Adaptive Learning Systems

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Executive Summary

Adaptive learning dynamically adjusts the level or types of instruction based on individual student abilities or preferences, and helps personalize instruction to improve or accelerate a student's performance. It does this by helping to address common learning challenges, including student motivation, diverse student backgrounds, and resource limitations. Targeting instruction to the abilities and content needs of the individual student can reduce course drop-out rates, improve student outcomes and/or speed of achieving those outcomes, and enable faculty to dedicate their attention where it is most needed.

While adaptive system developers refer to components of their structure differently, adaptive learning involves at least three components: a model of the structure of the content to be learned (a content model), a means of understanding student abilities (a learner model), and a method of matching the content and how it is presented to the student in a dynamic and personalized fashion (an instructional model).

Initial efforts funded by government grants were generally targeted to K-12 learning, primarily in math topics, and focused on modeling one-on-one tutoring (Intelligent Tutoring Systems). Some of these initial systems have been adapted to additional content domains, such as science, and expanded into higher education. Some have been commercialized and are sold through established publishers. Publishers have also developed proprietary systems, and the last several years have seen a series of partnerships and acquisitions enabling additional adaptive learning products and greater distribution of existing ones.

While adaptive learning systems have tended to use a publisher model, where the course content is built into the individual product itself, newer platform models provide authoring tools

that enable individual faculty or curriculum teams to create adaptive learning products. Simpler adaptive learning systems are rule-based, created using a series of if-then statements. These are more content-oriented and easier to understand in terms of functionality, but they are also far more limited in their ability to adapt to individual student abilities or needs. Algorithm-based systems take advantage of advanced mathematical formulas and machine learning concepts to adapt with greater and greater specificity to individual learners. Cloud computing technologies and techniques for managing big data have increased the power of algorithm-based systems to adapt more quickly.

Research continues into advancing the technologies used in adaptive learning systems. Natural language processing is being used to enable systems to better interpret written or even spoken student questions or other student input. The ability to detect a student's emotional state is in the experimental stage, with anticipation that systems will be able to respond with appropriate motivational techniques based on its interpretation of whether students feel bored, frustrated, etc. A continuing challenge involves content domains that are not clearly structured or do not involve right or wrong answers.

Adaptive learning systems are being used as fully online courses, as supplements for online courses, or within blended learning contexts. Challenges to implementation are increasingly operational rather than technological. Structural issues such as term-lengths can become problematic when students are advancing at different paces. In these cases, adaptive learning can be connected to other innovations such as competency-based learning. Incorporating adaptive learning into existing instructor-driven online courses as more than a supplement can be challenging, involving significant training needs for students, faculty, and student support personnel. How adaptive systems integrate with learning management systems and provide easy-to-use learning analytics will likely be a focus of the products as they continue to develop over the next several years.

Adaptive learning is likely to increase at an accelerating pace at all levels of U.S. education. A tipping point may only be a few years away, where adaptive learning becomes a standard and expected offering rather than a relative rarity.

What Is Adaptive Learning?

Adaptive learning refers broadly to a learning process where the content taught or the way such content is presented changes, or "adapts," based on the responses of the individual student. This paper will provide a more specific definition, but the breadth of this initial statement's application raises an important point: good teachers have always adapted to students. The quality of a faculty member can even largely (but not completely) be determined by how good he/she is at identifying not just that a student is incorrect, but why the student is incorrect and what can be done to alter the student's understanding. Over time, expert faculty can predict how someone can go wrong with particular concepts, identify common misconceptions, and correct them. In this sense, most classroom learning, and all individual tutoring, can be considered adaptive.

Technology-enhanced, computerized, or digital adaptive learning takes what the expert instructor does, automates it for scale, and potentially improves its effectiveness. Going forward, this paper will refer to adaptive learning systems, which is the term used to define such software by the Department of Education's Office of Educational Technology:

> Digital learning systems are considered adaptive when they can dynamically change to better suit the learning in response to information collected during the course of learning rather than on the basis of preexisting information such as a learner's gender, age, or achievement test score. Adaptive learning systems use information gained as the learner works with them to vary such features as the way a concept is represented, its difficulty, the sequencing of problems or tasks, and the nature of hints and feedback provided.
>
> (U.S. Department of Education, Office of Educational Technology, 2013)

The goal of an adaptive learning system is to personalize instruction in order to improve or accelerate a student's performance gain. At their core, such systems are intended to identify what a student does and doesn't understand, identify and provide content that will help the student learn it, assess again, help again, etc., until some defined learning goal is achieved. This potentially addresses some core practical challenges in teaching and learning:

- content that is too easy or too hard tends to de-motivate students, boring them if it's too easy and frustrating them if it's too hard;
- students come to a class with fundamentally different levels of prior knowledge; and
- costs of education prevent a student from receiving the one-on-one instructor attention that has been shown to make a major improvement in learning.[1]

The excitement over adaptive learning systems stems from their potential to target instruction at just above the student's ability level (to challenge but not discourage the student) and at the student's specific content needs. In addition, some adaptive learning systems address student preferences in learning, such as whether information is presented in text or audio format, whether they prefer to learn using case studies or multimedia testing tools, etc. By making personalized learning scalable, adaptive learning has the potential to:

- reduce course drop-out rates;
- be more effective at achieving outcomes;
- be more efficient for students, helping them achieve outcomes faster;
- free up faculty to focus on direct assistance where it is needed most.

[1] Most histories of adaptive learning in academia refer to a 1984 paper by Bloom, of Bloom's Taxonomy fame, which claimed that individual human tutoring increased the effectiveness or rate of learning by two standard deviations, which he referred to as the "2-Sigma Problem" (Bloom, 1984).

Studies have shown repeatedly that adaptive learning systems are more efficient and more effective in achieving student outcomes relative to traditional methods. A recent study concluded that some adaptive systems were nearly as effective as one-on-one human tutoring (VanLehn K. , 2011).

Three Core Elements of Adaptive Learning Systems

Adaptivity can sometimes be confused with straightforward interactivity. Appendix A provides simplified examples of functionalities from the student perspective and gives you an opportunity to consider whether these represent adaptive learning systems.

Even though the goals are always similar, adaptive learning systems can differ drastically in practice; the range of sophistication, level of detail, and even the diversity of user-interface designs, can make it difficult to know what someone is referring to exactly when they say a product is adaptive. While there may be exceptions, adaptive learning systems are generally built on three core elements: a content model, a learner model, and an instructional model.

A content model. This refers to the way the specific topic, or content domain, is structured, with thoroughly detailed learning outcomes and a definition of tasks that need to be learned. Some initial sequencing of content is pre-determined, although in many cases the idea of adaptive learning is that sequencing can change based on student performance. But the system must be able to identify which content is appropriate based on what the student knows at any point in time. Some systems may have larger chunks of content that go together, and a student is assessed only after this unit of learning; others may assess a student understanding at a finer level.[2]

A learner model. In order to adapt, many adaptive systems make statistical inferences about the student's knowledge based on their performance; they must "model" the learner. They may numerically estimate the student's ability level on different topics, or carefully track the student's existing knowledge base – what sub-topics they have mastered. They may even make inferences about a student's cognitive learning style, or the best time of day for a student to study. Learner models continue to become more complex, considering additional variables such as the student's motivational state and emotional response.

***An instructional model*.** The instructional model determines how a system selects specific content for a specific student at a specific time. In other words, it puts together the information from the learner model and content model to, ideally, generate the learning feedback or activity that will be most likely to advance the student's learning.

Growth of Adaptive Learning

Corporate training. We may tend to think of adaptive learning as being designed only for formal school contexts, but that is not the case. In many ways, adaptive learning is more common in corporate eLearning, arguably because the scope of learning tends to be relatively narrow and focused, which makes the content easier to put into an adaptive framework. Other factors may include the flexibility of time-frames for workplace learning, and the clear return-on-investment for self-study learning and learning that is more time efficient.

[2] "For example, instead of monitoring mastery of large topics such as 'solving equations,' new systems can monitor for fine-grained skills such as 'solving an equation of the form –x = a'" (U.S. Department of Education, Office of Educational Technology, 2013, p. 30).

Elementary and secondary education. Adaptive learning systems have also been more common in elementary and secondary education than at the college-level. This is because initial government grants funded projects geared towards public elementary and secondary schooling. The grants were provided to university researchers in cognitive psychology, education, mathematics, and computer science departments. Emerging from these research projects were systems generally referred to as Intelligent Tutoring Systems. Two of the systems that gained the greatest popularity and are still in use are Carnegie Learning's Cognitive Tutor, and ALEKS. ALEKS emerged from research at UC-Irvine and New York University, and Cognitive Tutor from research at Carnegie Mellon University. Both focused initially on math skills, and both were built using specific cognitive theories.[3] Over time, continued developed enabled both systems to work for science topics as well as math, and to be used for higher education use.

