

A Bayesian Race Model for Recognition Memory

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Abstract

Many psychological models (e.g. Nosofsky, 1987; Shirin & Steyvers, 1997; Taatgen et al., 2008) make use of the idea of a trace, which is a change in a person's cognitive state that arises as a result of processing a given stimulus. These models assume that a trace is always laid down when a stimulus is processed. In addition, some of these models explain how RTs and response accuracies arise from a process in which the different traces race against each other. We investigated a Bayesian hierarchical model of RT and accuracy in a difficult recognition memory experiment. The model includes a stochastic component that probabilistically determines whether a trace is laid down according to the weight of evidence presented. The RTs and accuracies are modeled using a minimum gamma race model, with extra model components that allow for the effects of stimulus, sequential dependencies, and trend. Subject-specific effects, as well as ancillary effects due to processes such as perceptual encoding and guessing, are also captured in the hierarchy. Marginal likelihood evaluations show better predictive performance of our model compared to an approximate Weibull model.

Background

For models of RT and simple choice, researchers typically discard outliers (e.g. Ratcliff & Tuerlinckx, 2002) and data from inattentive subjects (e.g. Kates et al., 2007) using arbitrary criteria based on summary statistics. This approach risks experimenter bias and provides little insight into how cognitive processes fail during performance. Therefore, we simultaneously model attentive and inattentive subjects' performance in a recognition memory task without discarding data. The key features of our model are:

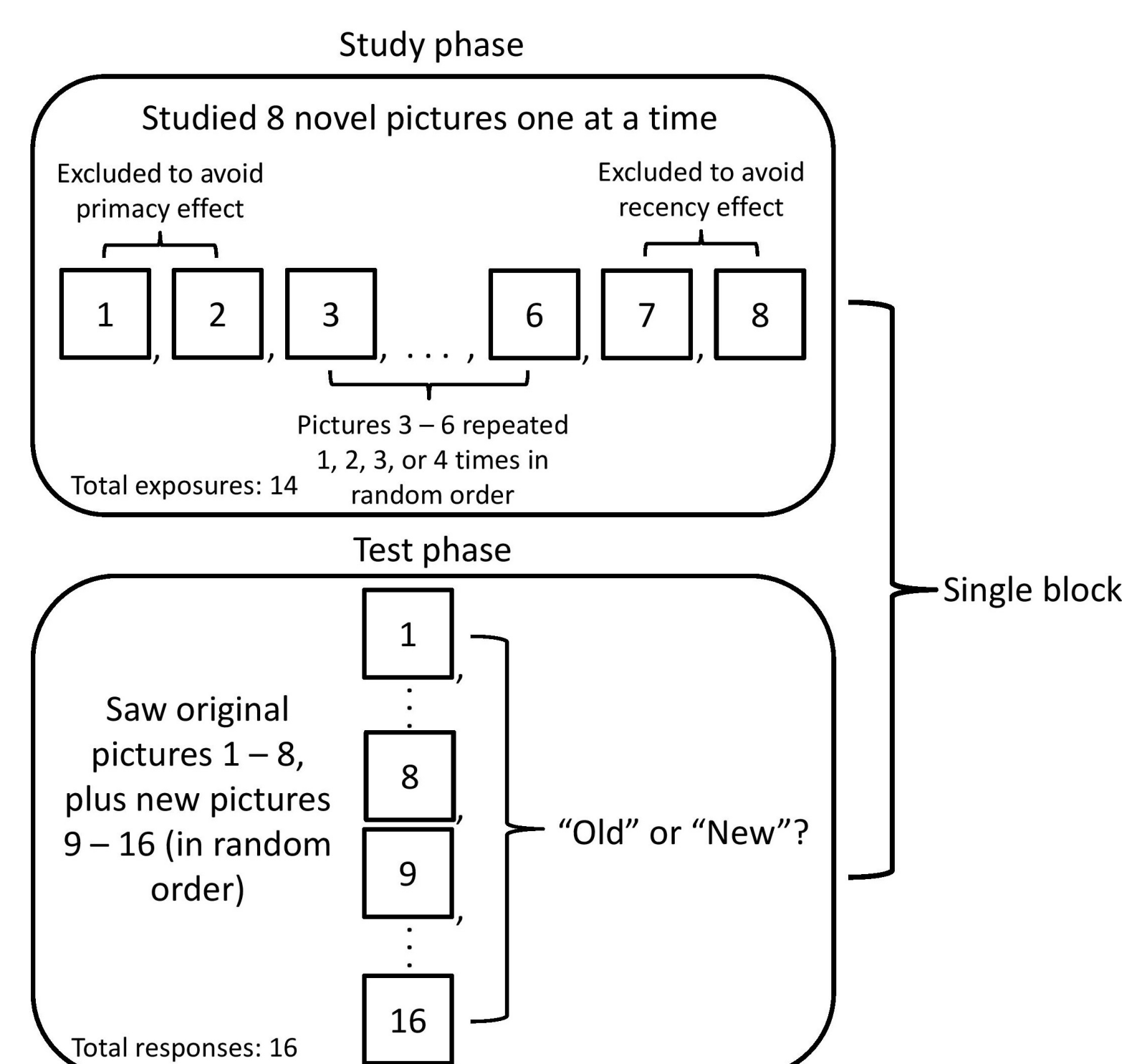
1. Unlike previous models in which a trace is always laid down following a stimulus exposure (e.g. Hintzman, 1988; Logan, 1988; Raaijmakers & Shiffrin, 1981), our model estimates the probability that a trace is established. This allows us to determine the subjects who do not build new traces (i.e. those who are not paying attention).
2. We explicitly model ancillary processes like fast guesses and attentional failures.
3. We incorporate a trend and an autoregressive error structure for the observed RTs to account for fatigue and practice effects.

