States of Learning as Revealed by ACT-R Modeling of fMRI Data

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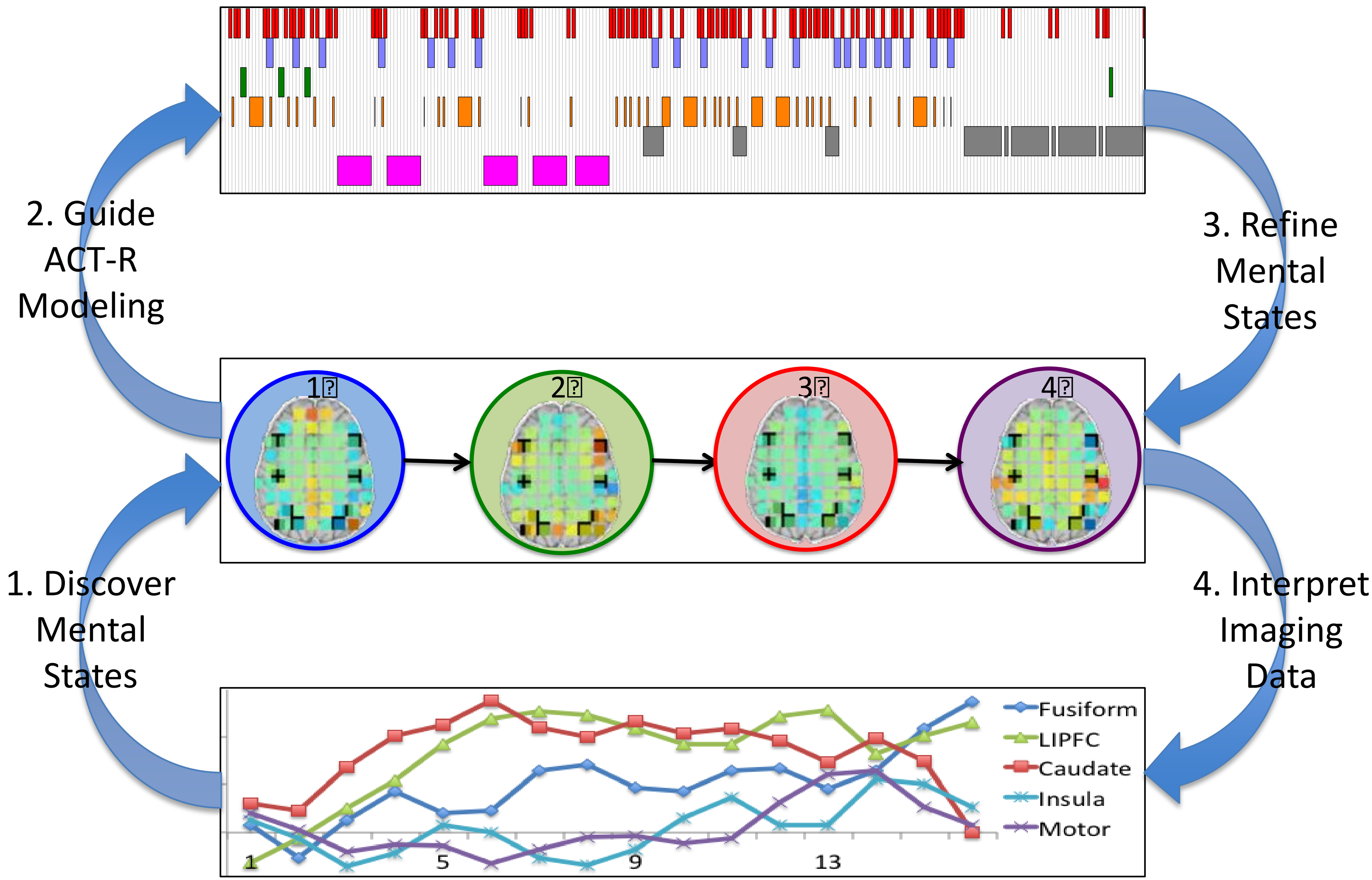
The Bidirectional Use of Data and Theory



Pyramid Problems

There is a notation for writing repeated addition where each term added is one less than the previous:

