Bayesian modeling…

and how to use brain data to arbitrate between models of cognition

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What is Bayesian modeling?

Bayesian modeling can mean two things:

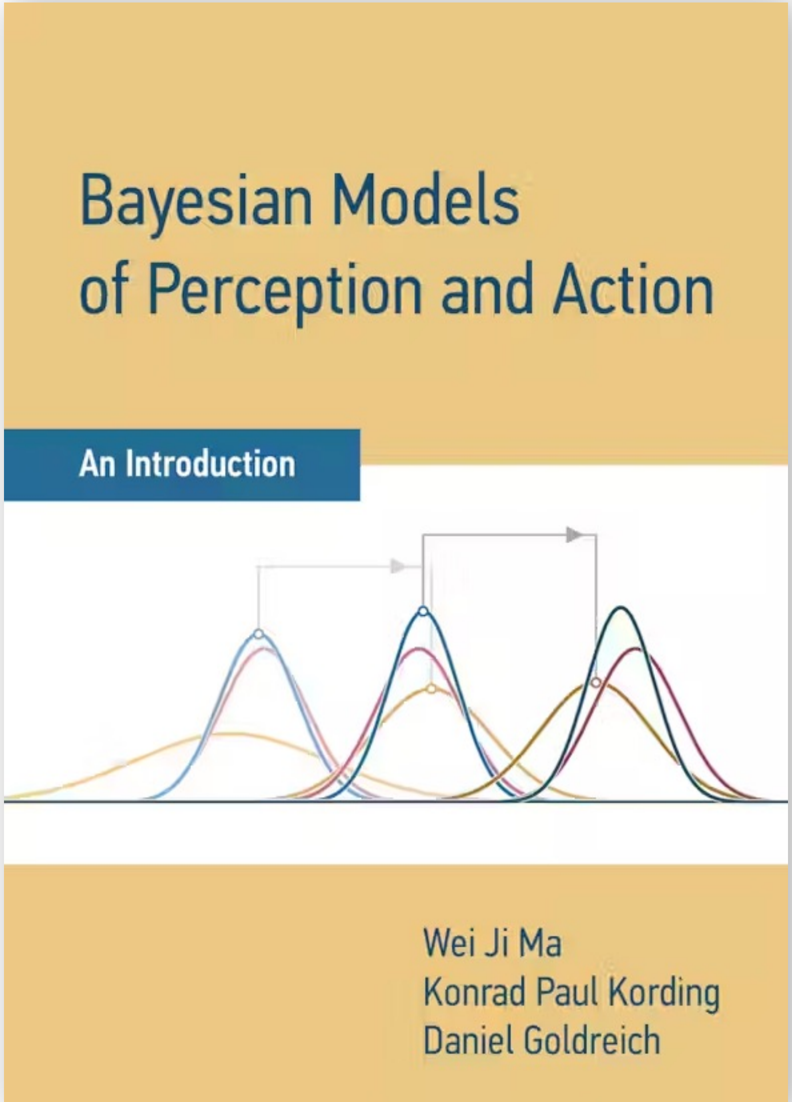
Meaning **A**:
Bayes rule as model of cognition under uncertainty

or

Meaning **B**:
Bayesian inference as machine learning framework for the fitting of cognitive models and the estimation of their free parameters

Today I will mean **A**!

What is Bayesian modeling?



Bayes rule:

$$\underbrace{p(\text{hyp}|\text{obs})}_{\text{Posterior}} \propto \underbrace{p(\text{obs}|\text{hyp})}_{\text{Likelihood}} \cdot \underbrace{p(\text{hyp})}_{\text{Prior}}$$

What is Bayesian modeling?

Most of the decisions that matter are uncertain.

perceptual	financial	political
		
eat strange fruit?	buy new crypto?	vote Macron?
hyp fruit is edible	hyp crypto will rise	hyp ???

What is Bayesian modeling?

Most of the decisions that matter are uncertain.

perceptual

eat strange fruit?

stomach pain

financial

buy new crypto?

hyp
crypto will rise

political

vote Macron?

hyp
???

What is Bayesian modeling?

Most of the decisions that matter are uncertain.

perceptual

eat strange fruit?

stomach pain

financial

buy new crypto?

savings gone

political

vote Macron?

hyp
???

What is Bayesian modeling?

Most of the decisions that matter are uncertain.

perceptual

eat strange fruit?

stomach pain

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buy new crypto?

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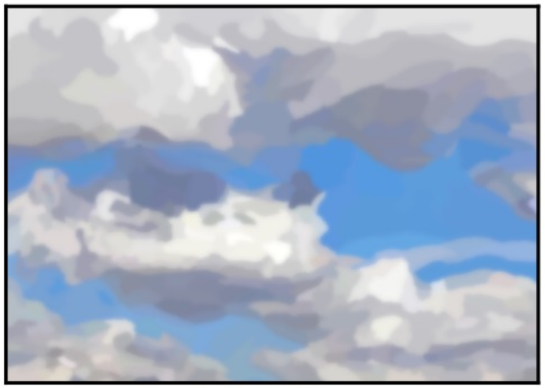
political

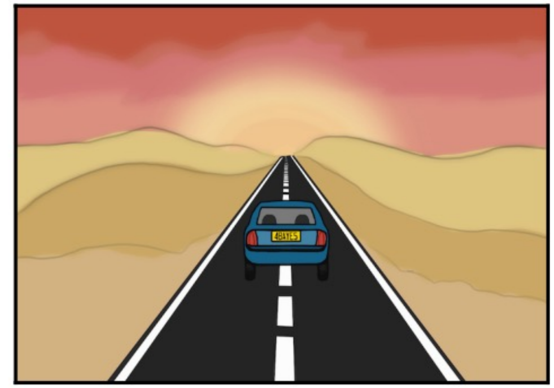
vote Macron?

big piles of trash

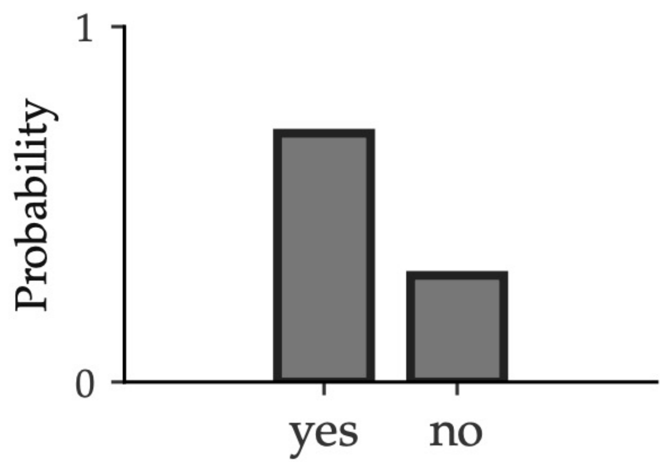
What is Bayesian modeling?

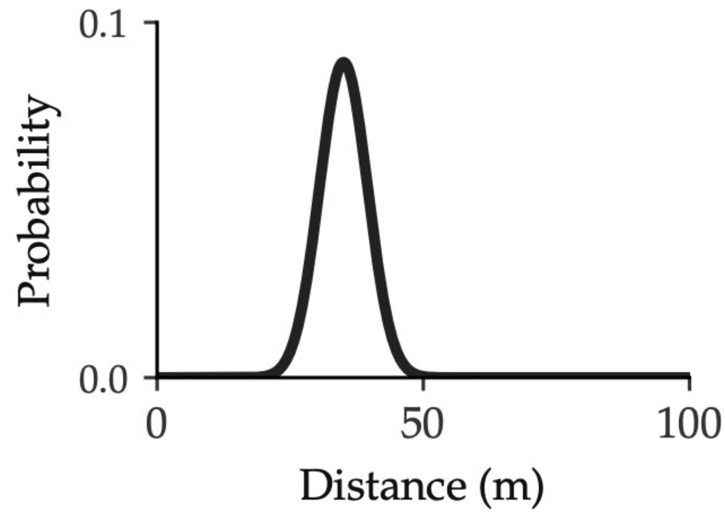


$p(\text{it is going to rain} \mid \text{cloudy sky})$



$p(\text{distance to car} \mid \text{visual image})$





Ma, Kording and Goldreich (2023)
Bayesian Models of Perception and Action, *MIT Press*

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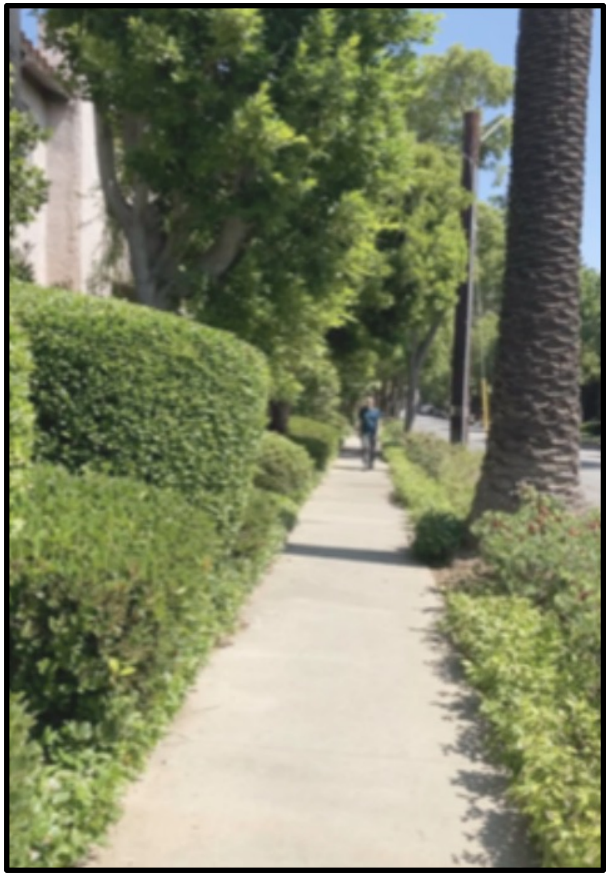
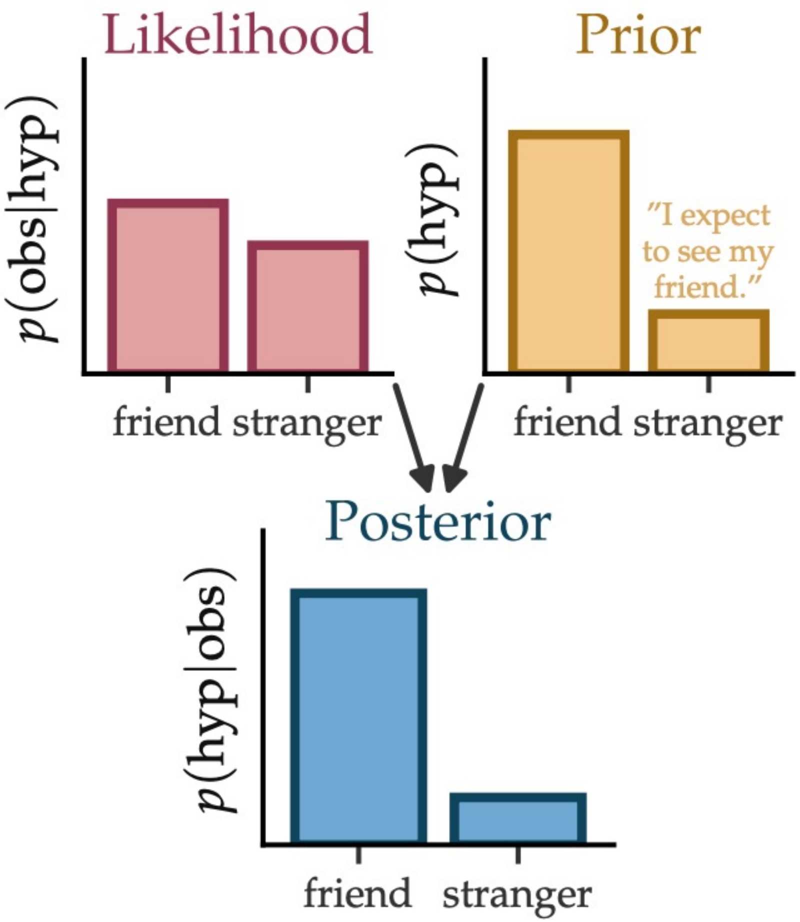


p(this is my friend)



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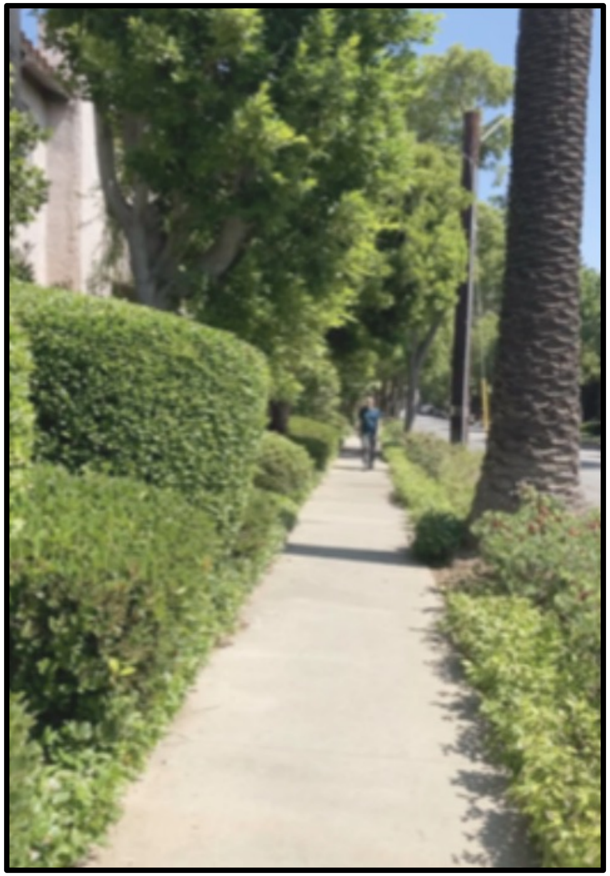

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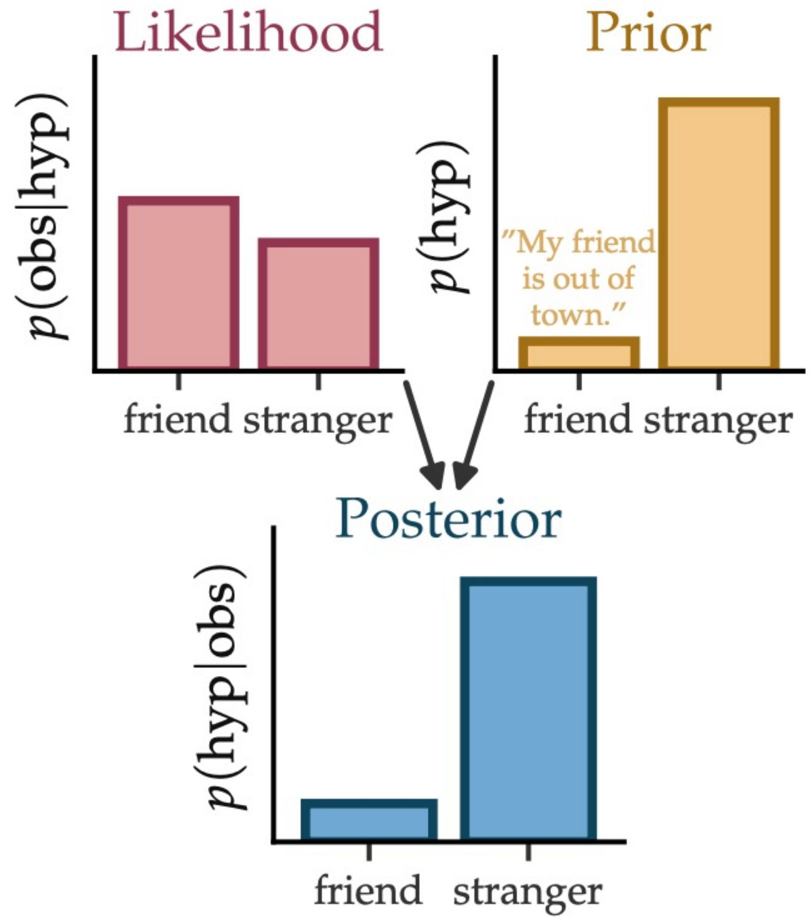

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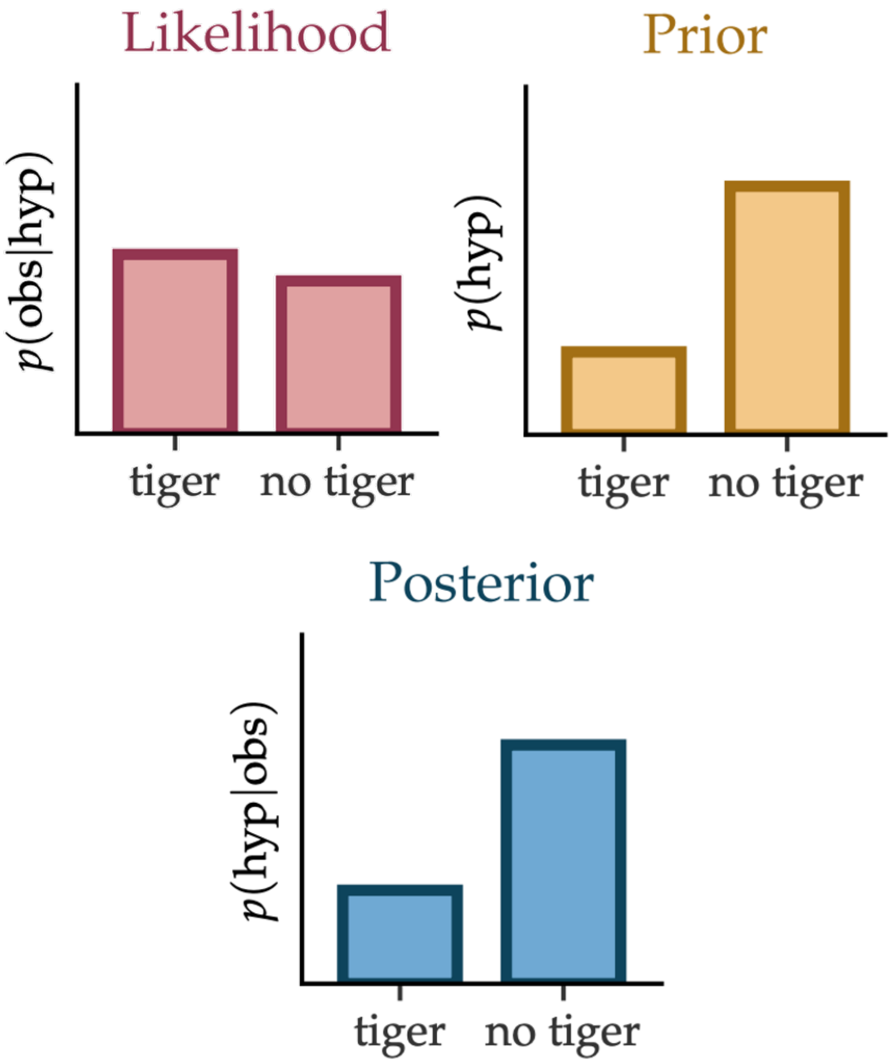

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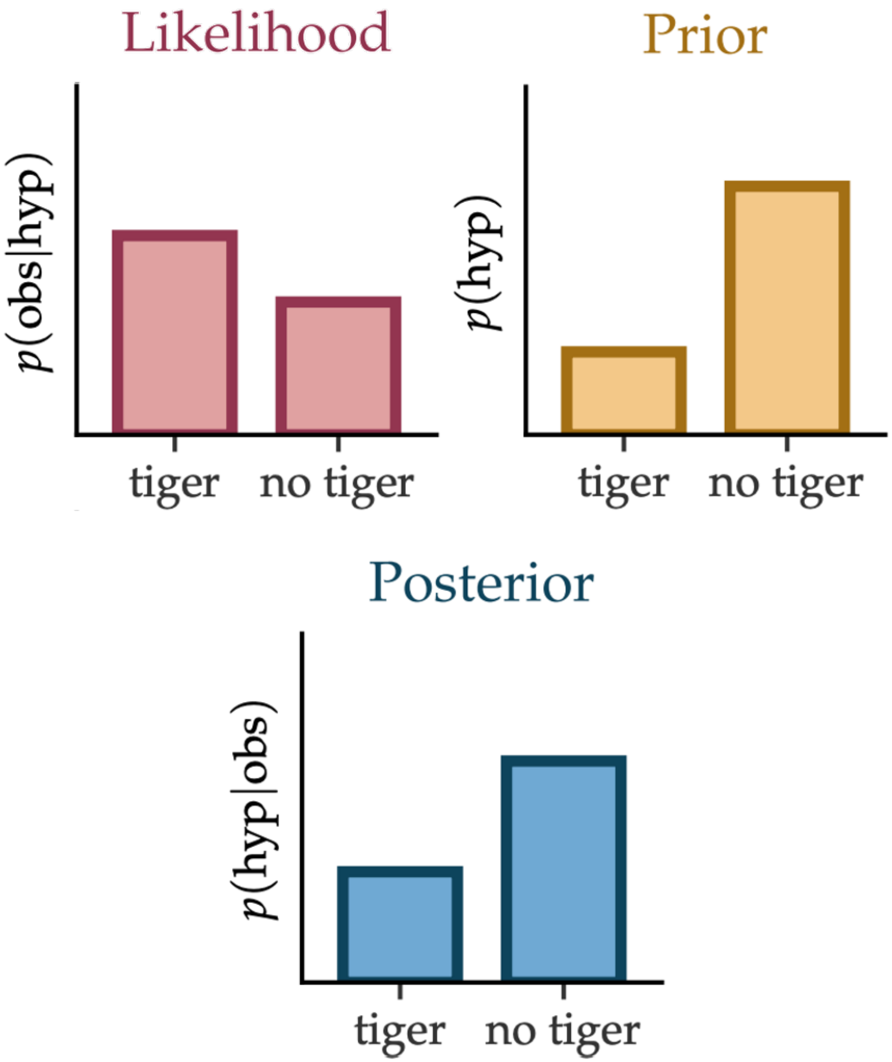

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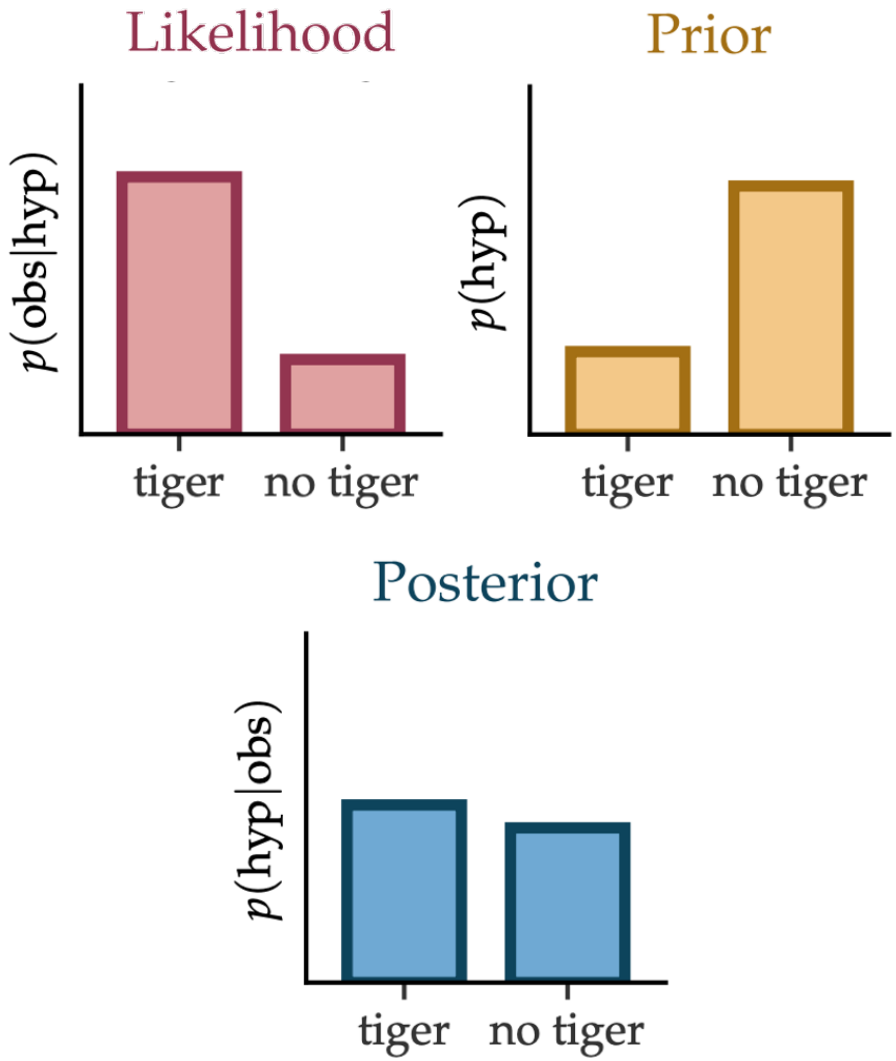

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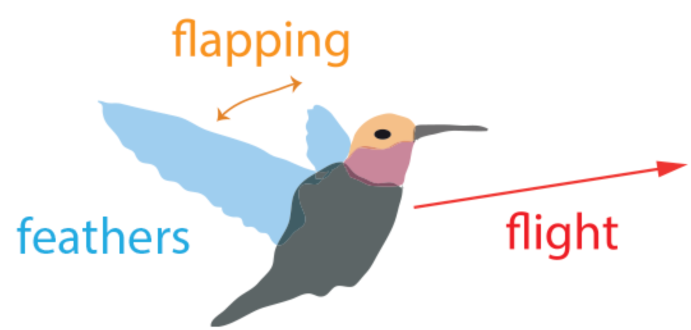
Flavors of Bayesian modeling

Marr's multi-level analysis of cognition

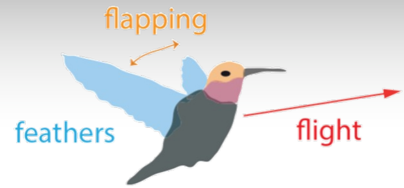
	LEVELS	
Computation	1	why (problem)
Algorithm	2	what (rules)
Implementation	3	how (physical)



Krakauer et al. (2016) *Neuron*
Neuroscience needs behavior: correcting a reductionist bias

