Apr 2016

Jisc Learning Analytics

UCISA CISG

Overview

- A brief introduction to Learning Analytics
- Why?
  - What problems could we solve?
- The pioneers
  - Evidence from previous projects
- The present
  - What is Jisc doing?
- The future
  - Where it could lead

Learning Analytics

A brief introduction

What do we mean by Learning Analytics?

- The application of **big data techniques** such as machine based learning and data mining to help learners and institutions **meet their goals**:
  - For our project:
    - improve retention (current project)
    - improve achievement (current project)
    - improve employability (current project)

What is Predictive Learning Analytics?

- Statistical analysis of historical and current data derived from the learning process to **create models that allow for predictions** that can be used to improve learning outcomes
- Models are developed by “mining” large amounts of data to find hidden patterns that correlate to specific outcomes
  - e.g. Mine VLE event data to find usage patterns that correlate to course grades

Why?

What problems do we need to solve?

Retention

- 178,100 students aged 16-18 failed to finish post-secondary school qualifications they started in the 2012/13 academic year
  - costing £814 million a year - 12 per cent of all government spending on post-16 education and skills (Centre for Economic and Social Inclusion
- 8% of undergraduates drop out in their first year of study
  - This costs universities around £33,000 per student
- students with 340 UCAS points or above were considerably less likely (4%) than those with less UCAS points (9%) to leave their courses without their award

Attainment

- 70% of students reporting a parent with HE qualifications achieved an upper degree, as against 64% of students reporting no parent with HE qualifications
- In all disciplines except Computer Science, Medicine and Dentistry, and Physical Science, students with a parent with an HE qualification were more likely to have achieved an upper degree
- Overall, 70% of White students and 52% of BME students achieved an upper degree

The Pioneers

Previous projects and services showing the potential of learning analytics

See: https://analytics.jiscinvolve.org/wp/2014/11/20/jisc-releases-new-report-on-learning-analytics-in-the-uk/ for UK examples

Marist College – Academic Early Alert System

Approach

- Supported by Bill and Melinda Gates Foundation. Investigated how use of Academic Early Alert systems impact on **final course grades** and **content mastery**

Outcome

- Analysis showed a statistically significant positive impact on final course grades
- The most important predictor of future academic success was found to be partial contributions to the final grade
- The predictive models developed at one institution can be transferred to very different institutions while retaining most of their predictive abilities
- Simply making them aware that they are at risk may suffice

New York Institute of Technology

Approach

- Data on previous students was used to train the model using four different mathematical approaches
- Key risk factors included grades, the major subject and the student's certainty in their choice of major subject, and financial data such as parental contribution to fees
- Dashboards showed the percentage confidence in that prediction from the model and the reasons for the prediction – this provided a basis for discussion with the student

Outcome

- **Three out of every four students** who do not return to their studies the following year had been **predicted** as at-risk by the model

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Predictive Analytics Reporting (PAR) framework

Approach

- Predictive Analytics Reporting (PAR) framework in the US has been set up to share data, analyses and findings across institutions
- One of its main achievements has been the creation of a set of common data definitions, defining common variables across US higher education institutions

Outcome

- It has now built up a database of two million de identified student records, which it claims can identify at-risk students with 90 per cent confidence (PAR, 2015)

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Signals at Purdue University

Approach

- Signals' predictive algorithm is based on performance, effort, prior academic history and student characteristics

Outcome

- Problems are identified as early as the second week in the semester
- Students are given feedback through traffic lights – and from messages tailored by their instructors
- Students using Signals seek help earlier and more frequently
- One study showed 10% more As and Bs were awarded for courses using Signals than for previous courses which did not use Signals

University of Maryland, Baltimore County

Approach

- Analytics to identify a particularly effective teaching strategy using a specific VLE tool

Outcome

- Students who obtain D or F grades at UMBC use the VLE around 40% less than those with C grades or higher; this finding remains constant, year after year
- Students who used a tool to compare their VLE activity with that of other students were 1.92 times more likely to be awarded grade C or higher compared with students who did not use it
- Innovations which led to improvements in student performance on one course appeared to lead them to perform better in subsequent courses too

Present

What Jisc is doing now

Three core strands:

Learning Analytics architecture and service

Toolkit

Community

Jisc Learning Analytics

Toolkit: Code of practice

Learning Analytics

A guide for students' unions

The following highlights some anticipated emerging issues with the use of learner analytics and student data in UK higher education and how students' unions might deal with them on their campuses.

Learning Analytics – the basics

Learner analytics is about using the increasing potential of data insight to improve students' learning. As IT infrastructures and processing power develops, it is now possible to record and store data relating to many aspects of the student learning experience: classroom and library/lab attendance; use of books, VLEs and other resources; assessment marks and feedback; and student profile and demographic data. Data models can identify trends and patterns to assist educators in designing personalised support and assistance for students, and to arrange interventions if there is evidence of a student struggling.

This has massive power and potential to tackle some of the problems and challenges that currently exist in UK higher education, such as avoiding unnecessary drop-outs, student demotivation, reducing the number of exam resits, enabling more reflective learning and engagement, and reducing inequalities such as the BME attainment gap.