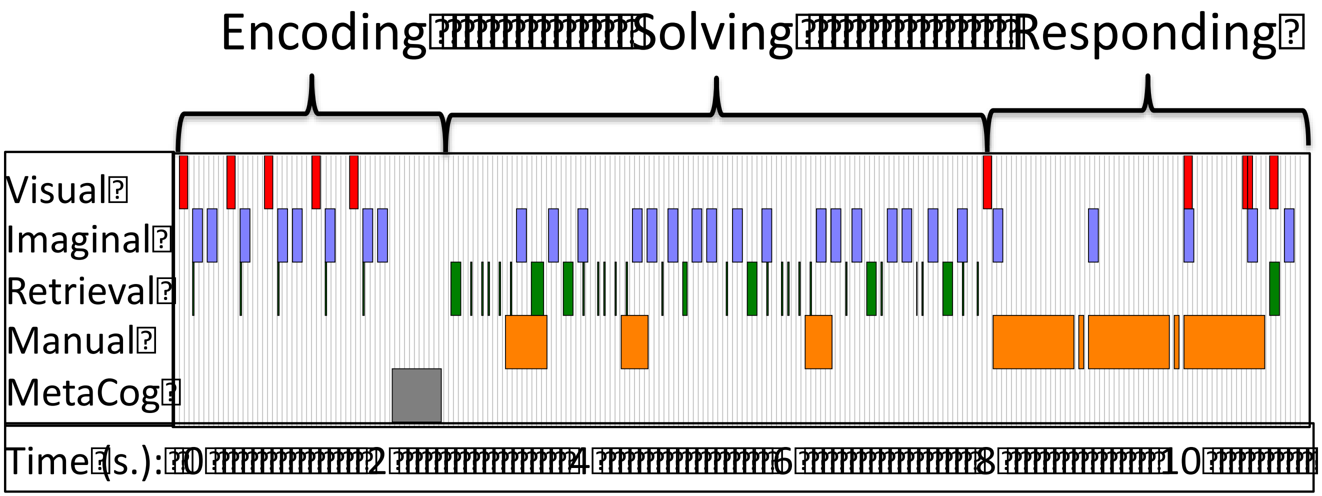
For instance 4 + 3 + 2 is written as 4 $ 3

Since 4 + 3 + 2 = 9 we would evaluate 4 $ 3 as 9 and write 4 $ 3 = 9
The parts of 4 $ 3 are given names:

4 is the base and reflects the number you start with
3 is the height and reflects the total number of items you add, including the base
4 $ 3 is called a pyramid

In this session, you will solve a series of these problems. For example, if you see 4 $ 3 = X, type 9 on the keypad and press enter.

