Article

RESEARCH *in* EDUCATION

Research in Education
2017, Vol. 98(1) 83–105

DOI: 10.1177/0034523717723391
journals.sagepub.com/home/rie

Learning analytics as assemblage: Criticality and contingency in online education

John Scott
University of California, Berkeley, USA

T Philip Nichols
University of Pennsylvania, USA

Abstract
Recently, the possibilities for leveraging "big data" in research and pedagogy have given rise to the growing field of "learning analytics" in online education. While much of this work has focused on quantitative metrics, some have called for critical perspectives that interrogate such data as an interplay between technical infrastructures and contingent social practices. Following such calls, this article conceptualizes "learning analytics" as an assemblage of technical, designed, and sociocognitive dimensions. Drawing on DeLanda's articulation of assemblage theory, we examine the ways online learning unfolds within and across these scales by using illustrative quantitative and qualitative data—click-data, user-generated content, and student interviews—from three online higher education courses. We consider how insights generated from such a stance might contribute to critical perspectives on how power circulates in online learning environments—a framework we call "critical learning analytics." We conclude by offering some possibilities for which such a framework might be put to use—not only to map learning analytics as assemblage, but also to imagine how they might be assembled otherwise to promote more ethical instruction and more equitable student flourishing.

Keywords
Learning analytics, big data, assemblage theory, online learning, critical education, higher education

Corresponding author:
T Philip Nichols, University of Pennsylvania, 3700 Walnut Street, Philadelphia, PA 19104, USA.
Email: tnich@gse.upenn.edu

Over the last decade, researchers and practitioners in higher education have looked to leverage the proliferation of computer technologies and the increased precision of digital metrics to augment and personalize online distance learning—a move that has given rise to the interdisciplinary field of ‘‘learning analytics’’ (Long and Siemens, 2011; Siemens, 2013). Buttressed by a broader cultural interest in numerical objectivity and its possibilities for rendering complex social interactions legible for quantitative analysis and predictive modeling (Hacking, 1990; Porter, 1995), ‘‘learning analytics’’ ostensibly promises to extend a computational logic to the otherwise messy work of teaching and learning. This promise has steadily taken on more weight in recent years, as a wider enchantment with ‘‘Big Data’’ has led researchers to imagine how large data sets might be leveraged to ameliorate long-standing social problems—from personal health and civic engagement to corporate marketing and urban planning (Halpern, 2015; Morozov, 2013; O'Neill, 2016; Turow, 2013). In education, where there is a long history of reform efforts to quantify learning outcomes and to implement ‘‘data-driven’’ instruction (e.g. Bambrick-Santoyo, 2010; Koretz, 2008; Marsh et al., 2006), Big Data—and, by extension, ‘‘learning analytics’’—are often positioned as offering solutions to many of the field's most persistent challenges: from increasing efficiency and personalizing curricula to ensuring equitable access for all learners (Herold, 2016; Lane and Zimpher, 2014; Mayer-Schönberger and Cukier, 2014).

Despite these possibilities, such computational approaches to teaching and learning are not without their critics. Historians of education, for example, have noted the tendency for numerical metrics to impose a reductive order on the classroom—one that tames the spontaneous facets of student learning by privileging those dimensions more readily amenable to counting and measuring (e.g. Kliebard, 2004). Others have noted the limited capacity of quantitative data to account for the rich heterogeneity of identities and experiences that animate students' classroom practices (e.g. Campano et al., 2013; Dutro and Selland, 2012; Nichols and Campano, 2017). And yet, while critiques like these are invaluable for teasing out the underlying assumptions in certain uses of quantitative data, such arguments are difficult to sustain when applied to online learning environments. Unlike traditional classrooms, online education is always already enmeshed in a tangled network of interfaces, protocols, and algorithms—each underwritten by a substrate of adaptive codes and numerical calculations (Van Dijck, 2013). In this way, online education marks a contested space where competing impulses in educational research come together: one that looks to quantitative data as a resource for bolstering the efficiency and efficacy of the classroom; and one that critiques the ways power is implicated in systems of educational measurement and evaluation.

In this paper, we aim to eschew the temptation of either of these poles and, instead, look to examine how the two might be braided together to address recent calls to interrogate the role of ‘‘Big Data’’ in conditioning educational practice (e.g. De Freitas et al., 2016) and to situate analytics as a sociomaterial phenomenon (e.g. Perrotta and Williamson, 2016; Wilson et al., 2017). To do so, we conceptualize a learning analytics that attends to ‘‘online distance education’’ not as a ready-made category, but rather, as an assemblage of technical, designed, and sociocognitive planes. Using DeLanda's (2006) articulation of "assemblage theory," we consider how the dynamic, emergent, and power-laden relationships within and across these dimensions constitute and animate the work of online teaching and learning, and we illustrate these relations using data generated from three online higher education courses: ART I (n = 38), EDU I (n = 126), and EDU II (n = 72). We argue that such an approach helps position online learning as an unfolding narrative of quantitative and qualitative entanglement, and we offer a framework of *critical learning analytics* to aid in understanding how their interplay underwrites the relations between humans, hardware, learning design, content, and code that, together, comprise the emergent character of online education.

"Learning analytics" in context

While "learning analytics" has emerged as the principal term for discussing the use of big data for academic purposes, the concept did not appear in a vacuum. Through the mid-2000s, some researchers referred to similar processes as "educational data mining"—a practice that stressed using data from educational settings to better understand both students and their learning environments (Baker and Yacef, 2009). Even as "learning analytics" first found footing as a term, it existed alongside other competing notions of "analytics" in education research. In 2005, for example, the technology consortium *Educause* published a paper on "academic analytics" that positioned the concept as something akin to "business intelligence" for institutions of higher education. This framing adopted a more institution-level focus than "learning analytics," which tended to be more concerned with individual student achievement. This latter, more personalized approach gained momentum in the late 2000s—manifested not only in discussions on public blogs and academic articles (e.g. Siemens, 2010), but also as it hardened into an area of interdisciplinary inquiry with its own professional organizations and events. In 2011, for instance, the Society of Learning Analytics Research hosted the first *Learning Analytics and Knowledge* conference and its debut issue of the *Journal of Learning Analytics* appeared in 2014.

In many ways, the core principle behind "learning analytics"—that of collecting and using data to inform pedagogy—is far from revolutionary. Instructors have long relied on formal and informal assessments to determine how they ought to organize future lessons—and, indeed, the larger national testing apparatus is often defended on grounds that it serves as a temperature check to drive future student growth and teacher effectiveness (Koretz, 2008). The difference between such forms of data-driven instruction and learning analytics, then, is one of scope more than kind. Rather than gathering information about student learning from traditional classroom activities, learning analytics allows instructors in online environments to collect large streams of data as students click buttons, share content, navigate interfaces, and interact with classmates. Taken together, these data can, in theory, be used to understand how individuals engage in the online course, which, in turn, can help instructors tailor activities to suit each student's needs. George Siemens, one of the leading figures in articulating learning analytics as a means for bringing Big Data to bear on higher education, states the promise of such an approach, saying, "Learning analytics can penetrate the fog of uncertainty around how to allocate resources, develop competitive advantages, and most important, improve the quality and value of the learning experience" (Long and Siemens, 2011: 40).

