

# Neural Likelihood

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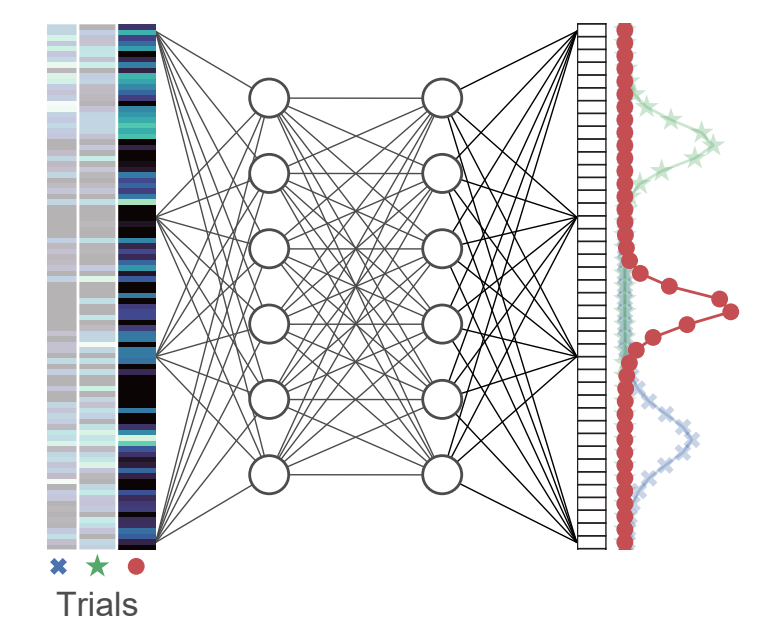
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## Introduction

- Perceptual decision making in humans and animals accounts for the uncertainty in the relevant stimulus variable
- The likelihood over the stimulus captures the uncertainty for a fixed neuronal response
- Full likelihood estimation can be challenging due to high dimensionality
- Previously used parametric models make **strong assumptions** about the form of the noise correlations
- We present a simple (yet general) neural network based method that makes **fewer assumptions** about the form of the likelihood function

