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UNESCO Institute for Information Technologies in Education

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LEARNING ANALYTICS

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CONTEXT

"Analytics" is a term used in business and science to refer to computational support for capturing digital data to help inform decision-making. With the growth of huge data sets and computational power, this extends to designing infrastructures that exploit rapid feedback, to inform more timely interventions, whose impact can in turn be monitored. Organisations have increasingly sensitive 'digital nervous system' providing real time feedback on the external environment and the effects of actions.

Learning Analytics appropriates this concept for education: *what should a digital nervous system look like when the focus is on learning outcomes, and to extend the metaphor, what kind of 'brain' or collective intelligence is needed to interpret the signals and adapt the system's behavior accordingly?*

Big Data

As people and devices are increasingly connected online, society is generating digital data traces at an extraordinary rate, unprecedented in human history.[1, 2] Social computing, networked appliances, e-business transactions, mobile computing, wearable 'lifelogging' sensors, and environmental scanners generate billions of events per second, many of which are stored for later analysis, or can be analysed as a real-time data stream. The term "Big Data" is used to reflect that a quantitative shift of this magnitude is in fact a qualitative shift demanding new ways of thinking, and new kinds of human and technical infrastructure. This raises a host of opportunities and challenges for society at large, and for institutions seeking to make sense of this data. Critical debates are developing around what is required to ensure that society can convert this "new oil" into a public good by fostering new kinds of literacies and ethics, and combining commercial services with open data and services.[3, 4]

Business Intelligence

Within commercial sectors, the field of Business Intelligence (BI) is establishing itself, seeking to equip institutions so that they can identify meaningful patterns in the data, using an array of technologies including data integration, data mining, predictive modelling and information visualization.[5] However, technology alone is just part of the story: appropriately skilled analysts are needed to make sense of the data, in order to inform decision-making, but the pace of development is outstripping the supply of such people.[2] Given the talent gap, and the culture shift needed to share and integrate data across organisational silos, proper embedding of such infrastructure requires senior leadership coupled with communication and training, championed by 'BI competency centres'. All institutions face the economic and business pressures to do more with less, and be publicly accountable, and are understandably attracted to strategies claiming to enhance collective capacity to orchestrate data, use this to inform decisions, and evidence impacts.

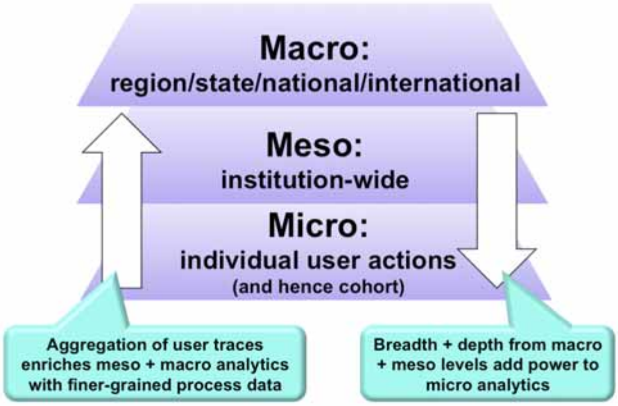
LEARNING ANALYTICS

Learning analytics has emerged as one of the most common terms for the community seeking to understand the implications of these developments for how we analyse learning data, and improve learning systems through evidence-based adaptation. The emerging conversation goes far beyond technologists (academic and commercial), to include researchers in education, leaders and policymakers, educational practitioners, organisational administrators, instructional designers, product vendors, and critically, the learners themselves (who are often the first adopters of new cloud applications, many of which make data available, and who are the primary consumers of certain kinds of learning analytic).

There are many good introductions to Learning Analytics, which add valuable perspectives.[6-10]

The Convergence of Macro, Meso and Micro-level Analytics

Learning analytics cover a wide range of analytic, which we will define as macro-, meso- and micro-levels:



- **Macro-level analytics** seek to enable cross-institutional analytics, for instance, through 'maturity' surveys of current institutional practices[11] or improving state-wide data access to standardized assessment data over students' lifetimes.[12] Macro-analytics will become increasingly real-time, incorporating more data from the finer-granularity meso/micro levels, and could conceivably benefit from benchmarking and data integration methodologies developed in non-educational sectors (although see below for concerns about the dangers of decontextualized data and the educational paradigms they implicitly perpetuate).

