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How Can I use Learning Analytics in my Teaching Practice

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How can I use Learning Analytics in my teaching practice?

Dr. Geraldine Gray
TU Dublin

CCT, Nov 2019

Outline

1. What is Learning Analytics?
2. Our Data

    ….and what we can do with it
3. Some of the pitfalls

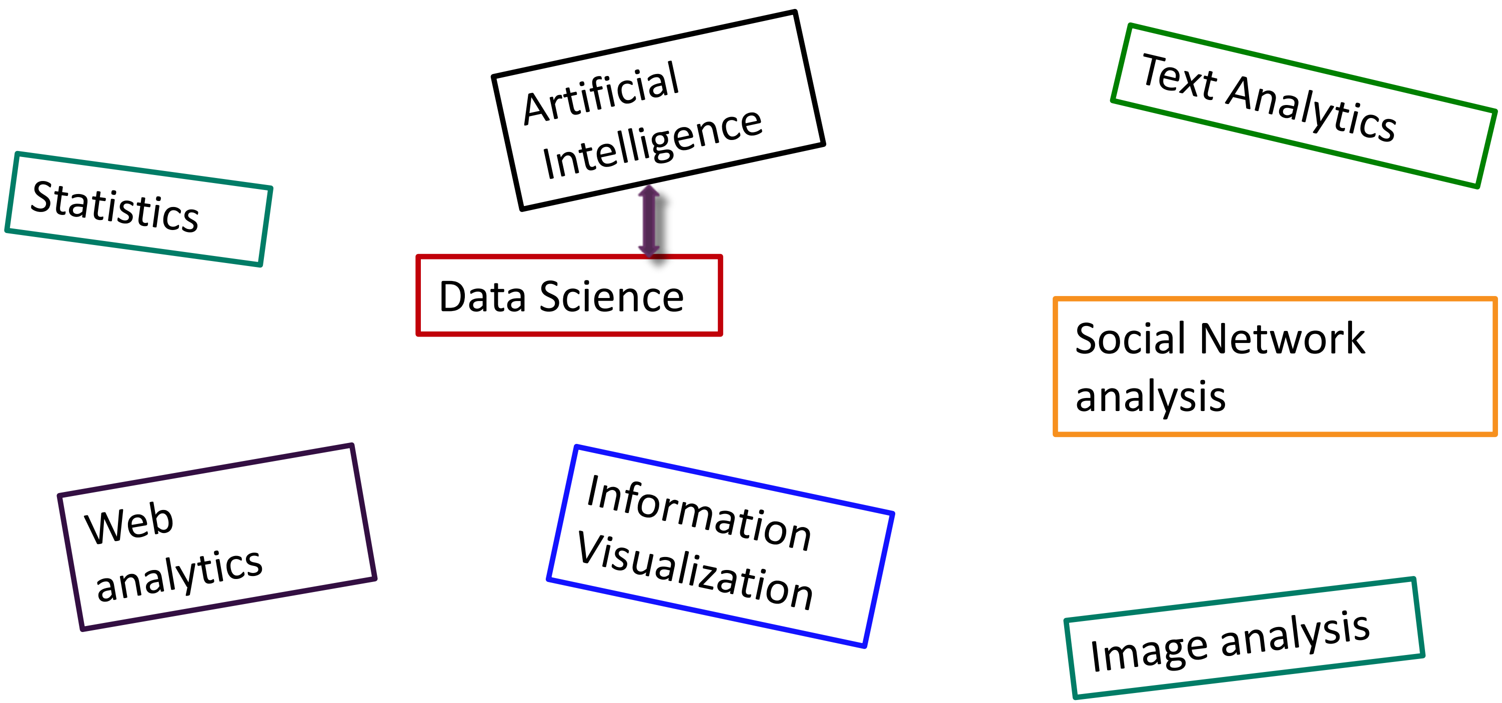
    ….and benefits
4. How do I get started

    ….and what supports do I need?

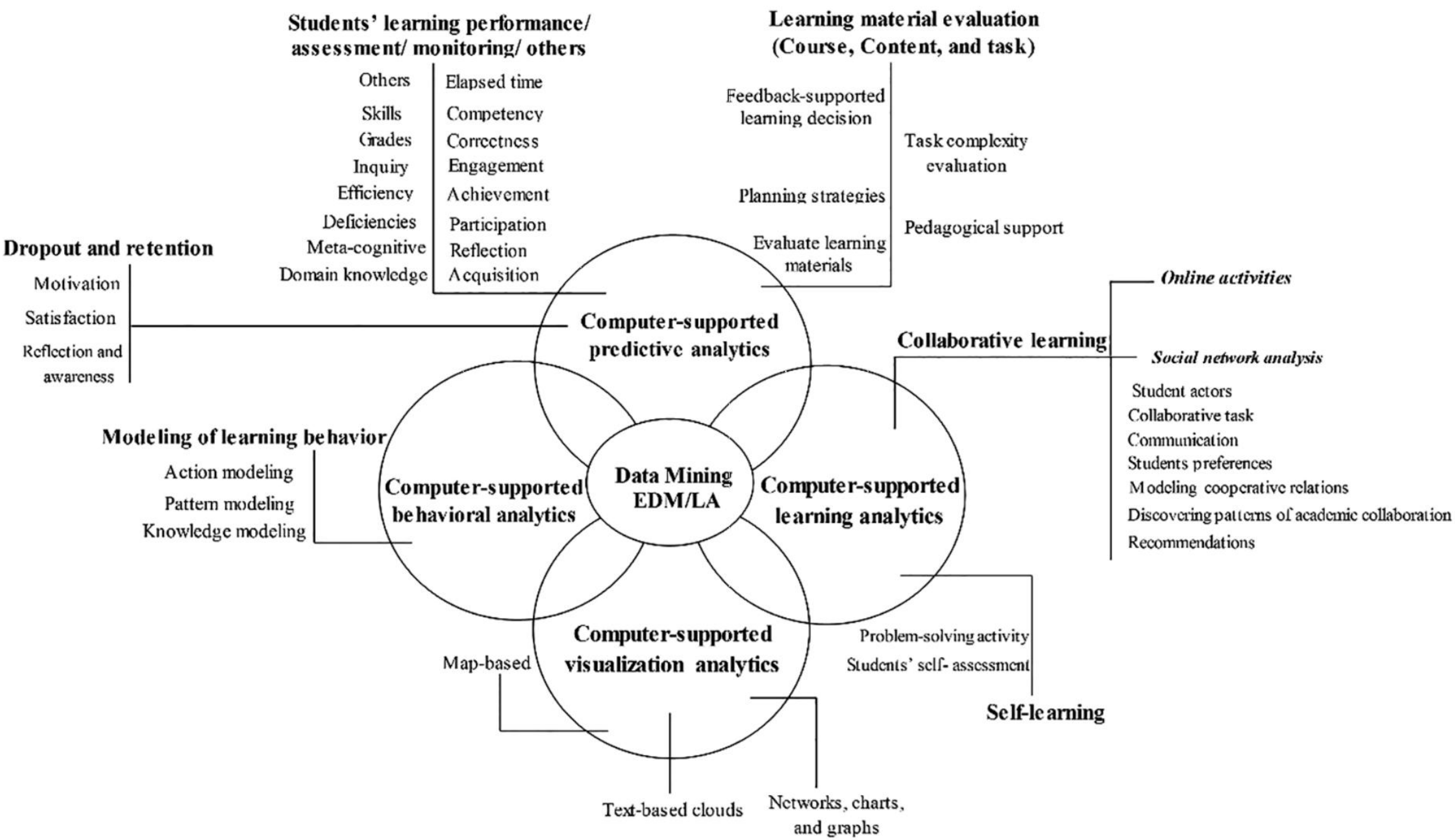
Learning analytics:

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.

(SoLAR – Society for Learning Analytics Research)



Learning analytics for 21st century HE



Aldowah, H., Al-Samarraie, H., & Fauzy, W. M. (2019). Educational Data Mining and Learning Analytics for 21stcentury higher education: A Review and Synthesis. *Telematics and Informatics*.

Goals of learning analytics: Is it to….?

Improve statistics on **student disengagement, retention, progression . . .**

Nurture the **skills and dispositions**, assessed under authentic conditions, that equip learners to cope with novel, complex situations.

- Developed capacity for learning to learn rather than learn to pass exams
- Prepare students for the world they will work in

Simon Buckingham Shum and Ruth Deakin Crick (2016). Learning analytics for 21st century competencies. Journal of Learning Analytics, 3(2), 6–21.

Two distinct trajectories . . .

Predictive tool to identify at risk students

- Model of implementation: a technical solution
- Provision of data to prompt action from educator
- Facilitate student engagement with existing model of learning

Develop understanding of, and improvements in, teaching and learning

- More complex model of implementation
- Bring understanding to learning and teaching practices
- Disruption and innovation to improve the quality of the student learning experience

Colvin, Cassandra, et al. "Student retention and learning analytics: A snapshot of Australian practices and a framework for advancement." Sydney: Australian Office for Learning and Teaching (2015).

