

# How to cope in a changing environment?

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## Summary

- \* In the *dynamic clicks task* (Piet, Hady & Brody, 2017) rats have shown the ability to discard old information in trials where the stimulus is **volatile**.
- \* We develop an **ideal-observer** model that maximizes the expected reward on this task and makes explicit the **evidence-discounting** phenomenon.
- \* A linear discounting model proves to be as efficient but less robust to parameter tuning.
- \* It remains unclear what model the rats use and how we may distinguish them based on data.

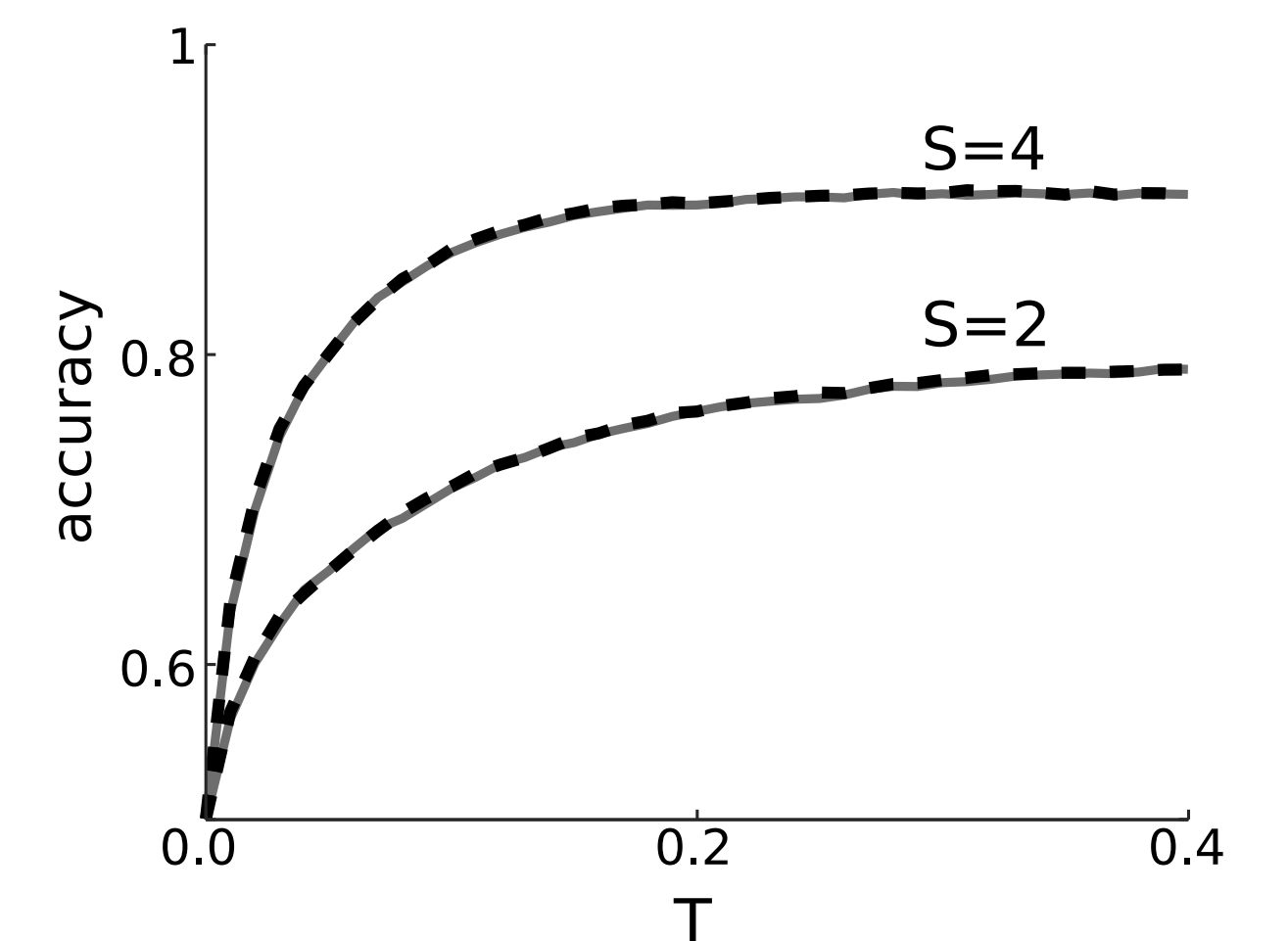
Debates and discussions are welcome!

