Black Box Learning Analytics? Beyond Algorithmic Transparency

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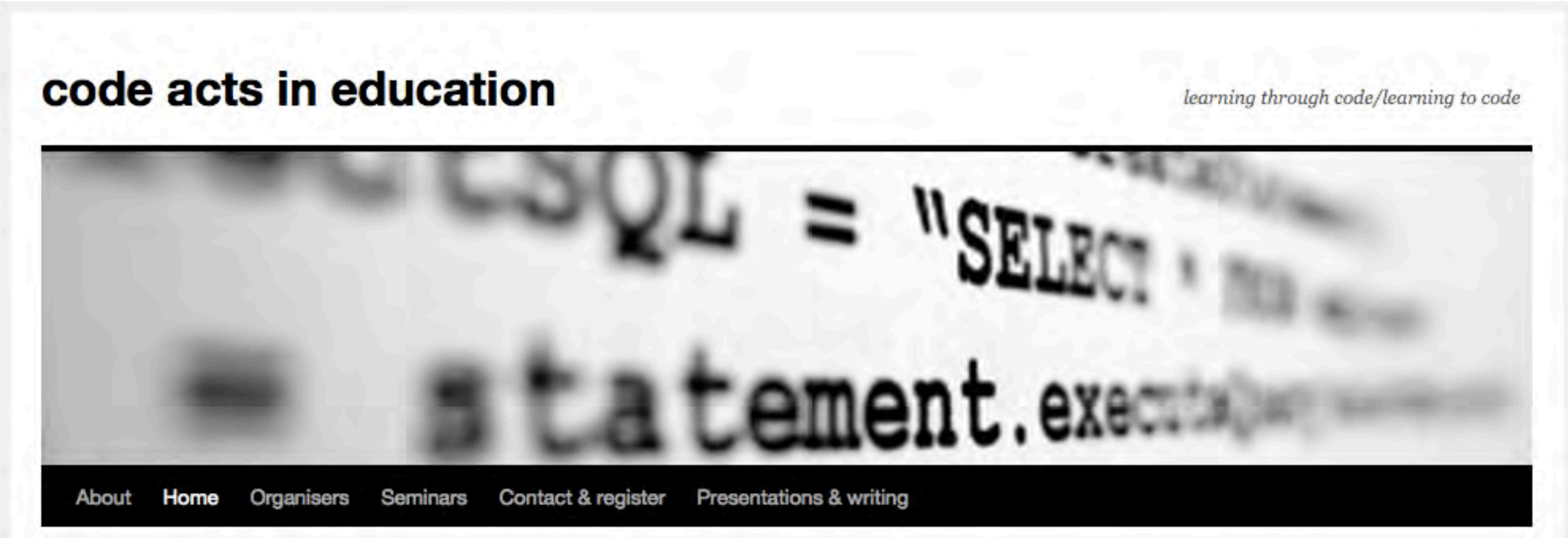
UTS

"Note: check the huge difference between knowing and measuring…"

https://twitter.com/Wiswijzer2/status/414055472451575808

I was speaking at this event



http://codeactsineducation.wordpress.com

I asked Siri to find the conference website…

"Find code acts in education"

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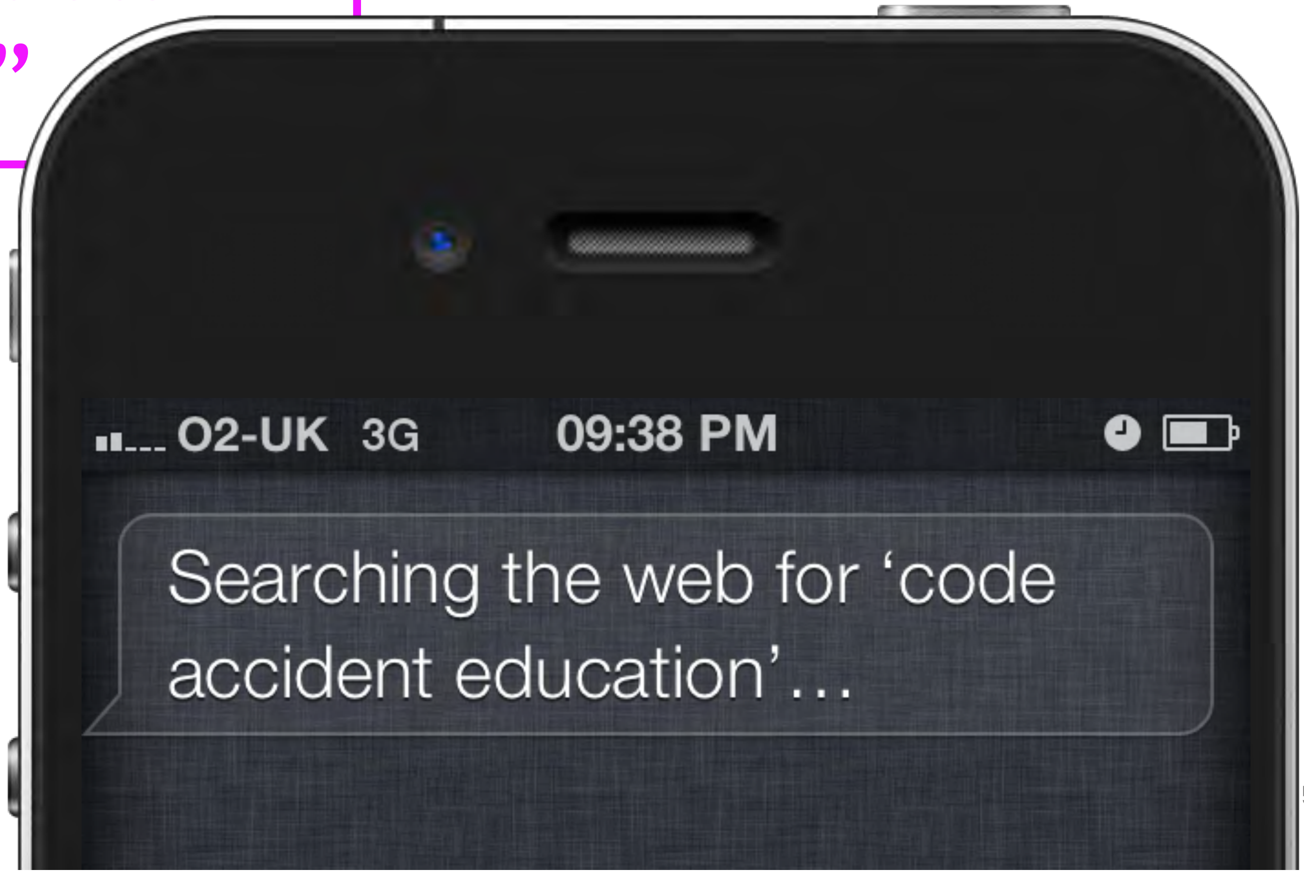
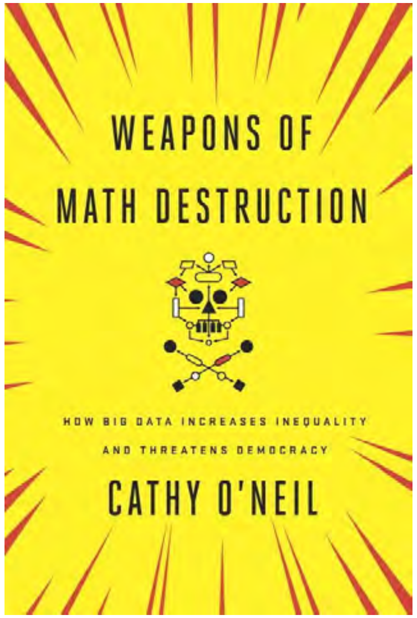
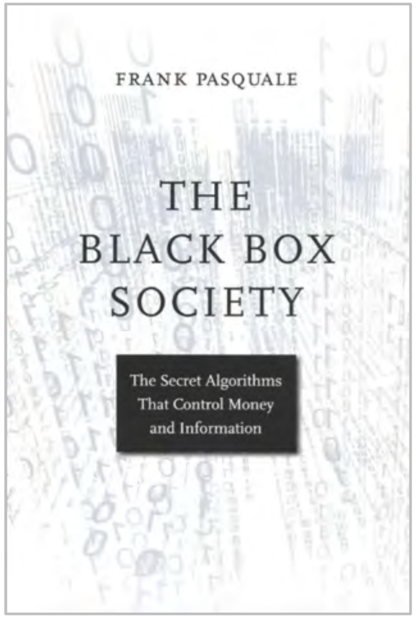


https://www.youtube.com/watch?v=Dlr4O1aEJvI&sns=em

Societal impact of data science is now reaching mass audiences





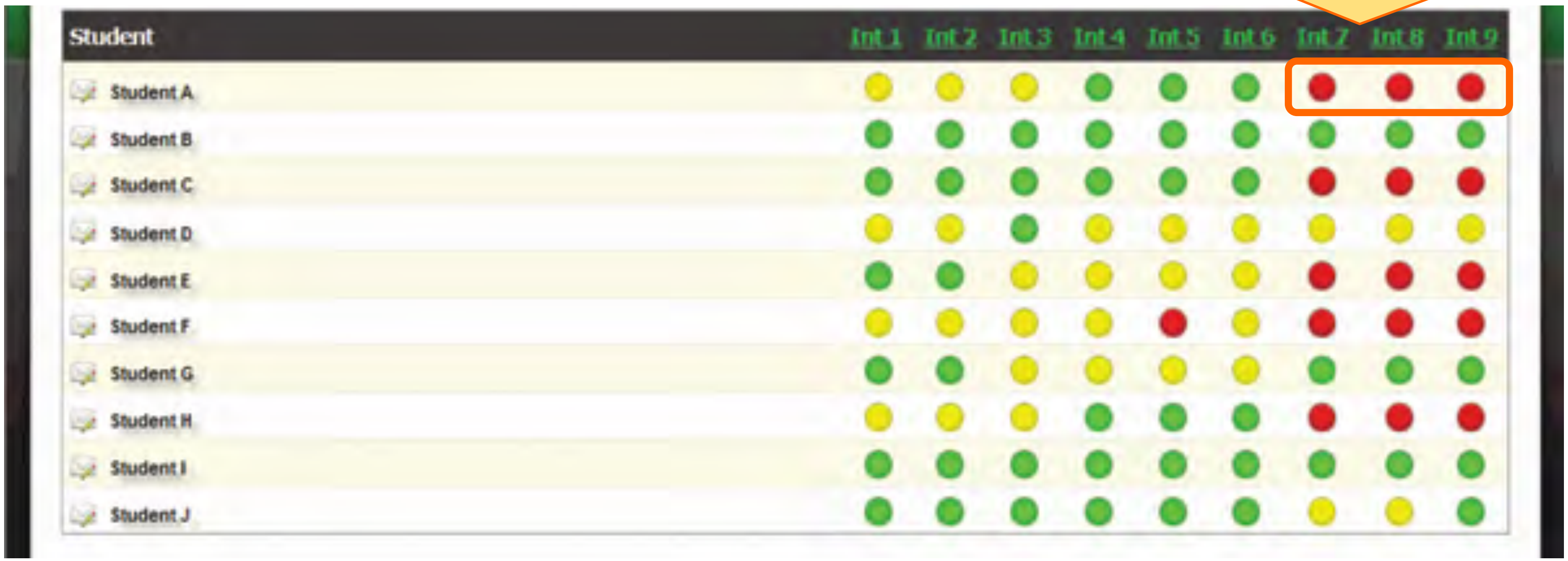
https://weaponsofmathdestructionbook.com • http://datasociety.net • http://artificialinteligencenow.com
• https://obamawhitehouse.archives.gov/blog/2016/05/04/big-risks-big-opportunities-intersection-big-data-and-civil-rights

thought

experiment

A student warning system, somewhere near you…

Student: "Being told by the LMS every time I login that I'm at grave risk of failing is stressful. I already informed Student Services about my disability and recent bereavement, and I'm working with my tutor to catch up…"



