Learning Analytics in Higher Education: A Summary of Tools and Approaches

Amara Atif, Deborah Richards
Department of Computing, Faculty of Science, Macquarie University
Ayse Bilgin
Department of Statistics, Faculty of Science, Macquarie University
Mauricio Marrone
Faculty of Business and Economics, Macquarie University

Higher education institutions recently have been drawing on methods from learning analytics to make decisions about learners' academic progress, predictions about future performance and to recognise potential issues. As the use of learning analytics in higher education is a relatively new area of practice and research, the intent of this paper is to provide an overview of learning analytics including a summary of some exemplar tools. Finally we conclude the paper with a discussion on challenges and ethical issues.

Keywords: Learning analytics, higher education, learner, tools, big data and stakeholders.

Introduction

There is increasing competition in the higher education (HE) sector to adopt practices to ensure organisational success at all levels by addressing questions about educating and retaining a larger and more diverse student population, admissions, fund raising and operational efficiency (van Barneveld, Arnold, & Campbell, 2012). In this competitive environment, Higher education institutions (HEIs) have entered the era of 'big data' and are collecting large volumes of data relating to their learners and the educational process. These vast amounts of data are stored in the student information systems (SIS); including learner interactions with various educational technologies such as learning/course management systems (LMS/CMS); and in various databases such as admissions files, library records and other systems (Tair & El-Halees, 2012). The extraction of the data derived from these technologies are potentially accessible for data mining, analysis (and interpretation) and has captured the attention of HE administrators, academics, researchers and government agencies.

There is a plethora of terms and definitions used for analytics in the academic domain. Examples include business analytics, educational data mining, academic analytics, learning analytics (LA), predictive analytics or action analytics. Some of these terms are conceptual (what it is) while others are more functional (what it does). However, this is basically due to the observation that these new forms of analytics can begin to address some of the concerns challenging the HE sector such as improving retention, addressing curriculum standards, increasing accountability, measuring teaching quality, graduation rates and employment placement (Arnold & Pistilli, 2012; Dawson, 2011; Kovacic, 2012). Therefore, in line with the conceptual framework of analytics in HE by van Barneveld et al., (2012), we can say that LA in the academic domain is focused specifically on learners, learning processes and their learning behaviours (Greller & Drachsler, 2012), gathering data from LMS and SIS in order to establish indicators of concepts such as knowledge construction, creativity, self-directed learning, sense of community, and assessing academic progress based on assessment and structured activities (Bienkowski, Feng, & Means, 2012; Dawson, 2011). This can be achieved by: predicting learners' performance; suggesting relevant learning resources; increased reflection and awareness on the part of the learner; detection of undesirable learning behaviours; and detecting emotional states such as dullness or frustration of the learner.

The 2013 horizon report identified LA as a key future trend in technology enhanced learning and teaching (Johnson et al., 2013). As an emerging field, the process of LA uses the data associated with a learner's interactions to draw out pedagogical patterns to inform decisions and evaluations (Arnold & Pistilli, 2012; Gammell, Allen, & Banach, 2012; Long & Siemens, 2011; van Barneveld et al., 2012). A key motivation for LA is to improve internal institutional cross collaboration and setting an agenda for the larger learning and teaching community (via socialisation, pedagogy and technology). Learning analytics is still in its infancy; however its short life has produced numerous conceptualisations. In an effort to add clarity to this landscape, the aim of this paper is to compile a summary of some exemplar tools based on four dimensions of LA (input, stakeholders, goals and techniques). In the following section we present five exemplary tools and their brief comparison. The paper concludes with a discussion on challenges and ethical issues.

Exemplar Tools and Approaches

To comply with the space constraints, we are describing only four tools. The following university-specific tools were chosen because they illustrate a combination of alternative purposes and goals of LA. The bigger objective behind all the tools is to improve student success and retention and to understand reasons for student disengagement and attrition. All tools were developed and implemented at Australian universities. Some of the tools are not publically available and most others only seem to work within very specific environments, although they may have been designed in a more general spirit.