## Natural parameters

- \* We found numerical evidence that accuracy at time  $T$  remains constant as long as  $SNR(T)$  and  $h/S^2$  are kept constant:

$$SNR(T) := \sqrt{T} \cdot S$$

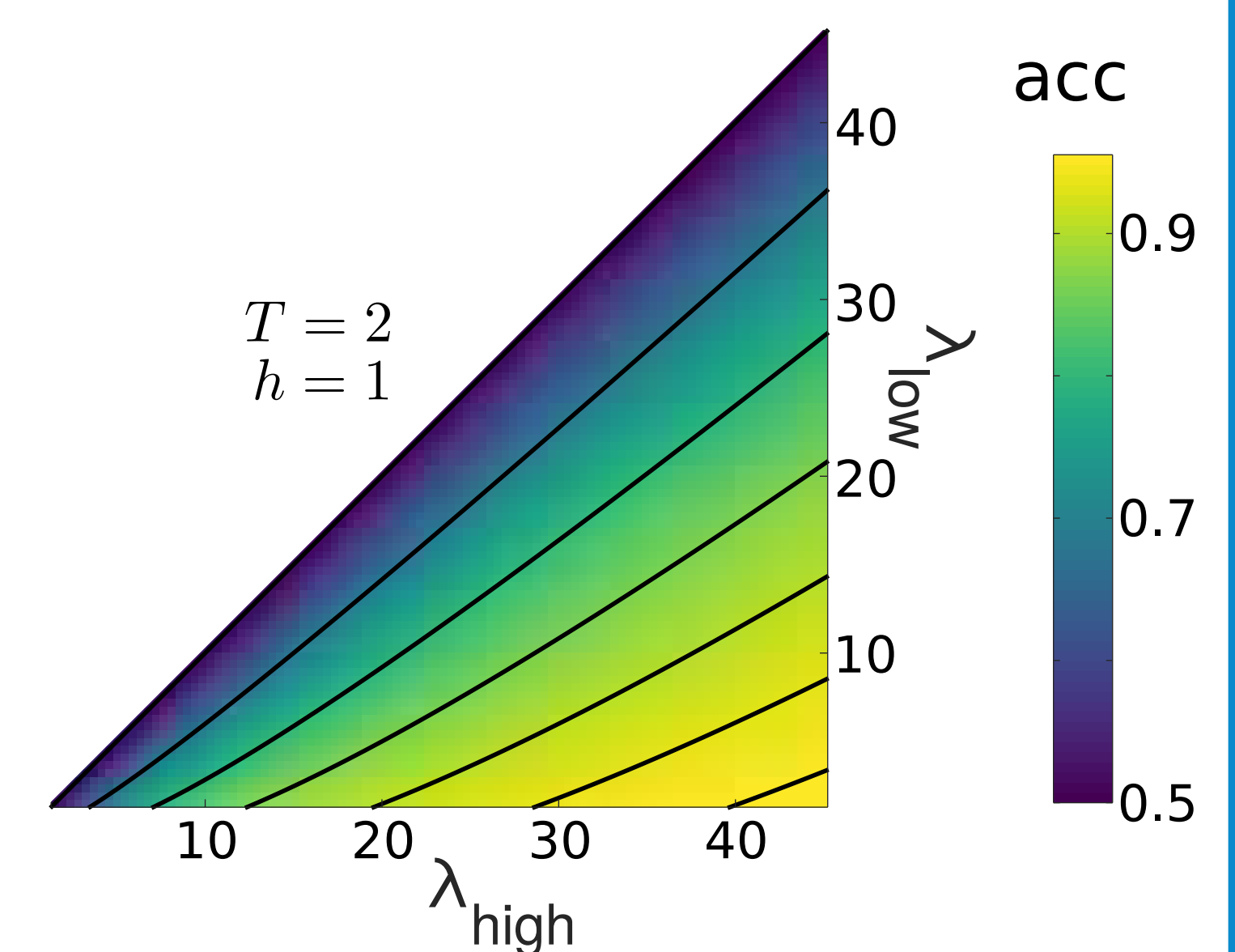
$$S := \frac{\lambda_{\text{high}} - \lambda_{\text{low}}}{\sqrt{\lambda_{\text{high}} + \lambda_{\text{low}}}}$$



