

A Generative Model of Human Performance on an Optimal Stopping Problem

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Whibley, James Campbell, Chrisi Lambos, Michael Webb, Gary Ewing &
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79.69

[1/5]

34.40

[2/5]

82.55

[3/5]

95.77

[4/5]

24.26

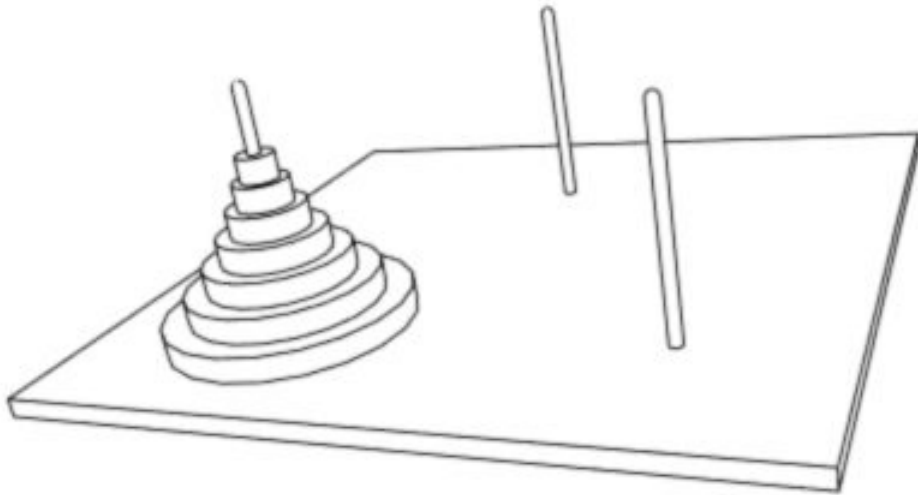
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Why Study This Problem?

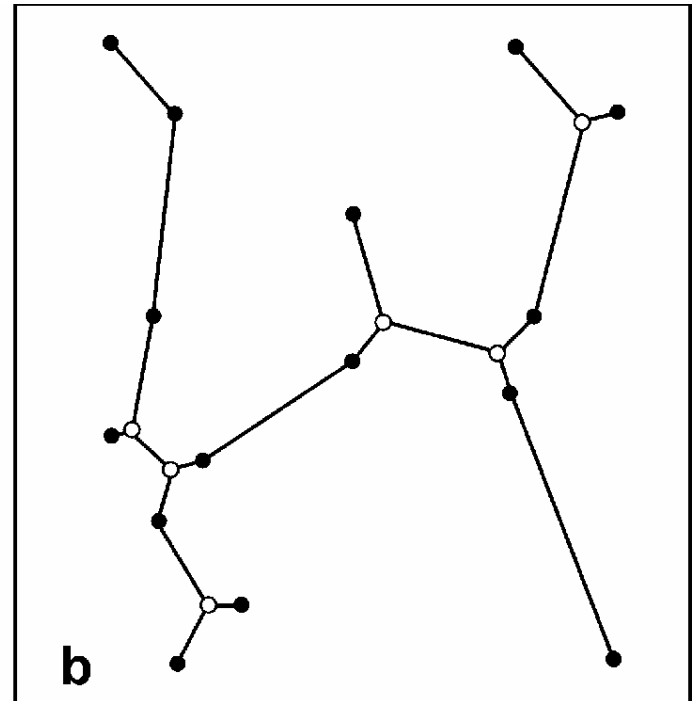
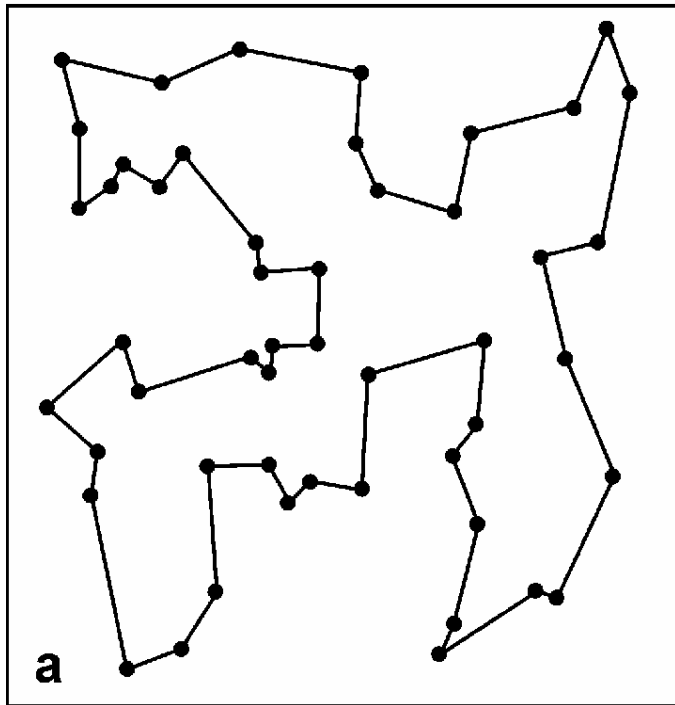
More Controlled than Knowledge-Rich