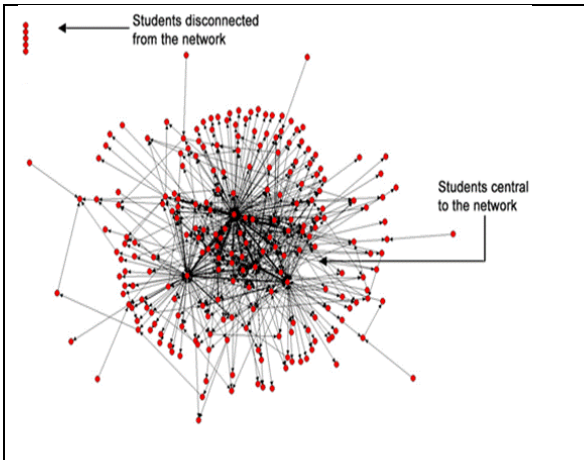

Figure 1: The SNAPP Tool

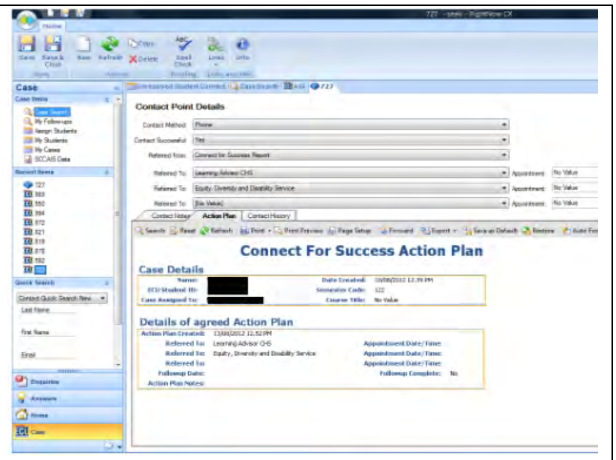

Figure 2: The C4S Tool

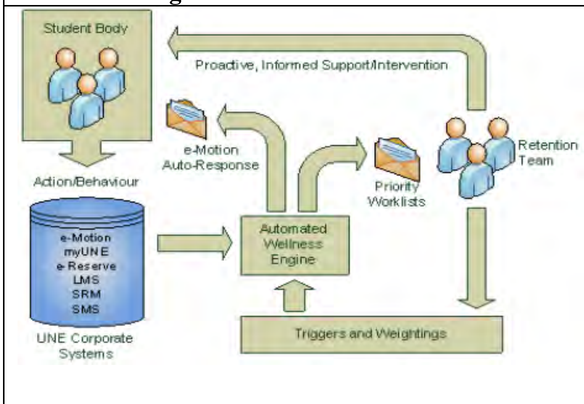

Figure 3: The AWE Tool

Figure 4: The PASS Tool

University of Wollongong (UOW)-The Social Networks Adapting Pedagogical Practice (SNAPP)

The SNAPP tool generates visual representations (social network diagrams) of user interactions, activity and patterns of behaviour on discussion forum posts and replies. The visual mapping illustrates the users' level of engagement and activity with the aim of identifying learners who are at risk of underperforming due to lower levels of participation in comparison to other learners (Figure 1). The tool retrieves data from, and generates reports based on, learner interactions from commercial (blackboard) and open-sourced (Moodle) LMS including log-in frequency, dwell time and number of downloads (Bakharia & Dawson, 2011).

Edith Cowan University (ECU)-Connect for Success (C4S)

The C4S is a proactive, university-wide and fully automated system based on enrolment data and pre-determined triggers (demographic data, behavioural data, student survey and self-report) will be supplemented with triggers fed from the other data sources (Blackboard, RightNow, academic referrals, mid semester grades). This early warning tool (Figure 2) seeks to improve learner success and by implication, their retention and graduation rates. The C4S automatically flag learners who are likely to require extra support to complete their studies. Once students have been identified, they will be referred onto the appropriate services within the university by the C4S team. In addition to daily reports, a series of consolidated reports will be sent to key support services and faculties within the university (Jackson & Read, 2012).

