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
11. 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

Proposition 1.1: A learning object has no external context independent of its instructional use.
Rationale: 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.

Proposition 1.2: The number of external contexts in which a learning object will instructionally fit is a function of the internal context of the learning object.
Rationale: 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.

Proposition 1.3: A large object has a greater internal context than a small object.
Rationale: 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.

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

Proposition 1.5: Metadata facilitates the discovery of learning objects.
Corollary 1.5.1: 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 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.