Anderson & Fincham:
ACT-R Model Solving 7$4=X



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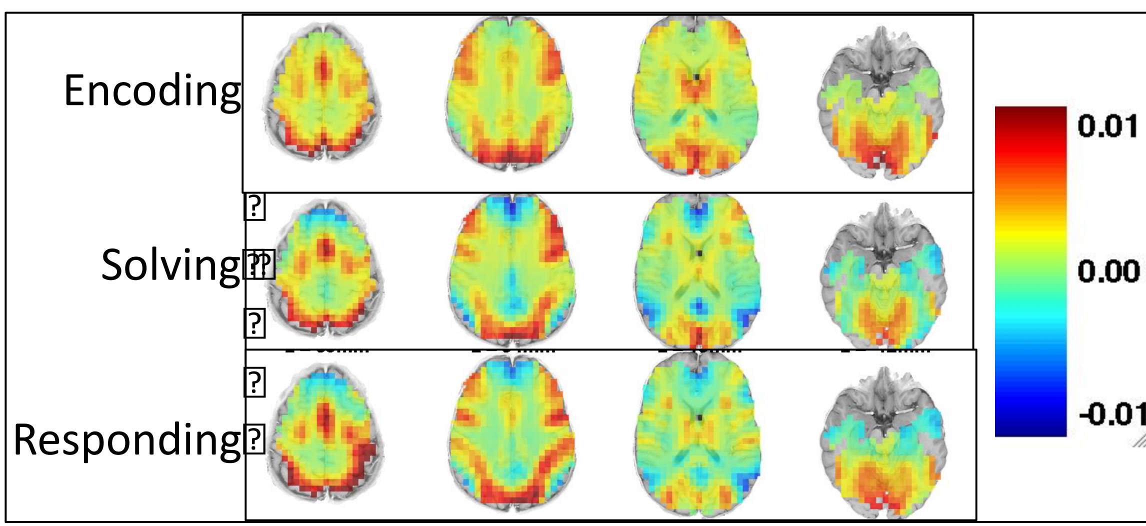
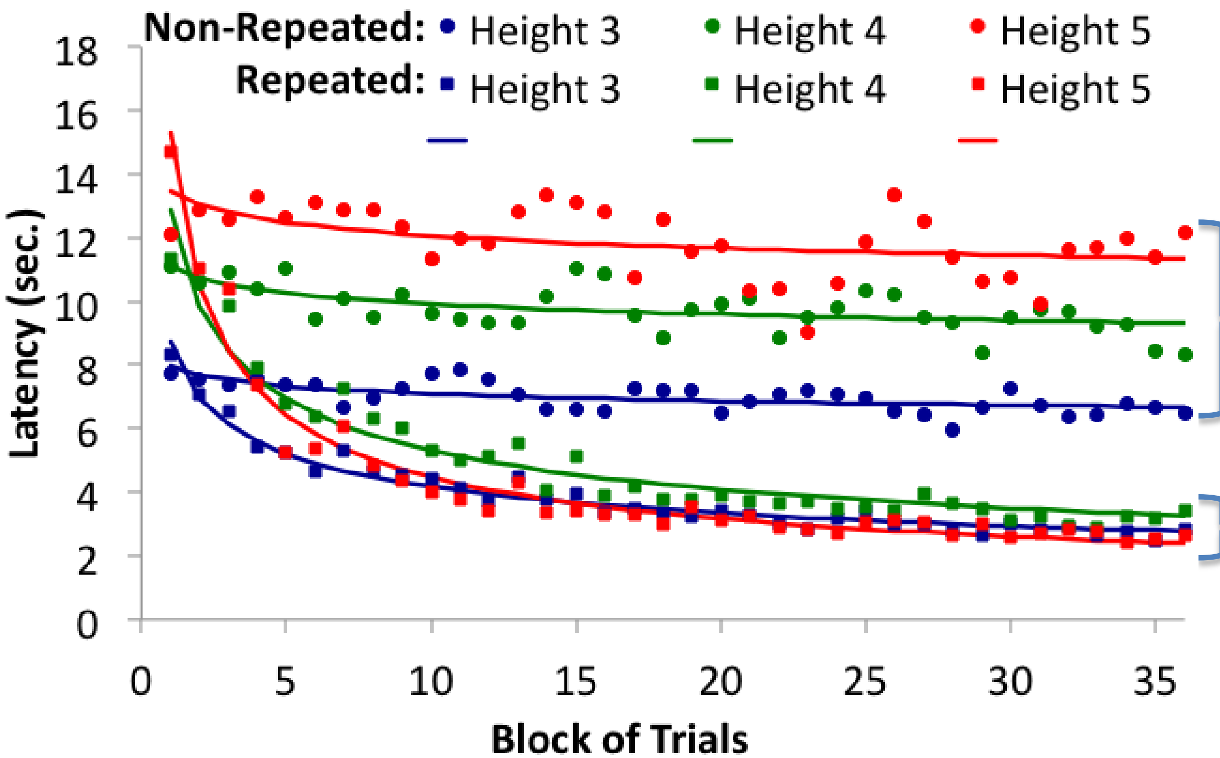
Each stage has its own brain signature that reflects the different concentration of module activity in that stage



Caitlin Tenison's Study:
Effects of Repeating the Same Problem



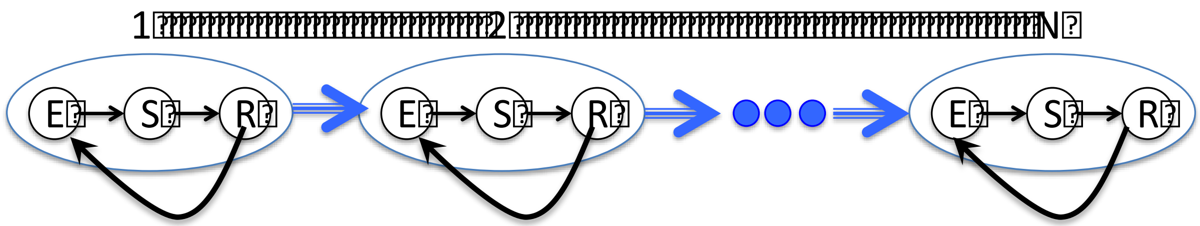
Height determines the number of mental additions.