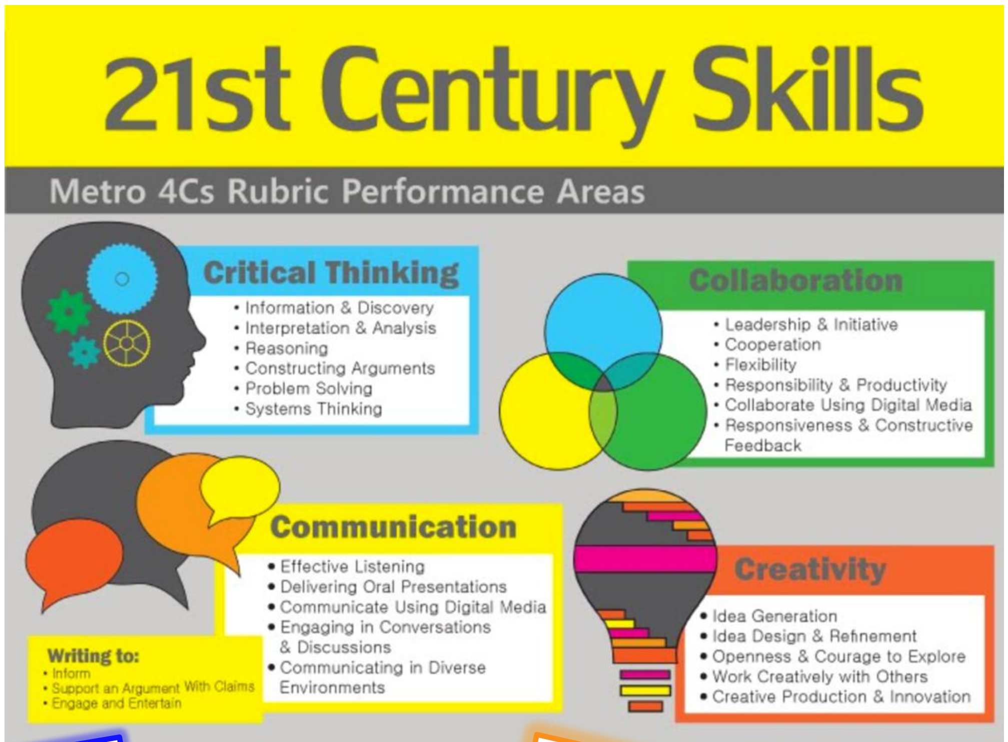
Learning Analytics as an enabler of high quality education

intellectual curiosity

self-efficacy

deep learning approach

persistence



setting learning goals

creativity

conscientiousness

open-mindedness

ability to self-regulate

Hershkovitz A., Knight S., Dawson S., Jovanović J., Gašević, D. (2016) About "learning" and "analytics". Journal of Learning Analytics, 3(2), 1–5

Analysis of skills correlated with assessment results:

Non-cognitive factors that correlate with assessment results indicate the skills and competencies we value

Deep learners?

Problem solvers?

Creativity?

What can be measured?

The easy stuff:

- Exam grades
- Attendance
- Enrollment data
- Logs of activities on Virtual Learning Environments (VLE)

Latent constructs:

- Learning itself
- Effective learning disposition: persistence; self-regulation; deep learning; creativity; . . . ..
- Affective state: boredom, engagement

Overt measurements:

Academic history and self reporting questionnaires

Correlates of final year dissertation mark and final degree mark (GPA).

	Dissertation Mark	Degree Mark (GPA)
Academic Self-Efficacy *(N = 66)*	**.289****	**.397****
Internal Academic Locus of Control *(N = 67)*	.183	.195
External Academic Locus of Control *(N = 67)*	−.111	−.169
Computer User Self-Efficacy *(N = 65)*	.075	.105
Deep *(N = 64)*	**.254***	**.308****
Strategic *(N = 66)*	**.237***	**.316****
Surface *(N = 64)*	.014	−.013
Apathetic *(N = 67)*	**−.254***	**−.279***
Self-Confidence *(N = 67)*	.178	.161
Student Perceived Academic Proficiency *(N = 66)*	.108	.187
Prior Academic Achievement *(N = 64)*	**.485****	**.519****
Age *(N = 67)*	**.364****	**.414****
Gender *(N = 67)*	.003	.152

Cassidy, Simon. "Exploring individual differences as determining factors in student academic achievement in higher education." Studies in Higher Education 37.7 (2012): 793-810.

Online behaviour on VLEs (and ITSs)

- The number of days a student accesses the system
- The number of logins
- The amount of time spent logged in
- The number of posts viewed
- The number of posts written

Linear correlations between each course behaviour and final grade

	Attendance behaviour			Interactivity behaviour	
	# days	# logins	Time spent	# posts viewed	# posts authored
All	.565***	.440***	.390***	.244***	.365***

Lowes, Susan, Peiyi Lin, and Brian Kinghorn. "Exploring the link between online behaviours and course performance in asynchronous online high school courses." Journal of Learning Analytics 2.2.

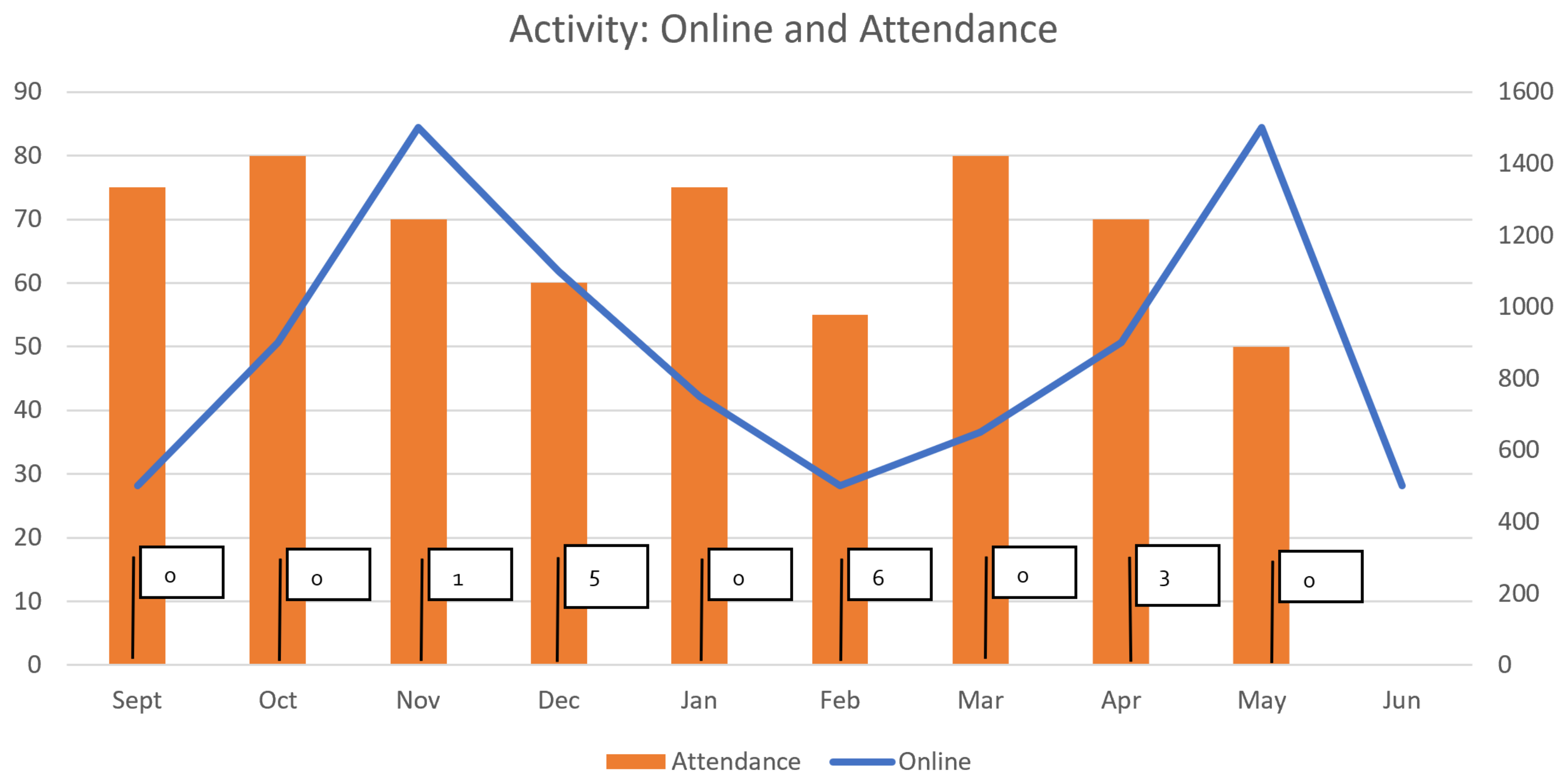
From: Niall Sclater, NF seminar series on LA, May 2018 @sclater

