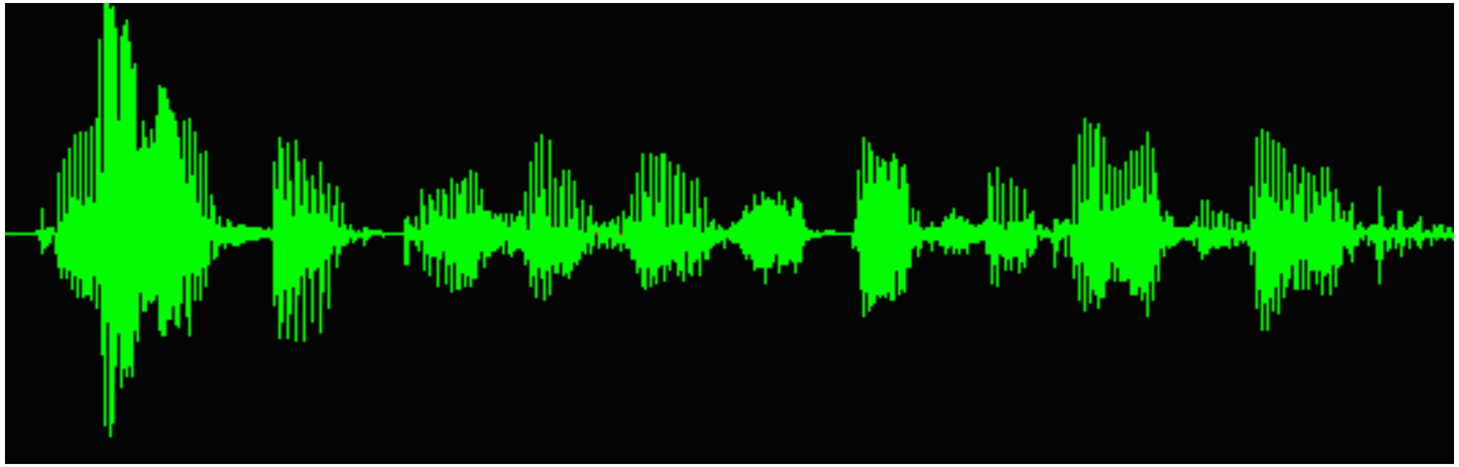
Circuits and computations for learning and exploiting sensory statistics

Athena Akrami

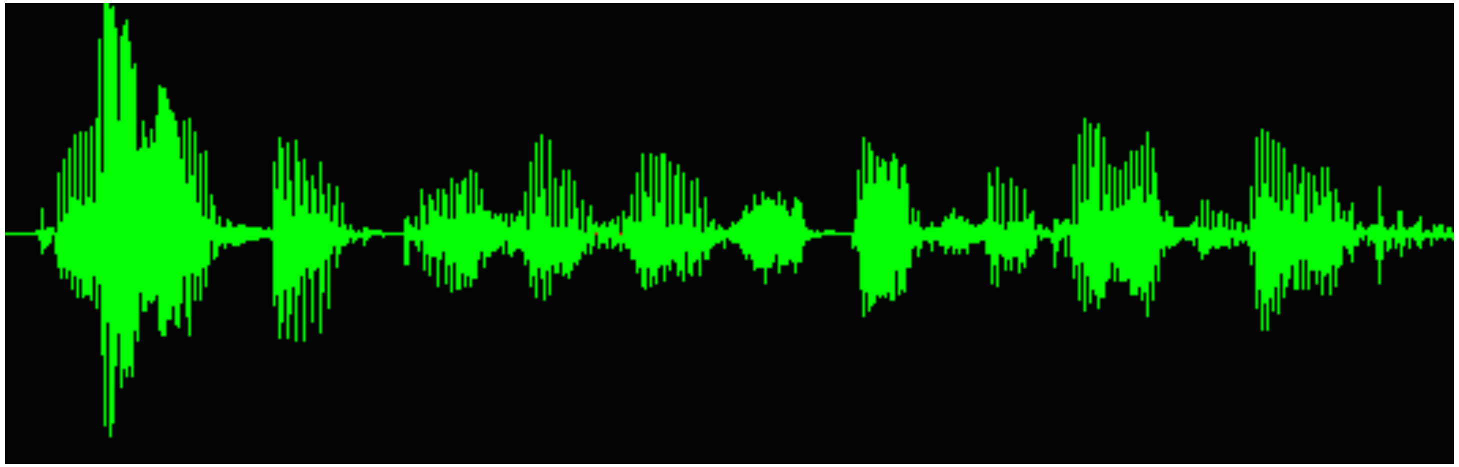
ISRC-CN3, Ulster University, August 2024

Prior experience and ambiguous stimuli



Stimulus

Prior experience and ambiguous stimuli



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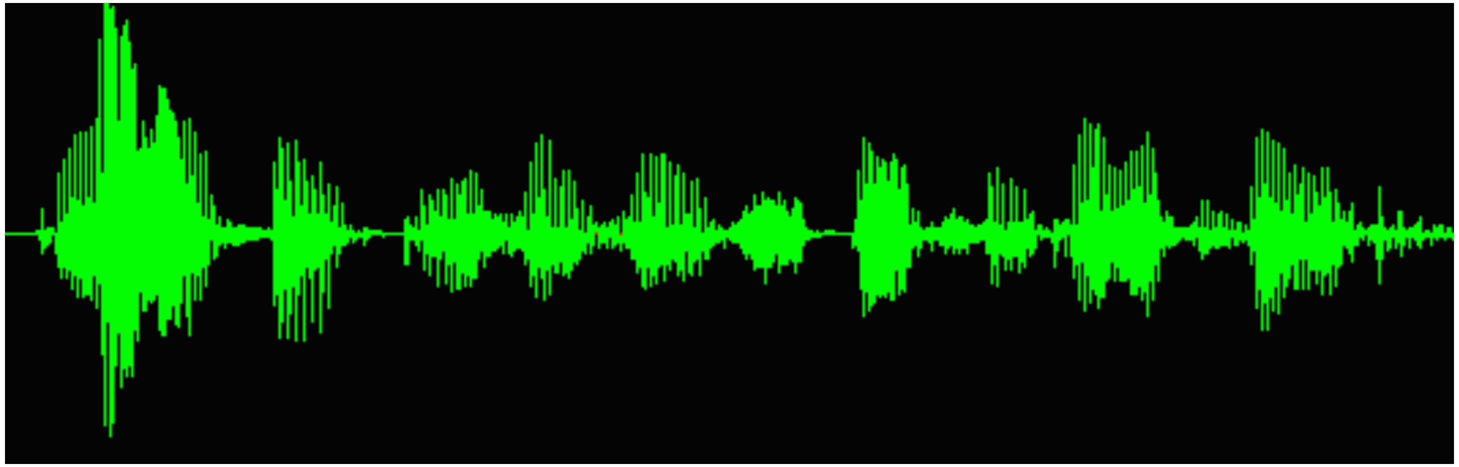
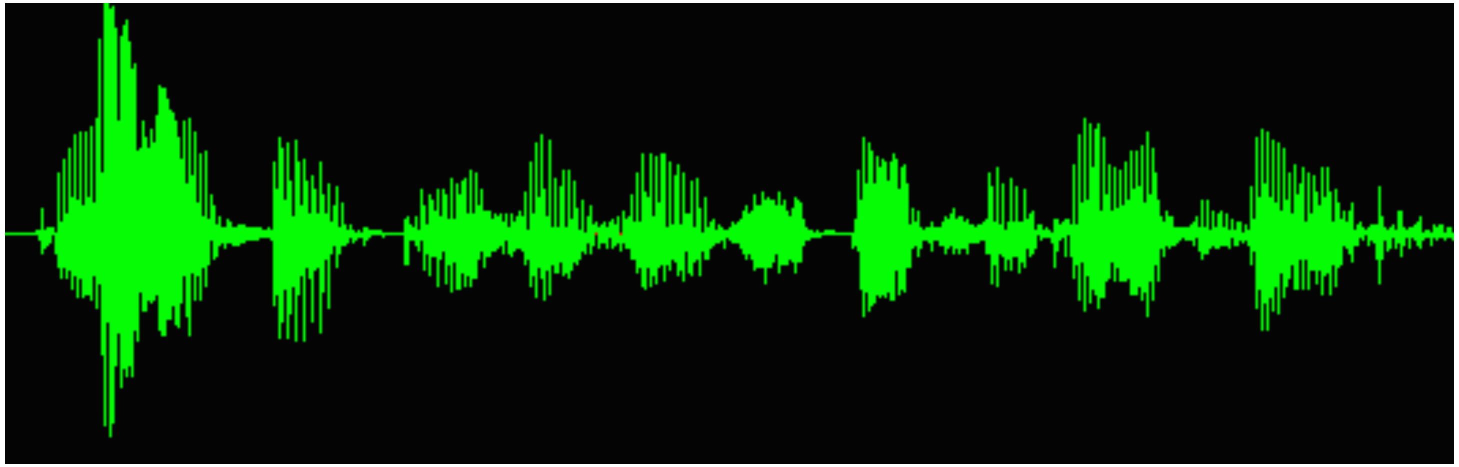


Prior

Prior experience and ambiguous stimuli



Stimulus

It deosn’t mttaer waht oredr the ltteers in a word are, the olny iprmoetnt tihng is taht the frist and lsat ltteres are at the rghit pclae

We can learn structures and use them in decision making

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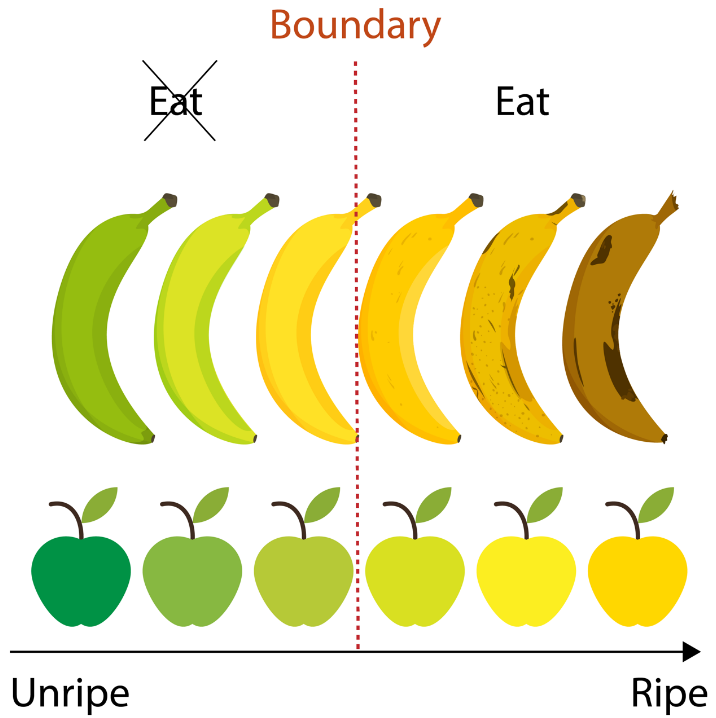

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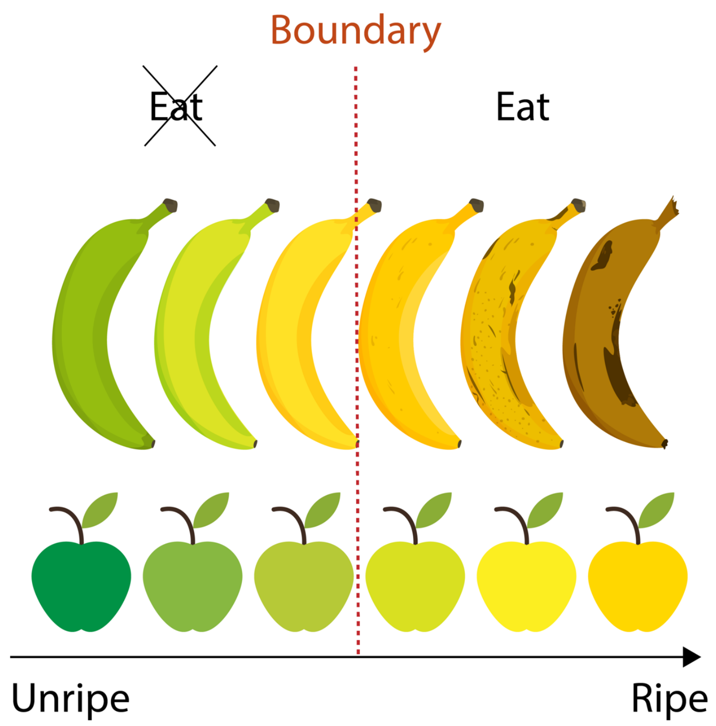

Incidental

Feedback based

Learning & Exploiting sensory statistics

Statistics → **Structures** → **Priors**

a fundamental property of the brain

Optimal/good decision making ↔ **Compromised in several psychiatric conditions**

Dyslexia: Lieder et al, 2019
Autism Spectrum Disorder: Pellicano et al 2012
Psychosis: Sterzer et al 2018

Learning and updating priors are impaired

Learning & Exploiting sensory statistics

Statistics → **Structures** → **Priors**

a fundamental property of the brain

The goal:

Understanding the mechanisms by which neural circuits give rise to learning and exploiting sensory structures

Learning & Exploiting sensory statistics

a fundamental property of the brain

Human cognition

Saffran et al 1996, Kording and Wolpert 2004, Turk-Browne et al 2009, Sherman et al 2020

Theoretical neuroscience

Knill and Pouget 2004; Thiessen et al 2013, Schapiro et al 2017, Whittington et al 2020

Learning & Exploiting sensory statistics

a fundamental property of the brain

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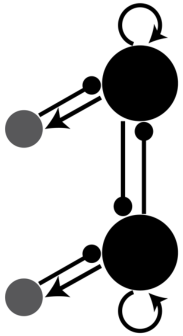
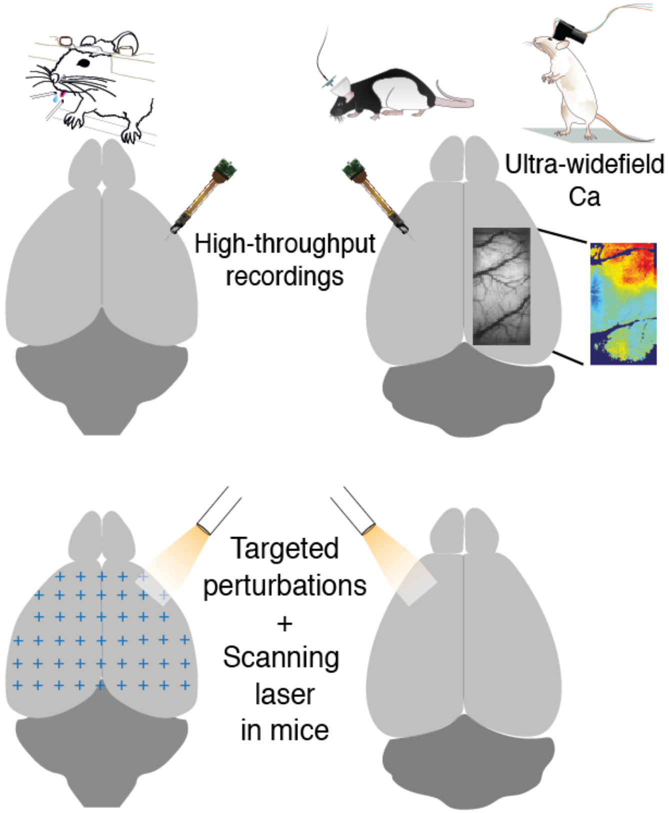
Data from animal research are scarce

Our approach

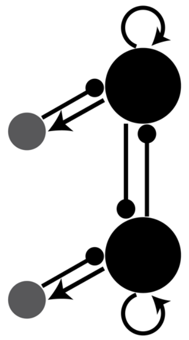


Well controlled comparative paradigms in models, humans, rats & mice

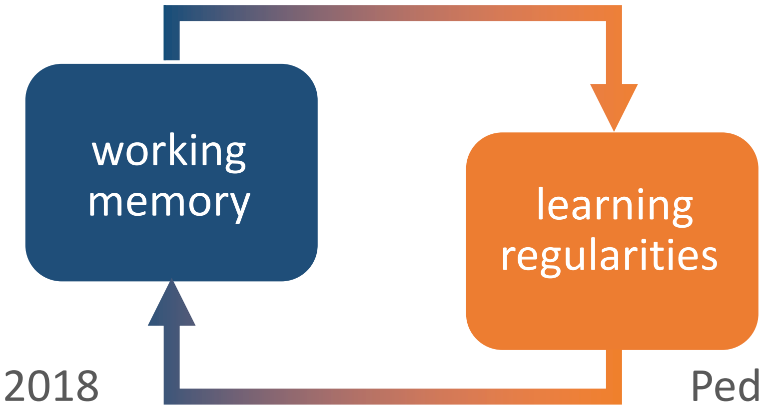
tractable organisms



Our approach



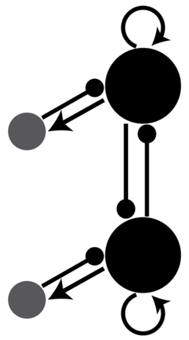
Well controlled comparative paradigms in humans, rats, mice and models



Akrami et al 2018
Fassihi* and Akrami* et al 2014
Boboeva et al 2024
Vincent, Sahani, Akrami (in preparation)

Pedrosa*, Menichini*, Pajot-Moric* et al 2023
Onih et al (in preparation)

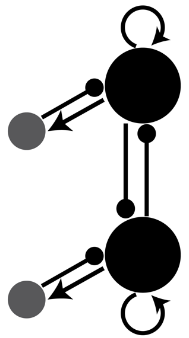
Our approach



Feedback-based learning

Incidental

Our approach



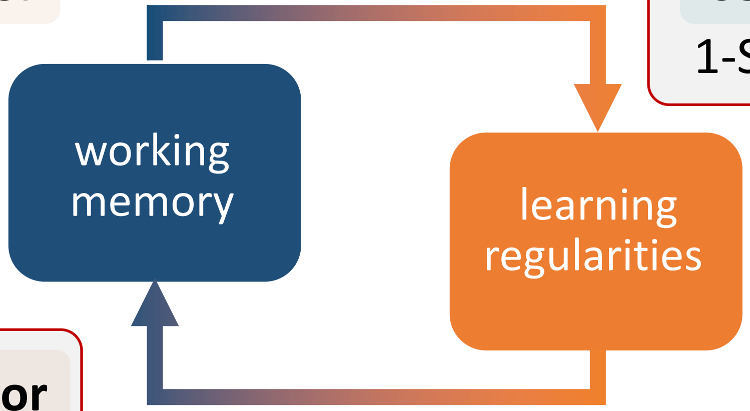
Feedback-based learning

sound → memory → category → motor

2-Step Sound Categorization

sound → category/motor

1-Step Sound Categorization



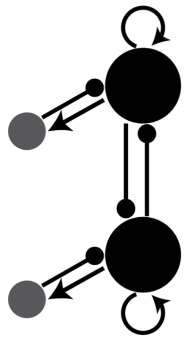
stimulus → memory → stimulus → motor

Parametric Working Memory

Incidental

X Detection paradigm

Our approach



Behaviour

Why?

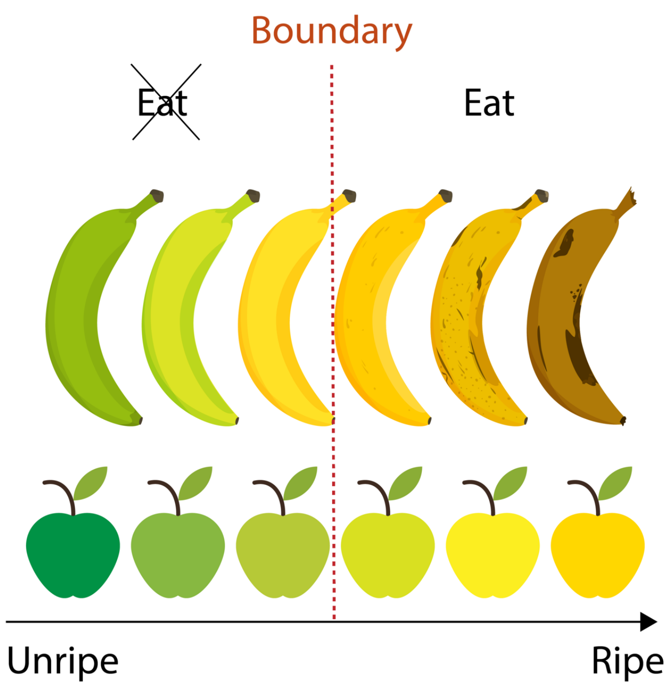
How?

Normative model

Learning model

Mechanistic model

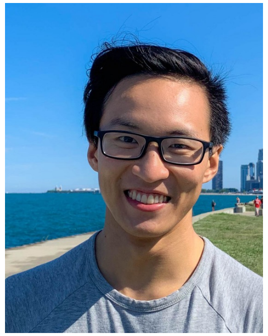
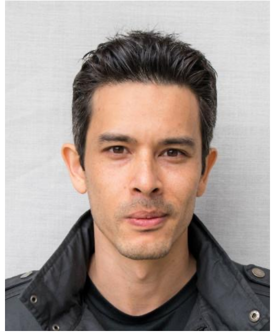
Statistical learning in categorisation behaviour



Learning and exploiting sensory statistics – Sound Categorisation



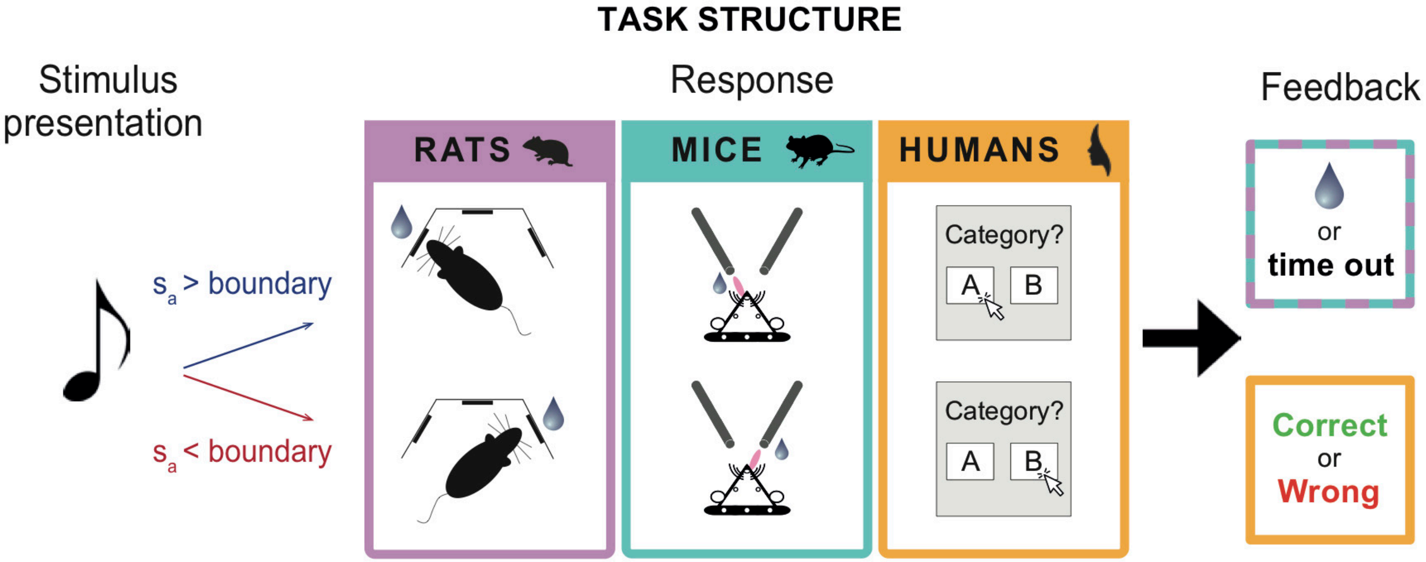
Elena Menichini Victor Pedrosa Quentin Pajot-Moric

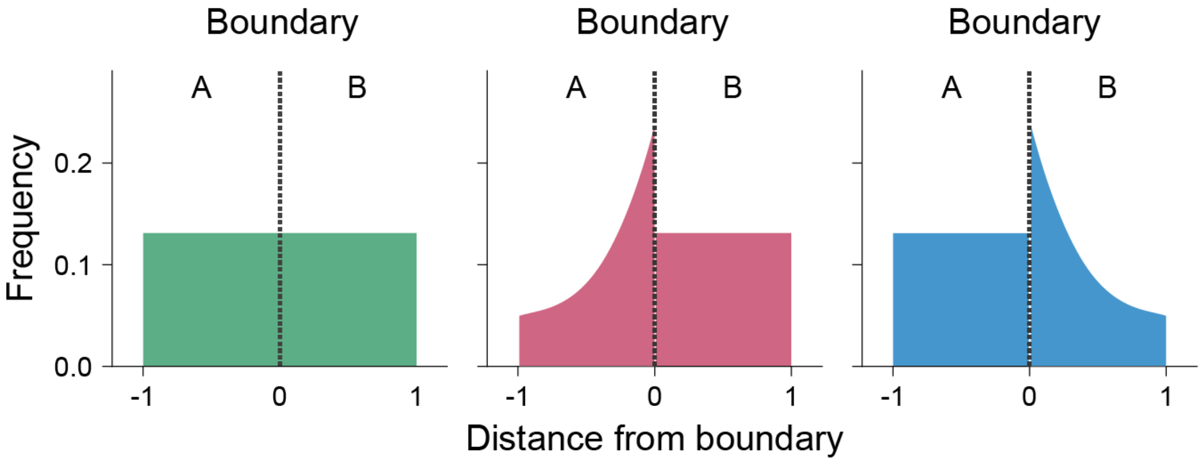
Peter Vincent Liang Zhou Ryan Low

GATSBY

ELSC The Edmond & Lily Safra Center for Brain Sciences

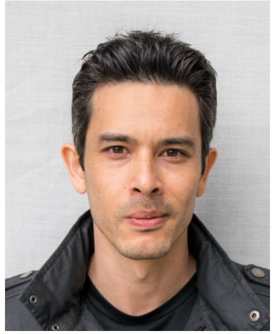


Different statistical contexts (priors)



Pedrosa, Menichini, Pajot-Moric, et al, bioRxiv 2023

What is the optimal behaviour?



Ryan Low

Behaviour

Why?

Normative model

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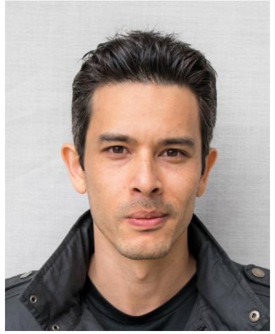
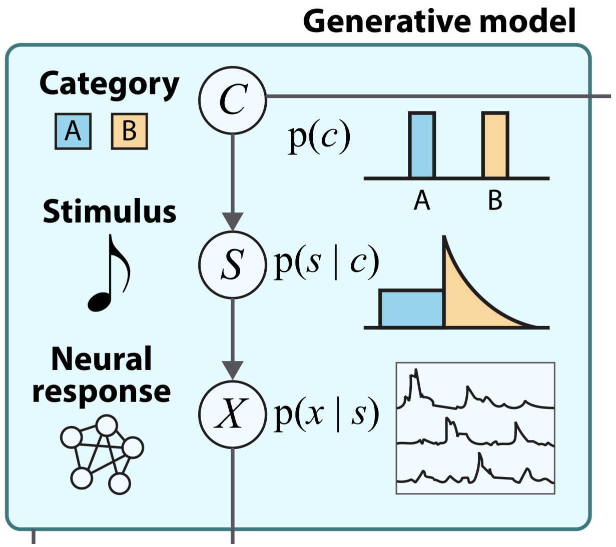


Ryan Low



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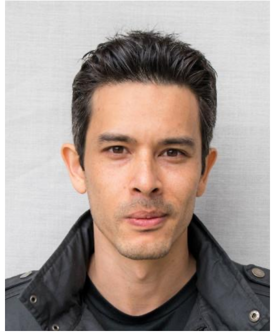
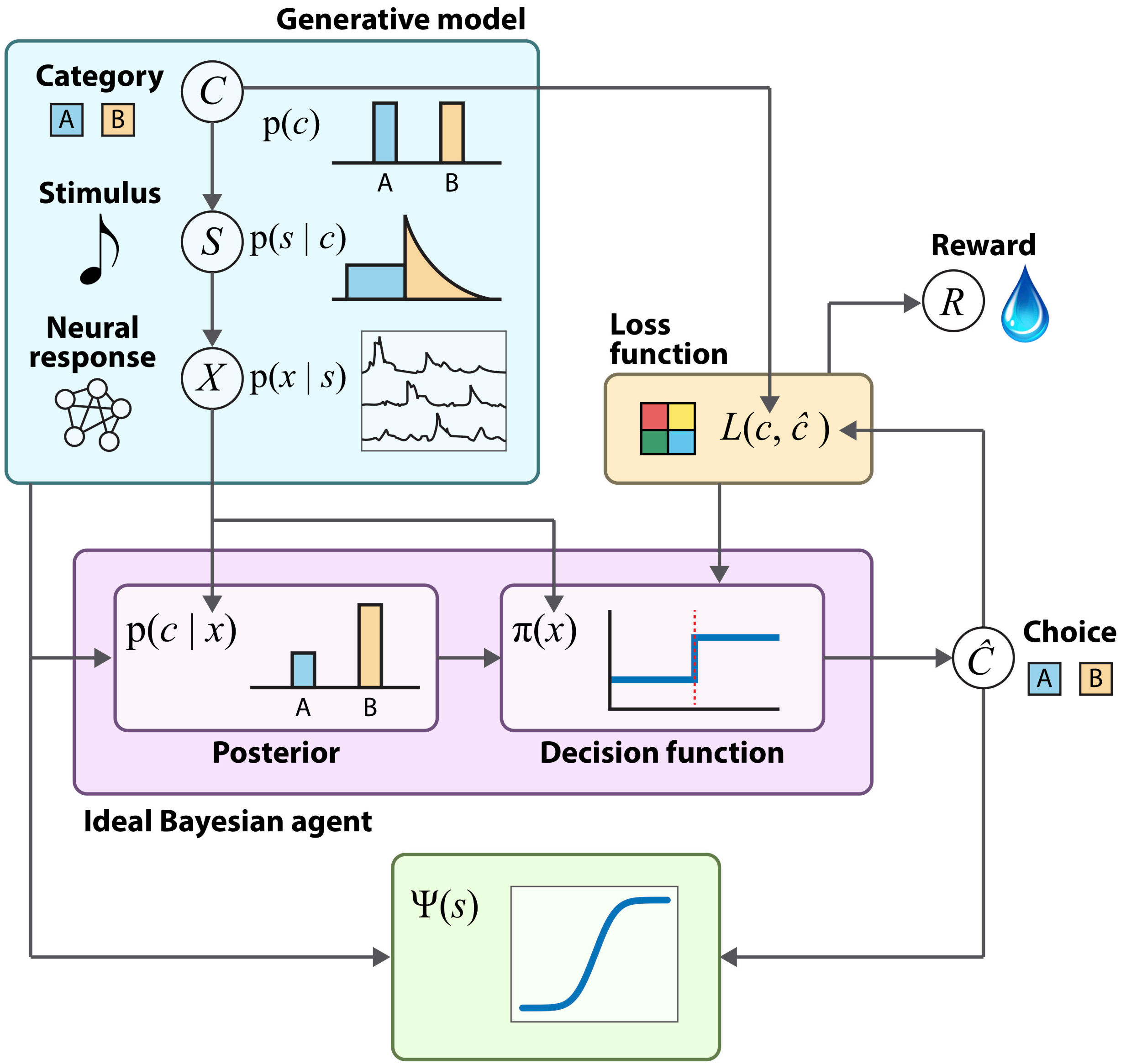


Ryan Low



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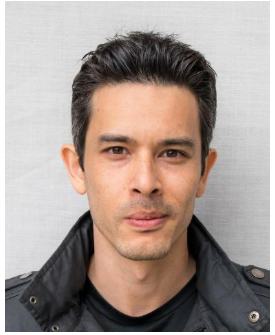
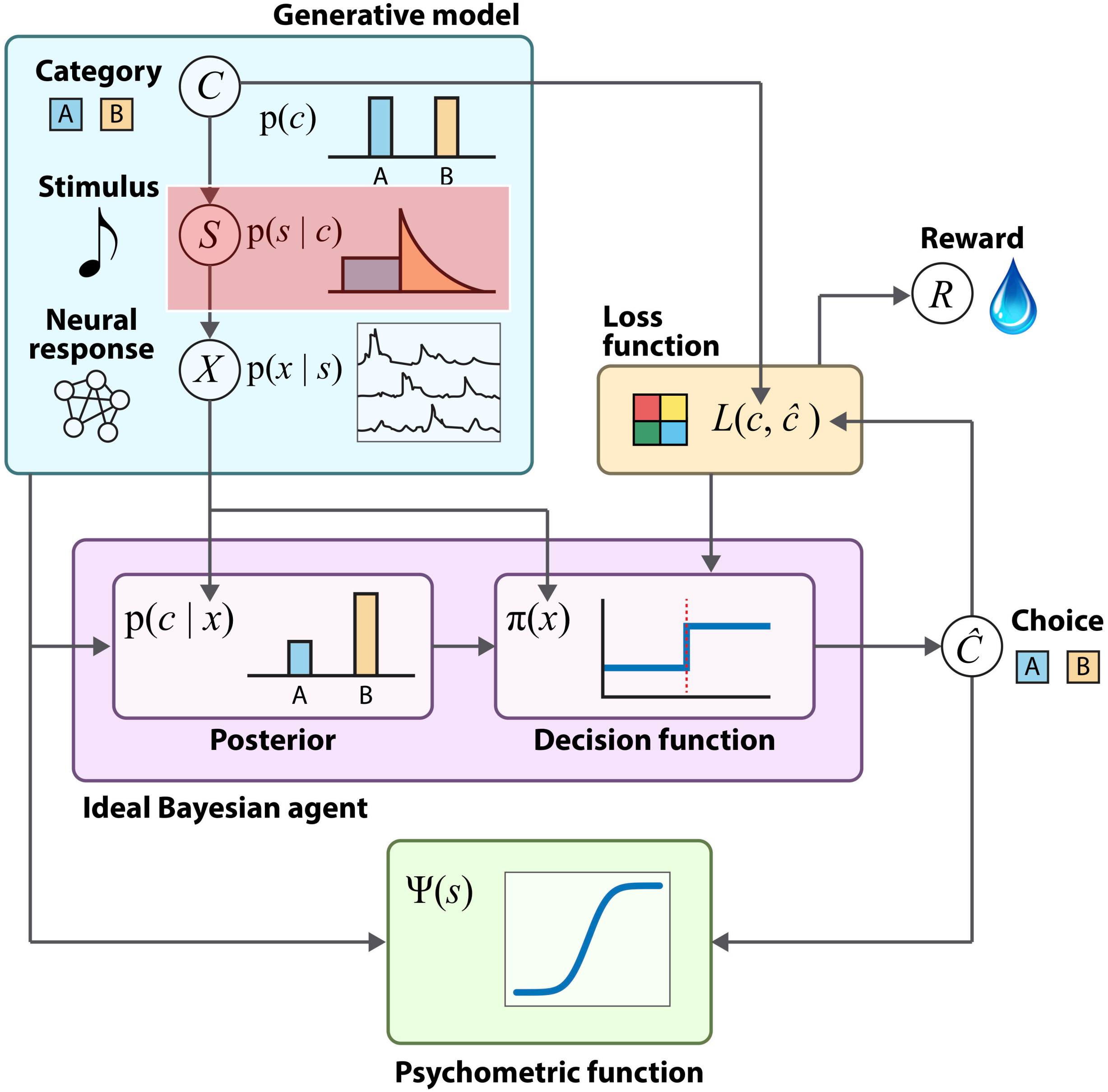
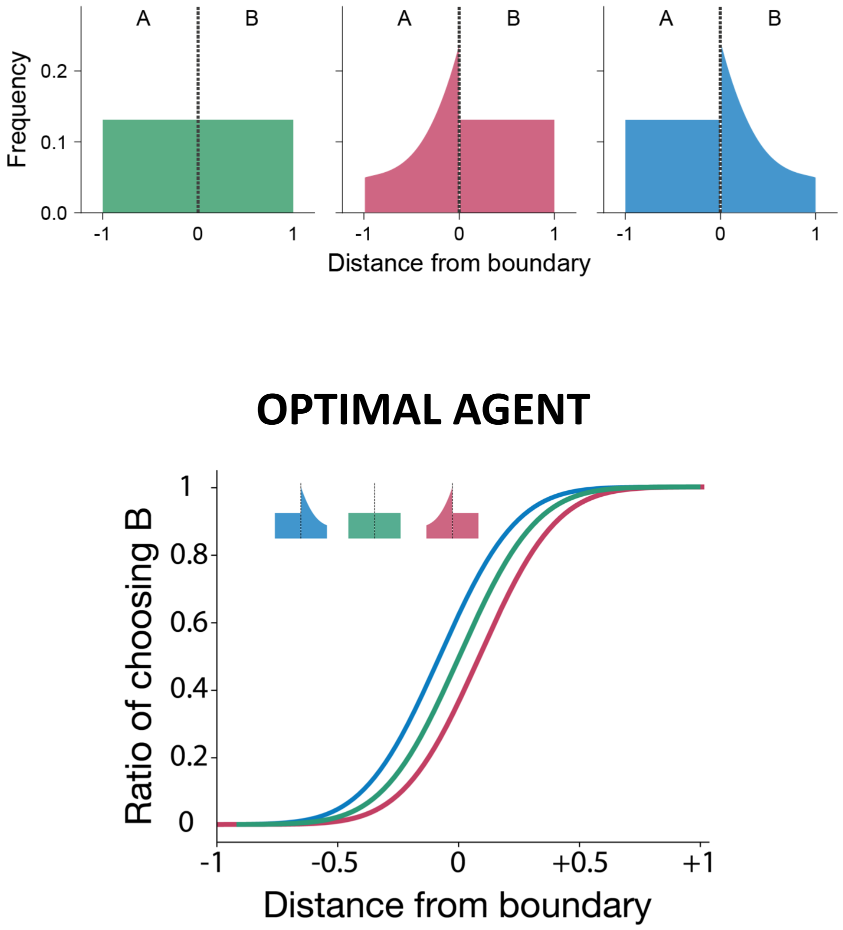


Ryan Low



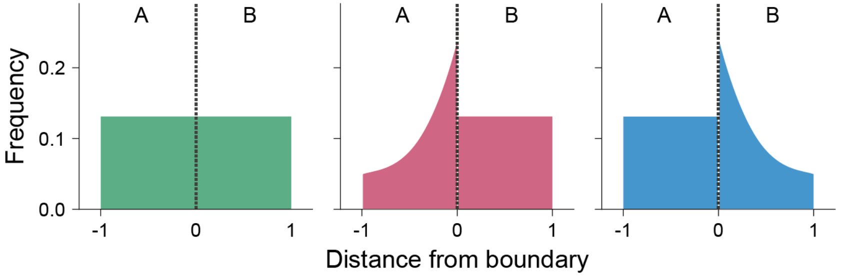


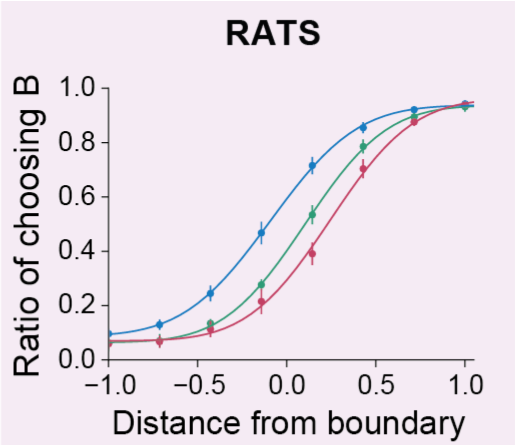
What is the optimal behaviour?

