Adaptive Learning and Learning Analytics: a new learning design paradigm

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Abstract

New learning technologies require designers and faculty to take a fresh approach to the design of the learner experience. Adaptive learning, responsive and predicative learning systems are emerging with advances in learning analytics, the process of collecting, measuring, analysing and reporting data with the intention of optimising the student learning experience itself and/or the environment in which the experience of learning occurs. However, it is suggested here that no matter how sophisticated the learning analytics platforms, algorithms and user interfaces may become it is the fundamentals of the learning, grounded in meaningful pedagogical and andragogical theories of learning that will ensure that technology solutions will deliver significant and sustainable benefits.

Introduction

> *Sasha's wrist screen vibrates gently. It's 08:12 and she's been on the tube a few minutes. Four short bullet points identifying the learning objectives for the learning unit she's studying appear on the 2cm by 4cm flexible screen. Three objectives are in black denoting them as 'standard', the fourth is in purple, her chosen notification colour. She taps the purple text and a diagram pops up on screen showing how this objective is a response to a learning challenge she experienced on the previous module. It's too small for her to work with and she anticipates there's more detail so she swipes the text from her wrist to the tablet on her knees. Her wrist screen goes back to the standby clock. The diagram is easier to see on the tablet's larger screen, and new text appears, allowing her to touch each element of the diagram and reveal new sources and references. This personal 'purple' objective is headed 'critique'. Holding her finger over the word 'critique' a list of learning units already completed appears where this is a theme, reassuring her progress has been, and is being, made. Sasha sees she has not completed successfully her previous critique activities on the first attempt. Obviously her Personal Adaptive Learning system (PAL) will keep encouraging her to work with these objectives. Sasha scans the interactive learning unit diagram for a few minutes, dragging tasks and elements onto her combined work and personal calendar; she has a train to Bristol this afternoon for work and will have time to complete all four stages of the 30 minute activity suggested by PAL. Sasha swipes the diagram off the tablet and is prompted with 'Course Related News'. Today's unit will include critiquing a particular French Trade Union's position on European Migrant Labour regulations; overnight new economic data on French agriculture, a story about Italy needing more seasonal workers and an article in a US journal have all appeared. Sasha flicks the first story to the trash but drags the other two onto the icon for her train trip to Bristol. The 'prompt' icon is glowing and she's happy for any help and advice; tapping the icon there is a prompt that tonight at 21:30 on CNN Europe there will be an interview with the Head of the IMF, an organisation she wrote about in her last journal piece for her other module. She pushes that to her personal diary space. It's 08:32 and her management of her learning path for the day has made her PAL icon glow green, always a motivator.*

Adaptive learning promises to be able to tailor individual learning experiences not just to competences and learning preferences but also to life contexts. Sasha's learning system knows she has time on the tube to plan her day, understands the difference between the technology spaces she works in and allows her to integrate her learning into her personal time management tools. To do this it needs not just to make syllabus suggestions and push new content at Sasha, it needs to integrate into her lifestyle. Ubiquitous wearable technology and intelligent adaptive systems make this scenario likely rather than merely plausible. However, since a similar imagined scenario described Shirley's virtual cat-suit geography fieldtrip to Niagara Falls in the opening chapter of Tiffin and Rajasingham's *In Search of the Virtual Class* in 1995, we are yet to see anything approximating to that envisioned learning experience (Tiffin & Rajasingham, 1995).

Hyperbole is never very far away in educational technology. At the height of the 'social media' *revolution* just a few years ago, barely an application, website services or technology start-up did not use the term 'social' somewhere in its self-advocacy and self-promotion. The term 'analytics' is currently undergoing a similar misappropriation with the casual use and abuse of an ill-defined term. Behind the hyperbole is a radical change that began with the networked communication innovations spawned by the Internet and the world-wide web, and continues through the current mobile, social and saturated data environment in which we now work, live and learn (Siemens & Matheos, 2010). Learning analytics is the process of collecting, measuring, analysing and reporting data on the context of the learner and the learner's engagement with learning with a view to optimising both. The intention is to be able to optimise the student learning experience itself and/or the environment in which learning is intended to occur. This optimisation is often defined in terms of 'adaptive learning' models or approaches. Learning analytics is one of a number of related fields, largely with their roots in business intelligence systems that seek to enhance, through 'adaptation', the process of learning and teaching by acquiring and using information intelligently. There are three distinct but interrelated fields of learning analytics, academic analytics and educational data mining which have different academic research communities and which are informed by different epistemological traditions.

