

LEARNING ANALYTICS: DREAM OR NIGHTMARE?

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In this talk I'm going to give a heads-up, very briefly, on some of the fundamental concerns that arise as we seek to lay the foundations for the field of learning analytics, and hone the ways in which we communicate it to different stakeholders in the education ecosystem, from national policymakers to individual learners.

Some concerns about the limits of big data and analytics are from educators, some from learners, and some are academic, in the very best sense of the word: deeply reflective analyses of the limits of computational categorization infrastructures.

Whether or not we see dream or nightmare scenarios unfolding, will depend on whether we go in with our eyes wide open to these.

I'm going to argue that ultimately, the emerging learning analytics infrastructure presents the perfect opportunity to ask what we're trying to accomplish as educators.

OVERVIEW

- Let me tell you a story...
- SciTech Studies 101
 - Data and Analytics are not neutral: someone defines them, and someone interprets them
- Educators and researchers concerns
 - The most important kinds of learning can't be quantified
 - This is my new performance indicator?
- *Learning Analytics?*
 - Beyond BusinessAnalytics.edu?
- Why are social learning analytics significant?
 - Strategically important learning for C21
 - Informal+formal learners in control



LEARNING ANALYTICS IN ENGLISH SCHOOLS

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Contextual Value Added Key Stage 1 to 2 : by subject

Analysis in this section focuses on the contextual value added for the National Curriculum core subjects (English, mathematics and science) in the current year. For all of the subject-based CVA analysis, prior attainment used in the CVA models was based on a combination of reading, writing and mathematics at Key Stage 1. A 95% confidence interval is shown. Where the confidence interval does not cross the national average line the school value differs significantly from that national average.

Chart 2.1.12

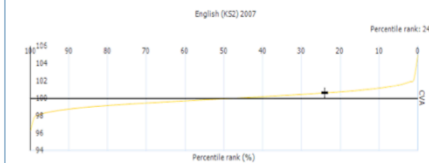
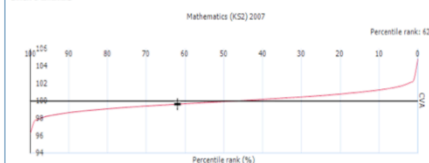


Chart 2.1.13



English	Cohort for CVA	72	76	64
	CVA School score	97.4	↓ 98.9	↑ 100.6
	95% confidence interval +/-	0.5	0.5	0.5
	Significance	Sig-	Sig-	Sig+
	Percentile rank	100	87	24
	Coverage	94%	94%	96%
Mathematics	Cohort for CVA	71	76	64
	CVA School score	98.4	98.6	99.6
	95% confidence interval +/-	0.6	0.6	0.6
	Significance	Sig-	Sig-	
	Percentile rank	93	91	62
	Coverage	92%	94%	96%

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In England we have a government driven analytics programme that results in the publication of school league tables in the national papers. A very public 'naming and shaming'.

Very high stakes: Headteachers lose their jobs if they are deemed to be failing for too long against these criteria. English pupils are amongst the most summative tested in the world, from the age of 8.

I know this is a further/higher education forum, but not only will this probably be coming to you soon — schools will be passing you their pupils' analytics to help you decide whether to give them a place.

LEARNING ANALYTICS IN ENGLISH SCHOOLS

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Education

Chart 2.1.22

For 2007 results, Mathematics (KS2)

The chart shows the proportion of pupils achieving level 4 or above in Key Stage 2 Mathematics (KS2) and for those who did not reach this threshold how they have progressed since Key Stage 1.



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This screen shows one of the visual analytics provided to schools, colour-coding student progress. Quite helpful, right?

Now let me tell you about Joe. When Joe arrived at the school, he was about as disengaged as they come, and would often literally fall asleep in class.

He could be aggressive to staff and peers with very little provocation.

He would show up perhaps 3 days/week.

His grades were a year behind what they should have been.

But he's one of the school's success stories: now his attendance is at 97%, his appetite to learn is insatiable, and he mentors peers who are like he was on arrival.

He's actually making faster progress than some of his more academic peers who are cruising and not stretching themselves.

Which one of these blue students is he?

None – he's the purple one "FALLING BEHIND", because on this analytic, he's way short of hitting what's been deemed to be 'normal'.

WILL OUR ANALYTICS REFLECT THE PROGRESS THAT 'JOE' HAS MADE ON SO MANY OTHER FRONTS – BUT NOT HIS SATS?