Early alert systems

Detail	Student ID	First Name	Last Name	Home Address	Engagement Rating	Enrolment Status	Course Level	Course Year	Course	Study Mode
Detail	3242fcbe81	Sabine	Legarra	4908 Long Road Beijing	low	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	6b3a48cedf	Sheryl	Katsari	15371 Long Road Berlin	sat	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	ce92a24e45	Roldn	Berrocosa	19822 Long Road Dubai	low	Terminated	Undergraduate	1	Sociology	Full-Time
Detail	7411633792	Kimber	Banfi	13320 Long Road London	high	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	6971a16287	Sle	Godecke	7721 Long Road Dubai	good	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	eebc69cf53	Uasal	Edler	4431 Long Road Berlin	good	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	7890fbbcc9	Scott	Jashkov	4534 Long Road Madrid	good	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	b7025a8753	Laima	Feldstein	13609 Long Road Dubai	good	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	87d44b0071	Kelsey	Janka	16914 Long Road Paris	sat	Enrolment	Undergraduate	1	Sociology	Full-Time
Detail	f2b76caae2	Rachel	Nedellec	24157 Long Road Berlin	good	Enrolment	Undergraduate	1	Sociology	Full-Time

From: Niall Sclater, NF seminar series on LA, May 2018 @sclater

Curriculum design



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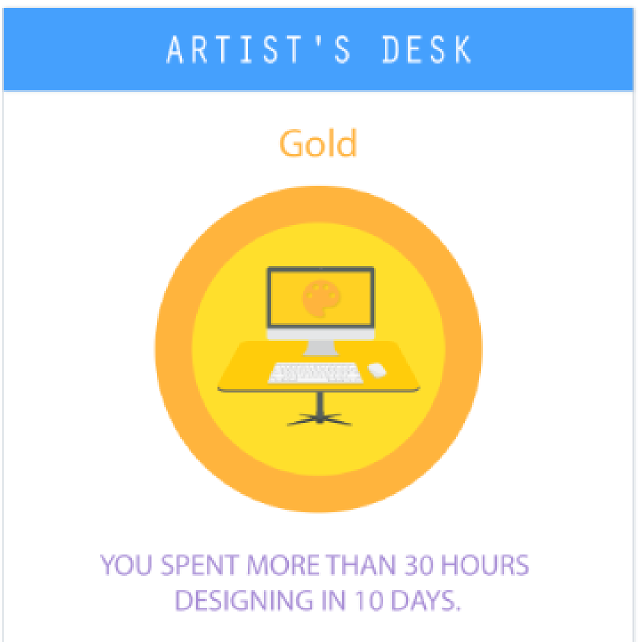
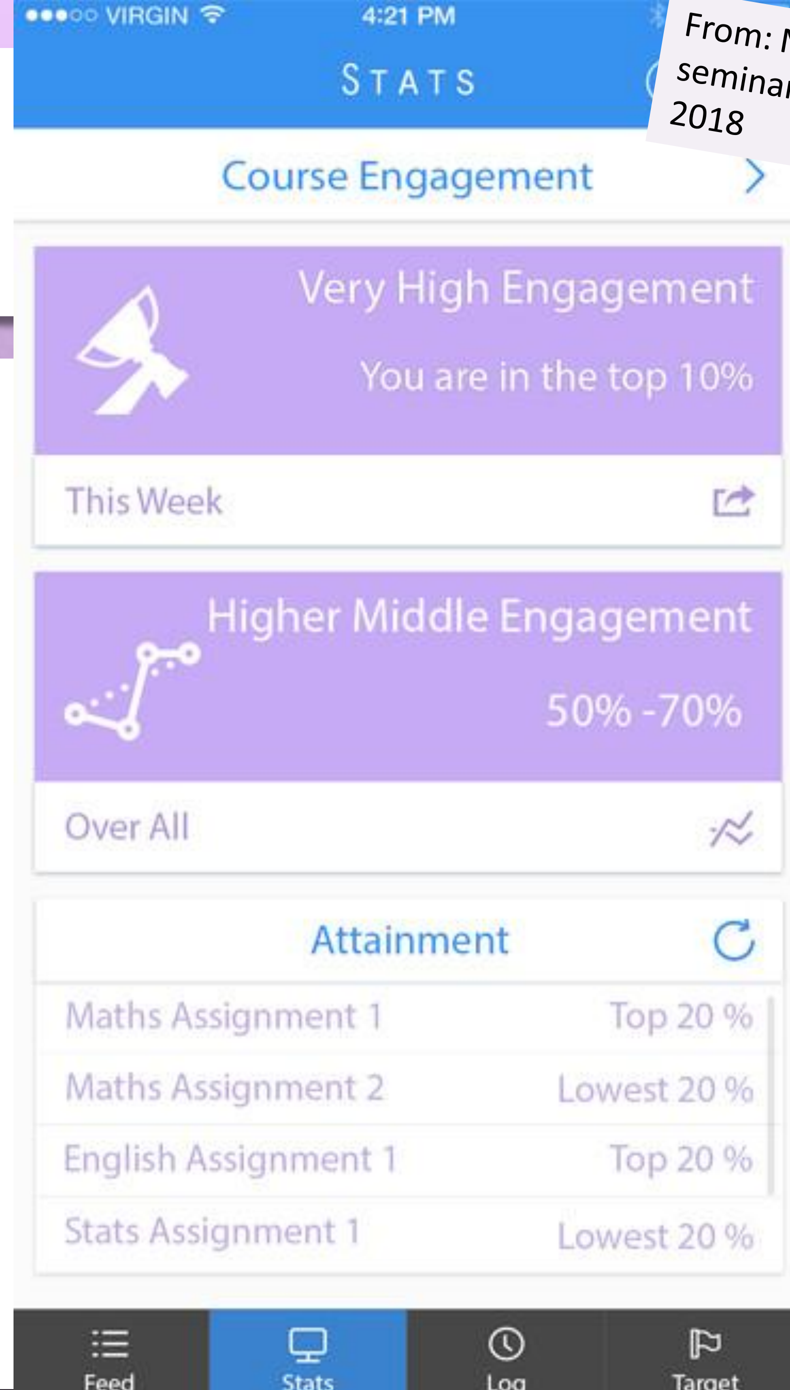
Students facing analytics





From: Niall Sclater, NF seminar series on LA, May 2018 @sclater

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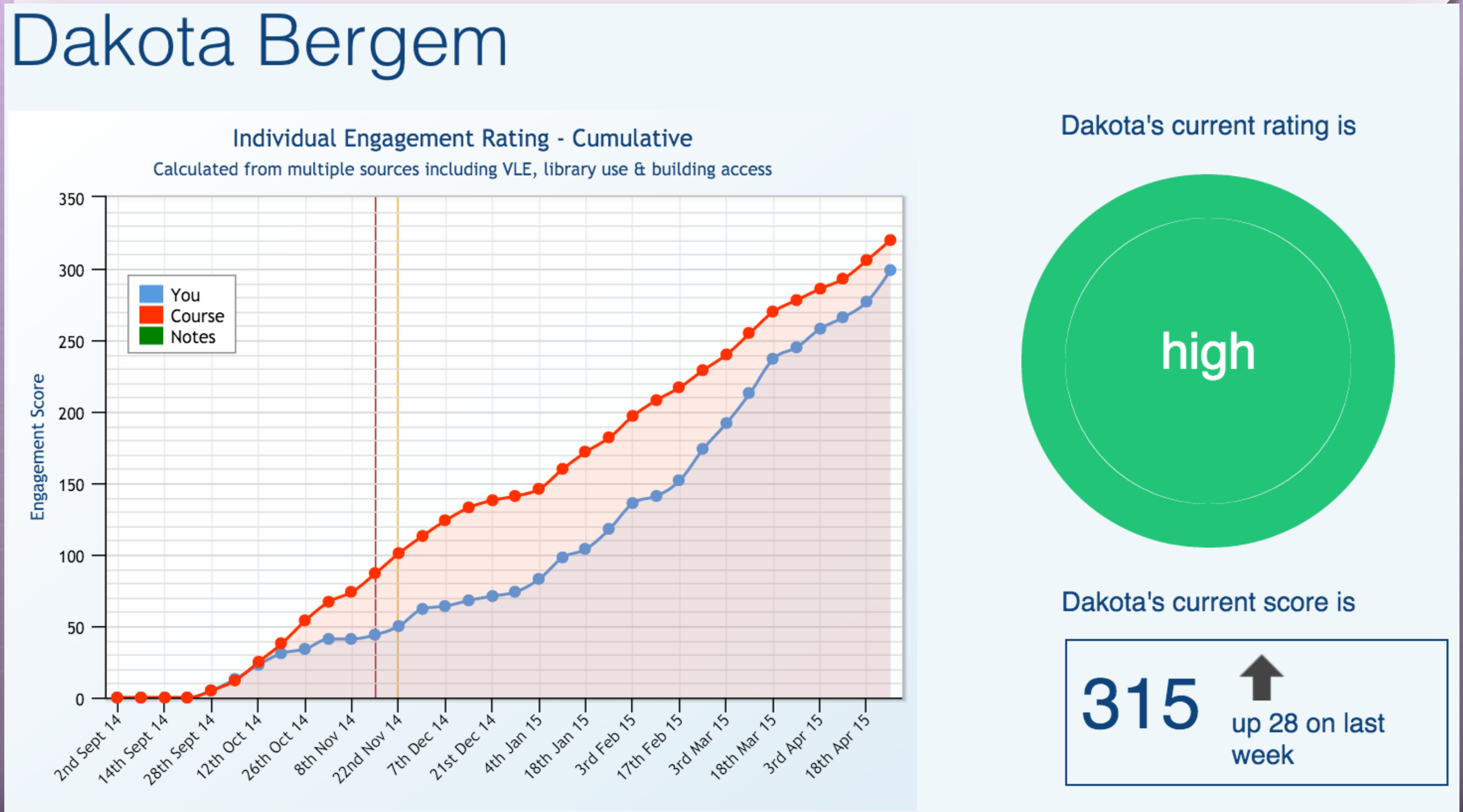
Comparison to class average

