Using computational models to answer the ‘why?’ of specific features of human cognition

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PSL Data Science Program

https://psl.eu/en/programmes-gradues/programme-data

Paris Artificial Intelligence Research Institute

https://prairie-institute.fr

The ‘how?’ and the ‘why?’

- Statistical models can test whether a behavioral effect of interest is significant
- Cognitive computational models can explain how this behavioral effect is generated.
- Human cognitive modeling has identified several suboptimalities in human cognition
- Hardest question: why are these specific features of cognition out there?

The ‘how?’ and the ‘why?’

nature human behaviour

ARTICLES

https://doi.org/10.1038/s41562-022-01445-0

Check for updates

Efficient stabilization of imprecise statistical inference through conditional belief updating

Julie Drevet[1,2] ✉, Jan Drugowitsch[3] and Valentin Wyart[1,2] ✉

Statistical inference is the optimal process for forming and maintaining accurate beliefs about uncertain environments. However, human inference comes with costs due to its associated biases and limited precision. Indeed, biased or imprecise inference can trigger variable beliefs and unwarranted changes in behaviour. Here, by studying decisions in a sequential categorization task based on noisy visual stimuli, we obtained converging evidence that humans reduce the variability of their beliefs by updating them only when the reliability of incoming sensory information is judged as sufficiently strong. Instead of integrating the evidence provided by all stimuli, participants actively discarded as much as a third of stimuli. This conditional belief updating strategy shows good test-retest reliability, correlates with perceptual confidence and explains human behaviour better than previously described strategies. This seemingly suboptimal strategy not only reduces the costs of imprecise computations but also, counterintuitively, increases the accuracy of resulting decisions.

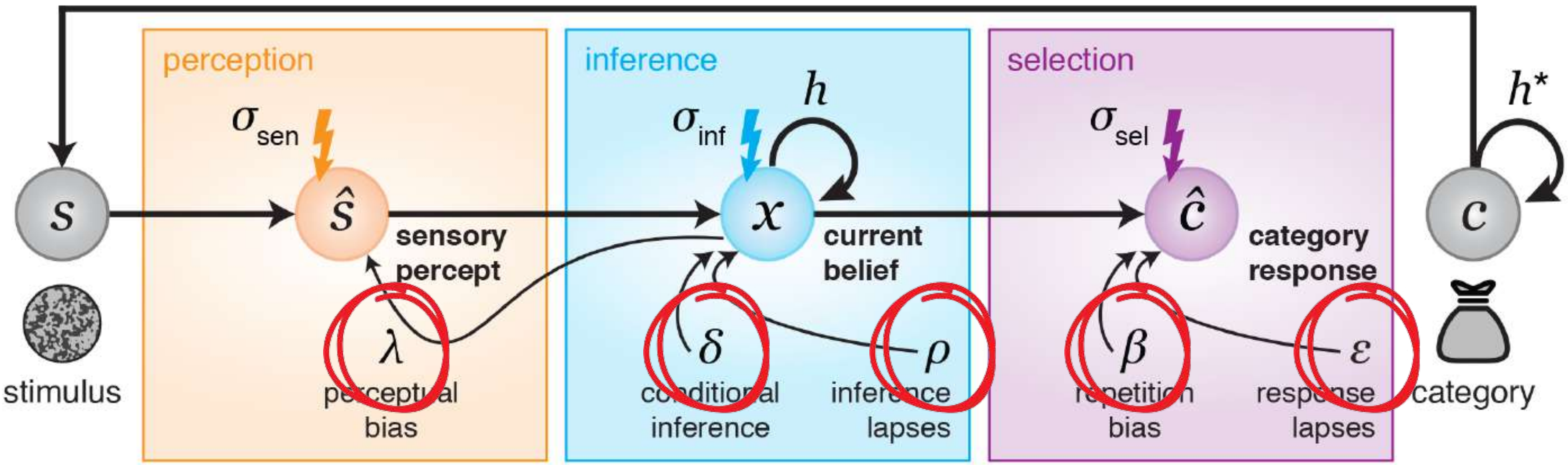
Efficient decision-making about the cause of noisy or ambiguous observations requires the accumulation of multiple pieces of evidence to form accurate beliefs[1,2], a process typically referred to as ‘statistical inference’. In stable environments, accu-

bag) were perceived as dark and vice versa (Fig. 1c and Methods). After each marble, participants were asked to identify the bag from which it was drawn (Fig. 1d). Importantly, marbles were not drawn randomly and independently across successive trials, but rather in episodes of multiple draws from the same bag. Decision-making in

The ‘how?’ and the ‘why?’

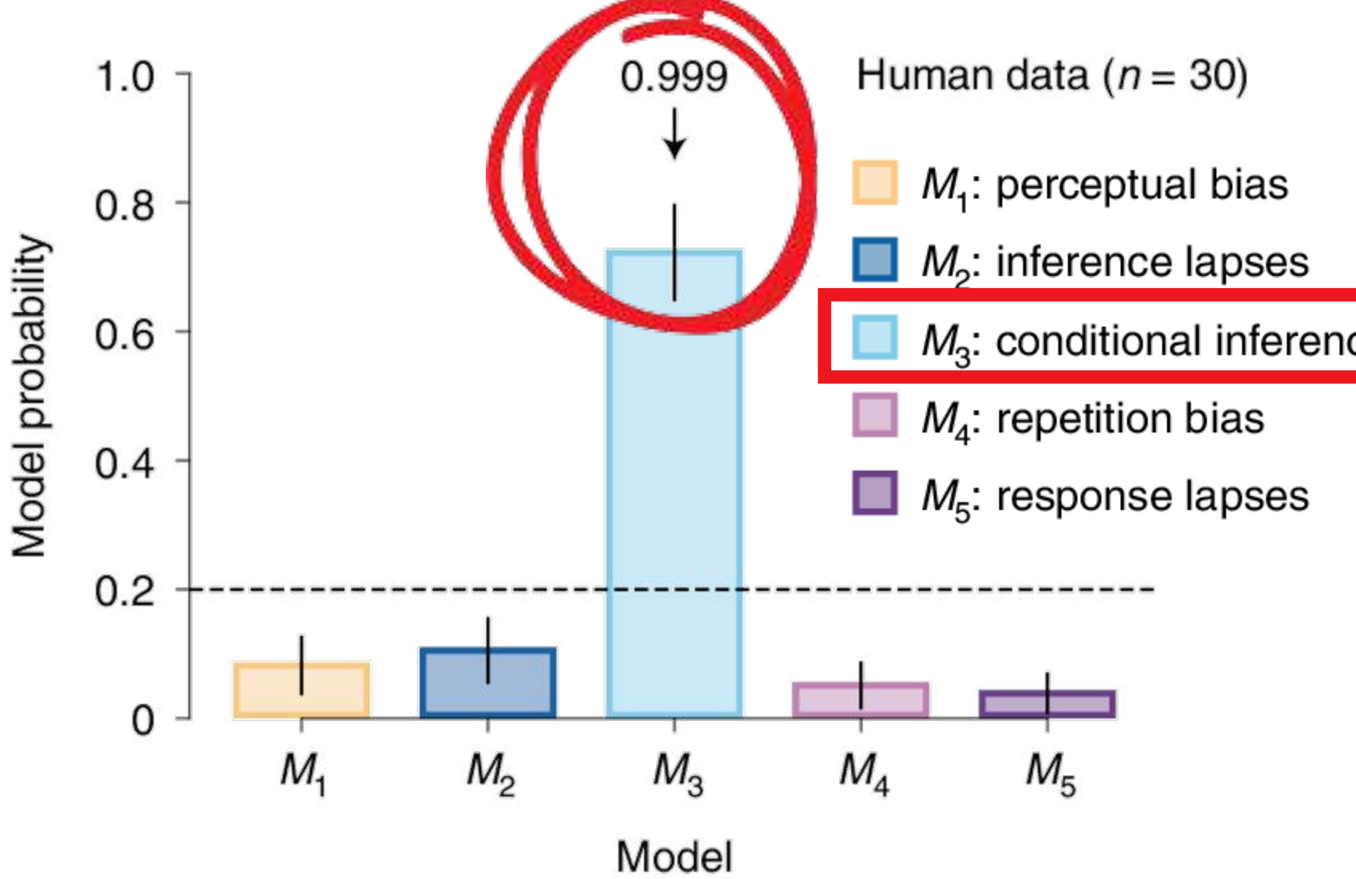
- Comparison of candidate cognitive strategies that could explain human behavior

hidden-state inference model



The ‘how?’ and the ‘why?’

- <u>Comparison</u> of candidate model parameters that could explain human behavior



The ‘how?’ and the ‘why?’

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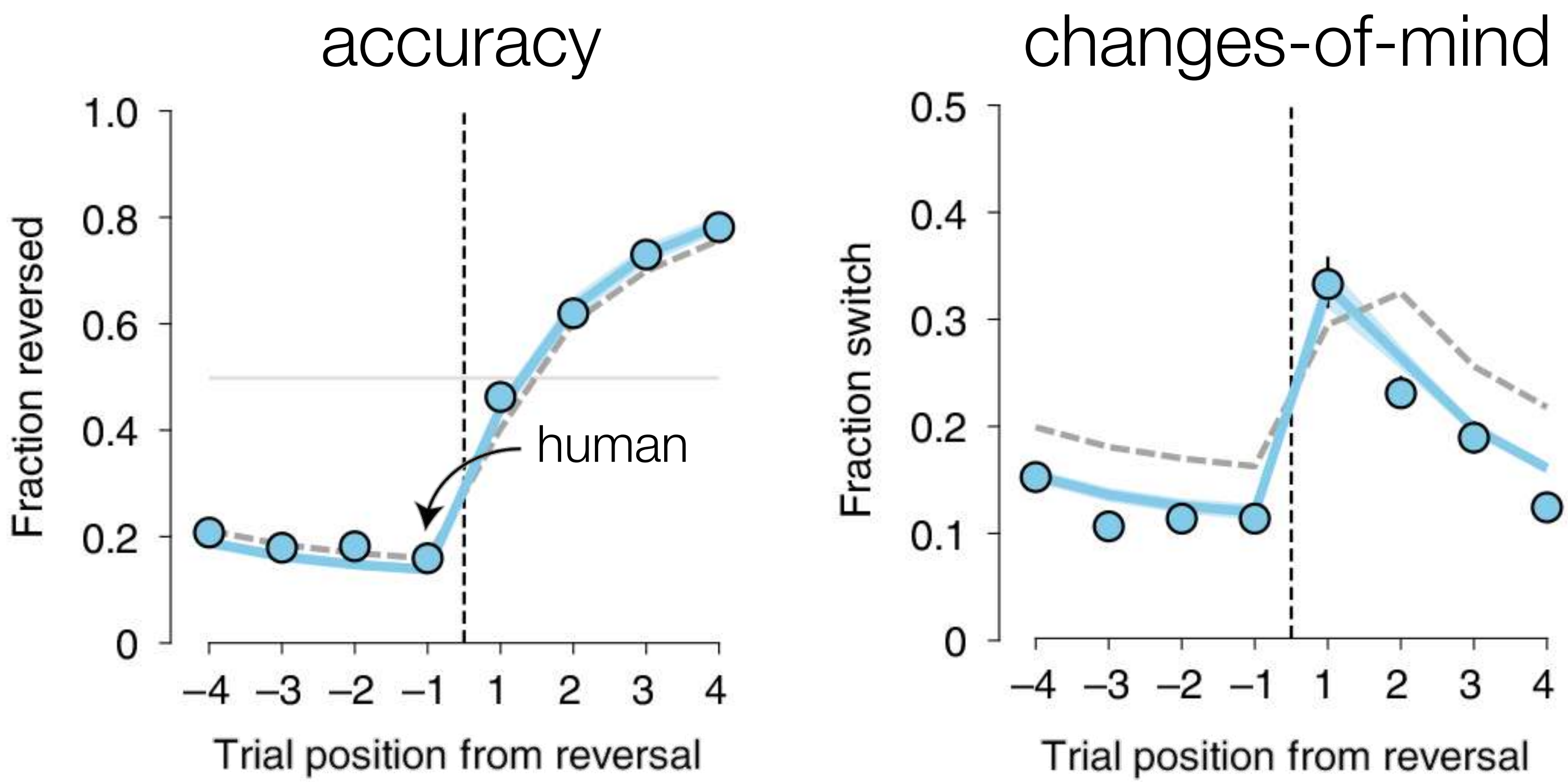


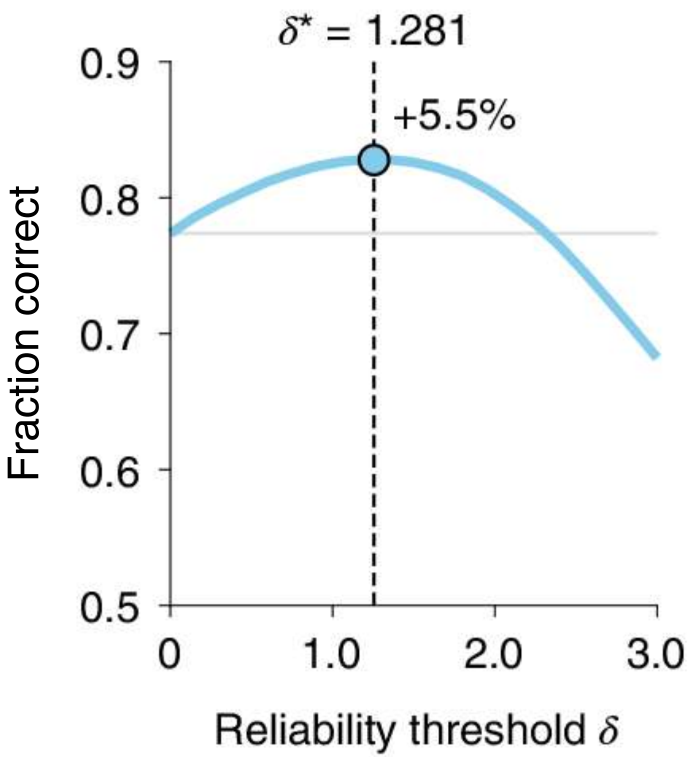
The ‘how?’ and the ‘why?’

- Comparison of candidate model parameters that could explain human behavior

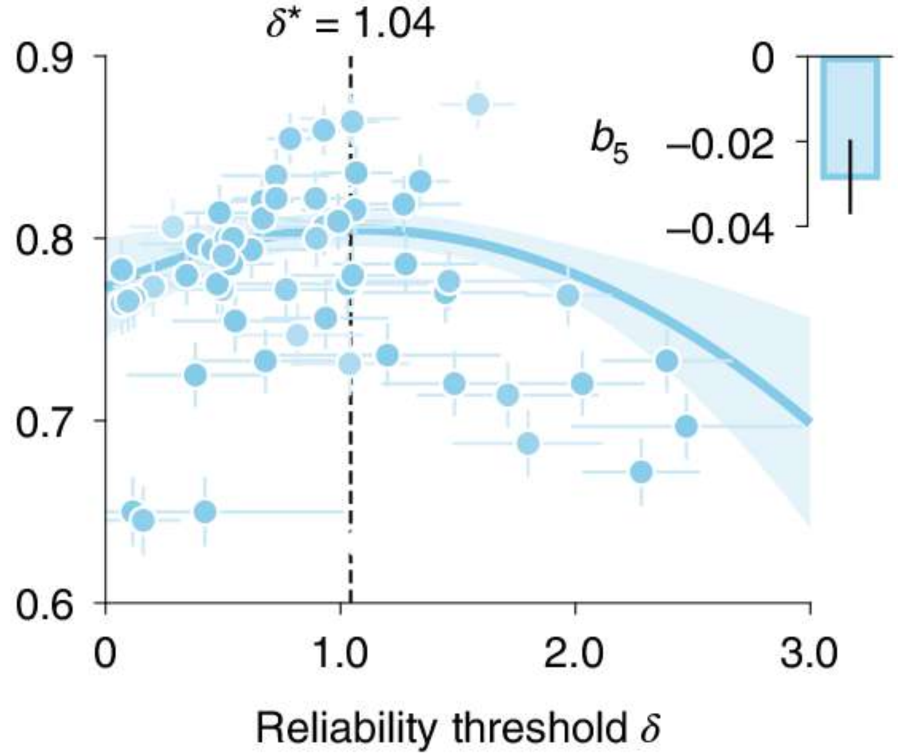
- Winning model: M_3 = conditional inference
“ignore marbles whose sensory evidence is less than a reliability threshold δ”

- Open question: why do human subjects ignore a third of presented marbles on average?
> sheer laziness
> hidden benefits of this cognitive strategy

model simulations



human data



The 'how?' and the 'why?'

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The ‘how?’ and the ‘why?’