Chart 2.1.22
For 2007 results, Mathematics (KS2)

The chart shows the proportion of pupils achieving level 4 or above in Key Stage 2 Mathematics (KS2) and for those who did not reach this threshold how they have progressed since Key Stage 1.

Key

- Level 4 or above
- Level 3
- Level 2
- Level 1
- Level 0
- Did not reach level 1 at KS1
- Did not reach level 0 at KS1
- Did not reach level 0 at KS1

1 Falling Behind

...an average of 6,440 ... to the child ... research indicates ... other forms of ... ider-reported and ... concordant with what ... people – many of ...

'I'm sick of Mum beating me, so I've run away, but I don't know where to go.'

...ing in drink or the prevalence of physical abuse in the UK.

...one-third suffer ... Other research has ... of 11-year-olds ... weekly, and that ... parents report hitting ... such as belts, slippers

...he third most common ... Childline, UK-wide ... cal violence is most ... hosen too young to ... toddlers are ... physical abuse, ... on child ... arch in England ... ants under the ... risk of being ... other person ... the age ... cidence of ... der

www.childline.org.uk

It's no wonder Joe falls asleep. He's often up several times a night feeding his baby sister while his mother is in a drugged sleep.

He was found by the police recently on the streets at 3am, on his way to collect drugs for her. The school regularly has to give him breakfast.

WHY AM I TELLING YOU THIS STORY?

It encapsulates some of the concerns that educators have about the misuse of blunt, blind analytics — proxy indicators that do not do justice to the complexity of real people, and the rich forms that authentic learning take.

Some of these concerns will be very pragmatic and reflect past managerial initiatives to define performance indicators: am I about to be judged by a blunt, blind set of analytics that does not reflect the genuine progress that I and my students are making?

I give another example of how analytics could be completely misread (from a videoconference seminar) <http://bit.ly/tPxlvu> (slide 41)

Moreover... in case anyone momentarily forgot, we are deep in an educational crisis in many of the 'developed countries': In his opening address, George Siemens reminded us of the scale of this with one graph <http://www.slideshare.net/gsiemens/eli-2012-sensemaking-analytics> (slide 3).

We summarise some of the shocking literature on disengagement — both active and passive in <http://oro.open.ac.uk/32823>. See also the Innovation Unit Learning Futures programme <http://bit.ly/qqwIZM>

Big questions need asking about our educational system's fitness for purpose. The EDUCAUSE supported NGLC are leading the charge on this front.

MEASUREMENT TOOLS ARE NOT NEUTRAL

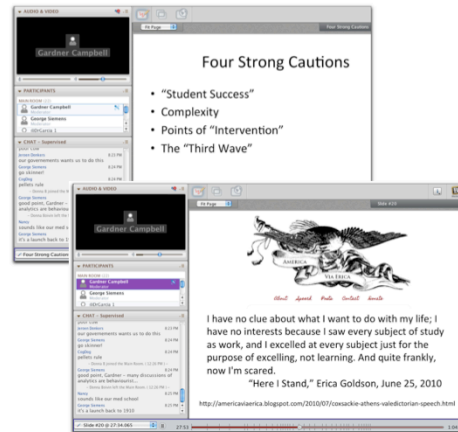
‘accounting tools...do not simply aid the measurement of economic activity, they shape the reality they measure’

Du Gay, P. and Pryke, M. (2002) Cultural Economy: Cultural Analysis and Commercial Life, Sage, London. pp. 12-13



COMPUTING THE UNCOMPUTABLE?

- The dangers of computational reductionism for learning analytics
- Gardner Campbell, LAK12 MOOC webinar
- <http://lak12.wikispaces.com/Recordings>



BEYOND BIG DATA HUBRIS

1. Automating Research Changes the Definition of Knowledge
2. Claims to Objectivity and Accuracy are Misleading
3. Bigger Data are Not Always Better Data
4. Not All Data Are Equivalent
5. Just Because it is Accessible Doesn't Make it Ethical
6. Limited Access to Big Data Creates New Digital Divides

boyd, d. and Crawford, K. (2011). **Six Provocations for Big Data.**
Presented to: *A Decade in Internet Time: Symposium on the Dynamics
of the Internet and Society*, Oxford Internet Institute, Sept. 21, 2011.
http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1926431



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An incisive critique of Big Data Hubris.