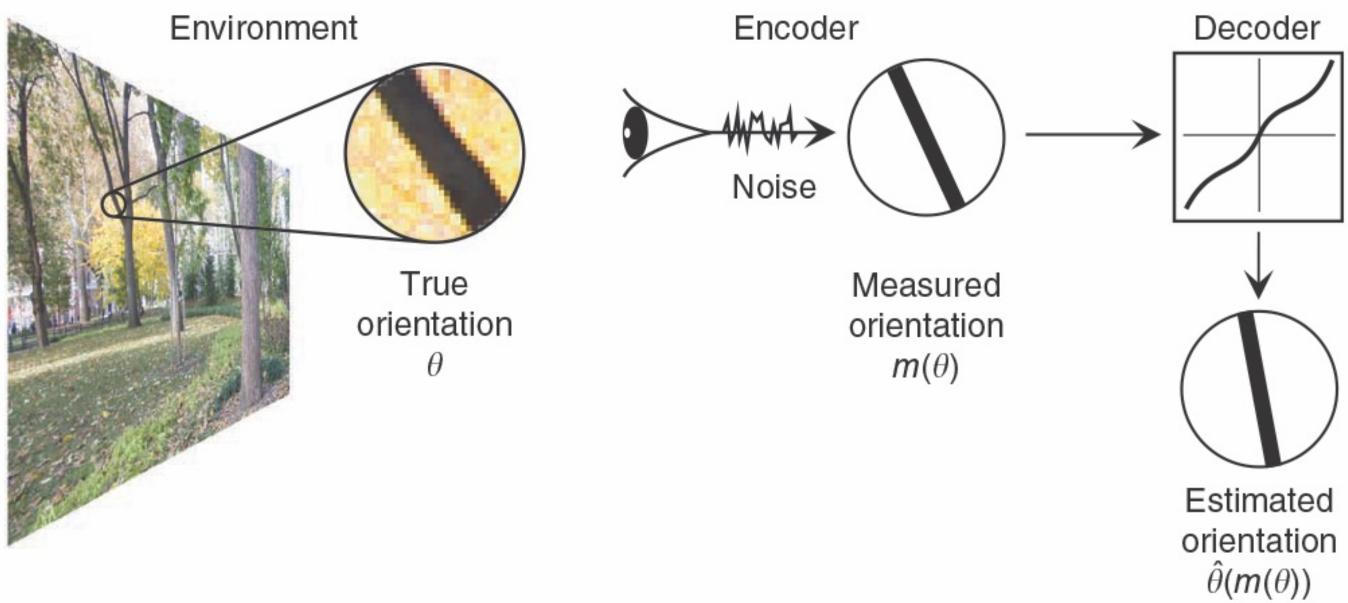
Bayesian models as statistical computations

1



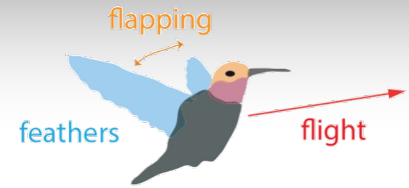
Bayesian models as <u>statistical computations</u>

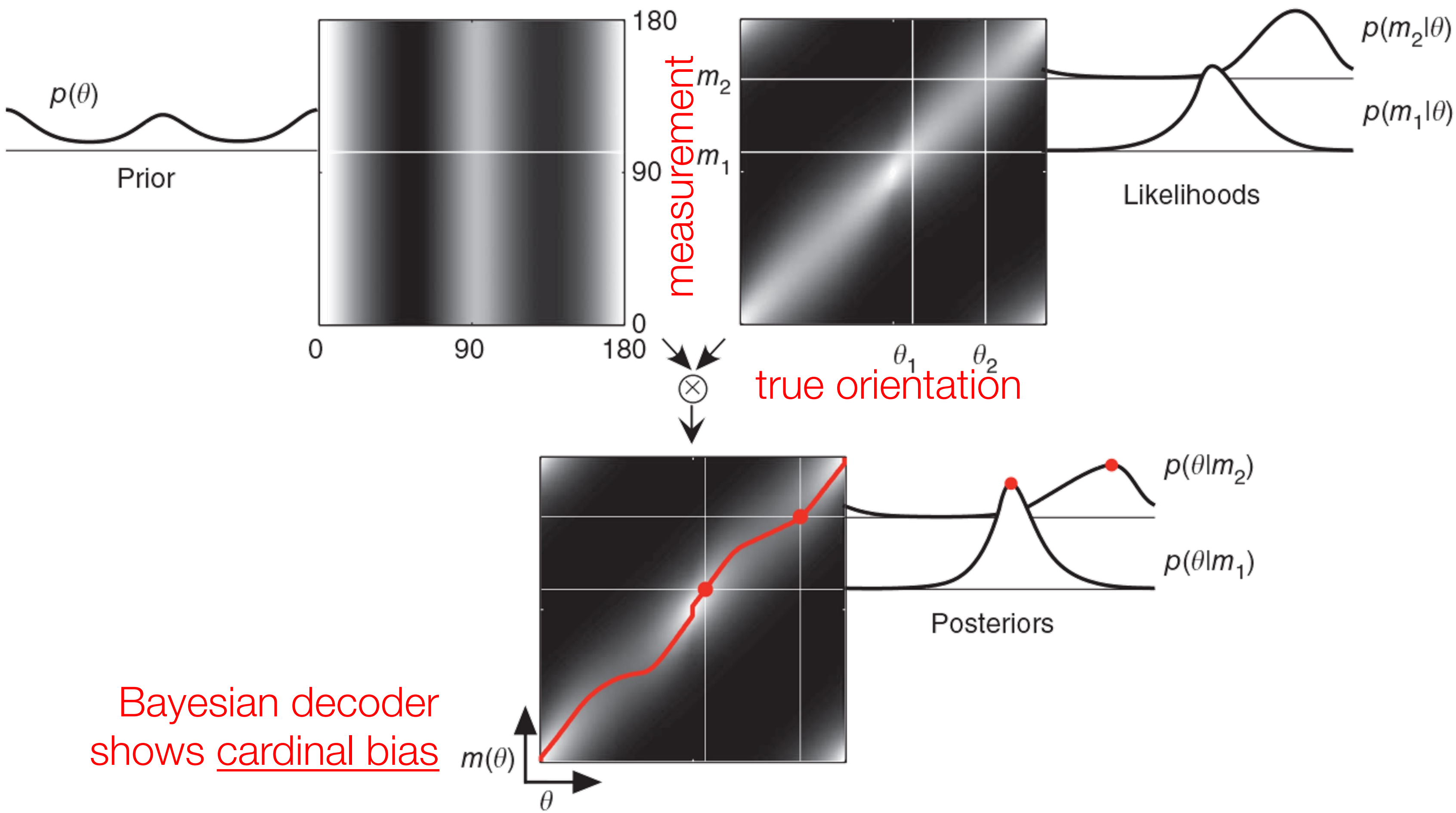
They define the (Bayes-)optimal solution to dealing with probabilistic uncertainty



Girshick et al. (2011) *Nature Neuroscience*
Cardinal rules: orientation perception reflects knowledge of environmental statistics

Bayesian models as statistical computations 1





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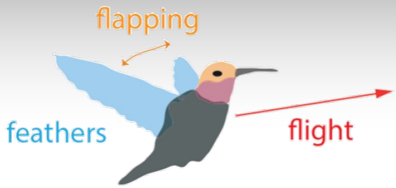
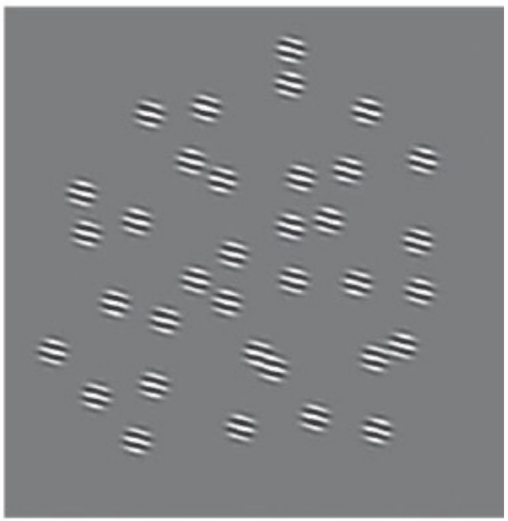
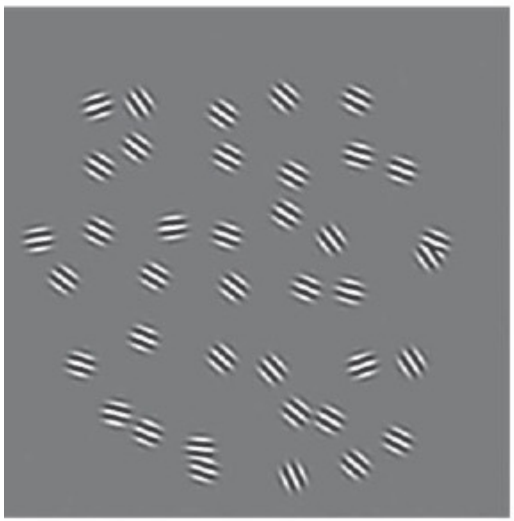


low-noise stimulus



high-noise stimulus



Is the right stimulus tilted counter-clockwise or clockwise relative to the left stimulus?

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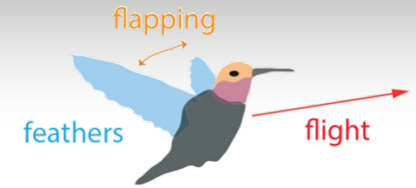
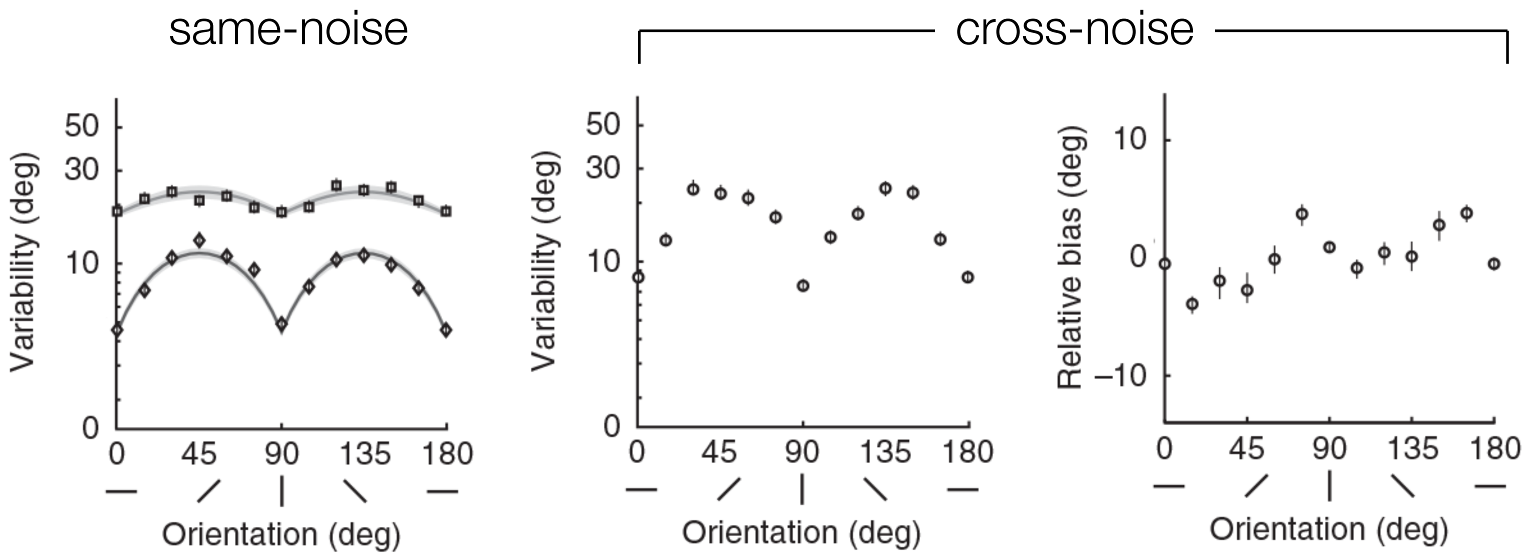


measure variability
in orientation perception

measure prior
distribution



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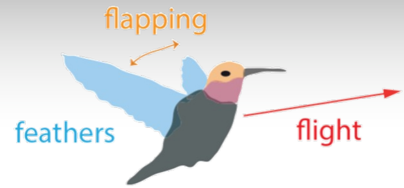
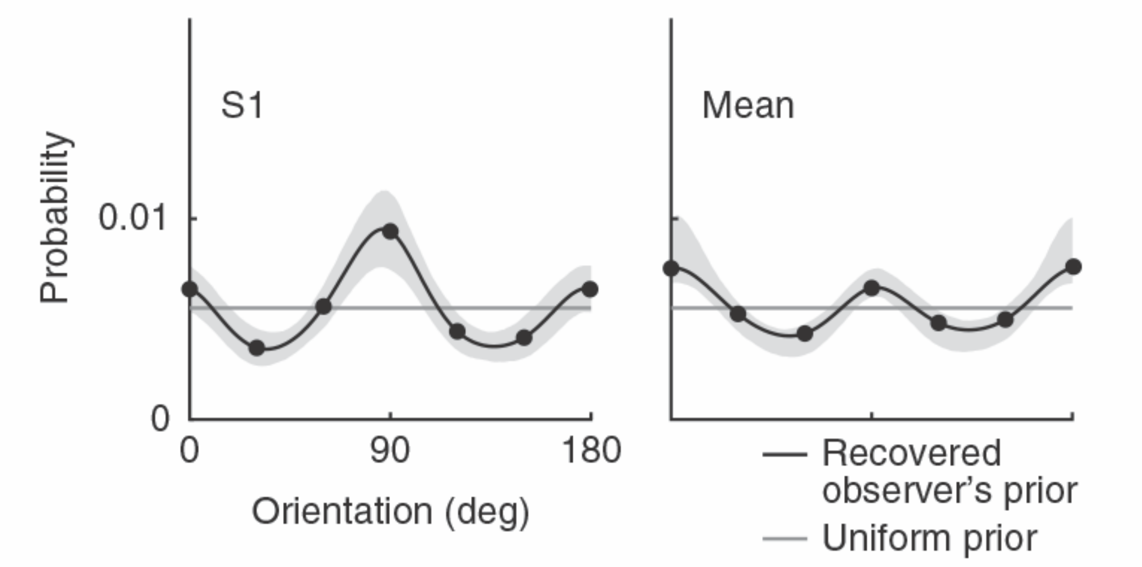


estimated <u>prior</u> distribution
from subject data



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Bayesian models as statistical computations

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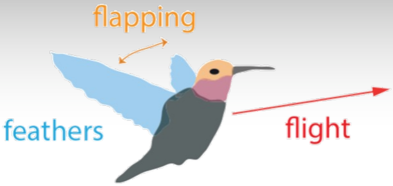
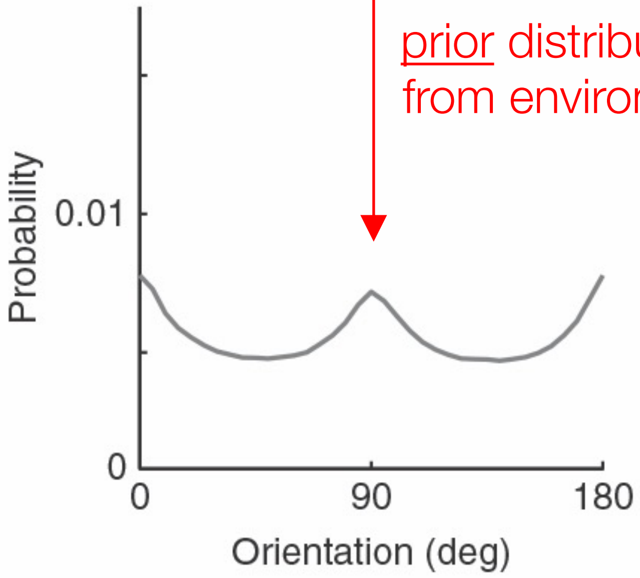


natural image database
oriented edge detection



prior distribution
from environment

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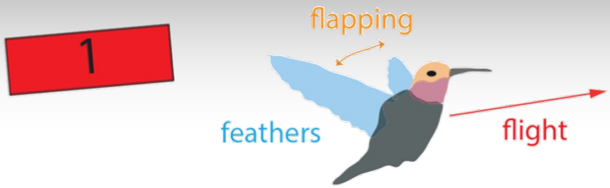
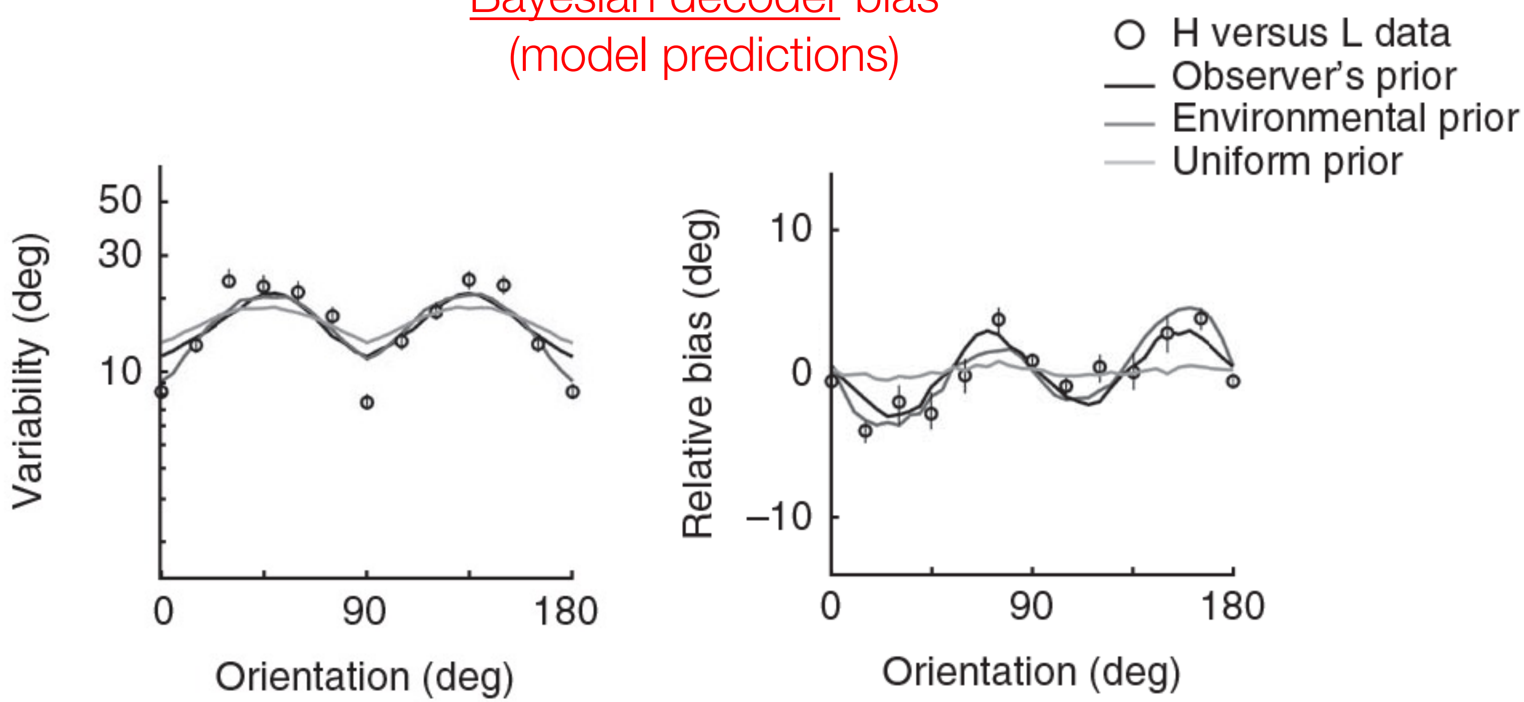
Bayesian models as statistical computations



compare human bias to
Bayesian decoder bias
(model predictions)



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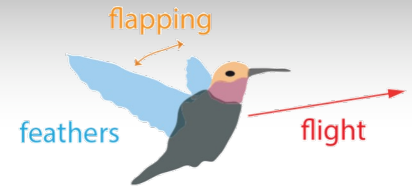
Cardinal rules: orientation perception reflects knowledge of environmental statistics

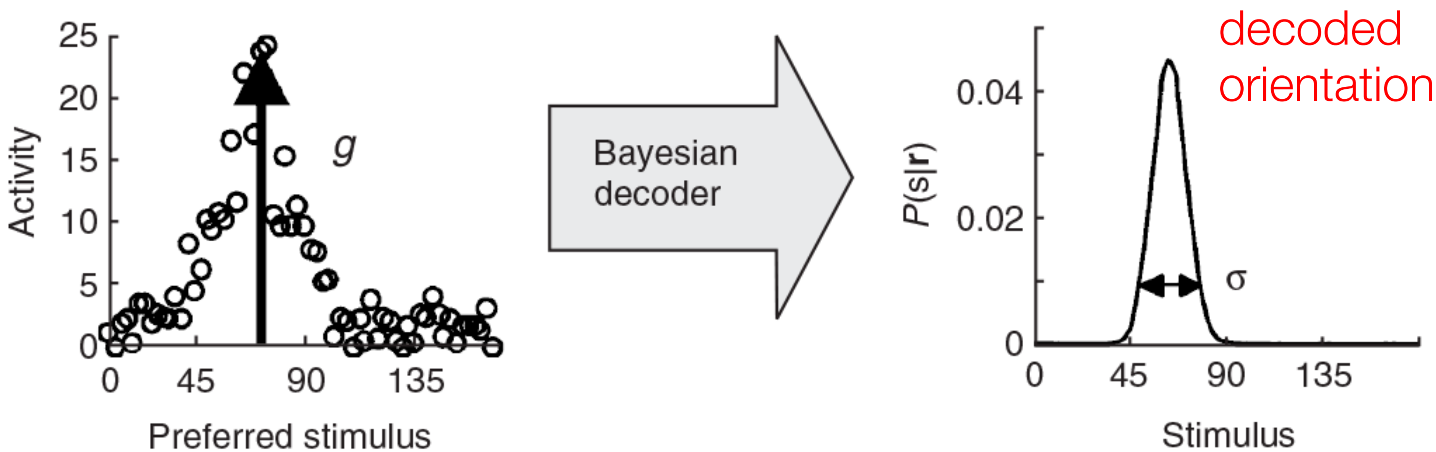
Bayesian models as neural mechanisms

3



Bayesian models as <u>neural mechanisms</u>

They define possible physical implementations of Bayesian inference by populations of neurons



Ma et al. (2006) *Nature Neuroscience*
Bayesian inference with probabilistic population codes

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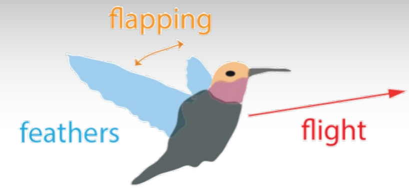

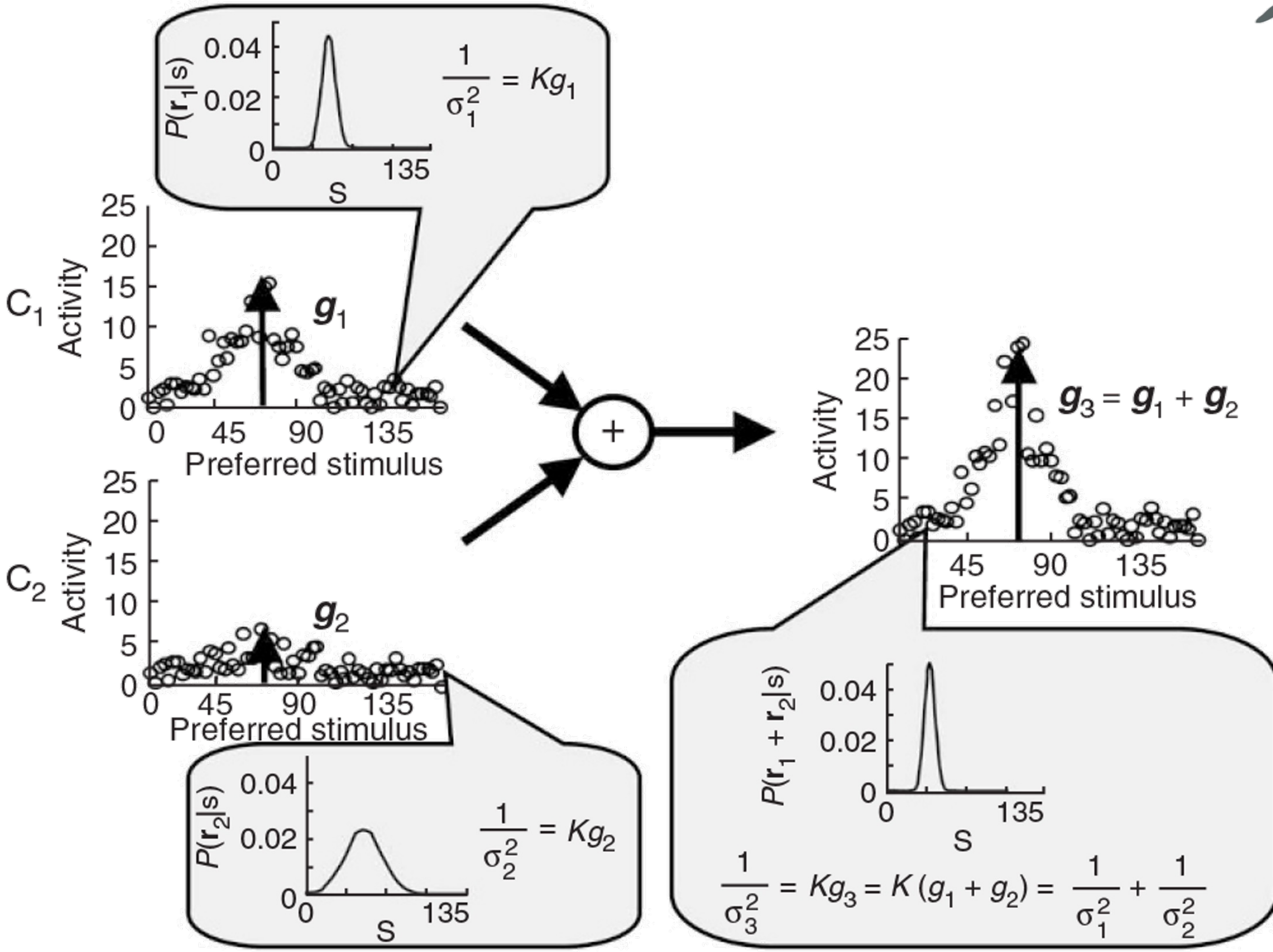

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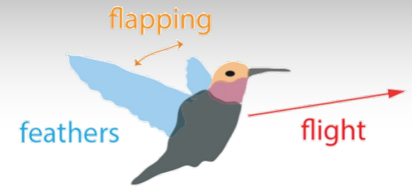