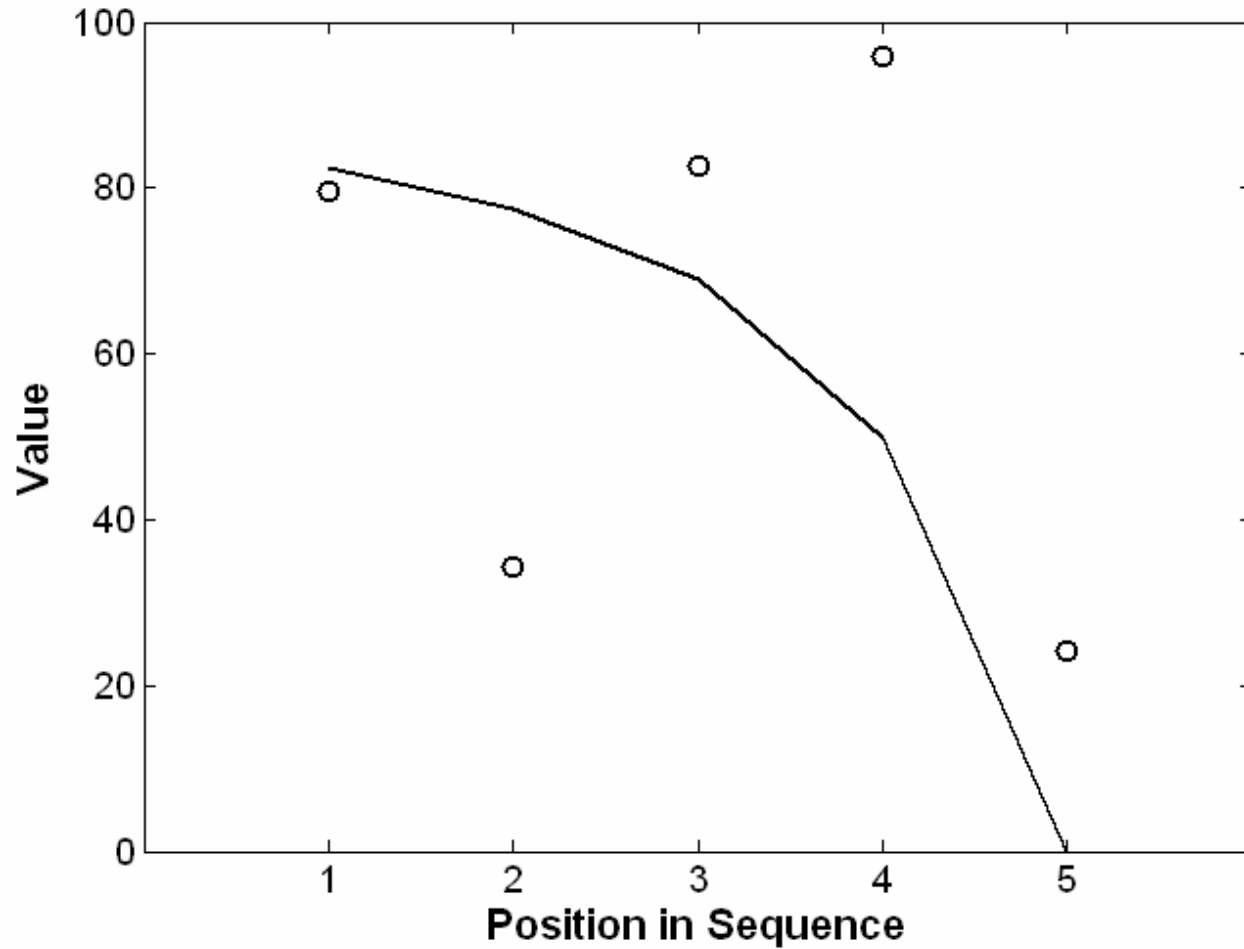
More Realistic than Knowledge-Learn



Complements Other Optimisation Problems

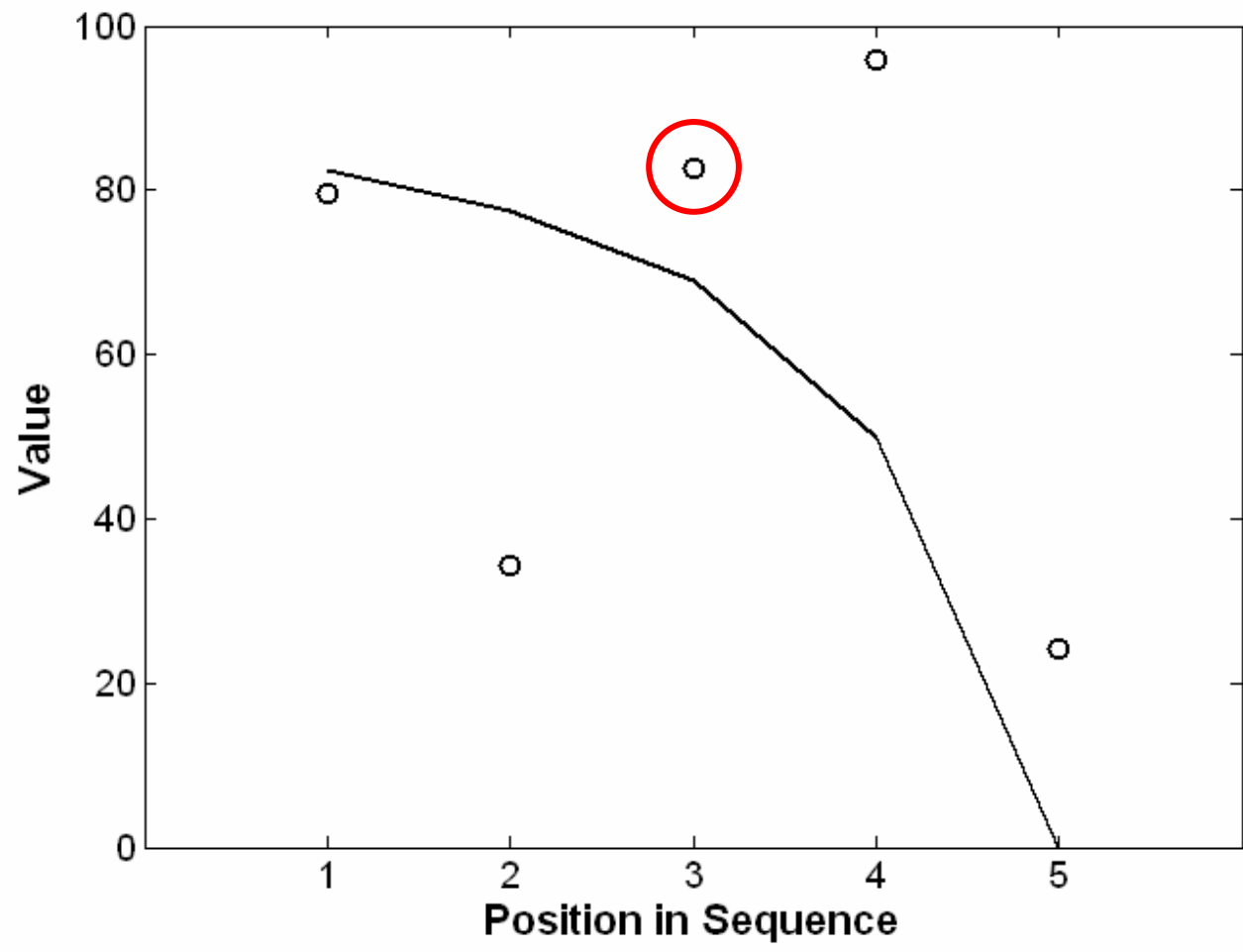


Optimal Decision Rule



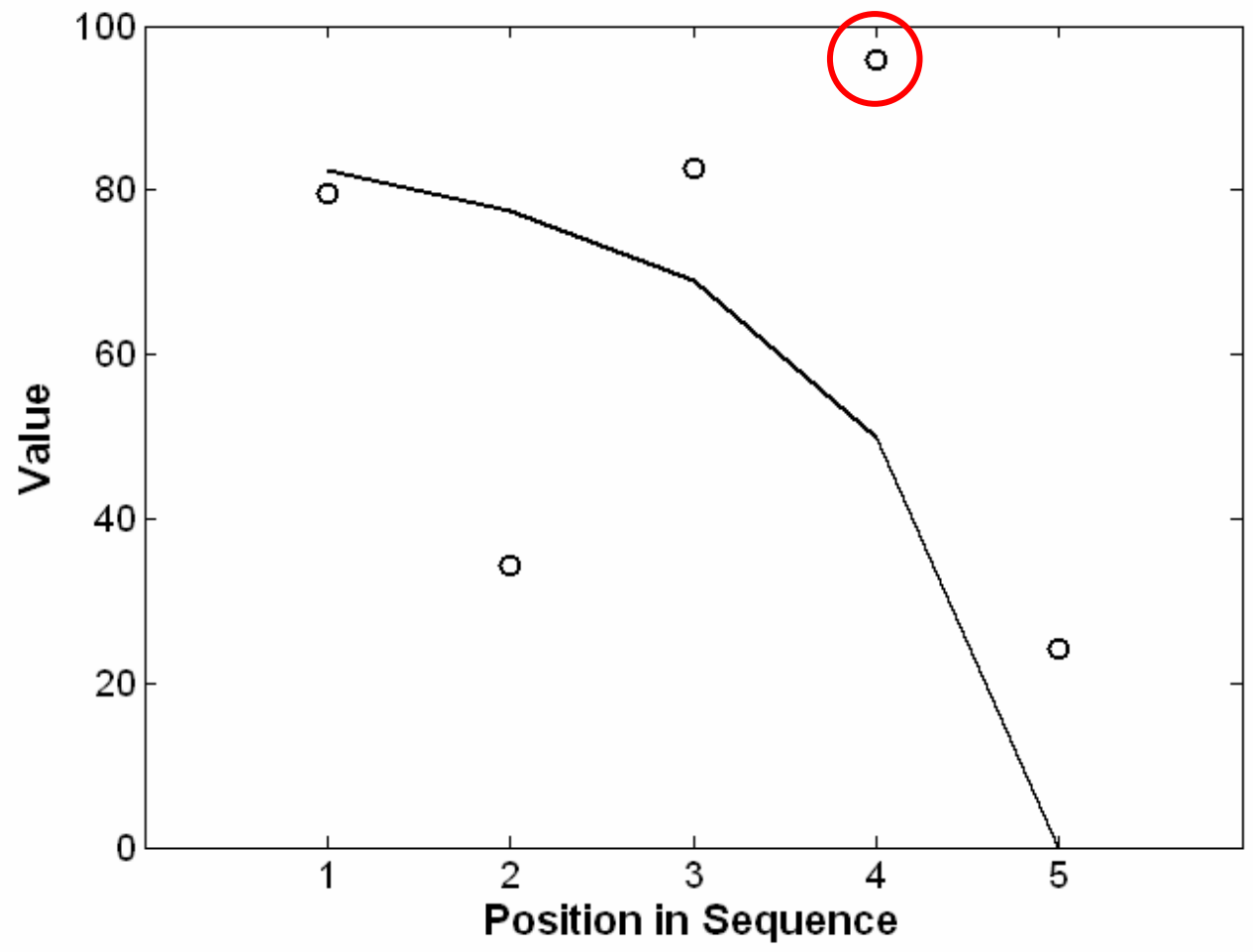
Two Optimal Decisions

follows decision rule
(good but unlucky)



Two Optimal Decisions

violates rule, but maximum value
(bad but lucky)