- **Meso-level analytics** operate at institutional level. To the extent that educational institutions share common business processes to sectors already benefitting from BI, they can be seen as a new BI market sector, who can usefully appropriate tools to integrate data silos in enterprise warehouses, optimize workflows, generate dashboards, mine unstructured data, better predict 'customer churn' and future markets, and so forth. It is the BI imperative to optimise business processes that partly motivates efforts to build institutional-level "academic analytics"[13], and we see communities of practice specifically for BI within educational organisations, which have their own cultures and legacy technologies.[14]

- **Micro-level analytics** support the tracking and interpretation of process-level data for individual learners (and by extension, groups). This data is of primary interest to learners themselves, and those responsible for their success, since it can provide the finest level of detail, ideally as rapidly as possible. This data is correspondingly the most personal, since (depending on platforms) it can disclose online activity click-by-click, physical activity such as geolocation, library loans, purchases, and interpersonal data such as social networks. Researchers are adapting techniques from fields including serious gaming, automated marking, educational data mining, computer-supported collaborative learning, recommender systems, intelligent tutoring systems/adaptive hypermedia, information visualization, computational linguistics and argumentation, and social network analysis.

As the figure shows, what we now see taking place is the integration of, and mutual enrichment between, these layers. Company mergers and partnerships show business intelligence products and enterprise analytics capacity from the corporate world being integrated with course delivery and social learning platforms that track micro-level user activity. The aggregation of thousands of learners' interaction histories across cohorts, temporal periods, institutions, regions and countries creates meso + macro level analytics with an unprecedented level of fine-grained process data (Scenario: comparing similar courses across institutions for the quality of online discourse in final year politics students). In turn, the creation of such large datasets begins to make possible the identification and validation of patterns that may be robust across the idiosyncrasies of specific contexts. In other words, the breadth and depth at the macro + meso levels add power to micro-analytics (Scenario: better predictive models and feedback to learners, because statistically, one may have greater confidence in the predictive power of key learner behaviours when they have been validated against a nationally aggregated dataset, than from an isolated institution).

EXAMPLES OF LEARNING ANALYTICS

As the preceding list demonstrates, this briefing cannot possibly represent the field evenly. The following examples hint at the breadth of learning analytics, with indications of their maturity. The *International Conference on Learning Analytics & Knowledge (LAK)* has archived proceedings and replayable presentations which are the best snapshot of the emerging state of the art[15] while *EDUCAUSE* is building a valuable resource bank and training events for educators/leaders/IT-administrators closer to immediate deployment options.[16] In contrast to BI companies who are trying to understand how their products map to the education market initially at the meso/macro-levels, educational startup companies are accelerating the pace at which learners will encounter micro-level analytics (e.g. the *Educational Innovation Summit*[17]).

An EDUCAUSE synthesis of emerging trends in 2012[9] identifies three kinds of predictors and indicators (*Dispositional, Activity & Performance,* and *Student Artifacts*), the key role of *Visualization* to support educational sensemaking (e.g. debate over what the analytics appear to be evidencing), and two kinds of interventions (*fully* and *semi-automated*).

LMS/VLE Analytics Dashboards

Concept. The first kinds of analytics that many institutions will encounter will be the analytics dashboards now appearing in most online learning platforms. This is essentially the impact of BI products on learning platforms. Until recently, data logs were not in a format that non-technical users could interpret, but these are now rendered via a range of graphs, tables and other visualizations, and custom reports designed for consumption by learners, educators, administrators and data analysts. More advanced functionality integrates data from other university systems (e.g. Helpdesk calls; Student Information Systems), and more powerful (but harder to learn) tools enable users to go beyond predefined reports and explore relationships between different variables. Learners may get basic analytics such as how they are doing relative to the cohort average (e.g. test scores, forum contributions, webinar participation). Some institutions are going further, and add additional information visualization products to assist in making sense of complex data, or enterprise-level analytics architectures from major vendors.