Intelligent Tutoring Systems (ITS) had a number of elements in common. Unlike early online courses that were being developed, ITSs were designed to closely mimic one-on-one tutoring. Multiple research studies examined the difference between expert and novice tutors, and developed certain guidelines and procedures that were built into the systems (Lehman, D'Mello, Cade, & Person, 2012). Rather than using multiple choice questions, these systems tended to focus on numerical inputs, and instead of a student providing just an answer, the student would fill in all the various steps taken towards a solution. The learner was, therefore, modeled at a very fine-grained level, and hints or feedback could be given either at each step along the way, or at the end of the problem. The system would then select the next question based on the information gained from student responses. This combination of finely-grained,

[3] Cognitive Tutor, as well as the CTAT authoring tools, are based on ACT-R, a cognitive architecture that distinguishes between declarative and procedural knowledge, and theorizes how students move from one "state" – a current level of understanding – to another, through a series of "productions." ALEKS, which stands for Assessment and Learning in Knowledge Spaces, is built using a theoretical approach called Knowledge Space Theory. This approach maps out a content domain and the relationships between its different knowledge components, using this content structure and student performance to estimate the student's "readiness" for certain material.

step-by-step detail, and content or question selection, has been referred to as a double-loop model (VanLehn, 2006).

These systems were initially designed to be used with computers in school facilities; after all, they expanded prior to the explosion of the internet. They were also primarily intended to supplement core course instruction. Cognitive Tutor was sold as part of an end-to-end curriculum solution, including Carnegie's Learning's printed instructional materials. Over time, ITSs have generally become more independent and geared towards pure self-study. ITSs that could be used regardless of curriculum had advantages in the market (VanLehn, et al., 2005).

In 2011, Cognitive Tutor was being used by 600,000 students in grades 6-12.[4] The ALEKS website specifically lists over 900 K-12 implementations of the software, some of which refer to individual schools and some to entire districts.[5] Millions of students have used ALEKS. Both systems have also been researched for their effectiveness. Carnegie Learning claims that Cognitive Tutor's Algebra I product improves performance of complex mathematical problem solving by 85%, and that students are 70% more likely to complete subsequent courses in Geometry and Algebra II[6]. A recent study by the University of Memphis found a significant increase in attendance and math performance when ALEKS was implemented in after-school programs (Craig, et al., 2011).

The government program Race to the Top, and the implementation of the Common Core Standards, along with cloud computing and mature technologies, have led to an explosion of adaptive learning systems available for elementary and high schools. Among start-up companies in this space are ScootPad, Dreambox Learning, and KnowRe.

[4] http://www.carnegielearning.com/press-room/press-releases/2011-08-02-apollo-group-to-acquire-carnegie-learning/
[5] http://www.aleks.com/k12/implementations
[6] http://www.carnegielearning.com/research/

Higher education. The use of adaptive learning in higher education has been slower to develop, and challenges that likely contributed to slow adoption remain. Whereas curriculum decisions are often made at the district or school level in elementary and secondary education, individual faculty members typically select learning materials in higher education. In essence, this means that adoption is done one course section at a time. The earliest implementations of adaptive learning, therefore, tended to be as non-credit remediation and placement tools as opposed to courseware.

Despite these challenges, adaptive learning is beginning to accelerate very rapidly in higher education courses, partly/largely driven by partnerships between publishers and adaptive learning companies. For example, McGraw-Hill partnered with software developer Area9 to create their adaptive LearnSmart product, which was first offered in 2008. The first products focused on subjects such as medical terminology, but have expanded since into 30 disciplines, including accounting, communication and psychology. In 2010, Knewton, an early private provider of a statistical infrastructure enabling adaptive learning, expanded beyond its initial GMAT prep product to partner with large universities to create adaptive remedial math education courses.[7] A key turning point was the 2011 partnership between Knewton and Pearson (the leading publisher of educational content) to have Knewton power Pearson's popular MyLabs products. Also in 2011, Apollo Education Group, owner of University of Phoenix, acquired Carnegie Learning for $75 Million. In 2012, Macmillan acquired PrepU, which is now deployed in nursing products as an adaptive testing system for students to gauge mastery.

[7] Among Knewton's initial clients were Arizona State University, Penn State University, University of Nevada-Las Vegas, and Washington State University.

