

PROJECT DESCRIPTION

1. Introduction

A post-secondary student or teacher logs online to find a learning object on “how to multiply two matrices.” The student learner wants help in understanding the concepts and procedures. The teacher, on the other hand, wants to use the learning object to improve instruction. Both find many learning objects, but some of them are tailored for high school students with minimal or no knowledge of matrices, while others are targeted for advanced learners with substantial background in matrix theory. Some are comprehensive, while others consist of only one of the elements that the learner or the teacher is looking for. Some have examples that are difficult to understand. Frustrated by such an avalanche of learning objects with very little or no information available to guide the appropriate choice, the learner or teacher gives up and goes back to the textbook.

The preceding scenario is far too common in the current world of on-line instructional resources. For example, Massachusetts Institute of Technology’s OpenCourseWare project publishes course materials online and provides a free and open educational resource for faculty, students, and self-learners. Take the “18.01, Single Variable Calculus” course for example. It has a set of five problems; however, the course provides no information on how a student should use the problems, how an instructor should incorporate them in his or her course, how difficult the problems are, how long it will take a student to solve the problems, what types of feedback should be given to the students, or how to adapt the problems to address different student needs. In short, the course provides very little information or insight to guide a learner or a teacher in using the problems effectively and efficiently.

Our proposed research on learning objects is designed to address this specific problem. Our long-range goal is to augment learning objects with **empirical usage intelligence**—how a learning object should be used, how it has been used, and how it has impacted instruction and learning. Use of this empirical usage intelligence will result in radical improvements in learning and instruction and contribute to the body of research in cognitive and computer science. As a result, the learners and teachers will be able to identify the learning objects that match their needs, educational and experiential backgrounds, and mode of learning or teaching. Learning management systems will be able to make use of the intelligence to sequence learning objects to build courses. In order to take a significant step toward our long-range goal, we propose an integrated (research and technology) and multidisciplinary (learning research and computer science education) approach with the following specific technology and learning goals:

Technology Goal 1: Create an **Intelligent Learning Object Guide (iLOG)** that tracks, diagnoses, and tags the empirical usage intelligence of learning objects.

Technology Goal 2: Revise and convert the online course materials for an undergraduate introductory CS course (CS1, already developed at the University of Nebraska-Lincoln [UNL]) into learning objects.

Learning Goal 1: Identify the salient learner attributes and content/pedagogical characteristics that can be empirically tracked to impact learning.

Learning Goal 2: Measure the impact of active learning and elaborative feedback on student learning with learning objects.

In terms of **technical innovations**, our proposed project will (1) add to the Shareable Content Object Reference Model (SCORM) metadata standard to include empirical usage history and statistics on each learning object, (2) result in a framework and a software system (i.e., iLOG) to empower learning objects with empirical usage intelligence, (3) develop advanced computer-based tracking and analysis tools that provide robust quantitative information on student

Learning objects are small, stand-alone mediated, content “chunks” that can be reused in multiple instructional contexts, serving as building blocks for lessons, modules, or courses. They can be rearranged, replaced, and modified for future changes in content and adapted to learner needs.

understanding and learning progress and (4) develop SCORM-compliant learning objects for the CS1 course that are interoperable across a variety of platforms and Learning Management Systems. In terms of **research advances**, our proposed project will advance our knowledge of (1) student conceptual learning processes, (2) creation of new strategies for using contemporary technology-based instructional approaches, (3) matching of instruction to meet specific needs and preferences of learners, and (4) anomaly diagnosis for intelligent systems such as iLOG interacting with human subjects in uncertain and dynamic learning environments.

The **expected significance** of the technical innovations and research advances of this project is the holistic treatment of learner and content/pedagogical characteristics (LO metadata) and the corresponding tracking, diagnosis, and tagging. It uses intelligent diagnosis techniques to pinpoint the likely cause of anomalies in learner and LO usage patterns to more accurately update the metadata, which is then evaluated and verified using learning research, and which in turn identifies what metadata to track.

Project Team and Resources: Key to our approach is the long-standing collaboration between faculty from computer science and education, building and maintaining a productive synergy where the design of CS course elements (including learning objects) is informed by educational psychology research and embedded with components intended to provide insight into how students learn computer science concepts. To identify the most effective instructional methods and strategies for students in introductory CS courses, we follow rigorous experimental protocols supported by and in accordance with current research in educational psychology and instructional technology. This team has the experience and expertise needed to successfully conduct this research; we have developed many educational resources, including tutoring software, and will be using our award-winning CS1 courseware as the basis of our learning objects. Our collaboration also represents a partnership among two major Centers on the University of Nebraska-Lincoln campus—the National Center for Information Technology in Education (NCITE) (housed in the Department of Computer Science and Engineering) and the Center for Research on Children, Youth, Families, and Schools (CYFS) (housed in the College of Education and Human Sciences). The project is also supported by the Extended Education and Outreach office at the University of Nebraska-Lincoln and the University of Wisconsin’s Advanced Distributed Learning (ADL) Academic Co-Lab. The latter is one of the Department of Defense’s premiere Co-Labs on the research, development, demonstration, assessment, and implementation of ADL tools and is responsible for the SCORM standards.

2. Research Context

2.1. Review of Literature Relevant to the Project

Continuous and significant changes in computer science technologies in the areas of software engineering and information technology pose considerable challenges to academic institutions. A CS curriculum that effectively accommodates both change and growth must be able to overcome difficulties inherent to rapid change, e.g., develop new instructional material, reorganize courses, and provide continuing education modules. Concomitantly, it must attract more students to this field despite the increasing technological complexity. Ever-changing technology makes it difficult for high schools to provide students with a consistent and current coursework foundation. As a result, college-level introductory CS courses are filled with students with diverse knowledge, exposure, and expectations. The need to adapt to student needs is a challenge to both students and educators. This is especially challenging with respect to many target populations, including women and minorities (Sturm & Moroh 1994; Dabbagh 1996; Rebelsky 2000). High dropout rates are indicative of the problem: 50% or higher as reported by Allan and Kolesar (1996) and Powers (1999) and 15%-30% as reported by Guzdial and Soloway (2002). Difficult-to-grasp concepts coupled with students’ diverse skill levels make existing lecture-based education in CS very challenging (Cox & Clark 1998; Urban-Lurain & Weinshank 1999). Traditional curriculum development methods were not designed to support this rapid rate of change and adaptation to individual student needs.

Learning Objects (LOs). The learning object model of instruction offers tremendous promise from the perspective of updating and customization of student learning. The value of the

learning object approach has been recommended by the Department of Defense (ADL 2003), business and industry (ASTD 2000), public schools (Grunwald 2002; Nugent 2005; Pasnik & Keisch 2003), and higher education (Koppi & Lavitt 2004; Francia 2003; van Zele *et al.* 2003). Major strengths cited were reusability; ease of updates, searches, and content management; customization; interoperability; and overall flexibility. Research on learning objects has also verified their instructional value (Boster *et al.* 2002; Bradley & Boyle 2003; Nugent *et al.*, to appear). While on-line modules have been used in CS education (Herrman *et al.* 2004; Herrmann *et al.* 2003; van Zele *et al.* 2003), after an extensive search of LO repositories we found only a handful of complete LOs—with all three instruction, practice, and assessment components—that have been developed for CS instruction. None of them are based on learning research, contain embedded monitoring capabilities, or adhere to the SCORM standard.

Active Learning and Feedback. Today's learning theories emphasize that learning is enhanced by actively engaging students in the learning process (Bransford & Schwartz 1999). In contrast to passively listening to a lecture, active learning requires students to dynamically make decisions and choices, which, in turn, influences the sequencing and instructional presentation.

Feedback is another critical design dimension. Studies of learning, transfer, and development show that feedback is extremely important and that, usually, it should be immediate (Bransford *et al.* 2000; Mory 2004). Several major review of the research (Natriello 1987; Crooks 1998; Kluger & DeNisi 1996; Black & William 1998; Nyquist 2003) have found consistently positive effects for the use of feedback. Kluger & DeNisi's review of 3000 research reports have also confirmed this finding (average effect size = .4). Nyquist's review isolated levels of feedback, beginning with simple knowledge of results (KoR) and adding explanation, actions for gap reduction, and specific activities. As the level of feedback increased, so did the effect size. E-learning can provide ongoing feedback to students and can allow for feedback that is specifically targeted to the needs of individual students.

Aptitude Treatment Interactions. Our project approach and research questions are also derived from the theoretical underpinnings of *aptitude-treatment interactions* (ATIs), originally conceived by Cronbach and Snow (1977). *Aptitude* is defined broadly as a learner's incoming knowledge, skills, interests and personal traits. *Treatment* is defined as the condition or environment that supports learning. Recently, ATI research has experienced a revitalization, due in large part to the use of computers to provide controlled learning environments (Shute & Towle, 2003; Maki & Maki, 2002; Woltz, 2003). Computers have also facilitated the presentation of multiple treatment levels and sophisticated data tracking needed to isolate effective types of treatments for particular types of learners. The underlying premise of this line of research is that to maximize learning effectiveness, the instructional method should be adapted to student characteristics, i.e. one instructional method may be superior for students exhibiting certain individual characteristics, while another method is superior for students with differing characteristics. Since our project involves tracking characteristics of the learner *and* characteristics of the treatment (LOs), we can begin to identify relevant interactions.

2.2. Preliminary Work

2.2.1. CS Curriculum Project

The proposed project is an outgrowth of four years of work accomplished by the project team through its *Reinventing Computer Science Curriculum Project* (Samal *et al.* 2005; <http://cse.unl.edu/reiventCS>). We have designed, developed, and deployed: (1) a placement test to determine enrollment in introductory CS courses (i.e., CS0, CS1 or CS2) and its evaluation and student assessment (Soh *et al.* 2005a; Nugent *et al.* 2006), (2) a framework for structured, hands-on laboratories and a set of laboratory modules for CS1 and CS2 (Soh *et al.* 2005b, 2005c; Soh *et al.* to appear, a) and related studies on cooperative learning (Lang *et al.* 2006), (3) two stand-alone web-based LOs for use in CS1 (Nugent *et al.* 2005b; Nugent *et al.* to appear), and (4) a framework of embedded learning research instruments including Institutional Review Board-approved studies and designs (Soh *et al.* to appear, b). As part of this ongoing project, the proposed activities will enjoy strong institutional support that includes the computing infrastructure and human resources from the Department of Computer Science and Engineering

and the Statistics and Research Methodology Unit from the Center for Research on Children, Youth, Families and Schools at UNL.

2.2.2. Learning Objects (LOs)

We have successfully designed, built, and evaluated two LOs on *Simple Class* and *Recursion*. (These may be viewed at <http://blackboard.unl.edu>. Login as "secc" with "secc" as the password, then follow CSCE155 link and proceed to "Course Documents" tab.) The two LOs were designed with extensive use of Flash animation and utilized multiple user input formats, including drag-and-drop, multiple choice, and model construction. They were designed to allow students who have a good understanding of the concepts to move ahead quickly while following a more deliberate path for students having difficulty. Students had to score 100% on individual exercises before they could progress to the next activity. Students who provided correct responses had the option of working on additional problems. Appropriate feedback was provided for students who required additional instruction. This self-pacing and mix of learner and program control allow for adaptation to individual student needs and background knowledge. It also provides a structured progression through the content, promoting mastery of concepts from basic through advanced.

Research and evaluation of the *Simple Class* and *Recursion* LOs confirmed their effectiveness. Students found the LOs easy to use and a valuable addition to the course, with an average rating (M) of 4.56 and 4.47 respectively on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The LOs maintained student interest (M = 4.25) and helped them better understand the computer science concept and content (M = 3.97). Overall, they rated the LO to be better than "Good-Excellent" (M = 4.31). Open-ended comments from the students also provided evidence of their effectiveness: "I really like this program and what it taught me"; "I like the real-time feedback"; "It is very informative, interactive, and fun".

Experimental comparisons between students randomly assigned to traditional instructional activities (completing in-class exercises with guidance from the instructor) versus the LOs showed no significant learning differences for either the simple class, $t(48) = 1.04, p = .30$, or recursion topics, $t(35) = 1.41, p = .17$. Results confirm the approximate equivalence of the LO and the traditional instructional experience in promoting student learning. However, results from qualitative analyses lead us to hypothesize that the individualized and adaptive LO approach may be particularly effective for students having difficulty with specific topics. The series of evaluation and research results confirm our belief that modular, web-based LO can be used successfully for independent learning of complex subject matter and provide flexibility in terms of anytime, anywhere access and utilization (Nugent *et al.* 2005b; Nugent *et al.* to appear).

2.2.3. Intelligent Tutoring System and Tracking

We have conducted preliminary research and development work in the form of an agent-based intelligent tutoring system called Intelligent Learning Materials Delivery Agent (ILMDA) (Soh 2006; Soh & Blank 2005; Soh & Miller 2005). ILMDA is powered with case-based reasoning (CBR), a database of LOs and primitive student modeling. ILMDA is designed to determine the most appropriate example or exercise to deliver to a student based on the situations that the system has experienced in the past. Thus, each case in this framework consists of a set of situation descriptors and a set of solution parameters. Situation parameters include (1) **learner attributes** consisting of relatively *static* parameters such as motivation, self-efficacy, interest, major, and GPA, and more *dynamic* parameters documenting aspects of students' online interaction such as time spent on each LO's tutorial, number of examples seen, number of exercise problems answered correctly, and number of times going back-and-forth between examples and tutorial pages, and number of quits for each section; and (2) **content characteristics** such as the average amount of time spent on a particular section, number of times students have answered questions correctly, average number of times students quit at which section, and text length. The solution parameters, on the other hand, describe the characteristics that the next example or exercise problem should have, such as the amount of scaffolding, Bloom's level (Bloom 1956), and the degree of difficulty. Thus, each case contains an instructional strategy on the next instructional item to deliver to the student. During each

interactive session, ILMDA observes a student and constantly updates both its parametric profiles of the student and the LO, and given each new request, it retrieves the best case, adapts its solution parameters based on the difference between the situation parameters for the case and the current request, and applies the adapted solution. ILMDA is also capable of learning new cases and refining its heuristics to improve its performance over time. Our studies, based on actual deployment of ILMDA in CS1, found that the number of section quits, time spent on the examples and the number of times a student went back to the examples when solving a problem were important factors in determining the Bloom's level and amount of scaffolding of the problems to be delivered to the students.

Extensive tracking was also built into a K-4 on-line project (*Bridges*) under the direction of Co-PI Nugent. The *Bridges* project involved an assessment management system that recorded, categorized (as response, early quit, or request for help) and time stamped every mouse click made by the students. The system computed summary statistics for various student groupings and individual items, sections, and completed activities. This research identified tracking parameters—including item difficulty level, student grade level, time on task, level of scaffolding, and early quits—which were related to student learning (Nugent *et al.* 2005a).

Our experience in developing these systems and the research results serve as the basis for our proposed research. Empirical usage intelligence proposed for this project is based on the learner attributes and the content/pedagogical characteristics that can be identified as associated with or predicting learning and potentially relevant for adaptation to student needs.

2.2.4. Online Course Materials for CS1

The Extended Education and Outreach (EEO) Program at UNL has developed two Advanced Placement (AP) CS courses, one of which has won the University Continuing Education Association's 2005 Community of Practice Distinguished Course Award (a national first place honor). The two-semester course has 30 lessons altogether. Each lesson in the course is composed of an introduction, lesson objectives, reading assignment, discussion topics, self-check tests, and a lesson quiz. Keys are provided for the self-check tests and lesson quizzes. The non-graded self-check tests and lesson quizzes are designed to help students assess their understanding of the concepts and theories presented and to prepare them to complete their projects successfully and take the final exam. "Consider This" activities in some lessons ask the students to think about how they would solve a particular problem. These questions have no specific correct answers, as they are designed to promote critical thinking about a topic that has been covered in the lesson. These activities are intended to help students critically evaluate the practical applications of the subjects they are studying. (*These course materials may be viewed at <http://nebraskahs.unl.edu>. Click on the "Log in to Way Cool" link and login as "uceademo" with "UCEAdemo1" as the password. You will see a new page and will be able to choose the two courses at the bottom of the page.*) We will use these courses as the content for our LOs, allowing us to *focus on the innovation and research* for this proposal.

3. Proposed New Work

In the following, we describe the four central elements of our proposal: Methods, Measures, Assessment and Evaluation. The Methods subsection will describe our approach to the following three tasks: (1) determining and validating the empirical usage intelligence parameters, (2) designing and implementing the **Intelligent Learning Object Guide (iLOG)**, and (3) incorporating active learning and elaborative feedback into LOs. Tasks 1 and 2 satisfy our Technology Goal 1 and Learning Goal 1. Task 3 facilitates Technology Goal 2 and Learning Goal 2. The Measures subsection will identify the critical student attributes and outcome variables that will be used in our assessment and evaluation. Some of these attributes are static parameters and some are dynamic and will be collected during the tracking process. The Assessment subsection describes a multistrategy approach to measure student learning performance to help achieve Learning Goal 1 and Technology Goal 2. The Evaluation subsection will outline three research questions to evaluate how well our design satisfies the above goals.

3.1. Methods

Our methods consist of three main tasks: the definition of empirical usage intelligence parameters, the development of the iLOG system, and the incorporation of active learning and elaborative feedback into the LOs. All three are interdependent. The incorporation of active learning and elaborative feedback enriches the LO-learner interaction, which is tracked by iLOG. Then, appropriate parameters (learner and LO profiles) are updated based on a diagnosis component of iLOG. Data mining is also performed offline to identify useful patterns that can be retrieved to improve the accuracy of the diagnosis.

3.1.1. Empirical Usage Intelligence Parameters

To determine the set of empirical usage intelligence parameters that captures how an LO should be used and has been used, we will focus on two profiles: learner and LO. A learner profile describes the background and experience of a learner using various LOs from the standpoint of the learner, while a LO profile describes content and pedagogical characteristics of an LO and how the LO has been used by students from the standpoint of the LO. Dovetailing these two profiles together allows one to compute more precise and accurate intelligence values for an LO. For example, this allows an LO to have a metadata tag that says: “This LO is successful 80% for students with high motivation.” With this in mind, even though the learner profiles are not part of the metadata to be embedded with an LO, they are critical in our proposed research. Table 1 shows an initial set of basic parameters for learner and LO profiles, based largely on learning theory and the results from our ILMDA and Bridges projects previously described in Section 2.2.3. Some of these parameters are static such as the gender, motivation, and ethnicity of a learner, and topic and difficulty level of an LO. Some are dynamic and are derived from the actual learner-LO interactions.

	Static Parameters	Dynamic Parameters
Learner Profile	Motivation Self-efficacy Gender Ethnicity Major Year (fr., so., jr., sr.) GPA SAT/ACT score CS Placement exam score	Average time spent on an LO for this learner Average no. of examples accessed for this learner Average no. of exercise problems attempted for this learner Average no. of exercise problems answered correctly for this learner Number of quits for this learner Average no. of mouse clicks for this learner Average no. of going back-and-forth between an example and tutorial for this learner Average no. of going back-and-forth between a problem and tutorial for this learner for this learner Average no. of going back-and-forth between a problem and an example for this learner for this learner Average time spent on each example (problem) for this learner
Learning Object (LO) Profile	Topic Length Degree of difficulty Bloom Level Amount of scaffolding Level of feedback. This category also includes the SCORM educational metatags (e.g., interactivityType, interactivityLevel)	Average time students spent for this LO Average no. of examples accessed for this LO Average no. of exercise problems attempted for this LO Average no. of exercise problems answered correctly for this LO Average no. of mouse clicks for this LO Average no. of quits for this LO Average no. of going back-and-forth between an example and tutorial for this LO Average no. of going back-and-forth between a problem and tutorial for this LO Average no. of going back-and-forth between a problem and an example for this LO Average time spent on each example (problem) for this LO Number of times this LO has been used Number of times this LO has been used successfully

Table 1. An initial set of parameters to be used to facilitate empirical use intelligence

Drawing on learning theory and based on our previous work, we have also arrived at a set of principles that will guide how we re-use, refine, and extend this initial set of learner and LO profile parameters as follows.

Principle 1 - Active learning and Interactivity. Evidence of active learning can be derived by examining the dynamic behavior of a learner. This can be measured in a number of ways including the number of mouse clicks, number of examples accessed, number of exercise problems accessed and completed, number of quits, evidence of re-accessing tutorials or worked examples, and choices of feedback or scaffolding. An LO may or may not be conducive to active learning. An instructor may prefer an LO that provides straightforward explanation and does not offer too much learner interactivity for a simple topic *but* may prefer a LO that offers sufficient learner interactivity for a complex topic that involves a host of examples and scenarios. On the other hand, a very well-designed example may lead to less activity even if the LO has many other examples. Capturing these parameters allows us to measure how different learners interact with different LOs and on different components of a LO.

Principle 2 - Diverse Student and Content Characteristics. Student behaviors are diverse, and thus the parameters should provide adequate resolution to differentiate distinct behaviors. For example, it is possible to cluster students into two groups by their motivation: (a) high and (b) low. How well an LO can adapt to a learner may very well depend on such information. It is important for the parameters to describe the behavior of an LO for such groupings instead of lumping all students into one group. This approach will improve the precision of the empirical usage intelligence of the LO. Similarly, an LO may have different sections: tutorial, examples, exercise problems, and assessment. The tutorial may be good but the examples may not be as good. The exercise problems may be reinforcing what the student has learned from the tutorial but the assessment may not test the student correctly. Thus, it is also important for the parameters to describe the behavior and the performance of the individual LO components.

Principle 3 - Historical or Temporal Usage Patterns. The usefulness and usage pattern of an LO changes over time. For example, an LO that teaches a particular computer programming syntax may become less popular or obsolete after a few years. A change in public school system in CS curriculum may produce a batch of freshmen taking CS1 with better self-efficacy or knowledge level. A change in institutional policy that requires all majors to have CS1 as a prerequisite may render some LOs unpopular. Thus, it is important to capture these patterns as empirical usage intelligence for each LO.

Applying the above principles, we will design and develop high precision LO metadata. Take for example a content characteristic of an LO: "Percentage of students who passed the LO's assessment component." Applying Principle 2, we can provide increased resolution to this parameter by taking into account the motivation of students. This results in two parameters (a) percentage of students with *low* motivation who passed the assessment component, and (b) percentage of students with *high* motivation who passed the assessment component. Applying Principle 3, we can obtain "*Trend* of percentage of students with low motivation who passed the assessment component."

3.1.2. Intelligent Learning Object Guide (iLOG)

We propose to build the Intelligent Learning Object Guide (iLOG) to perform three major functions: (1) track how an LO is used, (2) diagnose the tracked data to update the learner and LO profiles, and (3) tag an LO accordingly. With these capabilities, we will be able to metadata tag each LO with increased accuracy, based on the empirical data collected. We see iLOG as a software system that can be embedded into existing learning or course management systems. Figure 1 depicts how the three components work together in the iLOG system. First, the LOs are delivered through a learning management system such as Blackboard (<http://www.blackboard.com>). Within each LO, there are Javascripts that are triggered by mouse events during an interactive session with a student. Each trigger will result in a log in either the LO empirical usage database or the student profile database or both, or invoke another data processing function. For example, the time stamp will be used to determine the time spent on the previous section, and the source and destination pages will be used to

determine whether the student has chosen to go from an example back a tutorial page. After each session, iLOG's diagnosis module is invoked. This module decides how to update the metadata tags of the LO that has just been viewed. For unexpected results, we will use an evidential diagnosis protocol to identify why a session succeeded or failed. Of the three components, we have had experience in tracking using Javascripts, and have the expertise in our Senior Personnel Barker (Barker 2004) and partnership with the ADL Academic Co-Lab to implement the tagging. Thus our research and development of iLOG will focus on the diagnosis component.

Tracking. For the two LOs that we have built, we have implemented tracking using Javascripts event triggers. Within each LO, we have snippets of Javascripts at the exit and entry points of each page. When the page is loaded by the learning management system (such as Blackboard), these Javascripts are invoked automatically. Each invocation sends a data log to the corresponding databases identified by the script. Each data log has a time stamp, a destination page, a source page, and a mouse event type. When a higher level of *data processing* is needed, the data log also has a function call. For example, if the objective is to determine the time spent on the previous page, then the function call will retrieve the previous time stamp, find the difference between that time stamp and the current time stamp, and produce the result to be logged in the databases. We will use the same strategy in this project.

Diagnosis. In order to update the correct profiles accurately, iLOG needs to (1) identify whether a session is an anomaly, i.e., one with profile parameters that are not within the expected range of results, and (2) diagnose what likely causes the anomaly. Anomalous sessions will not be used to update the operational learner and LO profiles immediately and will instead be archived and mined. The corresponding diagnosis of an anomaly session, however, will be used immediately to update the empirical usage intelligence of the LO. Therefore, our proposed work in this diagnosis will consist of data mining to discover useful *anomaly-diagnosis* patterns from the archived sessions and to gradually and eventually implement the identification of these patterns so that iLOG can automatically perform the diagnosis. With this diagnosis component, our proposed iLOG system will be able to identify outliers as anomalies, obtain the most likely diagnosis by retrieving the nearest-matching anomaly from its knowledge base of anomaly-diagnosis patterns, and then update the corresponding profiles selectively. These updates are shown as tagging decisions in Figure 1.

The diagnosis will utilize domain *heuristics* provided by the content designers and empirical *statistics* that iLOG derives from the tracked LO-learner sessions. *Domain heuristics*, will be useful as a starting point to guide how iLOG should diagnose the LOs when there is not enough data to compute valid statistics on the LOs. For example, if a LO developer labels the LO as "difficulty level=easy" and a student failed the LO-learner session, then iLOG may assume that the LO has been labeled correctly and that the student does not match the targeted audience of

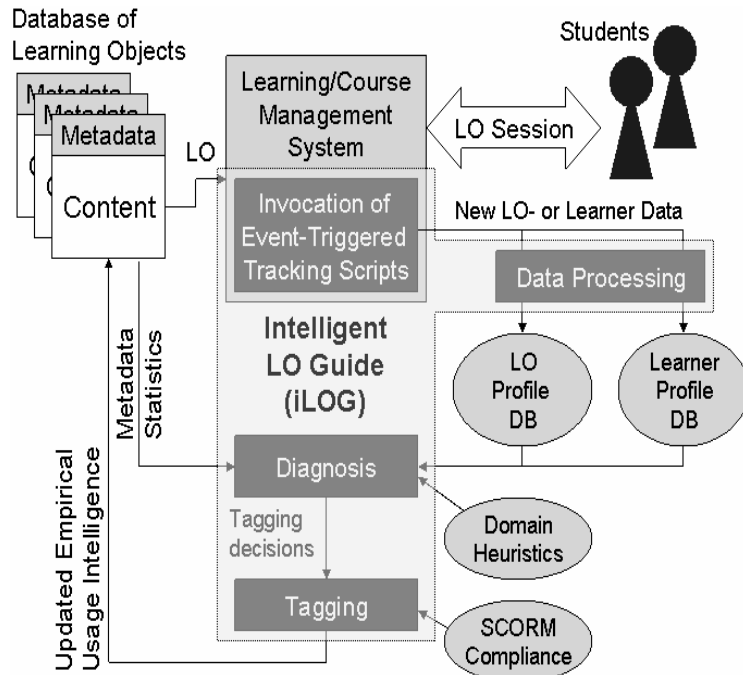


Figure 1. The design of the proposed iLOG system and how it interacts with LOs, the learning/course management system, data, heuristics and standards.

the LO because he/she does not have the prerequisite knowledge, motivation, and reasoning skills. Designers will provide these heuristics in the form of LO profile parameters such as the difficulty level, Bloom's level, targeted audience, and knowledge level of the LOs, similar to what is part of the existing SCORM metadata for LOs. *Statistical approaches*, on the other hand, will be useful to deal with uncertain and dynamic characteristics of the learners and possibly content that the LOs encounters. For example, from our ILMDA experience, the system once tracked a student spending more than 1 hour on a single problem, when the student usually spent an average of less than a minute on individual problems. It was evident that the student must have left the session for a while before returning. Such outliers can be identified statistically.

To identify and discover anomaly-diagnosis patterns, we will also rely on a combination of techniques from learning research and data mining. Mahalanobis distance, which considers multiple dimensions simultaneously, will be used to identify multivariate outliers. Mahalanobis distance is a standardized distance from a case to the centroid of the rest of the cases in the multivariate space. A case with large Mahalanobis distance is far away from the cluster of the remaining cases, thus, is an outlier. The outliers will be further explored in search of the reasons why the cases are extreme. The outlier status will be dummy coded (0 = outlier and 1 = not outlier) and correlated with other background variables. A discriminant function analysis will be conducted to examine the multivariate relationship between the background variables and the outlier status and to identify the factor that discriminates between the outliers and the mainstream group of students.

In terms of data mining techniques, association analysis and unsupervised clustering (Han & Kamber 2006, Parsons *et al.* 2004, Jain *et al.* 1999) will be used. Association analysis discovers rules that show attribute-value conditions that frequently co-occur. Given a set of parameters, M , the association rules are generally represented as $A \Rightarrow B[s, c]$, where $A, B \subset M$ and $A \cap B = \emptyset$, where s represents the *support* for the rule—the percentage of transactions that contain both A and B , and c represents the confidence of a rule—the percentage of transactions containing A that also contains B . Using these association rules, patterns such as “students with low motivation who complete a specific practice exercise score high in the assessment with a confidence of 0.75” can be identified. Unsupervised clustering divides data into clusters such that the inter-cluster distances are maximized and the intra-cluster distances are minimized to yield compact clusters that are far apart from each other. Clustering can show natural groupings in the learning space that may not be obvious and can be used as heuristics. We will use existing clustering tools such as C4.5 (Quinlan 1993).

Note that we are *not* proposing real-time, online data mining as that may increase the workload of iLOG and impact the interactivity of the LOs. Instead, we will add the mined patterns gradually to the domain heuristics so they can be readily retrieved by the diagnosis component. PI Soh and Co-PI Samal have had extensive experience in unsupervised clustering and data mining (Soh & Tsatsoulis 1999a, 1999b, 2000; Liu & Samal 2002a, 2002b; Zhang *et al.* 2005).

Tagging. We will develop SCORM-compliant metadata tags. SCORM is a set of technical specifications originating from the Department of Defense and is widely accepted as the standard for LOs. Presently, SCORM's metadata (ADL 2004) consists of nine categories, we will significantly improve two: (1) *educational* that describes the educational and pedagogic characteristics of a component, and (2) *relation* that describes features that define the relationship between a component and other targeted component. For example, the *educational category* keeps track of preset *interactivityType*, *interactivityLevel*, *semanticDensity*, *intendedEndUserRole*, *context*, *difficulty*, *typicalAgeRange*, *typicalLearningTime*, etc. iLOG will be able to collect actual, empirical intelligence on *typicalAgeRange* for an LO, its *typicalLearningTime*, level of difficulty, and so on. The *relation category* keeps track of *requires*, *isrequiredby*, *references*, *isreferencedby*, *isbasedon*, *isbasisfor*, etc. Once again, our iLOG, through its synthesis of LO and learner profiles, will be able to derive which LO is required by which LO based on the statistics. We will also add new, more detailed LO profile parameters to SCORM's metadata for iLOG. For example, we will be able to derive *observedEndUserRole* in greater details in terms of motivation, self-efficacy, and aptitude. Similarly, we will be able to determine the *interactivityLevel* by observing the number of events

triggered by the learner. Finally, we will also add new metadata tags that describe empirical usage intelligence of an LO—how it has been used, how successfully it has been used, etc.

3.1.3. Incorporating Active Learning and Elaborative Feedback into LOs

As mentioned previously, we have already developed the online course content for our LOs. We will, however, incorporate additional elaborative feedback and interactivity to support active learning when converting the existing course content to LOs.

Active Learning. Active learning requires the student to make decisions dynamically and respond to the activities in an LO. This is reflected in the interactivity level of the LO. We will add more interactive examples to the straightforward presentation that characterizes the existing course content. Learners will also be given the option of accessing additional examples, if they feel unsure of their level of understanding. This learner control is intended to promote self-regulation and self-monitoring that requires students to continuously assess their learning, recognize misunderstandings or confusion, and actively request additional explanations or examples.

Elaborative Feedback. We will design two levels of feedback: low feedback level, as reflected by knowledge of results, and elaborative feedback, as reflected in extensive explanations and models. In the two LOs that we have developed and studied, we have incorporated elaborative feedback. For each correct response, we re-iterate or summarize the key concept to reinforce student understanding. For each incorrect response, we have several types of elaborative feedback: (1) explanation through the identification of the misconception and mismodeling, (2) explanation through the illustration of an example or a counter-example, and (3) explanation through the re-iteration of the correct concept. We will use the same strategy in this project.

3.2. Measures

Here we describe the measures that are essential to assessment and evaluation our technology and learning goals.

Student Computer Science Learning (*Achievement*). We will convert lesson quizzes of the existing LOs into graded, online assessments. The project team has had considerable experience in the development and validation of on-line assessments, having developed and implemented the CS placement test currently in use at UNL (Nugent *et al.* 2006), as well as the post-test assessments developed for each of the existing CS1 laboratory sessions and the assessment developed as part of the simple class and recursion LOs.

Student Attitudes (*Self-efficacy and motivation*). We will also collect attitudinal measures ascertaining students' confidence in their CS knowledge and abilities (self-efficacy) and their intention to continue learning about CS (motivation). Self-efficacy has been shown to be a key student variable, with high correlations with academic motivation (Pintrich & Schunk 1995), career choices (Hackett 1995), and academic performance and achievement (Pajares 1996, 1997). Since student recruitment and retention in computer science is critical, it is important that these attitudinal measures be used in tandem with the achievement measure described above. The UNL project team has extensive research experience with an instrument based on the Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich and DeGroot (1990). The existing instrument contains six questions measuring two constructs: self-efficacy (e.g., "I am confident in my computer science knowledge and abilities,") and motivation ("I am motivated to learn more about computer science/technology.") Students respond to a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). For this research we will refine the instrument to also measure students' perceptions of the LOs in terms of interest, importance and utility.

Student General Aptitude/Achievement. We will use student ACT score, required for admission into the University, as a measure of general student aptitude and achievement.

Student Prior Computer Science Knowledge. Student prior knowledge level will be measured by scores on students' scores on the Computer Science Department Placement Test, developed and validated by the project team. This exam covers each of the major topics

recommended by the ACM/IEEE Computing Curricula 2001 guidelines and tests students' knowledge of each topic at multiple Bloom's taxonomic levels (Nugent *et al.* 2006).

3.3. Assessment

We will use a multi-strategy approach to student assessment. Success of the individual LOs will be assessed by measuring the percentage of students who successfully complete the LOs and their scores on the final assessment. Qualitative data will also be collected on student reaction to individual LOs through a brief on-line survey presented to students when they complete a particular LO. In addition, a more comprehensive survey will be administered at the end of a course soliciting feedback on the LOs. The overall survey will be administered along with the course evaluations at the end of a course. Responses will be analyzed by various student groupings and demographics, including gender, ethnicity, and college sector.

Research has shown that students develop knowledge structures that become increasingly organized and qualitatively different as learning occurs (Bransford *et al.* 1999). Data derived from the LOs will provide information to better understand the processes that occur in the minds of learners. With Principle 3 outlined in Section 3.1.1 earlier, we will collect data—i.e., the learner profiles—on individual student *learning trajectories* over the course of completing all LOs. Further, because of the high precision of the empirical usage intelligence, we will also be able to utilize LO profiles to corroborate on student learning over time and across different topics as well. We will begin by focusing on learning trajectories of students who are unsuccessful in completing LOs or who score low on the final LO assessment. Identifying problem areas from these students will provide a foundation for analysis and comparison with the larger group of students.

Scope. Our scope will cover the CSCE 166, the first introductory CS core course (i.e., CS1) offered here at UNL. CSCE155 has about 40-80 students per semester (depending on the Spring and Fall enrollments), majority of which are either CS or Computer Engineering majors.

3.4. Evaluation

Our evaluation will address the learning research and technical innovations of the project. We will focus on developing a research base to guide the matching of instruction to meet specific needs and preferences of individual learners. We will also emphasize the viability and technical feasibility of the metadata and iLOG. We will address three main questions, corresponding to our technology and learning goals outlined earlier in Section 1, as follows.

1. **Technology Goal 1:** *How well do the metadata and iLOG capture the empirical usage intelligence of learning objects?*

We will conduct preliminary studies in collaboration with ADL Academic Co-Lab to evaluate their existing repository and access of LOs in other topics. The evaluation here will be to investigate the technical feasibility of iLOG as a tool that accompanies the delivery of LOs on a learning management system: data storage, computing constraints, and correctness. Also, we will evaluate the viability of the metadata by sharing the intelligence collected of these LOs with the various ADL Academic Co-Lab partners using the LOs, to verify the insights.

2. **Learning Goal 1:** *What are the salient learner and content parameters that impact learning?*

The tracking component of the Bridges and ILMDA projects resulted in a tremendous amount of data, with statistics for individuals and, in the case of the Bridges project, aggregated data across certain demographic characteristics such as classrooms. These early projects showed that some tracking parameters were more useful in understanding and diagnosing student success or failure. A major research component of the proposed project will be identifying which of the many parameters identified are useful to predict learning and learning progress, as described earlier in Section 3.1.2. The research, using data from both the learner and LO profiles, and also results from student assessment, will rely on correlational and multiple regression methodologies to answer specific questions such as “Are static or dynamic parameters better predictors of learning?” “What content parameters are associated with high and low levels of learning?” “How well do the learner profiles capture student learning

approaches and progress through the LO instruction?” and “What content parameters are most correlated with student attitudes (self-efficacy, motivation)?”

3. Technology Goal 2: *Revise and convert existing online course materials for an undergraduate introductory CS course into learning objects and*

Learning Goal 2: *Measure the impact of active learning and elaborative feedback on student learning with learning objects.*

In converting the existing course material into learning objects, a major task will be incorporating active learning strategies and elaborative feedback. The impact of these strategies on student learning will be researched through a 2 X 2 factorial design incorporating a treatment variable (presence of active learning/elaborative feedback) and learner variables (aptitude, gender, prior knowledge, self-efficacy, and motivation). Students will be randomly assigned to the treatment condition. In order to provide clear differentiation between attribute levels, student attribute scores will be converted to dichotomous variables (high/low), using only the top and bottom third of students to develop the two categories. This design will allow testing of main effects (impact of active learning and elaborative feedback) as well as the identification of attribute-treatment interactions.

4. Integrative Research Strategy

Our research strategy, grounded in learning theory and research, relies on advanced, computer-based tracking, diagnosis, and tagging tools to implement specific research methodologies and analyses. The underpinning integrative research strategy is tightly coupled at two levels: the empirical usage intelligence itself and the computation of its values.

First, as indicated earlier, to determine the relevant metadata to facilitate empirical usage intelligence, we need to evaluate the impact of learner attributes and content/pedagogical characteristics. To generate these, we need CS technologies—tracking, diagnosis (and data mining), and tagging. To find out which are important, we need learning research to evaluate how each impacts or predicts student learning. Thus, CS technologies provide learning research with a feasibly tractable set of parameters, while learning research informs CS technologies which are most useful.

Second, identifying the metadata useful for the empirical usage intelligence is not enough; we still need a mechanism to compute the values for the metadata. Faced with uncertain and dynamic characteristics of learners and diverse and perhaps inconsistent designs of LOs, this computation task is non-trivial. Our approach is anomaly-based, one that uses unexpected results to trigger a diagnosis that identifies the most likely cause of the unexpected results. This approach combines domain heuristics and statistics. CS technologies such as data mining, coupled with educational research and statistical techniques, will help us discover anomaly-diagnosis patterns, which will inform learning research, and will also provide insights to student assessment. On the other hand, learning research will refine this diagnosis process, which will add to its introspective reasoning—how the system pinpoints its faulty components.

Therefore, our integrative research strategy relies on the synergy between CS and educational researchers. CS researchers will learn from the educational researchers on how to use assessment and research design to identify salient features, for example; and educational researchers will rely on CS personnel to provide computer-based tracking and analysis tools which can translate patterns into domain heuristics to help build intelligent educational applications.

5. Intellectual Merit

This proposed project will advance the existing knowledge base for both learning technology and educational research. In terms of technology, we will develop an intelligent system that can track, diagnose, and tag how an LO has been used, by taking into account learner attributes, and content/pedagogical characteristics. The diagnosis component will integrate domain heuristics, statistical approaches, and data mining to identify and discovery anomaly-diagnosis patterns to update LO metadata accurately. The assessment and evaluation will determine how

each LO metadata parameter impacts or predicts student learning and, in turn, identify important salient features. We will also incorporate active learning and elaborative feedback to enrich LO-learner interaction and evaluate their impact on student learning.

The proposed work is important for the research and development of advanced learning technologies in several novel ways: (1) embedding empirical usage intelligence in learning objects will significantly improve the correct use and longitudinal evaluation of LOs among learners and instructors, (2) the data mining process and the translation of useful anomaly-diagnosis patterns into heuristics will discover salient relationships between learner and content parameters that impact learning, and (3) the iLOG system will be an enabling technology for more personalized and adaptive instruction.

The unique innovation of our proposed activities lies in the symbiotic integration of computer science and learning research advances in the identification and evaluation of learner and learning object profiles at two levels: empirical usage intelligence (the *data* that describe how an LO should be and has been used) and iLOG (the *process* that updates the empirical usage intelligence). Without using advanced CS technologies, one will have to rely on only expert judgment to determine the choice of empirical usage intelligence parameters. Without considering well-designed learning research, one will not be able to design high-precision trackers or metadata taggers that are sensitive to both the learner and content properties.

Our proposal also derives its strength from the team. The three PIs have worked closely on the Reinventing CS Curriculum Project for the past 4 years. This interdisciplinary teamwork is built on strong interests in each other's areas—i.e., educational researchers want to use advanced CS-based technologies to inform instructional development and research, while CS researchers want to apply research-based educational strategies to CS education. This team has generated tangible products (software and courseware), learning results, and technology advances, and has authored five journal publications, one book chapter, and four conference papers in this short period.

6. Broader Impacts

Our project will extend the cycle of knowledge discovery and production and improvement of practice in undergraduate STEM education by contributing in three key areas: (a) enhancing SCORM metadata standard to describe with high precision how an LO has been used, (b) incorporating and evaluating active learning and elaborative feedback in LOs, and (c) conducting further research on adaptive undergraduate STEM teaching and learning. The expected results of the technology and learning research activities of this project will provide a better understanding of (1) how best to teach introductory CS courses with multiple entry points or customizations using different combinations of LOs and (2) how students learn from this dynamic form of instruction. Our research has the potential to provide the pathway for independent learning of complex subject matter and provide flexibility in terms of anytime, anywhere instruction.

Learning objects with embedded empirical usage intelligence can fundamentally revolutionize how to best utilize advanced technologies in the design and delivery of online instruction, how to best support the selection and use of such instruction among individual learners, and how to best support the experimentation, evaluation, and adoption of LOs in courses for instructors. For example, this will enable an innovative—and perhaps significantly more cost-efficient and effective—framework on how highly lightweight (content-independent, learner-independent, versatile, and with short development time) intelligent tutoring systems and educational testbeds can be built and fine-tuned quickly, by simply exploiting the embedded intelligence of learning objects. This will allow learning objects to be better developed, evaluated, labeled, adopted, and used. This has the potential, in the long term, to alleviate the workforce shortage in the areas of computer science and information technology in the U.S.