From: Niall Sclater, NF seminar series on LA, May 2018 @sclater



Comparison to class average

From: Niall Sclater, NF seminar series on LA, May 2018 @sclater

Individual Engagement Rating - Relative

Calculated from multiple sources including NOW, attendance, library use & building access

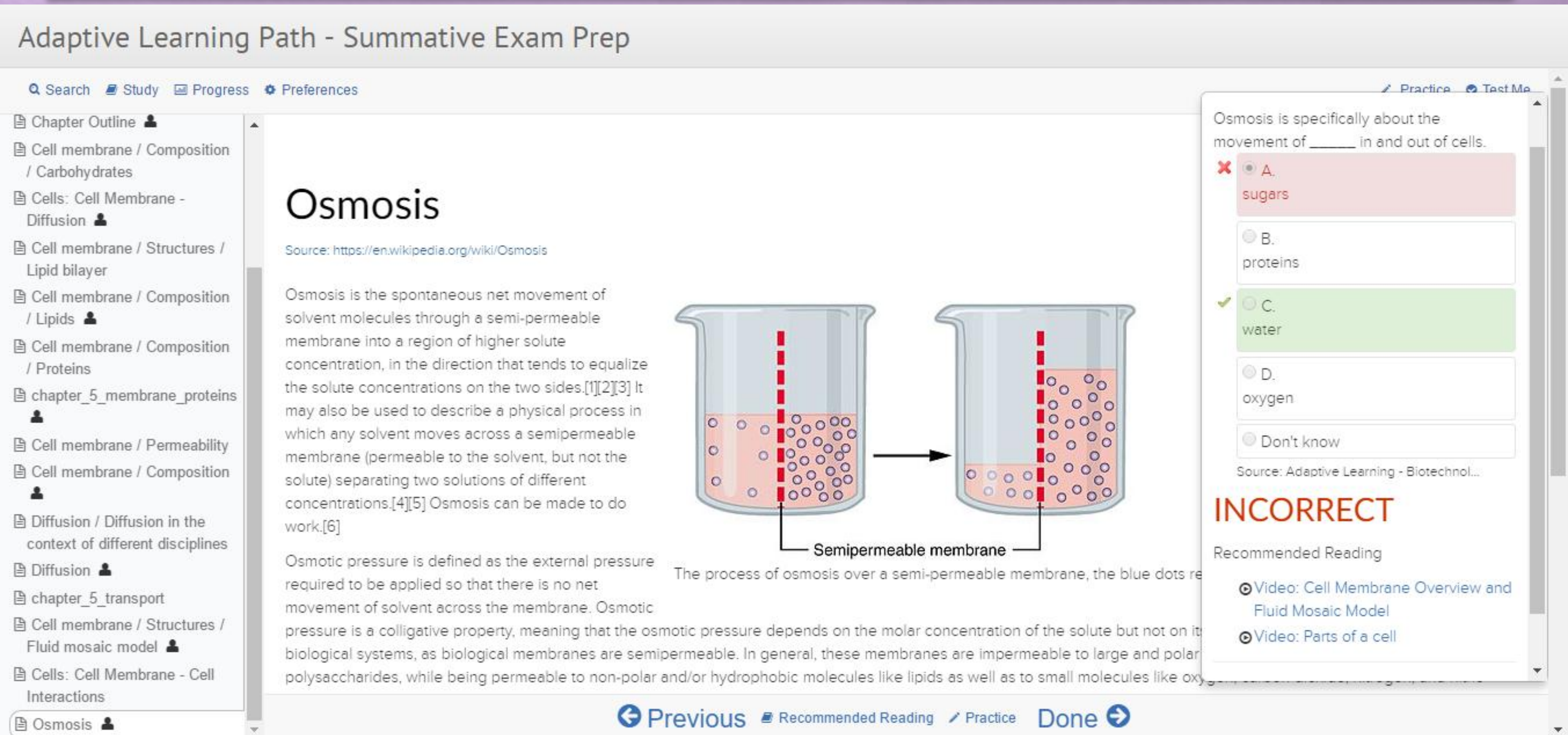
Individual Engagement Rating - 14 Day View

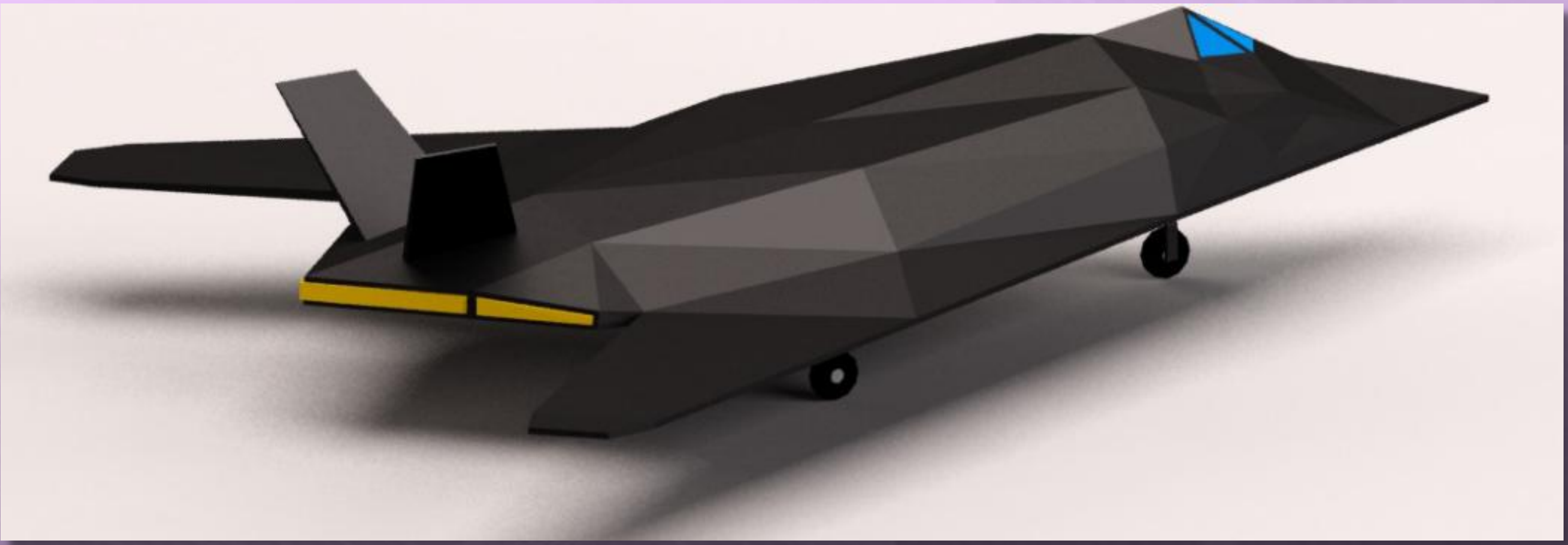
Week Two	18/08/2014	19/08/2014	20/08/2014	21/08/2014	22/08/2014	23/08/2014	24/08/2014
	Satisfactory	Satisfactory	Satisfactory	Good	Good	High	High
Week One	25/08/2014	26/08/2014	27/08/2014	28/08/2014	29/08/2014	30/08/2014	31/08/2014
	High	High	High	High	High	High	High

