A Distillation Approach to Refining Learning Objects

John Champaign and Robin Cohen
jchamapi@cs.uwaterloo.ca, rcohen@ai.uwaterloo.ca
David R. Cheriton School of Computer Science, University of Waterloo

1 Introduction

McCalla's ecological approach to e-learning systems [2] is described as "attaching models of learners to the learning objects they interact with, and then mining these models for patterns that are useful for various purposes." The starting point of our research is to honour McCalla's ecological approach by identifying which users in a system are similar to each other, to then preferentially recommend learning objects[1] that similar students have found useful.

We classify learning objects as atomic or non-atomic. An atomic learning object would be something that is indivisible, such as a simulation or a flash quiz that would need to be reprogrammed to break it into smaller parts. A non-atomic learning object would be something like a book, which could be broken into chapters, which in turn could be broken into sections, paragraphs, sentences or phrases.

Our approach in this work is to provide students with tools to (optionally) divide non-atomic lessons, turning a single learning object into multiple learning objects (at least one of which they feel is more valuable than the previous whole).

2 Corpus Algorithm

A function is needed that will divide the learning object, based on the student's suggestion, into two or more learning objects. Of these objects, the student will specify which are worthwhile (and implicitly, the remainder will be determined to be less worthwhile). The worthwhile objects are considered to have a good interaction with the dividing student, while the others are considered to have had a bad interaction with her. The newly created learning objects are then available to be assigned to students using the ITS.

For example, Carol has been watching a supplemental video about Scheme for her CS 101 class, and found it to be not very useful except for one part that gave a very clear analogy for recursion which she found useful. Within the ITS (at the completion of the lesson), she uses the clipping functionality to designate the beginning of this useful section and the end. Three new learning objects are added to the system, the beginning of the lecture, the section she found useful, and the end of the lecture.

In order to determine which learning object is shown to a student, the initial assignment can be done in a number of ways. In previous work [1] this was done by assigning learning objects which were beneficial to similar students. If a learning object that has been divided is assigned, the system will consider the student's history and whether or not

1 Learning objects can be considered anything that teaches a student something and can include, for example, chapters from a book, video, podcast, set of practice questions or training simulator.

he has already experienced one of the parts of the object already. If he has, then the learning object as a whole will be rejected (and another object assigned to the student). Conversely, if he has experienced one of the pieces, the learning object as a whole will no longer be a candidate.

As an example, Bob has watched the section of the lecture that Carol highlighted above and found it useful. Because it is similar to the original learning object, the system next recommends the complete lecture to him. Since he has already watched part of this, it isn't worthwhile to show him the entire lecture again and the system silently replaces this selection. It shows him the final part of the lecture instead. If no students found a certain object worthwhile, eventually that object would be ejected from the system.

This algorithm will be used to consider the set of all learning objects in the ITS and reason about which learning objects should be retained and which add little instructional value to any of the students who use the system. In its simplest form this can be considered a threshold of performance, below which a learning object is no longer shown to students.

At the same time, the system would track interactions so that the highest recommended objects may then be shown to other students. For example, if three "worthwhile" chapters are highlighted as recommended by one student, these pieces can be more useful than the whole. As a result of this positive interaction, these learning objects can be provided to similar students.

3 Validation

We are interested in validating this work first with simulated students and ultimately with real students. Previous work [1] has used simulations of students to demonstrate the effectiveness of techniques on groups of students that would be unfeasibly expensive to arrange for human trials.

In such an experiment, the effectiveness of this approach will be contrasted with a simulation where learning objects are randomly divided and to a simulation where the effectiveness of divisions is pre-calculated and only worthwhile refinements are made. This will allow us to position our approach between the base and optimal cases.

References

[1] Champaign, J., Cohen, R. A Model for Content Sequencing in Intelligent Tutoring Systems Based on the Ecological Approach and Its Validation Through Simulated Students. *Proceedings of the 23rd International FLAIRS Conference*, 2010. Daytona Beach, Florida.

[2] McCalla, G. The Ecological Approach to the Design of E-Learning Environments: Purpose-based capture and use of information about learners. *Journal of Interactive Media in Education: Special Issue on the Educational Semantic Web*, 2004, 7, p. 1–23