Learning analytics at the University of the Highlands and Islands

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Contents

Executive summary

Learning analytics (LA) is the part of academic analytics interested in fostering student retention, satisfaction and improving teaching. It has evolved, since 2010, as the instrument of choice to improve the student experience, especially in countries where the university system is based on a non-elitist selection of students which leads to high student diversity. In such countries, the diversity of student has increased over the years, influencing the type of courses offered, the design of courses and methods to teach them. New courses are being created following trends in learning theory and in learners' engagement through new technologies. However, as the university sector is facing funding shortages, learning and teaching strategies must be developed using new and relevant evidence rather than "business-as-usual" strategies. Analysis of student engagement and satisfaction data is a powerful tool to direct limited resources effectively within an institution. While LA used to aim almost exclusively at identifying students at risk, current trends are associated with identifying student engagement, student types based on learning theory theoretical constructs to foster a personalised approach to teaching. Since LA is a truly multidisciplinary field, some of the initiatives are focused more on what data is possible to collect with a certain technology rather than answering pedagogical questions. In this way, the field can be said to suffer from the "streetlight effect" which consist of looking for answers where it is easy to look for them. However, LA still offer real potential to improve a university's ability to improve learning, teaching and student satisfaction, improve accessibility and fairness on crosscutting issues such as gender, age and students with special needs.

Lessons learned from the LA international community (LAK16) include the fact that learning may not always be visible through the analysis of digital traces left by students, that timely feedback to student is most conducive to changes in learning behaviours, that our LA enquiry should be anchored in learning theory and that the human factor cannot be neglected if LA initiatives are to be successful. A strong ethical focus is necessary for any institution who wants to undertake LA initiatives. The legal framework for data protection, data security or anonymity must be taken into consideration and an institutional policy created. Noteworthy in the LA community are the issues on the consequence of identifying students, handling data in an ethical manner and consequences for the student of "opting out".

At the University of the Highlands and Island (UHI) no current LA initiative exists, although a variety of data are being collected in the view of improving the quality of teaching. The main sources of data are the National Student Survey (NSS), End of Module Survey (EMS), the red button, and SITS-student records. These data sources are not yet cross-analysed to gain insights about student retention and engagement, which could be a goal for the future. A LA initiative at UHI would have to be carried out using internal funding, and through re-prioritising the work across the different actors. The data would need modification to make it readable and usable, but no shortage of storage space is anticipated. A strong ethical framework would need to be put in place. While all staff interviewed felt that UHI had enough useful data, obtaining the data and the ability to intervene in a timely manner were mentioned as areas were improvement could take place. Overall, UHI would benefit from undergoing several audits such as a data, processes and LA readiness audits to best evaluate whether LA approaches may be of interest and may have a positive effect on UHI key performance indicators.

What is learning analytics?

The field of **analytics** deals with the use of large datasets to make evidence-based decisions. In business, analytics have been used for more than 10 years (e.g. Poulin & Freeman 2003) and are the basis for improving company processes and profits. In academia, the field of analytics is relatively new (Ferguson 2012) and can be divided into two broad categories:

1) **Academic analytics** which serves to improve operational practices. Academic analytics consists of gathering data in a systematic manner, through technological advances (soft- and hardware), to inform decisions on a range of operational issues (Table 1).

2) **Learning analytics (LA)** which helps inform University staff on the students' learning and university experience (Barneveld et al. 2012). The field of learning analytics has a range of working definitions (Table 2) emphasising the multidisciplinary nature of the field.

The field of learning analytics has been recognised as separate field to the general field of academic analytics since 2010 (Ferguson 2012), and many universities world-wide engage in LA initiatives.

Table 1: Differences between are of use in academic analytics and learning analytics

Academic analytics	
Academic analytics for operations	*Learning analytics (LA)*
Operational efficiency	Students' needs
Fund-raising	Students' learning behaviour
Strategic budget allocation	Students' experience
Savings	Course planning
Student recruitment	Learning effectiveness and mechanics
Alumni support (in kind, donations)	Use of blended learning
Strategic use of resources (equipment, room, staff)	Personalised education
Resources use	Development of pedagogy and course design
Cost estimate of study stream	Student engagement

Table 2: Current and published definitions of learning analytics

Learning analytics (LA) definitions	**Source**
"LA deals with the development of methods that harness educational data sets to support the learning process".	Muslim et al. 2016, p. 1
"Learning analytics is a fast-growing area of Technology-Enhanced Learning (TEL) research. It has strong roots in a variety of fields, particularly business intelligence, web analytics, educational data mining and recommender systems"	Ferguson, 2012, p. 305
Learning analytics is an "emergent field with multiple disciplinary ties to traditional areas of expertise (e.g., learning sciences, human computer interaction, computer science)"	Oster et al. 2016, p. 1
"Learning analytics is the 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"	Siemens & Gasevic 2012, p. 1

The field of learning analytics (LA) is rather new, and in 2011, the first Learning Analytics Knowledge conference (LAK2011) was held in Banff, Canada. North American higher education institutions have traditionally had the largest development and activity in the field, a dominance which was present at LAK13 (Ochoa et al. 2014), and was still reflected at the Learning Analytics Knowledge conference (LAK16) in Edinburgh in 2016 (Figure 1). The country affiliation of the first authors of papers presented at the LAK16 conference was predominantly USA, followed by the United Kingdom (UK) and Australia (Figure 1). Although the prevalence of UK papers may have been partially due to the ease of access to the conference location that year (it is traditionally held in North America), the involvement of the UK in learning analytics seems to increase over time. Unlike any other country, the UK has an organisation which unifies information relating to learning analytics. It is called Jisc (Joint Information Systems Committee) and it collaborates with many UK and foreign higher education institutions throughout the world. Jisc brings an efficient approach to LA in the UK (Sclater et al. 2016). The real potential of learning analytics to inform good practices in learning and teaching is apparent in the fact that nations such as Germany and Switzerland, where education is free and retention rate have not the same financial consequences, are also using LA to improve their universities teaching quality (Figure 1).

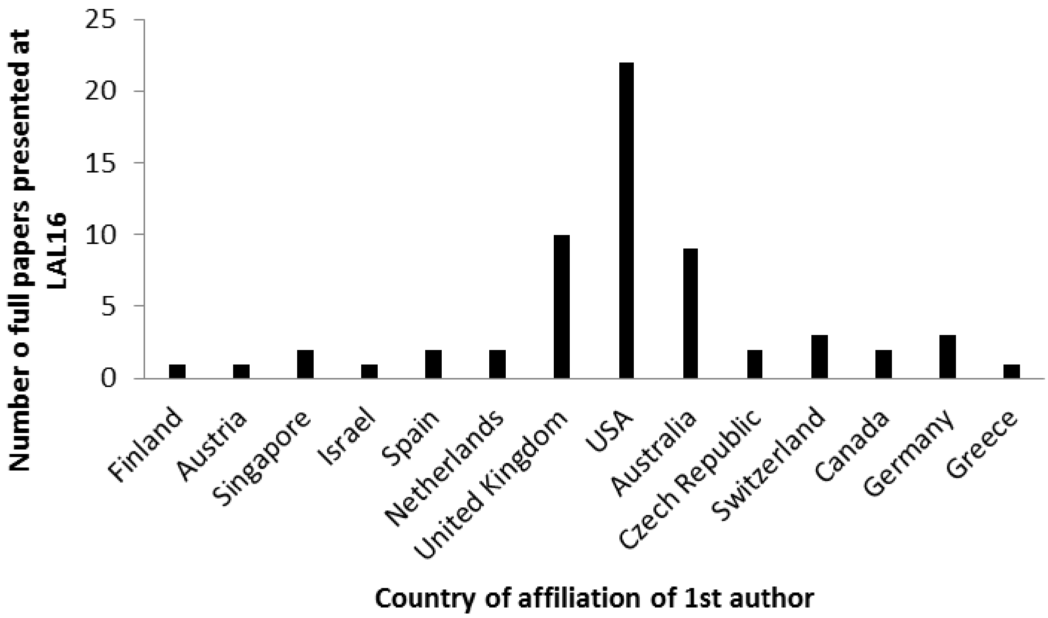

Figure 1: List of country affiliation for the 1st author of papers presented at the LAK16 in Edinburgh in 2016

Although still relatively young, the practice of LA in the UK is thought to have the potential to advance very quickly through the coordinated approach offered by Jisc who has published guiding documents such as the Jisc "Code of practice for learning analytics" (Sclater 2015) for Universities to use when developing their learning analytics activities. Jisc partners with UK universities to implement LA projects. For example, in a project with Nottingham Trent University average engagement (measured by door swipes, library use, logins to VLE, submission to VLE dropbox, new electronic resource use and attendance) was shown to link to student progression. Only 20% of student showing low engagement progressed to the next year. The longer the engagement is low the higher the risk of failing progression (Ed Foster- Annex 3, p. 36). However, 27% of students reported changing behaviour after reviewing the dashboard results with a tutor one to one.

LA is a field of research but also a suite of technical solutions, mostly IT related. Oster et al. (2016) identified that of all actors in the field of LA, the information technology (IT) actors are the most ready to implement LA. This is obvious in certain LA initiative reported at LA conferences where the lack of education theoretical background is showing. In some occasions, the LA projects seem to lack a problem to solve or a pedagogical research question. Professor Paul A. Kirschner, who gave a keynote speech at LAK16 identified that LA suffers from the "streetlight effect"(Freedman 2010) , which describe the propensity to look for answers in a place where it is easiest to look, thus creating an observational bias (Figure 2).

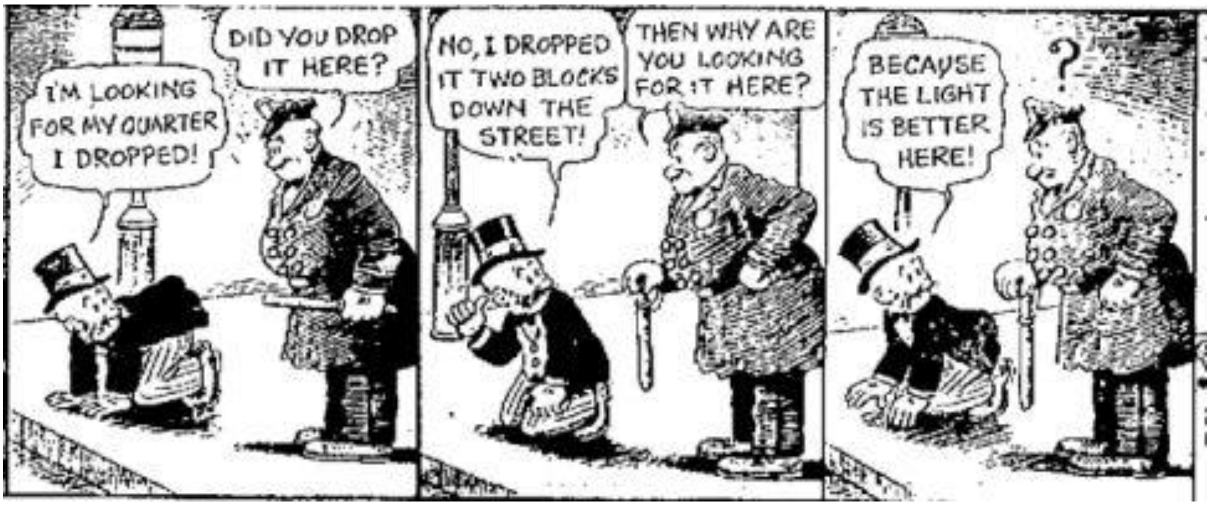

Figure 2: Cartoon depicting the "streetlight effect". **Source: Newspaper Archive: 1942 June 3, Florence Morning News, Mutt and Jeff Comic Strip, Page 7, Florence, South Carolina.**

The field of LA, probably due to its closeness to information technology, and fraught with the streetlight effect, has quickly been invested by companies providing LA solutions to higher education institution. Such companies provide software with aesthetic outputs such as dashboards which may or may not be of interest to an institution, depending on the pedagogical question that they are asking or the problem that they are trying to solve.

An institution's readiness to embrace LA is not a trivial issue and not all the actors that will ultimately be involved in an LA project (e.g. academic faculty/Deans, faculty development staff, institutional administrator/leader, institutional researcher, information technology professionals, student affairs professionals (Oster et al. 2016), course designers and curriculum developers, tutors) have the same level of readiness (Oster et al. 2016). Often, upper management is the less knowledgeable about the goals and mechanics and potential benefits of LA initiatives (Newland et al. 2015) and the information technology professionals may be enthused by the beauty of the technical solutions but without reference to pedagogical questions or learning theory background. Learning and information services (LIS) at universities are key actors in LA as they are at the forefront of data collection and are instrumental in delivering targeted solutions for student support. In the early days of LA, most of the research was carried out by LIS scholars, but over the years, LA research is present in other fields such as pedagogy, social networks and information technology, shifting the focus away from technology (Ferguson 2012). In short, the field of LA is currently data and technology rich but pedagogy- and theory-poor, although the general consensus is that the situation is improving.