Nottingham Trent University

Adaptive learning

From: Niall Sclater, NF seminar series on LA, May 2018
@sclater





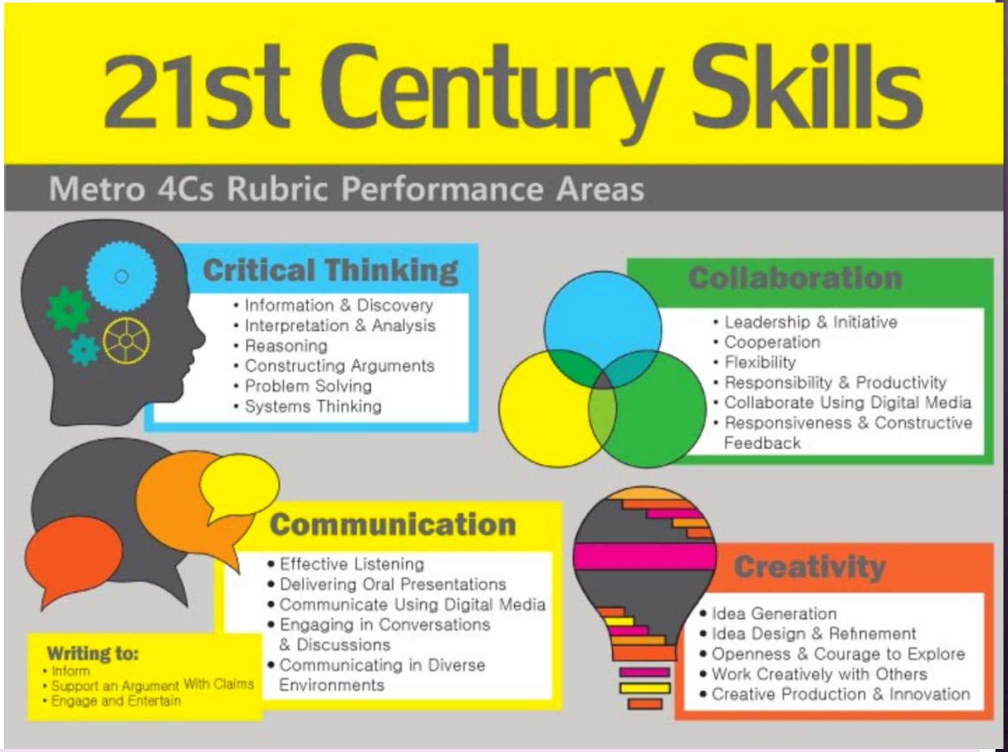
Stealth measurement

What can be implied from behaviour

Objective . . .

Measurement of constructs that are ill-defined, such as creativity, collaborative learning, self-regulated learning, or persistence:

21st century skills



Hershkovitz A., Knight S., Dawson S., Jovanović J., Gašević, D. (2016) About "learning" and "analytics". Journal of Learning Analytics, 3(2), 1–5

Analysis of reflective text for evidence of metacognition

Pattern	Corresponding phraseTags
possessive pronoun followed by any adjectives and nouns	selfPossessive (e.g., my team) groupPossessive (e.g., our group) othersPossessive (e.g., her project)
pronoun followed by any verbs, adverbs, conjunctions, and prepositions	consider (e.g., we decided to go) anticipate (e.g., we needed) emotive (e.g., i am coming along really well) generalPronounVerb (e.g., we had)

	Metacognition
Trigger (Regulation)	A conscious or unconscious cognitive event, particularly a problem or incongruence.
Monitor (Regulation)	Monitoring of cognitive processes, both consciously and unconsciously.
Control (Regulation)	Utilizing pre-learned strategies to control cognitive processes.
Goal (Regulation)	Resolution of the trigger problem or dissonance.
Knowledge	Memory dedicated to storing metacognitive knowledge in particular strategies and their efficacy. Used in the monitor–control loop.
Experience	Affective impact on monitor–control loop. Assists with strategy formation and evaluation.

metaTag	subTag	Phrase Tag Pattern
Regulation monitorControl AND (trigger OR goal)	Trigger	outcome
	Monitor and Control	temporal OR (pertains AND consider)
	Goal	anticipate OR definite OR possible
Knowledge		selfPossessive OR compare OR manner
Experience		emotive OR selfReflexive

Initial results are promising . . .

Gibson, Kitto, Bruaza, (2016). Towards the discovery of learner metacognition from reflective writing. *Journal of Learning Analytics*, 3(2), 22–36.

Behavioral data extracted from keystroke analyses

Table 1. Basic Keystroke Indices

Measure	Description
Verbosity	Number of keystrokes per essay
Backspaces	Number of backspaces per essay
Largest Latency	Largest time difference between keystrokes during essay writing
Smallest Latency	Smallest time difference between keystrokes during essay writing
Median Latency	Median of all the differences in time between keystrokes per essay (not including initial pause)
Initial Pause	Length of the first pause of an essay writing session
0.5 Second Pauses	Number of pauses above .5 seconds and
1 Second Pauses	
1.5 Second Pauses	
2 Second Pauses	
3 Second Pauses	

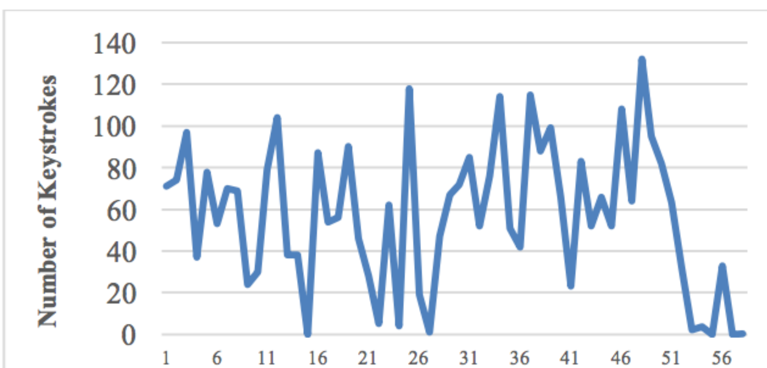


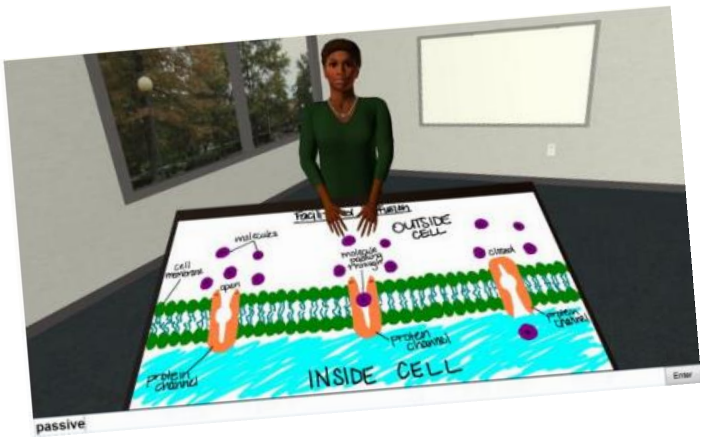
Table 2. Time-Sensitive Keystroke Indices

	Description
StDev Events	Standard deviation of the number of events in each time window
Slope Degree	Slope of the linear regression applied on the time series
Entropy	Shannon's Entropy calculated for the number of events in the windows normalized by the total number of events for the overall time series. If a student only typed in a single window, the entropy would be 0. When maintaining a constant typing rate, entropy converges toward the maximum value of log(n).
Degree of Uniformity	Uniformity of the time series (Jensen-Shannon divergence method), which is a symmetric and bounded function of similarity that calculates the similarity between two distributions: a uniform probability distribution of 1/n (i.e., a constant typing rate) and the probability of key presses in a given window (i.e., the actual time series produced by the student).
Local Extremes	Number of time windows for which the direction of the evolution of keystroke events changes. This reflects inconsistency in writing rates across the windows.
Average Recurrence	Average recurrence of events across the time windows. This recurrence is expressed as the distances between time windows that contain at least one keystroke event. This measure is useful for identifying writing pauses. If each time window has at least one event, recurrence is 0, whereas if students take long pauses that occasionally result in time windows of 0 events, recurrence increases (if they write every two time windows, recurrence will be one).
StdDev Recurrence	Standard deviation of the recurrence across the time windows

Note: All time-sensitive keystroke indices were calculated

Allen et. al. (2016), {ENTER}ing the Time Series {SPACE}: Uncovering the Writing Process through Keystroke Analyses, 9th International Conference on Educational Data Mining, Raleigh, NC, June 2016

The Eyes Have It: Gaze-based Detection of Mind Wandering during Learning



Modest results to date . . .

Table 1. Eye-gaze features

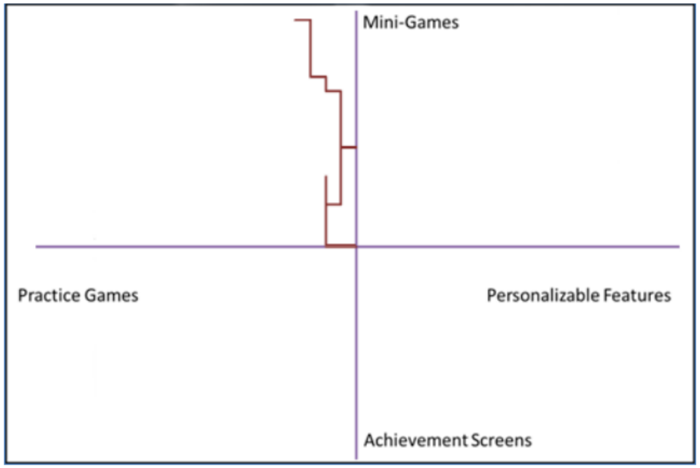
Fixation Duration	duration in milliseconds of fixation
Saccade Duration	duration in milliseconds of saccade
Saccade Length	distance of saccade
Saccade Angle Absolute	angle in degrees between the x-axis and the saccade
Saccade Angle Relative	angle of the saccade relative to previous gaze data.
Saccade Velocity	Saccade Length / Saccade Duration
Fixation Dispersion	root mean square of the distances from each fixation to the average fixation position in the window
Horizontal Saccade Proportion	proportion of saccades with angles no more than 30 degrees above or below the horizontal axis
Fixation Saccade Ratio	ratio of Fixation Duration to Saccade Duration

Note. Bolded cell indicates that the total number, mean, median

Hutt et. al. (2016), {ENTER}ing the Time Series {SPACE}: Uncovering the Writing Process through Keystroke Analyses, 9th International Conference on Educational Data Mining, Raleigh, NC, June 2016

Gaming in education: Self regulation measured via pathways chosen

- Game based ITS offer players a lot of choice
- Analysis of pathways through a game's choices can categories behaviour as organised/systematic or disorganised.
- Directly related to self-regulation



Snow, Erica, et al. "Entropy: A stealth measure of agency in learning environments." Educational Data Mining 2014.