A review of the English language academic literature suggests the field of learning analytics is dominated by US academic research with a growing engagement from Australia, the UK, Germany and some Canadian contributions. Topics focus more on K-12 rather than Higher Education and the dominant perspective is on the application of technology. Many of the academic papers are concerned either with the nature of the computer algorithms required to analyse or utilise the vast array of data being generated with analytics in mind, or on small scale case studies of specific attempts at data analysis and adaption. This paper attempts to explore some of the social implications of big data collection. It differentiates between the various fields of enquiry concerned with gathering and applying learner data to the learning process and goes on to articulate some of the challenges that such data collection involves and the opportunity it represents. Finally it explores the impact of learning analytics in particular on course design and faculty.

Overlapping Fields

There is value in defining the differences, and reviewing the similarities, of the educational fields of enquiry described as academic analytics (AA), educational data mining (EDM) and learning analytics (LA).

Academic Analytics

Academic analytics (AA) is a field concerned primarily with organisational efficiencies derived from the intelligent use of business data in the educational context. Rich data that identifies the efficiency of everything from the use of teaching space, to library storage and usage, to the popularity of programmes, modules and options are all used to 'refine' the organisational delivery of learning. The field is dominated by United States academics and focus is often on student retention and faculty effectiveness (Chacon, Spicer, & Valbuena, 2012). There is significant governmental and philanthropic interest in academic analytics as a means of making access to, and engagement with, higher education more effective and the field emphasises the societal benefits of effective decision making in publicly funded institutions (Campbell & Oblinger, 2007).

Educational Data Mining (EDM)

Educational data mining is a field that is growing alongside the contemporary interest in learning analytics. The field is heavily influenced by information science's traditional engagement with machine learning and experiments with predictive computer based training methodology. Large data sets are mined to identify predictive behaviours that students, under a given set of circumstances, are likely to carry out, allowing faculty to alter course designs or assessment forms on a cohort level. Techniques vary from classical statistical analysis of quantitative data sets to experimentation with neural networks (Romero & Ventura, 2011).

EDM has developed a range of approaches to the visualisation of large and complex data sets to support faculty in identifying probable student behaviours, grouping and streaming students and analysing social interactions. Large scale online delivery of learning (such as Massive Online Open Courseware – MOOCs) have given the EDM movement a fresh focus where there has long been a concern about the persistence of learning engagement and retention in online courses (Hershkovitz & Nachmias, 2011).

Learning Analytics (LA)

LA is closely associated with the EDM field but with a focus on systemic wholes. Where EDM might be said to focus on the use of data patterns to identify course level changes to assessment or delivery patterns, LA is more concerned with the means to support the individual learner experience in as broad a context as possible. Both EDM and LA are concerned with deriving maximum benefit for the learner from an analysis of data, to assist with systemic and individualised decision-making. LA is concerned with how students develop competence and seeks to identify successful patterns of behaviour, relate that behaviour to known social variables, and identify probable future 'optimal' learning experiences. Data analysis, in the form of visualisations, models or maps, then supports adjustments to the learning environment or the individual learner trajectory to ensure an optimal learning opportunity.

LA has built on existing research methodologies in fields such a network analysis, content analysis and discourse analysis. There is a great deal of concern with semantic analysis and increasingly with contextual conditions that impact on the learner. There is a focus on how students develop competence, often by acknowledging the social dimensions of learning and seeking to identify and facilitate optimal social engagement (Buckingham Shum & Ferguson, 2012). Concerned with 'collecting traces that learners leave behind and using those traces to improve learning', both the fields of data mining and visualisation are significant contributors to effective LA (Duval & Verbert, 2012). Making sense of individuals' behaviour and 'optimising' that behaviour within a given context (possibly shifting) against a backdrop of significant social variation, LA is the exploration of the connections between factors. Much of the current research focus is on examining the validity of connection interrogation techniques (Guba & Lincoln, 2005).