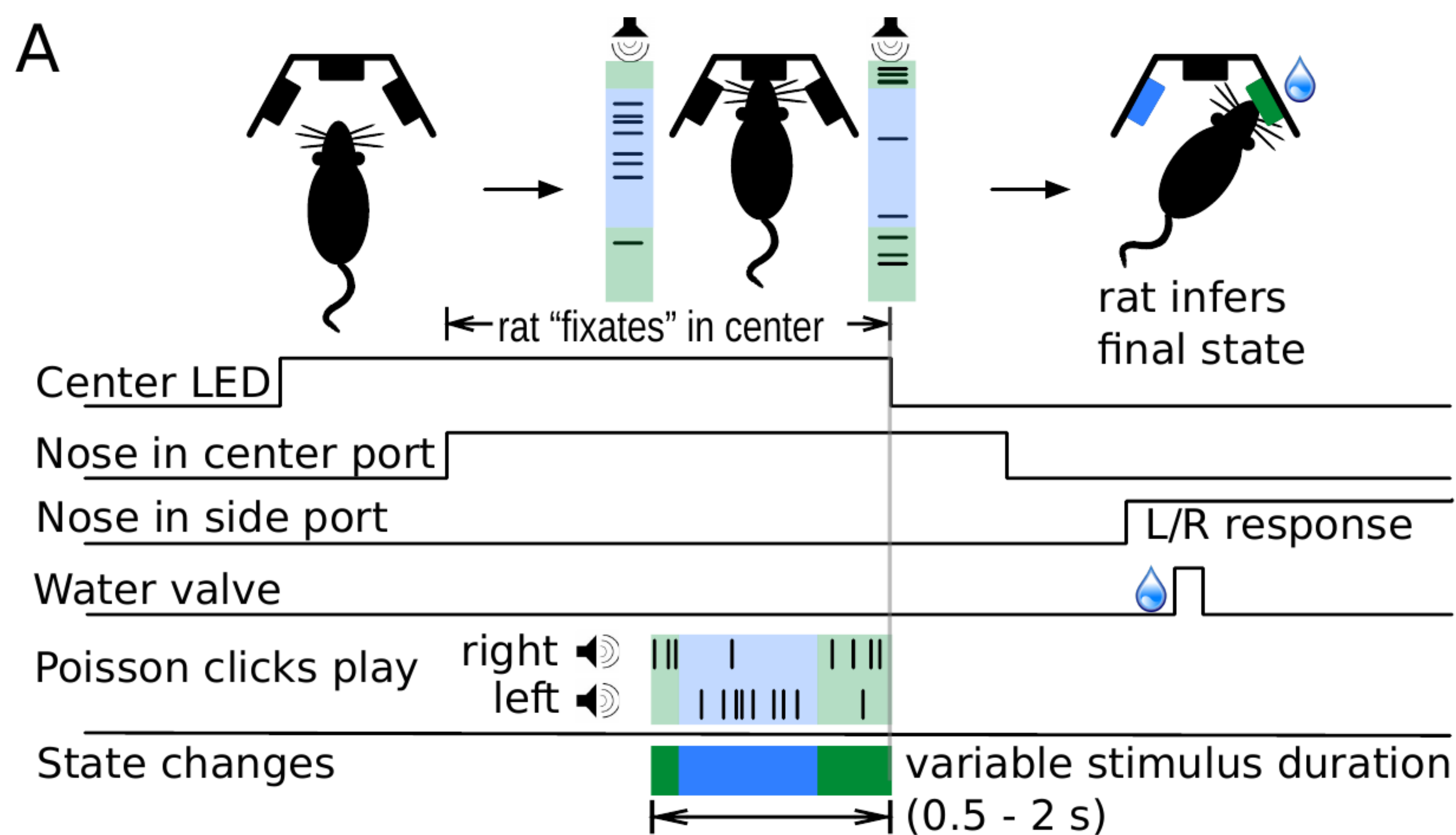
- \* So our system really is 2-dimensional

- \* If  $hT = \text{const.}$  the system becomes 1-dimensional!

- \* On the right, accuracy varies as a function of  $S$ . Black lines are the level curves.