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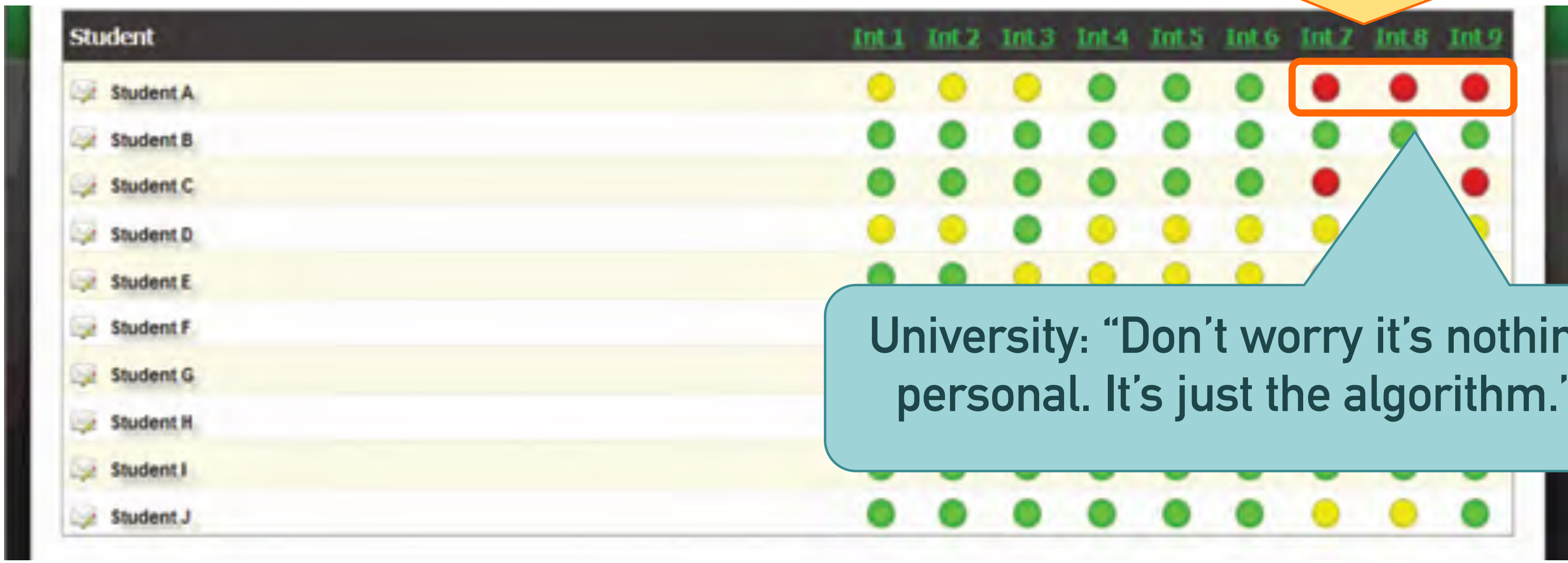
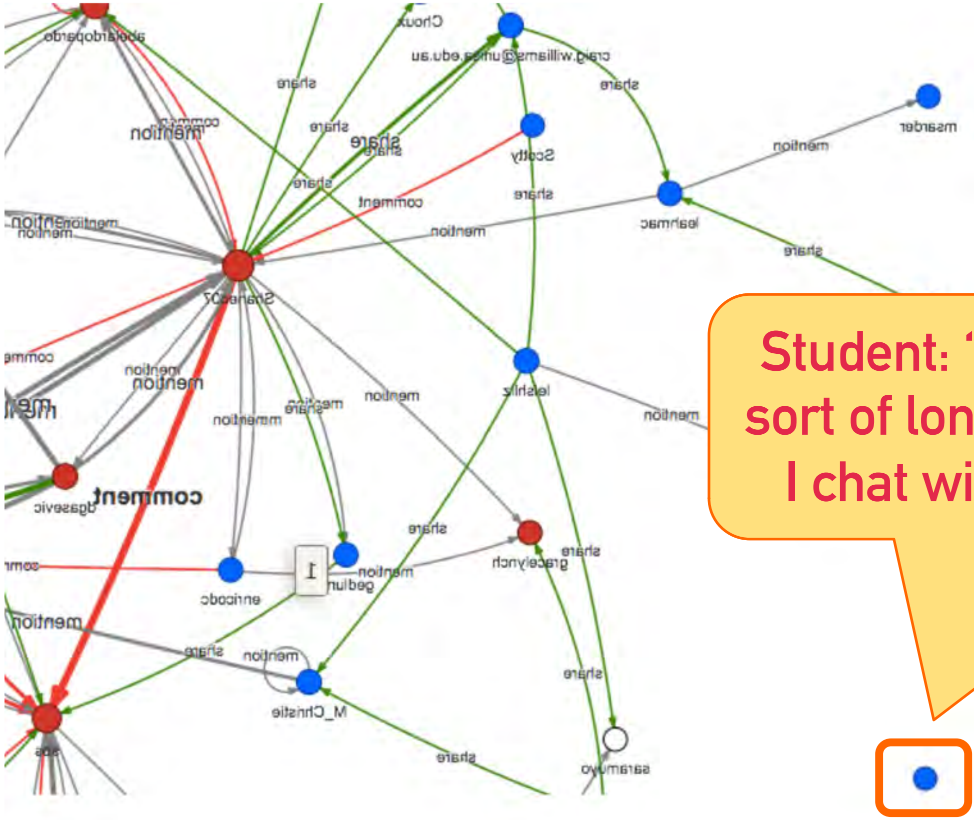


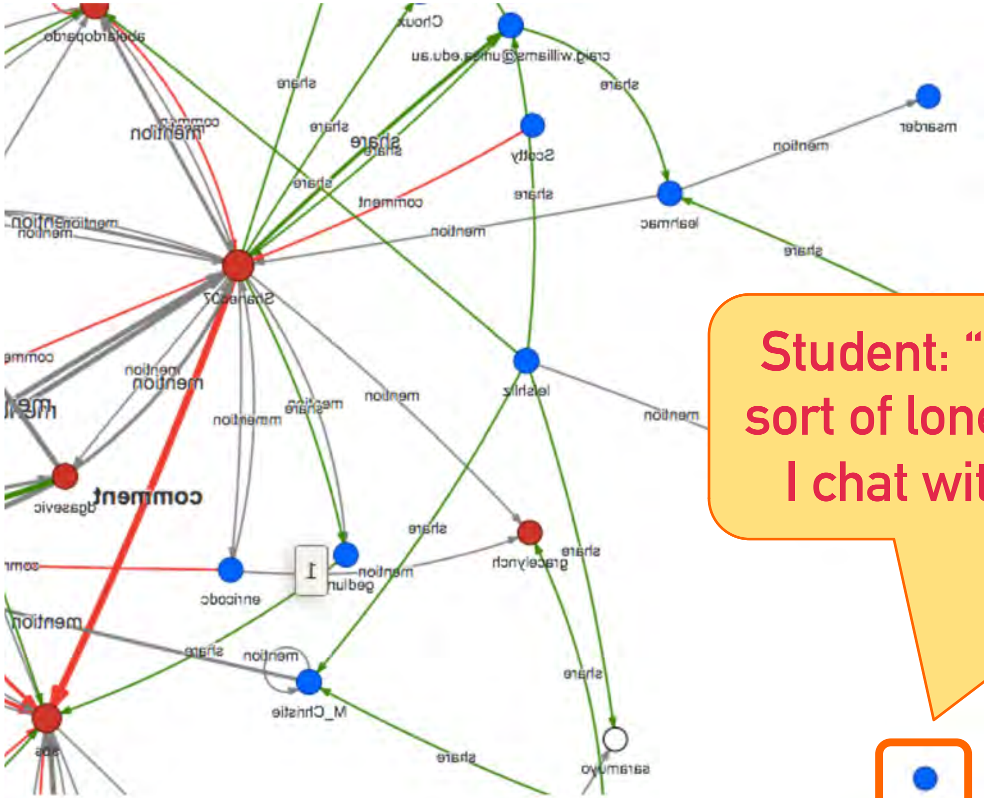
University: "Don't worry it's nothing personal. It's just the algorithm."

A social network visualisation, somewhere near you…



Student: "Being picked out like this as some sort of loner makes me feel uncomfortable… I chat with peers all the time in the cafes."

A social network visualisation, somewhere near you…



Student: “Being picked out like this as some sort of loner makes me feel uncomfortable… I chat with peers all the time in the cafes.”

University: “Don’t worry it’s nothing personal. It’s just the algorithm.”

What would it mean for learning analytics to be

accountable?

…there's intense societal interest right now in

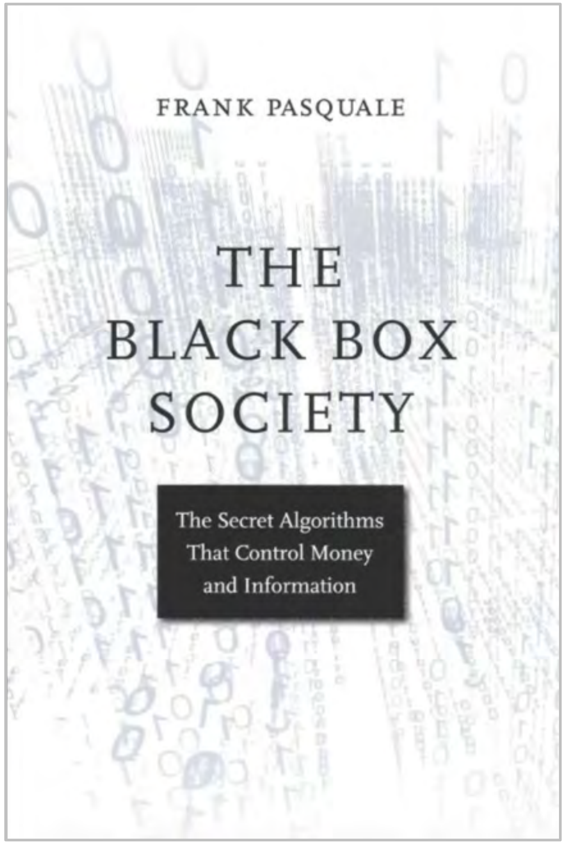
algorithms

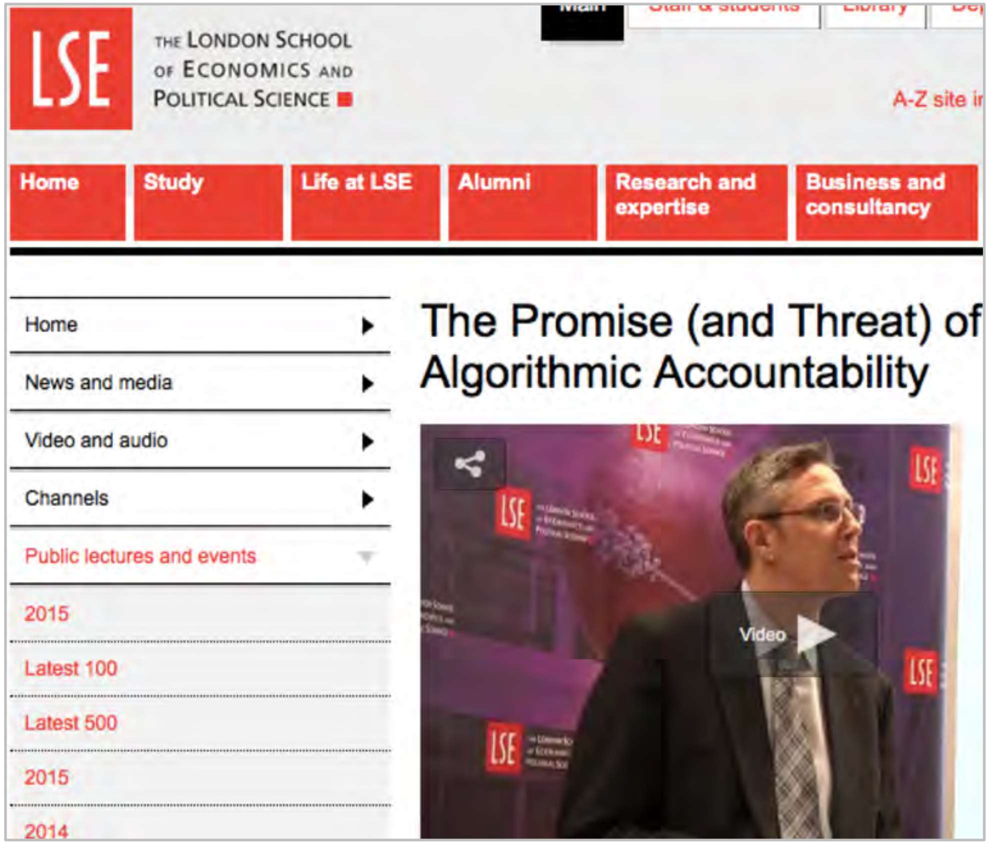
Algorithms are generating huge interest in the media, policy, social justice, and academia

In an increasingly algorithmic world [...] What, then, do we talk about when we talk about "governing algorithms"?

http://governingalgorithms.org

Be afraid: unaccountable algorithms are counting our money – and our other assets





http://www.lse.ac.uk/newsAndMedia/videoAndAudio/channels/publicLecturesAndEvents/player.aspx?id=3350

#AlgorithmicAccountability

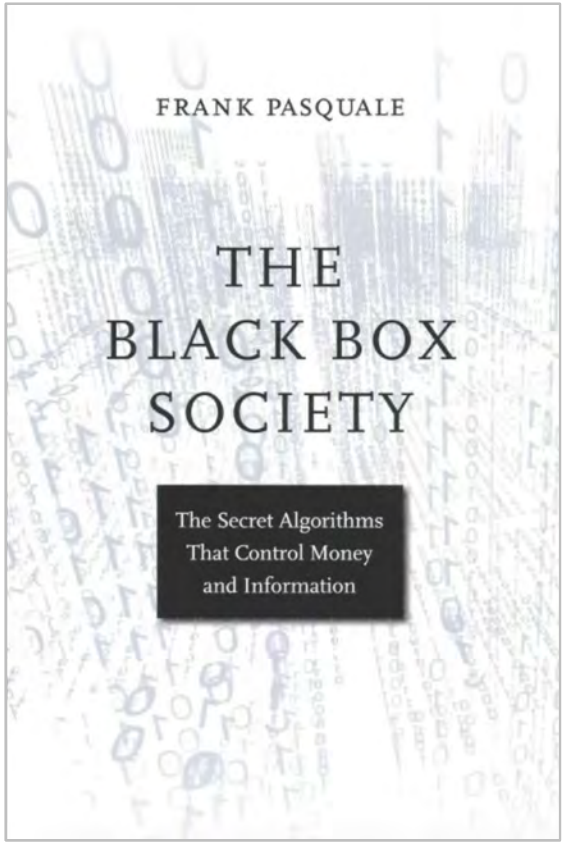
Meaning 1

Algorithms that make you Accountable

more objectively, efficiently and rewardingly than a human can

Meaning 2

Making
Algorithms that make you Accountable
Accountable



We must be able to open the black box
(Frank Pasquale)

A topic now engaging diverse expertises…

Statisticians / Data Miners

Programmers

Computer Scientists

Social Scientists

Designers

Historians

Lawyers

Policy Makers

Business Entrepreneurs

What are Algorithms?

abstract rules for transforming data

which to exert influence require

programming as executable code

operating on data structures

running on a platform

in an increasingly distributed architecture

Paul Dourish: *The Social Lives of Algorithms.* Lecture, 23 Feb. 2016, University of Melbourne. http://www.eng.unimelb.edu.au/engage/events/lectures/dourish-2016

What makes algorithms opaque?

intentional secrecy

technical illiteracy

complexity of infrastructure

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society* 3(1). http://doi.org/10.1177/2053951715622512

Algorithms are not to be found ‘in’ Pasquale’s black box

‘Algorithms’ are abstractions invented by computer scientists, mathematicians, etc. They may be impossible to reverse engineer from a live, material, distributed system.

