

An Eye for Detail: Techniques for Using Eye Tracker Data to Explore Learning in Computer-Mediated Environments

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Abstract: This paper describes two methods for analyzing student gaze in computer-mediated learning applications. More specifically, we demonstrate how to use eye-tracking data from an agent based modeling study to identify meaningful patterns in student learning processes. We do this by using techniques from network analysis and natural language processing which allow us to identify statistically significant differences among our two conditions. Finally, we conclude by motivating a larger study that will further utilize these techniques.

Introduction

Computer-mediated learning applications have become increasingly pervasive in today's technology-driven society. From intelligent tutoring systems, to educational games, to agent-based modeling environments, students are presented with a number of opportunities for computer-mediated learning. However, there remains a number of ways in which analyzing student learning in these environments can be quite challenging. Accordingly, many adopters of computer assisted learning resort to creating scripted environments that limit exploration. They also take advantage of techniques such as think-aloud and emote-aloud, to identify student learning processes. However, there are shortcomings in these approaches (Cooke and Cuddihy 2005). And while keyboard and mouse logging can capture student actions within the system, we wish to understand the complexities of student learning processes, especially at a micro-genetic scale. Accordingly, we will present two techniques that we recently developed to analyze data from a small scale study (n=4) of students interacting with an agent-based modeling environment.

Experimental Design

Four undergraduate engineering students were asked to participate in a thirty minute Netlogo study in which each explored three models related to the Ideal Gas Law. The four students were split into two conditions. The two conditions were identical except for the mode used to instruct the students about the Ideal Gas Law. The flow of the conditions was as follows: 1) Prior to interacting with the first model, students are informed that they will be asked to study each model for 3 to 5 minutes, after which they will be asked to describe what is happening in the model (Mayer, 2009 in Jukka, 2010); 2) student interact with Netlogo's Connected Chemistry "Temperature and Pressure" Model and provide a description of the model; 3) students read either an agent based modeling explanation of the gas laws, or a textbook based description of the gas law; 4) students interact with the "Gas in a Box model" and provide a description of what is happening in the model; 5) interact with the "Adiabatic Piston" model and provide a description of what is happening in the model; 6) Students watch the video of their eye tracking data and provide meta-cognition of their process (De Koning et al., 2010, Jarodzka et al., 2010 in Jukka, 2010). Finally, the study captured gaze, audio, video and student Netlogo logging history, but we will focus our attention on the gaze related data for this paper.

Methodological Approach

In order to analyze this data we used two techniques that build on previous eye-tracking data analysis techniques (Jukka, 2010, Conati & Merten, 2007, Slykhuis, Wiebe, Annetta, 2005, van Gog & Scheiter, 2010). For the first technique we wanted to investigate the relationship between student actions and the gaze events that take place between those actions. In order to accomplish this, we elected to segment the stream of gaze points using mouse clicks. This is to say that all of the gaze points that happen between two successive mouse clicks were grouped together. This mode of segmentation lets us consider how the various gazes that the student makes after clicking may be influential in determining their next behavior. For a given segment, we look at the total number of gaze points generated, and the number of unique gaze points that are generated. This distinction can theoretically be used to examine a couple of different ideas. First, a student that is focusing on a small number of elements may have a strong intuition about what will happen and need not look at more than a select number of elements (Canham and Hegarty, 2010, Jarodzka, 2010 in Jukka, 2010). A second explanation is that a student with a large number of unique gazes is able to process a larger cascade of causation and consider how changing a single element impacts several of the model's variables.

To further hone in on the types of cognitive connections that may be at work as the students interact with the models, we borrow techniques from network analysis. Doing so allows us to examine the centrality of any given gaze point, and its relationship to other gaze points. To do this, we create an edge between all

temporally adjacent gaze points, and then use this network representation to look at a number of salient aspects in network analysis research: average degree, average shortest path and degree distribution.

We conclude by encoding for patterns of behavior in the way that the students interact with the visual elements. More specifically, we look at the direction of each gaze; this is to say, whether the subject is moving their eyes from left to right, up to down, and any combination of these (left and up, right and up, etc.) Pairs of gaze points that are identical, i.e. those from a fixation point, are omitted for this portion of the analysis, since we are primarily interested in the direction that people were moving their eyes, when they moved them. Furthermore, we construct pairs and trios of directional movements, to see what types of patterns of movements people typically employed when interacting with these models. An example of a trio would be to look left, then right, and then left; or to look up, then down, then up – these are examples of what we will refer to as A-B-A patterns.

Results

The results from this analysis technique are multifaceted, and there remain a number of dimensions to explore further. We will begin by describing a quantitative result that we observed. While our goal in this initial study was to develop a qualitative understanding of the differences in how people visually interact with Netlogo models, we did observe a statistically significant result between our two conditions. The participants that read the agent-based modeling description of the gas laws had statistically significantly larger numbers of unique gaze points compared to those that read the textbook description. This occurred despite the two groups not having a statistically different number of unique gazes in the initial exploration (that which occurred just prior to reading the different descriptions of the Ideal Gas Law).

Another compelling observation arose from our analysis of the users' viewing patterns. Not surprisingly, most of the users primary gaze pattern was to look at one item, look at another, and then look back at the first item again (the A-B-A pattern). Students that read the agent-based modeling description were more likely to follow the A-B-A gaze pattern than students that read the textbook description. However, further analysis is needed to understand whether this indicated a more in-depth study of the model.

In terms of the network analysis techniques that we used, our preliminary results indicate that there are only a few sets of gaze points that have degree higher than 2. This means that most gaze points are only observed once. However, when using gaze point compression, the average degree ranges from 2.8 to 5.2 edges, depending on the model, and the parameters for compression. Further work will need to be completed to see if there is pedagogically meaningful data encoded in network characteristics.

Conclusion and Implications

In this paper we have presented two approaches for looking at gaze data, and have generally argued that this form of data can be useful in gaining a better understanding of the learning processes that students engage when interacting with computer-based learning applications. These approaches borrowed proven techniques from network analysis and natural language processing. Beyond this, we have presented initial findings that compare how students' interactions with agent based models are dependent on the type of instruction that they received. That said we are cognizant that there may be many elements at play that require further exploration and more rigorous controls. Furthermore, we recognize the need to dive deeper into some additional features of the data.

Despite the areas for improvement, adopting this form of analysis will become increasingly relevant, and necessary, as we move towards more technologically-enhanced learning environments as it affords accurate identification of student learning on a micro-genetic level.

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