Analytics also have the power to help us understand more about what cultivates effective student engagement and learning in higher education. Early indicators from those institutions pioneering analytics work has suggested that institutions could make huge strides in using engagement measures to increase student success and support, and that even very basic analytical models are being used to prevent unnecessary drop-outs.

Issues to consider

Despite all the exciting potential of learner analytics there are a number of issues that could prove problematic if the appropriate checks and balances are not in place to defend students' rights and interests.

Partnership

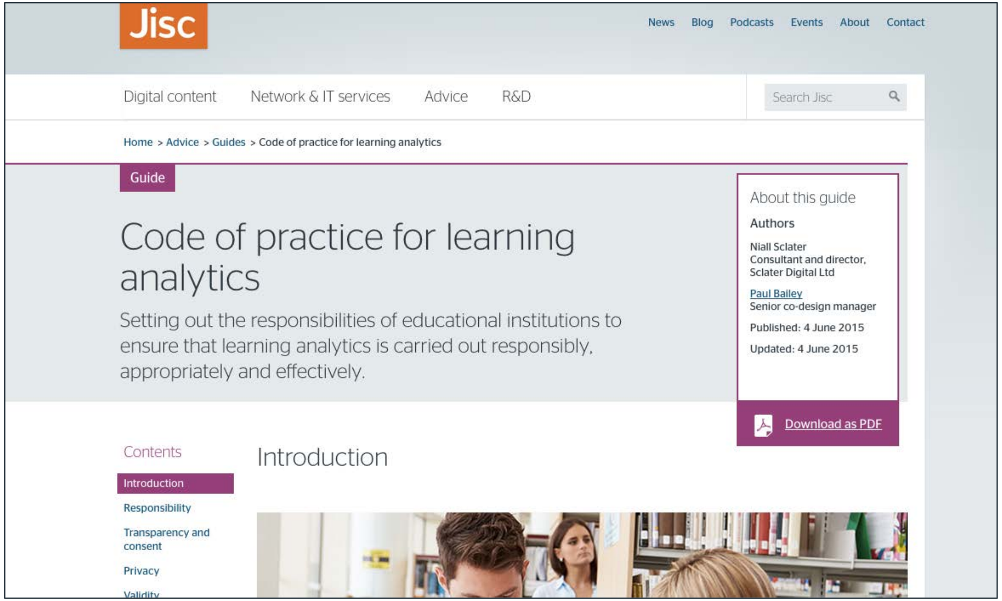
The prime purpose and use of analytics should be to support the student-teacher partnership that is at the heart of education. This sits nicely with Jisc's starting principle that analytics is a "transparent moral practice". In a partnership, the use of a students' data to support them and their peers must be seen as transparent, as a way of bringing out the best in students and educators, and must always be used whilst recognising the primacy of student individuality and independence.

The role of students' unions

The issues involved in the ethics and fair use of learner analytics are broad and unprecedented, and there will be many points of contention within institutions that are unforeseeable. Analytics development is built around 'secondary use' innovations of data (i.e. uses that we cannot anticipate yet). It is therefore vital that students' unions form a core part of institutions' considerations on the use of analytics and are given recourse or space to dispute uses that students object to. NUS will be on hand to support officers and staff in students' unions to engage with their institutions on learning analytics issues and to defend students' rights.

Learning Analytics briefing – August 2015

nus
national union of students



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Guide

Code of practice for learning analytics

Setting out the responsibilities of educational institutions to ensure that learning analytics is carried out responsibly, appropriately and effectively.

About this guide

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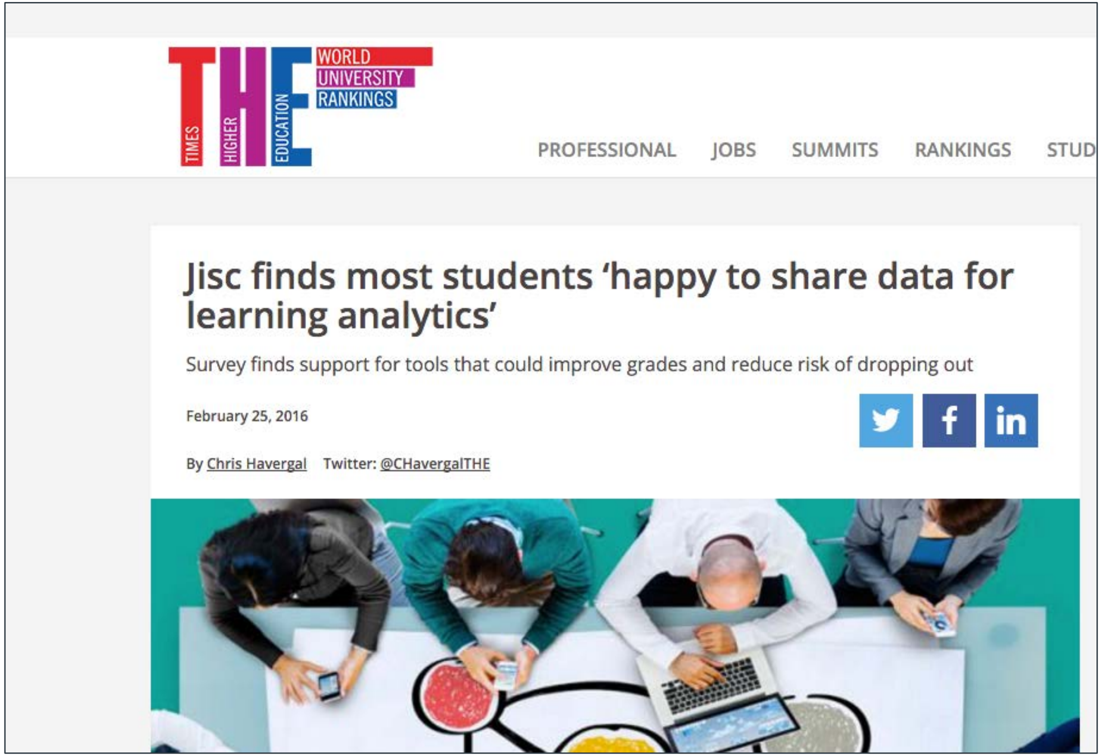
Introduction