The pros and cons of learning analytics

Pros

- Large amount of data available – known as "digital traces"
- True potential to improve learning, teaching and student satisfaction
- True potential to improve accessibility and fairness on crosscutting issues such as gender, age, student with special needs (learning disabilities, non-native speakers, etc.)
- "Real-time" nature of the data, allowing early detections of trends and allowing timely interventions

Cons

- The field is not particularly well anchored in learning-theory yet
- Many projects are started because a technological solution is available rather than because a question needs answering or a problem needs fixing
- The field cannot necessarily yield answers on "how does one learn?" as digital traces indicating student preferences of certain learning materials or task are not synonym of student learning
- Many of the relationships between the data and student success are correlative but it is unsure if they are predictive

Data for learning analytics

Learning analytics data can be used to help the institution's ability to provide quality teaching and improve student retention and satisfaction, but it can also be used in a student-focused way, to determine students' learning patterns, teaching resource use, virtual interactions with peers and academic success at the module level. While some of the data used to inform institutional or student-oriented questions may be the same, the time-frame for data collection, analysis and intervention are different, with the **student-oriented** LA taking place over **days or weeks**, while the **institutional interventions** take place over **months or years**. The consensus among the LA researchers and practitioners is that there is no point in collecting large amounts of data if corresponding interventions cannot follow the analysis of these data, and if the interventions are not timely.

The nature of the data that needs to be gathered to carry out learning analytics, what the data exactly measures and how it is related to student learning and engagement is not trivial and researchers are currently exploring which variables are best to collect, for what purpose and at what costs (Bach 2010). Some of the common data collected by institutions engaging in LA are shown in Table 3 along with emerging source of data, which may prove to be of use in the future.

Table 3: The type of data typically gathered by institutions for learning analytics (LA)

Typical data types for LA	Use
Registration date	Predictive. Those who register late seem to do worse academically (Schippers et al. 2016, Annex 3, p. 30-31).
Door swipes	Measuring building use and attendance.
Library records	Measuring library use.
Logins to VLE	Measuring engagement with the e-learning platform. Generally those "do more" on the platform seem to do better academically. Called the "doer effect" (Kenneth et al. 2016)
Submission to VLE dropbox	Measuring engagement with formative quizzes and with summative assignments. Students who submit more do better academically.
Electronic resources (e-books) use	Measuring the intent of reading, using an e-resource.
Goal setting	Measuring the study-specific or life-goals of students. Those who write about their goals, especially life-goals do better than those who do not.
Time on task	Correlate with academic success, e.g. (Kovanović et al. 2015)
Clicker data	Shows participation in classes where clickers are used.

New data types for LA	Use
Motivation level	Measures engagement with the task.
Personality (the big 5)	Schippers et al. 2016 in LAK16 notes in Annex 3, p. 30.
Individual differences in learning self-regulation	Bos and Brand-Gruwel 2016
Student disposition	To assess collaborative learning, e.g. Koh et al. 2016.
Affect feedback	Improve learning, e.g. Ambrose et al. 2016,Ruiz et al. 2016.
Real-time configuration of e-learning according to activity	Khan & Pardo 2016 in LAK16 notes in Annex 3.
Knowledge tracing	Martori & Augusta 2016
Eye tracking movement	Engagement and academic achievements vs academic boredom, e.g. The & Mavrikis 2016.
Game analytics	Learn about motivation. e.g. Hicks et al. 2016
Teaching analytics	The teaching action of a teacher who had wearable sensors during their teaching is measured against student engagement, Prieto et al. 2016.
Temporal analytics, tool-specific analytics, cohort dynamics, comparative analytics and contingency.	A Conceptual Framework linking Learning Design with Learning Analytics Learning Analytics (Bakharia et al. 2016)
Bio-physical measurements with wearable technologies	Improve learning (e.g. Pijeira-Díaz et al. 2016).
Pheromone analytics	Mentioned in Prof. Kirchner's keynote (see keynote links in box below) but without mention of specific use.

Clearly, the field of LA has a "meaningful data" challenge. What can easily be collected and what can be used to answer a pedagogical question are not necessarily the same. This is the reason why some institutions, such as the University of Edinburgh has a 2 prong approach to LA whereby research projects and operational projects are undertaken, informing best practice in LA (Learning Analytics@uni Edinburgh (http://www.ed.ac.uk/information-services/learning-technology/learning-analytics)).

International trends in learning analytics

The field of LA, although relatively new (first international conference in 2011 – LAK11), has already moved from being essentially about student retention to other topics. To capture the international trends currently of interest to the LA research community, the 62 papers presented at LAK16 were analysed for common themes. Each paper was assigned 3 possible themes which, when put together, yielded the following word cloud (Figure 3), where the size of words represents their frequency of the themes in the research papers.

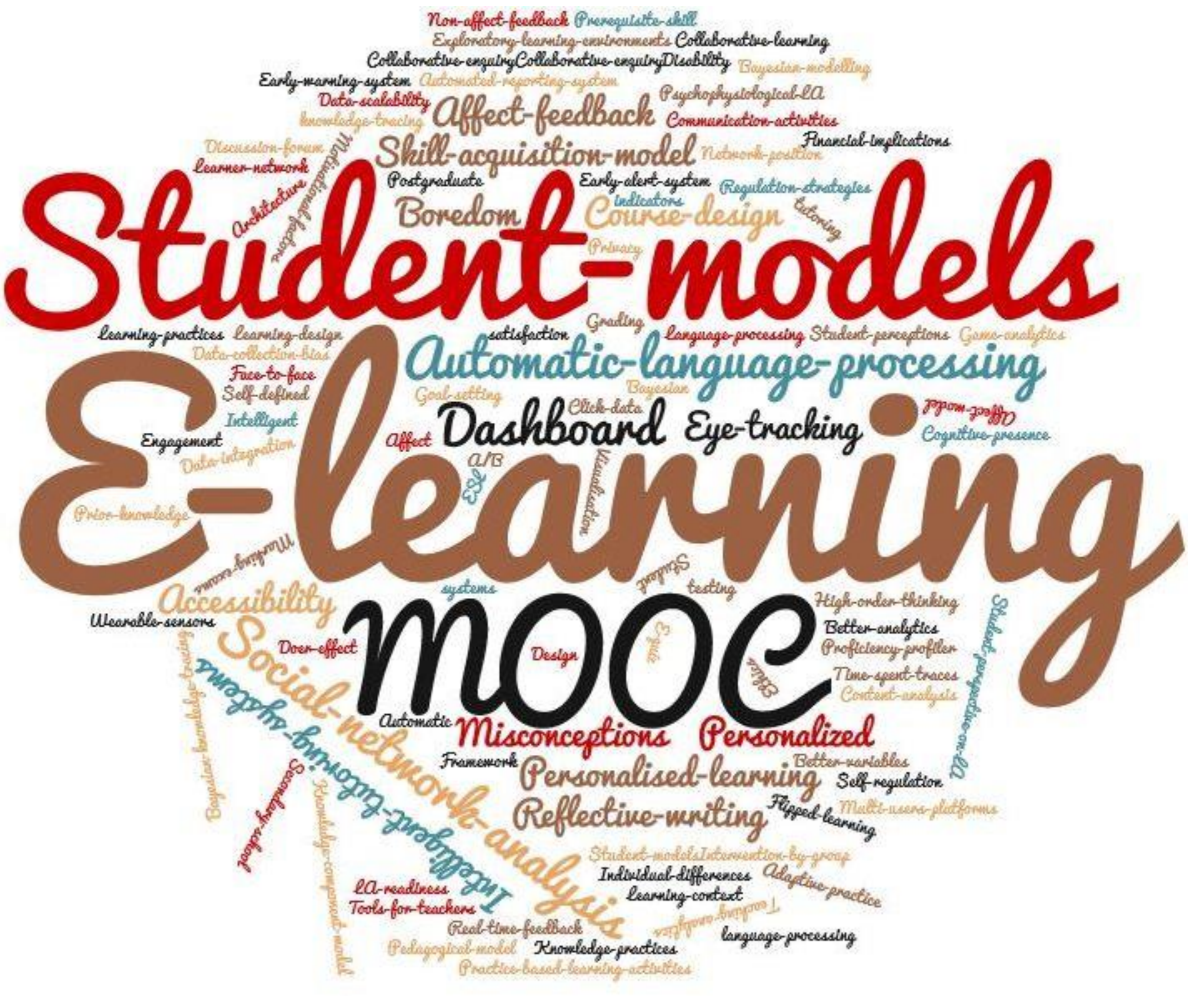

Figure 3: (Pardo et al. 2016)**ain themes represented in the 62 research papers presented at the learning analytics knowledge conference (LAK16) in Edinburgh in 2016**

The most frequent themes in the LAK16 papers were **e-learning**, M (16 counts), **student models** (10 counts, e.g.(Bos & Grand-Gruwel 2016, Mostafavi & Barnes 2016, and Pardo et al. 2016 and **MOOC**s (massive online open courses) (8 counts, e.g. (Hecking & Hoppe 2016, Poquet & Dawson 2016, and Wise et al. 2016). Emerging themes of interest are **social-network-analysis**, **automatic-language-processing**, **eye-tracking** (The & Mavrikis 2016), and **personalised-learning** (Muslim et al. 2016 and Ostrow et al. 2016).

E-learning had a prominent place in the LAK16 literature (Figure 3) (Kovanovic et al. 2016, Manai et al. 2016, Wells et al. 2016)). Virtual learning environments (VLE) are a common tool for blended learning, online courses such as MOOCS and distance education. Those systems generate a vast amount of digital traces which can be used for answering questions about the how students make use of the VLE and the resources provided by tutors.

Increasingly, researchers are trying to make **student models**, including models of successful students (Bos & Grand-Gruwel 2016), , model of student behaviour (Mostafavi & Barnes 2016), and hypothetical student types based on concepts in learning theory (Bos & Grand-Gruwel 2016), (Shirazi Beheshitha et al. 2016)(Table 4). There is concern that the dashboards frequently used in LA may foster the student's performance orientation (low risk taking so as to "look good", potentially decreased learning) rather than mastery orientation (taking high risk to fail several times, loose social status of being "smart" but gains much learning). The prevailing opinion is that education should foster mastery goals (Table 4) and not performance goals in students and that LA could help with finding out if the course design fosters what we want our students to learn. Using dashboards showing the class average fosters performance goal orientation whereas own past performance fosters mastery goal orientation.

Table 4: hypothetical student types based on learning theory

	Mastery goals	**Performance goals**
Approach oriented	Motivated to truly master academic task	Motivate to demonstrate they have more ability than peers
Avoidance oriented	Motivated to avoid misunderstanding the tasks	Motivated to avoid appearing incompetent or stupid in the eye of others

MOOCs are free tertiary level courses offered by universities to anyone, without any prerequisite. Accordingly, the drop-out rate is high, making MOOCs environment an ideal terrain to study the relationship between student motivation and e-resources use (e.g. (Hecking & Hoppe 2016, Poquet & Dawson 2016 Renz et al. 2016, Robinson et al. 2016, Wang et al. 2016 Wise et al. 2016).

Social network analysis was used by several authors (Joksimović et al. 2016) to measure social centrality (degree, closeness, "betweenness") and its impact on academic success, by Zhu et al. (2016) and Poquet & Dawson (2016) who found out that MOOC students that were more connected to the network were more successful.

Automatic language processing is gaining attention in LA research, mostly to automatically evaluate students' contributions in fora (Wise et al. 2016), exams (Hsiao & Lin 2016) and reflective writing (Shum et al. 2016).

Eye-tracking is one of the emerging fields of research in LA and results shared at the LAK16 showed that eye pattern distinguished 3 types of students in relation to their engagement patterns and the 3 groups had different academic performance (The & Mavrikis 2016). A study by Sharma et al. (2016) showed that those students who could follow the teacher with their gaze performed better academically than those who did not.

Personalised learning was also a trend at the LAK16, for example in the shape of self-definition of goals (rule-based) to generate indicators in flexible and dynamic ways (Muslim et al. 2016) and automated systems with a personalised component (Ostrow et al. 2016) according to goal orientation (Shirazi Beheshitha et al. 2016).