BOTTOM LINE: Don't forget that those pretty visual analytics on your dashboard are NOT OBJECTIVE: they're the product of a multiplicity of decisions at EVERY step of the data cycle – slide 7 from George Siemens <http://www.slideshare.net/gsiemens/eli-2012-sensemaking-analytics>

ANALYTICS PROVIDE MAPS = SYSTEMATIC WAYS OF DISTORTING REALITY

“A marker of the health of the learning analytics field will be the quality of debate around what the technology renders visible and leaves invisible.”

Buckingham Shum, S. and Deakin Crick, R. (2012). **Learning Dispositions and Transferable Competencies: Pedagogy, Modelling and Learning Analytics**. *Proc. 2nd Int. Conf. Learning Analytics & Knowledge*. (29 Apr-2 May, 2012, Vancouver, BC). ACM Press: New York. Eprint: <http://oro.open.ac.uk/32823>



**DEAR STUDENT: HERE ARE YOUR NEW
PERFORMANCE INDICATORS...**



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I and many others have argued that Learning Analytics tools need to be placed in the hands of the learners, not simply used by educators and institutions to analyse them.

However, could we explore ways in which students co-design those analytics so that they're not a metric they try to game, but which they collectively value?

**DEAR STUDENT: HERE ARE YOUR NEW
PERFORMANCE INDICATORS...**

**DEAR COLLEAGUE: HERE ARE YOUR NEW
PERFORMANCE INDICATORS...**



**DEAR STUDENT: HERE ARE YOUR NEW
PERFORMANCE INDICATORS...**

**DEAR COLLEAGUE: HERE ARE YOUR NEW
PERFORMANCE INDICATORS...**

**DEAR UNIVERSITY: HERE ARE YOUR NEW
PERFORMANCE INDICATORS...**



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Remember, in England school Headteachers are fired if they dip too low for too long on these indices: it doesn't matter if you're working in a catchment with huge social deprivation and with no control over student admissions, or in an affluent, selective admissions school. Such details are downplayed in the league tables, and in the school inspection regimes.



assuming we want to move beyond fight or flight,
what are the smart questions we should be asking?



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Assuming we don't want to simply freeze in the headlights of the oncoming juggernaut, what might be wise responses that move beyond fight or flight denial?

When I talk about going into analytics with our eyes wide open, I hope this is neither a Luddite reaction to technology, nor fundamentalist social science agonising about the problems of measuring anything.

We need a sophisticated approach for wielding these tools responsibly — with pedagogical, academic and ethical integrity.

If we don't take on board the kinds of critiques just mentioned, we leave ourselves wide open to charges of techno-centrism and extreme naivety:

- **From other academics, with whom academic researchers will need to engage effectively**
- **In case the views of academics don't particularly trouble you, remember they're also the faculty who you need to buy into these new tools**
- **But also from the students who may be offered these tools, or even required to use them when they appear in their LMS/VLE.**

So, what are some of the questions we should be actively debating?



Here's one way of framing the challenge: are we happy to take on board the wealth of tools and techniques developed for corporate Business Intelligence, and simply deploy them in an educational institution? **BusinessAnalytics.edu**

Or is there something special about learning and scholarship, generically and in subject-specific ways, which will lead to the development of a new breed of analytic tuned to educators' and learners' needs, and informed by sound educational practice and research? Such a breed of analytic might prove robust enough to power new kinds of **LearningAnalytics.com** services — middleware and visualization services to run on any LMS

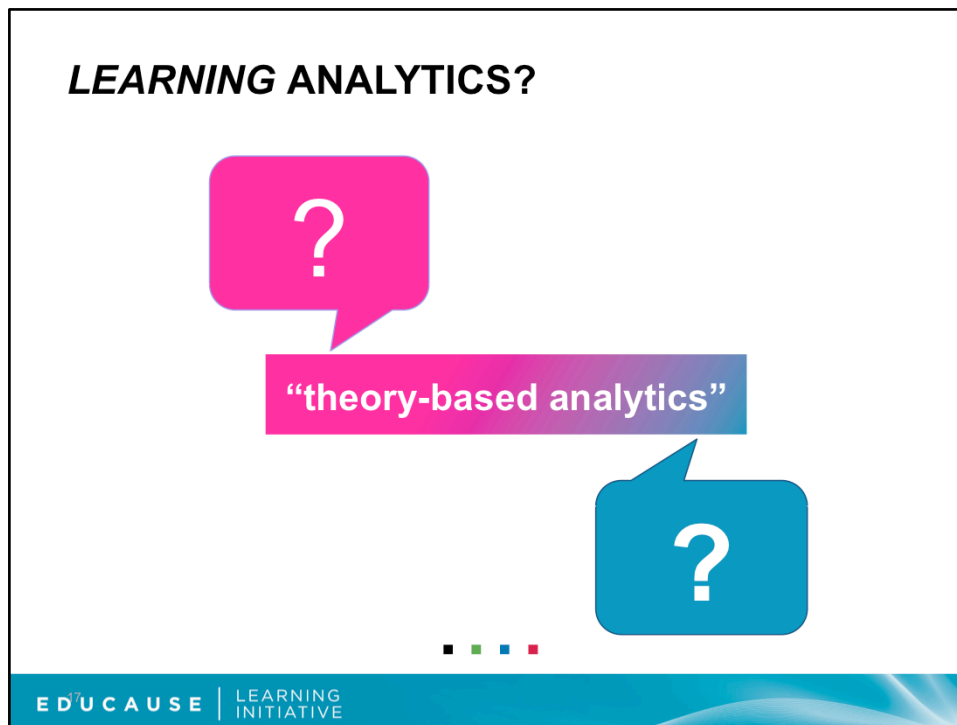
See the SoLAR white paper envisioning such as Open Learning Infrastructure which does not lock an institution into any single analytics provider: <http://www.solaresearch.org>



