Learning Analytics @ The Open University
JISC Networking Event 11th May 2016

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Learning Analytics @ The Open University

Where are you from?

- PVC Learning & Teaching
- CIO / IT
- Planning Office
- Student Support
- Faculty
Learning Analytics @ The Open University

Where are you from?

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OU Context

2014/15
174k students
The average age of our new undergraduate students is 29
40% new undergraduates have 1 A-Level or lower on entry
Over 21,000 OU students have disabilities
868k assessments submitted, 395k phone calls and 176k emails received from students
Analytics for student success vision

A clear vision statement was developed to galvanise effort across the institution on the focused use of analytics

Vision
To use and apply information strategically (through specified indicators) to retain students and progress them to complete their study goals

Mission
This needs to be achieved at:

- a macro level to aggregate information about the student learning experience at an institutional level to inform strategic priorities that will improve student retention and progression
- a micro level to use analytics to drive short, medium and long-term interventions
**Vision in action**

- **Recruit**
- **Retain**
- **Progress**
- **Complete**

**Success outcomes and leading indicators**

- **Learning & teaching activities**
- **Student support activities**

**Measures of our operational performance and interventions**

- **Indicators and measures fed into dashboards and reports at relevant levels**

**Evidence of the drivers of student success guides what we do and what we measure**

**Evaluation of the outcomes from interventions increases our evidence base of what drives student success**

**Dashboards / Reports / Tools**
- Institutional Dashboard
- PVCs
- Deans
- Programme Directors
- Module Teams
- Student Support Teams

**ACTION**

**Intervention**

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Analytics enhancement strategy

The OU recognises that three equally important strengths are required for the effective deployment of analytics.

Adapted from Barton and Court (2012)
Analytics enhancement strategy

- Early alert indicators using predictive analytics
- Policy on the ethical use of student data for learning analytics
- Analytics for action evaluation framework
- Impact of learning design on outcomes
Analytics enhancement strategy

- Early alert indicators using predictive analytics
  - Processes that impact student success
    - Direct intervention
    - Information advice and guidance
    - Continual quality enhancement
  - For action
- Policy on the ethical use of student data for learning analytics
- Analytics for action evaluation framework
- Impact of learning design on outcomes

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Current predictive indicators

Module probabilities

Integrated into the Student Support Intervention Tool

Predicts the probability of a student completing and passing the module
Current predictive indicators

OU Analyse

Predicts the submission of next assignment weekly

Deployed through OU Analyse Dashboard
Lessons

Create the right story for the user

Start small – find and nurture your champions

Don’t underestimate the guidance required

Create your super-users, create your case studies

Foreground the “should we” arguments

Repeat, repeat, repeat
Lessons

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Intervention potential

We have been working to assess the intervention potential of using frequent indicators

Measures
- Accuracy of predictions
- Volume of predictions
- Timeliness of predictions

**Accurate** predictions at a manageable **volume** that are **timely** in relation to a student’s decision to drop out

= Ability of Associate Lecturers (or others) to act on the information
Accuracy

- Using standard metrics where the condition we are predicting is the student NOT submitting (or completing/passing)

- **Accuracy** = % of all predictions that are correct
- **Precision** = % of non-submission predictions that are correct (the reverse of this is the false positive rate)
- **Recall** = % of actual non-submissions that are identified by the predictions (the reverse of this is the miss rate)
Accuracy
Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules...

Accuracy:

Predicted not to submit = ○  New prediction this week = ○  Actually did not submit =  ⊘
Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules...

Accuracy:
By week 5, 2/3rds of predictions true, but …
Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules...

Accuracy:
By week 5, 2/3rds of predictions true, but only identify half of non-submitters
Intervention potential

Based on an analysis of predictions made on 14J presentations for 11 modules…

**Accuracy:**
By week 5, 2/3rds of predictions true, but only identify half of non-submitters
By week 14, predictions identify 2/3rds of non-submitters

Predicted not to submit =  
New prediction this week =  
Actually did not submit =  

20
Percentage of weekly TMA predictions that are 'not submit' and the percentage of submit/not-submit predictions that have negatively changed from the previous week

module_code=K101 presentation_code=2014J
Intervention potential

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Accuracy:
By week 5, 2/3rds of predictions true, but only identify half of non-submitters
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Based on an analysis of predictions made on 14J presentations for 11 modules...