To understand them as phenomena, and perhaps to call them to account, we need to ask how they were conceived, with what intent, who sanctioned their implementation, etc… (Paul Dourish)

Paul Dourish: *The Social Lives of Algorithms.* Lecture, 23 Feb. 2016, University of Melbourne. http://www.eng.unimelb.edu.au/engage/events/lectures/dourish-2016

#LearningAnalytics

See the Society for Learning Analytics Research: http://SoLAResearch.org

~~#AlgorithmicAccountability~~

~~#AlgorithmicAccountability~~

Learning Analytics
System Integrity

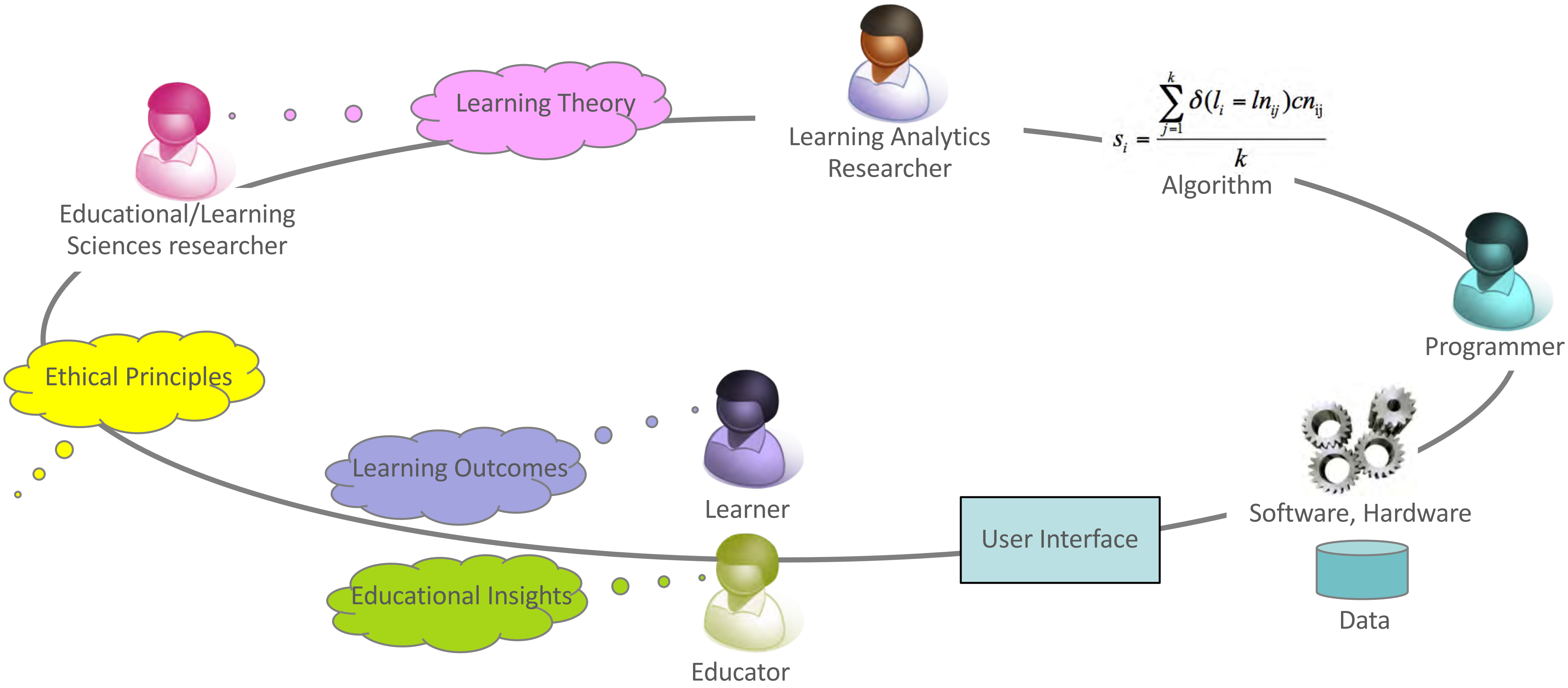
Algorithms don't act, it's the whole system that counts

"Algorithmic Assemblages" are more useful units of analysis

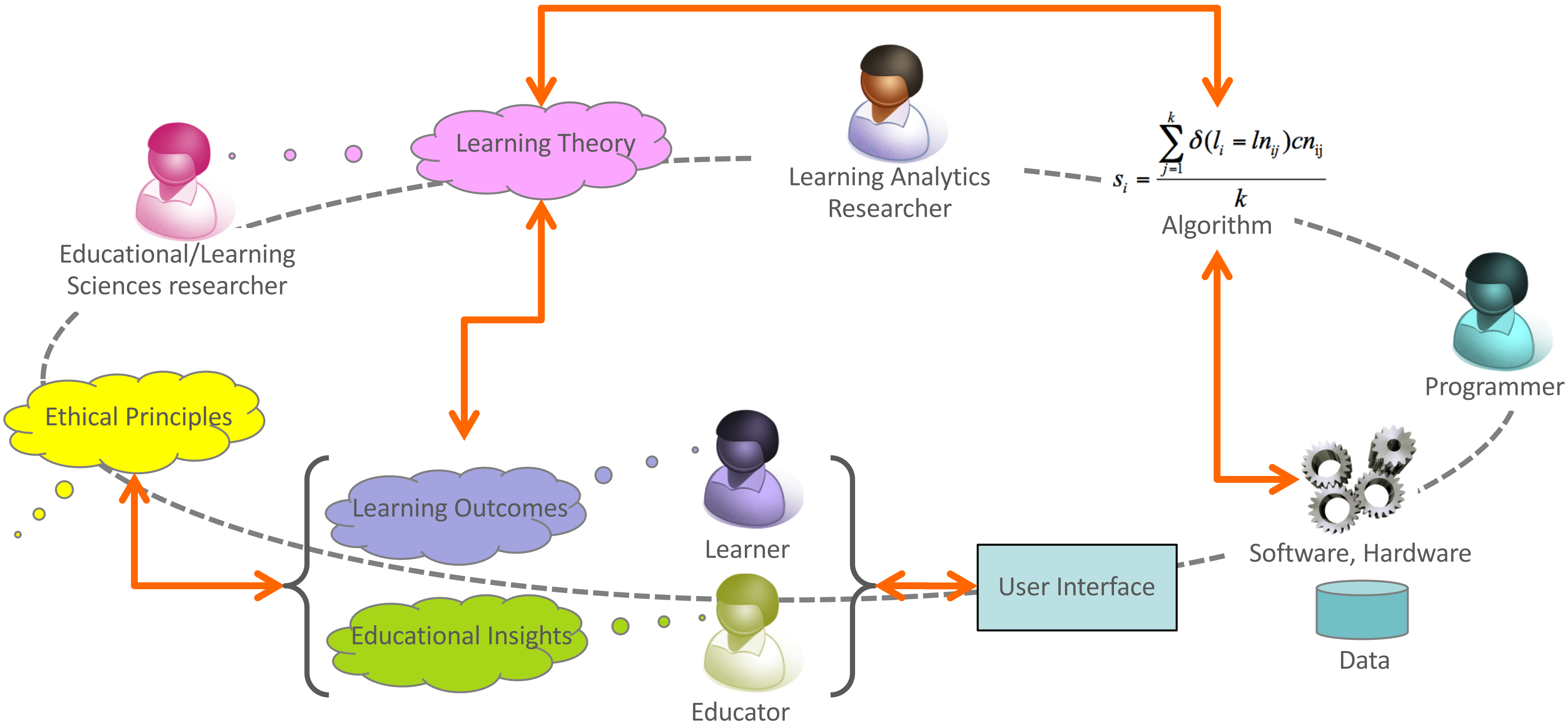
	Aggregation inferring associations	Classification inferring boundaries	Temporality inferring when to act
algo code			
work practices			
cultural norms			

Ananny, M., 2016. Toward an Ethics of Algorithms: Convening, Observation, Probability, and Timeliness. *Science, Technology & Human Values*, 41(1), pp.93–117

Stakeholders in a Learning Analytics system



Some accountability relationships in an analytics system



Forms of Algorithmic Accountability in Learning Analytics

Human-Centred Informatics Lenses

Ethics of Technology

Computer Science

Data Science

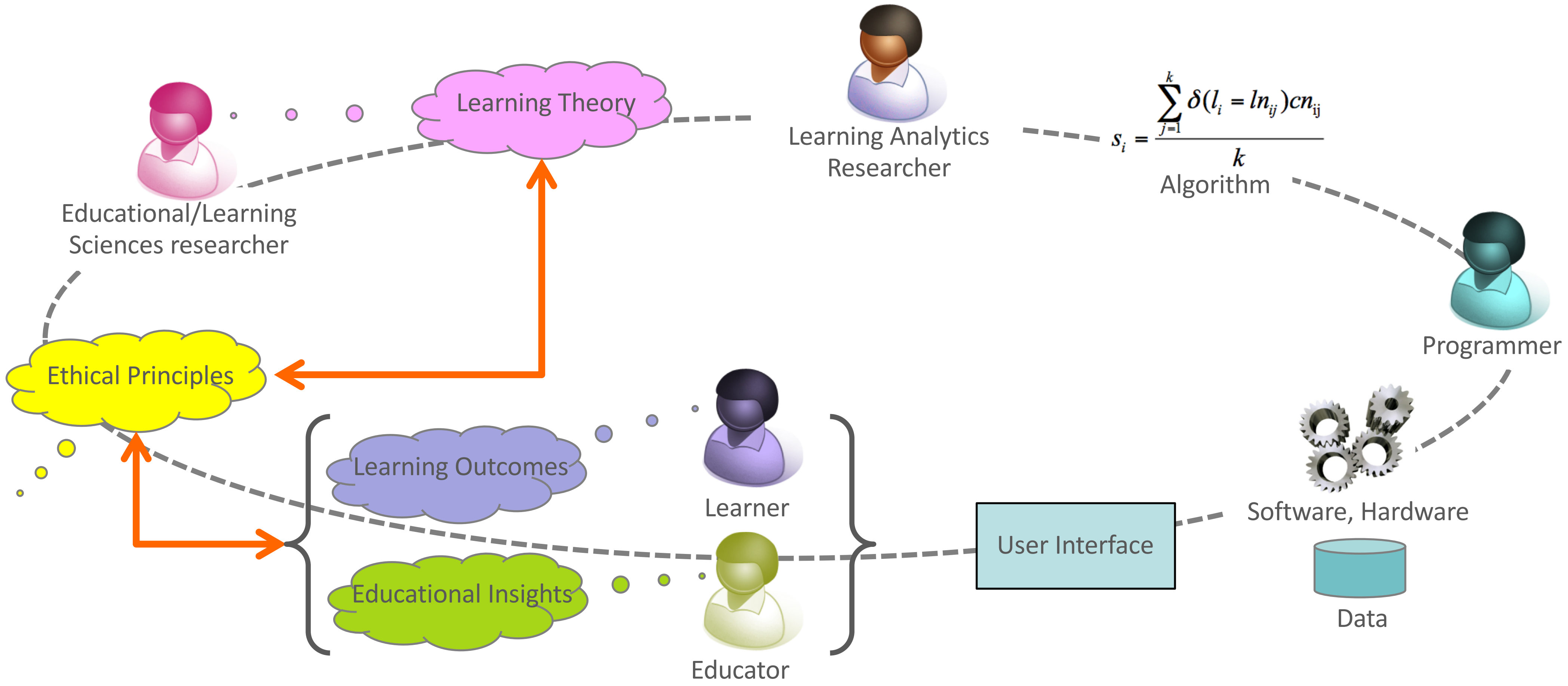
Human-Data Interaction

User-Centred Design

Learning Technology

Legal Accountability…?