Of course, it may in fact be the productive marriage of the two, with **BusinessAnalytics.edu** being of most immediate help for institutional level Academic Analytics.

Let's make very concrete the difference: An organizational context means you connect inquirers with answers as fast as possible. In an enterprise Business Intelligence and collaborative knowledge sharing context, if a colleague, or a recommendation engine, knows you have an information need, and thinks you should know about a relevant resource, they recommend it. It would be unacceptable to reason, "I know you're stuck with this problem, but I'm not going to tell you about this great resource, because it's good for you to figure this out yourself!" (Of course peers do not always help each other, for personal and political reasons)

But in a learning context, leaving someone to figure it out is precisely what you might do, because giving them the answer shortcuts the vital building of cognitive and social capacities. So how would a recommender be different? And what counts as "good for you to figure it out"? And how long do you watch someone struggle? And what's the most effective way to help them? This is where educational practice and the learning sciences kick in.



So let's consider what puts the LEARNING into LA.

Given a 'theory' of learning (pink bubble) what implications might that have for analytics (blue bubble)?

LEARNING ANALYTICS?

Premise: ANY analytic is an implicit theory of the world, in that it is a model, selecting specific data and claiming it as an adequate proxy for something more complex

“theory-based analytics”



of the human decisions that shape every step in the analytics data cycle: slide 7 from George Siemens <http://www.slideshare.net/gsiemens/eli-2012-sensemaking-analytics>

LEARNING ANALYTICS?

So for “Theory”, let’s include assumptions, as well as evidence-based findings, statistical models, instructional methods, as well as more academic “theories”

“theory-based analytics”

The question is whether this has INTEGRITY as a meaningful indicator, and WHO/WHAT ACTS on this data

LEARNING ANALYTICS?

A theory might tell you WHAT to attend to as significant/interesting system behaviour.

“theory-based analytics”

The analytics task is to meaningfully MINE from data, or ELICIT from learners, potential indicators in a computationally tractable form

LEARNING ANALYTICS?

A mature theory will tell you WHY a given pattern is significant system behaviour.

“theory-based analytics”

This might help in guiding how to
MEANINGFULLY, ETHICALLY PRESENT
ANALYTICS to different stakeholders,
aware of how they might react to them

LEARNING ANALYTICS?

A mature theory validated by pedagogical practices will tell you APPROPRIATE INTERVENTIONS to take given particular learner patterns

“theory-based analytics”

If formalizable, analytics might then be coupled with recommendation engines or adaptive system behaviours

LEARNING ANALYTICS?

A theory can shed new light on familiar data

“theory-based analytics”

