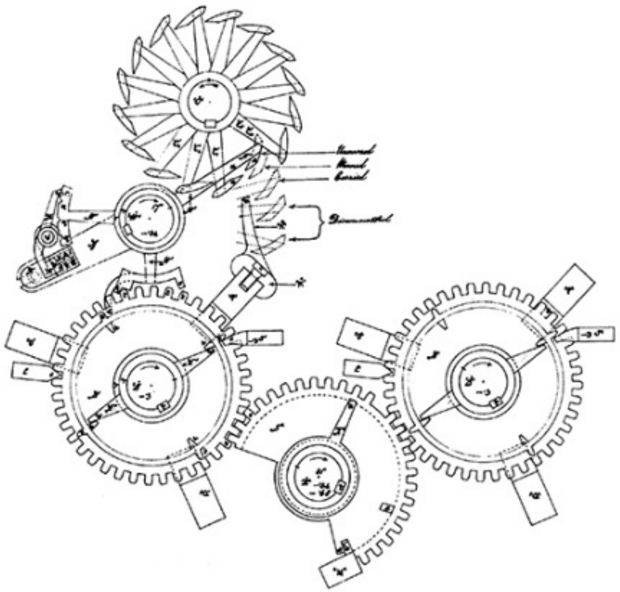
ESUP-DAYS #25
APEREO PARIS 2018

Learning Analytics 2018

Where We Are, and Where We Need to Go…



Presenters:

Ian Dolphin
Apereo Foundation
ian.dolphin@apereo.org

Michael Webb
Jisc
michael.webb@jisc.ac.uk

esup portail

apereo
Serving the Academic Mission

Agenda

Learning Analytics Defined
Big Data - What Could Go Wrong?
A Central Service: The UK Experience
Learning Analytics and Openness

A Distinction …

Academic Analytics
System or organisation wide data

Learner/ing Analytics
Actionable data about individuals

Learning Analytics Definition

“**Measurement**, **collection**, **analysis** and **reporting** of **data** about learners and their contexts, for purposes of **understanding** and **optimizing learning** and the **environments** in which it occurs” (1)

(1) Learning and Academic Analytics, Siemens, G., 5 August 2011, http://www.learninganalytics.net/?p=131

Learning Analytics Definition

Applying techniques associated with **big data** to data produced in course of learning.

Analysing historical aggregate data to identify potential failure/success.

#LSAC17 Keynote @dgasevic Recognising that learning analytics is about learning - not just big data #LearningAnalytics

The Critics


Weaponization
data
education
breaches
breach
Data
million
software
Equifax
fill
course
yet
whole
Security
Education
personal
insecurity
article
stolen
past
billion
beyond
number
single
easy
plague
continue
previous
Social
technology
including
Yahoo
series
years
every
happened
quite
admissions
Numbers
extends
cyberattacks
account
corporate
well
incidents
affected
high
profile
issue
witnessed
schools
starters

Big Data: What Could Go Wrong?

People write algorithms …

… or people write the algorithms that write algorithms …

WIRED What We Can Learn From the Epic Failure of Google Flu Trends

DAVID LAZER AND RYAN KENNEDY SCIENCE 10.01.15 7:00 AM

WHAT WE CAN LEARN FROM THE EPIC FAILURE OF GOOGLE FLU TRENDS

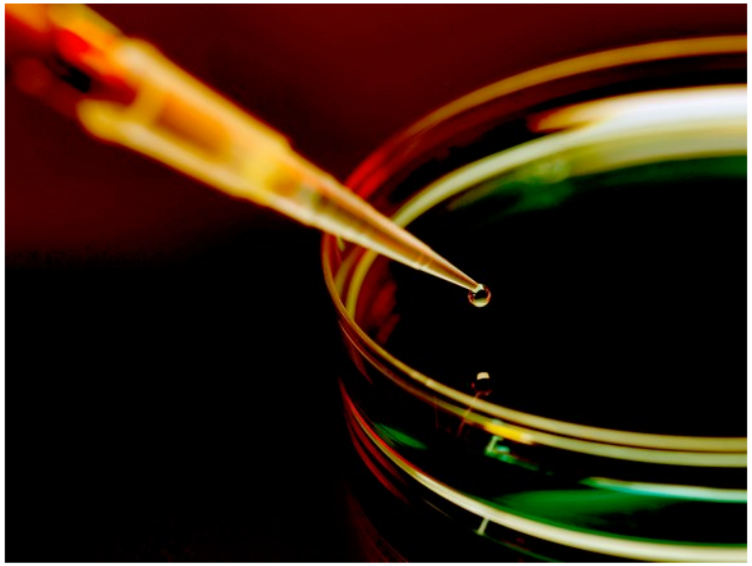
SHARE

SHARE 854

TWEET

COMMENT 10

EMAIL



RAFE SWAN/GETTY IMAGES

EVERY DAY, MILLIONS of people use Google to dig up information that drives their daily lives, from how long their commute will be to how to treat their child's illness. This

https://www.wired.com/2015/10/can-learn-epic-failure-google-flu-trends/

Tesla

Tesla driver dies in first fatal crash while using autopilot mode

The autopilot sensors on the Model S failed to distinguish a white tractor-trailer crossing the highway against a bright sky

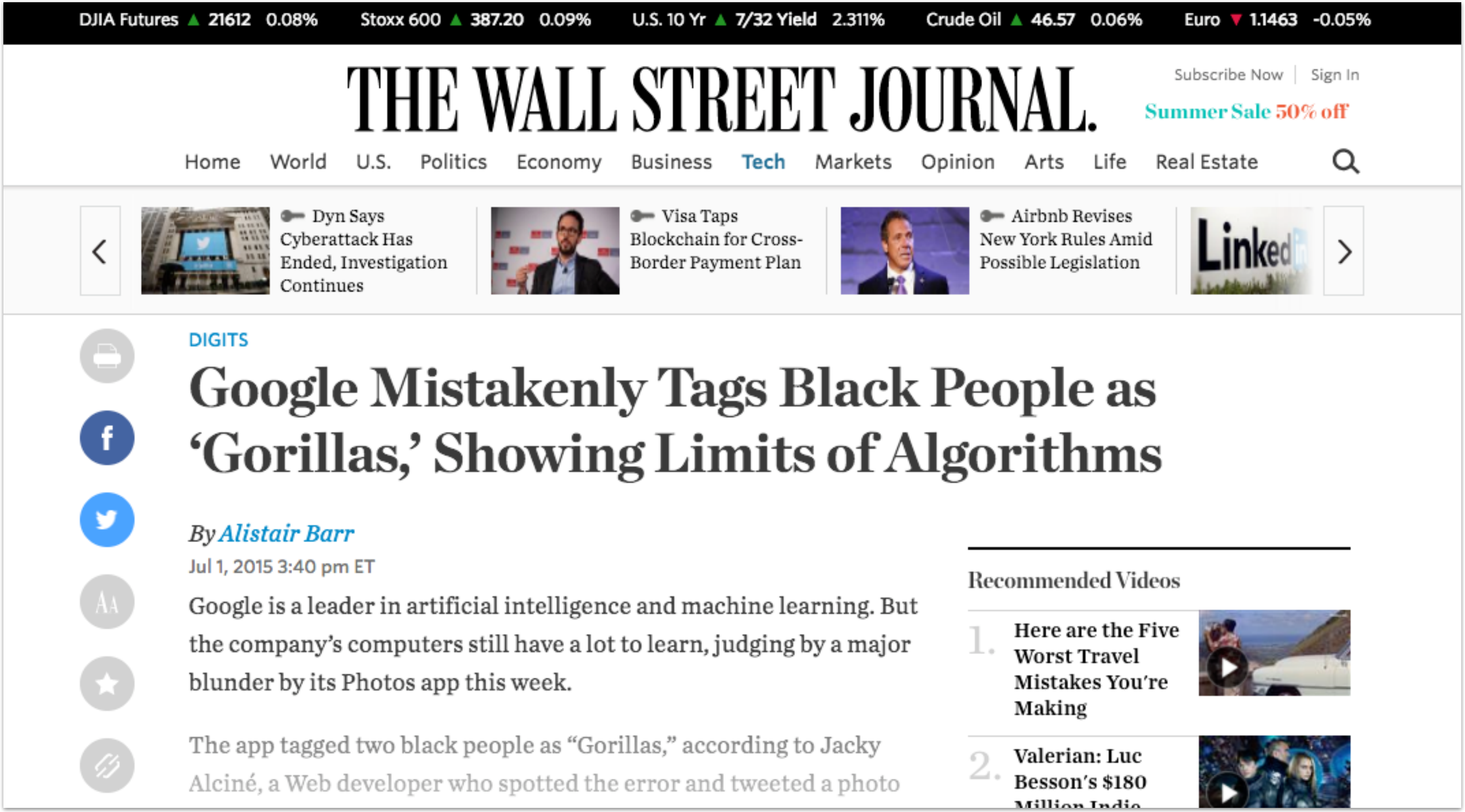
Most popular

Manchester's bike-share scheme isn't working - because people don't know how to share |...

