

*Broadening the scope and increasing the usefulness of learning analytics: the case for assessment analytics*

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## *Broadening the Scope and Increasing the Usefulness of Learning Analytics: The Case for Assessment Analytics*

### **Abstract**

This paper argues that the role that assessment could play within a learning analytics strategy is both significant and, as yet, underdeveloped and underexplored. It proposes that assessment analytics has the potential to make a valuable contribution to the field of learning and academic analytics by both broadening its scope and increasing its usefulness. In doing so it considers issues of operationalization and then moves on to define what we might understand as assessment analytics. It then speculates as to why assessment analytics is underexplored and then evaluates some of the tools available for assessment data mining. This paper concludes by offering some ideas for beginning work in the area of assessment analytics but emphasises that this be driven by pedagogical rather than statistical or technical motives. This paper proposes that asking the question 'why assess?' is a productive point of departure for this process and outlines some initial suggestions as to how we might go about doing this in practice.

### **Structured Practitioner Notes**

*What is already known about this topic*

- Learning Analytics is a new field of inquiry, which is growing in importance and significance across the Higher Education sector around the world.
- Learning Analytics is a form of business intelligence used within the Higher Education Sector which aims to bring about improvements in both efficacy and efficiency by making possible better informed (data-led) decision making to students, tutors, researchers, accrediting bodies and institutions.
- Much of the extant research on and application of learning analytics is limited in that it is limited in scope to 'at-risk' students, it is 'pedagogically neutral' and it is constrained by the feasibility of data-mining.
- The most significant challenge facing Learning Analytics is operationalization, something recognised in the 2011 Horizon Report.

*What this paper adds*

- While Learning Analytics is relatively nascent, however, there is very little, if any, published research into Assessment Analytics. This paper proposes that Assessment Analytics is potentially useful to the wider fields of Learning and Academic Analytics by both broadening its scope, increasing its usefulness and making operationalization easier.
- This paper suggests why Assessment Analytics is potentially useful to student learning, academic professional development and institutional teaching and learning strategies.
- It speculates as to why Assessment Analytics has been underexplored and proposes why and how further research in the area could, and should, be undertaken.
- It offers a 'point of departure' for starting work on Assessment Analytics which is pedagogically, rather than statistically motivated.

*Implications for practice and/or policy*

- Incorporating Assessment Analytics into the practice of teaching and learning within Higher Education institutions has the potential to bring significant benefits to students and teachers in terms of both efficiency and efficacy. It can allow students to make better-informed decisions about how and where to invest their time and effort and can offer valuable curriculum design information to teachers between and even within academic years.
- Incorporating Assessment Analytics into institutional Learning Analytics strategies can offer valuable information for planning, procedural and policy purposes and can also provide easy and quick access to high quality, reliable data for Professional Accreditation and Audit purposes.

- Joining Assessment Analytics into the pool of data sources available for Learning and Academic Analytics has significant potential in terms of providing valuable ‘end point’ information that tells us what impact observed patterns of behaviour have on such things as student completion and attainment.

## **Abstract**

In a time of diminishing resource, around the world and across the Higher Education sector institutions are being asked to do more with less. One of the strategies that many institutions are using to achieve this is the increased use of business intelligence: using data to inform decision making to bring about improvements in both efficiency and efficacy. This data-led decision making is starting to have an influence and impact on the core business of Higher Education: teaching and learning. This nascent and growing field of Learning Analytics offers considerable potential to Higher Education institutions (HEIs), the academic staff who work for them and the students they teach. This paper argues that the role that assessment could play within a learning analytics strategy is both significant and, as yet, underdeveloped and underexplored. It proposes that assessment analytics has the potential to make a valuable contribution to the field of learning and academic analytics by both broadening its scope and increasing its usefulness. In doing so it considers issues of operationalization and then moves on to define what we might understand as assessment analytics. It goes on to speculate as to why assessment analytics is underexplored and then evaluates some of the tools available for assessment data mining. This paper concludes by offering some ideas for beginning work in the area of assessment analytics but emphasises that this be driven by pedagogical rather than statistical or technical motives. This paper proposes that asking the question ‘why assess?’ is a productive point of departure for this process and outlines some initial suggestions as to how we might go about doing this in practice.

## **Learning Analytics**

Learning Analytics is a relatively new field of inquiry<sup>1</sup> and its precise meaning is both contested and fluid. There is a growing consensus, however, that Learning Analytics forms a subset of the larger and older field of Academic Analytics.<sup>2</sup> In her very useful review of the current state of play in the field, Ferguson (2012) suggests that the best working definition is that offered by the first LAK conference. Its call for papers defines Learning Analytics as:

the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimising, learning and the environment in which it occurs. (Ferguson, 2012 n.p.; LAK, n.d.)