## The dynamic clicks task



Piet, Hady, & Brody, (2017). Rats optimally accumulate and discount evidence in a dynamic environment. bioRxiv. <https://doi.org/10.1101/204248>

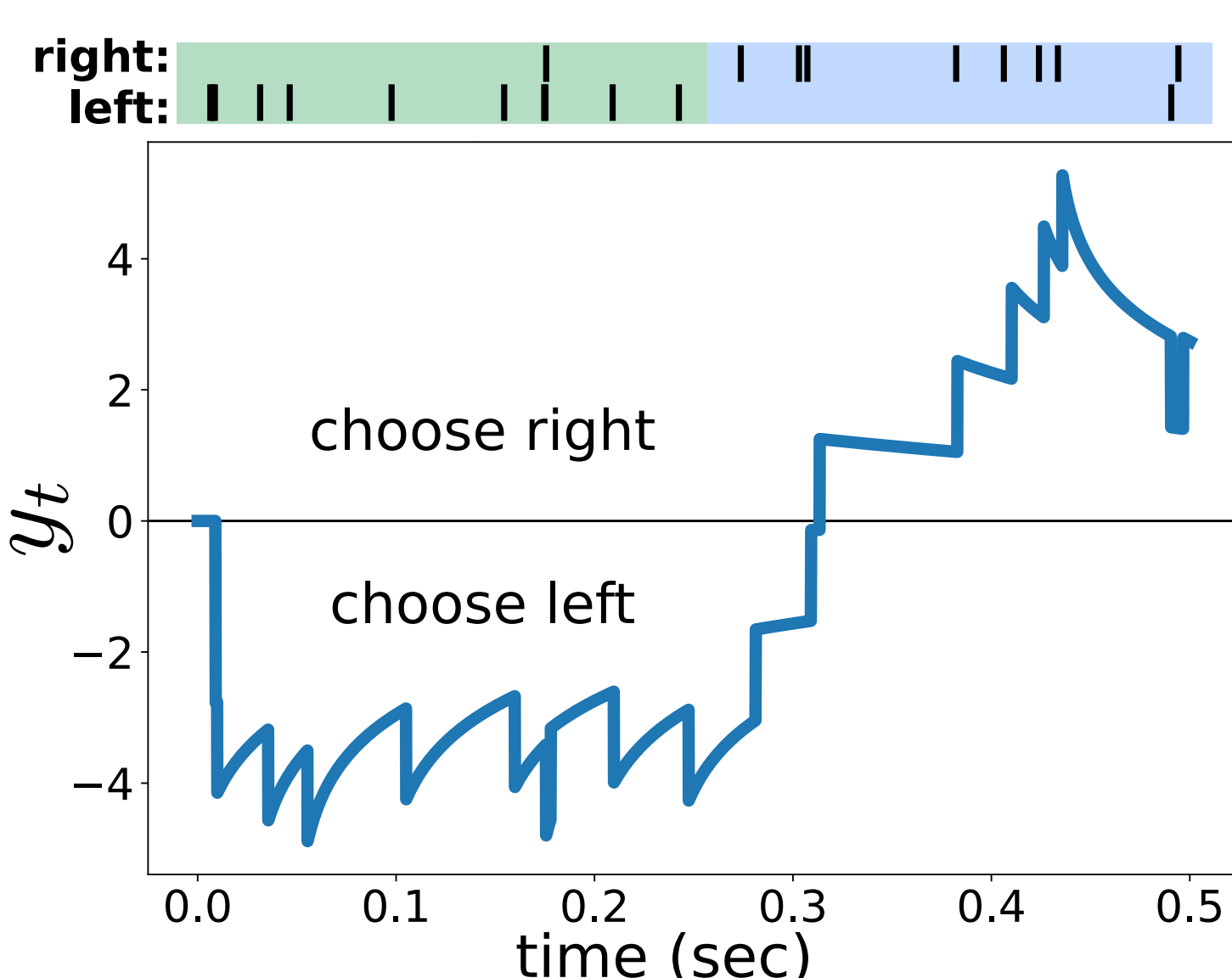
## KEY FEATURES OF THE STIMULUS

- \* Two coupled inhomogeneous Poisson processes (one per ear).
- \* Each intensity  $\lambda^R(t), \lambda^L(t) \in \{\lambda_{\text{low}}, \lambda_{\text{high}}\}$  alternates stochastically within a trial according to the **hazard rate**  $h$ .