Siemens's framing of learning analytics looks to balance both the instructional and the administrative facets of higher education. In their oft-cited article, Long and Siemens (2011) develop a scaled taxonomy for analyzing online learning that includes course-level activities (learning trails, social network analysis), educational data mining (predictive modeling, clustering), intelligent curriculum (semantically defined content resources), adaptive content (learning sequences based on user behavior), and adaptive learning (intelligent structures for learning support). They then situate such foci with regard to their possibilities for administrative organization, as well as individual learning. More recently, researchers at the Open University have developed these ideas further—giving shape to an emerging subfield termed "Social Learning Analytics" (SLA) (De Laat and Prinsen, 2014). Buckingham Shum and Ferguson (2012: 5) define SLA as a "distinctive subset of learning analytics that draws on the substantial body of work demonstrating that new skills and ideas are not solely individual achievements, but are developed, carried forward, and passed on through interaction and collaboration." They go on to delineate two categories of analysis for understanding how these social exchanges are constituted: the "inherently social," which they suggest can be studied using the resources of social network and discourse analysis; and the "socialized," which involves the study of disposition, content, and context within the online learning environment (Buckingham Shum and Ferguson, 2012: 3).

While this turn to analysis of "social learning" data in online education has yielded increased research in the ways peer-to-peer engagement takes different forms and serves different functions on certain platforms and in certain pedagogical situations, one dimension that that remains underdeveloped are those *critical* perspectives that trace the circulations of power and agency in sociotechnical systems. In interdisciplinary fields such as media studies, digital humanities, and "software studies," scholars have turned critical attention toward computational domains—for instance, using open APIs from sites like Twitter and Wikipedia and other data sources to analyze online representation, cultural and racial-centric networks, algorithmic bias, and the politics of platforms (e.g. boyd and Crawford, 2012; Bratton, 2016; Browne, 2015; Gillespie, 2010). And while these perspectives have gradually been integrated into discussions of education policy and practice (e.g. Lynch, 2015; Slade and Prinsloo, 2013), they have not enjoyed the same uptake in the framing or use of learning analytics. Some frameworks, for instance, may broadly nod to "critical" dimensions that might be areas of concern in learning analytics (e.g. Greller and Drachsler, 2012), but most actual analysis of power and politics in online learning has been reserved for larger, macro-social categories—like when Massive Open Online Courses from elite private universities have been integrated into public colleges, creating the potential for a two-tiered class system for online higher education (Haber, 2014; Kolowich, 2013). This has led some scholars to call for more sociomaterial approaches to the study of learning analytics—a framing that might better account for the ways such data are never discrete outputs from neutral formulae, but rather, are the upshots of precarious interchanges in human–machine networks (e.g. Wilson et al., 2017).

Following such calls to examine the emergent texture of online learning, the authors have looked to extend the generative frameworks of "social learning analytics" to include these contingent circulations of power and authority across distributed sociotechnical systems—an approach we call *critical learning analytics*. This stance is informed by three interrelated trajectories for inquiry. First, critical learning analytics traces the emergence of online learning data across multiple scales, that is not only at the level of code or hardware, but in the ways these (and other) layers interact with and mutually shape one another. Second, it organizes data generated from diverse participant structures to make learning communities more inclusive, such that a diversity of voices and modes of meaning-making color the interactions between participants. This may include qualitative and quantitative analysis of social ties in a community, cultural and racial representations in shared media artifacts, critical engagement or reflection related to course content, or emergent forms of knowledge generation and social connection in the online learning environment. Third, critical learning analytics looks to generate actionable insights for designing tools, content, and participation structures to make course experiences and assessments more hospitable and equitable for all learners. Such action items may range from computational strategies—like "inclusivity" algorithms that mediate student connections to diverse peer perspectives or content—to pedagogical strategies that provide more refined scaffolding for collaboration or knowledge generation. In the section that follows, we conceptualize online learning as a scaled, sociomaterial "assemblage" (DeLanda, 2006, 2016) in order to provide a framework through which we can see how these trajectories might work together to animate analysis of digitally mediated education.

Online learning as assemblage

To date, much of the literature on online higher education and the role of learning analytics therein has focused either on its quantitative or social dimension. Some studies conceptualize data in a manner that celebrates its possibilities for driving educational efficiency—a framing that seems to assume that education, catalyzed by technological developments, moves along a linear path toward progress (e.g. Picciano, 2016). Others take a more ethnographic approach, examining users' social practices related to navigating and participating in digital environments (e.g. Goodfellow and Lea, 2013). While such perspectives may be useful for answering particular kinds of pedagogical or sociological questions, they are less instructive for understanding the dynamic interplay of humans, hardware, and code that constitute the activities of online learning. Instead, they tend to leave the substrate of online learning black-boxed—or ''ready-made''—rather than examining the ways it is animated by sociomaterial contingencies (Latour, 1987). An important dimension of critical learning analytics, then, involves opening this black box to trace the complex interplay of technical, designed, and sociocognitive activities that underwrite the work of online education. Such a move looks to bridge learning analytics with emerging scholarship in media studies and human geography that has begun to theorize platforms, code, and data as sociomaterial ''assemblages'' (e.g. Kitchin and Dodge, 2011; Van Dijck, 2013)

Following this work, we have found philosopher, urbanist, and architect Manuel DeLanda's (2006, 2016) articulation of ''assemblage theory'' to be instructive for imagining an approach to learning analytics that takes seriously the multiple, tangled planes that constitute online education. While ''assemblage'' finds its roots in Deleuze and Guattari's (1987) notion of *agencement*, DeLanda suggests the authors' conception never fully congeals into a cohesive framework; instead, pieces are scattered through books and interviews, and are often contradicted and qualified in other parts of each writer's work. For this reason, DeLanda has devoted much of his career to organizing these fragments into a coherent theory that can be leveraged across disciplines and ''parametrized'' across temporal and spatial scales (DeLanda, 1997, 2002, 2006, 2016). Like Deleuze and Guattari, what is most central to DeLanda's framing of ''assemblage'' is that it must be understood as a network of component pieces that form a contingent and emergent process. In other words, even when an object or concept appears ''ready-made''—like the notion of an online learning environment—it is always constituted by the coming together of the component pieces that animate it—the user, the software, the hardware, the interface, the underlying algorithms and code, and so on. Crucially, DeLanda stresses that this whole never synthesizes into a totality—its component pieces are ''contingently obligatory,'' in that they may be necessary to constitute one assemblage, but they might, likewise, be unplugged from this assemblage and pulled into another. For example, the user navigating an online interface may form one sort of human–machine assemblage, and yet, when their activities bump up against limitations set by the platform's design or the software's coding, we can see how the discrete and observable digital practices of the user are tangled together with—and disrupted by—other assemblages at play. DeLanda refers to those processes that stabilize an assemblage as *territorialization* and those that destabilize an assemblage as *deterritorialization*.