Ferguson nuances this further:

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<sup>1</sup> For instance, the 2011 Horizon report identifies that Learning Analytics is ‘still in its early stages’ (Johnson, Smith, Willis, Levine, & Haywood, 2011, p.28). The first conference devoted entirely to Learning Analytics (the Learning Analytics and Knowledge (LAK11) Conference) was held in Banff in the same year (LAK, n.d.). As Ferguson (2012) points out, however, there is evidence that it has been taking place in some form since the 1970s (Ferguson, 2012, n.p.).

<sup>2</sup> Academic analytics is a term Goldstein and Katz (2005) have coined for Higher Education Business Intelligence (Goldstein & Katz, 2005, p.2). They suggest that there is a perception that the terminology used for analytics in the corporate sector is not well accepted in the field of Higher Education (Goldstein & Katz, 2005). Several scholars suggest that the Higher Education sector has lagged behind the corporate sector in this area (Bach, 2010; Dawson & McWilliam, 2008; Goldstein & Katz, 2005). The distinction between Academic and Learning Analytics is becoming clearer as the field of inquiry matures. For instance, the SOLAR concept paper makes a very useful distinction between academic analytics and learning analytics which is based on granularity (Siemens et al., 2011).

learning analytics make use of pre-existing, machine-readable data, that its techniques can be used to handle large data sets of data that would not be practicable to deal with manually. (Ferguson, 2012, n.p.)

As Ferguson points out, Learning Analytics is synonymous with, incorporates, has grown out of and sits alongside a bewildering array of different terms and analytical approaches.<sup>3</sup> There have been several drivers that have motivated the development of Learning Analytics, including pressure from funding bodies (particularly government but also fee-paying students and their parents) to achieve greater levels of transparency and accountability (Campbell & Oblinger, 2007, p. 2). It has also been informed by a wide array of pedagogical and learning theories.<sup>4</sup> At the same time, as Ferguson points out, some of the work in Learning Analytics was, as she puts it, ‘pedagogically neutral’ in that it was “not designed to support any specific approach to teaching and learning” (Ferguson, 2012, n.p.).

Much of the research in the field is focussed on questions of improvement in terms of better-informed (i.e. data-led) decision making at the level of the institution (Bach, 2010; Campbell & Oblinger, 2007; Siemens et al., 2011). As Campbell and Oblinger (2007) put it: “In higher education many institutional decisions are too important to be based only on intuition, anecdote, or presumption; critical decisions require facts and the testing of possible solutions” (Campbell & Oblinger, 2007, p. 2). There is, however, increasing emphasis on expanding this data-led decision making to tutors and to students themselves which offers a concomitant emphasis on improving student learning.<sup>5</sup>

Whether it be institution-, student- or tutor-facing a significant proportion of Learning Analytics is preoccupied with predictive strategies based on identified patterns of behaviour and activity that indicate a higher likelihood of certain outcomes. This paper argues, however, that there are two key limitations to learning analytics as it is currently envisaged and that assessment analytics may offer some useful ways of redressing these limitations. The first limitation is that learning analytics has only limited usefulness from both a practical and pedagogical perspective. The reasons for this are complex and complicated but are centred

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<sup>3</sup> These include (but are not limited to): Educational Data Mining (EDM): “concerned with developing methods for exploring the unique types of data that come from educational settings, and using these methods to better understand students, and the settings which they learn in” (Ferguson, 2012); Social Network Analysis (SNA): “explicitly situated within the constructivist paradigm that considers knowledge to be constructed through social negotiation [...SNA allows] detailed investigations of networks made up of ‘actors’ and the relations between them” (Aviv, Erlich, Ravid, & Geva, 2003; De Laat, Lally, Lipponen, & Simons, 2006; Ferguson, 2012); Content Analytics: “a broad heading for the variety of automated methods that can be used to examine, index and filter online media assets, with the intention of guiding learners through the ocean of potential resources available to them” (Drachler et al., 2010; Ferguson, 2012; Verbert et al., 2011).

<sup>4</sup> For example, SNA draws on the social constructivist pedagogical theories of Dewey and Vygotsky. In contrast, Discourse Analytics draws on, as Ferguson notes, “extensive previous work in such areas as exploratory dialogue, latent semantic analysis and computer-supported argumentation” (Dawson & McWilliam, 2008; Ferguson, 2012).