## Ideal-observer model

$$y_t := \log \frac{P(\lambda_{\text{high}}(t) \text{ on the right} \mid \text{observed streams})}{P(\lambda_{\text{high}}(t) \text{ on the left} \mid \text{observed streams})}$$

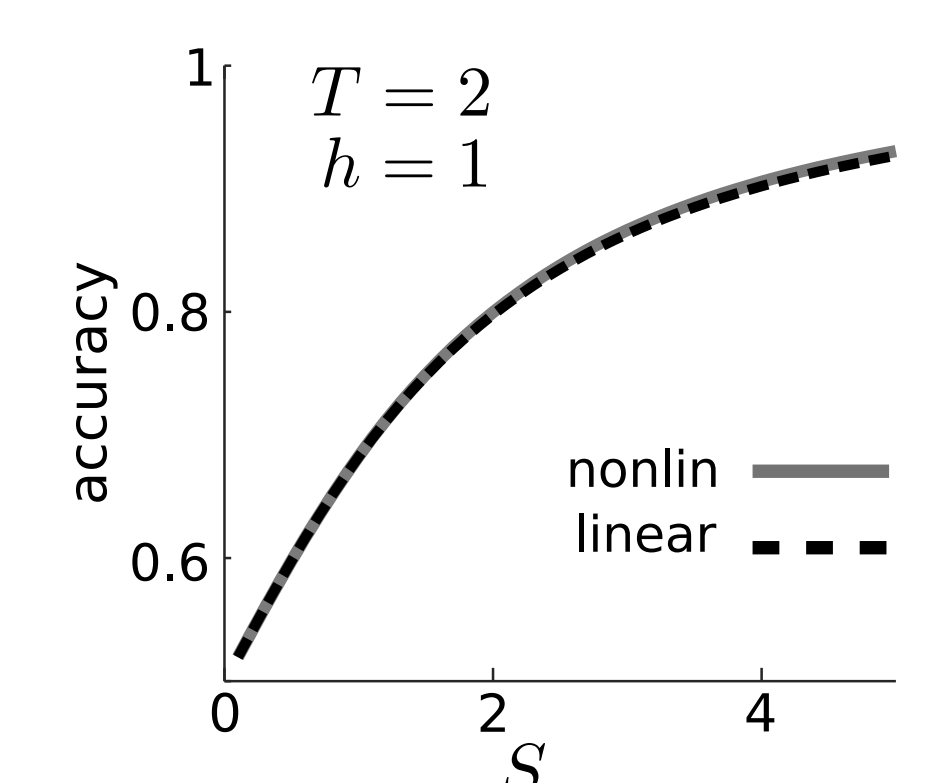
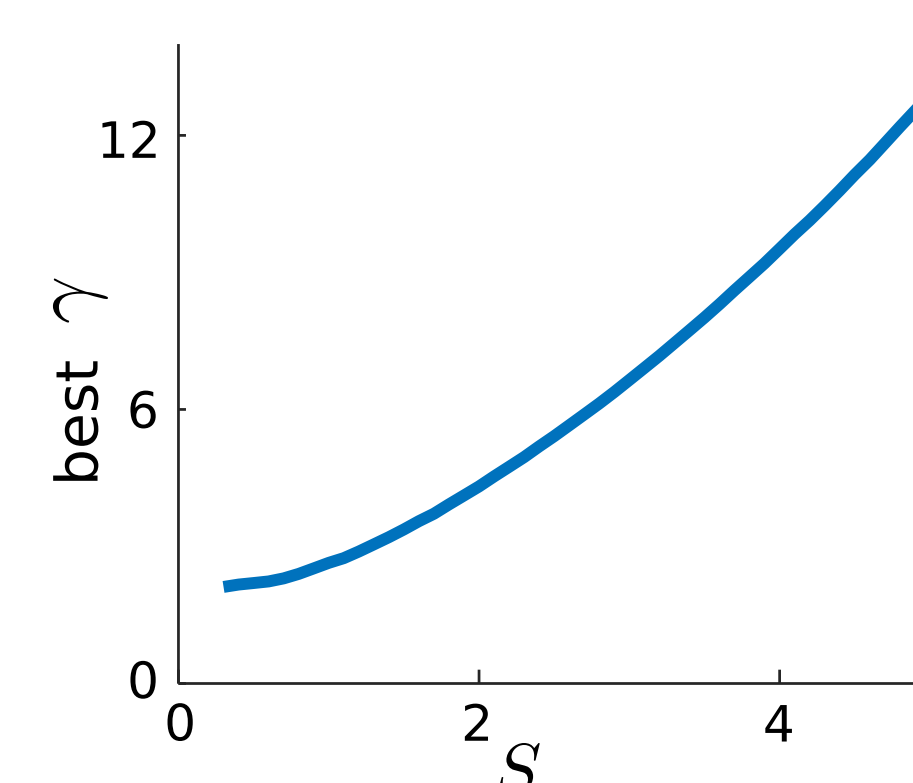
$$\frac{dy}{dt} = -2h \sinh y + \log \frac{\lambda_{\text{high}}}{\lambda_{\text{low}}} \sum_{t_{\text{click}}} \delta_i^R - \delta_j^L; \quad y_0 = 0; \quad h = \text{hazard rate}$$