Importantly, for DeLanda *territorialization* is something that occurs both within and across spatial and temporal *scales*. In the example of a user whose browsing is disrupted by the system's underlying code, both the user and the code enter this assemblage constituted by contingent temporal histories. The user, for example, carries not only a history of intersectional identity, but also a history of techno-social knowledge that allows them to smoothly (or clumsily) navigate the platform. Likewise, the code enters the assemblage with its own history—perhaps it was written specifically for use in this platform; or it was assembled from fragments of open-source scripts available online. Tracing how these assemblages merge across scales can help us better understand how the two mutually shape one another. For this reason, we have found it helpful to parse the online learning environment not as a singular space, but rather, as a multilayered, sociohistorical process—a confluence of hardware and software, of content and course design, of collaborative inquiry and of instrumental tactics. In the sections that follow, we elucidate how such a framing might not only allow us to understand the techno-social mechanisms at play in online education but also to consider how such understandings might be leveraged to examine or reconfigure circulations of power and agency along the trajectories associated with critical learning analytics.

Methods

To capture and express the dynamic social interactions characteristic of new digital learning environments—particularly those that include collaborative practices that stretch across multiple applications and spaces—a critical learning analytics requires more than the traditional taxonomy of metrics and measurements for cataloguing user activity. It demands a methodological apparatus that can organize complex systems of people, tools, and content as they converge and disperse within and across scales. To date, much of the online learning research has focused on the use of a single application or a limited set of interaction points; however, as multimedia-rich collaboration tools and diverse participant structures are slowly engrafted into familiar platforms, they bring with them fresh complexities for analyzing online activity. If the Educause vision for "The Next Generation Digital Learning Environment" comes to fruition, this complexity will be compounded further by a vibrant marketplace of modular, interchangeable tools, or "plug and play" environments (Brown et al., 2015). Further complicating the landscape, the age of "agile" software development, wherein updates and feature changes occur in regular "sprint cycles" that can alter a user experience, has resulted in applications that are in a constant state of flux. A comprehensive approach to online learning research today, then, must be able to work within and across changing layers of software and iterative course design, and be flexible enough to follow activities as they are territorialized and deterritorialized across scales.

To explore how such an approach can support a move toward critical learning analytics, we draw on illustrative data from the SuiteC software applications, as they were implemented in three course contexts: ART, EDU I, and EDU II. The three courses were taught by two lead instructors, with the assistance of graduate student instructors (GSI) (ART = 1 GSI; EDU I = 5 GSI; EDU II = 3 GSI) and included a combination of digital interactions using the Canvas Learning Management System (LMS), as well as periodic face-to-face meetings. Each course was designed to leverage the tools of the SuiteC applications to provide students with opportunities for collaboration and social interaction in a peer-driven, multimedia-rich online space. The SuiteC software, itself, includes an ensemble of three interconnected apps that integrate into the native tools of the

Canvas LMS and also work in tandem with other available applications. In this way, the suite captures many of the ‘‘plug and play’’ elements present in recent framings of ‘‘next generation’’ ed-tech environments (e.g. Brown et al., 2015). In addition, the SuiteC applications were also in active development using an iterative ‘‘agile’’ methodology during the time of data collection, providing a data set that reflects the fluctuations that occur as feature enhancements and alterations are continually rolled out across online tools, even as they are in active use. In an important sense, then, neither the applications nor their interactions with the Canvas platform nor their uptake among users can be understood as a hardened or discrete plane of activity: much like DeLanda’s (2006) notion of ‘‘assemblage,’’ the fluidity of updates and iterations sustained each in a state of perpetual emergence.

The three SuiteC applications work together to structure an environment where students can gather and share media resources, create collaborative compositions, and gauge their online participation in relation to their classmates. The first application, the Asset Library, is a database for uploading, curating, and tagging media artifacts—from images and audio files to video clips (see Figure 1). These are displayed for personal use, or they can be made public for the full course community to ‘‘like,’’ comment on, or make use of them. The second application, Whiteboards, is a collaborative multimedia composing space that allows students to synchronously or asynchronously generate text, shapes, or free-hand drawings, or import and manipulate media files from the Asset Library for remixing and concept mapping. The third application is the Engagement Index, which functions, on the one hand, as a space for instructors to associate point values with the different activities for which students might use the other tools (e.g. posting an Asset, ‘‘liking’’ an Asset, creating a collaborative Whiteboard, etc.); and, on the

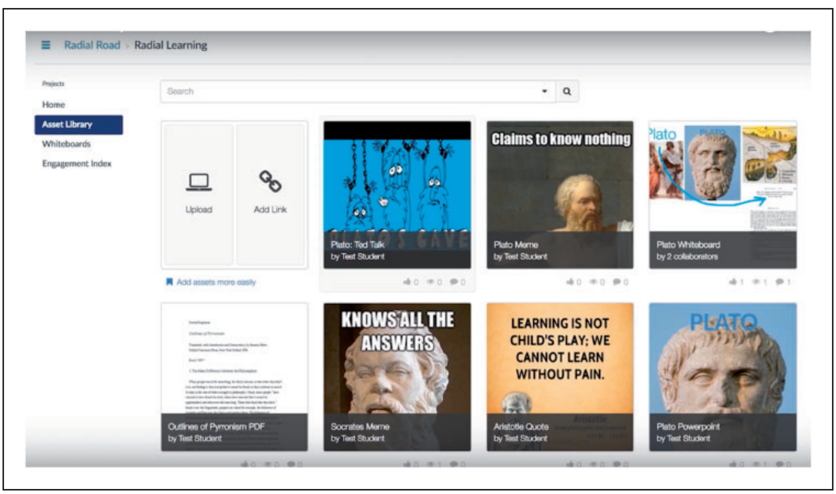


Figure 1. The Asset Library.

other hand, as a place where students can opt-into a course Leaderboard that displays their point totals in relation to others in the class (see Figure 2). In supporting an arc of learning activities, from curating and discussing media artifacts to creating and remixing content, the SuiteC tools help to mediate a range of individual and collaborative online practices that occur within a single set of interrelated tools. This not only provides instructors with detailed information about the ways interactions unfold across the applications, but also—through the Engagement Index—presents a student-facing analytics resource that, in theory, helps to make their own course participation visible.

The software logged click-data events to the SuiteC database, which were deidentified, organized into various CSVs based on the type of event, and then analyzed using various quantitative tools, including Mixpanel Analytics dashboard, Python, and STATA. The click-data represent click-to-click interactions of students across the three applications, such as "Launch the Asset Library," "Add Asset Comment," or "Add Whiteboard Element." Each event includes metadata, including timestamps, user ID, and other relevant features to the activity. Importantly, we examined this click-data—much of it underpinned by codes that quantify various forms of participation—in relation to its qualitative entanglements by zooming in on the course environments themselves to inductively and deductively code Asset comments and analyze Whiteboard compositions and media files as texts. These qualitative and quantitative data were then triangulated with survey responses taken at the middle of the semester, along with targeted, informal interviews with both the students and instructors.

