Learning Analytics: Using Data-Informed Decision-Making to Improve Teaching and Learning

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INTRODUCTION

Learning Analytics is the development and application of data science methods to the distinct characteristics, needs, and concerns of educational contexts and the data streams they generate for the purpose of better understanding and supporting learning processes and outcomes (see also an earlier definition by Siemens et al. 2011). It is both a field of scholarly pursuit and a technology for making concrete improvements within educational systems by enabling data-informed decision-making by teachers, students, and other educational stakeholders. Learning Analytics has been identified as a critical emerging technology of the twenty-first century, with high expectations to make a positive impact on learning and teaching (Johnson et al. 2016), both through short-cycle improvements to educational practice and long-cycle improvements to our understanding of learning.

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Although the collection and analysis of data to understand and support learning is not a new endeavor, there are three critical characteristics that distinguish learning analytics from prior educational research: the data the work is based on, the kinds of analyses employed, and the ways in which it is put to use. This chapter begins with an overview of the value proposition that learning analytics offers and is then organized around these three areas (data, analyses, and applications) to give readers a concise overview of what makes learning analytics a unique and especially promising technology to improve teaching and learning.

WHY DEVELOP LEARNING ANALYTICS?

The basic value proposition for learning analytics is that generating more information about how learning processes unfold can help us better improve them. This is true not only over the long term (by better understanding how learning occurred in the current situation we can design in a more informed way for the future), but also in the short term (by better understanding how learning is occurring up to the current moment, we can act in a more informed way right now). It is the latter use, to improve teaching and learning in "real-time" that is most novel and exciting to educators. From an instructor's perspective, learning analytics can both provide a way to check if the planned activities are occurring as intended (e.g. the goal is for pairs of students to argue opposing positions about the culpability of Lady Macbeth—is this actually happening?) and to identify particular groups that may need additional support (e.g. in some groups the conversation is balanced but in others one student dominates over their partner or the partners simply agree). Similar information can also be provided directly to students (either individually or in collaborative groups) to prompt reflection and regulation of their own learning processes. Another attractive use of learning analytics is to tailor educational experiences to better meet the specific needs of one or more students. Higher education has been accused of a "one size fits all" approach, in part because identifying meaningful difference between students' needs and acting on them each appropriately is incredibly time consuming when done manually by instructors. However, if the right dimensions of difference are known and can be detected in naturally generated data, then the vision of education tailored to each students' needs becomes tractable.

What Kinds of Data Are Learning Analytics Based on and What Makes Them Distinct?

Learning analytics is not defined primarily by the source of data but by its size. Size here refers to two distinct characteristics. The first is the *overall quantity of data* involved. Simply put, the computational analyses used in learning analytics generally require a greater amount of data than that used in traditional educational research. The larger amount can, in part, come from a greater number of people; however, in large degree it is a result of collecting a much greater number of measurements on each person. So, for example, learning data from MOOCs (massive open online courses) is large not just because there are thousands of learners, but because we can collect a data point for every single action a person takes in the system (producing tens of thousands of data points per learner). The second element of size is the *granularity of the individual data points* themselves. Here, the measurements taken are generally more micro than traditional data, with learning analytics often looking at fine-grained elements of the learning process. Importantly, the smaller grain size is not created artificially to inflate the data available (e.g. taking the temperature of a room every 30 s instead of every 30 min creates more data but not necessarily more information). It is a reflection of new tools that allow for the capture of learning activity at the grain size which it actually occurs; that is, action by action. Together, smaller and more numerous data points are a hallmark of learning analytics research.

Source, Quantity, and Granularity of Learning Analytics Data

Where does the size of learning analytics data come from? The increase in availability of large quantity/small unit-size data can be attributed, at least initially, to the rise of digital technologies used for learning. From generic learning management systems (LMSs) to focused intelligent tutoring systems (ITSs), from virtual discussion boards (and other social media tools) to face-to-face classroom response systems (clickers) the dramatic rise of technologies used to support teaching and learning has facilitated the efficient collection of diverse (though not comprehensive) forms of data from large numbers of students at many points in time. This aligns with the essential attributes of big data, described as volume, velocity, and variety (Laney 2001).