The social dimension of enquiry is perhaps a distinction between EDM approaches and those seen in LA. With learning taking place in social networks and through distributed learning platforms, there are multiple means of participation, each with different sociological and pedagogical affordances. The data generated by these different participatory forms, where they exist, are logged differently and tracked differently. The majority of students may resolve a complex conceptual problem during the commute to work in the 24 hours after an online webinar, but that fact is unlikely to be recorded in current data capture systems.

The challenge, therefore, is not just the volume of data to be captured but also the scope of that data. The use of mobile devices suggests learners may seek to learn different things in different spaces and this would represent valuable analytical detail to facilitate personalisation. Handling the complex multi-dimensional models that represent diverse and intricate data sources requires new analytic skills. In Sasha's example we can see she has chosen to integrate some technology contexts, her personal calendar, into their Personal Adaptive Learning system and allow data to flow from her courseware into personal spaces. She might also allow her TiVo/SkyBox digital TV recorder files to be shared so PAL can suggest programmes to record, or record them for her in her learning directory.

The challenge and opportunity of learning analytics

The rise of the MOOC has given significant impetus to the related fields mentioned above. There are both significant challenges in terms of retention and progress for students engaged in such large online, distance, and potentially impersonal, learning experiences, and opportunities in the richness of extremely large amounts of data being provided by students to the course designers.

Challenges

The challenges of collecting significant amounts of student data are enormous. Whilst a growing awareness of the value of raw data makes collection and storage a more viable proposition, there are issues around the physical requirements of virtual data storage, the legal frameworks for the security of data collected and the ethical and personal privacy dimensions which are only now being explored (Greller & Drachsler, 2012). As national legislation catches up with technology innovation we can expect to see significant disruption to privacy rules and regulations (Cavanagh, 2013).

There is a significant deficit in experience and understanding of how to use data for analytics in a practical context as faculty and IT specialists (with access previously to some, however inadequate, data) have rarely collaborated with the learners' quality of experience as a shared purpose. Not only the 'science' but also the personnel relationships are new and evolving. Even where there has been access to significant students data within existing learning management systems (LMS), these have rarely been taken advantage of, largely because the real value of data derived from the system relies on adaptively being built-in to the course at an early stage (Despotović-Zrakić, Marković, Bogdanović, Barać, & Krčo, 2012).

The fact that a great deal of the financial investment into learning analytics systems is coming from a number of corporate efforts to secure a commercial advantage presents a broader challenge. Blackboard has sought to position itself as providing 'full integration' for analytics into its LMS provision. Pearson, as well as developing their own applications, has taken a significant financial stake in Knewton,[1] and Apollo Group plans for its 'Classroom of the Future' using VCloud (Babcock, 2015). All are being challenged by a strengthening 'Open Learning Analytics' movement in which the OLA seeks to ensure that algorithms are open. The potential for significant integration of student learning patterns within adaptive learning systems suggests that institutions adopting the complex data storage and management protocols associated with their managed learning environment, such as Blackboard, are unlikely to find a move to an alternative platform a very practical proposition.

Opportunity

The opportunity that effective learning analytics presents is that it works on the basis of real-time live data, captured in the normal course of a student's learning engagement. This is a far superior form of evaluative data than self-reporting at the end of a course of study, or indeed on self-reporting and reflection during a programme of study.

It is important to remember, however, that the data being captured is only that likely to be seen through the instrument of capture. A browser based learning platform will record 'every-click' of a student's engagement with the browser. In so doing, it will be able to record how quickly a student completed a task, whether they read or re-read instructions, even where their mouse appeared on the screen throughout an activity. Learning analytics systems will record how long a student took to answer a question, whether they made a selection and changed their mind, whether they are routinely subject to select distracters or misinterpret instructions. What current learning analytics is unlikely to be able to tell us is whether the student had music playing in the background, had slept or eaten well, was feeling positive or is highly motivated.

The opportunity exists to capture a great deal but systems do not currently capture much of the tacit, incremental and social learning context that makes up our learning experience. Learning analytics is concerned with the holistic experience but necessarily engages with this wider picture

[1] Pearson and Knewton Partner to Advance Next Generation of Digital Education: Knewton Website (http://www.knewton.com/press-releases/pearson-partnership/) accessed 20 January 2015.

through a series of specific lenses. Significant analytics is required around learning content and its adaptivity (Vandewaetere, Vandercruysse, & Clarebout, 2012), on the responses and reaction to evolving learning spaces and roles (Atkinson, 2013), and on specific affordances within learning systems (Education Growth Advisors, 2013). However, the most evident data flowing from any learner's engagement with a virtual learning system is likely to be in terms of intervention and adaption (does the student ask for help, does the student follow guidance) and in the field of assessment.