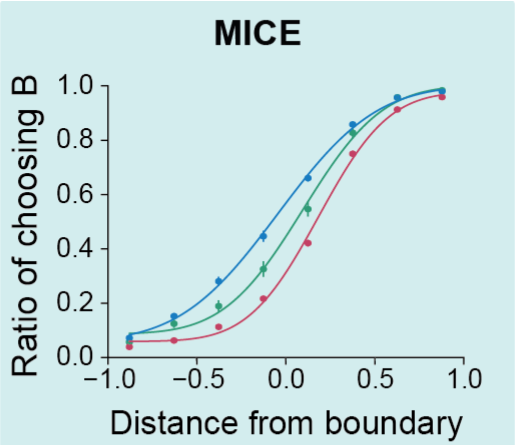

Elena Menichini

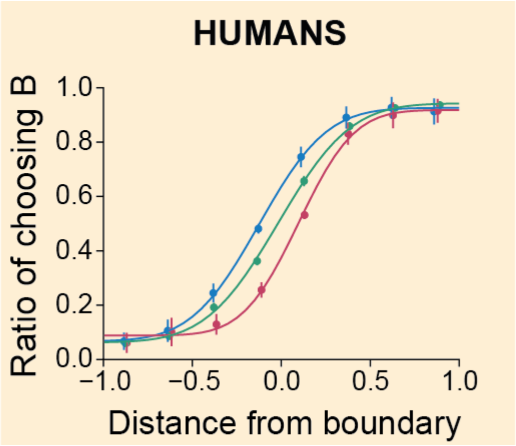

Victor Pedrosa


Quentin Pajot-Moric

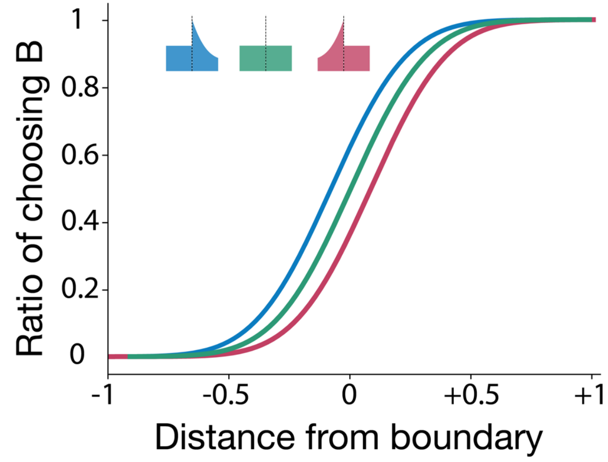






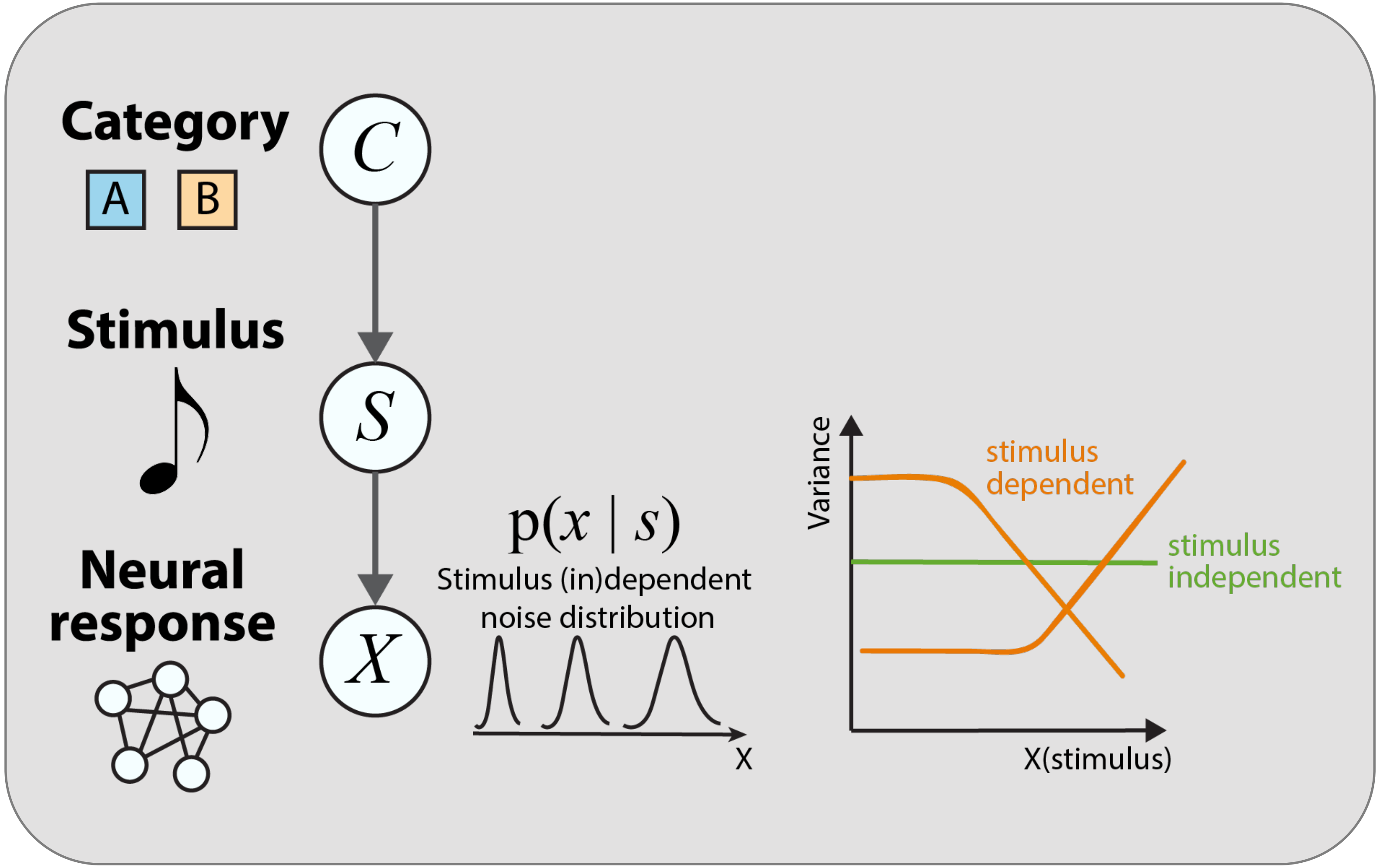


OPTIMAL AGENT



Pedrosa, Menichini, Pajot-Moric, et al, bioRxiv 2023

Fit the normative model to individual subjects



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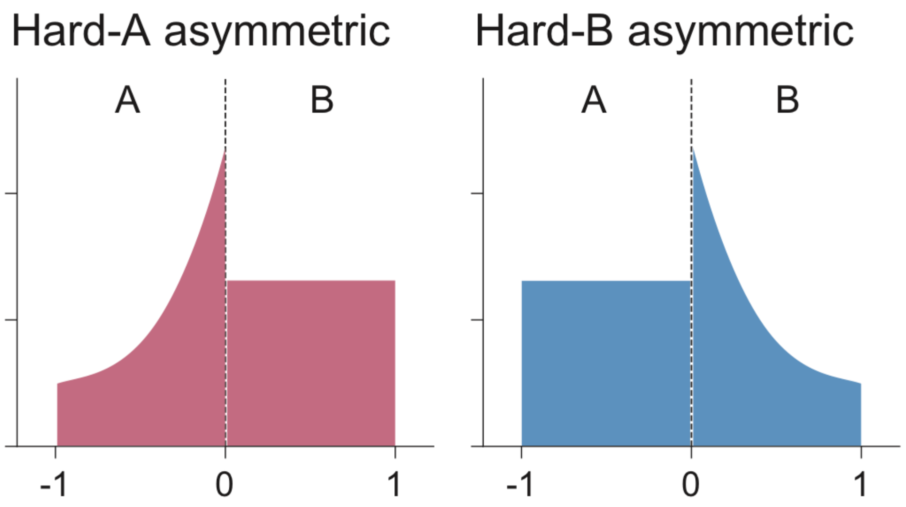
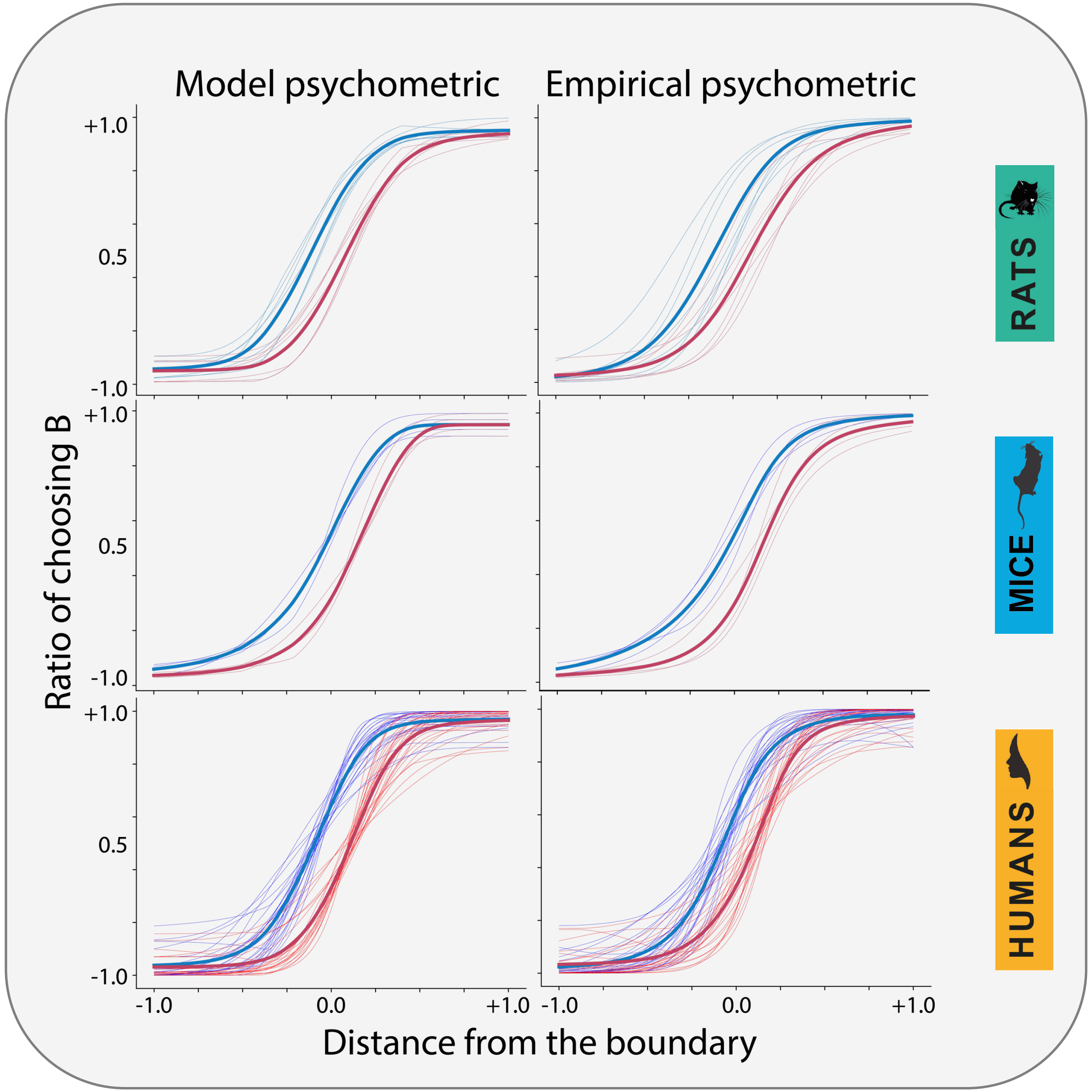
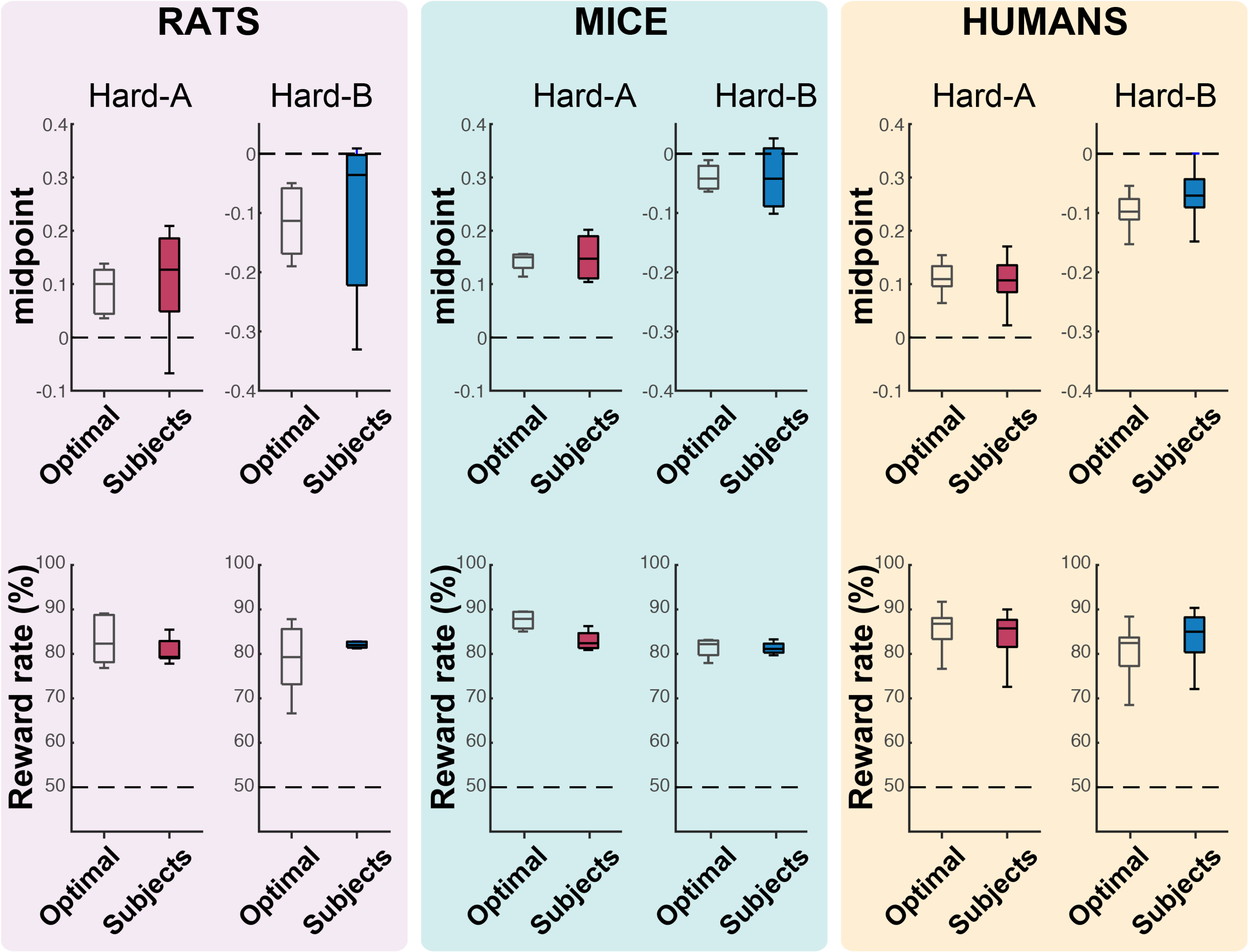
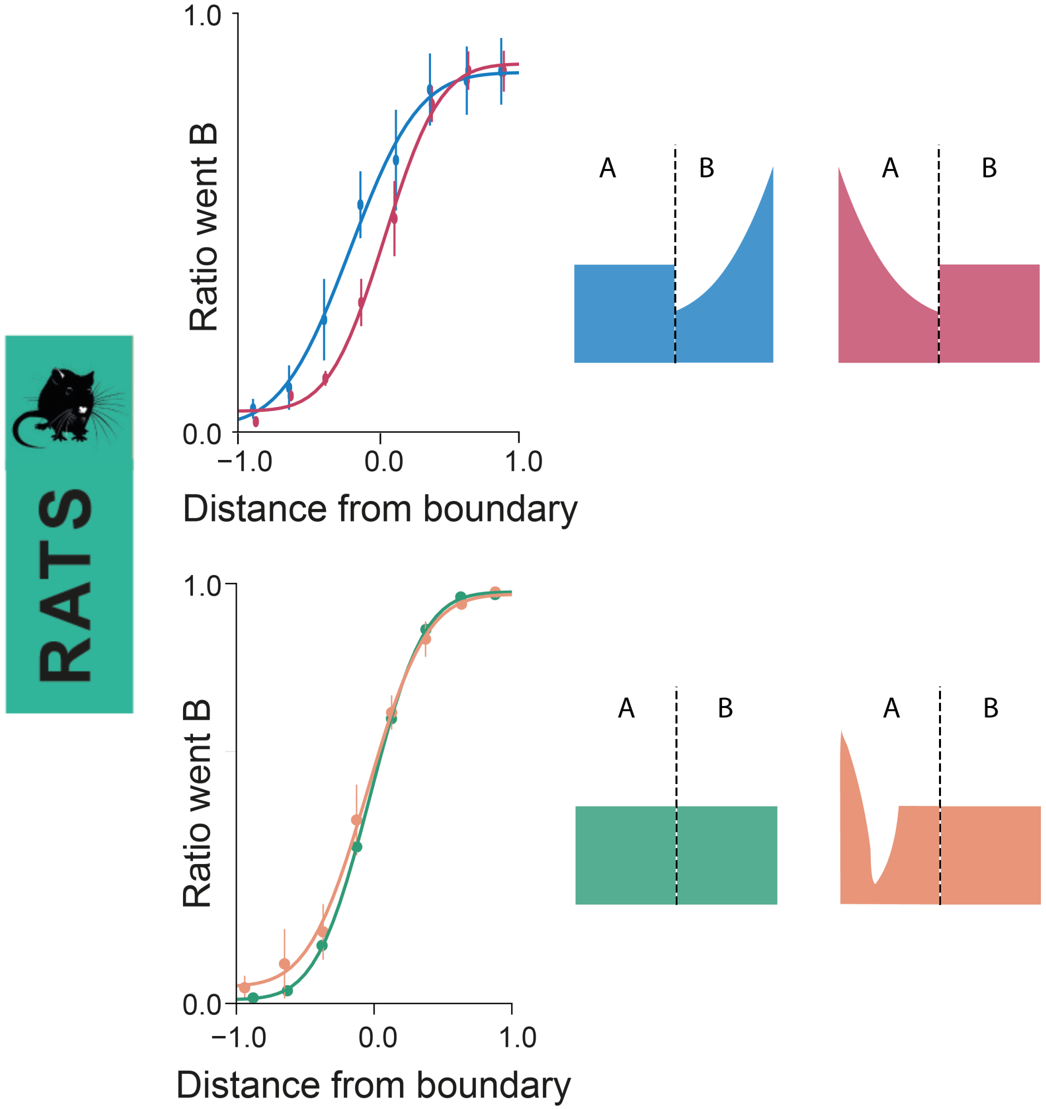




Adapt to sensory statistics to optimize performance and maximize reward



Asymmetry in distribution is exploited only if needed



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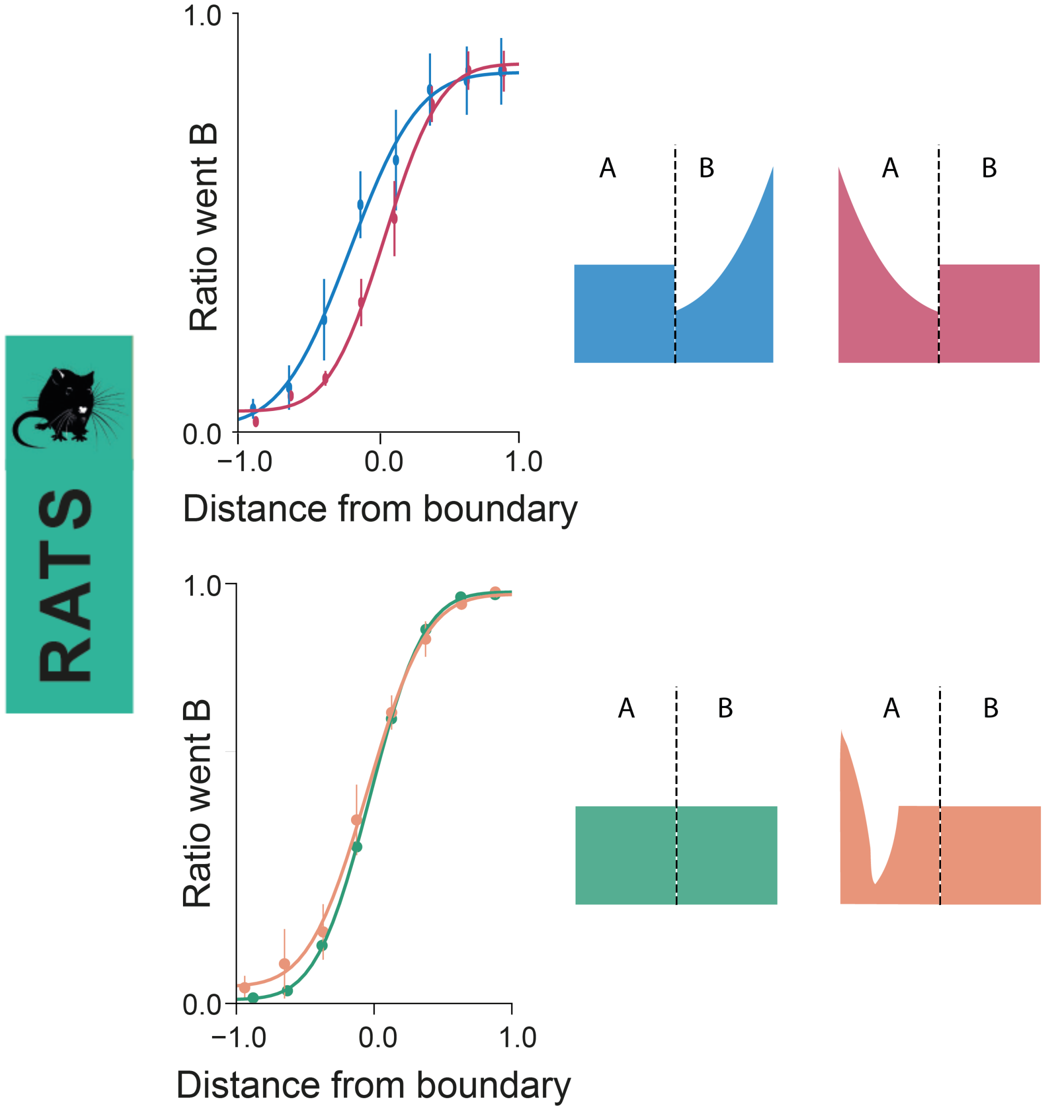
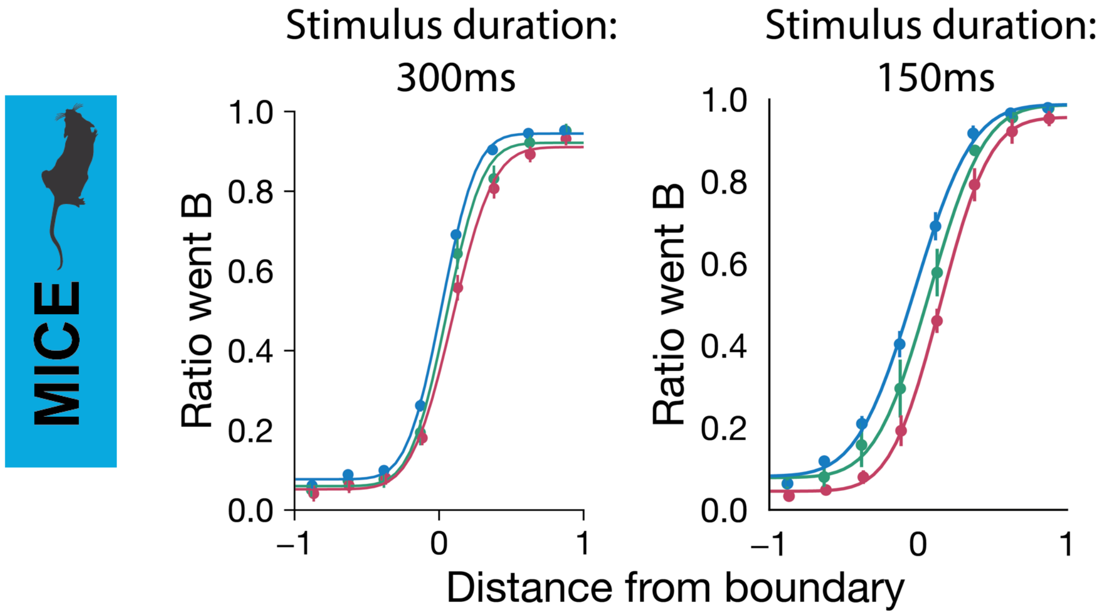
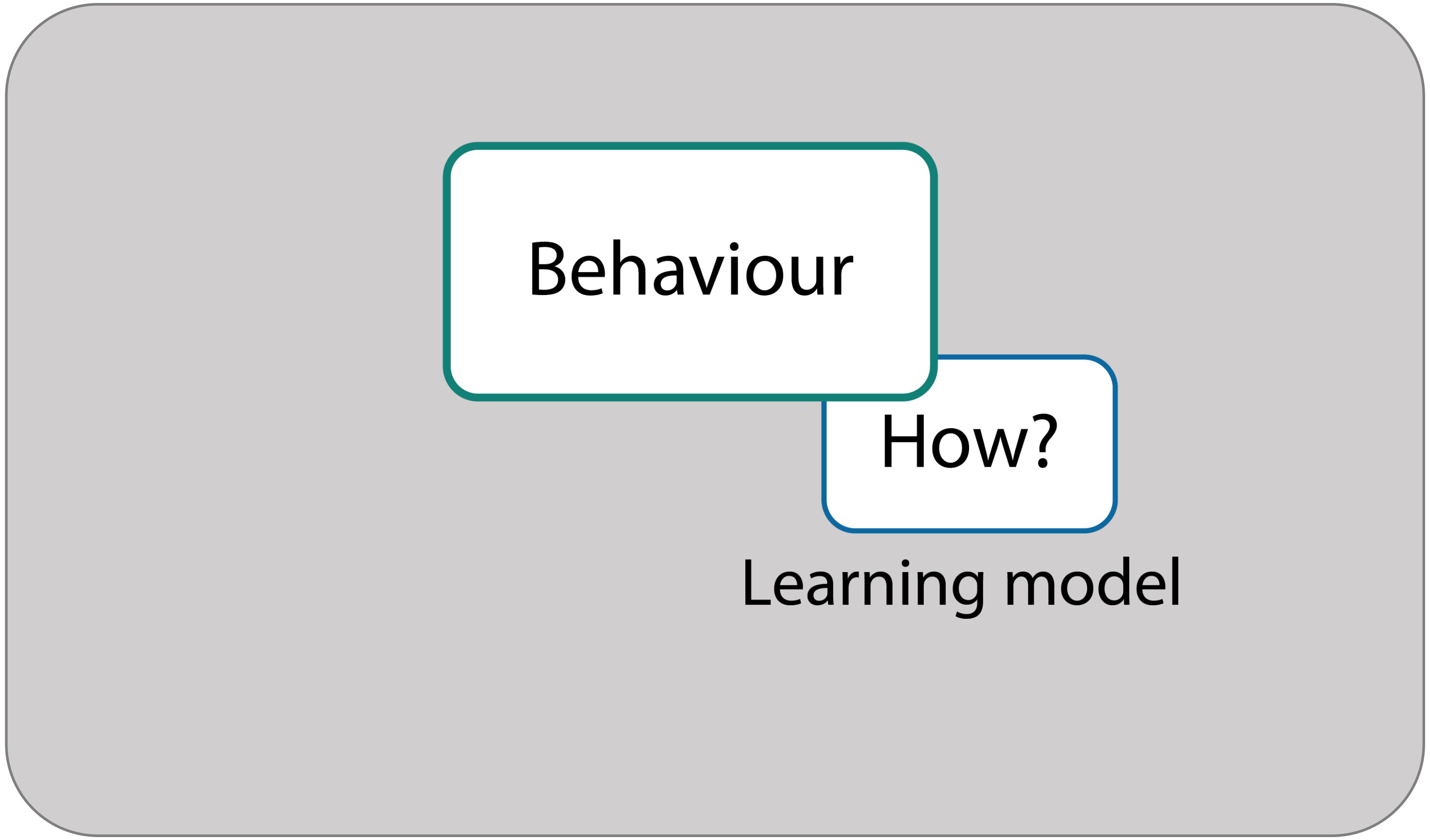




How is this optimal behaviour achieved?



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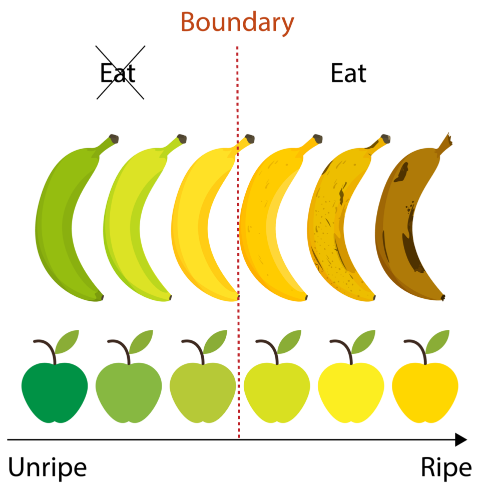

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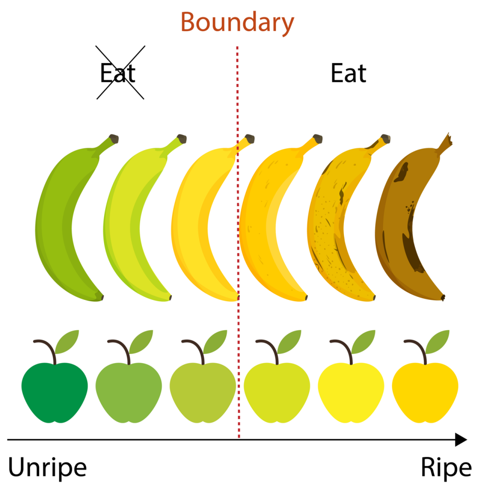
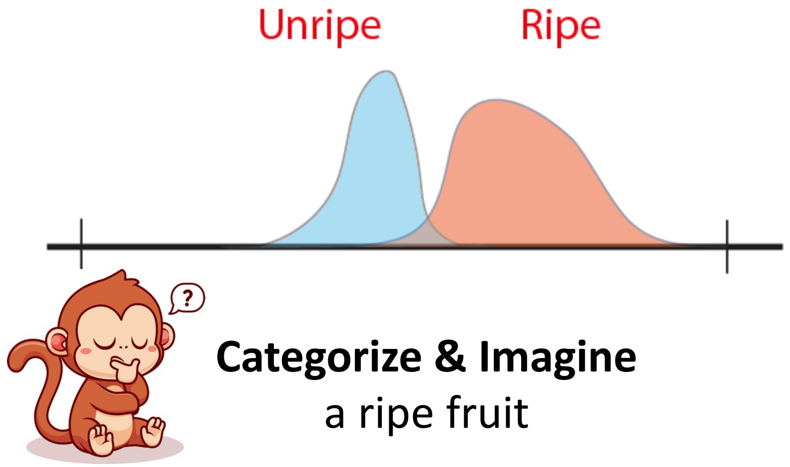


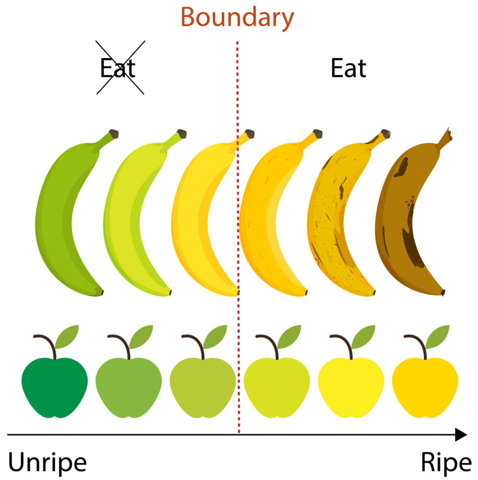
Sensory priors: Generative understanding of statistical relationships

Decision priors: Learning sensory to action to reward mappings



Categorize & Imagine
a ripe fruit

How is this optimal behaviour achieved?