It is likely that 2013 will be viewed as a watershed year, setting the stage for future adaptive learning use throughout the entire U.S. higher education system. Acquisition and partnerships included the following:

- Kaplan acquired Grockit (an adaptive test-prep start-up);
- McGraw-Hill purchased ALEKS (it had previously been the system's distributor);
- Learning Management System (LMS) provider Desire2Learn purchased Knowillage Systems, a start-up with an adaptive learning and analytics system called LeaP;
- Elsevier partnered with Cerego, a memory-building system originally created for language-learning;
- Wiley partnered with SnapWiz to build its adaptive learning system into Wiley's online environment, re-branded WileyPLUS;
- Career Education Corporation (CEC, owner of American InterContinental University, Colorado Technical University, International Academy of Design & Technology, and cooking school Le Cordon Bleu) partnered with CCKF to build 300 adaptive courses using its adaptive learning system RealizeIt, which will be branded Intelli-Path for CEC;
- Knewton partnered with additional publishers, including Cambridge University Press and Houghton Mifflin Harcourt.

We are certainly at the point where every major publisher producing online material for higher education will need to have some form of adaptive learning system as part of their offering. And while some LMS providers may incorporate specific adaptive learning capabilities, it is more certain that they will need to enable all the new systems from publishers and client schools to work with their existing platform. How these systems integrate with each other, and with publisher content, will be interesting to observe.

Cloud computing and statistical techniques for managing big data have also changed how these systems work. A cognitive theory about the structure of student understanding or a content domain is no longer necessary if large amounts of student performance data can be generated quickly and consolidated for analysis. This type of big data system, such as Knewton, compares learning success rates associated to particular content and combines that with data about a student's ability level on that content topic to select the most appropriate content for a student to interact with at any given time.[8]

Publisher vs. Platform

There is a key difference between systems that are designed to provide a platform for individual instructors or curriculum teams to create or import content in the system (platform-model), and those where the content is pre-built by the provider (publisher-model). For proprietary products, this question is really about the business model associated to the system: is it a software licensed to a school or corporation for the building of adaptive learning products; or is it sold as an existing "course" or course supplement to corporations or students (or included in tuition) as a textbook would be?

Publisher Model. To date, most systems have been of the latter publisher variety, providing pre-existing content; often the system is specifically developed for that content domain. Intelligent tutoring systems tend to be fully equipped with the content, since the content or cognitive mapping must be built into the tutor. Systems designed or altered to operate across domains may contain the ability for some rules or sequencing to be changed by the instructor, or

[8] Theoretically, no sequence for the content must pre-exist. If you want someone to learn A, you could have content available about many different topics. Eventually, the system would recognize that students who read material about A performed better on the assessment items related to A and, over time, all students would receive material on A only. Also over time, the system might recognize that most students performed better by taking two different content modules associated to A in a particular sequence. Eventually, the system would work so that most students did so. In practice, of course, it would be a terrible experience for the initial group of students who had to wade through completely un-sequenced material, so there will always be some structure to the content at the start that the system can refine over time.

for content to be added. But, as a general rule, the idea is for these systems to be plug-and-play. Adapt Courseware is a clear example, in essence providing online, adaptive textbooks that can be used as complete online courses if desired. MindEdge is a similar example. Pearson's MyLabs (using Knewton for its adaptive functionality), McGraw-Hill's LearnSmart (with an adaptive engine created by software developer Area9), etc., are established examples, although often used as a means of supplementing the sale of traditional textbooks or separate eBooks. An important differentiation in the publisher model is between systems that can be integrated into other LMSs versus those that have their own.

Platform Model. Other systems provide the platform and some means for faculty or instructional designers to author the content on the platform. This is a growing part of the market. And since the model is new, proprietary systems are primarily offered by start-ups. Smart Sparrow, CogBooks, and Cegero follow this model, which may also include the selling of instructional design services if requested. It is also likely that Blackboard and other learning management systems (LMS) will follow their competitors Desire2Learn and LoudCloud in incorporating such functionality into their course building tools. Tools also exist within the academic world to build adaptive systems, including the Cognitive Tutor Authoring Tools (CTAT) from Carnegie Mellon.[9]

Knewton is a platform model, in that the company does not create content. However, neither does their system seem to be set up to be used as an independent authoring tool, although the company has previously announced plans to create one. At least currently, partnership is required for Knewton to assist in converting the content into its adaptive system. Knewton has

[9] The website states that CTAT is free to use for research purposes only: http://ctat.pact.cs.cmu.edu/

partnered with publishers (such as Pearson) and some schools (such as Arizona State) to provide a content-agnostic platform infrastructure that enables adaptive learning through data analysis. Knewton's statistical system allows for less content structuring at the start than others (it is an algorithm-based system, as described in the next section).

Rule-Based or Algorithm-Based

While not necessarily visible to the student, there are two fundamentally different types of instructional (or selection) models for adaptive learning systems. Different labels have been used, but the most common is likely rule-based versus algorithm-based.