Examples. LMS/VLE vendors provide examples and webinars about their analytics dashboards, and the enterprise analytics/BI vendors are contextualizing their products to the education market.[18-24] A very useful compendium of higher education case studies is being compiled by EDUCAUSE, e.g. Arizona State University reports that it is seeing returns on its investment in academic and learning analytics, including a "Student 360" programme that integrates all that the institution knows about a student.[25]

Predictive Analytics

Concept. One of the more advanced uses of analytics that generates huge interest is the possibility that from the pattern of learners' static data (e.g. demographics; past attainment) and dynamic data (e.g. pattern of online logins; quantity of discussion posts) one can classify the trajectory that they are on (e.g. "at risk"; "high achiever"; "social learner"), and hence make more timely interventions (e.g. offer extra social and academic support; present more challenging tasks). Currently, one of the most reliable predictors of final exam results is still exam performance at the start of studies.[26, 27] The design of more complex data-driven predictive models must clearly improve on this, but requires statistical analysis to identify those variables in the data that can be historically validated as being the strongest predictors of 'success'. While at present these are most commonly defined as assignment/exam outcomes, the debate about assessment regimes (see below) draws attention to the role that analytics could play in providing formative feedback and the building of horizontal/transferable skills.

Examples. Work at Purdue University[28] on the *Course Signals* software is well known, and the technology is available as a product.[18] Signals provides a red/amber/green light to students on their progress. Their most recent evaluation reports: "Results thus far show that students who have engaged with Course Signals have **higher average grades** and **seek out help resources at a higher rate** than other students." University of Michigan report promising results with physics students from their E^2Coach infrastructure[26] which adapts personalised (open source) intervention technology[29] from validated health informatics research, to give customised feedback and motivate students to change their strategies. Paul Smith's college used Starfish EarlyAlert[30] to integrate staff feedback on students, and Rapid Insight tools[24] to build an accurate predictive model for identifying at-risk students.[31]

Models may be context-specific to the particular institution, culture, level of study, discipline, etc., or (most excitingly) may prove robust enough to generalise. The Predictive Analytics Reporting (PAR) Framework, developed and piloted with six US educational institutions, seeks to identify patterns in their collective student data. Initial results report a significant correlation between disenrollment and the number of concurrent courses in which students were enrolled.[32]

These approaches are designed for generic learning environments, agnostic to subject matter, but if one constrains the scope to a specific topic, new kinds of analytics are possible.

Adaptive Learning Analytics

Concept. Adaptive learning platforms build a model of a learner's understanding of a specific topic (e.g. algebra; photosynthesis; dental surgical procedures), sometimes in the context of standardised tests which dictate the curriculum and modes of testing. This enables fine-grained feedback (e.g. which concepts you have grasped and at what level), and adaptive presentation of content (e.g. not showing material that depends on having mastered concepts the learner has failed on). Naturally, dynamic modelling of learner cognition, and preparation of material for adaptive content engines, are far more resource intensive to design and build than conventional 'dumb' learning platforms. However, there is robust research evidence of the impact that such approaches can have, given the personalization that is possible.[33]

Examples. Significant research and investment in intelligent tutoring systems and adaptive hypermedia are bringing web platforms to market with a high quality user experience, and this is likely to continue to be a growth area. Examples include the free Open Learning Initiative[34] courses based on Carnegie Mellon University's research, and commercial services such as Grockit and Knewton.[35, 36]

Social Network Analytics

Concept. Social network analysis (sometimes called Organisational Network Analysis in corporate settings) makes visible the structures and dynamics of interpersonal networks, to understand how people develop and maintain these relations. People may form 'ties' of different sorts, ranging from extended, direct interaction reflecting significant ties, to more indirect ties. Research is beginning to demonstrate that the connections learners forge with each other, and the resulting group structures, can correlate with more or less effective learning.[37, 38]