Current Biology

CellPress

Article

Recurrent networks endowed with structural priors explain suboptimal animal behavior

Manuel Molano-Mazón,[1,6,*] Yuxiu Shao,[2] Daniel Duque,[1] Guangyu Robert Yang,[3,4,5] Srdjan Ostojic,[2] and Jaime de la Rocha[1]

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https://doi.org/10.1016/j.cub.2022.12.044

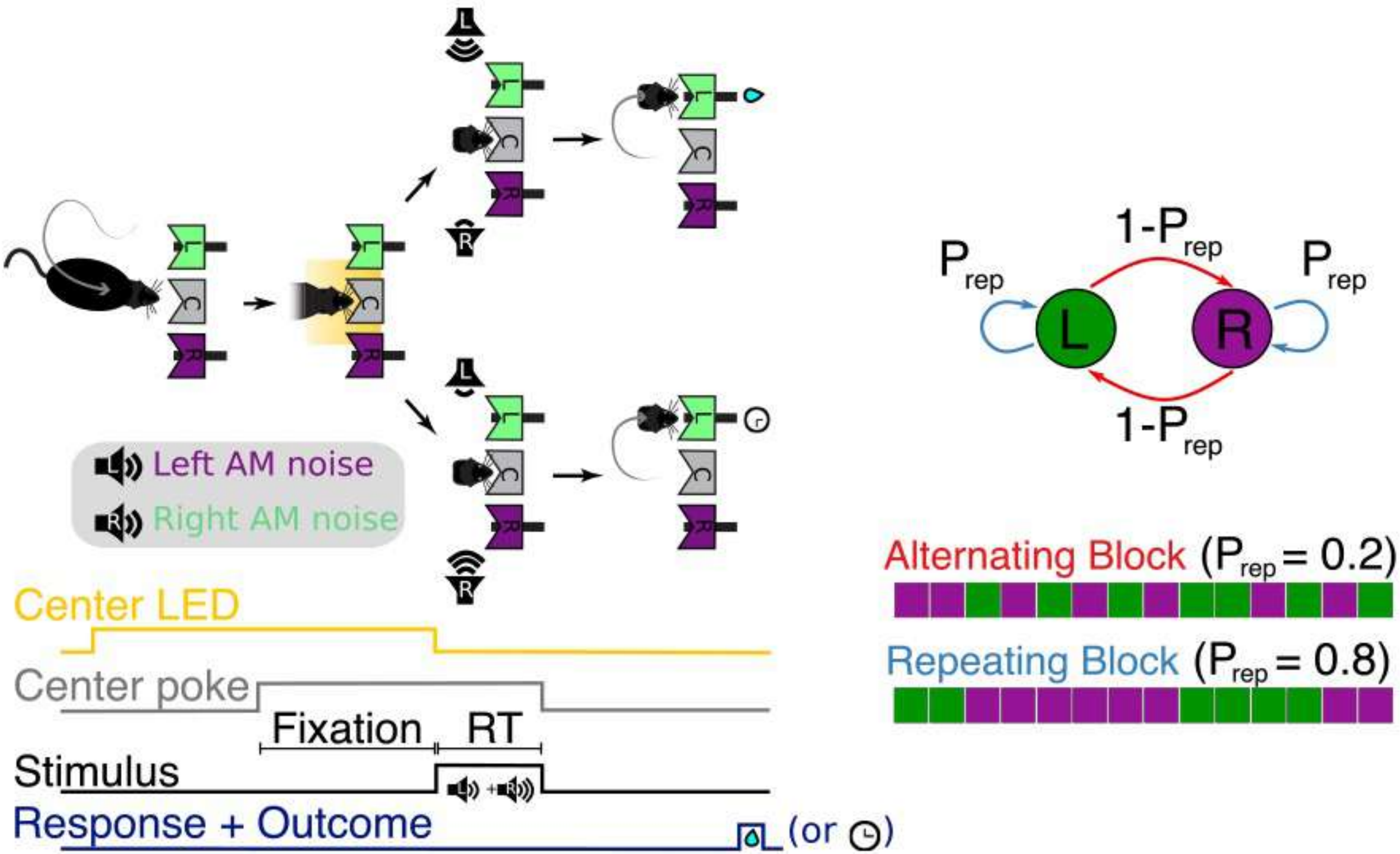
SUMMARY

The strategies found by animals facing a new task are determined both by individual experience and by structural priors evolved to leverage the statistics of natural environments. Rats quickly learn to capitalize on the trial sequence correlations of two-alternative forced choice (2AFC) tasks after correct trials but consistently deviate from optimal behavior after error trials. To understand this outcome-dependent gating, we first show that recurrent neural networks (RNNs) trained in the same 2AFC task outperform rats as they can readily learn to use across-trial information both after correct and error trials. We hypothesize that, although RNNs can optimize their behavior in the 2AFC task without any *a priori* restrictions, rats' strategy is constrained by a

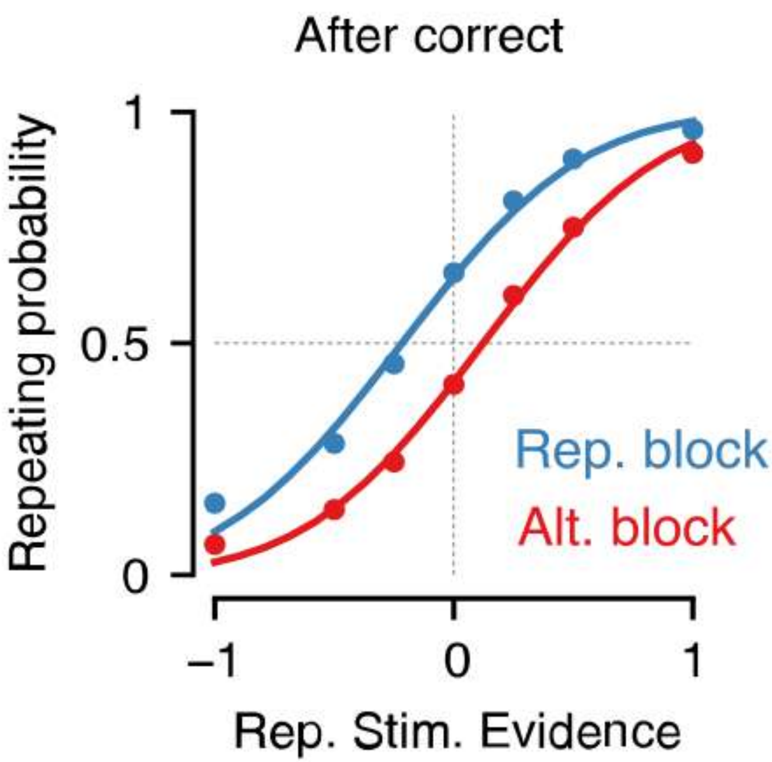
The ‘how?’ and the ‘why?’

- Like humans, rats can learn how to balance sensory evidence against prior expectations:
  >> $\mathcal{L}_t = \mathcal{F}(\mathcal{L}_{t-1}, h) + \ell_t$
- Rats consistently deviate from optimal behavior after error trials, by ignoring prior expectations
- Open question: why do human subjects ignore a third of presented marbles on average?
  > idiosyncrasy of animal behavior
  > hidden cause of this suboptimality

The 'how?' and the 'why?'

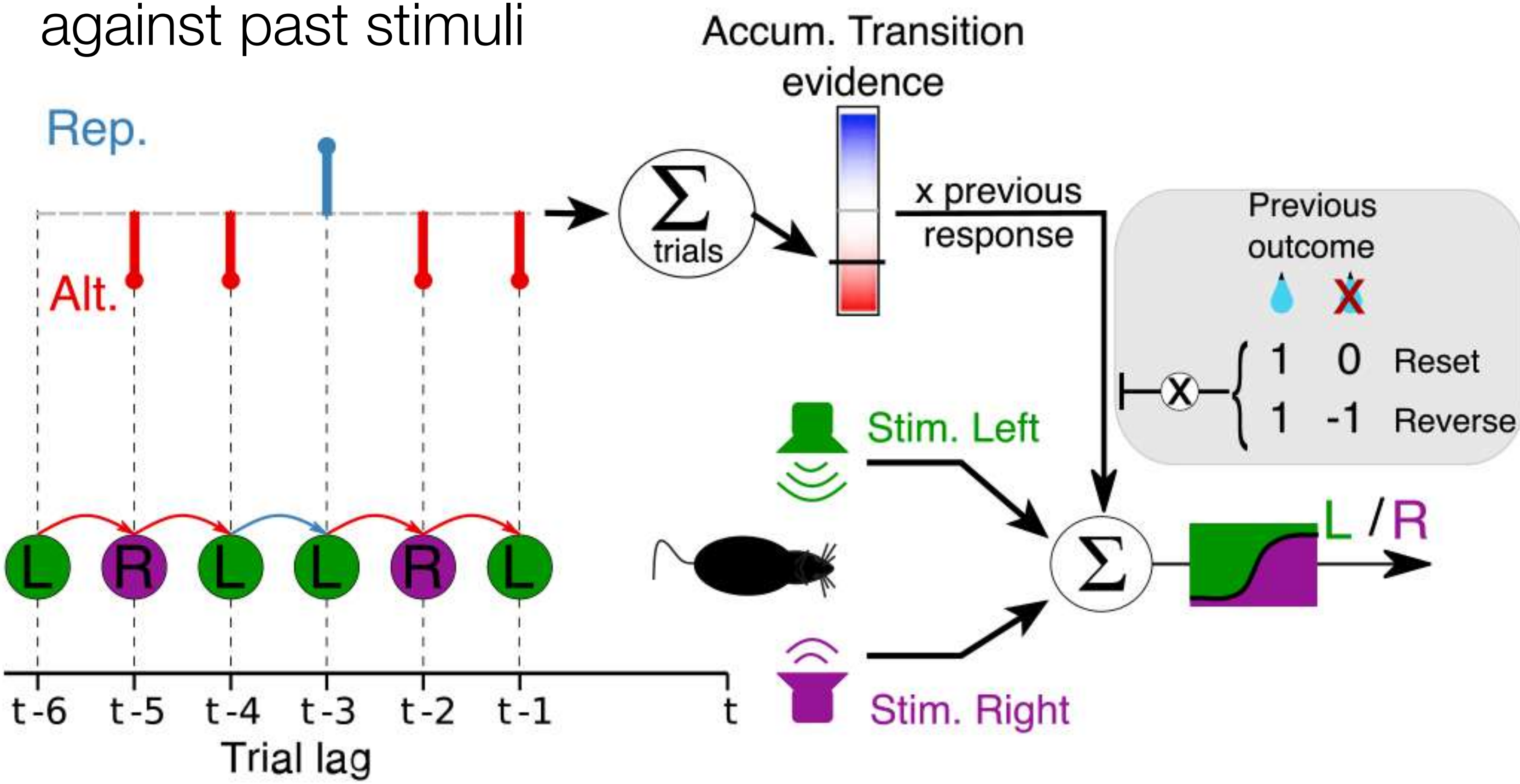


The ‘how?’ and the ‘why?’

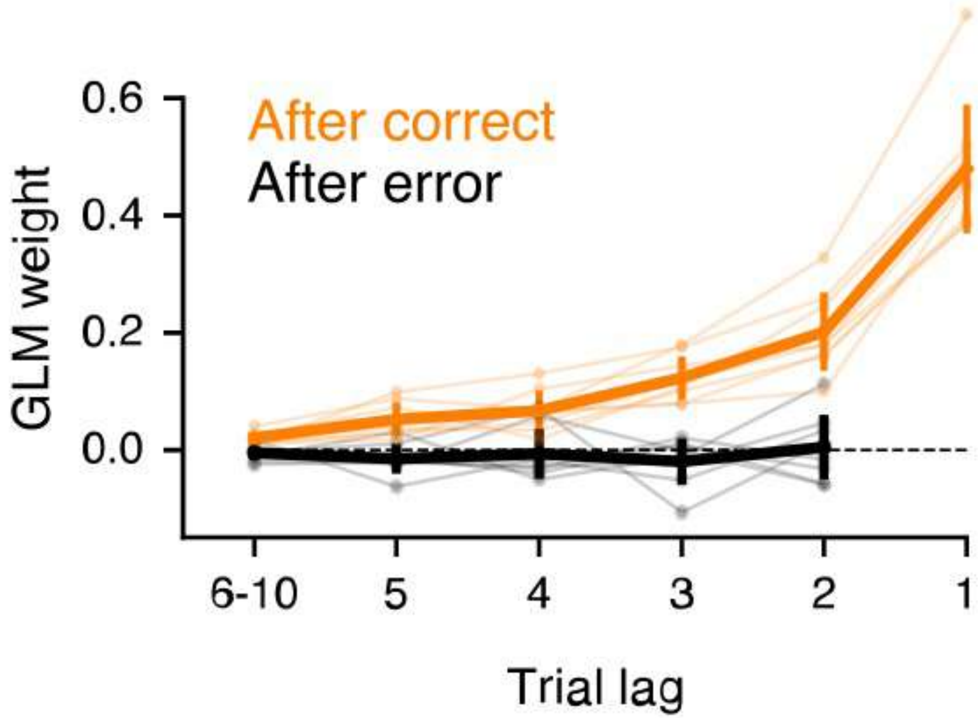


The ‘how?’ and the ‘why?’

logistic regression of choice
against past stimuli

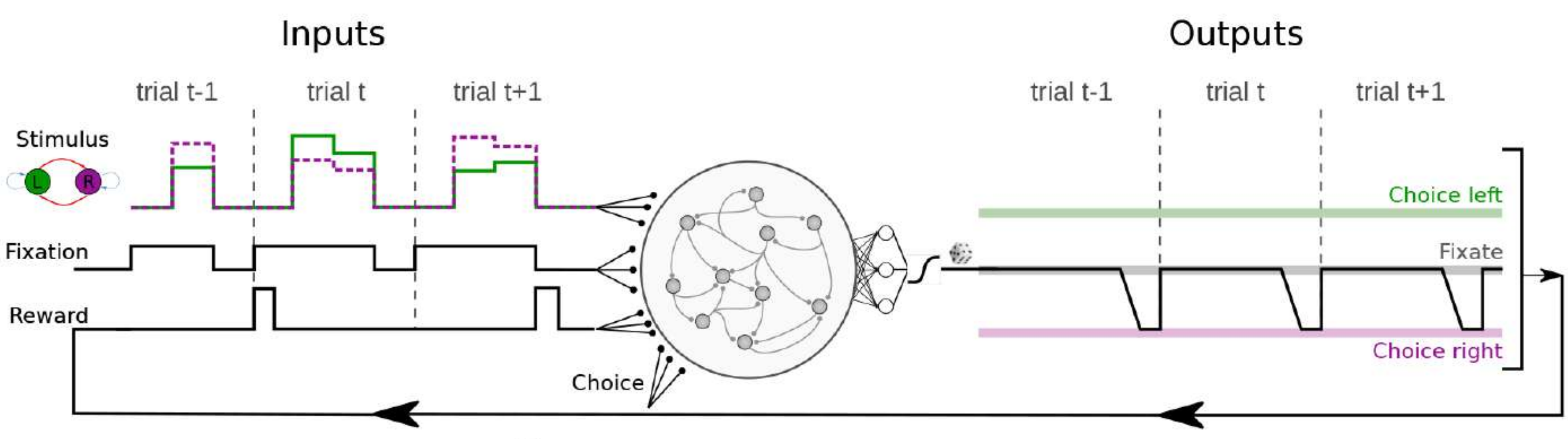


The ‘how?’ and the ‘why?’

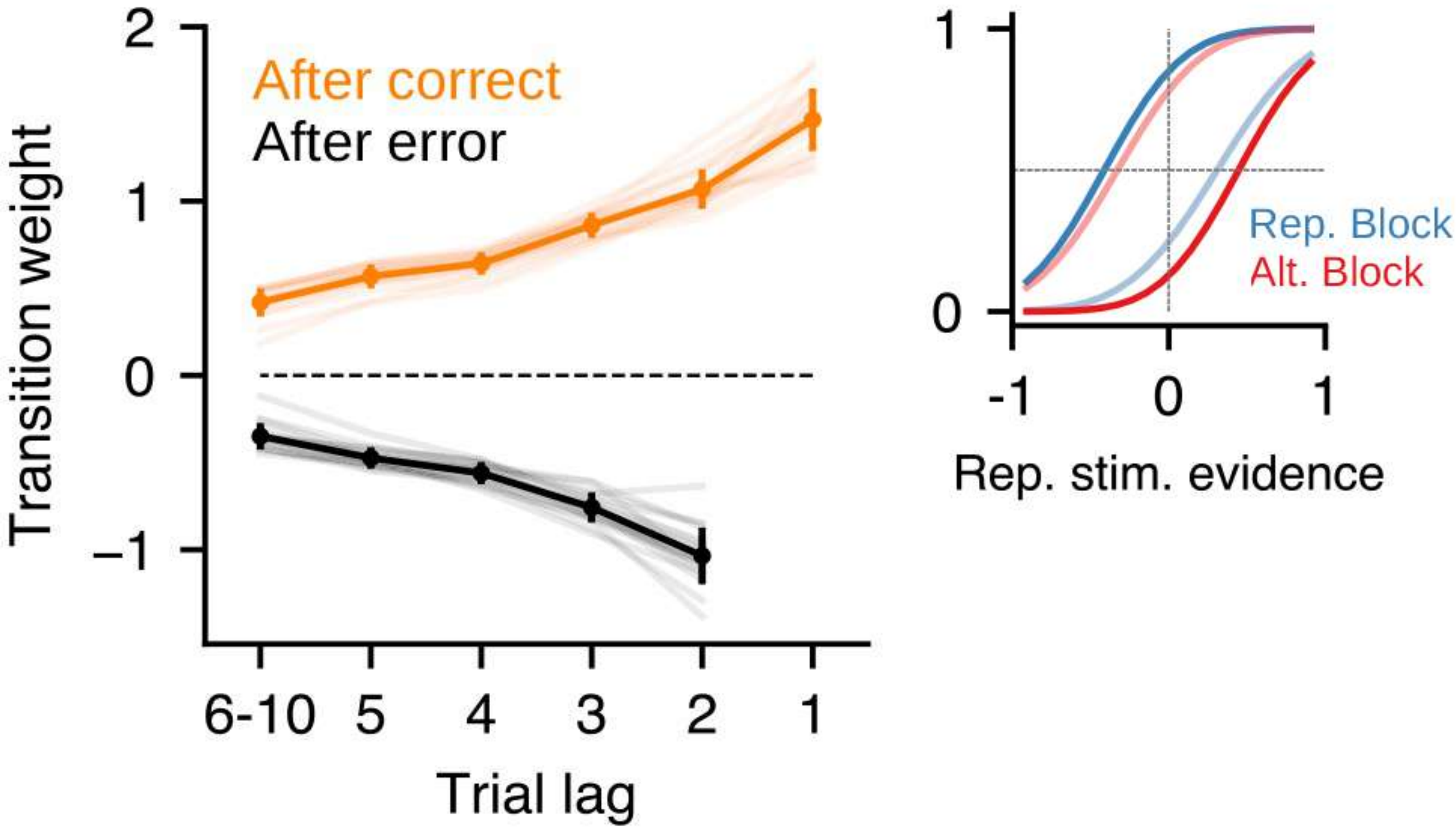


The 'how?' and the 'why?'