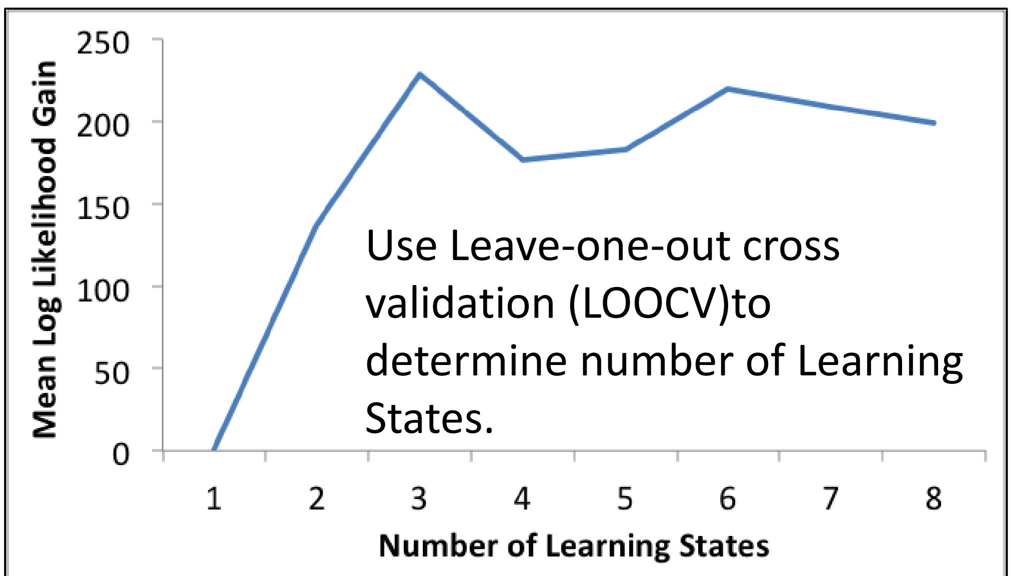
With practice subjects speed up and effect of height disappears.

- Such speed up has traditionally been assumed to reflect something like strengthening of procedures and declarative memories.
- However, our proposal is that the speed up is **largely** produced by discrete changes in how subjects perform the Encoding, Solving, and Responding steps.
- Each discrete state produces a new **State of Learning**.

Cognitive Stage/ Learning States

- We will assume that the brain signatures of the **Cognitive Stages** stay constant across states but what varies is the duration of these stage.
- Each discrete change in duration results in a new **Learning State.**
- This is represented by the following Markov model:



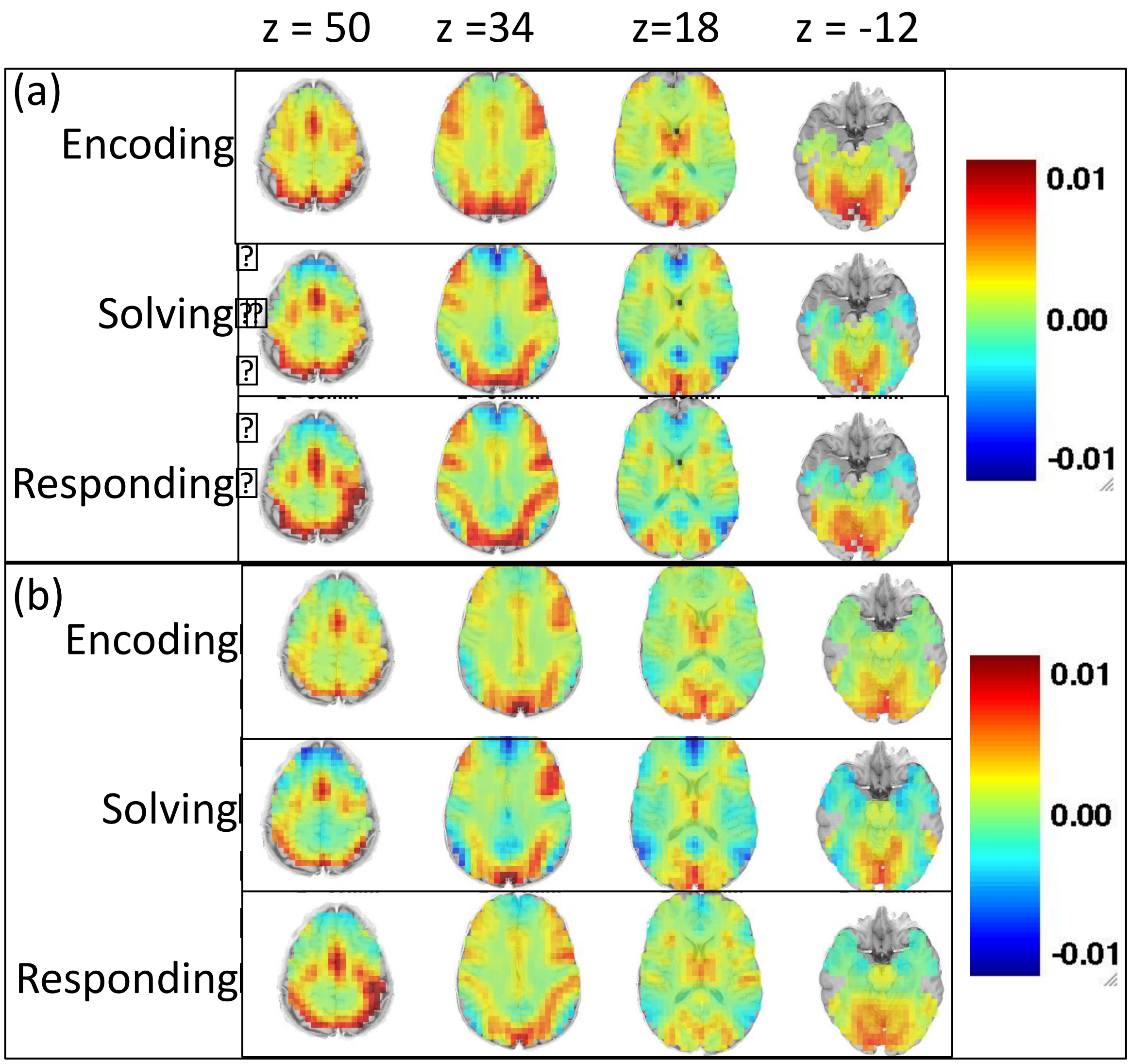


Brain Signatures of Stages Compared

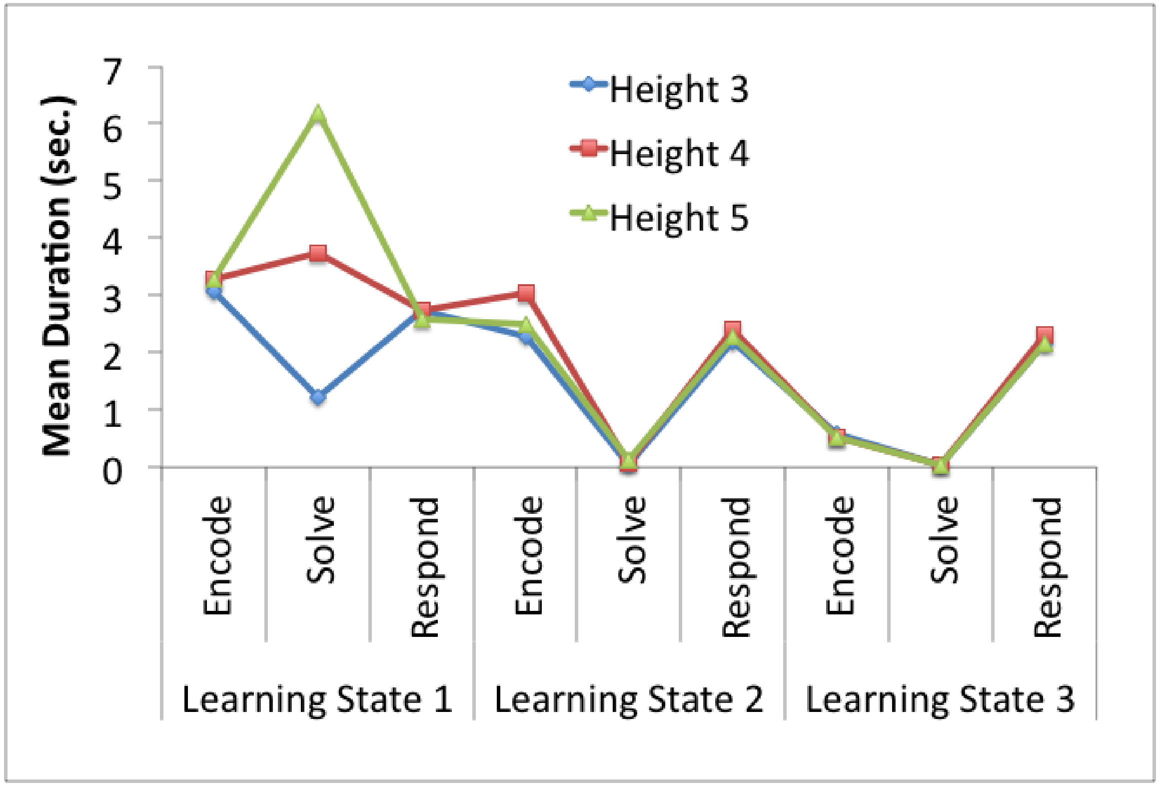
Anderson & Fincham

The brain signatures are constant across the states of learning.

