Learning analytics - are we at risk of missing the point?

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The rise of learning analytics in the last few years has seen fervent development from institutions, researchers, and vendors. However, it seems to have had a laggard reception in higher education. Peering behind some barriers to adoption, we question whether common approaches that address the economics of low hanging fruit distract us from asking and answering deeper questions about student learning. This may lead to destructive feedback loops where learning analytics, swept by the currents of institutional agendas and cultures, does not deliver upon its promises to those who need it most - students and educators.

Keywords: learning analytics, predictive analytics, retention, barriers to adoption.

Introduction

The education sector is currently undergoing a paradigm shift towards the collection and analysis of detailed datasets about user interactions with resources and other users (Long & Siemens, 2011). The field of learning analytics (LA) has recently emerged with the objective of measuring, collecting, analysing, and reporting data about learners and their contexts, for the purpose of understanding and optimizing learning and the environments in which it occurs (Siemens, Dawson, & Lynch, 2013). Initially, identifying students at risk of abandoning a course or the institution was an obvious target for the field, where data could have direct economic impact (De-La-Fuente-Valentín, Pardo, & Kloos, 2013). The rationale was that through the use of their data, 'at risk' students could be identified early and, ideally, the right set of actions could be taken to avoid attrition. After this initial problem, experts defined the ideal trajectories to be followed by educational institutions to embrace the use of data. Corresponding maturity models for LA have been framed around progression from reporting to predictive modelling to automatic triggering of business processes (Goldstein & Katz, 2005), or from reports on single systems to organisational and sector transformation through sharing of innovations (Siemens et al., 2013), or from static reporting to a pervasive culture of data-driven optimisation (Norris & Baer, 2013).

Despite lofty ambitions, adoption of LA has been slower than anticipated with most US institutions only using data for simple reporting purposes (Bichsel, 2012), and the situation in Australia is by no means more advanced (Colvin et al., 2015). Why is LA yet to be fully realised in learning and teaching? Effective LA is predicated on having the right tools, processes, and people to understand and optimise learning (Bichsel, 2012), and it appears that to date, developments in LA are primarily driven by diverse (and sometimes esoteric) research agendas, bespoke institutional hackery to achieve quick retention wins, or vendors designing business intelligence-like dashboards replete with bar graphs and colour-coded text – indeed, the authors and their institutions are perpetrators of this. Who of these players, if any, is missing the point of LA? In this discussion paper, we pose intentionally provocative conjectures regarding the relatively laggard uptake of LA around its development and validity, competing institutional agendas and cultures, and the needs of educators and students.

Three conjectures for debate

Muddied waters: the seduction of predictive analytics and retention rates

The preponderance of LA projects in the short history of the field have focussed on predicting student underperformance or dropout (Siemens et al., 2013). Purdue Course Signals (Arnold & Pistilli, 2012), the traffic light early warning system for identifying students at risk, is a poster child for this element of LA. The rash of projects that arose in its wake have followed somewhat of a formula: correlate independent variables (e.g. demographics, past performance, LMS usage) with an outcome variable (e.g. student performance or attrition), and apply resultant models to new data to identify students at risk and recommend resources and/or services. For many in higher education this has become the sine qua non of LA, and a recent comprehensive overview of the Australian LA landscape has found that many institutions mistakenly regard this form of predictive analytics as coextensive with LA as a whole (Colvin et al., 2015). However, it is difficult to argue against the institutional agendas served by this form of LA. Student attrition is a pain point for many universities and the widening of participation coupled with massification of higher education means it is now much more difficult to rely on traditional processes to identify students at risk, right at the juncture where there are likely to be more of them. Or, it may be that this is simply a stage of LA maturity that must be passed through: the identification of risk is low hanging fruit, especially in comparison with the more complex and difficult longitudinal questions that would need to be addressed for LA to cast light on learning processes (Gašević, Dawson, & Siemens, 2015).

There has certainly been uptake of this kind of LA. However, the algorithmic identification of students at risk implies that there is something wrong with the student, ostensibly reverting to a 'theory 1' perspective (Ramsden, 1993) of education. When algorithms are black boxes, this prevents academics from identifying teaching or curriculum issues that may be at play. Perhaps more problematic is the increasingly common business model to outsource at-risk student contact to internal or external outreach services, which means that the feedback to academics is usually very superficial and the feedback to students is disconnected from their learning. Overall, these processes typically distance educators from students and alienate educators from their practice. Whatever its benefits to the institution, these interventions are not about learning per se, but the outcomes of the assessment and engagement activities. Very little in LA has so far penetrated the relevant learning processes (Gašević et al., 2015), yet this is precisely where educators can act to make changes. Rather, predictive analytics is more about the identification of antecedent conditions in order to control behaviour (e.g. log in more, post more comments). It should not be a surprise that some see this as the advent of a new behaviourism (Lodge & Lewis, 2012; Dietrichson, 2013).