Adaptive assessment predates the broader learning analytics and adaptive education field by some years. Assessment is a field of learning that has long been searching for the optimal use of automated computer assistance, and the ability to respond to qualitative text based assessment with adaptive responses, and represent those to learners in useful visualisations, is an active field of research (Marinagi, Kaburlasos, & Tsoukalas, 2007; Rozali, Hassan, & Zamin, 2010; Silva & Restivo, 2012). The role of human intervention in qualitative assessment scenarios remains a barrier to significant scalability and, as a consequence, the current fascination with MOOCs remains largely within the scope of 'knowledge acquisition' domains and there are only rare instances of sophisticated assessment.

Representing Learning Analytics to Students and Faculty

> *We critique the assumption from at least first generation business intelligence, that analytics should be for the powerful few in the institution, although current BI seems to have some more emphasis on 'dashboards for all'*
> *(Buckingham Shum & Ferguson, 2011).*

Data is power. The question as to who determines, who controls, corrects, adjusts, amends and educates, the adaptive systems emerging from current EDM and learning analytics work presents an interesting challenge. Perhaps the biggest perceived advantage to learners of effective analytics is the opportunity it presents to them to **be seen** to be using their learning time effectively. Advanced organisers have been promoted as an opportunity to ensure students have a clear idea of the learning completed and the learning required, ensuring they do not use valuable 'working memory' to retain syllabus structures in mind when there is no need to do so (Jong, 2010). Advanced organisers also enable students to see connections between concepts, themes or topics and develop a relational awareness not possible without such visual representations as well as supporting them in planning their workload, timing engagements and planning for activities they anticipate to be challenging (Atkinson, 2011). Empowering students to see their progress and their future engagements is a fundamental part of effective design with future learning analytics in mind. Constructively aligned curricula, visually represented with the means to record progress and plan future activity does not require high order programming and complex software solutions. The Student-Owned Learning Engagement (SOLE) model is a learning design tool that also produces a simple Excel workbook that can allow students to use as an advance organiser [2]. This is likely to appeal in a context where the Learning Management System is fairly unsophisticated and now tracking is built in. Students may take responsibility for managing their own progression or feedback the data as a completed excel worksheet for compilation by faculty.

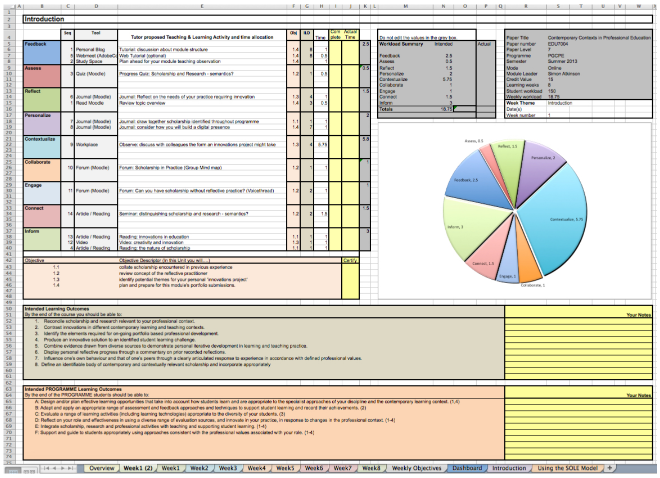

Figure 1 - Excel screenshot illustrating the student view of the advanced organiser for the SOLE Toolkit

The ubiquitous nature of information technologies is changing the relationship learners have with knowledge and with knowledge providers (Lankshear & Knobel, 2006) and MOOCs and other open learning environments suggest that learners are capable of generating and sharing content outside the confines of formalised deliver systems. In closed VLE systems where the barriers to accessing content 'outside' are high, the reliance on tutor guided content remains strong. With increasing ease of access to learning resources comes a shift in the 'content' decision away from the faculty member. Other forms of 'validation' of content are required. Students are likely to value content that is seen as effective over that which is not and so we see patterns of student ranking, or rating, content having a direct impact on student behaviour and one form of analytics attempts to do just this (Ghauth & Abdullah, 2011).