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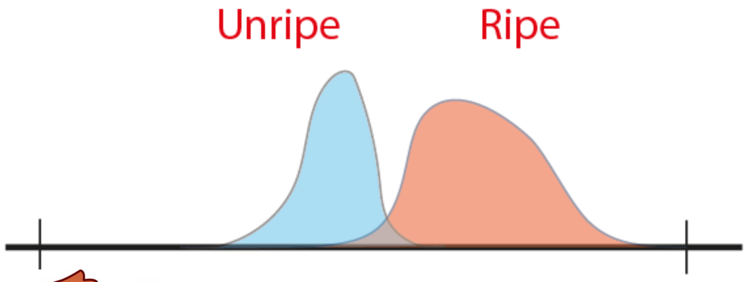

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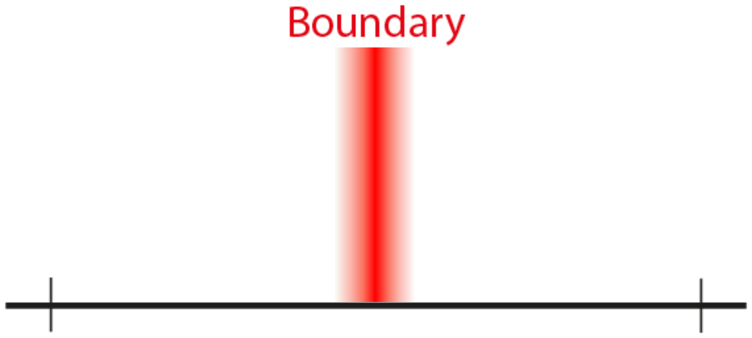


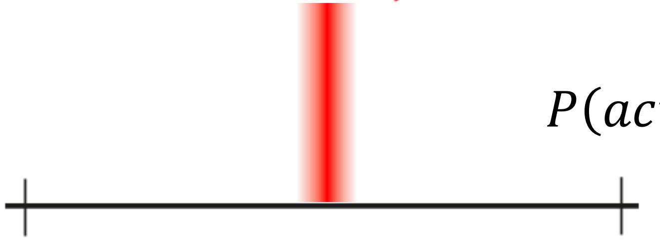
Categorize
a ripe fruit

Two learning models

Victor Pedrosa

Boundary learning

Boundary



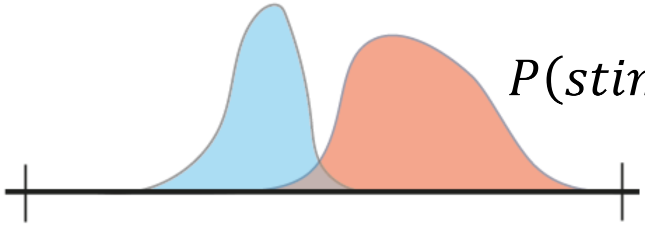
$P(action \mid stimulus)$

Decision prior

Sound

Category learning

Category B   Category A



$P(stimulus \mid category)$

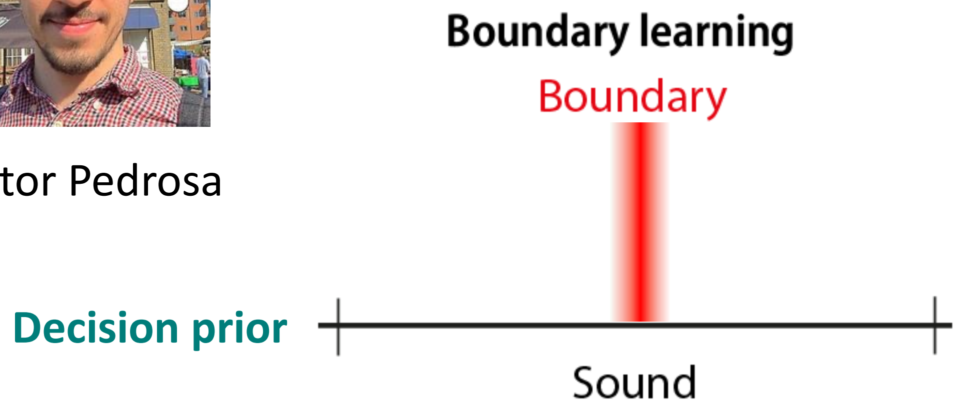
Sensory prior

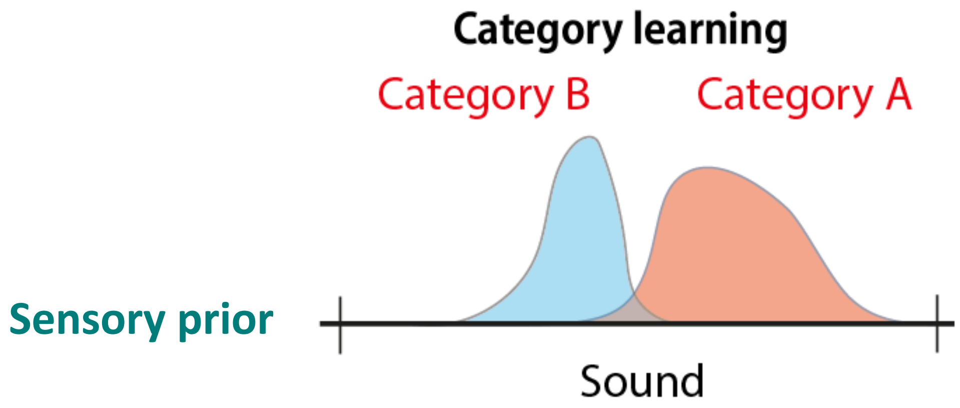
Sound

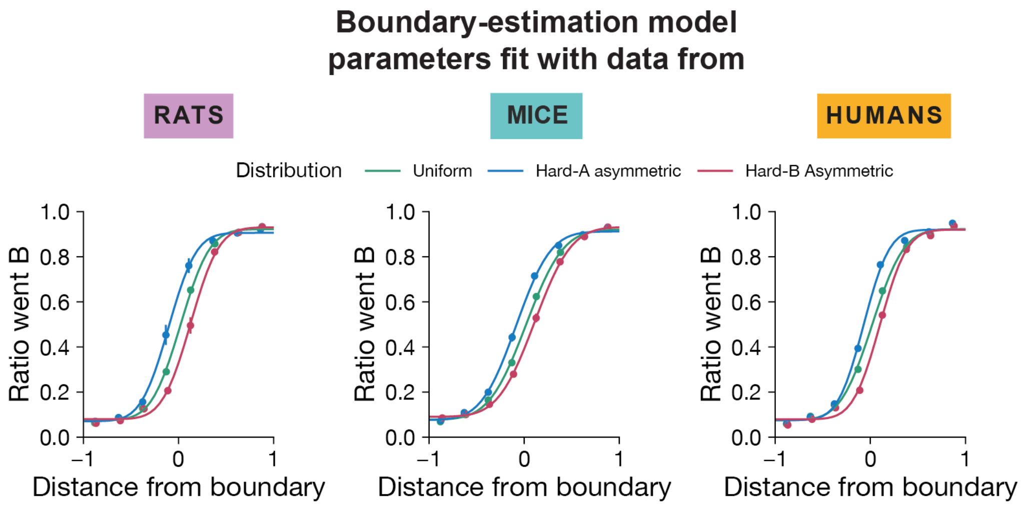
Pedrosa, Menichini, Pajot-Moric, et al, bioRxiv 2023

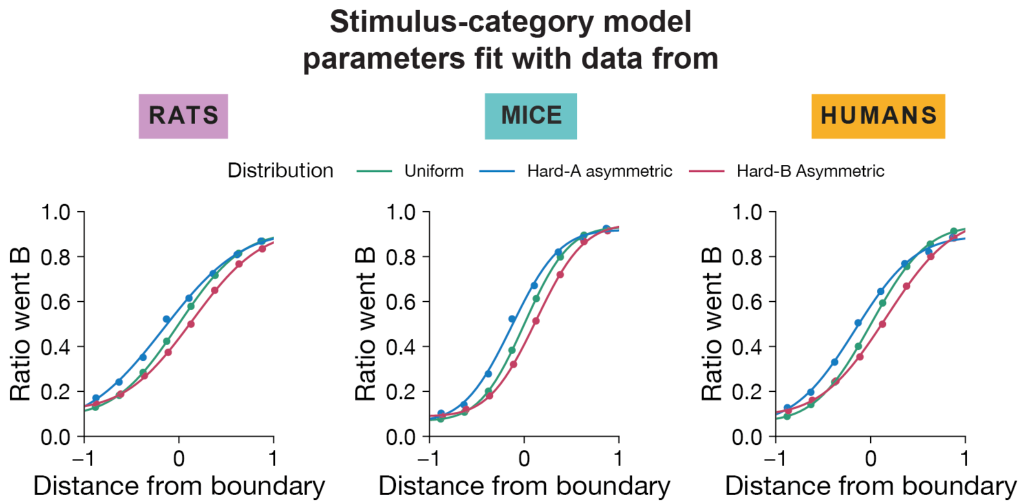
Both ‘Category’ and ‘Boundary’ learning models predict shift in psychometric

Victor Pedrosa



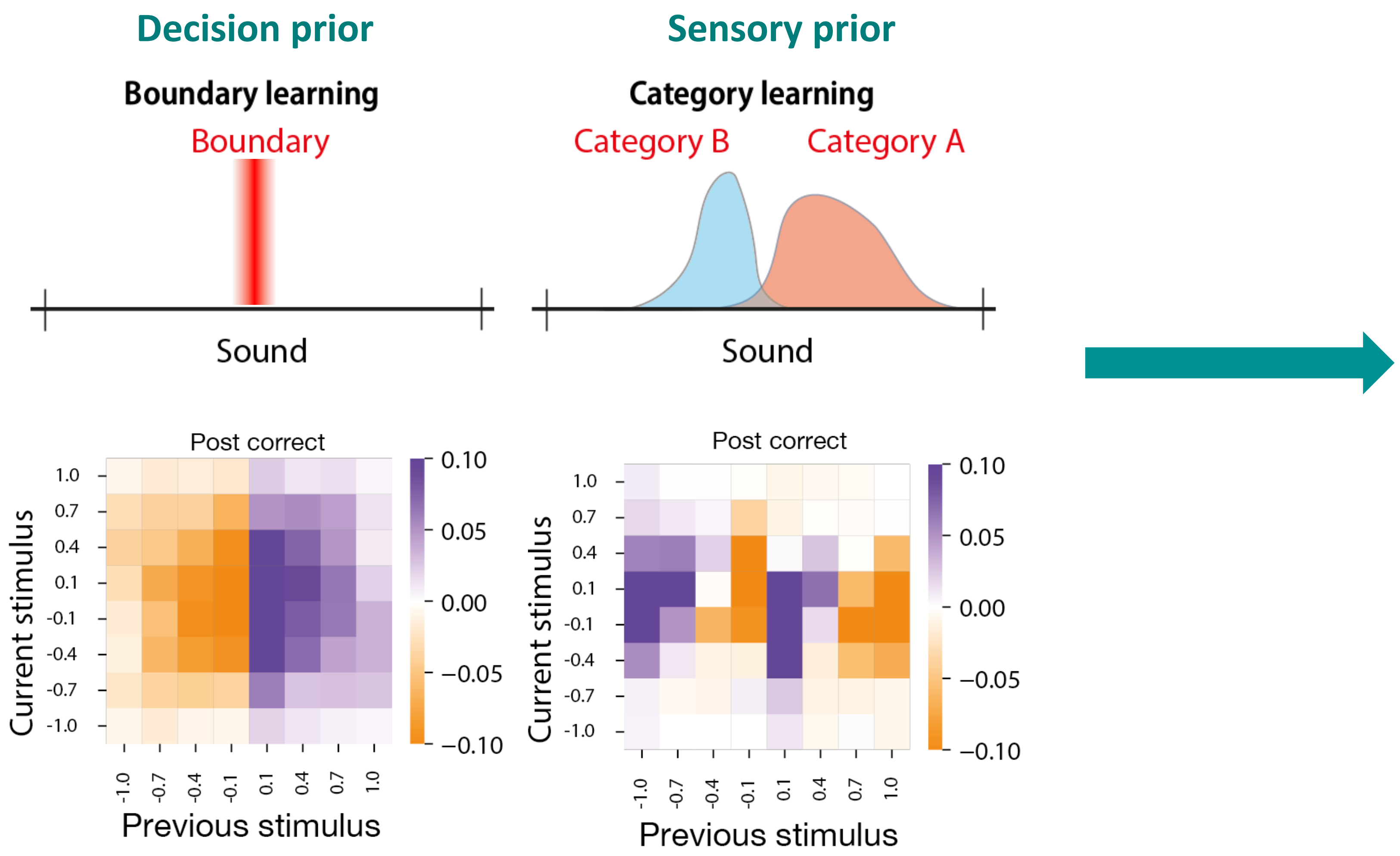




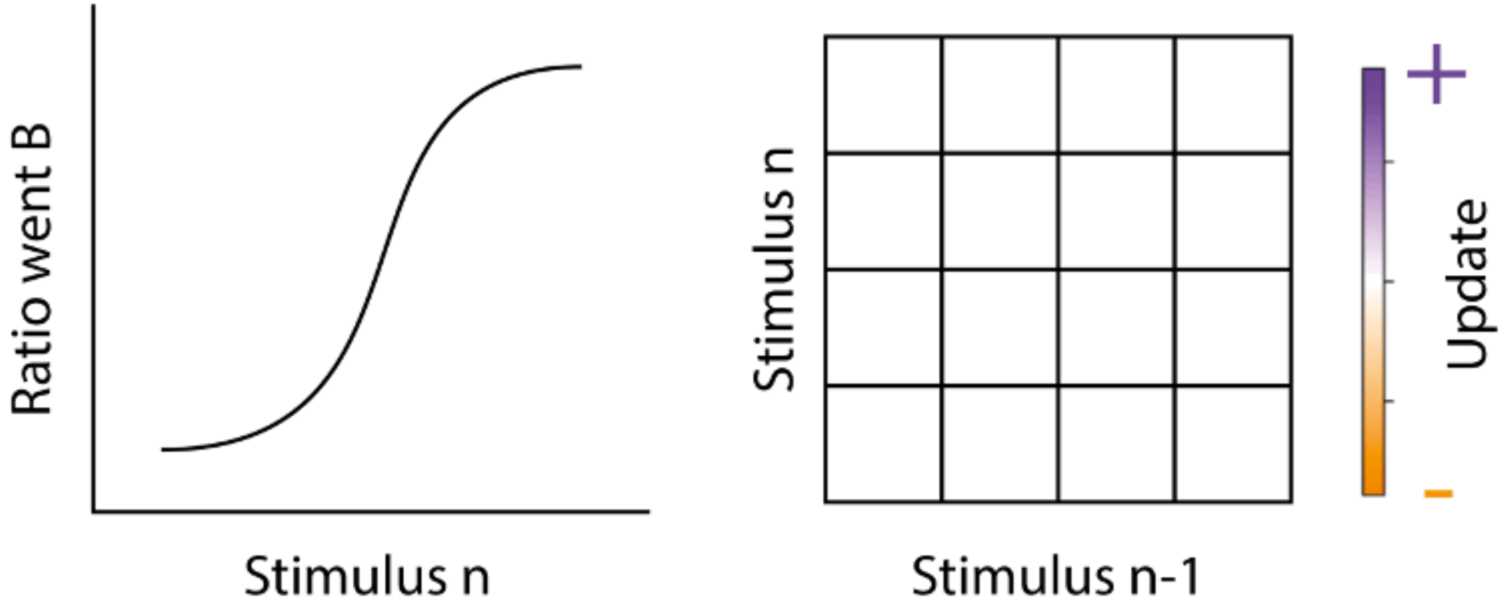


Pedrosa, Menichini, Pajot-Moric, et al, bioRxiv 2023

'Category' & 'Boundary' learning models predict different trial-to-trial choice update

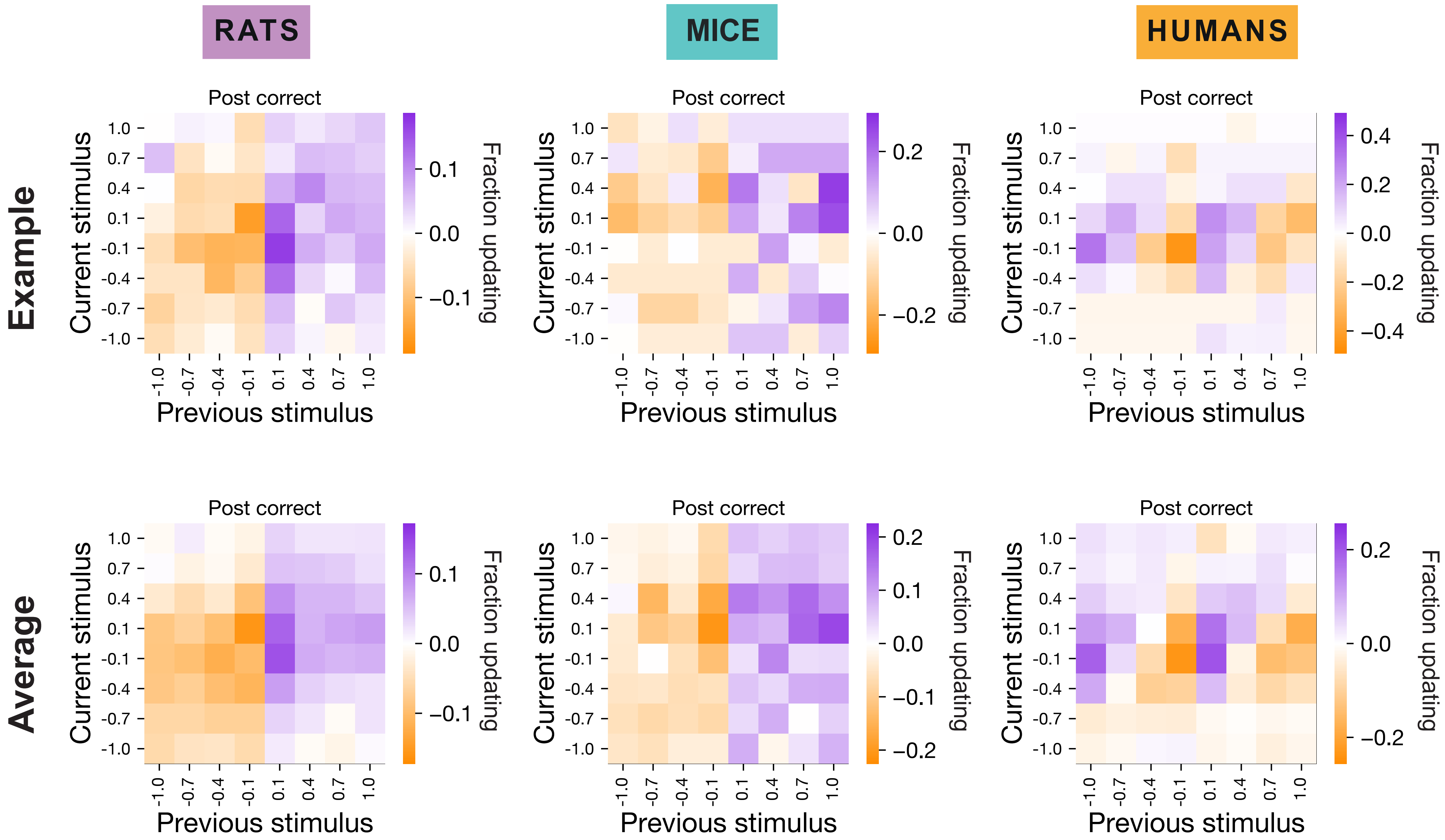


predict different trial-to-trial choice update

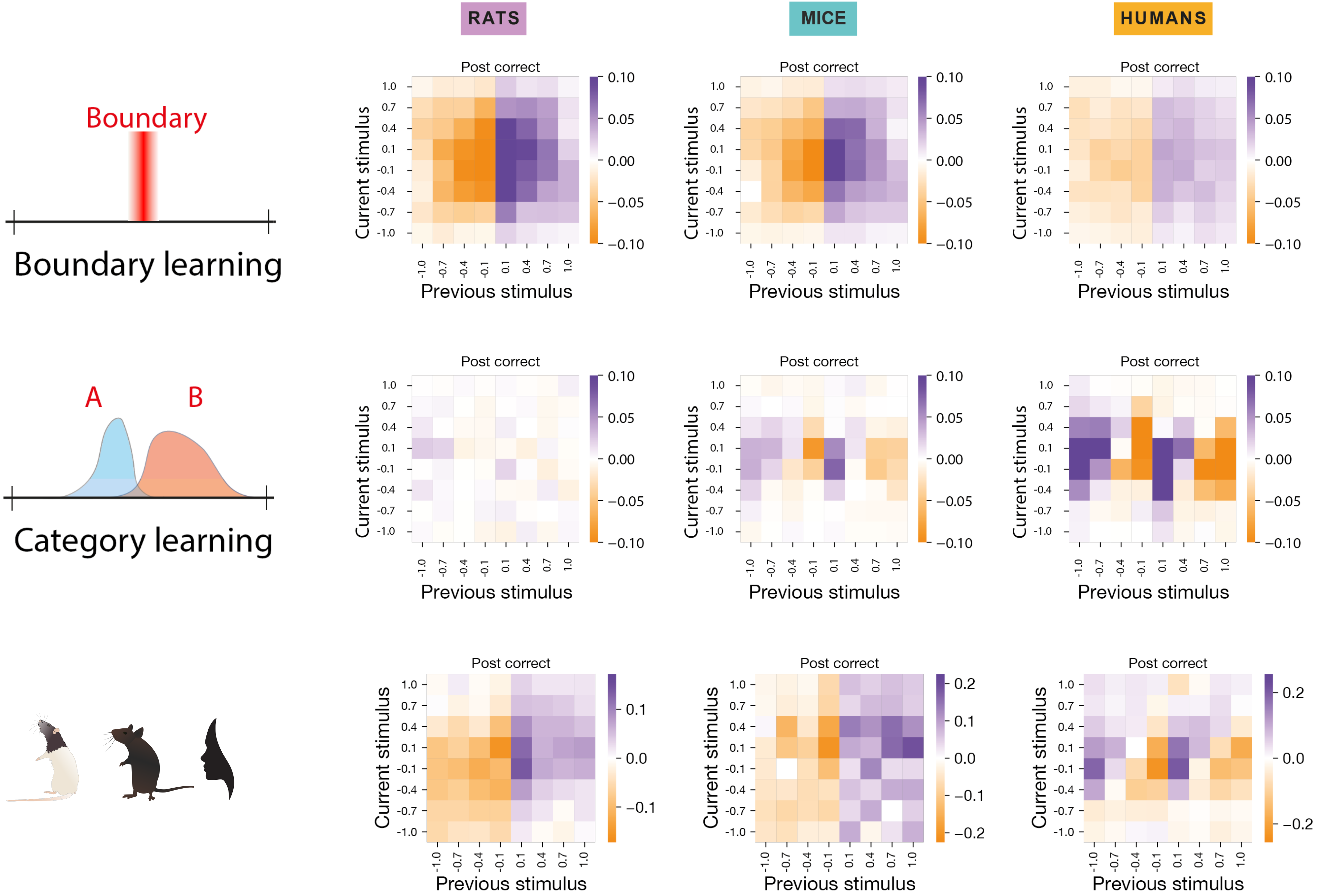


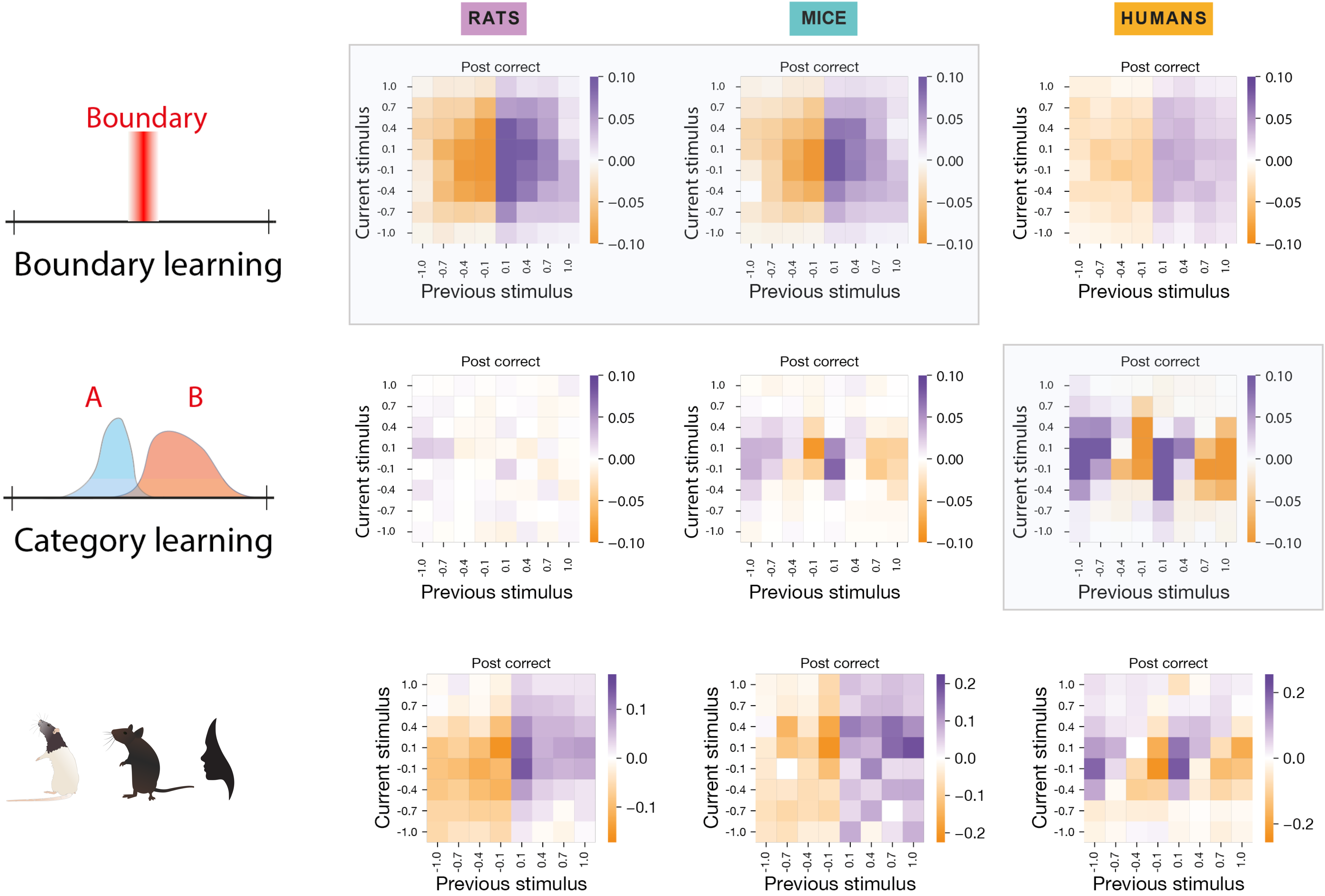
Update = distance from average
(black line)

Lak et al., eLife (2020)



RATS
MICE
HUMANS
Example
Average
Post correct
Current stimulus
Previous stimulus
Fraction updating
1.0
0.7
0.4
0.1
-0.1
-0.4
-0.7
-1.0
0.1
0.0
−0.1
0.2
−0.2
0.4
−0.4


RATS
MICE
HUMANS
Boundary
Boundary learning
A
B
Category learning
Post correct
Current stimulus
Previous stimulus
1.0
0.7
0.4
0.1
-0.1
-0.4
-0.7
-1.0
0.10
0.05
0.00
−0.05
−0.10
0.1
0.0
−0.1
0.2
−0.2



RATS
MICE
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Boundary learning
A
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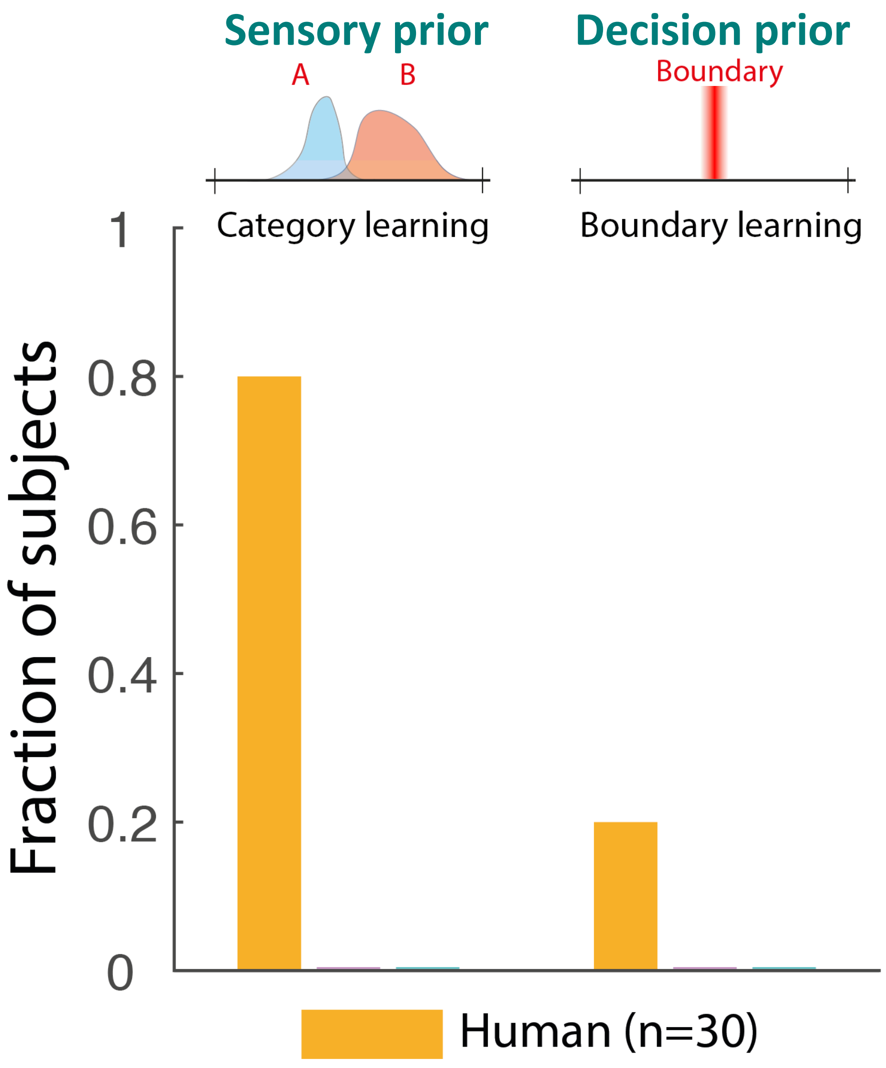
Category learning
Post correct
Current stimulus
Previous stimulus
1.0
0.7
0.4
0.1
-0.1
-0.4
-0.7
-1.0
0.10
0.05
0.00
−0.05
−0.10
0.1
0.0
−0.1
0.2
−0.2