Tenison & Anderson

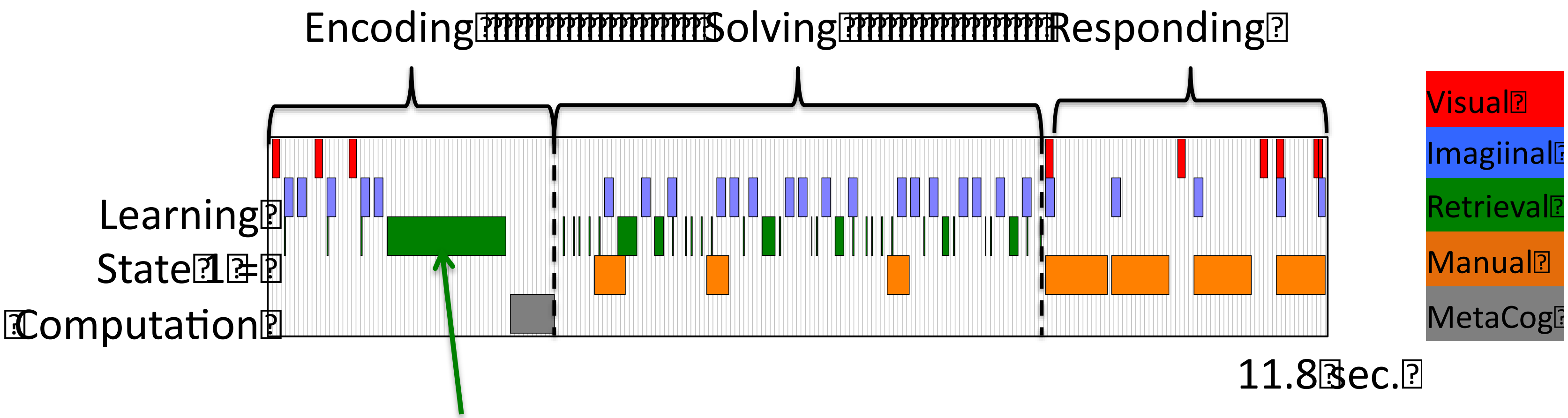


Mean Time in Cognitive Stages within Learning States

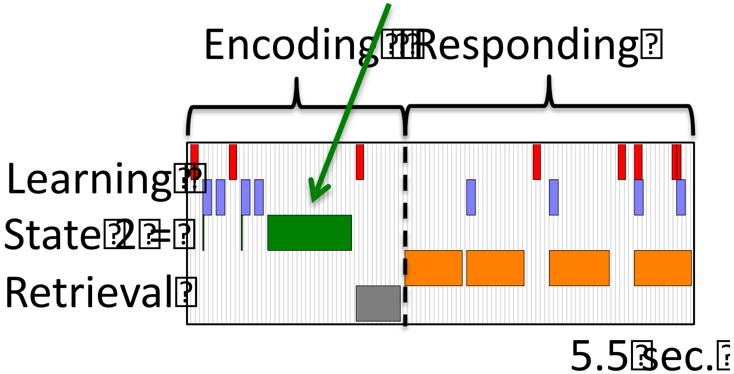


- Effect of Height only on Solving Stage in Learning State 1.
- Duration of solving stage near 0 in later learning states (.06 and .03 seconds).
- Steady decrease in duration of Encoding Stage (3.25, 2.43, .54 seconds).