Badges denoting the acquisition of particular skills are not new in education (Halavais, 2012), but are seen as of particular significance in the online learning spaces with greater inter-personal distances and the need to differentiate learner experiences, establish complementary or symbiotic study relationships, and provide the motivation of 'credit' without the complexity of academic validation processes. In some instances, such as the Peer 2 Peer University (P2Pu) project,[3] this ensures very low barriers to entry and the potential for developing a

[2] Student-Owned Learning Engagement model and toolkit is a freely available tool based entirely on Excel (accessed at http://www.solemodel.org on 15 January 2015)

[3] Peer 2 Peer university is a grassroots project that promotes internet based independent learning using Open educational resources intended to support, or run in parallel, to formal higher education (accessed at http://www.p2pu.org on 20 January 2015)

sustained relationship with lifelong learners who return to study in order to add, or upgrade, their P2Pu badges.

Learning providers remain focussed on their ability to demonstrate value to the learner and so a plethora of 'dashboards' is emerging that aim to demonstrate to students their progress, their direction, and the value of what they have been provided with. The 'power' to determine what the student sees remains clearly with the learning provider, even if there are options to turn things 'on and off'. An alternative approach is suggested by Stephen Downes and others with applications such as gRRShopper,[4] a tool that allows students to funnel any content, that generates an RSS feed, from their prescribed learning spaces and personal spaces into the 'comment ecosystem' that is designed to support learning. The student doesn't have to 'come to your space' but contributes in their space and funnels content to others who want it. The aggregator software has facilities to track inter-personal relationships and the 'flagging' of content and conversation deemed important to that individual. Designed with the facilitation of MOOCs in mind, such aggregation technologies promise to challenge the traditional 'knowledge curation' role of University IT services.

The implication is that each of these representational challenges, organisers, learner validated content, badges and aggregators, must also take into account of the different contexts in which learners approach their learning experience. Gender, ethnicity, cultural milieu, language, will all impact on the degree to which a student wants to 'see' their learning journey mapped out in front of them, to have a 'machine' determine their next learning steps, or to be re-directed to correct an 'error' or deficit in performance. We risk forgetting how fundamental assumptions about knowledge and the nature of learning underpin all our personal approaches to the learning experience; our personal epistemology matters greatly in any self-directed learning approach (Frambach, Driessen, Chan, & van der Vleuten, 2012). The advantages of representing analytical data to students is not so difficult to grasp, the challenges of doing so are significant.

Designing for Learning, Teaching and Analytics

If we are to be able to provide Sasha with the kind of personalised, tailored, and malleable learning experience she wants, we must not only make efficient use of the learning analytics data that she, and others, generate, we must also begin to re-evaluate our learning design processes. As learning designers, instructional designers and faculty, we must consider designing units of learning that can be disassembled and reconstructed in meaningful ways to enable the algorithms to work. Work in the early 2000s on reusable learning objects, xml schema and meta-data demonstrated that learning content could not simply be decontextualized and reused at random. On the contrary, the experiences of these early reuse projects was that content needed to be deliberately structured, assembled from carefully labelled parts in such a way that the context of use could be recorded, interpreted and amended, and reuse made of all or part of the object (Churchill, 2007; Lukasiak et al., 2005; Muzio, Heins, & Mundell, 2002).

Never has the risk of 'technology dictating learning' been more evident. Educators themselves must engage with their technology colleagues in order to promote effective learning designs that can keep pace with technology enhancements. Adaptive learning has always been a feature of good teaching. Whether it is the ability of a teacher to structure an in-class discussion to reveal conceptual misunderstandings, to guide stronger students to different readings than weaker students, or to create a flash-assessment to reinforce a learning point or punctuate progression, teachers – good teachers – analyse their own and their students' performance. In an online environment much of the teacher's ability to use 'natural feedback' appears to have been lost, but many have adapted to learn the syntax of the online text discussion forum, the art of the online quiz and the usefulness of the 'learner logs' or attendance records obscured in the management panel of the VLE.