Individual variability



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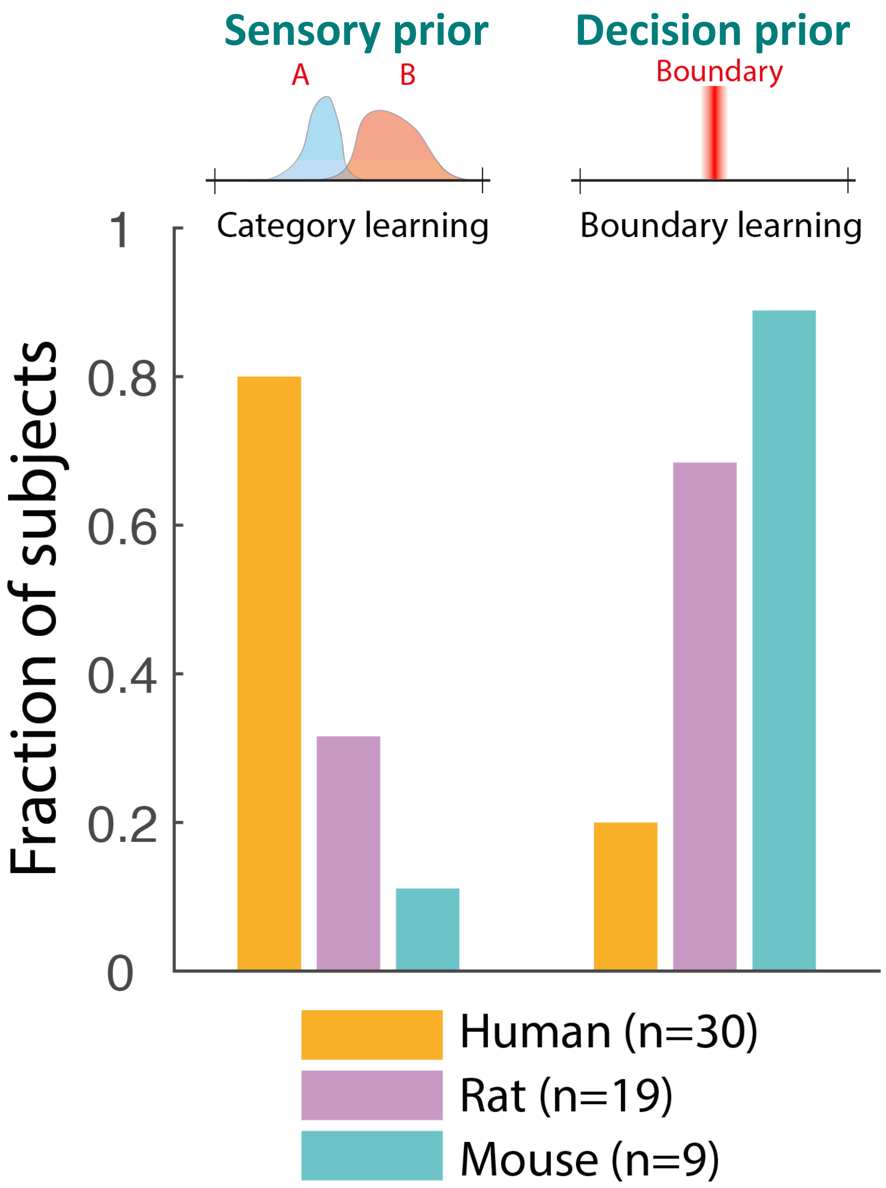
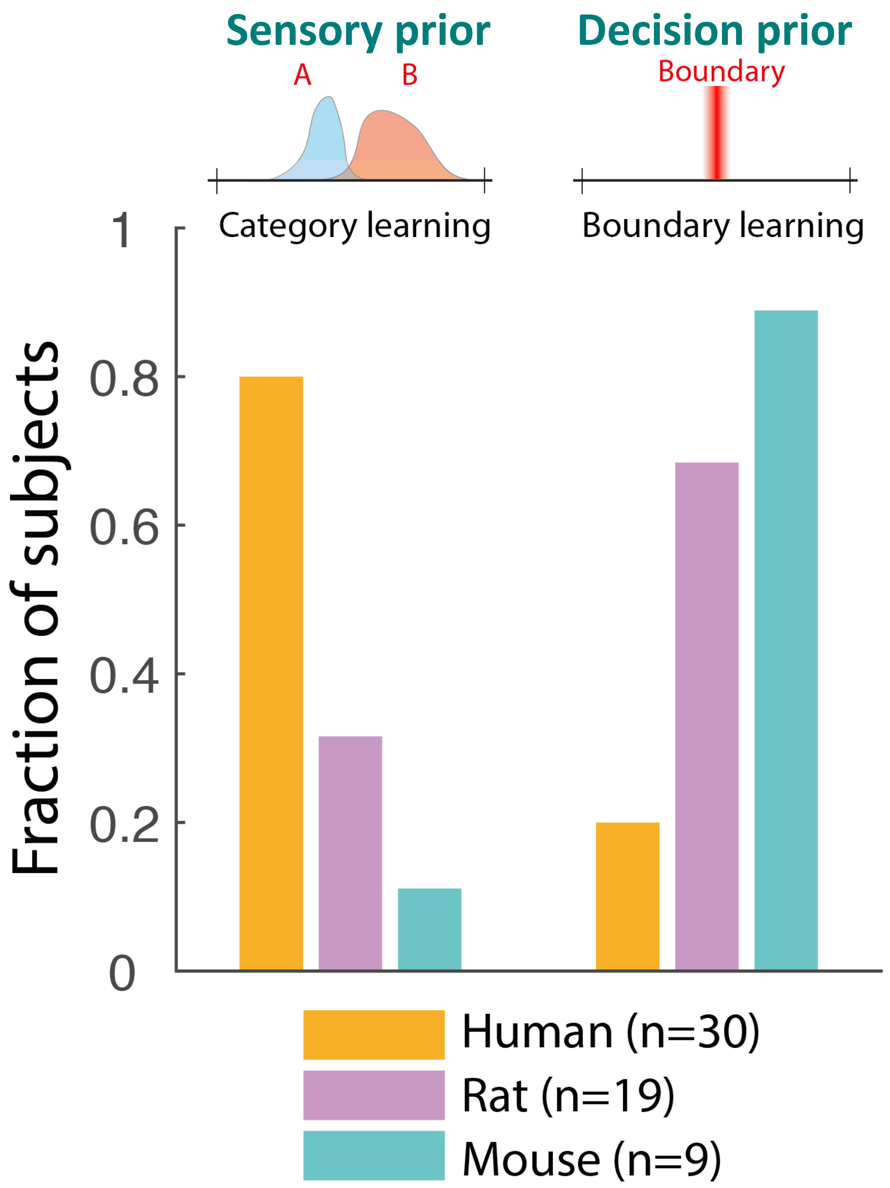
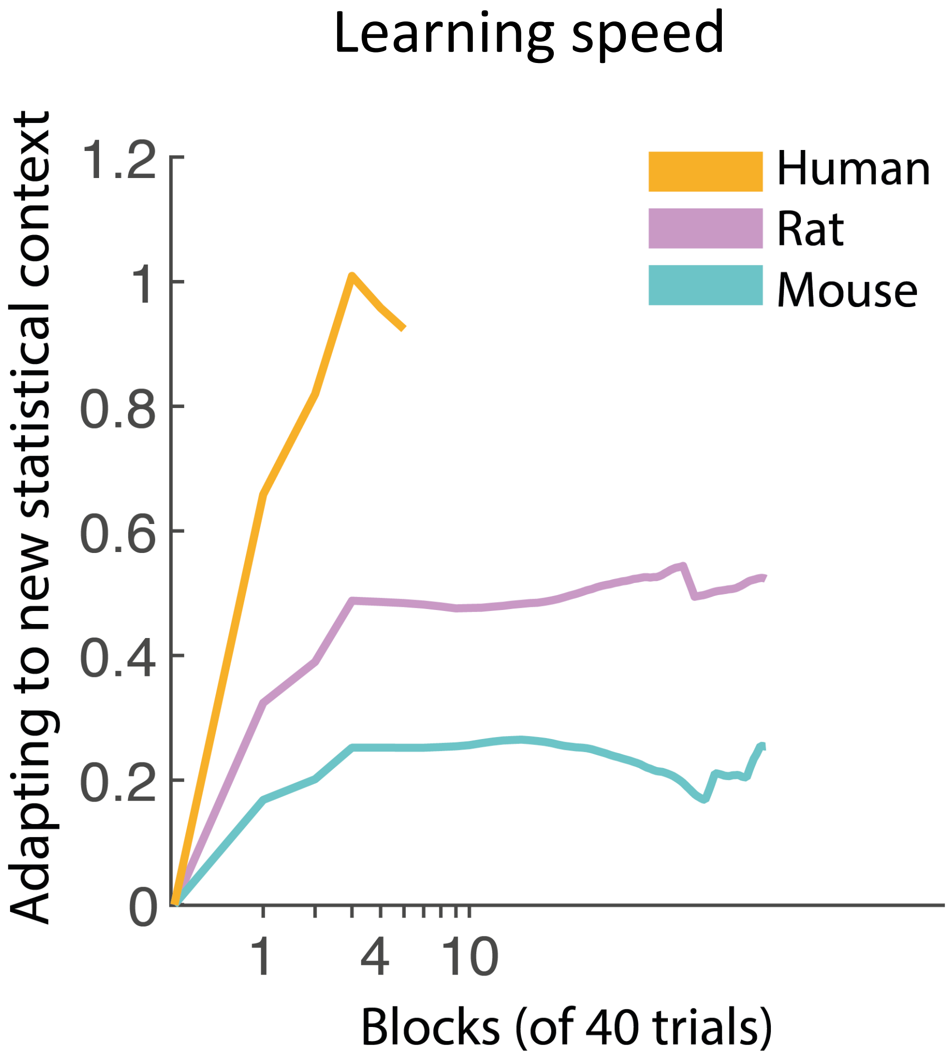


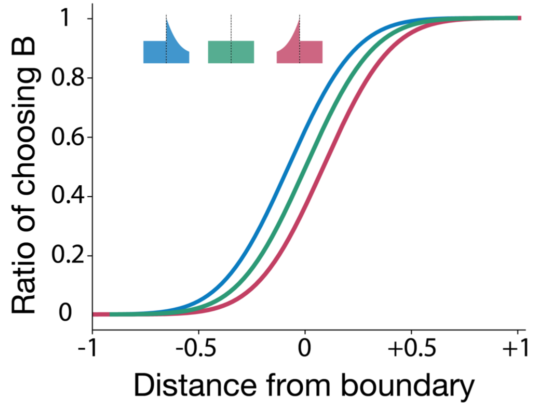
Individual variability





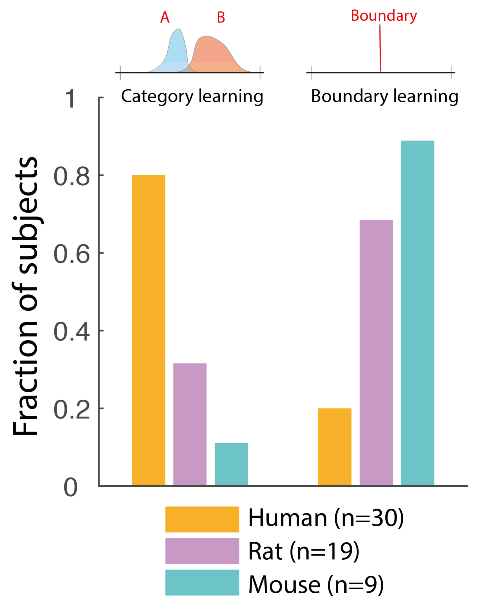
Interim summary (1)

- Humans, rats and mice adapt to sensory statistics to optimize performance and maximize reward.

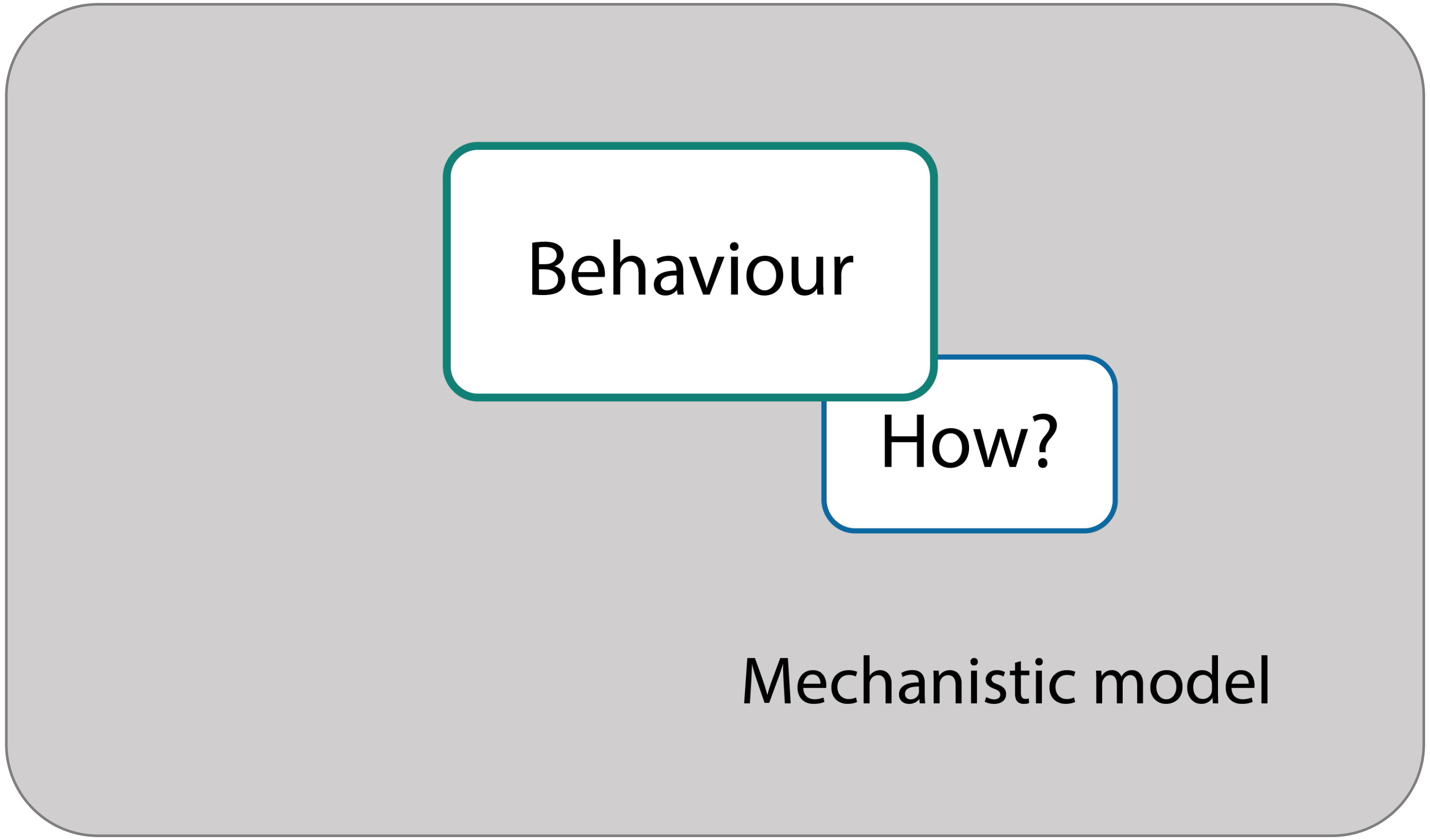


- Individuals have different trial-to-trial update of their policies

- Humans (and some rodents) show a more complex learning update, and more indicative of utilizing detailed sensory statistics.



What is the mechanism underlying this optimal behaviour ?



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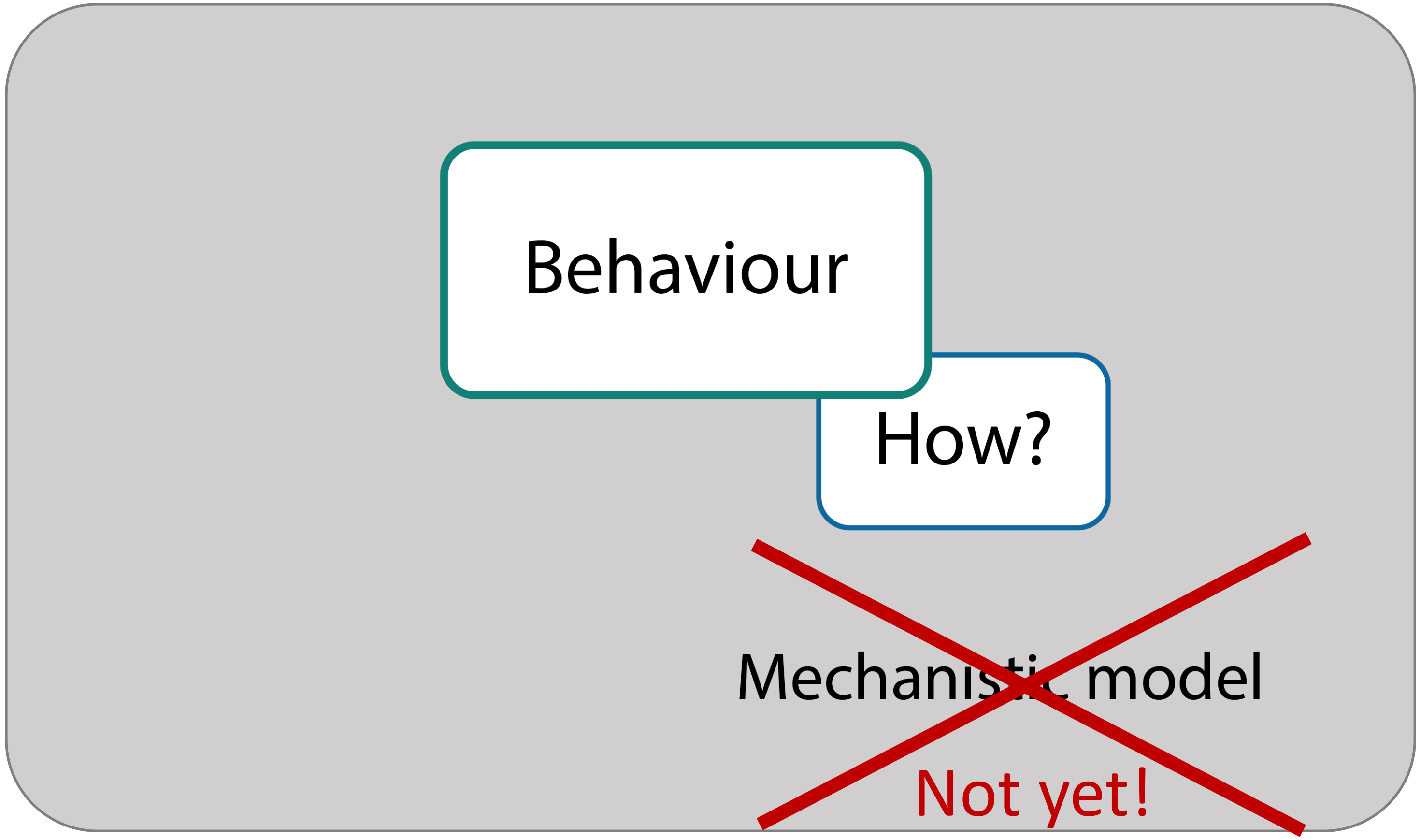
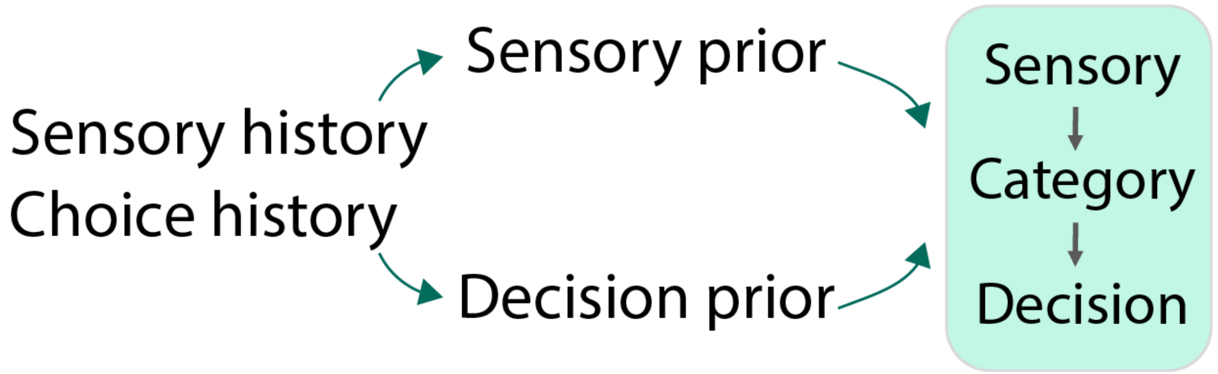


How is the context information learned?

How it affects sensory representation and decision?



How is the context information learned?
How it affects sensory representation and decision?

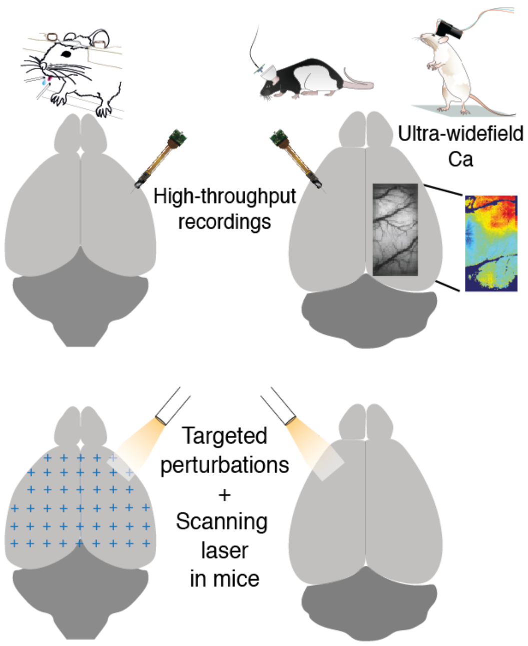
Approach

Mapping activity

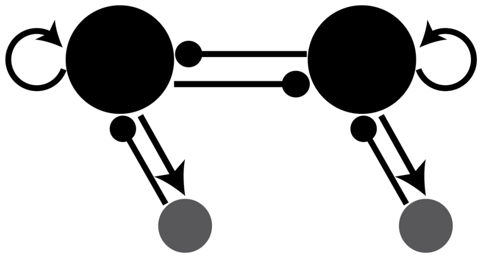
- Large-scale recordings

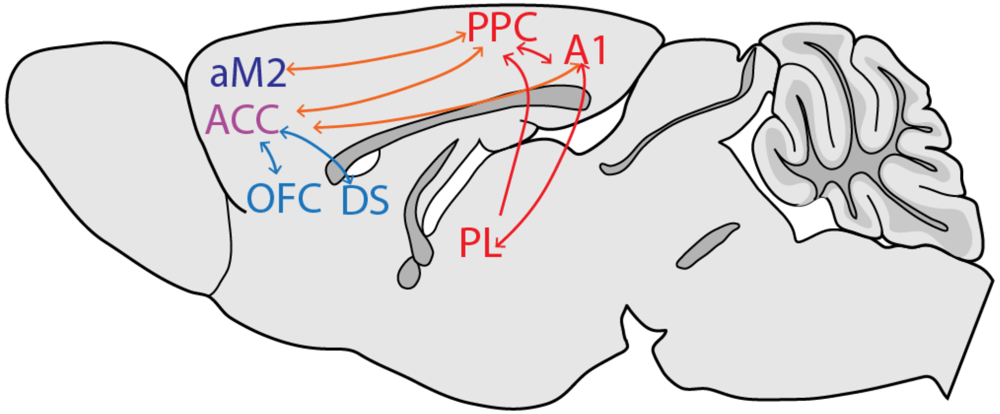
Targeted perturbations

- Scanning laser over the dorsal surface in mouse
- Fiber optics in rat



Circuit modeling





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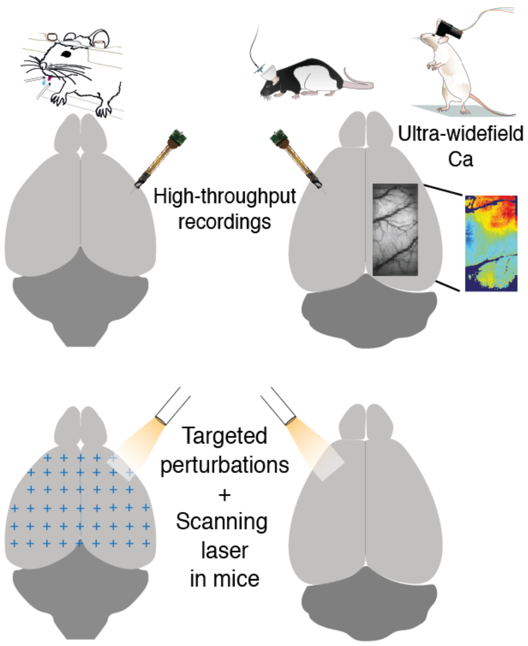

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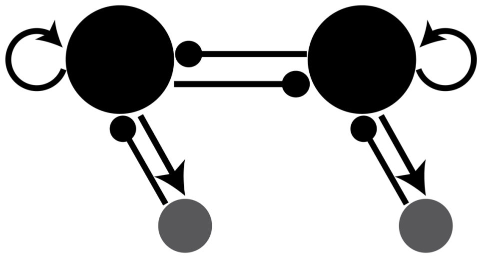

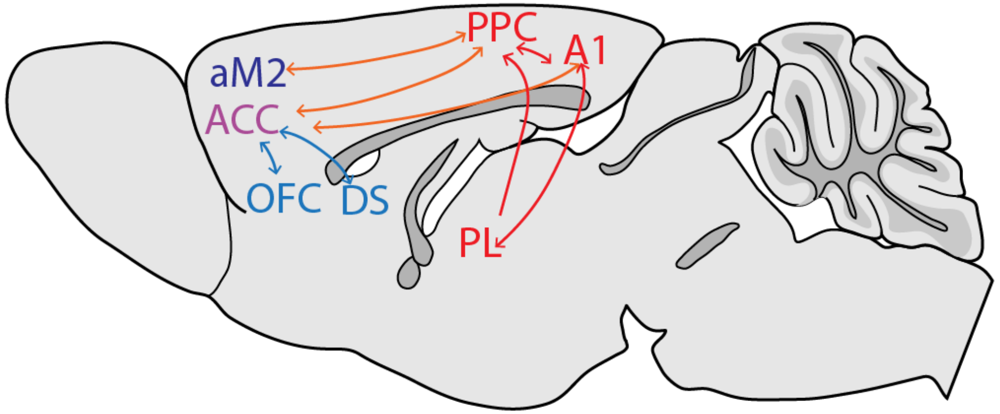

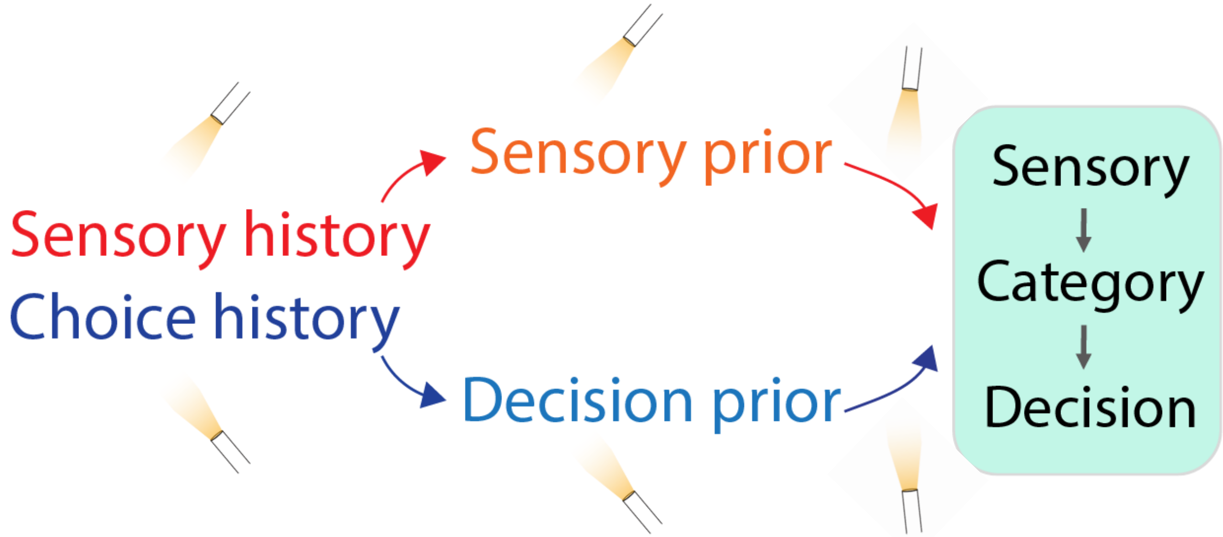

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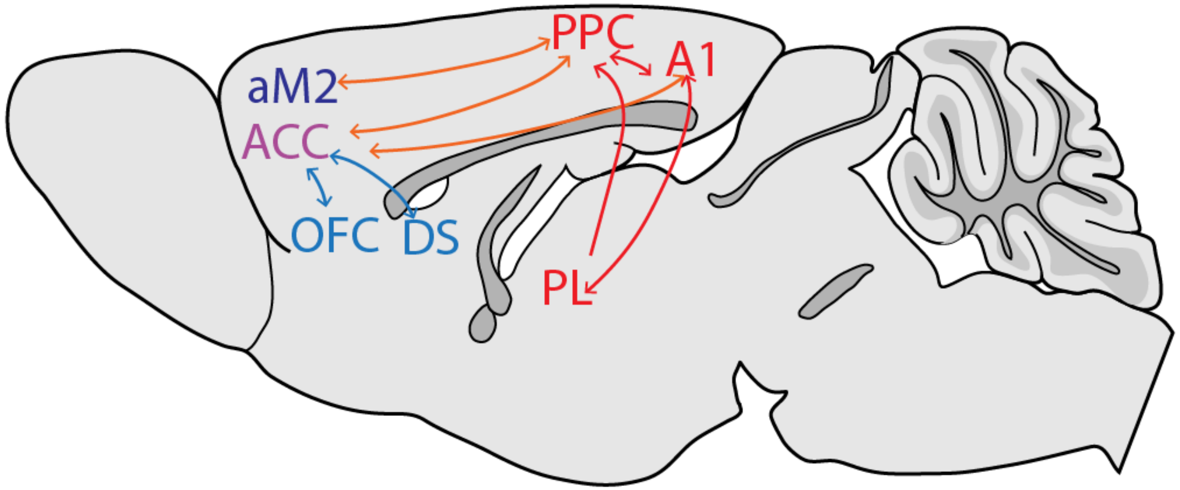
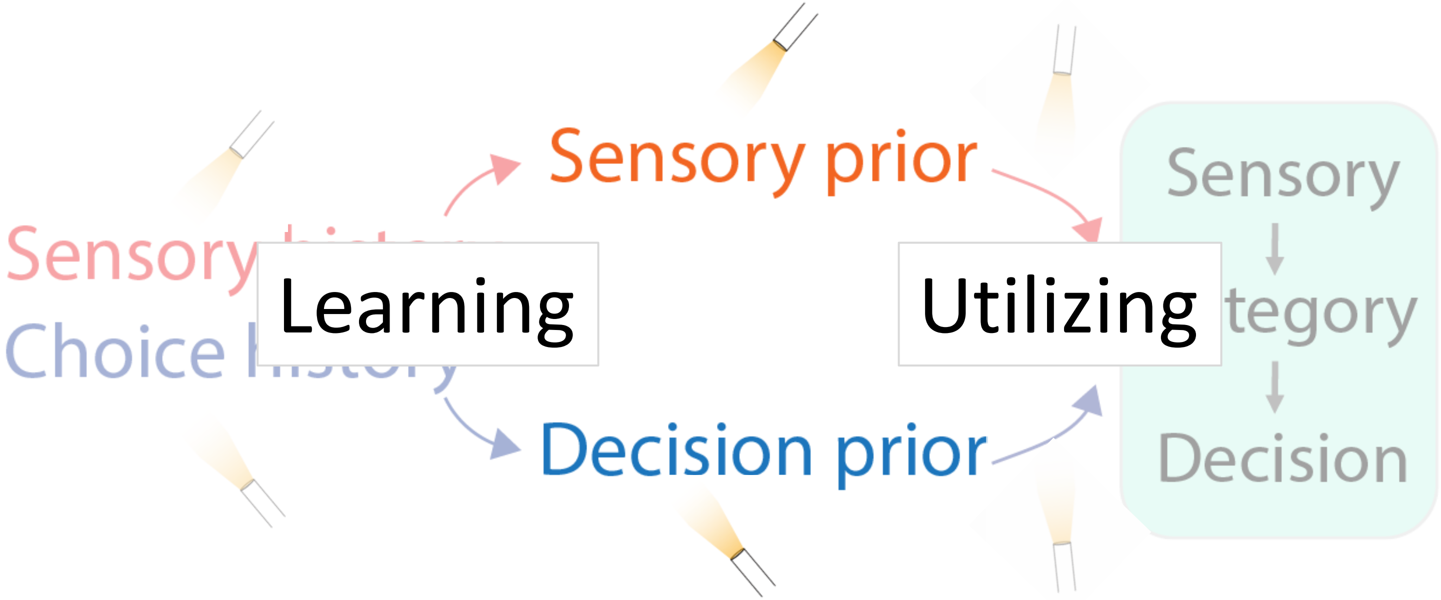
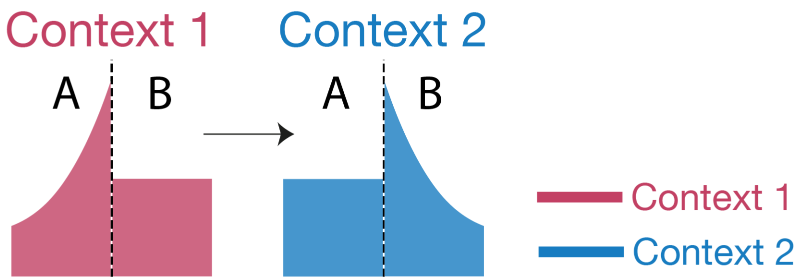