For example, while previously an instructor might record the overall grades of class members on a quiz, online tools can easily track item-level responses for everyone in the class on every assessment across the term. Similarly, once built, technologies lend themselves to use at scale, allowing the collection of data from much larger numbers of students than was possible previously (this is true for both formal learning environments such as MOOCs as well as informal learning support tools such as Piazza or even Twitter). Furthermore, while prior data were limited to what could be captured in the classroom (or self-reported by students), internet-based tools allow (potential) insight into student learning regardless of where it takes place. In short, as more and more of our (academic) lives take place with the support of digital tools, the virtual "footprints" we leave behind also become more abundant and detailed.

Kinds of Learning Analytics Data

Learning analytics data relates to the *process* of learning (as opposed to just its outcomes). Current forms of data commonly used in learning analytics work include activity data (traces of what students did) and artifact data (things that students created). Often, a single action by a student can produce both kinds of data: for example, if a student attempts a quiz question in an online tool there is an activity trace (student X answered question Y at time T) and an artifact created (the actual answer they gave, which might later be evaluated in some way). A third form, association data, is often constructed based on the prior two to index relationships between students and students, students and artifacts, or students and instructors (see Hoppe's description of a trinity of learning analytics approaches aligned with these data types in Suthers et al. 2015). In addition to these core data sources about the learning process, learning analytics may also incorporate other kinds of data, such as learning outcomes (either prior or current performance) and demographic information (Sclater 2017); since these data are pre-existing rather than generated during the course of learning, they can be considered in the category of archival data. Traditional self-reports are less commonly used in learning analytics research due to problems of inaccurate and selective recall related to learning behaviors and the degree of intrusion required to collect the data (Baker and Siemens 2014; Winne 2010). However, if there is a need to document aspects of students' perceptions, experience sampling methods (ESM, Csikszentmihalyi and Larson 2014) via mobile apps can be

used. Finally, learning environment data (such as a course's curriculum or pedagogical approach) can be important as an element of metadata (or secondary level data in a hierarchical analysis approach if multiple courses are studied) to contextualize the primary data and determine appropriate approaches to analysis.

Activity data most commonly take the form of log-file data, a record of actions a student took in an online system at specific points in times. Log-file data can be coarse or detailed depending on both the front-end user interface and back-end data structure. For example, an LMS record may indicate that a student "opened message #241783 in discussion #486" or simply that they "accessed the discussion forums." Similarly, some systems capture the exhaustive use of play/pause/rewind/ fast-forward controls used during video-playback, while others only indicate that a video was viewed. In addition to LMSs, activity data can also come from the use of digital library resources, e-books (if the publisher provides access), and other dedicated learning tools housed outside the LMS (e.g. adaptive testing, intelligent tutors, and simulations). While more instrumentation is required, activity data can also be collected from physical learning environments via multi-modal learning analytics tools. Multi-modal data can include the tracking of student gaze, gesture, posture, movement as well as physiological measures such as the heart rate, galvanic skin response, and electroencephalogram (EEG) readings (Ochoa and Worsley 2016).

Artifact data can be any object created by a student and stored by the system. Here, the level of granularity corresponds to the unit size submitted by the student. While audio, image, and video artifacts are certainly possible (e.g. Baltrušaitis et al. 2016; D'Angelo et al. 2015), by far the most common type of artifact is text-based, and includes objects such as answers to questions, discussion forum posts, student essays, and lines of code. Artifact data must undergo some assessment or decomposition during the analysis process to index a number of its qualities. In simple cases, an artifact such as a question answer (e.g. the number 7 entered by a student in response to the question "3×2=?") might be evaluated as correct or incorrect. In more complex cases, a series of metrics might be used to represent the artifact. For example, a student essay could be indexed by its word length, structural coherence (McNamara et al. 2010), and the extent to which vocabulary from the course readings was employed (Velazquez et al. 2016). Although traditional teacher assessment and educational research often involve the evaluation of student work manually by human raters using a rubric (e.g. in terms of the quality of writing, strength of

evidence presented, or justification of positions taken), learning analytics requires such evaluation to occur at scale. Thus, one major stream of learning analytics research is devoted to the development of computer models that can "learn" to perform this task based on a training set of human-coded data (Mu et al. 2012). Artifacts can also be used to infer qualities of the student producing them; for example in the intelligent tutoring system (ITS) literature where students' answers to problem-solving steps are used to build a model of the students' underlying knowledge state (Corbett and Anderson 1994).