This model allows us to parse out the cognitive processes that underlie both good and poor performance.

Method

Participants: 32 young adults (12 in a pilot study and then 20 more) were recruited from the participant pool at Ohio State University.

Design: Subjects completed a difficult recognition memory task.



Subjects completed 1 practice block followed by 20 additional blocks. Hence, each subject provided 240 responses for analysis (80 old, 160 new).

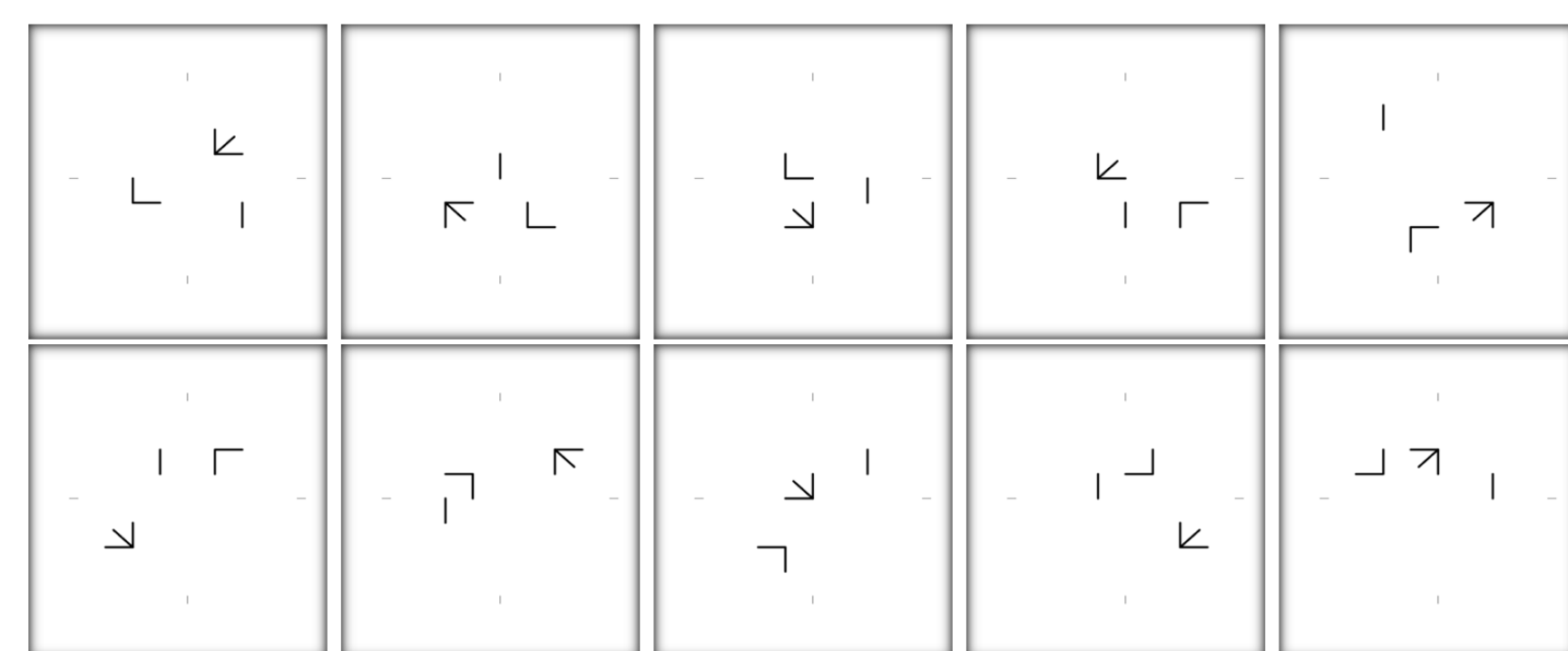


Figure 1: Example of stimuli shown to subjects.

Behavioral data

Subjects were divided into attentive ($d' > 0.3$) or inattentive ($d' < 0.3$) groups.