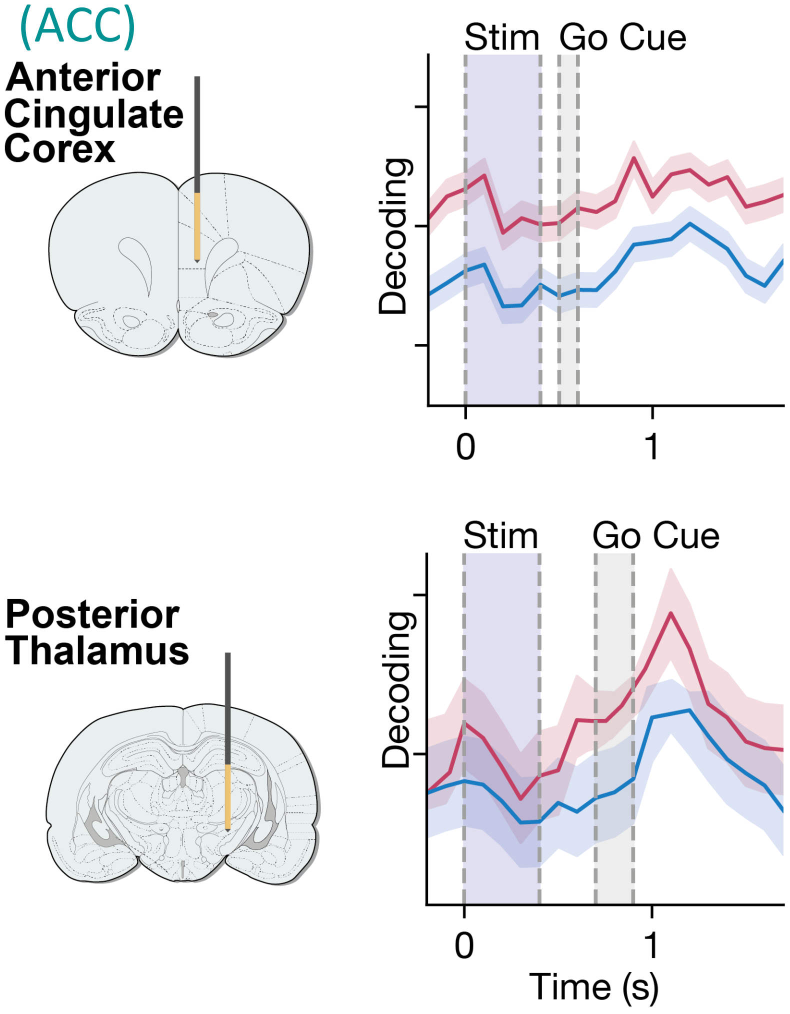


Anterior Cingulate Cortex in rats represent statistical context

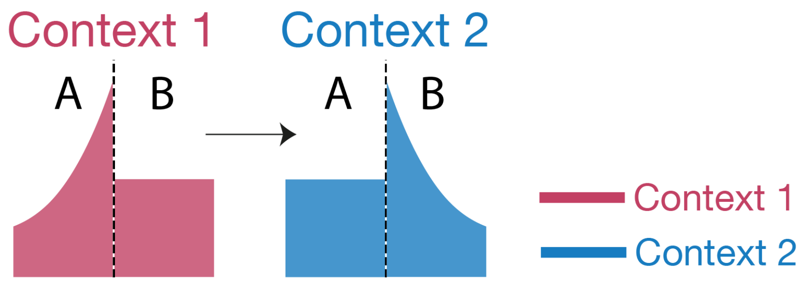
Elena Menichini

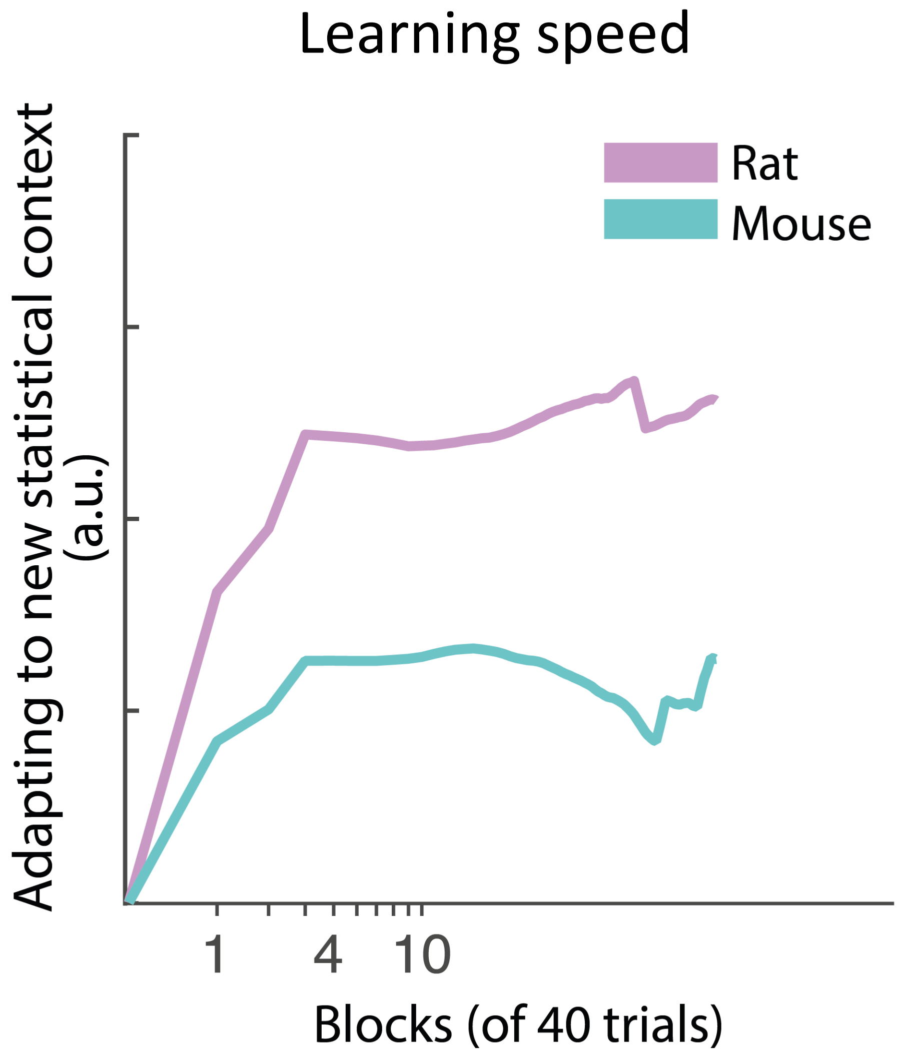
Neuropixel recordings





Learning & utilisation of statistics





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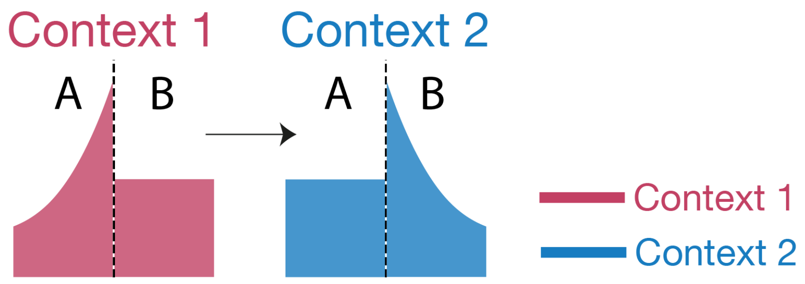
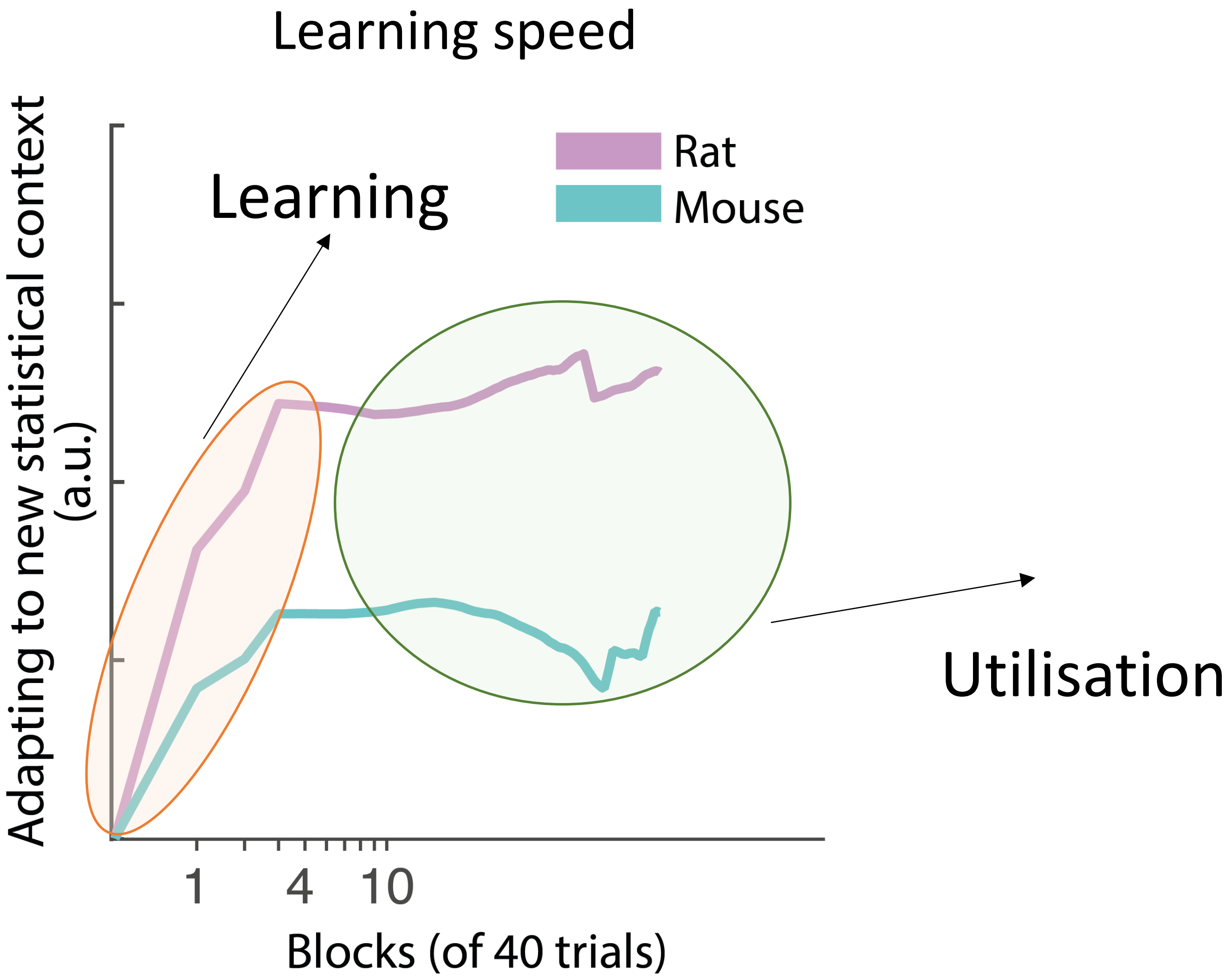
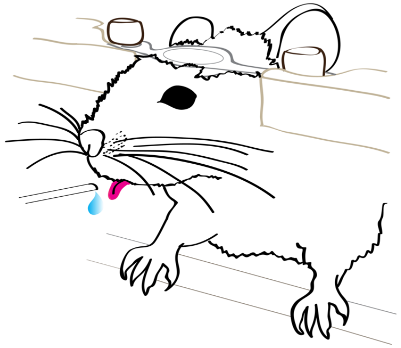
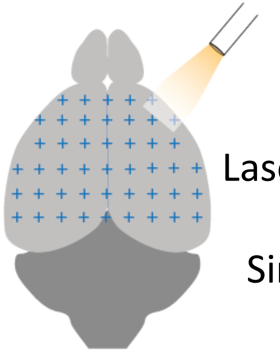




Quentin
Pajot-Moric

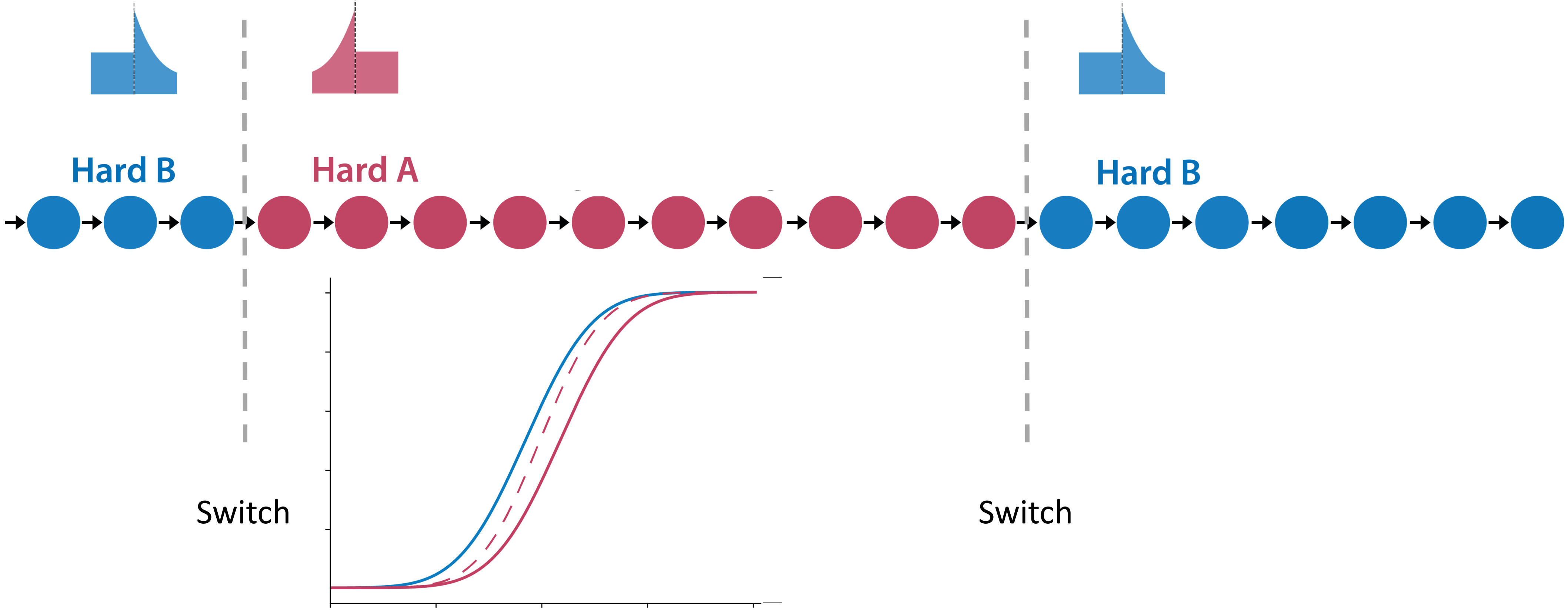
Head-fixed mice





Laser scanning
or
Single fibre

Anterior Cingulate Cortex
&
Utilisation?



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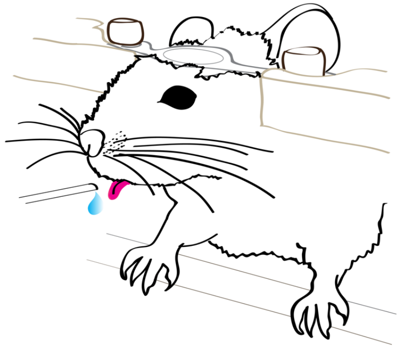

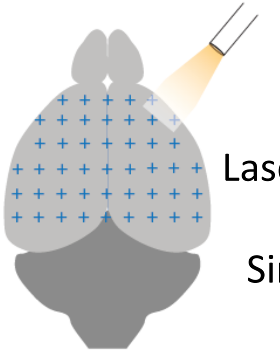

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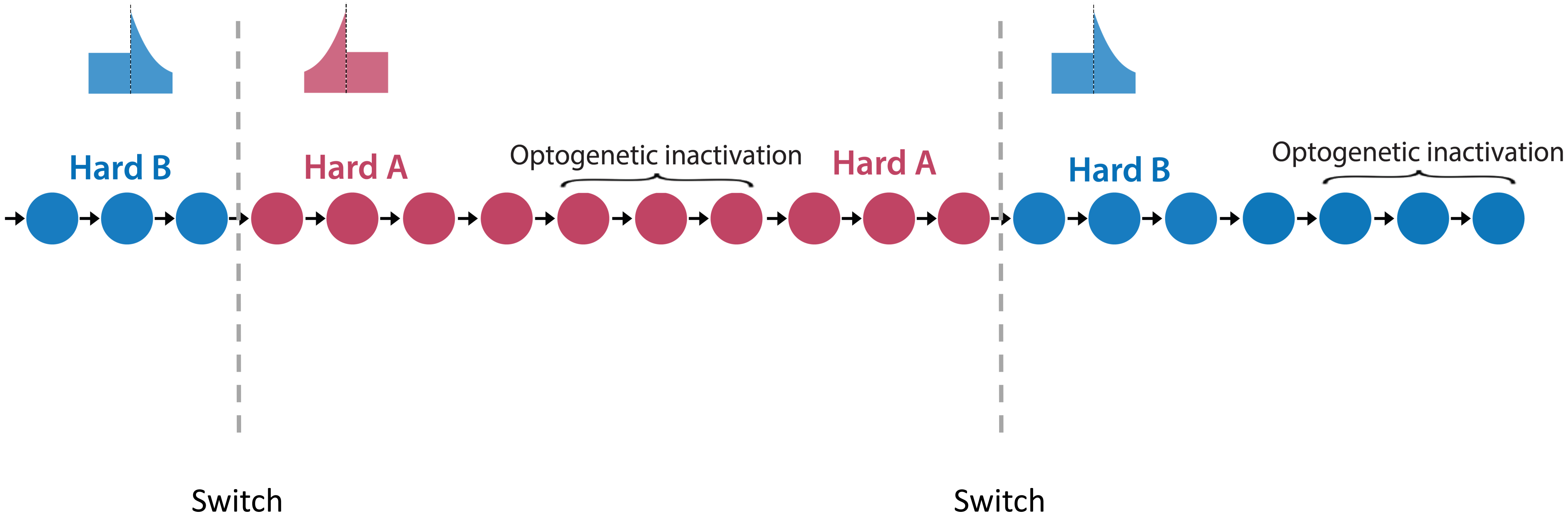

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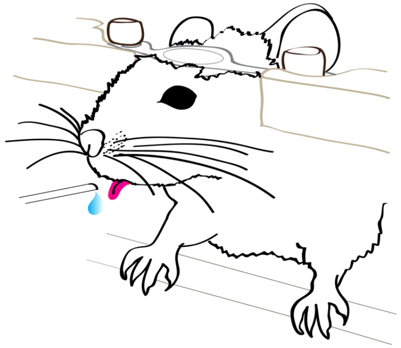

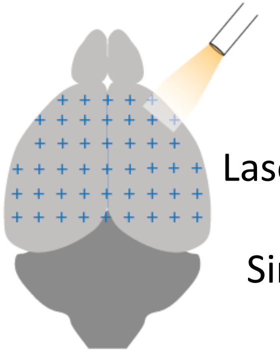

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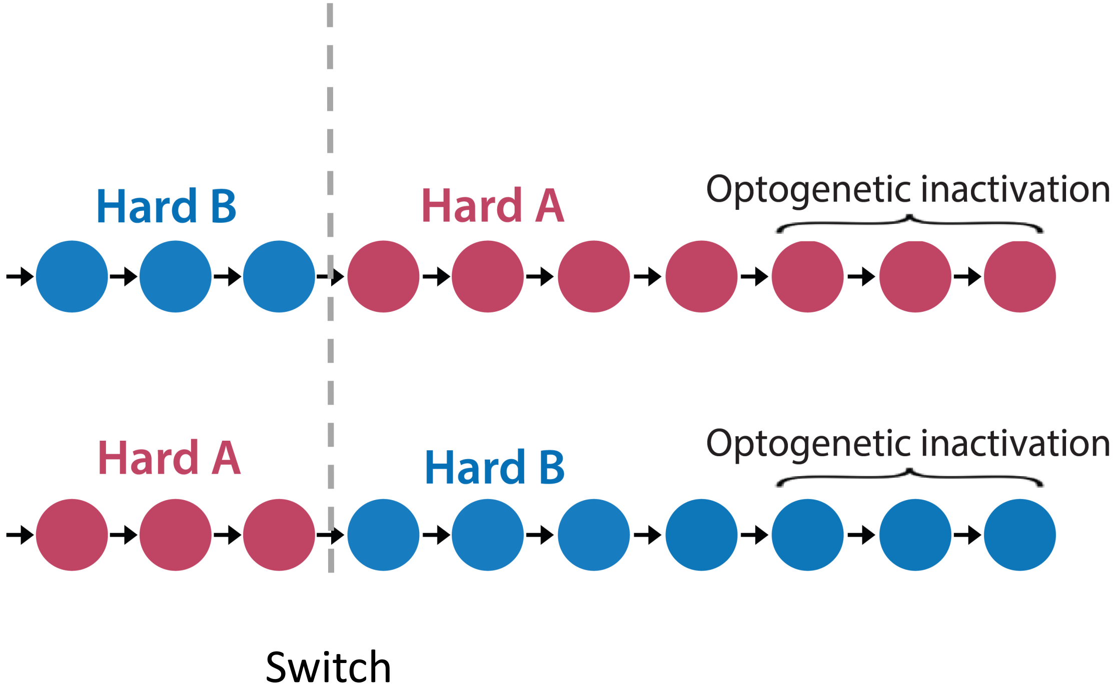

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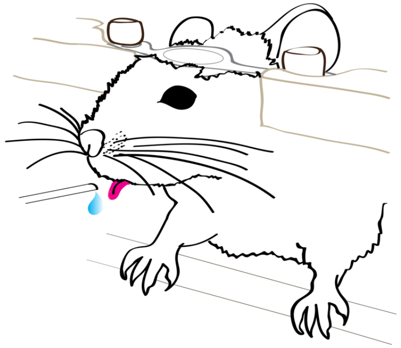

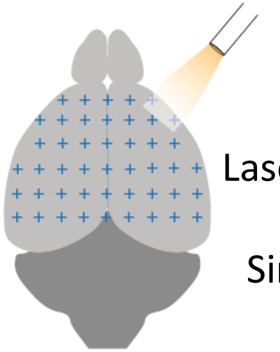

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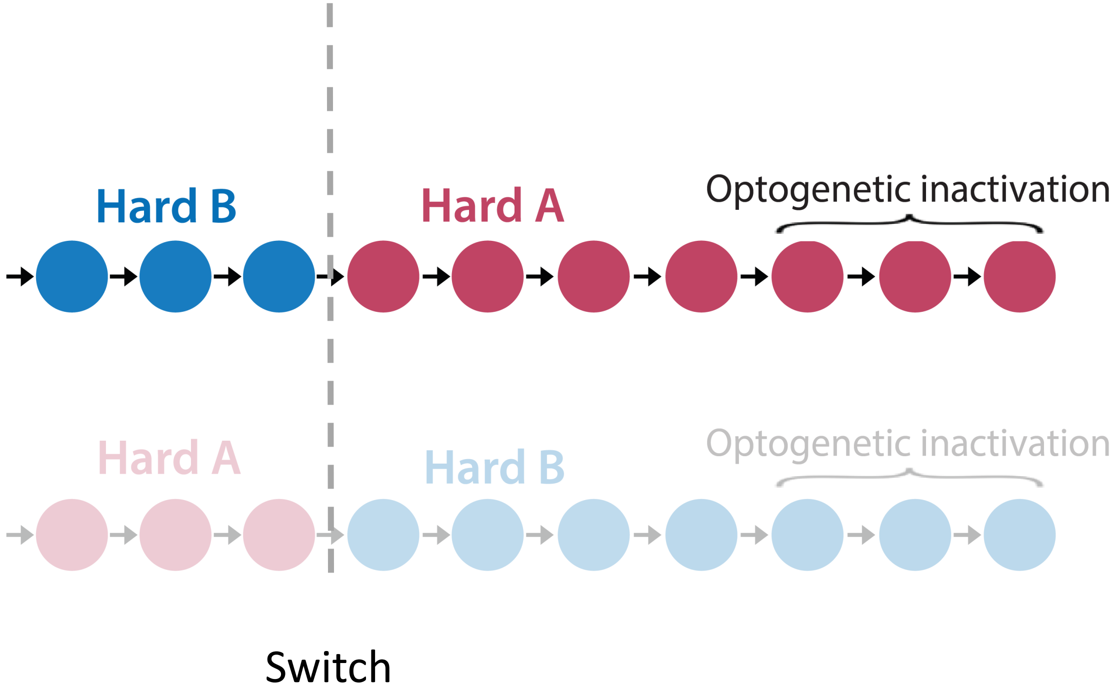

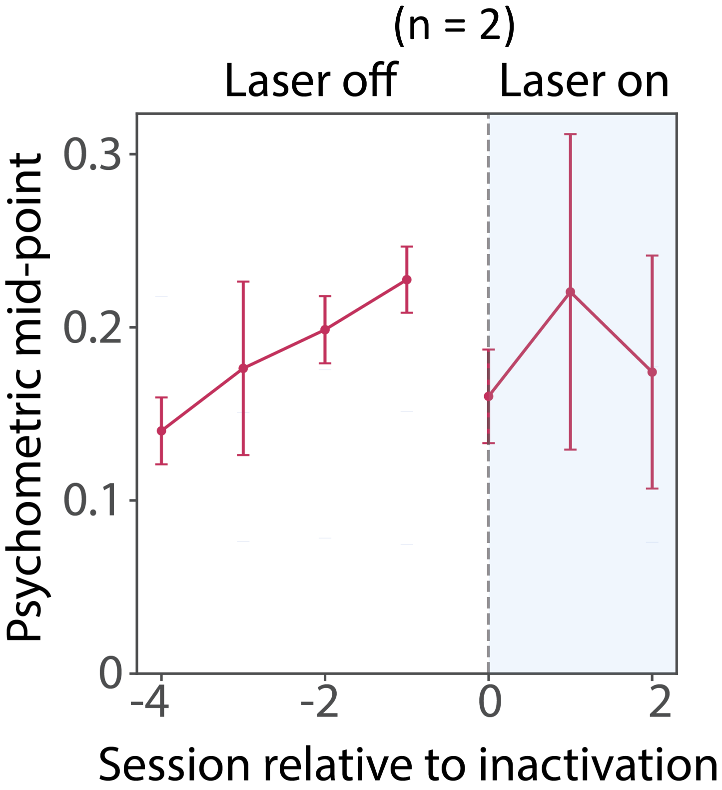

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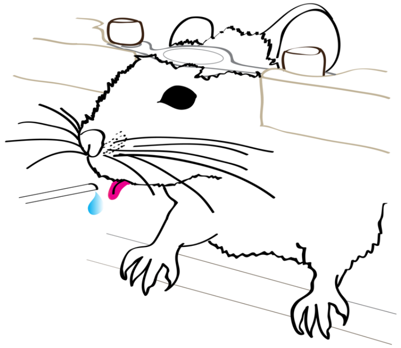

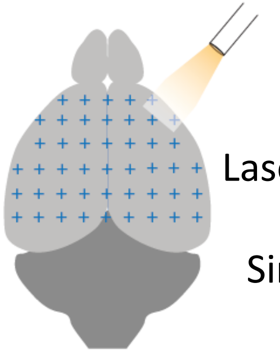

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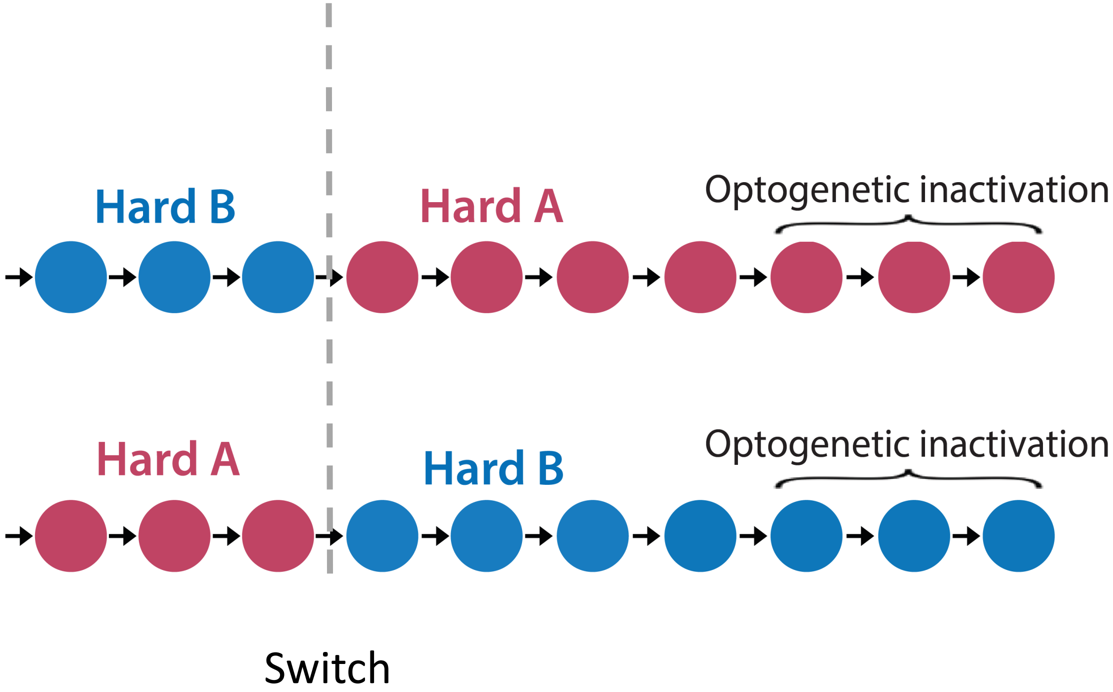
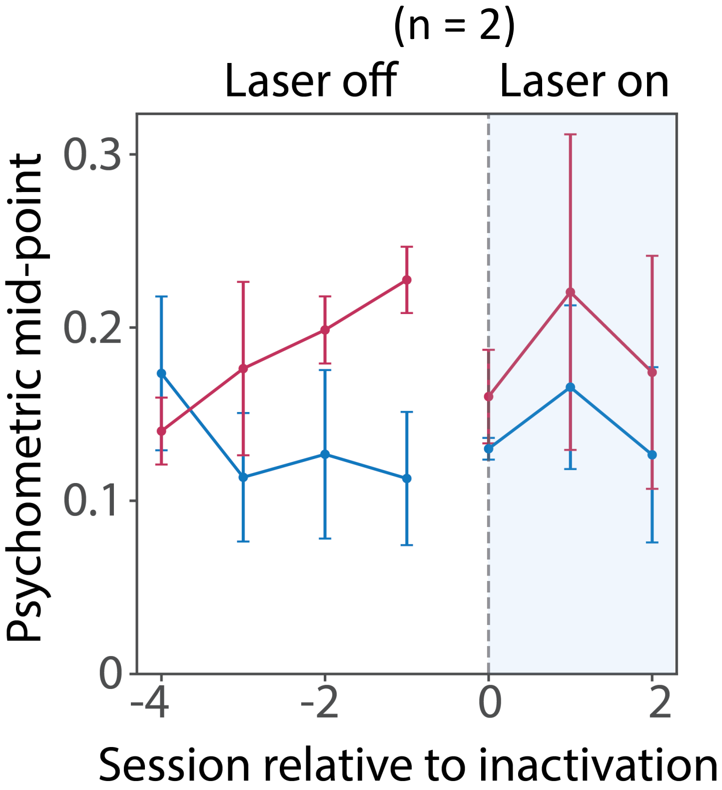
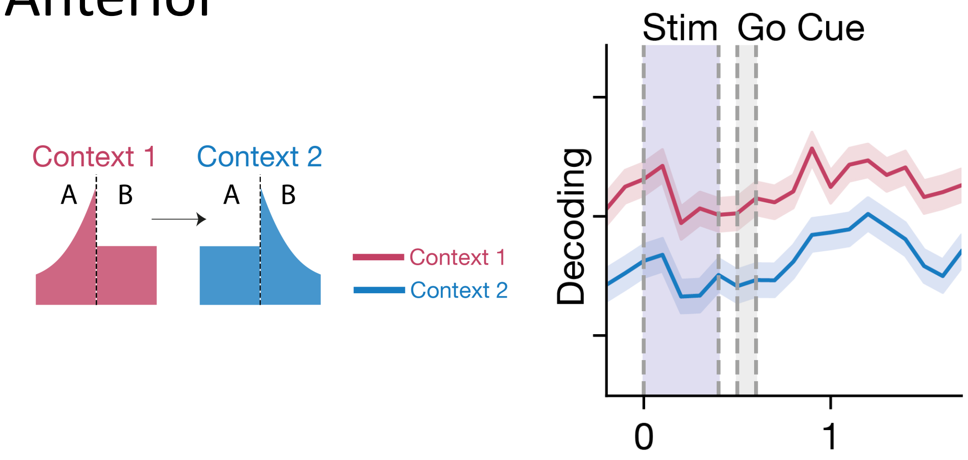


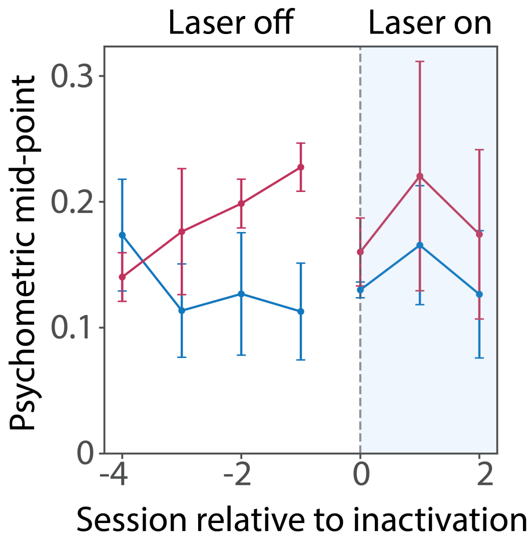


Interim summary (2)

- Context prior signal can be decoded from Anterior Cingulate Cortex (ACC) in rats

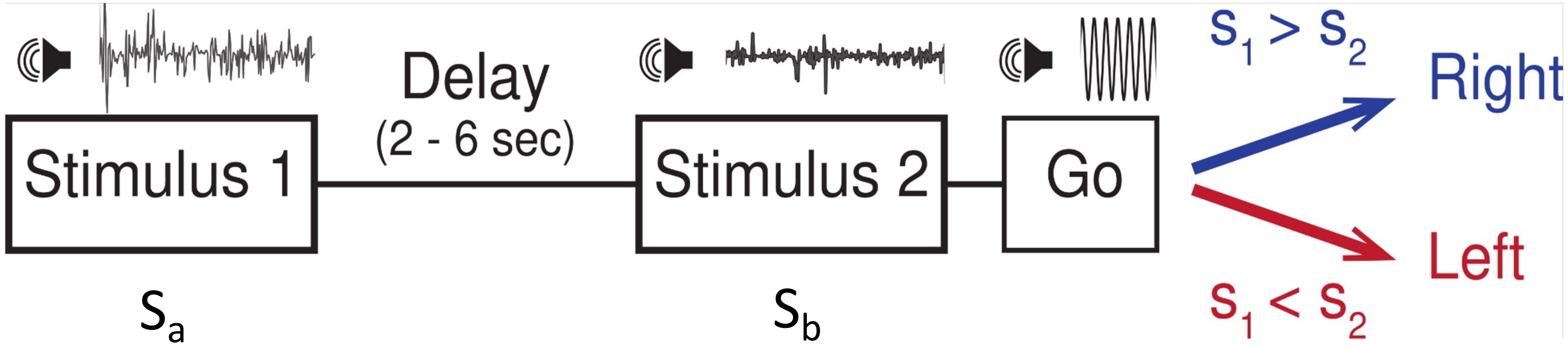


- Inactivation of ACC during utilisation of ‘context’ knowledge takes away the optimal shift in psychometric behaviour




working memory
learning regularities

Parametric Working Memory (PWM)



Romo & Salinas 2003

Akrami et al, Nature 2018;
Akrami* & Fassihi* et al, PNAS 2014;
Fassihi & Akrami et al, Cur Bio 2018

PRINCETON UNIVERSITY

hhmi Howard Hughes Medical Institute

PRINCETON Neuroscience INSTITUTE

Carlos Brody

Mathew Diamond

ma per seguir virtute e canoscenza SISSA

Working Memory *drift* due to *prior* (optimal strategy)

Contraction Bias

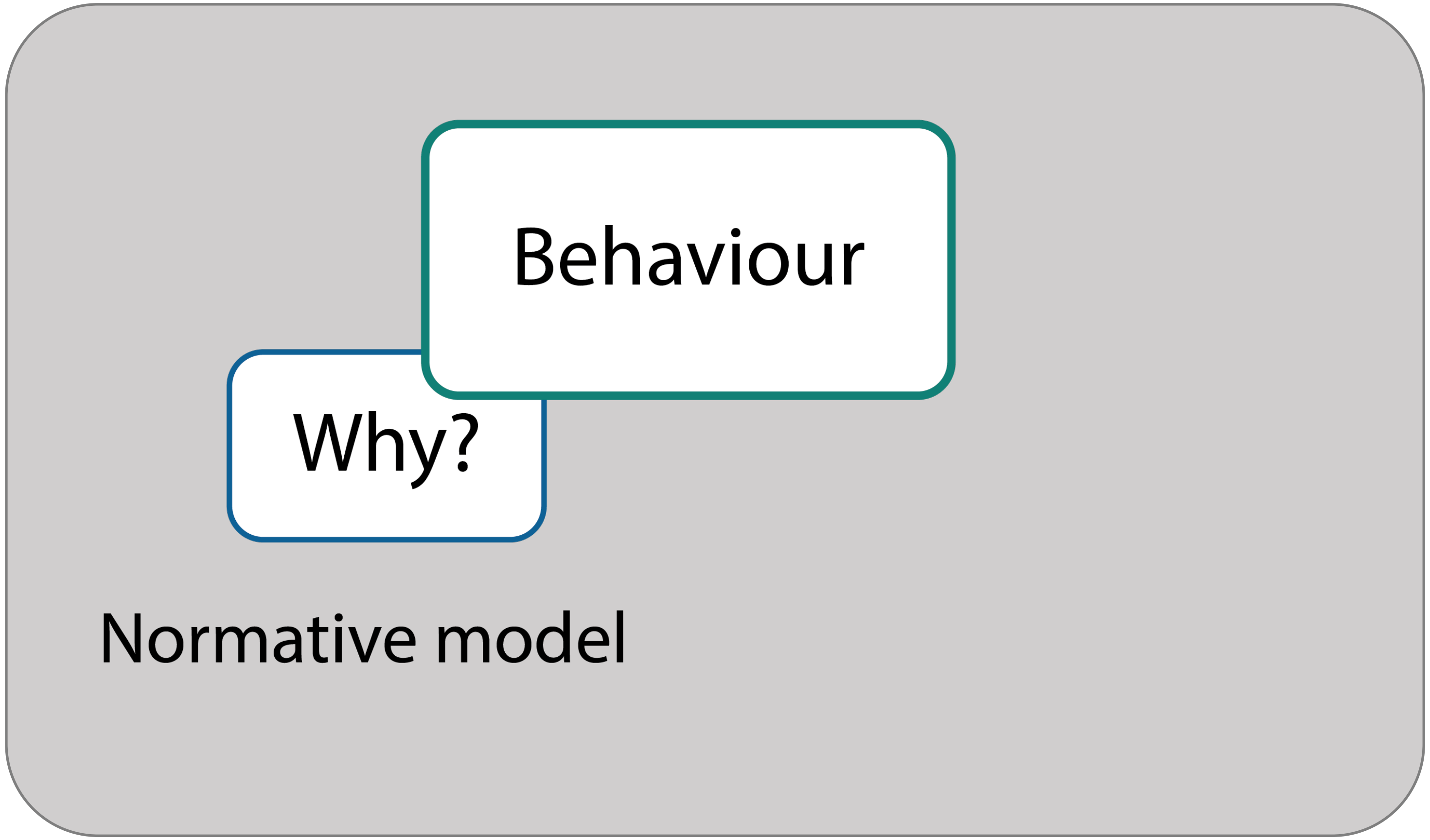
"prior sensory experience" affects working memory

HL Hollingworth, 1910
The Central Tendency of Judgment

- Berliner, Durlach, and Braida (1977)
- Hellstrom (1985)
- Ashourian and Loewenstein (2011)
- Raviv et al 2012
- Fischer and Whitney (2014)

The perceived value of items held in memory contracts towards the "prior" formed by the stimuli being used

Why is contraction bias optimal?



