Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics

An Issue Brief

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Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics: An Issue Brief

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Executive Summary

In data mining and data analytics, tools and techniques once confined to research laboratories are being adopted by forward-looking industries to generate business intelligence for improving decision making. Higher education institutions are beginning to use analytics for improving the services they provide and for increasing student grades and retention. The U.S. Department of Education's National Education Technology Plan, as one part of its model for 21st-century learning powered by technology, envisions ways of using data from online learning systems to improve instruction.

With analytics and data mining experiments in education starting to proliferate, sorting out fact from fiction and identifying research possibilities and practical applications are not easy. This issue brief is intended to help policymakers and administrators understand how analytics and data mining have been—and can be—applied for educational improvement.

At present, educational data mining tends to focus on *developing new tools* for discovering patterns in data. These patterns are generally about the microconcepts involved in learning: one-digit multiplication, subtraction with carries, and so on. Learning analytics—at least as it is currently contrasted with data mining—focuses on *applying tools* and techniques at larger scales, such as in courses and at schools and postsecondary institutions. But both disciplines work with patterns and prediction: If we can discern the pattern in the data and make sense of what is happening, we can predict what should come next and take the appropriate action.

Educational data mining and learning analytics are used to research and build models in several areas that can influence online learning systems. One area is user modeling, which encompasses what a learner knows, what a learner's behavior and motivation are, what the user experience is like, and how satisfied users are with online learning. At the simplest level, analytics can detect when a student in an online course is going astray and nudge him or her on to a course correction. At the most complex, they hold promise of detecting boredom from patterns of key clicks and redirecting the student's attention. Because these data are gathered in real time, there is a real possibility of continuous improvement via multiple feedback loops that operate at different time scales—immediate to the student for the next problem, daily to the teacher for the next day's teaching, monthly to the principal for judging progress, and annually to the district and state administrators for overall school improvement.

The same kinds of data that inform user or learner models can be used to profile users. Profiling as used here means grouping similar users into categories using salient characteristics. These categories then can be used to offer experiences to groups of users or to make recommendations to the users and adaptations to how a system performs.

User modeling and profiling are suggestive of real-time adaptations. In contrast, some applications of data mining and analytics are for more experimental purposes. Domain modeling is largely experimental with the goal of understanding how to present a topic and at what level of detail. The study of learning components and instructional principles also uses experimentation to understand what is effective at promoting learning.

These examples suggest that the actions from data mining and analytics are always automatic, but that is less often the case. Visual data analytics closely involve humans to help make sense of data, from initial pattern detection and model building to sophisticated data dashboards that present data in a way that humans can act upon. K–12 schools and school districts are starting to adopt such institution-level analyses for detecting areas for instructional improvement, setting policies, and measuring results. Making visible students' learning and assessment activities opens up the possibility for students to develop skills in monitoring their own learning and to see directly how their effort improves their success. Teachers gain views into students' performance that help them adapt their teaching or initiate tutoring, tailored assignments, and the like.

Robust applications of educational data mining and learning analytics techniques come with costs and challenges. Information technology (IT) departments will understand the costs associated with collecting and storing logged data, while algorithm developers will recognize the computational costs these techniques still require. Another technical challenge is that educational data systems are not interoperable, so bringing together administrative data and classroom-level data remains a challenge. Yet combining these data can give algorithms better predictive power. Combining data about student performance—online tracking, standardized tests, teacher-generated tests—to form one simplified picture of what a student knows can be difficult and must meet acceptable standards for validity. It also requires careful attention to student and teacher privacy and the ethical obligations associated with knowing and acting on student data.

Educational data mining and learning analytics have the potential to make visible data that have heretofore gone unseen, unnoticed, and therefore unactionable. To help further the fields and gain value from their practical applications, the recommendations are that educators and administrators:

- Develop a culture of using data for making instructional decisions.
- Involve IT departments in planning for data collection and use.
- Be smart data consumers who ask critical questions about commercial offerings and create demand for the most useful features and uses.
- Start with focused areas where data will help, show success, and then expand to new areas.
- Communicate with students and parents about where data come from and how the data are used.
- Help align state policies with technical requirements for online learning systems.

Researchers and software developers are encouraged to:

- Conduct research on usability and effectiveness of data displays.
- Help instructors be more effective in the classroom with more real-time and data-based decision support tools, including recommendation services.
- Continue to research methods for using identified student information where it will help most, anonymizing data when required, and understanding how to align data across different systems.
- Understand how to repurpose predictive models developed in one context to another.

A final recommendation is to create and continue strong collaboration across research, commercial, and educational sectors. Commercial companies operate on fast development cycles and can produce data useful for research. Districts and schools want properly vetted learning environments. Effective partnerships can help these organizations codesign the best tools.

Introduction

As more of our commerce, entertainment, communication, and learning are occurring over the Web, the amount of data online activities generate is skyrocketing. Commercial entities have led the way in developing techniques for harvesting insights from this mass of data for use in identifying likely consumers of their products, in refining their products to better fit consumer needs, and in tailoring their marketing and user experiences to the preferences of the individual. More recently, researchers and developers of online learning systems have begun to explore analogous techniques for gaining insights from learners' activities online.

This issue brief describes data analytics and data mining in the commercial world and how similar techniques (learner analytics and educational data mining) are starting to be applied in education. The brief examines the challenges being encountered and the potential of such efforts for improving student outcomes and the productivity of K–12 education systems. The goal is to help education policymakers and administrators understand how data mining and analytics work and how they can be applied within online learning systems to support education-related decision making.

Specifically, this issue brief addresses the following questions:

- What is educational data mining, and how is it applied? What kinds of questions can it answer, and what kinds of data are needed to answer these questions?
- How does learning analytics differ from data mining? Does it answer different questions and use different data?
- What are the broad application areas for which educational data mining and learning analytics are used?
- What are the benefits of educational data mining and learning analytics, and what factors have enabled these new approaches to be adopted?

Online Learning Systems and Adaptive Learning Environments

Online learning systems refer to online courses or to learning software or interactive learning environments that use intelligent tutoring systems, virtual labs, or simulations. Online courses may be offered through a learning or course management system (such as Blackboard, Moodle, or Sakai) or a learning platform (such as Knewton and DreamBox Learning). Examples of learning software and interactive learning environments are those from Kaplan, Khan Academy, and Agile Mind. When online learning systems use data to change in response to student performance, they become *adaptive* learning environments.

- What are the challenges and barriers to successful application of educational data mining and learning analytics?
- What new practices have to be adopted in order to successfully employ educational data mining and learning analytics for improving teaching and learning?

Learning management systems (LMS)

LMS are suites of software tools that provide comprehensive course-delivery functions—administration, documentation, content assembly and delivery, tracking and reporting of progress, user management and self-services, etc. LMS are Web based and are considered a platform on which to build and deliver modules and courses. Open-source examples include Moodle, Sakai, and ILIAS.

Sources of information for this brief consisted of:

- A review of selected publications and fugitive or gray literature (Web pages and unpublished documents) on educational data mining and learning analytics;
- Interviews of 15 data mining/analytics experts from learning software and learning management system companies and from companies offering other kinds of Web-based services; and
- Deliberations of a technical working group of eight academic experts in data mining and learning analytics.

This issue brief was inspired by the vision of personalized learning and embedded assessment in the U.S. Department of Education's National Education Technology Plan (NETP) (U.S. Department of Education 2010a). As described in the plan, increasing use of online learning offers opportunities to integrate assessment and learning so that information needed to improve future instruction can be gathered in nearly real time:

> When students are learning online, there are multiple opportunities to exploit the power of technology for formative assessment. The same technology that supports learning activities gathers data in the course of learning that can be used for assessment. … An online system can collect much more and much more detailed information about how students are learning than manual methods. As students work, the system can capture their inputs and collect evidence of their problem-solving sequences, knowledge, and strategy use, as reflected by the information each student selects or inputs, the number of attempts the student makes, the number of hints and feedback given, and the time allocation across parts of the problem. (U.S. Department of Education 2010a, p. 30)

While students can clearly benefit from this detailed learning data, the NETP also describes the potential value for the broader education community through the concept of an interconnected feedback system:

> The goal of creating an interconnected feedback system would be to ensure that key decisions about learning are informed by data and that data are aggregated and made accessible at all levels of the education system for continuous improvement.
> (U.S. Department of Education 2010a, p. 35)

The interconnected feedback systems envisioned by the NETP rely on online learning systems collecting, aggregating, and analyzing large amounts of data and making the data available to many stakeholders. These online or adaptive learning systems will be able to exploit detailed learner activity data not only to recommend what the next learning activity for a particular student should be, but also to predict how that student will perform with future learning content, including high-stakes examinations. Data-rich systems will be able to provide informative and actionable feedback to the learner, to the instructor, and to administrators. These learning systems also will provide software developers with feedback that is tremendously helpful in rapidly refining and improving their products. Finally, researchers will be able to use data from experimentation with adaptive learning systems to test and improve theories of teaching and learning.

In the remainder of this report, we:

1. Present scenarios that motivate research, development, and application efforts to collect and use data for personalization and adaptation.

2. Define the research base of educational data mining and learning analytics and describe the research goals researchers pursue and the questions they seek to answer about learning at all levels of the educational system.

3. Present an abstracted adaptive learning system to show how data are obtained and used, what major components are involved, and how various stakeholders use such systems.

4. Examine the major application areas for the tools and techniques in data mining and analytics, encompassing user and domain modeling.

5. Discuss the implementation and technical challenges and give recommendations for overcoming them.

Personalized Learning Scenarios

Online consumer experiences provide strong evidence that computer scientists are developing methods to exploit user activity data and adapt accordingly. Consider the experience a consumer has when using Netflix to choose a movie. Members can browse Netflix offerings by category (e.g., Comedy) or search by a specific actor, director, or title. On choosing a movie, the member can see a brief description of it and compare its average rating by Netflix users with that of other films in the same category. After watching a film, the member is asked to provide a simple rating of how much he or she enjoyed it. The next time the member returns to Netflix, his or her browsing, watching, and rating activity data are used as a basis for recommending more films. The more a person uses Netflix, the more Netflix learns about his or her preferences and the more accurate the predicted enjoyment. But that is not all the data that are used. Because many other members are browsing, watching, and rating the same movies, the Netflix recommendation algorithm is able to group members based on their activity data. Once members are matched, activities by some group members can be used to recommend movies to other group members. Such customization is not unique to Netflix, of course. Companies such as Amazon, Overstock, and Pandora keep track of users' online activities and provide personalized recommendations in a similar way.

Education is getting very close to a time when personalization will become commonplace in learning. Imagine an introductory biology course. The instructor is responsible for supporting student learning, but her role has changed to one of designing, orchestrating, and supporting learning experiences rather than "telling." Working within whatever parameters are set by the institution within which the course is offered, the instructor elaborates and communicates the course's learning objectives and identifies resources and experiences through which those learning goals can be attained. Rather than requiring all students to listen to the same lectures and complete the same homework in the same sequence and at the same pace, the instructor points students toward a rich set of resources, some of which are online, and some of which are provided within classrooms and laboratories. Thus, students learn the required material by building and following their own learning maps.

Suppose a student has reached a place where the next unit is population genetics. In an online learning system, the student's dashboard shows a set of 20 different population genetics learning resources, including lectures by a master teacher, sophisticated video productions emphasizing visual images related to the genetics concepts, interactive population genetics simulation games, an online collaborative group project, and combinations of text and practice exercises. Each resource comes with a rating of how much of the population genetics portion of the learning map it covers, the size and range of learning gains attained by students who have used it in the past, and student ratings of the resource for ease and enjoyment of use. These ratings are derived from past activities of all students, such as "like" indicators, assessment results, and correlations between student activity and assessment results. The student chooses a resource to work with, and his or her interactions with it are used to continuously update the system's model of how much he or she knows about population genetics. After the student has worked with the resource, the dashboard shows updated ratings for each population genetics learning resource; these ratings indicate how much of the unit content the student has not yet mastered is covered by each resource. At any time, the student may choose to take an online practice assessment for the population genetics unit. Student responses to this assessment give the system—and the student—an even better idea of what he or she has already mastered, how helpful different resources have been in achieving that mastery, and what still needs to be addressed. The teacher and the institution have access to the online learning data, which they can use to certify the student's accomplishments.