Empirical Data

Experimental Interface

77.66

YES **4/5** NO

Definitely Wrong

1

2

3

4

5

6

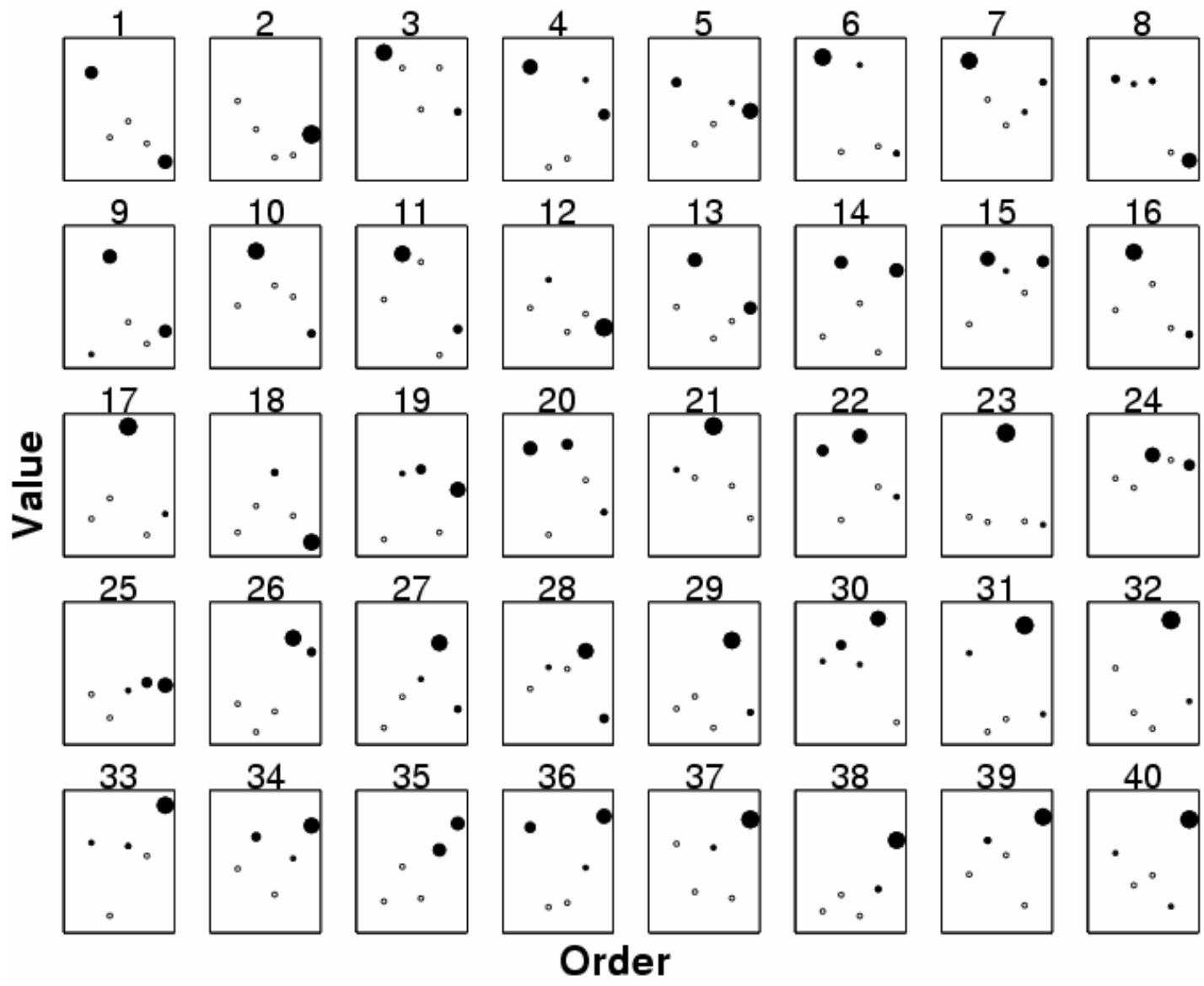
7

8

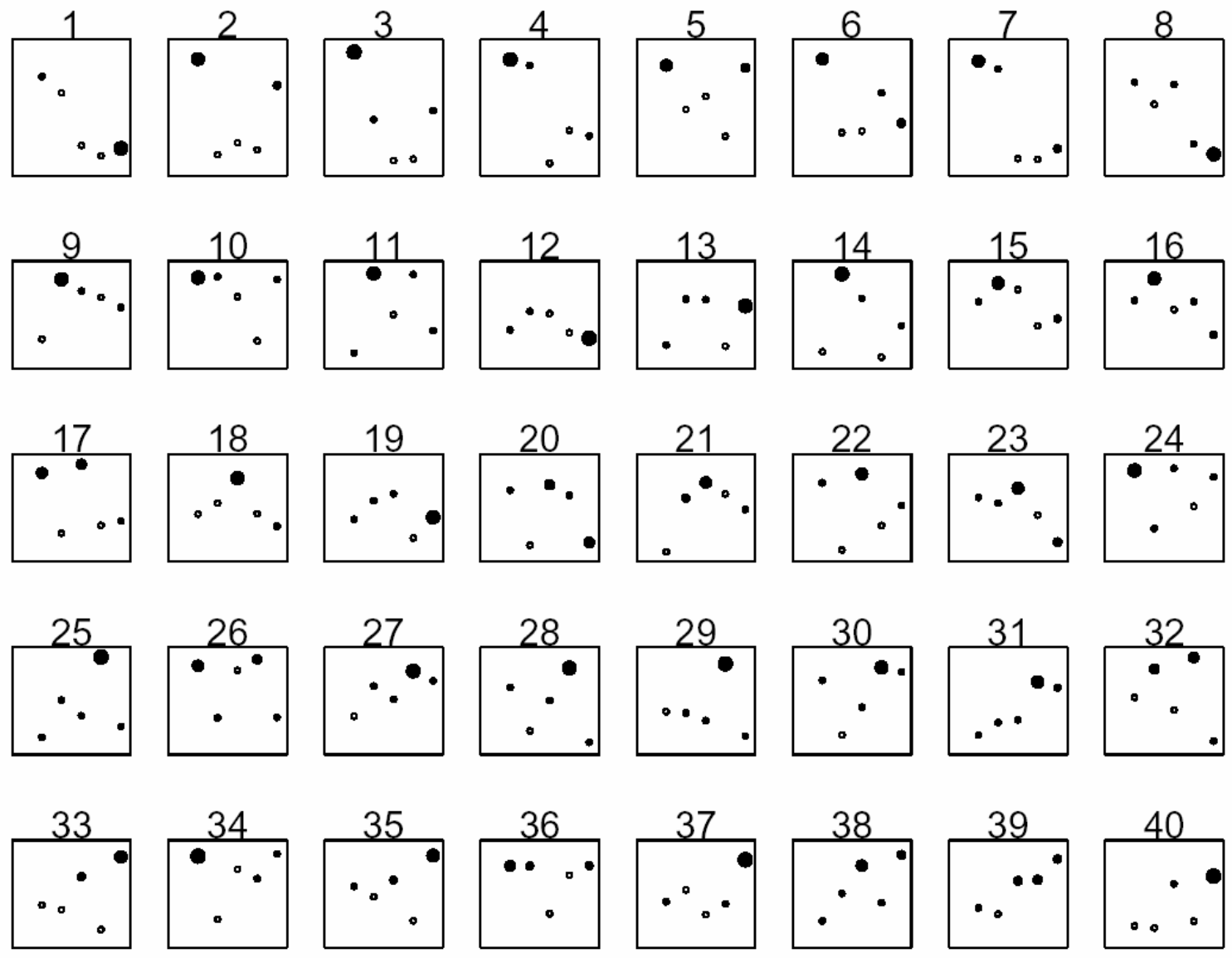
9

Definitely Correct

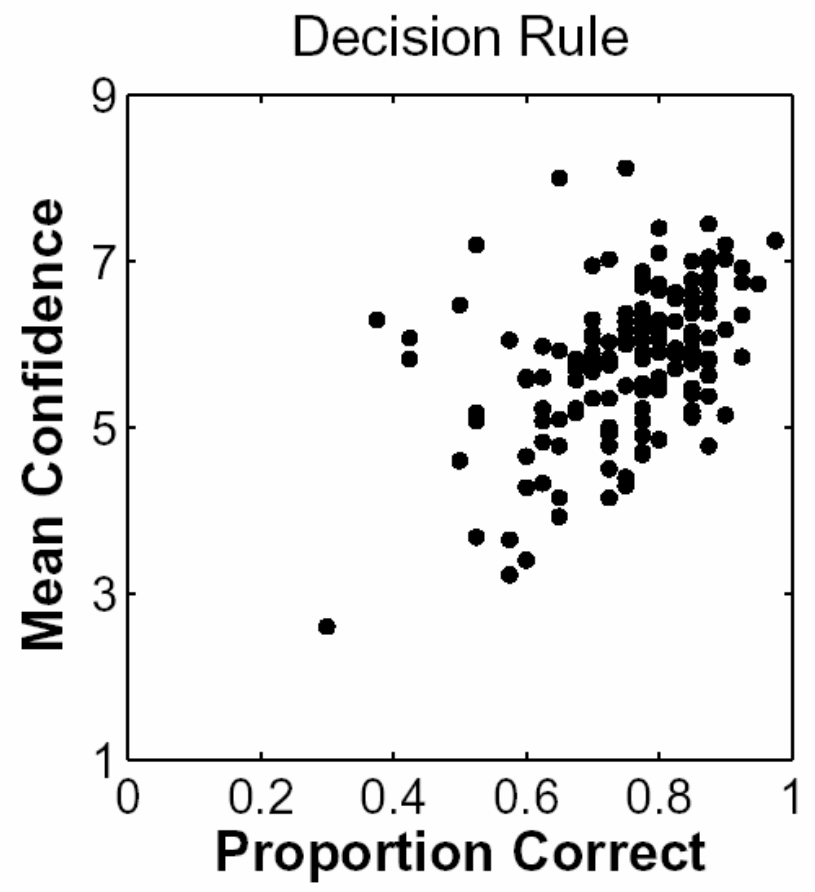
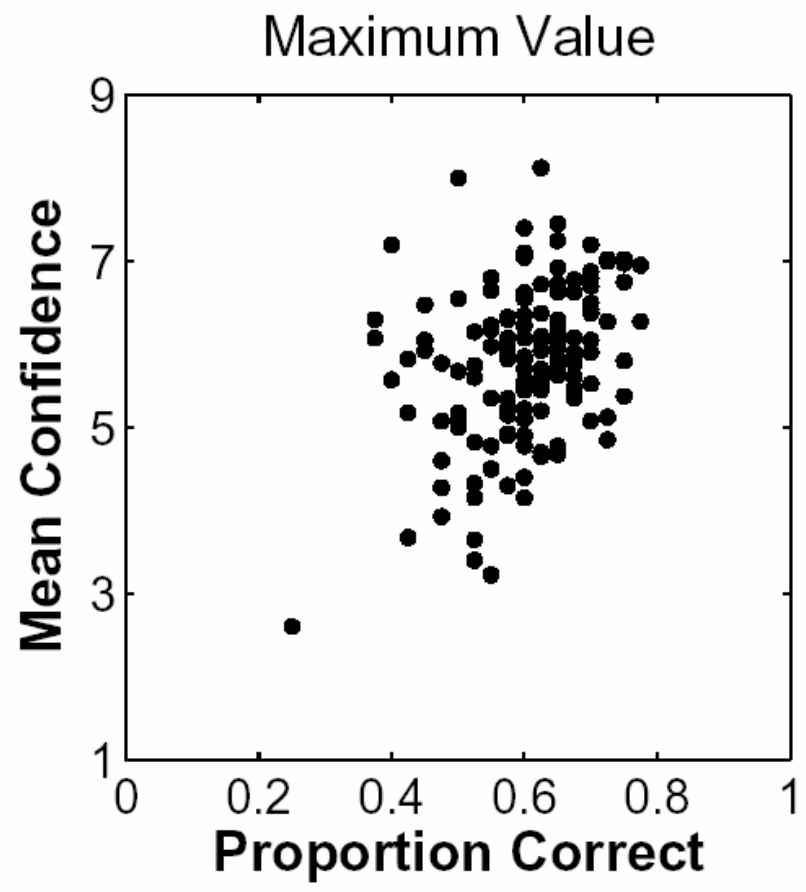
50 Subjects on 40 Five-Point Problems



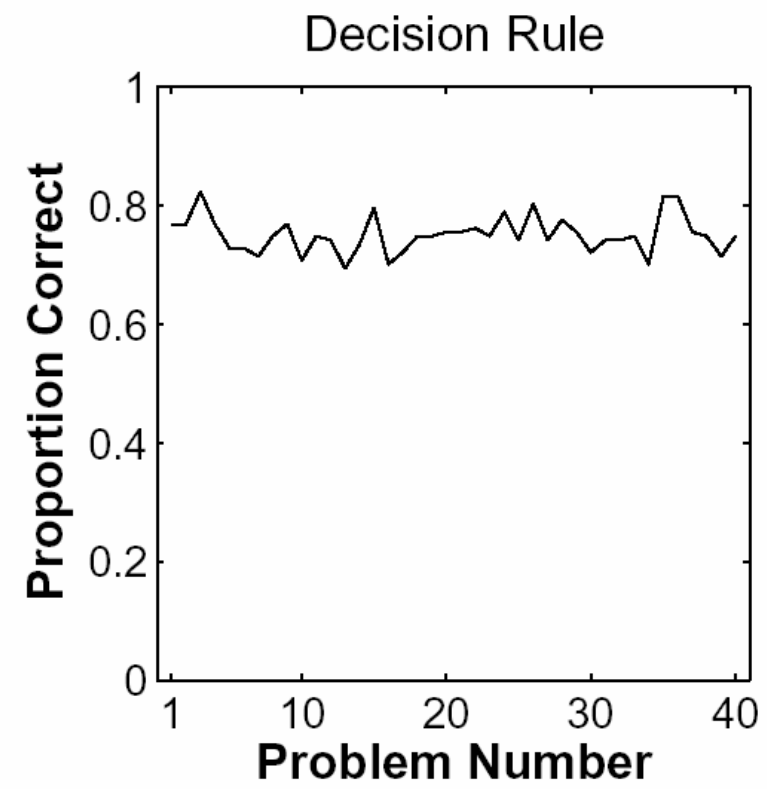
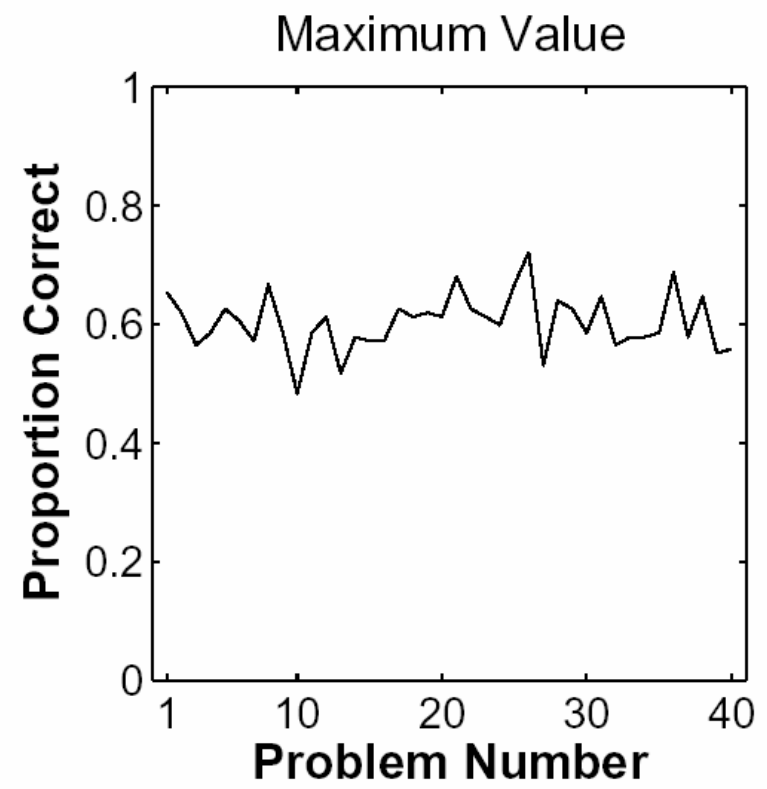
98 Subjects on 40 More Five-Point Problems