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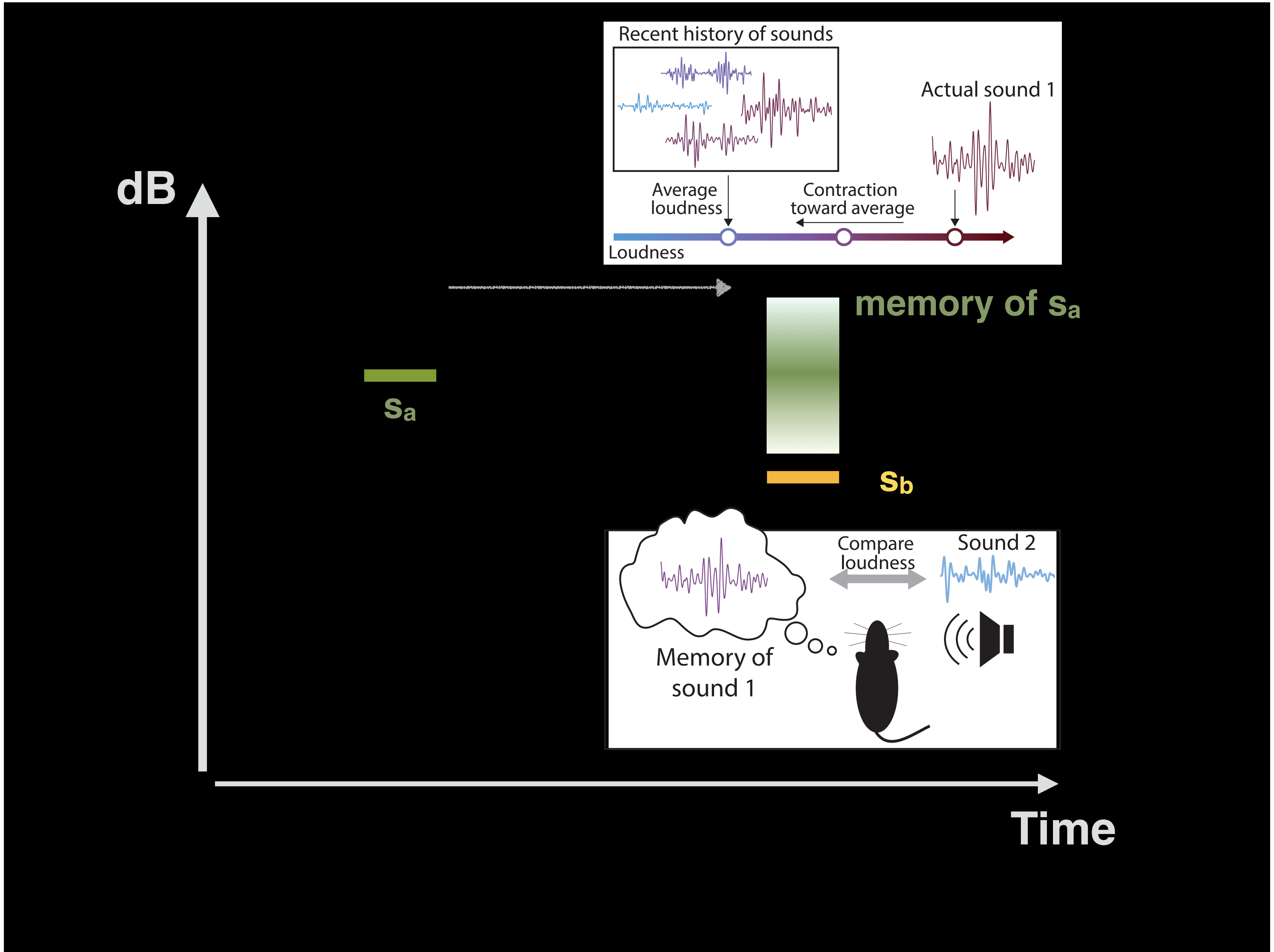
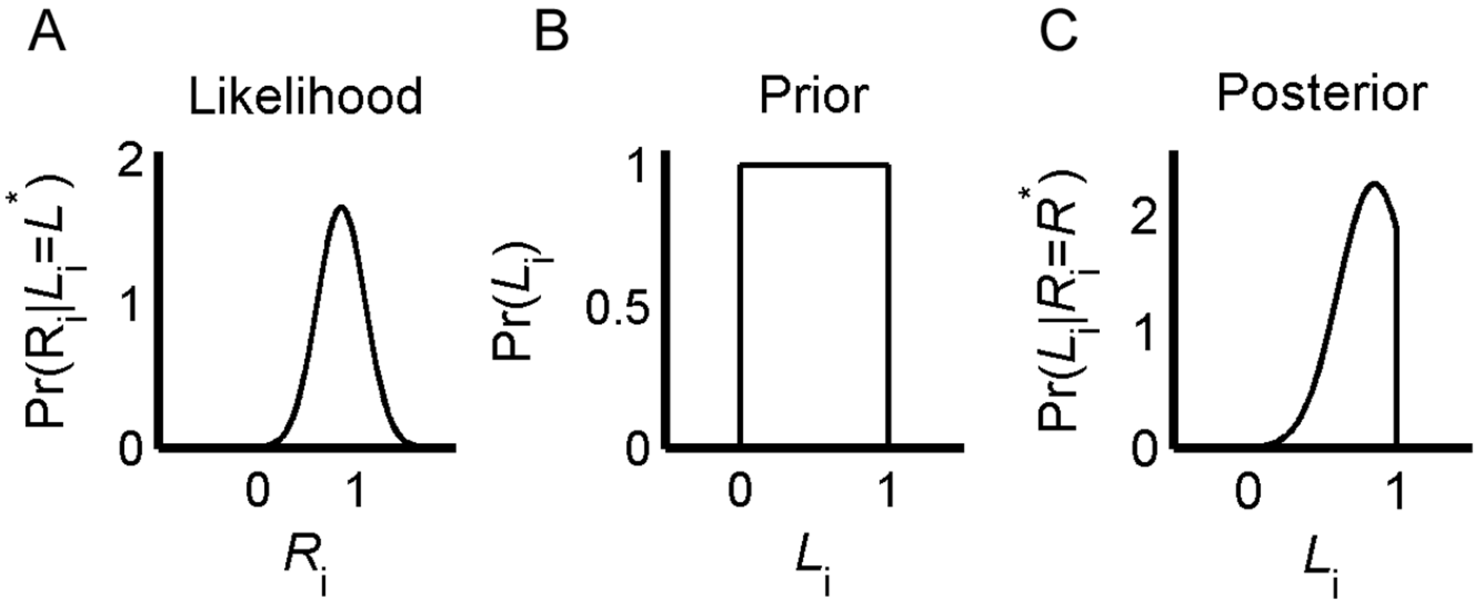
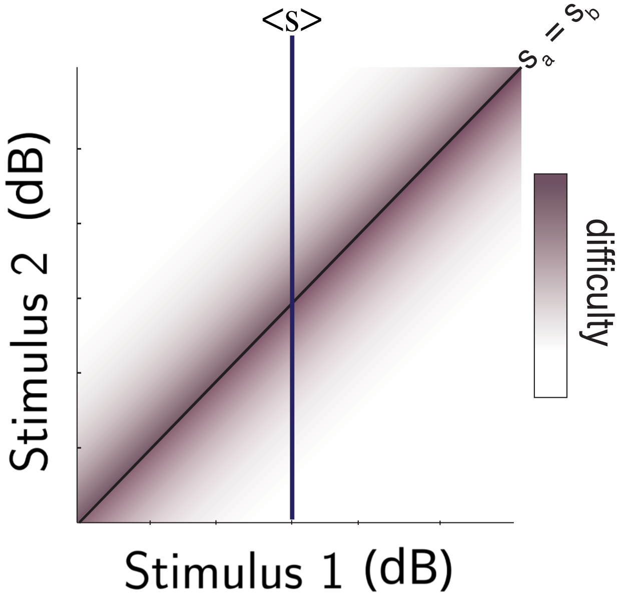


Bayesian model of contraction bias



Bayesian Inference Underlies the Contraction Bias
in Delayed Comparison Tasks
Ashourian & Loewenstein 2011

Working Memory *drift* due to *prior* (optimal strategy)



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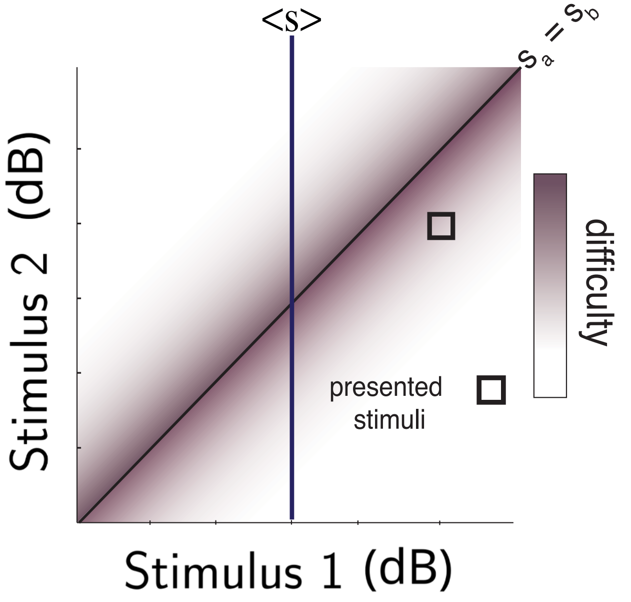

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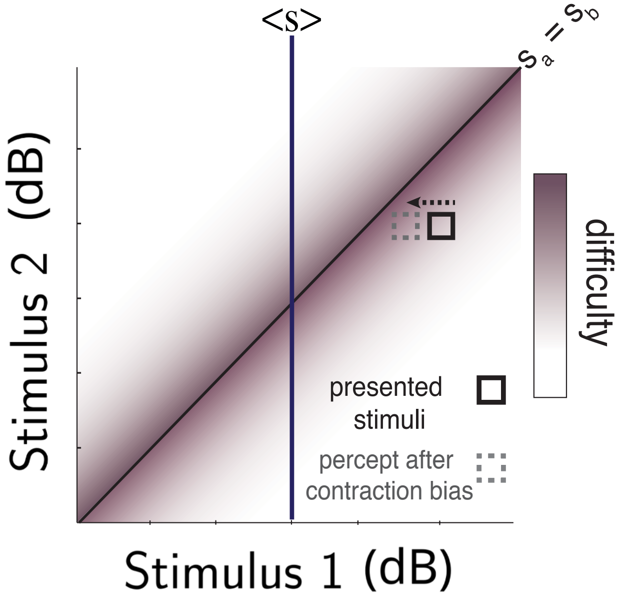

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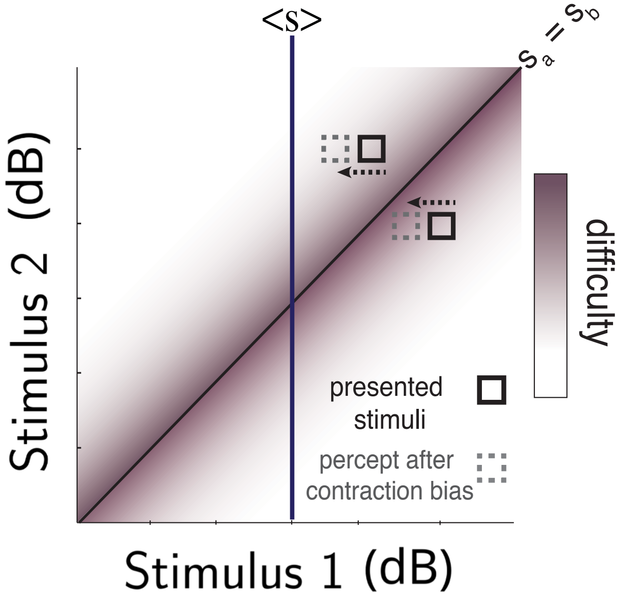

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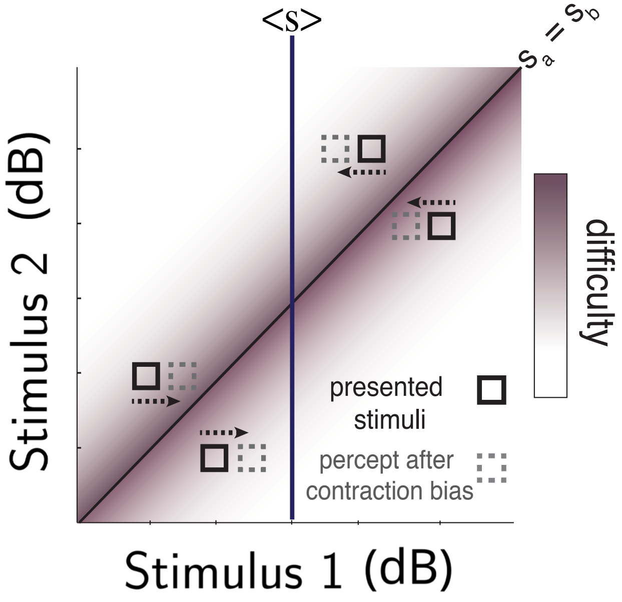

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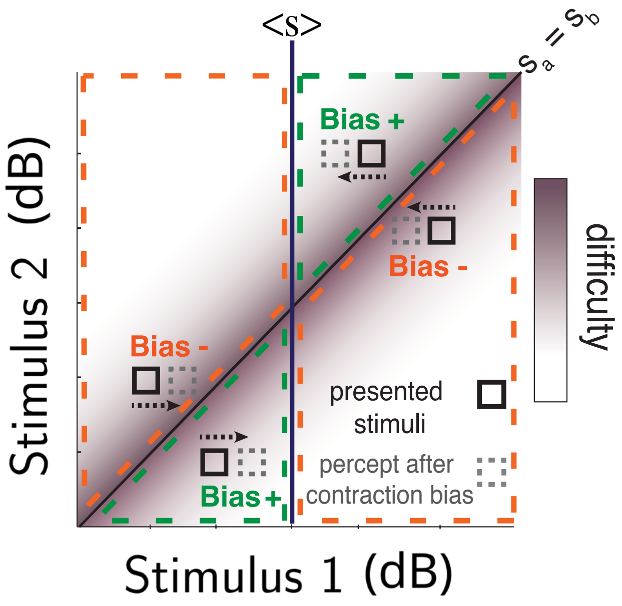

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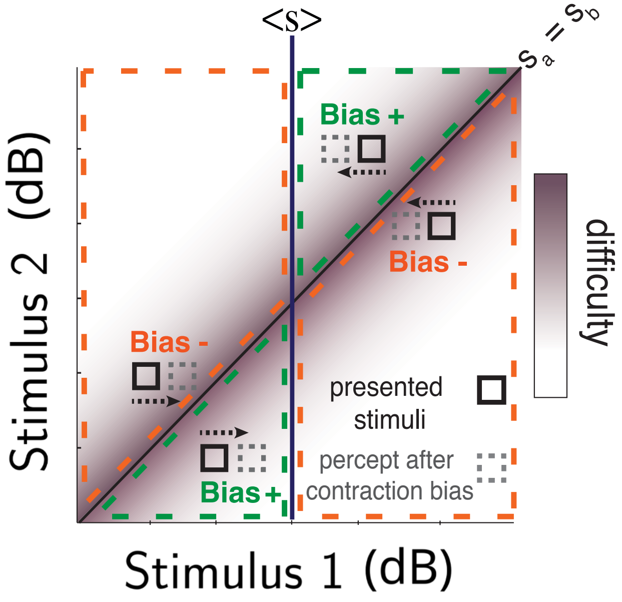
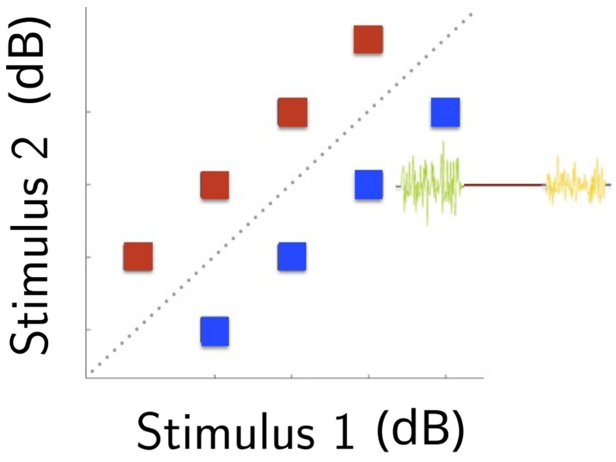
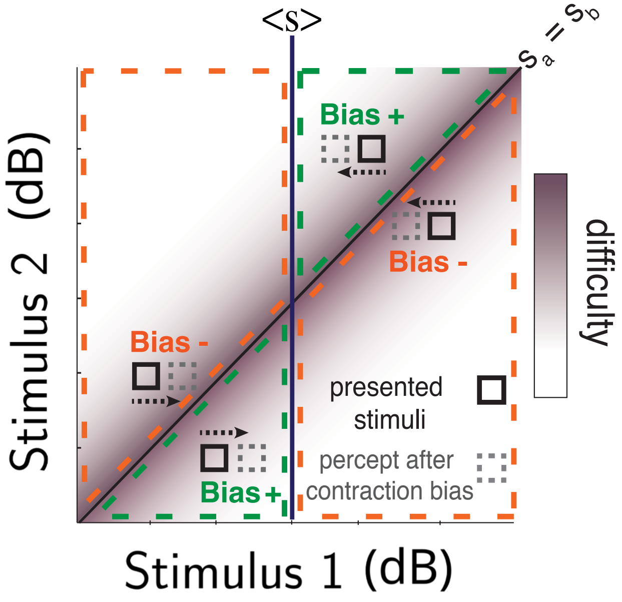
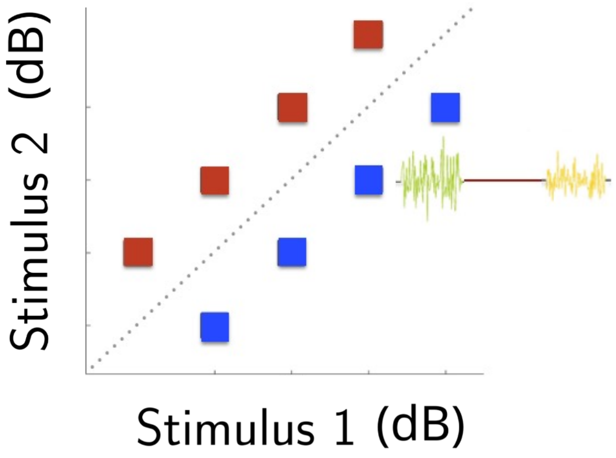




- All intermingled within a session
- Variable delay durations (1 - 12 seconds)

Working Memory *drift* due to *prior* (optimal strategy)





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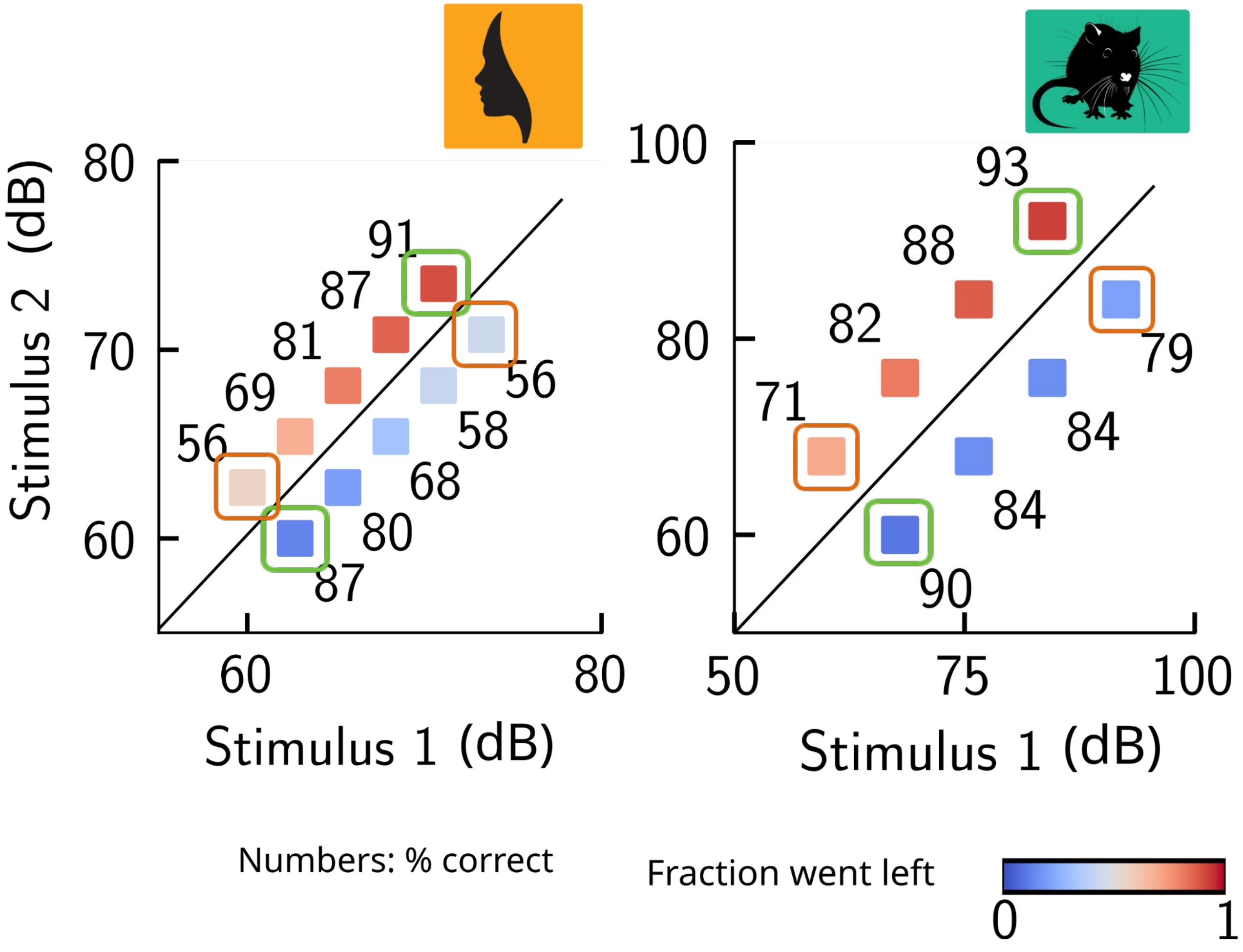
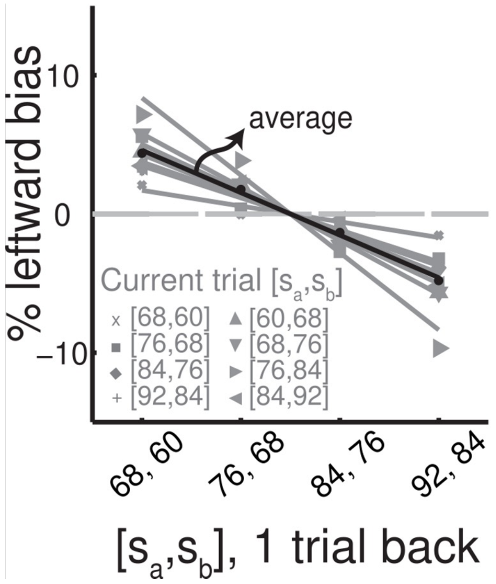
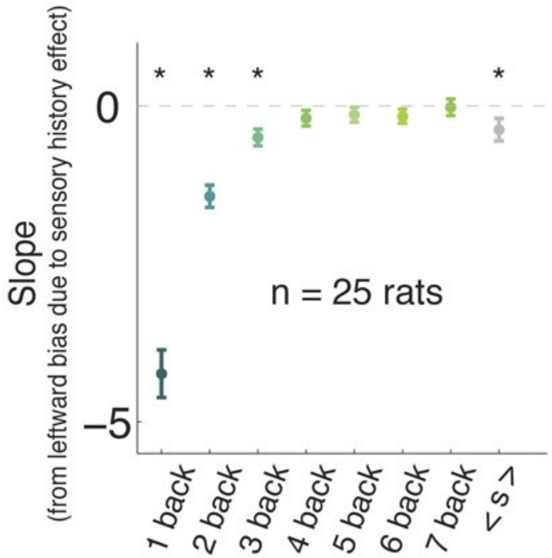


Akrami et al. 2018

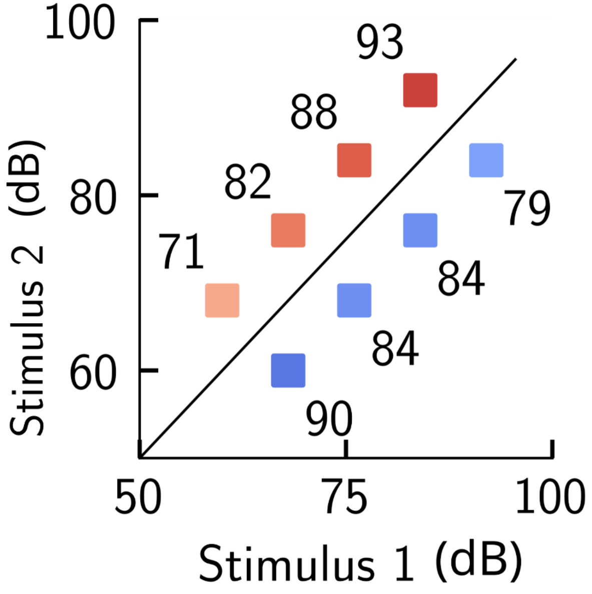
Previous trial exerts “attractive” bias

Rat (auditory, n=25)





“Contraction” bias



Akrami et al. 2018

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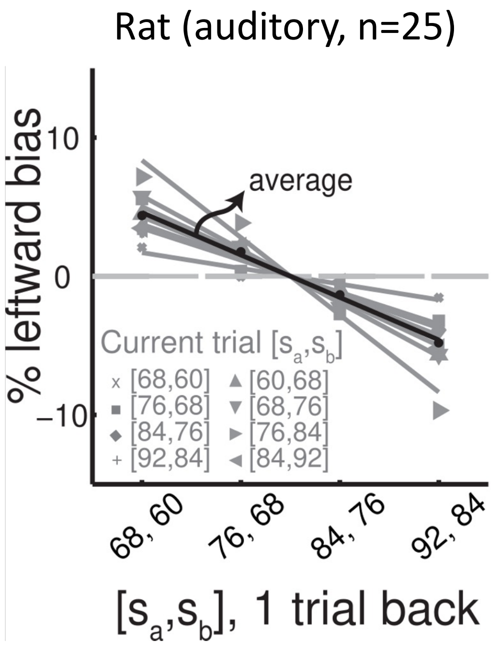
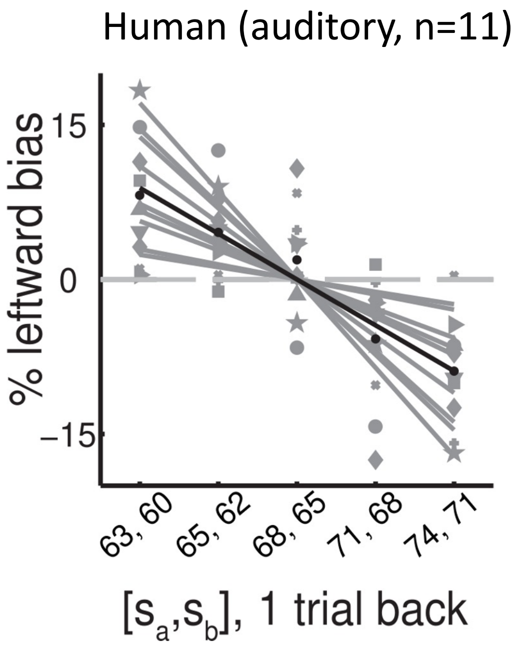
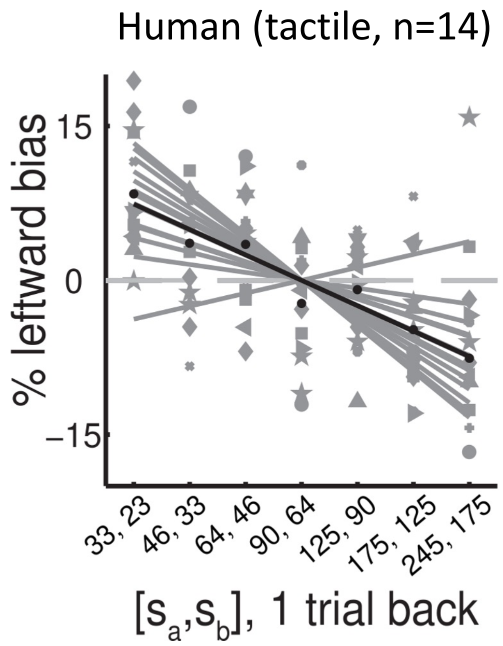
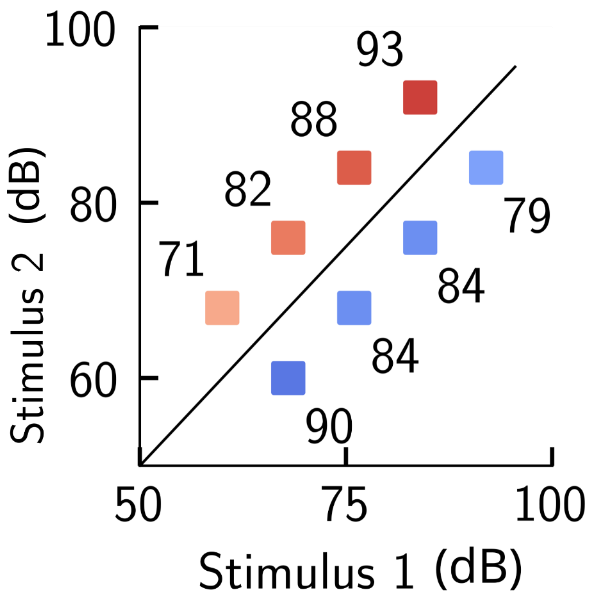
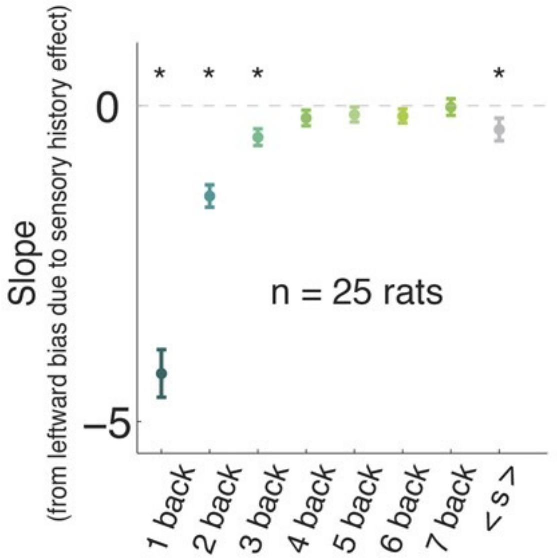


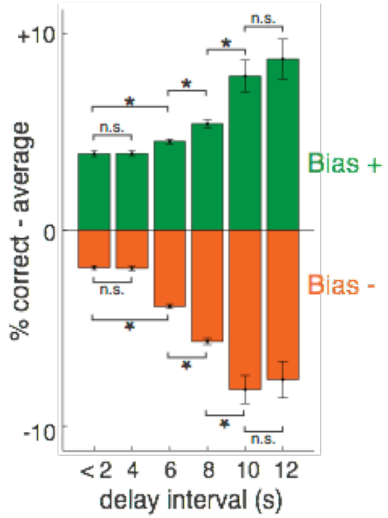




“Contraction” bias

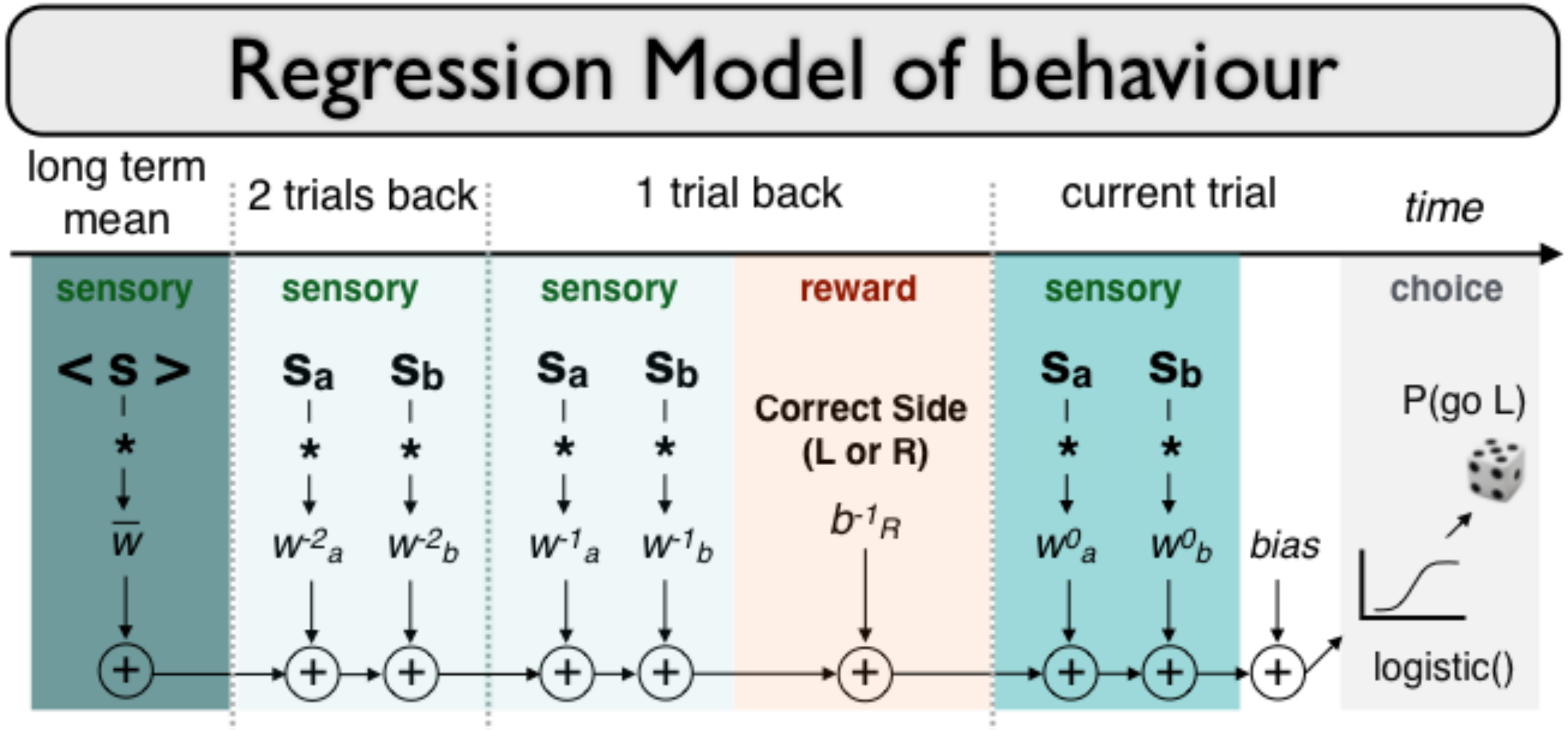






Sensory bias depends on delay interval

Akrami et al. 2018



Drift of Working Memory Towards Prior

(in both rats and humans)

Akrami et al. 2018

Contraction bias

Recency (short-term serial bias)

How are they related?