This might equate to reinterpreting business analytics through a learning lens



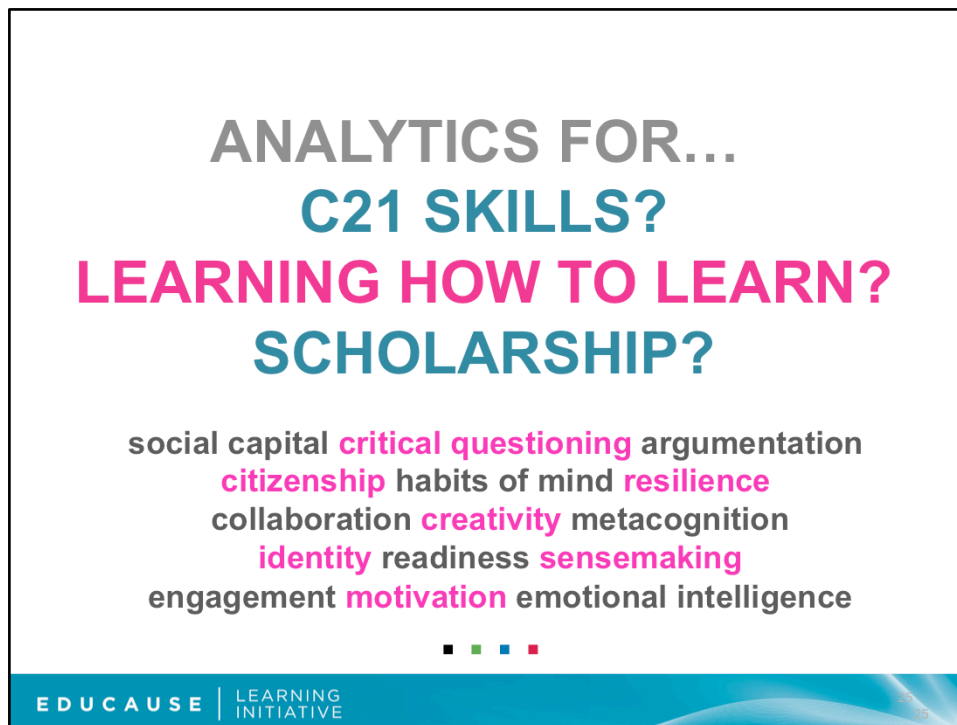
e.g. interpreting a social network visualization differently when you know this is a particular cohort of learners who are getting to know each other, not a high performing organizational team. A theory of effective social learning and group structure might inform which nodes in the network you attend to first, and how you intervene.

LEARNING ANALYTICS?

A theory might also predict future patterns based on a causal model

“theory-based analytics”

This might be formalizable as a predictive statistical model, or an algorithm in a rec-engine



I'd like to argue that we're not here merely to ask how can analytics help us do what we've always done at college and university.

The data, and political and business leaders, tell us that our education system is in crisis — no longer fit for purpose.

A potential disruptive innovation such as the emerging data and analytics infrastructure invites us to ask deep questions about the mission of further and higher education in these complex times.

And only then how can we ask how analytics help us realise that vision?

So while we can't measure all that's valuable, one thing big data and complexity science seem to confront us with is that things we never thought were measurable are.

To the extent that we try to measure what we value in analytics, "Your Analytics are Your Pedagogy"

And returning to Joe's story at the start, for deeply disengaged students, what does learning analytics have to offer? Real time, high definition visual analytics that tell you moment by moment how poor your performance is compared to the target standard, and to how your peers are doing, are not exactly motivating!...

**ANALYTICS THAT EQUIP FOR MANAGING
COMPLEXITY AND LIFELONG, LIFEWIDE LEARNING?**

“The test of successful education is not the amount of knowledge that pupils take away from school, but their appetite to know and their capacity to learn.”

Sir Richard Livingstone, 1941



**ANALYTICS THAT EQUIP FOR MANAGING
COMPLEXITY AND LIFELONG, LIFEWIDE LEARNING?**

“We are preparing students for jobs that do not exist yet, that will use technologies that have not been invented yet, in order to solve problems that are not even problems yet.”

“Shift Happens”

<http://shifthappens.wikispaces.com>



THINK ABOUT THE BEST LEARNERS YOU'VE KNOWN...

- Not necessarily the highest grade scorers — but the ones who loved learning, made really good progress, and did well after their studies.

What qualities come to mind?



THINK ABOUT THE BEST LEARNERS YOU'VE KNOWN...

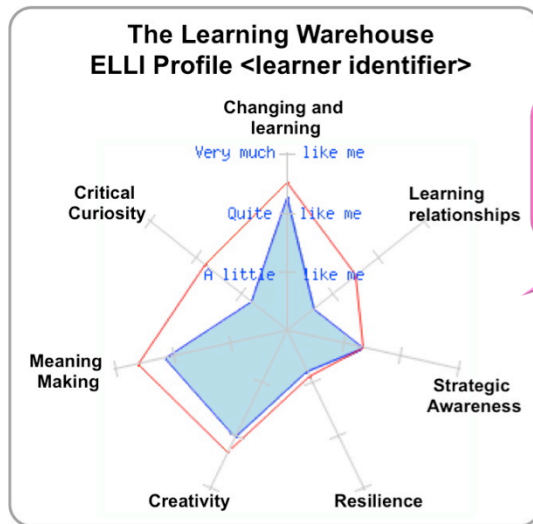
- Not necessarily the highest grade scorers — but the ones who loved learning, made really good progress, and did well after their studies.