Student buy-in



Times Higher, 25 Feb. 2016

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Jisc Learning Analytics architecture

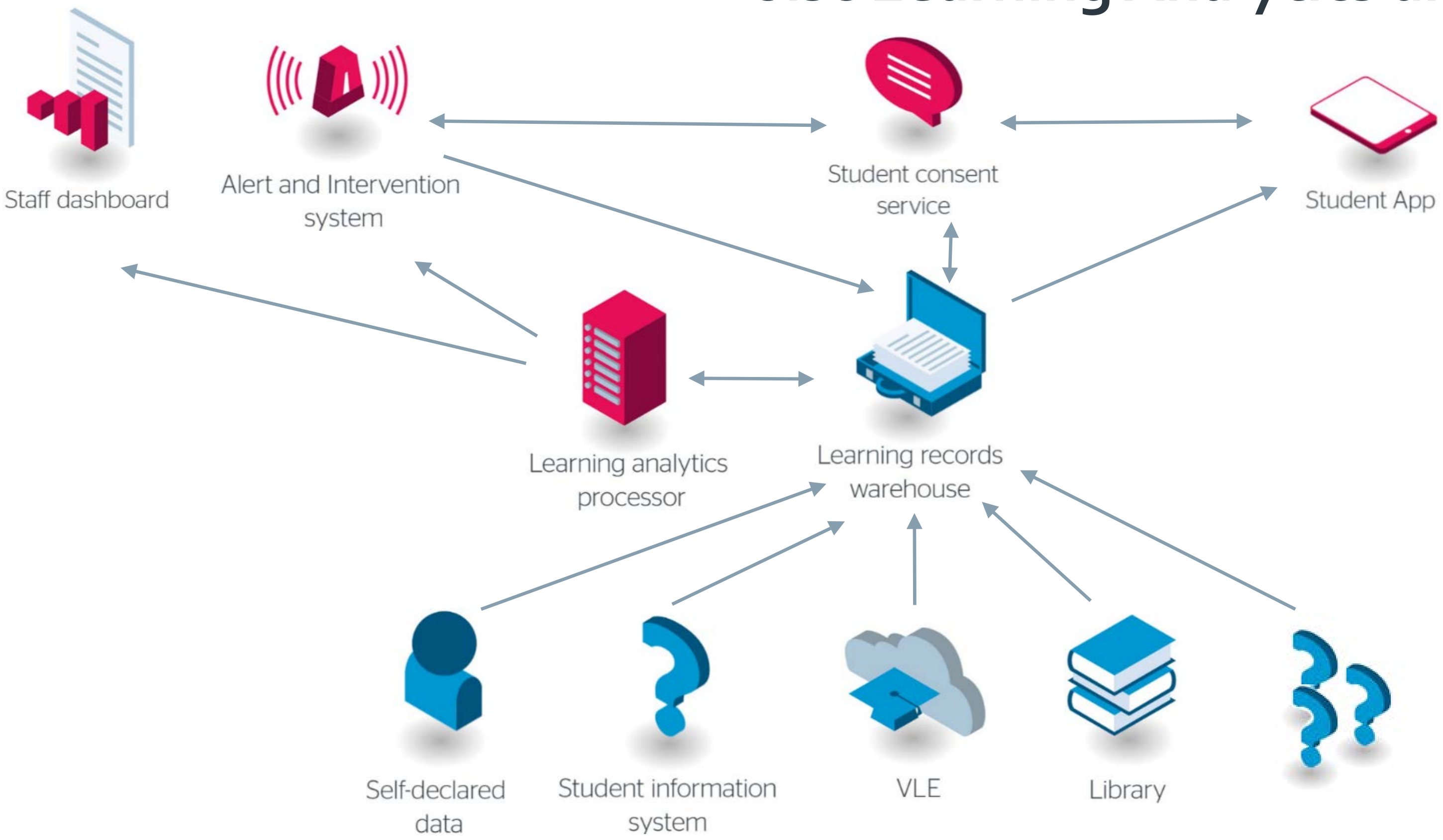
What

- Building a national architecture
- Defined standards and models
- Implementation with core services

Why?