Given the complex entanglements between these layers of user activity, click-data, uploaded and generated content, instructional design, as well as the iterative

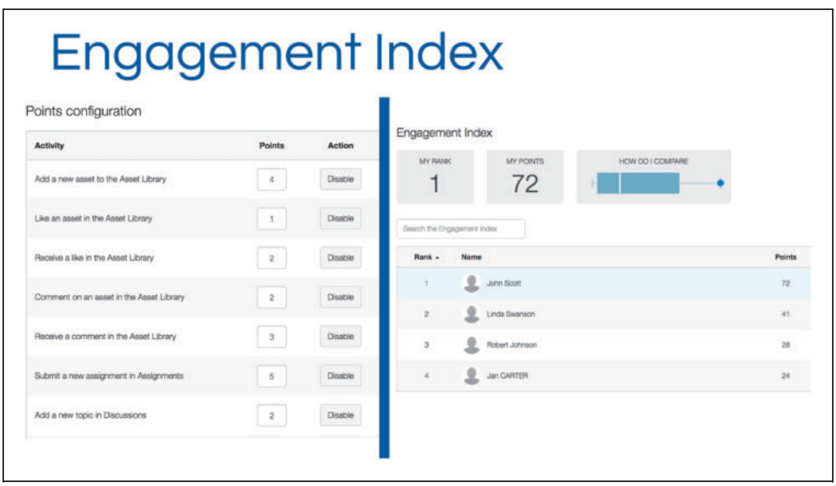


Figure 2. Engagement index.

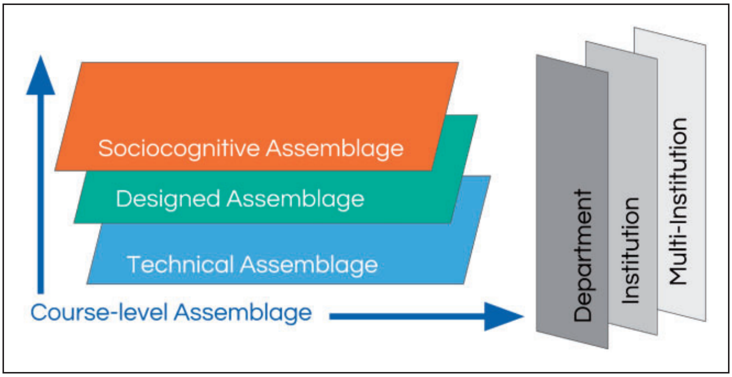


Figure 3. Course-level assemblage.

development of the SuiteC tools themselves, we have thought of these jostling, unfinished interchanges as component planes in a larger, emergent *course-assemblage* (see Figure 3). In the parlance of DeLanda (2006), by way of Deleuze and Guattari, these shifting pieces work to territorialize different unfolding course experiences for instructors and students. We focus here on three of these component layers—the **technical assemblage, designed assemblage, and sociocognitive assemblage**—to trace activities within and across each as they, together, help to constitute precarious forms of collaboration and social interaction that surface in the online environment. Of course, in reality, these planes do not actually operate in neatly divided "layers," nor are these the only possible planes with which we might map digital learning experiences: we could reasonably separate a host of other planes—from the economic to the biological—that are always already enmeshed with those planes we highlight here. As a heuristic for tracing course-level experience, then, these three planes allow us to diagram activities across assemblages as components become reconfigured from one plane to another. Consistencies found across configurations can illuminate fields of possibility for emergent effects, or "virtual" properties projected across planes that can help us understand or explain complex, dynamic social interactions in the online learning environment.

The **technical assemblage** indexes those software components of the online course environment and the relations between features, tools, and data in a multi-app system (see Figure 4). Technical components can be mapped to parallel configurations, such that one component may appear in relation to many different technical contexts or combinations of software/hardware. Beginning with the affordances or intentionalities of a single tool, the technical assemblage organizes these tools into relations with other tools, wherein the "emergent" properties of a tool are an expression of the contingent nature of the assemblage. The technical configuration, as in our case, may focus on the scale of the software assembled for a particular course but could be scaled up to include hardware and campus

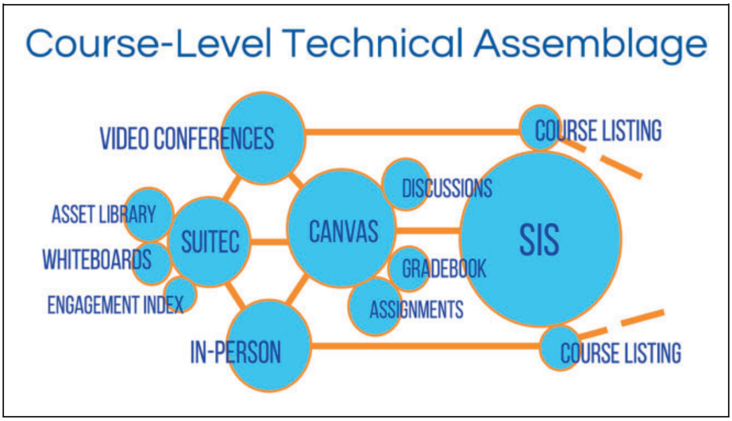


Figure 4. Course-level technical assemblage.

infrastructure, student information systems, etc. The "closeness" or nature of the relations between technical components may be determined at a more technical level, such as shared authentication systems or the flow of data and content between tools. Or they may be considered through various power metrics, such as in viewing the "gradebook" as a powerful component because of its role in mediating what for many students is the most important information and outcome for a course experience: course grades.

At the layer of the **designed assemblage**, technical components become reconfigured by the instructor or course designer with the introduction of pedagogical components such as instructional content, evaluative instruments, course procedures, and learning objects (see Figure 5). The design of a student experience tries to take advantage of the components of the technical assemblage (accounting for their inherent constraints) to produce a possible or preferred pathway for guiding students' future actions. At this layer, the technical components are given value and purpose in their usage beyond or even in contrast with their intended use. For example, Twitter may be used in one course as an optional space for posting questions and comments without any bearing on grade, whereas in another course, posting and participating on Twitter is a mandatory part of the course graded by the instructor. Although each use-case would maintain common metrics that are internal to Twitter's design, such as favoriting, following, and retweeting, both the quantitative and qualitative nature of Twitter's usage would likely look markedly different from one course to another.

The **sociocognitive assemblage,** then, is the layer at which the course unfolds, as students and instructors and other members of the learning community converge upon the designed assemblage (see Figure 6). From data events participants trigger in navigating a system to the content they generate, share, and interact with during a course, these digital footprints are themselves a new layer of components entering

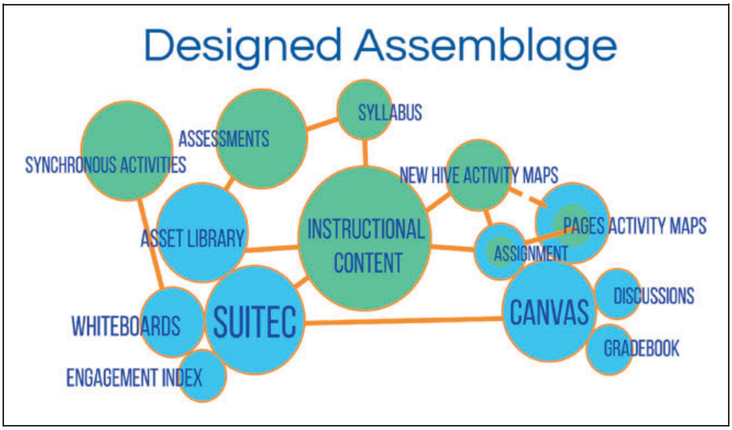


Figure 5. Designed assemblage.