Association data are generally constructed post hoc from activity and/or artifact data. Associations can be made on the basis of similarity (e.g. two students took the same course) or interaction (e.g. one student sent another student (or the instructor) a message). Associations can also exist between people and artifacts (e.g. a student accessed a certain video resource) or between two artifacts (e.g. similar vocabulary used across two essays). When using association data, it is important to be clear about what kind(s) of elements are being associated and what the nature of the association (similarity, interaction etc.) indicates. The existence of association data points to an important question in learning analytics about the unit of the analysis. Most learning analytics to date have focused on the individual student (and their activity, their artifacts, their associations) as the object of interest. However, there is increasing interest in collaborative learning analytics in which the object of interest is a small group or community (e.g. Chen and Zhang 2016).

Data, Features, and Proxy Indicators

More data do not necessarily mean more information and an important challenge that learning analytics work must address is crafting meaningful indicators from what is available. Because learning analytics researchers do not always have control over the design (both front-end interface and back-end data structure) of the tools from which they collect data, they must be creative in devising proxies, measurements that serve as reasonable representations of the construct or phenomenon they wish to study. From an educational perspective, the justified linking of an observation to a conceptual entity is a critical piece of the logic chain for establishing the validity of learning analytics work. For example, should more time spent in an LMS be taken as an indicator of engagement or effort? The answer may depend on if the time relates to solving a problem (more time indicates the student

exerted more effort) or reading discussion posts (more time indicates more engagement). Of course this also presumes a clear definition of what is meant by effort and engagement. When these are considered to be different things, aggregating the overall time will be problematic as it confounds the two.

From a data science perspective, the problem of selecting indicators focuses on how to transform the raw data into a set of features that best models the underlying phenomena. This process is referred to as feature engineering and includes feature construction (e.g. via various forms of data aggregation or decomposition), feature extraction (e.g. via dimensionality reduction techniques such as principal component analysis), and feature selection (choosing a subset of possible features to include based on some ranking of their anticipated importance in the model). See Sinha et al. (2014) for a particularly nice example of engineering interpretable learning features from low-level data using fuzzy pattern matching.

It is a debated question in the field as to what extent it is important for engineered features to be interpretable versus simply contribute strongly to a prediction (see Bergner 2017, pp. 41–42 for elaboration of the differences between explanatory and predictive models). While there are some cases where reliable prediction alone is useful, in the realm of education we generally want to understand why certain relationships exist and be able to take action to affect them. For example, it is difficult to help a student who is identified as being at risk for failing a course if there is no way to make sense of the factors that led them to be placed into this category. There are also concerns with the use of features that might (unintentionally) reinforce traditional educational inequalities (Slade and Prinsloo 2013). For these reasons, theory can be a powerful tool to constrain and shape the possible degrees of freedom for constructing, extracting, and selecting features (Wise and Shaffer 2015).

The Manufacture of Data

Finally, it is important to remember that learning data are neither natural nor neutral. Learning data are not "natural" because they are produced as students interact with designed environments. The data thus represent aspects of what students do in response to that *specific environment*. In order to properly generalize to other contexts, we need to index the important qualities of the environment which range from the technical (e.g. the tools available, how they are designed, interface and navigational features) to the pedagogical (e.g. is the course oriented toward acquisition

of facts, problem-solving skills, or construction of conceptual schema). Learning data are also not "neutral" in that what is captured is often as much a product of what is feasible as what is valuable. The data that are easiest to acquire may not be the most useful or important; for example, indexing students' activity based solely on their use of an LMS when in-class lectures and tutorials are a greater part of the course's pedagogy may produce a skewed picture. Furthermore, once LMS data are reified as a measure of "student activity," they become a target to be optimized. Thus students who are active in class and tutorials, but less so online, may feel misplaced pressure to increase their use of the LMS. In general, it is easier to try to improve one's standing on metrics that do exist, than to remember the value of those things which we cannot (yet) quantify; thus, we run the danger of becoming what we measure (Duval and Verbert 2012). As the field of learning analytics matures, we expect to see learning tools for which the design of the data produced is an integral concern from the start rather than an afterthought. This will generate more useful data both through better back-end structures and through the creation of front-end interfaces that more readily support inference-making from data.