An effective teacher can ensure this 'analytics' perspective is carried forward from the face-to-face classroom and into distance learning provision with revised models of in-class evaluations of the learner experience to guide delivery (Sherry, Fulford, & Zhang,1998). In a course's completion and review, assessment results are 'mined' for course enhancements, and critical review has led to changes for subsequent cohorts. Analytics' primary function might be seen by many faculty to assist them in replicating online the kind of proactive and sustained evaluation of their learners' experiences that they aspire to in the classroom (Sims, Dobbs, & Hand, 2002).

Learning has always been segmented and structured with varying degrees of conscious intent by the educator. Lesson plans and schedules have sought to structure, incrementally, the learning experience to ensure time is well spent. What is different about the current field of learning analytics is its scale and its potential intimacy. No matter how big a course might be, even the largest MOOC, each student should experience a personally constructed and optimised learning experience. To do that, we need to consider a number of learning design factors that would allow us to build a learning experience capable of being segmented, tracked and analysed in a meaningful way.

Designing online and distance learning in discreet units of learning is a good place to start. A learning loop, a process of identifying-illustrating-testing-verifying, is a sound basis for learning design with the power of learning analytics in mind, as it provides the student with a clarity and simplicity they can accommodate in a busy, highly distracted, lifestyle.

[4] gRSShopper is an application that allows you to define your own community of RSS feeds, aggregates content from those feeds and organizes it, and helps you integrate that content into your own posts, articles and other content (accessed at http://sourceforge.net/projects/grsshopper/ on 20 January 2015).

Where each 'learning unit' is conceived of as a four-stage 25-30 minute 'chunk', the student has the opportunity to close the loop for each unit, to record or acknowledge progress and 'move on'. Where possible, this verification of learning should be clear to the student, even to the extent that the associated analytic consequence is clear. Evidence of one's own progress has a significant motivation effect. The scope for analytics to inform theoretical perspectives on motivation is certainly exciting. Complex relationships identified by Wosnitza and Beltman between the context of learning (physical, social and formal), the 'level' of learning (micro-, meso-, exo- and macro-level), which in this context might best be interpreted as at the level of a learning unit, a topic, a paper, a professional stage and so on. Motivation is not a constant but varies depending on these complex relationships (Wosnitza & Beltman, 2012). It is only with a clear structure to learning process and items that one could hope to derive meaningful data that could be analysed within such a framework as that proposed by Wosnitza and Beltman.

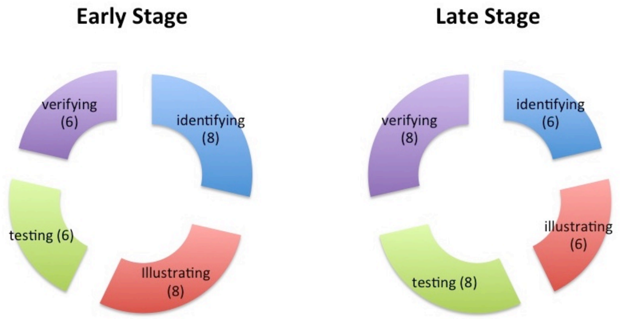

Figure 2 - changing balance of time across stages at different levels of progression

The design of any given learning-loop suggests that there would be an anticipated pattern of granularity, conceptualising learning units as amalgamations of four separate processes (identifying-illustrating-testing-verifying), each of which warrants seven minutes (+/- 1). This follows closely the model of action research of 'plan-act-observe-reflect', which produces effective reflective practice (Atkinson & Irving, 2013). Using this design template would result in units between 24 and 32 minutes in length. In practice, one would expect to see variations in the 'weighting' of different stages of the learning unit, suggesting one is likely to see a greater emphasis in knowledge acquisition on *identifying-illustrating* and less on student reflection through *verifying*. In higher cognitive skill-based activities, the degree of autonomy is reversed and one might expect a student to start a topic with an '8+8+6+6' experience (denoting minutes) and end with a '6+6+8+8' type experience as the learning responsibility shifts from the 'teacher' to the student. Scaffolding the learner experience in a dynamic, transparent and motivational fashion is important for learner success, although recent studies demonstrate that even deliberately structured environments cannot meet the expectations of all learner preferences (Rienties et al., 2012).