Age checks to be introduced on porn websites in UK

Doctor Who: Jodie

https://www.theguardian.com/technology/2016/jun/30/tesla-autopilot-death-self-driving-car-elon-musk



DJIA Futures ▲ 21612 0.08% Stoxx 600 ▲ 387.20 0.09% U.S. 10 Yr ▲ 7/32 Yield 2.311% Crude Oil ▲ 46.57 0.06% Euro ▼ 1.1463 -0.05%

THE WALL STREET JOURNAL.

Subscribe Now | Sign In

Summer Sale 50% off

Home World U.S. Politics Economy Business Tech Markets Opinion Arts Life Real Estate

Dyn Says Cyberattack Has Ended, Investigation Continues

Visa Taps Blockchain for Cross-Border Payment Plan

Airbnb Revises New York Rules Amid Possible Legislation

DIGITS

Google Mistakenly Tags Black People as 'Gorillas,' Showing Limits of Algorithms

By *Alistair Barr*

Jul 1, 2015 3:40 pm ET

Google is a leader in artificial intelligence and machine learning. But the company's computers still have a lot to learn, judging by a major blunder by its Photos app this week.

The app tagged two black people as "Gorillas," according to Jacky Alciné, a Web developer who spotted the error and tweeted a photo

Recommended Videos

1. Here are the Five Worst Travel Mistakes You're Making

2. Valerian: Luc Besson's $180 Million Indie

https://blogs.wsj.com/digits/2015/07/01/google-mistakenly-tags-black-people-as-gorillas-showing-limits-of-algorithms/

Why big-data analysis of police activity is inherently biased

May 10, 2017 by William Isaac And Andi Dixon, The Conversation

How does bad data affect predictive policing algorithms? Credit: Photosani/shutterstock.com

In early 2017, Chicago Mayor Rahm Emanuel announced a new initiative in the city's **ongoing battle with violent crime**. The most common solutions to this sort of problem involve **hiring more police officers or working more closely with community members**. But Emanuel declared that the Chicago Police Department would expand its use of software, enabling what is called

http://theconversation.com/why-big-data-analysis-of-police-activity-is-inherently-biased-72640

NATURE | COMMENT

Reform predictive policing

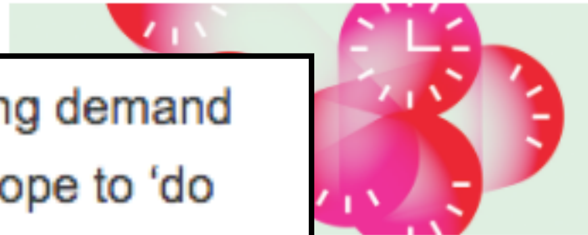
Aaron Shapiro

25 January 201

Police agencie
improves publ

PDF

Tangles in time



scramble cause and

quantum causality can

At the same time, tight policing budgets are increasing demand for law-enforcement technologies. Police agencies hope to 'do more with less' by outsourcing their evaluations of crime data to analytics and technology companies that produce 'predictive policing' systems. These use algorithms to forecast where crimes are likely to occur and who might commit them, and to make recommendations for allocating police resources. Despite wide adoption, predictive policing is still in its infancy, open to bias and hard to evaluate.

https://www.nature.com/news/reform-predictive-policing-1.21338


24/7 breaking news at hulldailymail.co.uk

HULL DAILY MAIL

At the heart of all things local

Saturday October 5 2013 50p

Withernsea Game King

KIDS SOFT PLAY BUY 1 GET 1 FREE

10 FREE GAMES OF BINGO

GREAT FAMILY DAY OUT

DANNY'S MY BOY

BRUCE STICKS BY STRIKER DESPITE GOAL DROUGHT BACK PAGE

LATEST TIGERS NEWS AT hulldailymail.co.uk

lotto

£40,000 TO BE WON

SEE PAGE 23

Enter online @ hulldailymail.co.uk

Criminal's DNA found after he snacks on vegetables

BURGLAR IS CAUGHT BY CUCUMBER

by **Nicky Harley**
Court Reporter
n.harley@mailnewsmedia.co.uk

have your say
Do you agree with sentence?
hulldailymail.co.uk

A DOZY burglar was caught by police after having a bite out of a cucumber.

Billy Joe Donnelly, 22, was peckish when he raided a greenhouse down a country lane.

During the raid, however, he couldn't resist sampling the home-grown produce and his DNA was later discovered on a cucumber.

The honorary Recorder of Hull and the East Riding, Judge Michael Mettyear, declared in disbelief: "He was caught by a cucumber."

Donnelly, of Wimbourne Close, Bransholme, ate a variety of produce and then burgled the home of the owners on August 21.

Prosecutor Jharna Jobes said: "The owner was going to sell the items he was growing in the greenhouse, but someone had been in there and eaten most of the vegetables and a cucumber. A cucumber was found with his DNA on it."

● Continued on page 2

PECKISH: Burglar Billy Joe Donnelly, left, was caught after taking a bite out of a cucumber.

INSIDE TODAY

Lucky escape as digger crushes car

NEWS: PAGE 5

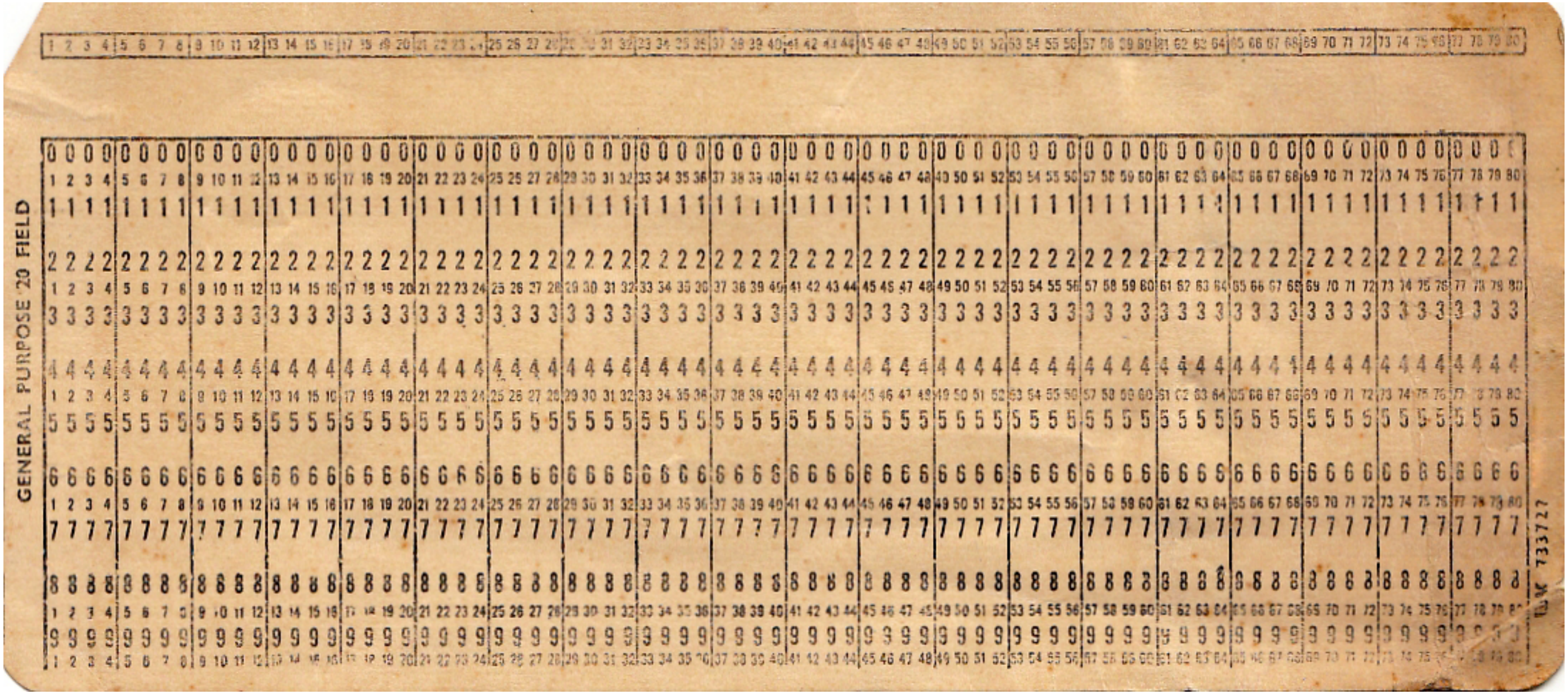
The pig farmer who sings like Sinatra

view on video

NEWS: PAGE 3

X Factor star's twin is his biggest fan

NEWS: PAGE 6



Ventriloquist - Own work

A scanned copy of a punched card given to me by a hydrologist around fifteen years ago.