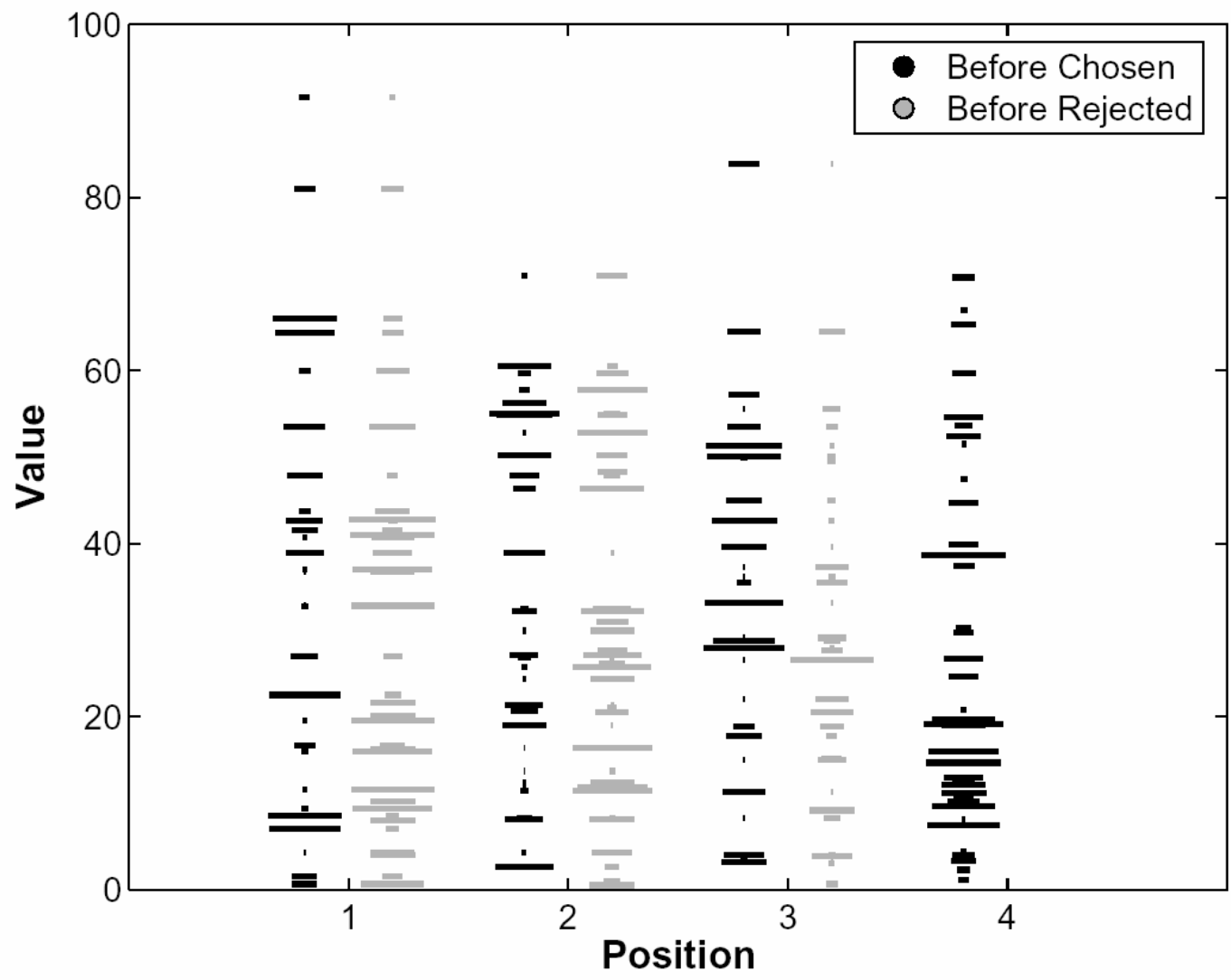
Individual Diffs in Accuracy & Confidence