Capturing the Moment of Learning by Tracking Game Players' Behaviors

The Wheeling Jesuit University's Cyber-enabled Teaching and Learning through Game-based, Metaphor-Enhanced Learning Objects (CyGaMEs) project was successful in measuring learning using assessments embedded in games. CyGaMEs quantifies game play activity to track timed progress toward the game's goal and uses this progress as a measure of player learning. CyGaMEs also captures a self-report on the game player's engagement or flow, i.e., feelings of skill and challenge, as these feelings vary throughout the game play. In addition to timed progress and self-report of engagement, CyGaMEs captures behaviors the player uses during play. Reese et al. (in press) showed that this behavior data exposed a prototypical "moment of learning" that was confirmed by the timed progress report. Research using the flow data to determine how user experience interacts with learning is ongoing.

This scenario shows the possibility of leveraging data for improving student performance; another example of data use for "sensing" student learning and engagement is described in the sidebar on the moment of learning and illustrates how using detailed behavior data can pinpoint cognitive events.

The increased ability to use data in these ways is due in part to developments in several fields of computer science and statistics. To support the understanding of what kinds of analyses are possible, the next section defines educational data mining, learning analytics, and visual data analytics, and describes the techniques they use to answer questions relevant to teaching and learning.

Data Mining and Analytics: The Research Base

Using data for making decisions is not new; companies use complex computations on customer data for *business intelligence* or *analytics*. Business intelligence techniques can discern historical patterns and trends from data and can create models that predict future trends and patterns. Analytics, broadly defined, comprises applied techniques from computer science, mathematics, and statistics for extracting *usable information* from very large datasets.

An early example of using data to explore online behavior is *Web analytics* using tools that log and report Web page visits, countries or domains where the visit was from, and the links that were clicked through. Web analytics are still used to understand and improve how people use the Web, but companies now have developed more sophisticated techniques to track more complex user interactions with their websites. Examples of such tracking include changes in buying habits in response to disruptive technology (e.g., e-readers), most-highlighted passages in e-books, browsing history for predicting likely Web pages of interest, and changes in game players' habits over time. Across the Web, social actions, such as bookmarking to social sites, posting to Twitter or blogs, and commenting on stories can be tracked and analyzed.

Unstructured Data and Machine Learning

Data are often put into a *structured format,* as in a relational database. Structured data are easy for computers to manipulate. In contrast, ***unstructured data*** have a semantic structure that is difficult to discern computationally (as in text or image analysis) without human aid. As a simple example, an email message has some structured parts—To, From, and Date Sent— and some unstructured parts—the Subject and the Body.

Machine learning approaches to data mining deal with unstructured data, finding patterns and regularities in the data or extracting semantically meaningful information.

Analyzing these new logged events requires new techniques to work with unstructured text and image data, data from multiple sources, and vast amounts of data ("big data"). Big data does not have a fixed size; any number assigned to define it would change as computing technology advances to handle more data. So "big data" is defined relative to current or "typical" capabilities. For example, Manyika et al. (2011) defines big data as "Datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze." Big data captured from users' online behaviors enables algorithms to infer the users' knowledge, intentions, and interests and to create models for predicting future behavior and interest.

Research on machine learning has yielded techniques for knowledge discovery (see sidebar for a definition) or data mining that discover novel and potentially useful information in large amounts of unstructured data. These techniques find patterns in data and then build *predictive models* that probabilistically predict an outcome. Applications of these models can then be used in computing analytics over large datasets.

Knowledge Discovery in Databases (KDD)

KDD is an interdisciplinary area focusing on methodologies for extracting useful knowledge from data. Extracting knowledge from data draws on research in statistics, databases, pattern recognition, machine learning, data visualization, optimization, and high-performance computing to deliver advanced business intelligence and Web discovery solutions.

http://researcher.ibm.com/view_pic.php?id=144

Two areas that are specific to the use of big data in education are *educational data mining* and *learning analytics.* Although there is no hard and fast distinction between these two fields, they have had somewhat different research histories and are developing as distinct research areas. Generally, *educational data mining* looks for new patterns in data and develops new algorithms and/or new models, while *learning analytics* applies known predictive models in instructional systems. Discussion on each follows below.

Educational Data Mining

Educational data mining is emerging as a research area with a suite of computational and psychological methods and research approaches for understanding how students learn. New computer-supported interactive learning methods and tools—intelligent tutoring systems, simulations, games—have opened up opportunities to collect and analyze student data, to discover patterns and trends in those data, and to make new discoveries and test hypotheses about how students learn. Data collected from online learning systems can be aggregated over large numbers of students and can contain many variables that data mining algorithms can explore for model building.

> **Educational Data Mining (EDM) and Learning Analytics**
>
> EDM develops methods and applies techniques from statistics, machine learning, and data mining to analyze data collected during teaching and learning. EDM tests learning theories and informs educational practice. **Learning analytics** applies techniques from information science, sociology, psychology, statistics, machine learning, and data mining to analyze data collected during education administration and services, teaching, and learning. Learning analytics creates applications that directly influence educational practice.

Just as with early efforts to understand online behaviors, early efforts at educational data mining involved mining website log data (Baker and Yacef 2009), but now more integrated, instrumented, and sophisticated online learning systems provide more kinds of data. Educational data mining generally emphasizes reducing learning into small components that can be analyzed and then influenced by software that adapts to the student (Siemens and Baker 2012). Student learning data collected by online learning systems are being explored to develop predictive models by applying educational data mining methods that classify data or find relationships. These models play a key role in building adaptive learning systems in which adaptations or interventions based on the model's predictions can be used to change what students experience next or even to recommend outside academic services to support their learning.

An important and unique feature of educational data is that they are hierarchical. Data at the keystroke level, the answer level, the session level, the student level, the classroom level, the teacher level, and the school level are nested inside one another (Baker 2011; Romero and Ventura 2010). Other important features are time, sequence, and context. Time is important to capture data, such as length of practice sessions or time to learn. Sequence represents how concepts build on one another and how practice and tutoring should be ordered. Context is important for explaining results and knowing where a model may or may not work. Methods for hierarchical data mining and longitudinal data modeling have been important developments in mining educational data.

Educational data mining researchers (e.g., Baker 2011; Baker and Yacef 2009) view the following as the goals for their research:

1. Predicting students' future learning behavior by creating student models that incorporate such detailed information as students' knowledge, motivation, metacognition, and attitudes;
2. Discovering or improving domain models that characterize the content to be learned and optimal instructional sequences;
3. Studying the effects of different kinds of pedagogical support that can be provided by learning software; and
4. Advancing scientific knowledge about learning and learners through building computational models that incorporate models of the student, the domain, and the software's pedagogy.

Educational Data Mining and Educational Data

"Educational data mining…exploits statistical, machine-learning, and data-mining…algorithms over...different types of educational data. … EDM is concerned with developing methods to explore the unique types of data in educational settings and, using these methods, to better understand students and the settings in which they learn. ... EDM seeks to...develop computational approaches that combine data and theory to transform practice…."

Romero and Ventura 2010, p.601

"Whether educational data is taken from students' use of interactive learning environments, computer-supported collaborative learning, or administrative data from schools and universities, it often has multiple levels of meaningful hierarchy, which often need to be determined by properties in the data itself, rather than in advance. Issues of time, sequence, and context also play important roles in the study of educational data."

http://www.educationaldatamining.org

To accomplish these four goals, educational data mining research uses the five categories of technical methods (Baker 2011) described below.

1. Prediction entails developing a model that can infer a single aspect of the data (predicted variable) from some combination of other aspects of the data (predictor variables). Examples of using prediction include detecting such student behaviors as when they are gaming the system, engaging in off-task behavior, or failing to answer a question correctly despite having a skill. Predictive models have been used for understanding what behaviors in an online learning environment—participation in discussion forums, taking practice tests and the like—will predict which students might fail a class. Prediction shows promise in developing domain models, such as connecting procedures or facts with the specific sequence and amount of practice items that best teach them, and forecasting and understanding student educational outcomes, such as success on posttests after tutoring (Baker, Gowda, and Corbett 2011).

2. Clustering refers to finding data points that naturally group together and can be used to split a full dataset into categories. Examples of clustering applications are grouping students based on their learning difficulties and interaction patterns, such as how and how much they use tools in a learning management system (Amershi and Conati 2009), and grouping users for purposes of recommending actions and resources to similar users. Data as varied as online learning resources, student cognitive interviews, and postings in discussion forums can be analyzed using techniques for working with unstructured data to extract characteristics of the data and then clustering the results. Clustering can be used in any domain that involves classifying, even to determine how much collaboration users exhibit based on postings in discussion forums (Anaya and Boticario 2009).

3. Relationship mining involves discovering relationships between variables in a dataset and encoding them as rules for later use. For example, relationship mining can identify the relationships among products purchased in online shopping (Romero and Ventura 2010).

- *Association rule mining* can be used for finding student mistakes that co-occur, associating content with user types to build recommendations for content that is likely to be interesting, or for making changes to teaching approaches (e.g., Merceron and Yacef 2010). These techniques can be used to associate student activity, in a learning management system or discussion forums, with student grades or to investigate such questions as why students' use of practice tests decreases over a semester of study.
- *Sequential pattern mining* builds rules that capture the connections between occurrences of sequential events, for example, finding temporal sequences, such as student mistakes followed by help seeking. This could be used to detect events, such as students regressing to making errors in mechanics when they are writing with more complex and critical thinking techniques, and to analyze interactions in online discussion forums.

Key educational applications of relationship mining include discovery of associations between student performance and course sequences and discovering which pedagogical strategies lead to more effective or robust learning. This latter area—called teaching analytics—is of growing importance and is intended to help researchers build automated systems that model how effective teachers operate by mining their use of educational systems.

4. Distillation for human judgment is a technique that involves depicting data in a way that enables a human to quickly identify or classify features of the data. This area of educational data mining improves machine-learning models because humans can identify patterns in, or features of, student learning actions, student behaviors, or data involving collaboration among students. This approach overlaps with visual data analytics (described in the third part of this section).

5. Discovery with models is a technique that involves using a validated model of a phenomenon (developed through prediction, clustering, or manual knowledge engineering) as a component in further analysis. For example, Jeong and Biswas (2008) built models that categorized student activity from basic behavior data: students' interactions with a game-like learning environment that uses learning by teaching. A sample student activity discerned from the data was "map probing." A model of map probing then was used within a second model of learning strategies and helped researchers study how the strategy varied across different experimental states. Discovery with models supports discovery of relationships between student behaviors and student characteristics or contextual variables, analysis of research questions across a wide variety of contexts, and integration of psychometric modeling frameworks into machine-learned models.

Using these techniques, educational data mining researchers can build models to answer such questions as:

- What sequence of topics is most effective for a specific student?
- What student actions are associated with more learning (e.g., higher course grades)?
- What student actions indicate satisfaction, engagement, learning progress, etc.?
- What features of an online learning environment lead to better learning?
- What will predict student success?

Learning Analytics

Learning analytics is becoming defined as an area of research and application and is related to academic analytics, action analytics, and predictive analytics.[1] Learning analytics draws on a broader array of academic disciplines than educational data mining, incorporating concepts and techniques from information science and sociology, in addition to computer science, statistics, psychology, and the learning sciences. Unlike educational data mining, learning analytics generally does not emphasize reducing learning into components but instead seeks to understand entire systems and to support human decision making.

Learning analytics emphasizes measurement and data collection as activities that institutions need to undertake and understand, and focuses on the analysis and reporting of the data. Unlike educational data mining, learning analytics does not generally address the development of new computational methods for data analysis but instead addresses the application of known methods and models to answer important questions that affect student learning and organizational learning systems. *The Horizon Report: 2011 Edition* describes the goal of learning analytics as enabling teachers and schools to tailor educational opportunities to each student's level of need and ability (Johnson et al. 2011). Unlike educational data mining, which emphasizes *system-generated* and *automated* responses to students, learning analytics enables *human tailoring* of responses, such as through adapting instructional content, intervening with at-risk students, and providing feedback.

Defining Learning Analytics

"Learning analytics refers to the interpretation of a wide range of data produced by and gathered on behalf of students in order to assess academic progress, predict future performance, and spot potential issues. Data are collected from explicit student actions, such as completing assignments and taking exams, and from tacit actions, including online social interactions, extracurricular activities, posts on discussion forums, and other activities that are not directly assessed as part of the student's educational progress. Analysis models that process and display the data assist faculty members and school personnel in interpretation. The goal of learning analytics is to enable teachers and schools to tailor educational opportunities to each student's level of need and ability."

"Learning analytics need not simply focus on student performance. It might be used as well to assess curricula, programs, and institutions. It could contribute to existing assessment efforts on a campus, helping provide a deeper analysis, or it might be used to transform pedagogy in a more radical manner. It might also be used by students themselves, creating opportunities for holistic synthesis across both formal and informal learning activities."