Accountability in terms of: Ethics of Technology



Accountability in terms of: Ethics of Technology

Ethics of Technology

Deontological critique: do the analytics produce results that satisfy current duties/rules/policies/principles, and/or correspond with how we already classify the world?

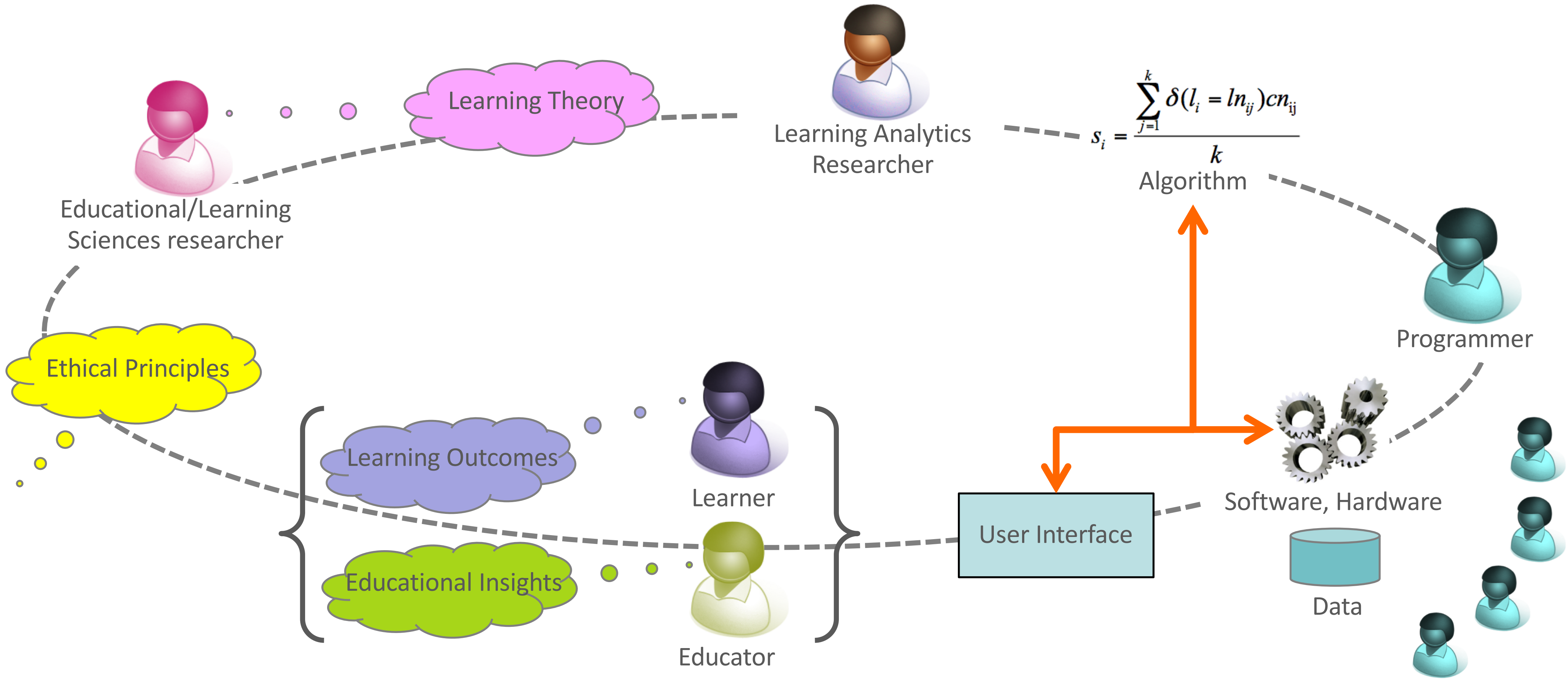
Teleological critique: do the analytics lead to consequences that we value?

Virtues critique: What are the values implicit/explicit in the design (at every level), and do stakeholders perceive and use the system as intended? (cf. HCI Claims Analysis)

…but for an emerging field, esp. with personalisation, D & T can be challenging to apply

Ananny, M., 2016. Toward an Ethics of Algorithms: Convening, Observation, Probability, and Timeliness. *Science, Technology & Human Values*, 41(1), pp.93–117

Accountability in terms of: Computer Science



Accountability in terms of: Computer Science

Computer Science

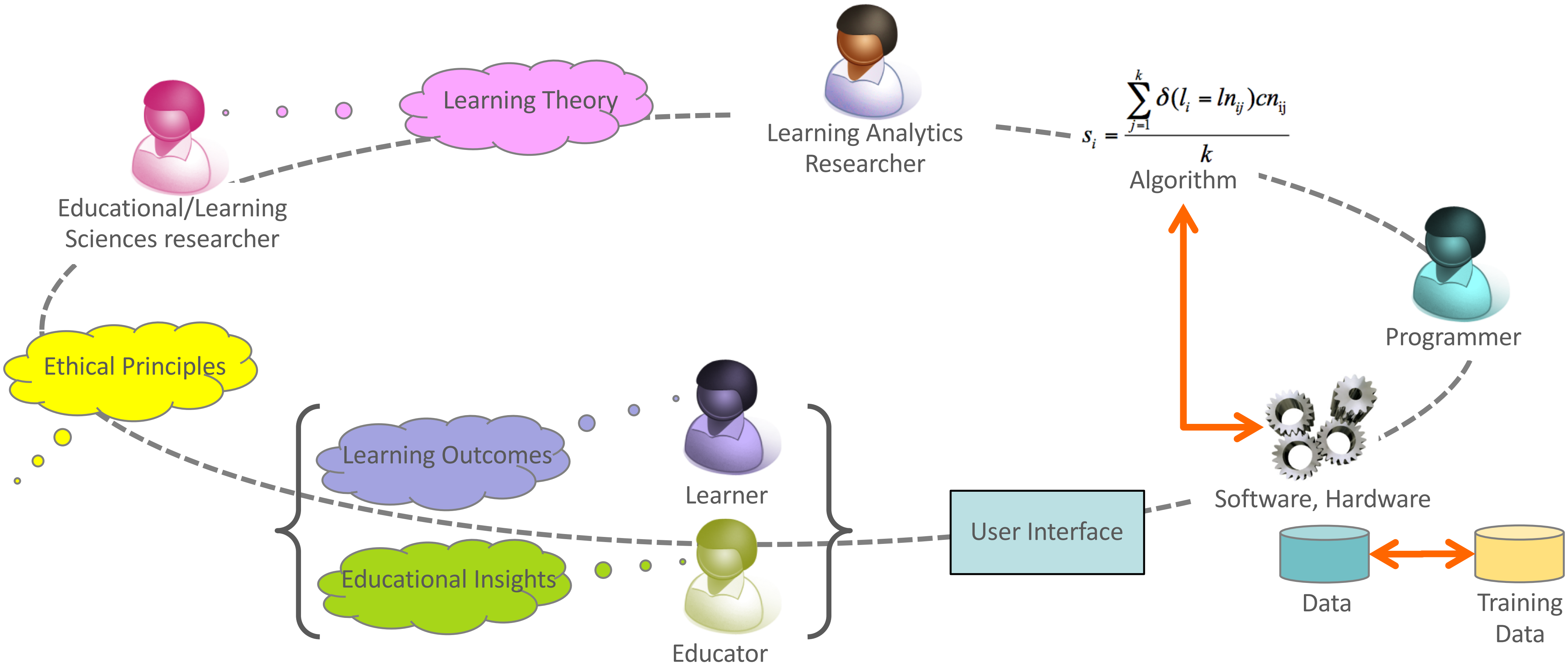
Algorithmic Integrity: does the running code (code+data+platform) operationalise the algorithm with integrity? Is it possible to reverse engineer the algorithm from the system?

Source code availability: to what extent can developers inspect and test the source code?

Source code maintainability: how easily can a developer modify the source code?

System output intelligibility: can we understand why the implemented system generates its outputs under different conditions? (a particular issue with machine learning)

Accountability in terms of: Data Science



Accountability in terms of: Data Science

Data Science

Training Data Integrity: for machine learning, does the training set embody discriminatory bias?

Model Integrity: for machine learning, do the target variables and class labels embody discriminatory bias?

Feature Selection Integrity: does the discriminatory power of features do justice to the complexity of the phenomenon?

Proxy Integrity: do apparent proxy features for a target quality embody discriminatory bias?

Barocas, S. and A. Selbst (In Press). Big Data's Disparate Impact. *California Law Review* 104. Preprint: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2477899

Algorithmic shortlisting for interview

Eleni Kalorkoti

TheUpshot

ROBO RECRUITING

Can an Algorithm Hire Better Than a Human?

Claire Cain Miller @clairecm JUNE 25, 2015

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Hiring and recruiting might seem like some of the least likely jobs to be automated. The whole process seems to need human skills that computers lack, like making conversation and reading social cues.

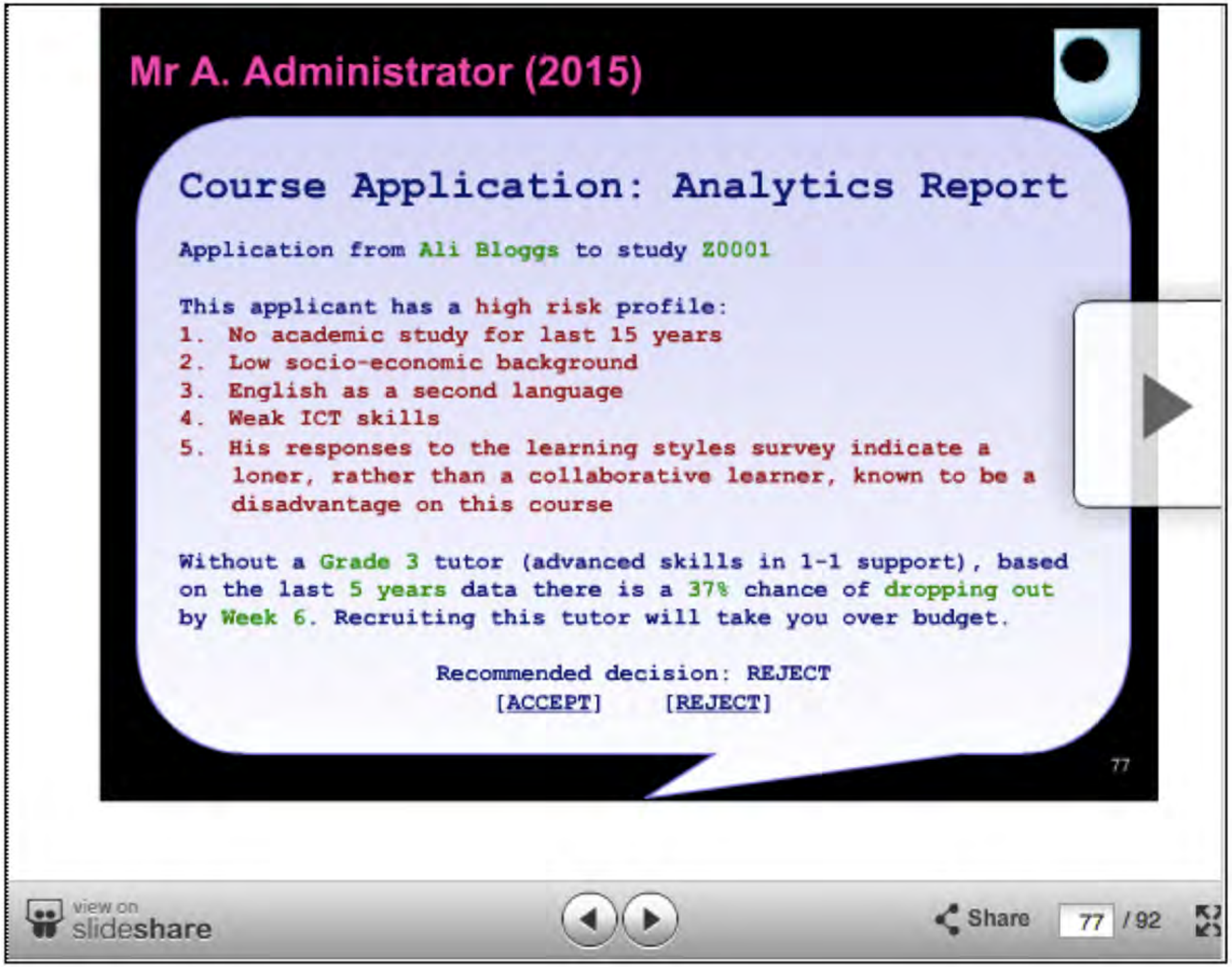
But people have biases and predilections. They make hiring decisions, often unconsciously, based on similarities that have nothing to do with the job requirements — like whether an applicant has a friend in common, went to the same school or likes the same sports.