Killing the pipeline: too much promise, not enough delivery

LA, to some extent, is analogous to the uptake of a new product or service and will follow some of the same principles. Studies of the uptake of organisational innovations sometimes present this as a 'pipeline' problem (Warren, 2008), in this case moving educators through specific states: from unaware of LA, to aware but not yet interested, to interested, to using, and finally integrating. At each stage, the hope is to 'pump' academics from one state to another. However, these flows may not go in the intended direction. At each flow point, initiatives are needed which are specific to the state educators are in. The 'marketing' of LA has been largely successful judging by the number of educators who have moved from unaware to aware (and some even interested) during the short history of the field. But the number of useful tools and products is low, potentially leaving interested educators unable to progress and therefore vulnerable to flowing back to the 'aware but not yet interested' pool.

One issue contributing to the developmental lag of LA is the propensity for universities to either develop their own tools individually or buy them from vendors. Evidence for this binary approach is implicit in a recent overview of LA in Australia (Colvin et al., 2015). What was not mentioned in this report, but known to the investigators ([author 2] being one of them), was the number of similar technical initiatives that were replicated at each university, and the low levels of knowledge sharing. By way of example, one university had developed competence in extracting a range of data from Moodle and other teaching sources while another university had a well-developed 'business' model for presenting Moodle data to educators in a way that could be harnessed for student intervention. Both universities could have benefitted from a close collaboration, and neither were in the same State (so could not be considered 'competitors'), yet even when aware of each other's initiatives they proceeded along the slow and expensive path of developing their missing piece of the picture from scratch. This low level of sector knowledge sharing slows down the development of tools, leaving academics who are interested in LA either unable to secure the right tool for their interest, or only able to access tools that are barely adequate and locked in a slow development cycle. The result may be frustration and flowing backwards rather than forwards on the adoption pipeline.

What do students and educators want?

Although educators and students receive the most benefit from LA (Drachsler & Greller, 2012), very little work has been done to ask them what they really want or need. Yet, simply asking is no panacea for uptake as they may be labouring under false understandings and expectations, and their conceptions may be affected by unconscious processes that distort rather than clarify. For example, a recent exercise carried out by JISC featured naive (with respect to LA) students designing 'app-like' interfaces for the kind of data they would like to see (Sclater, 2015). While probably a necessary exercise, it is not sufficient to inform the choice of data and its method of presentation. Several of the example screenshots show feedback suggestions that indicate students may be influenced by a performative rather than a mastery learning orientation (presumably unconsciously), and unhelpfully focus on outcomes rather than processes (Hattie & Timperley, 2007), potentially demotivating students with low self-efficacy while encouraging complacency in higher achievers (Corrin & de Barba, 2014).

Conclusions and provocations for the future

So is LA, as currently being courted by institutions, missing the point? The rise and rise of predictive analytics has certainly piqued interest in the field, but has also crowded out the development of tools focussed on the process of learning. In this context, idealised models of institutional LA maturity (e.g. Norris & Baer, 2013) usually do not help because although they may mention personalised learning, they are predicated on increasing levels of predictive utility. The issues that LA would need to address if it were to focus on learning would be predicated instead on explanatory adequacy, which may or may not increase predictive accuracy (Bhaskar, 1975). The question should be *why* did a learning event or program succeed or not, rather than *which* students did or did not succeed. While these questions are not necessarily mutually exclusive, the predictive analytics paradigm offers little help with the former (Rogers, Dawson, & Gašević, forthcoming). In order for LA to better address the deeper questions, universities and vendors need to work out mutual relationships that can springboard LA development (Siemens, 2012). We need to avoid a destructive feedback loop where a lack of innovative tools hinders uptake, the lack of uptake signals cautious investment in tools, leading to slow tool development, contributing to a lack of innovative tools… These phenomena are well-known in business (Sterman, 2000) and there is no reason to think higher education would be immune. Finally, as LA sits at the intersection of theory and practice, it needs to pay heed to its users as well as better integrate with significant learning theories to isolate the data and feedback that will truly be valuable to educators and students.

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Note: All published papers are refereed, having undergone a double-blind peer-review process.