Johnson et al. 2011, p. 28

[1] Academic analytics is described in Goldstein (2005). The term "learning analytics" began to be used in 2009. Differences among these terms are not important for purposes of this brief. The interested reader may wish to consult Elias (2011) or Long and Siemens (2011).

Technical methods used in learning analytics are varied and draw from those used in educational data mining. Additionally, learning analytics may employ:

- *Social network analysis* (e.g., analysis of student-to-student and student-to-teacher relationships and interactions to identify disconnected students, influencers, etc.) and
- *Social or "attention" metadata* to determine what a user is engaged with.

Sharing Learning Resource Data

The Learning Registry is being developed to take advantage of metadata and social metadata generated as educators and learners interact with online learning resources. Data published to the Learning Registry can serve as the basis for learning resource analytics to help recommend resources, detect trends in resource usage, and judge user experience.

http://www.learningregistry.org

As with educational data mining, providing a visual representation of analytics is critical to generate actionable analyses; information is often represented as "dashboards" that show data in an easily digestible form.

A key application of learning analytics is monitoring and predicting students' learning performance and spotting potential issues early so that interventions can be provided to identify students at risk of failing a course or program of study (EDUCAUSE 2010; Johnson et al. 2011). Several learning analytics models have been developed to identify student risk level in real time to increase the students' likelihood of success. Examples of such systems include Purdue University's Course Signals system (Arnold 2010) and the Moodog system being used at the course level at the University of California, Santa Barbara, and at the institutional level at the University of Alabama (EDUCAUSE 2010). Higher education institutions have shown increased interest in learning analytics as they face calls for more transparency and greater scrutiny of their student recruitment and retention practices.

Data mining of student behavior in online courses has revealed differences between successful and unsuccessful students (as measured by final course grades) in terms of such variables as level of participation in discussion boards, number of emails sent, and number of quizzes completed (Macfayden and Dawson 2010). Analytics based on these student behavior variables can be used in feedback loops to provide more fluid and flexible curricula and to support immediate course alterations (e.g., sequencing of examples, exercises, and self-assessments) based on analyses of real-time learning data (Graf and Kinshuk in press).

In summary, learning analytics systems apply models to answer such questions as:

- When are students ready to move on to the next topic?
- When are students falling behind in a course?
- When is a student at risk for not completing a course?
- What grade is a student likely to get without intervention?
- What is the best next course for a given student?
- Should a student be referred to a counselor for help?

Visual Data Analytics

> **Visual Data Analysis**
>
> Visual data analysis is a way of discovering and understanding patterns in large datasets via visual interpretation. It is used in the scientific analysis of complex processes. As the tools to interpret and display data have become more sophisticated, models can be manipulated in real time, and researchers are able to navigate and explore data in ways that were not possible previously. Visual data analysis is an emerging field, a blend of statistics, data mining, and visualization that promises to make it possible for anyone to sift through, display, and understand complex concepts and relationships.
>
> *Johnson et al. 2010, p. 7*

Visual data analysis blends highly advanced computational methods with sophisticated graphics engines to tap the ability of humans to see patterns and structure in complex visual presentations (Johnson et al. 2010). Visual data analysis is designed to help expose patterns, trends, and exceptions in very large heterogeneous and dynamic datasets collected from complex systems. A variety of techniques and tools are emerging to enable analysts to easily interpret all sorts of data. For instance, visual interactive principal components analysis (finding the components of a dataset that reduce many variables into few) is a technique once available only to statisticians that is now commonly used to detect trends and data correlations in multidimensional data sets. Gapminder (http://www.gapminder.org/), for example, uses this approach in its analysis of multivariate datasets over time. Websites, such as Many Eyes (http://www-958.ibm.com/software/data/cognos/manyeyes/), offer tools for any user to create visualizations (map-based, text-based clouds and networks, and charts and graphs) of personal datasets. Early in its release, the creators of Many Eyes discovered that it was being used for visual analytics, to check for data quality, to characterize social trends, and to reveal personal and collective sentiments or advocate for a position (Viégas et al. 2008). Like Many Eyes, other online services, such as Wordle and FlowingData, accept uploaded data and allow the user to configure the output to varying degrees. To facilitate the development of this field, the National Visualization and Analytics Center was established by the U.S. Department of Homeland Security to provide strategic leadership and coordination for visual analytics technology and tools nationwide, and this has broadened into a visual analytics community (http://vacommunity.org).

The Horizon Report: 2010 Edition (Johnson et al. 2010) describes the promise of visual data analysis (in the four- to five-year time frame) for teaching undergraduates to model complex processes in such subjects as quantum physics. Visual data analysis also may help expand our understanding of learning because of its ability to support the search for patterns. It may be applied, for example, to illustrate the relationship among the variables that influence informal learning and to “see” the social networking processes at work in the formation of learning communities.

Currently, the tools, techniques, and high-resolution displays that enable people to interactively manipulate variables or zoom through the analysis results are still found mostly in research settings. Because interpreting data generated for visual data analysis requires analytical knowledge, researchers have thus far been the major population to use this method. Nevertheless, such sites as GapMinder offer data aimed at educators and provide teacher professional development to help educators interpret the data. Social Explorer, for example, offers tools for exploring map-based census and demographic data visualizations and is used by both researchers and educators. In the future, advances in visual data analytics and human-computer interface design may well make it feasible to create tools, such as Many Eyes, that policymakers, administrators, and teachers can use.

This section has described the promise of educational data mining (seeking patterns in data across many student actions), learning analytics (applying predictive models that provide actionable information), and visual data analytics (interactive displays of analyzed data) and how they might serve the future of personalized learning and the development and continuous improvement of adaptive systems. How might they operate in an adaptive learning system? What inputs and outputs are to be expected? In the next section, these questions are addressed by giving a system-level view of how data mining and analytics could improve teaching and learning by creating feedback loops.

Data Use in Adaptive Learning Systems

Online learning systems—learning management systems, learning platforms, and learning software—have the ability to capture streams of fine-grained learner behaviors, and the tools and techniques described above can operate on the data to provide a variety of stakeholders with feedback to improve teaching, learning, and educational decision making. To demonstrate how such adaptive systems operate, using the predictive models created by educational data mining and the system-level view of learning analytics, this section describes a prototypical learning system with six components (Exhibit 1):

- A content management, maintenance, and delivery component interacts with students to deliver individualized subject content and assessments to support student learning.
- A student learning database (or other big data repository) stores time-stamped student input and behaviors captured as students work within the system.
- A predictive model combines demographic data (from an external student information system) and learning/behavior data from the student learning database to track a student's progress and make predictions about his or her future behaviors or performance, such as future course outcomes and dropouts.
- A reporting server uses the output of the predictive model to produce dashboards that provide visible feedback for various users.
- An adaption engine regulates the content delivery component based on the output of the predictive model to deliver material according to a student's performance level and interests, thus ensuring continuous learning improvement.
- An intervention engine allows teachers, administrators, or system developers to intervene and override the automated system to better serve a student's learning.

Exhibit 1.
The Components and Data Flow Through a Typical Adaptive Learning System

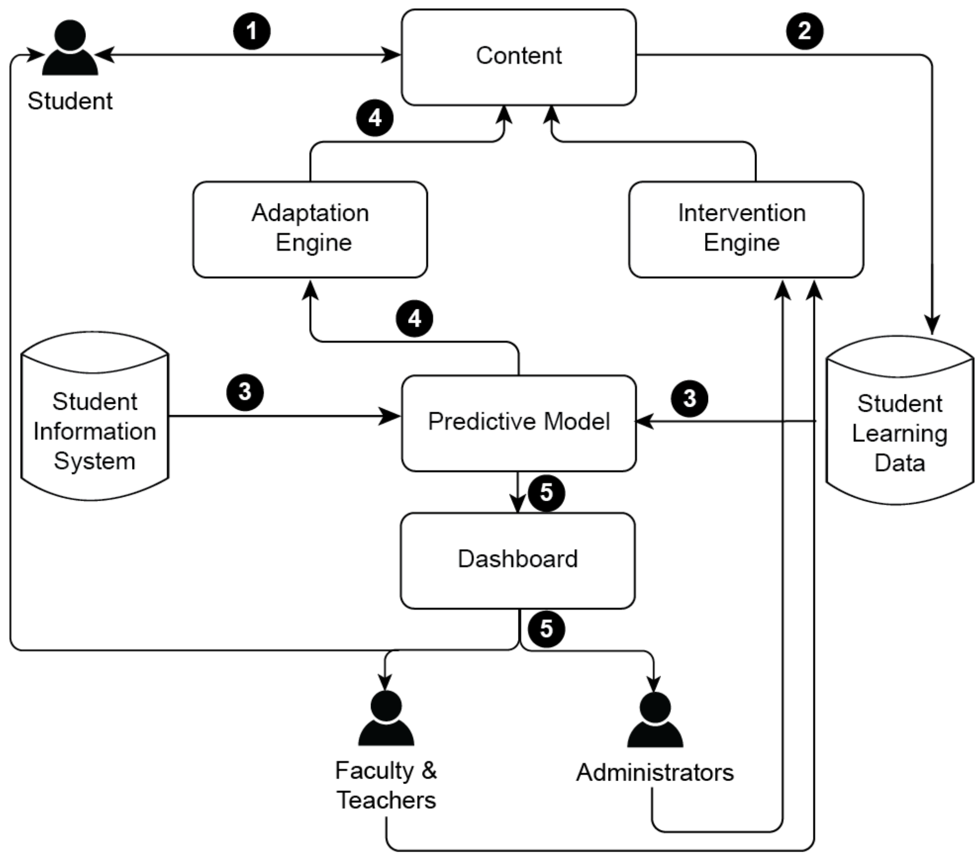


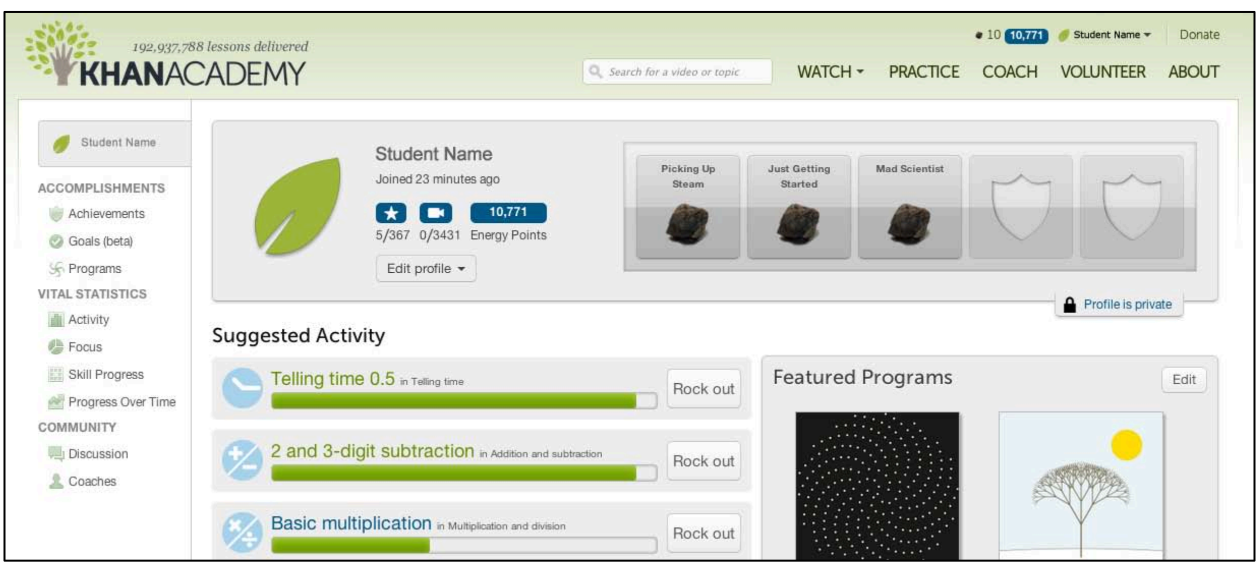
Exhibit reads: The data flow is shown through a box and arrows diagram with a content box on the top with an arrow to a student and two engines underneath shown as boxes: an adaptation engine and an intervention engine, with arrows for each up to the content box. Another arrow connects a predictive model box to the adaptation engine. The predictive model is connected to two databases with incoming arrows. On the right is the student learning database and on the left is the student information system. Below the predictive model and connected with an incoming arrow is a dashboard that is shown connected with arrows to faculty and educators and administrators.