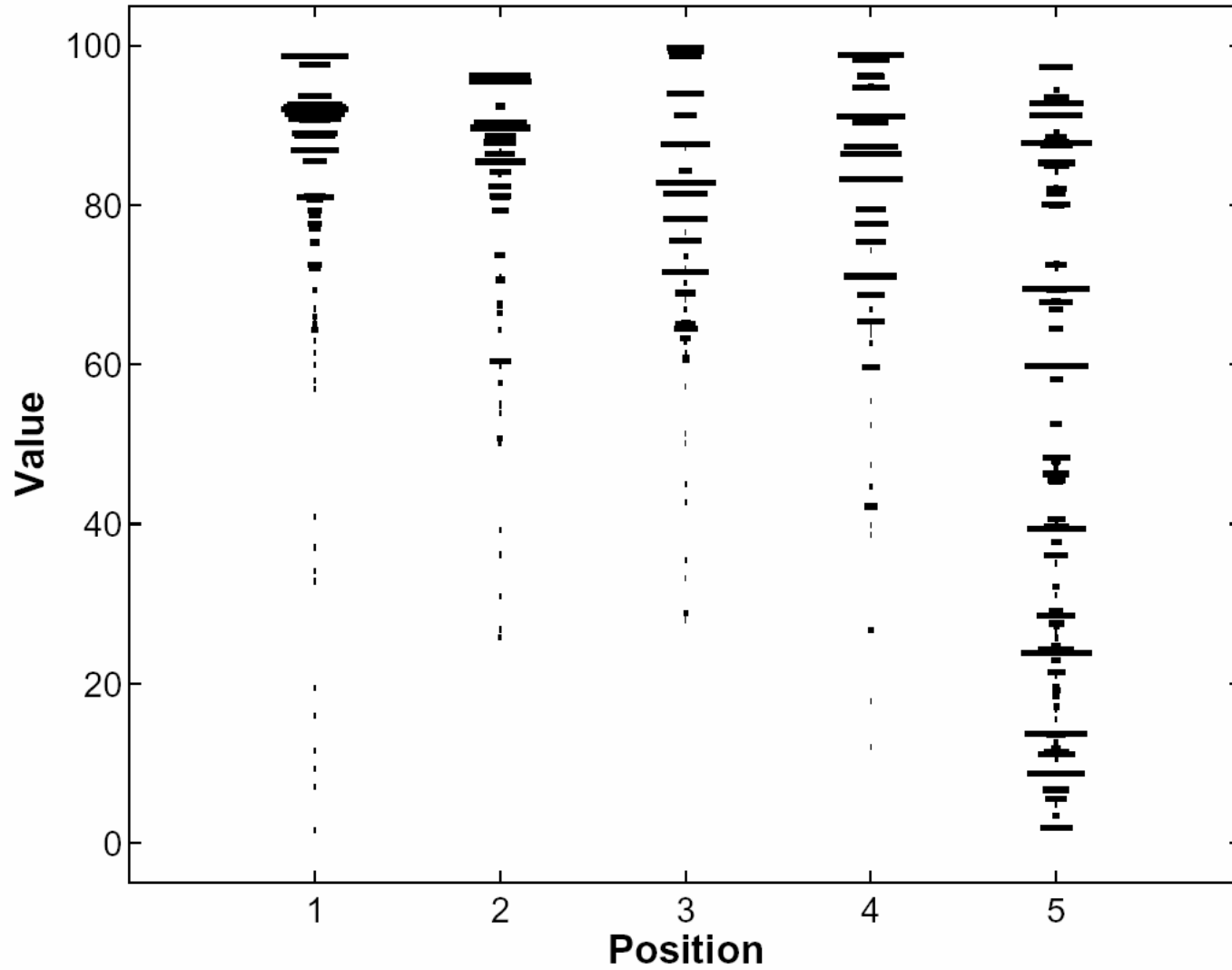
No Evidence of Learning



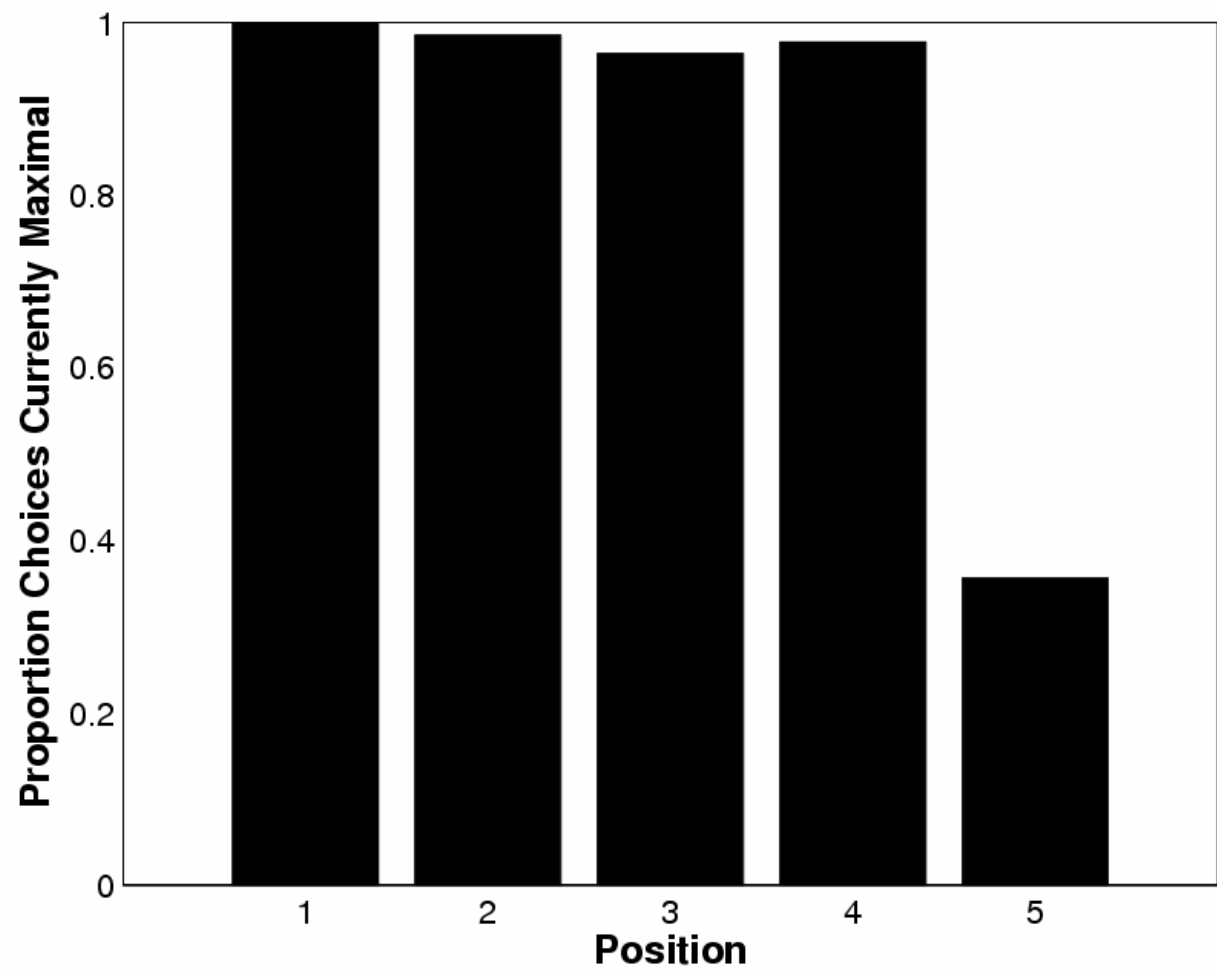
Other Values Don't Seem to Matter



Value in Position Matters



Being Currently Maximal Really Matters



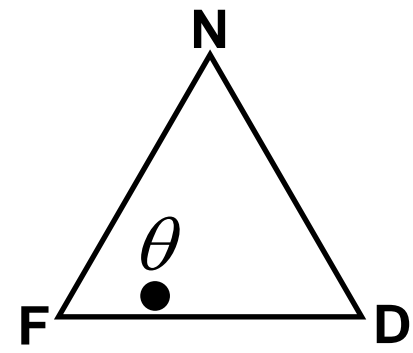
A Hierarchical Bayesian Generative Model

Why HBG Models?

- Hierarchical
 - represent knowledge at different levels of abstraction
 - formalize the structure of relationships between levels
- Generative
 - provide an account of how cognitive models are instantiated and bounded
 - quarantine core issues of modeling from secondary questions of inference
- Bayesian
 - provides a (the?) complete and coherent approach to statistical inference with models

Generative Framework

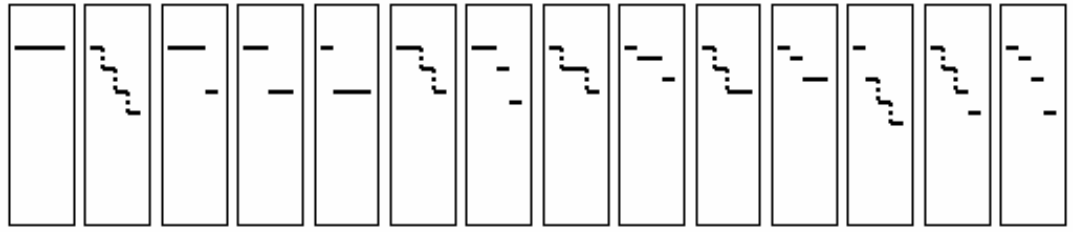
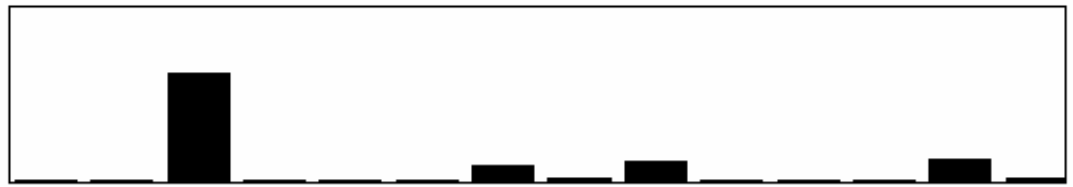
Generative Process



θ

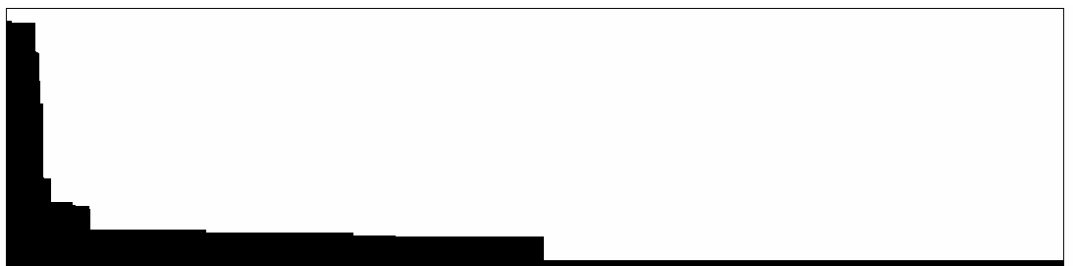
$p(M|\theta)$

Model Family



Indexed Sequences

$p(I|M, \theta)$

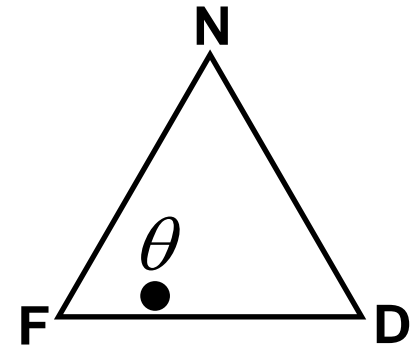


0 Indexed Sequences 3121

Making Inferences About Generative Process

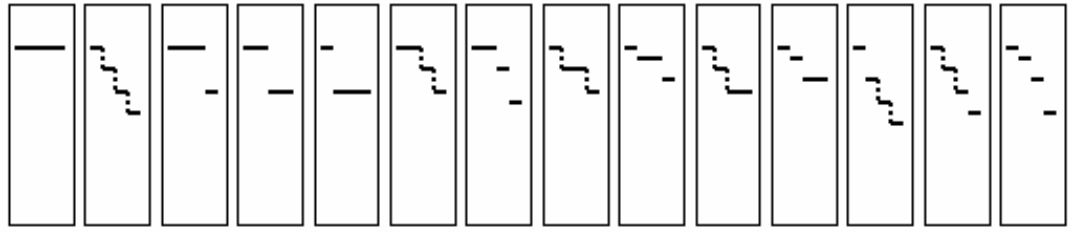
Generative Process

$$p(\theta|D)$$



$$p(D|M)$$

Model Family



Indexed Sequences

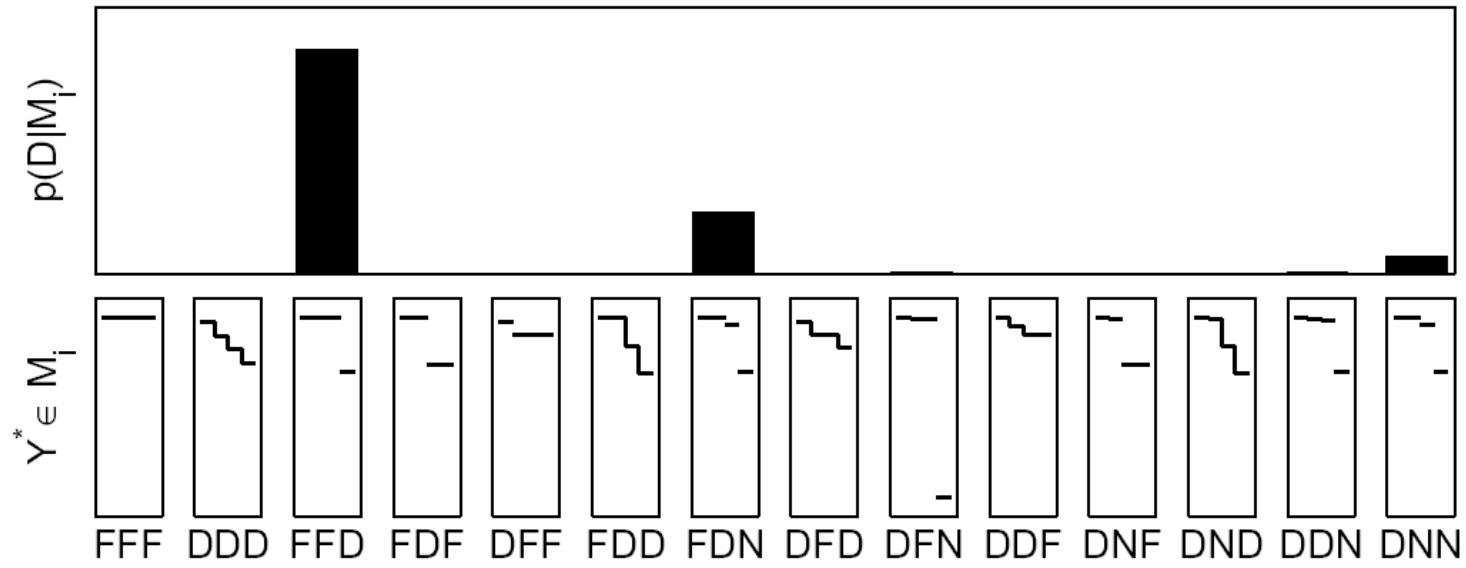
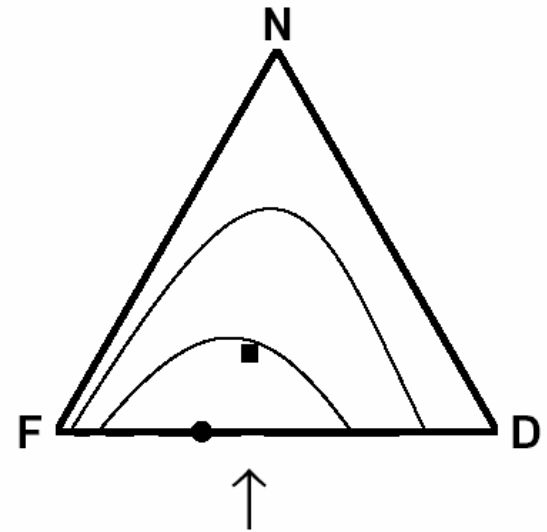
D



