A Link-Systems International, Inc. White Paper

Individualized, Problem-based Assessment and Remediation

The LSI Approach to Adaptive Learning

January 11, 2013

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Version: 1.75

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About the Author

Link-Systems International, Inc. (LSI) based in Tampa, Florida, is a software firm that has pioneered a number of platforms to assist in online education. The LSI adaptive learning engine is called Dynamical Problem-Based Objective Mastery (DPOM). This paper discusses DPOM and its implementation in the LSI MyAcademicWorkshop™ assessment, remediation, and homework solution for STEM courses.

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Introduction

Intelligent, computer-assisted learning is the outcome of a half century of work by theoretical computer scientists, philosophers, and educators. In 1966, philosopher and set theorist Patrick Suppes tested his Computer-Aided Instruction in a single school district. Since then, exponentially faster processors, global interconnectivity, and new generations of educators and developers have made possible increasingly better access and platforms for online learning. The early 1990s saw the success of some of the first large-scale experiments in online education in Europe and the US. By the end of the decade, entrepreneurs had brought to market a set of *Web*-based learning tools that were posed to irreversibly transform education around the world.

In the next fifteen years, schools from private K-12 institutions to public universities have "gone online." Every learning activity can be implemented virtually. And this is fortunate because all schools, particularly state and community colleges, face an unprecedented logistical and financial challenge.

More students than ever seek access to learning. However, up to 50% of students begin college without adequate preparation, especially in science, technology, engineering, and mathematics (STEM) subjects. Schools must place these students appropriately and provide remediation where developmental work is indicated.

In this paper, we discuss how Link-Systems International, Inc., a software-development firm long in the forefront of Web-based learning, has created an adaptive learning engine and a specialized STEM learning management system (LMS) to help institutions handle the placement and remediation crisis. We look at the history of adaptive learning and the theoretical basis for the LSI Dynamical Problem-Based Objective Mastery engine (DPOM), citing the painstaking research that gave rise to such an approach.

We examine the function of DPOM, the mathematics behind it, and its place in the constructivist learning theory driving all LSI development. We look at *why* it is important—the hard facts motivating the concern of academic institutions with developmental education. We show *what* DPOM is, that is, how it works in both the placement and Web-based learning contexts.

Throughout, we emphasize the dependence of the two sides of an effective adaptive learning engine. DPOM can objectively capture or emulate the way in which learners acquire knowledge. This is what makes adaptive learning and DPOM ideal for assessment. Furthermore, the assessment process is then turned around so that the DPOM engine can fuel, encourage, and assess remediation and true knowledge construction in an instructional mode.

Adaptive Learning in Higher Education

Current statistics show that one-third of today's college entrants are unprepared for college. Nearly one-third of all US students taking the ACT exam do not qualify as college-

Patrick Suppes

(1922—) Philosopher, mathematician, and pioneering education technologist, Suppes is Lucie Stern Professor of Philosophy Emeritus at Stanford University.

"The leading person, the pioneer and promoter [of e-learning] was Patrick Suppes, who, in 1966, proposed that developments in educational technology, and specifically in computer usage, would change the face of education in a very short space of time. Suppes continuously promoted using computers in education, most recently the Education Program for Gifted Youth of Stanford University …"
(Albert D. , E-Learning Future--The Contribution of Psychology, 2001)

ready in reading, while nearly one-half are unprepared for College Algebra (ACT, Inc., 2012). State colleges, in particular, tasked with accepting everyone willing to pursue a four-year degree, strain to accommodate and address this lack of preparedness. Putting a student in a course for which he or she is not prepared endangers program completion probability. On the other hand, placing a student by mistake in a subject he or she has already mastered is a waste of college resources.

The outstanding first attempt at reshaping learning using computer support was Computer-Aided Instruction, formulated by Patrick Suppes in the 1960s. This method focused on hyper-linking subject material, meaning that it relied entirely on a static background converted for computer presentation. However, this brought something new to education; the student could arrive at conclusions via different paths through the hypertext. This idea of a learner mastering a body of knowledge—in itself, an accurate approach—stopped just short of directly encouraging construction of new knowledge by the student.