Key literature

- Authentic Learning for the 21st Century: An Overview, Lombardi, M.M. (2007), ELI Paper1: 2007, EDUCAUSE Learning initiative
- Academic analytics: A new tool for a new era. EDUCAUSE review 42, 40. Campbell, J. P., DeBlois, P. B. & Oblinger, D. G. (2007) er.educause.edu/articles/2007/7/academicanalytics-a-new-tool-for-a-new-era
- From Bricks to Clicks: the Potential of Data and Analytics in Higher Education. Policy Connect. Higher Education Commission (2016)
- Improving the Quality and Productivity of the Higher Education Sector: Policy and Strategy for Systems-Level Deployment of Learning Analytics. 1–32. Society for Learning Analytics Research. Siemens, G., Dawson, S. & Lynch, G. (2013) solaresearch.org/Policy_Strategy_Analytics.pdf
- Learning Analytics in UK HE 2015: A HeLF Survey Report. Heads of eLearning Forum. Newland, B., Martin, L., Ringan, N. (2015). helfuk.blogspot.co.uk/2015/10/uk-he-learning analytics-survey-2015.html
- Learning Analytics and Educational Data Mining in Practice: A Systematic Literature Review of Empirical Evidence. Journal of Educational Technology & Society 17, 49–64. Papamitsiou, Z. & Economides, A. A. (2014) ifets.info/journals/17_4/4.pdf
- Learning analytics: the current state of play in UK higher and further education. Jisc. Sclater, N. (2014, November) repository.jisc.ac.uk/5657/1/Learning_analytics_report.pdf
- Open academic analytics initiative . Whyte & Jayaprakash 2014 (https://confluence.sakaiproject.org/pages/viewpage.action?pageId=75671025)
- Penetrating the Fog: Analytics in Learning and Education. EDUCAUSE Review. Long, P. & Siemens, G. (2015) http://net.educause.edu/ir/library/pdf/ERM1151.pdf
- Signals: Applying Academic Analytics. EDUCAUSE Review. Arnold, K. (2010, March 3). er.educause.edu/ articles/2010/3/signals-applying-academic-analytics

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Overall, the scholarly contributions at LAK16 seemed less focused on students at risk and students' performance and increasingly about modelling of student behaviour and alternate data sources to inform personalised learning and prior knowledge recognition, which is in line with the expectation that the LA international research community to be at the forefront of new research themes. On a more practical basis, the main focus of learning analytics in the UK is still on student retention and learning quality (Newland et al. 2015). Although there is a growing interest about LA in the UK, in 2015, 47.2 % of institutions surveyed had not engaged with LA yet (Newland et al. 2015). Of those who had embraced this new opportunity only 1.9 % had fully implemented systems and processes, leaving 51% of institutions having undergone partial implementation or working toward it (Newland et al. 2015).

Lessons learned from LAK 16

Attendance at the LAK16 yielded some lessons learnt that are summarised below. More notes on the content of the LAK16 are available in Appendix 3. Some of the unreferenced statements stem from the synthesis of the information obtained at LAK16 and through searches on the topic of LA.

Learning is not visible

At LAK16 the conference participants were warned that learning is not necessarily visible. Thinking that data gathered through LA project might render learning visible could be a fallacy. Also, self-reports on learning (e.g. self-completion survey or qualitative interviews) are often poor measurements of learning as people typically do not really know when they learn, or how. The hypothesis is that a learner's cognitive processes are not necessarily complex enough to be learning and to be aware of one's learning at the same time (Moos & Azevedo 2008). The digital traces left by the students, which may show that they liked an activity, is not necessarily indicative of them actually engaging in learning. Since learning is not necessarily visible, it is possible that what tutors want the students to learn may not be the same as what they are actually learning.

Timely feedback is paramount

Student who obtained timely feedback from their tutors learned twice as fast as those who did not have access to timely feedback (Koedinger et al. 2012). LA has a real potential to be able to deliver quick feedback to students. The dashboards offered by commercial companies may have a role to play to increase the amount of feedback given to the student, although the results displayed on the dashboard seem to be most useful to the students when analysed together with a tutor. Also, the initial guidance needed for dashboard users should not be under-estimated. Still, LA can help identify successful learning paths for different modules or degrees. While the value of timely feedback seems high, one aspect to keep in mind is the pressure on staff to give that kind of feedback. Also, if the staff is not involved in shaping the LA initiative at their university, there is a risk that some will perceive LA as a way to control their actions (did they act upon seeing a student poor performance).

Start with a theory

LA initiatives should start by asking questions grounded in educational theory (e.g. Shirazi Beheshitha et al. 2016). The topics of student models in LA, individual profiles and links to specific discipline practices are emerging, in contrast with the "one-size-fits all" approach to collecting, measuring, and reporting of data (Mcpherson et al. 2016) which has prevailed until now.

Take the human factor into account

The consensus among institutions that have implemented LA projects in the past, and who are in a position of reflect on the process, is that students and tutors should be involved in the process of developing an LA initiative. One such initiative is described here (http://www.de.ed.ac.uk/project/learning-analytics-report-card). If tutors are not involved in the process, there is a danger that the LA system will be perceived as a staff management tool, to control tutor intervention rather than a learning analytics tool (e.g. did the tutor act upon the alert for a student, and was the intervention timely). Such fears are better managed by early involvement of staff in such a project.

Super-users (super-tutors) are very beneficial to act as the interface of tutors and IT services, for example. Starting small and investing in nurturing the champions among the staff is recommended. Only accurate predictions which get to the tutor in a realistic volume and which are timely in relation to the behaviour of a student can be used to inform timely interventions. While the field moves towards real-time data, care must be taken not to burden tutors with an overload of intervention requests as the interventions may come at the cost of another activity that they will not be able to undertake.

Keynote speeches at LAK16

The slides of the three keynotes speakers are available online. Some additional notes about those keynote sessions can also be found in Appendix 3.

- Keynote lecture "Learning as a machine. Cross-overs between humans and machines" by Professor Mireille Hildebrandt (http://lak16.solaresearch.org/wp-content/uploads/2016/05/Learning-as-a-machine-sans-cartoons.pdf)
- Keynote lecture "Learning Analytics: Utopia or Dystopia" by Professor Paul A. Kirschner (http://lak16.solaresearch.org/wp-content/uploads/2016/05/lak16keynotelearninganalytics-utopiaofdystopia-160428103734.pdf)
- Keynote lecture "A Dispatch from the Psychometric Front" by Professor Robert J. Mislevy (http://lak16.solaresearch.org/wp-content/uploads/2016/05/Mislevy_LAK.Keynote.05-17-2016.pdf)

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Ethics in learning analytics[1]

Lawful and fair collection, processing and storage of LA data are paramount for any institution who wants to engage in LA. The Jisc "code of practice for learning analytics" offers guidance on the institution's responsibility, transparency & consent, privacy, validity, minimising adverse impact and stewardship of the data (Sclater & Bailey 2015, see box "Learning analytics ethics literature" below). Each institution should have a code of practice in place at the time LA implementation. Universities such as the Open University are ahead of traditional universities and have developed frameworks that can be used by those universities that are starting with LA now (see box "Learning analytics ethics literature" below).

Learning analytics ethics literature

- Drachsler & Greller 2016. Privacy and Analytics – it's a DELICATE Issue A Checklist for Trusted Learning Analytics. LAK16 paper. P. 89.
- Open University (2014) Policy on Ethical Use of Student Data for Learning Analytics http://www.open.ac.uk/students/charter/sites/www.open.ac.uk.students.charter/files/files/ecms/web-content/ethical-use-of-student-data-policy.pdf
- Sclater & Bailey 2015 Code of practice for learning analytics. Jisc. https://www.jisc.ac.uk/sites/default/files/jd0040_code_of_practice_for_learning_analytics_190515_v1.pdf
- Sclater, N. (2014) Code of practice for learning analytics: a literature review of the legal and ethical issues. Jisc. http://repository.jisc.ac.uk/5661/1/Learning_Analytics_A-_Literature_Review.pdf

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Identifying students

Although the field of LA started by identifying student at risk, current trends are showing less initiatives to model risk, but rather measure student engagement. Still, identifying a student for any purpose, even in a view to help, can be delicate, as a label once given is difficult to remove. What are the ethical considerations of identifying a student on the basis of their data, even if it is to help?

As good as the LA models might be, the predictions may still be erroneous due to individual differences in learning or sudden change in behaviour due to exceptional circumstances. A situation where students have to prove that the LA systems "got it wrong" must be avoided and "presumption of innocence" must exist. Transparency and trust building between the student and the institution are paramount so that the relation is not asymmetrical (e.g. students and staff have different screens in a dashboard). The student has a right to know that they have been "identified" by tutors.

[1] This whole section is purposefully under-referenced. The content come from notes made by the author at the LAK16 (25-29 April 2016, Edinburgh) and CISG Learner analytics – so many questions (12 April 2016, Birmingham).

Handling data ethically

Data privacy is not the same as data security or anonymity. All three aspects need to be formulated in an institutional policy, ideally well before any LA initiative start. When data cannot be fully anonymised, it might be pseudo-anonymised which consist in storing information in 2 places. Only when the 2 data sets are combined can the person be identified. Data about a person cannot be traced back to them because extra information would be necessary and that other information is kept separately. One must ensure that no privacy violations occur: for example, that no inferences can be made about health problems, lack of coping strategies, revealing things that the person did not know about herself. Usually, the data collected is context-bound and may or may not be re-purposed ethically.

The legal framework

The European Union (EU) has a general data protection directive http://ec.europa.eu/justice/data-protection/ which European universities are expected to follow. This general data protection regulation will become law in 2017. For the field of LA it will probably translate into giving student meaningful info (not algorithms) about the logic involved in the LA initiative, the envisaged consequences for the student (i.e. identification and intervention). The students have the right to be assessed by a human process, rather solely by an automated process. The following pieces of legislation are also of interest to shape the ethical framework around an LA initiative:

- Nuremberg code 1949
- Helsinki declaration 1964
- Belmont report 1978
- Right to be left alone (Westin 1968)
- Informational self-determination (Flaherty 1989)
- Informational, decisional, local privacy (Rössler 2005)
- EU data protection directive 95/46EC, 2016

These frameworks should help making LA initiative fair, lawful and ensure that no exploitation of students is taking place through their free contribution outside the commons.

Opting out

It is generally recognised that students should have an option to opt out of some data usage (e.g. usage leading to identification of a student). Student should be able to have the same educational opportunities even if they opt out of their data being applied in LA projects.

Learning analytics at the University of Highlands and Islands

At the University of Highlands and Islands (UHI) LA is has not been formally introduced yet. In order to start the process of enquiring about possible adoption of LA at UHI, a series of semi-structured interviews were carried out with key informants. Two kinds of questionnaires were administered, the first one for staff involved with the collection of data to inform UHI teaching quality and student experience (n= 5); the second one for staff at the senior management level (n=5). The questions were slightly different for the two groups, reflecting the activities of the staff interviewed. The participants' most salient answers were collated and are shown in Appendix 1 and 2. A summary of finding is presented below.

The type of data collected at UHI

The data that is currently being collected at UHI, is not currently used specifically for the usual goals of LA: increasing retention, providing better feedback to students, capturing attendance data, and enhancing teaching and learning (Shacklock 2016). The data currently collected is either part of the normal process of student registration and progression or is part of the quality assurance process put in place at the university. The nature of the data is quantitative and qualitative data is not being currently tapped into. The data collected at UHI comes from:

- End of module survey (EMS) (degree students only)
- National student survey (NSS)
- Data on resources, teaching, assessments (HNC only)
- SITS data (retention, achievement, and progression)
- SED (report on UHI's KPIs by module leaders)
- Red button
- Quality monitoring data
- External reviewers (direct communication with students)
- Small pedagogical projects (the UHI learning and teaching internal scholarships)
- Blackboard statistics (mostly online students: number of clicks, number of hours online and number of times entered the system)
- Record of academic misconduct and student appeal
- Exam board data
- Post-graduate taught experience survey (PTES)
- Data on early experience (some academic partners reported to the Scottish Funding Council (SFC)).
- Data from the student engagement group (2 x per year)
- Data from the student partnership agreement meeting (1x year)
- Qualitative data from the student association

In the future the following source of data could be collected: E-resources (e-books, e-journals), the new student portal "connect" (access to key services (UHI email, VLE, news, fee balance).

These data are being collected by a combination of automatic processes (e.g. EMS), manual processes (e.g. SED), Google analytics (e-resources). The data is being collected on different systems and there is no automatic process to triangulate all the data. Only some sources of data are being automatically compiled into reports (e.g. EMS surveys), but there is no current integration over different systems (SITS, EMS, VLE, etc.).

