

# Inferring relevance in a changing world

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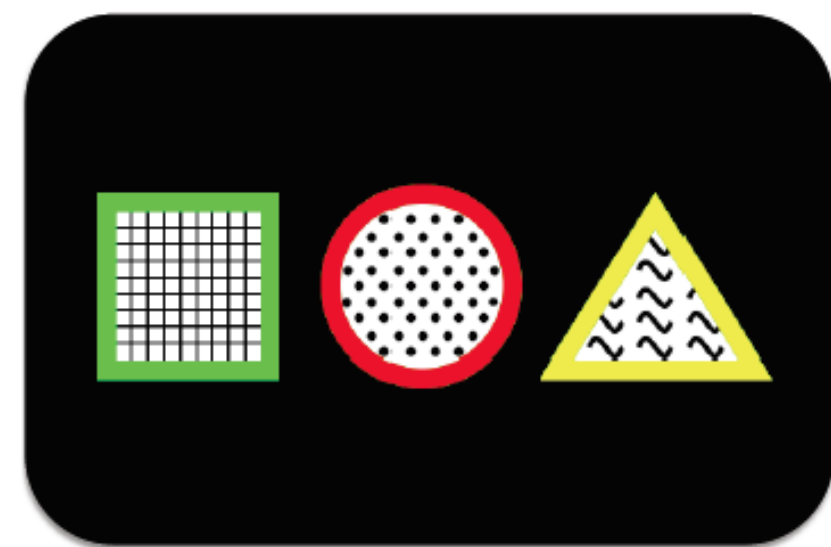
## Introduction

When Pavlov gives me food, how do I know that it's the bell that is relevant and not something I'm seeing, feeling or smelling?

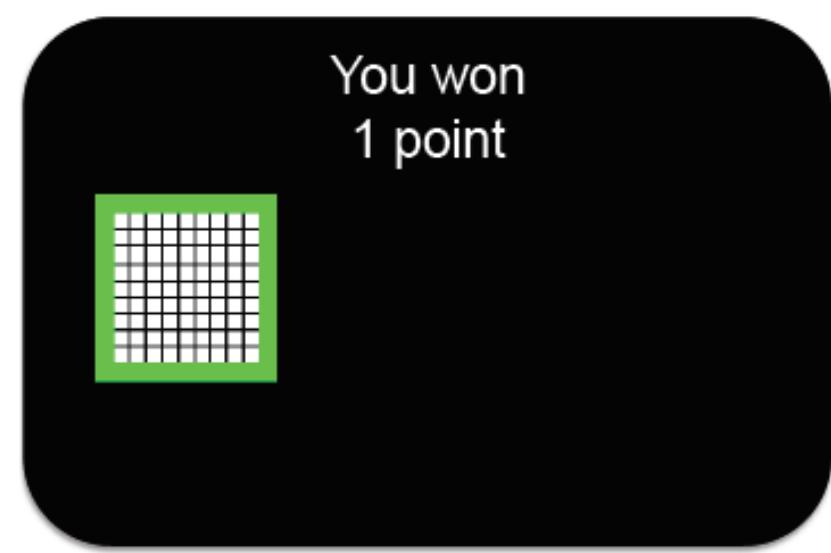


Q: How do we learn what to learn about in a multidimensional, noisy and dynamic world?

