

Characterizing Complexity of Computer Simulations and Implications for Student Learning

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Abstract. Interactive simulations can be engaging tools for student learning, allowing students to explore phenomena by asking questions and seeking answers through use of the sim. PhET simulations allow this process to happen dynamically so that students can continuously probe and explore the underlying science. For students to use simulations productively, understanding the science in the simulation must be challenging enough to maintain students' interest, but not so challenging that students are overwhelmed. A key aspect of achieving a good balance is the complexity of the simulation for students. We have formulated an initial model to quantify complexity based on the number, range, and effects of controls and representations within a simulation. We account for students' prior knowledge by adjusting the measured complexity depending on how students interpret the representations and conceptual connections within the simulation. Implications for simulation design and student engagement will be discussed in light of preliminary interview data.

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INTRODUCTION

When a student sits down in front of an interactive computer simulation, what do they see? Often, the student is presented with a number of graphical, mathematical, pictorial and textual representations. The student sees various controls and moveable objects. In a highly interactive simulation, such as a PhET simulation, [1] students can make changes in real time and see the effects immediately. This poses a significant design challenge – how to create interactive simulations that provide just enough flexibility and feedback to provide effective learning opportunities for students without being overwhelming.

In this paper, we describe initial work to characterize the complexity of interactive computer simulations (sims). Prior work has looked at the complexity of human-computer interactions. [2][3] These approaches entail a great deal of mathematical rigor, but we find they do not readily help us characterize complexity in a way that can directly inform design choices that foster student learning.

To first order, our measure of complexity entails the number of controls in a sim and what representations they affect. For instance, a simple sim might include a single on / off control and a single representation, say of an electrical switch. A more complex sim might include several switches, batteries,

and resistors which could be rearranged and have their values adjusted.

However, different individuals will view the same sim differently depending on their prior knowledge. For instance, a user that is familiar with kinetic and potential energy may be readily able to interpret graphs showing the energy vs. time for an object in motion. On the other hand, for a user not familiar with these ideas, interpreting an energy graph could significantly increase the relative complexity of a sim. Without an understanding of what the graph is showing, it might be more difficult to make sense of what the controls do and how to learn from the sim.

Our aim here is to characterize complexity along two dimensions: 1) features of the sim itself, and 2) prior knowledge of the user. We describe our model and apply it to analyze two existing sims below. We then describe data from preliminary student interviews which informs the utility of this model.

SIM-BASED COMPLEXITY

Force Law Lab

The Force Law Lab (FLL) sim (Figure 1) is designed for students to learn about gravitational forces. In this sim, two spheres are shown attached to ropes which are held by two “pullers”. The pullers lean backwards as the gravitational force between the

change – the bar itself and a numeric readout. The complexity of each slider is therefore 9, and the total sim complexity is 18 in this initial state.

Unlike FLL, ABS has additional options which can cause significant increases in complexity. In Table 2, we indicate this with a *C*, indicating *conditional* interaction. The beaker as shown in Figure 2 does not change with the sliders. However, checkboxes allow colored dots (representing ratios of chemical species) to be shown in the beaker (Figure 3). The numbers of dots change as the user moves the sliders. Turning on all of the checkboxes increases the total complexity to 35.

Notably, ABS contains a number of additional static representations. If a user were to associate the controls with each representation (static and dynamic), this could increase the complexity of ABS to over 100 depending on the number of options selected. We are currently exploring how to weigh static vs. dynamic representations in our model.

In addition, the strength slider in ABS has 5 possible regions of interest. Further development of this model should include this in the complexity measure. For instance, this could make the strength slider row of Table 2 larger by a factor of 5, giving an overall sim-based complexity of 54.

USER-ADJUSTED COMPLEXITY

Both FLL and ABS appear to have comparable sim-based complexities. However, ABS clearly *looks* more complex than FLL and our interviews support

that students perceive it as more complex. In our observations, students often ignore representations that do not change or do not make sense to them. This appears to be a way of reducing the *perceived* complexity so that the student can make some headway understanding the dynamic interactions.

How does prior knowledge affect the complexity of a sim? Both sims presented here use multiple representations of the same quantity, e.g. force is represented by an arrow and text. In order to make sense of these interactions, students may initially see these representations as representing two separate quantities. A user familiar with these topics, however, would readily interpret the arrows and text as both representing force. We model this affect of prior knowledge by collapsing the columns for arrows and text in Table 1, reducing the overall complexity from 28 to 10. Further, the forces shown are always equal and opposite, so we can collapse all of the force columns, as well as the pullers. These matrix operations result in a total complexity of 6 for a user familiar with the ideas in FLL.

Similarly, the complexity in ABS can be reduced to 9 by collapsing the bar and text columns in Table 2. In addition, rather than seeing four separate read outs, an expert chemist may be able to see the pattern of the four bars as representing the extent of dissociation. This may reduce the complexity to 4, since, to a user familiar with these ideas, the two sliders can be directly related to just two factors: *pH* and dissociation.