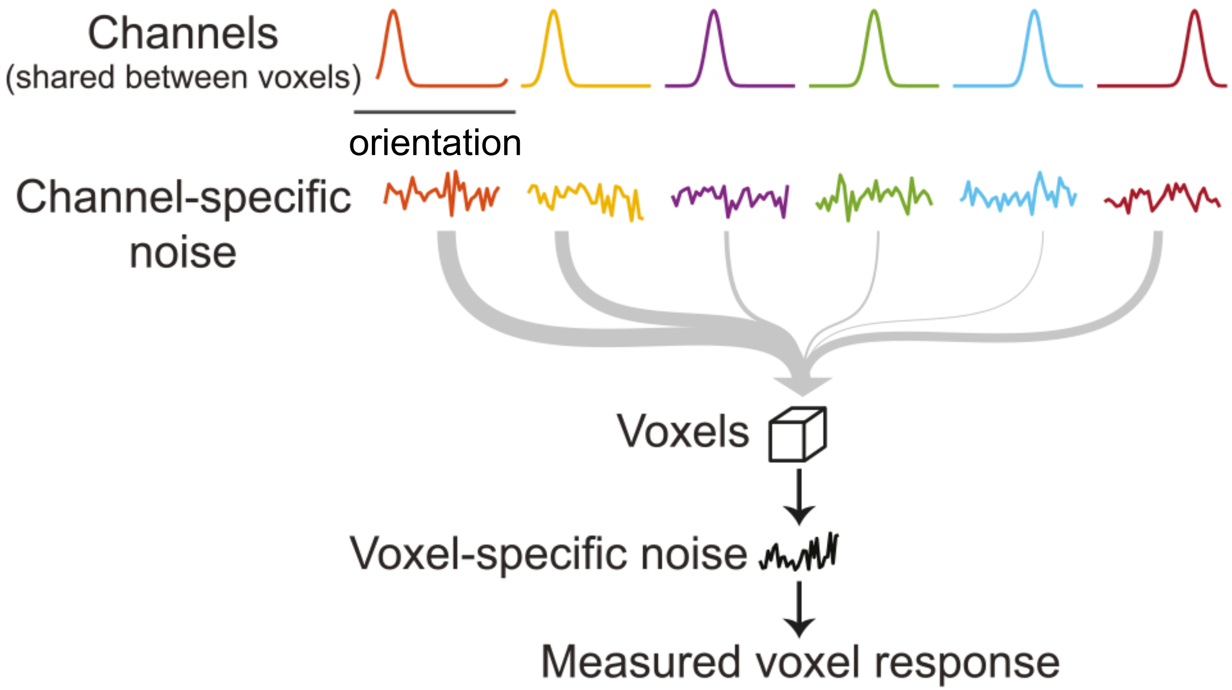

Geurts et al. (2022) *Nature Human Behaviour*
Subjective confidence reflects representation of Bayesian probability in cortex

Bayesian models as neural mechanisms

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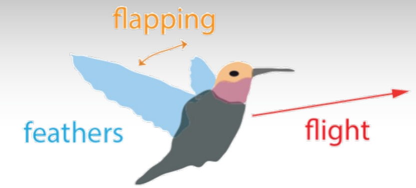

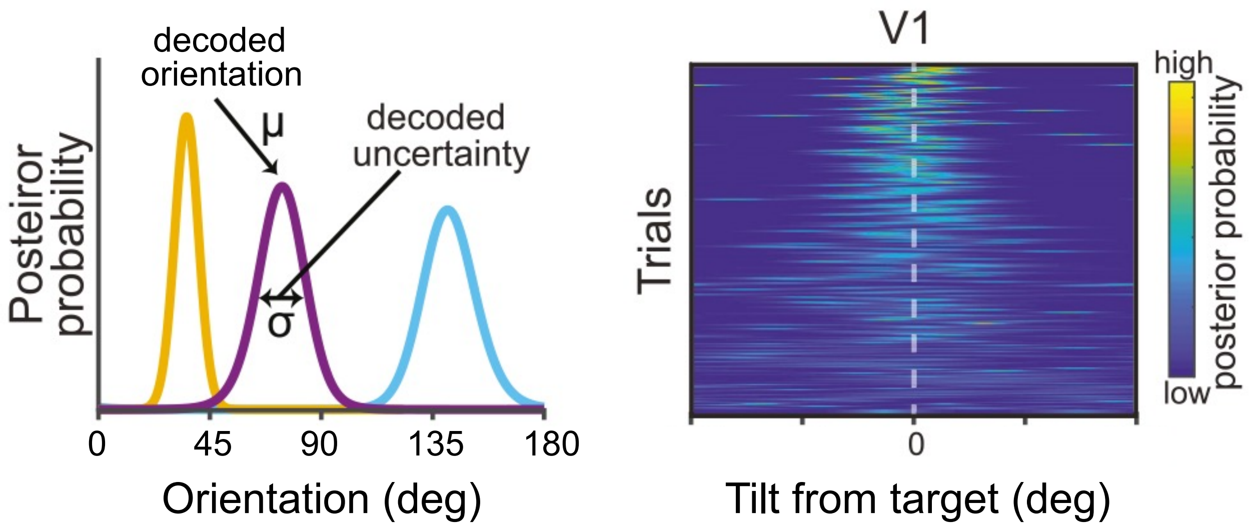

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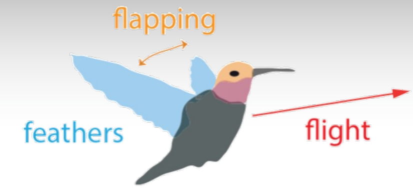
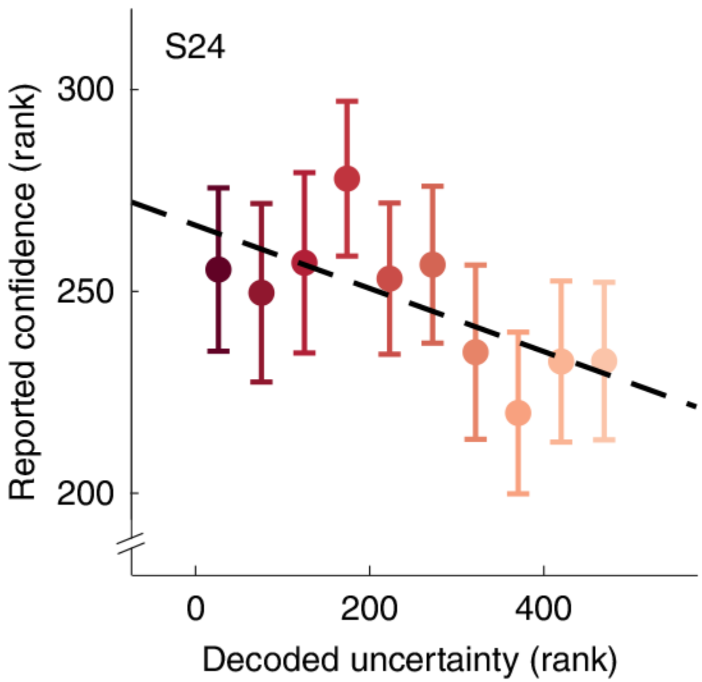
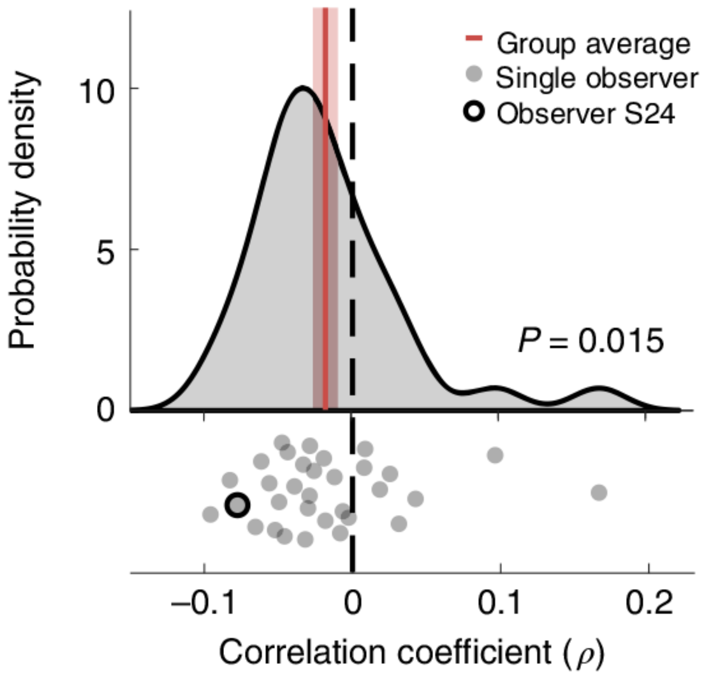


negative relation between Bayesian uncertainty and reported confidence





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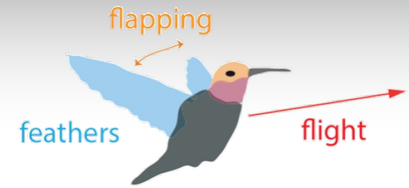
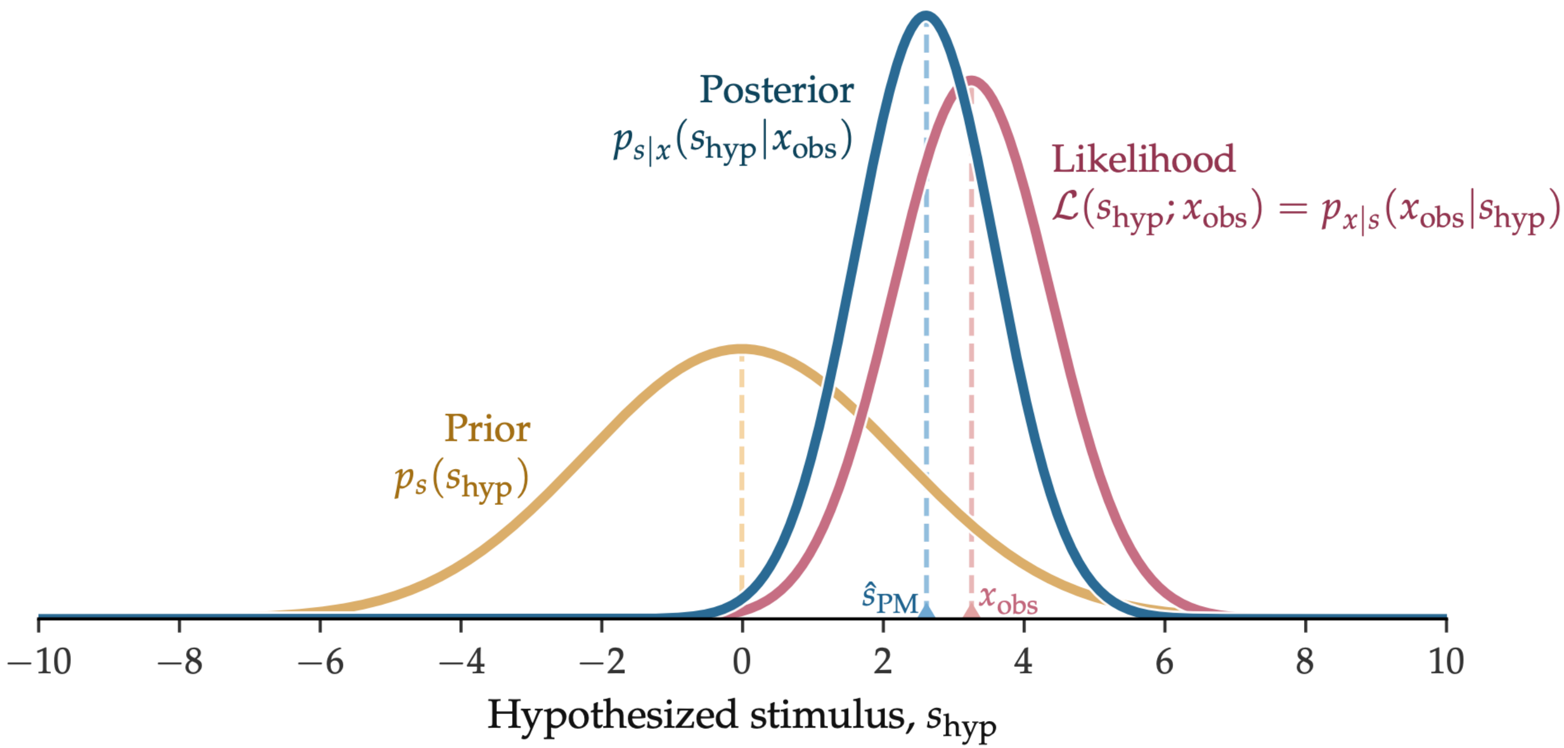
Bayesian models as cognitive algorithms 2



Bayesian models as <u>cognitive algorithms</u>

They define update rules for combining uncertain prior knowledge with uncertain evidence



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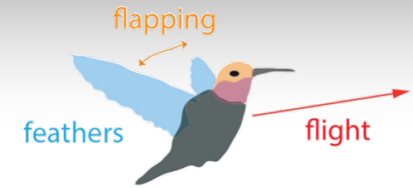
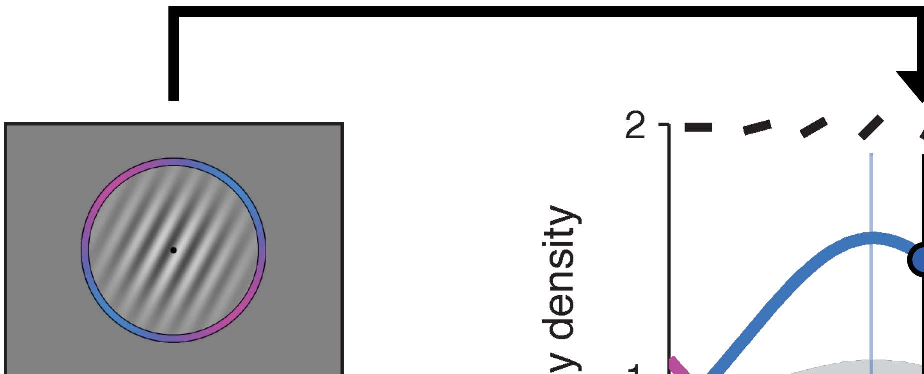
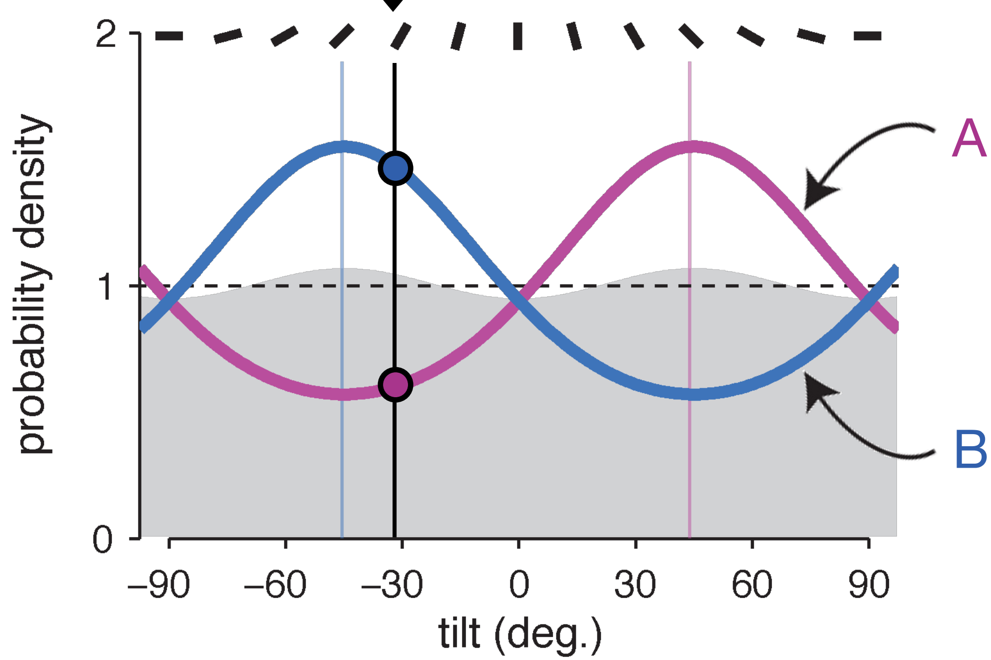




sample 1

$$\log\left(\frac{p(\theta_1 \mid \mathrm{A})}{p(\theta_1 \mid \mathrm{B})}\right)$$



Drugowitsch, Wyart et al. (2016) *Neuron*
Computational precision of inference as critical source of human choice suboptimality

Bayesian models as cognitive algorithms

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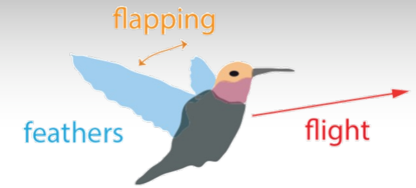

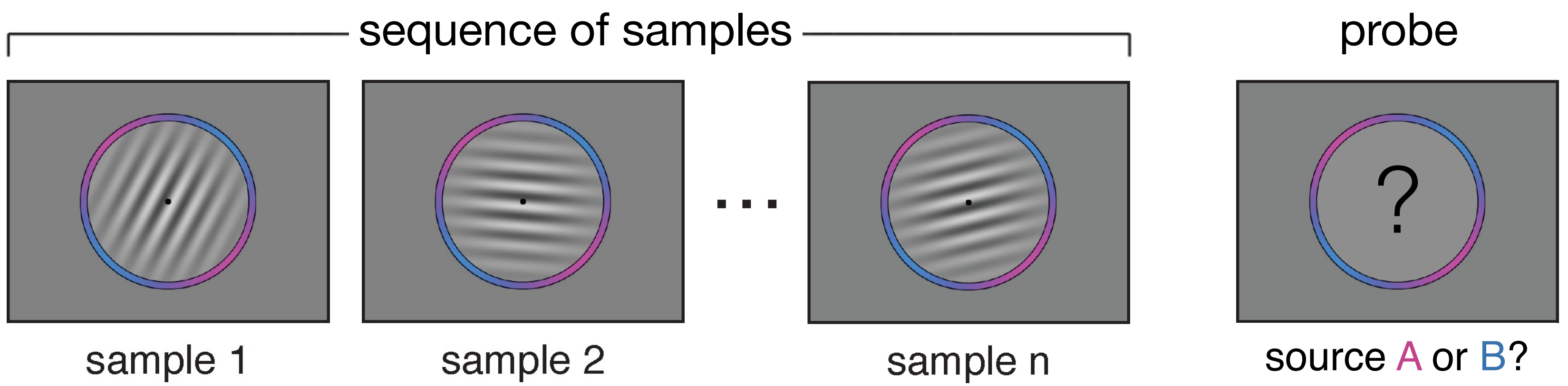

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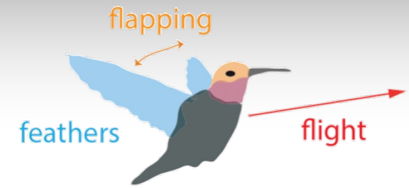

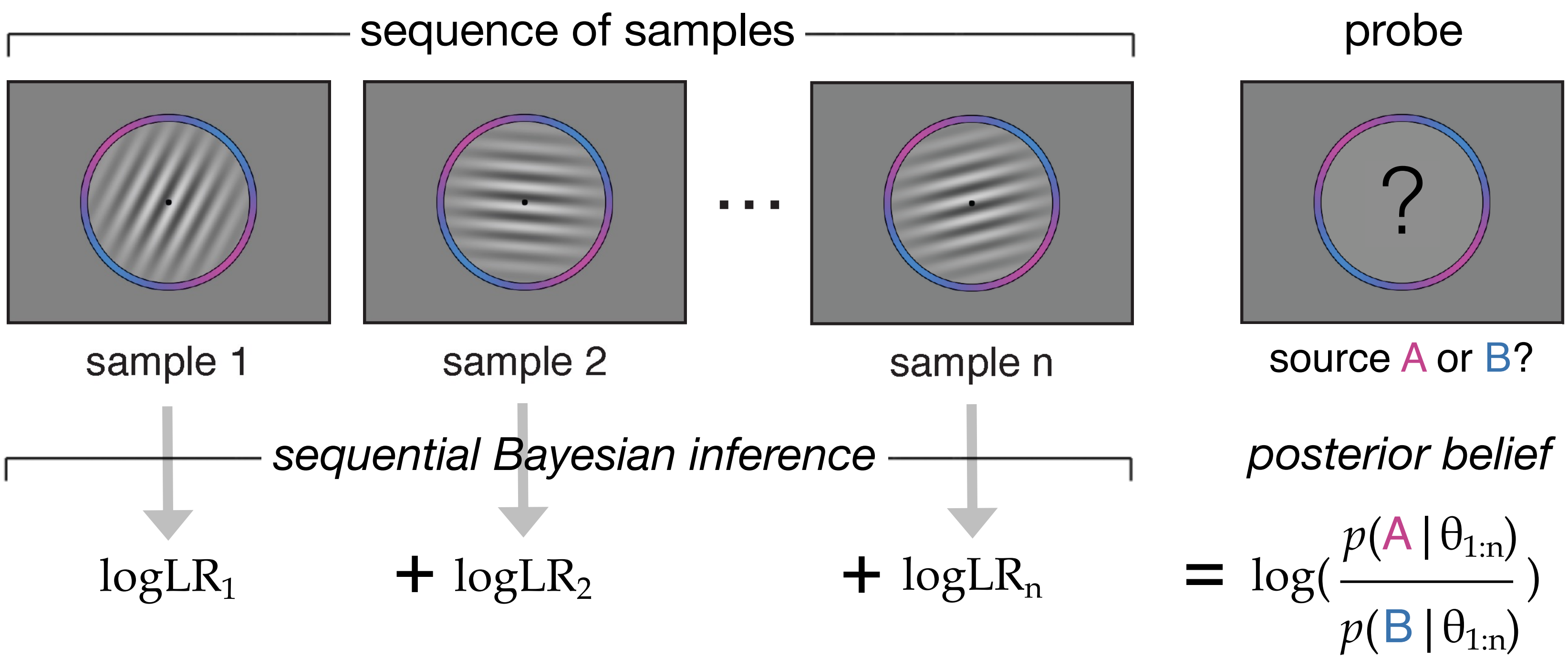

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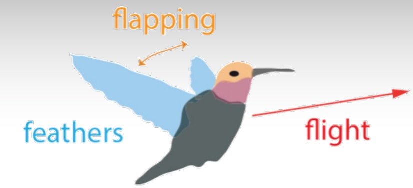