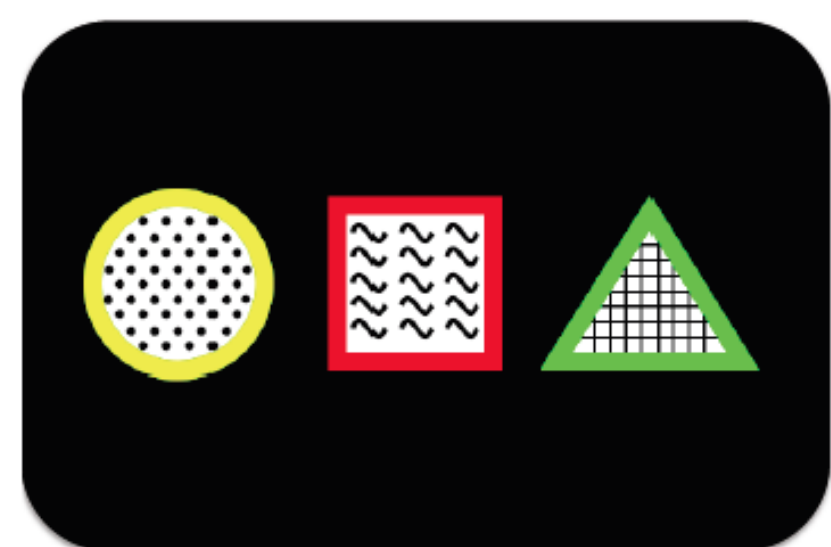
## The Task



Each stimulus 3 features: shape, color and texture.

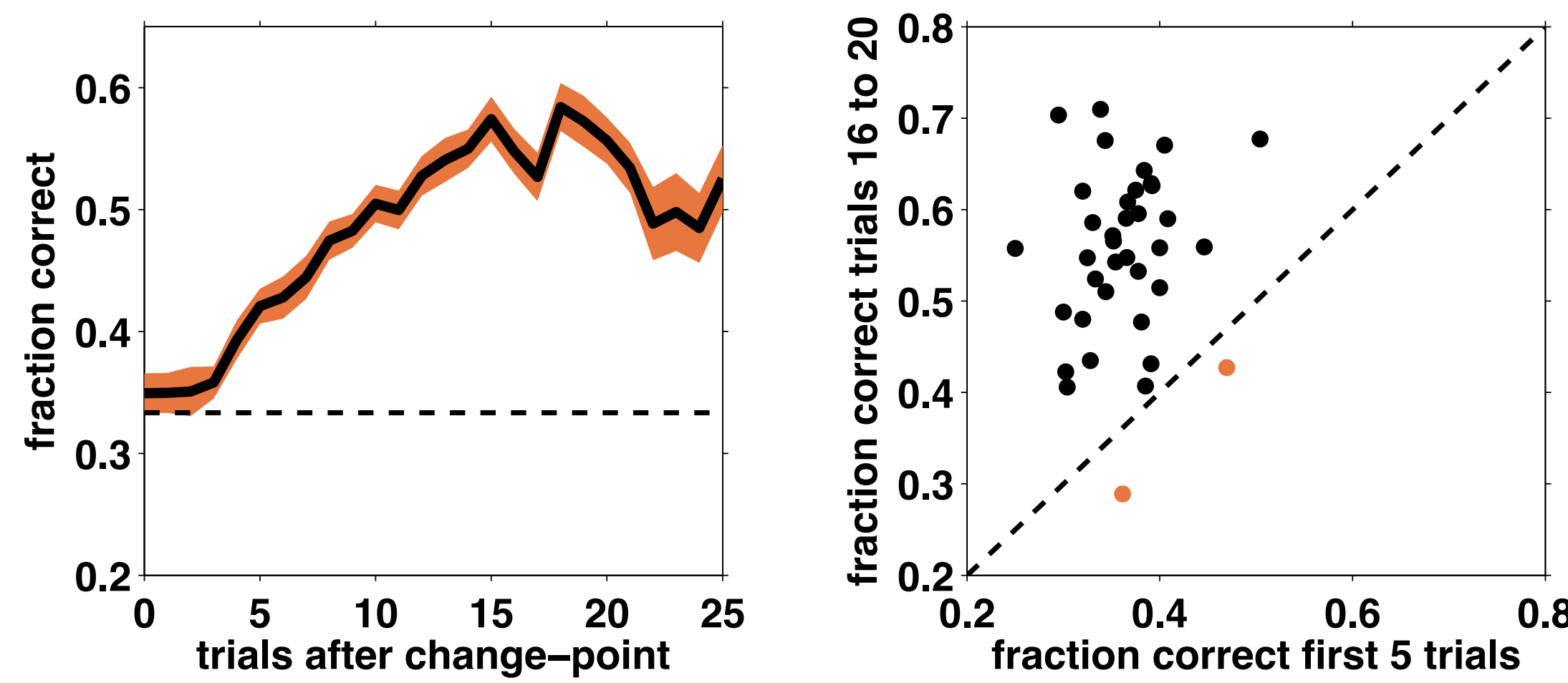


Subject chooses one. Probability of winning is high (75%) if chosen stimulus has relevant feature (e.g. **green**).



