

Student-Centered Learning Analytics

BY ANNA KRUSE & ROB PONGSAJAPAN

Abstract

Universities' excitement for learning analytics continues to grow, but the most common implementation of learning analytics, one focused on diagnoses and interventions, seriously short-changes the students it is meant to serve. We propose a student-centric, inquiry-based model of analytics that puts the tools and premises of analytics into the hands of students, empowering them as metacognitive agents of their own learning.

About the Authors

Anna Kruse joined CNDLS in 2007 as an English fellow. Since then, Anna has participated on a variety of teams and coordinated a number of projects at CNDLS. In her work with the Commons team, she focuses on helping users plan, customize, and make the most of the tools offered through the Commons, including ePortfolios. She also coordinates the Apprenticeship in Teaching program, a program designed to help prepare graduate student participants to become confident and reflective teachers.

Rob Pongsajapan serves as project lead for the Georgetown Commons and its associated tools and services. He is also currently the Wikipedia U.S. Education Program's regional ambassador for the D.C. area. He's especially interested in how communities of practice utilize social software, and has led sessions on content adaptation for the Web, online student media production, and standards-based Web design.

Being offered customized recommendations and ads is the stuff of an ordinary day on the web. From shopping on Amazon.com to watching a movie on Netflix, it's almost impossible to avoid being confronted with a prediction based on your previous activities on the site. These predictions, whether canny or off-the-mark, are made possible by the data you intentionally (or unintentionally) share with the service with which you are interacting. This is analytics, the process of capturing data and interpreting trends.

Today, educators and administrators are expressing great excitement over the promises and possibilities of using analytics in higher education. The scenarios generating the largest swath of enthusiasm generally involve putting analytics in the hands of administrators and, sometimes, faculty. Analytics applied in educational settings would, it is said, give institutions the opportunity to harness the data that learning management systems (LMSs) and other online databases are generating and use it to advance the interests of the university and, presumably, the students. While conversation is coalescing around the phrase "learning analytics," the primacy of "learning" and student interest in the conversation is debatable, sometimes overwhelmed by the urgency of other institutional concerns such as retention.¹ Nonetheless, the emerging popularity of the topic, represented by a rising tide of publications, conferences, and workshops, is clearly articulated by George Siemens in a 2011 *Elearn-space* blog post reflecting on takeaways from a learning analytics conference he had recently attended: "Analytics will be huge in education and are coming faster than almost anyone can anticipate."² But the number of unanswered questions, concerns, and hesitations that continue to arise during thoughtful discussions of analytics suggests that we move forward with caution and reflection.

Student learning, inquiry, and reflection. At CNDLS, we are constantly striving to connect teaching practices to the ultimate goal of educational institutions: student learning. During the ELI 2012 keynote address on learning analytics, Randy Bass, CNDLS's executive director, spoke for CNDLS and for the larger teaching and learning community when he

reminded us in a provocative statement not to be too hasty in implementing without reflecting: “I am at least sure about this: That the current enthusiasm for learning analytics is definitely a presenting symptom of education’s failure to respond to the last twenty years of research on teaching and learning.”³ He suggested that the “current and narrowing” view of learning analytics might not be as seductive were we more willing to interrogate our own practice as instructors with the best of research on teaching and learning. We would like to suggest a new model for learning analytics that pays heed to the ideals of scholarship on teaching and learning, but first, we will make a few comments on the “current and narrowing” view of learning analytics.

THE PROBLEM

Interventions: a lesson in passivity? A survey of the current literature on learning analytics will reveal a few popular words that offer a telling snapshot of the current focus of learning analytics; “intervention,” “underperforming,” “at-risk,” and “prediction” are some of the top repeats. Analytics implementations seem to be primarily concerned with students poised to fail. This constant language of “intervention” perpetuates an institutional culture of students as passive subjects—the targets of a flow of information—rather than as self-reflective learners given the cognitive tools to evaluate their own learning processes. Purdue University’s Signals project, an award-winning learning analytics system, is one such system that, despite its clear accomplishments, still begs a few questions about the nature of student success, especially for high achievers. The system analyzes a complex set of data points in order to give each student a different colored light that indicates his/her current status in a class: “red” means the student is in danger of failing, “yellow” suggests caution, and “green” indicates success.⁴ But what of those students who consistently see “green” when they check their Signals profiles? While “you’re doing fine; carry on” may be a reassuring message for those on track to meet at least the minimum threshold of success, it does not present a continued challenge. Does a green light encourage a student to strive for her best and more? Could it imply that she’ll simply get a good grade in the class rather than take away learning that will last? It seems that the current, popular trajectory of learning analytics is in service of those who are failing or in danger of failing and offers little to those who are already succeeding. This is serving an admirable need, but satisfaction of that need should not be an end in itself. As Trip Kirkpatrick put it in his *ITS Academic Technologies Blog* reflection on ELI 2012’s keynote address, “Are we serving the already-served if we make college about ‘completion rates’ and not about learning?”⁵