Access to this data occurs through self-enquiry, anecdotes, or formal UHI processes. Data are conveyed in meetings, fora, and committees. Through staff, quality insurance and enhancement (QIEC) at regular programme reviews. The PTES data is communicated in the research degree committee.

The reason the data are collected

The data are collected for the purpose of quality check, to find out what is generally satisfactory. The data inform specifically about student retention, value for e-resources, and data process improvement. For online students, the collection of data through the VLE provides immediate feedback to the lecturer to ensure continuous engagement of the students with the course material. These data are then used to strategically review of UHI's activity as a learning and teaching institution, to make the UHI modules more effective through continuous improvement. The data helps to ask questions about which direction UHI wants to adopt in the future. The data on progression and retention is used to identify potential problems to take action. Upper management staff at UHI obtains this information through a variety of mechanisms: self-enquiry, anecdotal, formal processes. Data is received already analysed, information is conveyed in meetings, fora, and committees through staff, quality insurance and enhancement committee (QIEC) at regular programme reviews and through research degree committees for PTES.

The expected investment in engaging in learning analytics at UHI

Modifying the current data for use

At UHI the end of module surveys (EMS) are largely automated now. Although the data collection through any other sources of data at UHI (see "The type of data collected at UHI" section above) is relatively straight forward, data would require manipulation and integration. The full-time equivalent (FTE) estimated by UHI staff for this task would represent roughly ½ FTE. If a full LA programme was implemented, the envisaged number of FTE would be 2, but considering the shortage of resources in higher education, it is unlikely that those positions would be new. A critical information/data and current activities audit would have to be carried out and 2 FTE freed from other tasks. An audit of whether data is currently only readable (e.g. spreadsheet) or usable (e.g. high level reports) is also necessary. Unless the LA initiatives were in shape of research project (UHI currently has enough data for several PhDs) the financing of an LA initiative would have to be self-financed.

While some staff members learn on their own how to use the statistical capabilities of the software that UHI uses, a cost associated with staff training must be considered for those who may need training. The readability and usability of data is not the same as data might be easy enough to retrieve in a readable form, but the integration with other datasets and human analysis might be necessary to render it usable and useful to those who need it for strategic decision-making at UHI. Automatic integration of several datasets and production of usable reports will more than likely require an investment in terms of human resources.

Data storage

There is a consensus among UHI staff that there is currently enough space to store the data, and that no space shortage is expected in the future. More critical is the location of the different databases and whether their location is conducive to successful integration in the future. There could be a cost associated with optimising the location of certain databases.

Note that while LA initiatives have clear financial costs for an institution, they also have financial benefits, as demonstrated by Harrison et al. (2016) at an Australian university.

Ethics

Currently, UHI students sign an agreement at the start of a module which regulates the use of personal data but UHI has currently no "opt-out" possibility. In the EMS there are few occasions when the identity of a UHI student could be uncovered, for example when the number of student in a class is very small. Other student data at UHI are not anonymised or pseudo-anonymised (identity and data stored in different places). At this stage, UHI does not have a process to get authorisation from the student to reuse the data and put it back to them in form of feedback. An internal review is underway to enable such data use in the future, which probably would have to be mediated through the declaration signed by the students when they enrol at UHI.

If the EMS was to be used for research, ethical approval would have to be sought. NSS data is anonymous but VLE data would have to be anonymised. UHI will have to report on social justice targets in 2020 by providing data on "protected characteristics" (age, disability, gender re-assignment, marriage & civil partnership, pregnancy & maternity, race, religion & belief, sex, sexual orientation). The purpose is to determine whether UHI is unknowingly discriminating against certain students. The process for this specific reporting has not yet been put in place at UHI.

The positive and negative in short

The general consensus among staff interviewed is that UHI currently has substantial amounts of data that could be used for a LA initiative. The upper management notes the great improvement of the EMS survey, which are now available automatically and in very usable form. Staff members feel that enough information is available and that it is comprehensive.

One challenging point is the participation levels (low sometimes) in EMS surveys which, should, ideally, be much higher. The reasons behind a student disengaging or not progressing are largely unknown and UHI could do more to collect and synthesise qualitative data on student success. Identifying the characteristics of past successful UHI students could help make a profile of "these are the characteristics of a successful UHI student" (there has been the beginning of an initiative about that by a UHI staff member). With qualitative data, UHI could find out if some students (e.g. mature-aged students, students who have to drive significant amount of time to get to a learning place) are being disadvantaged or more at risk to fail. The data that is currently being collected is not fed back to the students (see ethical consideration above for reasons why) and is not yet used in a timely manner to provide the student with quick enough feedback to foster a behaviour change. Staff training could help to dig further into the data to extract needed information in a timely manner. In modules especially, UHI might be able to increase student satisfaction if timely feedback was obtained early enough to intervene before the end of a module. A mechanism (dashboard?) should be present to make an explicit link between the LA data and the UHI key performance indicators (KPIs). The mode of delivery for this new information should be formal, occur on a regular basis and be timely, all in an "easy to digest" format.

Other consideration brought to light by the survey participants are found in the last category of Annex 1 and 2. Learning analytics initiatives at UHI could help the university attain its key performance indicators. Examples of which potential LA initiative could benefit which indicator are shown in Table 5.

Table 5: Which LA initiatives could potentially enhance the achievement of UHI key performance indicators (KPIs)?

Potential learning analytics initiative	UHI KPI[2]
Ensuring that no unintended discrimination is occurring on the base of geography	KPI 1c KPI 1g
Ensuring that no unintended discrimination is occurring on the base of the first-language/nationality of the student	KPI 1f
Ensuring that no unintended discrimination is occurring on young entrants to higher education from within the region	KPI 2a
Timely pedagogical interventions fostering changes in learning behaviour and academic success	KPI 3a KPI 3c KPI 5a KPI 5b KPI 6d
Fostering the use of LA data for research projects that will yield REFable publications	KPI 6a KPI 6b KPI 6c
Identifying the characteristics of students who progress from lower levels to HE	KPI 8
Teaching analytics	KPI 10c

Recommendations

- UHI current processes to foster teaching quality seem effective but timeliness may be an area where improvement can be occur in the future
- UHI does not seem to currently have student-oriented LA initiatives that would foster student behaviour change within the time frame of a module or of an academic year. A goal could be the timely collection of data that leads to quick interventions.
- Once UHI has an ethics policy in place and the possibility for students to opt-out, Blackboard statistics could be very useful tool to foster student-oriented initiatives. Such a project may require tutor training to use the full potential of the VLE.
- UHI has a unique teaching and operational model and LA initiatives may not be simply replicated in a UHI context. For this reason, a "readiness to LA" study would probably be beneficial. Oster et al. 2016 have carried out such a study in various USA institutions, and, when contacted, expressed their interest in conducting the survey in a context such as UHI.
- Ideally, if UHI were to initiate LA activities they should be meaningful. Intervention should be timely, and the feed-back would be given to both the student and staff (teaching analytics).
- There is no point into rushing into LA initiatives at UHI, if the mechanisms by which behaviour change can occur have not been specified. LA does not automatically lead to

[2] Anon (2015). Progress report on the 2015/20 strategic vision and plan critical and key performance indicators. University of the Highlands and Islands.

changes in teaching practices (Pardo et al. 2016), so teaching behaviour change also needs to be managed.

- UHI may want to obtain and analyse more qualitative data (e.g. analyse outliers, case studies) to improve the overall interpretation of the quantitative data that is already being collected.
- LA at UHI could be used to emphasise the ability of UHI to take HNC student who may go all the way to HE.
- Knowing that UHI has a unique teaching model, a study of what the differences are between students that do well throughout, badly throughout, starts well and end badly, start badly and finish well, could be of use to develop the "how to do well at UHI" profile.
- Ideally, the promise of LA would be assessed against concerns, its potential evaluated against the institutional risks. The financial benefit and costs should be estimated in the light of the need to stay competitive in the industry, but also of having a clearly defined goal for which unintended outcomes are reflected upon and avoided.

Proposed next steps for UHI and learning analytics

- Formulate an ethical framework on LA data collection and usage
- Identify a problem/question that learning analytics could potentially answer (see table on UHI KPIs and LA)
- Stocktake of the data collected, its storage location, and stocktake of current processes
- Carry out an institutional readiness to LA (e.g. Oester et al. 2016)
- Involve tutors and students in the discussion on LA
- Follow the development of LA through Jisc activities

Abbreviations list

Abbreviation	Meaning
BKT	Bayesian knowledge tracing
FTE	Full-time equivalent
ELIR	Enhancement-led institutional review
EMS	End of module surveys
EU	European union
FE	Further education
HE	Higher education
HNC	Higher national certificate
HIE	Highlands and Islands Enterprise
HISA	Highland and Island Student Association
ICT	Information and communication technologies
IT	Information technology
JISC	Joint information systems committee
KPI	Key performance indicator
LA	Learning analytics
LAK11	Learning analytics and knowledge conference in 2011
LAK13	Learning analytics and knowledge conference in 2013
LAK16	Learning analytics and knowledge conference in 2016
LIS	Learning and information services
MOOC	Massive online open course
PTES	Post-graduate taught experience survey
QIEC	Quality insurance and enhancement committee
REF	Research excellence framework
SED	Self-evaluation data form
SFC	Scottish Funding Council
SITS	Strategic information technology services
TEF	Teaching excellence framework
UK	United Kingdom
VC	Video conferencing
VLE	Virtual learning environment
VLE	Virtual learning environment

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Annex I: UHI interview results I

Table 6. Interview questions to UHI staff who is involved with data collection and consensus answers. N= 1

Interview question	Consensus answers
1. What is currently being done to gauge student engagement at UHI? What data is being collected?	There is no data measuring student engagement specifically. There are several sources of data measuring retention: End of module survey (EMS) (degree students), HN data on resources, teaching, assessments, SITS data (retention, achievement, and progression), SED part of quality assurance (report on KPIs by module leaders), red button, and quality monitoring data. E-resources (e-books, e-journals) could be used to gauge engagement. The new student portal "connect" may yield useful information on engagement as access to key services (UHI email, VLE, news). In the future information as the fee balance etc. will also be available. Attendance data is often used in other institution but it is difficult for UHI with VC delivery to get this kind of data. We may have to create our own model rather than follow that of other, more "classical" universities. For online students the engagement is mostly derived from the statistics on blackboard (number of clicks, of hours online and number of times entered the system are being recorded). Students cannot access the new learning material until they have looked at the existing learning material and got 100% at a test, to keep them engaged and progressing through the course material. But there is currently almost no use of these data. Not much qualitative data is being collected but there is plenty of quantitative data, not all of which is associated with learning analytics, but that could be used for this purpose. Small pedagogical projects funded through the UHI learning and teaching internal scholarships are also a source of data on student engagement. Data is also collect via external reviewers who talk to students directly.
2. Through what mean is this data being collected?	Automatic processes (e.g. EMS), manual processes (e.g. SED) Google analytics used to find out about the use of resources through the UHI website (e-resources etc.). The data is being collected on different systems and there is no automatic process to triangulate all the data. Some sources of data are being compiled into reports automatically (EMS surveys), but not across systems e.g. SITS to EMS to Blackboard learn etc. UHI does not have a system to bring it all together yet, however, classic models of doing LA may not work for UHI who has a unique delivery model. For online students, VLE-blackboard is the main source of student engagement information. The aim for collecting student engagement data for online students is to give the timely feedback which fosters self-directed learning.

3. What is the current reason behind collecting those data?	Quality check, find out what is generally ok, specific comments are useful feedback for staff. Student retention, engagement, value for e-resources, data process improvement. For online students, the collection of data through the VLE provides immediate feedback to the lecturer to ensure continuous engagement of the students with the course material. Strategic review of our activity as a learning institution. Make the UHI modules more effective through continuous improvement and the data helps to ask questions about which direction UHI wants to adopt in the future. The data on progression and retention is used to identify potential problems to take action.
4. Is the data as it is currently collected usable without further modifications?	End of module survey: yes. Now that all modules do the end of module survey the information has increased about 10-fold, but UHI has created dashboard so much less data crunching is necessary. Leaves time for other types of analyses with the data. Aside from the EMS, the data collected requires manual manipulation (1/2 FTE). The data on the use of e-resources is relatively automated. For online students, the data collected through Blackboard is relatively self-explanatory, but still the tutors receive little explanation on how to use the data that Blackboard statistics produces. Blackboard may have plugins to do automatic reporting. The readability and usability of data is not the same. Data might be easy enough to read but not useful to use. Although most data is probably readable, not all of it is yet usable. The use of the data at programme and subject network level. The VLE spreadsheet is readable but not very usable when wanting to communicate quickly on student engagement.
5. Among the data that is currently being collected what is the proportion that can be used without seeking consent/breaking ethical good practices?	Most of it for EMS but students' comments might lead to the identification of a student, especially in small groups but the students are warned about it. For other types of data, there is no automatic anonymization. The data is not anonymised and at this stage UHI does not have a process to get authorisation from the student to reuse the data and put it back to them. This would need to be included in the declaration when the student enrols. This is now in internal review. Students sign an agreement at the start of a module, but UHI has currently not "opt-out" possibility. Currently the learning analytics information is not used with the students, so there are no current issues but in the future this would have to be reviewed. EMS data is collected anonymously (but see above). If the EMS was to be used for research, ethical approval would have to be sought. NSS data is anonymous. VLE data would have to be anonymised. UHI need to ensure equality of opportunity for all students through the collection and monitoring of the protected characteristics (age, disability, gender re-assignment, marriage & civil partnership, pregnancy & maternity, race, religion & belief, sex, sexual orientation) and to find out if UHI is unknowingly discriminating certain students. There are social justice target that need to be reported on by 2020 and for which we are not yet in a position to report.