That is one reason researchers say traditional job searches are broken. The question is how to make them better.

http://www.nytimes.com/2015/06/26/upshot/can-an-algorithm-hire-better-than-a-human.html?_r=0

Obviously no university would vet student applications by algorithm… 😐

(fictional scenario)



Ascilite 2011 Keynote: Slide 77: http://people.kmi.open.ac.uk/sbs/2011/12/learning-analytics-ascilite2011-keynote

Obviously no university would vet student applications by algorithm… ☹

theguardian

australia world opinion sport football tech culture lifestyle fashion economy travel media all sections

home › economy › markets money

Big data
The data store: on big data

The problem with algorithms: magnifying misbehaviour

Computers that learn from and repeat human behaviour save time and money, but what happens when they repeat flawed

The prejudiced computer

For one British university, what began as a time-saving exercise ended in disgrace when a computer model set up to streamline its admissions process exposed - and then exacerbated - gender and racial discrimination.

As detailed here in the British Medical Journal, staff at St George's Hospital Medical School decided to write an algorithm that would automate the first round of its admissions process. The formulae used historical patterns in the characteristics of candidates whose applications were traditionally rejected to filter out new candidates whose profiles matched those of the least successful applicants.

Stella Lowry & Gordon Macpherson, *A Blot on the Profession*, 296 BRITISH MEDICAL J. 657 (1988).
http://www.theguardian.com/news/datablog/2013/aug/14/problem-with-algorithms-magnifying-misbehaviour

Returning to algorithmic staff recruitment…

Eleni Kalorkoti

"It is dangerously naïve, however, to believe that big data will automatically eliminate human bias from the decision-making process.

…inherit the prejudices of prior decision-makers

…reflect the widespread biases that persist in society

…Discover …regularities that are really just preexisting patterns of exclusion and inequality."

Written Testimony of Solon Barocas: *U.S. Equal Employment Opportunity Commission,* Meeting of July 1, 2015 - EEOC at 50: Progress and Continuing Challenges in Eradicating Employment Discrimination. http://www1.eeoc.gov//eeoc/meetings/7-1-15/barocas.cfm?renderforprint=1

Returning to algorithmic staff recruitment…

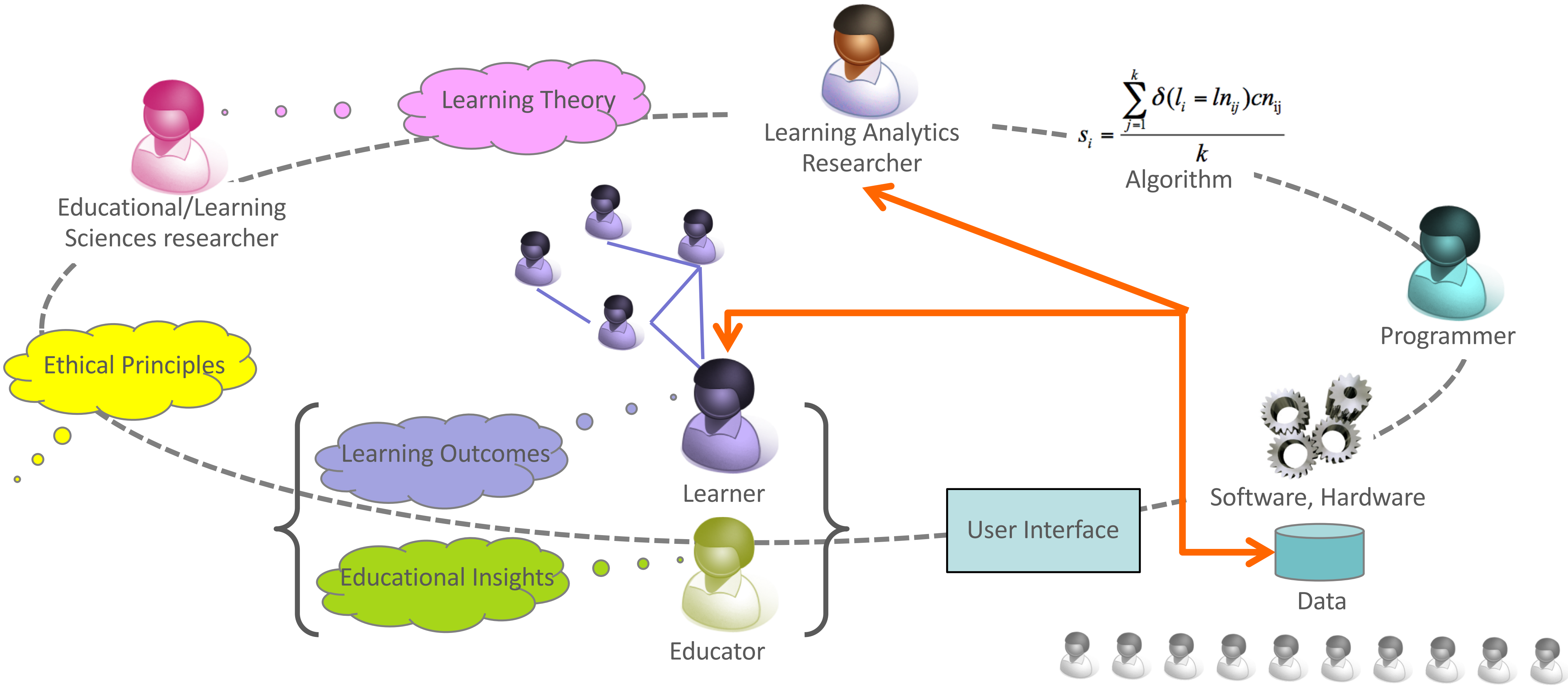
Eleni Kalorkoti

"…Adopted or applied without care, data mining can deny historically disadvantaged and vulnerable groups full participation in society."

"…it can be unusually hard to identify the source of the problem, to explain it to a court, or to remedy it technically or through legal action."

Written Testimony of Solon Barocas: *U.S. Equal Employment Opportunity Commission,* Meeting of July 1, 2015 - EEOC at 50: Progress and Continuing Challenges in Eradicating Employment Discrimination. http://www1.eeoc.gov//eeoc/meetings/7-1-15/barocas.cfm?renderforprint=1

Accountability in terms of: Human-Data Interaction



Accountability in terms of: Human-Data Interaction

Human-Data Interaction

"Accountable Data Transactions": does the data infrastructure have clear protocols for personal data requests, permission, and audit?

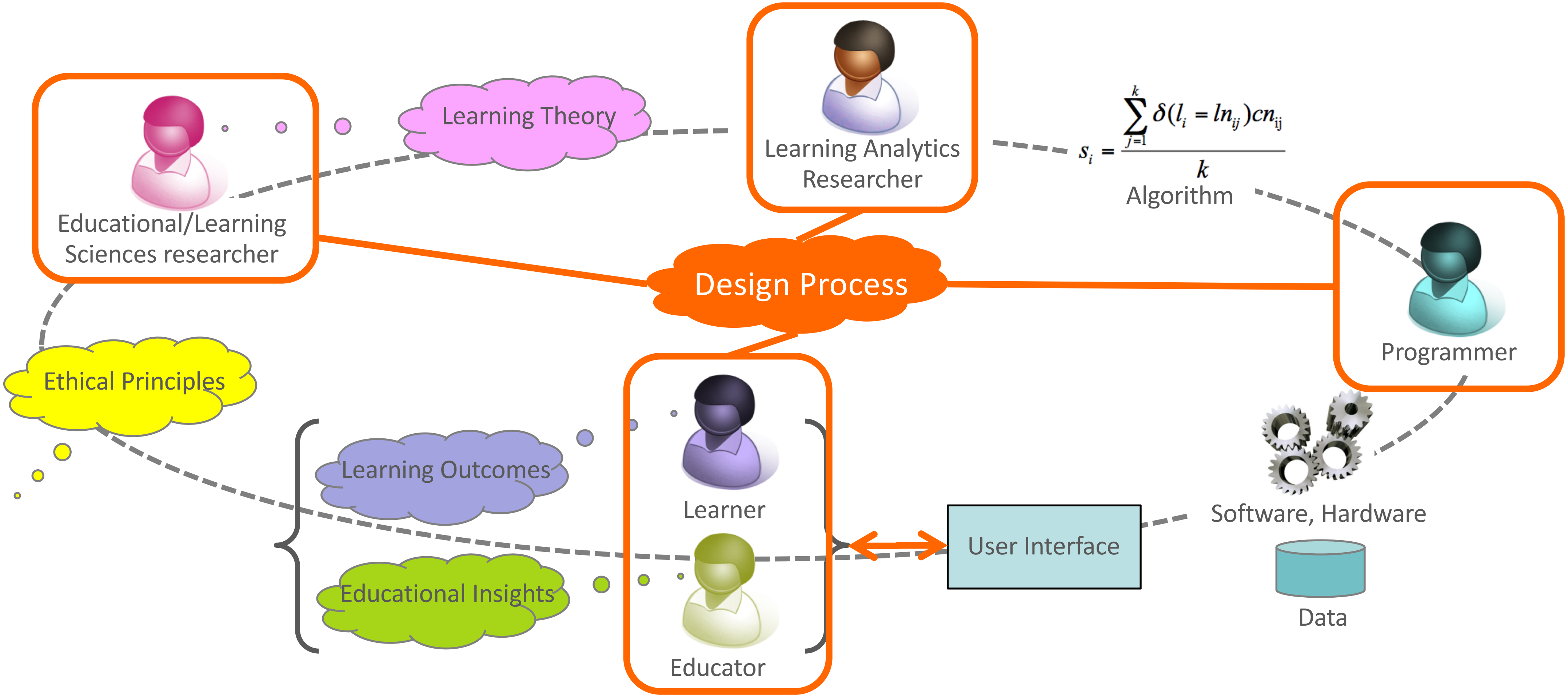
Social Data Infrastructure: as interactions around data are formalised and automated, can this infrastructure be held to account?

Collective Data Ownership: is collectively owned data handled in ways that preserve individual rights?

User Agency: to what degree do citizens have control over who accesses their data, and can they comprehend what analysis will be done, and by whom?

Crabtree, A. and R. Mortier (2015). Human Data Interaction: Historical Lessons from Social Studies and CSCW. *Proc. European Conference on Computer Supported Cooperative Work*, Oslo (19-23 Sept 2015), Springer: London. Preprint: http://mor1.github.io/publications/pdf/ecscw15-hdi.pdf

Accountability in terms of: User-Centred Design



Accountability in terms of: User-Centred Design

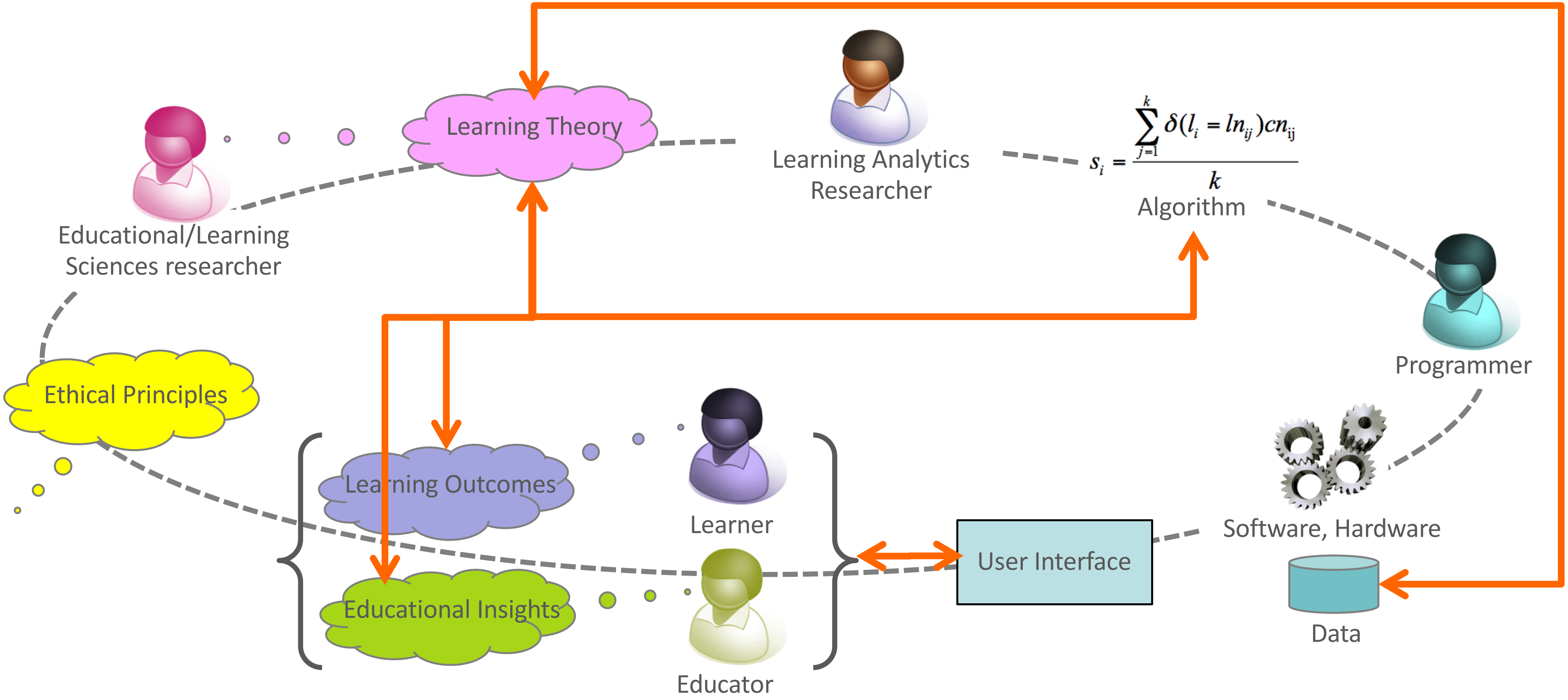
User-Centred Design

User Sensemaking: who are the target end-users, do they understand the analytic output, and can they take appropriate action based on it?