- File:Punched Card.jpg
- Created: 1 April 1997

Found https://en.wikipedia.org/wiki/Punched_card#/media/File:Punched_Card.jpg analytics 1/6

HONI SOIT

Features // Technology

The living laboratory: how the University watches your every move

From wi-fi tracking and facial recognition, to analysing your behaviour on blackboard

by Natassia Chrysanthos

May 18, 2017

http://honisoit.com/2017/05/the-living-laboratory-how-the-university-watches-your-every-move/

Uninvention or Influence & Shape?

There is evidence of LA success

Do we have the right to ignore this?

Jisc briefing

Learning analytics and student success – assessing the evidence

January 2017

Authors
Niall Sclater
Joel Mullan

Accurate predictive models identify students at risk

Learning analytics systems enable universities to track individual student engagement, attainment and progression in near-real time, flagging any potential issues to tutors or support staff. They can then receive the earliest possible alerts of students at risk of dropping out or under-achieving.

» Although many institutions develop their own specific models rather than adopting those created elsewhere, a key finding of the Open Academic Analytics Initiative led by Marist College, New York was that **the models developed at one institution can be transferred to very different institutions, while retaining most of**

Effective institutional interventions

It is only when actions are taken with students on the basis of the data that the true value of learning analytics becomes clear.

» At the University of Nebraska-Lincoln **the four year**

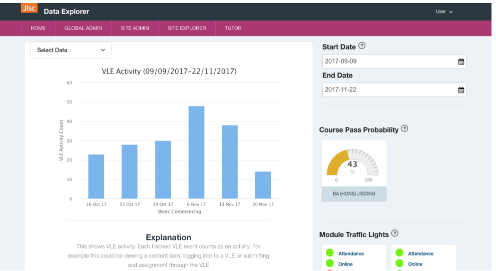
» At Strayer University, Virginia contact with **the students identified as most at risk in one learning analytics pilot resulted in a 5% increase in attendance, 12% increase in passing and 8% decrease in attrition – compared to a control group**[12]

http://repository.jisc.ac.uk/6560/1/learning-analytics_and_student_success.pdf

About Jisc

- UK's national IT member organisation for colleges and universities
- >600 member organisations
- Provide shared services, sector procurement deals and support and advice

https://jisc.ac.uk



Jisc Learning Analytics

- What do UK institutions want to achieve?
- What Jisc are doing to help.
- How the Jisc service is being used
- Lessons learned so far
    - Legal Issues, Consent
    - Understanding Predictive Models

What do institutions want to achieve?

- Improve Retention
- Teaching Learning Excellent Framework
- Widening participation

What we are doing to help?

- Building a national architecture
- Defined standards and models
- Providing core services
- Working with vendors to integrate their solutions

Who we are working with:

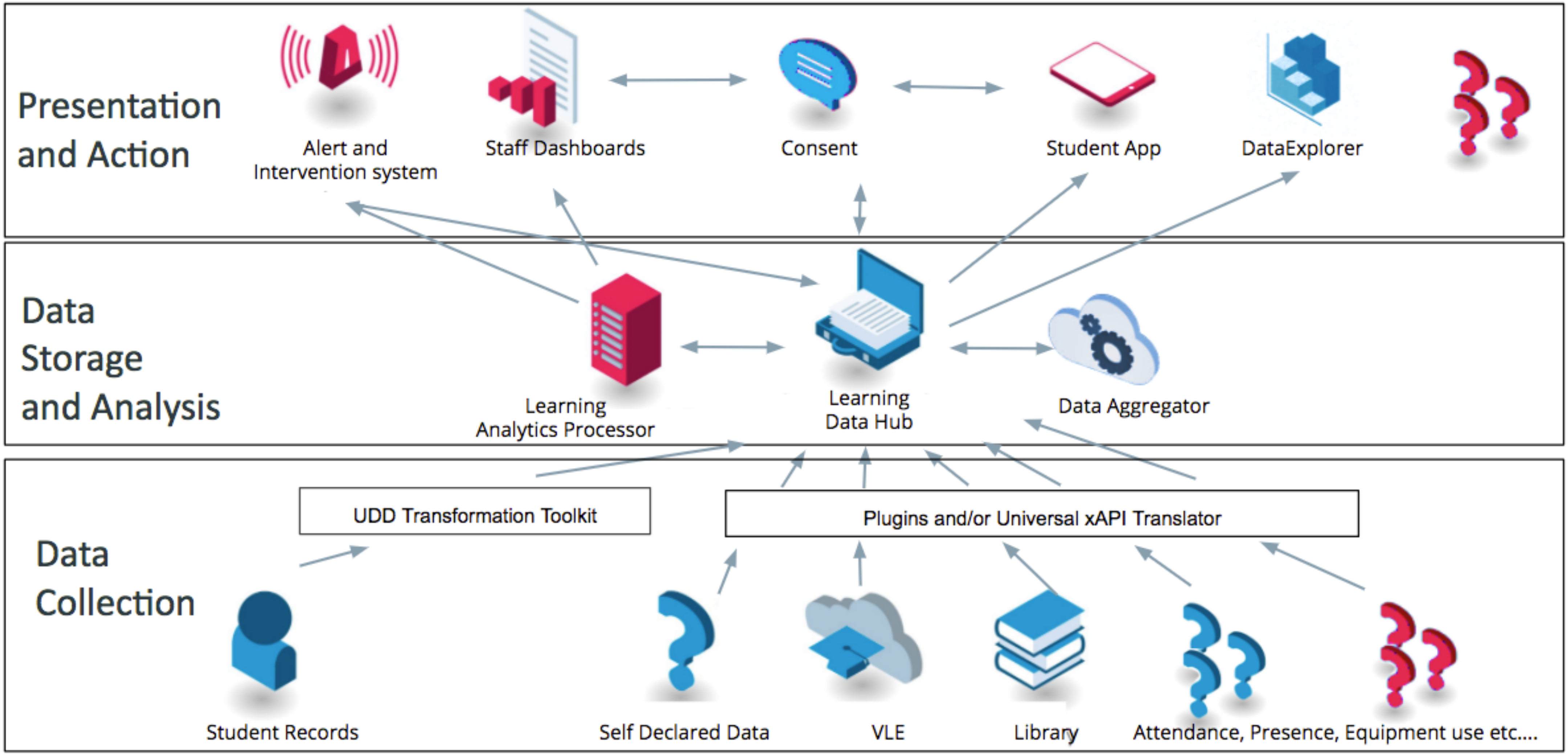
- Altis Global Ltd
- Blackboard International B.V.
- Civitas Learning International Ltd
- Deloitte MCS Ltd
- HT2 Ltd
- Civitas Learning International Ltd
- Kortext Ltd
- OCF PLC
- Phoenix Software Ltd
- Skillset Ltd
- SolutionPath Ltd
- Therapy Box Ltd
- Tribal Education Ltd

- 20 + UK Universities and colleges

Why are we building a national architecture?

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

Jisc Architecture



What data do we use?

Student Data

- Who the student is (name, general demographics etc).
- What course they are taking (title, level, outcome etc)
- What marks they achieved in the course (mark, data, dropout info etc).
- The individual assignment grades (name, date, grade/mark etc)

https://github.com/jiscdev/analytics-udd

Activity Data

- VLE data (login, items view, assignment submissions)
- Attendance data (event type, when, whether late etc.
- Library data (what borrowed, view etc).
- Intervention data (when, why etc)
- Presence data (card swipes, door access control etc.)

https://github.com/jiscdev/xapi

Learning analytics use cases today

1) To support personal tutor system

2) To enable course leaders to improve their courses

3) To enable students to understand their learning

Supporting Personal Tutor System Data Explorer

Overview of the process:

1) Predictive analytics helps identify students at risk

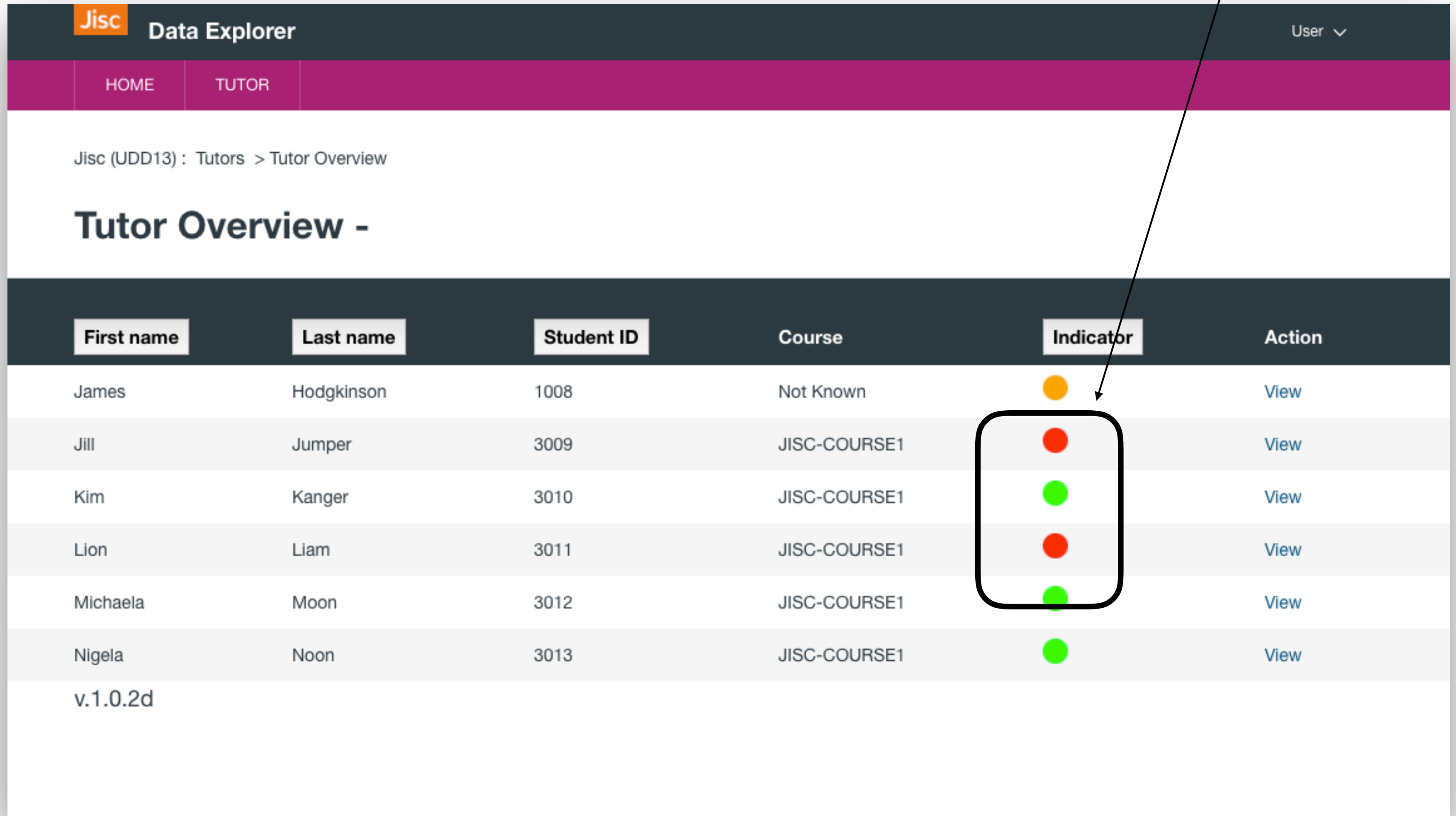
2) Descriptive analytics helps identify why

3) Tutor determines intervention

Supporting Personal Tutors:

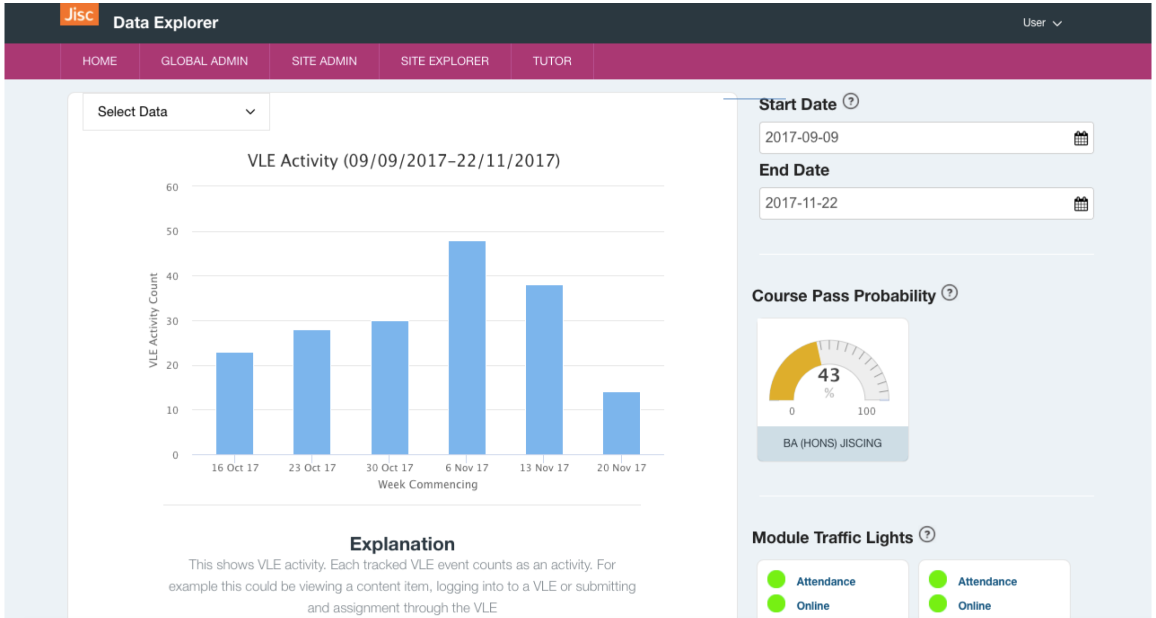
Showing students at risk

Students at risk

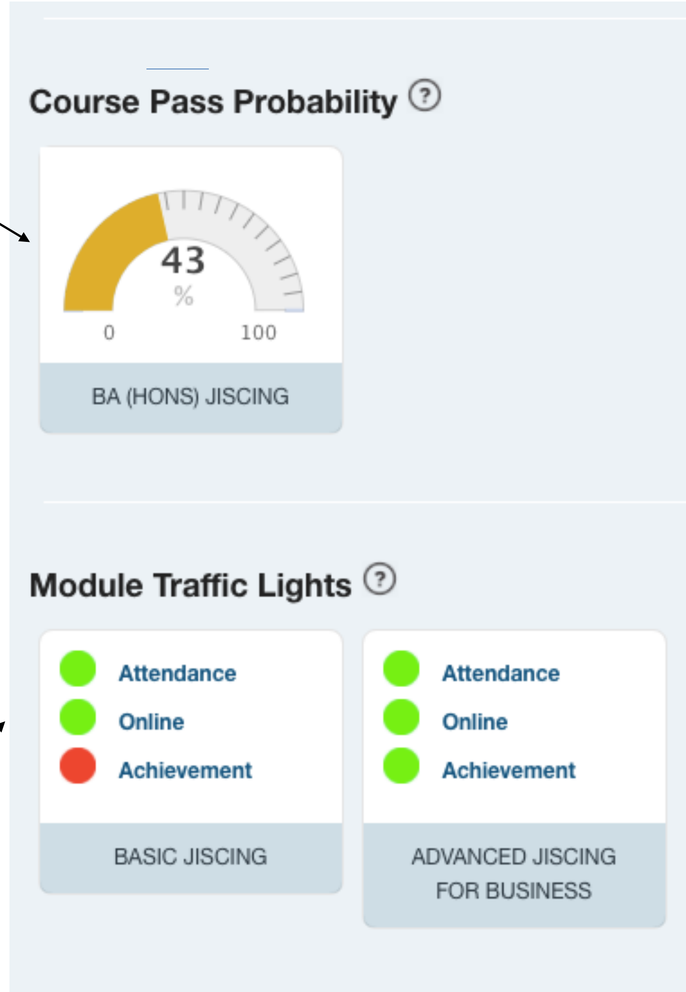


Supporting Personal Tutors:

Predictive and descriptive data



Predictive (Learning Analytics Predictor)