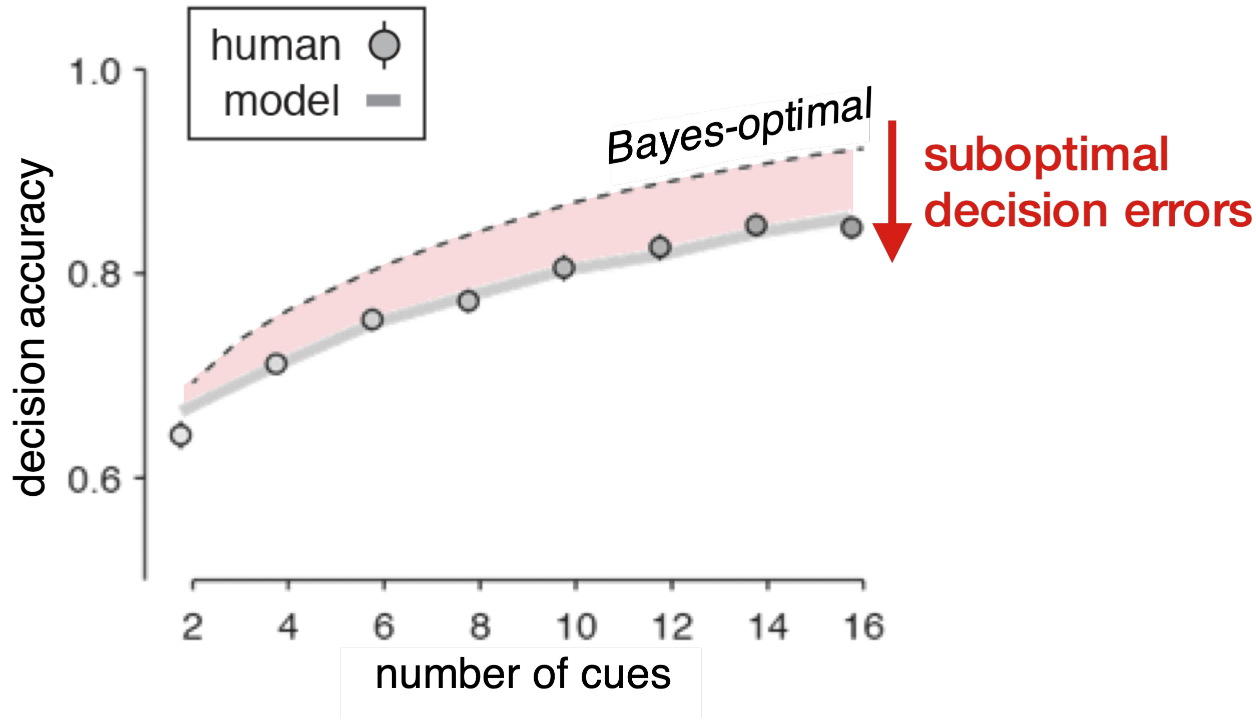

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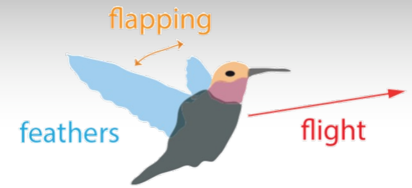
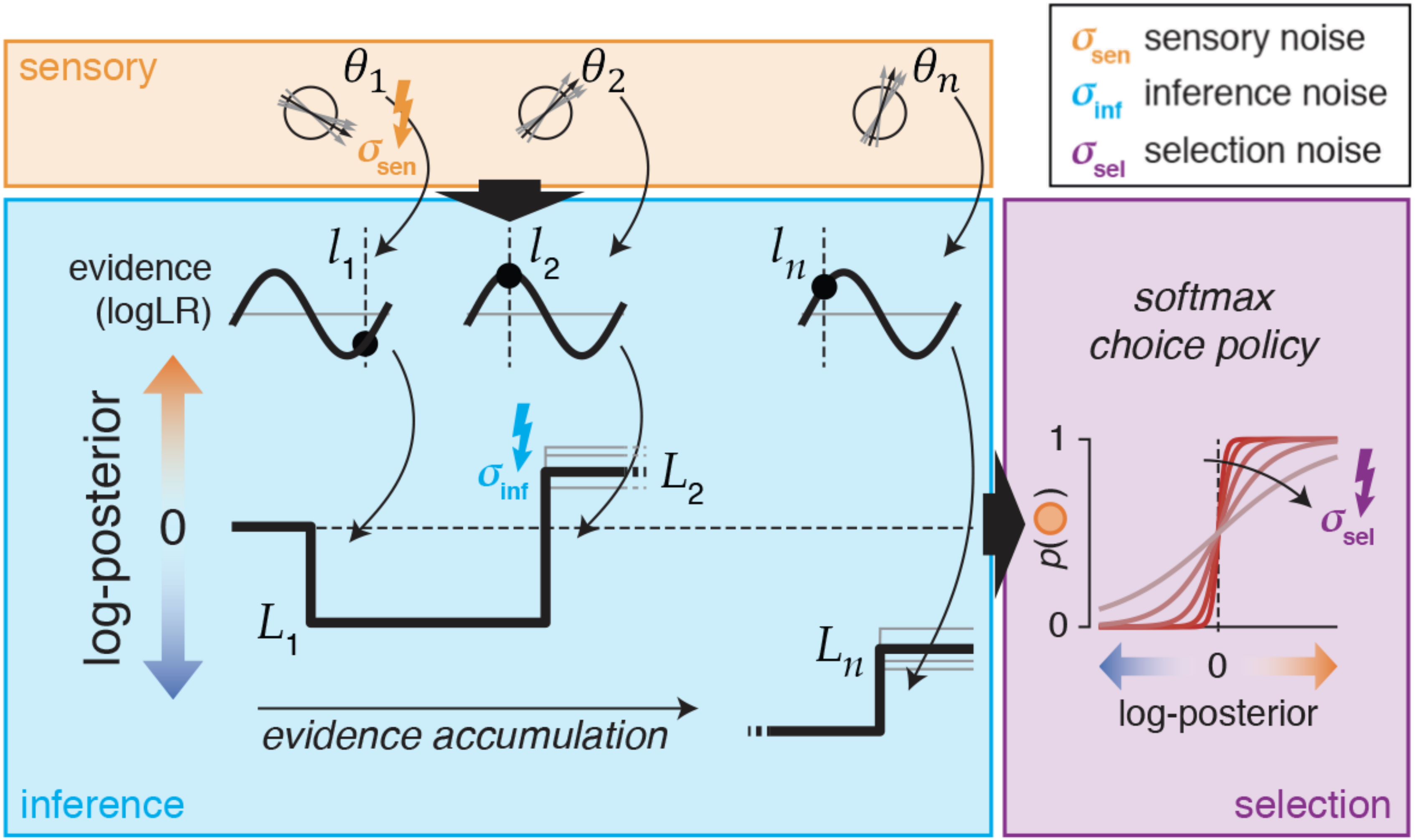


suboptimal Bayesian inference model



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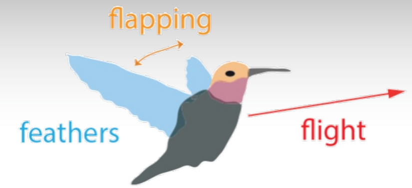

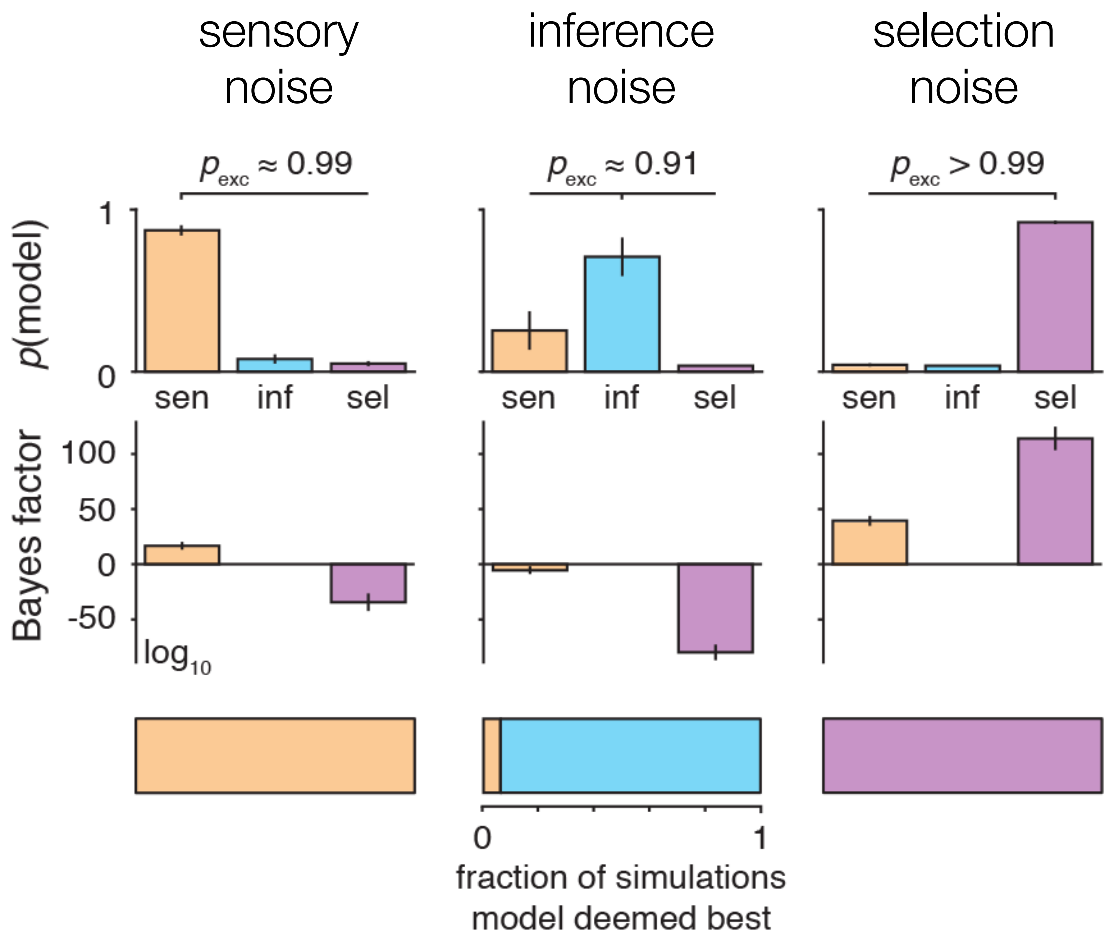

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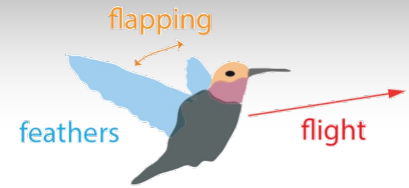

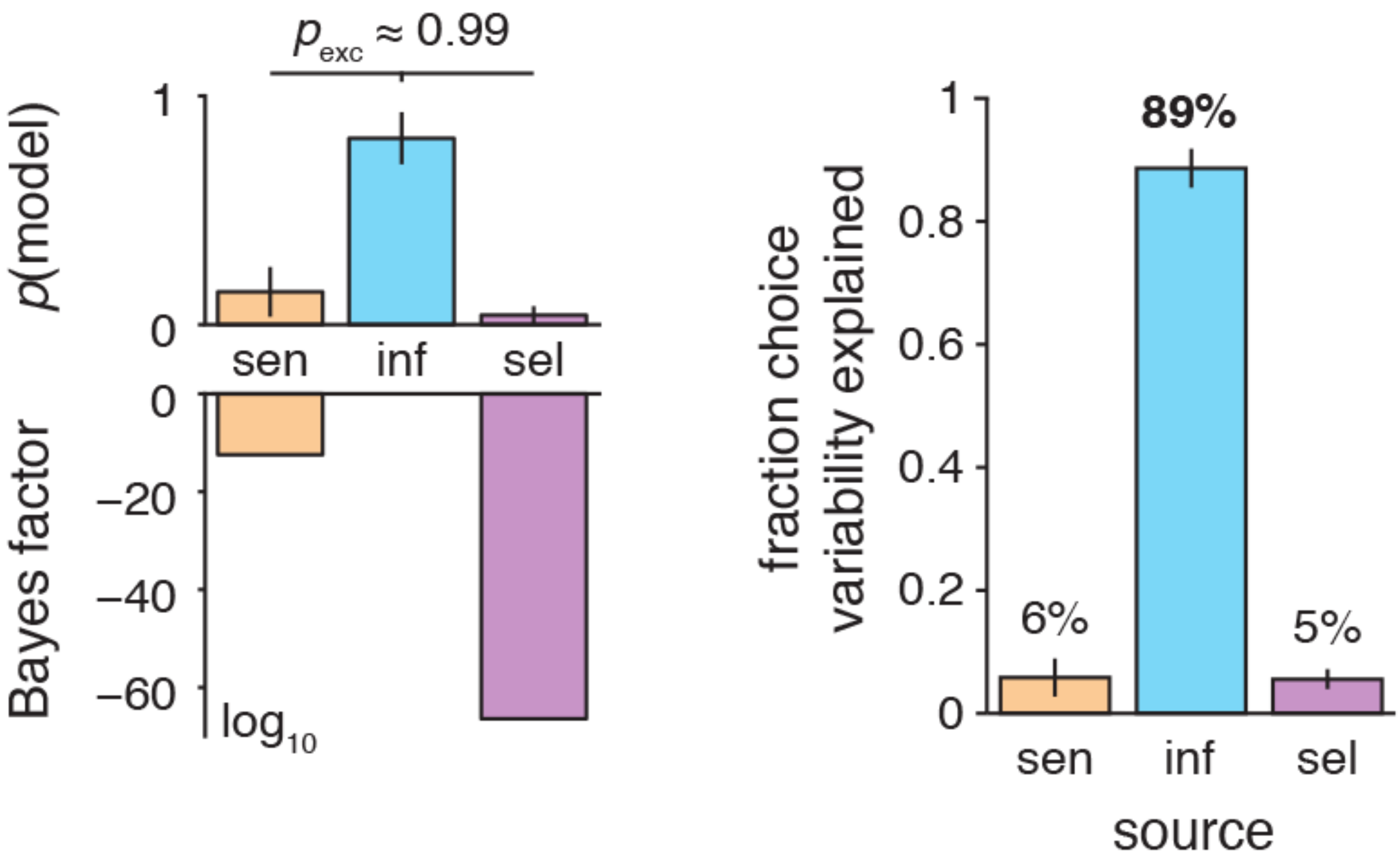

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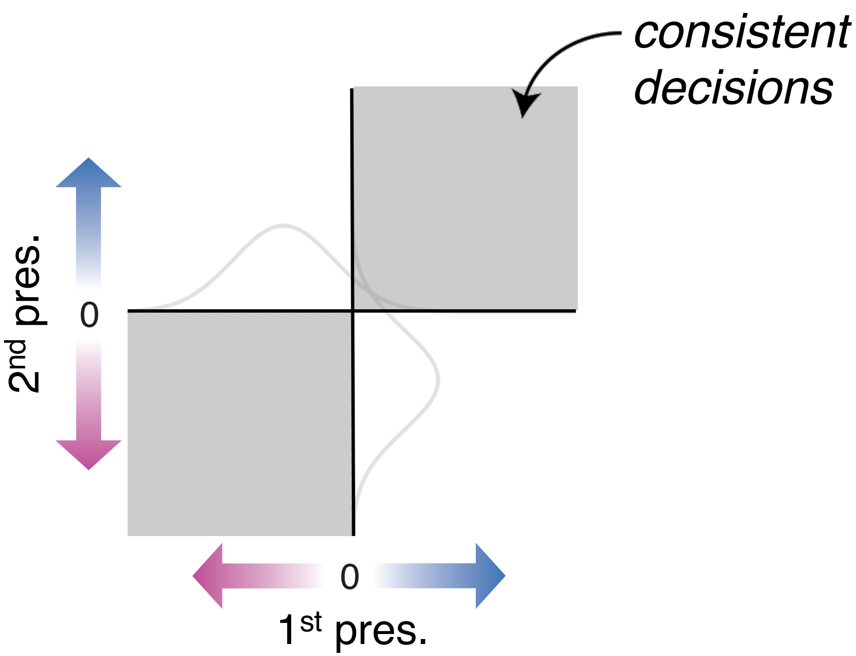
Bayesian models as cognitive algorithms

Bayes-optimal models can be used to quantify and qualify suboptimal human inferences



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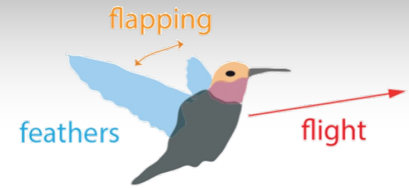

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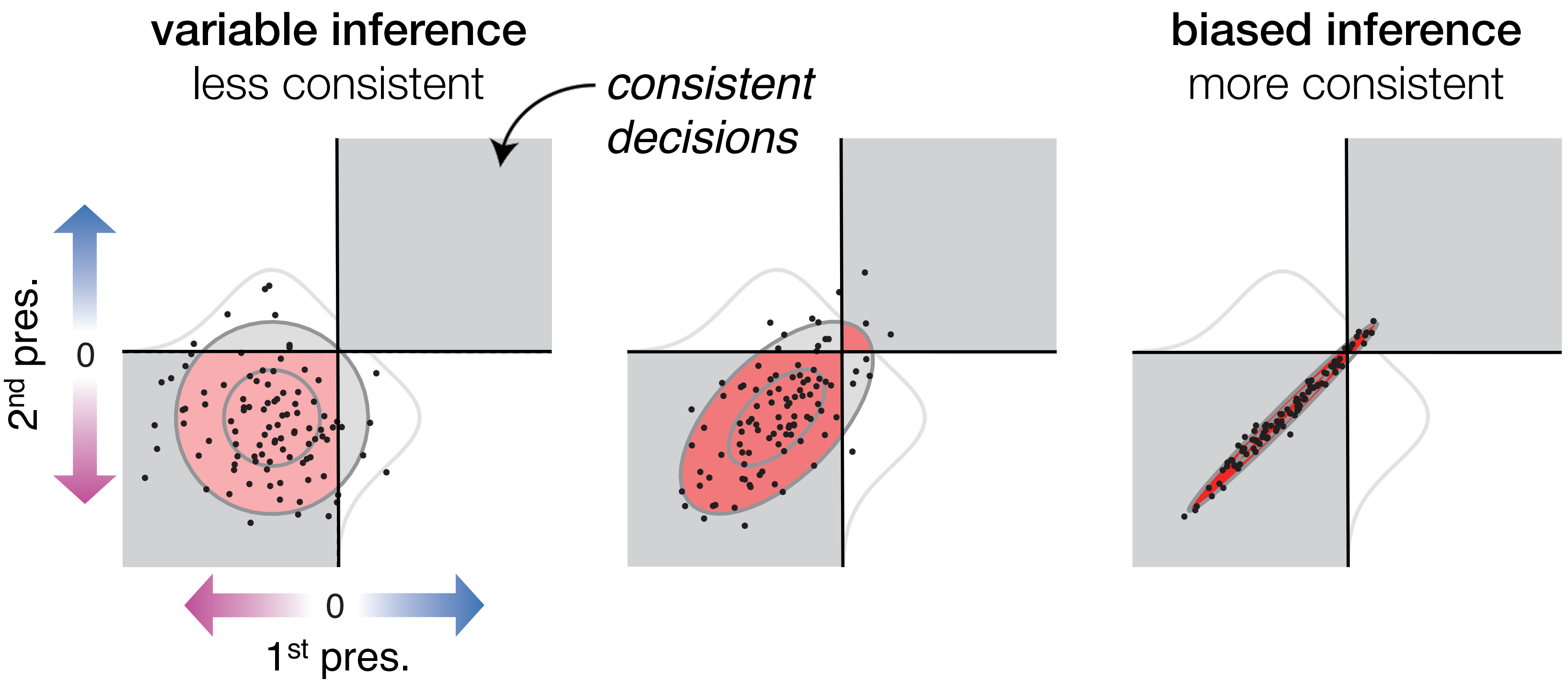

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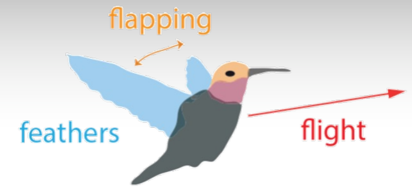
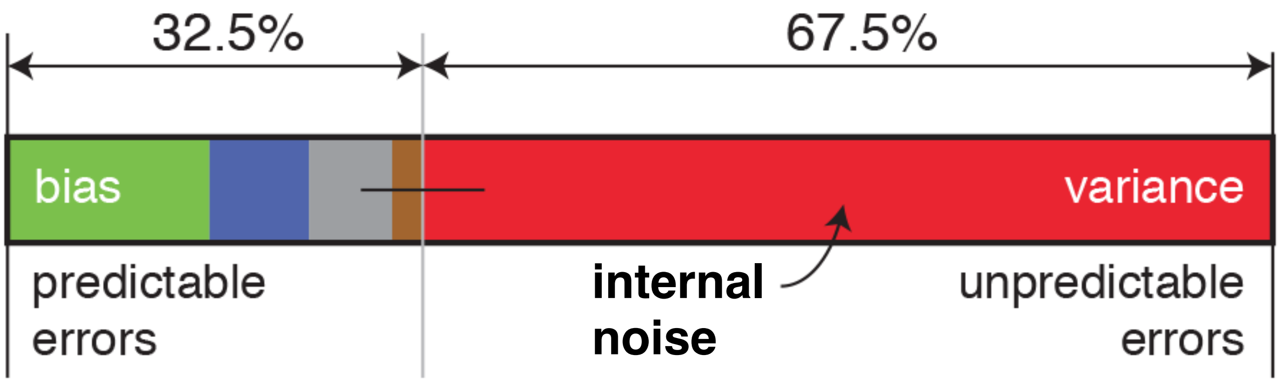
Bayesian models as cognitive algorithms

2



Bayes-optimal models can be used to quantify and qualify suboptimal human inferences



Drugowitsch, Wyart et al. (2016) *Neuron*
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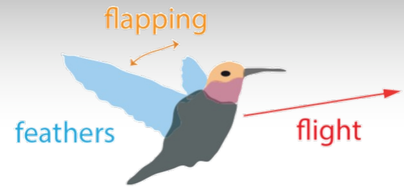
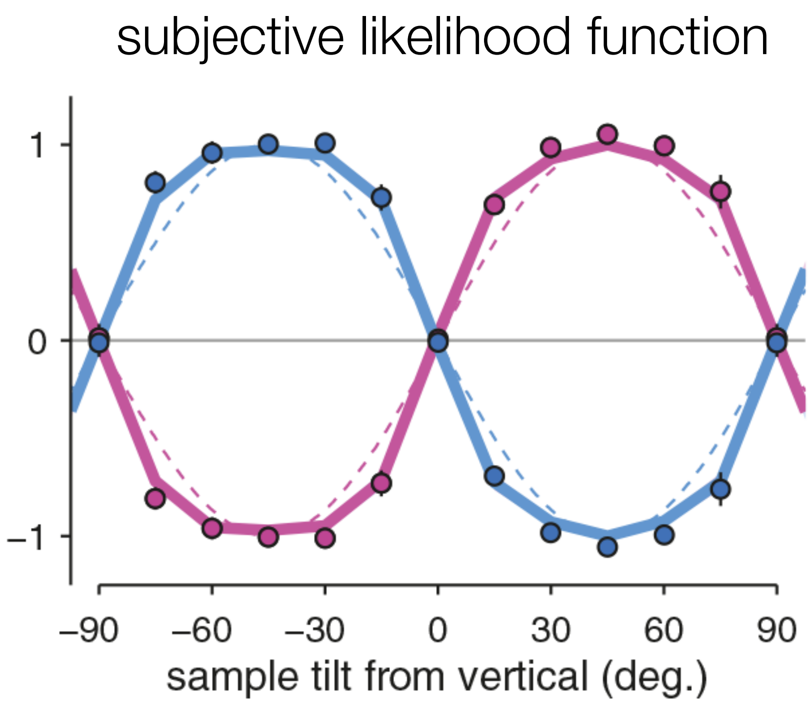
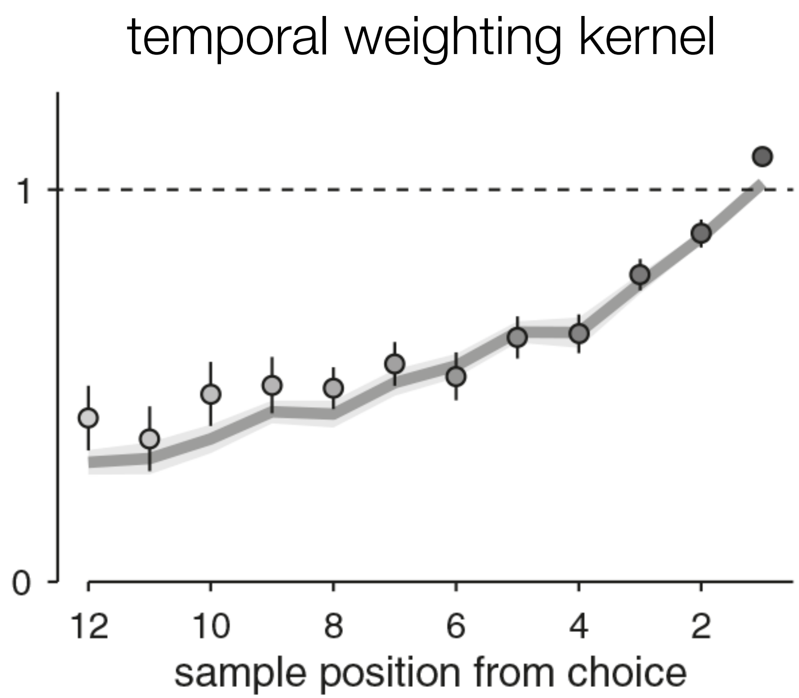


Bayes-optimal models can be used to quantify and qualify suboptimal human inferences





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Bayesian models as cognitive algorithms

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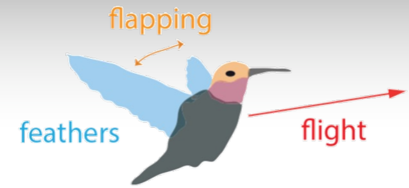
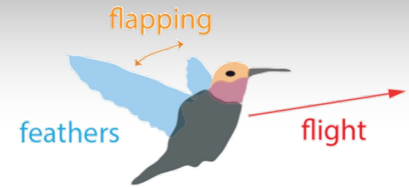
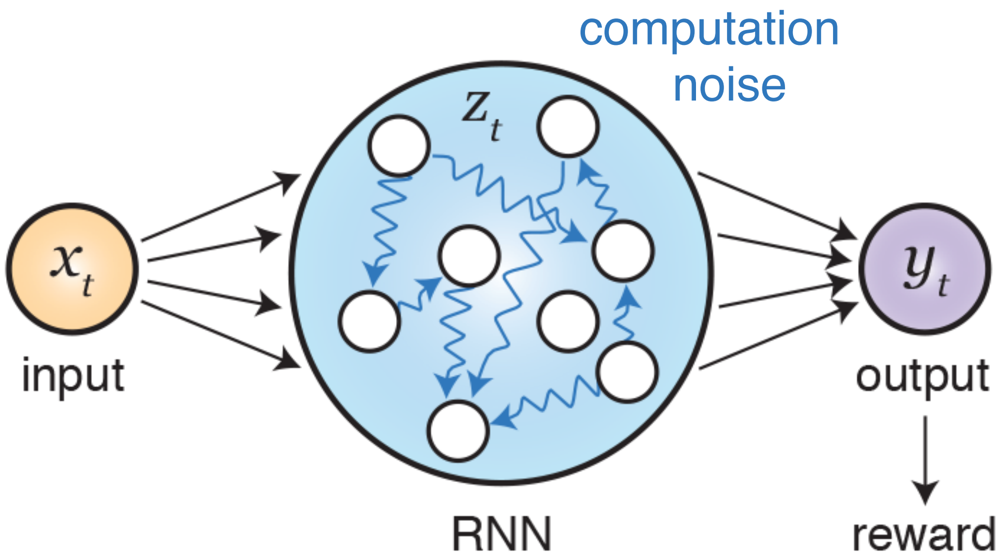


Charles Findling
Geneva University

Findling and Wyart (2020) *bioRxiv*
Computation noise promotes training-free adaptation to uncertainty in RNNs