- Standards mean models, visualisations and so on can be shared
- Lower cost per institutions through shared infrastructure
- Lower barrier to innovation – the underpinning work is already done

Jisc Learning Analytics architecture



Project partners

UNICON

MARIST

Blackboard

TRIBAL

therapybox

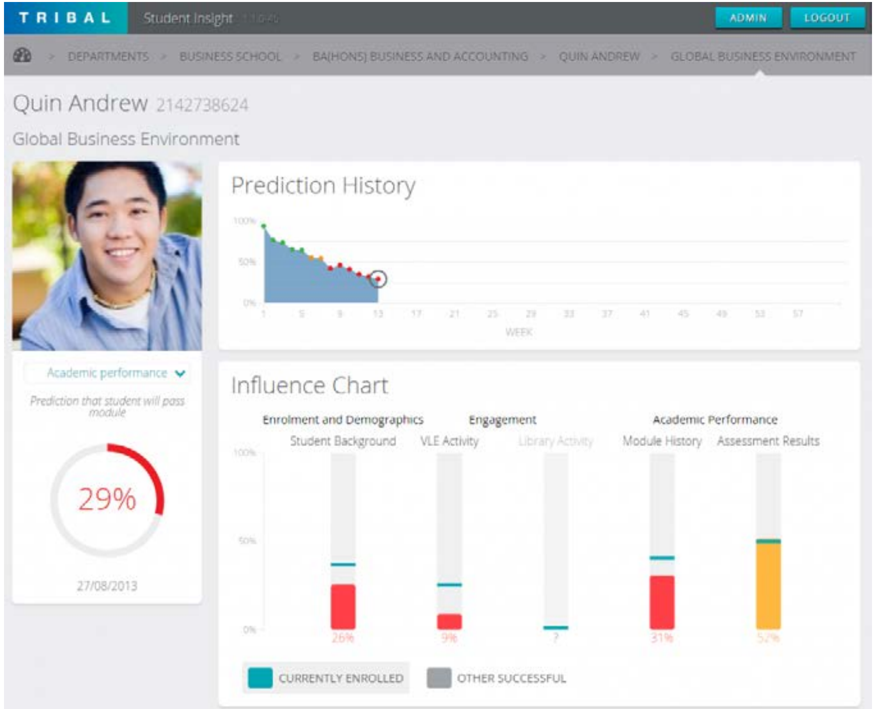
HT2

Service: Dashboards

Visual tools to allow lecturers, module leaders, senior staff and support staff to view:

- student engagement
- cohort comparisons
- etc…

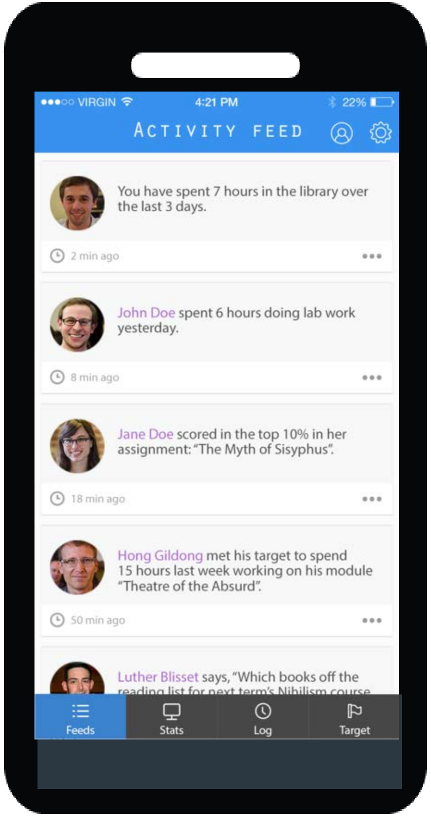
Based on either commercial tools from **Tribal** (Student Insight) or open source tools from **Unicon/Marist** (OpenDashBoard)



Service: Student app

- First version will include:
  - overall engagement
  - comparisons
  - self declared data
  - consent management