What qualities come to mind?

Type them in the text chat window...



VISUAL ANALYTIC REFLECTING BACK TO LEARNERS HOW THEY SEE THEMSELVES

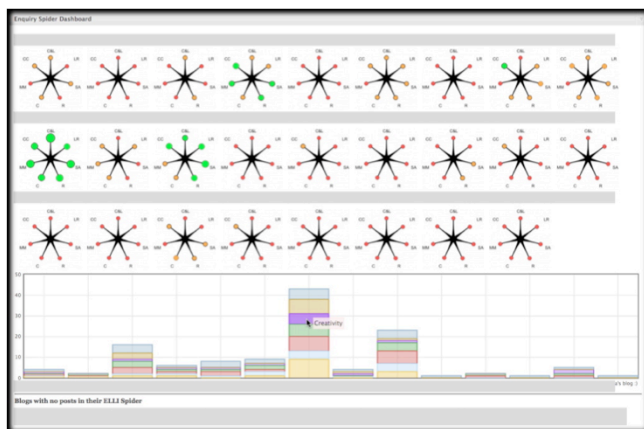


Learning dispositions can be modelled as a 7-dimensional construct, validated in numerous ways

Bristol and Open University are now embedding this in learning analytics

Buckingham Shum, S. and Deakin Crick, R. (2012), Learning Dispositions and Transferable Competencies: Pedagogy, Modelling and Learning Analytics. *Proc. 2nd Int. Conf. Learning Analytics & Knowledge*, (29 Apr-2 May, 2012, Vancouver, BC), ACM Press: New York. Eprint: <http://oro.open.ac.uk/32823>

ENQUIRYBLOGGER: COHORT DASHBOARD



Ferguson, R., Buckingham Shum, S. and Deakin Crick, R. (2011). **EnquiryBlogger: using widgets to support awareness and reflection in a PLE Setting**. In: *1st Workshop on Awareness and Reflection in Personal Learning Environments. PLE Conference 2011*, 11-13 July 2011, Southampton, UK. Eprint: <http://oro.open.ac.uk/30598>

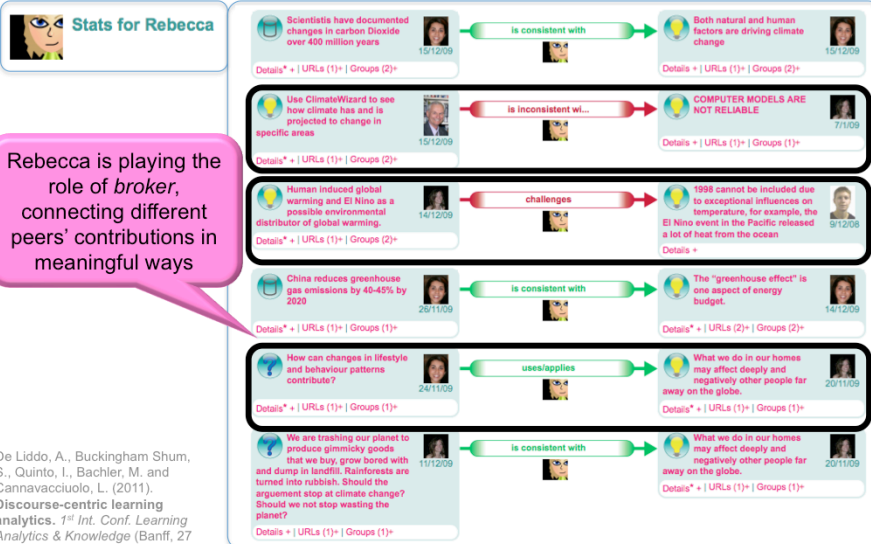


Analytics for learning conversations



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KMI'S COHERE: A WEB DELIBERATION PLATFORM ENABLING SEMANTIC SOCIAL NETWORK AND DISCOURSE NETWORK ANALYTICS



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AN AGENT REPORTS A CONNECTION OF INTEREST



Network Search Agent on: Top ten claims of climate sceptic dep 1

Search connection network on my data starting from **What are the top ten claims of climate sceptics?**