In addition to these six internal components, an adaptive learning system often uses the student information system (SIS) that is maintained by a school, district, or institution as an external data source. Student profiles from the SIS are usually downloaded in batch mode, as they do not change often, and then are linked with performance data in the student learning database using student identifiers in compliance with applicable law. Student profiles contain background information on students that can be used to group them into specific categories or to provide more variables that might suggest a particular student is at risk.

The numbers in Exhibit 1 signify the data flow that creates feedback loops between the users and the adaptive learning system. The data flow starts with Step 1, students generating inputs when interacting with the content delivery component. (In the future, a student may have a portable learning record that contains information from all past interactions with online learning systems.) The inputs are time-stamped and cleaned as necessary and stored in the student learning database according to predefined structure (Step 2). At certain times (not synchronized with student learning activities), the predictive model fetches data for analysis from both the student learning database and the SIS (Step 3). At this stage, different data mining and analytics tools and models might be applied depending on the purpose of the analysis. Once the analysis is completed, the results are used by the adaptation engine (Step 4) to adjust what should be done for a particular student. The content delivery component presents these adjusted computer tutoring and teaching strategies (Step 4) to the student. The findings also may flow to the dashboard (Step 5), and, in the last step in the data flow, various users of the system examine the reports for feedback and respond (using the intervention engine) in ways appropriate for their role.

These last steps complete feedback loops as stakeholders receive information to inform their future choices and activities. *Students* receive feedback on their interactions with the content they are learning through the adaptive learning system. The feedback typically includes the percentage correct on embedded assessments and lists of concepts they have demonstrated mastery on (Exhibit 2), but it also can include detailed learning activity information (e.g., hints requested and problems attempted). Detailed learning information for one student can be compared with that for students who earned high grades so that students can adjust their learning with the system accordingly.

Exhibit 2. Student Dashboard Showing Recommended Next Activities

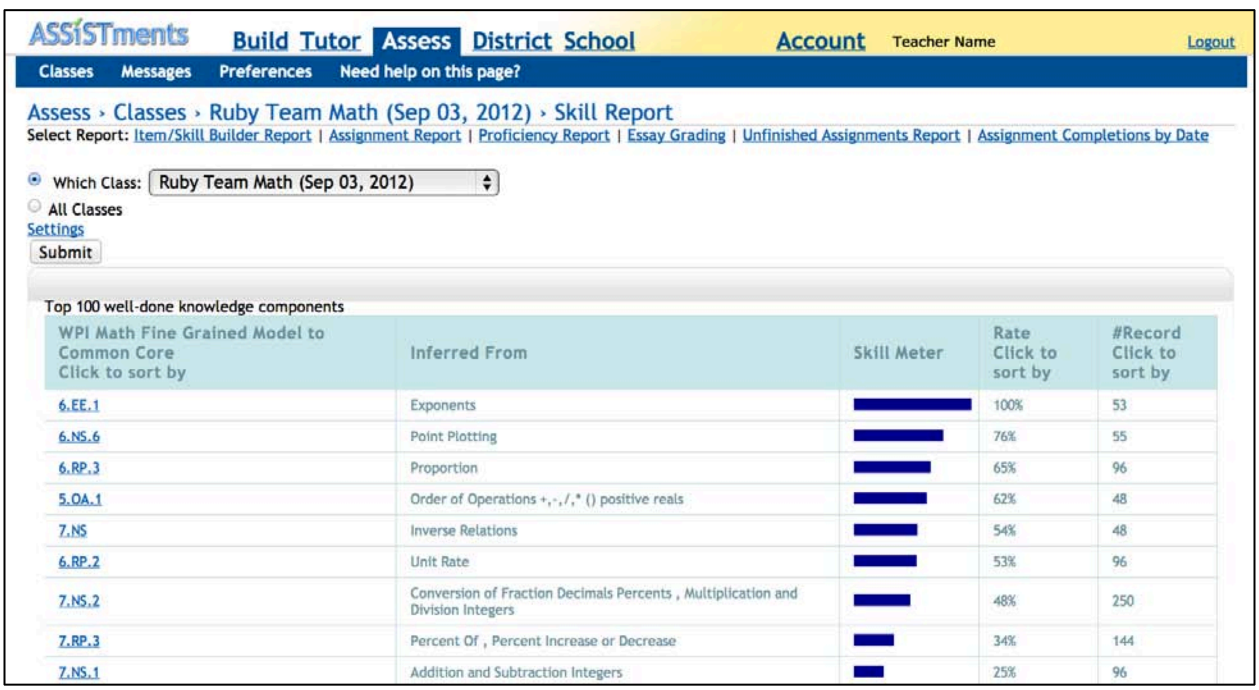


Teachers receive feedback on the performance of each individual student and of the class as a whole and adjust their instructional actions to influence student learning. By examining the feedback data, instructors can spot students who may need additional help or encouragement to spend more time on the content and identify areas where the class as a whole is struggling. The latter area can be addressed during class time when the instructor can respond to questions and address student misconceptions and lack of comprehension. For the former areas, teachers may choose to intervene with the system to adjust student learning pace or may assign additional learning materials targeting the skills that are not yet mastered (see Case Study 1 on page 22). Learning systems typically track the state of student mastery at the skill or topic level (e.g., the quadratic equation) and can provide this information to students so they know what to study and to teachers so they know the areas where they should concentrate further instruction (Exhibit 3). Researchers involved with the Open Learning Initiative at Carnegie-Mellon University have a similar vision of student and teacher feedback systems that is guiding their work in developing online courses (Bajzek et al. 2008) and is described in Case Study 2 on page 23.

Measuring Student Effort

Learning software collects such data as minutes spent on a unit, hints used, and common errors, and aggregates these data across many students in a school or schools in a district (Feng, Heffernan, and Koedinger 2009). Using these measures, teachers can distinguish between students who are not trying and those who are trying but still struggling and then differentiate instruction for each group.

Exhibit 3. Teacher Dashboard With Skill Meter for Math Class



ASSISTments Build Tutor Assess District School Account Teacher Name Logout

Classes Messages Preferences Need help on this page?

Assess › Classes › Ruby Team Math (Sep 03, 2012) › Skill Report

Select Report: Item/Skill Builder Report | Assignment Report | Proficiency Report | Essay Grading | Unfinished Assignments Report | Assignment Completions by Date

Which Class: Ruby Team Math (Sep 03, 2012)

All Classes

Settings

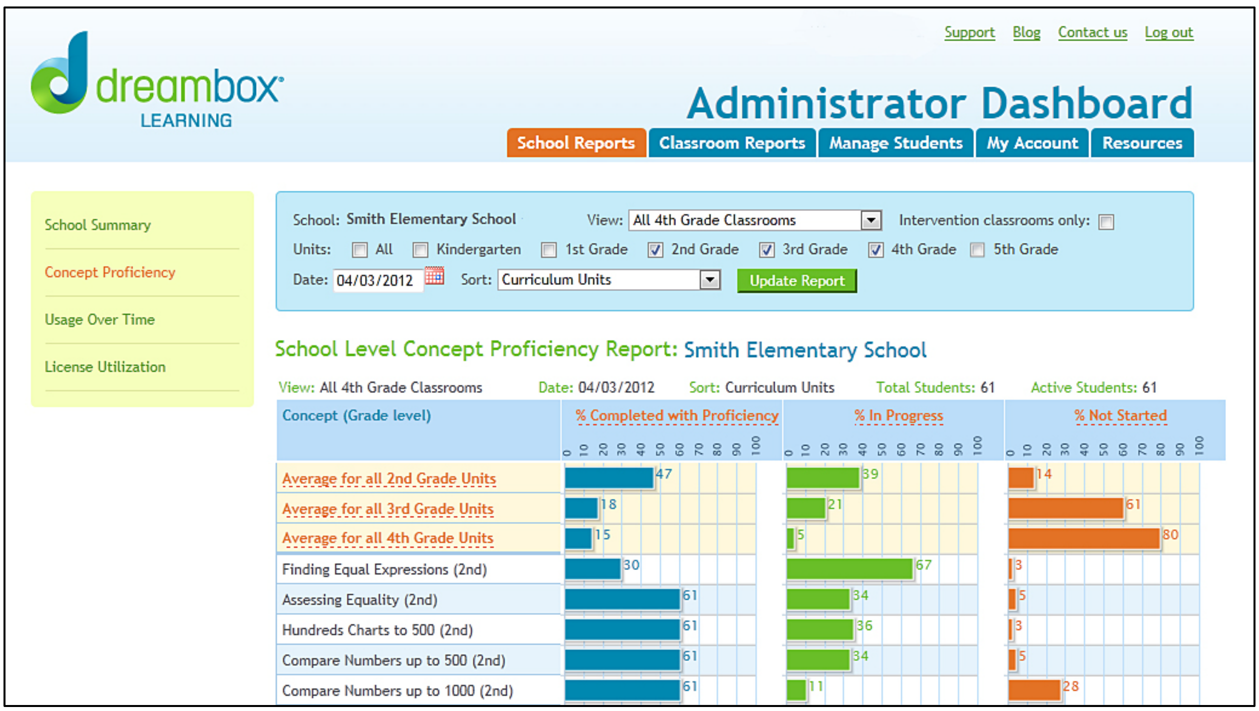
Submit

Top 100 well-done knowledge components

WPI Math Fine Grained Model to Common Core Click to sort by	Inferred From	Skill Meter	Rate Click to sort by	#Record Click to sort by
6.EE.1	Exponents		100%	53
6.NS.6	Point Plotting		76%	55
6.RP.3	Proportion		65%	96
5.OA.1	Order of Operations +,-,/,* () positive reals		62%	48
7.NS	Inverse Relations		54%	48
6.RP.2	Unit Rate		53%	96
7.NS.2	Conversion of Fraction Decimals Percents , Multiplication and Division Integers		48%	250
7.RP.3	Percent Of , Percent Increase or Decrease		34%	144
7.NS.1	Addition and Subtraction Integers		25%	96

Administrators can look at detailed data across different classes to examine progress for all students at a school, to see what works and what does not in a particular classroom, and to do so with less effort. District administrators can use data from this kind of dashboard as a basis for determining whether a particular learning intervention is effective at promoting student learning, even at the level of individual concepts (Exhibit 4). Typically, the detailed learning data the system provides can be disaggregated by student subgroup (for example, to see how students without a course prerequisite perform or to compare males' and females' progress in the course), by instructor, or by year. Learning system data can support analyses of how well students learn with particular interventions and how implementation of the intervention could be improved. Using the data, administrators can set policies, implement programs, and adapt the policies and programs to improve teaching, learning, and completion/retention/graduation rates.

Exhibit 4. Administrator Dashboard Showing Concept Proficiency for a Grade Level



Researchers can use fine-grained learner data to experiment with learning theories and to examine the effectiveness of different types of instructional practices and different course design elements. *Learning system developers* can conduct rapid testing with large numbers of users to improve online learning systems to better serve students, instructors, and administrators. Researchers using online learning systems can do experiments in which many students are assigned at random to receive different teaching or learning approaches, and learning system developers can show alternative versions of the software to many users: version A or version B. This so-called "A/B testing" process can answer research questions about student learning such as: Do students learn more quickly if they receive a lot of practice on a given type of problem all at once (“massed practice”) or if practice on that type of problem is spaced out over time (“spaced practice”)? What about students’ retention of this skill? Which kind of practice schedule is superior for fostering retention? For what kind of students, and in what contexts?

Case Study 1. Fine-grained Data Collection and Use: ASSISTments

Fine-grained student data can be structured into meaningful chunks to provide evidence of student problem-solving sequences, knowledge state, and strategy. An example of this use of fine-grained data that is in wide-scale use is the ASSISTments tutoring system, currently used by more than 20,000 students in the New England area. Designed by researchers at Worcester Polytechnic Institute and Carnegie Mellon University, ASSISTments combines online learning assistance and assessment activities. ASSISTments tutors students on concepts while they practice on problems, and provides educators with a detailed assessment of students’ developing skills. While ASSISTments is widely used in fourth to 10th grade mathematics and science, it is also finding use in English and social studies. This wider adoption across subjects is due in part to teachers’ ability to write their own questions.

When students respond to ASSISTments problems, they receive hints and tutoring to the extent they need them. At the same time, ASSISTments uses information on how individual students respond to the problems and how much support they need from the system to generate correct responses as assessment information. Each week, when students work on ASSISTments, it learns more about their abilities and, thus, can provide increasingly appropriate tutoring for each student and can generate increasingly accurate predictions of how well the students will do on the end-of-year standardized tests. In fact, the ASSISTments system, taking into account information on the quantity and quality of help that students request, has been found to be more accurate at predicting students’ performance on the state examinations than the number of items students get correct on benchmark assessments (Feng, Heffernan, and Koedinger 2009).