Rule-based. Rule-based systems are most often built using a series of if-then functions. At their simplest, these systems employ a straightforward branching architecture. A student is asked a question; if they get it right, they move on to the next selected activity; if they get it wrong, they are given some additional content to assist them. That assistance may be a hint, repeated content, or content that explains the material in a different way.

This type of rule-based system can gain in complexity or difficulty. The hint or content may be different depending on which answer choice the student selected. The re-assessment following the content "intervention" may be a new question testing the same concept rather than the same question that was asked originally. A system might be linear, giving the student no control, or it might provide an option to see a hint, to re-answer a question, or to skip and move on, etc.

Several factors drive complexity: the number of content “alternatives;” the extent to which a branching determination, based on one success (e.g., this student got it right when given a case study example), determines future sequencing of content alternatives; and the extent of rules that govern how a student progresses.

Adapt Courseware is a publisher that creates multimedia online courses that operate in this branching manner, referring to its content alternatives as “stacks.” Smart Sparrow is a form of Do-It-Yourself adaptive software, enabling individual faculty to create branching structures and progression or mastery rules for their content. The system then generates analytics, enabling the instructor to see how students performed.

While simpler from a software creation perspective, there is nothing wrong with rule-based systems, and they may provide some benefits over more complex approaches. In essence, this is a type of manual adaptivity, simpler to understand but not taking advantage of the computational power that is likely to drive the future of adaptive learning. Benefits of rule-based systems include clarity around their functionalities, and the ability for a subject matter expert to create (in the case of Smart Sparrow) or use (in the case of Adapt Courseware) them, without needing the assistance of a statistician, a cognitive scientist, or a major administrative support infrastructure. These systems are, however, limited in the extent to which they can adapt, with a finite and calculable number of paths a student can take through content towards achievement. That said, a very important and as yet unanswered question regarding adaptive learning systems is: how much adaptivity is enough, or optimal?

Algorithm-based. Algorithm-based systems are more complex. Software uses mathematical functions to analyze student performance, content performance, or both. At their most sophisticated, this type of adaptive learning system involves machine learning capabilities, where the system learns more and more about the student and content as it goes along. This enables it to pair the two more effectively. Such systems may make use of educational data mining and advanced analytics to deal with big data, and employ complex algorithms for predicting probabilities of a particular student being successful based on particular content. These algorithm-based systems gain in complexity based on the ways in which they might classify a student and classify content, and the number of variables they consider.

The algorithms used in adaptive learning have been the subject of many published research articles (Desmarais & Baker, 2012). Detailing them is out of scope here, so just a few of the options used will be mentioned. Most make some use of variations of Bayesian data analysis, which involves the calculation of conditional probabilities. Some use Bayesian inference networks (known as Bayes Nets) or slightly simplified classification systems called Naïve Bayesian analysis. Other systems are built on Knowledge Tracing techniques and Markov Chain analyses. Interestingly enough, adaptive assessment systems and adaptive learning systems developed separately. Computerized Adaptive Testing is now well-established and widely used for many high-stakes admissions and licensing exams. It uses a method referred to as Item Response Theory, which has only recently been more frequently incorporated into adaptive learning systems.[10]

Newer Functionalities

The functionalities of various systems are ever-expanding, due largely to the fact that the government continues to award large grants in this area of academic research. The ITS

[10] Item Response Theory is able to match an assessment item to a student based on an estimate of the student's ability, and continually re-calibrate its estimate based on student performance.

AutoTutor, for example, is an adaptive system created with natural language processing abilities, using computational linguistics to “understand” and respond to a student’s written solutions or even questions (Graesser, Penumatsa, Ventura, Cai, & Hu, 2011). Some new systems go so far as to seek awareness of the student’s emotional responses at any given time, using skin sensors to measure levels of arousal, chairs that provide input on a student’s posture, and facial expression recognition to detect a student’s level of boredom or frustration and adapt accordingly (D'Mello & Graesser, 2010). These emotion-oriented features remain experimental, but are functioning with some degree of success. These so-called “affective systems” are a focus of research in the interactive learning technologies space, and we are likely to see much more of them in the future. There has also been research into using data mining techniques to infer frustration or boredom within existing adaptive systems (Baker, D'Mello, Rodrigo, & Graesser, 2010).

One vexing challenge for adaptive learning has been how to develop such technology for content domains beyond math, science, and technology. Some systems exist for basic writing skills, and there have been efforts to support additional topics. But for conceptual areas, where there is no clear right or wrong answer or clear process to follow, the development has been exceptionally slow.