0 Data Sequences 5^{40}

Results for One Subject

Inference from Data



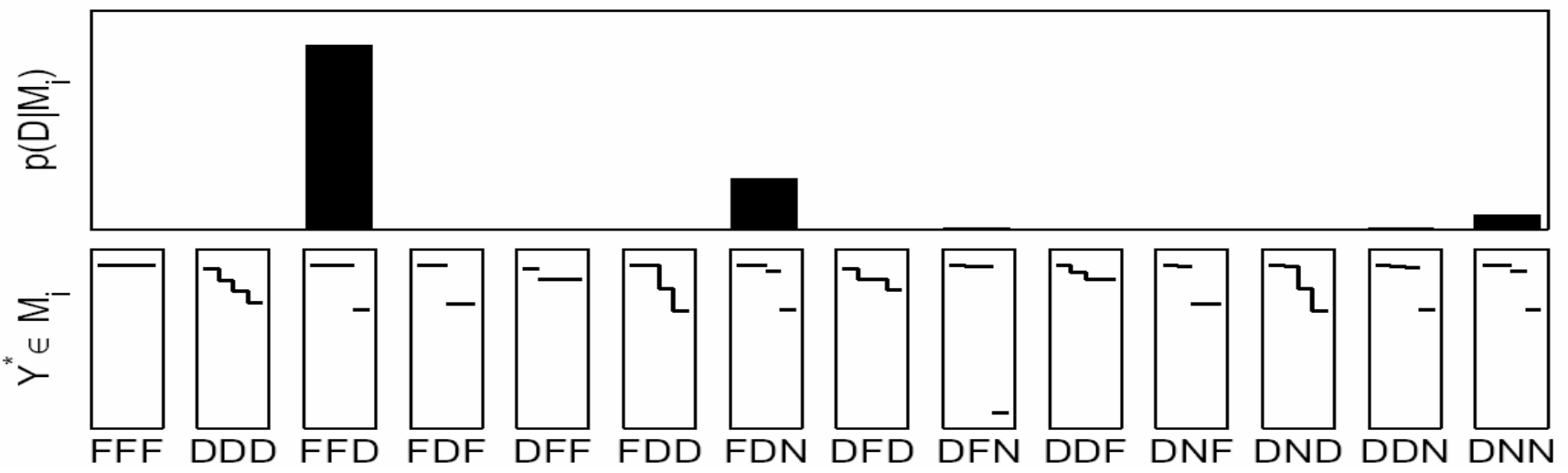
Building Predictive Models

$$p(M_i|D) = \frac{p(D|M_i)p(M_i)}{\sum_{j=1}^{14} p(D|M_j)p(M_j)}$$

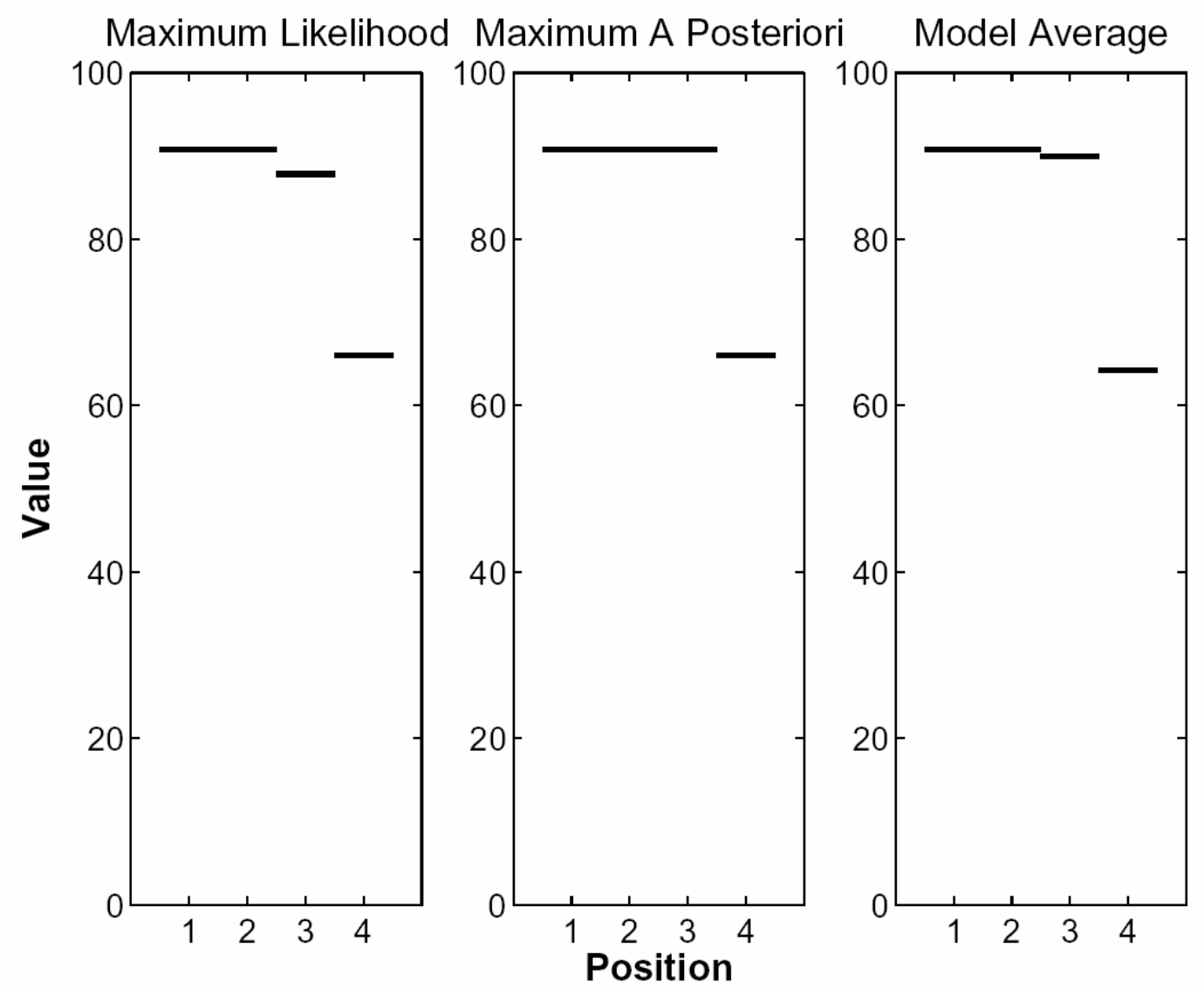
Model Average

MAP

ML

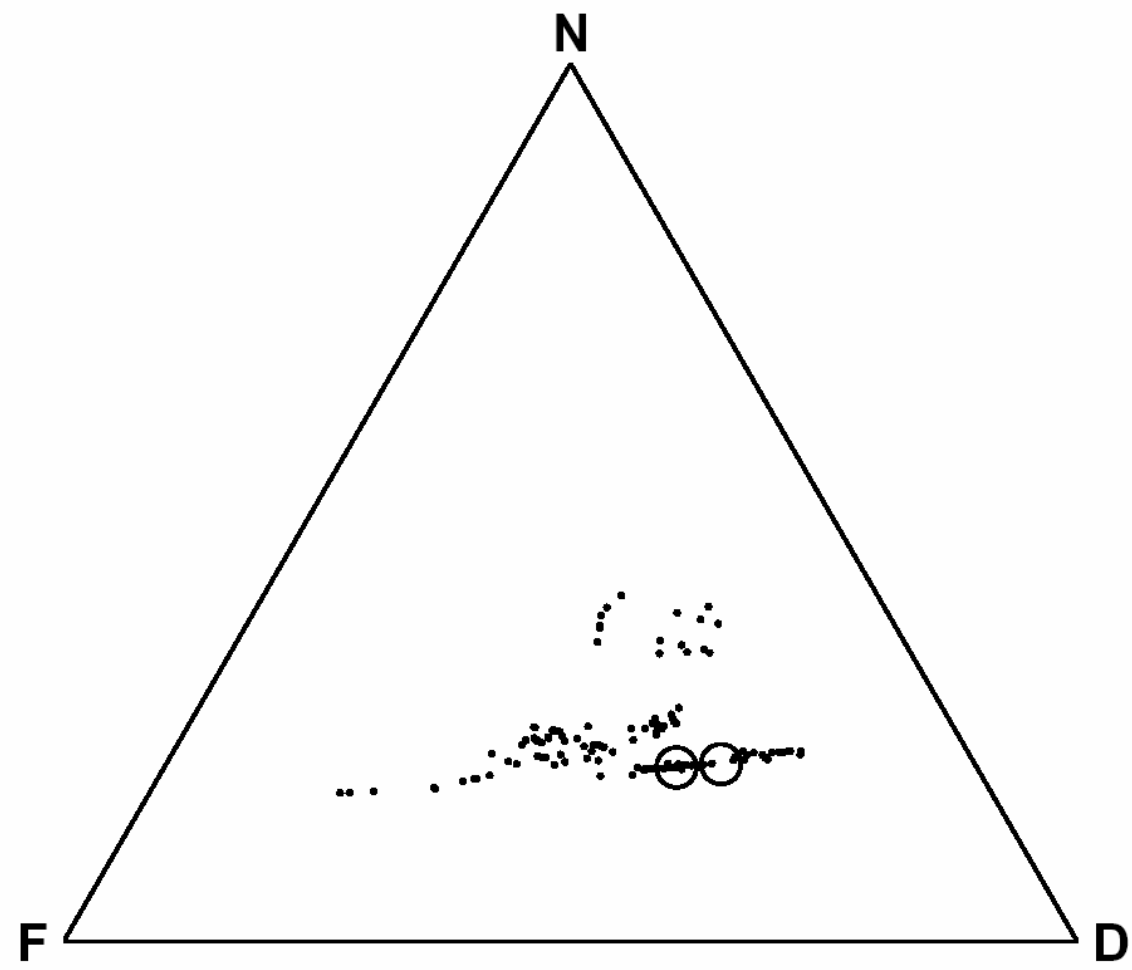


Posterior Predictive Models



Overall Evaluation

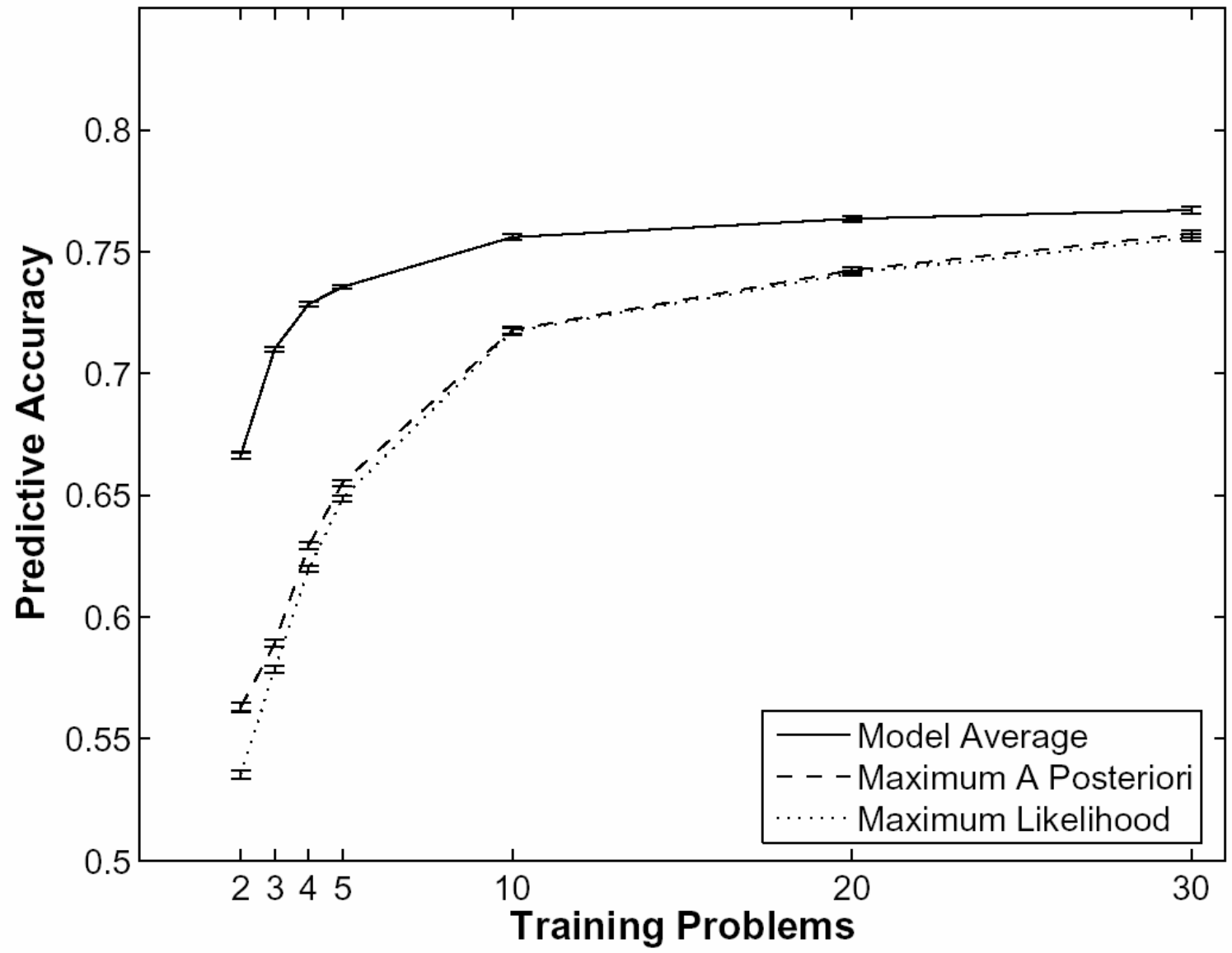
Individual Differences at Generative Level