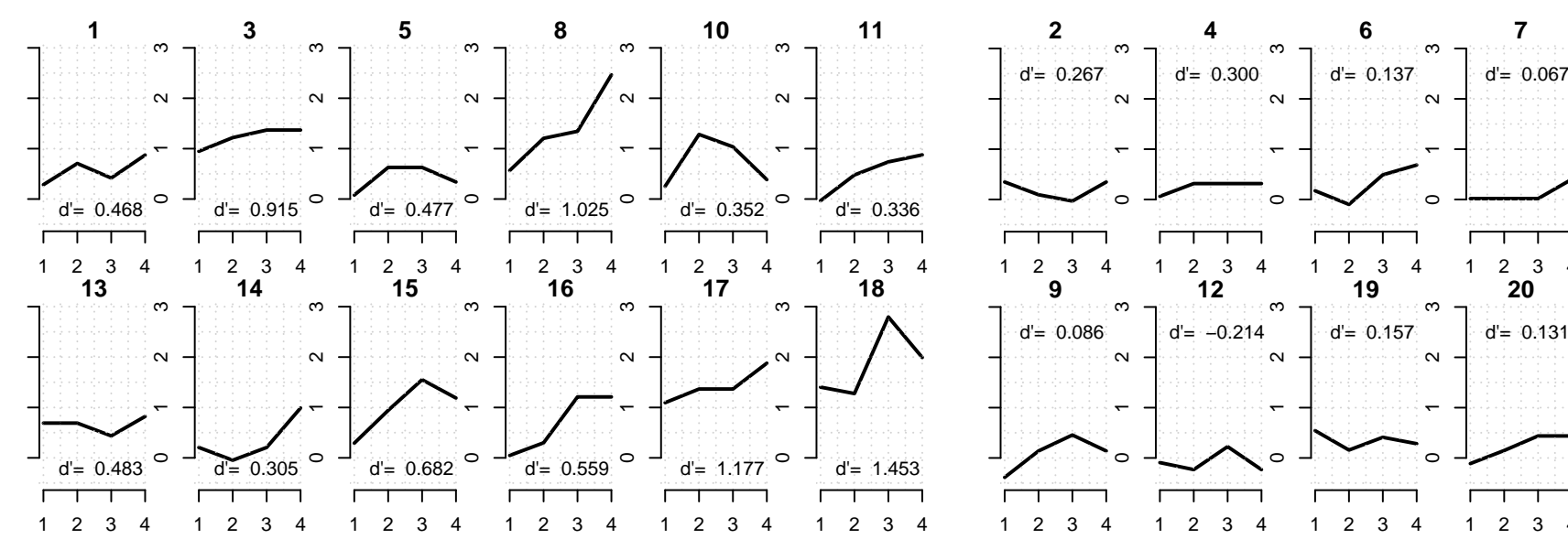


Figure 2: Individual d' values by number of exposures.

Traces may not be laid for all exposures because:

- d' does not always increase with more exposures;
- The quantiles of the RT distribution do not always decrease as the number of exposures increases.

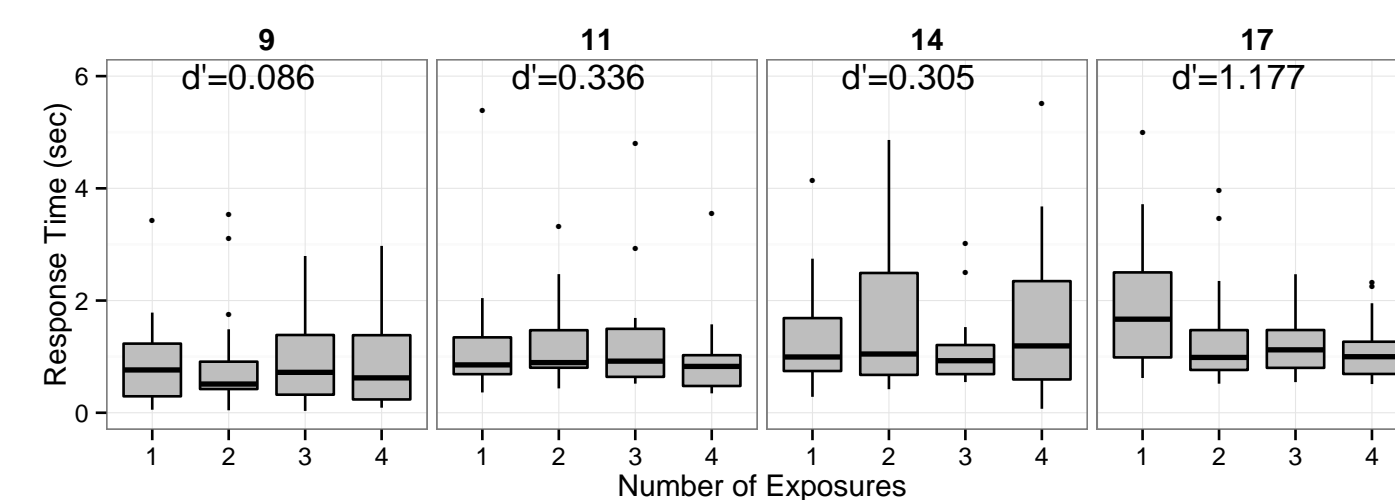


Figure 3: RT quantiles for select subjects based on the number of exposures.

Additionally the RT time-series plots suggest that:

- RT distributions are not stationary over blocks;
- There exist very fast and very slow responses that may reflect guesses and distractions.

