A sensorimotor paradigm for Bayesian model selection

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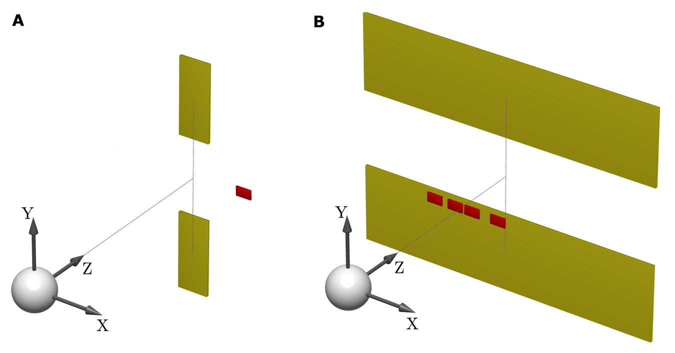
Introduction

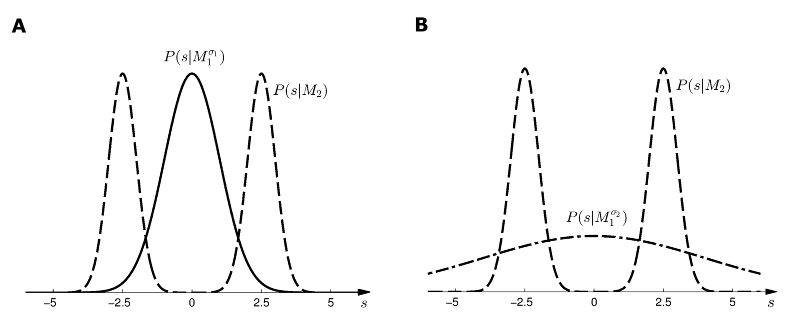
- Sensorimotor control is thought to rely on predictive internal models (Wolpert et al., 1995) that not only adapt their parameters but can also extract common structure between tasks (Braun et al., 2009).
- This raises the question of how, the motor system selects between different structures (or models).
- In particular, we test for Bayesian model selection in a sensorimotor task, since Bayesian models have been very successful in explaining human perceptual and sensorimotor learning (Knill and Pouget, 2004; Körding and Wolpert, 2004).

Experimental paradigm

Subjects had to use an observed visuomotor shift (parameter) to infer which one of two targets (model) was the correct one.