Individual Differences in Predictive Models



Cross Validation



Preliminary Results of Current Work

Feedback and Reward

0/1

Wrong

YES **1/5** NO

Definitely Wrong 1 2 3 4 5 6 7 8 9 Definitely Correct

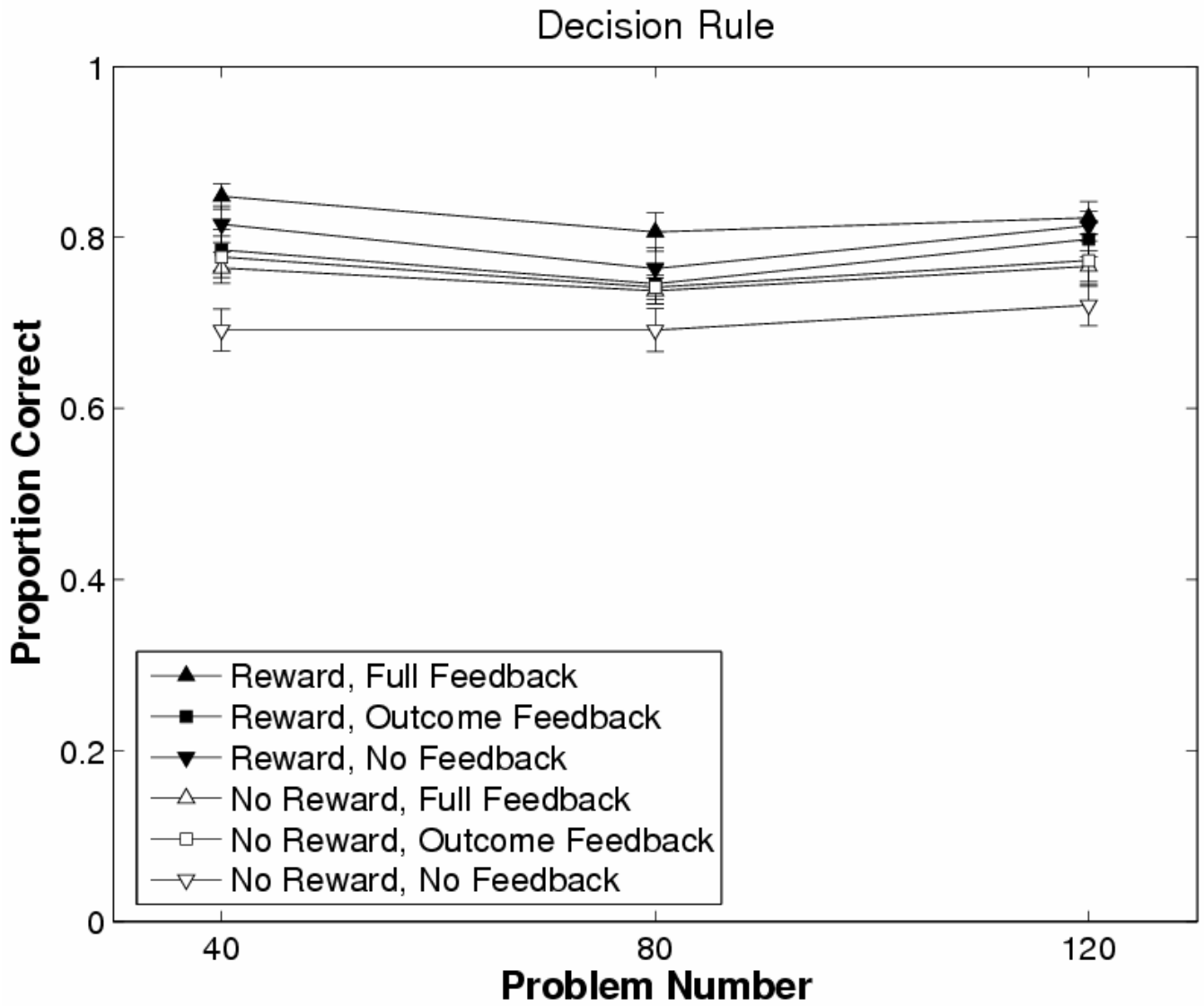
2/3

Category	Max	You
1	75.33	
2	71.00	
3	73.57	73.57
4	13.40	
5	6.67	

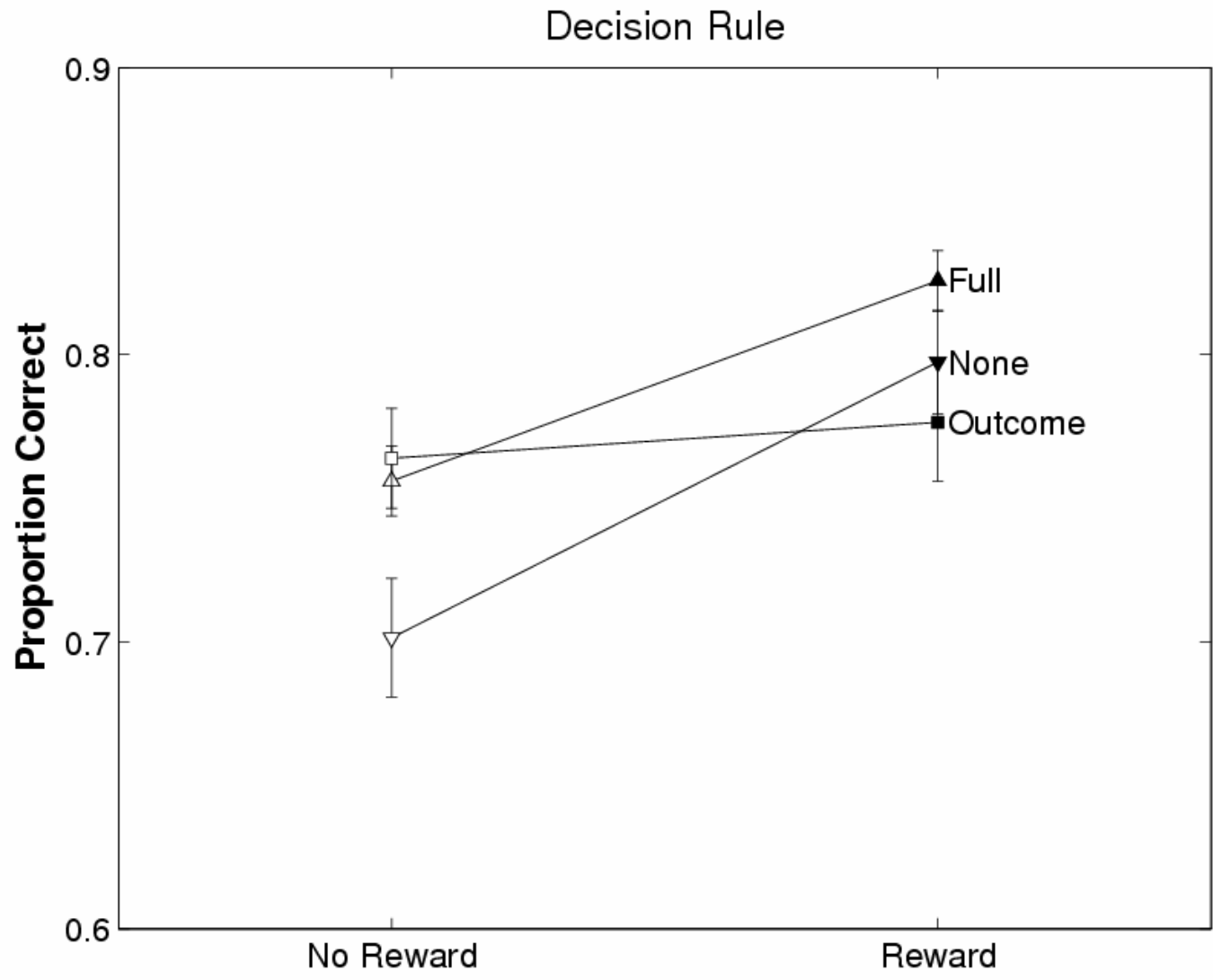