The ASSISTments system gives educators detailed reports of students’ mastery of 147 math skills from fourth grade to 10th grade, as well as their accuracy, speed, help-seeking behavior, and number of problem-solving attempts. The system can identify the difficulties that individual students are having and the weaknesses demonstrated by the class as a whole so that educators can tailor the focus of their upcoming instruction or tailor ASSISTments to adjust its instruction.

Case Study 2. Meshing Learning and Assessment in Online and Blended Instruction

The online learning systems being developed through the Open Learning Initiative (OLI) at Carnegie Mellon University illustrate the new advances that allow integration of learning and assessment systems. The OLI team set out to design learning systems incorporating the learning science principle of providing practice with feedback. In the OLI courses, feedback mechanisms are woven into a wide variety of activities. A biology course, for example, has the following components:

- Interactive simulations of biological processes that students can manipulate; the student's interaction with the simulation is interspersed with probes to gauge his or her understanding of how it works.
- *Did I Get This?* quizzes after presentation of new material so that students can check for themselves whether or not they understood, without any risk of hurting their course grade.
- Short essay questions embedded throughout the course material that call on students to make connections across concepts.
- *Muddiest Point* requests that ask students what they thought was confusing.

Tutored problem solving gives students a chance to work through complex problems and get scaffolds (e.g., showing how similar problems are solved) and hints to help them. The students receive feedback on their solution success after doing each problem, and the system keeps track of how much assistance students needed for each problem as well as whether or not they successfully solved it.

When OLI courses are implemented in a blended instruction mode that combines online and classroom learning, the instructors can use the data the learning system collects as students work online to identify the topics students most need help on so that they can plan upcoming classroom activities on those misconceptions and errors (Brown et al. 2006). OLI is now doing R&D on a digital dashboard to give instructors an easy-to-read summary of the online learning data from students taking their course.

OLI has developed learning systems for postsecondary classes in engineering statics, statistics, causal reasoning, economics, French, logic and proofs, biology, chemistry, physics, and calculus. A study contrasting the performance of students randomly assigned to the OLI statistics course with those in conventional classroom instruction found that the former achieved better learning outcomes in half the time (Lovett, Meyer, and Thille 2008).

These case studies demonstrate practical applications of data-rich feedback loops in adaptive learning systems. But they do not represent the full range of potential applications of educational data mining and learning analytics. To show this larger potential, the next section outlines broad areas where educational data mining and learning analytics can be applied, many inspired by industry practices.

Educational Data Mining and Learning Analytics Applications

Educational data mining and learning analytics research are beginning to answer increasingly complex questions about what a student knows and whether a student is engaged. For example, questions may concern what a short-term boost in performance in reading a word says about overall learning of that word, and whether gaze-tracking machinery can learn to detect student engagement. Researchers have experimented with new techniques for model building and also with new kinds of learning system data that have shown promise for predicting student outcomes. Previous sections presented the research goals and techniques used for educational data mining and learning/visual analytics. This section presents broad areas of applications that are found in practice, especially in emerging companies. These application areas were discerned from the review of the published and gray literature and were used to frame the interviews with industry experts. These areas represent the broad categories in which data mining and analytics can be applied to online activity, especially as it relates to learning online. This is in contrast to the more general areas for big data use, such as health care, manufacturing, and retail (see Manyika et al. 2011).

These application areas are (1) modeling of user knowledge, user behavior, and user experience; (2) user profiling; (3) modeling of key concepts in a domain and modeling a domain's knowledge components, (4) and trend analysis. Another application area concerns how analytics are used to adapt to or personalize the user's experience. Each of these application areas uses different sources of data, and Exhibit 5 briefly describes questions that these categories answer and lists data sources that have been used thus far in these applications. In the remainder of this section, each area is explored in more detail along with examples from both industry practice and academic research.

Exhibit 5
Application Areas for Educational Data Mining and Learning Analytics

Application Area	Questions	Type of Data Needed for Analysis
User knowledge modeling	What content does a student know (e.g., specific skills and concepts or procedural knowledge and higher order thinking skills)	Student's responses (correct, incorrect, partially correct), time spent before responding to a prompt or question, hints requested, repetitions of wrong answers, and errors made The skills that a student practiced and total opportunities for practice Student's performance level inferred from system work or collected from other sources, such as standardized tests
User behavior modeling	What do patterns of student behavior mean for their learning? Are students motivated?	Student's responses (correct, incorrect, partially correct), time spent before responding to a prompt or question, hints requested, repetitions of wrong answers, and errors made Any changes in the classroom/school context during the investigation period of time
User experience modeling	Are users satisfied with their experience?	Response to surveys or questionnaires Choices, behaviors, or performance in subsequent learning units or courses
User profiling	What groups do users cluster into?	Student's responses (correct, incorrect, partially correct), time spent before responding to a prompt or question, hints requested, repetitions of wrong answers, and errors made
Domain modeling	What is the correct level at which to divide topics into modules and how should these modules be sequenced?	Student's responses (correct, incorrect, partially correct) and performance on modules at different grain sizes compared to an external measure A domain model taxonomy Associations among problems and between skills and problems
Learning component analysis and instructional principle analysis	Which components are effective at promoting learning? What learning principles work well? How effective are whole curricula?	Student's responses (correct, incorrect, partially correct) and performance on modules at different levels of detail compared to an external measure A domain model taxonomy Association structure among problems and between skills and problems
Trend analysis	What changes over time and how?	Varies depending on what information is of interest; typically would need at least three data points longitudinally to be able to discern a trend Data collected include enrollment records, degrees, completion, student source, and high school data in consecutive years

Exhibit 5
Application Areas for Educational Data Mining and Learning Analytics (Continued)

Application Area	Questions	Type of Data Needed for Analysis
Adaptation and Personalization	What next actions can be suggested for the user?	Varies depending on the actual recommendation given
	How should the user experience be changed for the next user?	May need to collect historical data about the user and also related information on the product or service to be recommended
	How can the user experience be altered, most often in real time?	Student's academic performance record

User Knowledge Modeling

Researchers and developers build and tune user models that represent a collection of user-specific data, especially skills and knowledge. User models are used to customize and adapt the system's behaviors to users' specific needs so that the systems "say" the "right" thing at the "right" time in the "right" way (Gerhard 2001). Inferring what a user knows, i.e., user knowledge modeling, requires looking at accumulated data that represent the interactions between students and the learning system.[2] Knowledge can be inferred from such interactions as correctness of student responses alone or in a series, time spent on practice before attempting to answer a question, number and nature of hints requested, repetitions of wrong answers, and errors made. Such "inferences" can be made by a predictive computer model or by a teacher looking at student data on a dashboard.

Tailoring Learner Feedback

Adaptive learning systems can provide tailored feedback that gives guidance based on analysis of fine-grained data. The Knewton Math Readiness system uses analytics to deliver only the content each student needs and skips concepts the student has already shown he or she understands.

User knowledge modeling has been adopted to build adaptive hypermedia, recommender systems, expert systems, and intelligent tutoring systems. In intelligent tutoring systems, user knowledge models direct key operations, such as deciding which problems to give students. A popular method for estimating students' knowledge is Corbett and Anderson's knowledge tracing model (Corbett and Anderson 1994), an approach that uses a Bayesian-network-based model for estimating the probability that a student knows a skill based on observations of him or her attempting to perform the skill. More recently, Baker and colleagues proposed a new method for knowledge tracing using a machine learning approach to make contextual estimations of the probability that a student has guessed or slipped. Incorporating models of guessing and slipping into predictions of student future performance was shown to increase the accuracy of the predictions by up to 48 percent (Baker, Corbett, and Aleven 2008).

Advancing Instruction

Many learning technology experts are enthusiastic about the possibility of data completely driving the student's experience. By tracking a student's mastery of each skill, a learning system can give just the right amount of instruction. Other experts caution against allowing analytics to completely determine what problems or skills students practice next or whether they advance to the next topic. Automatically holding a student back on the assumption that difficulty with one topic will preclude making progress on another may not be the best course of action (Means, Chelemer, and Knapp 1991).

[2] Even though one could envision that continuous knowledge modeling could supplant traditional assessments, the technical working group still saw a need for end-of-course or state-level assessments as a check on this more local and possibly more formative type of assessment.

Student knowledge modeling is a common component of commercial learning software. How these models are used to adapt instruction varies. For example, one company builds dynamic student models for determining a student's readiness to move to new learning content and then advances the student automatically. Other companies resist automatic advancement, and instead their systems offer suggestions to teachers after detecting a student's placement. Other companies are trying a middle approach: If students are performing above average, they receive suggestions to move on to new content; otherwise, they are encouraged to consolidate current skills and work on prerequisites.

As an example of using student modeling, learning software can collect such data as how many minutes are spent on a unit, how many hints were used, and common errors. The data for an individual student can then be compared against a model built from a large number of students. The industry expert we interviewed from Agile Mind, a learning software company, explained that these data enable teachers to distinguish between students who are not trying and those who are trying but still struggling. This information then helps teachers use different instructional strategies for these two groups of students. Agile Mind, however, cautions against allowing the data to drive what a student sees next or allowing the data to prevent a student from advancing because, according to the data, he or she has not achieved "mastery." Not enough is known about the dependencies among topics to make these decisions in a completely automated manner.

In contrast, the Onsophic Inc. online learning platform collects data at a very granular level (per topic) for each student and detects student mastery at this topic level (e.g., quadratic equation) rather than at the course level. Plans are to provide students with detailed feedback, such as, "A week ago, you were 'yellow' on a prerequisite but now you are struggling on this topic. We suggest that you make sure you have a solid foundation on this topic through practicing on the prerequisite."

User Behavior Modeling

User behavior modeling in education often characterizes student actions as on- or off-task and can be used as a proxy for student engagement. It relies on the same kinds of learning data used in predicting user knowledge plus other measures, such as how much time a student has spent online (or on the system), whether a student has completed a course, documented changes in the classroom or school context, attendance, tardiness, and sometimes a student's level of knowledge as inferred from his or her work with the learning system or from other such data sources as standardized test scores. Baker and colleagues have conducted a series of studies on detecting and adapting to students' off-task behaviors (called gaming the system) in adaptive learning systems that teach algebra (Baker et al. 2004, 2006). They found that gaming behaviors (such as clicking until the system provides a correct answer and advancing within the curriculum by systematically taking advantage of regularities in the software's feedback and help) were strongly associated with less learning for students with below-average academic achievement levels. In response, they modified the system to detect and respond to these students and provide them with supplementary exercises, which led to considerably better learning. Similar research has been done in unscripted environments that are more open-ended than the well-defined domain of mathematics. For instance, Blikstein (2011) has presented an automated technique and a case study to assess, analyze, and visualize behaviors of students learning computer programming.

Online learning systems log student data that can be mined to detect student behaviors that correlate with learning. Macfayden and Dawson (2010) analyzed learning management system tracking data from a Blackboard Vista-supported course and found variables that correlated with student final grade. Fewer than five variables were found to account for 30 percent of the variation in student final grades, and their model could correctly pick 81 percent of students who failed the course.

Not all learning software companies have adopted user behavior modeling. Those that have collect and provide data to teachers to help them diagnose student learning issues. Carnegie Learning reported that its user behavior modeling was able to detect shifts in the classroom, such as the use of a substitute teacher, a teacher's lack of attention to an online learning system, or a classroom visit by a trainer for the learning system. Social gaming companies, such as Zynga, try to predict what users want and will do next in a game to find out how to make games more fun and get users more engaged. Others companies, such as Onsophic, Inc. are testing whether capturing on- and off-task behaviors can help them understand online learning through addressing such questions as: Does more interaction between the student and the system lead to increased learning? Do people learn more from items they show interest in? What patterns of interactions are associated with more learning?

User Experience Modeling

User experience modeling—ascertaining whether a student is satisfied with the learning experience—can be judged by students' responses to follow-up surveys or questionnaires and by their choices, behaviors, performance, and retention in subsequent learning units or courses.

User experience modeling has been most popular in such Web-based applications as online shopping. Some of the interviewees' companies model user experience through methods other than data mining. Zynga explicitly asks users for their reactions via a survey, conducts user studies, or has humans conduct postmortem analyses (much like Google's researchers who look at failed searches). Zynga described an extended approach to user experience modeling: A sample of users can be surveyed about their experience, and then their behavior can be correlated with their survey results as a way to confirm what they said. Zynga also is experimenting with a more leading-edge approach: analyzing free-text responses given by users in responding to a survey (this is most useful when the sample of users is large, e.g., 250,000 users).