Next trial. Three options with different mixtures of features.

Identity of relevant feature changes periodically, un signaled to subjects



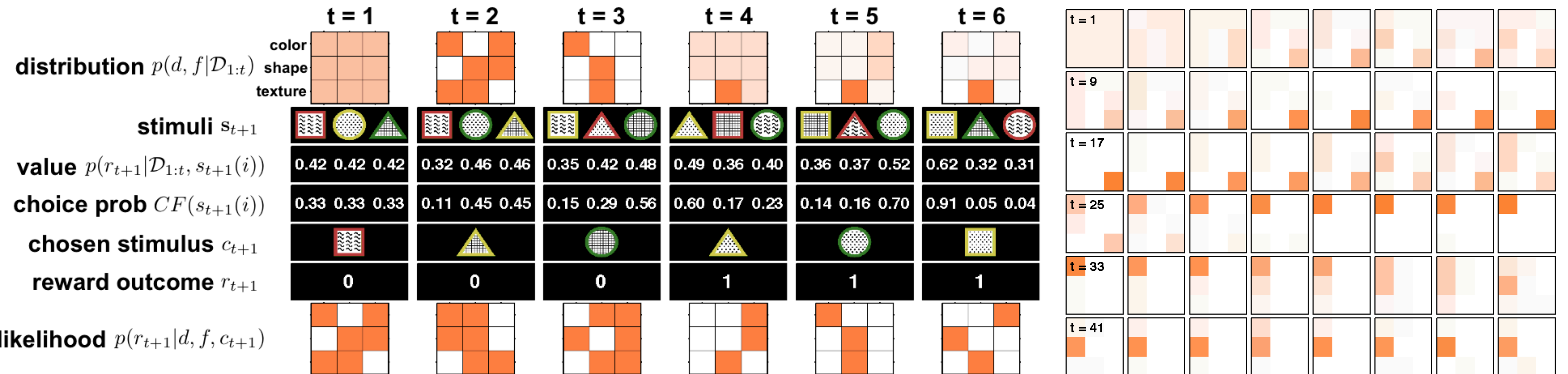
## Conclusions

Behavioral data suggest that subjects use selective attention to solve the task. This is a suboptimal strategy, but feasible (tractable) in real world situations.

## Models

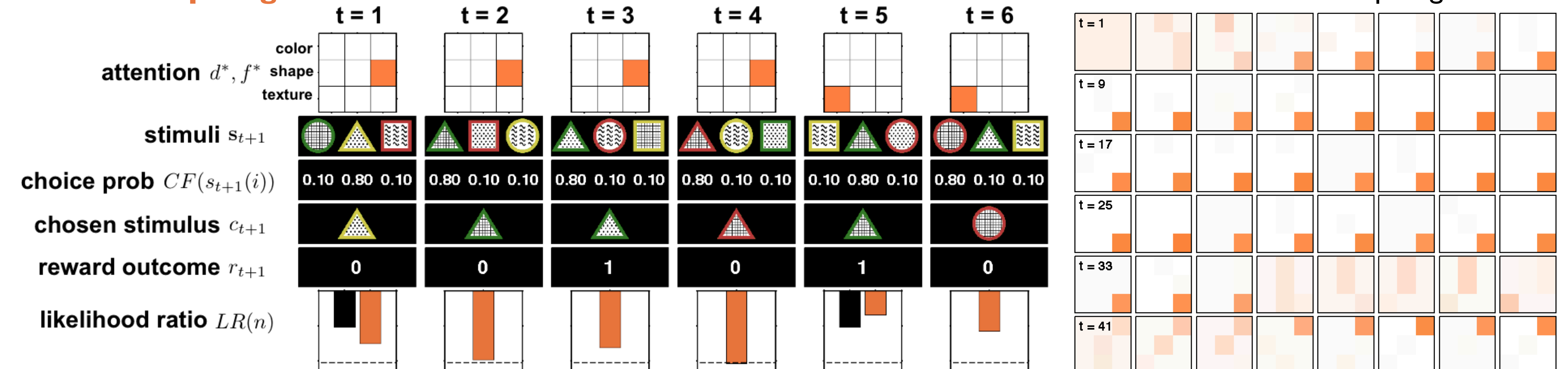
### 1. Optimal inference (OI) model :

Use Bayes' rule to compute **probability distribution** over identity of relevant dimension and value, averaging over possible change points. Use distribution to compute expected value of choosing each option.