Following links of type: responds to

In both directions, to a depth of 1

Looking for new connections added after: 08 Sep 2010 - 14:11

Network

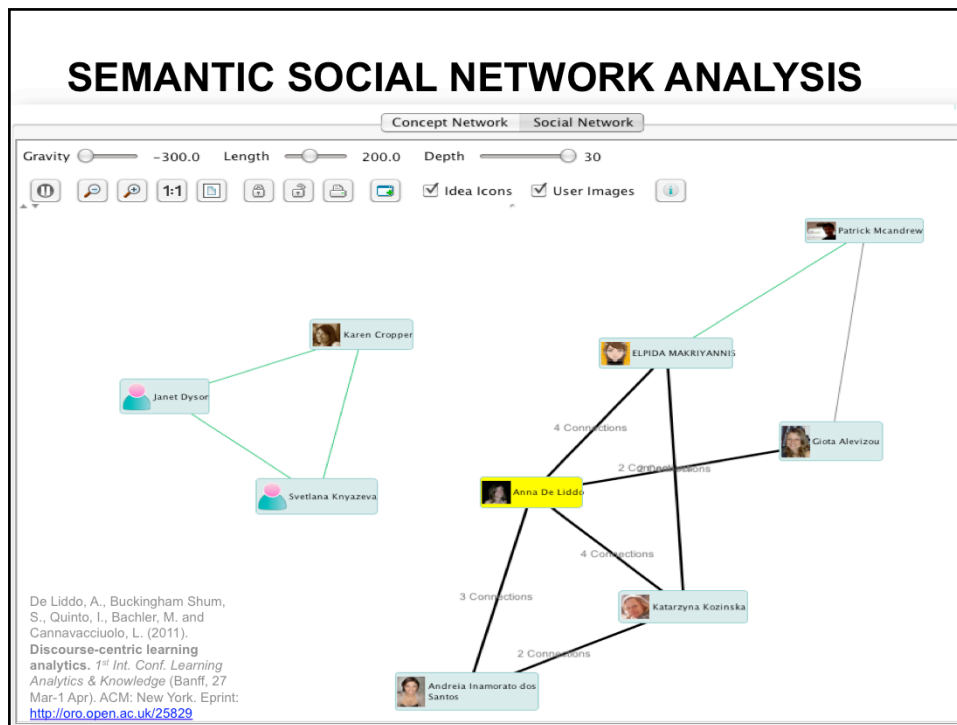


Gravity Length Depth



De Liddo, A., Buckingham Shum,
S., Quinto, I., Bachler, M. and
Cannavacciuolo, L. (2011).
Discourse-centric learning
analytics, 1st Int. Conf. Learning
Analytics & Knowledge (Banff, 27
Mar-1 Apr). ACM: New York. Eprint:
<http://oro.open.ac.uk/25829>





the social network maps the pattern of relationships among actors. In particular, we considered the users as nodes and we measured the edge between two users by counting the times that a user created a semantic connection that targeted a post authored by another user.

applies the main structural measures of SNA to Cohere' discourse network in order to analyze the typology of network which emerges from the online discussions.

Out degree measures the users' activity level;

In degree is a sort of indirect measure of quality and relevance of a user's posts.

In the table (Table 5), we show the results that emerge from the analysis of OLnet group social network.

ANALYTICS FOR IDENTIFYING EXPLORATORY TALK

Illuminate sessions can be very long – lasting for hours or even covering days of a conference

Whiteboard - Main Room (Scaled 94%)

Useful Links

- The Course Wiki
<http://climatechangecourse.wetpaint.com>
- sideCAP wiki (with resources)
sidecap.wetpaint.com

It would be useful if we could identify where quality learning conversations seem to be taking place, so we can recommend those sessions, and not have to sit through online chat about virtual biscuits

Ferguson, R. and Buckingham Shum, S. (2011). Learning Analytics to Identify Exploratory Dialogue within Synchronous Text Chat. *Proc. 1st Int. Conf. Learning Analytics & Knowledge*. Feb. 27-Mar 1, 2011, Banff. Eprint: <http://oro.open.ac.uk/28955>

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HUMAN AND MACHINE ANALYSIS OF A TEXT FOR KEY CONTRIBUTIONS

The primary goal of this project was to conduct an exploratory research study to determine if providing a professional development program using open education resources (OER) would help teachers begin to transform their curriculum and teaching through the use of technology. Our eight-year Maine Learning Technology Initiative (MLTI) experience had shown us that while providing laptops to all middle school teachers and students has had many positive impacts on schools, classrooms and learning, many mathematics teachers still had not fully integrated the laptop technology into their teaching. Accordingly, this research study was designed to determine the impacts of helping a group of middle school and high school mathematics teachers, through professional development with mathematics OER, to teach targeted algebra topics using technology.