Intelligibility: what, if any, explanation can a user ask the analytic system to provide about its behaviour, can they understand the answers, and can they give feedback?

Participatory Design: to what extent are stakeholders (e.g. academics; instructors; students) involved in the system design process, and are there interfaces for them to modify the deployed system's behaviour?

Accountability in terms of:
Learning Sciences & Educational Technology



Accountability in terms of:
Learning Sciences & Educational Technology

Learning Sciences & Educational Technology

Conceptual Integrity: does the algorithm implement the intended constructs (theory/model/rubric…) with integrity?

Conceptual Integrity: is the data congruent with other sources of educational evidence?

Improved Learning: in what ways do learners benefit from using the system?

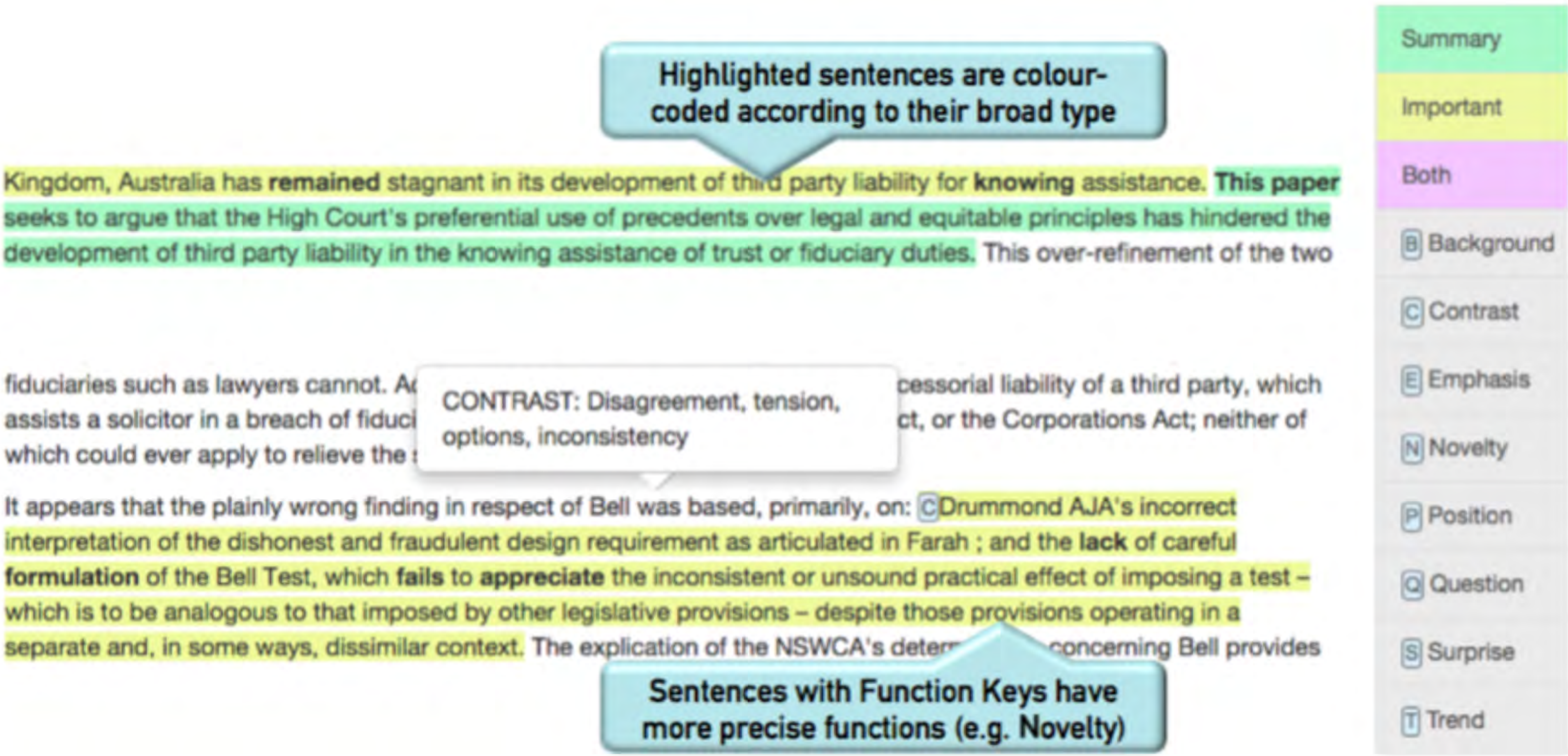
Improved Teaching: in what ways do educators benefit from using the system?

worked example 1

analytics for professional, academic, reflective writing

Buckingham Shum, S., Á. Sándor, R. Goldsmith, X. Wang, R. Bass and M. McWilliams (2016). Reflecting on Reflective Writing Analytics: Assessment Challenges and Iterative Evaluation of a Prototype Tool. *6th International Learning Analytics & Knowledge Conference (LAK16)*, Edinburgh, UK, April 25 - 29 2016, ACM, New York, NY. http://dx.doi.org/10.1145/2883851.2883955

Automated formative feedback on writing (Civil Law)



Automated formative feedback on writing (Civil Law)

consequence of the plainly **wrong** f … alia for the application of a second limb Barnes v Addy claim.

EMPHASIS: Additional emphasis to highlight importance

As above, it was not strictly necessary … was plainly wrong . However, Leeming JA held it was necessary to do so (see [X] above). E His Honour's application of the plainly wrong test with respect to Bell is **crucial** to **this discussion**.

interpretation is plainly wrong.

QUESTION: question or missing knowledge

Significantly, the High Court in Farah … tatutory law . As noted by Leeming JA, there are at least two complexities … mean to be convinced that an **interpretation** is plainly **wrong**? And to what decisions does it apply? Q And as expressed by Basten JA, the legal basis for such a principle is **unknown**, and consequently, has **created** uncertainties in the application of the rule. For

(established by separate inquiries) the … ly, a person seeking relief under s 1318 is not required to show they acte … conduct will attract protection under s 1318, it will be fail to enliven protectio … Leeming JA:

QUESTION: question or missing knowledge

What then is sufficient, according to Bell, to engage second limb Barnes v Addy liability? Q Not lightly would **I conclude** that the High Court has **reformulated** the law in a way which is **not** well **defined**.

COMPARISON OF HUMAN VS. MACHINE

human highlighting

Student Response

As I logged on to MyAccess to preregister for my first semester classes of freshman year, I was told to register for [course name]." Unknowing of what the course was like, I expected a regular class where we learned a set curriculum and talked about healthcare. However, contrary to my preconceptions, the class was an eye opening experience in which I was able to connect with other first year freshman who are going through the same things I am. Not only did it bring reassurance, but a new perspective on the transition that accompanies freshman year of college. This course consisted of many learning moments for me, among them being introductions, discussions on stress, and group presentations as a whole. To start, introductions are always intimidating yet exciting. Meeting someone for the first time is like creating a new bond—it starts with searching for common ground and a relatable characteristic or experience. In this course, everyone is automatically connected by being in a school focused on developing healthcare professions. This led to the ability to form a bond stronger than what we could form with other students at this point. So, we skipped the questions like "What school are you in?" and "What do you want to be?" but rather started with "How many siblings do you have?" and "What is your dog's name?" These questions are more intimate and informative, leaving behind the orientation dialogue. This allowed me to form several

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many resources for a bulk of different issues, and taking advantage can really help you be the best Hoya you can be. This class, unlike others, was tailored toward open, honest discussion, which is different from many other classes. While other classes are more about material, this class was about checking in and making sure that everyone was transitioning well. This class also displays the nature of the NHS—a community. [course name] is unique to the NHS in how it helps us transition into this big step, and makes sure that we are aware of what we should be doing, how we should be doing it, and what we can learn from those around us. The environment was welcoming and comfortable, so it was much easier to discuss matters such as those in a classroom with other students and a professor when normally conversations of that nature would take place among friends. [course name] cultivated an environment where we were able to learn from each other and build off of other ideas. Looking back on the semester, I don't think I could have felt as comfortable and at ease as I do now without this class. When I walk into a lecture hall, I look for a familiar face, perhaps one that I met during [course name]. I now know that when people ask, "How are you doing?" they genuinely care about how you are. I feel more comfortable talking in a group setting, as though I can contribute my thoughts in an atmosphere of incredibly brilliant individuals. I formed study groups with some of the individuals, opening my eyes to the fact that everyone wants everyone to succeed in whatever they do. Above all, I'm glad to have taken this class because I learned so much, and it contributed to my distressing every week. Learning is sometimes more about discussions, relating, and building off of other people than sticking to a strict curriculum, and that is what [course name] is all about.

automated highlighting

Not only did it bring reassurance, but a new perspective on the transition that accompanies freshman year of college.

One student mentioned art, and because I lack art ability, I have taken up journaling each night as a way to distress before going to sleep.

CA It showed me that even though **I** can **feel** alone sometimes in the issues I'm facing, the odds are someone else is either experiencing it or witnessing someone else experience it.

CA [course name] is unique to the NHS in how it helps us transition into this big step, and makes sure that **we** are **aware** of what we should be doing, how we should be doing it, and what **we can learn** from those around **us**.

w without

atmosphere

tressing

tilize both

CA He spoke with us about how **we can reach** forgiveness for ourselves and helped us talk about some qualities we would like to embody when we become nurses.

CO At times, **I found** it a bit offensive, specifically **when we** were **discussing** a scenario he created involving a girl who was kidnapped and raped **while** under the influence of alcohol.

When I walked into our first class in St. Mary's Hall, I did not know what to expect.

You need to strive for understanding to retain what matters to you, not sporadically memorizing.

After my first round of exams, I wasn't too disappointed with my grades, but I realized that learning instead of memorizing would help me grow intellectually and raise my grades.

In discussing the different types of models used to create a health promotion program, [Professor name] provided examples of campaigns at Georgetown and other colleges and universities across the country.

Our health policy project allowed us to look at controversial issues from differing practical, moral, ethical, and

	KEY:	Analyst	
		Correct	Incorrect
XIP	Selected	tp	fp
	Unselected	fn	tn

Example accountability analysis: writing feedback

Ethics: Does the system output results that match human analysts? Does instant feedback lead to novel benefits, or is it in fact damaging to students? What is the motivation behind the focus on reflection (e.g. rather than factual accuracy)?

Computer Science: Does the NLP platform implement the linguistic features with integrity?

Data Science: Do the linguistic features have sufficient discriminatory power? Do they ignore important qualities of value? Do they bias against certain kinds of student?

Human-Data Interaction: Do students consent to their writing being analysed?

User-Centred Design: Were students and educators involved in the design of the system? Can they make sense of the user interface and act on output?

Learning Technology: What is the educational basis for the parser rules? Does the algorithm implement the theory/rubric with integrity? Educator/student reaction?