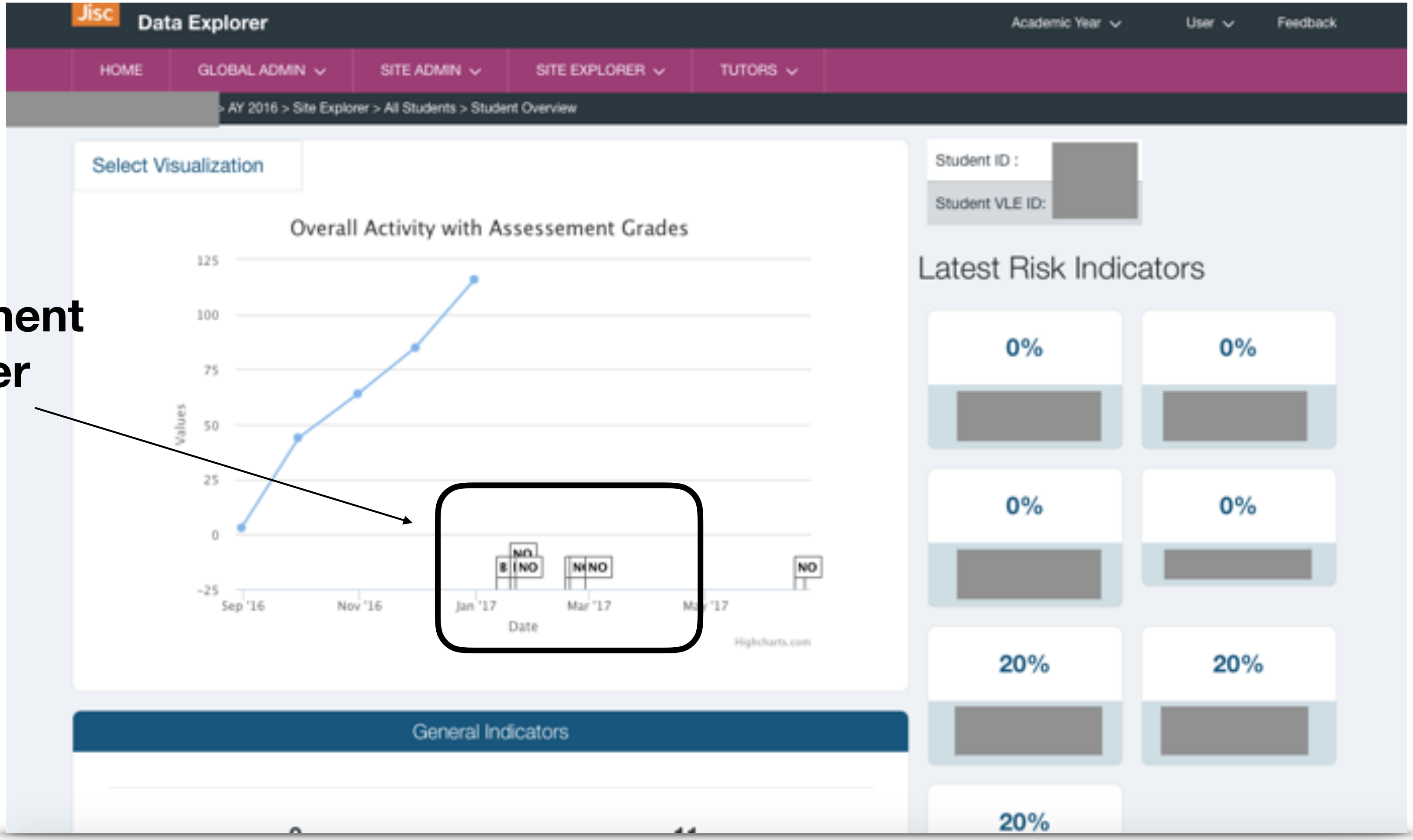


Rule-based (Traffic Light Calculator)

Supporting Personal Tutors:

Showing assessment cluster

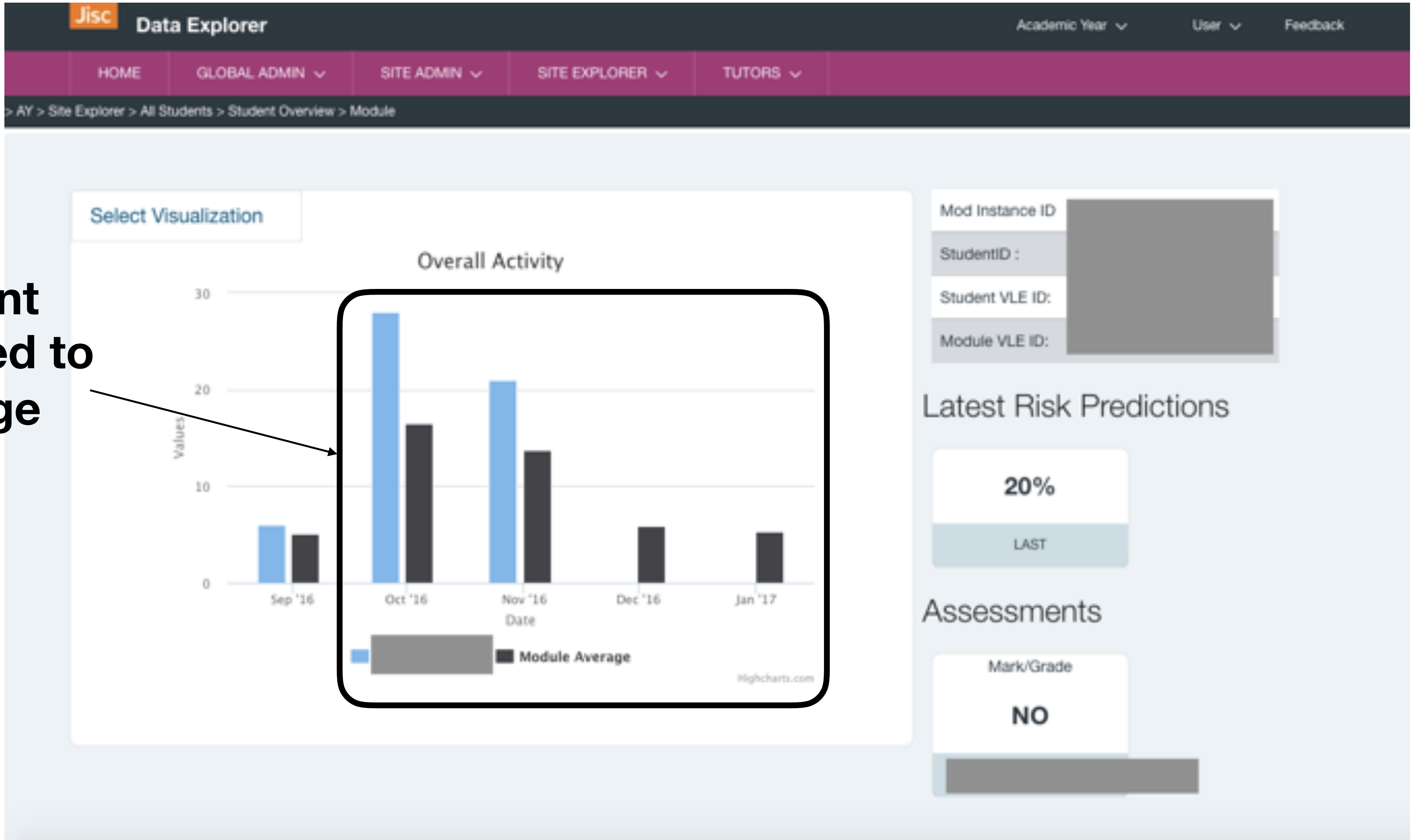
Assessment Cluster



Supporting Personal Tutors:

Showing student engaging less than average

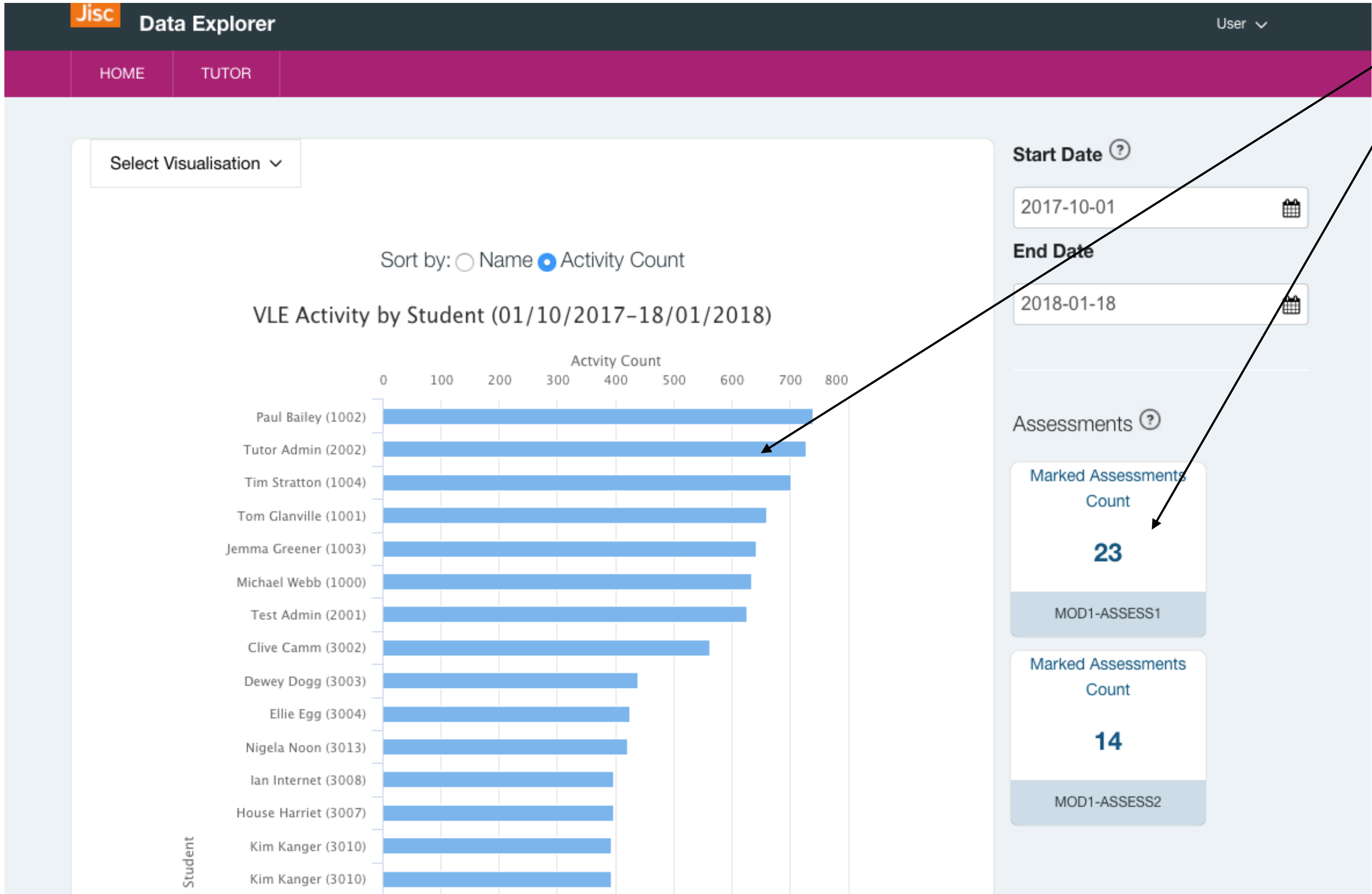
Student compared to average



Supporting course leaders

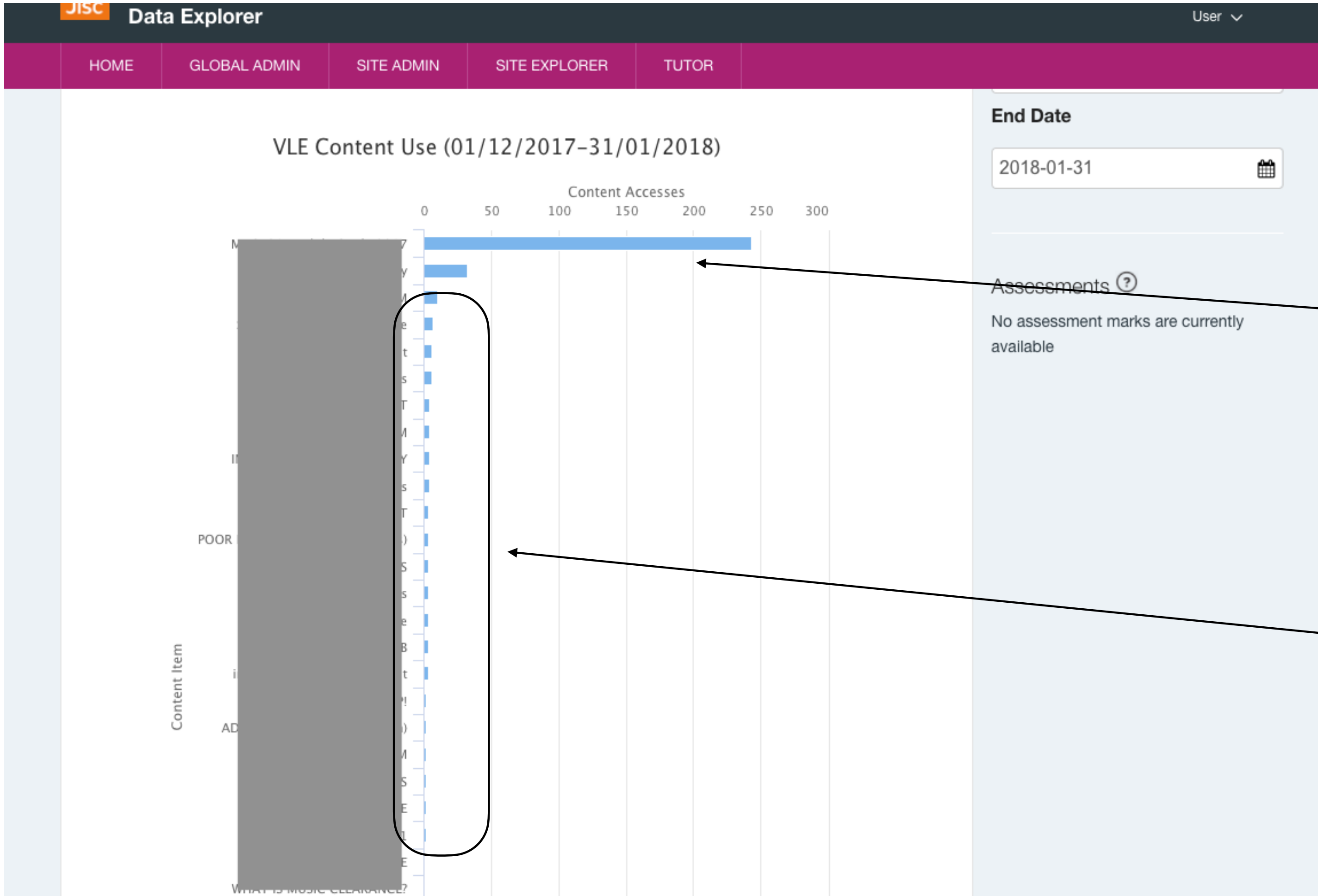
Are all students engaging?

Descriptive data about course



Supporting course leaders

Are my materials being used?

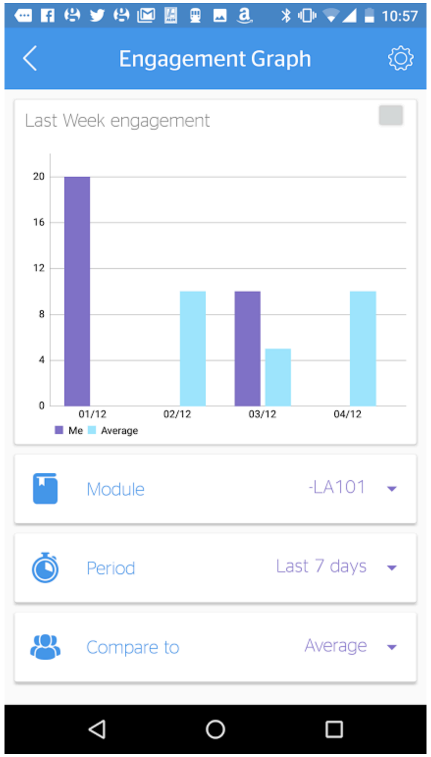


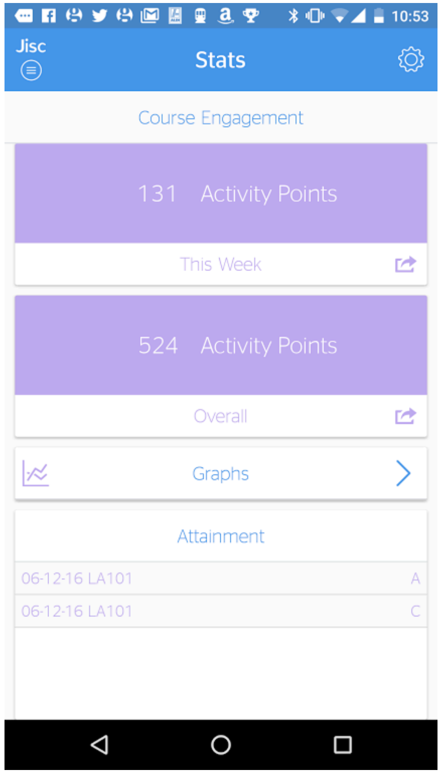
Students looking at this in the VLE

But not a lot else

Supporting students - Study Goal

Understanding their learning



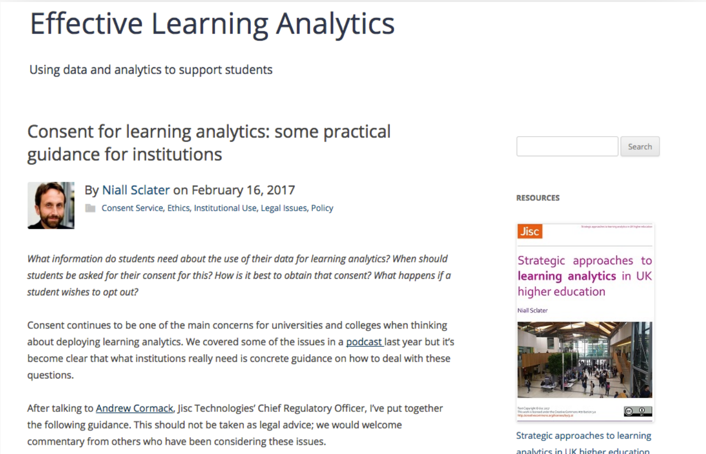


Key Lessons Learned

- 1: The team needs a number of core roles in order to succeed
- 2: The tools should be developed with users and match their terminology and processes.
- 3: Do not expect process change to occur quickly.
- 4: Applying standards to data really does work
- **5: Do not underestimate legal and contractual complexity**
- **6: Users want to understand predictive models (and that is hard)**
- 7: Consider the innovation chasm

legal and contractual complexity

Consent - Jisc View (1)



Effective Learning Analytics

Using data and analytics to support students

Consent for learning analytics: some practical guidance for institutions

By Niall Sclater on February 16, 2017

Consent Service, Ethics, Institutional Use, Legal Issues, Policy

What information do students need about the use of their data for learning analytics? When should students be asked for their consent for this? How is it best to obtain that consent? What happens if a student wishes to opt out?