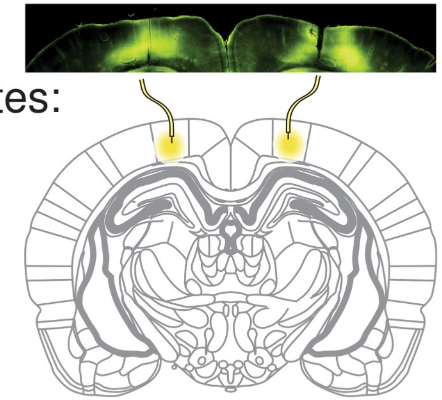
(Posterior Parietal Cortex in rats)

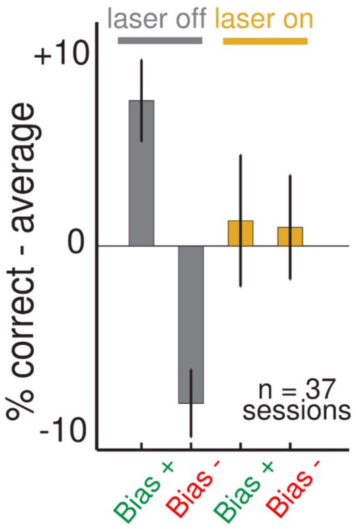
Target bregma coordinates:

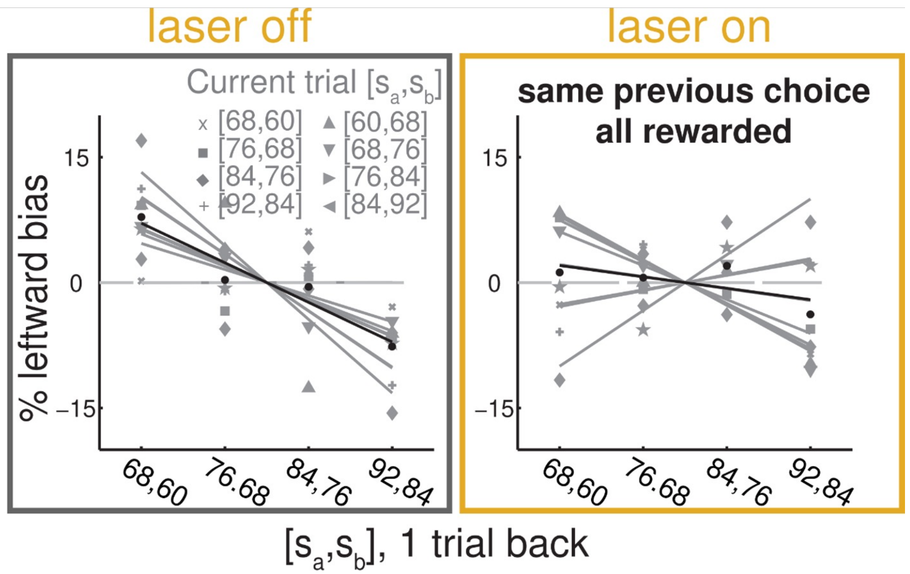
AP = -3.8 mm

ML = 2.5 mm

Full trial inactivation







Akrami et al. 2018

How are they related?

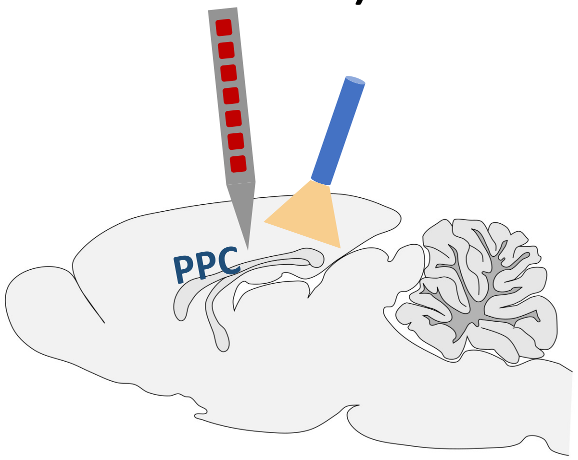
(Posterior Parietal Cortex in rats)

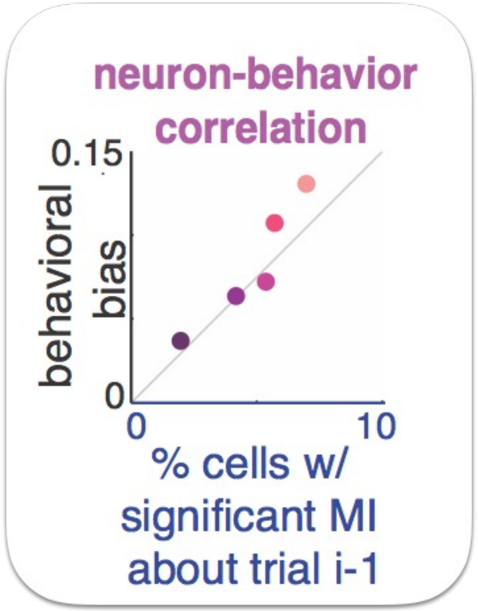
Target bregma coordinates:

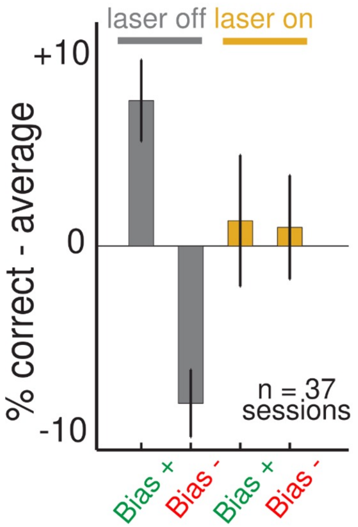
AP = -3.8 mm

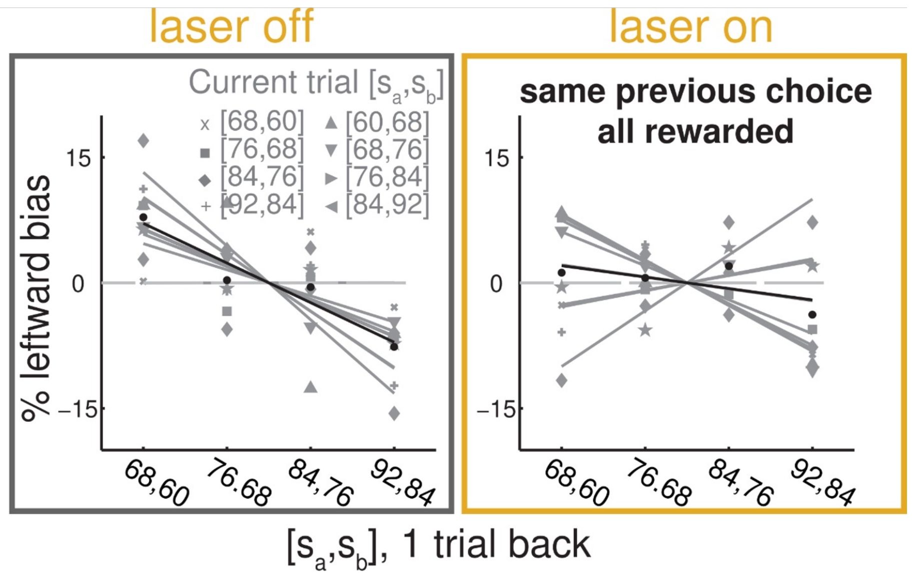
ML = 2.5 mm

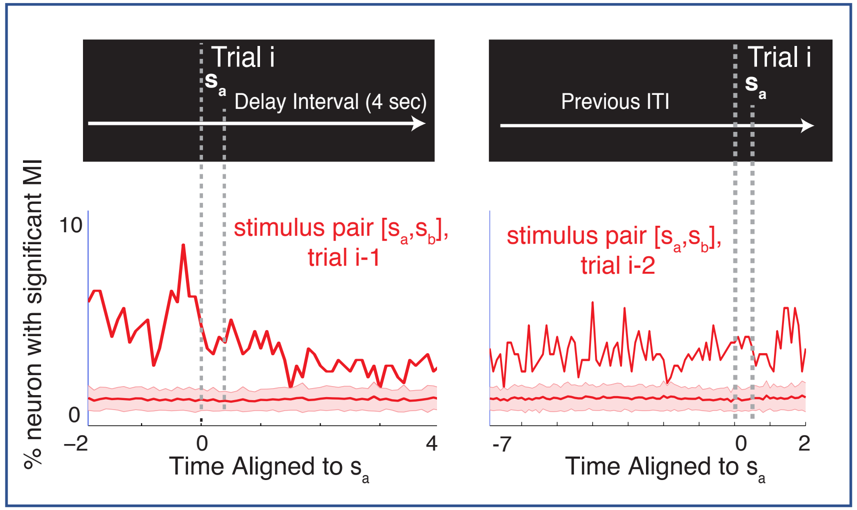
Full trial inactivation





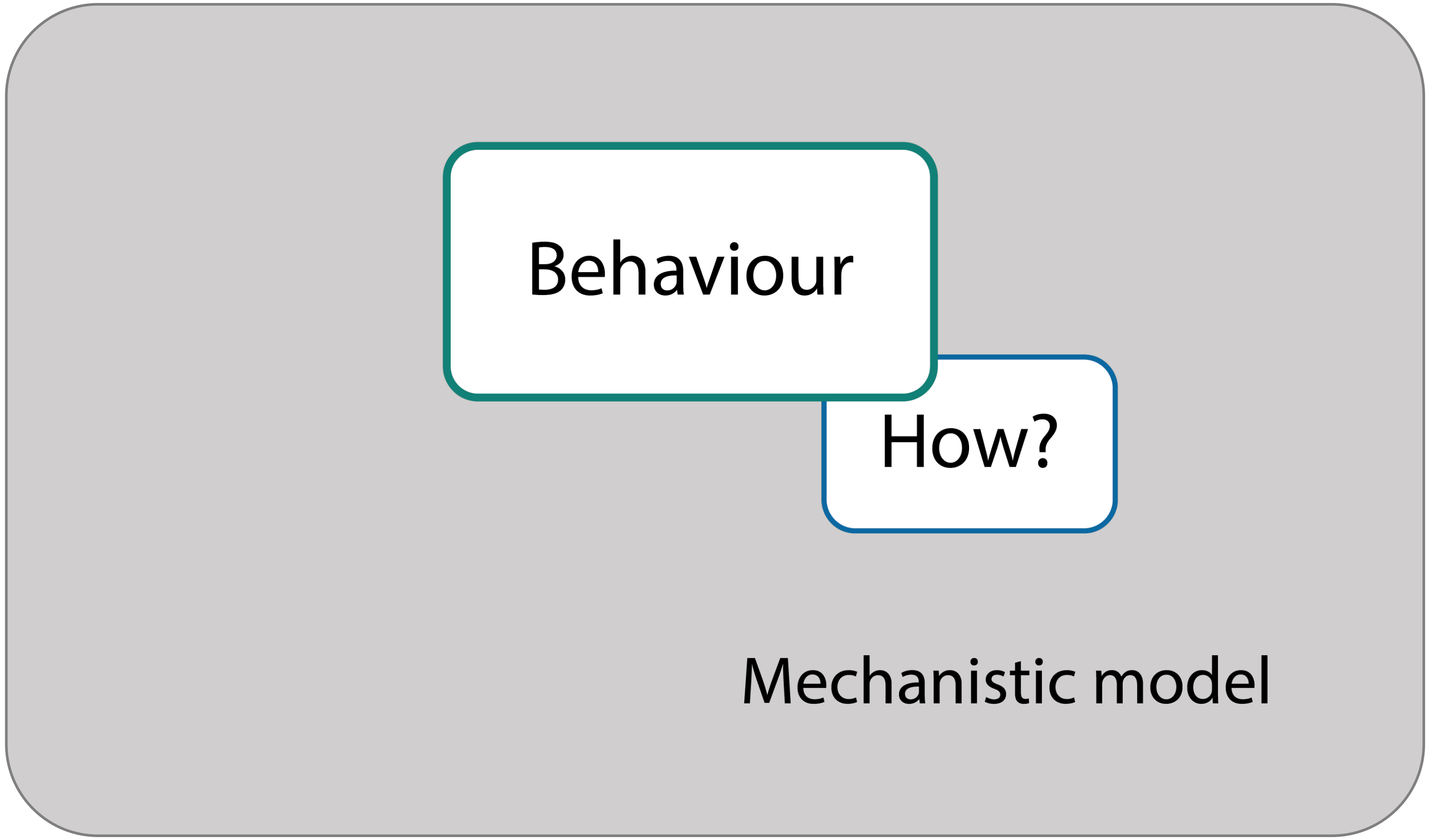




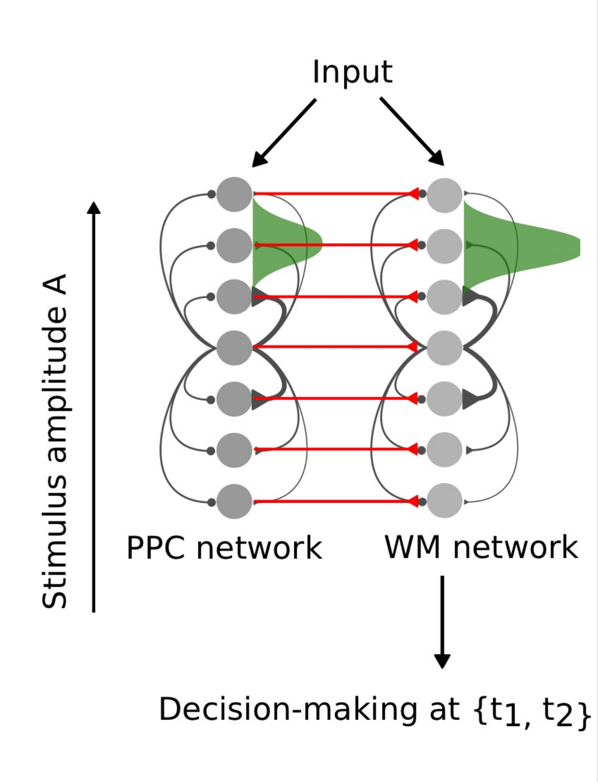


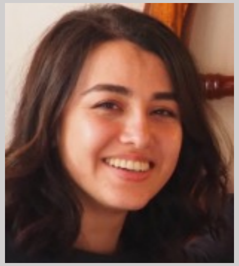
Akrami et al. 2018

What is the mechanism underlying contraction bias?



MODEL





Vezha Boboeva

Claudia Clopath

- Continuous one-dimensional attractor networks
- PPC: slower integrator network (with adaptation)

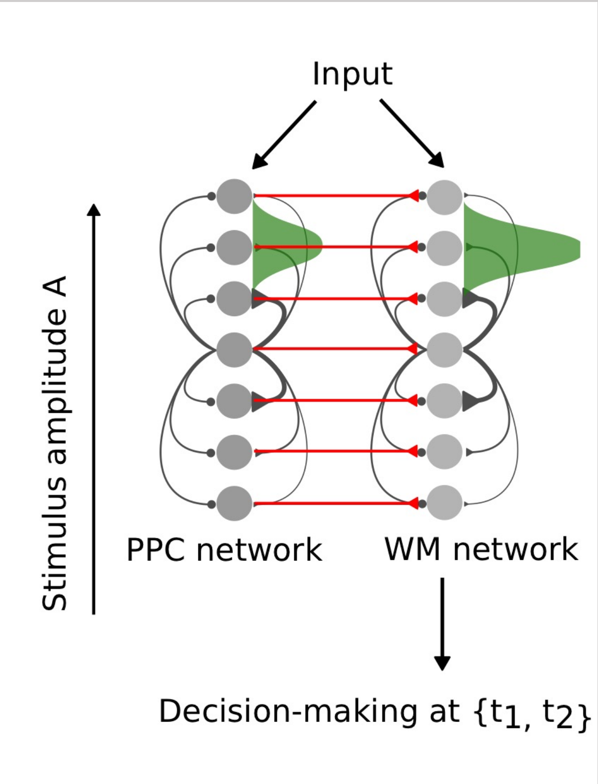
Contraction bias + n-back trial sensory bias

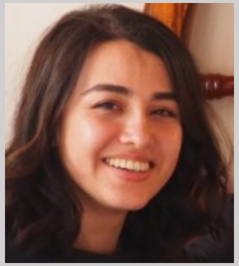
PPC inactivation does not impair working memory

PPC neurons carry information about past sensory

Boboeva et al. eLife 2024

MODEL

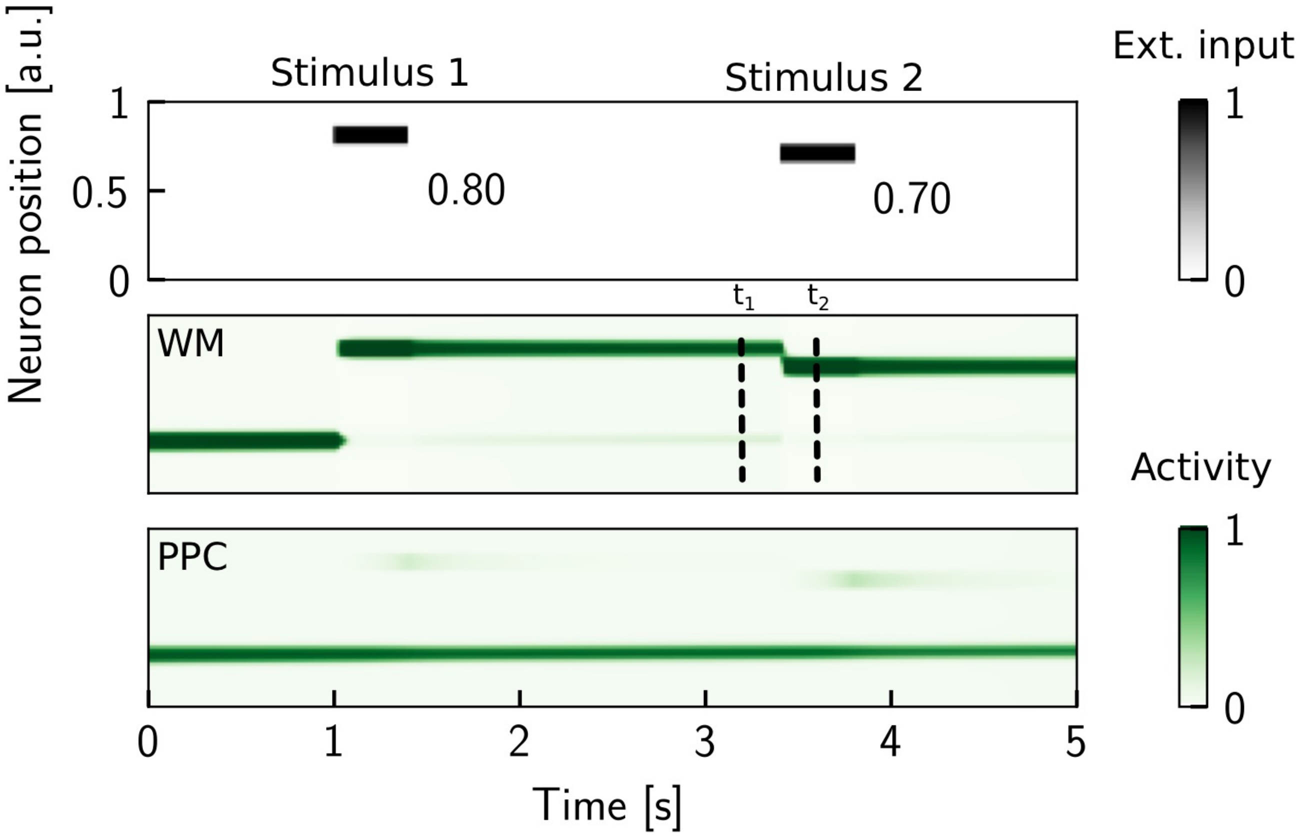




Vezha Boboeva Claudia Clopath

- Continuous one-dimensional attractor networks
- PPC: slower integrator network (with adaptation)

Sample trial



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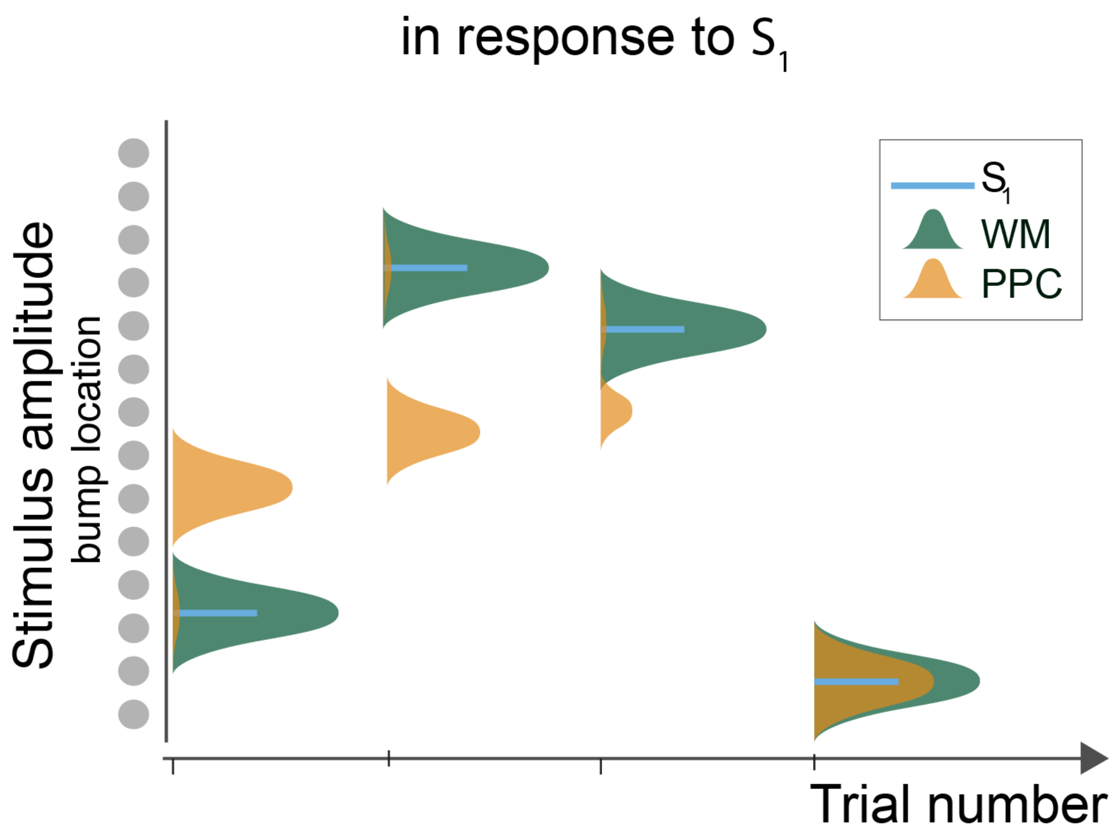
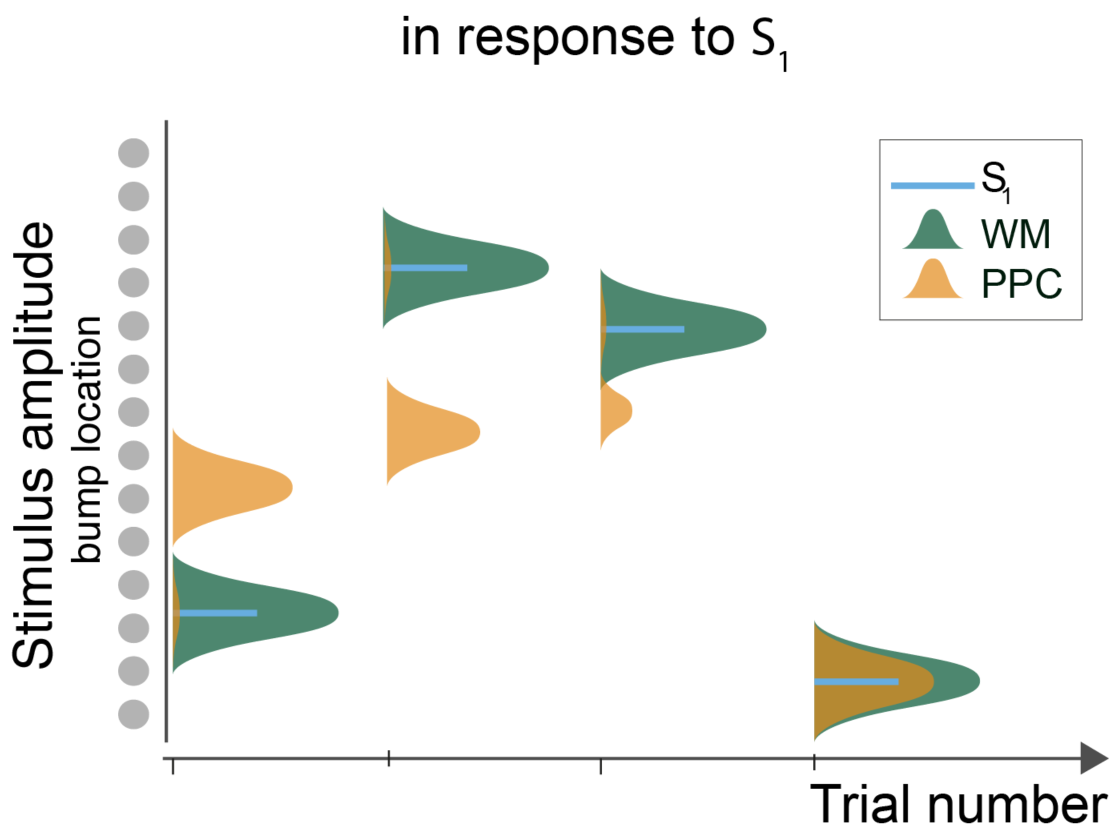
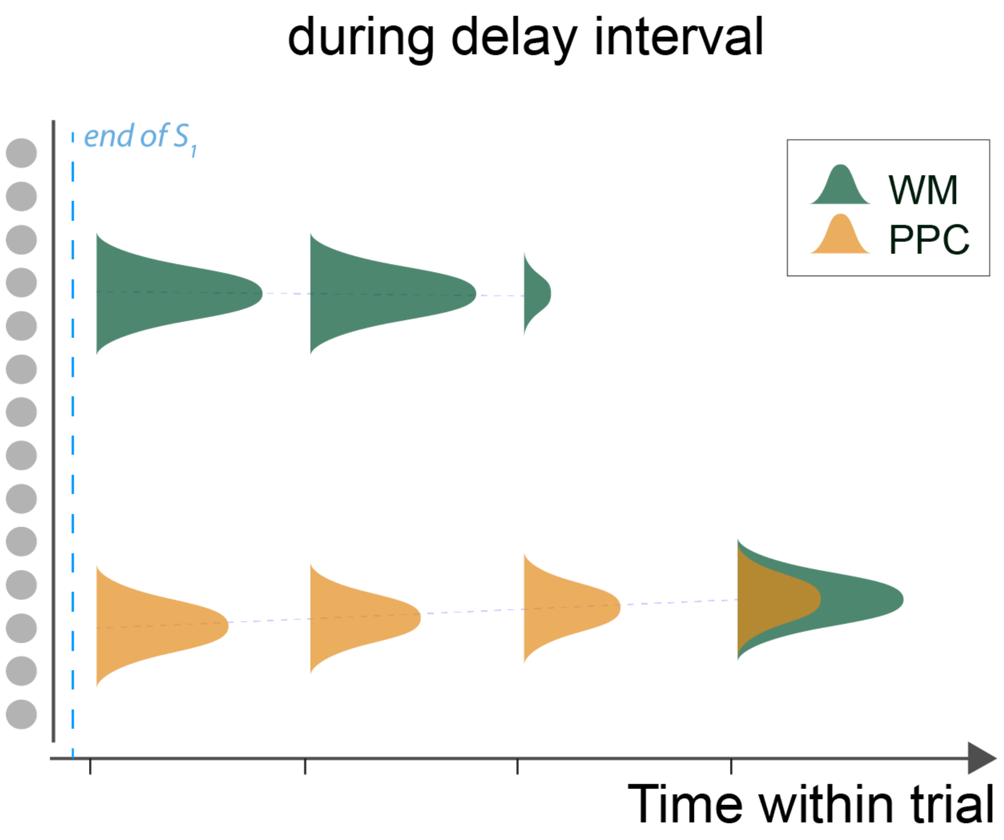
What's the mechanism?



WM responds fast to input
PPC drifts slowly and adapts, until a fresh bump forms

What's the mechanism?

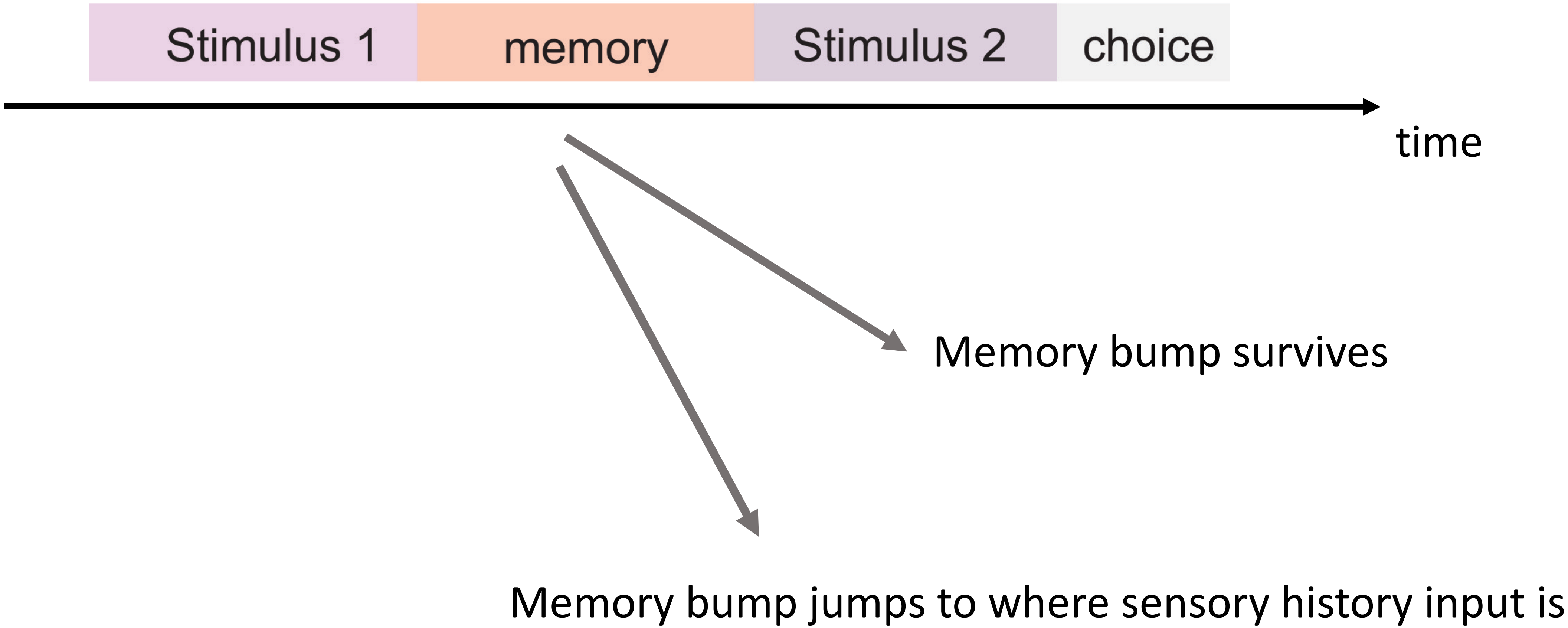




WM responds fast to input
PPC drifts slowly and adapts, until a fresh bump forms

Volatile WM bump moves by input from PPC

What’s the mechanism?!