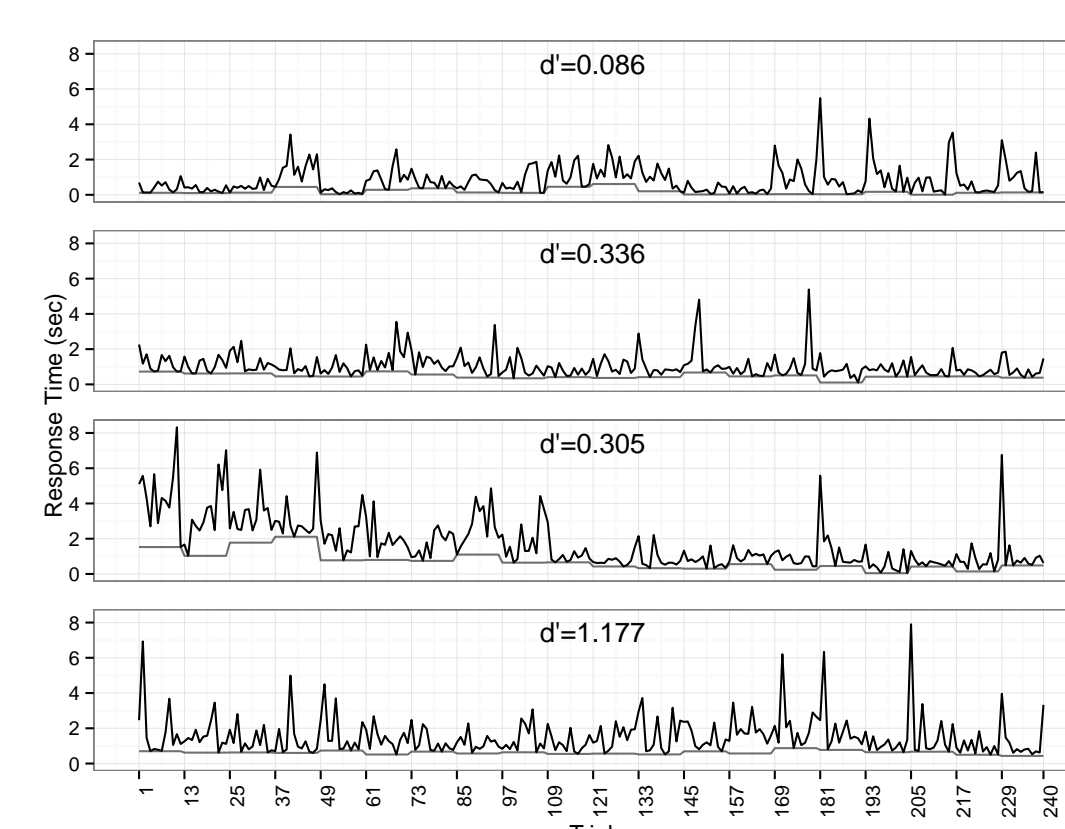


Figure 4: RT time series for subjects 9, 11, 14, and 17.