Rethinking “intrusive advising.”⁶ Ethical concerns continue to plague

the advancement of learning analytics. Language like “data...gathered on behalf of the students”⁷ is common in the literature and suggests helpfulness and service, belying the ethical murkiness of the practices it describes. Even putting aside the Family Educational Rights and Privacy Act (FERPA) and other student privacy laws, the question of whether it is ethical to capture student moves—whether clicks of the mouse on a Learning Management System (LMS), for example, or time on task—without students’ express approval is a compelling one. For one, data collected in this way cannot possibly be responsive to the variety of contingencies that will inevitably play out in the experiences of a handful of students each time. (For instance, the assignment may be open, but is the student really reading it? Conversely, a student may not have opened the assigned reading, but does that mean he isn’t accessing it some other way?). It is also fair to challenge the implications of data gathered in this way—if a “learning diagnosis” is based on faulty evidence, then the efforts to treat the diagnosed condition or failure will be misdirected, perhaps leading to inefficiency, resentment, and demotivation.

Finally, and most simply, surreptitious data collection undermines the culture of trust that we want to build in the classroom. To co-opt Google’s infamous slogan, “don’t be evil,” we should take to heart our call to be reliable stewards of students’ trust. A 2007 article about analytics raised some important points that remain to be satisfactorily addressed, noting that “the way in which students learn about institutional efforts on their behalf may affect their perceptions of privacy,” and going on to suggest that “the timing and content of [such] communications requires careful planning”.⁸ The suggestion that analytics administrators should tiptoe around a revelation of their work so as not to cause outcry does not inspire confidence in the forthrightness of the effort. Rather than collecting and processing data without students’ knowledge in order to advise them on how well they are doing (narrowly defined by such variables as quiz grades and “time on task”), we imagine a more open, forthright approach that will, through its very policy of transparency, address some of the ethical concerns currently growing around analytics in higher education. Without trust, other mechanisms are at play that have the potential to derail learning progress.

Myopic focus on LMSs. Currently, the field of learning analytics is closely tied to student activity on LMSs. Companies behind these systems are increasingly making data on student activity available to administrators and faculty members. There are, however, two potential issues with the marriage of LMSs and learning analytics. First is the assumption that such systems are used as sites of significant learning. Many LMSs are widely used by students, but the depth of interaction can be quite shallow—limited to checking quiz scores or downloading course

materials. Additionally, there is an assumption that LMSs are self-contained spaces for learning. The approach to learning analytics on LMSs generally ignores activity outside these systems, with the result that only a small portion of a student’s learning and engagement is being captured.

Second, such systems tend to privilege the administrator rather than the student—or even the instructor. The focus of learning analytics appears fixed to an institutional scale rather than a human scale. It remains to be seen whether students and faculty will be viewed as full participants in these systems’ learning analytics mechanisms or as unwitting generators of data for administrators and the companies behind these LMSs.

The difficulty of tracking ephemeral contributions. In a recent EDUCAUSE Learning Initiative (ELI) session, Brian McNely—an assistant professor of English at Ball State University—presented on a novel, small-scale experiment called Uatu. This project used data visualization to examine the practice of collaborative writing within a course. In the experiment, students worked in groups to edit cloud-based documents via Google Docs. Data was gathered about the students’ activity within these documents, including number of edits and amount of content added per edit.⁹

The experiment, however, was viewed as something of a failure by the researchers. The researchers concluded that (a) the data collection system was unable to capture comments made to the side of the main text and any chat activity (McNely called this “ephemeral collaboration”); and (b) the students’ preference for working in person hampered the ability of Uatu to provide a clear picture of the group interaction. These observations suggest that it will be difficult to rely on obtaining analytics from a single, presumably closed system going forward.