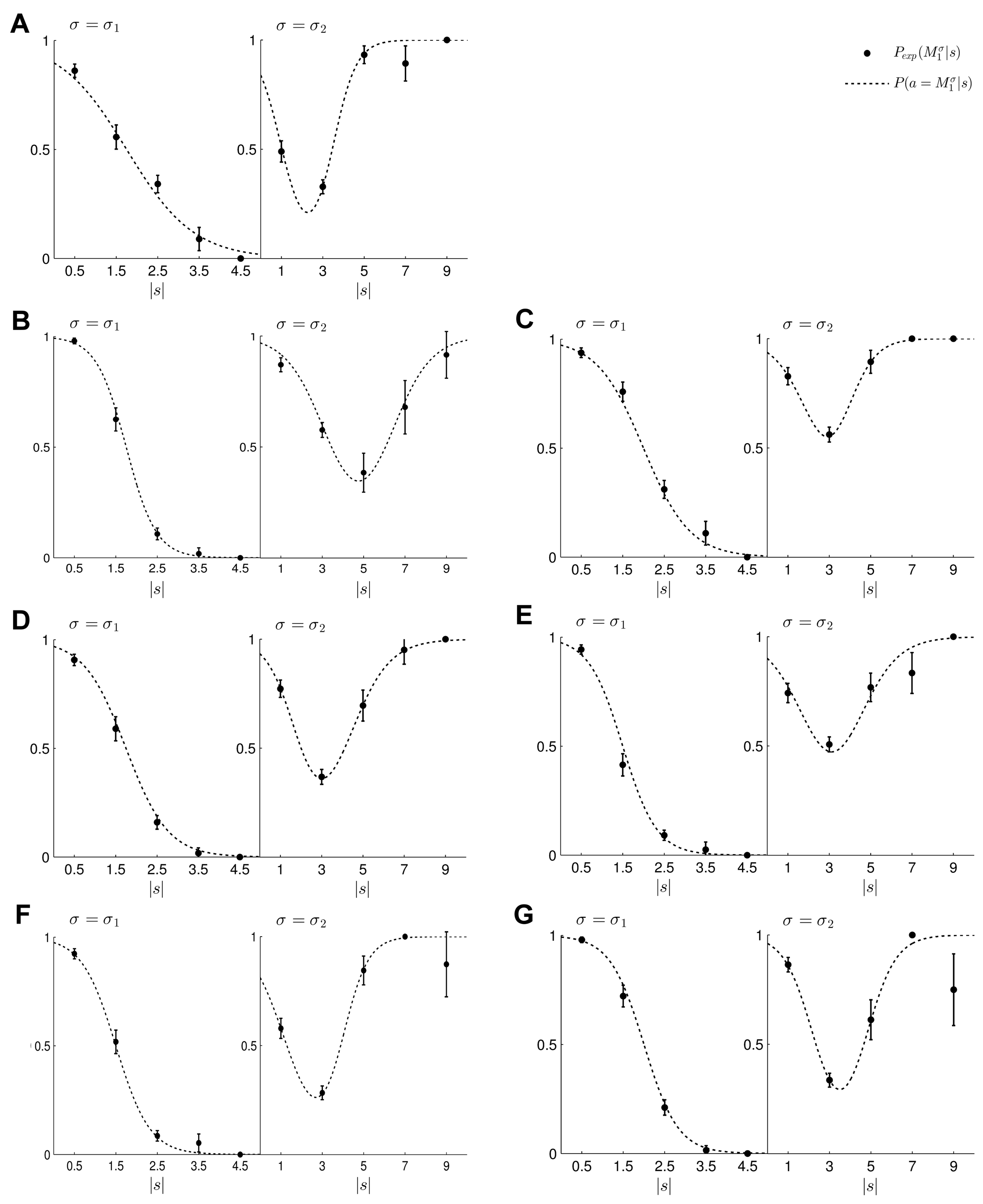


A: in *standard trials* subjects could directly observe the visuomotor shift. **B**: in *probe trials* the stimulus was ambiguous making it impossible to identify a unique shift. This way subjects were forced to "integrate" over possible shifts.



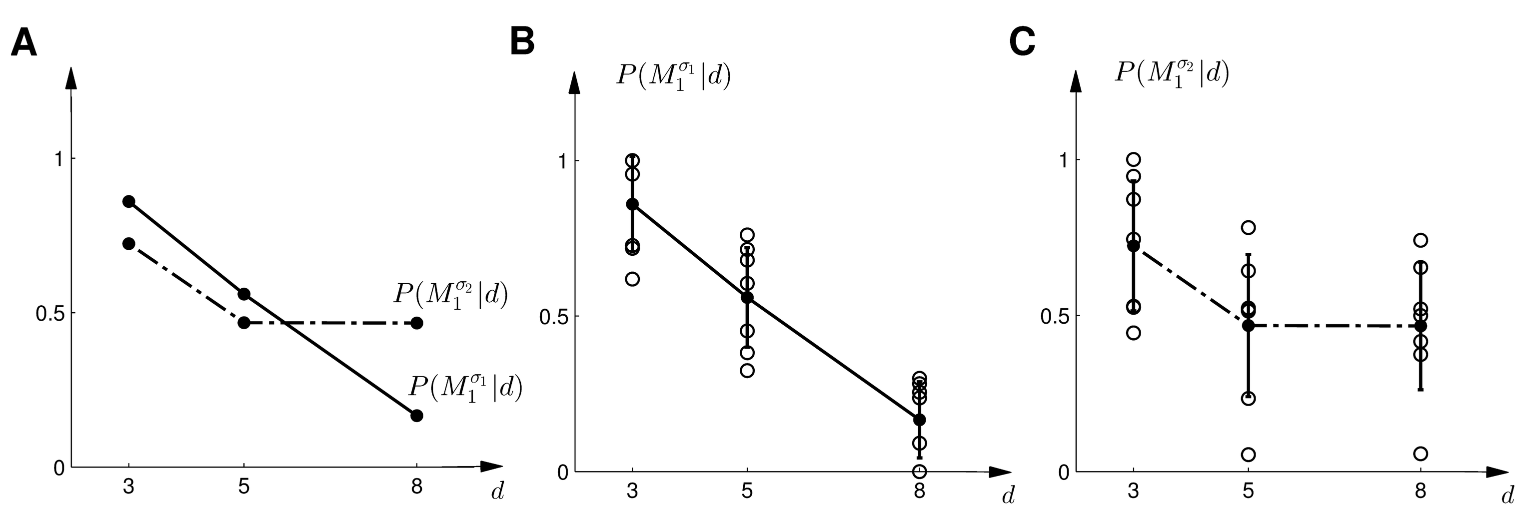
Prior distributions for the horizontal cursor-shift s. **A**: model $M_1^{\sigma 1}$ (solid line) and M_2 (dashed line) - *first part* of the study. **B**: model $M_1^{\sigma 2}$ (dash-dot line) and M_2 (dashed line) - *second part* of the study.