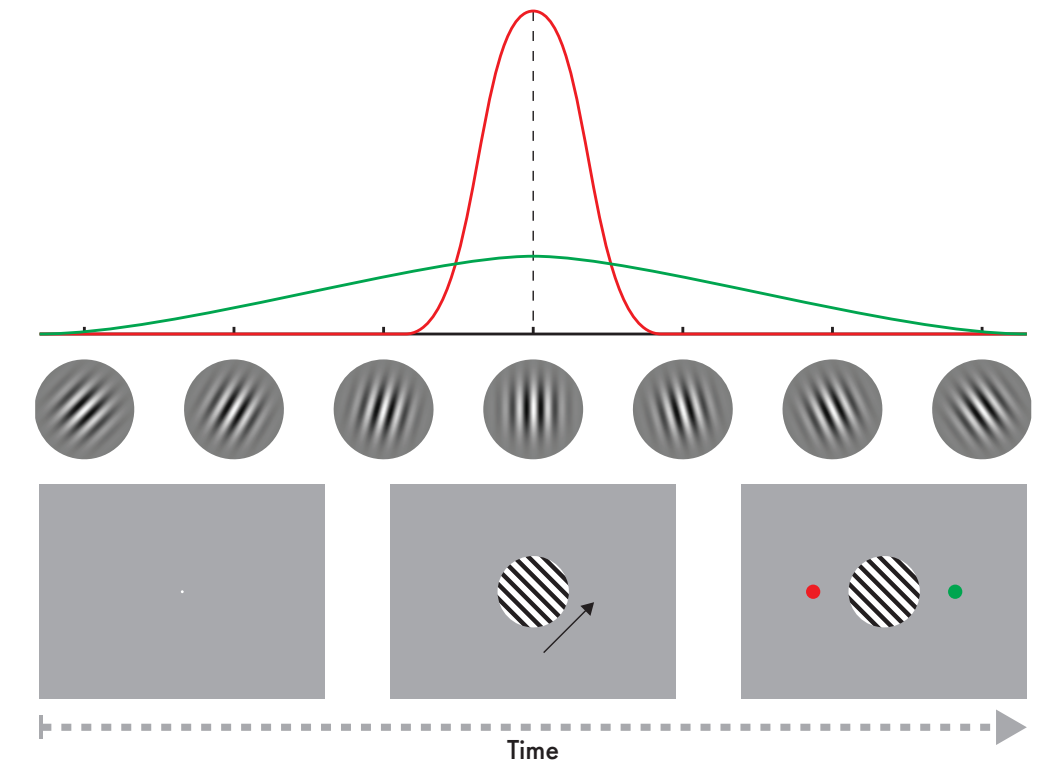
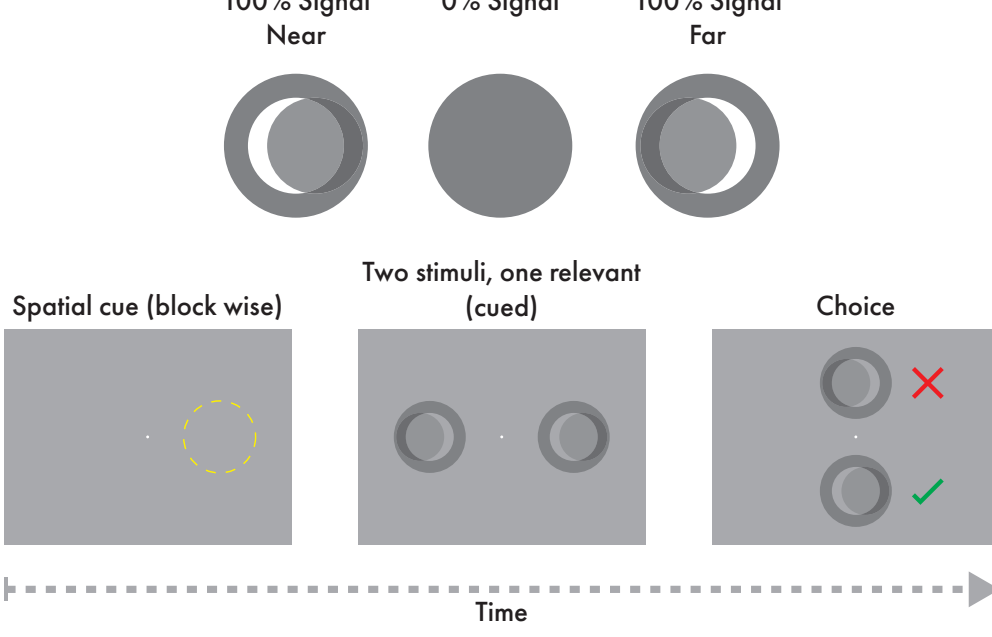
## Method

- Our method relies on two key steps:
1. Recover an unnormalized likelihood from a model of the posterior using the known prior
  2. Estimate the posterior using a neural network



## Experiments

- Monkeys classified trials into near or far, based on the predominantly occurring disparity in a random sequence of disparities.
- Multi-unit activity in V2 was recorded



- Monkey classified orientations as drawn from category 1 or 2 of known distributions.
- Contrast of stimulus was varied from trial to trial
- Multi-unit activity in V1 was recorded