Several key activities were undertaken in this project over an 18-month time period. First, we attempted to conduct an environmental scan to determine the challenges teachers encounter in using OER. Although the use of OER has grown quite extensively in higher education and K-12 settings in developing countries, OER use by K-12 teachers in the United States appears to be limited. The purpose of this activity was to explore why this was the case, to identify challenges teachers encounter in using OER, and to develop strategies for overcoming these challenges through our professional development program and research. This environmental scan consisted of several activities, including interviews with leading OER experts and proponents, surveys of teachers, and a limited number of focus groups. Through these activities we began to draw conclusions about the use of OER in K-12 school settings, and these conclusions are discussed below under Lessons Learned.

Comment (Paragraph 1): first sentence

Comment (Paragraph 2): context

Comment (Paragraph 3): goal (e.g. main, specific reasoning)

Comment (Paragraph 4): next (or return)

The primary goal of this project was to conduct an exploratory research study to determine if providing a professional development program using open education resources (OER) would help teachers begin to transform their curriculum and teaching through the use of technology. Our eight-year Maine Learning Technology Initiative (MLTI) experience had shown us that while providing laptops to all middle school teachers and students has had many positive impacts on schools, classrooms and learning, many mathematics teachers still had not fully integrated the laptop technology into their teaching. Accordingly, this research study was designed to determine the impacts of helping a group of middle school and high school mathematics teachers, through professional development with mathematics OER, to teach targeted algebra topics using technology.

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Document 1	19 sentences annotated	22 sentences annotated	
		11 sentences same as human annotation	
Document 2	71 sentences annotated	59 sentences annotated	
		42 sentences same as human annotation	

De Liddo, A., Sándor, Á. and Buckingham Shum, S. (2012, In Press). Contested Collective Intelligence: Rationale, Technologies, and a Human-Machine Annotation Study. Computer Supported Cooperative Work. Eprint: <http://oro.open.ac.uk/31052>

We see the preceding examples of Discourse Analytics and Social Network Analytics as instances of a broader, significant class we dub **Social Learning Analytics (SLA)**

These analytics are intrinsically social in nature, while others (e.g. Contextual and Dispositional Analytics) take on significant new dimensions when considered in a social context.

The article <http://oro.open.ac.uk/32910> sets out the rationale for why SLA are particularly important at this point given the societal trends and challenges:

- Explosive growth in **social media**
- The **open/free content paradigm**
- Evidence of a global shift in societal attitudes which increasingly **values participation**
- **Innovation** depends on reciprocal social relationships, tacit knowing

One of the most important forms of **Collective Intelligence (CI)** for our times is **Contested CI**: complex problems require diverse perspectives, visible discourse, and the mutual negotiation of strategies for wicked problems <http://oro.open.ac.uk/31052>

SUMMARY



Who gets to hold the magnifying glass?

<http://www.flickr.com/photos/somegeekintn/3709203268/>

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So, let's go in with our eyes wide open, aware of the various academic and political critiques, which all centre around the responsible wielding of the power to dictate what is measured and what happens as a consequence

SUMMARY



<http://www.flickr.com/photos/centralasian/6396004353/sizes/m/in/photostream/>

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So, possible answers to the talk's opening question: DREAM OR NIGHTMARE?...

At a time when many of us are questioning traditional forms of assessment, and education systems are increasingly deemed to be failing the next generation:

- the NIGHTMARE scenario is that:
 - Analytics freeze or even wind the clock back on all that we know about equipping learners for very complex turbulent times, simply because analytics are too blunt and myopic
 - Analytics impose forms of accountability that breed resentment on the part of institutions, educators and learners
 - Analytics pay no heed to the intrinsic limitations of computational data, mining and reasoning, which are not objective

The DREAM is that they:

- Provide an unprecedented evidence base to pilot and validate forms of learning on which students, educators and administrators are happy to be assessed
- Place a new generation of tools in the hands of learners to build their capacity for self-directed enquiry that prepares them to perform in extremely challenging organizational contexts, and to be lifelong, lifewide learners and citizens.
- Ultimately, accelerate the tectonic shifts needed to invent an education