Consent continues to be one of the main concerns for universities and colleges when thinking about deploying learning analytics. We covered some of the issues in a podcast last year but it's become clear that what institutions really need is concrete guidance on how to deal with these questions.

After talking to Andrew Cormack, Jisc Technologies' Chief Regulatory Officer, I've put together the following guidance. This should not be taken as legal advice; we would welcome commentary from others who have been considering these issues.

Search

RESOURCES

Jisc

Strategic approaches to **learning analytics** in UK higher education

Niall Sclater

Strategic approaches to learning analytics in UK higher education

See:

https://analytics.jiscinvolve.org/wp/2017/02/16/consent-for-learning-analytics-some-practical-guidance-for-institutions/

Most learning analytics is covered by:

a) **legitimate interests of the organisation**

b) **necessary for the performance of a contract with the data subject.**

Consent isn't the most appropriate basis for general learning analytics.

There are exceptions.

legal and contractual complexity

Consent - Jisc View (2)


Effective Learning Analytics

Using data and analytics to support students

Consent for learning analytics: some practical guidance for institutions

By Niall Sclater on February 16, 2017

Consent Service, Ethics, Institutional Use, Legal Issues, Policy

What information do students need about the use of their data for learning analytics? When should students be asked for their consent for this? How is it best to obtain that consent? What happens if a student wishes to opt out?

Consent continues to be one of the main concerns for universities and colleges when thinking about deploying learning analytics. We covered some of the issues in a podcast last year but it's become clear that what institutions really need is concrete guidance on how to deal with these questions.

After talking to Andrew Cormack, Jisc Technologies' Chief Regulatory Officer, I've put together the following guidance. This should not be taken as legal advice; we would welcome commentary from others who have been considering these issues.

Search

RESOURCES

Jisc

Strategic approaches to **learning analytics** in UK higher education

Niall Sclater

Strategic approaches to learning analytics in UK higher education

See:

https://analytics.jiscinvolve.org/wp/2017/02/16/consent-for-learning-analytics-some-practical-guidance-for-institutions/

Consent is required for the following:

a) using sensitive characteristics

This includes attributes such as a person's religion, ethnicity, health, trade union membership or political beliefs.

This data may need to be used if using learning analytics to support widening participation or addressing differential outcomes

b) for action based on automated decisions

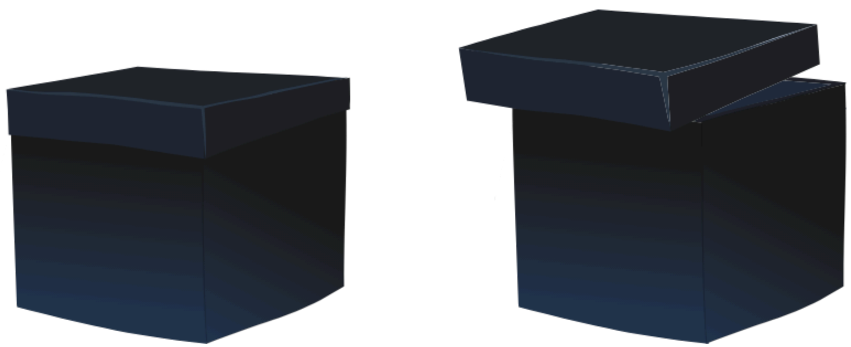
This is explicitly covered under GDPR

Openness for predictive models

How do we explain our algorithms to users in ways they can understand?

We want to avoid having a ‘Blackbox’

Non-technical staff can’t understand code.



Openness for predictive models

Institutions need to understand how the model works.

- Non data scientists need to understand the basic approach, and be able to explain to students.

- Jisc are trying a guide for non-data scientists to address this.

understanding predictive models

Jisc guide to machine learning

- Step 1. Determining the relative importance of the input data.
- Step 2. Data preparation for machine learning
- Step 3. Training the model
- Step 4. Running the model
- Step 5. Reviewing the model

understanding predictive models

Jisc guide to machine learning

Determining the relative importance of the input

Step 1

Example variables affecting retention

- Module outcome
- Level of module
- Class of entry qualifications
- Assessment outcome
- Parental education level
- Class of accommodation
- Class of degree type
- The year of study on the course
- Class of entry qualifications
- The year of study on the course
- Class of module level

- Class of entry qualifications
- Parental education level
- Socio-economic status growing up
- Class of degree type
- Ratio of how many credits taken were so far, were passed
- Assessment marks relative to the module cohort
- Module marks relative to the module cohort
- Relative number of VLE weeks active

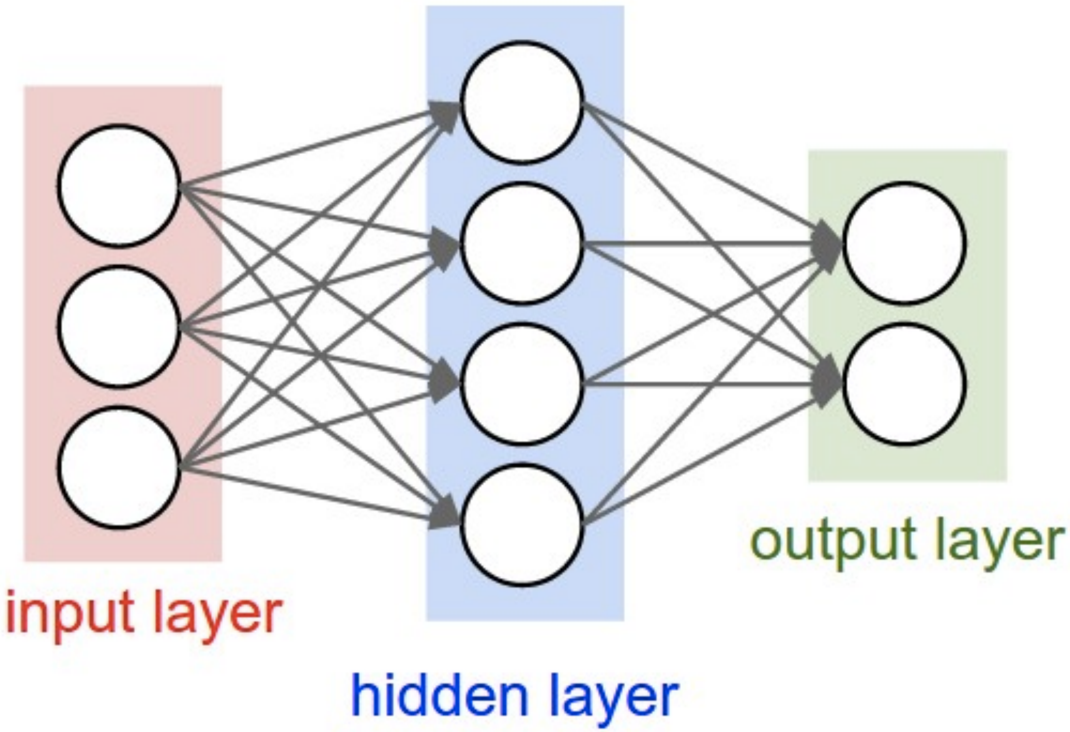
Jisc guide to machine learning

Step 3

Training the model: Neural Networks

Neural Nets

- Faster and better results
- Structure mimicking the brain.
- Constructed out of interconnected neurons in layers.
- The algorithm iterates to optimise the weight of connections between 'neurons'
- The structure of the weights produced in the trained network is hard to interpret.