What Kinds of Analyses Does Learning Analytics Employ and What Can They Tell Us?

Learning analytics methods include human and computational processes and tools used to manipulate data in order to produce meaningful insight into learning. Much learning analytics works draws on educational data-mining approaches (see Romero et al. 2010), though given that learning analytics also seeks to attend to underlying conceptual relationships and the situational context, the metaphors of data geology and data archeology have been proposed as more appropriate than that of mining (Wise and Shaffer 2015). Avoiding the politics of language, learning analytics can be said to employ educational data science methods to detect underlying relationships and patterns among variables and cases. There are several classes of methods commonly used to achieve this. Each is discussed below with an emphasis on application, that is, the kinds of things that can be learned from each approach and the ways it can be used to support learning. In line with this focus on application, the references provided offer examples of the ways each approach has been employed to provide insight into educational data, rather than serving as authoritative sources on the technical details of the method.

Prediction (Supervised) Approaches

One of the most common and useful approaches in learning analytics is prediction (Baker and Yacef 2009; Papamitsiou and Economides 2014). Prediction is a form of supervised machine learning; the "supervision" refers to the fact that values for the thing being predicted (the target) are known a priori for a training/test data set and thus the accuracy of the model can be evaluated with respect to these known values. Prediction models use a combination of attributes for a case (the predictor variables) to predict the value of another attribute (the target).

Prediction models can produce several different kinds of results useful to learning analytics. First, they can be used to forecast an attribute for a case (e.g. an assessment score or at-risk status for a student) when it is not known, either because it was not collected or has not yet occurred. A common application of this is early-alert systems developed by universities to identify students at risk for poor performance or dropping out (Arnold 2010). For example, Jayaprakash et al. (2014) developed a classifier that predicted whether students were likely to earn a grade of C or higher in a course ("successful completion") or not ("unsuccessful"). Their model was built based on a combination of attributes including demographics and academic records (archival data), prior scores (evaluated artifact data) and LMS usage (activity data). With a predictive goal in mind, Jayaprakash et al. (2014) were interested in developing an accurate model so that they could apply it to students at the start of the course to forecast who was likely to be unsuccessful. When the predicted value is correctness on future learning assessments the result is often used to drive adaptation in systems such as intelligent tutors (see Corbett and Anderson 1994 for an expanded explanation of knowledge tracing). A special case of forecasting that is particularly useful in learning analytics is the combination of prediction models with natural language processing techniques (see description below) to perform automated or semi-automated content analysis of artifact data (Cui et al. 2017; Rosé et al. 2008). This can be used to provide feedback to students or instructors on the work performed.

A second kind of use of prediction models is explanatory. In this case the focus is not on forecasting values for new students but to better understand relationships between variables (though unless factors were manipulated experimentally, claims of causality should be avoided). For example, Svihla et al. (2015) used six different log-file metrics indexing the different ways

students (the cases) revisited content in an online inquiry-learning tool (activity data predictors) to predict their score on a delayed cumulative project assessment (evaluated artifact data target). Their results showed that distributed visitation of a dynamic visualization was predictive of students' understanding of the content several weeks after the unit had been completed. Svihla et al.'s (2015) explanatory use of their model allowed them to make claims about the relationship between distributed revisiting and maintenance of understanding over time.

When prediction targets continuous variables (e.g. the delayed assessment score in Svihla et al. 2015), models such as linear regression, support vector machines, and regression trees are commonly used. For categorical (including binary) outcome variables, classification models (aka classifiers) are built. Common classification methods include decision trees, logistic regression, naïve Bayes and support vector machines. The quality of prediction models can be evaluated in various ways such as calculating accuracy, precision-recall values, AUC, or other metrics (see Zheng 2015); these metrics should be reported for cross-validation and external test-sets, not the same training set on which the model was developed. Generalizability can be assessed using similar metrics on external test-sets from different learning contexts (e.g. different populations, different years, different subject matter, different pedagogy). There is an inherent tradeoff in building models: sensitivity to specific features of a learning context comes at the cost of broad applicability to multiple situations while models built to be used across a wide range of contexts will be less sensitive to the data available in any particular one (Gašević et al. 2016).