Bayesian models as cognitive algorithms 2





network dynamics

$$\widehat{z}_t = W \cdot z_{t-1} + U \cdot x_t + b$$

$$z_t = \sigma_z(\mathcal{N}(\widehat{z}_t\,,\ \sigma))$$

computation noise level

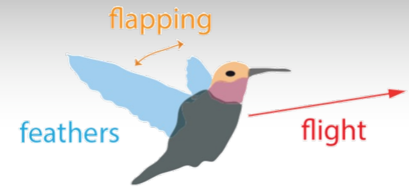
objective function

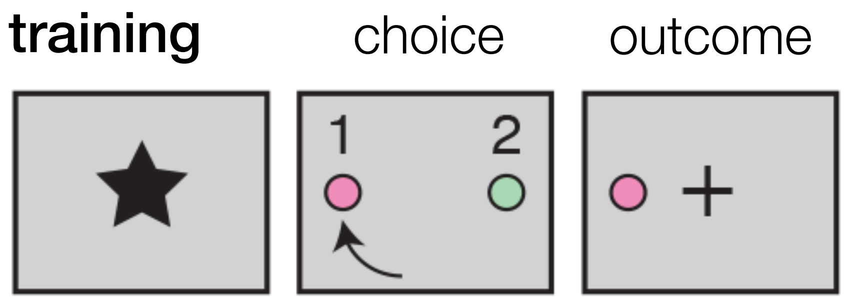
$$y_t = \sigma_y(V \cdot z_t)$$

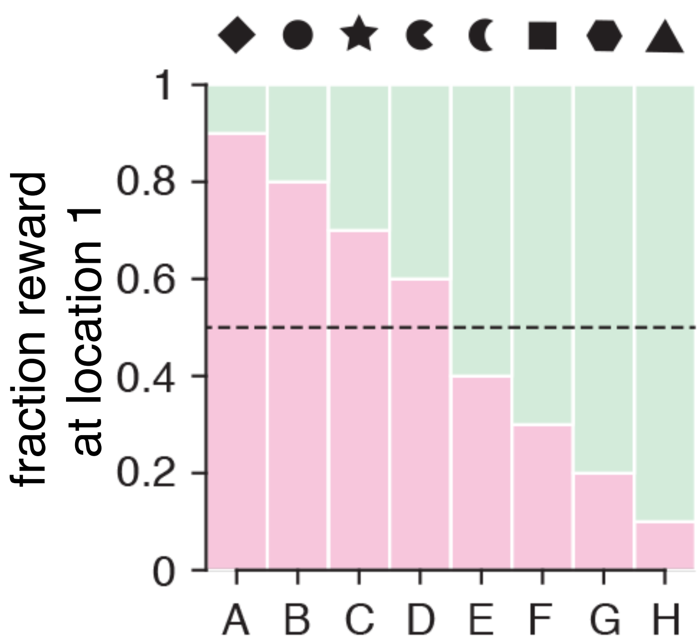
$$L(U, V, W, b) = \mathbb{E}^{\pi}[r]$$

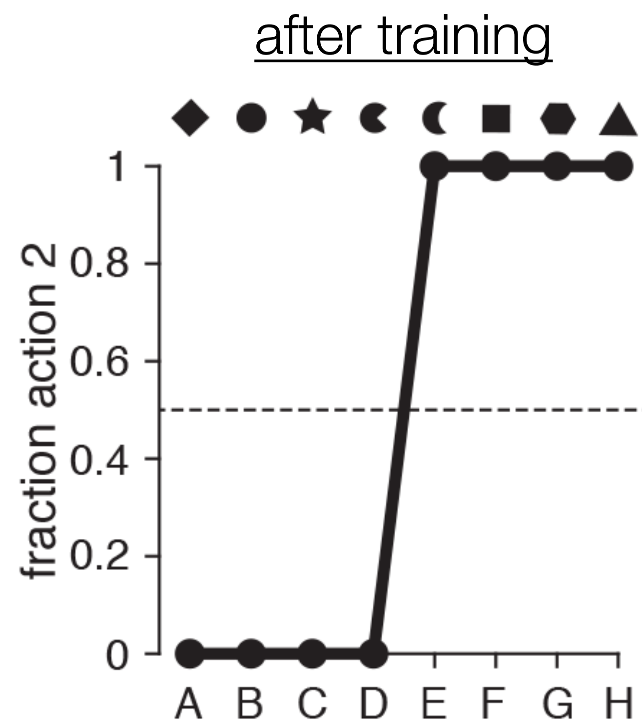
Findling and Wyart (2020) *bioRxiv*
Computation noise promotes training-free adaptation to uncertainty in RNNs

Bayesian models as cognitive algorithms 2









Findling and Wyart (2020) *bioRxiv*
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Bayesian models as cognitive algorithms

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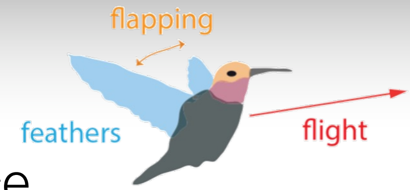

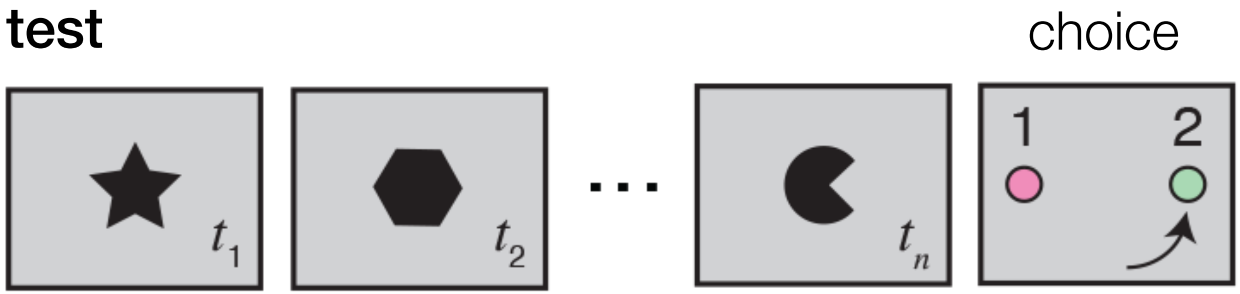

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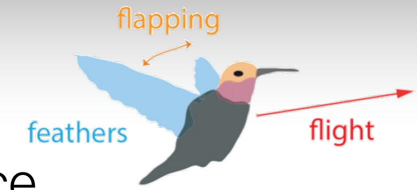
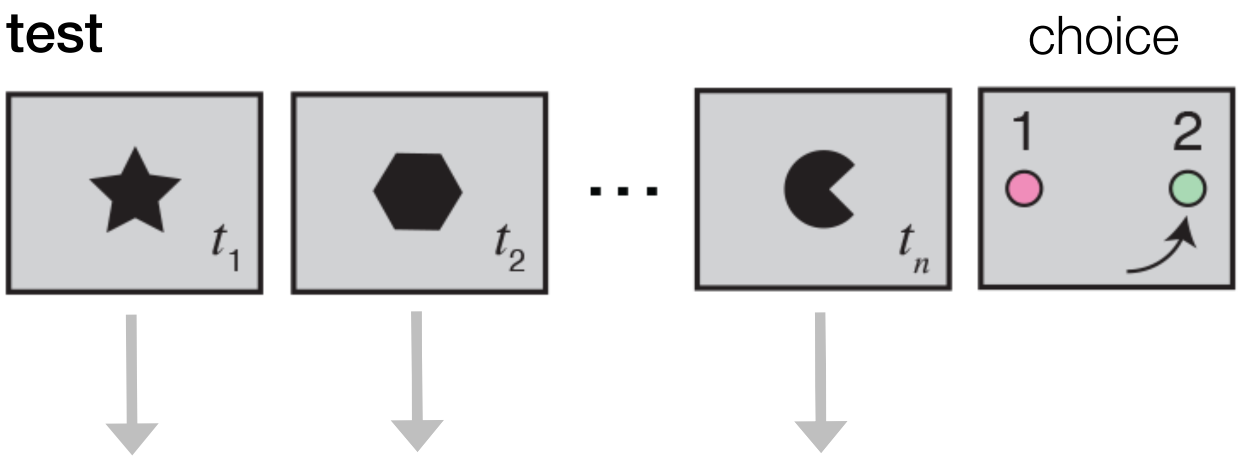




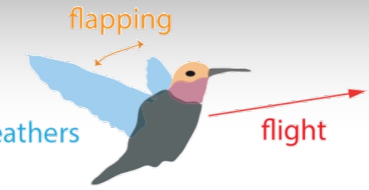
$$\log LR_1 + \log LR_2 + \log LR_n = \log PR$$

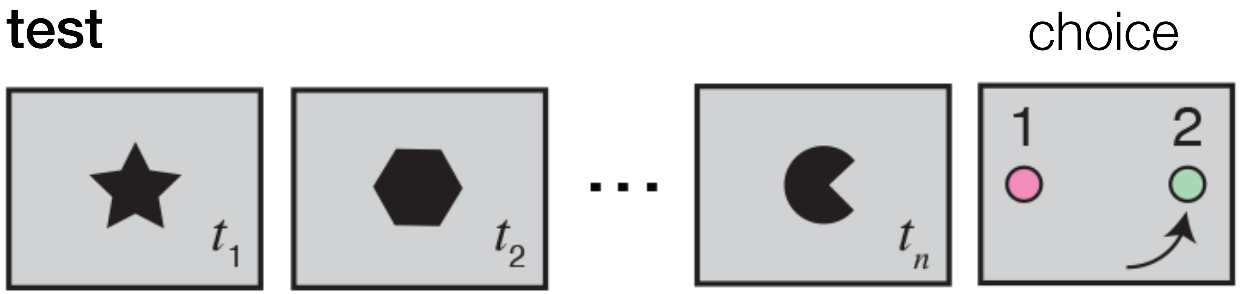
log-likelihood odds ratio

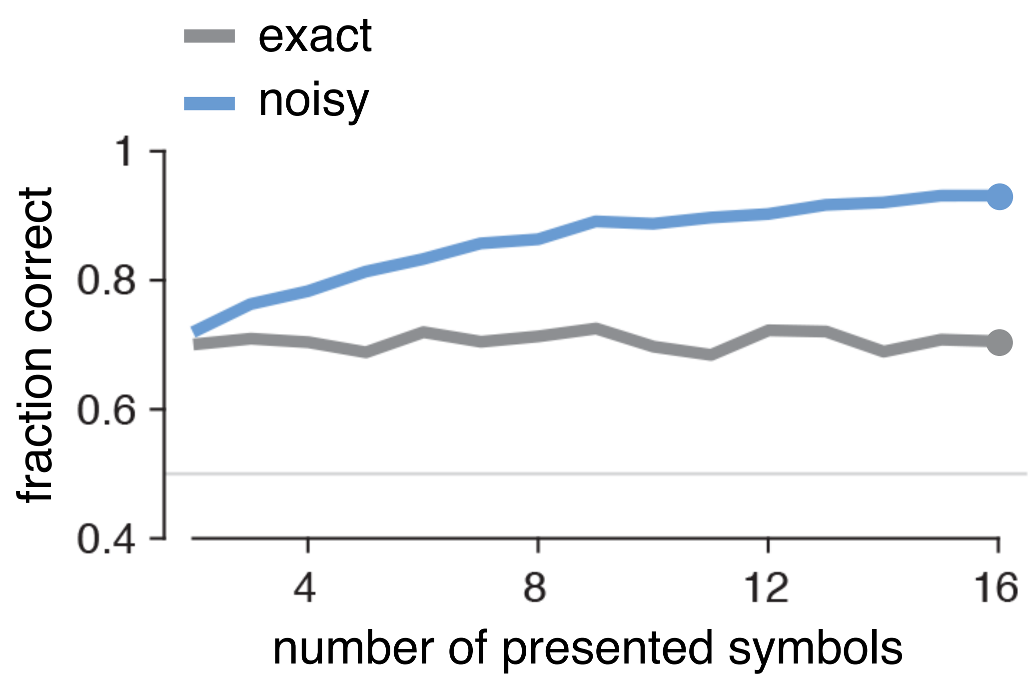
log-posterior odds ratio

Findling and Wyart (2020) *bioRxiv*
Computation noise promotes training-free adaptation to uncertainty in RNNs

Bayesian models as cognitive algorithms 2







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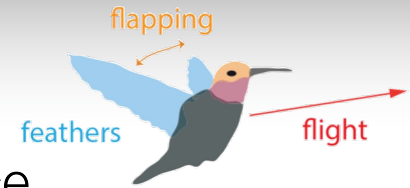

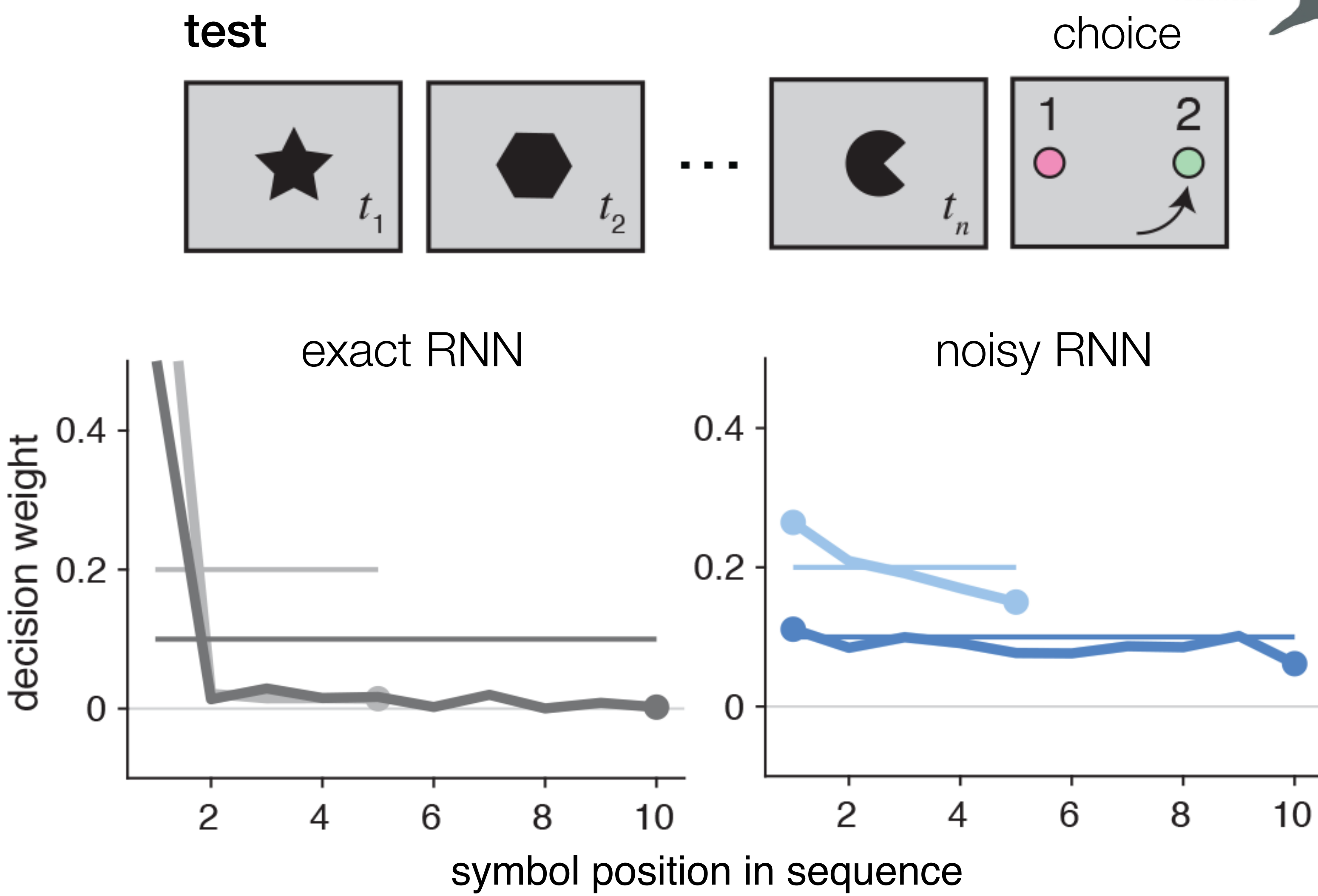

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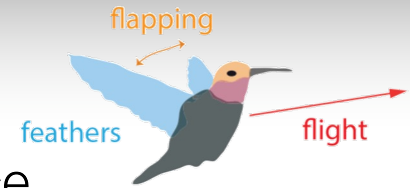

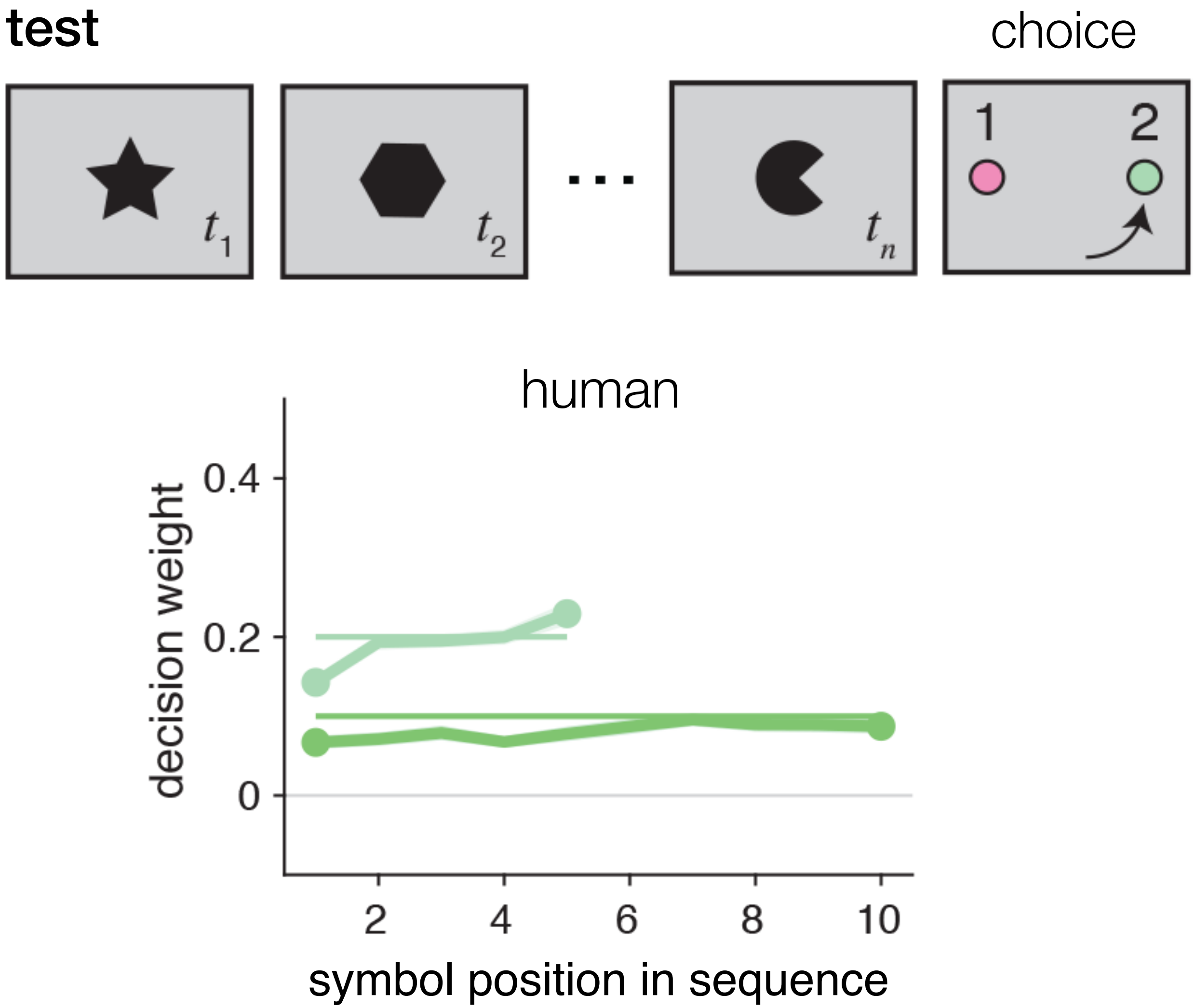

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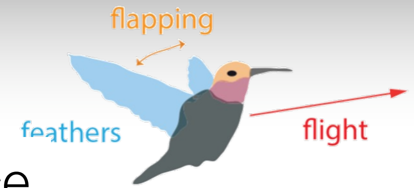

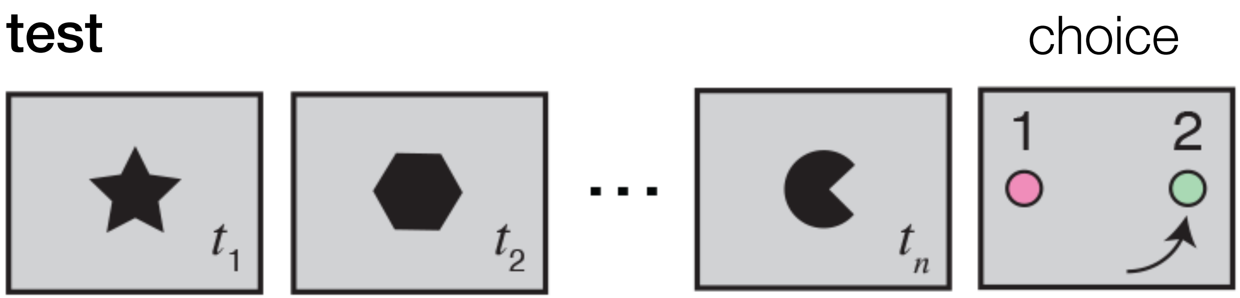

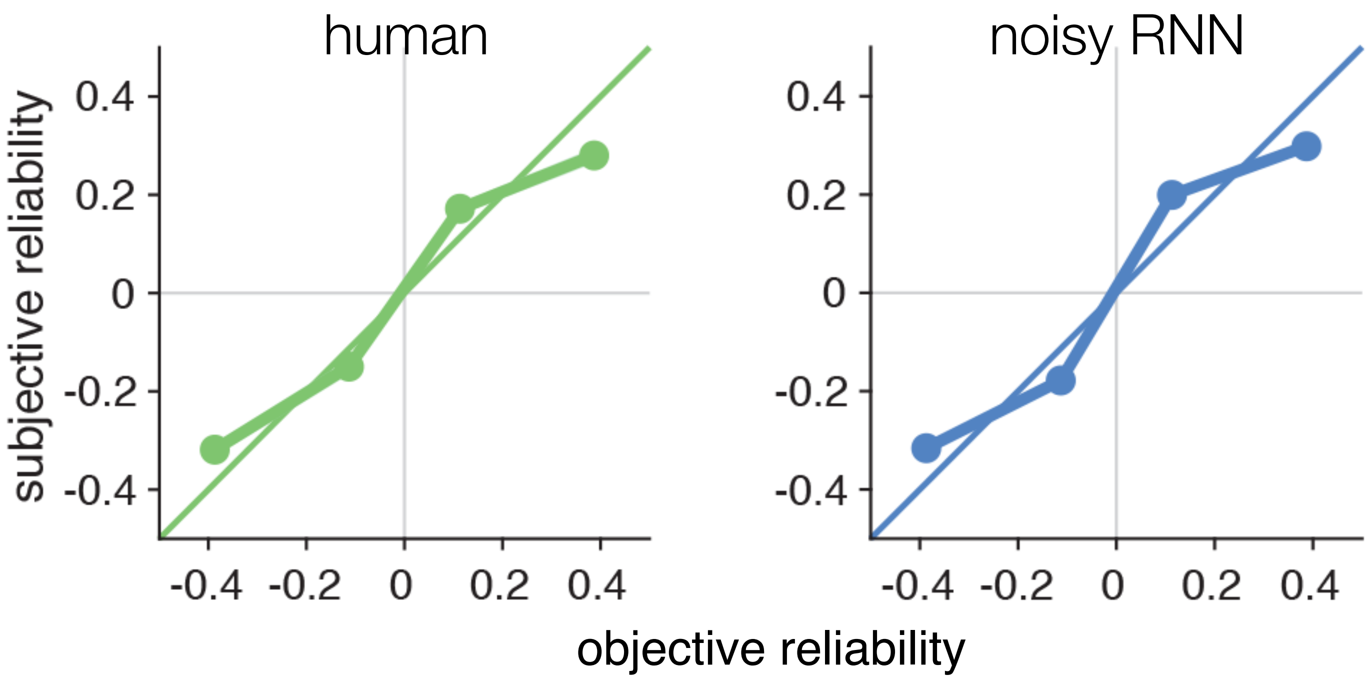

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Why Bayesian modeling?

Bayesian models provide the normative solution to dealing with probabilistic uncertainty

Bayesian models have behavioral signatures (such as the reliability-dependent weighting of evidence) that can be looked for in behavior

Bayesian models can be used to explain apparent biases (such as the cardinal bias) as rational

Bayesian models can be leveraged to quantify and qualify suboptimal inferences

Beyond brain mapping

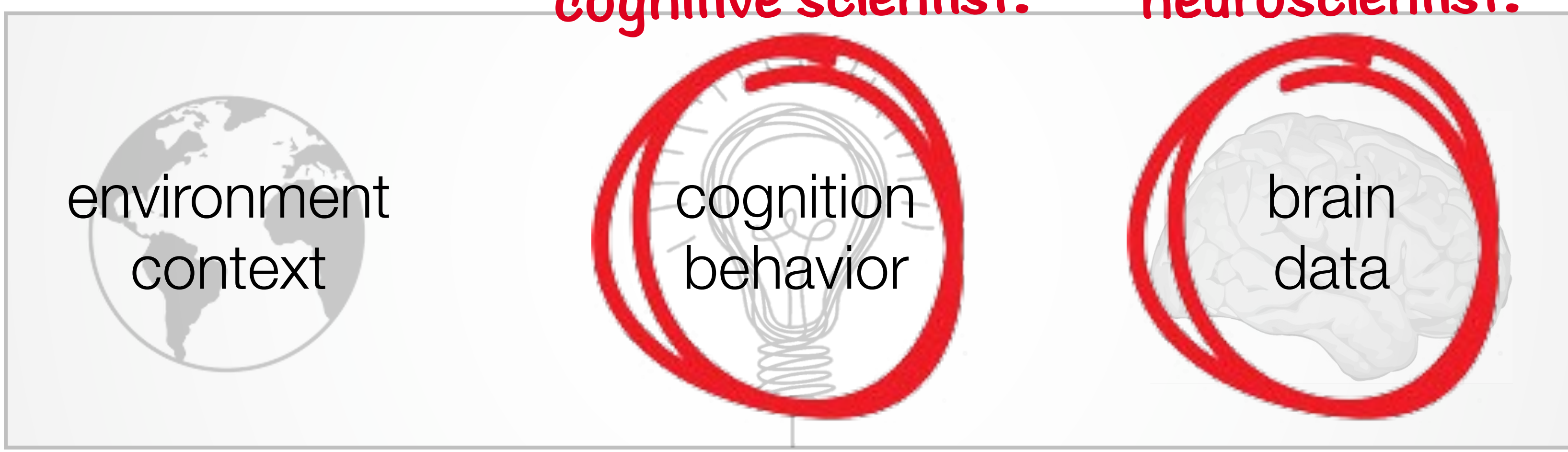
What kind of cognitive neuroscientist are you?

Goal A: understand how the brain works

Goal B: understand cognition and behavior

You are a cognitive scientist!

You are a neuroscientist!

