individuals. Learning analytics approaches can also be used to promote the development of key employability skills. Supporting staff to develop skills in working with learning analytics applications is also an investment in institutional capacity and leadership.

http://www.ed.ac.uk/academic-services/projects/learning-analytics-policy

1. Co-responsibility in an asymmetrical power and contractual relationship

…obligation to act is a *co-responsibility* of students and institution, tempered by the asymmetrical power and contractual relationship in which the institution has very specific moral and legal duties to respond

Image credit: https://pixabay.com/en/michelangelo-abstract-boy-child-71282/

Lessons Learned

- Built capacity and understanding
- No one size fits all
- Retention focus is of limited value at Edinburgh
- Learning analytics as a service, not a product
- Market does not provide
- Data protection, security, FOI all take more time
- Data validation takes time
- Learning analytics does not fit neatly into the organisation
- Our data are not always easy to work with

Next steps

- Using our governance
- Continue to capacity build
  - Course design
  - Feedback at scale

THE UNIVERSITY of EDINBURGH

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