Structure Discovery (Unsupervised) Approaches

Structure discovery is another common analytic approach that offers different ways to find patterns of similarity or relationship among cases (e.g. students, messages, essays, and curriculum) or variables (attributes of the cases). Unlike prediction, there is no predefined target to model or evaluate success against (for this reason, structure discovery methods are a form of unsupervised machine learning). Structure discovery methods such as correlation mining, association rule mining and factor analysis are useful to identify regularities in *variables* (e.g. students who re-watch online videos more tend to ask more questions in the discussion forum). Structure discovery methods such as clustering, social network analysis, and topic modeling are generally used to identify commonalities and differences

between *cases* (e.g. this set of resources are used by students early, but not late, in a course; this set of students tend to access many resources but do poorly on quizzes).

Correlation and association rule mining are similar to prediction in that the underlying algorithms identify recurring relationships between variables; however, relationships may be found between *any* combinations of variables. Correlation mining focuses on linear relationships between continuous variables (e.g. the more time a student spends on online practice questions the higher their grade on the actual test) while association rule mining is typically used to generate if-then rules about the co-occurrence of categorical variables (e.g. if a student takes both biology and chemistry they are likely to also take biochemistry). Given the large number of possible variables and relationships that may be identified due to chance, it is important to carefully control for false discovery (see Hero and Rajaratnam 2016) and to critically evaluate results with respect to both empirical standards (e.g. see discussion of measures of support, confidence, and interestingness by Merceron and Yacef 2008) and theoretical soundness (Wise and Shaffer 2015).

Factor analysis is a technique that finds groups of continuous variables whose values (for a given population) consistently align with each other and thus can be combined as a representation of some latent factor. This can both provide insight into the underlying structure of constructs that the variables index and also be used for dimensionality reduction. Dimensionality reduction (which can also be achieved using principal component analysis) is important to avoid over-fit and uninterpretable models. For example, Ahn (2013) used factor analysis to reduce 12 variables of Facebook usage data collected from university students (e.g. wall posts made, links shared) into four latent factors representing different classes of Facebook activity: messaging, information sharing, friending, and affiliating. The factors were then input into a regression model to predict the students' new media literacy skills.

Clustering, social network analysis, and topic modeling differ from the above methods in that the focus is generally on regularities in *cases* rather than *variables*. Clustering is commonly used to identify cases (often students, but at other times resources, courses, etc.) who consistently have similar values to each other across multiple variables, and thus can be thought of as being of the same "type." For example, Wise et al. (2013) performed a cluster analysis on log-file data indexing how students "listened" and "spoke" in online discussions to identify three underlying

groups: *Superficial Listeners, Intermittent Talkers, Concentrated Listeners, Integrated Talkers*; and *Broad Listeners, Reflective Talkers*. Importantly, as labeling clusters is a task of human interpretation, it can be useful to look closely at the data: Wise et al. performed targeted case studies on a representative member of each cluster that contributed important insight into cluster labels beyond that available from the aggregate variable values.

Topic modeling is a form of text-mining (other text-mining techniques are discussed below) that is used to represent the underlying structure across a corpus of documents (which could be student essays, social media messages, etc.) by identifying collections of topics (sets of co-occurring words) and the extent to which they are present in each document. A common application of topic modeling is to make sense of the large volume of messages that are contributed to online course discussions, MOOC forums, and social media. For example, Joksimović et al. (2015) examined what MOOC participants talked about in various social media venues and Vytasek et al. (2017) explored how topic models could provide classroom instructors with a useful big picture view of large and diverse online discussions.