<sup>5</sup> There are a wide variety of answers to the question ‘what does learning mean?’ and, theoretically at least, learning and assessment analytics is viably applicable to all of them. This paper, however, works from a constructivist pedagogical perspective, informed by Biggs, that learning and education is “about conceptual change, not just the acquisition of information” and that this takes place when “it is clear to students (and teachers) what is ‘appropriate’, what the objectives are, where all can see where they are supposed to be going, and where these objectives are buried in the assessment tasks” (Biggs, 1999, p.60). In other words, this paper works from the principle of constructive alignment whereby constructivism is “used as a framework to guide decision-making at all stages in instructional design: in deriving curriculum objectives in terms of performances that represent a suitably high cognitive level, in deciding teaching/learning activities judged to elicit those performances, and to assess and summatively report student performance” (Biggs, 1996, p.347).

around the challenges it faces in terms of operationalization. The second is that the scope of learning analytics is limited because it is largely focussed on only a portion of the student body. This paper now turns to consider these limitations in more detail.

### **The operationalization challenge of Learning Analytics**

The 2011 *Horizon Report* suggests that Learning Analytics is only just beginning to take shape and lists it as being four to five years away from widespread adoption (Johnson, Smith, Willis, Levine, & Haywood, 2011, p. 28). Clearly there are some significant challenges that stand in the way of realising this. Key amongst these is institutions' ability to effectively operationalize it.

One obvious barrier to achieving successful operationalization is the huge and growing volume of data that is potentially available for analysis. The Horizon report, for instance, refers to "an explosion of data" (Johnson et al., 2011, p. 29) in the Higher Education sector, something Ferguson argues is an example of 'big data' (Ferguson, 2012, n.p.; Maryika et al., n.d.). Ferguson asks the important question: "*How can we extract value from these big sets of learning-related data?*" (Ferguson, 2012, n.p.).

Added to this is the sheer complexity of the task at hand. As the SOLAR concept paper makes plain, this field is incredibly complex (Siemens et al., 2011). A product of this can be strategies (and scholarly literature reporting on them) that are virtually impenetrable to the lay audience.<sup>6</sup>

The next issue that arises is what to do with the data once it has been analysed. Ferguson (and others) point out that while most proprietary online learning tools provide data on student behaviour, activity and interaction, they have a tendency to offer very little in terms of teachers or learners being able to usefully act upon it in order to benefit student learning (Ferguson, 2012, n.p.). This returns us to the issues she identifies as 'pedagogic neutrality'. While it is difficult to understand precisely what 'neutrality' might mean in this context or even whether pedagogical neutrality is even possible, the point Ferguson is making here is, perhaps, better understood as having limited or ill-defined usefulness. While the very detailed work that is being undertaken in the field of Learning Analytics may well allow us a very rich understanding of such things as how social learning happens, the benefit that this might bring to student learning and the teachers who are engaged in facilitating it, remains unclear. Again, Ferguson asks a pertinent question: "*How can we substantially improve learning opportunities and educational results at national or international levels?*" (Ferguson, 2012, n.p.).

Even so, the problem of operationalization remains. This is because many of the strategies reported in the literature are based upon student activity, behaviour and interaction inside online learning and social environments; these are environments that, despite the predictions made in the late 20thC, are a long way from being used ubiquitously across the sector. To put it simply, learning analytics is not possible in the vast majority of face-to-face learning sessions that still prevail in most institutions because the learning interactions and outcomes cannot be viably captured. In terms of operationalization, then, it is likely that many if not most of the strategies for learning analytics that have been described in the literature will be ignored by academic staff or meet with resistance if not complete bewilderment.

Even taking all of this into account, as Goldstein and Katz (2005) point out, the effective operationalization of learning analytics, particularly in these early stages, offers a choice

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<sup>6</sup> 'Lay' here certainly includes all students alongside teaching academics whose research specialism falls outside, and sometimes those whose falls within, the key fields of learning theory, discourse analysis and technology enhanced learning.

between depth and breadth (Goldstein & Katz, 2005). This brings the issue of granularity into consideration. Behaviours such as considering students' engagement with a Virtual Learning Environment, and the number of contributions they have made to a blog or discussion board are relatively 'broad' while analysing the discourse used in those contributions and such things as "the pragmatic dimensions of conversational contributions" (De Liddo, Buckingham Shum, Quinto, Bachler, & Cannavacciuolo, 2011, p. 18) is very granular and therefore 'deep'. This is not to suggest that either depth or breadth is more important but rather to reiterate Bach's point that it is important to find the appropriate level of granularity of data for the outcomes that are envisaged (Bach, 2010, n.p.). Implicit within the consideration of granularity is the clear link that needs to be established between data mining and the intended outcomes of the analysis of it, not to mention the actions that can feasibly be performed as a result of it. This offers an important reminder that, especially in the early stages of operationalization, the risk of measuring the wrong things, measuring things that are not meaningful, measuring things simply because they are measurable and/or not measuring the right things remains high.