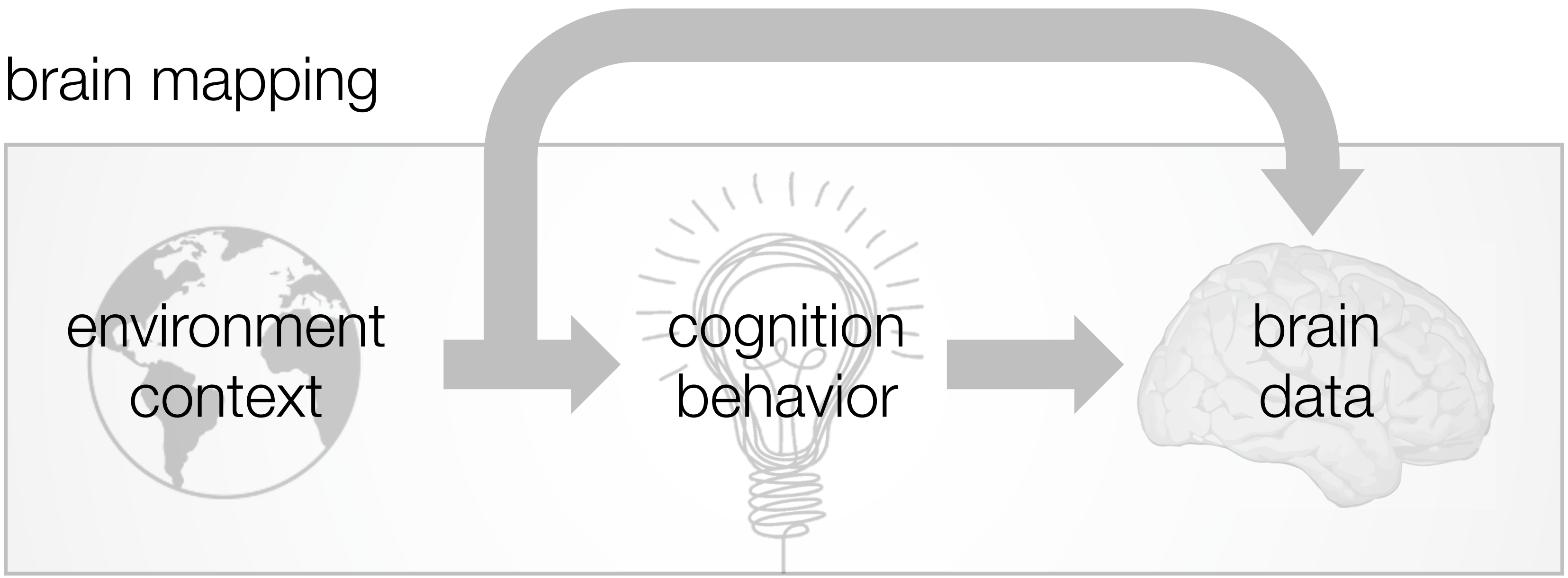


Beyond brain mapping

Brain mapping treats brain data as the <u>dependent variable</u> (to be explained).

But brain data should rather be seen as <u>mediating cognition and behavior</u>.

brain mapping



Beyond brain mapping

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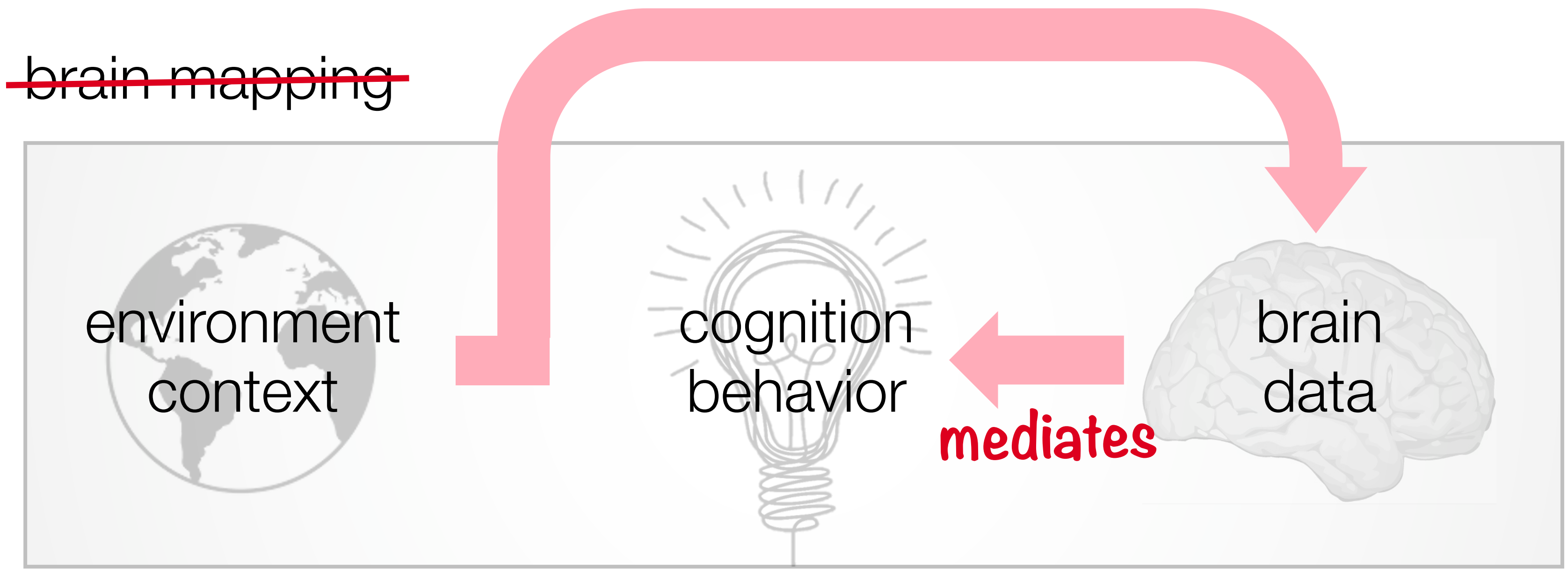
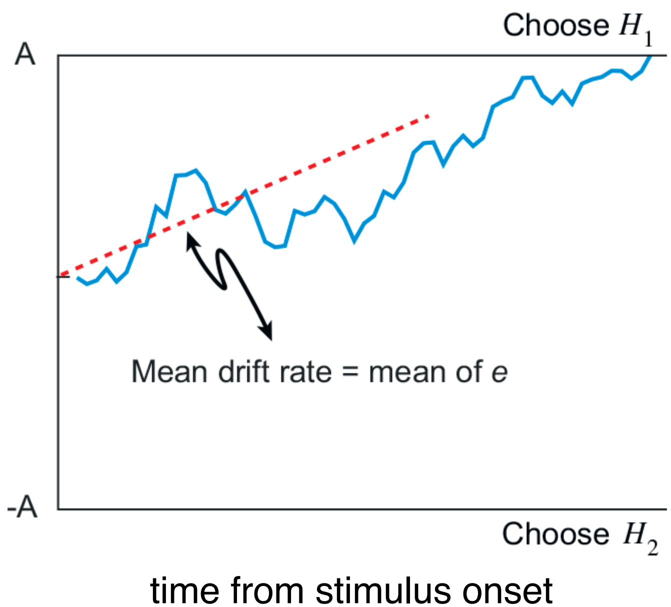


Beyond brain mapping

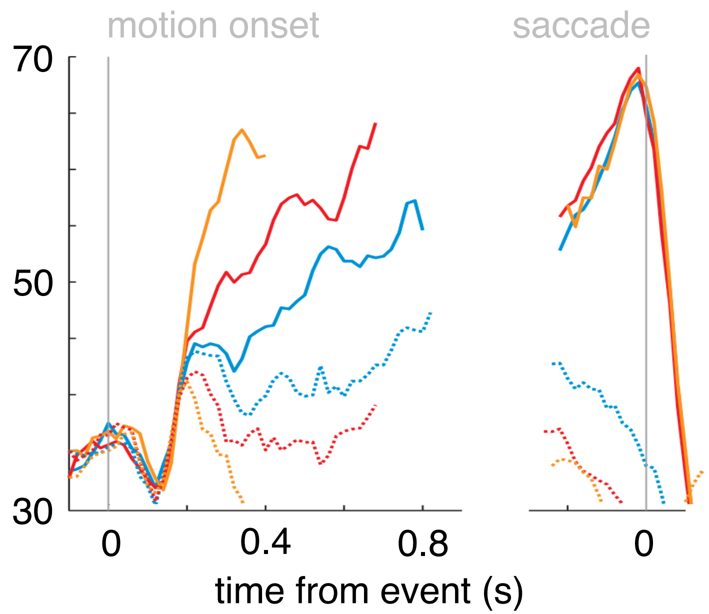
drift-diffusion model
(algorithm)

2



LIP spiking activity
(implementation)

3



Beyond brain mapping

If you are a neuroscientist, then you want 3
but you need to know 2 first.

If you are a cognitive scientist, then you want 2
but you can use 3 to validate 2.

In both cases, studying which **algorithm** is used
is necessary to look for its **implementation**.

Krakauer et al. (2016) *Neuron*
Neuroscience needs behavior: correcting a reductionist bias

Beyond brain mapping

American Psychological Association

Behavioral Neuroscience

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COMMENTARY

The Primacy of Behavioral Research for Understanding the Brain

Yael Niv
Department of Psychology and Neuroscience Institute, Princeton University

Understanding the brain requires us to answer both *what* the brain does, and *how* it does it. Using a series of examples, I make the case that behavior is often more useful than neuroscientific measurements for answering the first question.[1] Moreover, I show that even for "how" questions that pertain to neural mechanism, a well-crafted behavioral paradigm can offer deeper insight and stronger constraints on computational and mechanistic models than do many highly challenging (and very expensive) neural studies. I conclude that purely behavioral research is essential for understanding the brain—especially its cognitive functions—contrary to the opinion of prominent funding bodies and some scientific journals, who erroneously place neural data on a pedestal and consider behavior to be subsidiary.

Keywords: behavioral experiments, cognition, neuroscience, priorities

In an era of increasingly precise methods for measuring and perturbing neurons in the brain, it often seems that with more neural data, we will soon make untold breakthroughs in understanding the brain. Such anticipation has heralded neuroscience-data-focused projects such as the Brain Initiative and the Human Connectome Project. The focus on neural measurement has been accompanied by the demotion of animal and human behavioral research—the mainstays of psychology from where understanding of the brain and

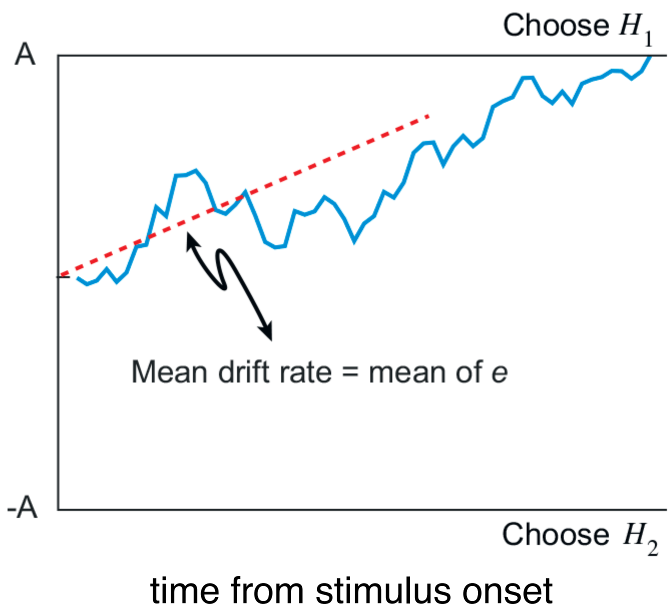
looking at single neurons, or even their ensembles, is like attempting to understand why people in Australia drive on the left side of the road from examination of their DNA. Neural firing patterns are the wrong level for investigating many pressing questions in neuroscience. Even if we could measure all the neurons in the brain with arbitrary precision, without an incisive behavioral paradigm we would not be able to answer many neuroscientific questions. Indeed, the insights about the brain that my lab has gleaned from our own research have almost all come from behavioral data, which explains

Beyond brain mapping

Example: decision as accumulation-to-bound

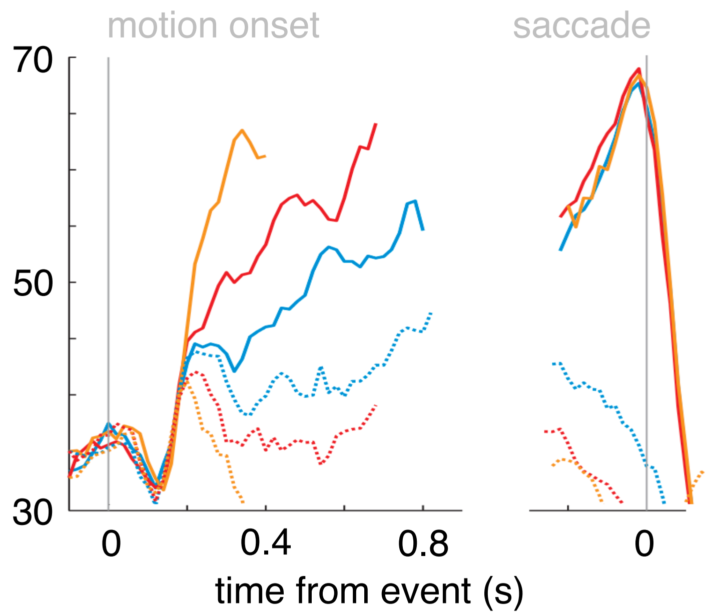
algorithm

Ratcliff (1978)
Psychological Review



implementation

Roitman and Shadlen (2002)
Journal of Neuroscience



Beyond brain mapping

Behavior alone can inform about the algorithms used by the brain to solve complex tasks.

Brain data can be used as additional observables for understanding cognition and behavior.

Case studies where we have used this approach for understanding human decision-making with different types of brain data.

Case study 1: covert bound on decision-making

Tarryn Balsdon
Glasgow University

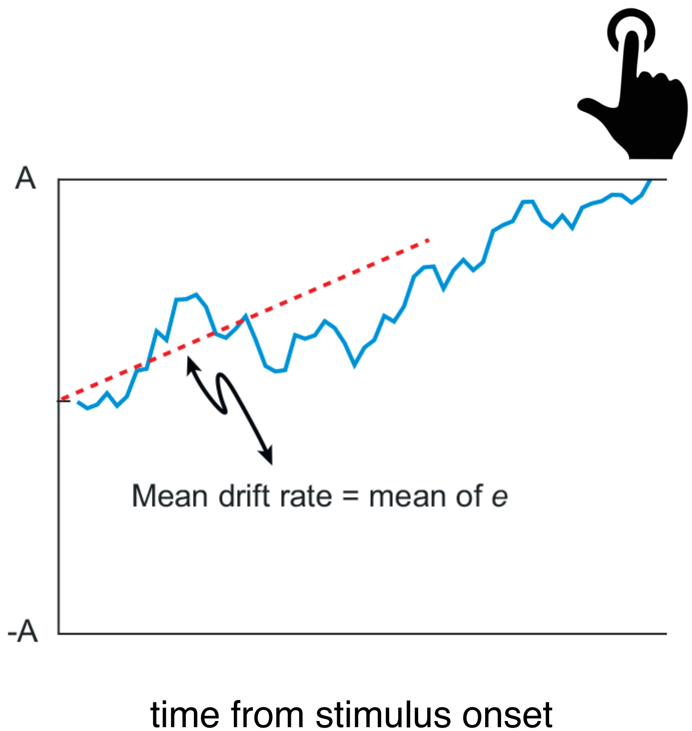
Pascal Mamassian
Ecole Normale Supérieure

Balsdon, Wyart and Mamassian (2020) *Nature Communications*
Confidence controls perceptual evidence accumulation

<u>Case study 1:</u> covert bound on decision-making

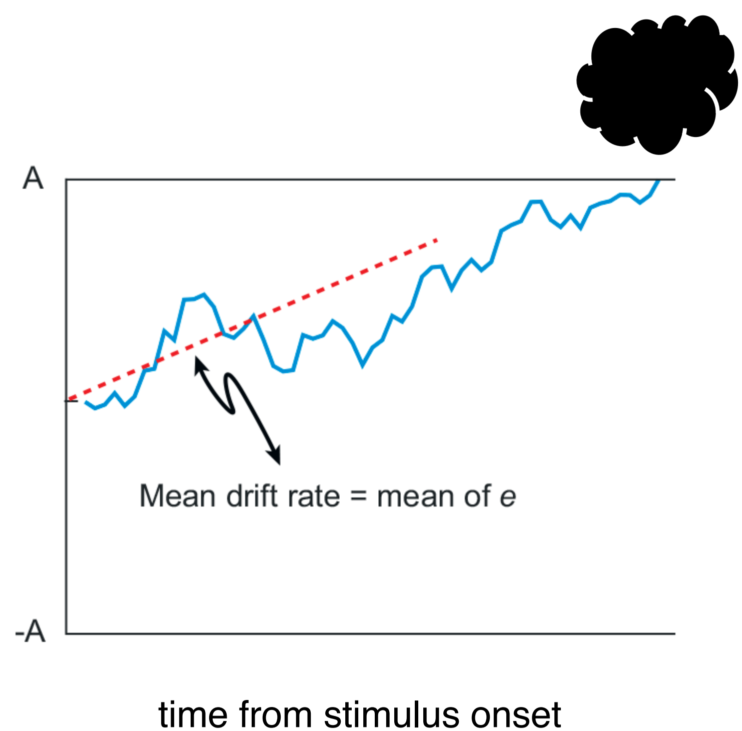
motor response

<u>overt</u> decision bound



mental commitment

<u>covert</u> decision bound



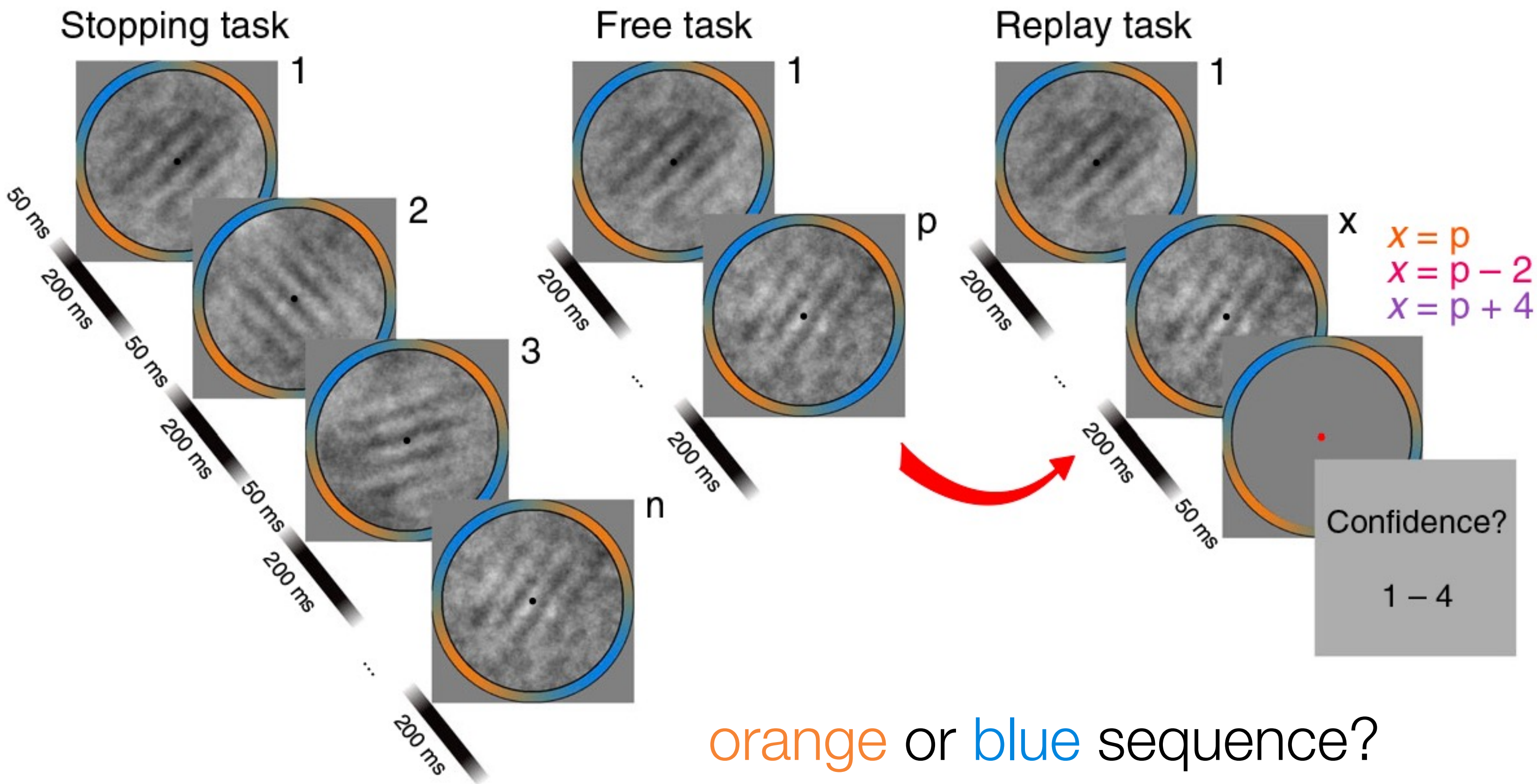
Balsdon, Wyart and Mamassian (2020) *Nature Communications*
Confidence controls perceptual evidence accumulation

<u>Case study 1:</u> covert bound on decision-making

<u>Brain data:</u> pupil dilation

Balsdon, Wyart and Mamassian (2020) *Nature Communications*
Confidence controls perceptual evidence accumulation

Case study 1: covert bound on decision-making



orange or blue sequence?

Balsdon, Wyart and Mamassian (2020) *Nature Communications*
Confidence controls perceptual evidence accumulation

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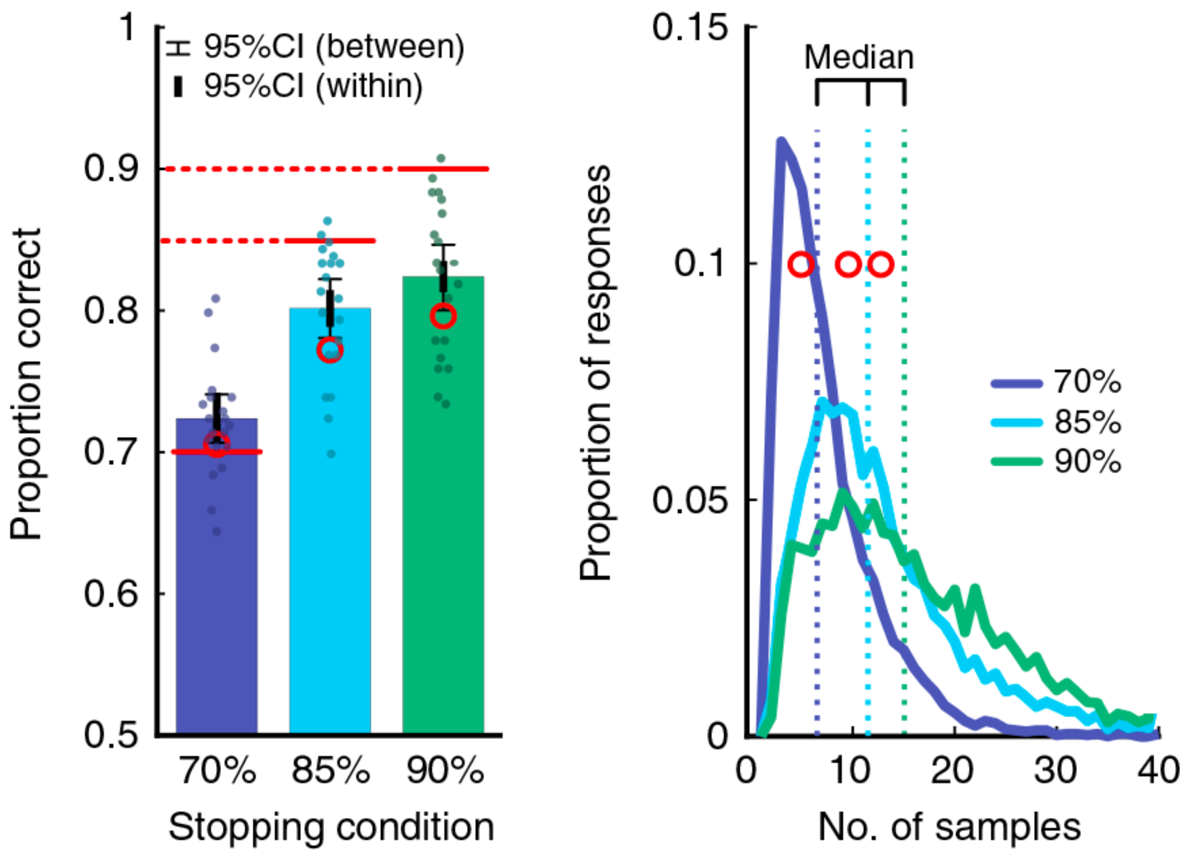