University of New England (UNE)-Automated Wellness Engine (AWE)

The AWE is an early alert engine designed and built to enhance learner engagement and retention at UNE (Figure 3). The AWE is based on the successful Emoticons identification activity embedded in the online UNE student portal (myUNE) and other data in different university systems (e-Motion, e-reserve, LMS, SRM-student relationship management, SMS-student management system, unit discontinuation poll and the Vibe) related to learners interactions with the university and their teachers, use of facilities and their responsiveness to deadlines. The AWE's, 'evidence-based system of retention' helps to identify high-risk learners who may be struggling or experiencing disengagement from their courses (Leece & Hale, 2009). Based on the indicators, the AWE generates daily or weekly wellness reports which details reasons for withdrawal and wellness-happiness ratings within individual schools and courses.

Open University Australia (OUA) - Personalised Adaptive Study Success (PASS)

In a Criterion Conference on Improving Student Retention and Success held at Sydney dated 27 June 2013, Dr Dirk Ifenthaler from OUA presented the PASS, an early alert tool designed and built to enhance learner engagement and retention in an online learning environment (Figure 4). Based on individual characteristics, social web, curriculum and physical data drawn from a number of systems (My study center-study buddies, smart thinking-online study support, discussion forums, social media pages, student success hub and others) in an online learning environment are integrated, processed and analysed by a learning analytics engine, personalisation and adaption engine and reporting engine helps to identify high-risk students who may be struggling or experiencing disengagement. Based on the various indicators used, the PASS generates visual signals, performance levels, self-assessment, predictive course mastery, highlight social interaction, recommends content and activities and provides a personalised environment.

Summary of Conceptual Analysis of Exemplar Learning Analytics Tools

The following Table 1 provides a summary of the tools based on what kind of data the tool are using for analysis (input), who is targeted by the analysis (stakeholders-academic institution, department and learner), the purpose of the analysis (goal), and how the tool performs analysis of the collected data (techniques).

Table 1: Summary of Learning Analytics Tools

	SNAPP	C4S	AWE	PASS
Input(s)				
Student information system (SIS)		X	X	X
Learning/course management system		X	X	X
Grade book				
Discussion forums	X		X	X
Social media pages			X	X
University specific systems		X	X	X
Stakeholder(s)				
Institution		X	X	
Department			X	X
Learner	X	X	X	X
Goal(s)				

Monitoring	X	X	X	X
Analysis	X	X	X	X
Prediction	X	X	X	X
Intervention	X	X	X	X
Adaptation		X	X	X
Tutoring/Mentoring				X
Assessment				X
Feedback				X
Personalisation		X	X	X
Recommendation		X	X	X
Reflection				X
Technique(s) used				
Learning analytics (LA)	X	X	X	X
Social network analysis (SNA)	X			X
Visualisation	X	X	X	X
Statistics	X	X	X	X
Emotional intelligence (EI)			X	

Discussion and Conclusion

The aim of our comparison is to expand our understanding of LA in the HE sector. Table 1 summarises the exemplar tools based on four dimensions of LA (input, stakeholders, goals and techniques used) to demonstrate how data residing in different HEI systems can track many aspects of learner performance and behaviour to develop new tools, such as intelligent early warning systems to predict learner performance. Eventually, such tools can provide information to HE administrators and learners to facilitate their decision making.

Recently, Willis and his colleagues suggested a thorough list that exemplifies the types of questions institutions must address when using big data. According to Willis, Campbell, and Pistilli (2013), some examples could be:

- Does the college administration let learners know their academic behaviours are being tracked?
- What and how much information should be provided to the learners?
- How much information does the institution give instructors (faculty members)?
- Does the institution provide a calculated probability of academic success?
- How should the instructors react to the data?
- Should the instructor contact the learner?
- Will the data influence perceptions of the learner and the grading of assignments?
- How many resources should the institution invest in learners who are unlikely to succeed in a course?
- What obligation does the learner have to seek assistance?