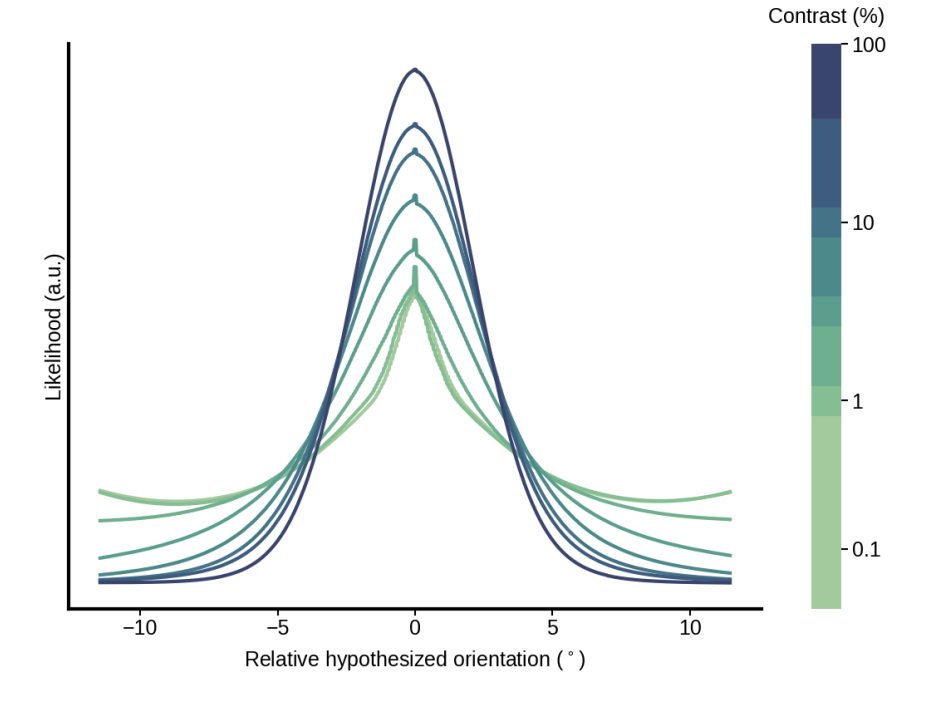
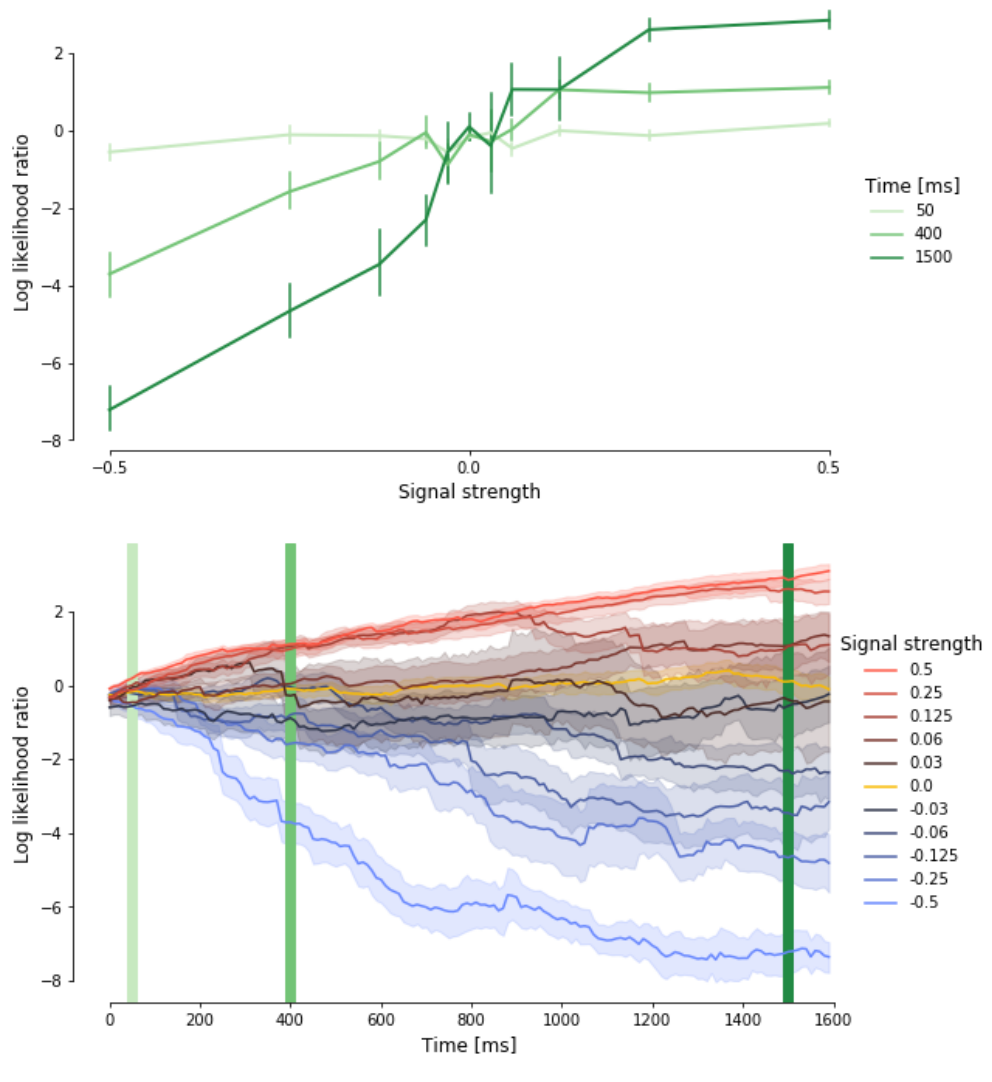
## Models