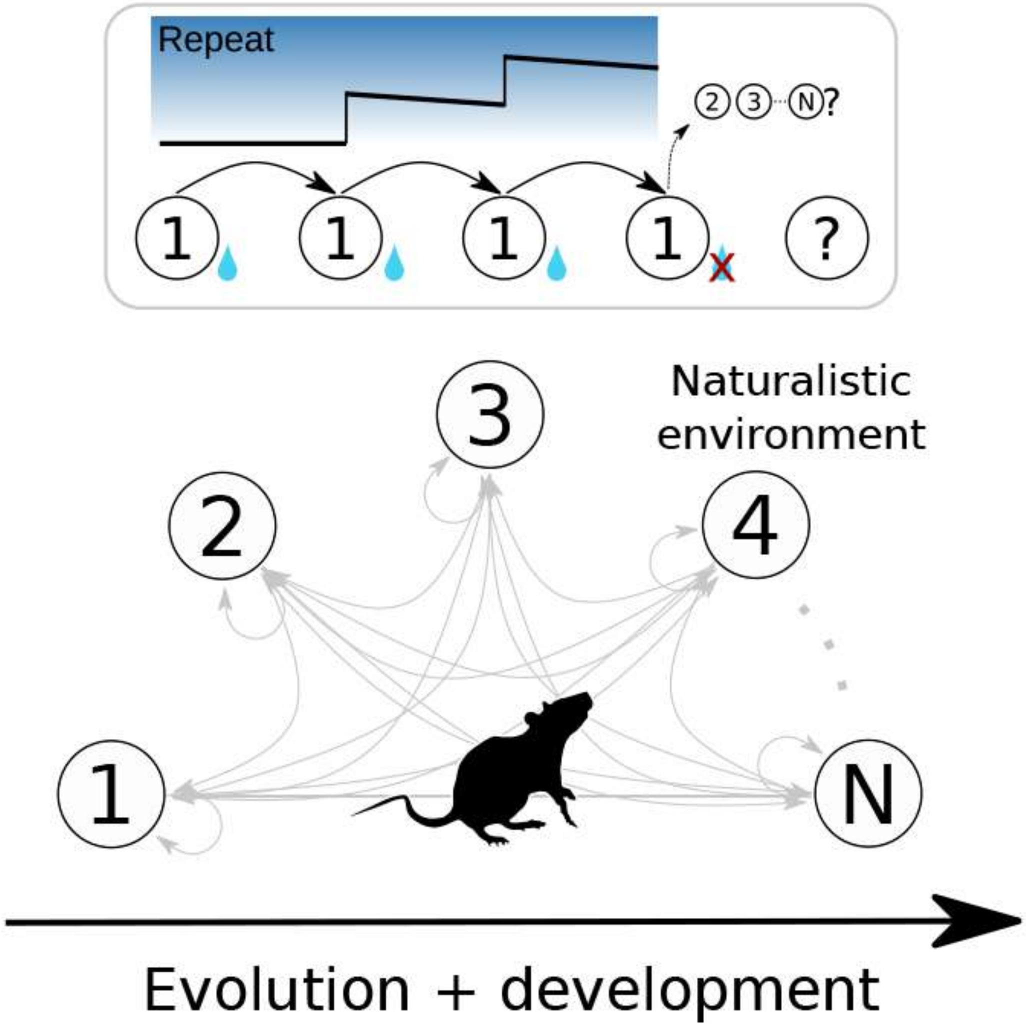
input/output of recurrent neural networks (RNNs) trained to perform the same task as rats



The ‘how?’ and the ‘why?’



The ‘how?’ and the ‘why?’



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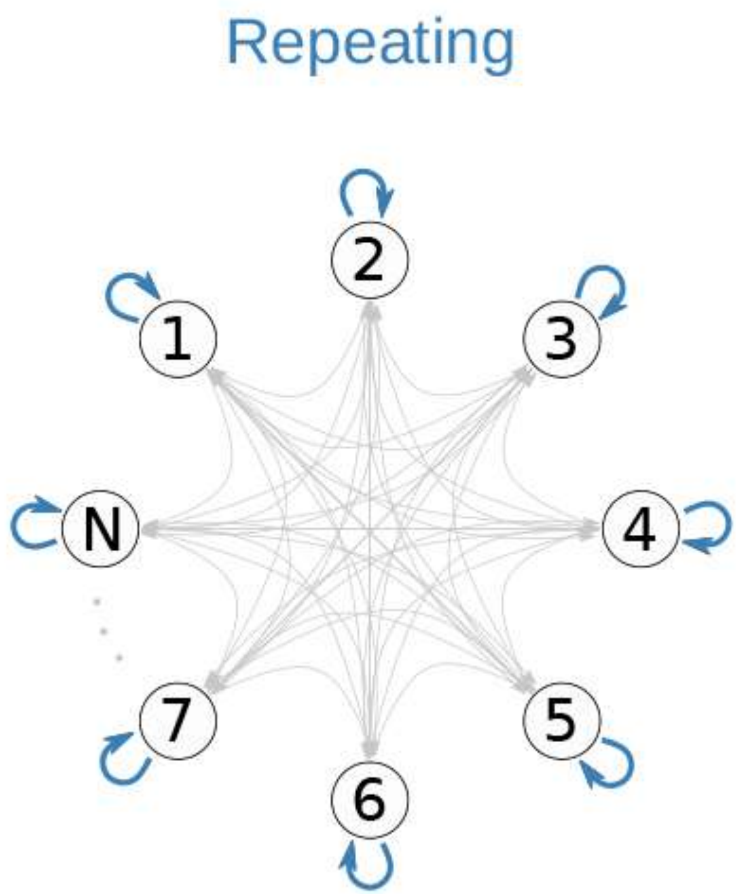
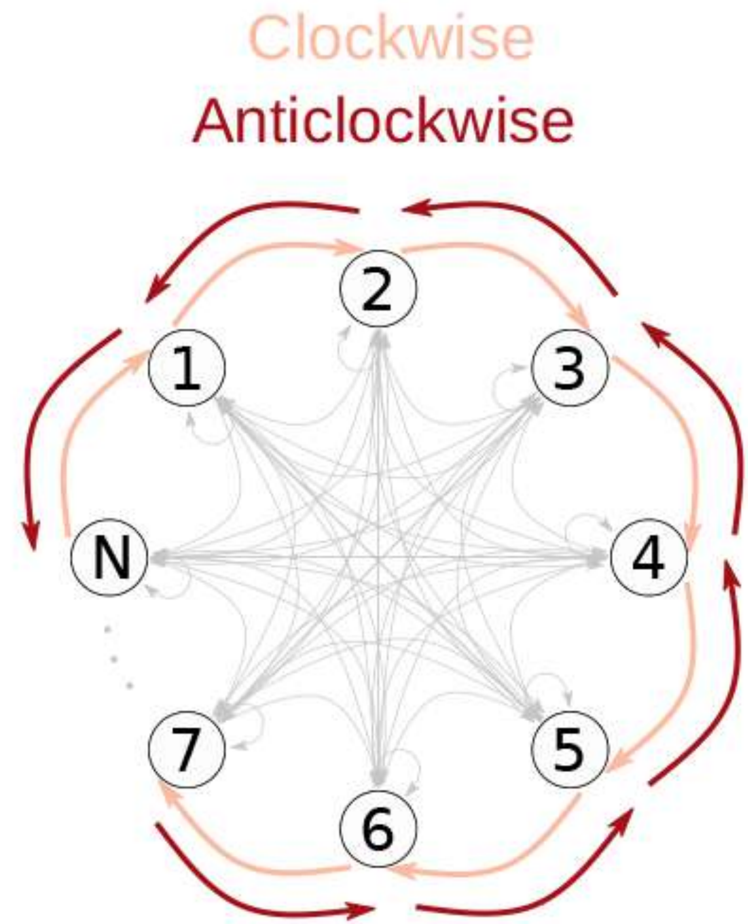
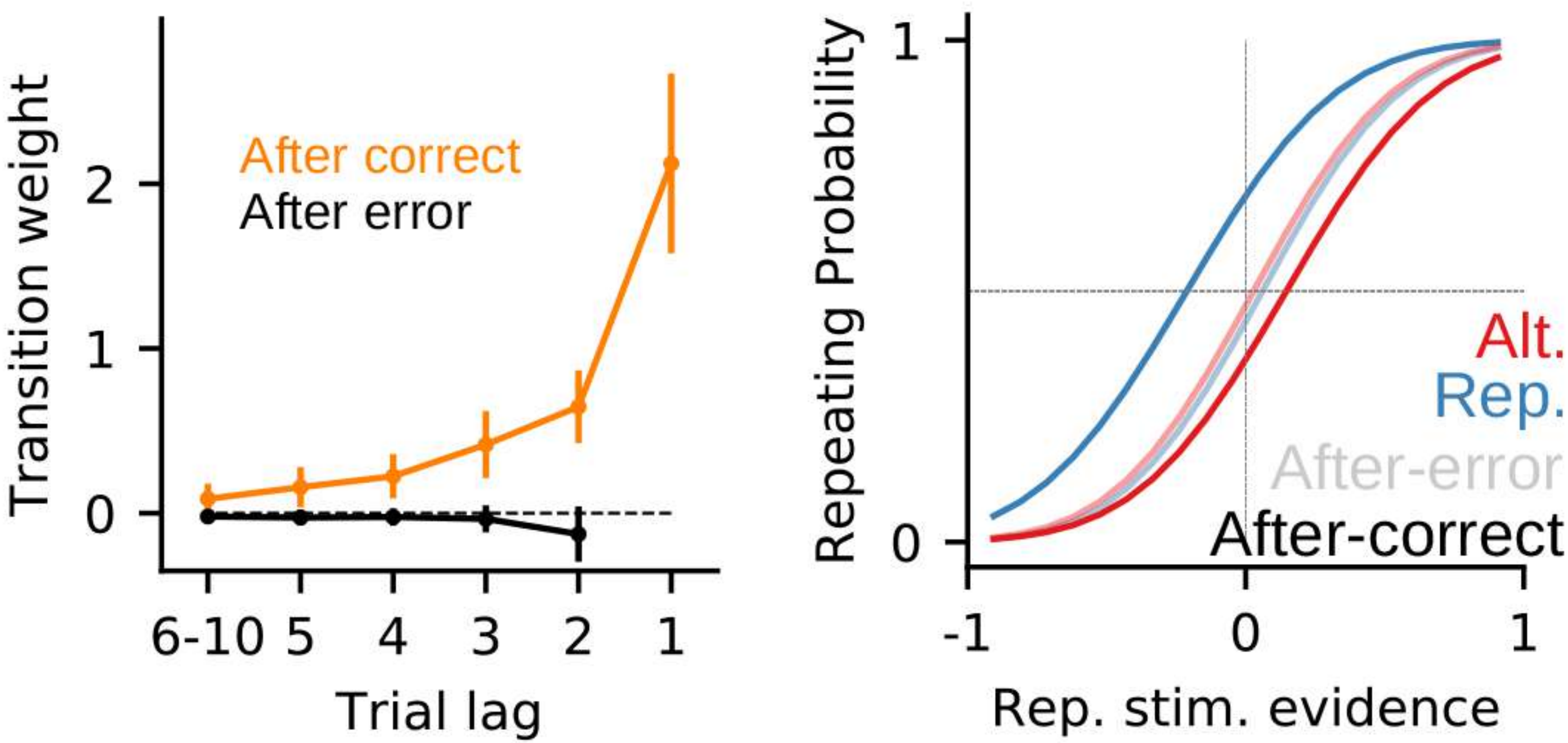




The ‘how?’ and the ‘why?’



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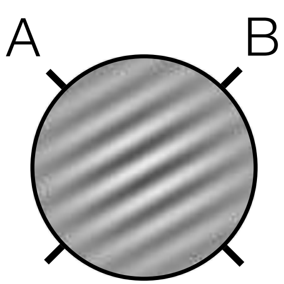
Effect of computation noise

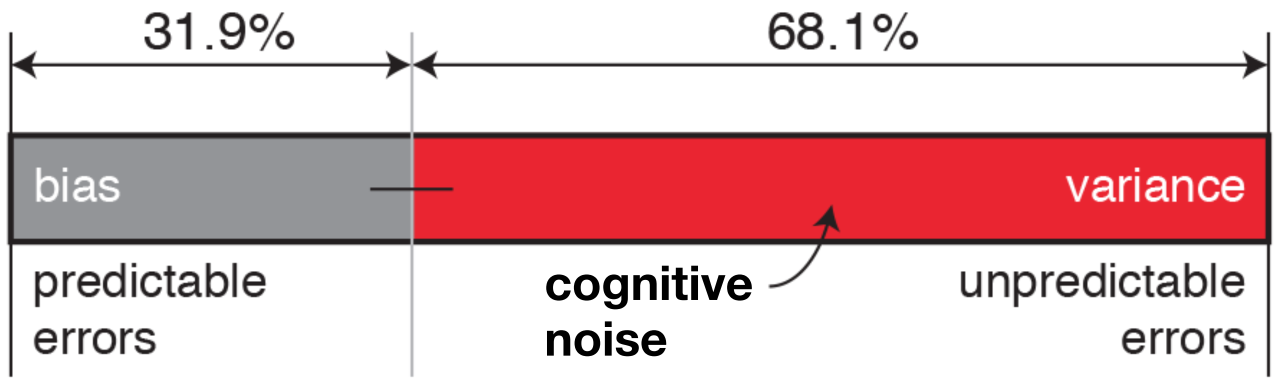
- Human decisions are variable under uncertainty.

reward-guided
decisions

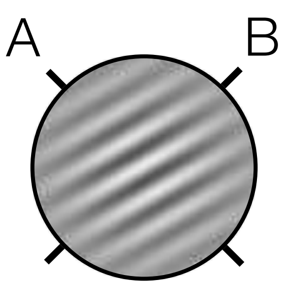


sensory-guided
decisions

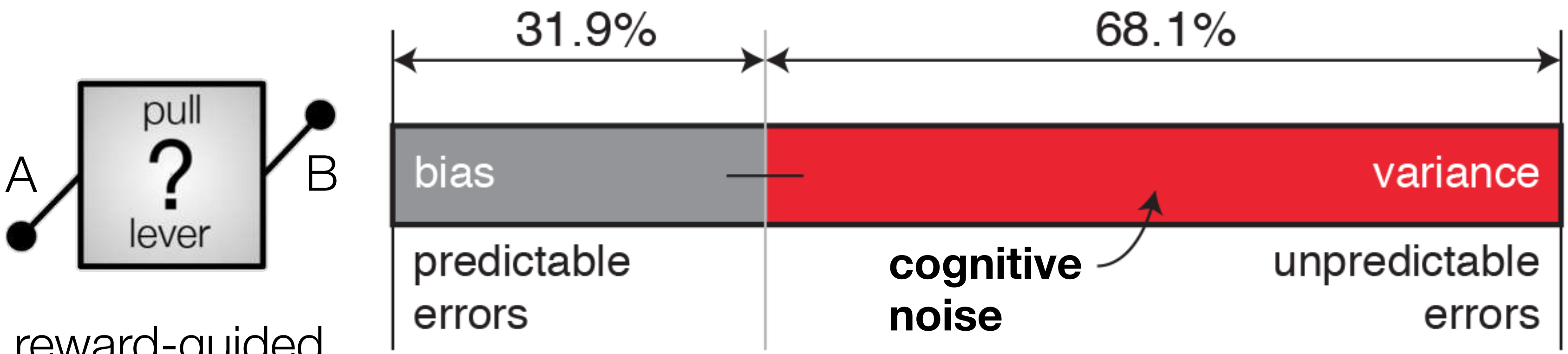
reward-guided decisions



from Findling, Skvortsova et al. *Nat. Neurosci.* (2019)



sensory-guided decisions



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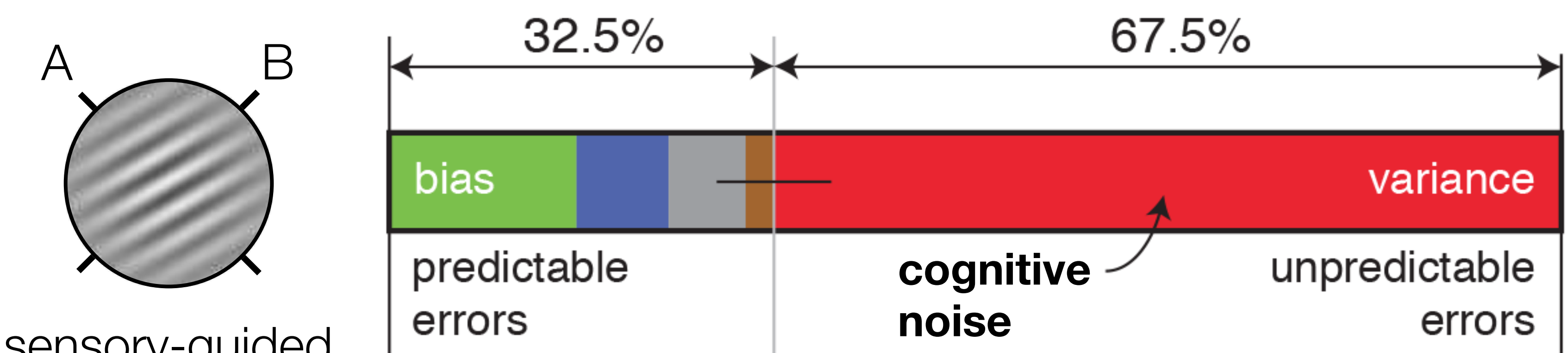


sensory-guided decisions

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

Effect of computation noise

- Human decisions are variable under uncertainty.
- Most of this variability arises from noise (not bias) in decision-making computations.
- Open question: why is all this noise still there?
  - ✓ H_1: cost of noise suppression too large
  - ✓ H_2: unidentified benefits of noise