Bespoke development by **Therapy Box**



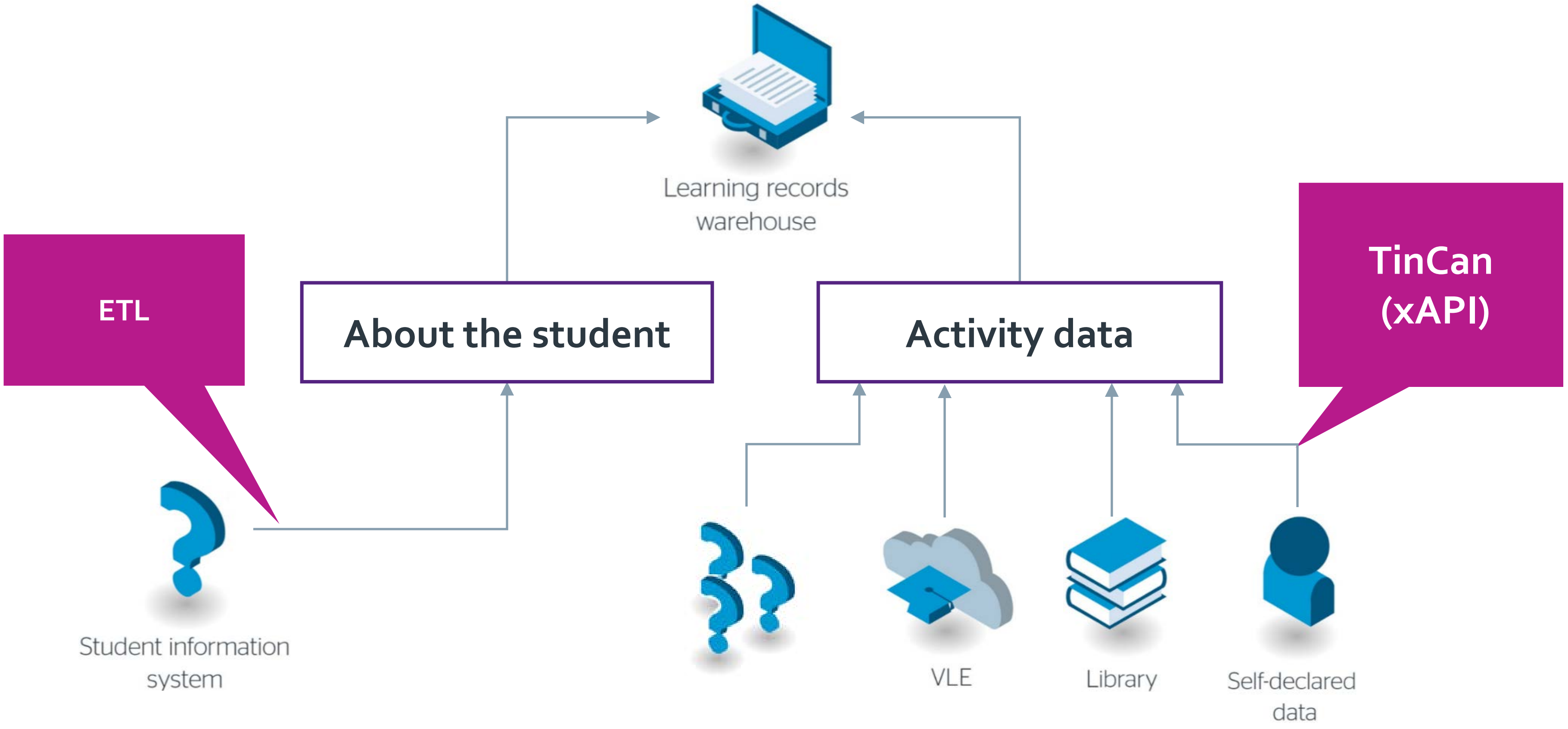
Service: Alert and intervention system

Tools to allow management of interactions with students once risk has been identified:

» case management
» intervention management
» data fed back into model
» etc…

Based on open source tools from **Unicon/Marist** (Student Success Plan)

Data collection



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xAPI 'Recipes' are key

- 'Recipes' are a shared way of describing activities
- So the data from '**accessing a course**' is the same whether Moodle or Blackboard is used
- The same holds for
  - 'attend a lecture'
  - 'borrow a book'
  - ...

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Jisc project in numbers

- **Expressions of interested:** 70
- **Engaged in activity:** 24
- **Discovery to Sept 16:** agreed (20), completed (11), reported (6)

- Over 1 million records collected in real-time
- **Moodle Historic Data Transformation:**
  - 41 million records transformed from Moodle log files to xAPI
- **Blackboard Data Transformation:**
  - 12 million blackboard records transformed from Blackboard Log to xAPI