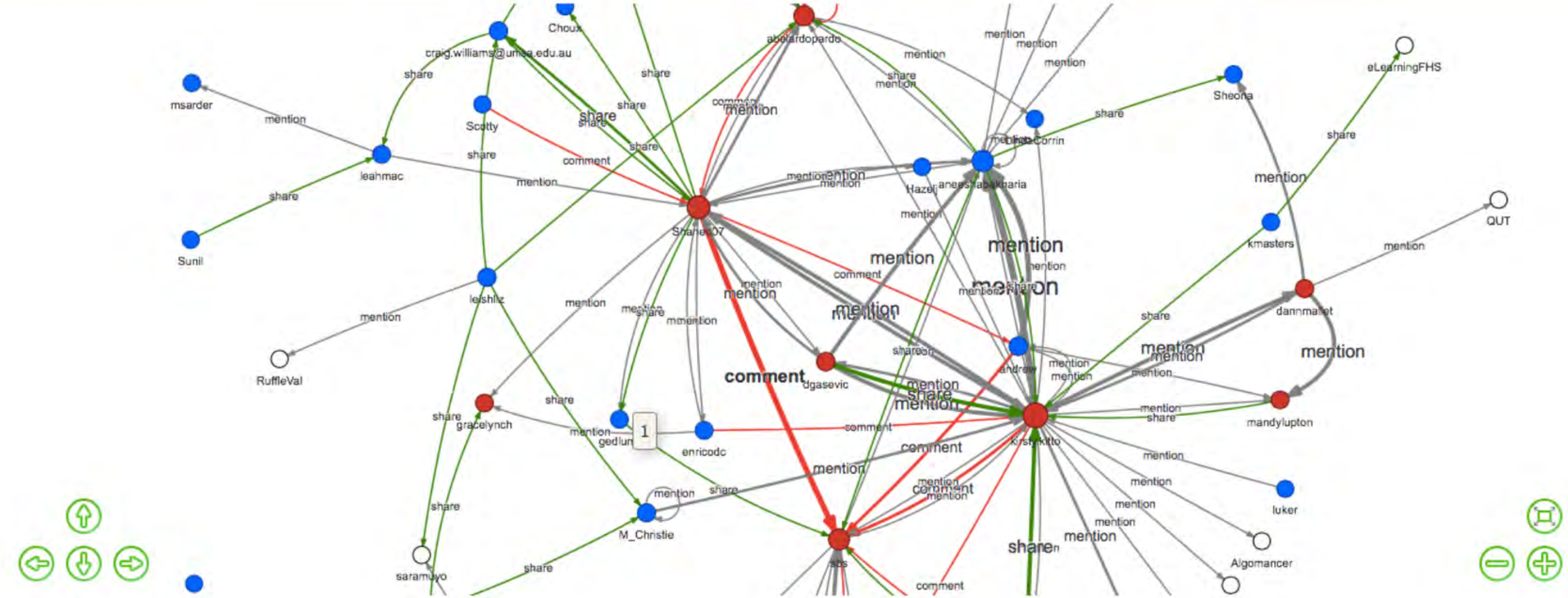
Legal: Could a student sue the university for parser errors, or discrimination?

worked example 2
building and visualizing a student social network

Kitto, K. *et al.* (2016). The Connected Learning Analytics Toolkit. *6th International Learning Analytics & Knowledge Conference (LAK16)*, Edinburgh, UK, April 25 - 29 2016, ACM, New York, NY. http://beyondlms.org

Social Network Visualisation of student activity

Click on your node to view the messages you have posted. Click on a link (or relationship) to view the messages that were shared or commented on by another user.



Legend:

- White Nodes: Mentioned users not registered with CLAToolkit
- Blue Nodes: Students
- Maroon Nodes: Teaching Staff

Connected Learning Analytics Toolkit: http://beyondlms.org

Example accountability analysis: SNA visualisation

Ethics: Do users validate the social networks? Does the system lead to novel benefits? What is the motivation behind the design of the system?

Computer Science: Does the social network tool implement SNA metrics correctly?

Data Science: Is the dataset biased or incomplete in important respects? Does the social network visualization bias against certain kinds of student?

Human-Data Interaction: Should students be permitted to control their degree of visibility on different platforms? Does disclosing peer data to a student violate peers' rights?

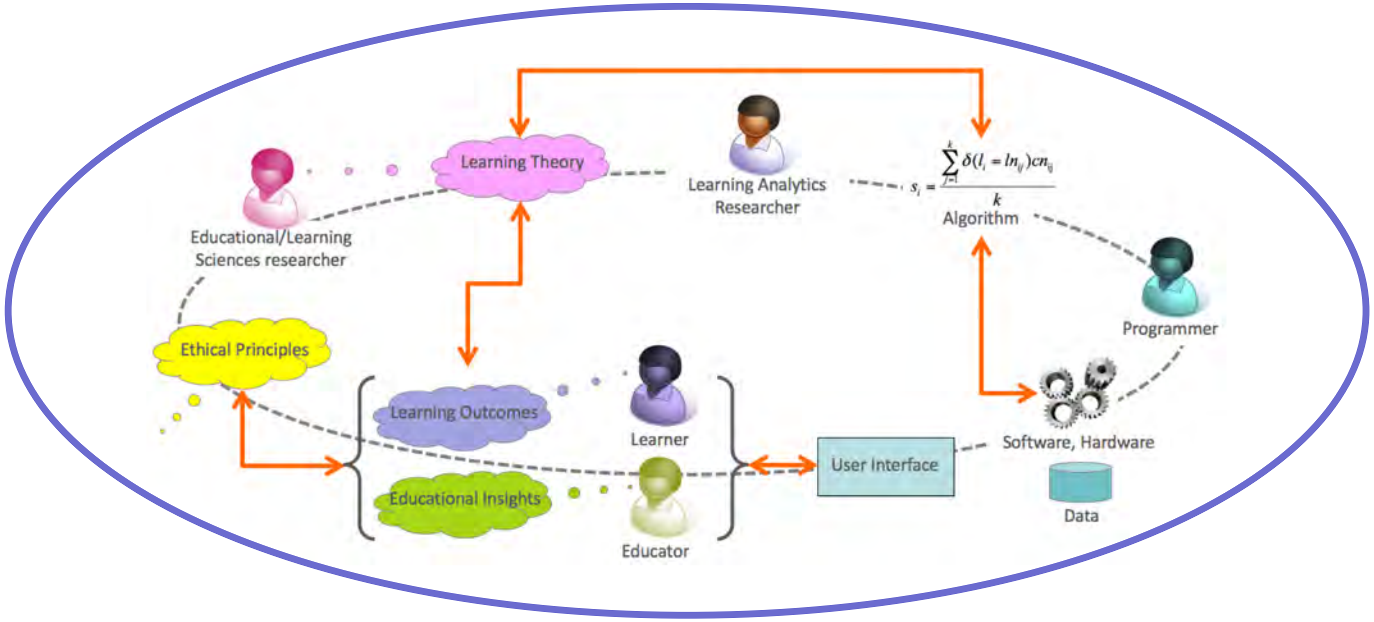
User-Centred Design: Were students and educators involved in the design of the system? Can they make sense of the user interface and act on output?

Learning Technology: What is the educational rationale for making social ties visible? Do the selected user actions implement this with integrity? Do students find it helpful?

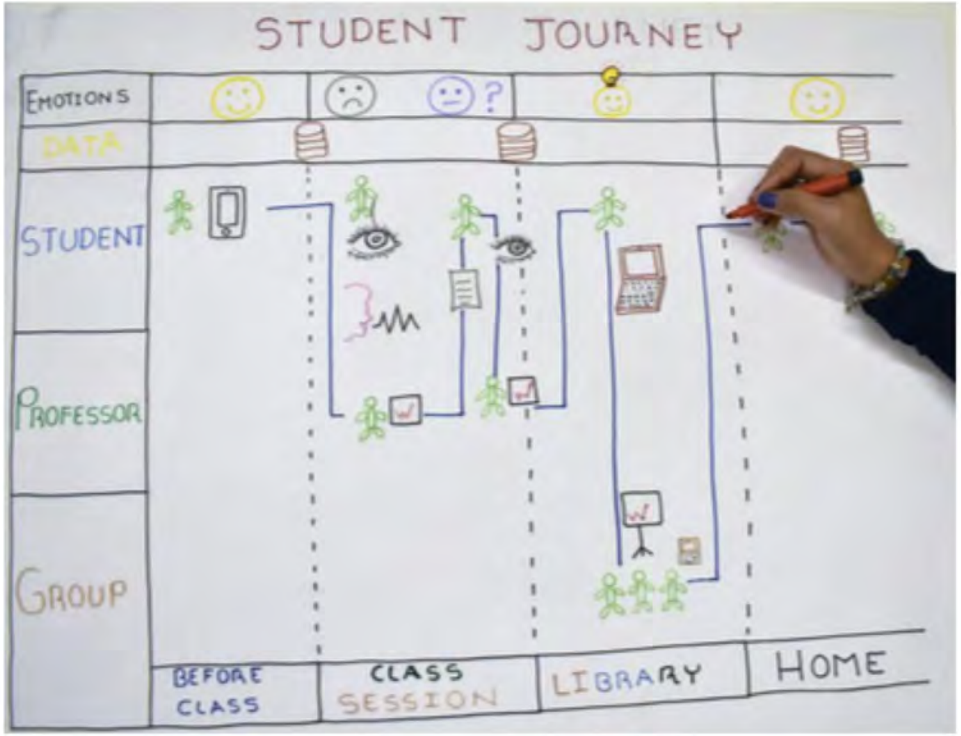
Legal: Could a student sue for discrimination due to the network map?

approaches to designing for

Learning Analytic System Integrity



Participatory design methods that build trust



Carlos G. Prieto-Alvarez, Roberto Martinez-Maldonado, Theresa Anderson (In Press). Co-designing in Learning Analytics: Tools and Techniques. In: Jason Lodge, Jared Cooney Horvath & Linda Corrin (Eds.), *From data and analytics to the classroom: Translating learning analytics for teachers.*

Communicating the algorithm to educators and students?

Design features that make assessment analytics trustworthy: a case study LaK DESIGN, March 2017, Vancouver, Canada

	LEVEL 1 READER	LEVEL 2 CONSUMER OF INSTRUCTION	LEVEL 3 SELF-REGULATED LEARNER	LEVEL 4 COLLABORATIVE LEARNER	LEVEL 5 RECIPROCAL TEACHER
Attending class	Accesses MOOC once	Accesses MOOC in several weeks	Accesses MOOC most weeks		Views forums in multiple weeks
Engaging widely	Watches videos	Tries in-video exercises	Uses in-video exercises routinely Reads some course readings	Accesses the range of course resources	Intensive forum user
Monitoring/producing		Tries practice quizzes	Repeats practice quizzes	Posts longer than a tweet	Posts at paragraph length
Perspective-taking		Cursory forum visitor	Occasionally uses forums	Explores forums	Reads many threads
Focusing			Revisits a thread Re-reads some course resources	Visits a thread more than twice Systematically repeats in-video exercises Re-reads many course resources	Visits a thread more than three times Re-reads many course resources Follows discussions in forums
Reaching out			Posts in forums	Posts in multiple threads	Posts in multiple weeks
Shaping debate				Posts in popular threads Votes up another's posts	Creates threads/new discussions Votes up other's posts more than once Posts in depth
Generating value				Receives a peer vote on a post	Receives peer votes on multiple posts

Milligan, S. and Oliveira, E. (2017). Design features that make assessment analytics trustworthy: a case study. *DesignLAK17 Workshop*, LAK17, Vancouver, March 2017. https://sites.google.com/site/designlak17

Make the mapping from clicks to constructs explicit

"Capability to learn in scaled environments"