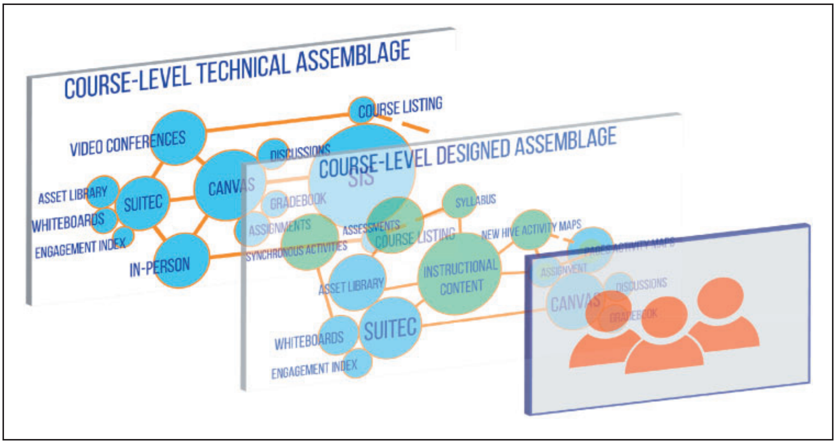


Figure 6. The sociocognitive assemblage.

into relation with those technical and designed. At this emergent layer, we can begin tracing how components in the technical and designed assemblage come into being, how they act upon each other and on users, as well as how users act upon them. As an analytical strategy, we can isolate a single component as it becomes reconfigured at different relational scales by tracing vectors through the same component or clusters of related components across multiple planes. Although the three planes organized in such a way can be used to communicate a kind of temporal flow, where the technical parts precede their integration into a course experience which precedes the activity of students, this flow is not limited to a single direction, also expressed in the notion of a vector from which we establish a position of viewing or inquiry.

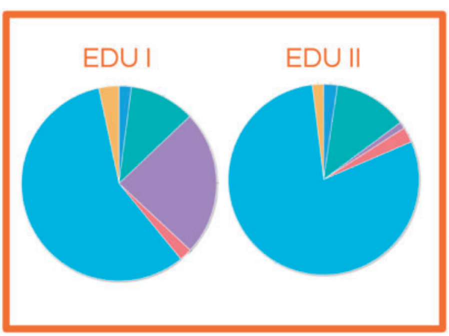
Insights from across assemblage planes

We applied this assemblage approach by focusing our initial inquiry around the SuiteC Engagement Index (see Figure 2) because of its complex interaction with the other tools in the environment and because of its potential influence on collaboration—both by quantifying and "gamifying" these practices. "Gamifying," or applying game-based techniques to nongaming environments, has been explored extensively in the online learning literature—for instance, in the use of achievement systems like "badges" to designate growth or unlock features in an online course (Deterding et al., 2011). Many of these studies have analyzed potential correlations between the introduction of game elements and various performance or engagement metrics (Dicheva and Dichev, 2015; Hamari et al., 2014), while others have outlined best practices for integrating gaming components into a course experience (Kapp, 2012; Simoes et al., 2013). By examining the integration of a gamification component—the Engagement Index—in a course assemblage, however, we orient our analysis not around the hypothetical relations between "gamification" and student achievement, but rather, as a means to understand the "emergent effects" that surface in the intentions and uses of this tool in the context of the larger sociomaterial system of the online learning environment.

As a software component in the course's technical infrastructure, the Engagement Index itself is an assemblage of features and code snippets that *intends* to motivate online participation through competition via a course Leaderboard. It also intends to provide students and instructors with high-level feedback on their engagement—as defined by click-activities assigned to point values—by making individual scores publicly visible. Of course, students can control whether or not to participate in the course "competition" by choosing whether or not to share their Engagement Index score on the Leaderboard; however, as Van Dijck (2013) notes, the tool's existence as a default means it is not a neutral presence: even when students opt-out, they may still be aware that their clicks and actions are being counted, and that their scores may be used by instructors to assess or grade course participation. By design, these scores represent the sum total of student activities, each weighted by the instructor with a specific point value, and instructors can change the value of all 20 tracked activities at any time. Tracked activities not only include engaging in specific practices oneself but also in *receiving* engagement from others. This means that, in the ecosystem of the online class, a student can get points both for "liking" another student's Asset or Whiteboard, or for garnering "likes" from their peers. This is a unique set of metrics, configured as such as a way to prioritize reciprocity in interactions and to reward media compositions that engage others. Weighting the value of activities against each other, then, can, in theory, be leveraged by the instructor to motivate engagement with some activities over others—for instance, in ascribing more value to certain forms of collaboration than smaller actions, like commenting on a post.

While the utility of the Engagement Index may vary from class to class based on its integration with a particular course design, and its configuration by the instructor, its efficacy can be measured fairly consistently, as it tends to motivate its targeted forms of participation—those weighed more heavily—with varying degrees of quality. For students competing in the ‘‘game’’ of the class—or for those who have opted out, yet remain aware that their activities are being monitored, a degradation in quality could be considered a symptom of what are commonly called ‘‘gaming behaviors,’’ or strategic decisions that are made to optimize the accumulation of points, even if at the expense of more important course goals or content knowledge (Dominguez et al., 2013). Fundamentally, then, the Engagement Index reflects an inherent tension in professional and academic spaces where individuals are simultaneously collaborating and competing with one another to reach either immediate or long-term goals. For the Engagement Index, how an instructor positions the rewards of competition versus collaboration can have a significant impact on how participation and interaction between students unfolds, in a similar way that grading exams on a ranked curve may dissuade students from sharing study tips or insights.

While insights like these about the Engagement Index as a tool allow us to the see its capacities and constraints in constructing ‘‘engagement’’ in particular ways, it is also important to situate the application in relation to other parts of the course assemblage. Where the former can help parse the Index’s affordances, the latter allows us to trace the emergent effects that surface as the tool is brought to bear in a range of shifting course contexts. To map these effects, we began by organizing high-level usage statistics in the EDU I and EDU II courses (see Figure 7) in order to examine possible macro-level patterns across these environments. While the smaller N in the EDU II course contributes to the overall lower totals,



	EDU I	EDU II
Views	54,140	39,730
Likes	22,618	559
Comments	1,950	1,168
Assets	10,202	6,243
Whiteboard	2,002	1,302
EI Launch	3,131	962

Figure 7. Statistics in the EDU I and EDU II courses.

one discrepancy that immediately stands out is the dramatic fall in Asset "likes" between semesters—a 98% decrease. By looking at the Leaderboard activity, it becomes possible to see how students in the EDU I course were using these "likes"—those in the top three positions had secured their places largely through "liking" activity. So much so, in fact, that the student who finished in first place had, at one point, liked 825 Assets in one hour—a number greater than the 559 total likes given in the entire EDU II class over the whole semester.