- Slight decrease in Responding Stage (2.89, 2.31, and 2.20 seconds)

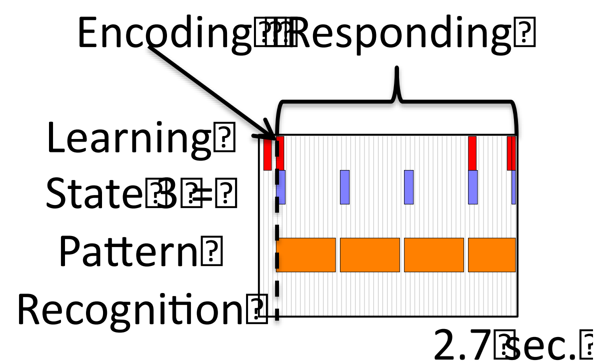
Top Down: ACT-R Model for 7$4



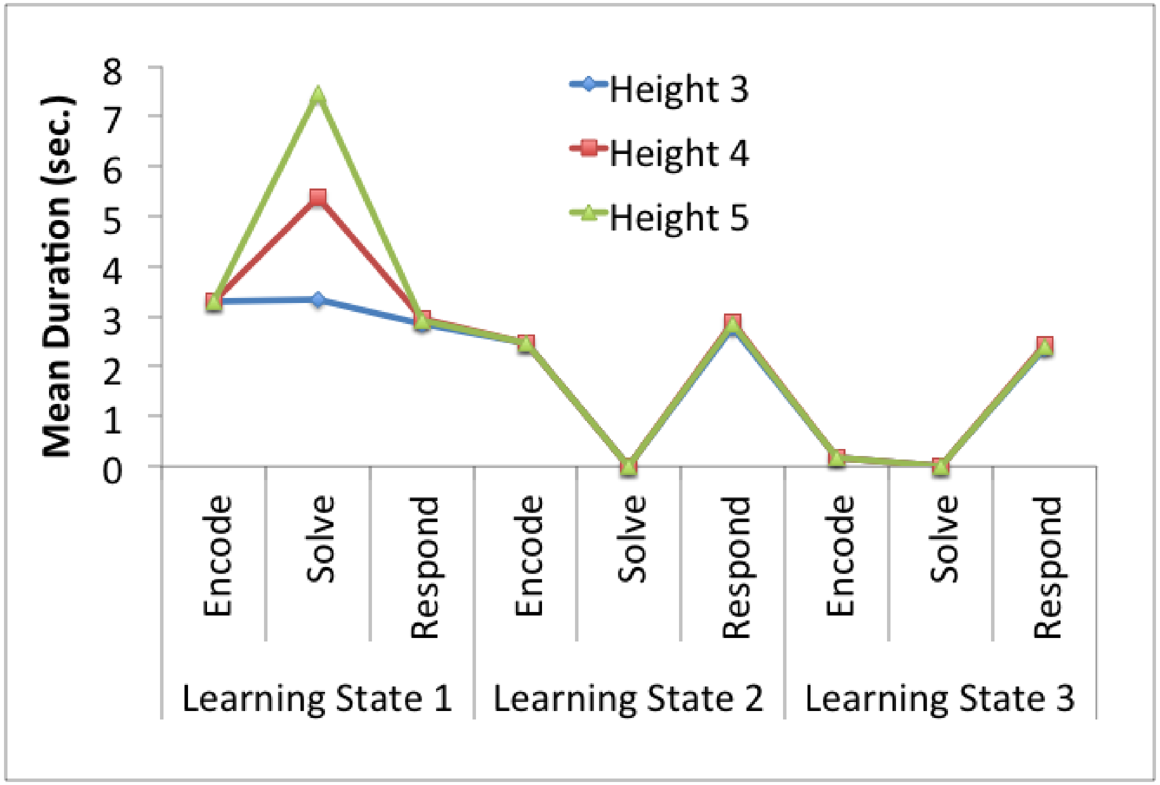
The model tries but fails to retrieve answer and must compute. When the encoding of the answer is sufficiently strong the model transitions to the second Learning State where the answer is retrieved.