### **Broadening the Scope of Learning Analytics**

It is on this final point – that currently we might not be measuring some of the things we need to – that this paper now turns to consider. As Ferguson points out, the impetus for a lot of this work came from a desire to reduce student attrition rates and as such, the outcomes upon which a great deal of it has been and remains focussed is student withdrawal or failure. As already argued, this paper suggests that the current intense focus on these 'at-risk' students limits the reach and effectiveness of learning analytics. The SOLAR concept paper proposes that the actions and interventions activated by learning analytics needs to be separated into three strands: "learners demonstrating a) difficulty with course materials b) strong competence and needing more complex or different challenges, and c) at risk for drop out" (Siemens et al., 2011, p.14). The concern raised by this paper is that these three groups of learners constitute only a portion of the student body yet they are receiving (and this is particularly the case for the first and third of these groups) the lion's share of the attention in the literature (and therefore presumably the work) on learning analytics. As such, learning analytics virtually ignores all other students in the achievement spectrum. This paper argues that what almost always constitutes a significant proportion of students – those whose results fall between the 'fail' or 'nearly fail' criterion and the highest criterion (students averaging a C or B/Credit or Distinction/2.2 or 2.1) – are effectively being ignored by the field of learning analytics and therefore constitute a blind spot within it. This paper suggests that this blind spot needs to be addressed and proposes that assessment analytics is an appropriate mechanism through which to achieve this. There exists alongside it, however, a corresponding blind spot: the fact that assessment data is almost never considered or referred to as part of the available data-sets that can inform learning analytics.<sup>7</sup> It is to this that this paper now turns to consider in more detail.

### **The Blind Spot of Assessment Analytics**

It is worth speculating at this point as to why this blind spot around assessment analytics might exist. First, there may be an implicit assumption that analysing social learning and interactions offers a more meaningful insight into, and therefore a more authentic way of measuring, student learning than traditional assessment instruments can provide. However attractive this scenario may be, it is unlikely given that there is very little indication in the corresponding literature that this is a desired outcome of this research (recalling Ferguson's point about much of this work being 'pedagogically neutral'). Secondly, a perception of a

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<sup>7</sup> Assessment data is not mentioned in Campbell and Oblinger's table of Types and Sources of Institutional Data (Campbell & Oblinger, 2007). There is no mention of assessment analytics in the SOLAR report (Siemens et al., 2011), in Ferguson's overview paper (Ferguson, 2012) or the 2011 Horizon Report section on Learning Analytics (Johnson et al., 2011).

potentially inherent unreliability of the data could derive from the need to assume that the assessment designs upon which student achievement is being measured is valid in and of themselves and, also, that it is being reliably measured (specifically inter- and intra-rater reliability). Accounting for this kind of ‘unreliability’ is, however, well established in statistic modelling so it is unlikely to be a significant factor. Thirdly, the blind spot could be there because the available data is not granular enough. In other words, it could be that the level of granularity that most (if not all) HEIs currently mine and store (down to the level of assessment task results) does not offer appropriate detail about what individual students did well or poorly or, more importantly, what they need to do to improve. For instance, two students may receive precisely the same mark or grade for the same assessment task but have demonstrated vastly different strengths and weaknesses to prompt their tutors to arrive at that grade. Derived from this is the fourth possibility, which this paper argues is the most likely: that the more granular (deep) level of data (such as student achievement against individual learning outcomes) has been, up to now, too difficult to collect and collate. This is a direct product of the continuing prevalence and persistence of paper-based marking systems that, like face-to-face learning, are difficult if not impossible to use for the purposes of learning analytics. This paper argues, therefore, that the blind spot around assessment analytics is most likely to be a direct product of the fact that, until relatively recently, the possibility of collecting and collating assessment data at a level of granularity that is meaningful and useful has simply been unthinkable. With the advent of useable, affordable and reliable electronic marking tools and the upsurge in interest across the sector to move towards Electronic Assessment Management (EAM) this is, arguably, about to change. This paper will turn to consider the availability and specific affordances of these marking tools later, but at this point it will turn to define what might be included within the ‘remit’ of Assessment Analytics.