The model

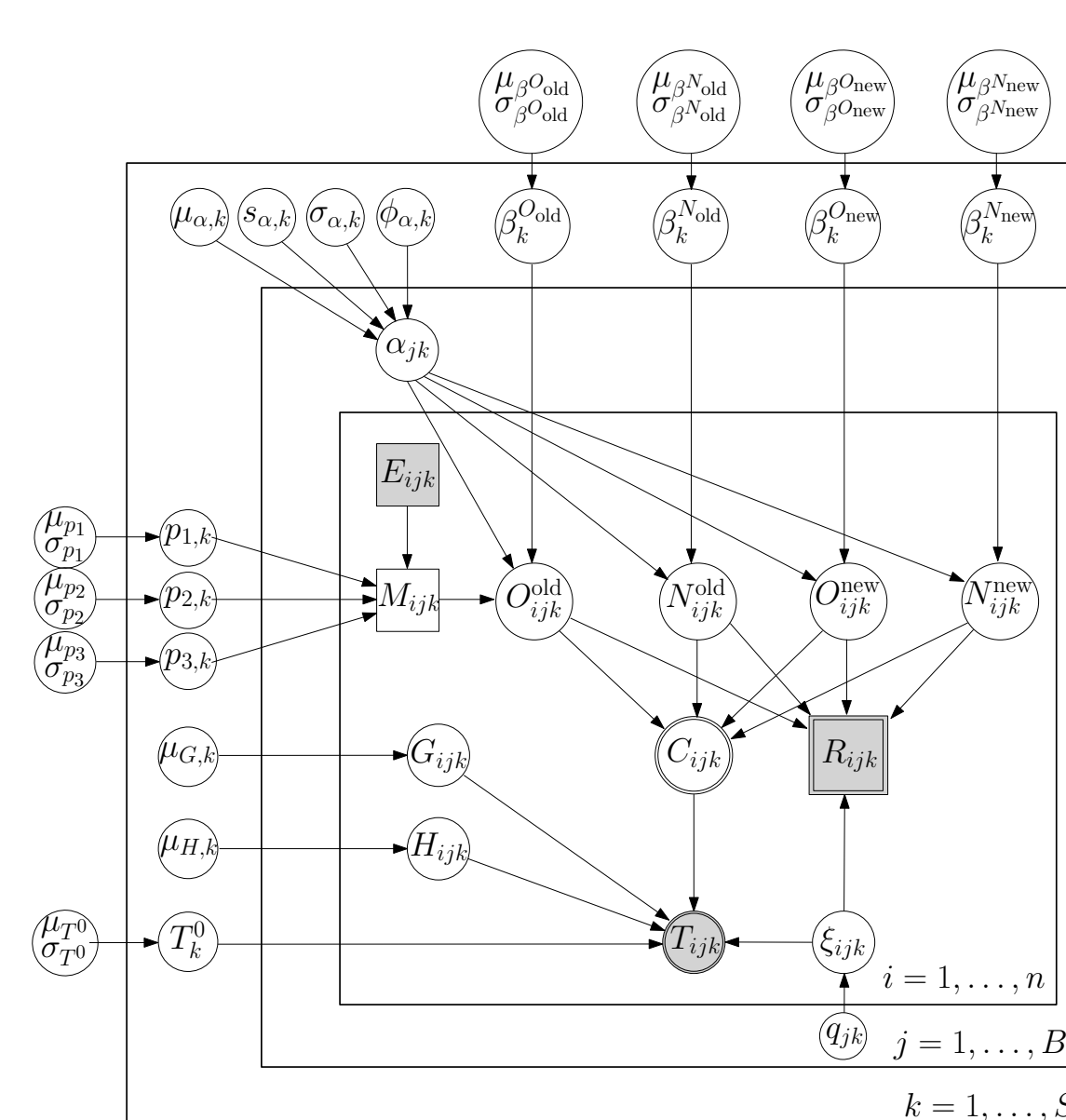


Figure 5: Bayesian graphical model.

The model consists of 4 gamma racers (one for each response type); the winning racer determines the RT (T) and the choice (R).

- The shape parameter α_{jk} refers to the total evidence needed for a response.
- The scale parameter β_k equals the quality of evidence towards the response.

	Old picture	New picture
Choose old	Y^{old}	Y^{new}
Choose new	N^{old}	N^{new}

Y^{old} is based on the number of traces laid down (which depends on the number of exposures E). The probability of adding a new trace given l existing traces is p_l (first exposure of any new stimulus always adds a trace, so $p_0 = 1$). Additionally...

- We include fast guesses (G) and attentional failures (H) using a mixture model.
- The log of α_{jk} varies over blocks as a linear trend plus an autoregressive process.
- We include subject-specific effects into a hierarchical model.

We sample from the posterior distribution using a MCMC algorithm.

Results

Our key findings were:

1. The actual number of traces M laid down with repeated stimulus exposures can be less than the number of exposures E .
2. The probability of adding a trace increases with more exposures.