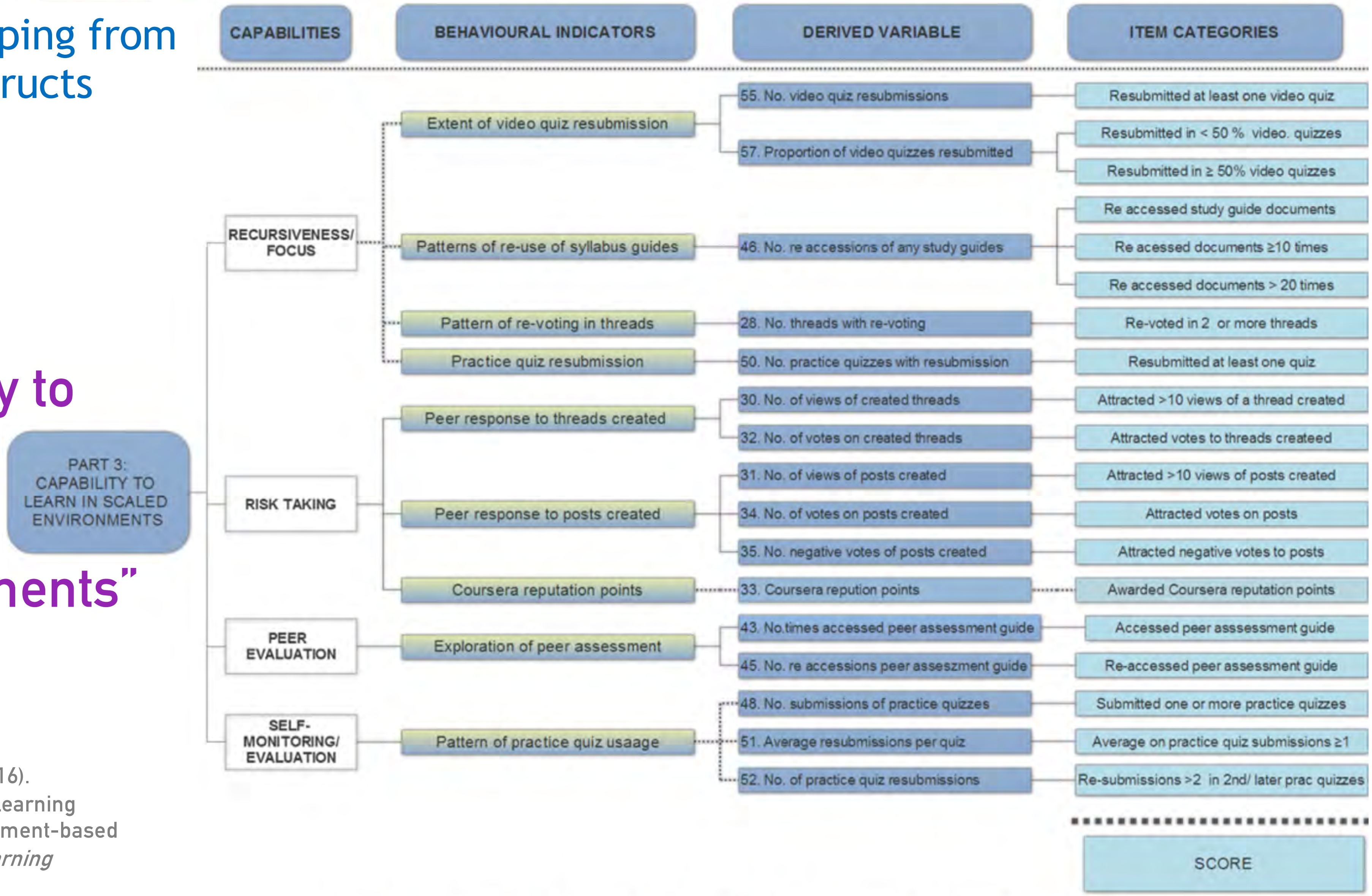
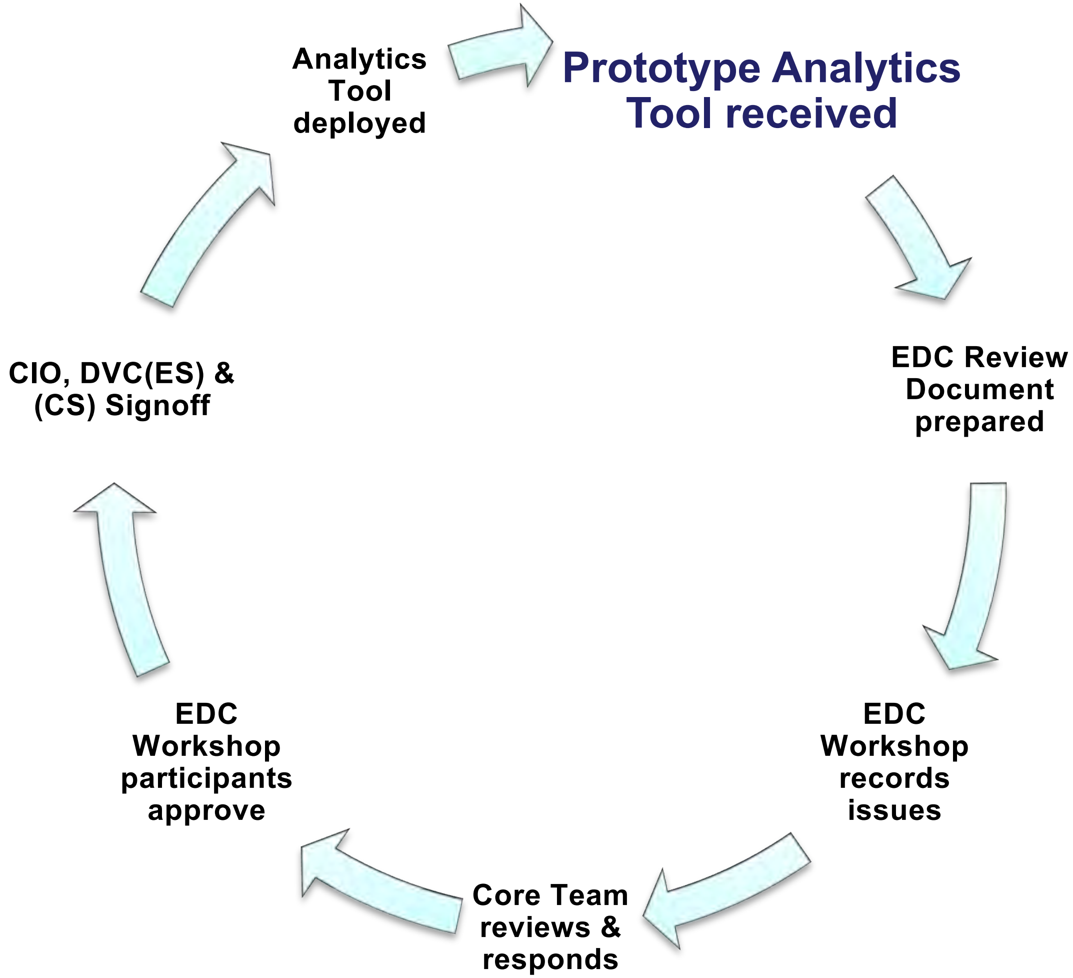


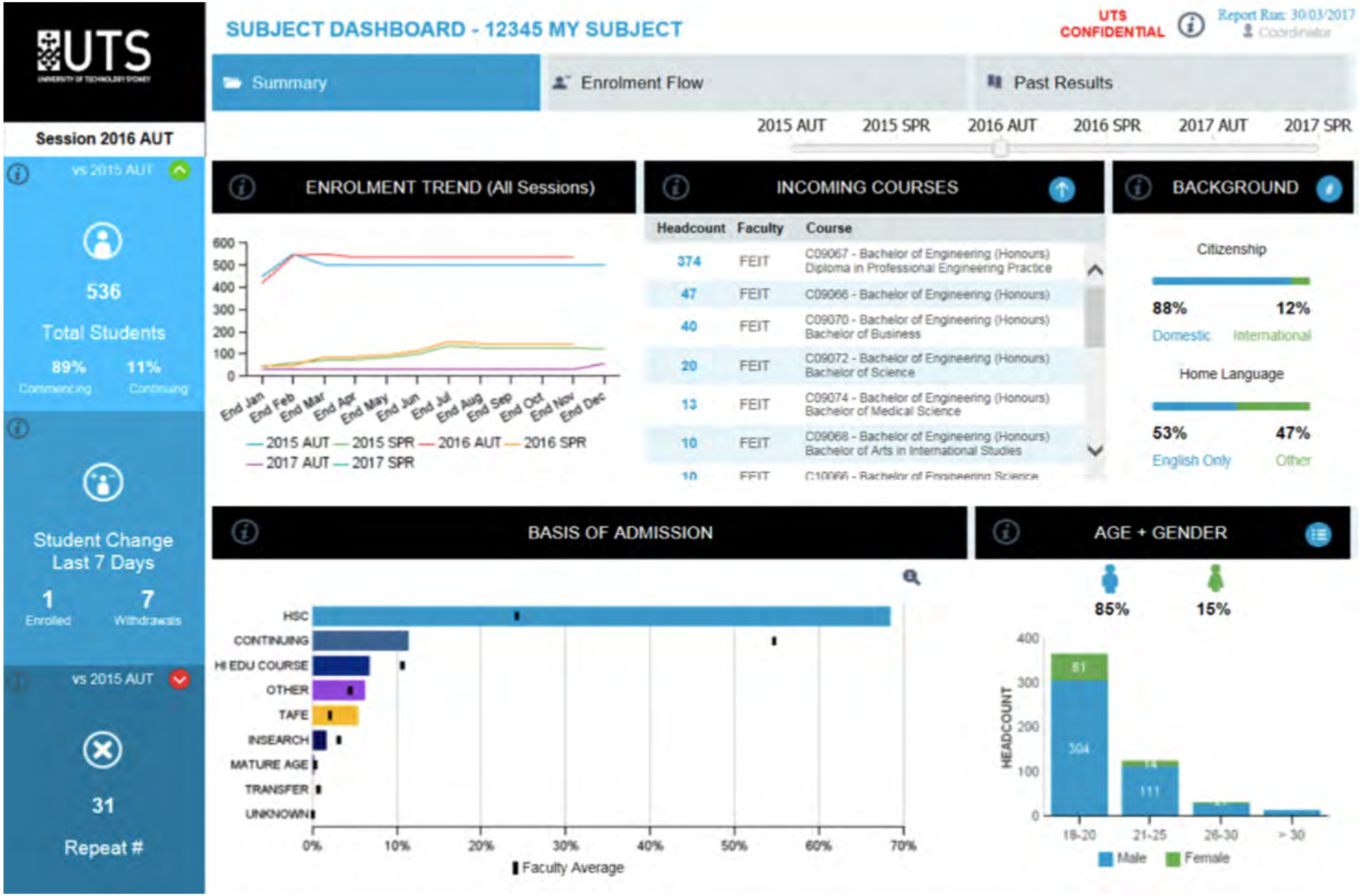
Figure 1: Construct map for the C-SL capability as expressed in MOOC log stream data

Milligan, S. and Griffin, P. (2016). Understanding learning and learning design in MOOCs: A measurement-based interpretation. *Journal of Learning Analytics*, *3*(2), 88– 115. http://dx.doi.org/10.18608/jla.2016.32.5

ETHICAL DESIGN CRITIQUE (EDC) PROCESS



CIC team
Pro-VC Education
Equity & Diversity Unit
Planning & Quality Unit
IT Division
Director, Risk
Director, Teaching Innovation
Data Privacy Officer
Indigenous Students Centre

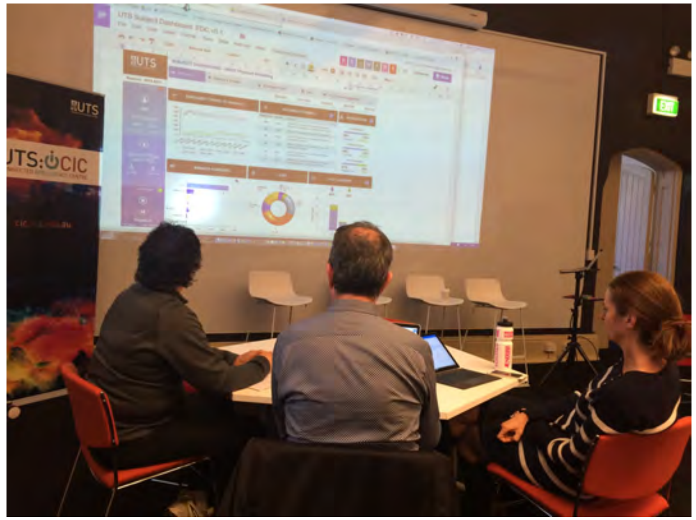

UTS
UNIVERSITY OF TECHNOLOGY SYDNEY
Session 2016 AUT
SUBJECT DASHBOARD - 12345 MY SUBJECT
UTS CONFIDENTIAL
Report Run: 30/03/2017
Coordinator
Summary
Enrolment Flow
Past Results
2015 AUT
2015 SPR
2016 AUT
2016 SPR
2017 AUT
2017 SPR
vs 2015 AUT
536
Total Students
89%
Commencing
11%
Continuing
Student Change Last 7 Days
1
Enrolled
7
Withdrawals
vs 2015 AUT
31
Repeat #
ENROLMENT TREND (All Sessions)
600
500
400
300
200
100
0
End Jan
End Feb
End Mar
End Apr
End May
End Jun
End Jul
End Aug
End Sep
End Oct
End Nov
End Dec
2015 AUT
2015 SPR
2016 AUT
2016 SPR
2017 AUT
2017 SPR
INCOMING COURSES
Headcount
Faculty
Course
374
FEIT
C09067 - Bachelor of Engineering (Honours) Diploma in Professional Engineering Practice
47
FEIT
C09066 - Bachelor of Engineering (Honours)
40
FEIT
C09070 - Bachelor of Engineering (Honours) Bachelor of Business
20
FEIT
C09072 - Bachelor of Engineering (Honours) Bachelor of Science
13
FEIT
C09074 - Bachelor of Engineering (Honours) Bachelor of Medical Science
10
FEIT
C09068 - Bachelor of Engineering (Honours) Bachelor of Arts in International Studies
BACKGROUND
Citizenship
88%
12%
Domestic
International
Home Language
53%
47%
English Only
Other
BASIS OF ADMISSION
HSC
CONTINUING
HI EDU COURSE
OTHER
TAFE
INSEARCH
MATURE AGE
TRANSFER
UNKNOWN
0%
10%
20%
30%
40%
50%
60%
70%
Faculty Average
AGE + GENDER
85%
15%
400
300
200
100
0
HEADCOUNT
61
304
111
18-20
21-25
26-30
> 30
Male
Female

EDC: ETHICAL DESIGN CRITIQUE

The EDC Template

<insert screenshot of dashboard element>

EDC team is invited to comment on:



Strengths

- **e.g. Data is at an appropriate level that it does not disclose inappropriate information about a cohort or individuals**

EDC: ETHICAL DESIGN CRITIQUE

Indicate concerns *e.g.*

- **Data is displayed from incomplete sources, or has been filtered in ways, that users might not expect (Specify why this violates expectations)**
- **Data is shown for which there is no apparent reasonable use (Recommend removal)**
- **There is scope for misinterpretation due to poor design (Suggest improvement)**
- **This data is useful but could be inappropriately used (Caution and specify examples of inappropriate usage)**

Conclusion: a new career in the Learning Analytics profession?

“Certified LASI Engineer”

Trained to audit Learning Analytics System Integrity at multiple levels, via multiple lenses

-> New principles to guide design, vendor selection, academic peer review (and maybe legal deliberation)

Learning Analytics Summer Institute, Ann Arbor, June 2017

Black Box Learning Analytics?
Beyond Algorithmic Transparency

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