### **Defining Assessment Analytics**

Given the absence of detailed consideration of Assessment Analytics in the literature, this paper proposes to offer a preliminary definition of what it might constitute. Assessment data include, but are not limited to, the following data sets (moving from ‘breadth’ to ‘depth’ in terms of granularity):

- completed degree attainment (eg. degree classifications or end-of-degree grade point averages)
- progression results (eg. End-of-semester or end-of-year grade point averages)
- module results (eg. Final grades for individual subjects, classes or modules within a degree programme)
- Individual assessment results (final grades for individual pieces of coursework/exams usually in the form of a number/percentage or letter grade (A, B, C etc))
- Achievement mapped against explicit learning outcomes or assessment criteria (eg rubric results)
- Specific strengths and weaknesses within an individual student’s work (eg. Existence and/or frequency of common errors such as punctuation, expression, statistics, reasoning etc)

Alongside this are ipsative achievement data – or markers of student improvement against their previous levels of achievement. These can be undertaken at the institution, school, course, subject and individual-student level and include:

- Level of improvement from a formative to a summative task, level of improvement from one assessment task, module, semester or year to the next (sometimes referred to as ‘exit trajectory’)
- Persistence (or lack thereof) of strengths and weaknesses (eg. common errors that recur from one task to the next).

Collectively, I argue, these can be usefully understood as constituting the basic data upon which we can undertake assessment analytics. It is important now to turn to consider in more detail some of the reasons why including assessment data into the potential data sets available for learning and academic analytics is worthwhile

### **The Potential Value of Assessment Analytics**

The first and most important reason why assessment data is worth analysing is its potential to benefit student learning. This is because, as far as students are concerned, assessment is very meaningful. In other words, assessment is fundamentally important to students in that it is widely recognised to motivate learning (Bloxham & Boyd, 2007; Boud & Falchikov, 2007; Dochy, Segers, Gijbels, & Struyven, 2007; Scouller, 1998; Snyder, 1973). To a large and growing extent, it is also what students pay for when they decide to invest their time and money into gaining a higher-education qualification. As Taras (2001) puts it, in a fees-based culture “students as paying customers have invested in higher education and their returns are seen to materialise in the form of assessment grades” (Taras, 2001, p. 606). It also provides students with tangible evidence of their learning attainment and progress. Assessment analytics, therefore, offers the potential for students to measure attainment across time, in comparison to their starting point (ipsative development), to their peers, and/or against benchmarks or standards. It is clear that well designed and well supported, student-facing assessment analytics have significant potential to directly benefit student learning.

The second compelling reason as to why assessment analytics is worthwhile is because of the potential benefits it might bring to academic teaching staff. Marking student assessment is where academic expertise is explicitly useful and is directly applied to the learning of individual students. Sadler (2011) describes grading as “professional consensus among experts using student work as the primary evidence” going on to say: “There is nothing more direct, nothing more fundamental” (Sadler, 2011, p. 89). Elsewhere he argues that grading relies, to a certain extent, on the kind of tacit knowledge that comes with expertise saying “it is well established that experts in a variety of fields can recognise quality when they see it – even when they are unable to define or explain it formally in words” (Sadler, 2009a, p. 820). This expert judgement and tacit knowledge is, to return to Taras’s point above, what students and therefore institutions, are investing in when they pay for academic staff labour. In addition, marking student work constitutes a significant proportion of this labour that is both an expensive and a finite resource. Finding ways to get more value out of this investment is well worth pursuing. Marking can also be a source of significant frustration for academic staff, particularly when they see students making the same errors year after year. This can have an impact on their job satisfaction that, in turn, can have an impact on the effort and time they are prepared to invest in marking in the future. To put it simply, not only do academics spend a lot of their time marking, they also, frankly, tend to derive very little pleasure or satisfaction from it. Finding ways of motivating students to engage with and act on their feedback as well as providing targeted feedforward, timely or even automated interventions (such as cohort- or even student-specific, bespoke study skills support) is likely to go at least some way toward making the labour of marking feel more rewarding for the academics doing it. In a context of constructive alignment (as outlined above) assessment analytics also has the potential to inform teaching and learning practice and curriculum design. In this sense, the development and implementation of assessment analytics is linked to the development of learning outcomes assessment development (Bach, 2010). Bach suggests that “the introduction of learning outcomes and learning characteristics data” can ‘refine’ learning analytics strategies (which measure such things as retention and persistence) already in use (Bach, 2010, n.p.). In fact, in several higher education sectors around the world, there are increased accountability demands such that institutions are being required to map student-



learning achievement against published sets of learning outcomes (such as Graduate Attributes in the Australian tertiary education sector).<sup>8</sup>