Data that is not about student . . .

What about our learning resources?

Predict ‘Liveliness’ in Educational Videos

Online educational videos have emerged as one of the most popular modes of learning in the recent years. Studies have shown that liveliness is highly correlated to engagement in educational videos.

classification accuracy of 86.08%

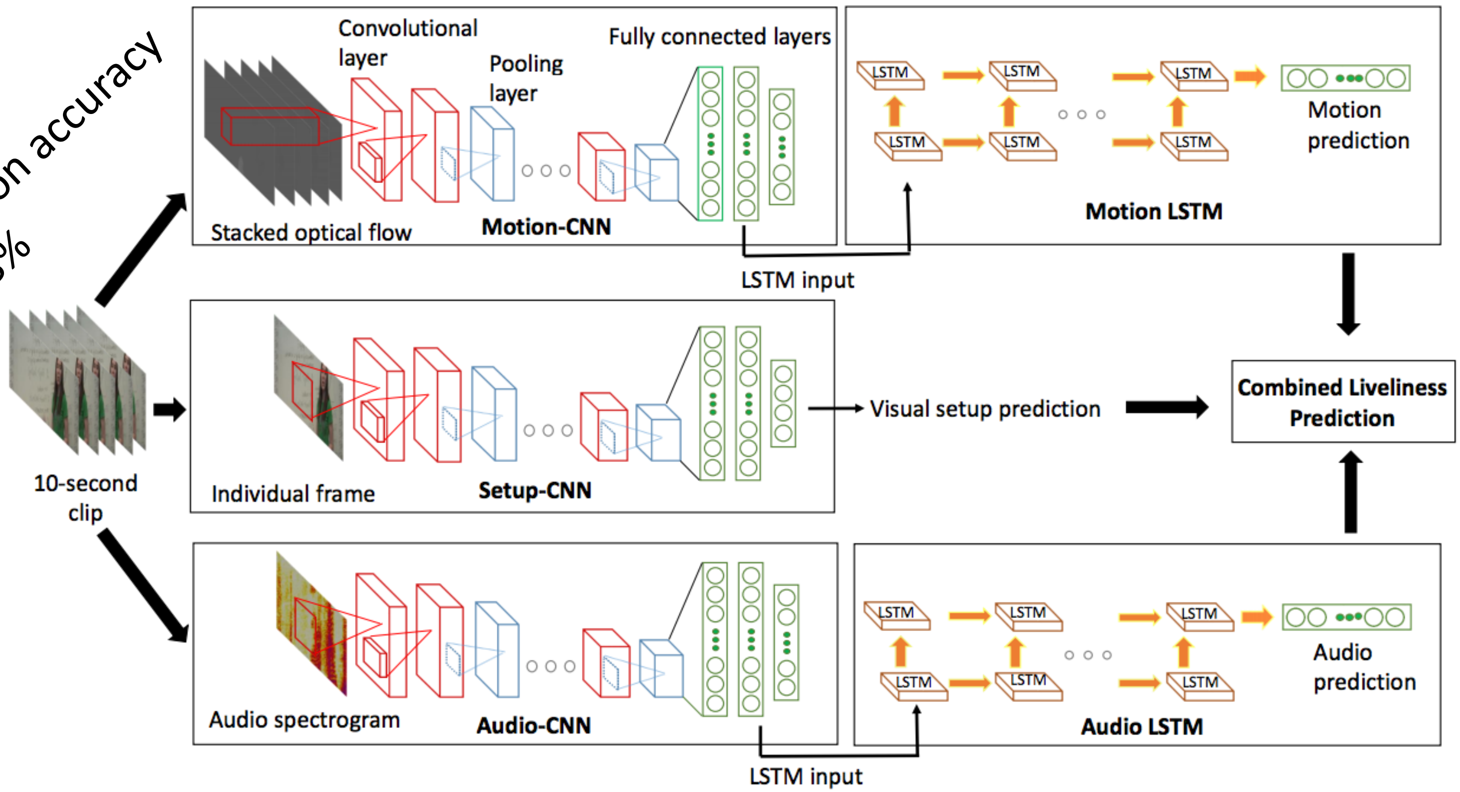


Figure 1: The overall pipeline of the proposed approach LIVELINET. The input to the system is a 10-second clip and output is the liveliness prediction label.

Sharma et. al. (2016), LIVELINET: A Multimodal Deep Recurrent Neural Network to Predict Liveliness in Educational Videos 9th International Conference on Educational Data Mining, Raleigh, NC, June 2016

In Summary

The first decade of Learning Analytics has focused more on technical systems than human ones

This represents a large gulf with what is known about best practices for Human-Computer Interaction Design

Consequently there is now great interest in involving the intended users of learning analytics in their design

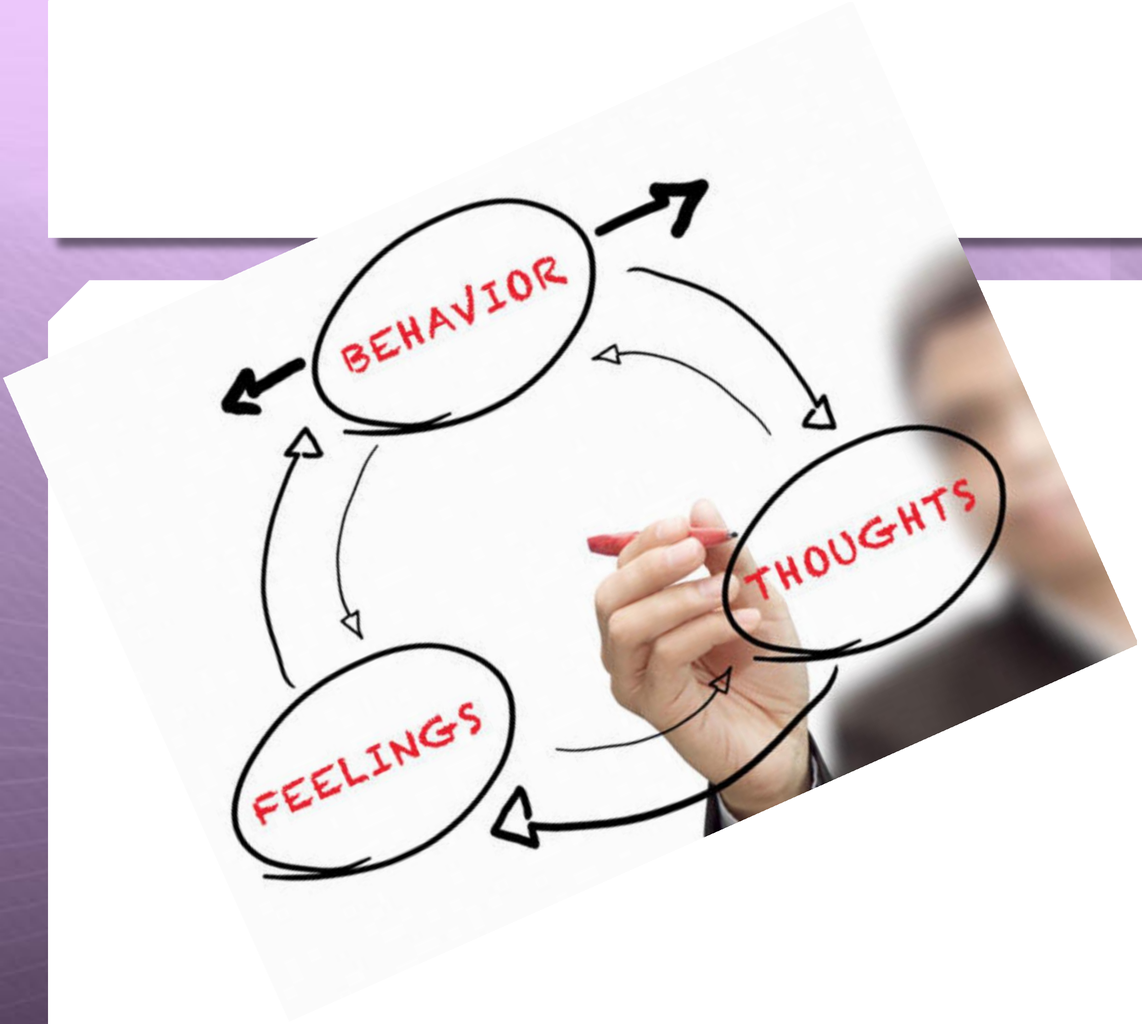
Spotlight on these issues in recent JLA Special Section on Human-Centred Learning Analytics

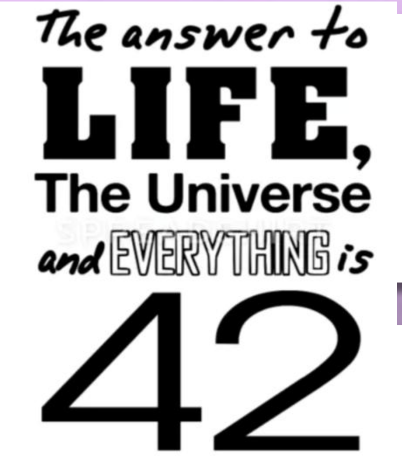
Prof. Alyssa Wise, NYU; SoLAR seminar series, Oct 2019 https://www.youtube.com/watch?v=VF1IkC6DJl8

Some limitations . . .