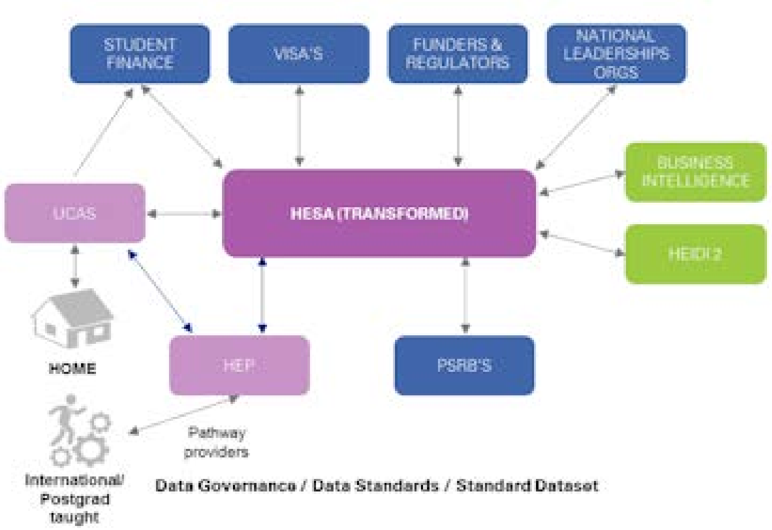
Example HE activity

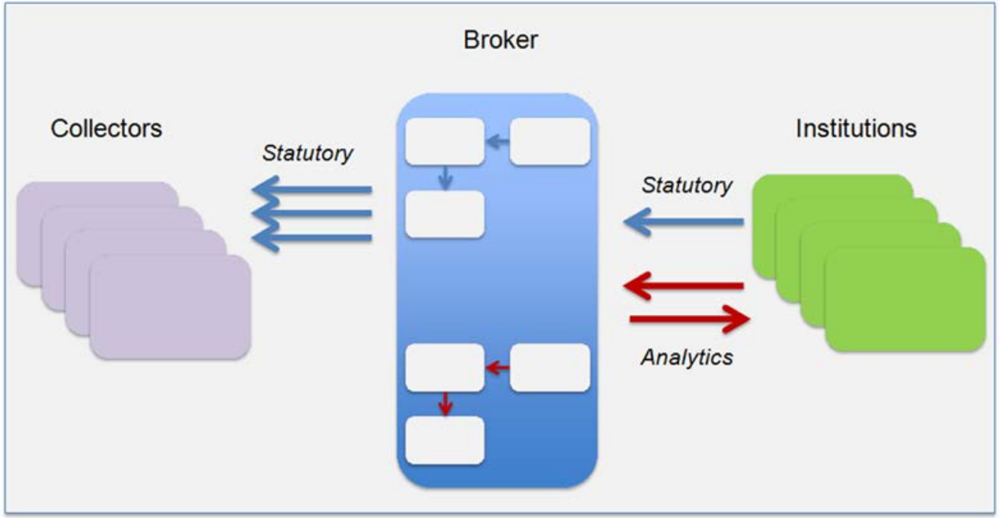
Profile	Aim	Activity	Data sources
Russell Group	Retention of widening participation + support for students to achieve 2.1 or better	Discovery + Tribal Insight + Learning Locker	Moodle + Student Records
Research led University	Retention, improve teaching, empowering students	Discovery + OpenSource Suite + Student App	Moodle + Attendance+ Student Records
Teaching led University with WP mission	Retention - requirement to make identifying students more efficient so they can focus on interventions	Tribal Insight + Learning Locker	Blackboard + Attendance + Student Records
Research led University	Student engagement	Discovery + Student app + Learning Locker	Moodle + Student Records
Teaching Lead	Understanding of how Learning Analytics can be used	Discovery + Technical Integration	Moodle

Future

Where learning analytics could take us

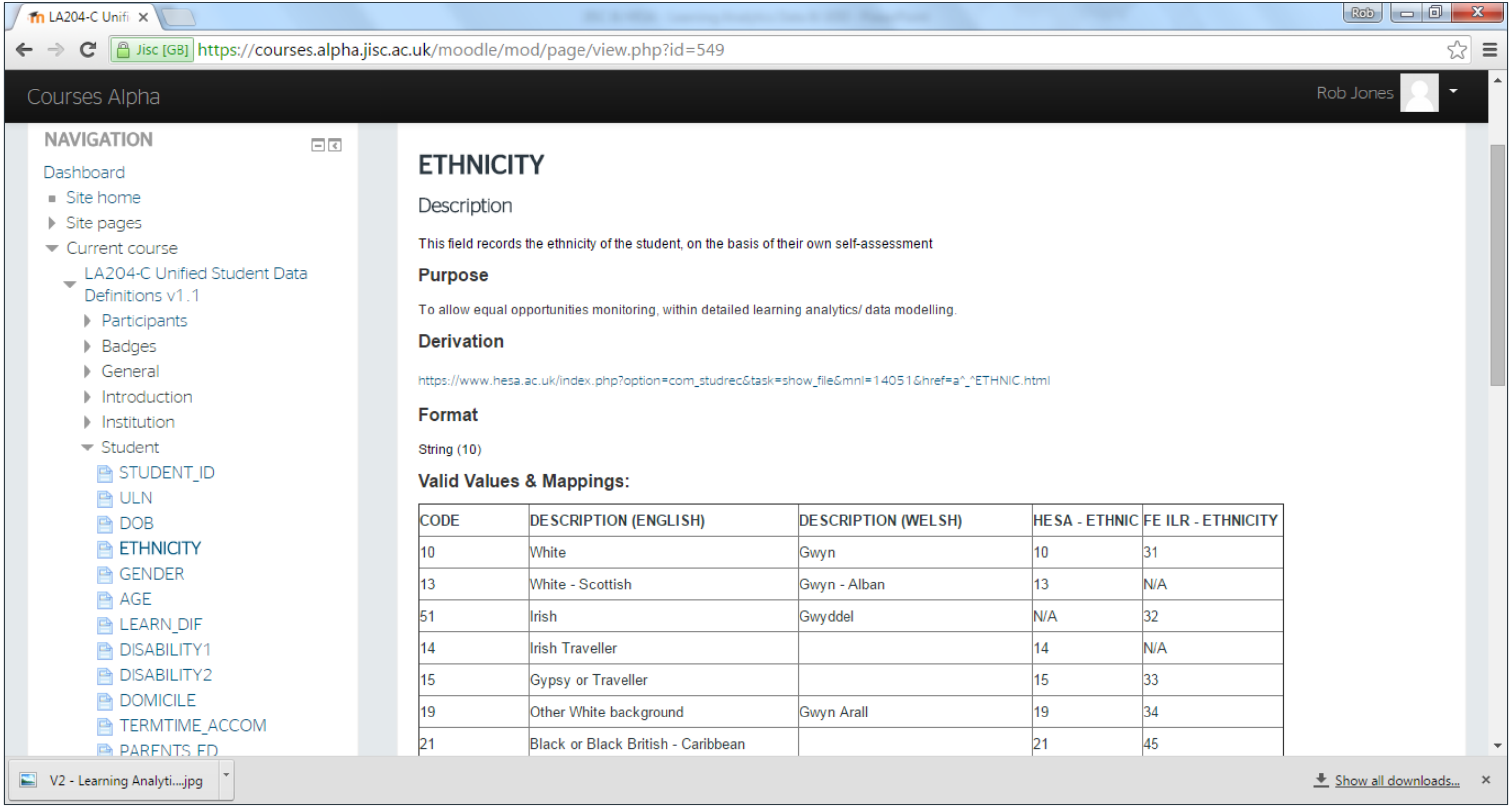
Data model consistent with HEDIIP landscape