The third reason is the potential benefits that assessment analytics can bring at the institutional level. Assessment analytics could usefully inform annual course and module evaluation by providing meaningful inter-cohort, intra- and inter-school comparison and intra- and inter-institutional comparison. As indicated above, in comparison to other learning and academic analytics strategies, it offers much better penetration into the entire student body rather than simply concentrating on low-achieving, very-high-achieving or at-risk students. By being able to identify areas for targeted intervention at each level of achievement, it has the potential to benefit all students. It also, potentially, might benefit institutions' recruitment strategies. It is worth investigating, for instance, whether the capacity to track and provide targeted support throughout students' degree programmes offers added value to prospective students in comparison to competitor institutions. Finally, and perhaps most importantly, in comparison to other learning analytics strategies, assessment analytics is reasonably easy to operationalize. This is simply because, unlike such things as the use of online environments for student interaction, assessment is already ubiquitous across all institutions and its place and role is already widely accepted and understood by all stakeholders. In other words, all students are assessed and some levels of assessment data are already being reliably collected within institutions as part of their ordinary operational procedures. Coupled with the widespread move towards EAM and eMarking across the sector, assessment data that is more granular (and therefore potentially meaningful and useful) is now starting to be collected. The familiarity of collecting and making use of assessment data is also likely to mean that it will encounter significantly less academic staff resistance than other forms of learning analytics and will also achieve higher levels of understanding in its use.

## **Assessment Analytics Tools**

This paper now turns to consider the sorts of tools that are currently available to students, academic staff, institutions and researchers for the purposes of assessment analytics data collection. These fall into four key headings: automatic marking tools, feedback tools, marking tools and originality checking tools. These headings are not clearly demarcated, and there are some tools whose affordances overlap two or more. Automatic marking tools include automatically marked quizzes and short-answer, free-text marking tools. These can be embedded within Virtual Learning Environments (VLEs), offered via stand-alone quiz tools or facilitated in class with the use of individual student response systems or 'clickers'.<sup>9</sup> Feedback tools allow tutors to enter marks, to assign results against assessment criteria (using rubric calculators or 'sliders'), which in some instances can be mapped against such things as programme learning outcomes or graduate attributes. They also allow tutors to provide discursive feedback and feedforward to students in written and/or oral formats. In some instances, these require the submission of assessment elsewhere and all require tutors' engagement with it (eg reading and annotating it) to be facilitated elsewhere.<sup>10</sup> At another layer of complexity, marking tools have many if not all of the features of feedback tools with the added affordances of providing a mechanism for engaging with (reading and contextually annotating) the assessment. Many also allow tutors to use banks of common comments for

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<sup>8</sup> It is important, however, to be attentive to the potential risks that are associated with what James Avis refers to as 'managerialism' in the construction of such things as Learning Outcomes (Avis, 2000).

<sup>9</sup> Some examples of automatic marking tools include: Respondus StudyMate, Adobe Captivate, OnDemand Presenter, Quibble, SMART Response.

<sup>10</sup> Examples of feedback tools include ReView, the Open University's ETMA and Blackboard's Assignment Handler.

this annotation, to customise their own sets of reusable comments and therefore to track the frequency of common strengths and weaknesses in student work. These are therefore most appropriate for handling assessment tasks that are presented in the form of type-written text (eg essays, reports) but that can be adapted to handle other types of assessment that cannot be submitted directly to them.<sup>11</sup> Those tools which also handle student submissions as well as feedback, automate many if not all of the standard administrative requirements for assessment handling including date and time stamping, issuing a proof of receipt, logging submission, distributing work to academic staff for marking, double marking/moderation, external examination and then returning back to students.<sup>12</sup> Alongside, and sometimes embedded within these tools, are originality checking tools which check student work against databases of extant writing. These can be used to identify instances of academic misconduct (such as plagiarism and collusion) and are frequently used as part of the academic integrity instruction provided within the institution.<sup>13</sup>

One of the key benefits of using tools such as these to inform assessment analytics is speed. The capacity for assessment data to inform just-in-time or automated interventions after, between or even before student submissions is now possible and feasible. Because of the frequency of student assessment submission, the lead-time required for meaningful patterns to be identified is relatively short in comparison to other types of learning and academic analytical data.

It is also important to consider some reasons as to why assessment analytics *might not* be undertaken in order to consider how to best mitigate against potentially negative or ‘backwash’ effects. While it is outside the scope of this paper to consider these possible objections in detail, it is worth identifying them at this point. Prime amongst these is the issue of ethics on behalf of both students and tutors. The concern that some may have at being ‘surveilled’ through an analytics strategy may raise concerns about privacy and academic freedom and may raise the spectre of a ‘big brother’ institution. Mitigating these concerns with clear lines of consent and strategic purposes (to improve student learning rather than to ‘police’ poor teaching) will be important. Another concern is that the aggregation of feedback is an instance of infantilising or ‘spoon feeding’ students. Ensuring that analytics automate, make easier, more convenient or more obvious things that we are offering them anyway (such as the identification of strengths and weaknesses) and, as Campbell and Oblinger (2007) argue, are designed to “steer students toward self-sufficiency” are both important (Campbell & Oblinger, 2007, p. 10). Finally, concerns that this strategy might have a ‘flattening’ effect on assessment by leading the pedagogy (rather than responding to or supporting it) are significant. Amongst these concerns we can usefully include concerns focused on grade integrity and the use of assessment criteria and rubrics to evaluate student work (Sadler, 2007, 2009a, 2009b, 2010). It is also important to consider concerns about the potential impact this might have on knowledge acquisition and accumulation (Avis, 2000; Clegg, 2011; Maton, 2009).<sup>14</sup> If, and only if, we can mitigate against these concerns, then it is important to then consider what strategies might be employed for Assessment Analytics.