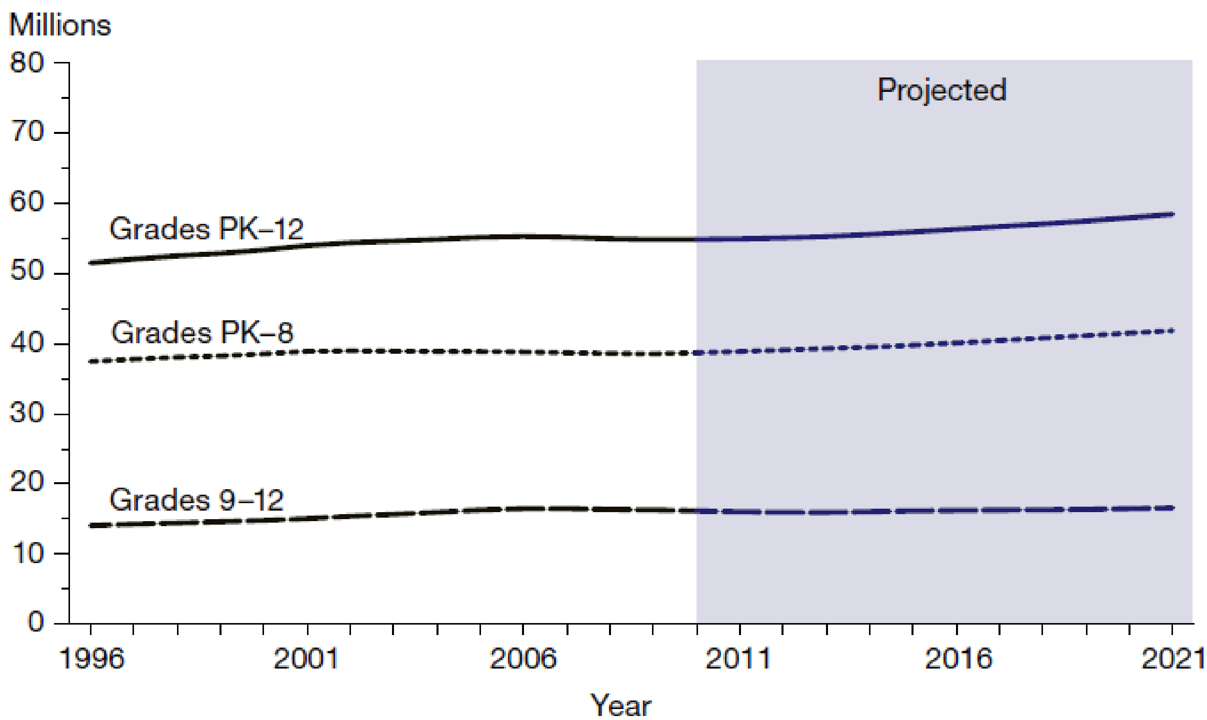

Figure 1 - Actual and Projected K-12 Enrollment, 1996-2021
(Hussar & Bailey, 2013)

Viewed this way, the Web and Internet communication are transformative agents in education. Web and Internet technologies make it possible to break altogether from the model of the learner as passively absorbing received textual material. The technology replaces passivity with activity and interactivity. In place of a model of instruction as delivery of material (known as the "sage-on-a-stage" approach), the technology reinforces a model of instruction as facilitation of learning (known as the "guide-at-the-side" approach). From search engines to collaborative interfaces, from registration to grading, saving, and printing results, online interaction comprises a new medium of teaching and learning with consequent changes in administration. Teachers can use computer intelligence to help them understand and more quickly address the unique needs of the learner; students can access and more readily participate in discussions; database records of the educational process are permanent and provide a more automated source for the documentation of program quality and student outcomes.

The possibility of anywhere-anytime access to Internet resources addresses the other vulnerability present in traditional approaches to remediation. Standard face-to-face developmental courses can strand even dedicated students who arrive with learning deficits in semester after semester of non-credit-bearing courses. It may be partially for this reason that current statistics indicate that program completion rates of those entering developmental courses are dismally low (Hussar & Bailey, 2013).

By contrast, Web-based learning stores goals, problems, and results on servers that are always on and always open for students to explore. If, in addition, remedial material is served to students via an adaptive learning approach sensitive to their accomplishments, the process can be transformed from a trap into a challenge. Because it is a self-paced activity, adaptive remediation can proceed much more rapidly and produce more solid evidence of real student progress than the corresponding classroom.

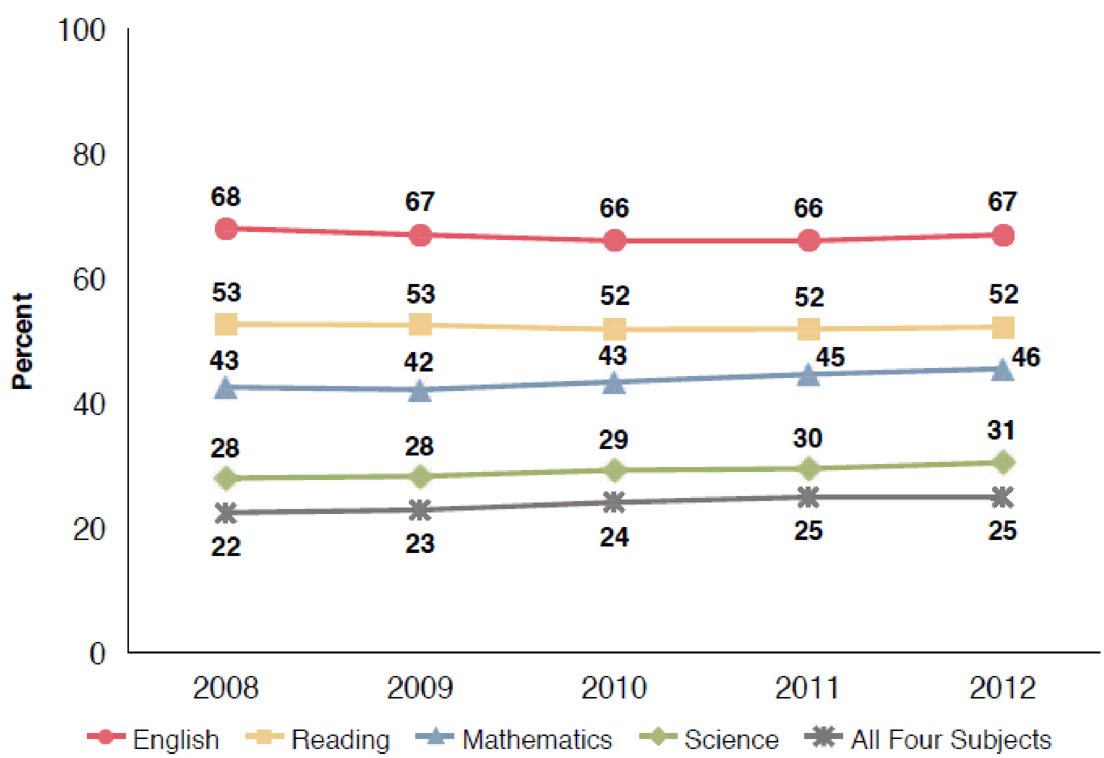

Figure 2 - College Readiness: Percent of ACT-Tested High School Graduates Meeting ACT College Readiness Benchmarks, 2008-2012 (ACT, Inc., 2012)

With the potential for using machine intelligence to model constructivist learning and for on-demand technology to streamline education and reduce facility costs, many institutions seek assistance on two fronts. From one vendor they purchase automated placement software to interactively evaluate student preparation, usually on a fee-per-test basis. From another vendor they obtain developmental education content addressed to those areas not covered by courses offered on campus. However, as we will show, a truly integrated adaptive learning engine can address both assessment and remediation.

The management and leading developers at Link-Systems International, Inc. (LSI) were among the first to specialize in Web-based software solutions and to work with academic institutions to implement them. The company was incorporated in Florida in 1996, when Web applications for education were a new concept. In its first years of existence, LSI conversion experts and, later, content authors, developed platforms for online presentation of educational materials. First among these technologies was its WorldWideWhiteboard online collaborative learning environment. This provided the basis for the founding of the LSI NetTutor® online tutoring service. Then in 1999, LSI released its WorldWideTestbank® platform for direct authoring of algorithmic homework and workflows.

LSI collaborated with major publishers as they struggled to use the Internet and digital solutions to transform textbooks. In line with the evident need faced by schools to engage learners in actively constructing knowledge, publishers hoped to move from serving the delivery-of-knowledge or "sage-on-a-stage" instructional outlook, in which the textbook was simply a repository of ideas. Students could use Google as an alternative. Publishing companies needed to find a new and unique form of commitment to educators, one that incorporated problem-based learning and other constructivist instructional strategies.

…[T]he developers and subject-matter experts at LSI fashioned a new adaptive learning engine designed to directly meet the needs of practicing educators.

LSI platforms reached beyond this. After collaborating with some of the world's experts in learning and contributing content to others' online homework and evaluation technologies, LSI set out to combine the contextualized online learning and cognitive and standards-based content into a single product. To do this, the company rethought existing adaptive algorithms and integrated them into a single, fully-thought-out and research-supported learning engine called Dynamical Problem-Based Objective Mastery (DPOM). The package was to be initially dedicated to the company's area of unquestionable expertise, namely in STEM courses.

The Adaptive Learning Background of LSI

The commonly accepted ingredients of adaptive learning are (1) a means of measuring learning accomplishment that is progressively more accurate, (2) a resulting algorithm for the recognition of learning progress, and (3) the anticipation or generation of next elements of learning based upon observed past performance. Software that meets these conditions is called an adaptive learning engine.

From 1997 to 2000, collaborators of mathematicians Jean-Paul Doignon and Jean-Claude Falmagne worked to implement Knowledge Space Theory (KST) to measure and promote student progress using software. According to KST, the student's level of knowledge is a point in a metric (i.e., measurable) "space" of specific learning goals, in which dimensions of knowledge extend beyond getting answers right or wrong to such quantities as the amount of time it takes the student to respond. Paralleling this work, researchers led by John Anderson at Carnegie Mellon Institute elaborated the problem of adaptive learning specifically as one of machine-learning. Anderson maintained that a specified set of algorithms, called Adaptive Control of Thought-Rational (ACT-R), modeled cognitive elements of learning closely enough to perform elementary tutoring functions. Moreover, in subsequent experiments, Anderson and others have proven that, while running ACT-R software, a computer activates modules of the algorithm in synchrony with the activation of corresponding areas of the brain of a human learning the same material (Anderson, J., Bothell, Byrne, Douglass, Lebiere, & Qin, 2004).

LSI's DPOM engine derives theoretically from a larger picture that treats learning as occurring *within* the whole social context of the student social context, *including* the constellation of requirements and expectations, resources and course formats that constitute the student's current learning context. This understanding of how learning takes place is called the Integrated Cognitive-Contextualized Learning theory (ICCL). LSI views the online learning environment as the strongest verification of constructivist learning theory in general and of ICCL in particular. Inspired by the growing body of evidence that adaptive learning engines could promote student success, the LSI research and development team set to work equipping its problem-generating platform with an algorithm capable of dynamically assigning problems and using problem outcomes as the input for the next step of the algorithm. The content authors at LSI, already adept at creating online mathematics and science problems, merged mathematical-psychological and cognitive-technological ideas, modified according to the ICCL premise that "[q]uestions of which learning style to use are best determined in practice, whereas learning goals are best set ahead of time" (Kephart, 2012). Over a period of two years, from 2008 to 2010, the developers and subject-matter experts at LSI fashioned a new adaptive learning engine designed to directly meet the needs of practicing educators.

In DPOM, LSI offers a model of adaptive learning that is neither confined to statistical-situational measurement nor solely to the emulation in software of the human cognitive process. This model instead incorporates mathematically sound approximation of learning ability, an agreed-upon structure of expected achievements, and the additional provision for learners to reflect upon and absorb the learning process. Making use of the Internet and cloud-based algorithmic problem-generation via the LSI WorldWideTestbank platform, LSI's DPOM adaptive learning engine supplies a continuously replenished list of rigorous standards-based and engaging problems in such a way as to encourage students to reflect on their progress.

In the remainder of this paper, we explain LSI's DPOM-based adaptive learning engine and how it works to provide a precise picture of student ability and create the conditions for an adaptive approach to supplying deficits to student preparation for courses. The next section elaborates the two "halves" of the model – problem-based learning equipped with standards of objective mastery.

Why Problem-Based? Why Orient Towards the Mastery of Objectives?

Problem-based learning means posing questions (problems) that are at the same time as immediate to student concerns as possible (drawn from real-life, everyday questions, for instance) and also use the problem-solving experience to help students draw course-related conclusions. As such, it is a thoroughly constructivist approach to instruction. Not only that—like all constructivist approaches, it takes on issues that are seemingly intractable from the traditional standpoint. For instance, how, in a large lecture, would an instructor tailor content to student difficulties *during the lecture*?

While it is relatively straightforward to present the concepts and methods in a lecture-style format, it is a different matter to pose questions that actively involve the student in creating solutions. Traditional instruction is linked to methods of testing that, for example, run through a fixed list of questions. Lectures and static tests do promote rote memorization but may not adequately encourage comprehension or higher cognitive achievement. By contrast, problem-based learning and adaptive evaluation hinge upon connections between ideas and aim at capturing and measuring all forms of cognitive development.

Tests based on problem-solving occur in a sequential fashion; one problem follows the next. As this is, in itself, a linear process, adaptive testing can capture the full range of student strengths and weaknesses, which is not at all one dimensional. To do so, the adaptive learning engine must have mathematical sophistication; it must address the "dimensionality" problem, as it is known in mathematics. In the case of DPOM, the complexity of the student context is answered by the assumption, as we will see, of the relative randomness and presumed mutual independence of student responses.

This concern, at its heart, is about the *accuracy* of placement and has undoubted validity where the vendor has no commitment to the ultimate remediation of student deficits, as asserted by Scott Hirsch in his article "Standardized Tests that Fail" (Hirsch, 2012). However, problem-based learning assessment, backed by a properly constructed algorithm directed at cognitive issues, reduces the impact of the multiple dimensionality of learning on assessment conclusions, particularly when the placement strategy is paired with an equally sensitive remediation approach. In DPOM, the mathematical core of this is the use of conditional probability or what is called a naïve Bayesian classifier. Each problem presented is regarded as statistically *independent* of all others.

The social context of students entering school or a given course is ultimately a cohesive whole and, in its own way, organized. Therefore, performance on independent external factors—the problems—is, cumulatively, highly indicative of level of preparedness, area of deficit, and so on. As differentiated as cultural background may be, the Bayesian approach – *precisely because of the mutual independence of factors in each problem* – is enormously powerful. Certain other statistical models address this issue but may fail to detect a whole region of missing knowledge.

To go further with the adaptive process, it is required that the learning goals being tested have been previously organized according to the development of cognitive competence required for mastery of the subject. The hierarchical arrangement of facts and concepts in science or mathematics, for instance, is the product of the efforts and writings of trained and recognized experts in those fields. LSI relies on the consensus of education researchers, the authoring ability of its own subject-matter experts, and the active incorporation of global, national, state and local standards-creating bodies to create and maintain a realistic and reliable taxonomy of learning goals. The DPOM engine links student performance to preceding and following learning-goals using this taxonomy.

In the 1950s, Benjamin Bloom's taxonomy advanced a general picture of the cognitive activities characteristic of stages of learning (Bloom, 1956). Today's Common Core Objectives are a refinement of this idea, with respect to specific subject content. In both cases, the taxonomy expresses a general picture of progress within a subject. Bloom's taxonomy has been revised to lay out activities that identify student progress toward high-level cognitive mastery (Anderson, 2001). While course standards such as Common Core focus less on cognitive details, Bloom's taxonomy is not subject specific. However, each is a hierarchical arrangement of observable objectives, whether seen as cognitive accomplishments or subject prerequisites; each leads to a single goal, namely, the mastery of a subject.

The twin considerations that problem-solving is a valid basis for learning because it can relate learning goals to the learner's social context and that it is possible to define concrete steps in cognitive development yield the following premises for adaptive learning:

1) Students experience mastery of a subject by attempting and succeeding at solving problems they understand. The action of problem solving facilitates the learning process by verifying the connection of concepts to outcomes.

2) Each present advance in learning connects to objectively recognizable future learning goals, meaning that the individual learner's project is one component within a definable hierarchy of goals (Cosyn & Thiéry, 2000).

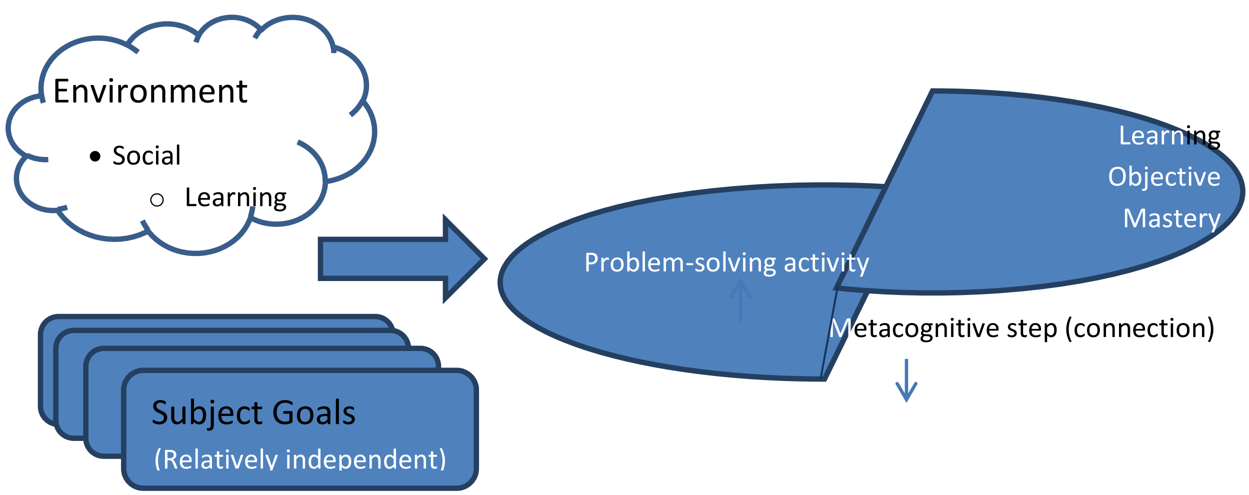

Figure 3 - Conditions for Adaptive Learning

The first of these points means that sufficiently "smart" adaptive learning need not prescribe an approach or procedure. In fact, a well-designed adaptive learning engine offers a variety of solution methods by presenting problems that can be conceptualized in a variety of ways. The adaptive learning engine, whether used as a tool for evaluation or for instruction, can be said to learn to help the student. The second point, which relates the individual learning experience to the broader, socially formulated goals, means that an effective adaptive learning engine guards against any aimlessness in the posing of problems to students. The system must "know" that if the solution of problem A derives hierarchically from the solutions of problems B and C, and the student is stymied by A, then this indicates precisely a deficit in B or C.

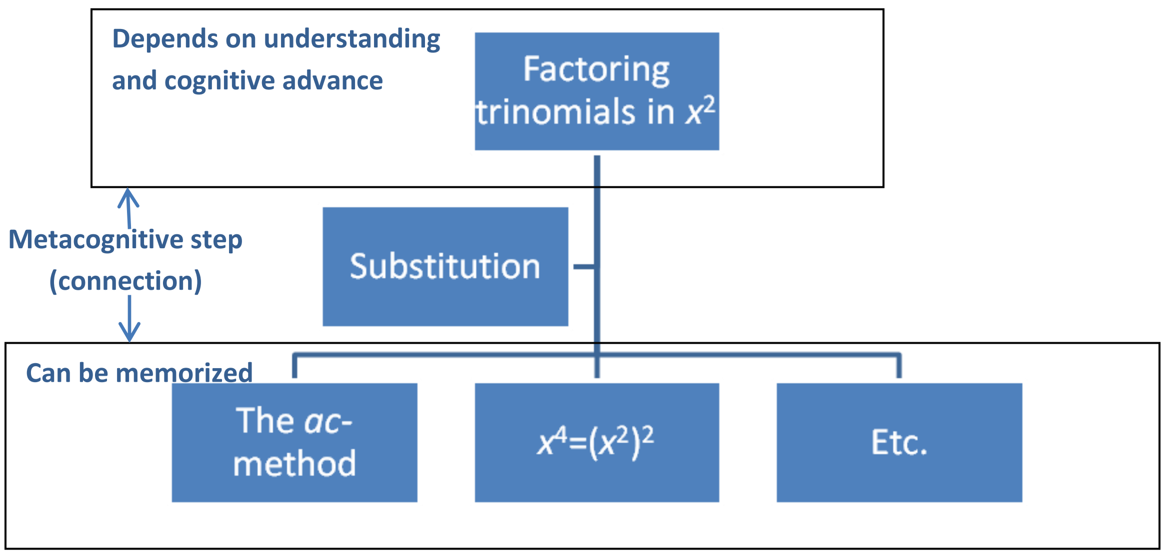

Figure 4 - Hierarchy of Related Learning Goals

It is clear enough that the two aspects of adaptive learning function together, objective mastery being proof of problem-solving success. However, it may not be obvious that, with adaptive learning as with all effective teaching, the student must draw conclusions *about learning*, through a process called *metacognition.* Metacognition enables the student to relate problem-solving attempts to the mastery of learning objectives.

An Example and the Decisive Role of Metacognition

An example drawn from mathematics may make this clear. Say that a student learns to factor a trinomial using the fact that the coefficient of the linear term can be expressed as the sum of factors of the quadratic and constant coefficients (the *ac* method). Suppose, as well, that the exponent product rule is also solved as a problem. If the student cannot follow this up by factoring a trinomial in x^2, for instance by substituting u for x^2, we conclude that the student's grasp of the two underlying facts is likely to be more procedural than conceptual.

Missing on the student's side is the reflection that substitution might be possible. More essentially, the student must also observe that the expressions still "say the same things" when rewritten in a manner consistent with mathematical laws—in this case, to make it easier to factor the trinomial. These are essentially observations about *learning algebra*. In a larger sense, they sum up the cognitive acquisition of generalizing from two unrelated relationships to address a third. The explicit extraction and statement by the student of the relationship between concepts, procedures, and conclusions is the proof of the successful construction of knowledge.

In a classroom setting, the most effective instructors seek out commentary from *the student* on what seems to be missing from the more advanced objective – that is, the more developed problem. It means that the instructor must wonder aloud about what to do with x^4.

In the adaptive placement context, assessment must be rapid so that, while students must complete evaluations within a specified time, a reasonable amount of time is allotted for the student to think about what to "say" to the computer. In a customized adaptive learning program, such as MyAcademicWorkshop, students may be asked to comment on what they have learned as frequently as desired. Students may respond to surveys after each question or may be required to create journals. The exact details depend, at the least, on institutional requirements. The precise content of problems or the order of objectives without direct hierarchical dependencies may be made to depend on the pedagogies of individual programs or courses in a given institution.

DPOM objective: **Factor**		
	Problem #1 $2x^2$-$5x$+2	Student response: $=2x(x-2)-1(x-2)=(2x-1)(x-2)$ ✓
	Problem #2: x^4 (as a perfect square)	Student response: $=(x^2)^2$ (because $(a^b)^c=a^{bc}$) ✓
	Problem #3: $2x^4$-$5x^2$+1	Student response: $=x^2(2x^2-5)+1$ ✗

Figure 5 - DPOM Makes the "Can Factor Trinomials" Data Point into a Naive Bayesian Classifier

The existing research shows that, through the self-reflection of metacognition, one agrees to think of oneself as a learner and commits to the learning process. Additionally, research with Functional Magnetic Resonance Imaging (FMRI) suggests that metacognition activates pathways in the brain associated with social involvement (Fincham & Anderson, 2006). This gives a very concrete meaning to the term "engaged learning."

How Problem-Based Measure of Learning Objective Mastery Works

The measurement of student competence by naïve Bayesian classifiers is many times more efficient and exponentially more accurate than random questioning. Likewise, instruction adapted on the fly to observed student capabilities—also essentially Bayesian or "boosted tree" methodology—can capture even exceptional situations with extraordinary accuracy. The one necessity is that the method of adaptation must emulate the human knowledge-construction process in an unbiased manner.

The LSI adaptive engine combines the hints present in student responses to individual problems related to a learning objective, called *weak indicators*, into a single *strong indicator* of mastery or non-mastery of that objective (the "boosted tree" approach) as one data point for decisions. Far more importantly, DPOM relies on a ready supply of carefully measured, standards-based problems and a platform for delivering algorithmically generated versions of problems in real-time and also relies upon a system for evaluating students' responses (the condition for considering placement a naïve Bayesian classifier).

DPOM Adaptive Placement

The adaptive placement of DPOM results in an accurate estimate of student competence. The first point for this estimate is established by posing sufficiently many problems (albeit each question by itself may be only a weak indicator of objective mastery) to formulate a cumulative and "almost certain" conclusion about the student's general knowledge of the subject area. To simplify somewhat, the student's performance may be shown by this first estimate to reflect mastery of the whole hierarchy of learning goals prerequisite for the first credit-bearing course. This student, most likely, requires no remediation. On the other hand, for another student, the results may indicate that the student is completely unprepared in the subject and is a candidate for the lowest available level of remediation.

Subsequent problems are chosen with relation to previous data points so as to place the student with successively greater degrees of precision in intermediate levels of remediation. It is required that the data points be processed intelligently by the engine, but it is even more important to have carefully defined the hierarchy of learning goals used to create data points.

The process terminates when further refinement of placement is unnecessary. For example, suppose the placement alternatives are developmental math, non-credit pre-algebra, intermediate algebra, and college algebra. A student who has mastered some but not most of intermediate algebra should take intermediate algebra. That is, the process terminates when the student's needs are clear or, in statistical terms, "almost certain." The result is a recommendation of which course the student needs to take.

DPOM Individualized Adaptive Learning Plans

A student may be placed into a level that does not correspond to any course offered on the campus. DPOM adaptive learning can then function as a source for self-remediation. The efficiency of DPOM remediation derives from the fact that the initial set-up of for self-remediation is a product of the individual's assessment.

That is, the outcome of the placement process is, in DPOM, the premise for adaptive learning. This is an individualized learning plan–the composite of all deficit objectives requiring remediation. But it is also a first step toward self-remediation, embodied in an initial collection of problems for the student to work out. For example, consider a student who places into basic math. She has a grasp of addition and subtraction, perhaps, but stumbles on fractions and decimals. The DPOM adaptive learning engine now works in reverse, by revealing to her a set of unsolved problems and helping her to master the learning objective or objectives they embody.

The student progresses through the course by choosing one problem to work and solving it. The student may make repeated attempts at the problem, each time working an essentially different version, since LSI's algorithmic testing platform is incorporated directly into the engine. In effect, the process of finding the solution signifies that the student is prepared to retake the placement evaluation; it indicates the student is ready for the next course.

As the student masters objectives, the pool of problems changes. Eventually she has successfully addressed the objectives of basic math and can take a placement test to verify this. Optionally, DPOM can also reinforce metacognition by requesting that the student complete a survey.

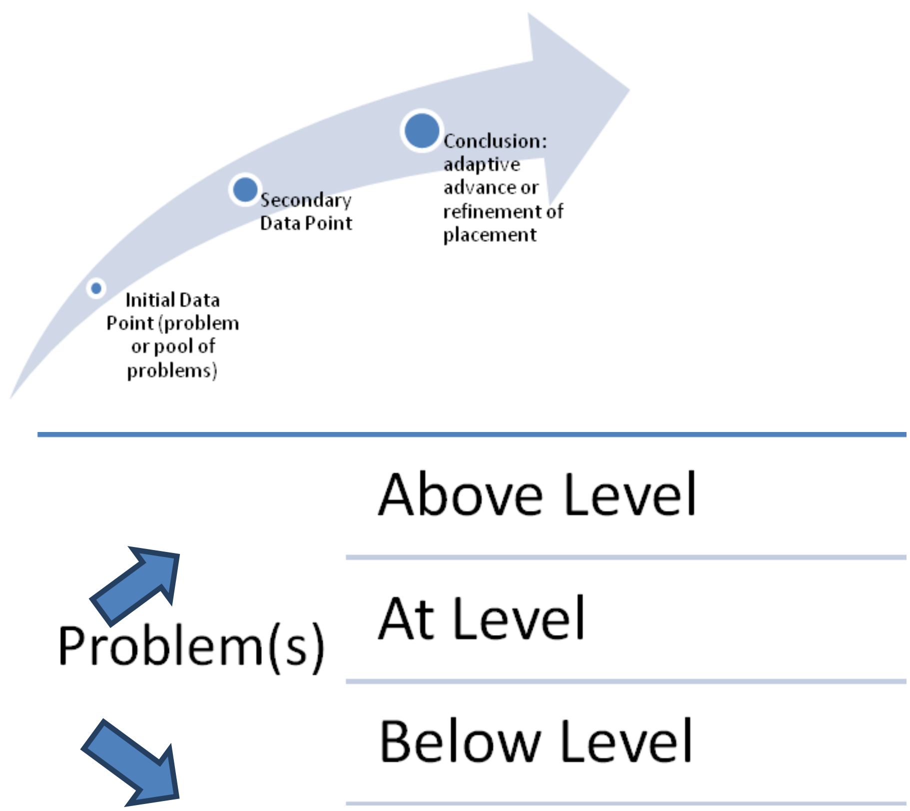

Figure 6 - DPOM Knowledge Assessment Starts at Above-level Performance to Detect Below-level Performance

In adaptive individualized learning, the initial placement test itself is the origin of a pool of assigned problems from which the student chooses. Each time the student chooses and attempts a problem, the result is used to dynamically recreate the pool of problems and to direct the student through the accomplishment of all learning objectives.

How DPOM Adaptive Learning Relates to the Zone of Proximal Development

As we have observed, DPOM adaptive learning is both a placement and instructional tool.

We have seen that the border of what the student has mastered is defined not only by a collection of problems –multiple "data points," as we have called them –but also multiple learning objectives. This corresponds to an important concept dating from the origin of constructivist education theory. Lev Vygotsky (1896-1936), the eminent Russian psychologist widely regarded as the father of constructivist learning theory, believed that the learning process involved the student gaining progressively greater access to development through learning. In Vygotsky's view, knowledge construction internalizes future social development accessible to the individual. He called material ready to use in personal development the student's "Zone of Proximal Development" (ZPD) (Vygotsky, 1962).

Looking back at how the DPOM adaptive learning engine—from one pool of learning goals to the next—it is clear that DPOM is allowing the learning to construct knowledge precisely in the Zone of Proximal Development. The learning goals closest to those already mastered by the students are the next ones the student is invited to attack. Once the system begins to place the student within the context of the subject's learning goals, DPOM begins to elicit learner participation in remediation and reflection on learning. This iteration of learning goals continues until the measured mastery corresponds to the targeted learning goals of the subject.

Borrowing from Vygotsky, the LSI adaptive engine allows the student to construct not only specific knowledge but also awareness of learning progress. Through successive iterations of a pool of potential problems, the student instrumentally expands and seeks to expand his or her Zone of Proximal Development. Because the progress is aligned to mastery of defined objectives, the student, from the standpoint of the school, prepares to study along the specific lines of the curriculum.

Features of DPOM Adaptive Learning

Given the pressing issues of placement assessment and providing a remediation alternative, institutions may be tempted to prioritize these above related matters. However, the DPOM adaptive learning engine and its implementation in MyAcademicWorkshop go beyond satisfying the placement and remediation issues. Three additional characteristics of the LSI approach are as follows: (1) DPOM safeguards the essential ingredient of pedagogy neutrality; (2) implementation of DPOM provides instructors with access to the algorithmic problem-generation platform; (3) and years of research demonstrate the validity of the adaptive learning approach and LSI technology. In this section, we take a look at each of these factors.

Pedagogy-neutral Base

We have gone into some detail as to how DPOM employs the statistics and mathematics of knowledge and how it is linked to the psychology of learning. Equally important is the fact that the DPOM adaptive learning engine is pedagogy-neutral. That is, nowhere in its implementation or programming does MyAcademicWorkshop make any assumptions about how in-course education takes place.

Pedagogy-neutrality is a conscious design decision. Looking forward to when the student goes on to take credit-bearing courses on the campus, a vital factor to success will be the seamless fashion in which self-remediation connects to the future learning environment.

When the student enters the classroom, remediation using DPOM ensures that there is no culture shock. The structure, for instance, of MyAcademicWorkshop may be customized according to the prerequisites of the institution's curriculum.

The entire platform integrates directly into a campus LMS. Notably, MyAcademicWorkshop can function as a specialized LMS, and the culture of the testing and remediation may be shared with the campus. Ultimately, customized placement and remediation can increase the effectiveness of regular courses. The amount of in-course review time can be minimized, for instance, simply by assuring that students do meet the course prerequisites, as the DPOM engine will verify.

The alignment of objectives for mastery and campus-specific approaches requires an element unique to the LSI DPOM. Part of every set-up of MyAcademicWorkshop is an inventory of instructor and administration expectations.

Online Content Creation

As mentioned at the outset, LSI has well over a decade of experience at creating online content for universities, publishers, and other partners of higher education. The WorldWideTestbank platform is a part of MyAcademicWorkshop, meaning that the instructor can use it to create or modify online content to supplement material used in the course.

Online content creation is an ongoing aspect of LSI service. The company has created well over one million distinct content items. Critical to their application in MyAcademicWorkshop and DPOM adaptive learning, all of these items are coded so that information about their hierarchical relationship within a universal taxonomy can be adapted to any state requirements or school specifications.

That is, DPOM adaptive learning and MyAcademicWorkshop serve the needs of the teacher as well as the student. Access to standards-based content not tied to a particular textbook, a performance-monitoring system with customizable alerts and notification, and interoperability with other LSI platforms are all part of the package.

Research about LSI, DPOM, and Adaptive Learning Engines

A consistent feature of effective application of technology in education is that it not only embodies great ideas but also obtains concrete evidence of their value. This tradition dates all the way back to Suppes, who tested Computer-Aided Instruction on school-children in East Palo Alto in the 1960s. The developer, like the school administrator, looks for proof that innovative technology answers human needs in gold-standard educational research as much as in market success. For LSI's MyAcademicWorkshop, research support has come over the past decade in a variety of forms. To understand the way in which its content relates to STEM courses, the reader is urged to look at the LSI white paper *MyAcademicWorkshop in the Technical College Classroom* (Hamrick & Kephart, 2012).

There is also a large body of published analysis and empirical research associating KST and ACT-R to favorable learning outcomes. Studies in school districts of Pittsburgh have shown the effectiveness of the cognition-modeling approach of John Anderson and his colleagues.

Other studies have found that the LSI platforms for online collaboration (WorldWideWhiteboard®) and online tutoring (NetTutor®) are not only the earliest and most warmly received by the academic community but also the most effective of their kind. Of interest to educators who contemplate using NetTutor to support student inquiries during self-remediation is the fact that NetTutor has been shown to contribute to a 25% increase in course persistence (Kersaint, Barber, Dogbey, & Kephart, 2011).

It is to be emphasized, of course, that the full evaluation of available data is a work in progress. The DPOM adaptive learning engine, neither a single invariable algorithm nor a fixed statistical weighting, is evolving as the art and science of problem-based learning develop. Integral to the DPOM machine is an assumption that ideas about learning and about the relevance of and relationship between learning objectives will grow. For this reason, the continued success of DPOM is tied to its responsiveness to the living and changing needs of students using the system.

Critics of remediation programs today point to insufficient numbers of placement tests, lack of student involvement, and the over-investment of precious semester hours in remediation (Dana, 2012). It is notable that, while DPOM provides a one-stop solution to college remediation and placement woes, it is also a complete solution. It relies on repeated verification of assessment, the broadest possible collection of original, standards-based content, and the direct elicitation of self-reflection, all of which assist students to understand and accelerate their progress.

Conclusion

As the only final constant in education is change, the ability of software to facilitate learning hinges upon its ability to respond and redirect student inquiries and evaluations. Adaptive learning is the name for this ability. It is most important that a provider offering testing and remediation or supplemental study software uses an adaptive learning engine with the demonstrated ability to refine and reflect details of student competencies. The LSI Dynamical Problem-based Objective Mastery adaptive learning engine embodies the best practices and procedures of such software.

LSI's MyAcademicWorkshop software offers testing, smart remediation, and course support, all in a single platform. In addition, it is linked to the LSI WorldWideTestbank content authoring and workflow platform to provide homework presentation and assessment capability. Complementing the latter, there is a grade book for tracking in-course performance. This combination of features makes

MyAcademicWorkshop an excellent supplement to an existing LMS, one that brings the full potential of online technology to the support science, technology, engineering, and mathematics programs.

Placement Testing

Students are posed with problems linked to learning taxonomy in general and to the specific core concepts of the subjects in which they are being placed. Data points about student competency are formed from a plurality of problem solutions. Each data point contributes to a further traversing of the subject learning objective to hone in on the precise level of student mastery. Assessment is independent of teaching methodology.

Individualized Learning Plans

A customized learning approach iterates through course learning objectives by eliciting student responses to basic problems and, optionally, metacognitive reflection on learning issues. The pool of problems alters at each step, in effect developing with the student a mastery of the required concepts. Rather than relying upon impersonal statistical results, the plan evolves to address unique development issues. Progression is, by default, independent of teaching approach but reflects campus prerequisites.

Supplemental Course Support

Once a student places into a campus-taught course, the work of the adaptive learning engine is complete. However, MyAcademicWorkshop continues to give instructors or departments access to a huge corpus of problems. These are templates that can be edited by the instructor. They can be set to change numbers and variable names each time the student attempts the problem. A grade book built into the platform automatically delivers notifications in a form selected by the instructor when there is evidence that the student in not progressing as desired, the standard for which also being determined by the instructor. In short, the content and optional forums for metacognitive student input essential to the DPOM engine can also be used to assist instructional design in which student engagement is a high priority.

The software at the heart of MyAcademicWorkshop is supported by over a decade of close work with the academic community in elaborating online materials for courses and publications. It is also supported by investigations into problem-based learning and the mathematical and practical effectiveness of adaptive learning. The LSI Dynamical Problem-based Objective Mastery adaptive learning engine built into the MyAcademicWorkshop platform embodies the best-known and most widely proven methods of adaptive learning. We look forward to continuing research and innovative applications of this tool.

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About Link-Systems International, Inc.

LSI Mission Statement

Link-Systems International is the leader in providing integrated technology and service solutions to educators in order to improve the quality of education and training, ensure student success and retention, and provide affordable education to students, workers, and their families.

Our Company

Link-Systems International, Incorporated (LSI) is a privately held technology services and content development company that has been dedicated to student success and student retention in K-12 education, higher education, and workforce development education since 1995.

Our core technologies include a very flexible online tutoring/teaching platform, an online grade book, an online algorithm engine with metadata and workflow capabilities, and an online business intelligence/data mining technology designed to provide real-time alerts regarding student/school/teacher performance, attendance, and other metrics.

Our core services include content development, consulting, and online tutoring through our NetTutor® brand.

Our customers include K-12 publishers, higher education publishers, virtual high schools, higher education institutions, technology companies, and joint programs dedicated to providing online educational content to members of organized labor and their families.

We are located in Tampa, Florida, a few miles from the University of South Florida. Along with the Moffitt Cancer Center—one of the premier medical research institutions in the United States—USF has excellent engineering, computer science, and mathematics programs, providing LSI many of its employees.

Launched in 1995, LSI has created several unique and powerful technologies that facilitate the sharing of content over the Internet. We specialize in mathematics, technical, and scientific content—the most critical types of online content with respect to student success, and the most difficult to share online.

Today, LSI is recognized by a variety of publishers and educational institutions not only for its high-quality work and dedication to meeting commitments, but also for its unique ability to develop digital strategies that are custom-tailored to the needs of its customers.

Our partners and customers have come to value and trust LSI because we are the only company that offers a complete suite of interoperable solutions that address the entire life cycle of the student, with an overt focus on the bottom line: student success and student retention. That student life cycle includes:

* Online Assessment and Placement
* Content Authoring
* Content Recovery, Content Management, and Metadata Management
* Online Teaching, Collaborating, and Tutoring
* Online Homework and Testing
* Online Grade Book Technologies
* Online Real-Time Performance Monitoring and Intervention

Through a relationship with LSI, educators acquire the ability to construct a complete, holistic approach to student success and student retention.

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About Academic Research at LSI

We are enthusiastic about the commitment of institutions and academics to the use of technology with proven benefits to their students. If you would like to write about the impact of Web-based technology, please let us know. We encourage educational research and will work with you and your staff to develop scientific studies into the relationship of the online learning experience to successful student outcomes. Please contact our Academic Research Department.

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