Eventually a production is compiled that processes the problem as a word and directly produces the answer.

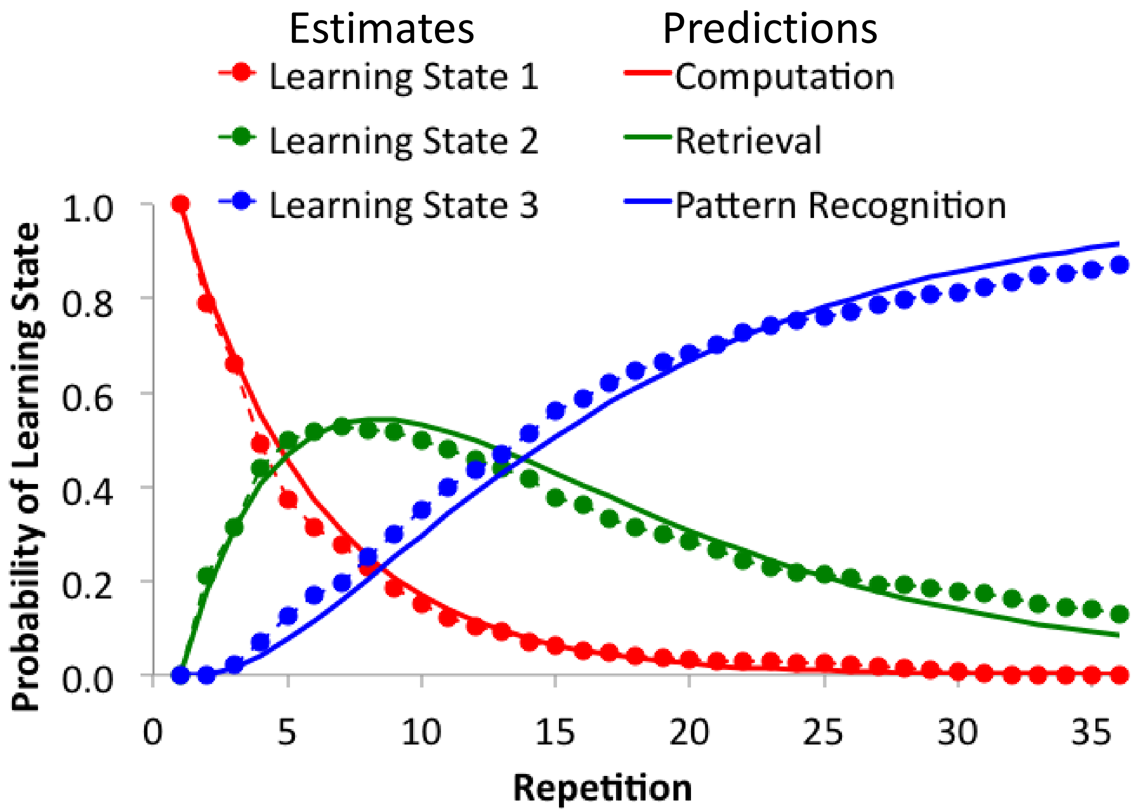


ACT-R Time Estimates and Fit



- The ACT-R times for stage duration are similar to bottom-up estimates but not identical.
- Because it it more constrained the model fits better in LOOCV -- fitting 28 of the 40 subjects better with a mean log-likelihood gain of 6.0.

The States of Learning



- The data bottom-up provide strong evidence that the major source of speed up is transition among three learning states.
- The model top-down provides strong evidence that the transition from State 1 to State 2 is produced by learning the answer and that the transition to State 3 is produced by creating a rule that just recognizes the problem as a pattern.