Embedding and Validating Empirical Usage Intelligence in Learning Objects
G. Nugent, L.-K. Soh, A. Samal, and L.D. Miller

Abstract: The iLOG (Intelligent Learning Object Guide) Project is designed to augment multimedia learning objects with empirical usage intelligence—how a learning object (LO) should be used, how it has been used, and how it has impacted instruction and learning. The goal of the project is to provide metatags that will help learners and teachers identify learning objects that match their needs, educational and experiential backgrounds, and mode of learning or teaching. This paper provides an overview of our NSF-funded project (Advanced Learning Technologies) and focuses on the learning approach and research.

Project Goals

The iLOG (Intelligent Learning Object Guide) Project targets a combination of technology and learning goals. The technology goals are to: (1) revise and reformat a current on-line course for introductory undergraduate computer science into learning objects and (2) create a system that tracks, diagnoses and tags the empirical usage intelligence of the resulting learning objects. The learning goals are to (1) identify the salient learner attributes and content/pedagogical characteristics that can be empirically tracked to impact learning and attitudes and (2) measure the impact of active learning and elaborative feedback on student learning.

These goals are based on two concurrent research and development agendas of the project team: (1) the development and testing of stand-alone web-based learning objects for undergraduate computer science classes and (2) the development and testing of student tracking and agent-based intelligent systems. The following sections elaborate on project goals and discuss the project team’s research and development activities that form the basis of the iLOG work.

Technology Goal 1: Development of Stand-alone Learning Objects

The project team has designed and extensively tested two Shareable Content Object Reference Model (SCORM) compliant learning objects (LOs) for undergraduate computer science education which provide the model for LO development for iLOG. SCORM is a set of technical specifications originating from the Department of Defense and is widely accepted as the standard for LOs. The current LOs, focusing on the topics of simple class and recursion, were designed with extensive use of Flash animation and used multiple user input formats, including drag-and-drop, multiple choice, and model construction. The design was grounded in current learning theory, focusing on the cognitive theories of multimedia learning (Mayer, 2001) and cognitive load (Sweller, 1999). The learning objects include real-world examples of key concepts, interactive exercises, and worked examples and problems, models, and sample code. For example, Figure 1 shows an example from the LO dealing with recursion.

Previous testing of the existing LOs by the project team used both evaluation and research approaches. Evaluation results were positive, with students reporting that the LOs maintained their interest (M = 4.25 on 5-point scale) and helped them better understand the topic (M = 3.97). Their overall ratings were “Good-Excellent” (M = 4.31). Research comparison of outcomes from students randomly assigned to use the LOs versus students who participated in traditional classroom activities confirmed the approximate equivalence of the LO and the traditional instructional experience in promoting student learning as measured by a multiple choice post-test (traditional M = 26.42, learning object M = 26.88, t (48) = .20, p = .84). Results confirm our belief that the use of modular, Web-based learning objects can be successfully used for independent learning of complex subject matter.
Technology Goal 2: Create a System That Tracks, Diagnoses, and Tags Learning Objects

The iLOG framework consists of three major functions: (1) tracking how a LO is used, (2) diagnosing the tracked data, and (3) tagging an LO accordingly. Figure 2 depicts how the three components work together in the iLOG system, which can be embedded into existing learning or course management systems. There are two database profiles. The LO Profile database stores data for the learning objects. This consists of multiple sessions with different users on the same learning object. The Learner Profile tracks learner attributes and behavior, consisting of relatively static parameters such as motivation, self-efficacy, gender, and GPA, and dynamic parameters documenting aspects of students’ online interaction such as time spent on the LO, number of examples seen, number of exercise problems answered correctly, and number of quits. The Learner Profile database stores session data for each individual user over multiple learning objects. The Learner Profile provides an overall assessment of a student’s performance and behavior, while the LO Profile provides an overall evaluation of a LOs performance and use data as learning material. With these capabilities, we will be able to metadata tag each LO with increased accuracy, based on the empirical data collected.

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 html events (mouse clicks, keyboard activities, etc.) during an interactive session with a student. Each trigger will result in a log in either the LO Profile database or the Learner 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 section, and the source and destination pages will be used to determine whether the student has chosen to go from an example back to 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.
**Tracking.** Within each LO, iLOG uses an html wrapper containing snippets of Javascripts for tracking the html events. When the page in the LO is loaded by the learning management system, these Javascripts are invoked automatically. Each invocation sends a data log over the network to the corresponding databases identified by the script. Each data log has a time stamp, a destination page, a source page, and an html 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. Because all the event tracking is done in an html wrapper, iLOG does not need modify the LO content. This allows iLOG to be used with existing learning objects.

**Tagging.** We will develop SCORM-compliant metadata tags. Presently, SCORM’s metadata (ADL 2004) consists of nine categories; we will significantly improve two: (1) *educational*, which describes the educational and pedagogic characteristics of a component, and (2) *relation*, which describes features that define the relationship between a component and another targeted component. For example, the *educational category* keeps track of preset interactivityType, interactivityLevel, semanticDensity, intendedEndUserRole, context, difficulty, typicalAgeRange, typicalLearningTime, etc. iLOG will collect actual, empirical intelligence 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, 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. Both the educational and relational metadata tags will be based on the data tracked from the wrapper described above. This data is stored in the LO and Learner Profiles, two relational databases. We will also add new, more detailed LO profile parameters to SCORM’s metadata for iLOG. For example, we will derive *observedEndUserRole* in greater detail in terms of motivation, self-efficacy, and aptitude. Similarly, we will 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. As with the educational and relation metadata, the new SCORM metadata will be derived from session data stored in the LO Profile and Learner Profile databases.

