

# What *Are* They Thinking? Decomposing a Complex Task

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## Introduction

In this research, we use neuroimaging data to better understand the cognitive processes underlying geometry problem-solving. Our ultimate goal is to design instructional interventions that will improve students' ability to do proofs in geometry. In order to properly address the educational questions surrounding geometry problem-solving, we feel that it is important to understand the underlying cognitive processes that take place during the task. There has been some success (e. g., Qin et al., 2003) in using brain imaging and the theory of ACT-R to identify brain regions—posterior parietal, prefrontal, caudate, anterior cingulate, and motor cortex—and understand the processes—imaginal, retrieval, procedural, goal, and motor, respectively—that support algebra problem solving. This research draws from those methods.

## Method

We trained 15 adult participants to proficiency at a geometry proof task and then scanned them as they performed the task in an fMRI machine. Proof problems had three levels of difficulty: proofs that could be completed with one logical inference, three logical inferences, or proofs that could not be completed.

## Imaging Results

In our five regions of interest we found three distinct patterns of activity. The parietal, prefrontal, and anterior cingulate regions differed significantly from the caudate and motor regions, which differed significantly from each other. This is illustrated in Figure 2. All regions except the caudate showed significant effects of problem difficulty.

## Model Details

We developed a simple cognitive model based on the theory of ACT-R (Anderson et al., 2003). This model is shown in Figure 1. If we estimate that each step of the model requires 2.1 seconds to complete, the model produces a relatively good fit to the latency data.

This model provides a simple all-or-none demand function that we can use to predict the BOLD response in the corresponding brain regions by convolving the demand function with an empirically-derived estimate of the hemodynamic response function.

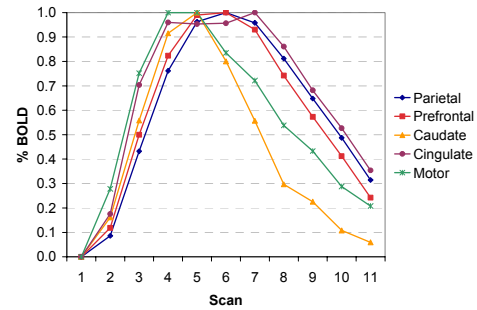


Figure 1: Normalized BOLD responses in all five predefined regions.

Step	Imaginal	Retrieval	Procedural	Goal	Motor
1	Encode Proof Statement	Retrieve Template	Extra Effort	Encode	Extra Effort
2	Encode Givens		Regular		Pointing
3	Inference	Inference	Regular	Answer = 1	Pointing
4	Inference	Inference	Regular		Pointing
5	Inference	Inference	Regular	Answer = 3	Pointing
6	Inference	Inference	Regular		Pointing
7	Inference	Inference	Regular	Answer = 5	Pointing
8	Represent Feedback		Regular	Respond	Press Key

Figure 2: Model of geometry task

## Acknowledgments

This research was supported by a Research on Learning and Education grant from the National Science Foundation.

## References

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