"There are three kinds of lies: lies, damned lies, and statistics."

British Prime Minister Benjamin Disraeli

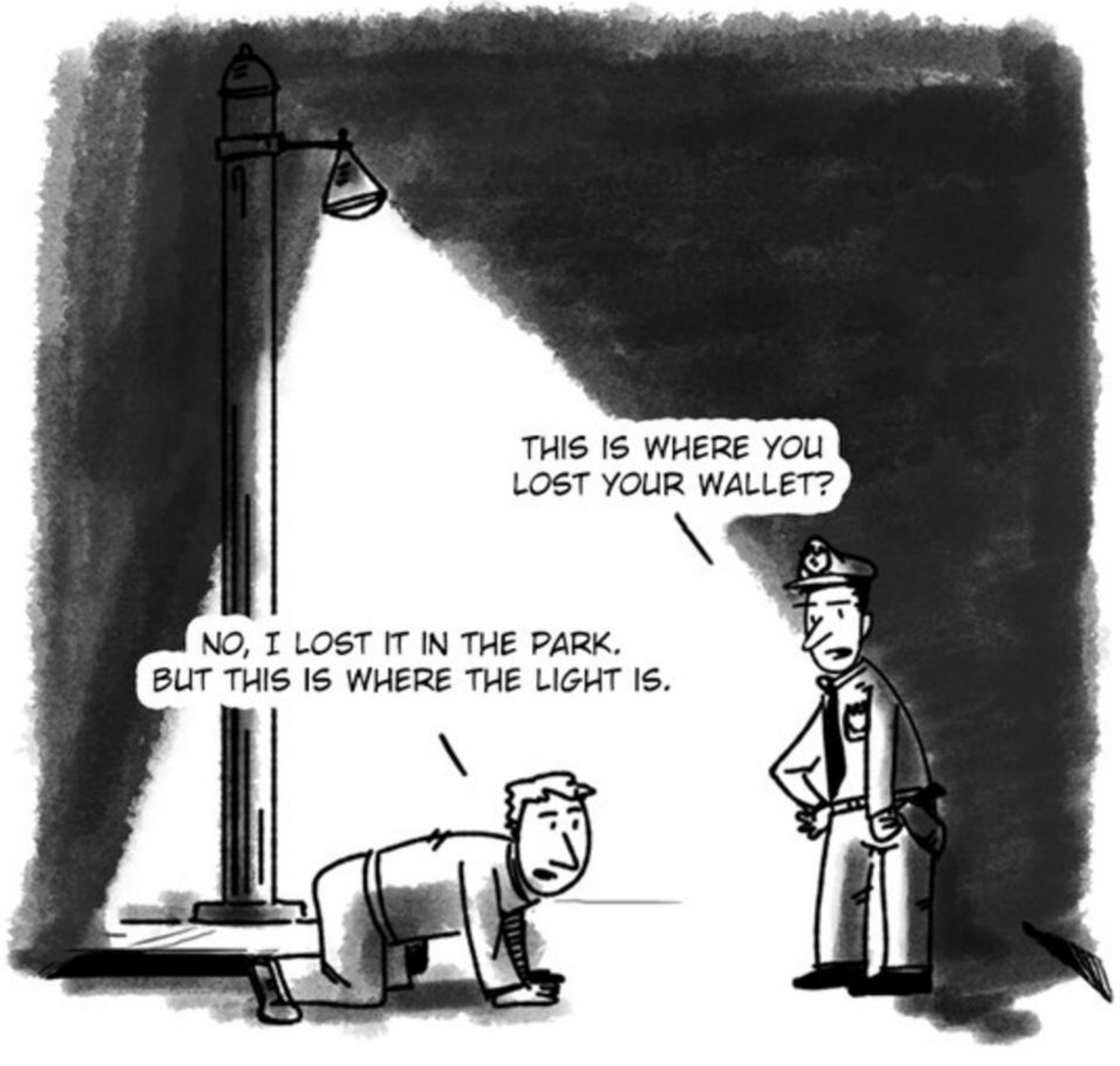




Is it correct or useful to depicting people as a vector of number?

Age	Gender	CAO points	1st year GPA
27	0	240	3.7

Street light effect . . .



Interpreting information correctly

"I've forgotten what this represents, but apparently we're terrible at it. So there's that."

"We're still not sure what happened here, but I think we can all agree that we're glad it's over."

Can people be pigeon-holed?

The wrong feedback?

"Giving mastery oriented students information about their poor performance relative to the rest of the class, it reduced their mastery behaviour and promoted shallow learning behaviour."

What is the right feedback?

Privacy and ethics in Learning Analytics

Ferguson, Rebecca, et al. "Guest editorial: Ethics and privacy in learning analytics." Journal of Learning Analytics 3.1 (2016): 5-15.

D — **DETERMINATION** – Why you want to apply Learning Analytics?
- What is the added value (Organisational and data subjects)?
- What are the rights of the data subjects (e.g., EU Directive 95/46/EC)

E — **EXPLAIN** – Be open about your intentions and objectives
- What data will be collected for which purpose?
- How long will this data be stored?
- Who has access to the data?

L — **LEGITIMATE** – Why you are allowed to have the data?
- Which data sources you have already (aren't they enough)?
- Why are you allowed to collect additional data?

I — **INVOLVE** – Involve all stakeholders and the data subjects
- Be open about privacy concerns (of data subjects)
- Provide access to the personal data collected (about the data subjects)
- Training and qualification of staff

C — **CONSENT** – Make a contract with the data subjects
- Ask for a consent from the data subjects before the data collection
- Define clear and understandable consent questions (Yes / No options)
- Offer the possibility to opt-out of the data collection without consequences

A — **ANONYMISE** – Make the individual not retrievable
- Anonymise the data as far as possible
- Aggregate data to generate abstract metadata models (Those do not fall under EU Directive 95/46/EC)

T — **TECHNICAL** – Procedures to guarantee privacy
- Monitor regularly who has access to the data
- If the analytics change, update the privacy regulations (new consent needed)
- Make sure the data storage fulfills international security standards

E — **EXTERNAL** – If you work with external providers
- Make sure they also fulfil the national and organisational rules
- Sign a contract that clearly states responsibilities for data security
- Data should only be used for the intended services and no other purposes

1.	Use data to benefit learners
2.	Provide accurate and timely data
3.	Ensure accuracy and validity of analyzed results
4.	Offer opportunities to correct data and analysis
5.	Ensure results are comprehensible to end users
6.	Present data/results in a way that supports learning
7.	Gain informed consent
8.	Safeguard individuals' interests and rights
9.	Provide additional safeguards for vulnerable individuals
10.	Publicize mechanisms for complaint and correction of errors
11.	Share insights and findings across digital divides
12.	Comply with the law
13.	Ensure that data collection, usage, and involvement of third parties a
14.	Integrate data from different sources with care
15.	Manage and care for data responsibly
16.	Consider how, and to whom, data will be accessible
17.	Ensure data are held securely
18.	Limit time for which data are held before destruction and for which c
19.	Clarify ownership of data
20.	Anonymize and de-identify individuals
21.	Provide additional safeguards for sensitive data

So is it worth it?

Benefits of learning analytics

1. Scalable

2. Inclusive

3.Personalisable

Bring understanding to learning and teaching practices.
Disruptive innovation to improve the quality of the student learning experience

G. Gray

Getting started…

What evidence does the data provide

How do we get from **DATA**……. to INFORMATION ?