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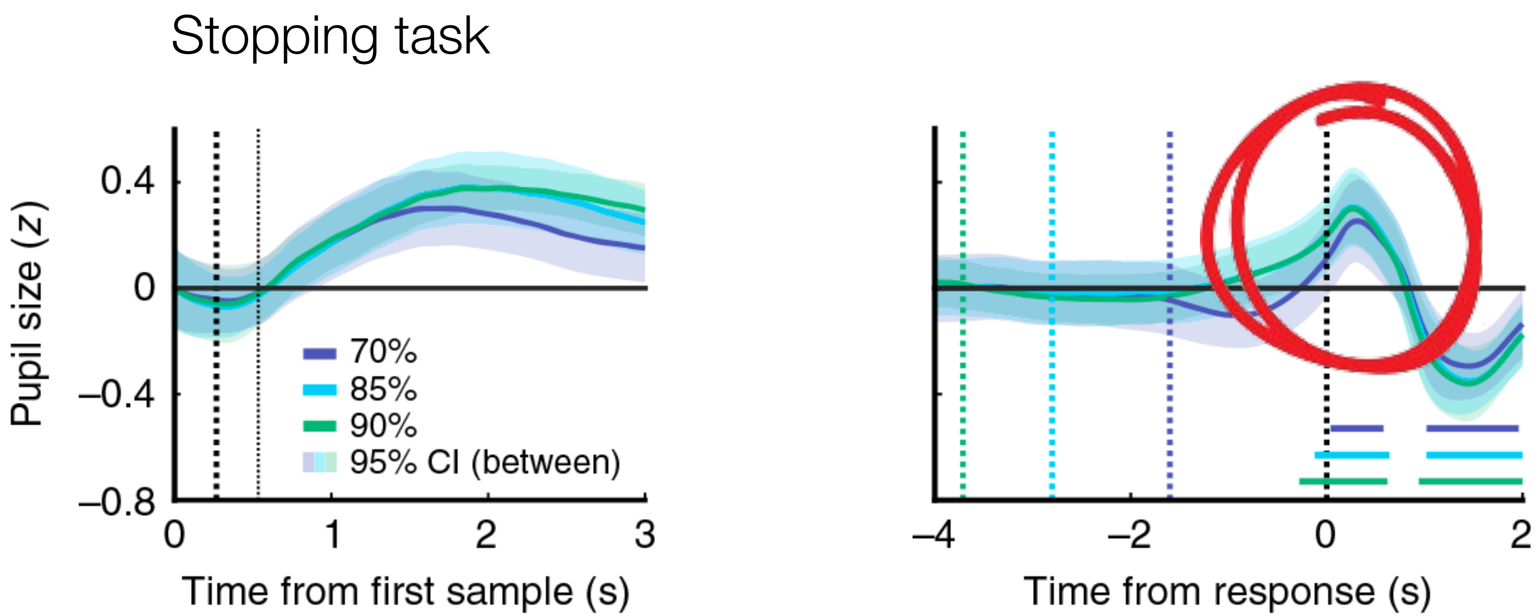

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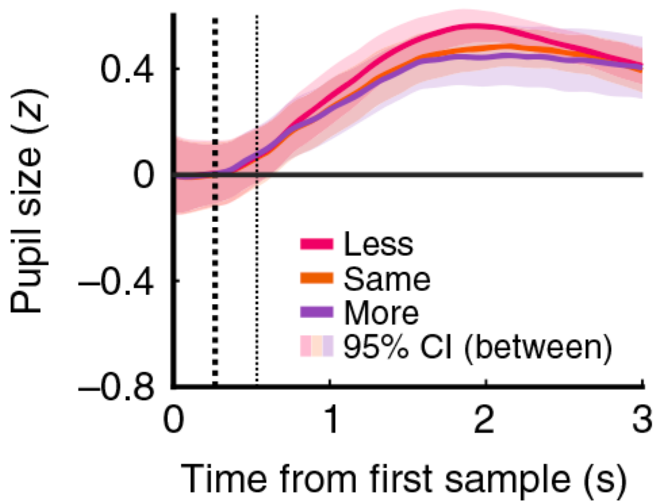
Confidence controls perceptual evidence accumulation

Case study 1: covert bound on decision-making

Replay task



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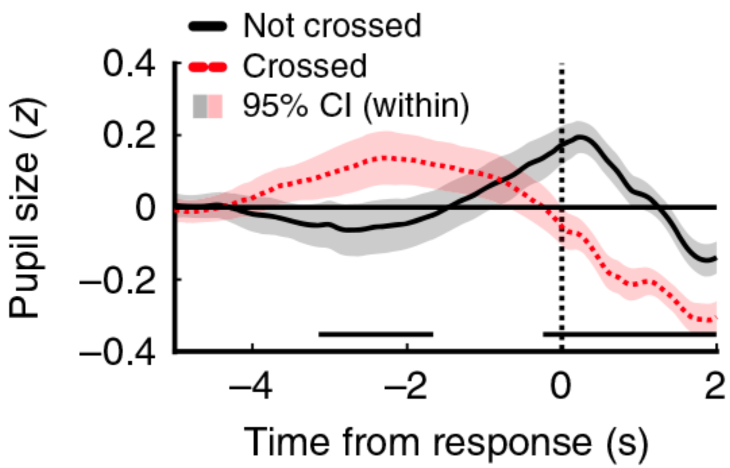
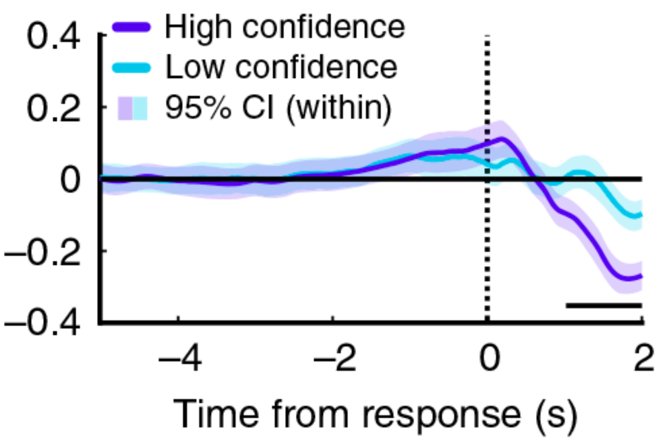
Confidence controls perceptual evidence accumulation

Case study 1: covert bound on decision-making

bound crossing effect



decision confidence effect



Balsdon, Wyart and Mamassian (2020) *Nature Communications*
Confidence controls perceptual evidence accumulation

Case study 1: covert bound on decision-making

Pupil dilation reveals a covert bound on decision-making (not directly visible from behavior).

Understanding the origin of pupil dilation is not needed to draw this conclusion.

Pupil dilation is used to refine cognitive models of decision-making, not to map pupillary correlates of decision-making.

Balsdon, Wyart and Mamassian (2020) *Nature Communications*
Confidence controls perceptual evidence accumulation

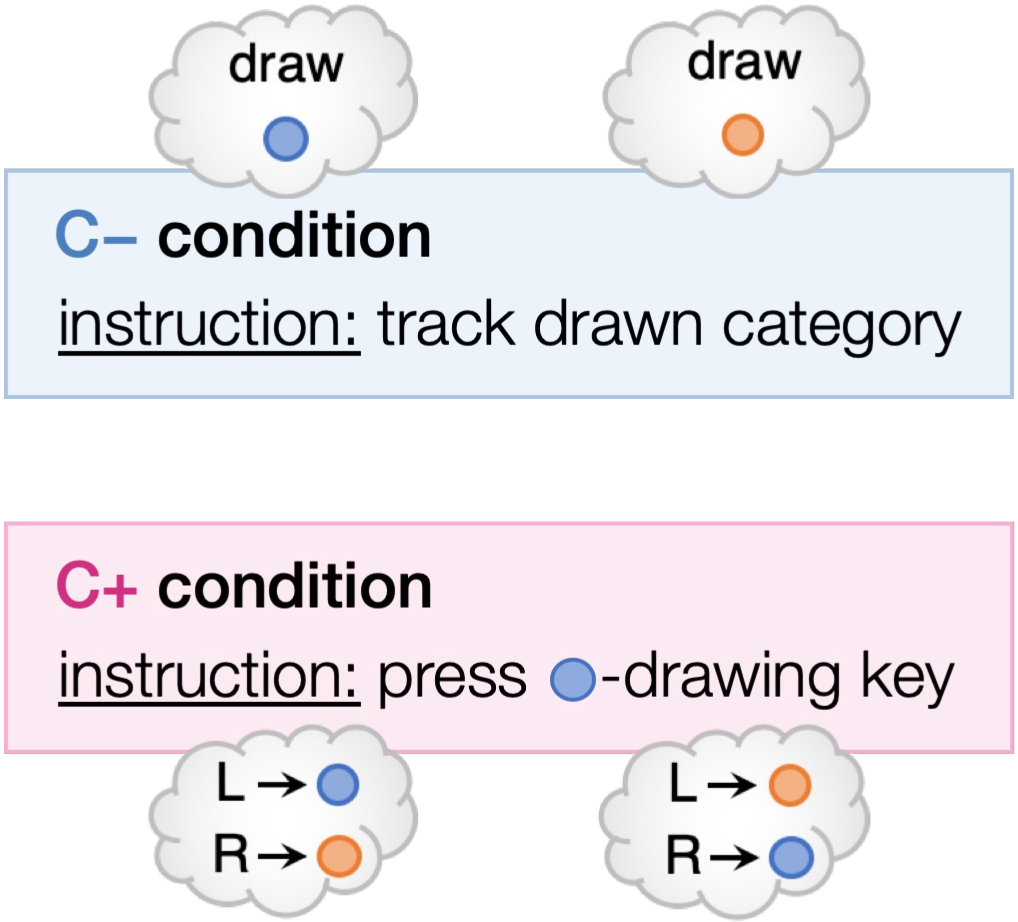
Case study 2: effect of controllability on decision-making

Aurélien Weiss
PhD student

Marion Rouault
Brain Institute, Paris

Weiss et al. (2021) *Nature Communications*
Interacting with volatile environments stabilizes hidden-state inference

Case study 2: effect of controllability on decision-making



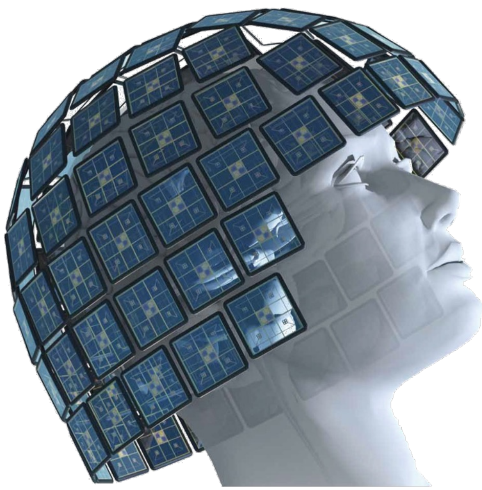
passive sampling
not controllable

active sampling
controllable

Weiss et al. (2021) *Nature Communications*
Interacting with volatile environments stabilizes hidden-state inference

Case study 2: effect of controllability on decision-making

Brain data: MEG activity



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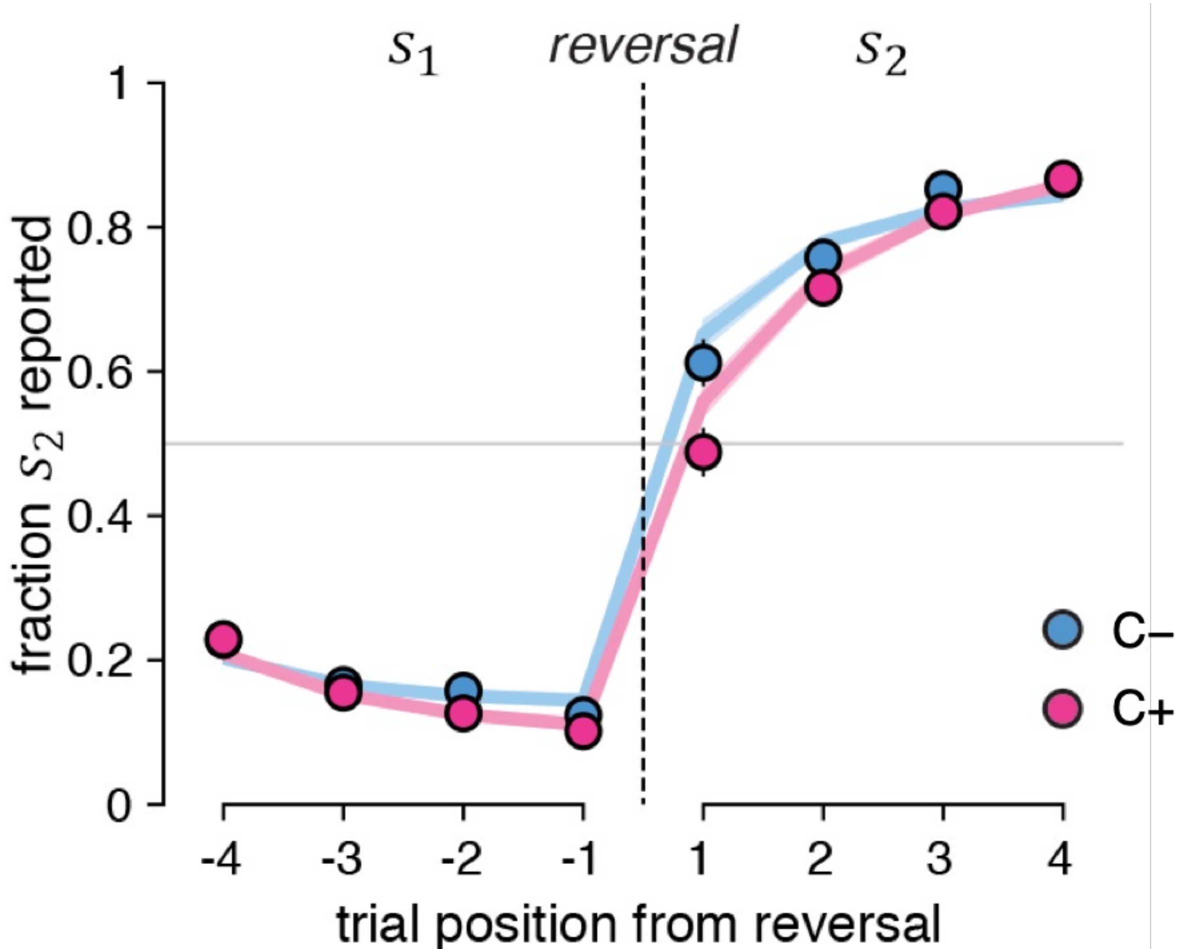

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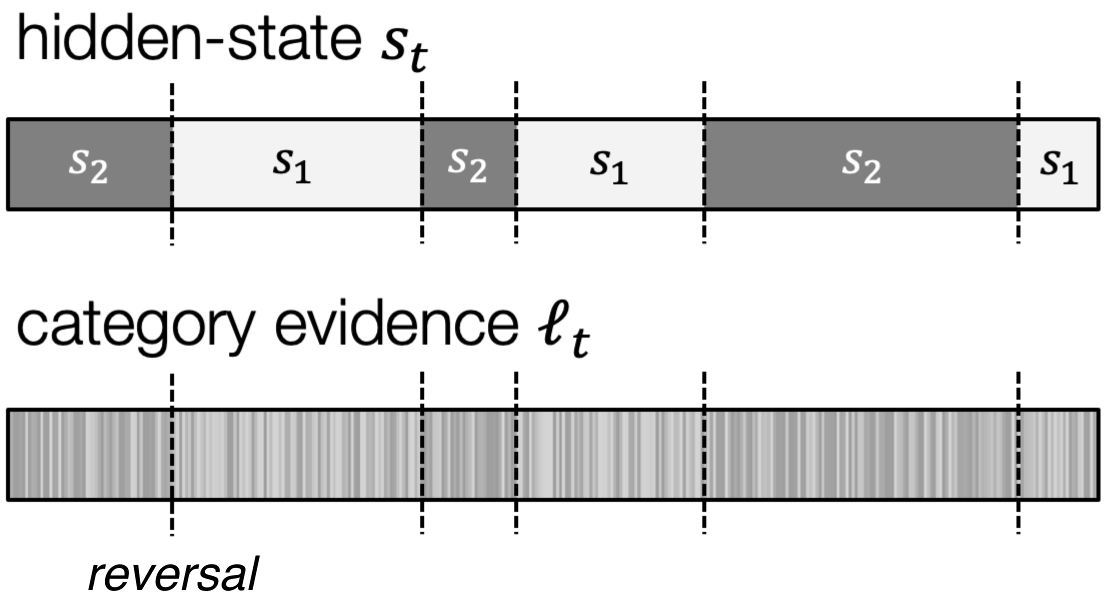

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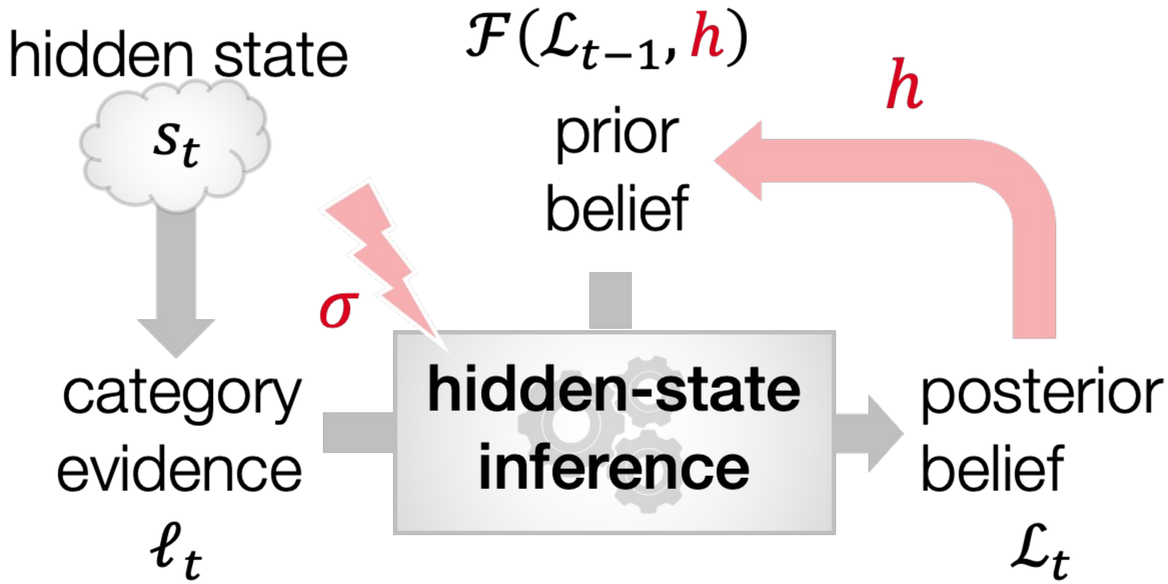

h = perceived reversal rate

σ = computation noise

Weiss et al. (2021) *Nature Communications*
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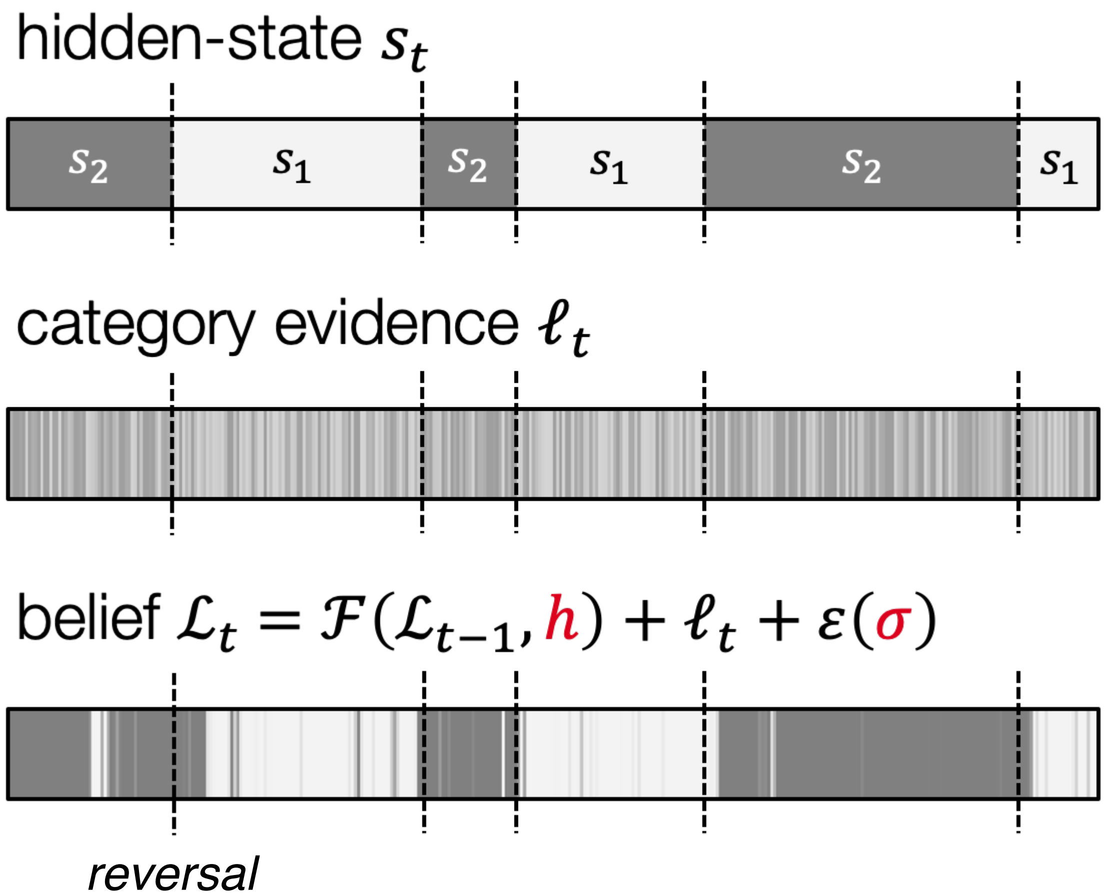

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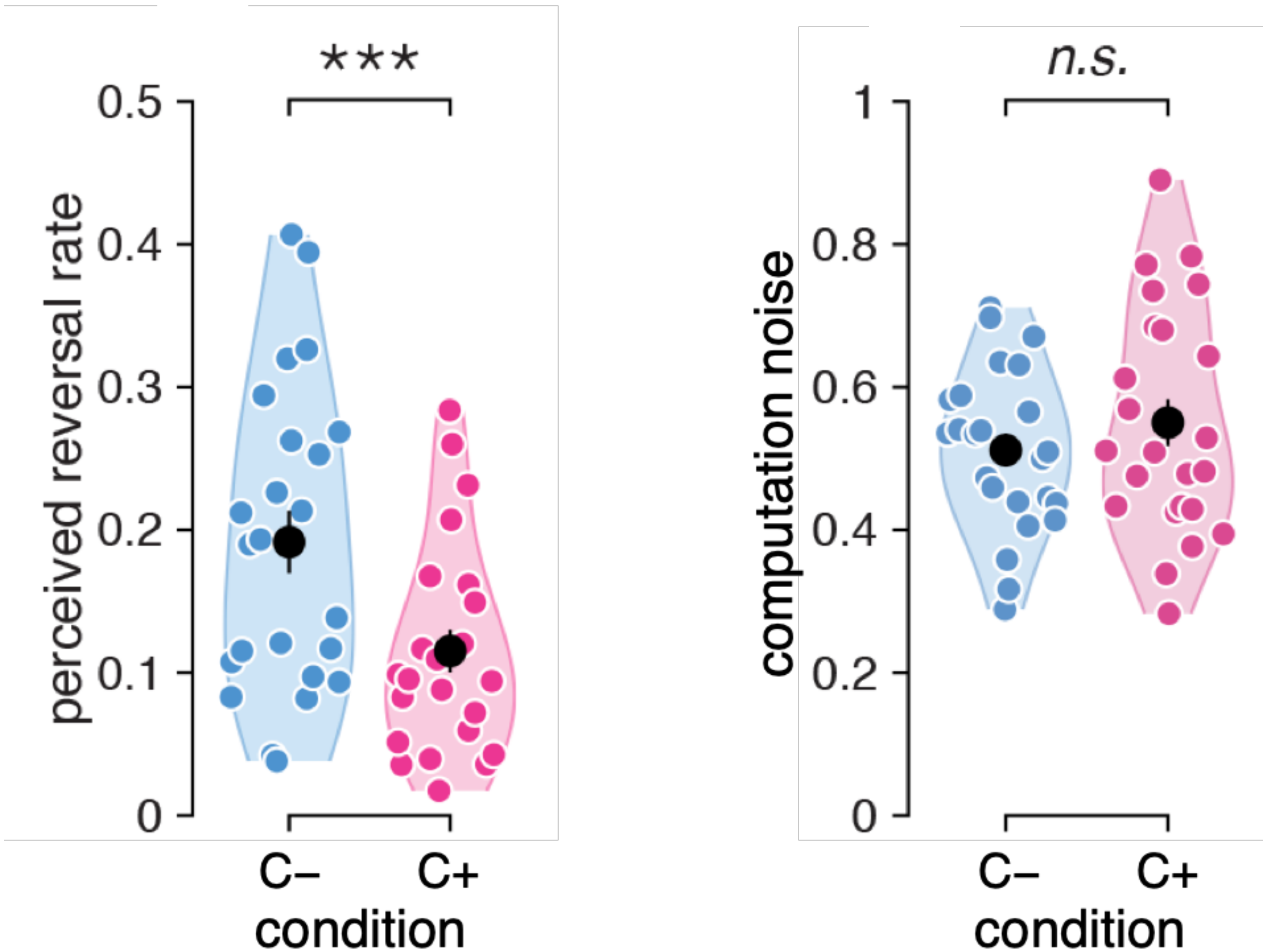