YES **3/5** NO

Definitely Wrong 1 2 3 4 5 6 7 8 9 Definitely Correct

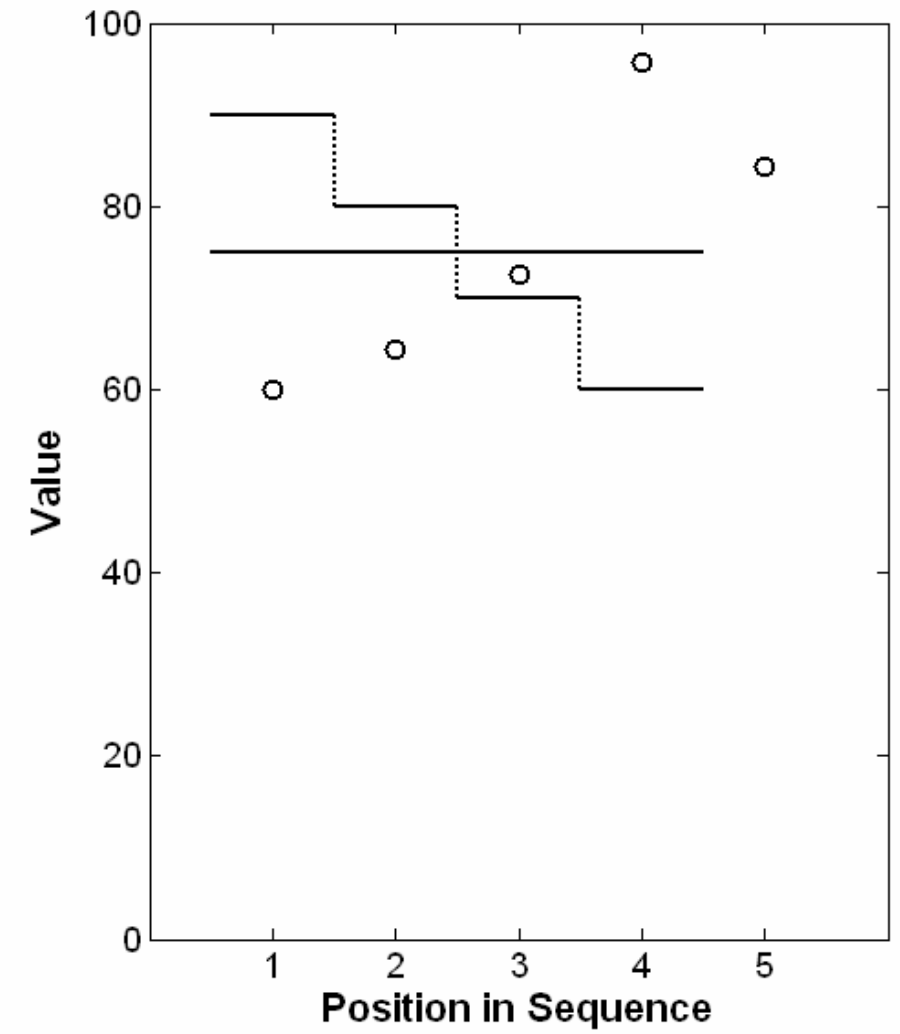
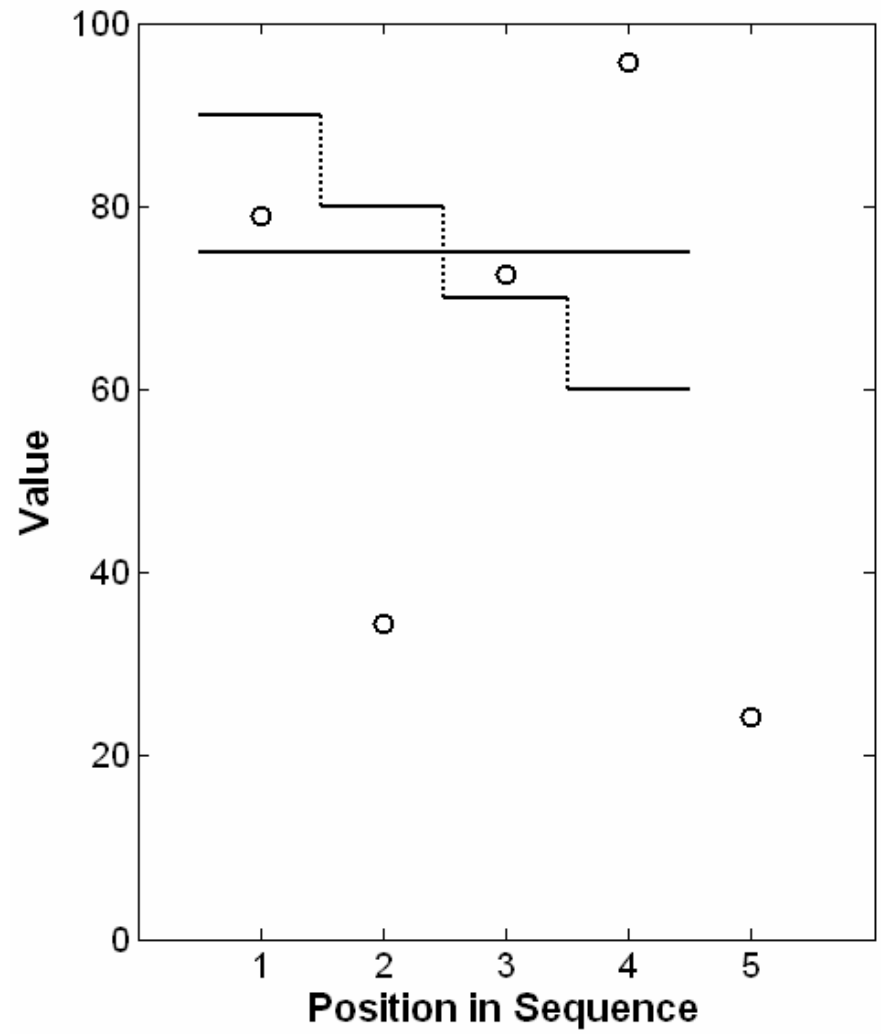
Evidence of Motivation, but not of Learning?



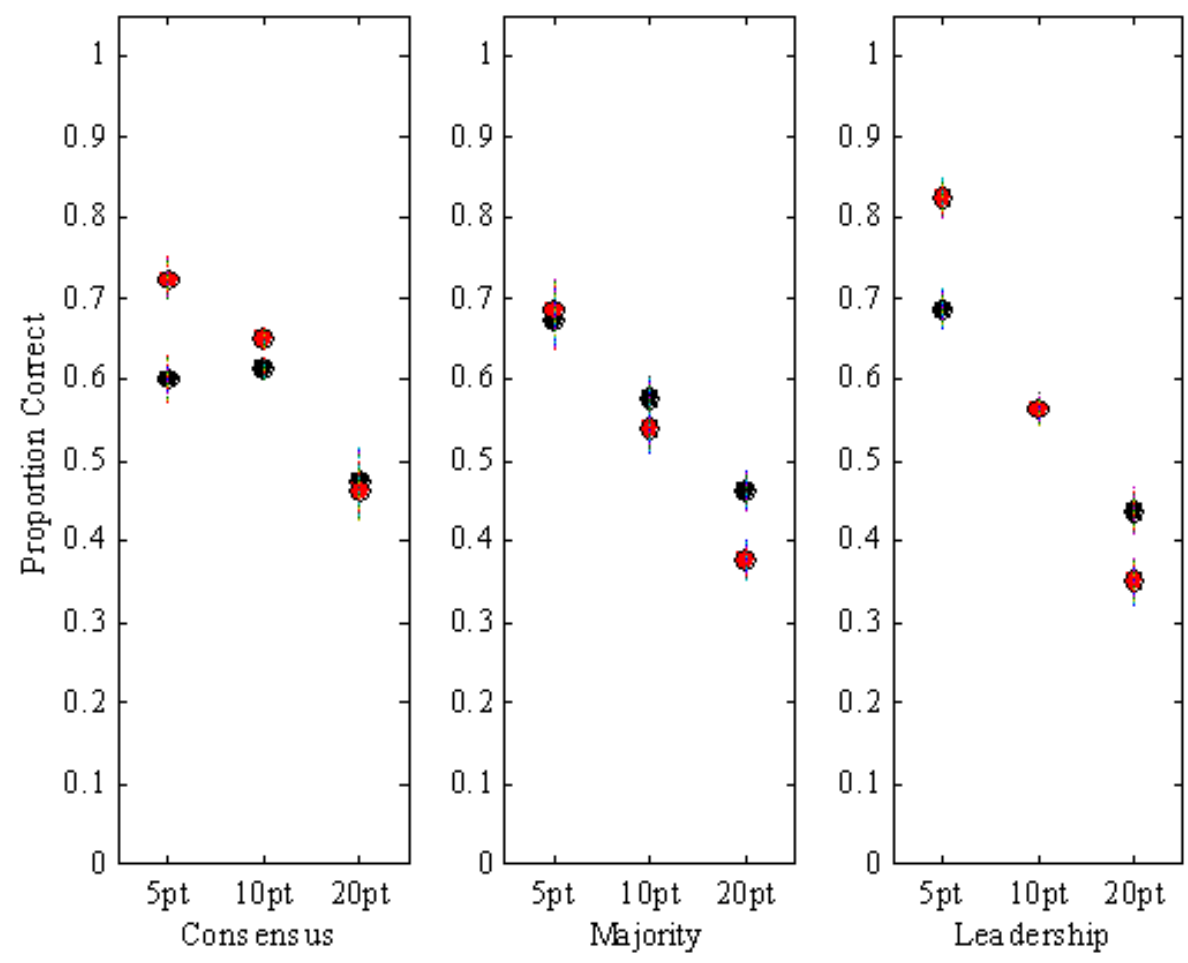
Interesting Feedback by Reward Interaction?



Group Decision-Making



Leadership to Extremes?



Thanks!
Questions?