Data - standard trials



A to **G**: fitted choice probabilities in dependence of the shift (dotted line) for all subjects. Left plot: first part of the study. Right plot: second part of the study.

Data - probe trials



Experimentally observed choice behavior - probe trials. **A**: average taken over all subjects. Solid line: first part of the study; dash-dot line: second part of the study.**B**: details of first part - individual choice behavior (circles) and standard deviation error bars. **C**: same as **B**, but for second part of study.

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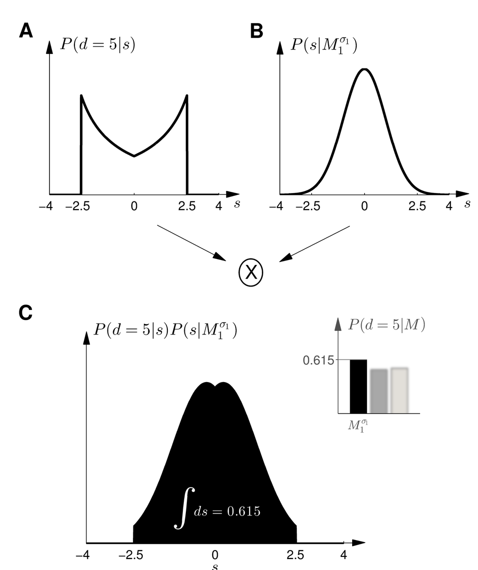
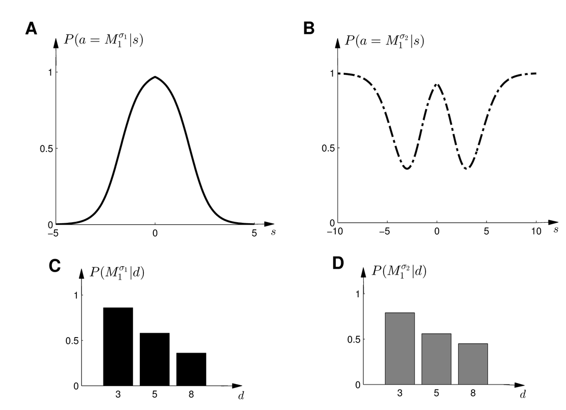
Bayes factors



Posterior (**C**) equals likelihood of each shift s given the observed array width d (**A**), multiplied by the prior over the shift s. Integration over s leads to the evidence for model $M_1^{\sigma 1}$. Comparing the model evidence is used to predict choice probabilities.

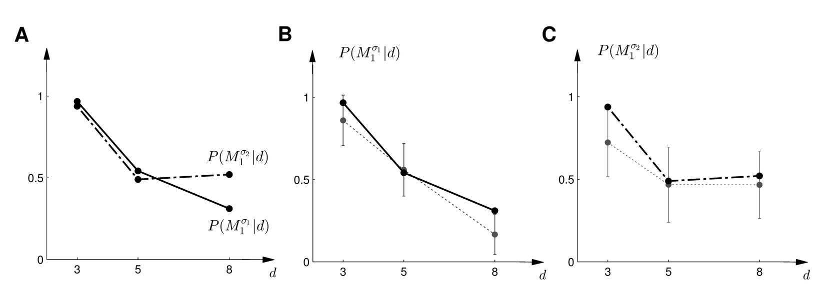
Bayesian policy inference



A, **B**: response curves fitted on standard trials for the first (**A**) and second (**B**) part of the study. **C,D**: predicted choice probability of selecting model M_1 following a probabilistic weighting of the response values (shown in **A,B**).