Effect of computation noise

SCIENCE ADVANCES | RESEARCH ARTICLE

COGNITIVE NEUROSCIENCE

Computation noise promotes zero-shot adaptation to uncertainty during decision-making in artificial neural networks

Charles Findling[1,2]* and Valentin Wyart[1,3,4]*

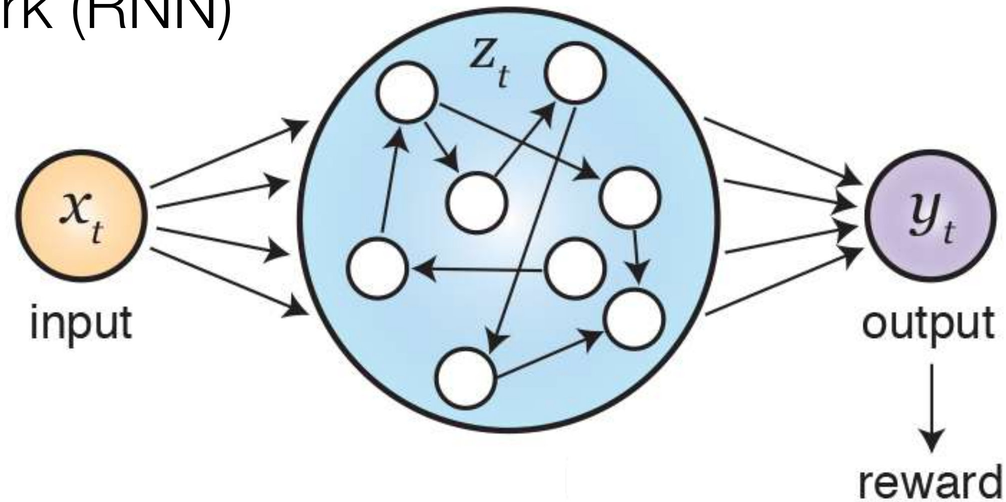
Random noise in information processing systems is widely seen as detrimental to function. But despite the large trial-to-trial variability of neural activity, humans show a remarkable adaptability to conditions with uncertainty during goal-directed behavior. The origin of this cognitive ability, constitutive of general intelligence, remains elusive. Here, we show that moderate levels of computation noise in artificial neural networks promote zero-shot generalization for decision-making under uncertainty. Unlike networks featuring noise-free computations, but like human participants tested on similar decision problems (ranging from probabilistic reasoning to reversal learning), noisy networks exhibit behavioral hallmarks of optimal inference in uncertain conditions entirely unseen during training. Computation noise enables this cognitive ability jointly through "structural" regularization of network weights during training and "functional" regularization by shaping the stochastic dynamics of network activity after training. Together, these findings indicate that human cognition may ride on neural variability to support adaptive decisions under uncertainty without extensive experience or engineered sophistication.

INTRODUCTION

Extracting signal from noise is seen as a core feature of efficient information processing systems, from gravitational-wave detectors to neural networks. In this context, noise is usually defined as irrelevant input that should be filtered out to improve signal detection. But beyond this input noise, brains process and respond to input with a

ways, e.g., by allowing transitions between otherwise stable states (*18*, *19*). These two effects can be seen as distinct forms of regularization: (i) structural regularization by tuning the connection weights of artificial neural networks and (ii) functional regularization by shaping the dynamics of stochastic nonlinear systems. These two forms of regularization are observed across different systems shaped by different sources of variability, variability (e.g., the random inacti-

recurrent neural
network (RNN)



network dynamics

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

$$z_t = \sigma_z(\widehat{z}_t)$$

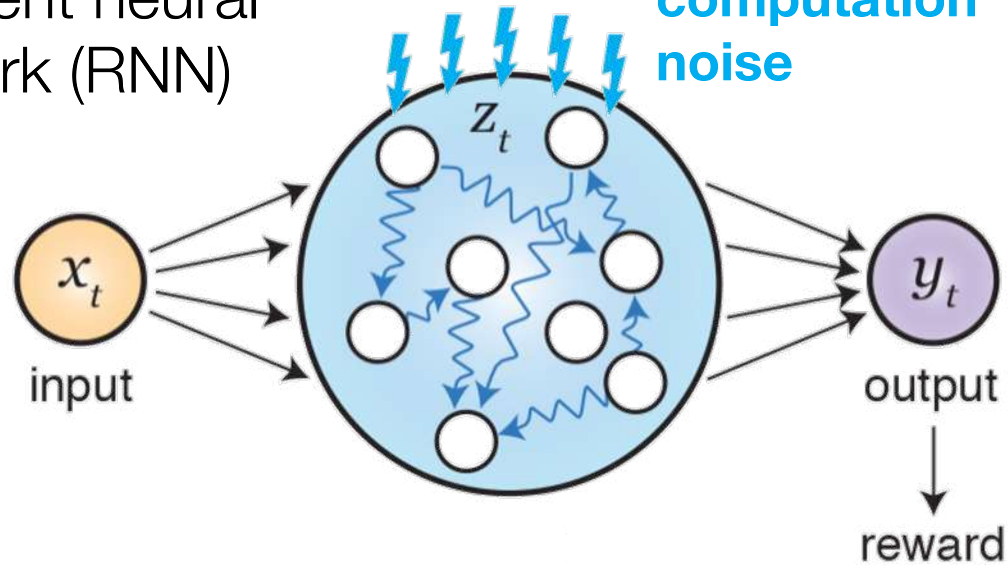
objective function

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

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

recurrent neural network (RNN)

computation noise



network dynamics

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

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

objective function

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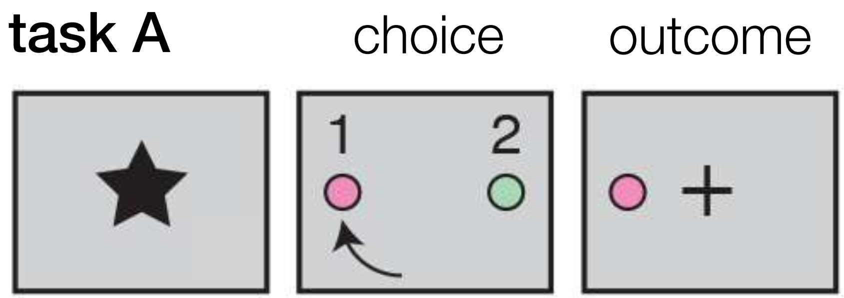
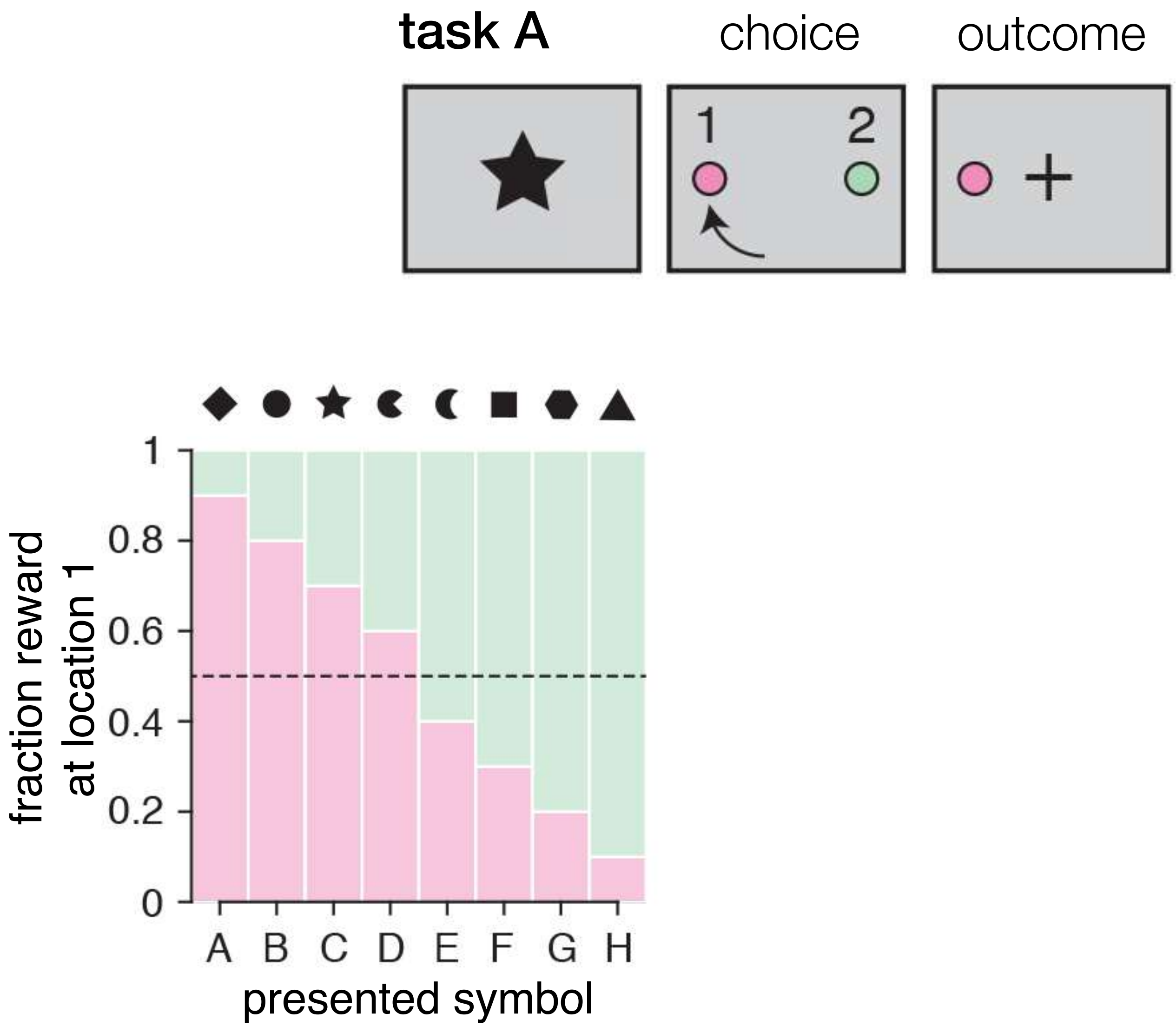
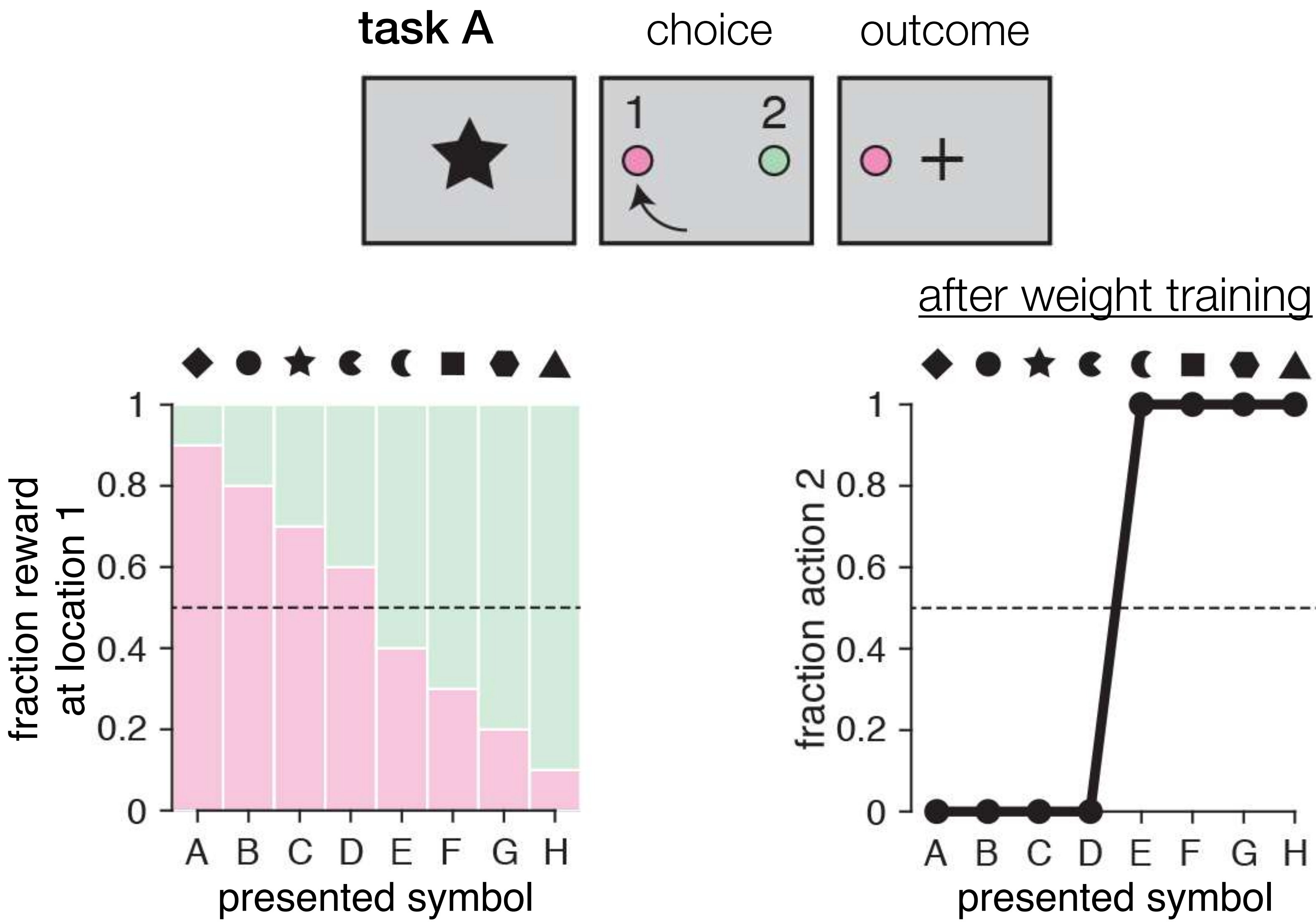
$$L(U, V, W, b) = \mathbb{E}^{\pi}[r]$$


task A
choice
outcome
1
2


task A
choice
outcome
1
2
fraction reward
at location 1
1
0.8
0.6
0.4
0.2
0
A B C D E F G H
presented symbol



task A
choice
outcome
1
2
after weight training
fraction reward at location 1
fraction action 2
1
0.8
0.6
0.4
0.2
0
A B C D E F G H
presented symbol

What have the networks learnt?

What have the networks learnt?

fixed stimulus-response rules,
blind to expected uncertainty?

e.g., ★ triggers a response toward

What have the networks learnt?

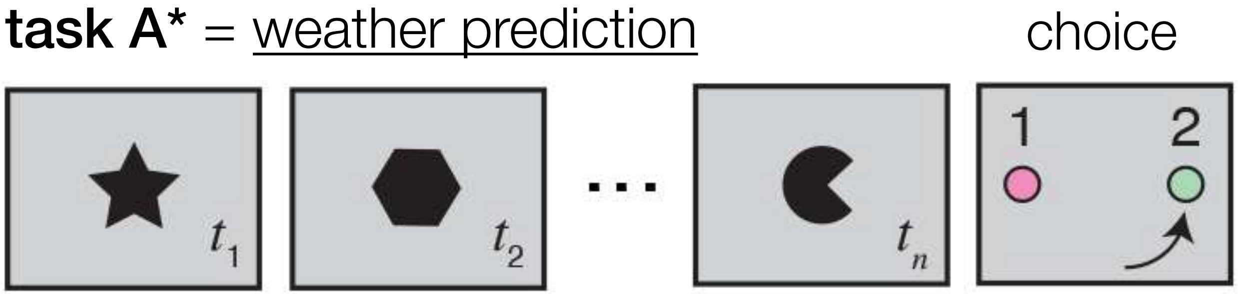
fixed stimulus-response rules,
blind to expected uncertainty?

