Exploring the Role of Visualization and Engagement in Computer Science Education

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Recent surveys of computer science educators suggest a widespread belief that visualization technology positively impacts learning [1]. However, experimental studies designed to substantiate the educational effectiveness of such visualization technology simply do not bear this out [4].

Closer inspection of past experimental studies reveals an important trend in those studies: that learners who are actively engaged with the visualization technology have consistently outperformed learners who passively view visualizations [4].

It therefore makes sense to study the educational benefits of various forms of active engagement. This charge was given to the working group on "Improving the Educational Impact of Algorithm Visualization" at the 2002 ITiCSE conference in Århus, Denmark [1]. The thesis developed by that group (of which we were co-chairs) is that *visualization technology must engage learners in active learning to be effective*. If this is true, we need to actively engage learners with visualization technology to achieve a positive impact on their learning.

We broadly define six different forms of learner engagement with visualization technology. Since it is certainly possible to learn an algorithm without the use of visualization technology, the first category is "No viewing," which indicates that no visualization technology is used at all.

No viewing uses no type of visualization,

Viewing can be considered the core form of engagement, since all other forms of engagement with visualization technology fundamentally entail some kind of viewing. The Venn diagram of Figure 1 indicates this by providing "Viewing" as the universe in which all other forms of engagement exist.

Responding to questions asked about the content, for example "What will the next frame in this visualization look like?" (prediction) or "What source code does this visualization represent?" (coding)

Changing entails modifying the visualization. The most common example of such modification is allowing the learner to change the input of the algorithm under study in order to explore the algorithm's behavior in different cases (for example, [5, Chapter 9]).

Constructing means that learners construct their own visualizations of the algorithms under study. Note that "Constructing" does not necessarily entail coding the algorithm.

Presenting a visualization to an audience for feedback and discussion.

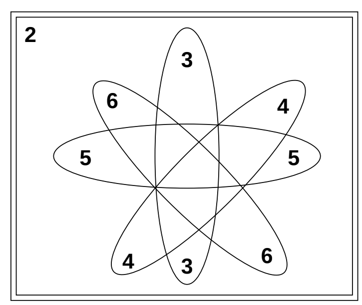

Figure 1: Possible Overlaps in the Engagement Taxonomy. Basic regions are 2 (Viewing), 3 (Responding), 4 (Changing), 5 (Constructing), 6 (Presenting)

While this taxonomy does in some sense reflect increasing levels of learner engagement, we do not consider this to be an ordinal scale. The relationships among these forms of engagement do not form a simple hierarchical relationship. Figure 1 illustrates, in the form of a Venn Diagram, the overlapping possibilities among the last five of these engagement categories, with "Viewing" forming the universe on which all of the more active forms of engagement must occur.

We further consider six different levels of learner understanding based on Bloom's taxonomy as follows:

Level 1: Knowledge - factual recall with no real understanding of the deeper meaning.

Level 2: Comprehension - the learner is able to discern the meaning behind the facts.

Level 3: Application - the learner can apply the learned material in specific new situations.

Level 4: Analysis - the learner can divide a complex problem into simpler components.

Level 5: Synthesis - the learner can generalize and draw conclusions from facts learned at prior levels.

Level 6: Evaluation - the learner can compare, evaluate and discriminate among different approaches.

Applying the metrics to our engagement taxonomy, we postulate the the following hypotheses for further study:

- *Viewing* alone results in learning outcomes equivalent to no visualization (and thus *no viewing*). Studies such as [2] have shown that mere passive viewing provides no significant improvement over no visualization, but these studies were based on small sample populations. Our study may be able to verify this with larger numbers.

- *Responding* results in significantly better learning outcomes than only *viewing*, as indicated for example in [3, 2].

- *Changing* results in significantly better learning outcomes than *responding*.

- *Constructing* results in significantly better learning outcomes than *changing*.

- *Presenting* results in significantly better learning outcomes than *constructing*.

- *Multiple engagements* A mix of several forms of engagement is natural and we expect this to occur in experiments, especially in the latter types of engagement. This sixth hypothesis merely states "More is better." That is, the higher the level or the more forms of engagement that occur when using visualization, the better the learning becomes.

As a short example of how these hypotheses could be verified, we regard using *Quicksort* in CS 1 to test the hypothesis that responding is more effective than viewing. This experiment requires a tool that allows the user to view the animation of Quicksort.

Viewing could mean looking at an animation of the algorithm on given data sets. The animation may or may not have controls associated with it such as pausing and stepping through the phases. The animation could be viewed with given data sets that illustrate the worst case and average case.

Responding could mean viewing Quicksort with either prediction built into the software or a worksheet containing questions that learners must answer while stepping through the animation. Learners must answer questions such as "Which element will be chosen as the next pivot? What will the array look like after the call to find the next pivot? Which section of the array will be sent in the next call of recursion? Which section of the array at this point in time is guaranteed to be in sorted order?"

Concepts to focus on are the understanding of the overall algorithm, understanding the recursive part of the algorithm, and understanding the choice of pivot and the partition algorithm for the rearrangement of the data around the pivot.

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