Finally, social network analysis (SNA) is a technique that looks for regularities not in the attributes of the cases themselves but in the relationships between them. This can provide insights about individuals (e.g. measures of their centrality), the entire network (e.g. its density), or some subset of it (e.g. the presence of cliques). A key decision in SNA is how to define the nodes and the linkages between them. A common approach is to take nodes as students and to create linkages based on their interaction (e.g. Wise et al. 2017); however linkages based on similarities (e.g. Hecking et al. 2016) and bi-partite networks which include both individuals and objects they interact with (e.g. resources accessed) are also possible (Poquet and Dawson 2016). SNA has been useful for understanding general characteristics of social interactions and relationships (e.g. Dowell et al. 2015), exploring their relationship with learning outcomes (Dawson 2010; Rabbany et al. 2011), and identifying small groups within larger networks worthy of more detailed attention (Wise et al. 2017). While standard SNA approaches produce descriptions of connections in aggregate, more sophisticated techniques, such as ERGM (exponential random graph models) and dSNA (dynamic social network analysis), allow for inference testing and the study of network evolution over time respectively (e.g. Joksimović et al. 2016; Zhu et al. 2016).

Temporal Approaches

Similar to structure discovery, temporal approaches to data analysis look to discover previously undefined patterns in the data, but in this case, the patterns relate to the sequence and flow of events over time (Knight et al. 2015). Temporal approaches are a particularly important set of methods for learning analytics as they leverage traces of activity to address the field's fundamental concern with studying and understanding learning as a process (Suthers et al. 2015); however, they have been underutilized in the field thus far (Chen et al. 2016). Temporal approaches in learning analytics can be roughly divided as those which deal with time explicitly through examination of flow and fluctuation in features of the learning process over time (e.g. survival analysis, Yang et al. 2013) and those which deal with time implicitly through examination of sequences of events in the learning process (e.g. sequential pattern mining, Poon et al. 2017; lag-sequence analysis, Chen and Resendes 2014; (hidden) Markov modeling, Jeong et al. 2010). Temporal analyses can also be used to divide a learning process into different phases of activity (e.g. via sequential discourse analysis, Wise and Chiu 2011).

Natural Language Processing Approaches

Natural language processing (NLP) approaches in learning analytics use computational techniques to assess various linguistic features of texts (McNamara et al. 2017). It is an exciting area in active development that allows for direct inspection of a wide variety of textual data sources that includes: standalone student artifacts such as student essays or short answers; traces of dialogue among students and instructors; and collections of instructional resources. Roughly these differences align with the distinct concerns and applications of writing analytics (Shum et al. 2016), discourse analytics (Knight and Littleton 2015; Rosé 2017), and content analytics (Kovanović et al. 2017). NLP approaches are frequently used in combination with other analysis approaches already discussed including prediction (e.g. Mu et al. 2012), structure discovery methods (e.g. Dowell et al. 2015), and temporal analysis (e.g. Suthers and Desiato 2012). NLP approaches useful for learning analytics extract linguistic features about words and their assemblages. Analyses performed on words may assess basic presence (e.g. frequency of particular n-grams, parts of speech, or LIWC (linguistic inquiry word count) categories) or delve more deeply into their underlying meaning (e.g. via LSA (latent semantic

analysis, different from the temporal technique of lag-sequence analysis, see Landauer et al. 2011 for a wide-ranging overview of theory, methods, and applications of the technique). Other techniques examine the use of particular parts of speech (such as verbs), syntactic structure, and the cohesion across a text (McNamara et al. 2017). When considering relations between texts, measures of semantic similarity (often calculated using LSA) are particularly useful.

Visual Approaches

Much of the work in learning analytics using visualization is not actual visual analysis per se, but the visualization of the outputs of other analyses for communication with various stakeholders. Learning analytics dashboards, for example, often employ graphical representations of analytic results designed to evoke particular responsive actions (Klerkx et al. 2017). In contrast, true visual analytics exploit visualization techniques and human perceptual abilities as part of the analytic process itself (Shneiderman 2014). This is done by visually representing data in ways that support human recognition of patterns and aberrations, often via an interactive interface that allows for manipulation and permutation of the visualizations (Ritsos and Roberts 2014). While some limited examples of static visual learning analytics exist, for example, human inspection of heat maps (Pecaric et al. 2017; Serrano-Laguna et al. 2014) and moment-by-moment learning curves (Baker et al. 2013), there is great room for further development of interactive visual analytics.