MOVING FORWARD

Inquiry-guided analytics. Making analytics about student learning could mean a return to the basics—remembering that meaningful progress and lifelong passion for learning is born of curiosity, not passive consumption. Michael Wesch identifies part of the problem: “Our schools are generally still organized around answers,” he observes, “rather than questions.”¹⁰ To reimagine analytics in the service of learning, we should transform it into a practice characterized by a spirit of questioning and inquiry. So an alternative to the existing intervention-centric approach to learning analytics might involve the student as a co-interpreter of his own data—and perhaps even as a participant in the identification and gathering of that data. In this scenario, the student becomes aware of his own actions in the system and uses that data to reflect on and potentially

alter his behavior. This reimagining of analytics is supported by decades of research on what helps students learn. It has been demonstrated repeatedly that what students are told is much less effective in helping their learning than what they can discover for themselves. “The deepest, most usable kind of knowledge,” one learning theorist writes, “is best attained by learners when they...actively construct their knowledge.”¹¹ This perspective echoes that voiced in *Understanding by Design*, a pivotal book on learning theory: “Students have to do the subject, not just learn its results.”¹² And Randy Bass writes that “research...has convincingly demonstrated increased learning gains, in certain well-designed conditions, when students are first presented with a challenge and then learn what they need to know to address the challenge.”¹³ In other words, asking students to find the problems—and strong points—in their learning is much more effective than handing it to them.

Inquiry-guided learning, an established learning approach that shares these values of student-centered discovery of knowledge, offers a useful framework that could be directly and fruitfully mapped onto analytics. Virginia Lee writes that:

*Rather than teaching the results of others' investigations, which students learn passively, instructors assist students in mastering and learning through the process of active investigation itself. This process involves the ability to formulate good questions, identify and collect appropriate evidence, present results systematically, analyze and interpret results, formulate conclusions...*¹⁴

Here, the role of the teacher is not as a presenter of information but as an “assistant” who actively helps the students learn. Giving students the opportunity to engage at that level transforms them from passive learners into active ones. We propose the development of classroom activities around analytics; helping students learn how to ask questions of themselves and their learning that will set them on a productive course of inquiry; guiding them through exercises that uncover their own metacognitive strengths and weaknesses; putting tools in their hands that bring life to their discoveries about themselves, like powerful and compelling visualizations. And through all this the academic environment should be a safe place of experimentation and self-discovery, perhaps discussed in small groups or pairs, perhaps undertaken in a quiet moment hours after the class has been dismissed.

Caveats and concerns. We must mention that, while little literature or conversation seems to exist around the possibilities of using analytics in this way, the idea is not entirely without precedent. For example, the Horizon Report 2011 offers a brief reference to student-centered learning

analytics, couching it in terms of possibility rather than obvious value: “[Analytics] might also be used by students themselves, creating opportunities for holistic synthesis across both formal and informal learning activities.”¹⁵ Research at the Knowledge Media Institute in Britain has also brought to light some of the major disadvantages of the state of learning analytics today and gestures at a future where the student has more control over the interpretation of results.¹⁶ But ultimately, while a search for “learning analytics” and “metacognition” turns up some results, the concept of putting analytics in the hands of students doesn’t seem to make an appearance in any of the top-hit articles on analytics—the ones most likely to serve as an introduction to the topic for many. It seems a largely unexplored approach.

In terms of challenges, one of the most pressing is finding a way to visualize and present the data in a way that will be meaningful to the learner. While there are many visualization tools available for use free of charge, extracting meaning from the visualization can be challenging if the assignment relies exclusively on the visualization for meaning. In other words, the “wow” potential of the visualization must be taken to a deeper level through reflection in order to become a meaningful learning tool. Well-designed scaffolding provided by the assignment, including hypothesizing (pre-visualization) and reflecting (post-visualization), can help offset this tendency to rely too heavily on the “wow” factor of the visualization.