e.g., ★ triggers a response toward ●

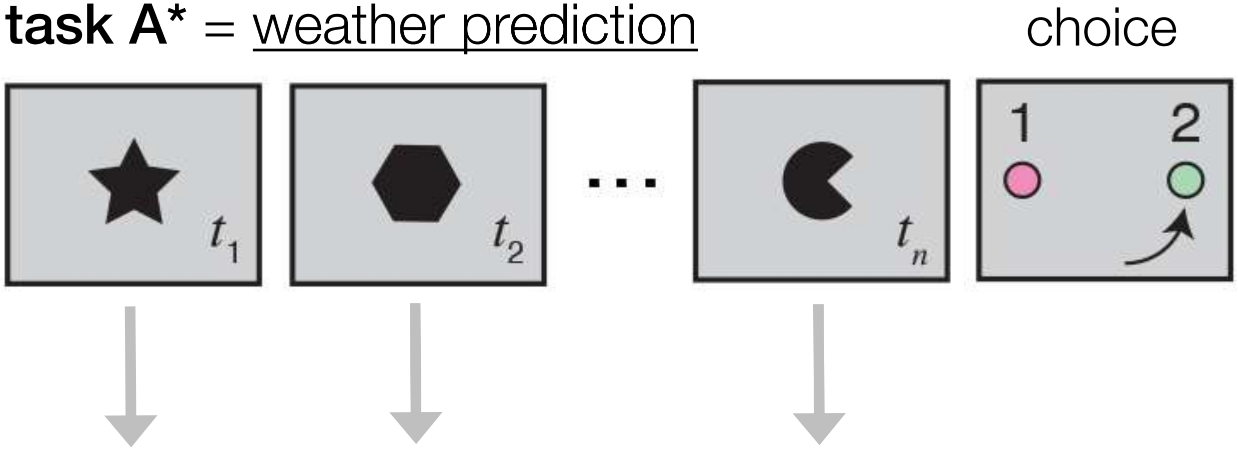
probabilistic associations
between symbols and rewards

e.g., ★ predicts ● with 70% reliability

task A* = <u>weather prediction</u>



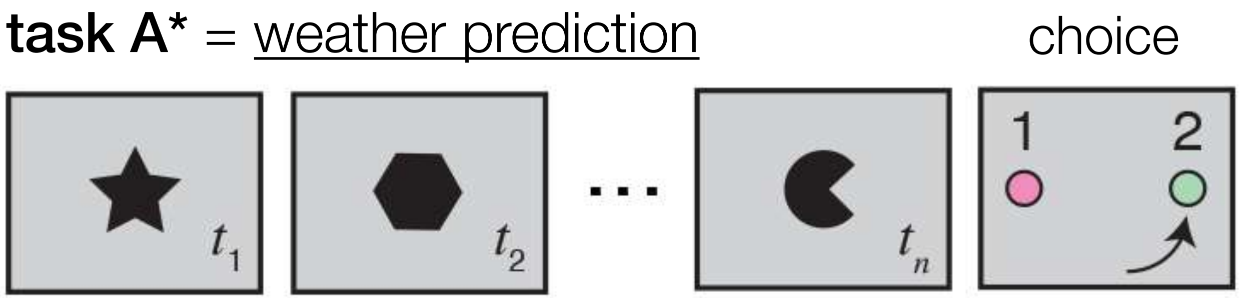
task A* = <u>weather prediction</u>

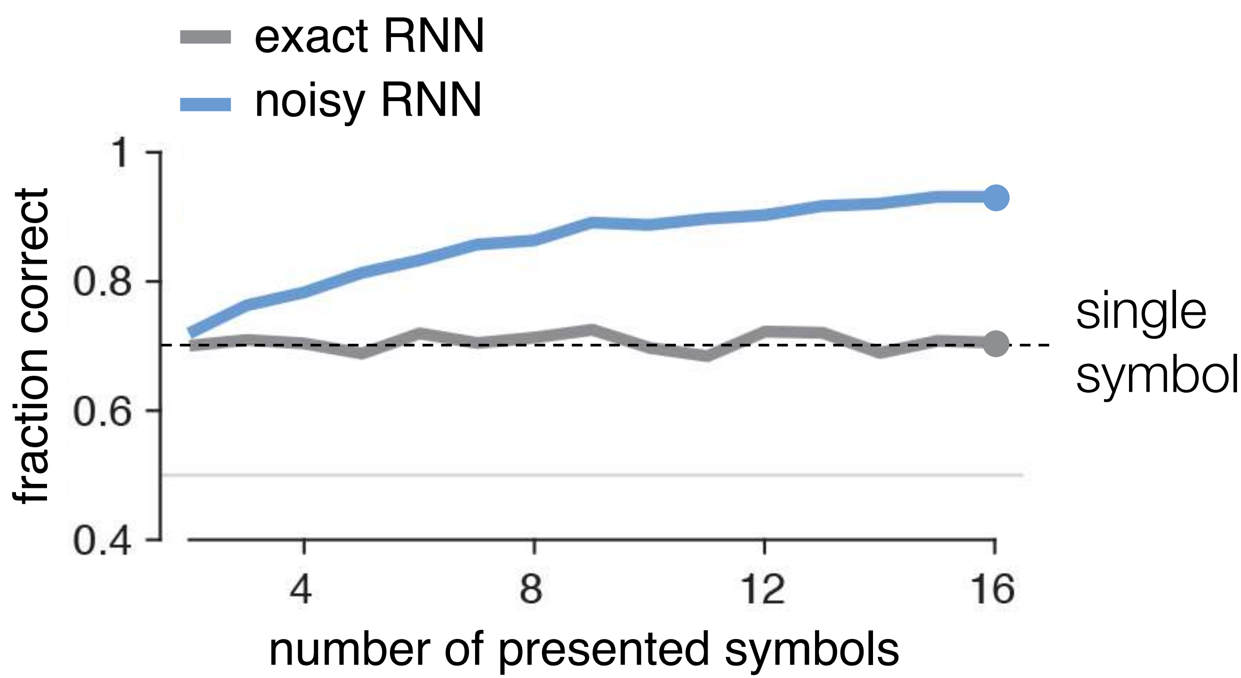


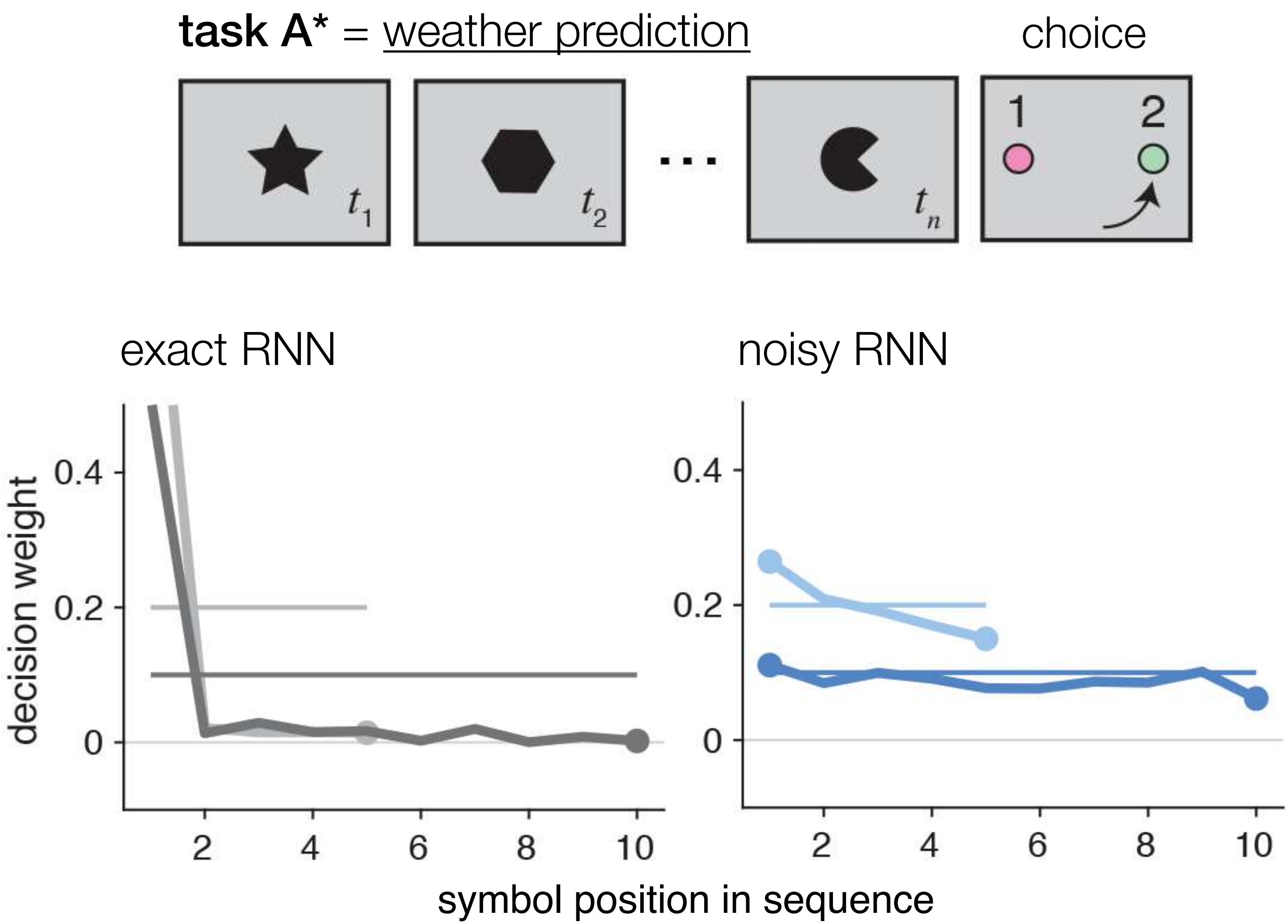
$$\log LR_1 + \log LR_2 \quad \cdots \quad + \log LR_n = \log PR$$

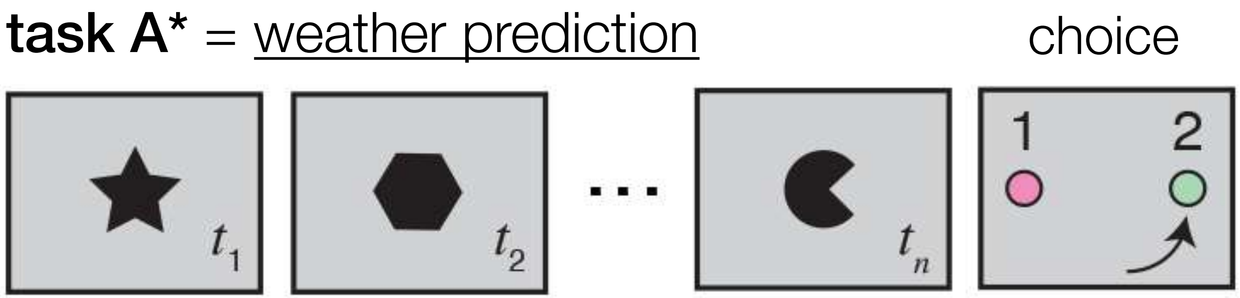
log-likelihood odds ratio

log-posterior odds ratio

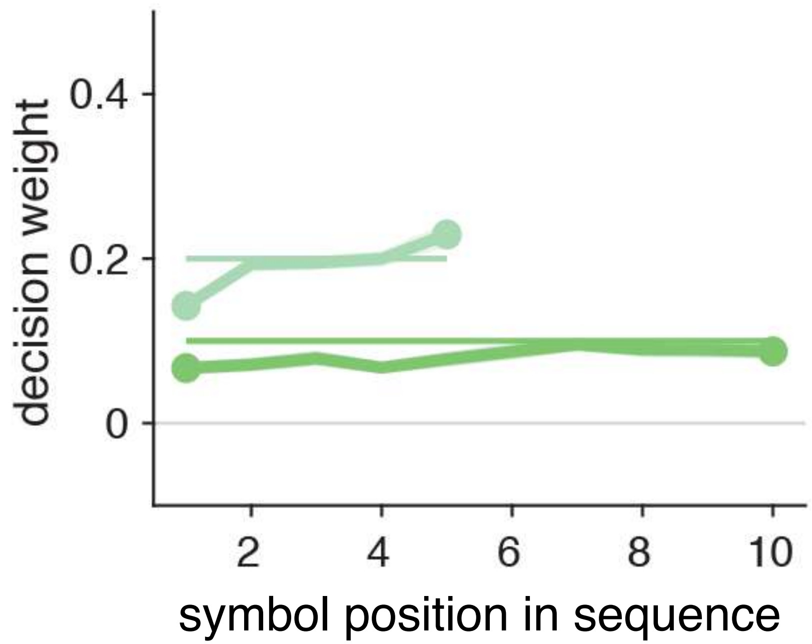

task A* = weather prediction
choice
t_1
t_2
t_n
1
2

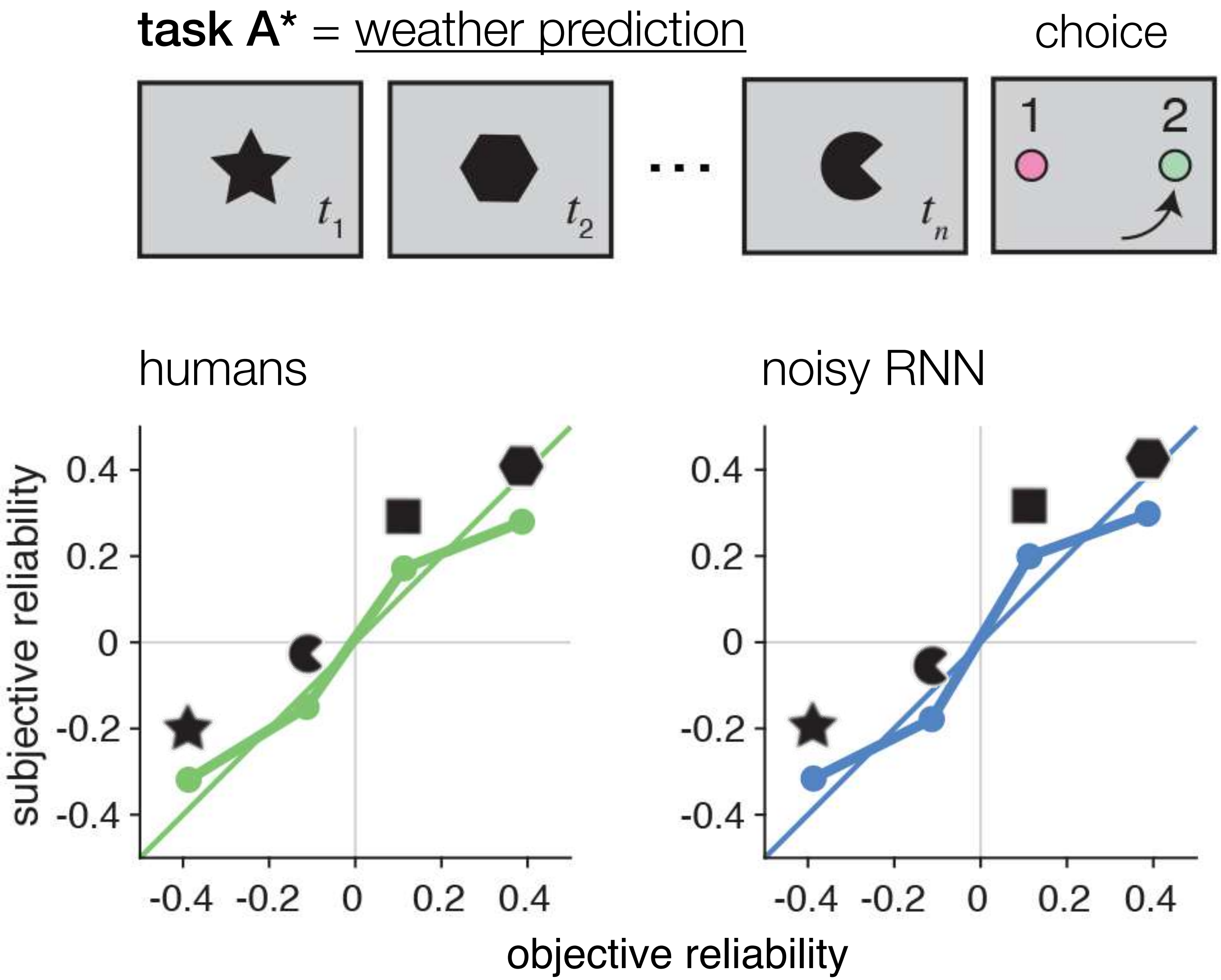

exact RNN
noisy RNN
fraction correct
1
0.8
0.6
0.4
4
8
12
16
number of presented symbols
single symbol

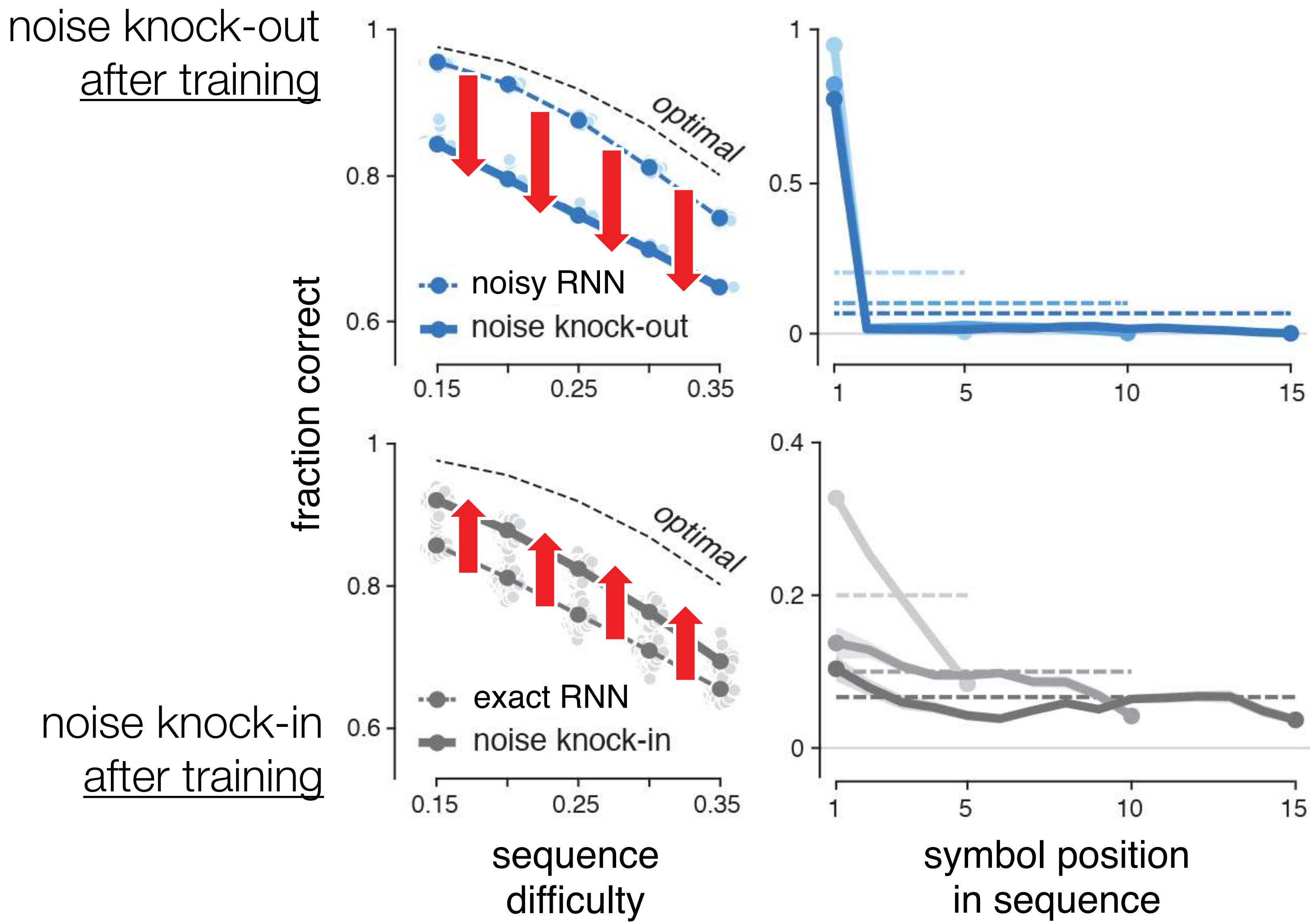

task A* = weather prediction
choice
t_1
t_2
t_n
1
2
exact RNN
noisy RNN
decision weight
0.4
0.2
0
2
4
6
8
10
symbol position in sequence