We can begin to understand this discrepancy as an *emergent* sociomaterial activity if we step back and trace the evolution of the Engagement Index and its shifting relations with the surrounding technical assemblage. As part of the iterative design of the SuiteC applications, updates were regularly being pushed out to the tools both during and between semesters—many of which altered their form and function. In the EDU I course, for example, shared Assets appeared in the library as thumbnails, displayed in rows of four and infinitely scrollable in a time-based feed. Accompanying each of these thumbnails was a "thumbs-up" icon that, when clicked, would trigger a Like. However, between semesters, one feature tweak that was rolled out to the application restructured this process. By the start of EDU II, there was no longer a "thumbs-up" icon—instead, a user had to click on the thumbnail to expand a full view of the Asset before they could Like it. According to the developers, they had made this choice in order to increase the "value" of a Like by requiring more labor relative to other activities tracked by the Engagement Index. This decision, then, made at the scale of the software itself invariably reoriented activities of other planes of activity—in how (and how often) students interacted with one another, and, in turn, in how "engagement" was constructed in the context of the course.

From here, we can proceed to trace practices of "gaming" and social interaction as components in adjacent assemblages along the contingent vectors that extend through the assemblages of the three course contexts. When the Engagement Index was implemented in the ART course, for example, students *could* Like an Asset thumbnail, but this was not an activity exploited for points to such an extreme degree as in the EDU I course. The difference cannot be attributed to a lack of motivation to earn points in the ART course, given that the Engagement Index score actually counted for 60% of student grade. This is a marked difference from the EDU courses, where the score was consulted but not directly counted toward a student's participation grade and worth only 20% of final grade. Instead, the difference can be found in the way the two course designs put the tools to use in the weekly learning activities on the platform. In the ART course, students only added one "art piece" to the Gallery each week—and with only 38 students in the class and a low-point value, Liking had limited upside for obtaining the necessary amount of points to achieve an A in the course. Conversely, in the EDU I course, with over 120 students contributing upward of seven to eight artifacts per week, the volume of Assets in the Library invited this kind of mass-Liking practice to emerge. In the context of the ART class then, the presence of the Engagement Index helped facilitate an alternate approach to navigating the demands of the technical and designed planes. In a discussion thread that invited students to reflect on the role of the Index in the ART class, many students noted, with frustration, that "spammy" comments on Assets had degraded the quality of the classroom discourse and were blamed as a gaming behavior that some students used to gain points to reach a total that might warrant an A.

Unlike the ART course, where students suggested commenting provided a means to "game" the system at the expense of quality discourse, and the EDU I course where excessive Liking provided a pathway for points, if diminishing the value of a "thumbs up," not all of the emergent practices that took shape in the intersection of technical, designed, and sociocognitive planes resulted in "gaming." Whether due to a lack of easy means for earning points, or a lack of motivation to play "the game" of the class, or a lack of instructor emphasis on points, the EDU II course did not have the same sort of "gaming" indicators as in the other classes. In one interview, a student mentioned that she would, at times, add additional Assets to her Whiteboards in order to gain extra points. And another student described consulting the Engagement Index on occasion to ensure that he kept in the top 50% of the class—a personal goal he had set for himself. But there was no widespread activity that emerged across the class. In fact, in a survey administered halfway through the semester, a quarter of the students reported that they did not even know what the Engagement Index was—and a much larger percent chose to opt-out of the Leaderboard altogether, meaning they could not see the scores of others, or their own class rank.

Most surprising to us, however, was that the top two students on the Leaderboard in EDU II had chosen not to expose their position to the rest of the class, so their rank was only visible to the instructors. When we looked at the third place student who opted-in to the Leaderboard, and thereby appeared in first place to other students, the third place participation data present some gaming behaviors, such as Liking more Assets than average in small bursts (though still only a fraction of the amount in EDU I's Liking practices) and in checking the Engagement Index with greater frequency during those bursts (including the end of the term, as a way to maintain rank). Had the student been aware she was actually in third place, she might have perhaps made an even greater push at the end of the term for first place. But we were left wondering, were the top two students unaware of the "game" or just uninterested in the score and rank? When we looked more closely at their click-data and features of the Engagement Index, however, we noticed something. Several times during the semester, including at the very end, the first place student would opt-in to check his rank, and then immediately opt-out. His partner on many Whiteboards in the class was the second place student, so even though we do not have a record in our database of the second place student checking her Engagement Index score, it is still possible she was aware of it since she does show a spike in activity at the very end of the semester. Although their participations across activities do not convey any obvious signs of gaming, this evidence of the first place student opting-in and out of the Leaderboard reveals an awareness and interest in his standing among peers—even if he is uninterested in broadcasting this position publicly, as students did in the EDU I and ART courses.

One way of framing—and further complicating—such activities is through the paired notions of "strategies" and "tactics." In his seminal work, *The Practice of Everyday Life* (1984), De Certeau articulates a distinction between the two by giving the example of an individual walking through a city: the material configuration and design of urban space present a "strategy" for organizing movement and behavior; and, by contrast, the improvisational or subversive deviations that people use to navigate this strategy are "tactics." Applied to an online context, there is a sense where we can understand students' behaviors across the EDU I, EDU II, and ART classes as emergent "tactics," intended to exploit loopholes in or navigate the "strategies" constructed by the technical and designed assemblages of the courses. However, when situated in the larger course assemblage, such distinctions can begin to break down. For example, according to De Certeau, strategies are almost always a space of external imposition, that is they are a kind of "foreign power" (p. 37) that exerts pressures and enacts constraints on participating individuals and groups. While it is certainly true that student users of an online environment are subjected to the powers of the technical and designed course planes, there is also a sense where these assemblages, likewise, exist under the constraints of still other external powers. The instructor's course design, for instance, is conditioned by the capacities, limits, and defaults of the technical plane—if no Engagement Index existed, or if it took other factors into account in calculating scores, it is possible they might dramatically reorient their metrics for tracking "engagement." Likewise, the technical plane of the applications is always at the mercy of both the instructors who configure it for use, as well as the developers—who, in turn, make their iterative adjustments in response to the activities users. In other words, while there are certainly structures in place in the online environment that create parameters for engagement, we cannot easily pinpoint a distinct locus of power that animates the strategies of the course assemblage. In DeLanda's phrasing, they are deterritorialized at one scale, even as they are territorialized on another.

In this way, when reading across the technical, designed, and sociocognitive planes, power circulates within and across each, giving rise both to new strategies and to emergent, subversive tactics—sometimes from students (e.g. leaving "spammy" comments to get points), sometimes from instructors (e.g. making use of the available Engagement Index to monitor student participation), and sometimes from technicians (e.g. coding and pushing-out new features designed for instructors' and students' needs). Of course, this does not mean that power always circulates evenly across these dimensions: students' position relative to instructors, for instance, means their subversive tactics almost always leave them more vulnerable to punitive responses. However, recognizing the ways that power is distributed and that strategies and tactics emerge from contingent interplay across these dimensions can provide a frame for better understanding how such imbalances take shape and work in the networks that give rise to learning analytics.

Such a perspective can, in turn, yield critical insights into how these planes might be configured otherwise, for more equitable student flourishing.