- Single-layer gated recurrent unit
- Same linear readout at each time step
- Initial hidden state is learned

- Flow model

## Results

- Evidence for particular class increases...
- ...over time
  - ...with higher signal strength



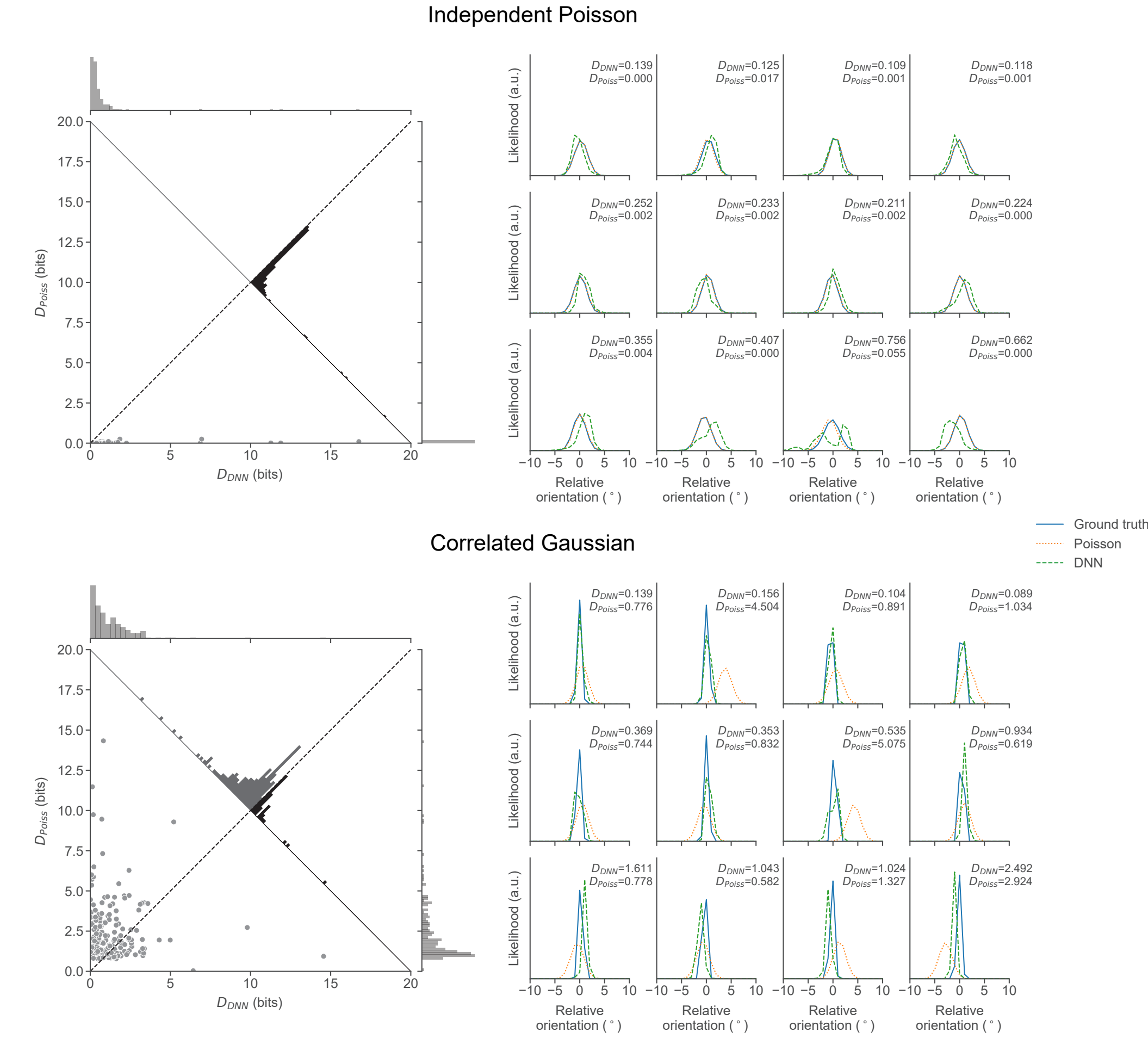
- For low contrast the uncertainty about the stimulus is higher so the likelihood curves become wider