6. Where is the data being stored, and do we expect running out of space if the data collection was carried out for a significant amount of time?	The end of module surveys are now stored in the same place as SITS which will facilitate integration of data in the future. No storage issues envisaged. Very unlikely. The space for storing the data is not as important to think about compared to where strategically the data should be stored to ensure adequate sharing across users (and avoiding storage on individual computers). To ensure use the data would need to have easy access for academic staff across different contexts (programmes and subject networks).
7. Will there be storage issue if new data is collected in the future?	Not an issue, we have plenty of space. For the statistics derived from Blackboard, there should not be an issue as there are currently no automatic reports being generated. Probably not, places for raw data and analysed data need to be thought about.
8. Is there a sufficient amount of staff that can look after the data? (collect, store, analyse, report on)	The dashboard for the EMS is saving a lot of work but the programmes have now more to do with all this information they receive. The dashboard outputs need refining and new reports should be made for staff members who require them. The current staffing is all right but any additional task that does not involve reallocating task but creating new ones would need to get extra staffing. ICT can be a resource to any project for a distinct period of time. There is probably enough staff if tasks are re-prioritised. There would be a benefit in having a certain number of staff specialising in learning analytics data. Either existing staff or some new experts (2) would probably be appropriate. Staff members who currently deal with data that could be used for LA would have a definite role to play even though they might not spend 100% of their time on LA. For this, an overview of what the staff is currently doing would be of use, through an information/data audit which would outline current practices which could be strategized in the light of an LA activity in the future.
9. Which data is currently used to inform UHI on students' learning, and engagement?	Group work under the Leadership of Iain Morisson. Note the paper "what makes a successful UHI student". Further education students: VLE data, SITS, number of assignments attempted, class registers. Qualitative data is also gathered the student association, but not a huge amount of analysis is being done on this data.
10. What are the processes that currently occur between data collection and data use?	Dashboard, pdfs, manual processing. Data manipulation, integration of several datasets that end up in reports. E. g: combining 3 data sets comparing e-books reading list for a module versus books actually read. For online students, individual tutors analyse the VLE statistics on an *ad hoc* basis. There is not systematic reporting yet. The data such as gender balance in a module is not yet fed back to course committees yet. An audit of how usable the data is as opposed to readable would be good. This might help get the programmes and subject networks what they need. UHI needs to improve in providing trends in student engagement quickly to allow a reactive and timely dissemination of results to foster evidence-based practices in learning and teaching and find out "what works?".

11. What are the most salient **positive** points about the data and the process of gathering data on students' learning and engagement data now?	SITS is easy to use. Many of the data we need are being collected already. UHI has lots of data that could be used that are already being collected. Soon the reading list for each module will have 1 pt of reference and we will be able to know if the books bought are being used, what the stock is like and the students will have one point of entry for their module reading list. The data that we could use is either already being collected or would be easy to collect (e.g. turn on the statistic function in VLE). There is plenty of data available and UHI has already some good practices in data collection and use.
12. What are the most salient **negative** points about the data and the process of gathering data on students' learning and engagement data now	Since the email requesting the student to take the EMS survey comes from UHI and not from their module leader or the person who does the delivery, it might be discounted or overlooked. Staff are too busy to do it manually. Sending the survey automatically is convenient but impersonal and does not foster participation. There is no current use of the more qualitative information such as reasons for a student stopping a course. We are either not collecting this information yet or not spending time analysing it. We are not monitoring attendance data systematically and consistently yet. Technically, it would be possible to monitor the use of Jabber from home but attendance in VC studios is difficult. The data we currently collect is not yet shaped to be useful to the students and we are not taking opportunities to find out e.g. are mature-aged students struggling with the UHI delivery model especially with the VLE? Is there a bias in accessibility with gender? The data collected is not yet analysed to know if those students who drop out find the module too easy, too hard or whether other circumstances are at play. UHI is not yet using all the data in a useful and timely manner. The integration of qualitative (experiential) data is yet to happen.
13. Other points mentioned	What do we want to achieve? What will we do with the answer? In the process, not underestimate the technical and staff resources needed. We could start by using what we have. There are research opportunities with the dataset that we currently have, e.g. identify successful students at UHI, what differentiate them from the rest? Instead of using models from other universities which might not work for UHI, we should identify our own successful students. What attributes do you have to have to be a successful UHI student? What interventions can we realistically implement across the partnership? Also needed: better analysis of students comments. Better attend to NSS data and triangulate with UHI data. Analyse trends between EMS and SITS. Find out about the reasons for the low response rate (less than 50%) to some of the EMS which may not yield representative results. Produce reports using the EMS data and SITS data (longer an deeper trend analysis of gender, age, distance travelled to attend VC, etc.). There is no current permission to use the data to feed it back to the students after collection, even if anonymized, so a process would have to be created for that. A potential PhD project could look at whether engagement on blackboard is predictive of success.

	UHI could invest in an electronic solution to measure attendance (swipe cards).

Annex 2: UHI interview results II

Table 7: Interview questions to staff who receives reports and is involved in strategic decisions at UHI (deans) and consensus answers. N= 1

Interview question	Consensus answers
1. What information do you currently receive about UHI's students' learning and engagement?	End of module survey (EMS) (degree students), HN data on resources, teaching, assessments, SITS data (retention, achievement, progression), SED part of quality assurance (report on KPIs by module leaders), red button, quality monitoring data. Student appeal, academic misconduct. Exam board. Programmes /subject network collate the module evaluation surveys. Number of graduating students. Post-graduate taught experience survey (PTES). Survey on early experience run by some academic partners (reported to the Scottish Funding Council (SFC). Data also obtained from the student engagement group 2 x per year and the student partnership agreement meeting, yearly.
2. Where do you receive this information from? Through which mechanism?	Self-enquiry, anecdotal, formal processes. Data is received already analysed, information is conveyed in meetings, fora, committees. Through staff, Quality insurance and enhancement (QIEC) at regular programme reviews. Research degree committees for PTES.
3. Is the information that you receive sufficient?	Sufficient but not timely, the information is obtained too late to influence the outcome. Comprehensive information received. The EMS has improved a lot in the last 7 years. They used to be lots of raw data that needed interpreting, reports that are intuitive to read are produced. The data is probably sufficient but the information isn't. Perceived lack of staff or training for staff to report on deeper more meaningful metrics. These limitations are apparent when a specific question occurs and the standard produced reports cannot answer it. Qualitative information is more difficult to obtain for undergraduates due to the numbers.
4. If not, which additional information would you like to receive in the future?	Timely data for early intervention in modules. Data showing the student experience according to geographical region, access to colleges or learning points, academic partner or research institute, distance to VC studio etc. to ensure equality of good experience no matter where the student is learning. Dashboards would be a useful format if it links to UHI strategic plan and KPI. The current link is rather implicit than explicit. A dashboard might have the merit of making the links between the KPIs and the strategic plan explicit. Interrogation of the outliers is currently not done, other main data processed automatically but UHI may not have enough staff time to lead those queries.

	Qualitative reasons for lack of student progression or student. An institutional review of the student experience would be beneficial to move from reactive to proactive measures. The format should be user-friendly. Data about care leavers and generally vulnerable students.
5. In which format would this new information that you would receive be most useful for you?	Formal, regular basis and timely (dashboard?) (So as to be able to intervene) would be most useful. SITS data (attainment, progression and pass while useful for long-term quality assurance, does comes too late for timely/quick intervention. Digest of information and analysis of reason why for lack of progress over a few years to enhance UHI's ability to take action. Table, pictures, numbers all in a "easy to digest" format and online, not paper.
6. Do you know of a category of information that UHI is currently not collecting but that would be paramount to have, from your point of view, to improve students' learning and engagement?	Information about how the students use the learning resources and how that contributes to attainment. The EMS questions are very general, not specific to an initiative taken. No data on how providing new resources in a module leads to a change in general satisfaction. Maybe we need to revise and review the processes: what is the data telling us, then add data that would be paramount to have. Not really, the information that is given is comprehensive. There are no perceived gaps currently. However, when the teaching excellence framework goes ahead and when Scotland's position is clear, gaps may emerge then. Although potentially politically problematic data on "how are staff using their time" could be useful to match with student engagement and satisfaction. Are the staff engaging with activities that do not foster student satisfaction and engagement. One data set that would allow us to answer the question "why is this student just scraping through, why are we losing students" would be useful as we might be able to intervene through more staff, or increase the amount of support. UHI needs to look at commuting students and see if there is a relationship between the commuting time and the progression, engagement, and performance.
7. Do you have good grounds to think that there could be a budget found to accommodate the technical and staff requirements necessary to obtaining this information?	No, no new budget can be envisaged in a context of cuts in the sector. The funds would have to be found through smart use of staff capabilities and re-strategizing the current use of funds. The system must be able to accommodate this. No budget is necessary, the key is to keep UHI's activities under review and reallocate resource accordingly. The general future trends indicates further cuts to higher education and so a learning analytic activity at UHI would have to happen without a new budget for it. It will be difficult to find a budget because it is difficult to show clearly the effects of interventions on retention. Yet, if the NSS score and retention score increase this may have an effect on cash flow but there will always be a lag. The whole UHI partnership is concerned so could participate in funding this, but mostly it will be a case of prioritising and re-allocation resources (money and personnel). It will probably not be prioritised and postgrad programme have little resources for such activities. If a dashboard solution was deemed necessary, one would have to factor in the yearly cost of having the rights to the software. Keeping UHI on the right track is an

	ongoing issue o that is why internal funding needs to fund such an initiative. UHI as a whole is getting increasingly better at knowing what questions to address but UHI needs to move from a reactive to a proactive strategy. The student record section is already understaffed, but no additional budget will be envisaged for this, so re-prioritising will be paramount. UHI needs evidence-based decision-making and a systematic approach, so this need to get prioritised.
8. If no internal budget seems available for this, which external funding sources could you envisage applying for to fund this improvement?	None, this is clearly something that needs to be funded internally. Potentially, JISC could help support UHI with the rollout of an LA initiative. HIE might have an interest in funding a specific initiative if it relates to employability. EU funding if the results of the study/project had applicability to other European regions. Not really, this is a normal part of a University's activities, not a special project. Specific project (e.g. PhD research could be initiated and that would get its own funding). If a consortium of universities would agree, research projects could be started to address some of the questions and would inform further strategies at UHI. E.g. University of West Scotland, combined universities of Cornwall, and Federation University of Australia (who has a very similar delivery model as UHI). This is not a subject for external funding, except for specific research projects.
9. Other points mentioned	Ethics, how will the data be used in the future and is the current process adequate to make sure we proceed with ethical considerations. The process of ethics needs to be user-friendly and not thwart development but ensure ethical way of proceeding at the same time. The process needs to encourage staff to use the data, not make them scared of making blunders. Due to the UHI unique delivery model (online, face-to-face, VC, blended, academic partner). Get an angle: if the data show that we are doing a fine job, we will have the data to prove it. Timeliness: this needs to be done soon, so a strategic decision needs to be made and UHI needs to give itself the means of doing this. UHI has a statutory obligation of delivering outcomes in Gaelic language according to its Gaelic plan to be reported to the board of Gaelic (Bòrd na Gàidhlig). See the ELIR report 2011 (external review of the University, conducted by Quality Assurance Agency Scotland (QAA Scotland), every 4 years) and the academic standard and quality regulation, self-evaluation document 2015-2016. Proper understanding of the tutors about the UHI teaching and learning strategy is paramount as they are people ultimately responsible for using good pedagogical principles in their modules. UHI is missing an opportunity in that they are not using social media for teaching purposes. There are some difficulties associated with it (data belongs to the social media company) but useful learning experience data could be derived from using social media. In view of the TEF UHI will need publicly available data to show its teaching excellence. UHI is good at "added value" with students and the data should be able to show this. Going from reactive to proactive. Highland and Island Student Association (HISA) should be part of the process.