### 2. Selective attention (SA) model :

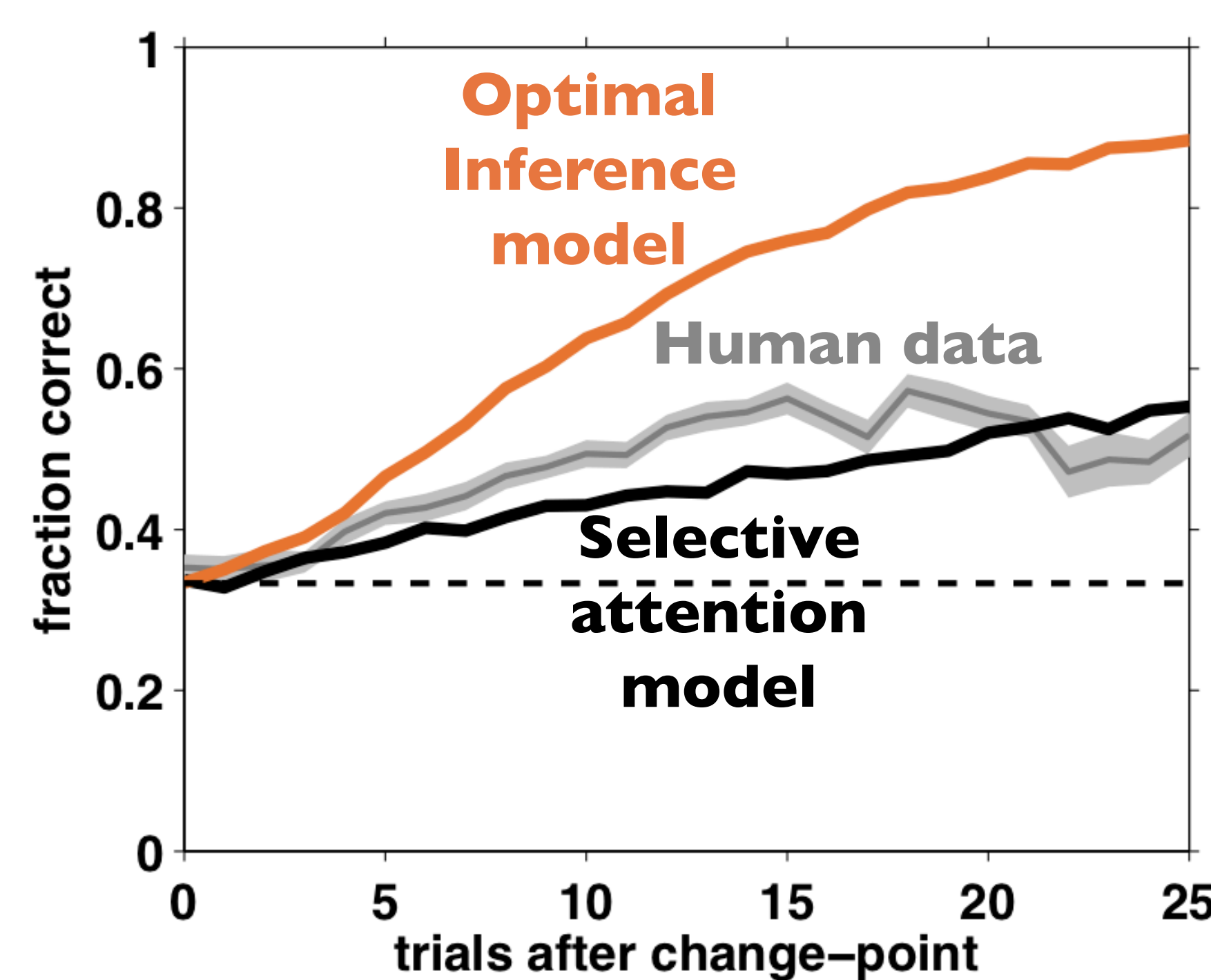
**Attention spotlight** on one feature at a time. Likelihood ratio to determine relevance and when to move spotlight.