The Role of Faculty

Many adaptive learning systems can be used either as a wholly online product or within a blended context. Even when a system is built so that it can function as a full online course, there is usually nothing that prevents a school from adding classroom opportunities or requirements. Carnegie Mellon’s Open Learning Initiative (OLI), which includes some courses with adaptive functionality, were initially intended to be stand-alone courses, not even intended to be taken for credit. However, they have been used as an Open Educational Resource (OER) by some institutions in a blended context. A report using experimental methods compared sections of a statistics courses where these OLI resources were used to those where they were not, and found that students in the sections with the OLI resources achieved the same outcomes 25% more quickly (Bowen, Chingos, Lack, & Nygren, 2012).

Some systems were designed to be a complement to additional instruction, either as an educational resource (in essence, replacing the textbook) or as a supplement. As an example of the latter, McGraw-Hill's LearnSmart system was first used as an up-sell product for medical terminology textbooks. The advantage of such a supplemental product is that faculty don't necessarily need extensive training and don't need to incorporate the product into their formal curriculum; students either use the supplemental resource or do not. When a system is designed to accompany a very specific curriculum (as with the original Cognitive Tutor products), or to drive sequencing of topics in a course, faculty must alter their teaching to conform to the systems.

The question of the faculty role has less to do with the nature of the adaptive learning system itself than with the context in which it is used. The systems are likely to develop in the future based on how they're used in practice, and how they align with existing educational systems. For example, if terms are set lengths, what happens to the students who are able to finish in significantly less time? What does that mean for the credit hour? In this case, the issue of adaptive learning becomes inseparable from that of competency-based credit granting.

It is relatively easy to imagine the model that could develop using adaptive systems as stand-alone courses. Western Governors University (WGU) provides students with access to multiple potential resources. Students can use McGraw-Hill’s LearnSmart or Pearson’s MyLab when available for the course. WGU pays based on what students use, not what they have access to. Instructors serve as Course Mentors, and use data to determine when an instructional intervention is appropriate. The variations here would involve increasing sophistication of learning analytics and communication systems to determine when and how to intervene.

It’s less clear how to integrate adaptive learning systems into existing online or classroom courses when they are more than a supplemental student tool or textbook replacement. And even those relatively straightforward uses become complicated based on whether the adaptive system can be integrated cleanly into an existing LMS, or whether it requires students to sign on somewhere else. Either way, students likely need some training on how to use the system, and instructors or other support personnel need training on how to assist them.

Ideally, the adaptive system would provide good, clear data that could be used by the student, instructor, and those developing or updating curriculum. Functionality exists now for faculty to get data from LMS systems, and a system doesn’t necessarily have to be adaptive to provide actionable intelligence on student performance. But whether the data is usable based on its ease of access and ease of interpretation is a separate question from the potential value of the data. Perhaps the biggest obstacles to the implementation of adaptive systems is clarity around the best metrics to use, the best visual means of representing them, and the best ways of training faculty to actually put to the data to effective use.

Conclusion

Adaptive learning will only become more and more pervasive throughout all levels of education in the U.S. The initial research at universities proved the concept as well as the effectiveness of adaptive learning systems. The mathematical algorithms involved are complex but not secretive. Authoring tools are beginning to enable individual schools and even individual teachers to create adaptive learning, while cloud computing has enabled faster iterations of initial models, potentially reducing the intensive instructional design work required for implementation (although the work involved remains significant and should not be under-estimated).

Challenges of further implementation are now structural and operational rather than technological. Government entities and the highly influential Bill and Melinda Gates Foundation have expressed interest in accelerating the adoption of adaptive learning. At the K-12 level, the Common Core Standards enable commercial vendors to develop such products for a national distribution, creating a viable profit model and leading to a plethora of companies entering the space. At the college level, competency-based learning models may potentially lead to some form of common standards, at least by institution, which can only increase the incentive to create courses using advanced technologies. And a tipping point may only be a few years away, where adaptive learning becomes a standard and expected offering rather than a relative rarity.

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Summary of Selected Sources

Desmarais, M. C., & d Baker, R. S. (2012). A review of recent advances in learner and skill modeling in intelligent learning environments. *User Modeling and User-Adapted Interaction*, *22*(1-2), 9-38.