Annex 3

=LAK16 conference on learning analytic - notes

University of Edinburgh

25-29.4.2016

25.4.2016

No access as registration only included programme from 26.4.2016 pm only.

26.4.2016

Learning through goal setting

http://52.51.32.155/#!/signin

for the app.

Workshop

EU project EDUworks

Open vs institutionalised learning

Catherine Zhao- intro

Emerging issues in goal setting

How to motivate students to set up a goal, to link it to course material

Alignment, integrate in the course design

Validation, how does goalsetting promote success

Scaffold

Vladimer Kobayashi

Goal setting app

App features

- Set goal with deadline
- Set subgoal with deadline
- Option goal private or public

- Tag goals
- Dashboard
- Reminder

Hooked up on a learning record store (database where all activities of app are stored)

App pilot study

To find out if the app can help going from shallow learner to deep learner

Teacher can approve or disapprove of goal through a rating.

The effects of 3 goal types setting

Michaela Schippers- keynote

Rotterdam school of mgt

Goal settings helps even if you don't know what you want (life goals), where you are going. Goals most effective if made public. Students had pic taken and goal posted in corridors on massive posters! Ikigai, in Japanese, what is our life goal? Those with a strong sense of purpose have boosted immune system, and lower stress hormones, so grapple with difficulties of life and live longer, so veering away from small goals towards life goals. Goal setting intervention: part 1: guided writing about habits, learning intentions, social life (family), leisure, family, career, get students to write 3000-4000 words about that. Then, describe ideal future as opposed to live want to avoid. Part 2: describe future plan, specify 6-8 goals, ranking them, write a plan and backup plan, how do you know if you have reached your goal. Part 3: Formulate an "I will" statement. Eg. I will consider every challenge as an opportunity to grow. Overall academic performance increased by 20%.

Both retention rate and number of ETCS obtained increase as a consequence of the measure. No difference if the follow up was linked tightly to the goals or not. Retention rate increased most in majority females, then majority males, then minority male and females least. Possible risk: student finds out that the course does not fit the life-goal and drops out. Stretch goals only effective for women. Additional effect of goal diaries. The size of the class could be a confounding factor. Setting a goal in itself seems to be beneficial, academic goals did not yield better results than then life goals (academic placebo?).

Journey towards goal driven Mooc

Simon McIntyre, Lorenzo Vigentini, Negin Mirriahi, Catherine Zhao

Learning to teach online MOOC

Same yardstick to measure a MOOC than other courses, so maybe not appropriate. How to build technology to integrate with all MOOC platforms. Change of goal over time present, some started without the intention of getting a certificate and ended up getting one and vice versa. Is there a link between a goal and a behaviour, can those behaviours patterns be used to offer sth of interest to participants. Most engagement into video, some forum. Goal setting improved last login and outcome.

Cognitive involvement enhances goal effectiveness even without goal specificity

Michaela Schippers et al.

Study choice meetings. Those who did not participate had 12 ECTS, full participation 43 ECTS, but not necessarily causal relationship. 6.7 % of those who did not participate were retained against 69.5% of those who fully participate. Age, gender, big five, registration date (those who register late do worse), core self-evaluation, need for cognition.

Controlling for all those variables, goal setting and I will statements had an effect on study success and retention usually through participation to exams. Kind of goal was unrelated to study success, number of words was related, additional variance explained by words written on strategies and obstacles. No correlation between strategies and obstacle writing with exam attendance, total number of ECTS or retention rate and no sig. correlation with motivation and personality. Cognitive involvement enhances goal effectiveness even if goals are not specific. Number of words and strategies and obstacles further explain the difference, goal type was unrelated, in goal diaries, no difference for grps who reflected on goal and activities. Reflection on goals did not add to the success of students.

Keynote

Practical learning research at scale Ken Koedinger-Carnegie Mellon

You cannot see learning so be aware of illusions, data breaks illusions (student need feedback, instructors need assessment data). The challenges for practical learning science, we don’t know what we know, many ways to learn, 1 size does not fit all. Educational science & technology can help drive iterative improvement, through increased access, personalisation.

What we know in learning science

- Students do now know when they are learning and we cannot see it. Learning and knowing not same. Eva et al. 2004 Jee et al 2008.
- Liking is not learning. They might like it but may not learn. Sitymann et al. 2008.

- Looks of confusion are not predictive of learning
- Moos and Acevedo 2008: not enough cognitive to learn and work out whether they learn at the same time

Progress with what we don't know e-learning science of instruction, Pashler, Pavlik, Roediger, Sweller Klahr, PNAS 2016 chi vs Williams (explaining is good vs bad), Rohere vs Carvalho (interleaving vs blocking).

How big is the design space? By Koedinger, Brooth and Khlar 2013, Instruction complexity and the scien to constrain it, Science.

Scale applications of learning by doing with feedback leads 2x faster learning, cognitive tutor. He explained the KLI framework from the learnlab. Koedinger, Corbett & Perfetti 2012.

Learn by doing or by studying? Testing effect Roediger and Karpicke 2006. Or worked example effects. Theory says testing produces desirable difficulties, worked examples reduce cognitive load.

Weller and cooper 1985 Roedinger and Karpick 2006. Worked examples improved efficiency and understanding.

To improve a course use CTA (cognitive task analysis) to produce better learning 1.5 SD effect size Clark et al 70% of expertise is tacit.

Quantitative cognitive task analysis

An accurate model should produce a smooth learning curve. Error rate vs opportunity, error rate should be going down.

27.4.2016

424 participants this year

Shift in themes, increase behaviour modelling alternate data source, decrease student at risk and performance. More full papers, 44 countries represented this year. All sessions videoed and live streamed.

Learning as a machine. Cross-overs between humans and machines

by Professor Mireille Hildebrandt

Qs: http://bit.ly?LAK16_K1, see word kahoot (game ?)

Making learning awesome through big data as opposed to start from the learner's needs.

Is data the same as facts? Is looking at data enough? Shall we come to depend on LA? Will LA be the next comfort zone?

First level of intervention in LA

Intervention of an identifiable (also indirectly) student both when collecting data and when applying the results of LA to her, whether she is aware of it or not, identification involves being singled out. Behavioural data from e-learning platforms (also in social media outside of academics), out of context data can be correlates with the learning habits (ethical, or not, legal or not, but possible). Real time feedback from student, real time configuration of her learning, put in a class or categorised as a "potential dropout", inferences made on public security risk, drug abuse etc.

Second level of LA

Analysis of data that prepare potential interventions with regards to student. Pseudonymous data: data that cannot be traced to a person because extra info would be necessary, which is kept separately. Identification of relevant correlations and associations. Patterns at this level used at first level.

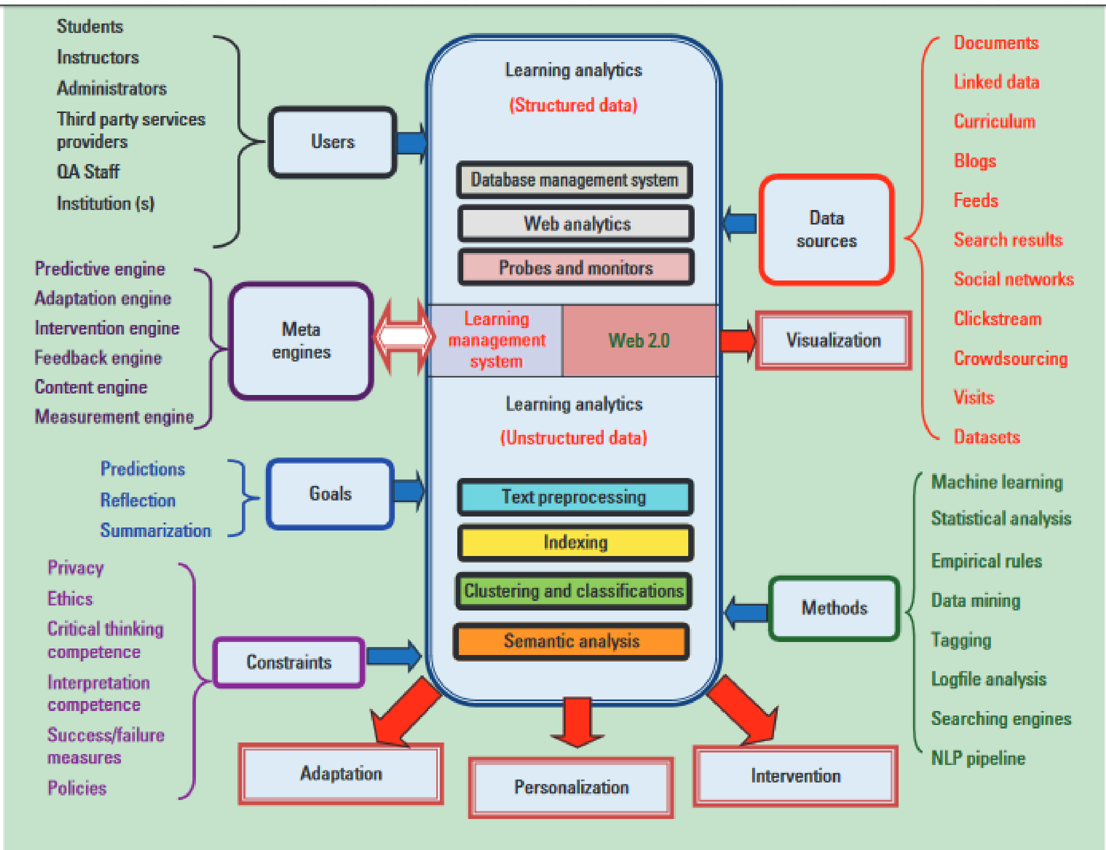
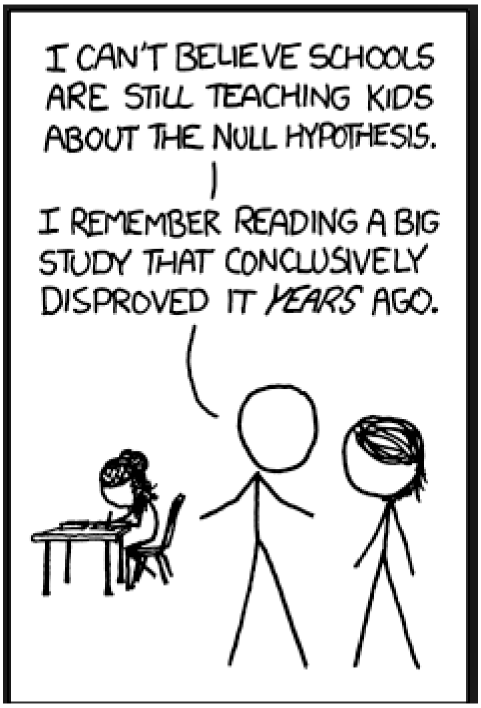


Figure 1. A comprehensive learning analytics architecture.

Fig 1: Jinan Fiaidhi, The next step for LA IT pro Sept/Oct 2014 IEEE

What machine learning does, how it may transform HL.

Behaviourist approach. Can observed behaviour help predict the organism's next move? If we know statistically how people learn we can reconfigure their environment so that they indeed learn, what we think they should learn. Intractability will increase with rise of computational advances. How and what to learn will be removed from free choice.



Simon's approach, Gibson approach.

Humans learn from the machine but vice versa too.

See https://en.wikipedia.org/wiki/Learning_analytics

First level issues

- Identifying students
- Applying results of LA to students
- Privacy violation: inferences can indicate health problems, lack of coping strategies, revealing things about herself that she did not know, can foster discrimination.
- Due process and presumption of innocence
- Prediction may lead to student having to prove that the computer got it wrong

Second level issues

- MIT, Max Planck systems for pseudoanonymisation (http://www.jiscdigitalmedia.ac.uk/clinical-recordings/storage_anonymisation.html)
- LA creates a novel set of affordances (actionability of the environment)
- Old school learning affords reflection
- Legal protection by design, general data protection directive (http://ec.europa.eu/justice/data-protection/), which is going to be introduced will
    - Create a level playing field
    - Require a data protection impact assessment
    - Privilege the processing of pseudonymous data
- Profile transparency, automated decision making, profiling. The uni will have to give the following info to the student: must give meaningful info (not algorithms) about the logic involved, envisaged consequences for the data subject. Right of student not to be solely

assessed on automated processing which produces legal or similar effects on her. Data protection, privacy, and discrimination, due process, presumption of innocence all relevant to LA. Students are not data engines!