# Deep-learning based likelihood decoders for perceptual decision making make fewer assumptions about the form of the likelihood function.

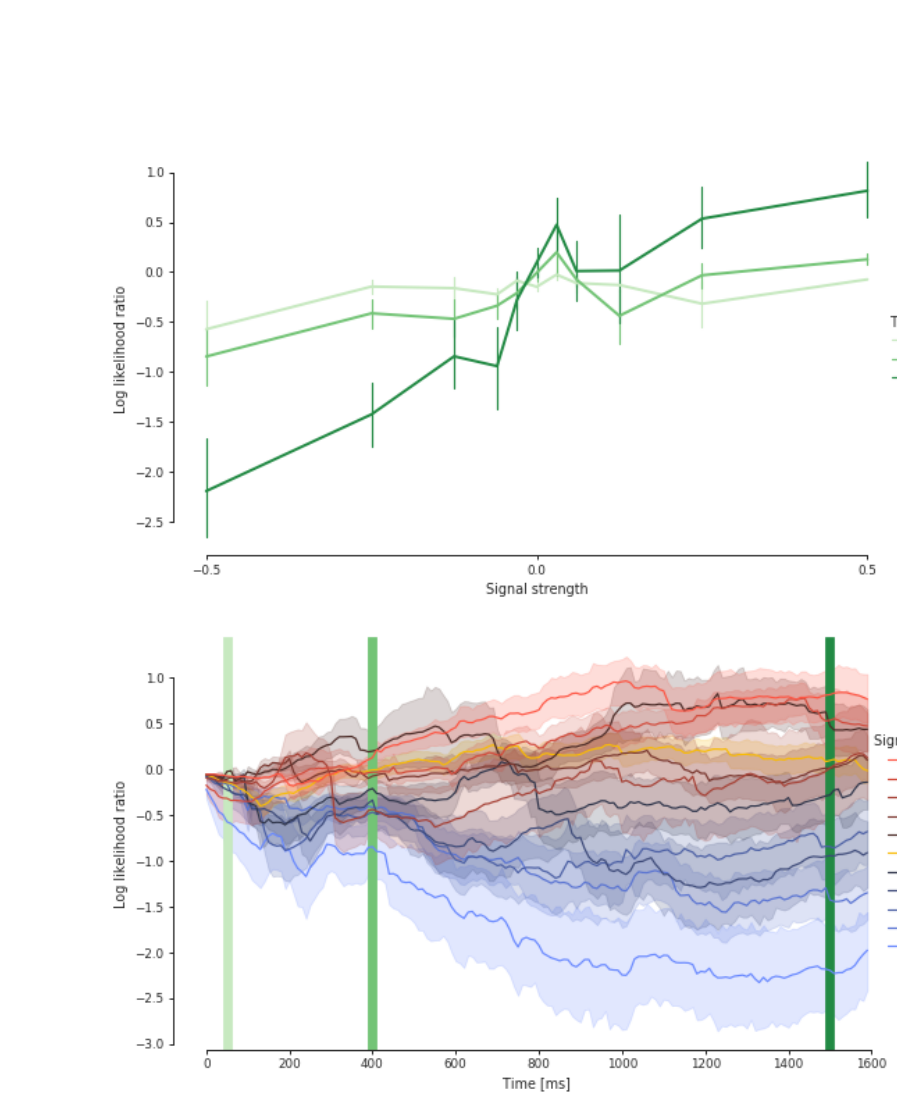


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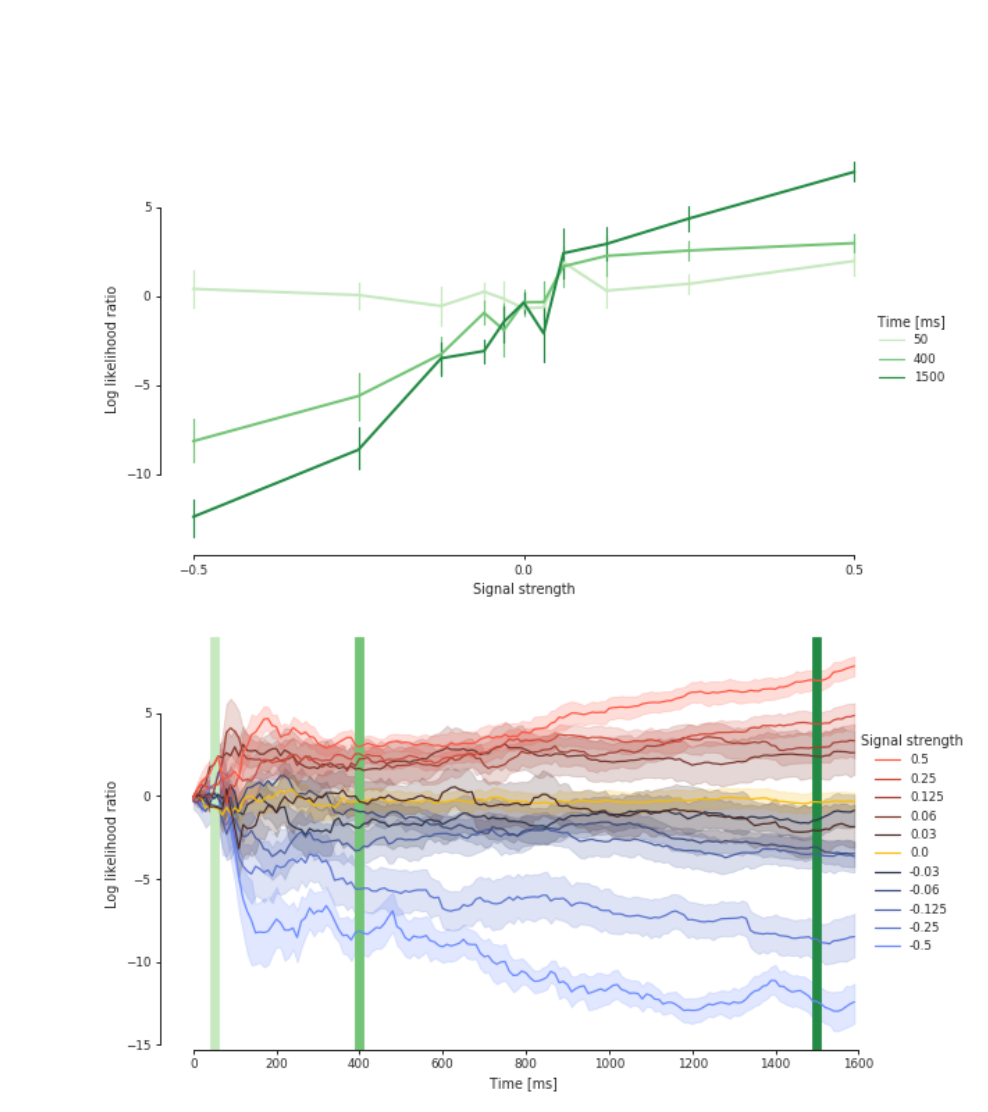
## Toy Data