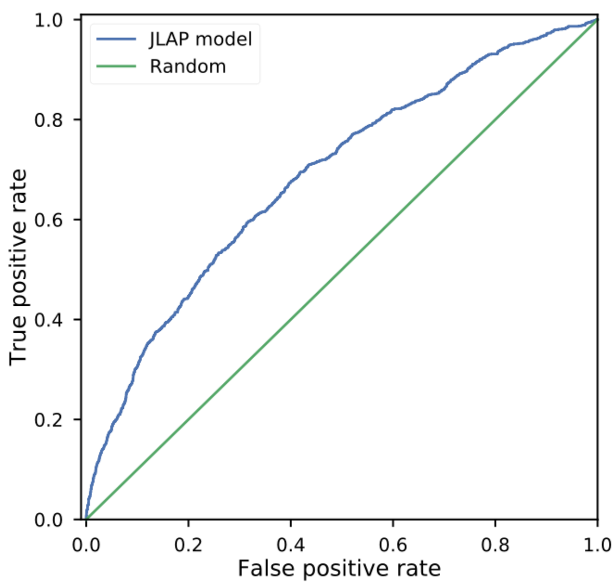


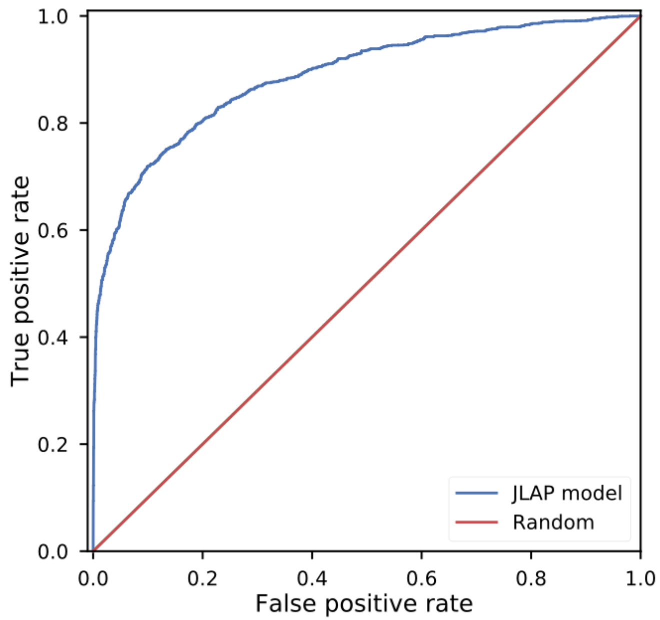
understanding predictive models

Jisc guide to machine learning

Step 5

Eg reviewing the model: ROC curve at different times





understanding predictive models

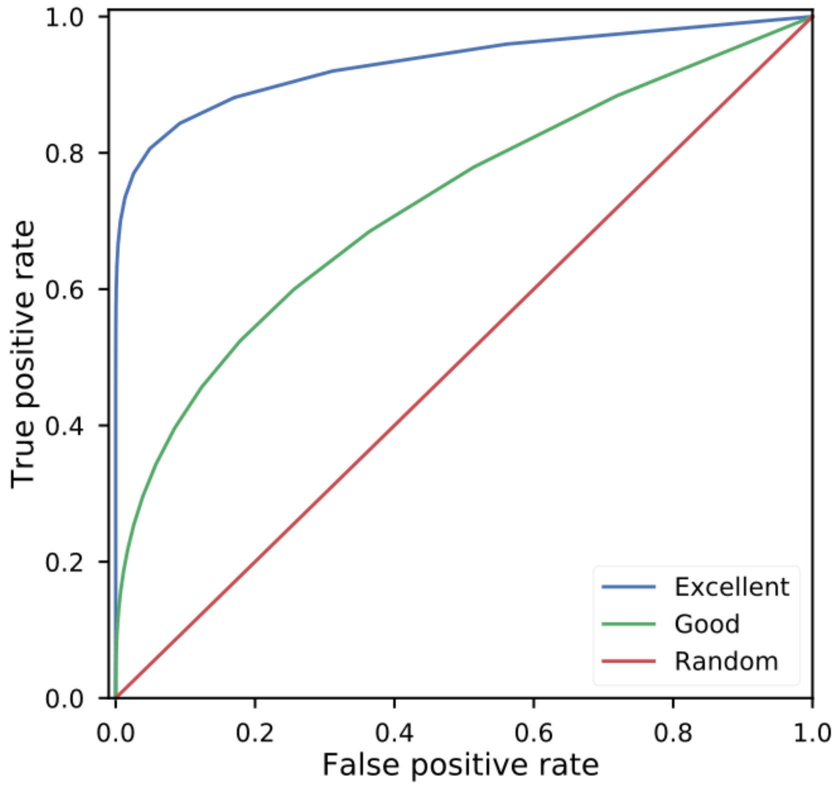
Jisc guide to machine learning

Step 5

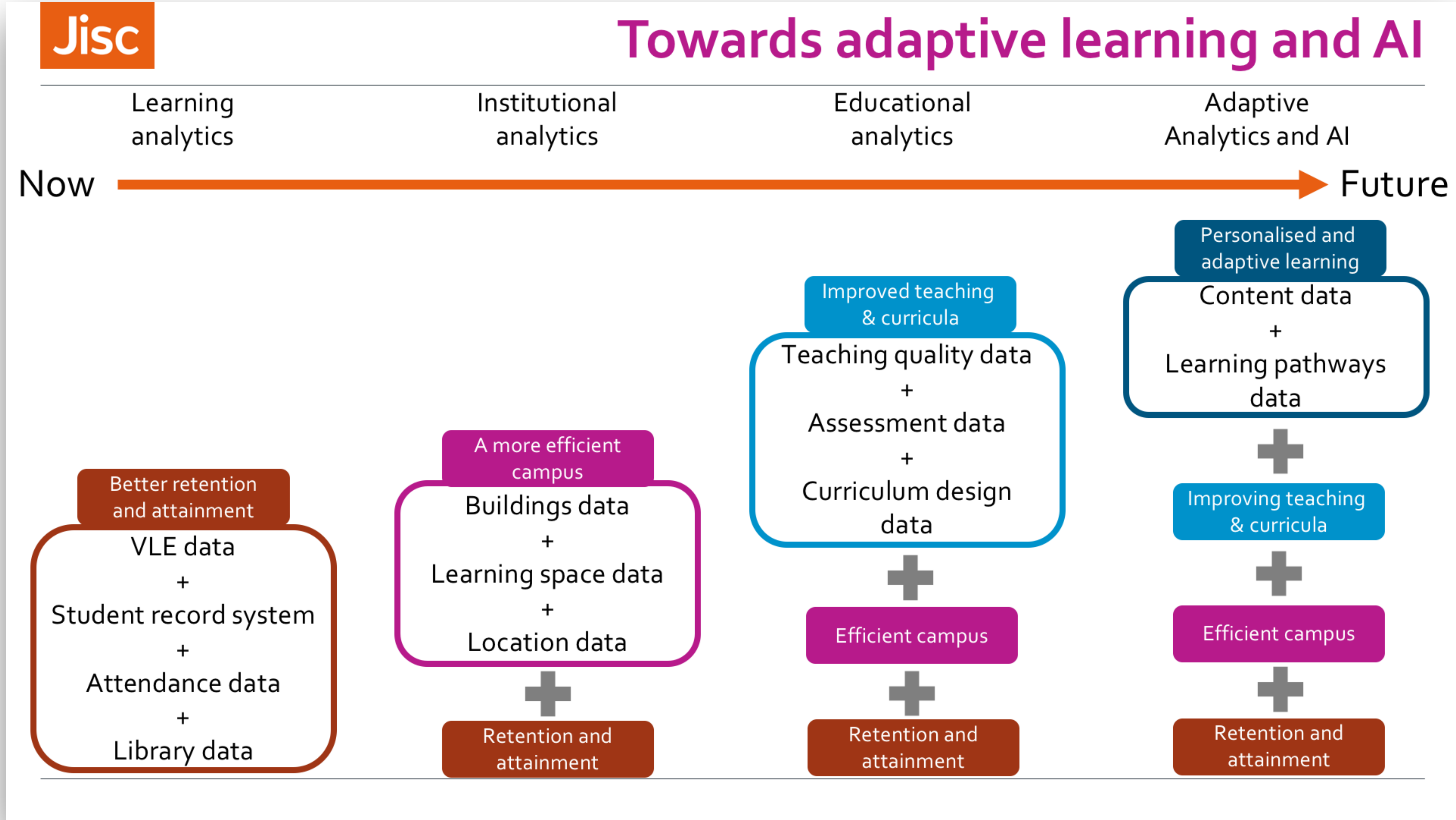
Reviewing the model

Once we have trained the model we can test its effectiveness and generality using a portion of the data excluded from the training process, the testing data.

One method of assessing the effectiveness of the model is to use a ROC curve.



What next...



Jisc
Towards adaptive learning and AI
Learning analytics
Institutional analytics
Educational analytics
Adaptive Analytics and AI
Now
Future
Personalised and adaptive learning
Content data
+
Learning pathways data
Improved teaching & curricula
Teaching quality data
+
Assessment data
+
Curriculum design data
A more efficient campus
Buildings data
+
Learning space data
+
Location data
Better retention and attainment
VLE data
+
Student record system
+
Attendance data
+
Library data
Improving teaching & curricula
Efficient campus
Efficient campus
Retention and attainment
Retention and attainment
Retention and attainment

Eight-fold Path to Analytics Openness

Open **Purpose**

Open **Ethics**

Open and **Inclusive Governance**

Open **Source Software**

Open **Platform**

Open **Standards**

Open **Algorithms**

Open **Consent** - and Consent Management

Challenges

Open Algorithms?
What do we need to effectively share?

Consent
How well do we manage consent?
What more do we need?

Consent - Two Elements

Mechanics of Managing Consent
(and Managing Withdrawal of consent)

Educating about purposes and rights

Informed or educated consent