Granularity is not intended to unnecessarily constrain learning designers but rather structure their creativity to allow for further assemblages. The fourth stage of the loop is the one the learner is likely to need to record. Stages one and two are 'standard' (although different students might see different versions of the standard content depending on recorded learning preferences), stage three personalised but likely transient, stage four is the record of learning. Designing in such a granular way makes the reusability of content potentially easier and then allows for the technology assistance underpinning delivery of the learning experience (likely a VLE) to change without everything being overly integrated.

The challenge for many current faculty and learning designers is that such a granular model relies less on raw 'content' than on the articulated relationships between these different stages or hermeneutical units, within the learning unit. If we conceive of the four stages as 'thought units', then there is a need to dovetail them, so they represent a coherent whole, yet ensure that individual elements (particularly of stage one and two) can be modified and updated without disrupting the purpose and efficacy of stages three and four. The content represented in identify and Illustrate can (and probably will/should) change, but the overall structure remains consistent because the design is built around the linkages of the four stages and not the content itself.

While individual learning preferences determine whether a student makes full use of any online recording tools provided, it is important for learning designers and designers of learning analytic systems to ensure the learning designs we are building now, and the future learning analytic platforms we know, are going to be necessary in the future. This means that mechanisms are required to meta-tag each of the four stage elements as well as the learning units themselves and to send/distribute/export the stages, and a record of associated activity, if appropriate. Most obviously, the final fourth loop stage, 'verification', is something we should be delivering to the student via the student's email, or exported to a preconfigured e-portfolio, so as to build up a record of their personal progress. This information would not only record their incremental development and progress record, but would identify strengths and weaknesses overtly to the student, allowing them to approach subsequent learning and revision conscious of how the learning environment perceives them.

Conclusions

We do not currently live in an environment sufficiently rich in data about all facets of human activity to enable a learning analytics system to account for all variables. The current challenge is to consolidate as many multiple forms of participation in learning processes as possible and to build up, over time as many different factors that are utterly unique to each individual. Attempts to develop agreed international standards for the collection of such diverse data are in the early stages but there are a number of initiatives, such as the Tin Can API,[5] which is beginning to attempt this.

The influences on the learner beyond the control of the learning provider, employer or indeed the individual themselves, are extremely diverse. Behaviours in social media may not be reflected in work contexts, and patterns of learning in one discipline or field of experience may not be effective in another. The only possible solution to the fragmentation and intricacy of our identities is to have more, and more interconnected, data and that poses a significant problem. Privacy issues are likely to provide a natural break on the innovation of learning analytics. Individuals may not feel that there is sufficient value to them personally to reveal significant information about themselves to data collectors outside the immediate learning experience and that information may simply be inadequate to make effective adaptive decisions. Indeed, the value of the personal data associated with the learning analytics platforms emerging may soon see a two tier pricing arrangement whereby a student pays a lower fee if they engage fully in the data gathering process, providing the learning provider with social and personal data, as well as their learning activity, and higher fees for those that wish to opt-out of the 'data immersion'.

However sophisticated the learning analytics platforms, algorithms and user interfaces become in the next few years, it is the fundamentals of the learning design process which will ensure that learning providers do not need to 're-tool' every 12 months as technology advances and that the optimum benefit for the learner is achieved. Much of the current commercial effort, informed by 'big data' and 'every-click-counts' models of Internet application development, is largely devoid of any educational understanding. There are rich veins of academic traditional and practice in anthropology, sociology and psychology, in particular, that can usefully inform enquiries into discourse analysis, social network analysis, motivation, empathy and sentiment study, predictive modelling and visualisation and engagement and adaptive uses of semantic content (Siemens, 2012). It is the scholarship and research informed learning design itself, grounded in meaningful pedagogical and andragogical theories of learning that will ensure that technology solutions deliver significant and sustainable benefits.

To consciously misparaphrase American satirist Tom Lehrer, learning analytics and adaptive learning platforms are "like sewers, you only get out of them, what you put into them'.

[5] Tin Can API (sometimes known as the Experience API) is a specification for learning technology that makes it possible to collect data about the wide range of experiences a person has (online and offline). This API captures data in a consistent format about a person or group's activities from many technologies (http://tincanapi.com) accessed 20 January 2015.

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