Another challenge is finding and using the most useful tool and type of visualization. Visualization tools range from simple and user-friendly (e.g. Wordle) to more complicated (e.g. Google Fusion Tables). Then there are tools to help make sense of different types of data, such as tools for social network analysis, which allow students to reflect on their position in the social network of the class in the context of their own learning. The nature of the learning being targeted will dictate the type of tool needed.

An imagined case. Students majoring in English take a capstone course their final semester. In this course, the professor wants them not just to prove themselves competent in the discipline, but to understand why they are competent and what makes them so. To that end, the professor designs a set of learning analytics activities that the students will take on throughout the semester. One is an analysis of their rhetorical growth and development of disciplinary expertise. In this activity, the students read through a set of their own papers from previous courses, then work in small groups to identify some of the rhetorical moves in their later papers that demonstrate their growth in the discipline. The students then plug their papers into a visualization tool that graphs their increasingly

frequent use of those identified moves. They then write reflections on what they see on the graph. Other activities follow some variation of this pattern: individual reflection, discussion in small groups, intentional and intensive analysis of differences (in language, in structure, in tone) that emerge from a comparison of work products, and visualizations of those trends in order to grasp the scope of change in a single snapshot. And the role of the professor in these activities is to coach students as they think metacognitively about their learning progress (and process). This, of course, is only one example of the possibilities for a more student-centered approach to analytics.

Conclusion. At the moment, the future of learning analytics is concurrently full of possibility and in need of caution. Universities are keen to see what analytics can do for them, and conversations on analytics are enthusiastic and lively. Nonetheless, the path many analytics implementations are taking may not be a sustainable one, with ethical concerns and questions of meaningful effect bringing much-needed sobriety to a conversation that might otherwise lead higher education astray with hype. In this article we have proposed a new focus for analytics, and that focus is both simple and traditional—student learning. By rejecting the flashy appeal of big data and refocusing on the lifelong learning of our students, analytics will be an approach worth championing.

Endnotes

¹In an EDUCAUSE article on learning analytics, “Penetrating the Fog: Analytics and Education,” the section “The Value of Analytics for Higher Education” offers 9 concrete benefits of using analytics in higher education; only 2 of the 9 explicitly mention “learners” or “learning.”

²George Siemens, “Learning Analytics 2011: Reflections,” *Elearnspace* blog, March 11, 2011, <http://www.elearnspace.org/blog/2011/03/11/learning-analytics-2011-reflections>.

³Randy Bass, “You Get What You Measure, So What Are We Measuring? A Panel Debate on Learning Analytics” (panel featured session, Austin, TX, February 13, 2012), <http://www.educause.edu/ELI12/Program/FS02>.

⁴Purdue Signals Project, “Course Signals Explanation” video, <http://www.itap.purdue.edu/learning/tools/signals/> and <http://youtu.be/KxYewO9iAgw>.

⁵Trip Kirkpatrick, “ELI 2012, Day One,” *ITS Academic Technologies Blog*, February 13, 2012, <http://itg.yale.edu/2012/02/eli-2012-day-1/>.

⁶“Intrusive advising” is a term used by Campbell, et al. in their article “Academic Analytics: A New Tool for a New Era.”

⁷New Media Consortium, *Horizon Report 2011*, 28, <http://net.educause.edu/ir/library/pdf/HR2011.pdf>.

⁸John P. Campbell, Peter B. DeBlois, and Diana G. Oblinger. “Academic Analytics: A

New Tool for a New Era.” *EDUCAUSE Review* 42.4 (2007), <http://www.educause.edu/ero/article/academic-analytics-new-tool-new-era>.

⁹J. Holden Hill, Phillip Parli-Horne, Paul Gestwicki, and Brian McNely, “The Uatu System for Visualizing Networked Writing Activity,” <http://www.cs.bsu.edu/techreports/2011-01.pdf>.

¹⁰Michael Wesch, quoted in John K. Water, “John Q. Netizen,” *Campus Technology* 25.7 (2012), 21.

¹¹T. Creed, quoted in Richard Slatta, “Enhancing Inquiry-Guided Learning with Technology in History Courses,” in *Teaching and Learning Through Inquiry*, ed. Virginia Lee (Sterling, VA: Stylus, 2004), 96.

¹²Grant Wiggins and Jay McTighe, *Understanding By Design* (Upper Saddle River, NJ: Prentice Hall, 2001), 99.