WHAT KINDS OF PEDAGOGICAL USES CAN LEARNING ANALYTICS SERVE AND HOW DO THEY SUPPORT LEARNING?

Tailoring Educational Experiences

An initial class of pedagogical use of learning analytics is for tailoring educational experiences to better meet the specific needs of one or more students. In this model of use, the analytics are used to create some sort of a (static or dynamic) profile of learners with the educational experience provided for them differing in response to this. This has been referred to at times under the label of "personalized learning," but such terminology is overly narrow because it assumes that the target for the tailoring is an individual, when it

could also be a group of learners, and it implies that the activity is done for learners, when in many cases the learner must actively take up a recommendation that is provided. Tailoring of educational experiences for individuals or groups can occur through both adaptive (computer driven) and adaptable (human driven) changes to a system that makes it more appropriate for the learning of those involved. Common analytic techniques that drive tailoring include prediction models, clustering to identify groups of students with similar profiles, and association rule mining.

A high-profile class of tailoring applications are adaptive systems in which the resources, questions, or other learning materials provided to students are determined based on an underlying analytics model. One of the earliest set of adaptive learning tools were intelligent tutoring systems which construct a model of both the domain and learner in order to provide immediate customized feedback to students (Nwana 1990). Recently, a large number of companies, including textbook publishers, have also moved into the adaptive learning space. Adaptive learning tools may be designed around specific pre-determined content or exist as platforms for instructors or institutions to input their own content. They do not need to only involve static content and problems to be solved but can incorporate (or be embedded in) games and simulations as well. It is important to distinguish between tools which make adaptations directly based on learner activity versus those which use more sophisticated approximations of learner's cognitive skills.

Different from adaptive tools in which the tailoring is fully enacted by a system and may not be apparent to the learner, recommendation engines are systems that provide tailored suggestions (of courses or learning resources) to students. Two well-known course recommendation systems are Stanford's CourseRank system (Parameswaran et al. 2011) and Degree Compass (Denley 2013), originally developed at Austin Peay State University, and recently acquired by Desire to Learn. Systems for recommending useful learning resources (or useful sequences of resources) are generally developed in the context of particular learning tools (see Drachsler et al. 2015 for a review of 82 different recommender systems). Finally, early-alert systems use predictive models to identify students at risk of failing a course or dropping out of university. Studies have shown that simply making students aware that they are at risk can have an impact on their academic standing (Arnold 2010); though providing students with actionable strategies is much preferred. In a recent review of early alert systems, Sclater (2017) points out that more evidence about when and why such systems are effective is needed.

Informing Student Self-Direction

Different from tailoring the materials that are given to students, another pedagogical use of analytics is to support students in conscious attention to and improvement of their own learning processes. This model of use draws heavily on psychological theories of experiential learning Kolb (1984), self-reflection Schön (1983), and self-regulated learning (Winne 2017) in which learning analytics provide feedback that students can use to adjust or experiment with changes in their learning behaviors. A wide variety of tools exist to provide students with feedback on their academic status and study habits (e.g. E2Coach at the University of Michigan, Huberth et al. 2015; Check My Activity at the University of Maryland, Baltimore County, Fritz 2011), essays (e.g. OpenEssayist, Whitelock et al. 2015), and discussion forum participation (e.g. E-Listening Analytics Suite, see Wise et al. 2014). Such feedback can be provided in a variety of forms which may be embedded directly into the learning environment or extracted from it (Wise et al. 2014), for example via email messages or real-time dashboards that can be accessed at any time. The challenges for students in interpreting and using such information are great, however, and the most powerful systems provide not only the analytic feedback but also some sort of structure or support for making sense of and acting on the information provided (Wise and Vytasek 2017).