"Semantic Visual Analytics for Today's Programming Courses" (short paper) *by Sharon Hsiao, Sesha Kumar Pandhalkudi Govindarajan and Yiling Lin*

Problem statement: blended instruction classes, face to face online tools (self-assessments quizzes, and CMS), provides greater flexibility to instruct topics in class, paper based exams. Difficult to give feedback in traditional blended classroom, missing LA traces. Before using new technology, Visual learning analytics and student modelling from current VLE. Semantic visual analysis approach used, capture data points, deliver solutions. Develop research platform architecture. Use system to create paper exams and guide the teacher. Automatic indexing of papers, validated experts. Questions, are faculty ready to put the initial effort to make this work, answer they would have to learn the new technologies if you went for that.

"The Role of Achievement Goal Orientations When Studying Effect of Learning Analytics Visualizations" (full paper) by Sanam Shirazi Beheshtiha, Marek Hatala, Dragan Gašević and Srećko Joksimović Simon Fraser Uni Edinburgh

LA have long been focused on institutions to inform instructors, but can also be used from student's prospective so student-centered LA visualisation for awareness (though visualisations), reflection, sense making and impact. Those visualisations must be in line with learning theory. Positive influence on learning for the overall population, through self-assessment, lab setting and course settings. Differential readiness of student to profit from a treatment in a specific context (Snow 1991) and Aptitudes (or other theoretical constructs) can explain differences in students.

Study: look up AGOs (self approach or avoidance, task approach or avoidance) impact on learning of LA visualisations. Co-metrix analysis (computational semantics analysis). 2 things measured, number of posts of the student compared to average number of posts, number of contributions in forum compared to the 5 top contributors, quality of contributions in forum.

LA visualisations to learn student's behaviour, individual differences make difference on whether the effect is positive or negative. So studies in real course necessary, individual differences in LA visualisation are necessary, use fine-grained data.

Q: student made use of visualisation at beginning & end, not so much in middle.

Master versus performance orientation of student will also have an impact.

The NTU Student Dashboard: Implementing a whole institution learning analytics platform to improve student engagement" (practitioner presentation)

Ed Foster, Nottingham Trent University

Why did NTU develop the dashboard?

What are the factors that make student stay, institutional change. Audit showed that retention was not bad but staff had no access to students, IS dept went to talk to LA commercial sector. Wanted to show progression to student, foster the sense of belonging and link to tutor and sense of attainment.

The dashboard show student's engagement (not risk of failing) with the course measured by door swipes, library use, logins to VLE, submission to VLE dropbox, new electronic resource use and attendance (may include ebooks and attendance later).

5 ratings, high, good partial, low, not fully enrolled (student who never completed enrolment or have withdrawn). Staff and student have the same view. Staff has a few mgt screens and can make notes.

1) Course average graph, with student in comparison, cumulative graph
2) Week by week graph with same data

Developmental journey

Small grp of people with experts, regular meetings, quick exchange of ideas, experts from different places. Graduated to governance

Bottom: ethics, uni system group, informal student grp feed into Dashboard Operation Grp, feed into Dashboard governance grp (academics, students, …,…).

Is it accurate?

Average engagement is 56% takes weekends and holidays into account where the activity will be reduced. Is there a relationship between engagement as shown by dashboard and progression? Yes, average engagement does link to progression, low engagement students only 20% of them progressed to the next year. The longer the engagement is low the higher the risk of failing progression.

Student feedback

27% of student reported changing behaviour. If the staff used the dashboard for a 1 to 1, student found it very useful.

Staff feedback

More use did not yield confidence on usefulness of dashboard. Staff is worried that this is a staff mgt tool rather than learning analytics tool (e.g. did they act upon the alert for a student).

LA is enabling but not sure how much of a behaviour changer…LA is only useful as the actions it instigates.

Lessons learned

Needed: Time, training, motivation, easy access to data for staff, room to talk to student or space to email them. Q: introduction of super tutor between tutors and LA system designers.

"Privacy and Analytics – it's a DELICATE Issue. A Checklist for Trusted Learning Analytics."

by Hendrik Drachsler and Wolfgang Greller

LACE

http://www.laceproject.eu/ethics-privacy/

http://www.laceproject.eu/learning-analytics-review/is-privacy-a-show-stopper/

Jisc code of practice for learning analytics

Ethical use of student data

The learning analytics report card

http://www.de.ed.ac.uk/project/learning-analytics-report-card

Determination, explain, legitimate, involve, consent, anonymise, technical, external.

- Mgt teams concerns about LA
- Promise vs concerns
- Potential vs risk
- Benefit vs cost
- Purpose vs competitive pressure
- Intentions vs hesitations

Privacy is a show-stopper for LA (In bloom had to close, snappet (https://nl.snappet.org/)), ignoring public fear can lead to lack of acceptance, protest or failure.

Historical

Nuremberg code 1949, Helsinki declaration 1964, Belmont report 1978, mid 90s biomedical science then responsible research and innovation.

Data privacy

- Right to be left alone (Westin 1968)
- Informational self-determination (Flaherty 1989)
- Informational, decisional, local privacy (Roessler 2005)
- Not same as data security or anonymity!
- Contextual integrity vs big data research
- Context bound information vs re-purposing of data

Legal frameworks

EU data protection directive 95/46EC, 2016 General data protection regulation will become law in 2017. Right to be forgotten.

Modernisation of EU university, see recommendation 14/15.
http://ec.europa.eu/education/library/reports....

Student should be able to have the same educational opportunities even if they opt out of their data being used.

Fears with LA implementation

- Power-relationship: Asymmetrical, no benefit to the user.
- Exploitation: free labour, free contribution, crowd sourcing outside the commons.
- Data ownership: curator of own data
- Anonymity and data security: no absolute anonymity or de-identification, integration of multiple data sources increase compromised personal identity
- Privacy and data identity: system identity (you may now know exist, outside your geographical range maybe) vs social identity, boxed into models through approximation of data, data subject have no say in the designed in the data models
- Transparency and trust: one leads to more of the other, also asymmetrical, so transparency can be used as means of control (demanding explanation for behaviour of people)

8 point check list to use as guide.

Journal of HE- special edition LA on implication of learning analytics for higher education, currently call for papers, follow through.

Bit.ly/1qXTaNz

http://www.zfhe.at/index.php/zfhe/announcement/view/48

Deadline 10 June 2016

Q: where is the "right to redress" in those criteria.

Using predictive indicators of student success at scale – implementation successes, issues and lessons from the Open University

Kevin Mayles-Open University

2 approaches: module probabilities, probability of a student passing a module. Used at beginning, to garget most vulnerable students. OU analyse tool: predicts submission of next assignment, prediction produced weekly.

Lessons learned

- Create the right story for the user
- Start small- find and nurture your champions in your staff
- Don’t underestimate the guidance required for users
- Create your super-user (someone like users), create your case studies
- Foreground the “should we “ arguments around ethics see http://www.open.ac.uk/students/charter/essential-documents/a-to-z
- Repeat, repeat, repeat

Measures: accuracy of predictions, volume and timeliness of predictions. Accurate predictions at a manageable volume which are timely in relation to a student’s decision to drop out.

By week 5, 2/3 of predictions are true, but only ID half of non-submitters.

By week 14, predictions ID 2/3 of non-submitters. Precision 80-85%.

One new prediction per fortnight.

Timeliness

Distance between changes in prediction made (between positive to negative) and last engagement date, windows of opportunity. Within 2 weeks of them disengaging, the tutor needs to nudge.

What Can Analytics Contribute to Accessibility in e-Learning Systems and to Disabled Students’ Learning

Martyn Cooper, Rebecca Ferguson and **Annika Wolff**

…

Investigating Boredom and Engagement during Writing Using Multiple Sources of Information: The Essay, The Writer, and Keystrokes

Laura Allen, Caitlin Mills, Matthew Jacovina, Scott Crossley, Sidney D’Mello and Danielle McNamara

…

Going Enterprise: Challenges Faced and Lessons Learned When Scaling and Integrating a Research-based Product for Commercial Distribution

Aleksander Dietrichson, Vera Friedrichs, Diego Forteza and John Whitmer

x-ray analytics

Enhancing impact through design (collect data, build customised models), analyse, intervene (make experiments), evaluate, design gain

Firehose session

1 minute pitch talks about posters
Annouschka Van Leeuwen, teaching and learning analytics
Shuchi Grover et al., multimodal analytics
Xiao, Hu, assessment of collaborative writing (wiki), automatic assessment
Rebecca Ferguson, evidence hub (http://evidence.laceproject.eu/)
Multimodal learning analytics in hand on STEM activities,
Kimberle Koile, machine analysis to make maths thinking visible
Sandeep M. Jayapradesh, student performance in online courses using interactive learning activity radars
John Dillon, Student affect during learning with a MOOC
Daniella Hagood, Physical activity data in a video game as dashboard
B.A Schwendimann, overview of learning dashboard studies. Lit. rev of 50 papers
Bart Rienties et al.,3 case studies
Jos; Ruiperez-Valente, intentionality of student towards badges at Khan Academy
Mingu Feng, Data intensive research method and researcher practitioner partnership
Yohan Jo, pipeline of learning analytics of social learning
Alan Berg, XAPI recipe
Sandra Milligan, audit of your validity argument
…, Sth Africa,
Elle Yuan, factor related to post-MOOC career advancement
Korinn Ostrow, towards a sound environment for robust learning analytics
Hector Pijerra Diaz, Biosensor data to enrich analytics in collaborative learning
Garron Hillaire, sentiment analysis, core effect
Michael Brown, in a large lecture group, which learning tools do they use, so use social network learning analytics
Jenna Mittelmeier, groupwork in blended classrooms, social tensions from multi-culti classes
Caitlin Holman, assignment pathways, using data-driven personas
Lativa, Australia, impacts of adopting of LA in different academic microcultures

LAK16 Hackathon outcomes (38 people)

Moodle, saltbox, watershed, learning locker, watershed, experience xAPI

28.4.2016

Learning Analytics: Utopia or Dystopia

Professor Paul A. Kirschner

What is learning?
Fast developing field still. Long-term change in memory. So tertiary ed, foster 1 type of education.

LA
Capture, report (query), predict, act, refine in Academic analytics Campbel et al EDUCAUSE white paper 2007.

Learning analytics model (Siemens 2013) check publication

LA is currently Academic or institutional analytics not much about learning yet! For now LA is much about digging about to find an answer to unasked question, hoping that the data you have will yield some answer (discover patterns and associations, exploratory only, not good causal conclusions about how to intervene you only get what relates to what). Strong connections with the learning sciences still lacking. **LA is currently data rich but theory poor.** Make use of what there is but not what is needed. (car key search image, streetlight effect).

Learning science theory
Variable to include in a model, potential confounds, subgrps, covariate, which results to attend to, framework to interpret the results, how to make results actionable, generalisation of results to other context and populations.

Looking at wrong or invalid variables
No empirical justification to tailor instruction to learning styles.
Zimmerman, self-regulated learning styles: cognitive process that transform … into academic outcomes.

Correlation still taken as meaning causation in LA
Need framework before hand

Unintended and unwanted effects, unintended consequences.
Eg.

	Mastery goals	Performance goals
Approach oriented	Motivated to truly master academic task	Motivate to demonstrate they have more ability than peers
Avoidance oriented	Motivated to seek to avoid misunderstanding given tasks	Motivated to avoid appearing incompetent or stupid in the eye of others

But education should be about mastery, so we should not foster performance goals, some that used to be mastery become performance students which exactly what we don-t want.

LA noble intentions but can lead to pigeonhole, profile, stereotyping. Once a label has been given very difficult to remove, also the learner may not even know the label has been given. Learner's bias, where tutor or institution has a biased view of the student.

LACE horizon report, sole reliance on technology at the cost of education could cause greater social exclusion

LA is a system but systemic, so far reductionist.
All ingredients in a carrot don't make a carrot.

So, so far LA has potential but no recognised value yet.

LA aims to predict
(see yogi berra quotes)

Simple data (VLE data for eg).
Learning & Educational technology research unit EARLI conference 29.11.2016-1.12.2016 in Finland.

Set of technique proven to work in green (find slides).
Ten steps to complex learning book (http://www.tensteps.info/)

Learning effort, should be included in LA

Recommend, advise, intervene
The right thing for the right learner at the right time.
Hattie Timperley 2007 The power of feedback, review of educational research 77 (1), 81-112.

Better learning environment with LA?
Course improvement, staff feedback etc.
www.slamproject.org/blog using physiological data self regulating data.
LA is a tool to get somewhere, it is not the place where we want to be.