## Assessment Analytics Strategies

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<sup>11</sup> Examples of marking tools include Turnitin’s Grademark and ReMarks PDF.

<sup>12</sup> These are all vital components of the ‘efficiency’ imperative that Yorke explores in his work on Assessment Management (Yorke, 1998, p.105).

<sup>13</sup> The leaders in this field are Turnitin by iParadigms and SafeAssign by Blackboard. For an evaluation of the effectiveness of the use of text-matching tools in academic integrity instruction see (Davis & Carroll, 2009).

<sup>14</sup> It is worth noting that, within Maton’s research into cumulative knowledge, assessment analytics are used as part of the analytical methodology in the form of the ‘analyses of students’ work products’ (Maton, 2009, p.43).

In terms of building a strategy, as Campbell and Oblinger point out, knowing why you are doing analytics is an important starting point (Campbell & Oblinger, 2007). One of the potential pitfalls of learning analytics is that it can be driven by the wrong motivating factors. As outlined above, this could mean measuring the wrong things, not measuring the right things or measuring things simply because they are measurable. It is for this reason that this paper proposes that when it comes to assessment analytics that it is most appropriate to work from first principles and that those principles be pedagogical rather than statistical. In other words, the factors which motivate what is measured, how it is measured, what patterns are identified, how it is acted upon, who acts upon it and when, should be derived from assessment pedagogy rather than simply by what data is available.

Therefore, an appropriate point of departure is the rich and well-established field of assessment and feedback theory. For the purposes of this paper, that point of departure is derived from the work of Sue Bloxham and Pete Boyd who in their 2007 book *Developing Assessment in Higher Education* offer four key answers to the question “why assess?” (Bloxham & Boyd, 2007). One answer to this question, they argue, is that assessment provides certification that allows stakeholders (such as potential employers) to discriminate between levels of achievement and between students, while also providing selection for further study or licence to practice. Secondly, they suggest that assessment is useful for quality assurance in that it provides evidence for stakeholders (such as government funding bodies) and to judge standards of student achievement. Thirdly they argue that assessment has a significant impact on student learning in that it can motivate students, steering their approach. It can also, they argue, inform teaching strategies and curriculum design. Finally, its role is important, they suggest, to support life-long learning by encouraging skills development and support the development of self-regulated learning and self-evaluation (Bloxham & Boyd, 2007, pp. 31-32). They suggest that in many instances these principles or reasons for assessing can work at cross purposes to each other and different types of assessment can prioritise some of these at the cost of others (Bloxham & Boyd, 2007, pp. 32-34, 44). These four reasons for assessing students also fall into two halves: with the first two most usefully understood as assessment *of* learning and the other two as assessment *for* learning (Bloxham & Boyd, 2007, p. 45). Importantly, Bloxham and Boyd are not suggesting that either of these approaches is better or worse than the other, but that an appropriate balance between them is required for good quality learning and assessment in Higher Education.

This paper now turns to suggest some of the assessment analytics data and reporting strategies that may be useful to inform each of these four reasons for assessing. These suggestions are, at this stage, speculative and are not offered as comprehensive. They provide, however, a starting point for assessment-data-collection strategies as well as some potential curriculum-intervention strategies that might be derived from them.

### *Certification:*

Feedback and marking tools tend to offer the affordance of being able to mark students against defined assessment criteria, usually in the form of a qualitative or scored rubric. So while the judgement that is made can be (and usually is) still that of the tutor, the tools allow for this to be recorded in a way which is potentially more transparent to the student as well as being available for analysis. This, therefore, allows an individual student to see which level of attainment they have achieved against the criteria while also allowing the analysis of student achievement that, for instance, indicates which students have demonstrated which attributes and to what level of attainment, at any point within, as well as at the end of, their course of study. The ability to efficiently and effectively report this information can be particularly useful for professionally accredited degrees or those requiring license to practice: both to the institutions offering them and the professional, statutory or regulatory bodies that

provide the accreditation or licence. It can also furnish students and admissions tutors with evidence on things such as research skills and written and oral communication skills to inform the selection of candidates to postgraduate degree programmes.