This book chapter provides a comprehensive technical overview of different statistical approaches to modeling learners and content among well-known intelligent tutoring systems. It distinguishes between "families" of tutors, particularly between (1) problem-solving and solution analysis tutors (Carnegie Learning's Cognitive Tutor is the prime example) and (2) curriculum sequencing approaches (ALEKS is the prime example). The former "relies on the ability to provide just-in-time remedial feedback and decide when to move on to a new topic," while the latter focuses on "tailoring the learning content based on an accurate assessment of a large array of skills with the least possible amount of evidence." After this distinction, the paper reviews many modern methods of modeling learner skills, including various approaches using Bayesian Networks (including graphical models), Item Response Theory (and recently developed latent trait models), and Bayesian Knowledge-Tracing (and within that, Markov Chain procedures). It is particularly interesting in its discussion of which approaches require a prior domain structure to exist and which approaches can build such a model based on data, as well as advantages/disadvantages of each. It then discusses the means by which such models are validated, and finishes by discussing newer learner models that seek to model meta-cognition, motivation, and emotion. An extremely valuable read for those who wish to gain a deep understanding of the statistics involved with adaptive learning, this is for the advanced statistical reader only. Its practical value would be ability to discuss such approaches with a company like Knewton in order to understand the inter-relationship between an existing domain structure and data modeling and to question them on validation methodology. Such an understanding would provide knowledge into what work would be required from content experts and the extent to which faculty gain value from understanding the underlying logic of the systems.

Educational Growth Advisors White Paper

Funded by a grant from the Gates Foundation, higher education consulting firm Educational Growth Advisors created this white paper to assist schools with selection of adaptive learning vendors. It is a very well-written piece, most valuable for the taxonomies it creates to help differentiate different providers and what their technologies offer, and how readily the systems might be integrated into a university's existing technology structure. It also presents a framework for evaluating organizations as a means of conducting change management planning. Finally, it uses its categorization schemes to evaluate eight vendors offering different solutions: Adapt Courseware, Cerego, Cog Books, Jones & Bartlett Learning, LoudCloud Systems, McGraw-Hill Education-LearnSmart, Open Learning Initiative, and Smart Sparrow. This is an extremely valuable read and covers issues not discussed in the White Paper.

VanLehn et al. 2005. *The Andes physics tutoring system: Lessons learned*, International Journal of Artificial Intelligence in Education 15(3)

This research article reviews the background of a system designed to grade and provide adaptive feedback for physics courses, and then discusses the lessons learned from attempting to implement it. This is a very valuable article for those wishing to gain a detailed understanding how intelligent tutoring systems work without being bogged down in the statistics. The system is designed very specifically as a "homework helper," intended to be usable independent of any textbook or content reform, and intended to relieve instructors of having to grade homework while still providing valuable, individualized feedback to students. The system is built using a pre-existing cognitive model for physics called Cascade, but after that selection, the article walks through all of the various choices that needed to be made and the research considerations associated to them. It provides example images of authoring and user interfaces, and discusses how results were measured. Written as an academic research case study, the article effectively reveals in-depth the thinking of those creating an intelligent tutor.

APPENDIX A

Clarifying Adaptivity: Examples of adaptive and non-adaptive technology functions

It can be harder to identify a learning technology as adaptive or non-adaptive than one might think. Adaptivity can sometimes be confused with straightforward interactivity. This section is intended to provide simplified examples of functionalities from the student perspective, and to consider whether these represent adaptive learning systems or not. It is also intended to demonstrate how adaptivity can exist on a continuum, and how systems can vary at fundamental levels and still be adaptive. Again, please note that these are highly simplified scenarios targeting basic adaptive functionality; they do not in any way represent the range of adaptive functionalities available. As you read, it is recommended that you stop to think about whether the described functionality is adaptive or not. Text in lighter gray signifies that this functionality repeats from the previous scenario.

Scenario 1

A student reads a chapter (or views videos) online at their own pace. When ready, the student takes a quiz. Based on the results, the student receives feedback from the system, telling them what they answered correctly and incorrectly.

Not adaptive. This is not adaptive because the system provides data but does not alter the instruction based on this data. Note that the information provided might make non-computerized adaptive learning possible *outside* of the system and can bring value, but labeling such a system as adaptive would make nearly all online systems incorporating even a basic testing functionality fall within the category.

<u>Examples:</u> Khan Academy, Respondus and other testing software, most LMSs have such testing and reporting capability

<u>Variations:</u> The variations here involve the specificity of the data provided in the results. Students might receive a chart with strengths/weaknesses in the topic areas covered by the test, given them a sense of what weaknesses they should work on. The system might signify which questions were incorrect and allow students to interactively click on those questions and be able to see which answer they selected as well as the correct answer. Aggregated data of such results by student and by section might be provided to a faculty member, enabling the instructor to adapt learning plans based on individual or group results.