Supporting Instructor Planning and Orchestration

For instructors, pedagogical uses of learning analytics can be used to support refinement of both the overarching learning design and the decisions they make to orchestrate classroom activity within it. From the perspective of learning analytics and learning design, analytics offer a way to empirically verify (or refute) assumptions about the classroom (be it physical or virtual). The process for doing so requires instructors to document their pedagogical intentions (the design), describe activity patterns that indicate fulfillment of these intentions (targets), and then use the analytics to evaluate the degree to which the patterns occurred (Lockyer et al. 2013). Systems that provide feedback to instructors about their learning design are typically presented via teacher dashboards (see review in Verbert et al. 2013). Examples of this cycle in action are given in Brooks et al. (2014) who look at instructors' modification of their discussion forum practices based on SNA diagrams and Roll et al. (2016) who examined how course designers of a MOOC planned for revisions based on the analytic feedback provided to them.

In addition to supporting critical attention to the activity outcomes of course design, learning analytics can also assist instructors in orchestrating their class. Analytics can provide information that helps instructors identify struggling students (and ideally know how or why they are struggling), recognize groups that are collaborating more or less productively (van Leeuwen 2015) and pinpoint prevalent points of difficulty for a class (Ali et al. 2012). Ideally, the analytics are used not only to identify "problem" situations, but as part of a regular feedback mechanism of tuning and adjustment (Wise et al. 2016). In addition, another way in which analytics can help inform orchestration is by identifying types of students (or student behaviors) that occur repeatedly. Such information can be used by instructors to more easily identify and address common patterns or can be fed back to create accommodations or greater support structures in the learning design.

What Are Key Issues for the Future of Learning Analytics?

The optimistic vision of learning analytics in higher education described above is far from inevitable. Others have countered such images of a rosy future with the potential for (intentional or unintentional) misuse of analytics leading to a dystopian future of oversight and control (Rummel et al. 2016). There is also the concern that, like so many promising educational technologies, learning analytics will not live up to the hype and fail to make a substantial impact (Cuban 2001; Ertmer 1999). In a comprehensive review of the empirical research on learning analytics use to date, Ferguson et al. (2016) emphasize that expectations are yet to be realized and evidence of successful and impactful implementation is still scarce. Key systemic and societal issues that will determine the fate of learning analytics include deliberate consideration of the policy needs required to govern the ethical dimensions of analytics use and proactive planning for the required infrastructure.

In terms of infrastructure, universities need to consider now what kinds of data streams and stores they will want to be able to access in the next 5–10 years. Data infrastructure planning includes attention not only to what data will be collected, but how (and where) the data will be stored, what metadata will be used to index the data, and how (and by whom) the data will be queriable. Critically, system interoperability and the integra-

tion of multiple data streams (e.g. from learning management systems, student information systems, external tools, and human input) are core technical challenges to be addressed. Going further, universities will need to think about the analytic literacy of those who will want to ask questions of the data and what tools, people, and processes are needed to support these activities for both research and day-to-day teaching and learning purposes.

In terms of policy, institutions need to put in place clear guidelines for practices around data and analytics use (Prinsloo and Slade 2013). Specifically, policies are needed to: allocate responsibility for data assets and analytic processes; establish procedures for giving consent/opting-out of data use, providing students with access to their own data, and protecting student privacy; set-up systems to check that inferences made based on data and algorithms are valid and transparent; and maximize positive analytics implementations while minimizing any potential adverse impacts (Sclater 2014). Importantly, as students are critical stakeholders (and the primary intended beneficiaries) of learning analytics, they should be consulted as such policies are developed (Slade and Prinsloo 2014). Other overarching important ethical issues to keep in mind include broad attention to algorithmic accountability (ACM US Public Policy Council 2017), maintaining institutional value on those things that are not well-indexed by analytics, and remaining vigilant for unintended systemic consequences.

CONCLUSION

Learning Analytics is the development and application of data science methods to the distinct characteristics, needs, and concerns of educational contexts and the data streams they generate. The goal is to better understand and support learning processes and outcomes through both short-cycle improvements to educational practice and long-cycle improvements to the underlying knowledge base. This chapter has overviewed the distinct character of the data used in learning analytics, the kinds of analyses applied, and the pedagogical uses to which the analytics can be put; together these characteristics highlight why learning analytics is seen as an especially promising technology to improve teaching and learning. To make this vision a reality, universities will need to be proactive in building up the requisite technical and policy infrastructure.

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