jisc.ac.uk/rd/projects/information-hub-prototype

Unified data definitions



LA204-C Unifi

https://courses.alpha.jisc.ac.uk/moodle/mod/page/view.php?id=549

Courses Alpha

Rob Jones

NAVIGATION

Dashboard
- Site home
- Site pages
- Current course
  - LA204-C Unified Student Data Definitions v1.1
    - Participants
    - Badges
    - General
    - Introduction
    - Institution
    - Student
      - STUDENT_ID
      - ULN
      - DOB
      - ETHNICITY
      - GENDER
      - AGE
      - LEARN_DIF
      - DISABILITY1
      - DISABILITY2
      - DOMICILE
      - TERMTIME_ACCOM
      - PARENTS_ED

ETHNICITY

Description

This field records the ethnicity of the student, on the basis of their own self-assessment

Purpose

To allow equal opportunities monitoring, within detailed learning analytics/ data modelling.

Derivation

https://www.hesa.ac.uk/index.php?option=com_studrec&task=show_file&mnl=14051&href=a^_^ETHNIC.html

Format

String (10)

Valid Values & Mappings:

CODE	DESCRIPTION (ENGLISH)	DESCRIPTION (WELSH)	HESA - ETHNIC	FE ILR - ETHNICITY
10	White	Gwyn	10	31
13	White - Scottish	Gwyn - Alban	13	N/A
51	Irish	Gwyddel	N/A	32
14	Irish Traveller		14	N/A
15	Gypsy or Traveller		15	33
19	Other White background	Gwyn Arall	19	34
21	Black or Black British - Caribbean		21	45

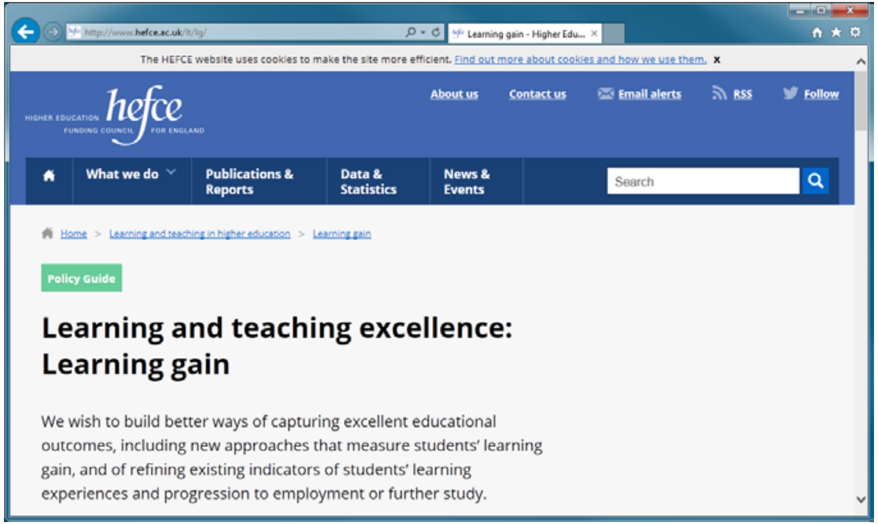
V2 - Learning Analyti....jpg

Show all downloads...

HEFCE learning gain call May 2015

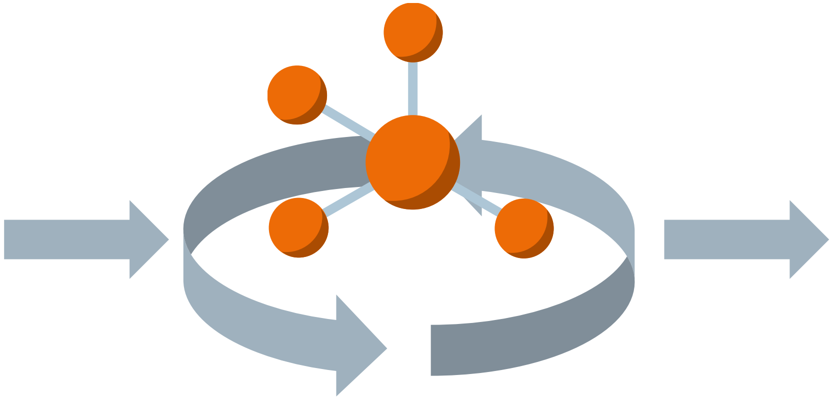
May 2015 call:

- Standardised tests
- Grades
- Self-reporting surveys
- Mixed methods
- Other qualitative methods



deCODE – Iceland genomics research

Iceland's genetic data bank



Reference data

- » Family trees
- » Personal health records

Analytics number crunching

Outcomes

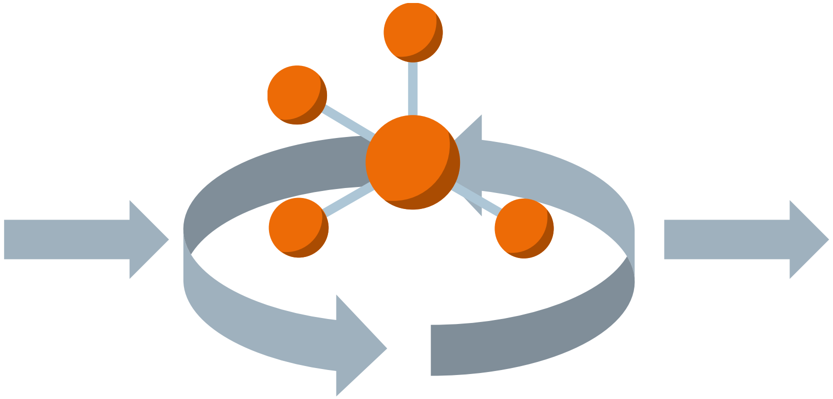
- » Understanding genetic nature of diseases
- » Predictors of future health
- » Personalised medicine

LA warehouse: our DNA bank for higher E-Learning?

Reference data

- » Demographics
- » Entry qualifications
- » Learning and employment outcomes

UK learning data warehouse

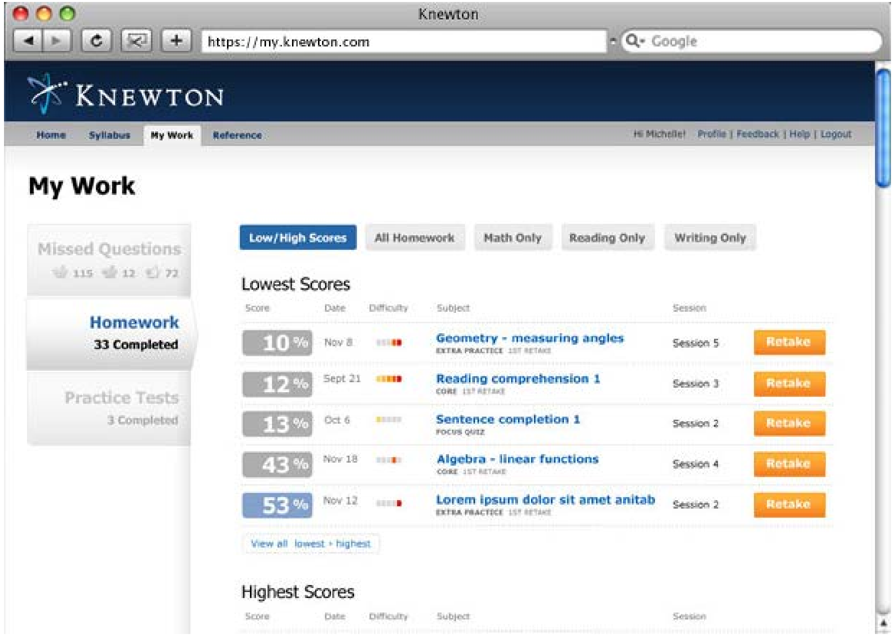


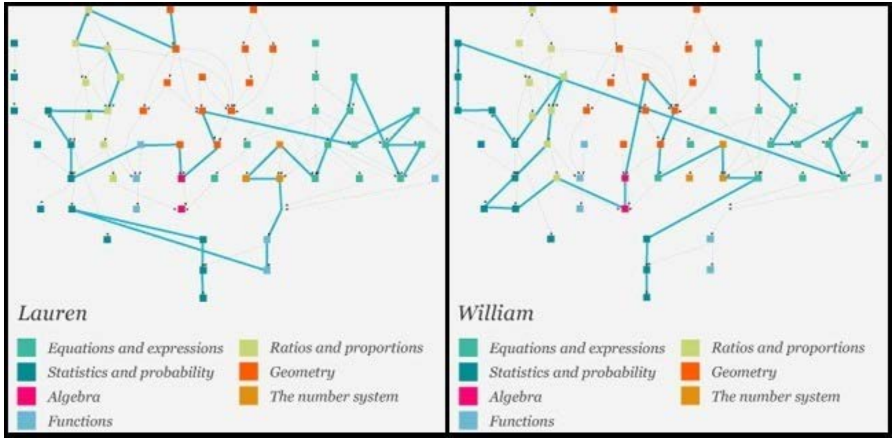
Analytics number crunching

Outcomes

- » Deep understanding of e-learning
- » Metrics for engagement, learning gain
- » Personalised next generation e-learning

UK-led personalised next generation E-learning?





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