## Results

### 1. Simulations

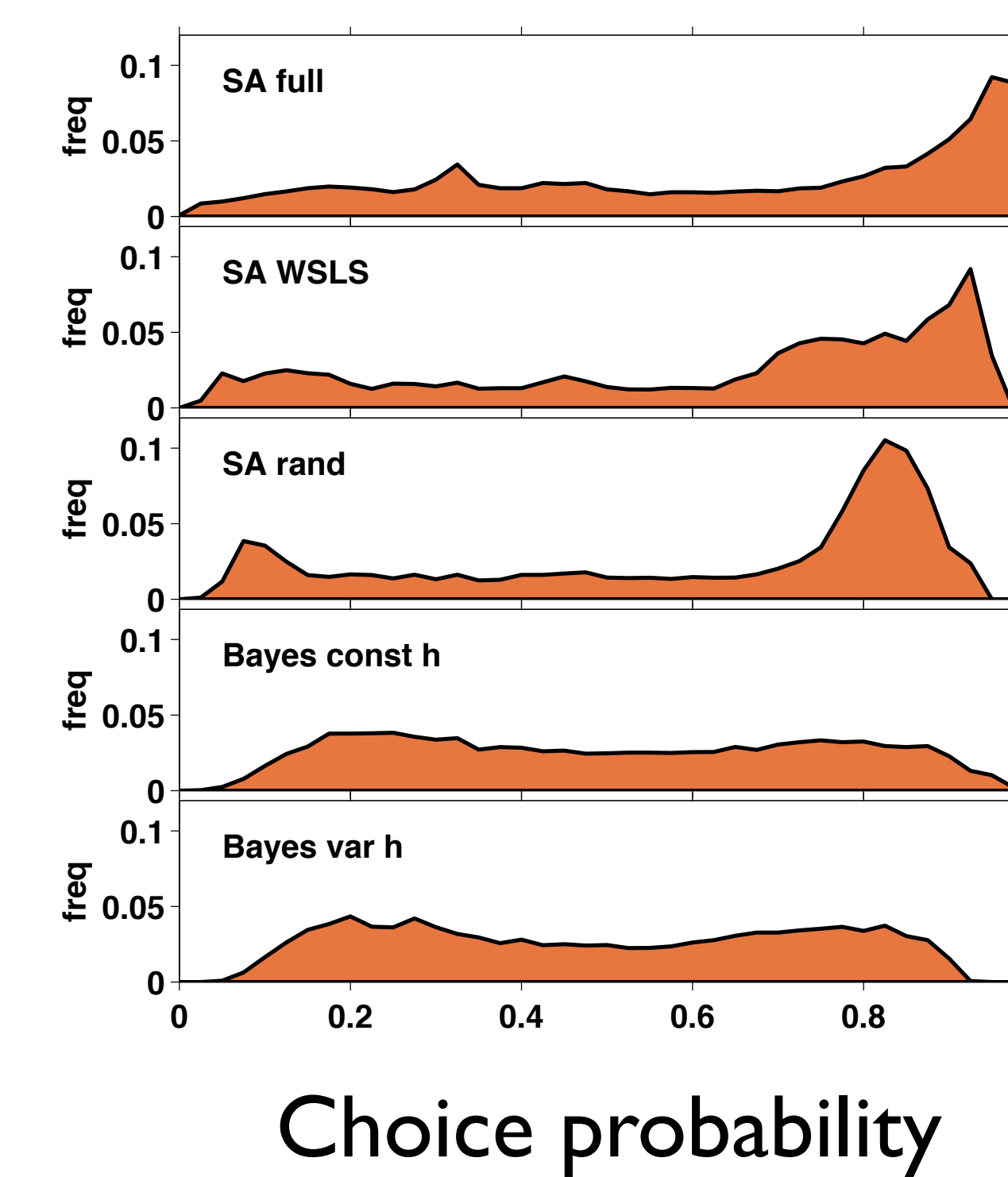
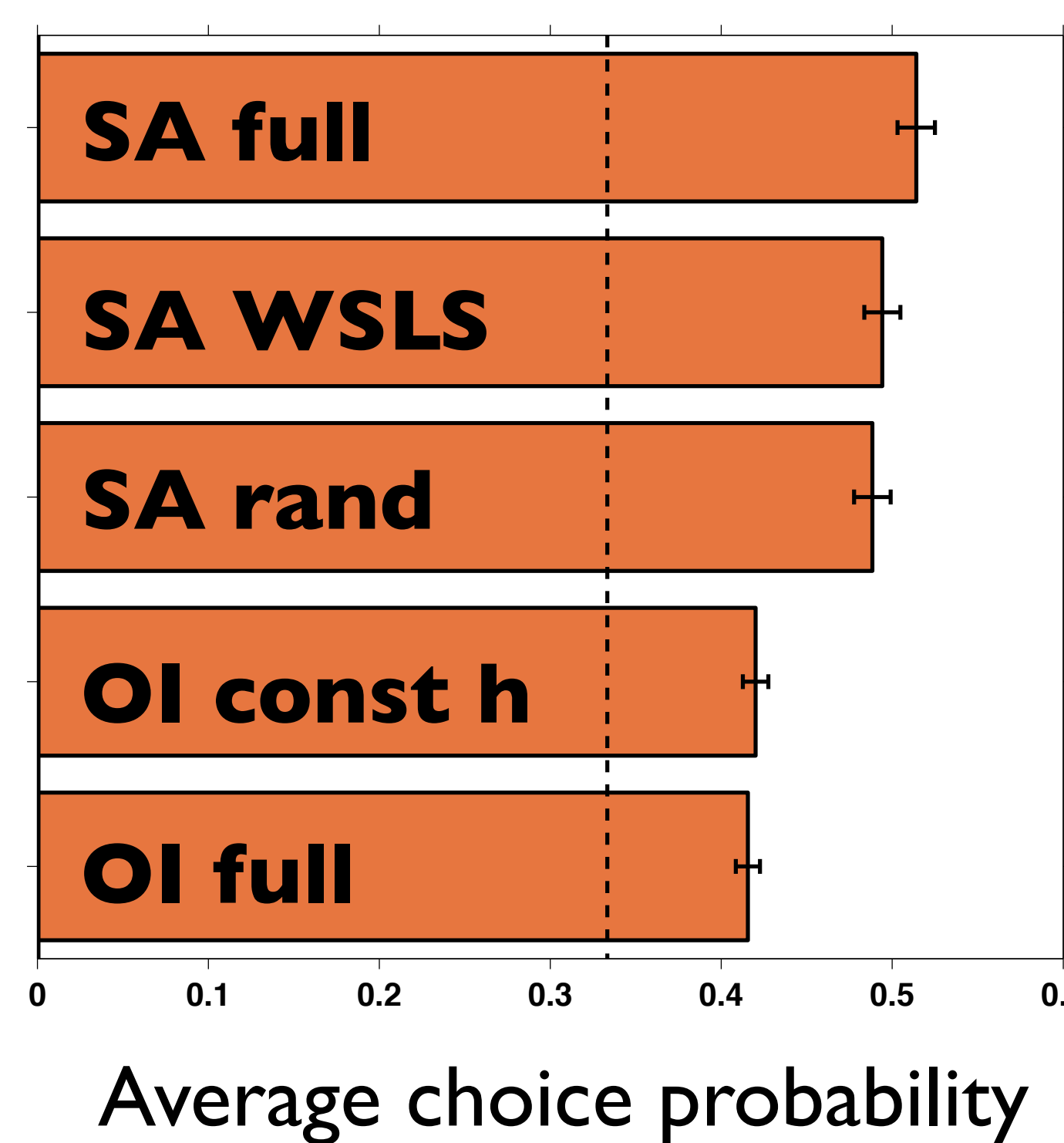
Learning curves for each model with optimal parameter values



### 2. Model fitting to trial by trial choice behavior & learning dynamics

Average probability of each choice (related to Bayesian evidence)

Average across 35 subjects



Single subject data