The data we collect currently:

- Generally:
  - Exam grades
  - Logs from centrally resourced technologies
  - Library accesses
  - Enrollment data
- From collaborative software
  - Interactions
  - Social networks

The latent constructs we want to measure:

- Improvement in the **learning experience**
- Improvement in the **quality** of **learning**
  - Effective learning disposition: persistence; self-regulation; deep learning; creativity; . . . .
  - Affective state: boredom, engagement

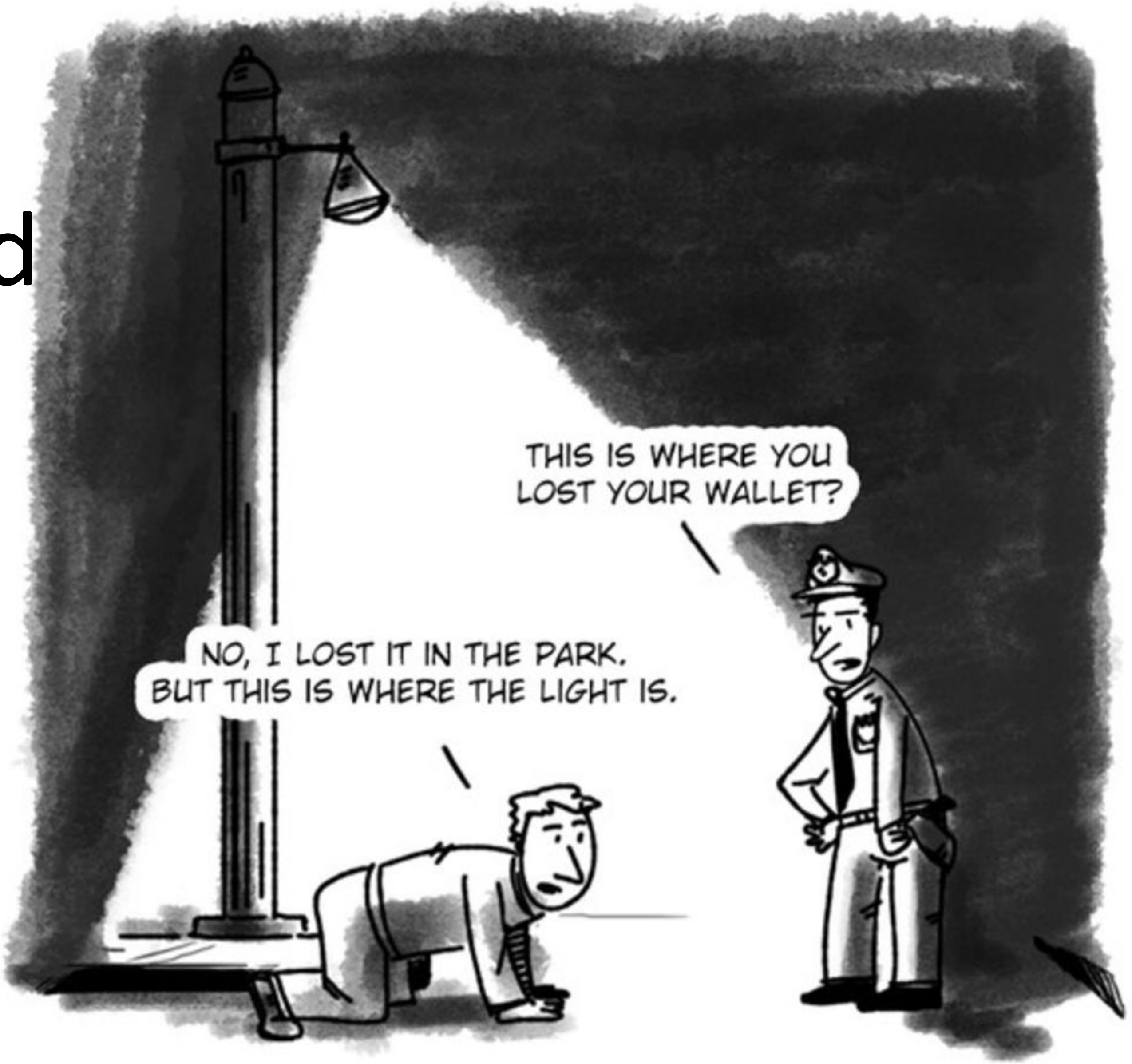
What do we **COUNT?**

What can we INFER from COUNTS?

How do we get from the INFORMATION we want, to the **DATA** we need to collect?

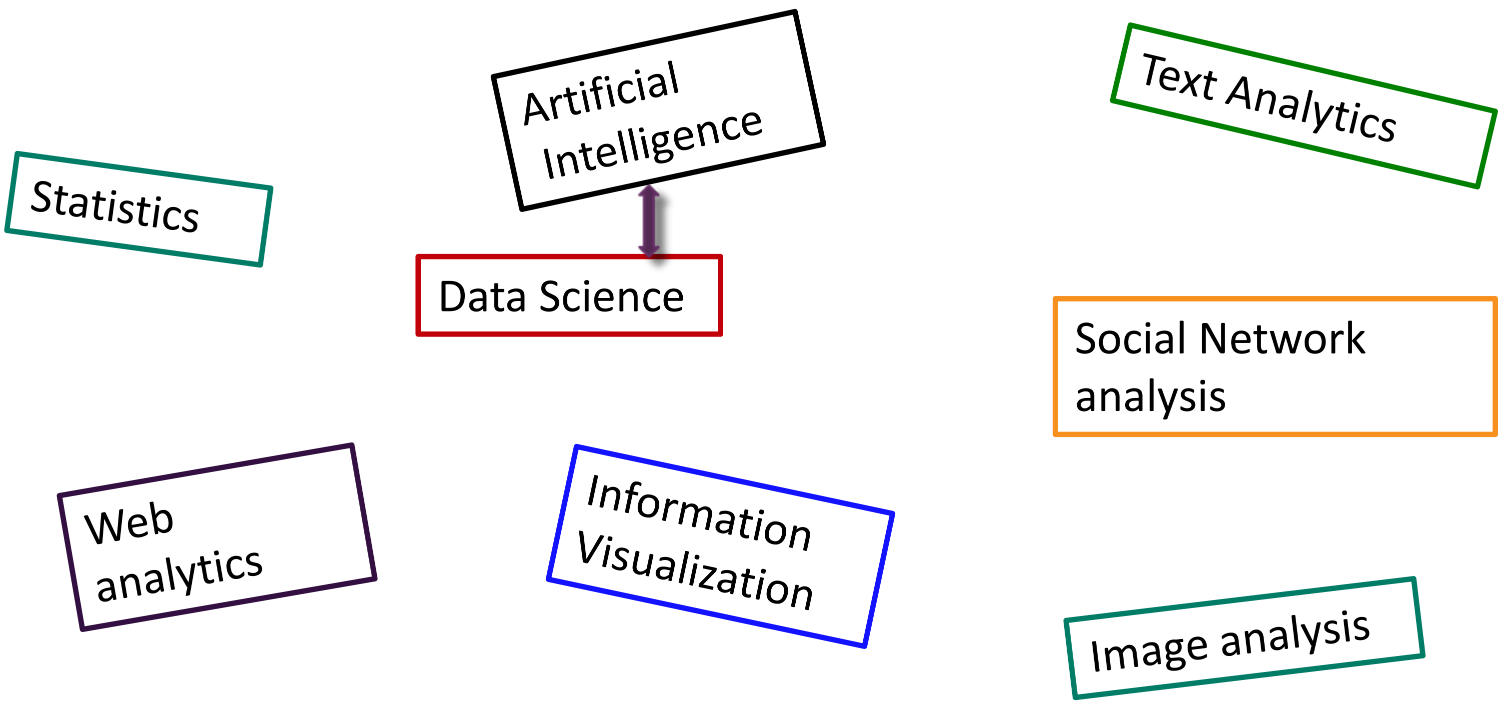
What could we count?

Back to the street light effect . . .



How do we translate counts into information, and for whom?

Student facing analytics; staff facing analytics; both?



Who is responsible for acting on the information <u>suggested by</u> learning analytics?

- How are the results used, and by whom?
- How is this resourced?

ORLA project, NF: https://www.teachingandlearning.ie/orla

DALTAÍ project (Developing all Learners Through Analytics: https://daltai-he.ie/

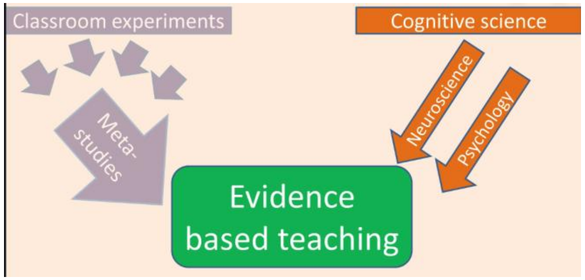
In conclusion. . . .

1) What are we trying to accomplish?

2) How will we know that a change is an improvement?

3) What change can we make that will result in improvement?

Answering these deceptively simple questions is complex work, and central to that work is the role of measurement.



Krumm et al (2016). Practical measurement and productive persistence: Strategies for using digital learning system data. *Journal of Learning Analytics*, 3(2), 116–138.

Your turn . . .

Based on staff focus groups template, SHEILA project framework: https://sheilaproject.eu/

1. What Data is useful….:
   - What are legitimate purposes for the college to use student data?
   - What kind of information would be useful for you in your professional development?
   - What kind of information would be useful for you in improving the student experience?
2. Policy
   - Do your policies cover these uses?

Your turn . . .

Based on staff focus groups template, SHEILA project framework: https://sheilaproject.eu/

3. What training would be useful to enable you engage with student data?
4. Do you have concerns about incorporating learning analytics into your job?
5. How do you think staff should approach acting on output from learning analytics?
   - Module level / programme level