<u>Scenario 2</u>

A student reads a chapter (or views videos) online at their own pace. When ready, they take a quiz. Based on the results, they receive feedback from the system, telling them what they answered correctly and incorrectly. Depending on a student's selection of a particular answer choice to any given question, a specific explanation is provided detailing why their specific answer is wrong, and referring them to a section of the reading for review.

Very minimally adaptive. In this instance some actual content (certain explanations based on certain responses) will be seen by some students and not others depending on student responses, and thus this can be considered minimally adaptive. But it can easily be argued that this is a distinction without a difference. How different is this than a system that, following the answer to a question, the student sees the feedback associated to all of the answer choices and the specific explanations and corrective information associated to them? In that case, the content is the same for all students, and the system would not be considered adaptive, even though the practical impact seems extremely close to (and perhaps even better than) the initial instance. While this initial scenario fits the definition of adaptive learning, it barely does so.

Example: This is based on the pitch that MOOC provider Coursera has been making, arguing that misconceptions can be corrected based on specific answer choices selected. Again, most testing software and some LMSs have configurability to reveal explanations, some at the answer choice level.

Variations: This type of system can become more adaptive by adding additional features, such as taking students directly to content requiring review, or bring key parts of the content up in split screen mode.

Scenario 3

A student reads a chapter (or views videos) online at their own pace. When ready, they take a quiz. Based on the results, they receive feedback of what they got correct/incorrect and recommendations for specific content to review. The system stores this information, and in the next chapter review quiz, includes questions that the student had missed previously to see if their learning has improved. In addition, the system asks more difficult or easier questions depending on student responses. The student is able to track their progress and levels of mastery on a dashboard.

Adaptive at assessment level. The content does not change for students, but what is asked changes based on prior performance and student progress is tracked. This can be made more adaptive by ensuring certain content is reviewed based on assessment performance, and by increasing the level of detail in the tracking.

Examples: While not representing a specific product, this is similar to supplemental products such as LearnSmart's medical terminology product, and to the functionality of memory builder Cerego.

Variation: The system might track when the student last demonstrated knowledge of a term or concept and, based on a memory decay model, ensure that the term or concepted is repeated at specific frequencies.

Scenario 4

A student reads a chapter (or views videos) online at their own pace. When ready, they take a quiz. Based on the results, the system generates an individualized learning plan to fill in gaps based on the results of the quiz. The learning plan includes content that statistically has been shown to be most effective at filling in the knowledge gaps identified by the quiz. After the learning plan is complete, the student takes another quiz that ensures the student is re-tested on their prior weaknesses and the process begins again.

Adaptive at both the assessment and content level

Example: Knewton

Variation: This system could be made even more adaptive by tracking additional variables, such as the time of day a student studies most effectively and the length of study time that is most productive for the student.

Scenario 5

A student is asked a math or science problem, and asked to fill in slots for each step along the way to a solution. (For example, in solving an equation with one variable, the student would enter each step involved with isolating the variable on one side of the equation.) Feedback is given either after each step or at the end of the problem. Feedback is based on an analysis of the steps the student took, compared to the most effective methods for solving such a problem. The system then selects the next question based on an evaluation of the student's readiness.

Highly adaptive with a very small grain-size of adaptivity.

Examples: This is a generic description of an intelligent tutoring system such as ALEKS or Carnegie Learning's Cognitive Tutor

Variations: The system might provide certain "constraints" in the steps that keep the student on a certain track toward solving the problem. Systems can provide hints or examples.

Scenario 6

In this role-play exercise, the student is provided with an identity and a management role and presented with profiles of two or three imagined direct reports, describing the job functions and personalities of each. A case study begins where the student must make choices of how to respond to situations brought to them by their direct reports. A typical situation might include a project that is falling behind schedule due to a cross-team collaborator, or where the worker is distracted by outside events. Options of how to respond (in multiple choice question form) are presented to the student. Based on the option selected, the case study develops in a certain way, and the worker returns to update the student on either progress or deterioration of the situation.

Depending on the choices made by the student, the situation can end well, badly, or somewhere in between. At the end of the case study, the student is provided with feedback based on the choices selected, including guidance on why other options may have led to different results.

Example: This example is taken from an early adaptive learning model from the 1990s, used for corporate leadership training. Harvard Business School published similar eLearning products.

Variation: This is a good example of a rule-based system, which we contrast in the White Paper with algorithm-based systems. In this example, there are no mathematical formulas underlying the adaptation of the system. There are a series of if-then functions that determine what will occur next if the student makes a particular choice. Variations over time included increasing the complexity of the simulated possibilities, enabling students to select their “avatar” and fictional team members, etc.