2 books
LA in massively multiuser environments
JCAL special issue code JCALLAK16

Urban myths about learning and education

In short:

- Have a good theory
- Stop using those self-measures of learning as people actually don't know how they learn
- What you want people to learn is not the same as what they are actually learning
- Reward for trying confounds whether you are learning
- Pheromone analytics, routes that lead to nothing are being followed, but better to follow how alumni behaved and gained success.

Data2U: Scalable Real time Student Feedback in Active Learning Environments" (short paper)

by Imran Khan and Abelardo Pardo

Instructor might be the bottleneck for real-time feedback.

Students are able to interpret the data and increase motivation after seeing the data. Identify populations of students on how they use the dashboard, found 4 different ones. Dashboards do not correlate with academic performance. In this study the class average was with people who did engage with the one activity.

Measuring financial implications of an early alert system" (full paper)

by Scott Harrison, Rene Villano, Grace Lynch and George Chen

How much should an institution spend to attain an improvement in student outcomes?

Do early warning systems have a positive return on investment if so by how much?

If changes are made to the system, can we measure them?

Australia future unlimited

Early Alert System (EAS)

Study with treatment effect modelling. Treatment and no treatment. Inputing missing outcomes (values) by modelling. Give after treatment effect.

Caliendo and Kopeinig 2008

Cost of discontinuing

Per student basis, ca.4600 AUD compared to those who enrolled, about 6000 if they enrolled and completed.

1% increase in enrolled instead of drop out roughly 500'000 AUD

4000 AUD between an identified student and non-identified student.

Financial implication of EAS identification

If you get identified and then drop out lose 5100 AUD. So if we support student and then they drop out we lose more. Not all schools had the same values, value in early id system in all schools.

Value of the EAS over time

The value of identifying a student is still 4000, 2600, 3400 in 1,2,3rd year.

Prior knowledge and prior engagement should be included to match the students.

Getting Started with Learning Analytics: Implementing a Predictive Model Validation Project at North Carolina State University

by Josh Baron, Lou Harrison and Sandeep Jayaprakash

EDUCAUSE next generation learning challenges (NGLC)

Open source academic early alert system

Open academic analytics initiative.

https://confluence.sakaiproject.org/pages/viewpage.action?pageId=75671025

Learn @scale.

http://learningatscale.acm.org/las2016/

Early alert of academically at risk students an open source analytics initiative journal of learning analytics 1 1 6-47

https://epress.lib.uts.edu.au/journals/index.php/JLA/article/view/3249

Early is best for intervention but later is better to get more accuracy of the model, multiple (cohort) models refine accuracy, cost more to develop and maintain…

A Conceptual Framework linking Learning Design with Learning Analytics" (full paper)

by Aneesha Bakharia, Linda Corrin, Paula de Barba, Gregor Kennedy, Dragan Gasevic, Raoul Mulder, David Williams, Shane Dawson and Lori Lockyer

Learning design=pedagogical intent

Actions in relation to data teachers got not done in round 1

Opportunity to articulate the design

Lockyer Heathcote and Dawson 2013

http://abs.sagepub.com/content/early/2013/03/11/0002764213479367

Methods: Review on existing learning analytics tools, interview with teaching staff, specific user scenarios. Put the teacher in the loop.

- They requested temporal, tool specific and cohort dynamics, did a comparative analysis.
- Intervention support tools
- Learning and teaching context, course structure and curriculum design, learning design…

Temporal analysis

- Access statistics for the course to find out what material was valuable to the students.
- Visualise pre and post event

Tools specifics analysis

- Metrics for quizzes

- Metrics for forums

Cohort dynamics and patterns

- Finding students who access content and those who don't

Comparative analysis

- Comparing the impact of different learning activities
- Review student's participation comparatively

Key take away: teachers are important!

Contingency and decision support tools

- ID students
- Email clusters of similar students
- Allowing teacher to find students with similar attributes

Loop tool

- Soon to be open source

The impact of 151 learning designs on student satisfaction and performance: social learning (analytics) matters" (short paper)

by Bart Rienties and Lisette Toetenel

Failing leads to lots of learning

Constructivist approach. Assessment driven productive social constructivist curves.

…

Student differences in regulation strategies and their use of learning resources:

implications for educational design

by Nynke Bos and Saskia Brand-Gruwel

Money to LA went to IT at Uni Amsterdam. Lack of goal, focus and lack of problems to solve for examples: Predictive value, which data, course performance, quality of education, one size fits all?

Current practice LA modelling student behaviour, predicting course performance so predictors for failure and focus on course level.

Challenges: individual differences in uses for education technology, causes for differences to act, impact on course design (face-to-face, blended).

Individual differences

Students use only one of the resources, some do not use resources at all, some use as substitute for face-to-face.

Lust et al 2013 a, b

Kovanovic et al 2015 Ellis et al 2008, Bos et al 2016

Regulation of learning

Self-regulation, external regulation (teacher, should I know this for the exam) and lack of regulation

Course design

- Online learning vs blended learning
- Validating each and every course?

Are regulation strategies good clusters for student? Do they use the resources differently?

Two more research questions see paper.

Data collected

- Attendance face-to-face lectures
- Viewing of the recorded lectures
- Digital workbook, formative assessment grades and number taken
- LMS data hits and duration
- Regulation strategies questionnaire
- Score of summative assessment

Clusters found

- No clear regulation pattern
- Combination lack and external
- Combination self and external

How did clusters use the resources?

No differences!!!

Combinations do explain variance in data? So when use is linked to course performance the combination self and external did not do better.

Can regulations be inferred from use of resources? No user, focused selective, content-focus intensive, socially-focused intensive.

Expertise reversal effect? So self-regulated students are held back

Contextualisation of LA data is crucial in establishing the impact of the learning data analysis since these conditions affect the learning process

So

- Not all clicks are equal
- Low predictive LMS use on course performance
- The order in which the student use the resource is potentially important and could increase the predictive power of LMS
- Dashboards (one size fits all) should be examined critically.

Promoting self-regulated learning

- Help student make choices
- Explain added value of tools
- Less face-to-safe lectures (more knowledge snippets videos)
- Open course ware
- Monitoring of progress (no forcing)

Danny , lieu et al. Macquarie uni Understanding learning path overlaying data course outcomes

29.4.2016

Robert J. Mislevy

Educational testing service

A dispatch from the psychometric front

Standard Ed measurement paradigm, measuring a construct framed in trait or behavioural psy, usu only 1 single measure is desired. Items are made then item score, test score accumulates evidence over items, (latent variable model such as item response theory).

Insights from psychometrics

- Probability-based reasoning
- Building models that suited an inferential problem case in psychological theory with germane data
- See Messick 1994 (reliability, validity, comparability, generaliblity and fairness not just as measurement issues but social value that have meaning and force outside…

Standard Ed measurement paradigm

- Measurement paradigm of observation and control over 150 yrs is a layer over the examination paradigm that was valid for 2000 yrs.
- In early days, no much focus on cognitive or learning process
- Data: human ratings of performances hide complexity and don't scale
- Objective scoring scale better and can be automated but less observational situation and performance

- Models used to be data mining: regressions, correlations, cluster analysis, factor analysis and path diagrams

Probability-based reasoning

- Probability is not about number it is about the structure of reasoning (Glenn Shafer, quoted in Paerl, 1998)
- Bayesian inference
- Modularity

Situative and socio-cognitive psychology

- Person acting in a situation not removed from it
- What we experience is the tip of the iceberg, there are patterns that are outside our socio-cognitive perception. Recognising and becoming attune to those patterns that enable you to get the task done in that context. Within-individual processes give rise to individual actions but relate to the LCS patterns and adapt to unique situation.

What is important to know?

- What is important to notice
- What does that mean
- What will happen next
- What kinds of things can I say or do next
- How can I create or negotiate situations

Implications for psychometric models

- Constructs (hence latent variables) the constructs can point out to what resources the person has to deal with a specific situation
- But context of learning will strongly influence the outcome

Forecasting Student Achievement in MOOCs with Natural Language Processing" (short paper)

by Carly Robinson, Michael Yeomans, Justin Reich, Chris Hulleman and Hunter Gehlbach

- Writing what you plan is at the beginning of the class seem to have a positive effect on completing the MOOC

"Is the Doer Effect a Causal Relationship? How Can We Tell and Why It's Important" (full paper)

by Kenneth R. Koedinger, Elizabeth A. McLaughlin, Julianna Zhuxin Jia and Norman L. Bier

- Amount of online interactive practice increases their outcome
- Limited casual inference low internal validity of that kind of data, but high external validity
- OLI open learning initiative website

- Learning by doing, deliberate practice or testing effect theories relevant?
- Introduction to psychology at OLI or at Coursera
- Learning is not a spectator sport: doing is better than watching for learning from a MOOC Proceeding of the second ACM conference on learning at scale, Koedinger, Kim Jia, McLaughlin and Bier 2015.
- Watching a lot does not lead to being able to avoid poor performance, but doing a lot might.
- 0.2 effect size of doing on outcome, almost no effect of reading and watching
- Doing has a onsistent doer effect across courses whereas reading does not
- Amount of online activities and practice has generally a positive effect on learning outcome, but we do not know yet if it is causal
- Future research questions might include: is doing more with feedback more beneficial than just doing?
- See LearnSphere's workflow tool (http://learnsphere.org/)

"Towards triggering higher-order thinking behaviours in MOOCs" (full paper)

by Xu Wang, Miaomiao Wen and Carolyn Rose

- ICAP framework: passive, active, interactive, constructive ways of engaging (see Chi and Wylie 2014.The ICAP framework: linking cognitive engagement active learning outcome).
- Coding manual of the ICAP framework
- Interactive and constructive high-order thinking behaviour.
- High-order thinking behaviour is more beneficial than paying attention and more beneficial than off-topic forum discussion
- So are the students showing high-order learning a different type of learner?
- What discussion behaviour leads to more learning? Topic model to find out which topic elicits more discussion of high order learning.

Exploring the relation between Self-regulation, Online Activities, and Academic Performance: A case study" (full paper)

by Abelardo Pardo, Feifei Han and Robert Ellis

- See his paper for references on
- SRL instrument, self-regulation section (9 items) of the motivated strategies for learning questionnaire, MSLQ
- Engineering course with 145 students, blended learning with some online activity
- Digital footprint instrument (positive self-regulation strategy and negative self-regulation strategy), exploratory factor analysis.
- Academic performance was slightly negatively correlated to positive self-regulation, but AP did correlate to 0.2 with negative self-regulation strategy
- Negative self-regulation has a higher impact on all resources given
- When grouped into 2 clusters high-reg low-reg, behaved differently online.
- No direct influence of online activities on academic performance
- Negative (PSRS) influence on academic performance is not mediated by interaction with online activity, so we don't know if there is a potential there to improve things.

- Positive influence of online activities on ap, strong
- Weak positive influence of PSRS on AP (Indirect influence though online activity)
- Strategies to reduce negative self-regulation are paramount (reflective task as part of online activity)
- Propose: self-reflection for those with NSRS followed by feedback with tutor

Fostering 21st century literacies through a collaborative critical reading and learning analytics environment: User-perceived benefits and problematics" (short paper)

by Jennifer Pei-Ling Tan, Simon Yang, Elizabeth Koh and Christin Jonathan

- Voice of learners as critical stakeholders
- Conventional Singapore print-based fail to engage pupils to master literacy and numeracy, limited opportunities for other formative activities
- Multimodal social dialogic learning and dynamic visual learning analytics
- Socio-constructivist learning theory, multi-literacies framework, situated practice, transformed practice, overt instruction and critical framing
- 5 critical lenses, I think that, I think so because, I agree, I disagree, I need to ask…
- Message purpose audience, assumption,…
- Dashboard for reading achievement (visual texts, narrative texts, information texts). It did change the behaviour of some of the students
- Attitude towards learning and teacher trust
- How healthy is my learning mindset? Me and class average (desire to prove competence ability or desire to improve skills and knowledge)
- Sociograms reflecting the student engagement with other learners
- Learning attitudes were reflected upon

Improving efficacy attribution in a self-directed learning environment using prior knowledge individualization" (short paper)

by Zachary Pardos and Yanbo Xu

- EdX MOOC
- Items in the online environment get a probability of learning from it if students show a heightened probability of learning after watching the video
- BKT learning analysis (Rau and Pardos, 2012)
- BKT learning analysis of turorial strategies (Pardos, Dailey Heffernan 2011)
- Vocabulary assistance experiment (Aist & Mostow, 2000)
- Resource use is negatively correlated with ability! (champaign et al. 2014)