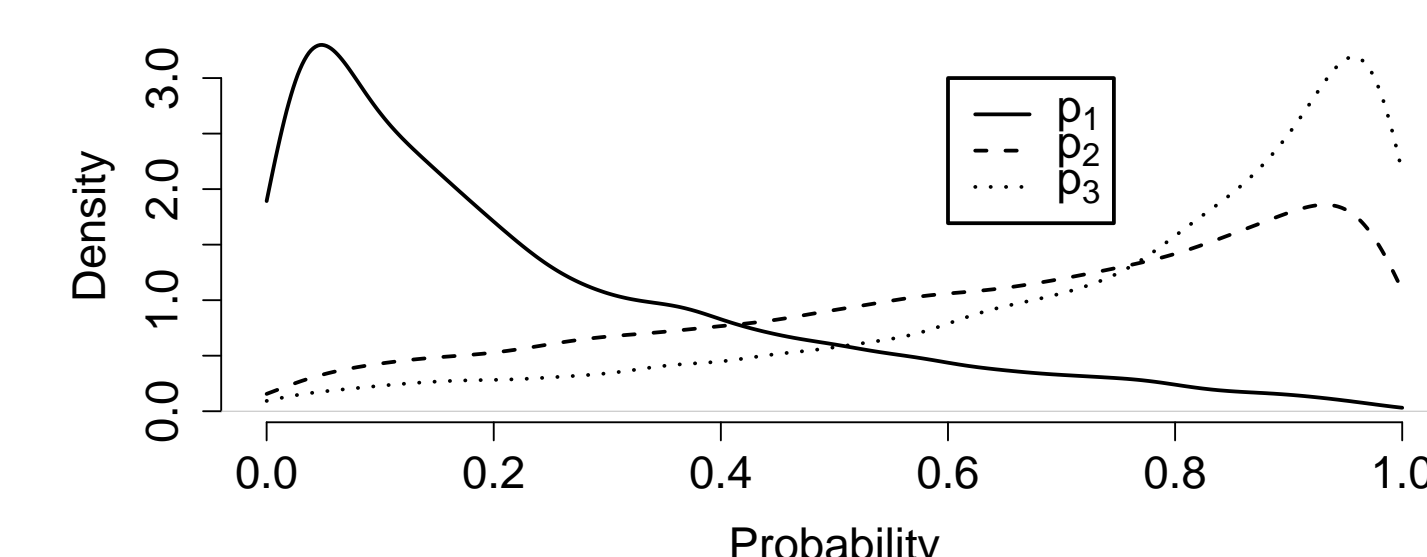


Figure 6: Posterior distributions for p_1 , p_2 , and p_3 (Probability of adding a 2nd, 3rd, or 4th trace given previous one was laid).

3. The model accounts for both good and poor performance and allows parsing out the different underlying reasons for such performance across subjects. We defined 3 measures of performance:

- p_k equals the proportion of fast guesses;
- $p_{1,k}$ equals the probability of laying down a second trace;
- λ_k equals the ratio of new and old accumulation process rates when an old item was presented.

