A Method for Predicting Insight-Directed Behavior in a Brain Imaging Analysis Task

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Abstract— The analysis of brain imaging data is key to many vital research areas in neuroscience and cognition. However, as in many applications in scientific visualization, analyzing these data is both difficult and slow-paced. Improvements to the speed and accuracy of the analysis process could have a significant impact on the ability of these researchers to perform more and better experiments. In this work, we present a pilot study demonstrating a novel approach to identifying the patterns that lead to wasted time in the analysis process, as well as the patterns that are most productive. Our approach combines observation-driven task analysis with insight evaluation and measures of cognitive load to isolate common interaction patterns that either precede or lead away from useful discoveries. Our preliminary results show a predictable set of patterns that could be automatically identified as part of evaluation or adaptive analysis software.

1 Introduction

- Motivation: brain imaging analysis. Critical area. Lots of different types of data, mishmash of analysis software. Bottleneck in research.
- What's needed is a better understanding of the analysis process; how it works, what makes it not work.
- Our approach: task analysis + insight and cognitive load. Task analysis with more data about what's going on in the black box.

2 Related Work

The goal of this project is to build on existing task analysis work by combining this overall strategy with evaluation methods that tell us more about critical points in the users process: insight evaluation and cognitive load measurement.

2.1 Task Analysis in Scientific Visualization

This work adds to a body of knowledge established by previous task analysis work in the visualization domain. Springmeyer et al. [10] studied scientific data analysis in research which helped to place visualization use in the context of a larger workflow, and were among the first to argue that visualization systems should include a way to record users analytic processes. Pirolli and Cards cognitive task analysis [8] produced the Sensemaking Loop model for intelligence analysis, which has since become influential in visual analytics theory and design. More recently, Isenberg et al.s study [4] of collaborative analytical behavior provides a general model for how we perform a more focused task analysis. This work shows that task analysis can have a significant impact on research, but is more high-level than the analysis we intend our method to produce. By studying a more specific situation at a greater level of detail, we believe we have a better chance at uncovering the users cognitive process.

2.2 Insight Evaluation

Insight evaluation is an increasingly well-studied method for visualization evaluation that focuses on insights, or units of significant discovery, as goal of analysis. Supporters argue that it offers an advantage over more traditional accuracy and response time measures by focusing on a more realistic task style and metric of success. The concept was introduced by Saraiya et al. [9] and expanded upon in North [5]. In an insight evaluation, the user performs an open-ended analysis and is asked to self-report insights that she gained from analysis, and these insights are later coded by an expert on scales of depth and complexity. Yi et al. [11] contribute a taxonomy of the processes that lead to insight, which we use in our coding scheme. Insight evaluation contributes to our method by providing a guide to productive user behavior, but it does not help to identify unproductive user actions.

2.3 Cognitive Load and Visualization

In addition to identifying the areas of productive behavior, we also want to identify frustrating and unproductive inteRaction patterns. Cognitive load analysis can assist in this. Introduced in Paas and van Merrienboer [7], cognitive load is a multi-dimensional measure of the amount of mental effort a task takes to perform. Cognitive load can be measured in a variety of ways, as discussed in Paas [6], including both self-reported rating scales and having the participant perform a secondary task and measuring how much performance on that task degrades at points in the primary task. in our work, we choose to employ a rating scale, as this is likely to be less disruptive to the main task than a secondary task.

Huang et al. [3] have previously applied cognitive load to the evaluation of graph visualization, showing that it can illuminate differences between techniques in a way that adds to traditional evaluation methods. We expand on this by integrating it with insight evaluation and task analysis. our ultimate goal is to make the task analysis more directly applicable to models by using both insight and cognitive load as measures of what and how the user is thinking, in addition to measuring how the user interacts. In the following section we describe our observation methods.

3 Methods

- First we interview the participant for qualitative task requirements and overall story. Also get information on how to rate insights for depth and complexity, producing a 1-5 rating scheme on these dimensions.
- Then we observe actual analysis for an hour. Take video and screen capture, etc.
- Participant records insights in a brief note. Instructed to keep it short (so as not to interrupt analysis too much) but be specific enough for recall afterwards.
- At 3-minute intervals, the participant is asked to rate their cognitive load on Paass 9 point scale.

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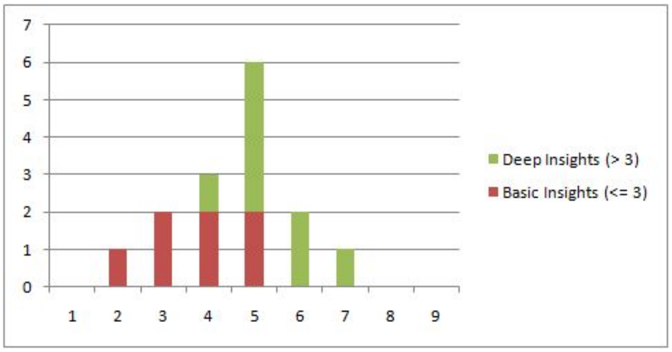

Fig. 2. Number of insights found at varying cognitive load levels (from 1 - 9).

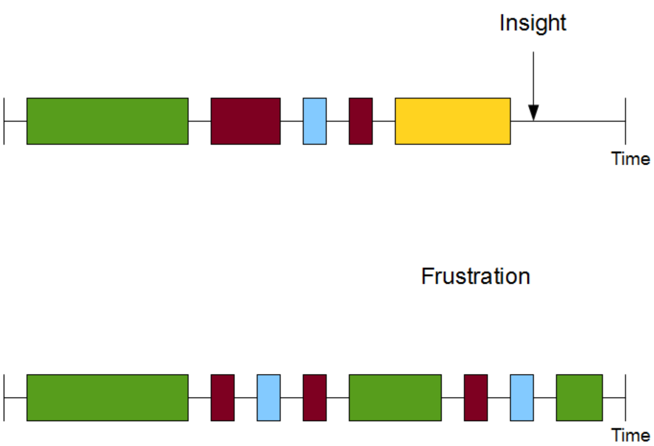

Fig. 1. Common operation patterns associated with productive and unproductive behavior.

4 Results

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4.1 Analysis Procedure

- One coder, coding schemes based on Gotz and Zhou [2], Amar et al. [1], and insight ratings
- Then we combine this timeline with cognitive load and insight annotations for visual analysis.
- Statistical analysis focuses on state of load and action type at points of insight.

4.2 Findings

- Common patterns in general. Are there individual differences? Can they be grouped?
- Patterns correlated with insights and cognitive load. What patterns precede frustration points? What patterns precede an insight? What about different qualities of insight?
- More detail about patterns: is there a point where a good pattern turns into a bad pattern?

5 Discussion

- Are the patterns predictable? Do they associate with heuristics about good analysis, interface design?
- More about individual differences if there are any.
- Modeling for evaluation as a followup.
- What other situations might this be generalized to?

6 Conclusion

- Limitations, future work. Model? Generalizing?
- Restate introduction, etc.

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