### *Quality Assurance:*

Assessment analytics data that map student learning against programme or degree-level Learning Outcomes or Graduate Attributes can be useful for benchmarking purposes and for Quality Assurance auditing bodies (such as the QAA in the UK or AUQA in Australia). Data on instances and actions against plagiarism can also be usefully mapped against sector-wide averages or 'benchmarks' to identify areas of best or poor practice. This can, in turn, inform "dialogue and sharing practice across disciplinary communities" that Price, O'Donovan, Rust and Carroll (2008) propose are so important to supporting and defining assessment standards (Price, O'Donovan, Rust, & Carroll, 2008, n.p.).

### *Student learning and lifelong learning*

It is in the area of student learning and lifelong learning that assessment analytics has the most potential in terms of the core business of higher education because of its capacity to directly benefit student learning. As outlined above, Bloxham and Boyd's suggestion that student learning and lifelong learning are both key reasons why we assess is linked to the capacity for assessment to motivate students and guide their approach, to inform teaching strategies, to encourage skills development and to develop self-evaluation and self-regulation capacity (Bloxham & Boyd, 2007). The contribution that assessment analytics can make in this area is a mixture of those which inform teachers' decisions as to which interventions are of most benefit to students and/or those which are directly student facing and therefore inform students' decisions. I will now list some examples of how these data might be used in practice. Pre-submission feedback (eg in the form of a lecture, a self-paced screencast or a FAQ), which is informed by evidence from the strengths and weaknesses of previous student cohorts in response to a specific assessment task, can guide students in their approach to that same assessment task. Post-submission feedback may be useful in motivating students to engage with their feedback, take steps to understand it and to act upon it. As the SOLAR concept paper puts it: Learning Analytics can "contribute to learner motivation by providing detailed information about her performance" (Siemens et al., 2011, p. 6). Providing students, for instance, with information about where their result places them in the cohort (in terms of final results, achievement against specified learning outcomes and even in the frequency of common problems such as punctuation and grammatical errors) may have the potential to motivate students to improve and aspire to higher levels of achievement. Evidence of common errors and cohort-wide weaknesses (for instance identifying criteria against which most students have lost the most marks) may also provide targets for just-in-time interventions. In any higher education curriculum (but particularly in those which are content-heavy) where only a limited amount of time and space is ever going to be available for embedded skills support, knowing with which skills each cohort (and even individual students within it) require the most support can ensure teachers and learning support tutors make much more effective use of that time. Inter-cohort comparisons against assessment criteria can identify which support interventions, teaching strategies and curriculum adaptations have been successful (or not) and therefore whether they are worth making permanent. Marking tools can be used to gather student self-evaluation data (eg. measured via assessment criteria in the form of a rubric). By comparing this data to tutor-evaluations against the same criteria, it is possible to identify the development of self-evaluation skills as well as which assessment criteria are least well understood by individual students and the cohort as a whole.

Assessment analytics that are directly student facing might be used to allow them to track their progress over time. This could feed into and thereby inform their reflective practice and

professional development planning. Integrating this into a social learning context could allow students to develop and harness folksonomies whereby the attitudes and behaviours of high-achieving students are visible to and shared with lower-achieving students, thus guiding and motivating their behaviour. Gamification (whereby students are 'rewarded' for achieving against markers which are known to be attendant to student success such as making regular use of the library) may also have some potential. In these contexts, assessment analytics could operate as a kind of nudge analytics: by making plain which pathways, behaviours and strategies are most likely to result in success.

## Conclusions

It is clear that Academic and Learning Analytics offer an exciting and powerful new direction in Higher Education. This paper argues that the role that assessment could play in this is significant in that it is primarily meaningful in terms of student behaviour and learning, and because it is relatively easy to operationalize in comparison to other types of learning analytics. It remains, however, underdeveloped and underexplored and the reasons for this are both multiple and complex. This paper has suggested that not only do Higher Education Institutions already have the tools that are required to generate and gather assessment data but that the academic staff who work within them also already have the inclination to do so. It is clear that while there are powerful reasons why assessment analytics strategies should be pursued in Higher Education, there are also important counter arguments that need to be taken into consideration so that an assessment analytics strategy does not have a flattening or 'negative backwash' effect. It is clear, however, that the appropriate design principles for an assessment analytics strategy should be informed by the pedagogical theory of assessment and feedback. This should concentrate on retaining the fundamental principles of assessment but also, and perhaps more importantly, allowing us to provide *informed* answers to the question 'why assess?' What remains, now, is to begin the practical work of piloting and evaluating these curriculum interventions to establish which are both practicable (efficient) *and* effective in achieving the outcomes envisaged here. This is an exciting area for future research and development.

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