As a final comment, various open issues need to be addressed before institutions can make use of learner data. Issues for LA fall into the following broad, often overlapping categories: the location and interpretation of data; informed consent and privacy of data; and the management and classification of data. To address some of these issues, Slade and Prinsloo (July, 2013) propose an ethical framework for HEI to address the ethical issues and challenges in LA which in turn can help to increase the quality and effectiveness of learning and teaching.

References

Arnold, K. E. & Pistilli, M. D. (2012). Course Signals at Purdue: Using Learning Analytics to Increase Student Success. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, 267-270.

Bakharia, A. & Dawson, S. (2011). SNAPP: A Bird's-Eye View of Temporal Participant Interaction. *Proceedings of the 1st International Conference on Learning Analytics and Knowledge*, 168-173.

Bienkowski, M., Feng, M. & Means, B. (2012). *Enhancing Teaching and Learning through Educational Data Mining and Learning Analytics: An Issue Brief*. US Department of Education, Washington, D.C.

Dawson, S. (2011). Analytics to Literacies: Emergent Learning Analytics to Evaluate New Literacies. *Workshop on New Media, New Literacies, and New Forms of Learning*. London.

Gammell, W., Allen, G. & Banach, P. (2012). Leveraging Existing Data: Indicators of Engagement as Early Predictors of Student Retention. *Proceedingsof the 1st North East Regional Learning Analytics (NERLA) Symposium*, 9-17.

Greller, W. & Drachsler, H. (2012). Translating Learning into Numbers: A Generic Framework for Learning Analytics. *Educational Technology & Society*, 15(3), 42-57.
Jackson, G. & Read, M. (2012). *Connect 4 Success: A Proactive Student Identification and Support Program*. ECU: Australia, 1-5. Retrieved from fyhe.com.au/past_papers/papers12/Papers/9B.pdf
Johnson, L., Adams, S., Cummins, M., Estrada, V., Freeman, A. & Ludgate, H. (2013). *The NMC Horizon Report: 2013 Higher Education Edition*. Austin, Texas: The New Media Consortium.
Kovacic, Z. J. (2012). Predicting Student Success by Mining Enrolment Data. *Research in Higher Education Journal*, 15, 1 – 20. Retrieved from http://www.aabri.com/manuscripts/11939.pdf
Leece, R. & Hale, R. (2009). *Student Engagement and Retention through e-Motional Intelligence*. UNE: Australia. Retrieved from http://www.educationalpolicy.org/events/R09/PDF/Leece_E-Motion.pdf
Long, P. & Siemens, G. (2011). Penetrating the Fog. Analytics in Learning and Education. *EDUCAUSE Review*. Retrieved from http://net.educause.edu/ir/library/pdf/ELI7079.pdf
Slade, S. & Prinsloo, P. (2013). Learning Analytics: Ethical Issues and Dilemmas. *American Behavioural Scientist*. SAGE Publications. https://doi.org/10.1177/0002764213479366
Tair, M. A. & El-Halees, A. (2012). Mining Educational Data to Improve Students' Performance: A Case Study. *International Journal of Information and Communication Technology Research*, 2(2), 140-146.
van Barneveld, A., Arnold, K. & Campbell, J. (2012). Analytics in Higher Education: Establishing a Common Language. *EDUCAUSE Learning Initiative (ELI)*, 1, 1-11.
Willis, J., Campbell, J. & Pistilli, M. (2013). Ethics, Big Data and Analytics: A Model for Application. *EDUCAUSE Review*.

Author contact details:
Amara Atif, amara.atif@mq.edu.au
Deborah Richards, deborah.richards@mq.edu.au
Ayse Bilgin, ayse.bilgin@mq.edu.au
Mauricio Marrone, mauricio.marrone@mq.edu.au

Please cite as: Atif, A., Richards. D., Bilgin, A. and Marrone, M. (2013). A Panorama of Learning Analytics Featuring the Technologies for the Learning and Teaching Domain. In H. Carter, M. Gosper and J. Hedberg (Eds.), *Electric Dreams. Proceedings ascilite 2013 Sydney*. (pp.68-72)
https://doi.org/10.14742/apubs.2013.1524