Compared with commercial applications of user experience modeling, less work has been done in education to use analytics to improve students’ learning experience and foster their success and retention rate. Dawson, Heathcote, and Poole (2010) examined how effective higher education institutions have been in harnessing the data-capture mechanisms from their student information systems, learning management systems, and communication tools for improving student learning experiences and informing practitioners of the achievement of specific learning outcomes. They found that if the multiple means through which students engage with university systems are considered, individual activity can be tracked throughout the entire student life cycle—from initial admission through course progression, and finally graduation and employment transitions. The combined data captured by various systems build a detailed picture of the activities that students, instructors, service areas, and the institution as a whole undertake and can be used to improve relevance, efficiency, and effectiveness in a higher education institution.

User experience, as measured by retention, is important for companies offering commercial online courses. Kaplan, Inc. uses retention to judge whether its product is meeting customer needs. Kaplan has experimented with course redesigns using analytics. In one redesign experiment, it changed courses on topics, such as nutrition, interpersonal communication, and medical terminology. The old courses had students follow a classic online learning sequence of “Read, Write, Discuss,” and the new courses were more active, using a “Prepare, Practice, Perform” learning sequence. The new courses were carefully designed to make them easy to use and to give them a clean, simple look with good production values, paying attention to research on how media, audio, and text best reinforce, as opposed to distract from, learning. The redesigned versions offered opportunities for students to get help when they need it, as well as built-in assessments and quick surveys of self-efficacy and perceived value, and provided much more structured support for faculty as well.

Kaplan’s analytics group collected time spent on redesigned course components, periodic surveys of students’ motivation state during the course, and learning performance. Kaplan then looked at instructor satisfaction, student satisfaction, performance on embedded learning assessments, whether the student passed the course, and whether the student was retained until the next semester. Through A/B testing Kaplan was able to ascertain that the new course was better overall. But this was visible only via multiple measures: Instructors preferred the redesign; students did better on the assessments, spent more time on the materials, and were more likely to pass and take the next course. Of interest, however, is that students reported liking the old version more.

User Profiling

A user profile is a collection of personal data describing the essential characteristics of a user. User profiling refers to the process of constructing and applying student or group profiles using data mining and machine learning algorithms. Because students differ in their preferences, interests, background, and even goals for learning, the long-term objective of user profiling is often to provide adapted and personalized learning environments for individuals or groups of students to maximize learning effectiveness and efficiency.

Profiling technologies can be applied in a variety of domains and for a variety of purposes. Knowledge about customer behavior and preferences is of great interest to the commercial sector. With profiling technologies, companies can predict the behavior of different types of customers. Marketing strategies, such as personalized advertising, then can be tailored to the people fitting these types.

In education, data mining techniques, such as classification and clustering, are often used to categorize (or profile) students based on the kinds of personal learning data described in the section on the research base, on student demographic data, or both. Kardan and Conati (2011) proposed a user modeling framework that relies on interaction logs to identify different types of learners, as well as their characteristic interactions with the learning system. This information would then be used to classify new learners, with the long-term goal of providing adaptive interaction support when behaviors detrimental to learning are detected, or to learn ways to support engaged behavior. Classification also can group students together into study groups or other joint learning activities.

Gaming companies automatically cluster users into groups using behavioral data and use different strategies with each group to increase engagement and reduce drop-offs in playing. These groups emerge from the data and often are named based on human interpretations of the emergent patterns, for example, casual players, weekenders, social players, big spenders, decorators, and the like. In practice, these user groups may not always be informative or actionable, although groupings based on purchasing habits have proven useful for recommendation services. Representatives of one of the learning companies interviewed were hesitant to provide automatic recommendations for students based on profiles, believing that evidence for the effectiveness of such adaptations is not sufficient. Instead, this company has found that concentrating on assignments, concept strands, standards, and students who do or do not have mastery of the concepts in a standard is more fruitful than classifying students into groups based on learner types. In contrast, those of another company interviewed for this report are working to classify users based on understandings, learning trajectories, motivation, and possibly even cultural background. They are researching how this helps teachers differentiate instruction.

Domain Modeling

A domain model is often created to represent the key concepts that make up a subject or topic area like mathematics or art history (i.e., domains). The domain model also identifies the relationships among all the key concepts or units of study. Research in domain modeling in educational data mining and learning analytics investigates how learning is affected by differences in how a topic is divided into key concepts at a particular level of generalization. For example, a state may specify that students in eighth grade must learn data analysis, statistics, and probability. A finer level requires teaching students to understand data presentation techniques; that is, students learn that data can be represented as number lines, bar graphs, circle graphs, stem and leaf plots, and so on. For a learning environment, it may be sufficient to test student performance and adapt at the "data presentation" level. However, there may be advantages to presenting sequences of related concepts (such as graph types) in a specific order. Researchers who use data mining to study difference in approaches to domain modeling use a taxonomy of the domain, associations among skills (such as prerequisites), user responses (including correctness), and actions over time on individual learning resources (such as a unit concept like multiplication of whole numbers).

Domain modeling has been adopted as an approach to fine-tune learning systems to better serve learning and instruction. For instance, Martin et al. (2011) described three studies to demonstrate how learning curves can be used to drive changes in the user model for personalized learning environments. Learning curves (i.e., some measure of performance against opportunities to learn and practice) for subsets of the domain model were shown to yield insight into the appropriateness of the model's structure and granularity. Martin et al. also used learning curves to analyze large amounts of user data to fine-tune a system's domain model.

In the education industry, some learning software companies have the goal of collecting data on "atomic learning objects" (i.e., objects that teach one concept that cannot be decomposed) and creating linking relationships among topics based on user tags or other actions. They intend to pair this technique with a feature that enables users to improve on any automatically built relationships or to create their own taxonomies.

Learning System Components and Instructional Principle Analysis

Instructional principle analysis examines components of a learning system and types of instructional practices adopted at various time points or for various student groups to address such questions as:

- Which learning components are effective at promoting learning?
- Does a newly developed curriculum enable more learning than an alternative?
- What types of instructional practice are more effective in promoting learning (e.g., massed practice vs. spaced practice)?

Answering these questions entails collecting such data as student input and response correctness, student actions on learning system components over time, when and to which group a specific instructional strategy was applied, and students' performance on pre/posttests and/or delayed tests or their standardized test results.

Because studying the effectiveness of different learning system components and instructional practices can contribute to the design of better learning systems and has strong implications for student learning, it has been a key area of interest for educational data mining and analytics researchers, as evidenced by widely cited papers that reported using educational data mining to study and improve online courses (Baker and Yacef 2009). For example, researchers and educators from Carnegie Learning, Inc. and Carnegie Mellon University have been working to build cognitive models of mathematics, which have become the basis for middle school and high school curricula incorporating the Cognitive Tutor, an intelligent tutoring system. In these systems, complex tasks are decomposed into individual knowledge components, and a model is used to follow students' actions and diagnose their strategy in solving a problem. Each action that the student takes is associated with one or more skills. In this way researchers have been able to use Cognitive Tutor data to dynamically evaluate the effectiveness of instruction at a more detailed level. Evaluations and improvements have been conducted over the past 15 years (Ritter et al. 2007).

To discover which pedagogical support is most effective, Beck and Mostow (2008) proposed learning decomposition as an alternative to traditional A/B testing methods. As a type of relationship mining, learning decomposition involves fitting exponential learning curves to performance data and relating student success to the amount of each type of pedagogical support a student has received (with a weight for each type of support). The weights indicate how effective each type of pedagogical support is for improving learning.

One company uses data from many teachers to identify the pedagogical patterns of effective teachers, i.e., teachers whose students learn the most or are most engaged. The company is training other teachers in the same techniques and studying what happens in the learning system when these other teachers adopt those patterns.

Trend Analysis

Trend analysis in general refers to the practice of collecting information and attempting to spot a sequential pattern, or trend, in the information over time. Web-based companies use trend analysis to predict what users might be searching for or be interested in or how user participation ramps up or falls off. In education, trend analysis helps answer such questions as what changes have occurred in student learning over time and how learning has changed. At the school level, trend analysis can be used to examine test scores and other student indicators over time to help administrators determine the impact of policies. In educational data mining, trend analysis often refers to techniques for extracting an underlying pattern, which might be partly or nearly completely hidden by data that does not contribute to the pattern (i.e., noise). Although the actual data needed for trend analysis vary depending on what information is of interest, typically longitudinal data from at least three points in time are required.

As an example of trend analysis, the Postsecondary Education Commission of California provides a trend analysis tool at http://www.cpec.ca.gov/OnLineData/Mining.asp. This tool can be used to examine the commission's database tables to identify trends. It also can be used to discover anomalies with the data, such as large numerical differences between consecutive years and gaps when no data were reported. Visitors can generate customized reports on enrollment, degree completion, student home school, and high school data.

Adaptation and Personalization

Personalization, as defined in the NETP (U.S. Department of Education, 2010a), indicates adaptive pacing, styling instruction to learning preferences, and tailoring content to learners' interest. We use *adaptation* to indicate the changes a system (interface or behavior) or instructor makes in response to students, thereby personalizing their experience. Adaptation and personalization address such questions as: How should the user experience be changed for this user? How can user experience be altered to best serve individual users in real time? User classification techniques and trend or sequence analyses are often applied to create models for adapting instruction to students' needs. These adaptations may include recommendations or feedback to students about their best next actions and changes to their experience with an online learning system (such as different content, more practice, or signals about their progress through a course).

To adapt instruction or personalize student learning experiences, such data as sequences of student activity, information on the problems or steps a user has attempted, and student demographic information are often collected and used to create a personal profile for each system user. Researchers from Austria (Köck and Paramythis 2011) investigated the monitoring and interpretation of sequential learning activities to improve adaptation and personalize educational environments. They analyzed student problem-solving data from a physics tutoring system (VanLehn et al. 2005) by first converting activity sequences in the raw data into chain-like models and then clustering sequences to detect problem-solving styles. These models are used to adapt the tutoring system to students' preferred learning methods.

This section has described broad categories of applications that exploit educational data mining and learning analytics techniques to adapt and personalize learning and improve teaching. These represent the promise of educational data mining and learning analytics, with the caveat that some are still in the research stage. The next section examines challenges and considerations to bring these techniques into K–12 and higher education.

Implementation Challenges and Considerations

New technology start-ups founded on big data (e.g., Knewton, Desire2Learn) are optimistic about applying data mining and analytics—user and domain modeling and trend analysis—to adapt their online learning systems to offer users a personalized experience. Companies that "own" personal data (e.g., Yahoo!, Google, LinkedIn, Facebook) have supported open-source developments of big data software (e.g., Apache Foundation's Hadoop) and encourage collective learning through public gatherings of developers to train them on the use of these tools (called hackdays or hackathons). The big data community is, in general, more tolerant of public trial-and-error efforts as they push data mining and analytics technology to maturity.[3] What is the gap between the big data applications in the commerce, social, and service sectors and K–20 education? The 2012 *Horizon Report*'s short list of projects to watch in higher education shows learning analytics in the two- to three-year range for widespread adoption (New Media Consortium 2012). Given that learning analytics practices have been applied primarily in higher education thus far, the time to full adoption may be longer in different educational settings, such as K–12 institutions.

This section describes the challenges in implementing data mining and learning analytics within K–20 settings. Experts pose a range of implementation considerations and potential barriers to adopting educational data mining and learning analytics, including technical challenges, institutional capacity, legal, and ethical issues. Successful application of educational data mining and learning analytics will not come without effort, cost, and a change in educational culture to more frequent use of data to make decisions (U.S. Department of Education 2010b).

[3] As an example, consider the contrasting cases described for user profiling. Representatives of one learning company believed it was ineffective, while representatives of another were willing to experiment with it as a differentiator for their company.

Technical Challenges

Online learning technologies offer researchers and developers opportunities for creating personalized learning environments based on large datasets that can be analyzed to support continuous improvement. However, these benefits depend on managing all the data that can now be captured in real time across many students. A challenge for successful implementation of educational data mining and learning analytics techniques is having sufficient technical resources for using big data and incurring the expenses associated with software services and storage in either remote servers provided by a company or local servers. Although data mining and analytics are used in some courses and institutions, computer scientists are still working on reducing the computer memory requirements needed to support advanced algorithms, and some experts are not optimistic about the near-term resolution of this issue.

In response to this big data challenge, a few key issues must be considered for each case when implementing data mining and analytics. These include choosing what data to collect, focusing on the questions to be answered, and making sure that the data align with the questions. Developers must be strategic about what data to collect and study the analytic techniques needed to answer the most pressing questions. One expert interviewed stressed the importance of starting out by understanding what questions data mining and analytics can answer: “If you have 100 people working, I would allocate 99 for identifying what questions to answer and one for [the technical process of] data mining.”