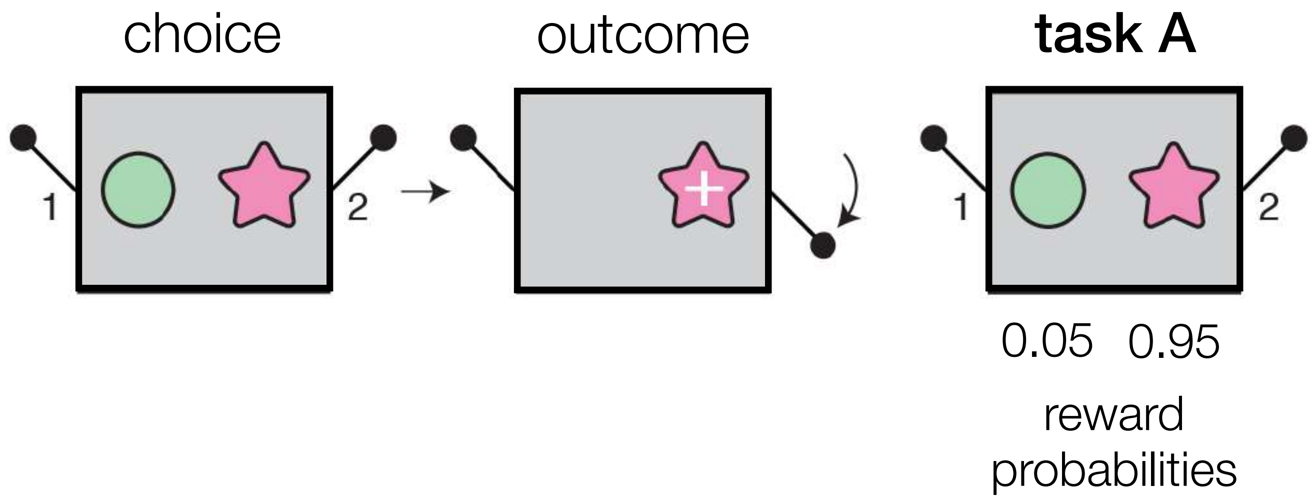


humans trained on task A

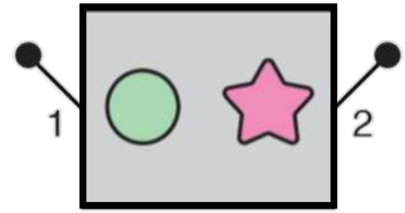



task A* = weather prediction
choice
1
2
t_1
t_2
t_n
humans
noisy RNN
subjective reliability
objective reliability
0.4
0.2
0
-0.2
-0.4


noise knock-out
after training
noise knock-in
after training
fraction correct
optimal
noisy RNN
noise knock-out
exact RNN
noise knock-in
1
0.8
0.6
0.5
0
0.4
0.2
0.15
0.25
0.35
1
5
10
15
sequence difficulty
symbol position in sequence


choice
1
2
outcome
task A
1
2
0.05
0.95
reward
probabilities

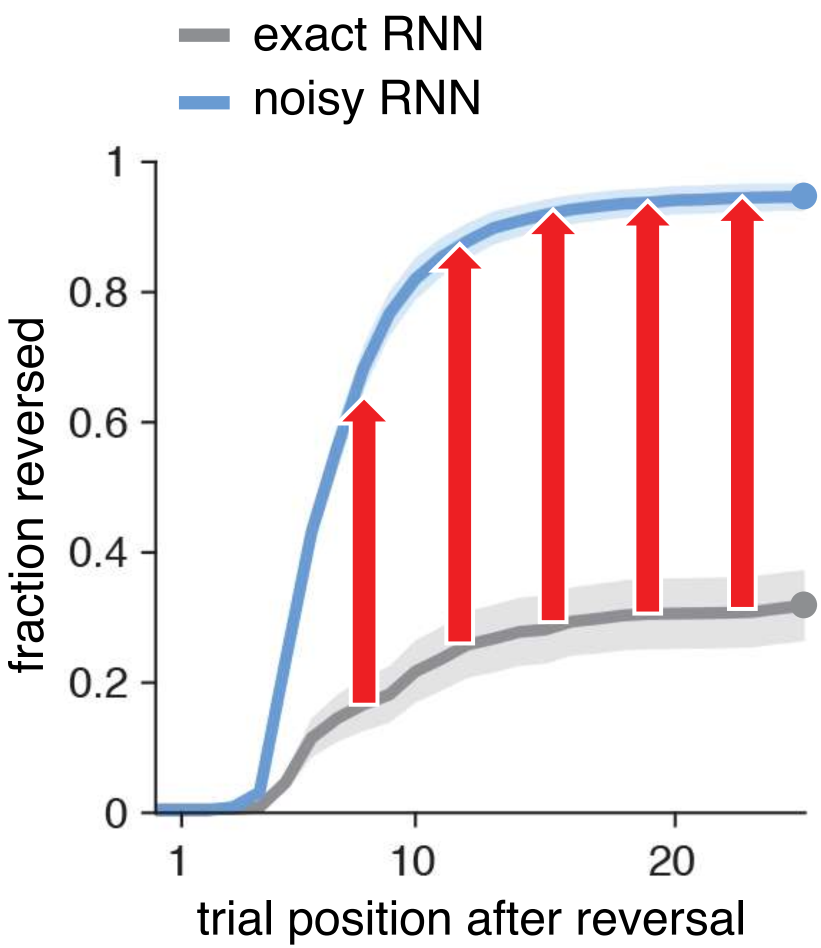
task A*



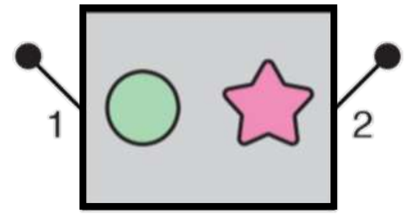
~~0.05~~ ~~0.95~~

0.95 0.05

non-cued
reversal



task A*

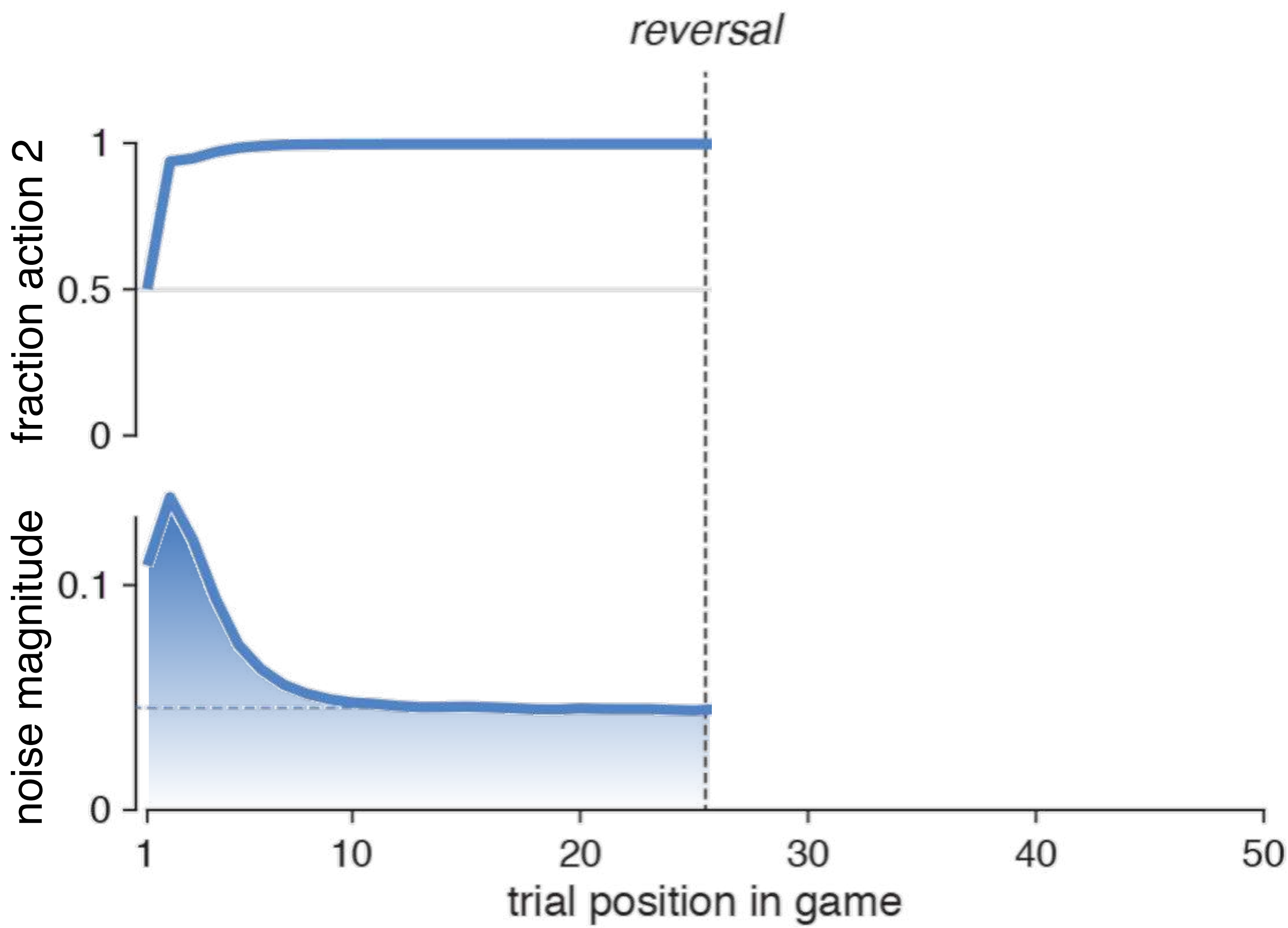


~~0.05~~ ~~0.95~~

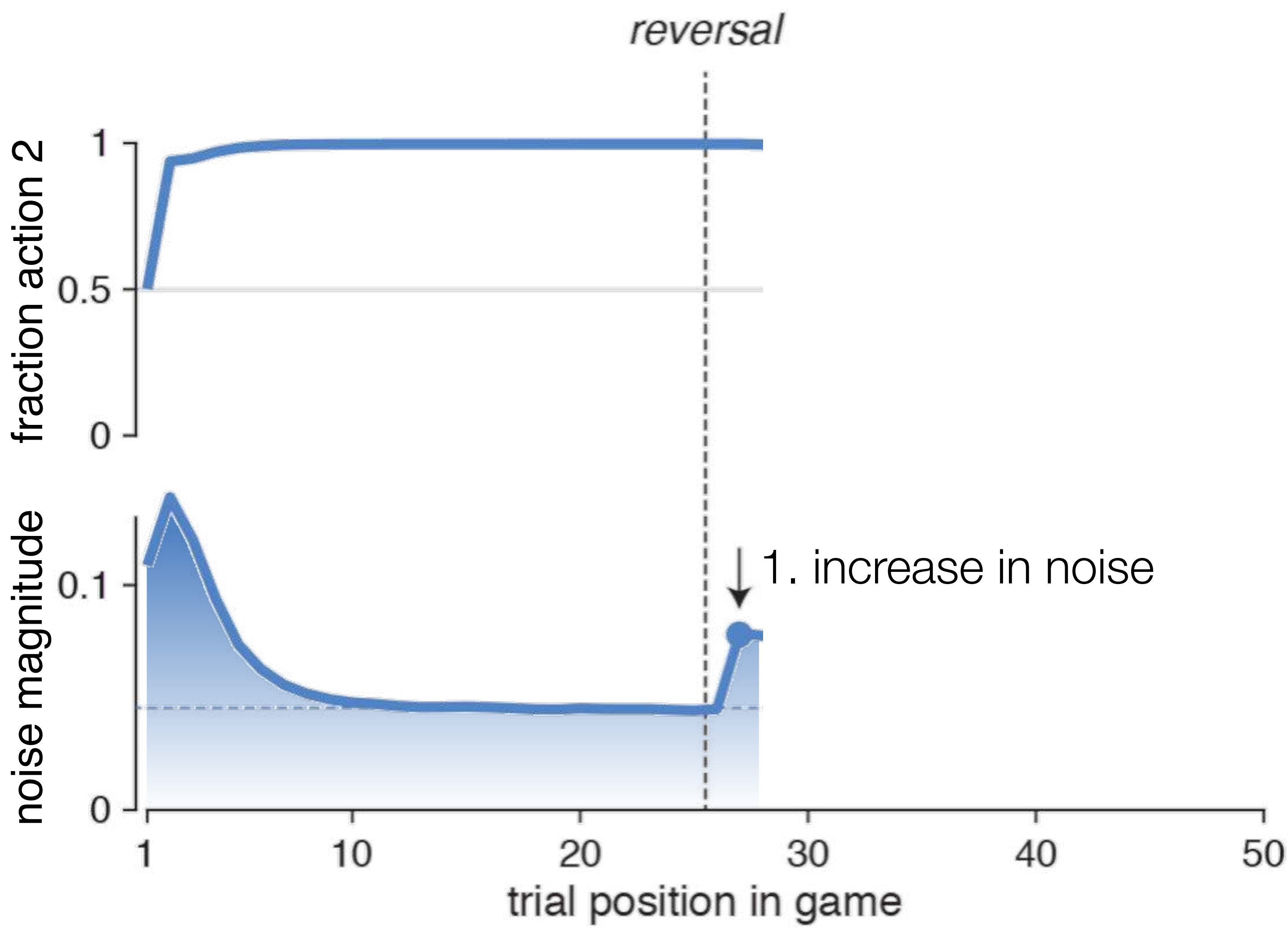
0.95 0.05

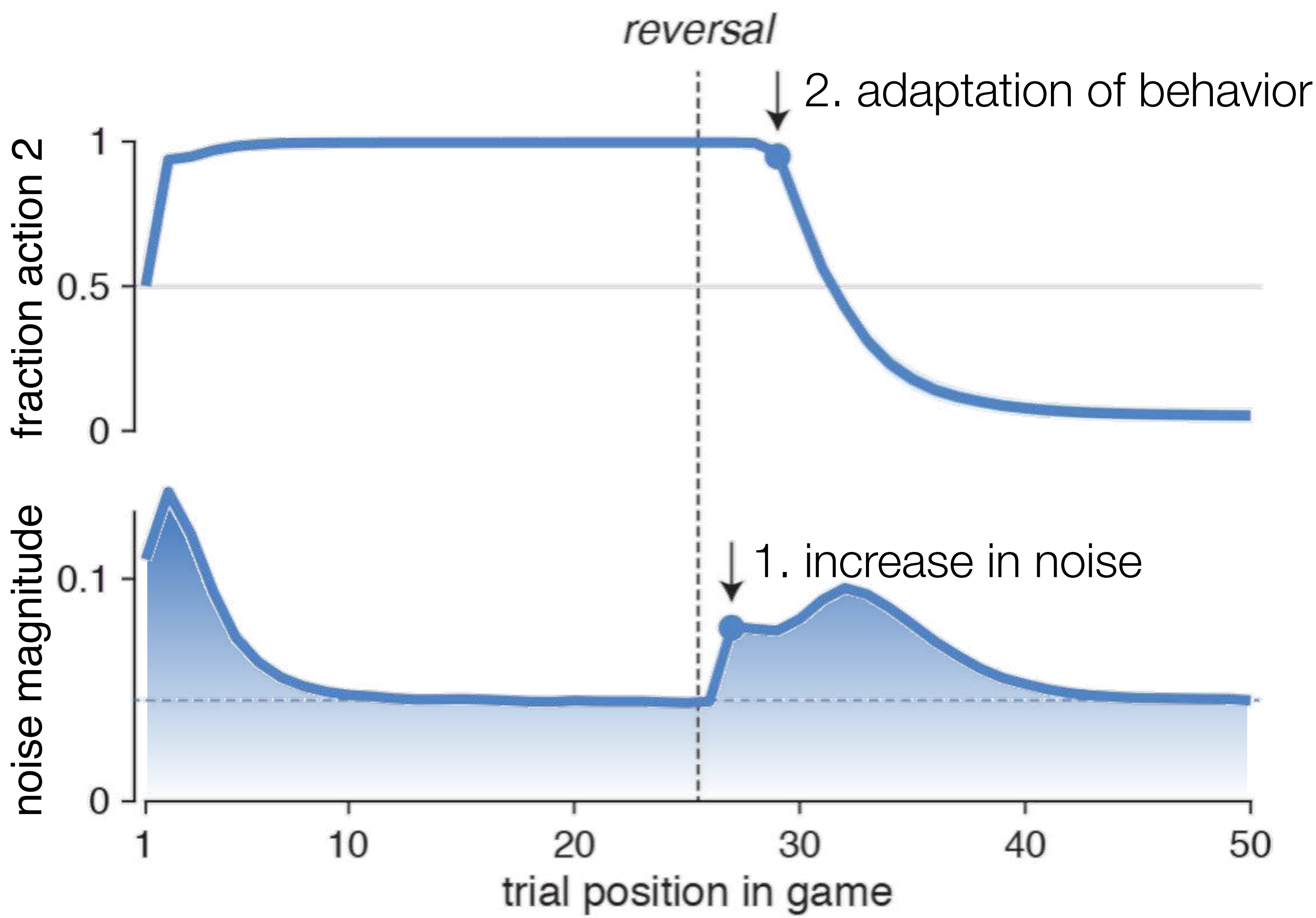
non-cued reversal

adaptation to a source of uncertainty <u>unseen during weight training</u>



reversal
fraction action 2
1
0.5
0
noise magnitude
0.1
0
1
10
20
30
40
50
trial position in game


reversal
fraction action 2
1
0.5
0
noise magnitude
0.1
0
1. increase in noise
1
10
20
30
40
50
trial position in game


reversal
2. adaptation of behavior
fraction action 2
1
0.5
0
noise magnitude
0.1
0
1. increase in noise
1
10
20
30
40
50
trial position in game