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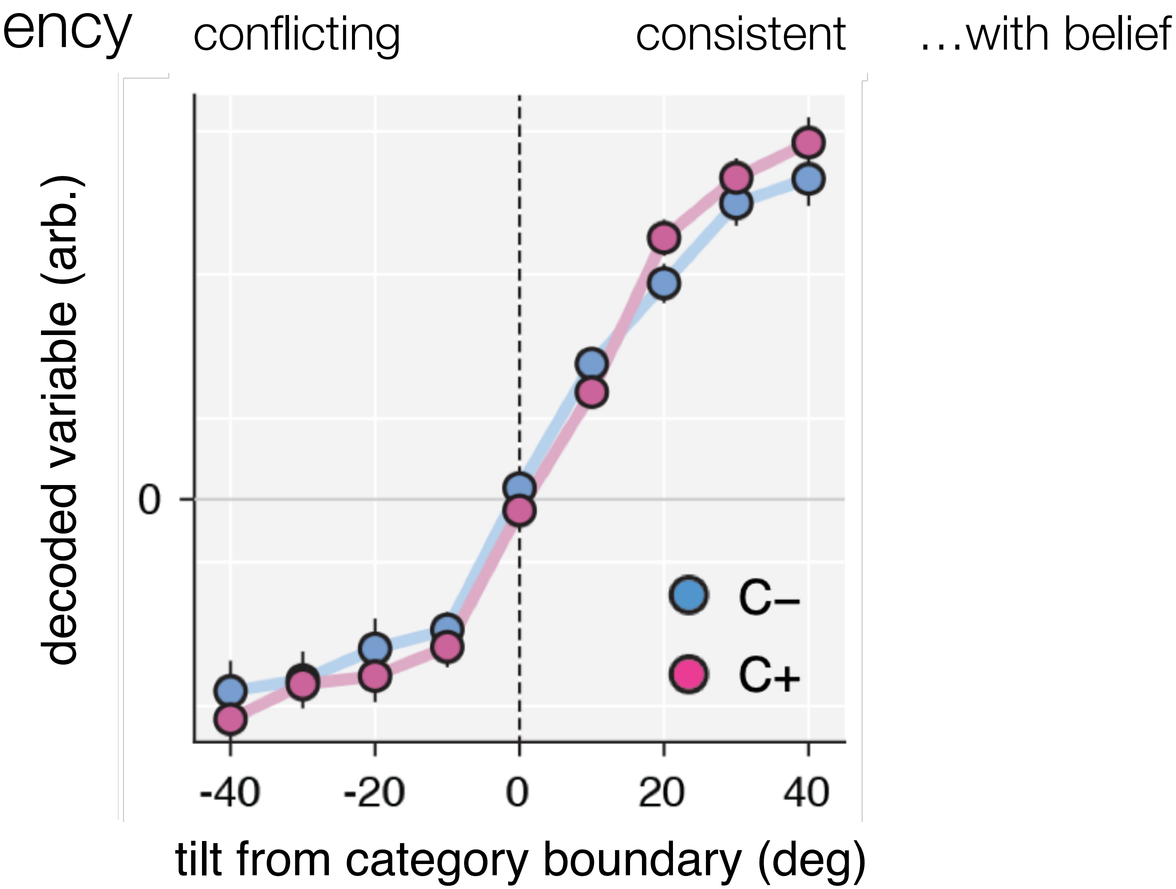
Case study 2: effect of controllability on decision-making

evidence consistency



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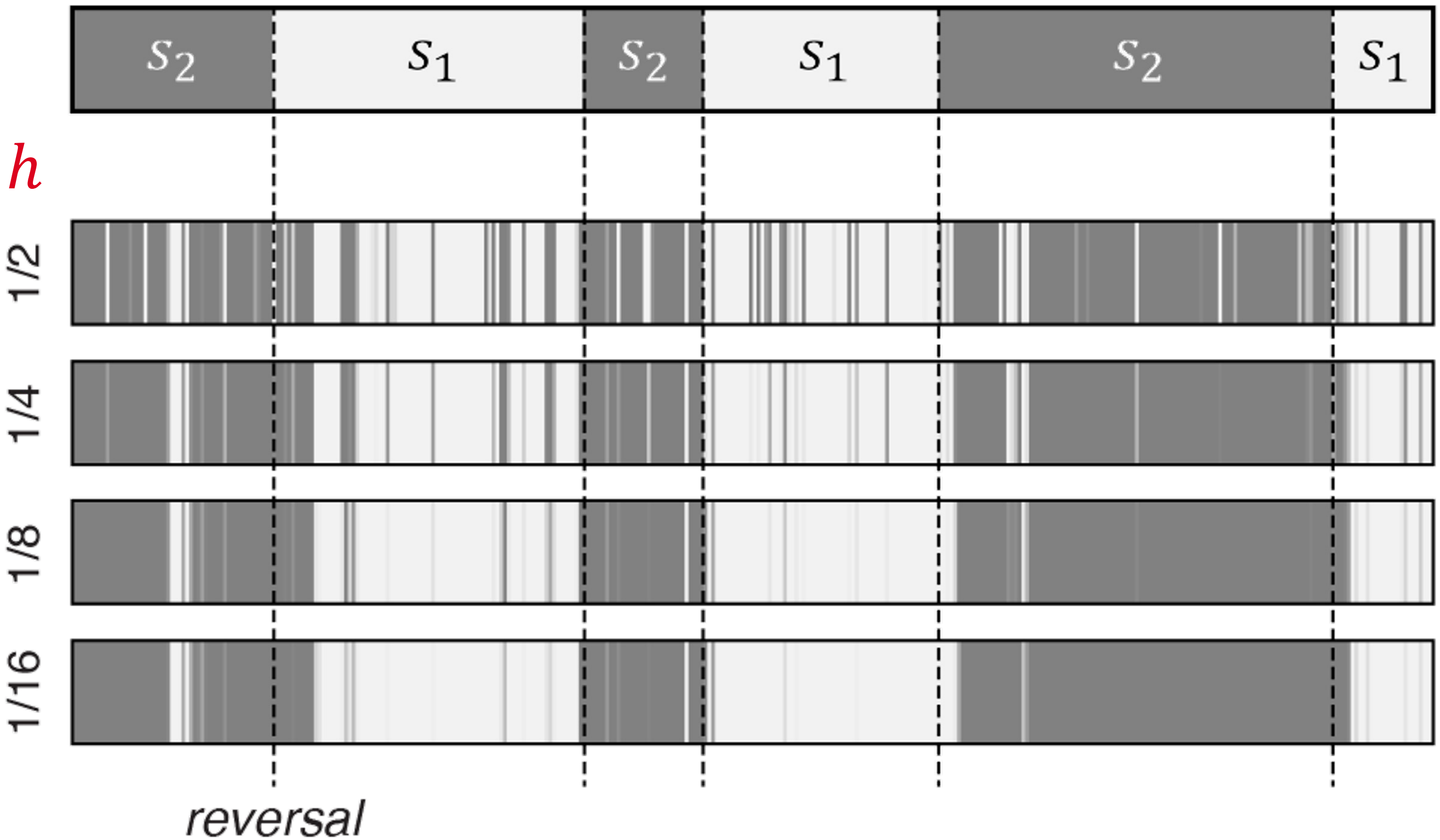
Interacting with volatile environments stabilizes hidden-state inference

Case study 2: effect of controllability on decision-making

belief $\mathcal{L}_t = \mathcal{F}(\mathcal{L}_{t-1}, h) + \ell_t + \varepsilon(\sigma)$



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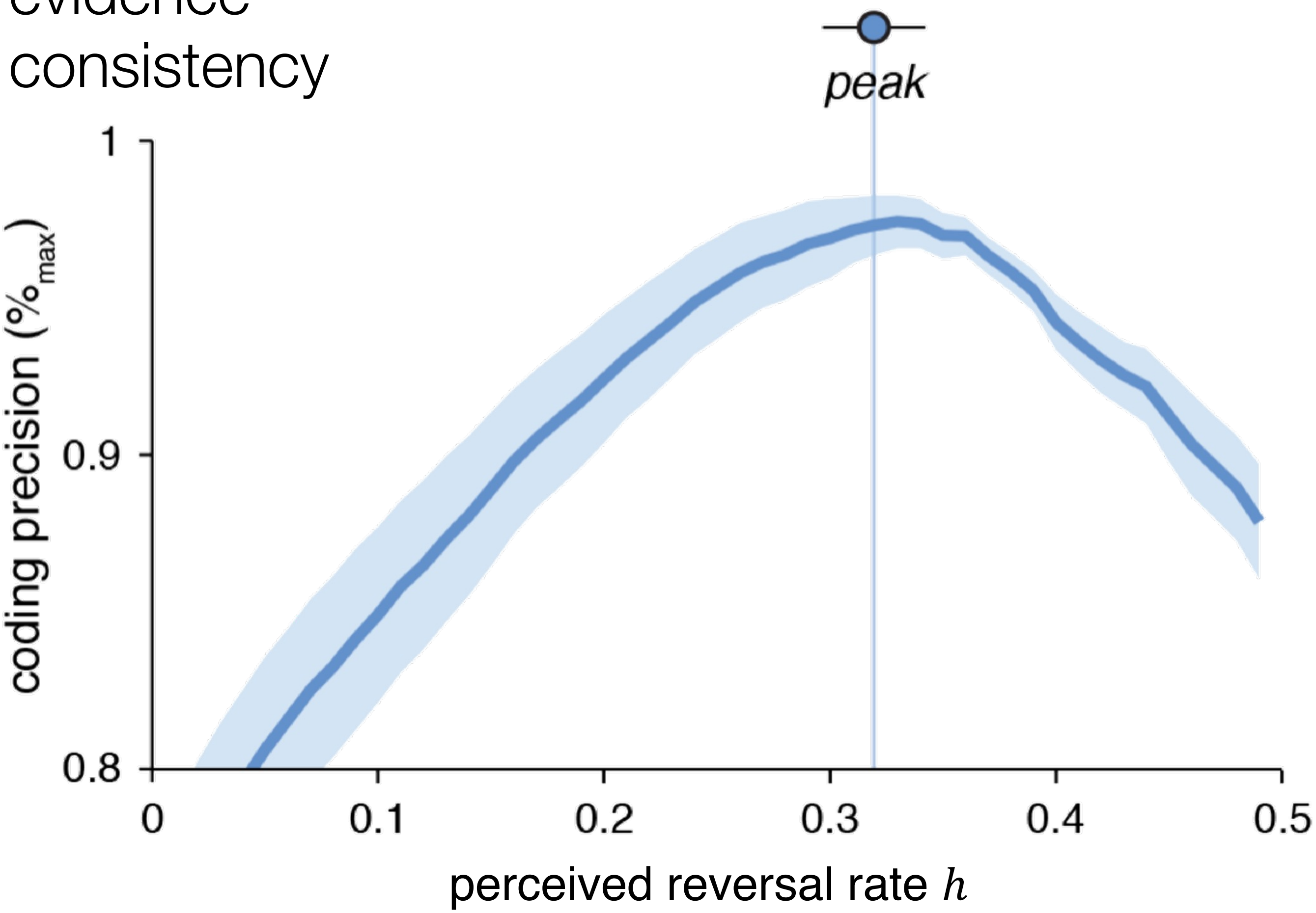
<u>Case study 2:</u> effect of controllability on decision-making

evidence
consistency



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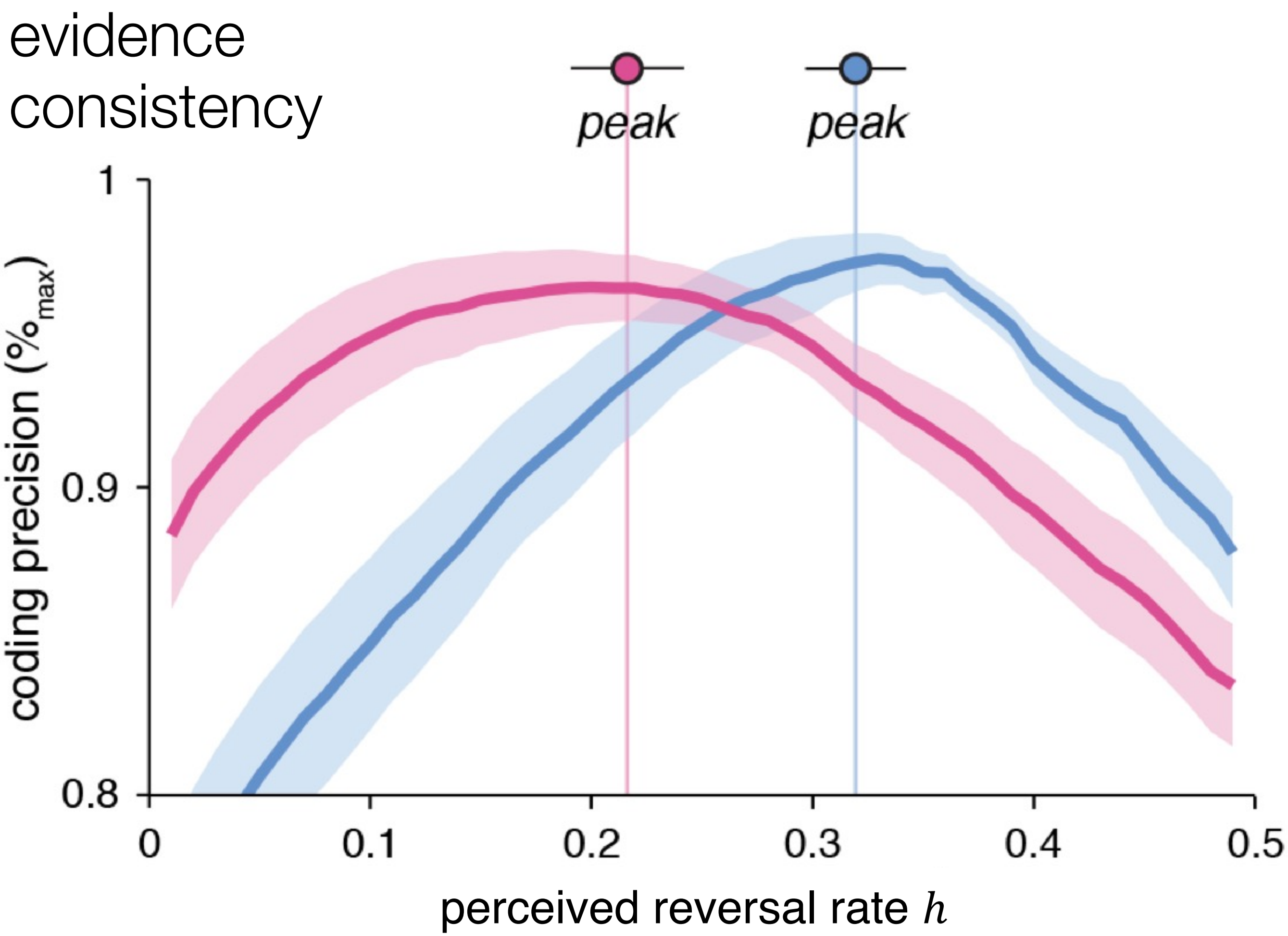


Weiss et al. (2021) *Nature Communications*
Interacting with volatile environments stabilizes hidden-state inference

Case study 2: effect of controllability on decision-making

MEG activity patterns support a specific effect of controllability on decision-making.

Mapping the source of MEG activity is not needed to draw this conclusion.

MEG activity is used to fit a parameter of hidden-state inference, not to map the MEG correlates of decision-making.

Weiss et al. (2021) *Nature Communications*
Interacting with volatile environments stabilizes hidden-state inference

Is this approach perfectly conclusive? **NO**

Brain data, as any type of data, provide empirical and partial support for a cognitive hypothesis.

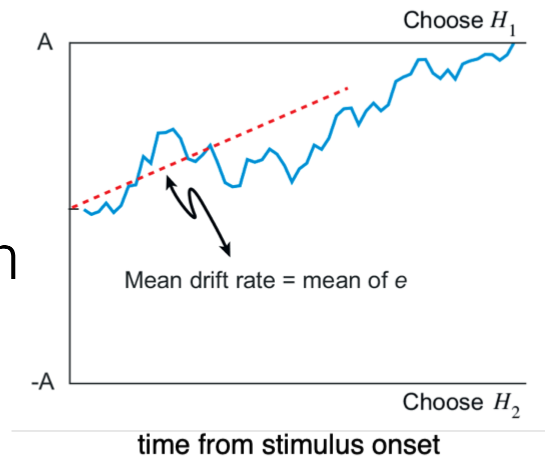
Is this approach different from brain mapping? **YES**

It treats brain data not as a special type of data (to be explained), but as an additional observable for understanding cognition and behavior.

Beyond brain mapping

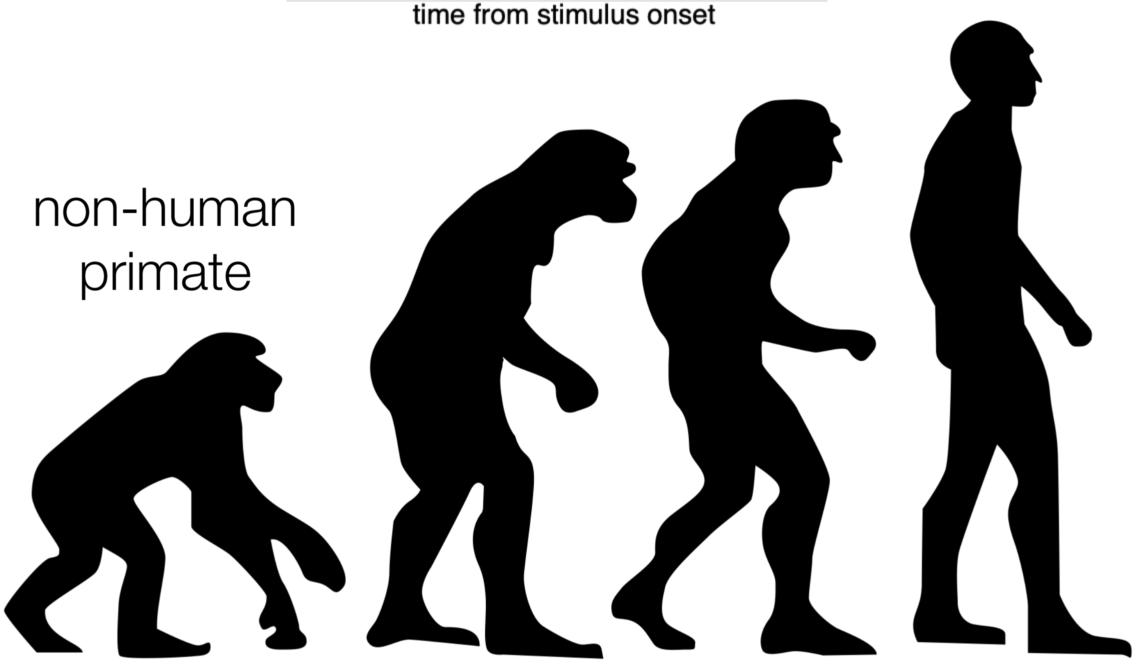
2

algorithm

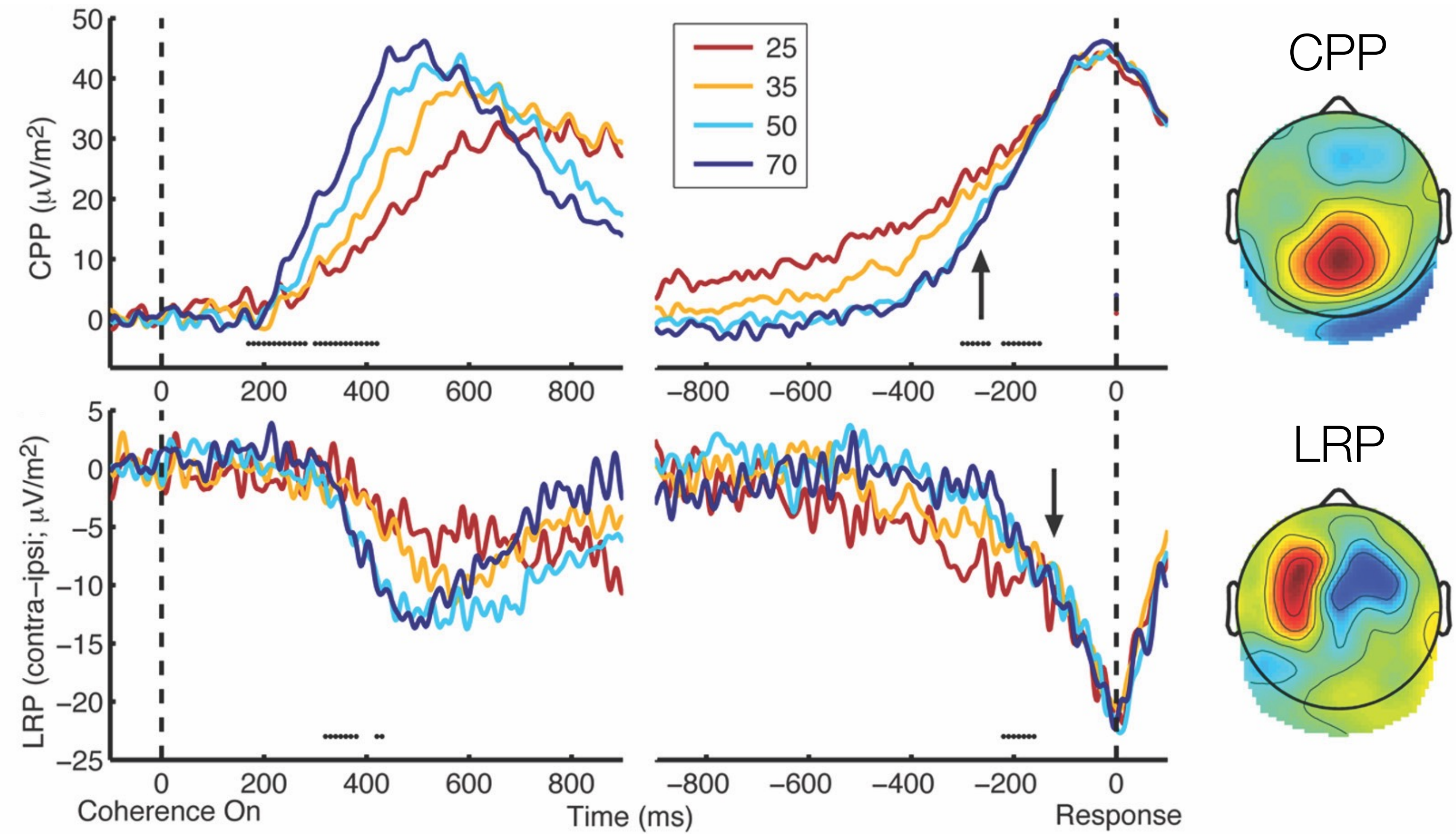


human

non-human
primate

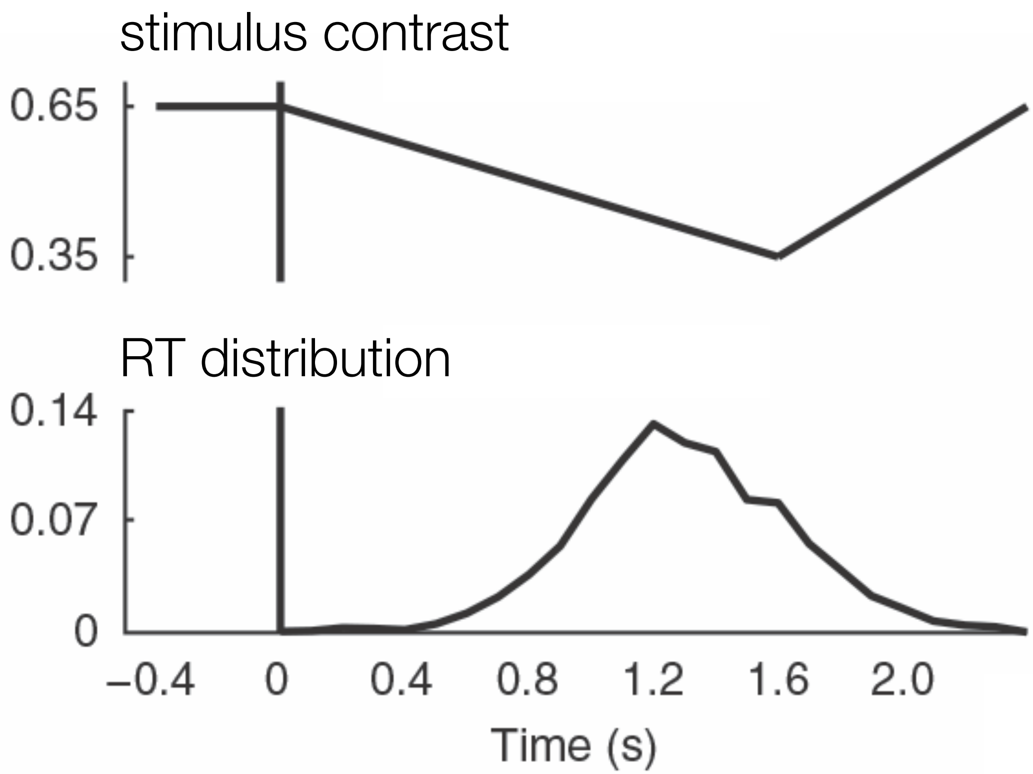


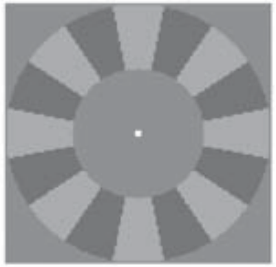
Beyond brain mapping



Kelly and O'Connell (2013) *Journal of Neuroscience*
Internal and external influences on the rate of sensory evidence accumulation

Beyond brain mapping



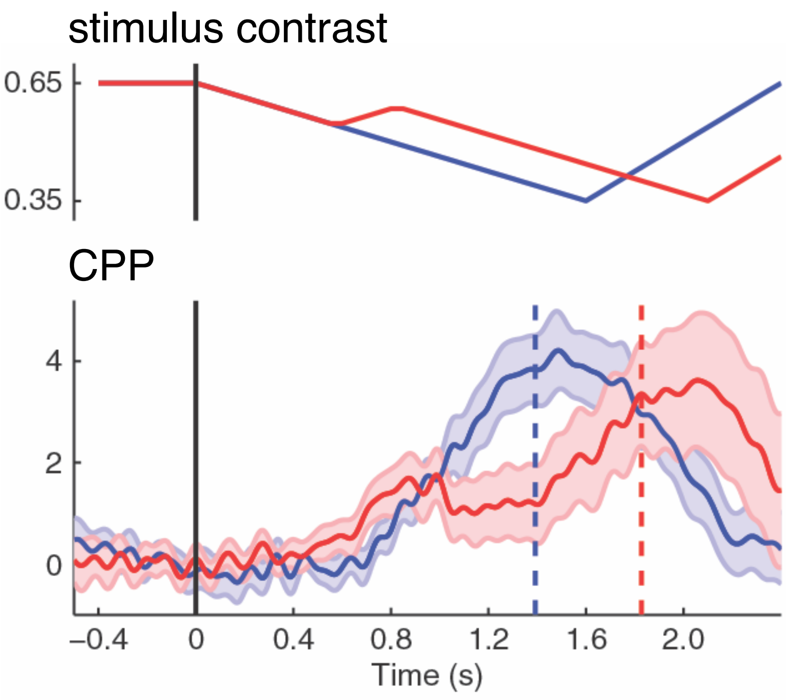


new stimulus
(contrast change)

O’Connell et al. (2012) *Nature Neuroscience*
A supramodal accumulation-to-bound signal that determines perceptual decisions

Beyond brain mapping

button press
<u>overt</u> decision bound



O'Connell et al. (2012) *Nature Neuroscience*
A supramodal accumulation-to-bound signal that determines perceptual decisions

Beyond brain mapping

<u>Practical requirements:</u>

1. implement cognitive hypotheses in terms of <u>competing algorithms</u>
2. develop experimental tasks where competing algorithms make <u>distinct predictions</u>
3. use brain data not as dependent variables, but for <u>arbitrating between competing algorithms</u>

There is much more to cognitive neuroscience than brain mapping and reverse inferences.

Bayesian modeling…

and how to use brain data to arbitrate between models of cognition

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