- \* Discontinuous jumps at clicks, nonlinear decay in-between
- \* Interrogate at time  $T$  and decide based on sign of  $y_T$
- \* This model maximizes the expected reward on every trial

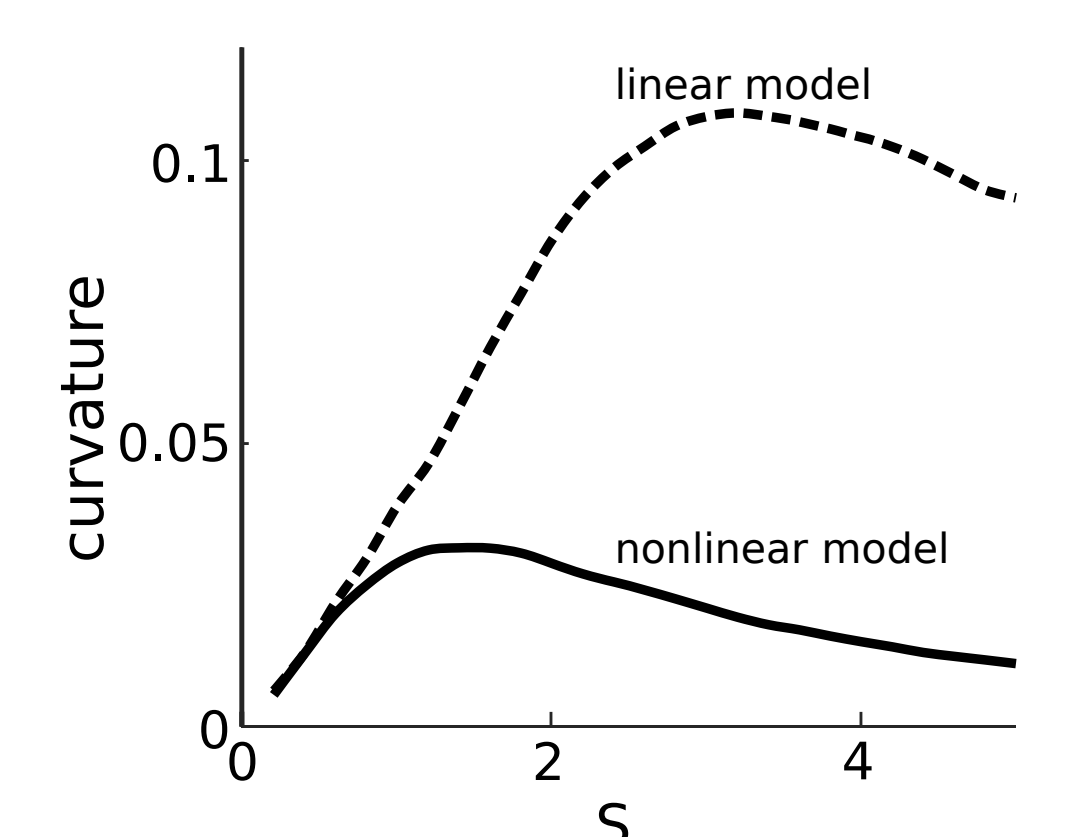
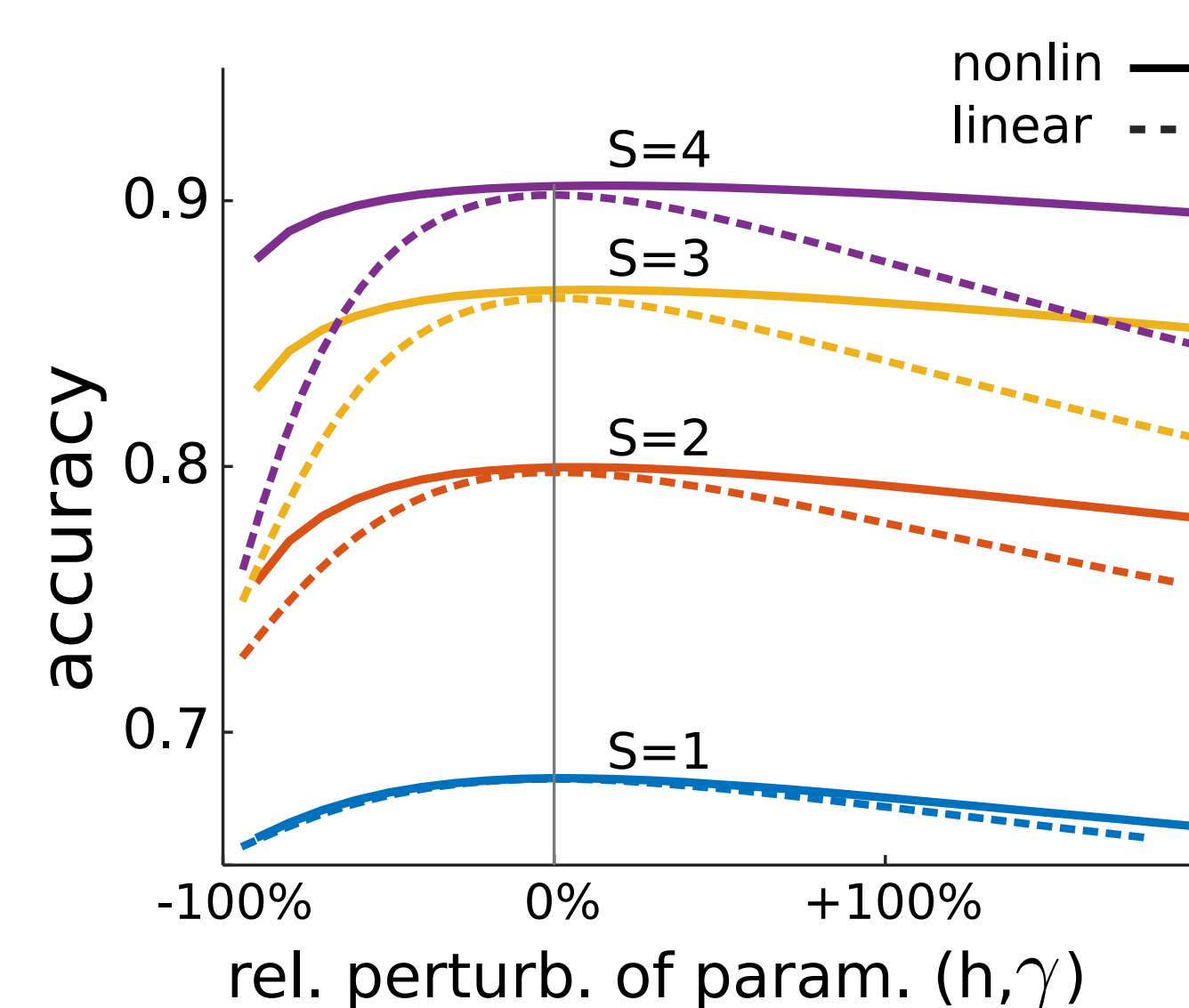
## Linear model is near-optimal...

$$\frac{dy}{dt} = -2\gamma \cdot y + \log \frac{\lambda_{\text{high}}}{\lambda_{\text{low}}} \sum_{t_{\text{click}}} \delta_i^R - \delta_j^L; \quad y_0 = 0; \quad \gamma = \text{discounting rate}$$



## ... but more sensitive to errors

- \* When discounting parameter is misspecified, performance drops faster in the linear model



## The inverse problem

- \* Given the stimulus and decision data from our models, how well can we:

- identify the model?
- recover its parameters?