Effect of computation noise

- Computation noise confers <u>zero-shot</u> (training-free) adaptability to uncertainty.
- <u>Causal manipulation</u> of computation noise during training and testing of RNNs:
  - ✓ computation noise = <u>functional</u> regularizer
  - ✓ <u>same effect</u> across probabilistic reasoning and multi-armed bandit tasks

Effect of computation noise

Simulating a Primary Visual Cortex at the Front of CNNs Improves Robustness to Image Perturbations

Joel Dapello[*,1,2,3], **Tiago Marques**[*,1,2,4]
Martin Schrimpf[1,2,4], **Franziska Geiger**[2,5,6,7], **David D. Cox**[8,3], **James J. DiCarlo**[1,2,4]

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[2]McGovern Institute for Brain Research, MIT, Cambridge, MA02139
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[4]Center for Brains, Minds and Machines, MIT, Cambridge, MA02139
[5]University of Augsburg
[6]Ludwig Maximilian University
[7]Technical University of Munich
[8]MIT-IBM Watson AI Lab

dapello@mit.edu tmarques@mit.edu

original image

<u>subtle</u> perturbation

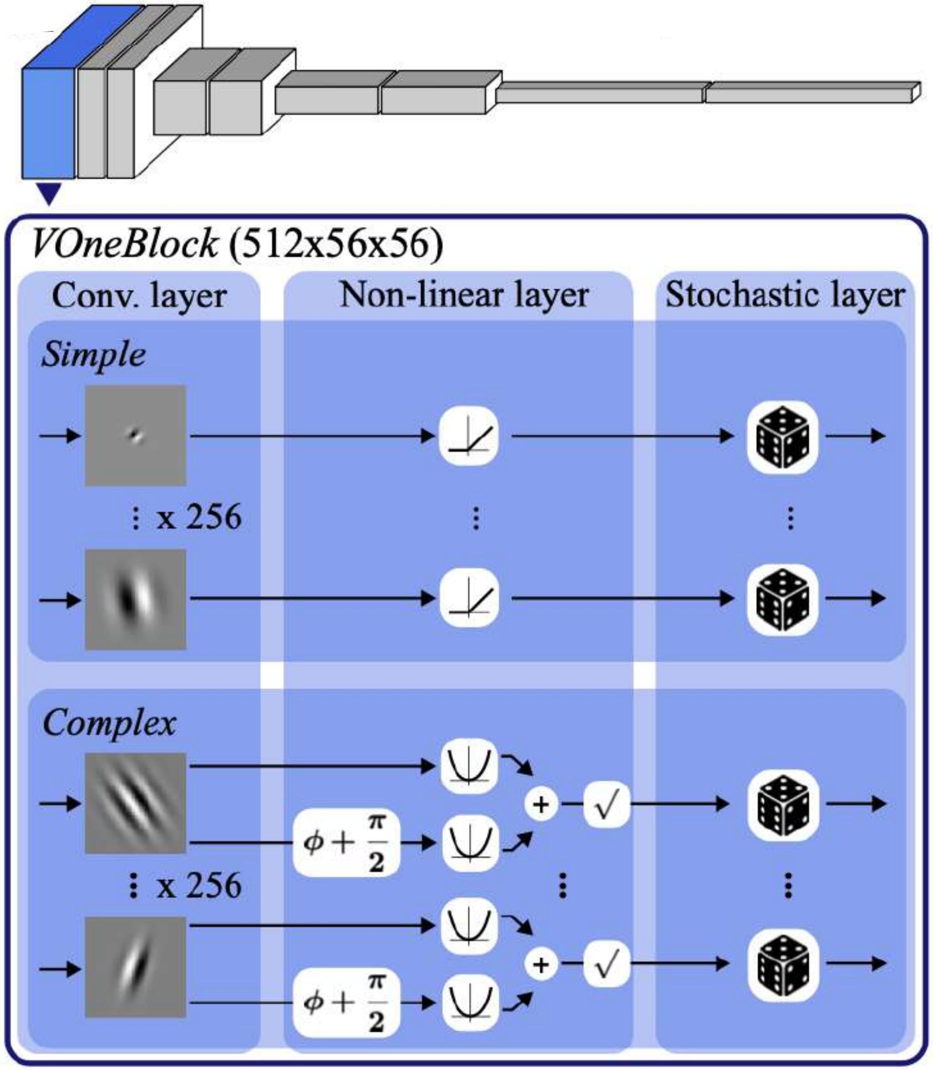
test image

original image

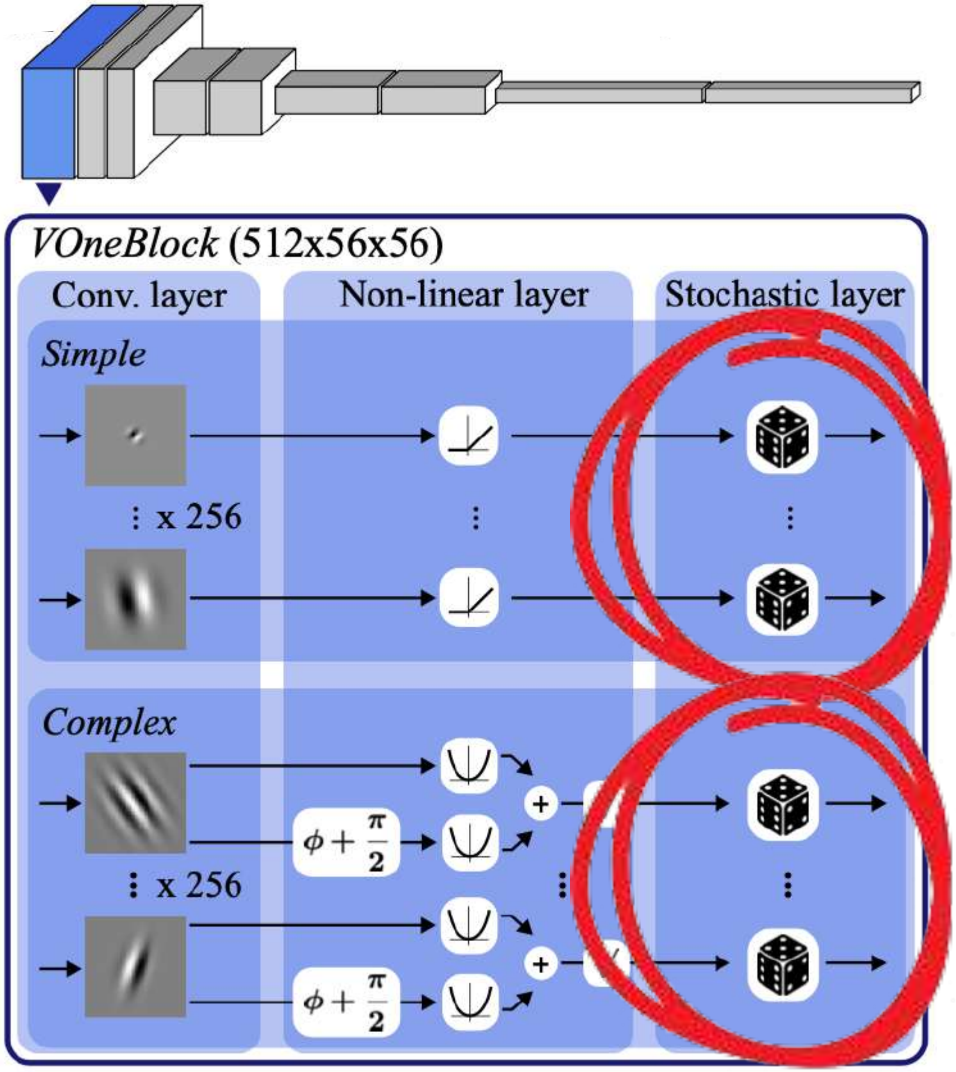
<u>subtle</u> perturbation

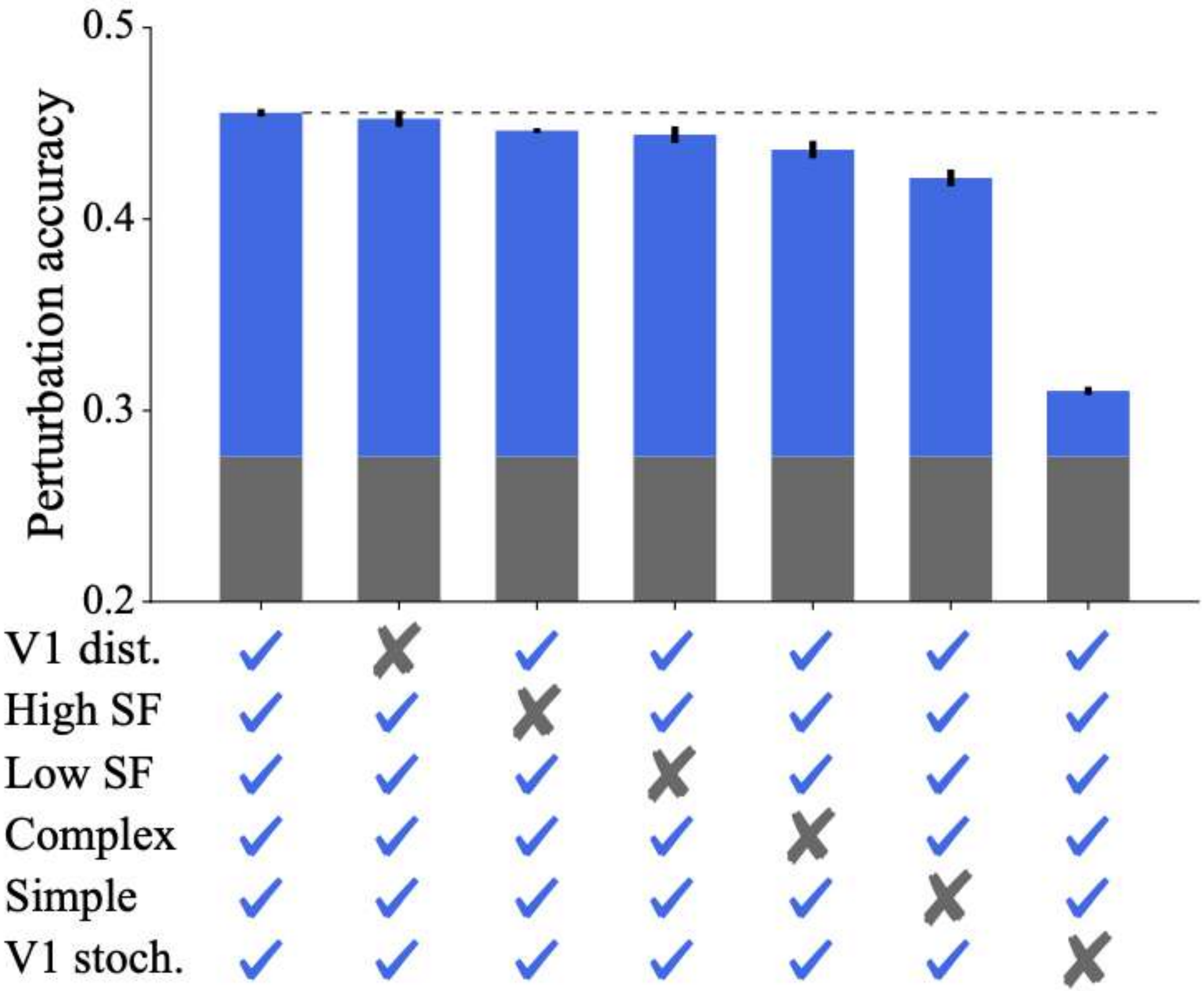
test image

feedforward
deep CNN

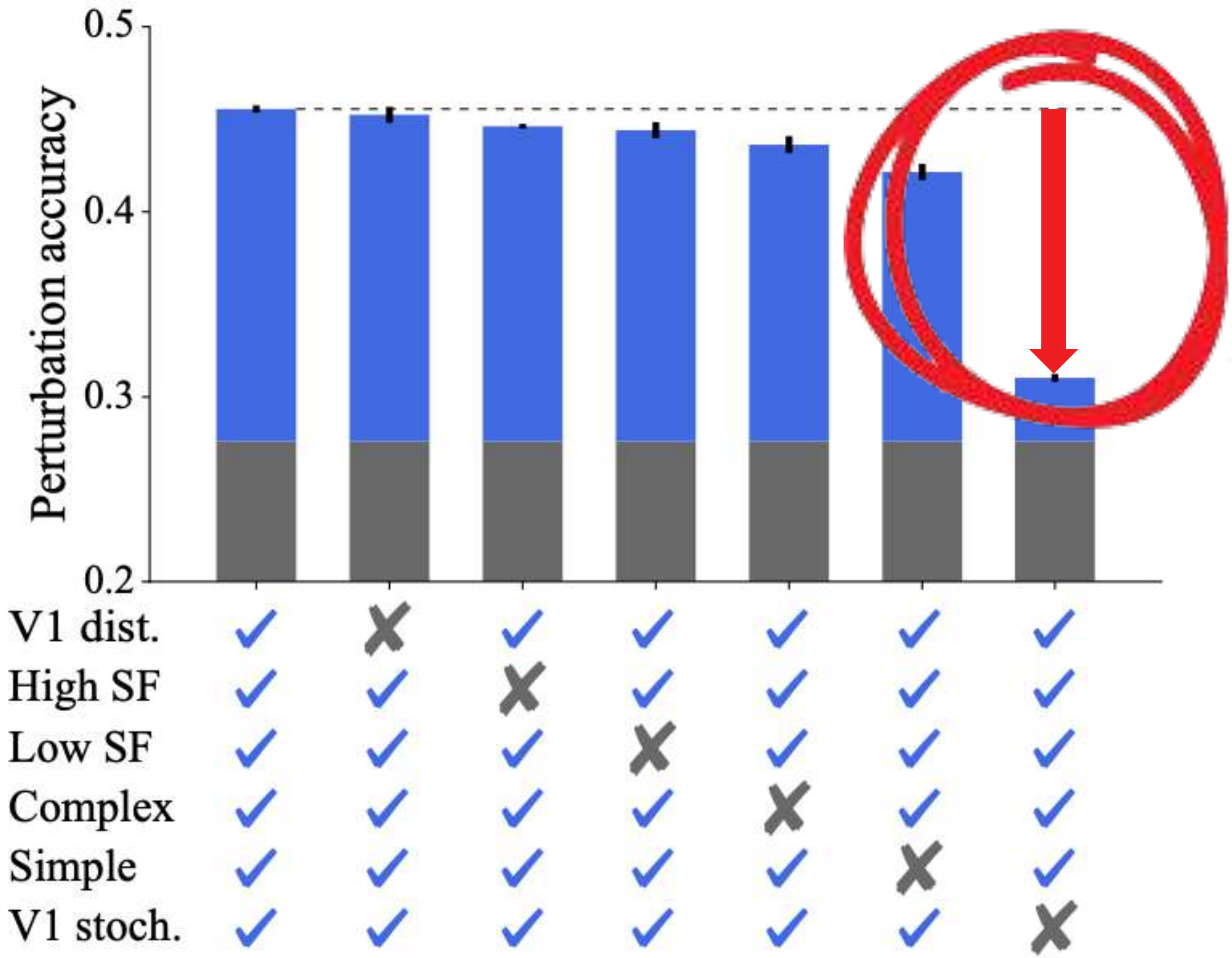


feedforward
deep CNN





Perturbation accuracy
0.5
0.4
0.3
0.2
V1 dist.
High SF
Low SF
Complex
Simple