Examples. "Enterprise 2.0" products can be used to identify the most active users in an online network, and those who are likely to have most influence on the activity of others.[39] There are numerous free tools for interactive visualisation and analysis of networks.[40] One tool specifically designed for learning networks is SNAPP[41] which renders discussion forum postings as a network diagram to help trace the growth of a cohort, identify disconnected students, or visualise how teacher support is employed within the network. Another is NAT, designed to help teachers see their offline social networks, which annotates social ties with the relevant topics.[42]

Discourse Analytics

Concept. It is simple for a learning platform to count how many times a learner has executed basic actions such as logging in, viewing a forum and posting a message: this is the level at which most current analytics products operate. However, analytics could go beyond simple quantitative logs, and provide feedback to educators and learners on the *quality* of the contributions. Researchers are beginning to draw on extensive prior work on how tutors mark essays and discussion posts, how spoken and written dialogue shape learning, and how computers can recognize good argumentation, in order to design analytics that can assess the quality of text, with the ultimate goal of scaffolding the higher order thinking and writing that we seek to instill in students.

Examples. Discourse analytics specifically tuned for learning[31, 32] or sensemaking in contested domains[43, 44] are at the stage of research prototypes. There are numerous open source research platforms[45] and enterprise grade products[46] capable of analysing written and spoken natural language to assist computational reasoning, but they have not been designed with learning specifically in mind. As such, they represent raw technologies with intriguing possibilities for learning analytics researchers to contextualize to education.

IMPACT AT DIFFERENT LEVELS

Given the multiple levels at which Learning Analytics operate, and the rich diversity of numerical, textual and semantic data that different techniques process, their impact on higher education could be profound when implemented systemically, with sound pedagogical design and the necessary staff development to turn raw technologies into useful tools. In one briefing summarised below, several forms of impact are proposed, which are grouped using this briefing's three-level scheme:[8]

Micro-level benefits:

- Identify at-risk learners and provide interventions.
- Provide learners with insight into their own learning habits and give recommendations for improvement.

Meso-level benefits:

- Improve administrative decision-making and organizational resource allocation.
- More transparent data and analysis could create a shared understanding of the institution's successes and challenges.
- Make better sense of complex topics through combinations of analytics (e.g. from social, technical and information networks).
- Support holistic decision-making through better understanding the impact of different variables.
- Increase organizational productivity by providing up-to-date information and allowing rapid response to challenges.
- Help leaders determine the hard (e.g. patents, research) and soft (e.g. reputation, profile, quality of teaching) value generated by faculty activity.

Macro-level benefits:

- Ultimately the above might transform the college/university system, as well as academic models and pedagogical approaches.

Learning: Towards a Data-Driven Science?

This last point merits further elaboration. Other scientific fields are being transformed by big data and automated analytics, introducing data-driven exploratory methodologies, and redefining the researcher's workbench and skillset. The study of learning and teaching may be standing on the threshold of a similar revolution, where for the first time learners can be studied at a scale and fidelity of action which was previously impractical. The free hosting of learning platforms and courses by initiatives such as Harvard+MIT's edX are quite openly motivated by the opportunities that come with the ownership of unprecedented data sets from millions of learners' interactions.[47]

LEARNING ANALYTICS DEBATES

Important debates are beginning to develop around the (often implicit) assumptions underpinning learning analytics, and by extension, their limitations if used crudely.

Data Is Not Neutral

Information systems filter and categorise the world. When done well, simplified models help us grasp overwhelming complexity, but done badly, they ignore important details. 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. A recent critique of the rhetoric around Big Data reminds us to enter this field with caution:[48]

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

In the context of learning analytics, every step of the lifecycle — from data to analytics to insight to intervention — is infused with human judgment. In short, it is as naïve to believe that 'data speaks for itself' as it is to believe that a text has a single, objectively discernible meaning for all contexts.