Lack of data interoperability[4] among different data systems imposes a challenge to data mining and analytics that rely on diverse and distributed data. Over time, piecemeal purchases of software can lead to significant decentralization of the source of education data, such as student information systems, teachers’ online grade books, homework submission systems, and publishers’ online assignments, homework help, and assessments. The National Center for Education Statistics (NCES) is supporting efforts to create interoperability for state longitudinal data (early learning through the workforce) that includes, in some cases, grades, standardized test scores, attendance, enrollment, and other administrative and demographic data. The Common Education Data Standards (https://ceds.ed.gov/) is an NCES-supported effort to create and encourage the use of voluntary standards for student data. Adoption of these standards is an important first step to moving data across disparate data systems, and across institutions, education levels, and school years.

[4] Data interoperability refers to a property of a system whose input/output data flow and formats are completely understood by other systems so that data from such systems can be integrated or exchanged seamlessly for analysis.

Researchers in educational data mining and learning analytics seek to make claims about a student's learning topics or concepts based on the student's interaction with an online learning system. These claims can be validated by comparing scores on assessments and course grades. Going beyond one dataset to combining multiple sources of data (e.g., multiple tests, both teacher-made and standardized; behavioral assessments; or online behavior tracking) in order to provide an integrated view of a student's progress is not a straightforward task. Existing datasets may not have been designed to support creating profiles of student behaviors and, for example, may leave out data that could be an important variable in a model. Combining disparate data sources to make claims about student learning is known to be fraught with difficulties in assessment and, when used for high-stakes actions, must meet appropriate standards for valid student assessment.

Limitations in Institutional Capacity

Technical challenges can be overcome through research, development, and testing; computing and storage can be budgeted as part of an institution's infrastructure costs. However, implementing data mining and learning analytics in K–20 institutions has costs that go beyond simply computing and storage. Significant human resources also are needed for data preparation, processing, and analysis. Integrating existing data systems, such as grade books, with student information systems can be expensive, and the requirements can exceed the capabilities of the information technology department of a single institution. Our experts reported that at least 70 percent and often 80 to 85 percent of the effort in data analytics is devoted to data cleaning, formatting, and alignment and suggested that education has the further complication of needing to move data across different levels of the system, back and forth between classroom, school, district, and state databases.

If technical challenges can be overcome and data can be prepared and analyzed, smart consumers are needed to use the data. Today, teachers and school leaders are surrounded by many data reports and often are frustrated by how much work is required to sort the useful from the useless. Data dashboards need to be adapted to everyday users. Education researchers and software developers must obtain a good understanding of the challenges from the users' perspective for adoption and implementation of data mining and analytics in classrooms, schools, districts, and other institutions to be successful. This will enable them to pose questions that matter to teachers and other users and to frame findings in a thoughtful, informative way that highlights and recommends clear actions.

In reports about the newest technologies for adaptation, personalization, and recommendation, the role of human judgment is sometimes underemphasized (with the exception of visual data analytics). All the experts consulted for this issue brief emphasized the key role that people play in many

Open Research Questions

What is the right amount of data to collect?

Experts from the learning analytics field tend to favor a top-down approach: Meaningful questions should be posed to drive the data collection and analysis. They advocate a targeted strategy of collecting the right data in the right form at the outset.

In contrast, data mining researchers favor a bottom-up approach supported by a more inclusive data collection strategy. They believe that collecting more data allows for exploratory data mining approaches in which a main question drives analysis, but the large amount of data collected supports finding unexpected patterns.

Solutions from commercial companies have also shown promise in a middle ground, such as collecting dense usage data from a randomly selected sample of users to inform product improvement.

What is the right data structure?

Given the heterogeneous (many data sources) and hierarchical (multiple levels) nature of educational data, determining data structures and data formats that accurately represent an event under consideration become key. A basic data format may be a "learning transaction" generated by the system, the student, or the interactions between the two.

The best data structure and analytic techniques are determined by the types of problems to be solved. Answering a focused question takes extensive data cleaning and extraction, and it is very important to have the best analytic algorithm. Pattern-seeking approaches, such as outlier detection (e.g., to detect atypical student behavior, such as novice mistakes or irregular learning), on the other hand, require less data cleaning and can employ a coarser algorithm.

steps of the data mining and analytics process. Smart data consumers can help determine what questions to address, what data to collect, and how to make reports meaningful and actionable. They can also help interpret data, discern and label patterns, and guide model building. Data mining and analytics technology play a supporting role in the essentially human and social effort of making meaning out of experience. One expert interviewed stressed that data mining and analytics do not give answers when just unleashed on a big data warehouse. Instead, the recommendation was to approach the problem in an informed way, considering what can be acted on, what evidence can came from data analysis, and what early pilots of the data mining and analytics applications reveal.

Smart data consumers must learn to keep an open mind to what the data say. Data mining and analytics techniques can confirm or disconfirm teachers' and students' beliefs about student knowledge, abilities, and effort. Sometimes, these beliefs are not consistent with the data: Teachers may believe particular students are more or less capable than they are, and students may report spending more time and effort on learning than they actually do. For example, one company found in an A/B study it conducted on the use of visualizations that students were more engaged when complex visualizations were included in the software. Students identified complexity as a source of their engagement, but teachers thought the visualizations were too complex, underestimating what the students were capable of understanding.

Privacy and Ethics Issues

It has been acknowledged for many years (e.g., Kobsa 1990) that personalized interaction and user modeling have significant privacy implications because personal information about users needs to be collected to customize software to individuals. Press coverage and recent Federal Trade Commission rulings have highlighted online companies' privacy protection lapses. Data mining researchers have exposed obvious weaknesses, e.g., querying a social network for registered email addresses on a large scale (Balduzzi et al. 2010).[5] Consumer surveys (ChoiceStream 2005) often show that while online users value personalized content, they are also concerned about their privacy on the Internet. At the same time, privacy versus personalization is not a simple trade-off: A more complete set of factors includes personal and community attitudes, how far the disclosed information differs from the norm, and even how much users know about what was disclosed and how much control they have over it (Kobsa 2007).

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[5] Starting with a list of about 10.4 million email addresses, Balduzzi et al. (2010) were able to automatically identify more than 1.2 million user profiles associated with the addresses. By searching through these profiles, they collected publicly available personal information about each user. After being exposed, this social network's vulnerability was repaired.

Education institutions must consider privacy, policy and legal issues when collecting, storing, analyzing, and disclosing personally identifiable information from students' education records to third parties for data mining and analytics. The *Family Educational Rights and Privacy Act* (*FERPA*) is a federal law that protects the privacy of students' education records. However, *FERPA* generally allows for the disclosure of personally identifiable information from a student's education record without consent to "school officials" if there is a legitimate education interest.[6] When a school controls learning software on its own hardware, or hosting is provided by a district or county computing facility, its IT department standards are in force as they would be for any student data, such as a grade book and attendance records. If the institution purchases an externally hosted analytics-based solution from a third party, de-identified student and teacher data will need to be released to fine-tune predictive models or be used in models to generate actionable intelligence. As with other kinds of analyses on large sets of longitudinal data, analyses that result in disclosure may be hard to foresee. In such cases, the more features of the data that are released (e.g., time of day homework was done simultaneously) the more valuable predictions can be (e.g., hours of operation for school-based homework centers) and the higher the likelihood of unintended disclosure (e.g., by pinpointing students who work after school).

A full discussion of privacy and confidentiality is beyond the scope of this document. The move to build statewide longitudinal data systems has raised similar concerns, and, in response, resources are available that address data management for education and research purposes, such as the technical brief series from the Department's National Center for Educational Statistics (e.g., U.S. Department of Education, 2010c). Recent guidance on *FERPA* (U.S. Department of Education, 2012a) has helped clarify how institutions may use detailed and longitudinal student data for research, accountability, and school improvement under certain conditions in compliance with *FERPA*. These revisions to the existing *FERPA* regulations increase access to data for research and evaluation (including sharing across levels, such as from high school to college) while maintaining student privacy and parents' rights (U.S. Department of Education, 2012b).

Educational data mining and learning analytics make predictions and recommend actions based on increased visibility into student actions, and these give rise to a number of social and ethical concerns. Experts cited the ethical obligation to act on the knowledge about students gained through data mining. Educational data analysts should share their insights with those who can benefit from them (for example, students, teachers, and school districts), and what is shared must be framed in a way that benefits rather than harms. For example, is it useful to share with a particular student that he has only a 20 percent chance of success in a course given his past

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[6] Pursuant to 34 CFR § 99.31(a)(1) of the *FERPA* regulations, prior consent is not required to disclose education records to "school officials" with "legitimate educational interests" so long as the disclosing education institution or agency provides annual notification to its students regarding who constitutes a school official and what constitutes a legitimate education interest.

performance? What is the impact of this finding on the classroom and on the teacher's practices? What will happen to the student-teacher relationship once such results are released?

Policymakers bear an ethical responsibility to investigate the validity of any predictive model that is used to make consequential decisions about students. Policymakers must be able to explain the evidence for predictions and the actions taken by the computer system on the basis of learning analytics. Analysts conducting data mining may discover patterns or associations that were previously unknown and that involve sensitive information (e.g., teacher performance or student's family situation), and validating them with external observations and further data collection will be needed.

Recommendations

Education institutions pioneering the use of data mining and learning analytics are starting to see a payoff in improved learning and student retention (Koedinger, McLaughlin, and Heffernan 2010). As described in a practice guide of the Department of Education's Institute of Education Sciences (Hamilton et al. 2009), working from student data can help educators both track academic progress and understand which instructional practices are effective. The guide describes also how students can examine their own assessment data to identify their strengths and weaknesses and set learning goals for themselves. Recommendations from this guide are that K–12 schools should have a clear strategy for developing a data-driven culture and a concentrated focus on building the infrastructure required to aggregate and visualize data trends in timely and meaningful ways, a strategy that builds in privacy and ethical considerations at the beginning. The vision that data can be used by educators to drive instructional improvement and by students to help monitor their own learning is not new (e.g., Wayman 2005). However, the feasibility of implementing a data-driven approach to learning is greater with the more detailed learning microdata generated when students learn online, with newly available tools for data mining and analytics, with more awareness of how these data and tools can be used for product improvement and in commercial applications, and with growing evidence of their practical application and utility in K–12 and higher education. There is also substantial evidence of effectiveness in other areas, such as energy and health care (Manyika et al. 2011).

Internet businesses—both providers of general commodities and services, and learning software companies—have discovered the power of using data for rapid improvement of their practices through experimentation and measurement of change that is *understandable* and that leads to *actionable* next steps. The key for data analysis consumers, such as students, parents, teachers, and administrators, is that the data are presented in such a way that they are clearly answering a question being asked and point toward an action that is within the data consumer's repertoire.

In the remainder of this section, in addition to these existing recommendations specific ones for educators, researchers, and developers using educational data mining and learning analytics are provided. Possible collaborations across sectors, and the role of states in supporting the adoption of analytics applications, also are addressed.

Educators

Stakeholders in the K–12 and higher education sectors should increase the use of educational data mining and learning analytics to improve student learning. The experts and TWG recommendations to facilitate adoption, including the role of states, are as follows.

Educators should develop a culture of using data for making instructional decisions. This brief builds on the recommendations of the U.S. Department of Education (2010b) report calling for development of the mind-set that using data more strategically can drive school improvement. Educators need to experience having student data that tell them something useful and actionable about teaching and learning. This means that instructors must have near-real-time access to easy-to-understand visual representations of student learning data at a level of detail that can inform their instructional decisions. Scores on an achievement test taken six months ago do not tell a teacher how to help a particular student tomorrow. The kinds of data provided to instructors need to be truly helpful in making instructional decisions, and instructors will need to come to these learning data with a different mind-set than that engendered by data systems geared to serving purposes of accountability.

Districts and institutions of higher education need to understand that their information technology department is part of the effort to improve instruction but is not the only responsible department. Establishing a data-driven culture requires much more than simply buying a computer system. District staff from the information technology department need to join with assessment, curriculum, and instruction staff, as well as top decision makers, and work together to iteratively develop and improve data collection, processing, analysis, and dissemination. A U.S. Department of Education report (Hamilton et al. 2009) suggests that districts foster a culture of using data by beginning with such questions as: Which instructional materials or approaches have been most effective in promoting student learning of this area of math content? Are there differences in course success rates for students coming in to our high schools from different feeder schools? Are there teachers who are particularly successful in terms of their students' learning gains whose practice might serve as a model for others?

