Using Multimodal Learning Analytics to Study Learning Mechanisms in Hands-on Environments

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ABSTRACT

In this paper, we propose multimodal learning analytics as a new approach for studying the intricacies of different learning mechanisms. More specifically, we conduct two analyses of a hands-on, engineering design study (N=20) in which students received different treatments. In the first analysis, we used machine learning to analyze hand-labeled video data. The findings of this analysis suggest that one of the treatments resulted in students initially engaging in more planning, while the other resulted in students initially engaging in more building. In accordance with prior literature, beginning with dedicated planning tends to be associated with improved success and improved learning. In the second analysis we introduce a completely automated multimodal analysis of speech, actions and stress. This automated analysis uses multimodal states to show that students in the two conditions engaged in different amounts of speech and building during the second half of the activity. These findings mirror prior work on teamwork, expertise and engineering education. They also represent two novel approaches for studying complex, non-computer mediated learning environments and provide new ways to understand learning.

Keywords

Learning Sciences, Qualitative, Computational, Constructionism

1. INTRODUCTION

Despite the many years that humans have studied learning and human cognition there are still many unanswered questions in how people learn. This has partially been the result of limitations in the ways that we are able to study learners. More specifically, a large portion of prior research was limited by a tradeoff between the types of learning environments that could be studied, and the scale at which a given phenomenon could be analyzed.

However, as the tools of educational data mining and learning analytics continue to advance, we are beginning to dismantle this tradeoff. We are now able to analyze a far greater variety of learning environments and at unprecedented scales. In this study, in order to keep the analysis verifiable, we do not yet venture to tackle big data as it relates to a large number of participants. Instead, we tackle the big data question as it relates to analyzing extremely high frequency data, from several data streams. We use multimodal learning analytic [1, 2] techniques to study speech, gesture and electro dermal activation among pairs of students as they complete a hands-on engineering design task.

The context for this paper is an extension of our prior work [3], where we present two different approaches that students use in engineering design: example-based reasoning – using personal examples from the real-world as an entry point into solving a task; and principle-based reasoning – using engineering fundamentals as the basis for one's design. These two reasoning strategies complement prior work on learning by analogy [4], expertise [5, 6] and forward-backward reasoning [7]. In [3] we describe example-based reasoning and principle-based reasoning in qualitative terms, and then proceed to use these two approaches in a controlled study (N=20) that compares how each approach impacts learning gains and performance during a collaborative hands-on activity. In that study we found that principle-based reasoning improves the quality of designs ($p < 0.05$) as well as the learning of important engineering principles ($p < 0.002$). The goal of this paper is to expound upon why these differences may have arisen between the two conditions. As such, we employ multimodal learning analytic techniques as a way to systematically study how example- and principle-based reasoning are associated with different multimodal behaviors as observed in the each student's process.

2. METHODS

In this paper, we briefly present results from two complementary analyses of example- and principle-based reasoning. The overall approach closely mirrors our previous work [8, 9] on analyzing design strategies and success in hands-on engineering tasks. Specifically, in the first analysis we manually annotate the students' actions, and segment the data based on when they explicitly evaluates their structure. The proportions of actions in the different segments are used to find representative clusters, which are subsequently used to re-label each user's sequence of segments. Finally, we compare sequences across participants.

In the second analysis we again use clustering to reduce the set of multimodal states from several hundred, down to four. However, it differs from analysis 1 in that all of the data is automatically derived from speech, gesture and skin conductance data. Additionally, instead of segmenting the data when students evaluate their structure, we use fixed 30-second time windows.

3. RESULTS

The results from the first analysis, which combined qualitative coding with X-means clustering, demonstrated that students in the principle-based condition were more likely to start the task by planning (see PREPARE in Figure 1). Planning has been associated with increased success in several domains [10,11,12,13,14]. In contrast the example-based condition was typified by students who immediately began to build their projects and overlooked the importance of thinking about and planning their structure (see IMPLEMENT in Figure 1). Furthermore, the first analysis also found that success correlates with students beginning with planning. Hence the principle-based conditioned was associated with increased planning, which may have facilitated their improved performance.

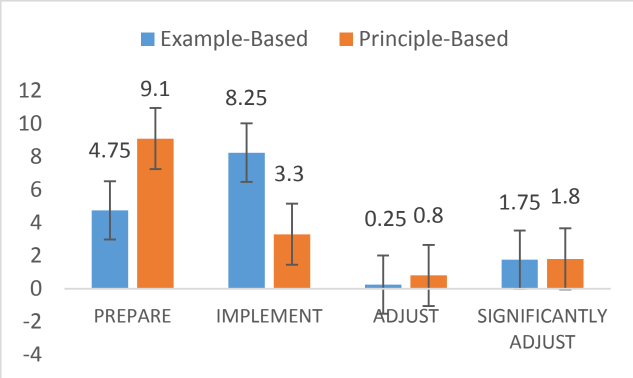

Figure 1 - Scaled Frequency of Cluster Use by Condition - the y-axis is the count of times used, and the x-axis is the different clusters, or states of user actions, as derived from clustering

In the fully-automated multimodal analysis our initial results suggest that students in the example-based condition are much more likely to transition towards an increase in speech during the latter half of the activity. This is in contrast to the principle-based group which shows no significant changes in speech, gesture or stress, over the course of the activity. In our ongoing work we are looking to better understand the nature of the multimodal interactions and what caused the students in the example based condition to engage in significantly more dialogue. We have several initial hypotheses that we will describe in future work. For example, an initial analysis of student speech during the intervention phase of the experiment found significant differences between the two conditions. Namely, students in the principle-based conditions generated more speech during the intervention phase than the example-based condition. This may have helped the students be better prepared for the activity, and allowed them to circumvent the talking observed in the latter half of the experiment for the example-based condition. However, additional analysis is required to determine a link between the speech during these two phases of the experiment.

4. CONCLUSION

Taken in concert, these two analyses provided initial explanations concerning why principle-based reasoning produced higher quality designs and greater learning gains than example-based reasoning. Based on the analysis of hand-labeled process-oriented data, in conjunction with machine learning, we were able to show how students in the principle-based reasoning condition were more likely to begin the task with planning. In contrast, students in the example-based condition were more likely to start by building. These findings aligned with previous observations made in a number of disciplines. In the second analysis, we used a completely automated multimodal algorithm to construct generalizable multimodal states and found that students in the principle-based condition had less variation in their speech, gesture and skin conductance over the course of the activity. This difference was particularly noticeable during the second half of the activity. Both of these seem to point to students being better prepared after participating in the principle-based reasoning intervention. Thus, we have shown that in addition to producing differences in learning and success, the two conditions resulted in different processes. This is important because it provides researchers with a more fine-grained representation of how the two treatments differed. Examining the underlying mechanics of different treatments provides educators and designers with a more complete set of strategies to adopt and utilize in their teaching and designing. To this end, beyond simply saying that the conditions are different, multimodal learning analytics provides us with a tool that explains how they are different, and, in so doing, starts to answer questions around why they differ. That said, there remain a number of important questions and opportunities in studying the mechanics of successful learning interventions. We intend to more closely examine the findings reported in this paper, and investigate additional hypothesis that would explain the noted differences in student outcomes in our ongoing research.

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