¹³Randy Bass, “Disrupting Ourselves: The Problem of Learning in Higher Education,” *EDUCAUSE Review* 47.2 (2012), <http://www.educause.edu/ero/article/disrupting-ourselves-problem-learning-higher-education>.

¹⁴Virginia Lee, et al. “What is Inquiry-Guided Learning?” in *Teaching and Learning Through Inquiry*, ed. Virginia Lee (Sterling, VA: Stylus, 2004), 9.

¹⁵New Media Consortium (NMC), *Horizon Report 2011*, 28, <http://net.educause.edu/ir/library/pdf/HR2011.pdf>.

¹⁶Simon Buckingham Shum and Rebecca Ferguson, “Social Learning Analytics,” (Milton Keynes, UK: Knowledge Media Institute, June 2011), <http://kmi.open.ac.uk/publications/pdf/kmi-11-01.pdf>.

Bibliography

Bass, Randy. “You Get What You Measure, So What Are We Measuring? A Panel Debate on Learning Analytics.” Panel feature session at the Annual ELI Meeting, Austin, TX, February 13, 2012.

———. “Disrupting Ourselves: The Problem of Learning in Higher Education.” *EDUCAUSE Review* 47.2 (2012). <http://www.educause.edu/ero/article/disrupting-ourselves-problem-learning-higher-education>.

Campbell, John P., Peter B. DeBlois, and Diana G. Oblinger. “Academic Analytics: A New Tool for a New Era.” *EDUCAUSE Review* 42.4 (2007): 40-57. <http://www.educause.edu/ero/article/academic-analytics-new-tool-new-era>.

Hill, J. Holden, et al. “The Uatu System for Visualizing Networked Writing Activity.” <http://www.cs.bsu.edu/techreports/2011-01.pdf>.

Kirkpatrick, Trip. *ITS Academic Technologies Blog* (blog). <http://itg.yale.edu/>.

Lee, Virginia, et al. “What Is Inquiry-Guided Learning?” In Lee, *Teaching and Learning Through Inquiry*, 3-16.

Lee, Virginia. *Teaching and Learning Through Inquiry*. Sterling, VA:

- Stylus, 2004.
- New Media Consortium (NMC). *Horizon Report 2011*. <http://net.educause.edu/ir/library/pdf/HR2011.pdf>.
- Purdue Signals Project. "Course Signals Explanation." YouTube video, 2:16, <http://youtu.be/KxYewO9iAgw>.
- Shum, Simon Buckingham and Rebecca Ferguson. "Social Learning Analytics." Milton Keynes, UK: Knowledge Media Institute, The Open University, 2011. <http://kmi.open.ac.uk/publications/pdf/kmi-11-01.pdf>.
- Siemens, George. *Elearnspace* (blog). <http://www.elearnspace.org/blog/>.
- Siemens, George and Phil Long. "Penetrating the Fog: Analytics in Learning and Education." *EDUCAUSE Review* 46.5 (2011). <http://www.educause.edu/ero/article/penetrating-fog-analytics-learning-and-education>.
- Slatta, Richard. "Enhancing Inquiry-Guided Learning with Technology in History Courses." In Lee, *Teaching and Learning Through Inquiry*, 93-102.
- Water, John K. "John Q. Netizen." *Campus Technology* 25.7 (2012): 19-22. <http://campustechnology.com/articles/2012/03/01/john-q-netizen.aspx>.
- Wiggins, Grant and Jay McTighe. *Understanding by Design*. Upper Saddle River, NJ: Prentice Hall, 2001.



This work is licensed under the Creative Commons Attribution-NonCommercial-NoDerivs 3.0 Unported License. To view a copy of this license, visit <http://creativecommons.org/licenses/by-nc-nd/3.0/> or send a letter to Creative Commons, 444 Castro Street, Suite 900, Mountain View, California, 94041, USA.

About CNDLS Thought Papers

CNDLS Thought Papers, written by CNDLS staff members and affiliates, are short opinion pieces that address forward-looking technologies and trends that are (or will be) impacting the classroom. They reflect the opinions of their authors and are meant to serve as the beginning of a conversation on the pedagogical value of the tools and approaches they address. Find more Thought Papers at cndls.georgetown.edu/publications/.