Making a critical turn

Locating power as something distributed, that circulates across the tangled planes of the larger course assemblage can open generative pathways for thinking about learning analytics. It situates research on education in online environments in conversation with emerging interdisciplinary scholarship that interrogates the fragile construction of taken-for-granted terms, like data, platforms, interfaces, and algorithms (e.g. Bogost and Montfort, 2009; Galloway, 2012; Gillespie, 2010; Wilson et al., 2017). Further, it allows us to parse other component assemblages that animate course activities, including those that are not always brought into discussions of educational technology. Mahoney-Roberts et al. (2016), for example, have examined the ways ‘‘personalized learning’’—a phrase often nested in discussions of Big Data and learning analytics—has been leveraged in furthering the agenda of corporate school reform. By approaching learning analytics as an assemblage, then, our research can attend not only to the quantified data generated in online spaces and the qualitative practices cultivated in digital exchanges, but also to the ways these activities are always imbricated in other political and economic networks that can escape our purview when we are too narrowly focused on tallying Likes or ranking student participation.

And yet, such a critical perspective in learning analytics must also have purchase in these more prosaic tasks too—in the ways we organize courses, the ways we interact with students. It is here a return to the Engagement Index can be instructive. While we have focused on a single component in the SuiteC software, the consideration of both the macro-level categories of participation, as well as the individual tactics that students used to navigate the ‘‘game’’ of the course can provide a starting place for inquiry into the relationship between technology and pedagogy. For instance, critical considerations for the Engagement Index might begin by interrogating the different Liking practices that emerged and contrasting them with parallel practices that exist in face-to-face classrooms or in other social media environments. This, in turn, might lead to further questions about which practices were most beneficial or harmful to the functioning of the community? To the depth of student learning? Certainly, compromising the quality of the discourse between peers in the ART course seemed, on the surface, to be the most intrusive activity and a more explicit violation of class norms or etiquette. And yet, the prevalence of ‘‘comment spamming’’ does not appear especially widespread across the courses—and even in the ART class some of this feedback was counter-balanced with descriptions of positive experiences in receiving and reading peer commentary. While more subtle, the practice of opting-in and out of the Leaderboard as in EDU II could, if practiced en masse, have far more wide-reaching consequences for the community as a whole. Opting-in signifies to others you are playing ‘‘the game,’’ and serves as a kind of tacit agreement of mutual disclosure in sharing points.

If everyone were to use this tactic of opting in and then immediately opting out, there would no longer be a game to play because the Leaderboard would be vacated. And yet, if the option were taken away—for instance, with a tweak in the technical assemblage—there is no way to know what other, alternate tactics might emerge instead.

Similarly, when it comes to the excessive Liking practices of EDU I, a critical reading teases out how this behavior affects both the individual and the community at various scales. From the perspective of an instructor, time spent Liking Assets only to *win* the Leaderboard could be time better spent engaging deeply with Assets and course materials for the sake of learning. From the vantage point of the community, these hours of Liking could be viewed as an act of altruism, as more people and more content received a form of acknowledgment from someone in the community. Students could not see who Liked their Assets, so excessive Liking was not viewed as a form of spamming Likes, though seeing Likes on duplicate content in the Asset Library more subtly revealed that Likes were being given without much thought to the Asset.

Compare this anonymity in Liking to a site such as Facebook, where Likes are attributed to a person and thereby, the value of those Likes are measured in relation to people's known Liking practices (‘‘a person known to Like everything Likes my new profile picture'') and the personal relationship between the giver and the receiver (‘‘my ex-girlfriend Liked my new profile picture''). In social media, receiving Likes or other forms of acknowledgment from a network are valued as a form of social capital to the extent that young people will talk about deleting Instagram posts if they do not pass a minimum Like threshold. As microinteractions that do not require much labor *to give*, Liking emerges as an important way for maintaining social ties in networks because they circulate feelings of presentness among distant others. So as a feature in social media environments, a user can often Like something without fully engaging or ‘‘Viewing'' it, similar to the Like feature in EDU I. Given the 98% drop from EDU I to EDU II, perhaps social media trends suggest the Asset Library might be improved by reallowing thumbnail Liking to promote more interaction—though there is still the issue of maintaining the value of receiving a Like. These kinds of critical questions about networked relations and the various features and tools that mediate those interactions can be generated and explored by mapping components, which can, in turn, help pave directions for technical and pedagogical innovation.

Whether these inquiries lead to the development of better tools or to improvements in the design of a course experience, a focus for critical action can be traced along the different ways these data can be used. Considering again, the Liking practices in the course versus the Liking practices in social media, the latter awards popularity with increased visibility. Yet from a critical learning perspective, we should also be mindful of student voices in the online environment who are not being heard—comments or contributions that are not taken up or given notice by the community. A critical learning analytics framework, therefore, must also pursue technical and pedagogical solutions to help support diverse perspectives and content. Instead of only relying on problematic categories of gender and race to describe the participants of a learning community, a critical analytics approach can leverage social interaction data to express the fluidity of identities under construction by students in various collaborative relationships online—and can use data generated not only as a means to rank or sort students, but also to refine those questions for reflexive inquiry that can lead to more just and equitable instruction. Far from a simple calculus of weighing the costs and benefits of one classroom or technological configuration or another, then, a critical learning analytics framework approaches online education as a contingent process of emergence. Rather than valorizing "personalized learning" or "Big Data" for their own sake, it aims to engage in deeper pedagogical reflection about the aims and values that underpin assemblages of instructional design, even as it humbly recognizes that these visions may be shaped and reshaped as they are layered together with the students and technologies who, likewise, share the precarious work of animating larger course assemblages.

Conclusion

In this article, we put forth a heuristic for organizing the assemblages of an online course experience at various scales and layers, focusing mainly on the mapping of a single component—the Engagement Index—across three assemblages: the technical, designed, and sociocognitive. The analysis and subsequent discoveries outlined regarding the emergence of strategies and tactics in the three course instances demonstrate the purchase gained from this assemblage approach to learning analytics. As "emergent wholes," assemblage concepts are aptly equipped for describing networks in perpetual motion, and for tracing components across scales and temporalities—those that are territorialized, yet never harden into a totality. Our work here has not articulated a formalized visual architecture for mapping the contingencies between component parts, such that we could more deliberately trace changes subtle changes in features, flows in various forms of power and data, and pedagogically connected course activities. However, we hope it has illuminated the utility of the assemblage as a theoretical and methodological construct for the study of digital learning environments, and aided in laying groundwork for the design of a more deliberate organization of components and the relations between them.

In marrying assemblage concepts with metrics described in learning analytics, we also endeavored to shed light on how analytics can be applied at various scales and across contexts. Zooming in from high-level click-data to the more qualitative nature of discourse in a discussion and moving adjacently from one course instance to another, we have tried to model the movement of multiplicitous components across scaled, mutually constitutive configurations. In doing so, we have worked to make legible the ways the entanglement of quantitative metrics and qualitative practices might build on emerging interdisciplinary scholarship that might help us conceptualize learning analytics differently. Rather than simply leveraging

Big Data for more refined calculations of participation or more textured accounts of online interaction, a critical learning analytics allows researchers to contextualize such data as contingent upshots of enmeshed sociotechnical assemblages. And in doing so, it invites us to imagine how these assemblages might be configured for more ethical modes of instruction and more equitable forms of engagement.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

References

Baker RSJD and Yacef K (2009) The state of educational data mining in 2009: A review and future visions. *Journal of Educational Data Mining* 1(1): 3–17.

Bambrick-Santoyo P (2010) *Driven by Data: A Practical Guide to Improve Instruction*. San Francisco, CA: Jossey-Bass.