Predicted choice behavior

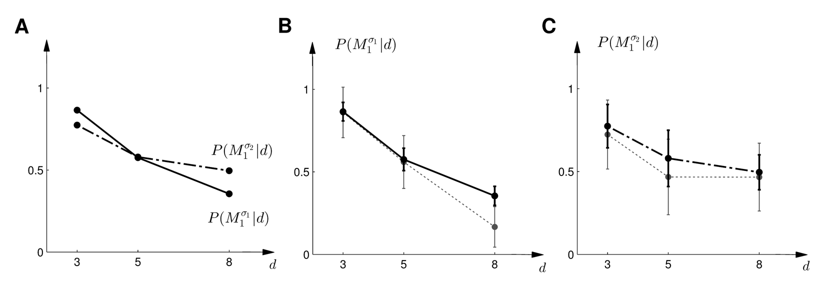
Bayes factors



$$P(a = M_1) = \frac{1}{1 + e^{-\alpha \log \frac{P(d|M_1)}{P(d|M_2)}}}$$

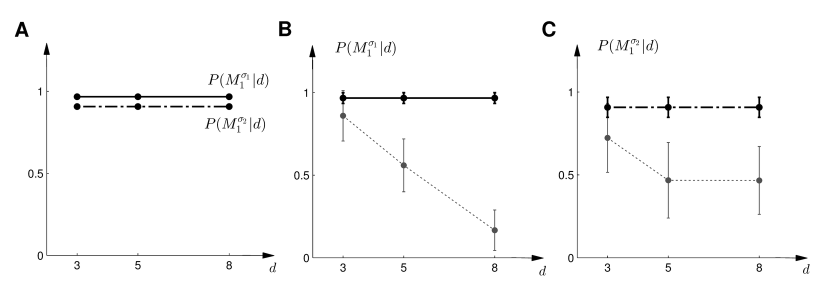
$$P(d|M_i) = \int ds P(d|s, M_i)P(s|M_i)$$

Bayesian policy inference



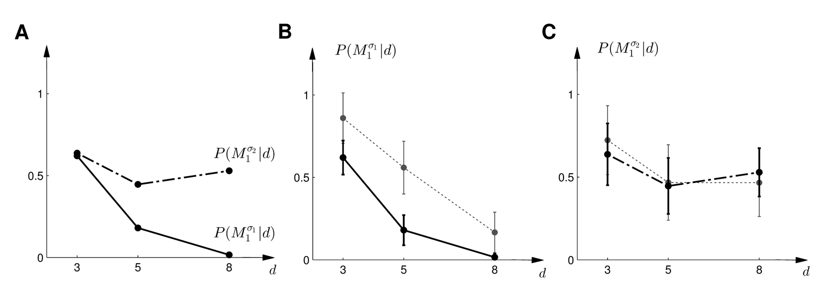
$$P(a = M_1|d) = \int ds\, P(s|d)P(a = M_1|s)$$

"Average shift" heuristic



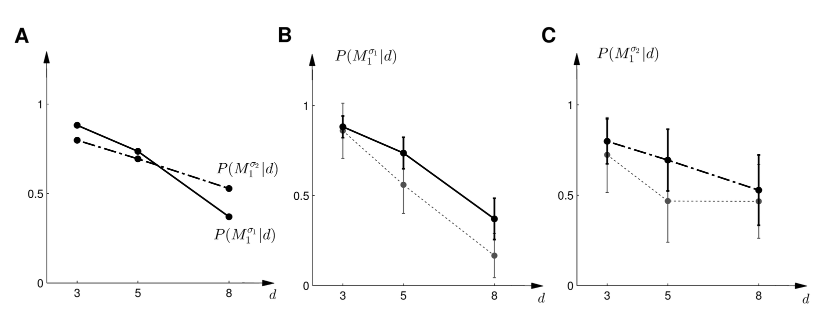
$$P(a = M_1|d) = P(a = M_1|s = 0)$$

"Biggest shift" heuristic



$$P(a = M_1|d) = P(a = M_1|s = d/2)$$

"Halfway shift" heuristic



$$P(a = M_1|d) = P(a = M_1|s = d/4)$$

Conclusions

- We designed a visuomotor experiment where we could distinguish between parameter variables and model variables. In probe trials that did not require subjects to compensate, the shift variable could be "integrated out".
- This allowed us to directly compare subjects' choice probabilities to the selection probabilities predicted by five different schemes of model selection.
- We found that the Bayesian model selection procedures explained our data best, whereas the three heuristics were worse in explaining choice behavior.

References

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