Learning Analytics Perpetuate Assessment Regimes

Learning analytics are intended to improve student success. They are, consequently, always designed with a particular conception of 'success', thus defining the patterns deemed to be evidence of progress, and hence, the data that should be captured. The primary driver of mainstream teaching practice, and hence the learner's experience, is the assessment regime. Micro-level learning analytics are in essence, new assessment technology, capable at their best of providing personalized, timely, specific, actionable feedback. Since assessment regimes are a hotly contested issue within educational research and policy, by extension, an intelligent approach to learning analytics must engage with this debate, making clear what assessment regimes and pedagogical commitments a given learning analytic promotes. Due to the complexity of implementing good assessment for learning,[49] designing tools of this sort remains a primary challenge for learning analytics researchers.[50, 51] The promise is that done well, analytics could be the key enabler for delivering formative assessment for learning *at scale*, placing new kinds of tools in the hands of learners.[52] The risk is that research and development focuses on the data which is simplest to log computationally, perpetuating the dominant pedagogies and learning outcomes from an industrial era, when most educational thought-leaders point to the additional dispositions and skills needed for lifelong, lifewide learning, and the capacity to thrive in a very turbulent world.

Ethics

As in any field concerned with the sharing and interpretation of personal data, ethical issues pervade learning analytics. Who decides which data are important to log, how it is 'cleaned' for aggregation with other datasets, and whether those datasets are compatible? Who decide how the data are rendered visually, and are those seeing them literate enough to interpret them? Should learners see analytics about themselves, or their peers? Are teachers skilled enough to devise appropriate interventions based on them? Can data be anonymised adequately, and can access be controlled appropriately? Are attempts to formalise educational theories to embed them in computational algorithms valid? The research field requires information technology ethicists to inform its work, since most if not all the issues around learning analytics have arisen in other domains.

RECOMMENDATIONS

In the light of the preceding analysis, the following recommendations are proposed to help educational and business leaders orient to the opportunities and risks, and to catalyse a wider debate around the educational worldview underpinning Learning Analytics.

1. Learning Analytics are never neutral: they unavoidably embody and thus perpetuate particular pedagogy and assessment regimes. Changing these is a profound challenge that spans the micro—macro, given the inertia to thinking about assessment in fresh ways in the educational ecosystem (primary/secondary/tertiary/workplace). **Governments and institutions can use the possible introduction of analytics to catalyse debate on their vision for teaching and learning for the 21st Century.**

2. There is a pressing need to plug the widening analytics talent gap. **Institutions should train staff and researchers in the design and evaluation of learning analytics** — to ensure that there is the organisational capacity to deploy analytics with integrity, sustain quality dialogue about how they are used, ask the right questions of vendors, and to satisfy the societal demand for this workforce.

3. Compared to many other sectors, educational institutions are currently 'driving blind'. **They should invest in analytics infrastructures for two reasons: (1) to optimise student success, and (2) to enable their own researchers to ask foundational questions about learning and teaching in the 21st century.** To research learning without an analytics infrastructure may soon become like a theoretical physicist with no access to CERN, or a geneticist without genome databases.

4. The field is moving fast, with companies innovating to meet perceived markets. To keep up, the normally slower pace of educational research and professional development must be accelerated, or institutions are at risk of making purchasing decisions based on what's available, rather than what's needed. **Institutions should collaborate on establishing trusted partnerships and robust mechanisms to share student data, analytics techniques and information visualization tools.** To complement innovation driven by what can be done economically on today's infrastructure and taken to market rapidly, we need to turbocharge innovation which is driven by research-validated, educationally sound practice and next generation technologies. An open analytics platform and community is one proposed vehicle for such work.[53]

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(All links are illustrative and should not be taken as endorsements of products)

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Learning Analytics is a rapidly growing research field and commercial market, with potentially disruptive potential. While educational researchers have for many years used computational techniques to analyse learner data, generate visualizations of learning dynamics, and build predictive models to test theories — for the first time, these techniques are becoming available to educators, learners and policy makers. Learning analytics promise is to transform educational research into a data-driven science, and educational institutions into organisations that make evidence-based decisions. However, critical debate is needed on the limits of computational modelling, the ethics of analytics, and the educational paradigms that learning analytics promote.

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