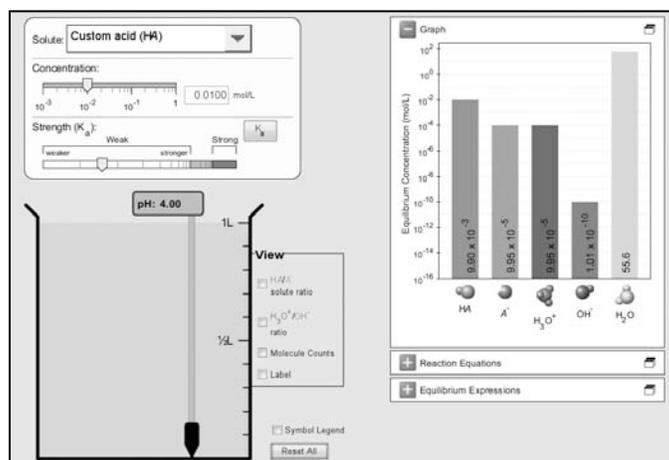


FIGURE 2. Acid-Base Solutions simulation. Sliders to upper-left adjust the concentration and strength.

TABLE 2. Acid-Base Sim-Based Complexity; 0 / 1 indicates whether a control (rows) affects a readout (columns).

| | Concentration | Strength | pH | HA Bar | HA Text | A- Bar | A- Text | H ₃ O ⁺ Bar | H ₃ O ⁺ Text | OH ⁻ Bar | OH ⁻ Text | H ₂ O Bar | H ₂ O Text | Beaker |
|---------------|---------------|----------|----|--------|---------|--------|---------|-----------------------------------|------------------------------------|---------------------|----------------------|----------------------|-----------------------|--------|
| Concentration | - | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | C |
| Strength | 0 | - | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | C |

While observing users it's clear that there can be more to calculating complexity than just counting representations. For example, ABS can show the concentrations as dots in the beaker instead of bar graphs (Figure 3). Although this view can present the same number of representations, it appears to be perceived as less complex by students possibly because of the metaphor [4] “*number of dots is concentration of molecules*” is more intuitive than “*height of bar is number of molecules.*” In other words, complexity may depend not only on the number of controls and representations, but also on how well those representations cue salient pieces of knowledge for students. We are currently exploring ways of including this way of reducing complexity in the model. One possibility is to use numbers lower than 1 in the complexity matrix.

PRELIMINARY INTERVIEW DATA

In an attempt to measure the impact of perceived complexity on student learning, we performed eight “think-aloud” interviews with students using ABS. These students were enrolled in the first semester of general chemistry. Half of the students were presented with the original start-up state, the “graph” view, while the other half were given the alternate start-up state shown in Figure 3, the “dot” view. Students were presented with the sim and asked to play around and talk about what they were thinking.

We found that students in the graph group were more likely to voice confusion on first viewing the ABS sim. A common response was, “Wow, there’s a lot going on!” This initial reaction was not found in the dot group. Graph-group students’ confusion tended to subside as students used the sim and could elect to hide confusing features. This suggests that the overall complexity may change dynamically, decreasing as users interact with the sim and build new ideas.

At the end of the interview, students were asked to “draw what you think you would see if you could look at a weak base solution through a magnifying glass.” Students in the “graph” group all drew markedly different representations, whereas those in the “dot” group drew strikingly similar pictures. This result agrees with the entropic theory of user-interface complexity, [2] in that the less complex the interaction, the more precisely one can predict the actions of the user. Even though all students eventually played with every feature in the sim (including the dot view for graph users), the perceived complexity of the sim on start-up appears to have affected what they learned from the sim. This is consistent with the findings of Adams et al. [5]

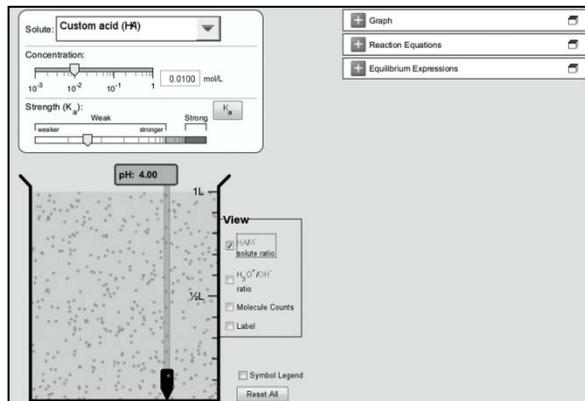


FIGURE 3. ABS in initial state with graphs closed and dots shown in the beaker. Colored dots (Green=HA; orange=A⁻) change in number as the user moves the two sliders.

CONCLUSION

We have developed an initial model to quantify the complexity of interactive computer simulations. This model accounts for complexity due to the number of controls and interactions between sim elements, as well as how what is shown fits with users’ prior knowledge. Preliminary interviews appear to support the utility of this model. Further examination of interview data is needed to help refine this model. At this stage, we are particularly interested in determining how to weigh the relative contributions of sim-based complexity and prior knowledge effects on student learning with interactive computer simulations.

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