Modelling network behavior

Mathematical model of performance

Stimuli at trial t $\quad s_1^t,\ s_2^t$

$1-\epsilon$ $\quad\quad$ ϵ

Percept $\quad s_1^t,\ s_2^t$ $\quad\quad$ $\hat{s} \sim p_m,$

$p_\mathrm{c} = 1 - p_\mathrm{e}$ $\quad\quad$ p_e

Outcome $\quad$ Correct $\quad\quad$ Error

$$\mathrm{Prob}\{\mathrm{error}\} = \epsilon\, p_\mathrm{e}$$

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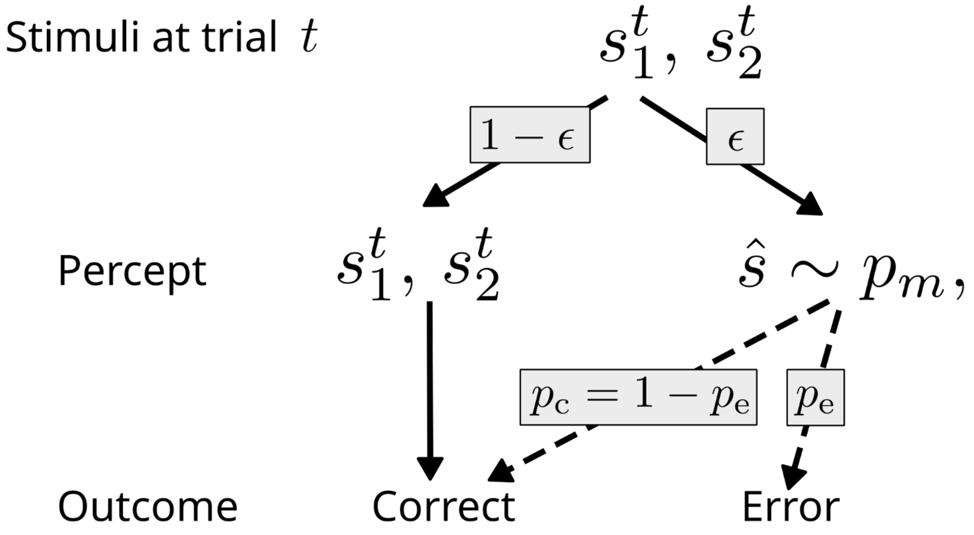
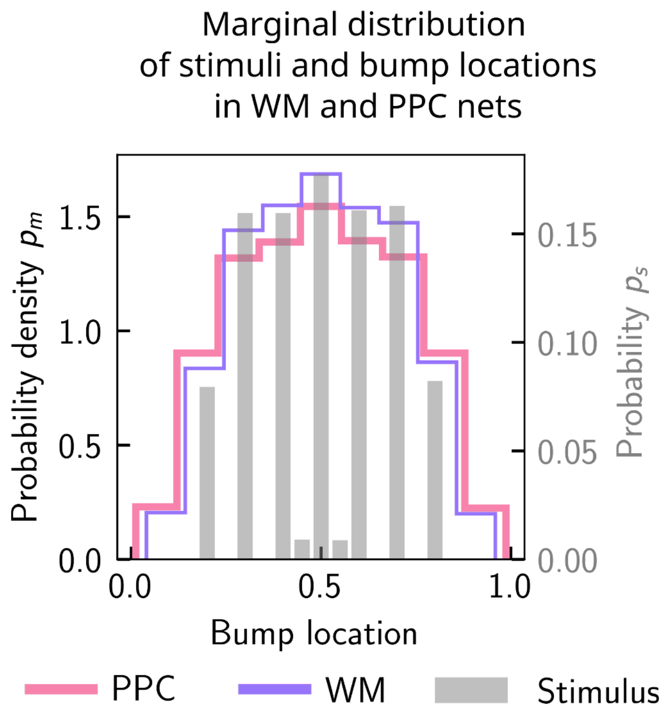
Modelling network behavior

Mathematical model of performance



$$\text{Prob}\{\text{error}\} = \epsilon\, p_e$$



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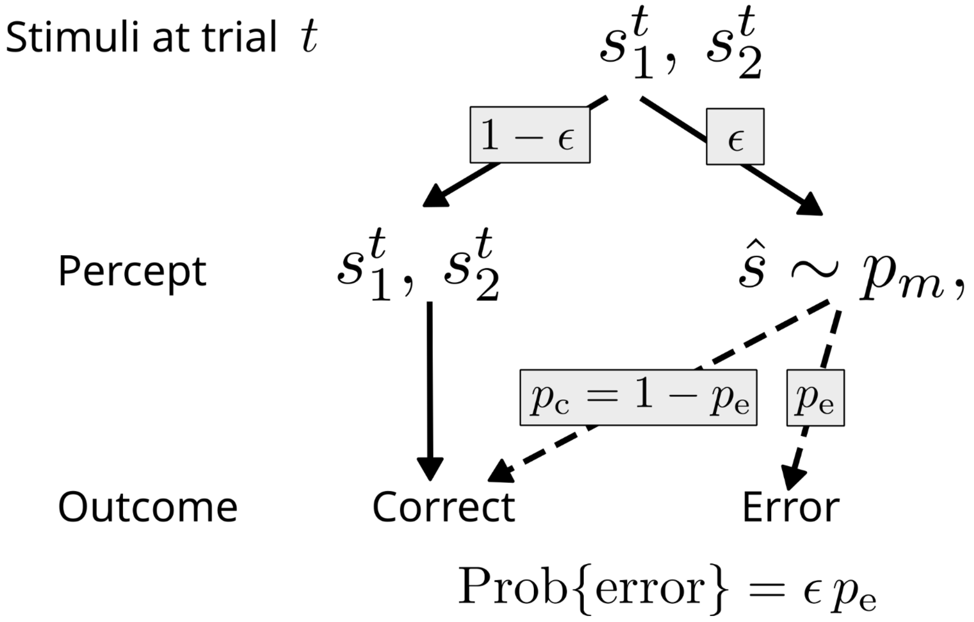
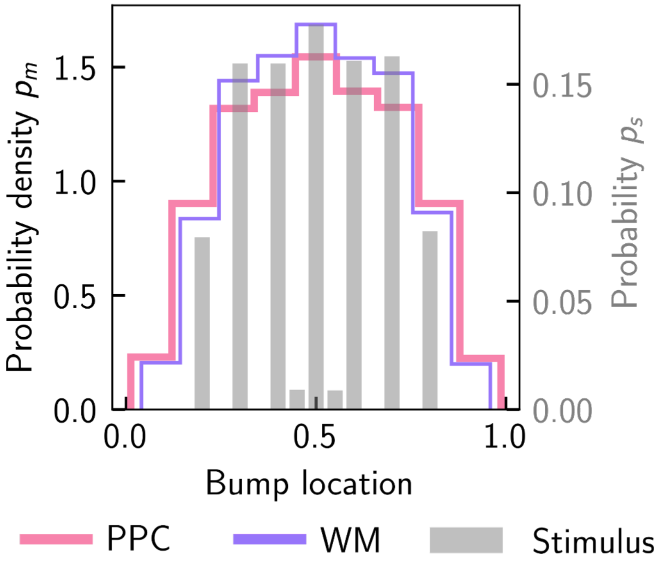
Modelling network behavior

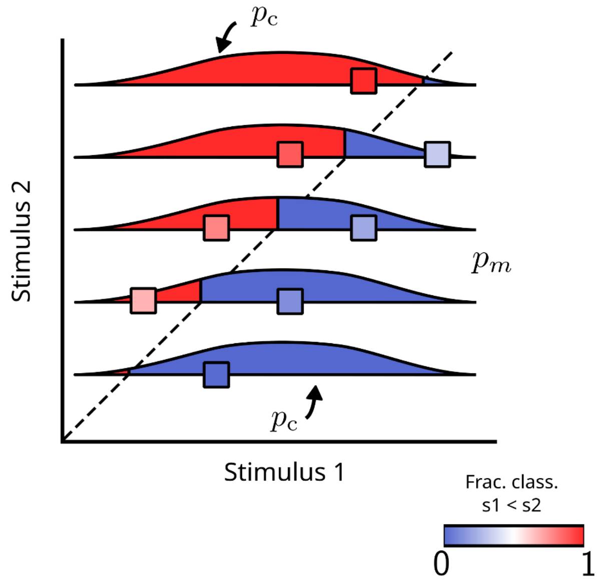
Mathematical model of performance



Marginal distribution of stimuli and bump locations in WM and PPC nets



Computational basis of contraction bias



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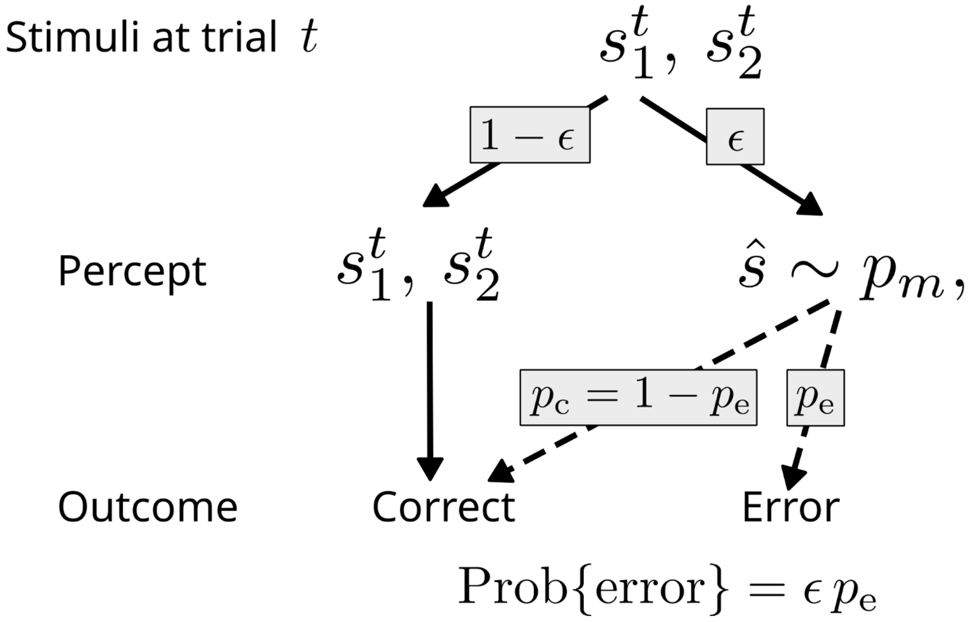
Modelling network behavior

Mathematical model of performance



Marginal distribution
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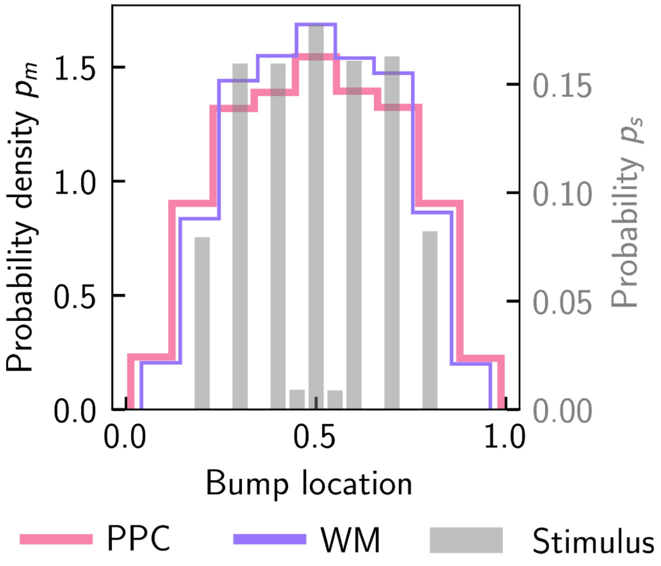
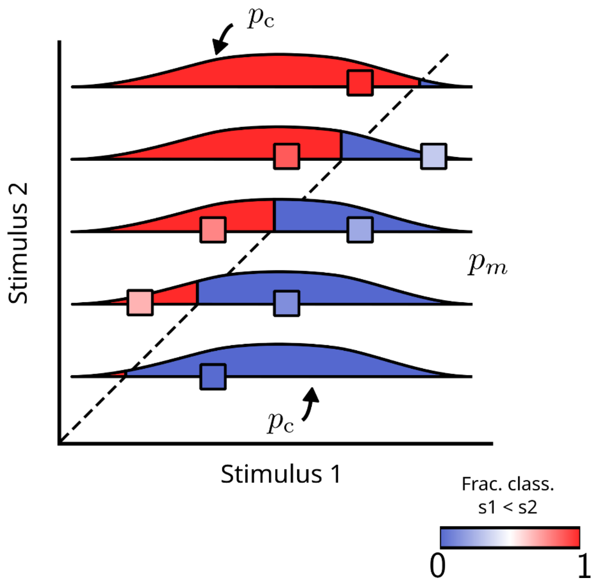
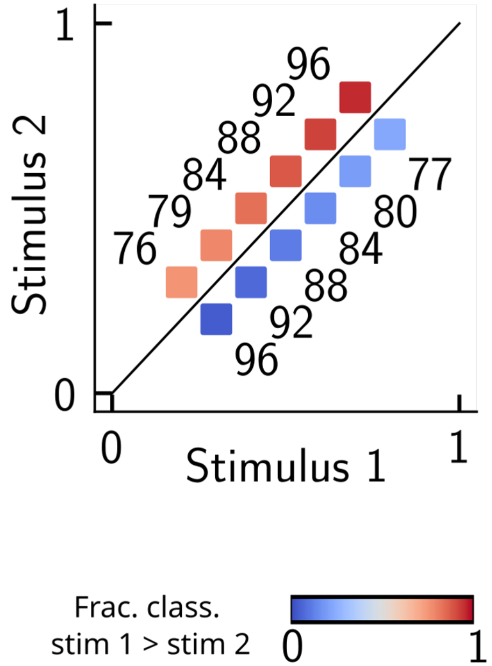
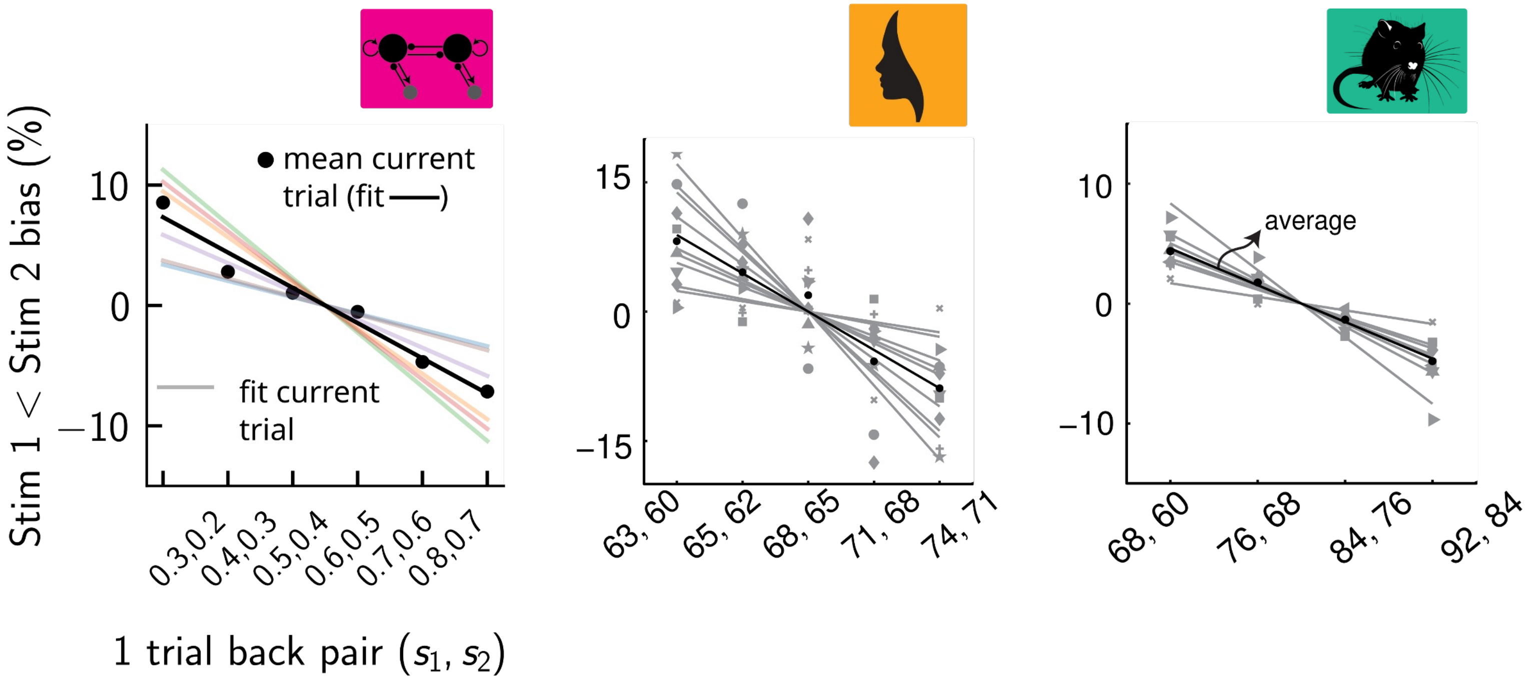


Computational basis
of contraction bias

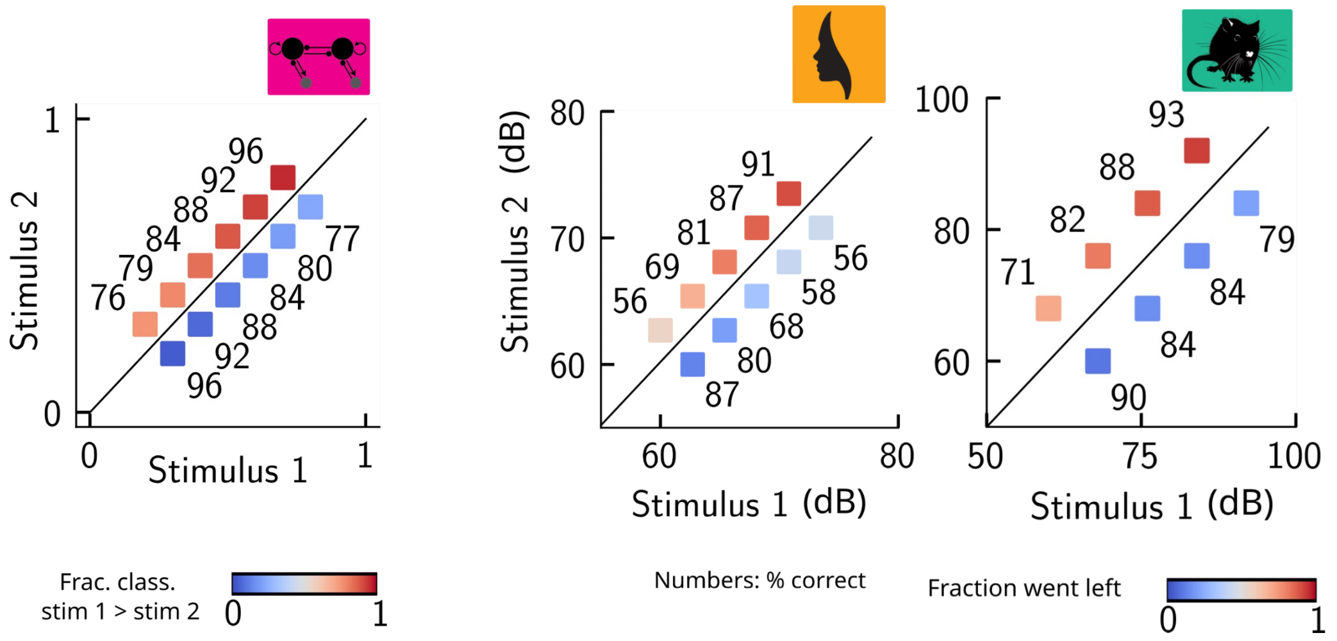




Serial biases



Contraction biases



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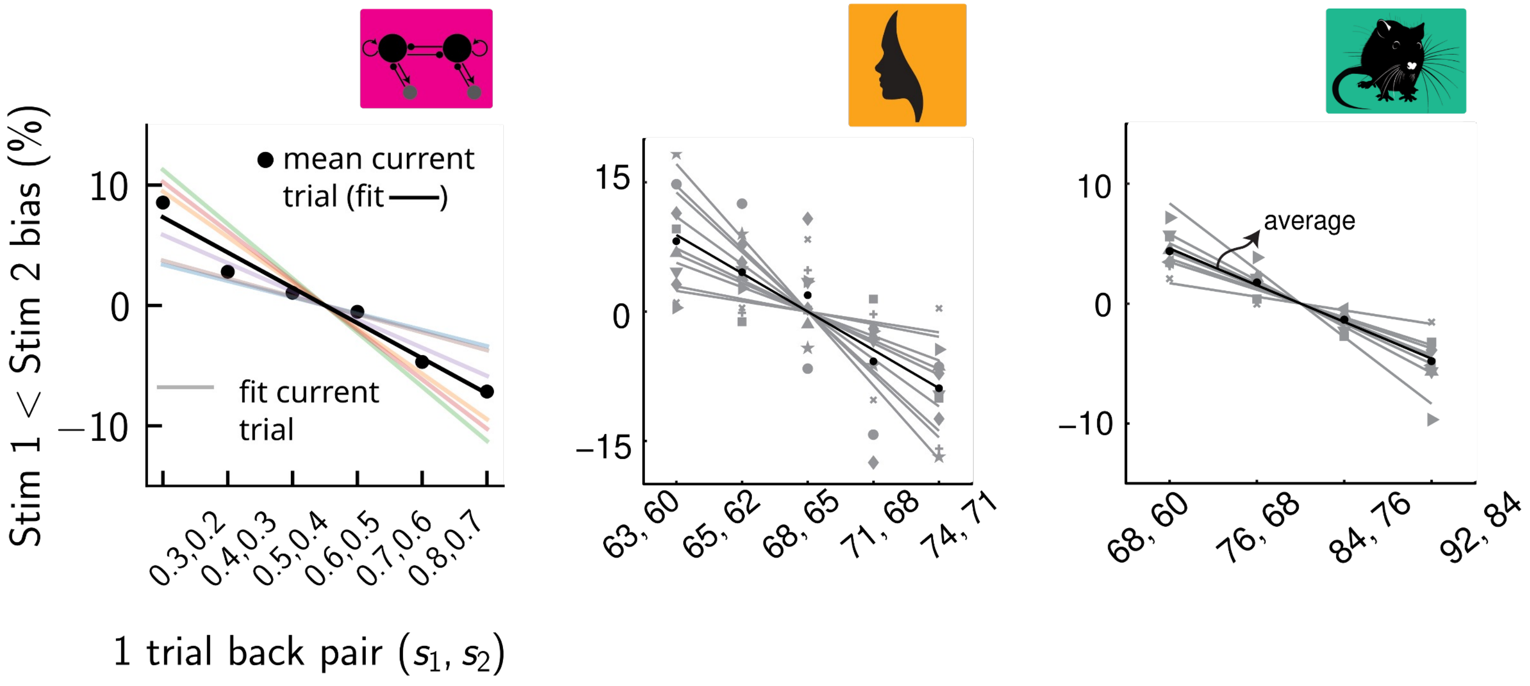
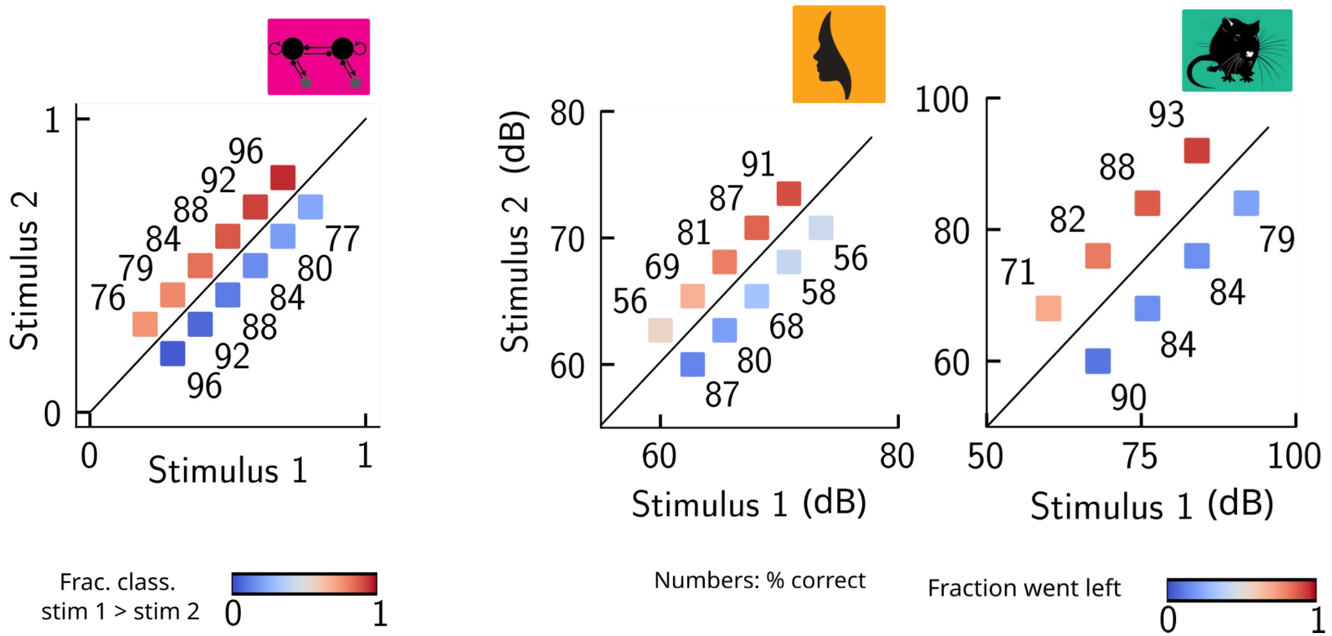
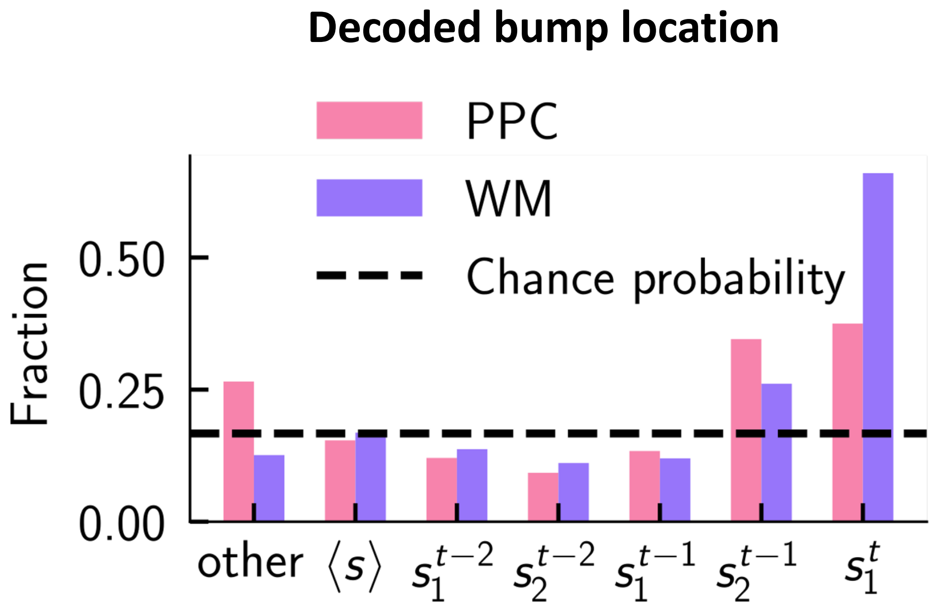
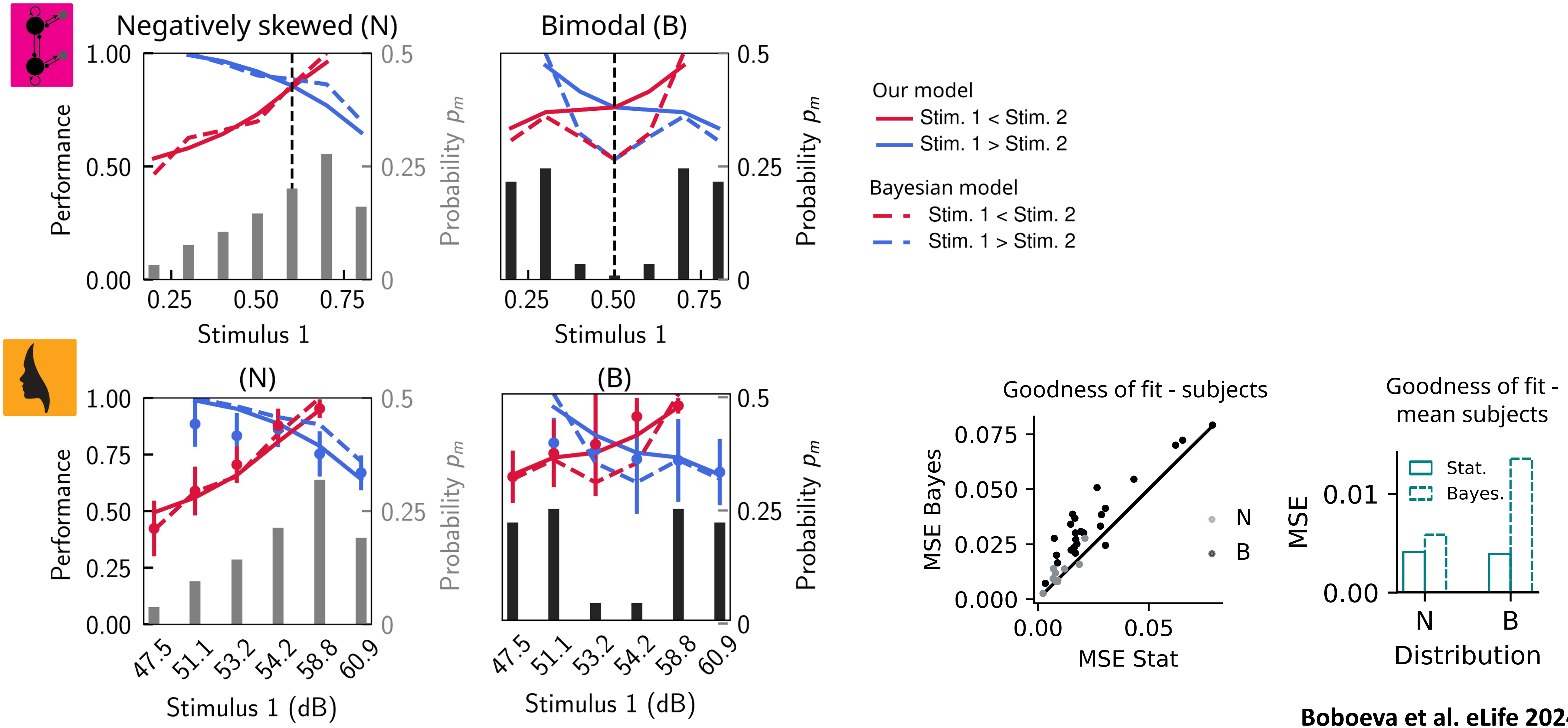
Serial biases







Testing model predictions



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Model predictions

Performance based on

- Different stimulus distributions
- Inter-Trial-Interval
- Inter-Stimulus-Interval
- Interleaved vs Block designs

Attraction vs repulsion

Timescale of adaptation

Neural dynamics in WM vs PPC network

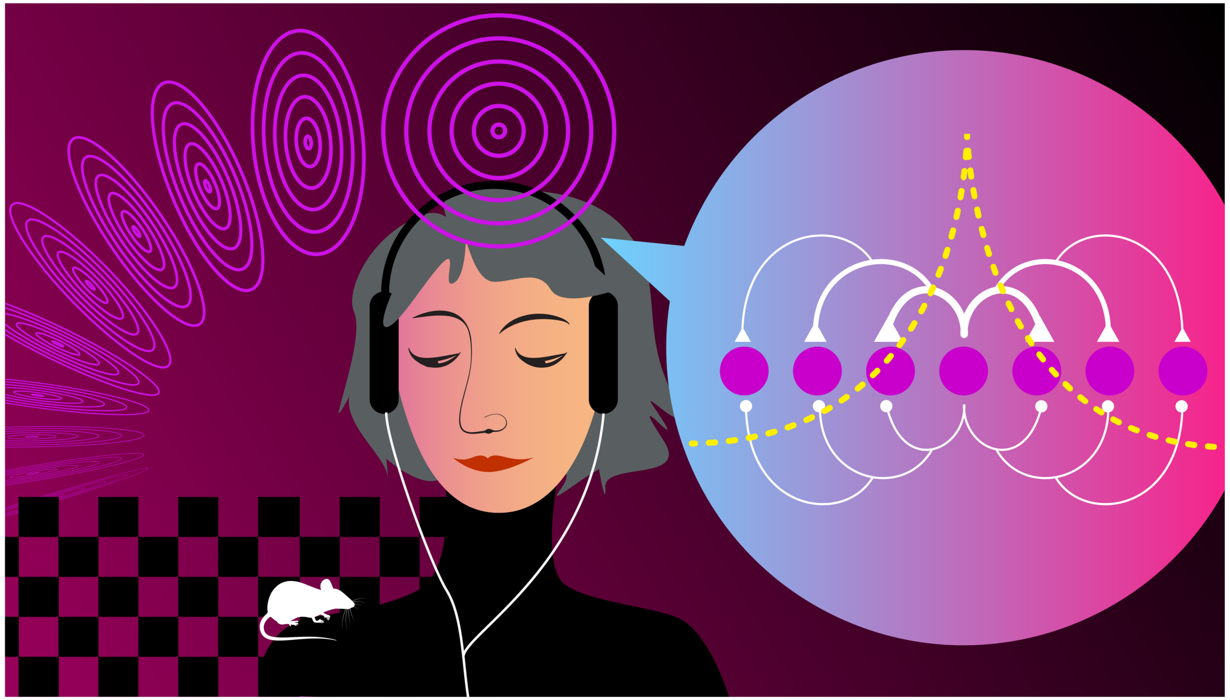


Illustration by: Julia Kuhl

Vezha Boboeva

Unifying network model links recency and contraction biases in working memory
Vezha Boboeva, Alberto Pezzotta, Claudia Clopath*, Athena Akrami*, eLife 2024

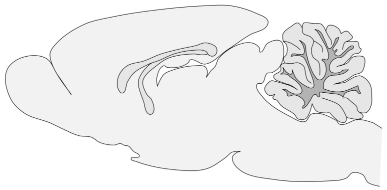
Interim summary (3)

- Working memory is impacted by history of sensory events – optimal?!
- Two components in such biases: recency (n-back trials) & contraction bias
- Posterior Parietal Cortex (PPC) in rats causally represents this sensory history. Removal of sensory history, by inactivating PPC, reduces the sensory biases, without disrupting WM
- Our continuous attractor model for PPC (slow integrator with adaptation) can replicate all behavioural results
- The contraction bias towards mean is an average effect over trials. In each single trial, volatile WM is displaced towards the input from the history network (PPC).
- A possible mechanism for the brain to approximate Bayesian inference?!

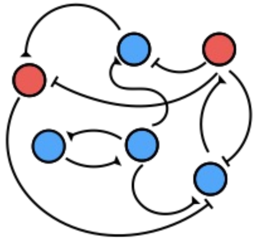
multi-level understanding of statistical learning in the brain

Behavior

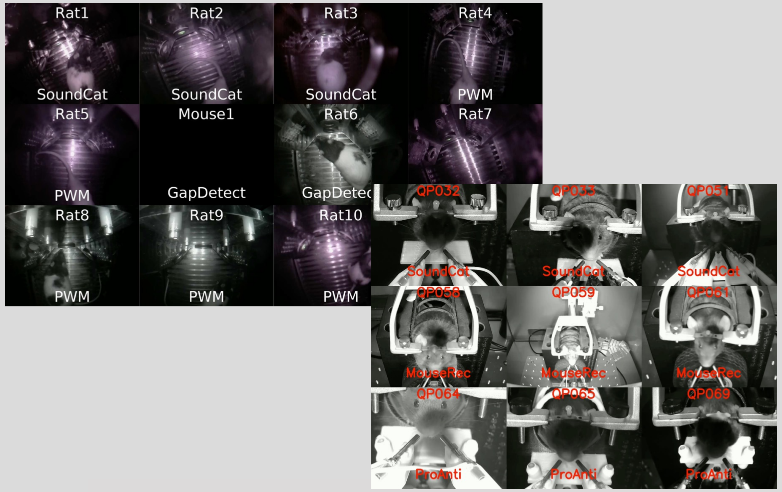
Neuronal circuits



Modeling

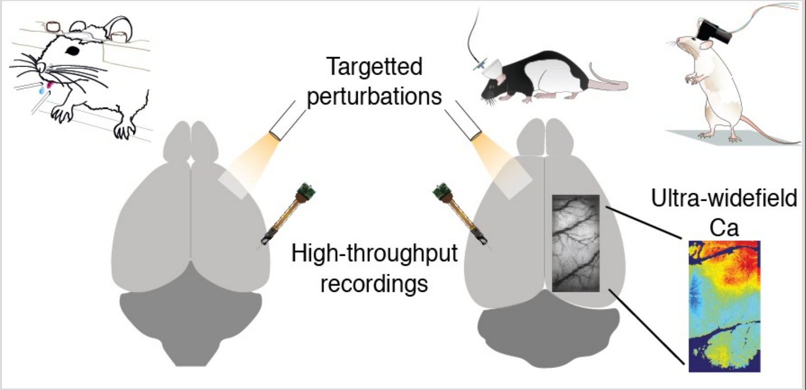


High throughput behavior
(rats and mice)

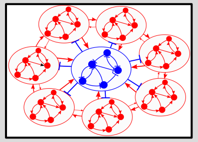
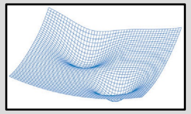
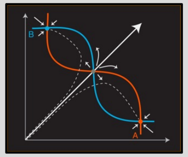


Training 70 animals per day

Neural measurement/perturbation



Theory

- neural networks 
- attractor dynamics 
- normative models 

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Kay Lee

HUMANS

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Peter Latham

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