Understand all details of a proposed solution. When purchasing learning software or learning management systems, districts should demand details about the kinds of learning analytics the system will generate and make sure the system will provide teachers and school leaders with information they can use to improve teaching and learning: What are the analytics based on? Have these measures been validated? Who gets to see the analytic data and in what format, and what do they have to do to gain access? If students, teachers, and district administrators will use visualizations or other reports from a data mining or an analytics package, they should evaluate the solution to make sure the data are presented in a comprehensible way. Give teachers the opportunity to ask questions about data mining and analytics that go beyond the numbers, colors, or charts and instead probe the value that the analytics system will bring to them and the steps they can take in response to the data the system will give them. Any predictive models proposed for consequential use (such as assigning students to services or qualifying them for advanced courses) should be transparent and backed up by solid empirical evidence based on data from similar institutions.

Start small and leverage the work of others. It can be tempting to latch on to a solution that promises to integrate all data systems to support powerful learning analytics. But the experience of districts pioneering the use of data-driven decision making suggests that there are no easy turnkey solutions (Hamilton et al. 2009). Districts and higher education institutions typically have much more data than they actually use to inform their actions. Part of the problem is that data reside in multiple systems in different formats. The development of standards for education information systems, software to facilitate data integration from multiple systems, and designing easy-to-use data dashboards on top of different data systems are all active areas of technology development. At the present time, however, districts typically incur significant costs when trying to integrate data across different systems. In addition to technology and user interface development costs are the costs involved in developing staff capacity for using data in smart ways. Adoption should be conceptualized as a set of processes and ongoing investments rather than a one-time purchase of a single product or technology. Data mining and analytics can be done on a small scale. In fact, starting with a small-scale application can be a strategy for building a receptive culture for data use and continuous improvement that can prepare a district to make the best use of more powerful, economical systems as they become available. Starting small can mean looking at data from assessments embedded in low-cost or open learning systems and correlating those data with student grades and achievement test scores. Some open educational software systems that provide analytics are listed in the "Selected Websites: Online Learning Systems with Analytics" section at the end of this report.

Help students and parents understand the source and usefulness of learning data. As colleges and schools move toward the use of fine-grained data from learning systems and student data aggregated from multiple sources, they need to help students understand where the data come from, how the data are used by learning systems, and how they can use the data to inform their own choices and actions. Feedback is an important variable in changing behavior, and research on systems like Purdue's Signals suggests that many students will respond appropriately in the face of feedback that they understand. Similarly, parents can help their children make smarter choices if they have access to student data and understand how the data are generated and what they mean.

Align state policy to support the move to online learning. State policy plays an important leadership role in the changes required to adopt an analytics-focused approach to education. To support adoption of online and digital learning at the district and school level, state-level organizations must advocate for and set policies to follow road maps to implement change. Efforts to support reform implementations, such as Digital Learning Now (http://digitallearningnow.com) and the Data Quality Campaign (http://www.dataqualitycampaign.org), highlight requirements for better data systems, broader and faster Internet connections, one-to-one Internet access for all students, online assessments tuned to measure mastery, interoperable and portable electronic student records, and professional development for educators and administrators. Leadership across the state is required from governors, education chiefs, legislators, and education boards.

Taking advantage of this kind of digital data infrastructure also will require research to develop and validate new techniques for efficiently extracting evidence of the effectiveness of specific instructional interventions or approaches. Learning and education research provide a basis for identifying key variables to examine as potential predictors of students' learning and educational attainment. If these variables are captured in connected data systems, data analytics techniques can determine the extent to which there are relationships between them and desired outcomes, providing evidence both for improving and for choosing among instructional products and practices. While such analyses would not meet the current gold standard of evidence from random-assignment experiments, they would prove convincing to many educational practitioners, particularly when they are replicated across multiple data sets by multiple researchers. An ongoing effort, sponsored by the Office of Educational Technology, is examining the issue of an appropriate evidence framework for digital learning and a draft report is expected by the end of 2012.

Researchers and Developers

R&D in educational data mining and learning analytics occurs in both academic and commercial organizations. Research and development are tightly linked, as the field seeks to understand basic processes of data interpretation, decision making, and learning and to use those insights to develop better systems. We encourage the R&D community to consider these recommendations, as well as continuing experimentation that show evidence of the impact of these approaches on student learning.

Conduct research on the usability and impact of alternative ways of presenting fine-grained learning data to instructors, students, and parents. Data visualizations provide an important bridge between technology systems and data analytics, and determining how to design visualizations that practitioners can easily interpret is an active area of research. Solving this problem will require identifying the kinds of choices or decisions that teachers, students, and parents want to make with fine-grained learning data, and the time pressure and cognitive load factors present when different kinds of decisions are made.

Develop decision supports and recommendation engines that minimize the extent to which instructors need to actively analyze data. The teacher in a truly instrumented classroom would have much more than access to student scores on state and district tests. Diagnostic real-time assessment tools and decision support systems would enable the instructor to work with automated systems to make decisions "on the fly" to improve instruction for all students (Crawford et al. 2008). But conscious labor-intensive processing of data is not possible under the time constraints of efficient classroom management. To support teachers in the act of instruction, we need decision supports and recommendation systems that link student learning profiles to recommended instructional actions and learning resources. We give such tools to physicians and military decision makers; education is no less complex and no less important.

Continue to perfect the anonymization of data and tools for data aggregation and disaggregation that protect individual privacy yet ensure advancements in the use of educational data. Recent amendments to the *FERPA* regulations have provided clarification on the legality of states and school districts disclosing student data for audit, evaluation, or study purposes. Much remains to be done, however, in figuring out how to support aggregation and disaggregation of student data at different levels of the education system (classroom, school, district, state) in ways that make it possible to combine data from different sources yet protect student privacy in compliance with applicable law.

Develop models for how learning analytics and recommendation systems developed in one context can be adapted and repurposed efficiently for other contexts. Differences in educational contexts have made it a challenge to transfer developed predictive models across educational settings. Because students, administrative policies, course programs (e.g., four-year vs. community colleges), and/or adopted learning systems often vary among institutions, student learning data that can be collected changes, too. Thus, a model developed for one institution usually cannot be applied directly and efficiently to another without research into whether it must be changed for the new context (Lauría and Baron 2011). Understanding how this process can become more efficient will be key to scaling up the use of learning analytics.

Collaborations Across Sectors

As noted above, building the capacity of education organizations to use data mining and analytics meaningfully is a major undertaking. This section addresses R&D collaborations that can aid the process. The advisors consulted recommended collaboration among learning system designers (often commercial entities), learning scientists, and educators. Learning product designers want access to the knowledge base built by academic researchers. Policymakers want findings about student learning and clear-cut guidelines for practice (e.g., O'Neil 2005). As the education system moves from print to digital classrooms, learning products will change rapidly, and academic institutions and policies must respond accordingly. It is anticipated that the next five years will bring an increase in models for collaboration among learning system designers, researchers, and educators. Possibilities for such collaborations include the following:

- Learning labs where commercial designers can make data from their learning systems available to the research community, as is being done through the Pittsburgh Science of Learning Center's DataShop (Koedinger et al. 2010)
- Partnerships between research organizations and education organizations to improve research-based products. For example, the Strategic Education Research Partnership (SERP) is an organization that stimulates innovation in education through sustained collaboration among distinguished researchers, educators, and designers. Under SERP, researchers built a set of in-depth partnerships with large school systems and developed tools and interventions in Boston and San Francisco to help middle and high school teachers, particularly those in science, social studies, and other content areas, incorporate academic vocabulary into their teaching.
- Organizational structures that bring together people with the requisite expertise from industry, academia, and school systems in a sustained interaction to improve learning systems. The recent program called Digital Promise (http://www.digitalpromise.org/) has the goal of fostering sustained investments in such partnerships, which are much more likely to have an impact than simply publishing research and expecting that the commercial sector will incorporate it into products.

Conclusion

Working with big data using data mining and analytics is rapidly becoming common in the commercial sector. Tools and techniques once confined to research laboratories are being adopted by forward-looking industries, most notably those serving end users through online systems. Higher education institutions are applying learning analytics to improve the services they provide and to improve visible and measurable targets such as grades and retention. K–12 schools and school districts are starting to adopt such institution-level analyses for detecting areas for improvement, setting policies, and measuring results.

Now, with advances in adaptive learning systems, possibilities exist to harness the power of feedback loops at the level of individual teachers and students. Measuring and making visible students' learning and assessment activities open up the possibility for students to develop skills in monitoring their own learning and to see directly how their effort improves their success. Teachers gain views into students' performance that help them adapt their teaching or initiate interventions in the form of tutoring, tailored assignments, and the like. Adaptive learning systems enable educators to quickly see the effectiveness of their adaptations and interventions, providing feedback for continuous improvement. Researchers and developers can more rapidly compare versions A and B of designs, products, and approaches to teaching and learning, enabling the state of the art and the state of the practice to keep pace with the rapid pace of adoption of online and blended learning environments.

Open source tools for adaptive learning systems, commercial offerings, and increased understanding of what data reveal are leading to fundamental shifts in teaching and learning systems. As content moves online and mobile devices for interacting with content enable teaching to be always on, educational data mining and learning analytics will enable learning to be always assessed. Educators at all levels will benefit from understanding the possibilities of the developments described in the use of big data herein.

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Patil, D.J. 2012, September. *Building Data Science Teams*. @dpatil shares his advice on "what data scientists add to an organization, how they fit in, and how to hire and build effective data science teams." He also presents highlights of how Internet companies use big data. http://radar.oreilly.com/2011/09/building-data-science-teams.html

Romero, C. R., and S. Ventura. 2010. "Educational Data Mining: A Review of the State of the Art." *IEEE Transactions on Systems, Man and Cybernetics, Part C: Applications and Reviews* 40 (6): 601–618. In the introduction, Romero and Ventura describe different types of data mining techniques, both classical and emergent, used for educational tasks by different stakeholders.

Romero, C., S. Ventura, M. Pechenizkiy, and R. S. J. d. Baker (eds.). 2010. *Handbook of Educational Data Mining*. Boca Raton, FL: CRC Press. This book provides a technical overview of the current state of knowledge in educational data mining. It helps education experts understand what types of questions data mining can address and helps data miners understand what types of questions are important in education decision making.

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Selected Websites

Visualization and Data Exploration

http://www-958.ibm.com/software/data/cognos/manyeyes/. Many Eyes lets users explore existing visualized datasets and upload their own for exploration. Users can comment on visualizations or create topic areas for discussion. Visualization types are organized by how they show the data (e.g., "See the parts of a whole" for data laid out in pie charts and "See the world" for data laid out on maps) and datasets can be numerical, textual, or spatial.

http://hint.fm/. Data visualization meets art in this site showing work by Fernanda Viégas and Martin Wattenberg.

http://research.uow.edu.au/learningnetworks/seeing/snapp/index.html. Social Networks Adapting Pedagogical Practice (SNAPP) is a tool for visualizing networks resulting from the posts and replies to discussion forums as a measure of student interactions.

http://www.socialexplorer.com/. Social Explorer is an online tool that allows map- and report-based visualizations of census data and demographic information. Flexible enough for use in sectors ranging from education to journalism.

http://www.tableausoftware.com/products/public. Tableau Software offers a free data visualization tool that companies, individuals, and journalists use. Visualizations are stored on the Tableau Public site but are embeddable into blogs or websites.

Online Learning Systems With Analytics

http://www.assistments.org. The ASSISTments online platform helps teachers write questions for assessments and then see reports on how their students performed. Students can get immediate tutoring while they are being assessed.

http://wayangoutpost.com/. Wayang Outpost is an intelligent tutoring system that helps middle and high school students study for standardized tests and adjusts instruction as they progress.

http://oli.web.cmu.edu/openlearning/forstudents/freecourses. The Open Learning Initiative (OLI) offers open and free courses on such subjects as biology, programming, chemistry, and statistics. Both students and instructors get timely and targeted feedback.

http://www.khanacademy.org/. Khan Academy provides a library of videos, worked examples, and practice exercises, organized into knowledge maps, for self-paced learning in many topic areas. Khan Academy keeps track of students' progress and shows at-a-glance displays for students, parents, and educators.

Professional Organizations

http://www.educationaldatamining.org. Educational data mining researchers have been organizing yearly international conferences since 2008. The *Journal of Educational Data Mining* was launched in 2009, and in 2011 the International Educational Data Mining Society was founded by the International Working Group on Educational Data Mining.

http://www.solaresearch.org. In 2011, a professional society for exploring analytics in teaching, learning, training and development systems was founded, the Society for Learning Analytics Research. Beginning in 2010, a yearly conference has been held, the International Conference on Learning Analytics and Knowledge.

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