Bogost I and Montfort N (2009) Platform studies: Frequently questioned answers. In: *Paper presented at the digital arts and culture conference*, 12–15 December, Irvine, California, pp.1–6.

boyd d and Crawford K (2012) Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, Communication, and Society* 15(5): 662–679.

Bratton B (2016) *The Stack: On Software and Sovereignty*. Cambridge: The MIT Press.

Brown M, Dehoney J and Millichap N (2015) The next generation digital learning environment: A report on research. *Educause* Learning Initiative paper.

Browne S (2015) *Dark Matters: On the Surveillance of Blackness*. Durham, NC: Duke University Press.

Buckingham Shum S and Ferguson R (2012) Social learning analytics. *Educational Technology and Society* 15(3): 3–26.

Campano G, Ghiso MP and Sánchez L (2013) "Nobody knows the...amount of a person": Elementary students critiquing dehumanization through organic critical literacies. *Research in the Teaching of English* 48: 98–125.

De Certeau M (1984) *The Practice of Everyday Life*. Berkeley: University of California Press.

de Freitas E, Dixon-Román E and Lather P (2016) Alternative ontologies of the number: Rethinking the quantitative in computational culture. *Cultural Studies ↔ Critical Methodologies* 16(5): 431–434.

De Laat M and Prinsen FR (2014) Social learning analytics for higher education. *Research and Practice in Assessment* 9(2): 51–60.

DeLanda M (1997) *A Thousand Years of Nonlinear History*. Brooklyn, NY: Zone Books.

DeLanda M (2002) *Intensive Science and Virtual Philosophy*. New York: Bloomsbury.

DeLanda M (2006) *A New Philosophy of Society: Assemblage Theory and Social Complexity*. New York: Continuum.

DeLanda M (2016) *Assemblage Theory*. Edinburgh: University of Edinburgh Press.

Deleuze G and Guattari F (1987) *A Thousand Plateaus*. Minneapolis: University of Minnesota Press.

Deterding S, Dixon D, Khaled R, et al. (2011) From game design elements to gamefulness: defining "Gamification." In: *15th International academic mindtrek conference: Envisioning future media environments*, New York, NY, pp.9–15. ACM.

Dicheva D and Dichev C (2015) Gamification in education: Where are we in 2015? In: *World conference on E-Learning (ELEARN 2015)*, Kona, Hawaii, 19–22 October, pp.1276–1284. Chesapeake: AACE.

Dominguez A, Saenz-de-Navarrete J, de-Marcos L, et al. (2013) Gamifying learning experiences: Practical implications and outcomes. *Computers in Education* 63: 380–392.

Dutro E and Selland M (2012) "I like to read, but I know I'm not good at it": Children's perspectives on high-stakes testing in a high-poverty school. *Curriculum Inquiry* 42: 340–367.

Galloway A (2012) *The Interface Effect*. Malden, MA: Polity.

Gillespie T (2010) The politics of platforms. *New Media and Society* 12(3): 347–364.

Goodfellow R and Lea M (2013) *Literacy in the Digital University: Critical Perspectives on Learning, Scholarship, and Technology*. New York: Routledge.

Greller W and Drachsler H (2012) Translating learning into numbers: A generic framework for learning analytics. *Educational Technology and Society* 15(3): 42–57.

Haber J (2014) *MOOCs*. Cambridge: The MIT Press.

Hacking I (1990) *The Taming Of chance*. New York: Cambridge University Press.

Halpern O (2015) *Beautiful Data: A History of Vision and Reason Since 1945*. Durham, NC: Duke University Press.

Hamari J, Koivisto J and Sarsa, H (2014) Does gamification work? – A literature review of empirical studies on gamification. In: *Paper presented at the 2014 47th Hawaii international conference on system sciences*, pp.3025–3034. DOI:10.1109/HICSS.2014.377.

Herold B (2016) The future of big data and analytics in K-12 education. *Education Week* 35(17): 2–7.

Kapp KM (2012) *The Gamification of Learning and Instruction: Game-Based Methods and Strategies for Training and Education*. San Francisco, CA: Pfeiffer.

Kitchin R and Dodge M (2011) *Code/Space: Software and Everyday Life*. Cambridge: The MIT Press.

Kliebard HM(2004) *The Struggle for the American Curriculum, 1893–1958*. 3rd ed. New York: Routledge.

Kolowich S (2013) Why professors at San Jose State won't use a Harvard professor's MOOC. *Chronicle of Higher Education*. Available at: http://www.chronicle.com/article/Why-Professors-at-San-Jose/138941 (accessed 5 March 2017).

Koretz D (2008) *Measuring Up: What Educational Testing Really Tells Us*. Cambridge, MA: Harvard University Press.

Lane JE and Zimpher NL (2014) *Building a Smarter University: Big Data, Innovation, and Analytics*. Albany: SUNY Press.

Latour B (1987) *Science in Action: How to Follow Scientists and Engineers Through Society*. Cambridge, MA: Harvard University Press.

Long P and Siemens G (2011) Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review* 46(5): 31–40.
Lynch TL (2015) *The Hidden Role of Software in Educational Research: Policy to Practice*. New York: Routledge.
Mahoney-Roberts H, Means A and Garrison M (2015) Netflixing human capital development: Personalized learning technology and the corporatization of K-12 education. *Journal of Education Policy* 31(4): 405–442.
Marsh JA, Pane JF and Hamilton SL (2006) *Making Sense of Data-Driven Decision Making in Education: Evidence from Recent RAND Research* (OP-170). Santa Monica, CA: RAND Corporation.
Mayer-Schönberger V and Cukier K (2014) *Learning with Big Data: The Future of Education*. New York: Houghton Mifflin Harcourt.
Morozov E (2013) *To Save Everything, Click Here: The Folly of Technological Solutionism*. New York: Public Affairs.
Nichols TP and Campano G (2017) Post-humanism and literacy studies. *Language Arts* 94(4): 245–251.
O'Neil C (2016) *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. New York: Crown.
Perrotta C and Williamson B (2016) The social life of learning analytics: Cluster analysis and the 'performance' of algorithmic education. *Learning, Media and Technology* 7: 33–43.
Picciano A (2016) *Online Education Policy and Practice: The Past, Present, and Future of the Digital University*. New York: Routledge.
Porter T (1995) *Trust in Numbers: The Pursuit of Objectivity in Science and Public Life*. Princeton, NJ: Princeton University Press.
Siemens G (2013) Learning analytics: The emergence of a discipline. *American Behavioral Scientist* 57(10): 1380–1400.
Simoes J, Redondo R, Vilas A, et al. (2013) A gamification framework to improve participation in social learning environments. *eLearning Papers* 35: 1–11.
Slade S and Prinsloo P (2013) Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist* 57(10): 1509–1528.
Turow J (2013) *The Daily You: How the New Advertising Industry Is Defining Your Identity and Your Worth*. New Haven, CT: Yale University Press.
van Dijck J (2013) *The Culture of Connectivity*. New York: Oxford.
Wilson A, Watson C, Thompson TL, et al. (2017) Learning analytics: Challenges and limitations. *Teaching in Higher Education* 22: 1–17.