**Diagnosis.** At the current phase of our system development, we have not yet investigated the diagnosis component. We are relying on past research with intelligent tutoring systems that are adaptive to faults in
their reasoning and modeling. We will focus on this component this spring and will include more explanation in the final paper for this conference.

**Learning Goal 1: Identification of Learner Attributes and Pedagogical Characteristics to Be Tracked**

At the heart of development and refinement of the project tracking system is identifying the salient learner attributes and content/pedagogical characteristics that impact learning and attitudes. There are myriad variables that can be tracked during a learner’s on-line session; and with the system tracking literally every mouse click made by a student, there is a tremendous amount of data generated. Our previous experience with tracking systems showed that it is easy to become overwhelmed with the amount of data. Consequently, it is important that the system track variables that can best contribute to the goal of developing metatags that inform instructional use. Our early projects showed that some tracking parameters are more useful in understanding and diagnosing student success or failure. A major research component of our project is identifying which of the many possible parameters are most useful to predict learning and learning progress. 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)?”

Research by the project team has provided initial evidence relevant to our goal of identifying learner attributes and instructional strategies that impact student learning and attitudes towards on-line instruction. Our research has shown that the amount of time students spend on the examples and the number of times a student goes back to the examples are important factors in determining the amount of scaffolding needed by individual students. Other research, using regression statistics, has shown that topic and item difficulty level, time on task, level of scaffolding, and number of early quits are factors related to student learning from on-line instruction.

Results from our research have led us to hypothesize that the individualized and adaptive LO approach may be particularly effective for students having difficulty with specific topics. For example, non-computer science (CS) majors rated the LO on simple class higher than computer science majors (Table 1), while students in regular sections rated the recursion LO higher than honors sections (Table 2). We believe that students in the regular computer science course, and particularly those who were non-computer science majors, need more explanations and scaffolding to understand the material, and as a result, consider the LOs more valuable. Results also showed that students who received lower grades in the class had higher ratings of the LO and felt that more class material should be presented in the LO format. For example, the correlation between LO rating and final grade in the course for the recursion LO was negative ($r = -.26$, $p = .03$), indicating the higher the LO rating the lower the final grade. This result provides further evidence for the value of the LO to lower performing students.

### Table 1. Comparison of Computer Science and Non-Computer Science Student Reactions to *Simple Class* LO

<table>
<thead>
<tr>
<th>Question</th>
<th>Non-CS Major (n = 13) Mean</th>
<th>CS Major (n = 8) Mean</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graphics added a lot to the content presentation.</td>
<td>4.23</td>
<td>3.25</td>
<td>2.77*</td>
</tr>
<tr>
<td>The LO is a valuable addition to the course.</td>
<td>3.85</td>
<td>3.13</td>
<td>1.31</td>
</tr>
<tr>
<td>More of the course material should be presented through the web.</td>
<td>3.54</td>
<td>2.50</td>
<td>2.09*</td>
</tr>
<tr>
<td>I will use the LO again if I have questions about the topic.</td>
<td>3.54</td>
<td>2.75</td>
<td>1.54</td>
</tr>
</tbody>
</table>

$P < .05$
Table 2. Comparison of Regular and Honors Sections Student Reactions to Recursion LO

<table>
<thead>
<tr>
<th>Question</th>
<th>Regular CS Section (n = 21)</th>
<th>Honors CS Section (n = 26)</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graphics added a lot to the content presentation.</td>
<td>3.67</td>
<td>3.38</td>
<td>.96</td>
</tr>
<tr>
<td>The LO is a valuable addition to the course.</td>
<td>3.52</td>
<td>3.00</td>
<td>1.74</td>
</tr>
<tr>
<td>More of the course material should be presented via the web.</td>
<td>3.14</td>
<td>2.42</td>
<td>2.18*</td>
</tr>
<tr>
<td>I will use the LO again if I have questions about the topic.</td>
<td>3.00</td>
<td>2.46</td>
<td>1.85</td>
</tr>
</tbody>
</table>

*p < .05

We also looked for any gender differences in response to the LOs. Our research to date has shown that gender is not a good predictor of LO ratings; there was no difference in male and female ratings of the LOs.

**Learning Goal 2: The Impact of Active Learning and Elaborative Feedback**

In converting the existing computer science on-line course into learning objects, a major task is incorporating active learning strategies and elaborative feedback. Today’s learning theories emphasize that learning is enhanced by actively engaging students in the learning process (Bransford & Schwartz, 1999).

For our research we will develop two versions of LOs for comparison—one with straightforward presentation of content in a textual format and one with use of interactive examples requiring active response from the student.

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 (Black & William, 1998; Bransford et al. 2000; Crooks 1998; Mory 2004; Natriello 1987). Kluger & DeNisi’s review (1996) of 3000 research reports showed an average effect size of .4. Nyquist’s review (2003) 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.

Our research focuses on two levels of feedback: (1) low level feedback, 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 incorporated elaborative feedback. For each correct response, we reiterate 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 the iLOG project. The data analysis for this research will not only focus on the two treatment effects [type of feedback (2 levels) and active learning (2 levels)] but will also incorporate gender, aptitude scores, prior knowledge, self-efficacy, and motivation by means of multiple regressions analyses.

**Summary**

The iLOG project is grounded in the premise that the learning object model of instruction offers tremendous promise from the perspective of updating and customizing student instruction. The project team’s previous research and development with learning objects and student tracking/intelligent systems has provided the background for development of iLOG. The prototype system is currently under development, with the tracking and tagging functions operational. The system will be tested with students during spring, 2008 semester. Research results, identifying salient learner attributes and content/pedagogical characteristics and the impact of active learning and elaborative feedback, will be shared during the June 2008 Ed Media Conference.
References

Note: No references to project team publications are cited here to provide author anonymity for blind review.