Accuracy:
By week 5, 2/3rds of predictions true, but only identify half of non-submitters
By week 14, predictions identify 2/3rds of non-submitters

Volume:
Manageable – one new prediction per fortnight
Timeliness

Gap from FIRST TMA non-submission prediction to last engagement

Mean: -14 days
St Dev.: 80 days

-30 days to 0: 15% of all first predictions
+1 days to +14: 9% of all first predictions

NB: last engagement date = Last date of either visit to VLE site, submit assessment, respond to study engagement check email
Caution – this is crude proxy measure
**Timeliness**

Gap from changes in TMA non-submission prediction to last

Mean: -42 days  
St Dev.: 65 days

-30 days to 0: 19% of all prediction changes  
+1 days to +14: 12% of all prediction changes

NB: last engagement date = Last date of either visit to VLE site, submit assessment, respond to study engagement check email  
Caution – this is crude proxy measure
Intervention potential

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By week 5, 2/3rds of predictions true, but only identify half of non-submitters
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By week 14, predictions identify 2/3rds of non-submitters

Volume:
Manageable – one new prediction per fortnight

Timeliness:
One in three of all new predictions fall in a six week “window of opportunity” around the last engagement date based on an analysis of predictions for non-completers

- Predicted not to submit = 0
- New prediction this week = 32%
- Actually did not submit = 68%
Lessons

- Create the right story for the user
- Start small – find and nurture your champions
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- Foreground the “should we” arguments
- Repeat, repeat, repeat
Champions

Health and Social Care

Chris Kubiak
Lessons

Create the right story for the user

Start small – find and nurture your champions

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Guidance and help materials
Lessons

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Super-users

2 AL Super users recruited

Briefings  Catch-ups  Support and feedback
Outcomes of current pilots

Summary of the interim evaluation of piloting as at March 2016

- There is a mixed picture in the quantitative analysis on the impact in the pilot tutor groups on withdrawal rates and assignment submissions (note that tutors are self selected and the expectations to intervene are not consistent across the module piloting)
- It is a useful tool for understanding students and their participation
- Predictions generally agree with tutors' experience and intuitions of which students might potentially be at risk
- A (potential) USP of OU Analyse was the information provided between the assignment submission in relation to students' engagement with learning materials
- Overall, all tutors interviewed were positive about the affordances of OUA, and are keen to use it again (for a range of reasons) in their next module
“I love it it’s brilliant. It brings together things I already do [...] it’s an easy way to find information without researching around such as in the forums and look for students to see what they do when I have no contact with them [...] if they do not answer emails or phones there is not much I can do. OUA tells me whether they are engaged and gives me an early indicator rather than waiting for the day they submit”
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PRINCIPLES for the ethical use of student data for learning analytics

01
Learning analytics is an ethical practice that should align with core principles, such as open entry to undergraduate level study.

02
The OU has a responsibility to all stakeholders to use and extract meaning from student data for the benefit of students where feasible.

03
Students should not be wholly defined by their visible data or our interpretation of it.

04
The purpose and boundaries regarding the use of learning analytics should be well defined and visible.

05
Students should be engaged as active agents in the implementation of learning analytics (e.g., personalised learning paths, interventions, etc.).

06
The University is transparent regarding data collection, and will provide students with the opportunity to update their own data at regular intervals.

07
Modelling and interventions based on analysis of data should be sound and free from bias.

08
Adoption of learning analytics with the OU requires broad acceptance of the values and benefits (organisational culture) and the development of appropriate skills across the culture.

Information for students

How the OU uses student data

Learning analytics and you

Related Help

Your Help Centre

Found what you're looking for?  Yes  No  Save this page
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Are there any questions?

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References: