Getting axiomatic about learning objects

In which it is demonstrated that the automated assembly of certain types of learning objects is not possible, and by-hand assembly of learning objects is legitimized.

Disclaimer

In the following discussion learning objects of two types are assumed to exist: "small" and "large." In practice, the designators "small" and "large" represent ends of a continuum on which all learning objects may be measured. While more types of learning objects exist than simply "small" and "large," these two types do exist, and the differences between them as discussed below remain when additional types of objects are admitted to exist along the continuum between them. The simplified discussion below could be extended to these other types of learning objects with some effort, but this effort is unnecessary to make the point of this article: it is not possible to automate the assembly of certain types of learning objects.

Instructions

Read the propositions, referring to the definitions as necessary.

Definitions

1. *learning object* - a digital resource that can be reused to facilitate learning
2. *small object* - a single *learning object* uncombined with any other (e.g., a single JPEG)
3. *large object* - many *learning objects* combined to make a bigger, aggregate *learning object* (e.g., a webpage including a text file, several images, and an animation)
4. a learning object's *internal context* – the elements (e.g., other learning objects) juxtaposed (e.g., spatially or temporally) within a learning object
5. a learning object's *external context* – the elements (e.g., other learning objects) against which a learning object is juxtaposed (e.g., spatially or temporally) to facilitate learning
6. *instructional use* of a learning object – the automated or by-hand placing of a learning object within an *external context*
7. *instructional fit* – the degree to which the *instructional use* of a *learning object*, as opposed to other variables, facilitates learning (e.g., the Pythagorean theorem would not *fit* well in a second grade math lesson)
8. *learning object user* – a system or human that makes *instructional use* of a *learning object*
9. *metadata* – descriptive information about properties of a *learning object*
10. *learning object discovery* – the process by which a *user* locates a candidate (for *use*) *learning object*
11. *objective metadata* – properties of a *learning object* to which meaningfully

falsifiable values can be assigned, such as the *learning object*'s author, file size, or mime type

12. *subjective metadata* – properties of a *learning object* to which meaningfully falsifiable values cannot be assigned, such as the *learning object*'s meaning or usefulness
13. *instructional architecture* – a known configuration of *external contexts* (e.g., instructional templates which learning objects may be "plugged into" in order to facilitate learning)

Example Case

An webpage containing an art history lesson composed of an image of the Mona Lisa, an image of DaVinci, text describing the history of DaVinci and the Mona Lisa, and an animation of DaVinci's face being overlaid on the Mona Lisa.

Propositions

<u>Proposition 1.1</u>: A *learning object* has no *external context* independent of its *instructional use*.
<u>Rationale</u>: *External context* has been defined as the juxtaposition of a *learning object* against other elements (e.g., other *learning objects*). When an object is not in *use* (i.e., the object alone, as it exists in the digital library) there is no juxtaposition, and therefore no *external context*.

<u>Proposition 1.2</u>: The number of *external contexts* in which a *learning object* will *instructionally fit* is a function of the *internal context* of the *learning object*.
<u>Rationale</u>: The example case *learning object* (an art history website, which is a *large object*) is usable in an art history curriculum (and perhaps in some meta-content-domains such as website design). This is because the component *learning objects* have been *instructionally used* specifically to facilitate learning in (i.e., to *fit* into) the domain of art history. A component *learning object*, such as the image of the Mona Lisa, *fits* in these and additional *external contexts*, because the specificity of the art history domain is in its *external context*, and is solely a function of its *instructional use*. Independent of that *use*, the *learning object* will *fit* units on popular culture, attitude, or in the creation of a collage.

<u>Proposition 1.3</u>: A *large object* has a greater *internal context* than a *small object*.
<u>Rationale</u>: Two or more small objects are contained in a large object. Because the internal context of the large object consists of the internal contexts of its components, it follows that (in this case) the sum of the parts will be larger than any one part.

<u>Proposition 1.4</u>: *Large objects fit* into fewer *external contexts* than *small objects*.
<u>Rationale</u>: Follows from Propositions 1.2 and 1.3.

<u>Proposition 1.5</u>: *Metadata* facilitates the *discovery* of *learning objects*.
<u>Corollary 1.5.1</u>: *Metadata* facilitates the *instructional use* of *learning objects*.

Rationale: Because many *learning objects* are non-textual, they cannot be discovered via full-text searching. *Metadata* provide a way for these learning objects to be discovered or located. A *learning object* cannot be *used* unless it is known to the *user*.

Proposition 1.6: *Metadata* about the *internal context* of *large objects* is more valuable to *users* of a *learning object* than *metadata* about the *learning object*'s previous *external contexts*.
Rationale: A *large object* has an *internal context* sufficient to restrict its use to a closed set of learning (i.e., *external*) *contexts* (Proposition 1.4). Before a *learning object* can be *used instructionally* the possible *externals contexts* of *use* must be identified, and a decision must be made regarding the *instructional fit* of a *learning object* into the target *external context*. *Fit* can only be assessed by examining the *internal context* of the *learning object* and comparing it to the target *external context*, making *metadata* regarding the *internal context* of the *learning object* necessary to its *use* (assuming that *users* will not examine every *learning object* individually and will rely on *metadata* to support *learning object discovery*).

Proposition 1.7: *Metadata* about the *external context* of *small objects* is more valuable to *users* of a *learning object* than *metadata* about the *learning object*'s *internal context*.
Rationale: *Small objects* are by definition uncombined, single elements. While *small objects* exhibit some juxtaposition of internal elements (e.g., the foreground and background of a photograph), this *internal context* is much less significant than that of a *large object*, meaning that the possible *external contexts* of *use* of a *small object* are significantly greater in number than those of a *large object*. Since the *internal context* of a *small object* does not eliminate it from *use* in many *external contexts* (as the *large object*'s *internal context* does), *metadata* regarding the *internal context* of a *small object* provides less support to *users* making *use* decisions regarding the *small object*. However, examples of the manner in which others *users* have *used* the *small object* may provide valuable *use* data that supports *small object use* decisions by *learning object users*.

Proposition 1.8: The potential for *instructional use* of different types of *learning objects* will be maximized by different types of *metadata*.
Rationale: Follows from Propositions 1.6 and 1.7.

Proposition 1.9: The value of *objective metadata* in facilitating *learning object discovery* is stable across *learning object* types, be they *small* or *large*.
Corollary 1.9.1: A stable set of *objective metadata* should be captured for each *learning object*.
Rationale: Proposition 1.8 states that different types of *metadata* must be used to maximize the potential for *use* of different types of *learning objects*. Propositions 1.6 and 1.7 demonstrated that the specific metadata needed to facilitate *discovery* (and therefore *instructional use*, Corollary 1.5.1) relate to the *internal* and *external contexts* of the *learning object*. Because the interpretation of *context* is a subjective matter, the differences in necessary metadata are differences in necessary *subjective metadata*, meaning that the value of *objective metadata* is the same for all *learning object* types.

Proposition 1.10: *Subjective metadata* for *small objects* should focus on capturing the *external contexts* of *use* of the *small object*.
Rationale: Follows from Propositions 1.6, 1.7, and 1.8.

Proposition 1.11: *Subjective metadata* for *large objects* should focus on capturing the *internal context* of the *large object*.
Rationale: Follows from Propositions 1.6, 1.7, and 1.8.

Proposition 1.12: The *instructional use* of *large objects* can be automated.
Corollary 1.12.1: *Large objects* are best suited to *use* by automated *users* (systems).
Rationale: The *internal context* of a *large object* significantly limits the *external contexts* into which it will *instructionally fit* (Proposition 1.4). This limitation of possible *external contexts* of *use* can be combined with an *instructional architecture* (i.e., a known configuration of *external contexts*) to facilitate the automation of the placing of *large objects* into *external contexts* in which they will *fit*. (See Wiley (1999) for a description of a simple instructional architecture which concretely demonstrates the substance of this Proposition).

Proposition 1.13: The *instructional use* of *small objects* cannot be automated.
Corollary 1.13.1: *Small objects* are best suited to *use* by human *users*.
Rationale: The *internal context* of a *small object* constrains the number of *external contexts* into which it could *fit* much less than the *internal context* of a *large object* does (Proposition 1.4). This necessitates the use of additional decision support data to select one of several potentially *fitting* learning objects, that is, it forces *instructional fit* decisions to rely on data other than that expressed in *metadata* (*objective*, *subjective-internal*, and *subjective-external*). Deprived of decision support data, an automated system is incapable of reliably *using small objects*.

Proposition 1.14: Different types of *learning objects* are best suited to *instructional use* by different types of *learning object users*.
Rationale: Follows from Propositions 1.12 and 1.13.

Narrative

One of the primary reasons people are interested in "learning objects" is their purported reusability. Reusability, if achieved, facilitates the creation of generative systems, adaptive systems, and scalable systems; in fact, it facilitates the creation of generative, adaptive, scalable systems. Gibbons and his associates claim that these three properties are nothing less than the goals of computerized instruction (Gibbons, et al., 2000). For this reason the automated approach to learning object assembly, which is necessary to achieve these three goals, has been reverenced as the one true goal of the learning objects movement, if such a thing can be said to exist. However, there is another view of the desirability of reusable educational content.

When educational media is created as a learning object, that is, when it is created in a reusable digital format, the economics of media use change. In the physical world, educational media is created, horded, and occasionally used (South & Monson, 2000). The ratio of production cost to number of uses is prohibitively high. However, in the digital world, where any number of people can access and use a single learning object simultaneously, the ratio changes. With the repeated reuse facilitated by the growing ubiquity of the Internet, cost recovery can become a reality. More importantly, however, once the ratio of production cost to number of uses nears zero, access to learning objects can be made available for free. Better yet, open source development models can be adopted to drive the cost of learning object creation toward zero (the ratio of development work to volunteer developers), making learning objects freely available from their genesis. Finally, advertising will continue to support free access to some online content and services. Each of these scenarios can provide teachers and learners with access to high quality educational materials *they could never afford or produce individually*.

Having attended public schools in West Virginia as a child, I speak about this viewpoint with a certain passion. Access to interactive maps for geography study, Java applets for physics study, and graphing scientific calculators for use in math would have been wonderful. Today, each of these and many more “learning objects” are freely available on the Internet. While the goal of automated instructional systems based on learning objects is worthwhile, there are two important reasons that the by-hand, human assembly of learning objects should not be passed over.

First, human assembly of learning objects works best with small objects. Fortuitously, the majority of the data available on the public Internet are “small objects” – images, text files, etc. If promoting reuse is the goal of the learning objects movement, how can it ignore 15 some odd terabytes of existing learning objects? And yet it *is* being ignored, mostly because it will not fit into automated systems. If services existed to facilitate the instructional use of these “small objects,” the educational impact could be significant.

Second, common sense would suggest that we can only automate that which we know how to do by hand. Could the automation of coal mining or automobile assembly ever have occurred without the lessons learned by years of humans performing these same tasks by hand? I do not believe so. Likewise, before humans can build automated systems to assemble learning objects, they must first learn the lessons to be gained combining those objects by hand.

Conclusion

It has been the goal of this paper to tear down the notion that the automated assembly of every learning object with every other learning object – even when “learning object” is defined narrowly – is possible, and to demonstrate that non-automated solutions to learning object assembly are not only legitimate, they are desirable.