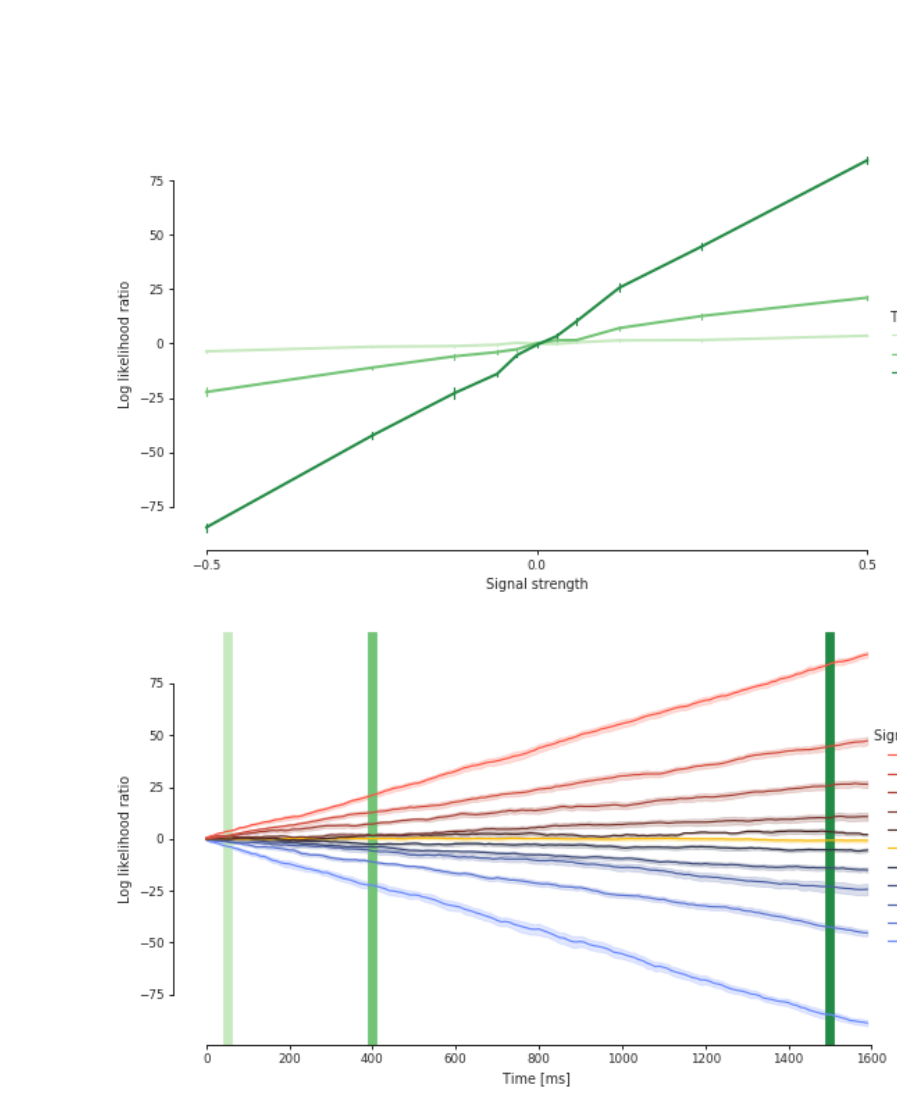
## Different Readouts



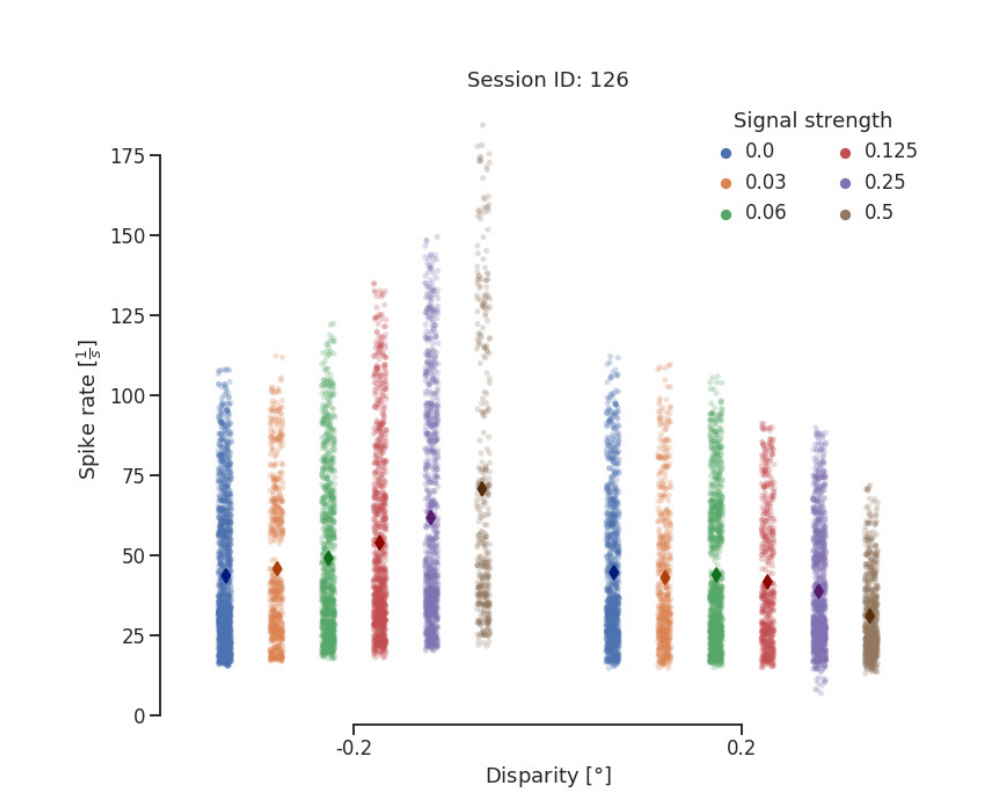
## Logistic Regression



## Ideal Observer



## Spike Rate Analysis



## Acknowledgements

Supported by the Institutional Strategy of the University of Tübingen (Deutsche Forschungsgemeinschaft, ZUK 63); the Carl-Zeiss-Stiftung; the DFG Cluster of Excellence 'Machine Learning - New Perspectives for Science', EXC 2064/1, project number 390727645; CRC 1233 'Robust Vision' project number 276693517, FOR 1847 project NI1718/1-1; by National Science Foundation Grant IIS-1132009; NIH DP1 EY023176 Pioneer Grant; NIH RO1 EY026927.