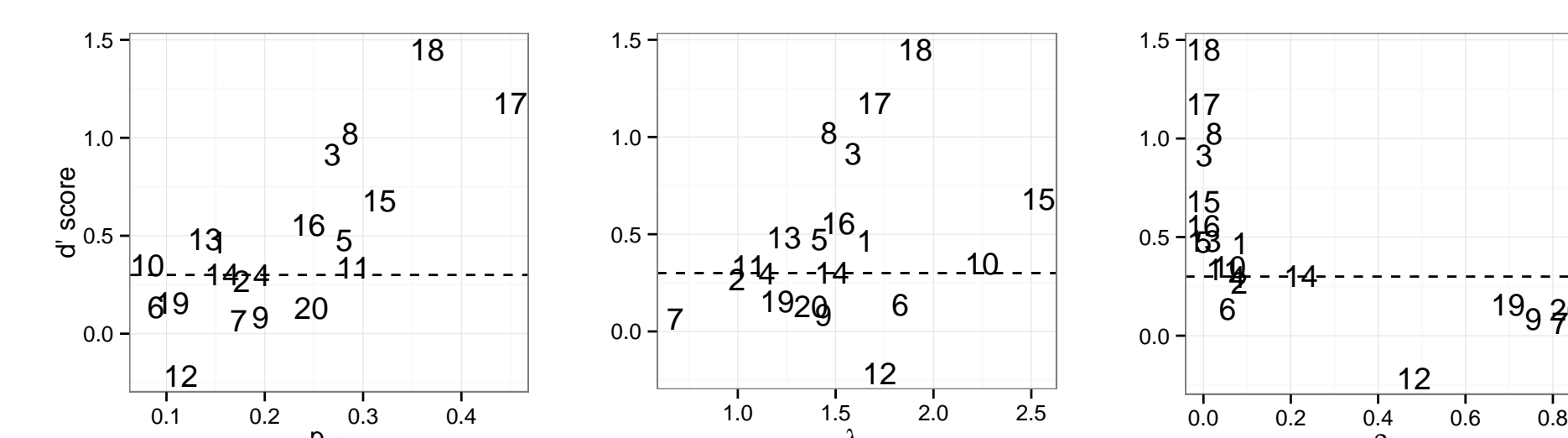


Figure 7: Discriminability d' versus the posterior means of p_k , $p_{1,k}$ and λ_k for the 20 subjects.

4. When predicting the final two blocks from the rest of the data, our model with an explicit race for laying down traces showed better performance compared to a model in which the race (i.e. Y^{old}) was approximated by a Weibull distribution.

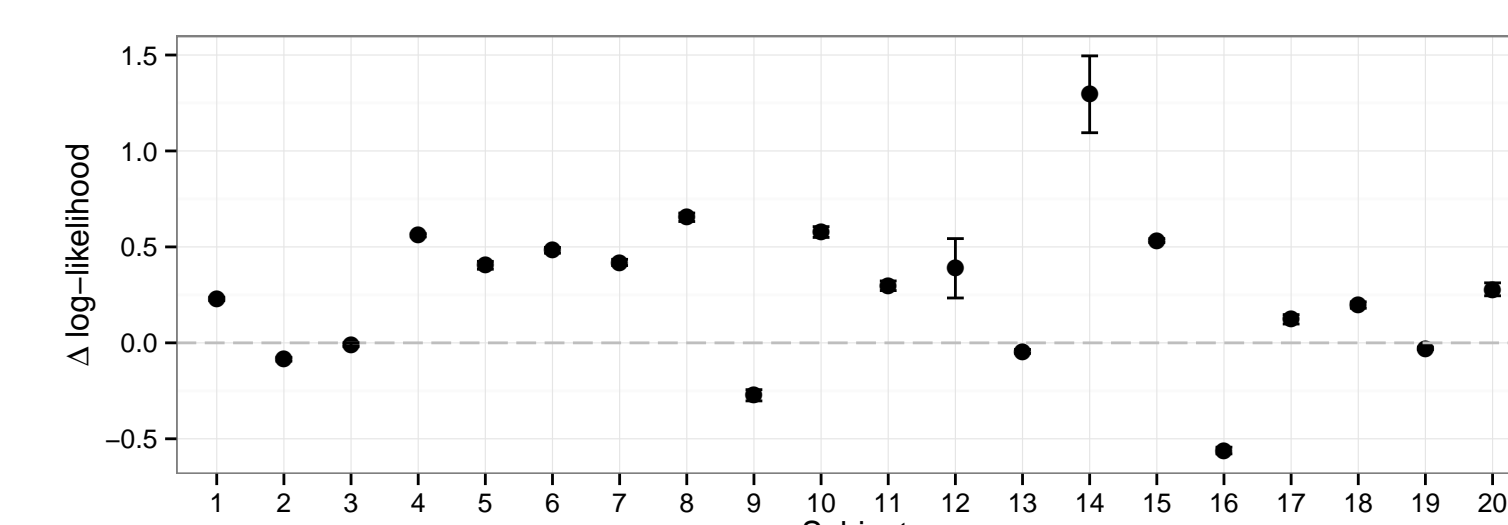


Figure 8: Differences in log-marginal likelihoods for predicting performance in blocks 19 and 20 by subject.

Discussion

Our model shows that...

1. The assumption that a trace is laid down with each exposure is untenable. Memory traces get laid down probabilistically.
2. Once a trace is laid down, it is easier for the subject to lay down a second or third trace (Repetition priming). Previous research has not detected such priming due to the assumption that traces were always laid down with every stimulus exposure.

If our model can be extended to a greater number of traces than just 4, this may explain why RTs behave as a power law for large numbers of repeated exposures.

Acknowledgements

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