V1 stoch.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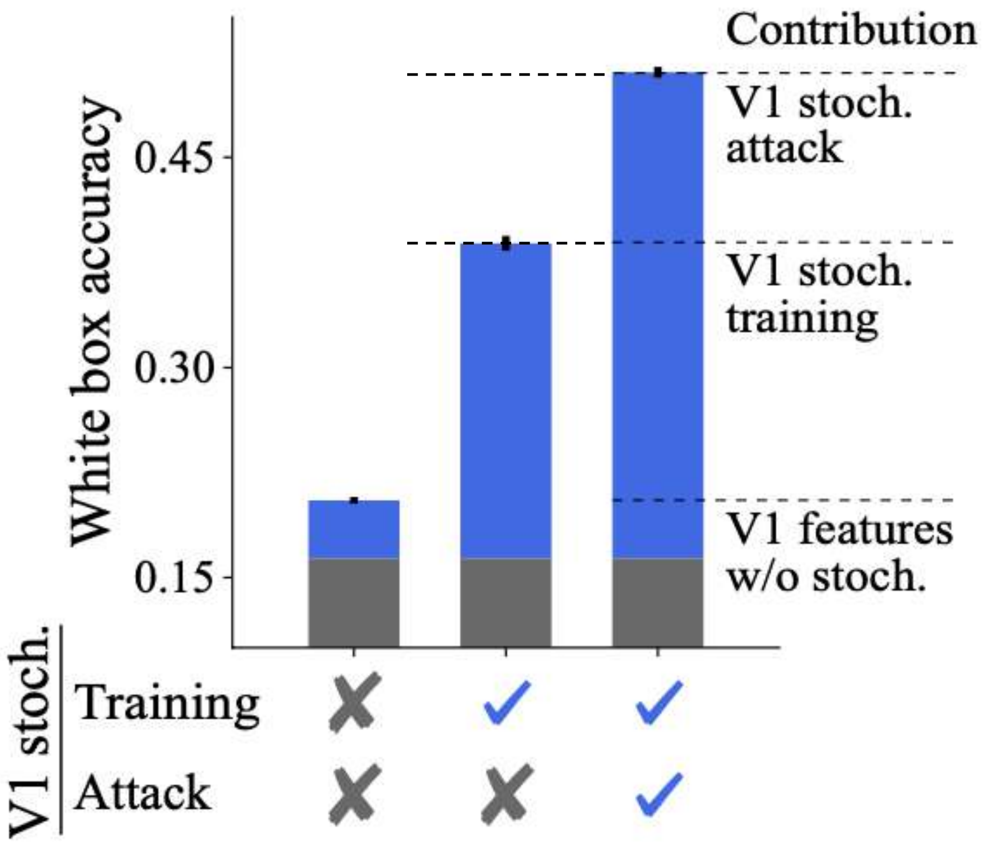
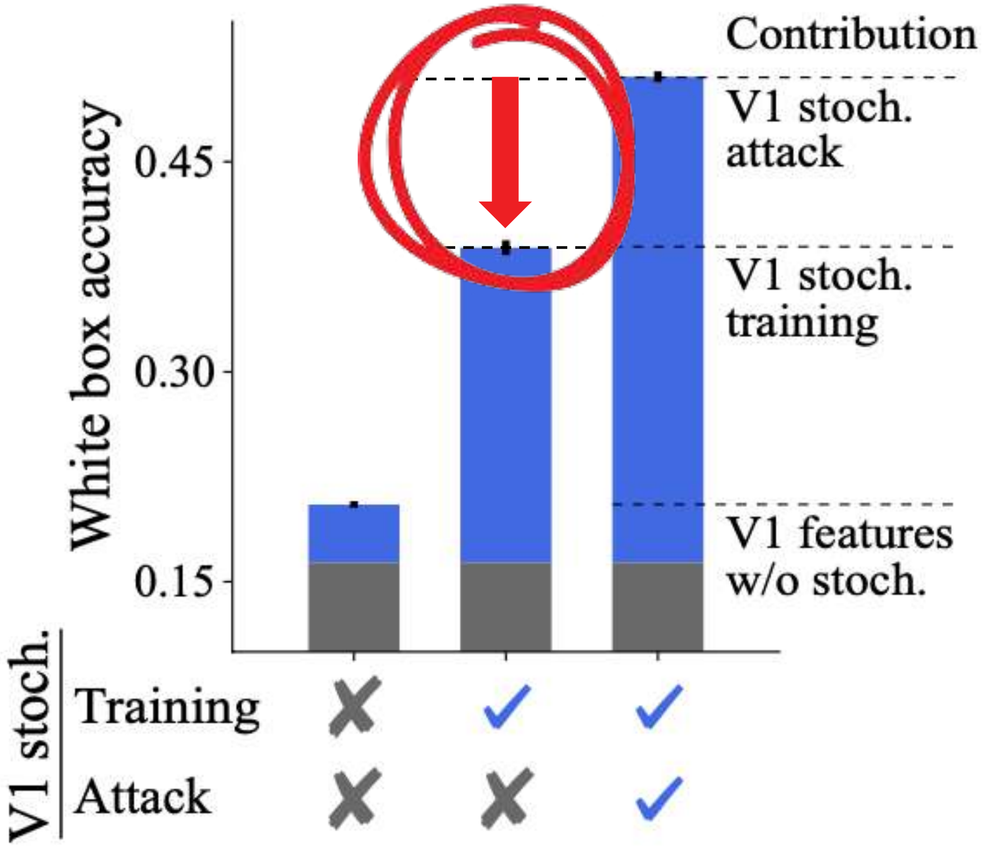


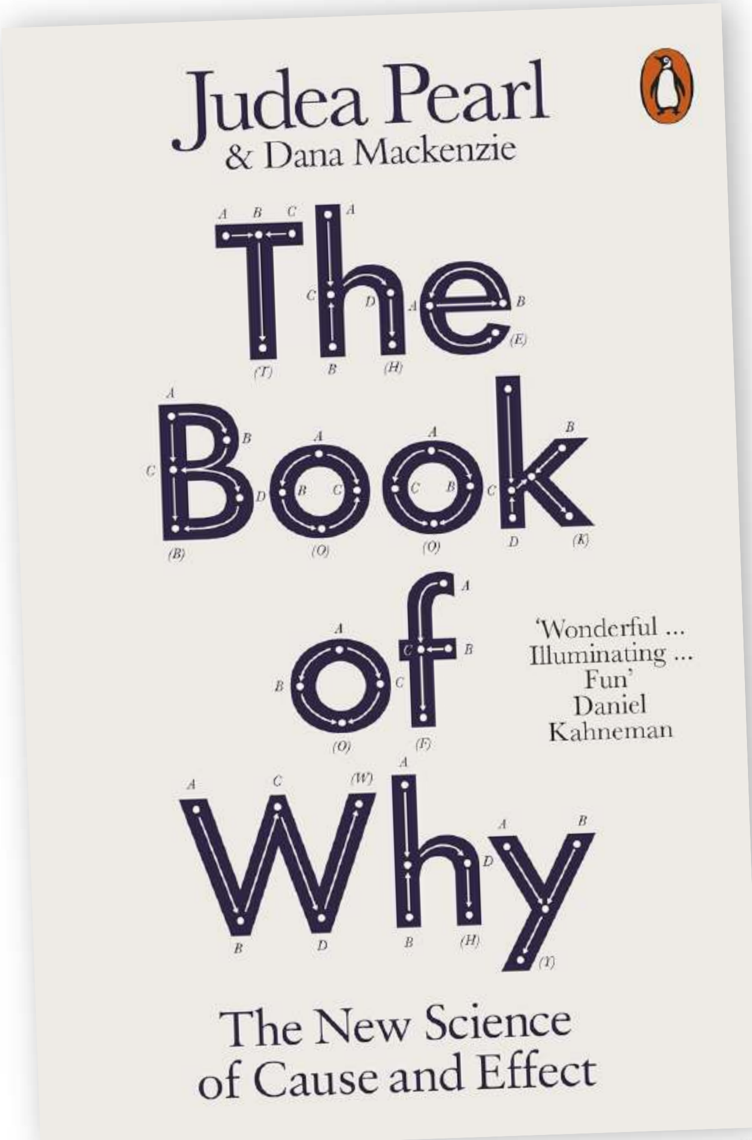
White box accuracy
0.45
0.30
0.15
Contribution
V1 stoch. attack
V1 stoch. training
V1 features w/o stoch.
V1 stoch.
Training
Attack

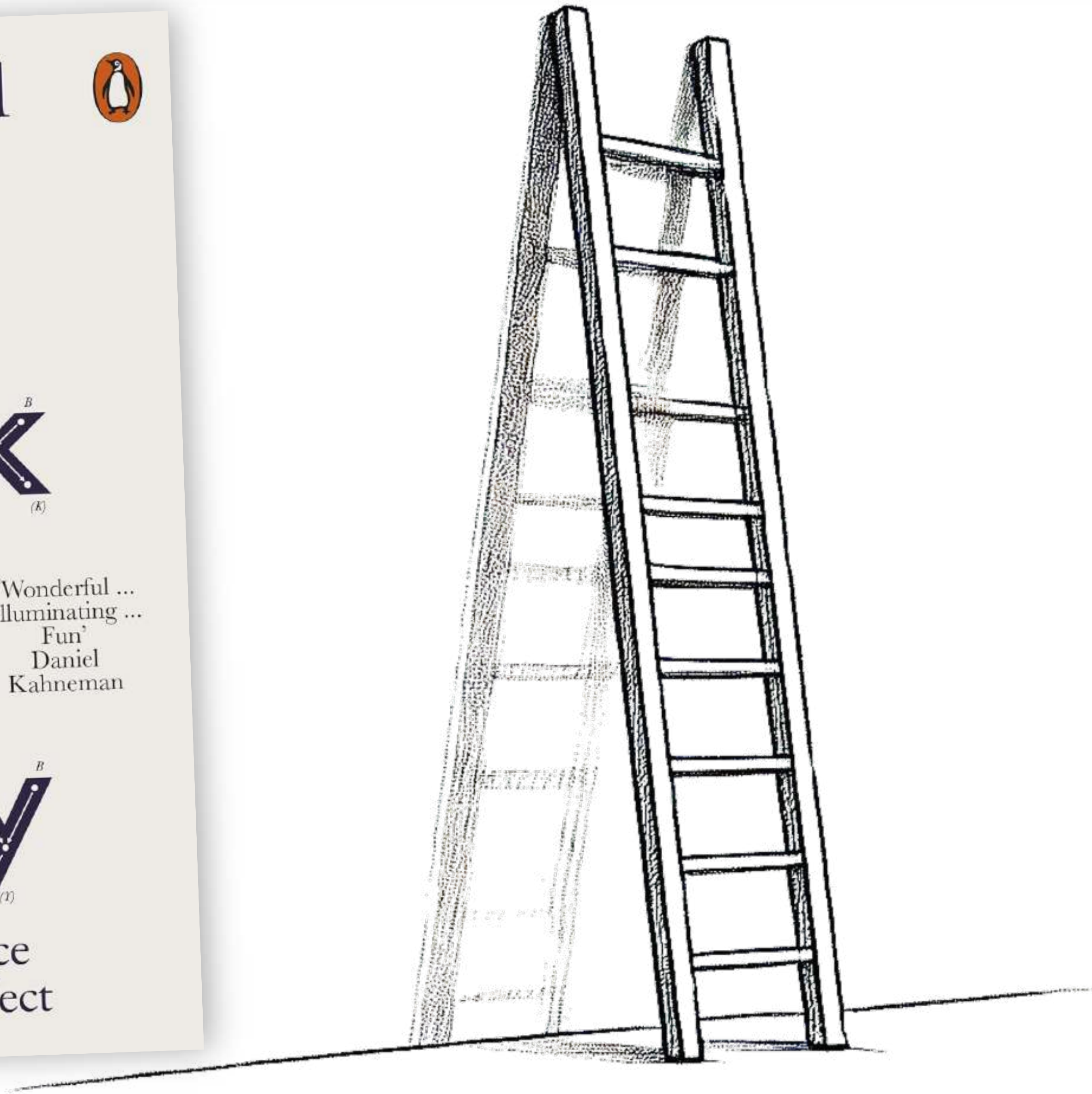


White box accuracy
0.45
0.30
0.15
Contribution
V1 stoch.
attack
V1 stoch.
training
V1 features
w/o stoch.
V1 stoch.
Training
Attack

Effect of computation noise

- Computation noise confers zero-shot (training-free) adaptability to uncertainty in RNNs during reasoning and multi-armed learning.
- Same benefits of computation noise in CNNs during image recognition
- Same causal manipulations of models across different architectures and tasks


Judea Pearl
& Dana Mackenzie
The Book of Why
'Wonderful ... Illuminating ... Fun' Daniel Kahneman
The New Science of Cause and Effect

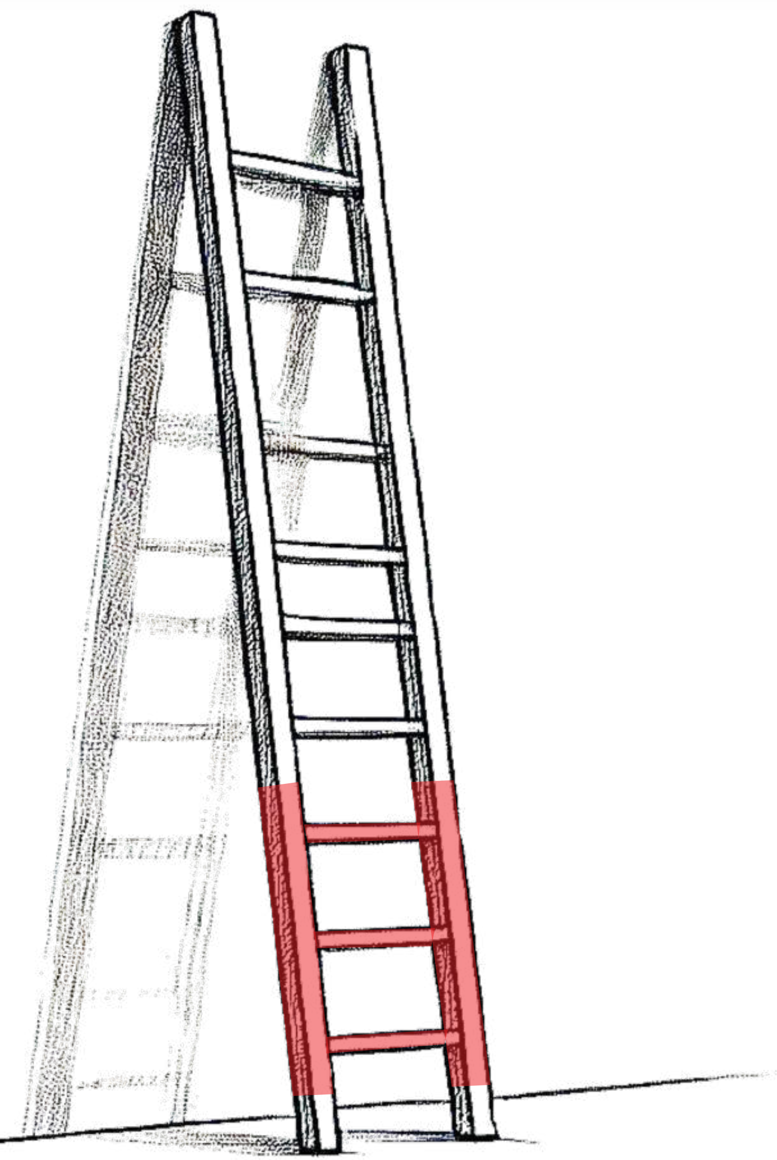


1. Observing

learning,
inference

<u>Definition:</u>
Identifying associations and patterns between events

<u>Example:</u>
When the sky is cloudy,
it tends to rain.



2. Doing

exploration,
foraging

Definition:
Understanding what happens when you interact with the environment

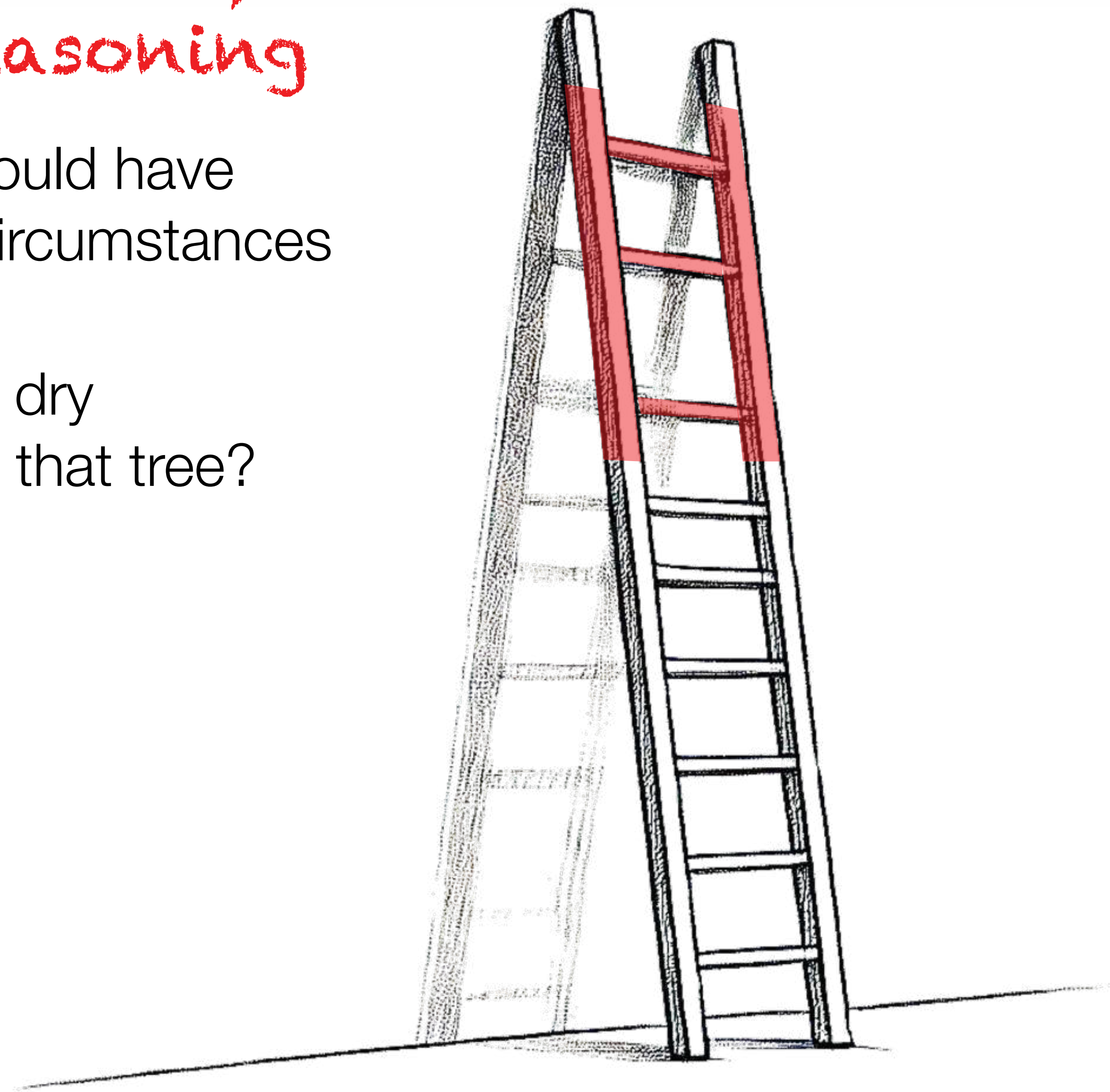
Example:
If I carry an umbrella,
I stay dry under the rain.

3. Imagining

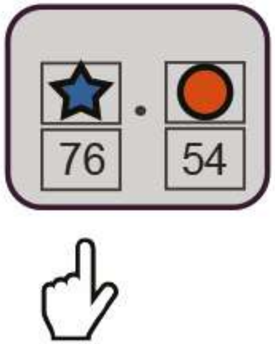
counterfactual reasoning

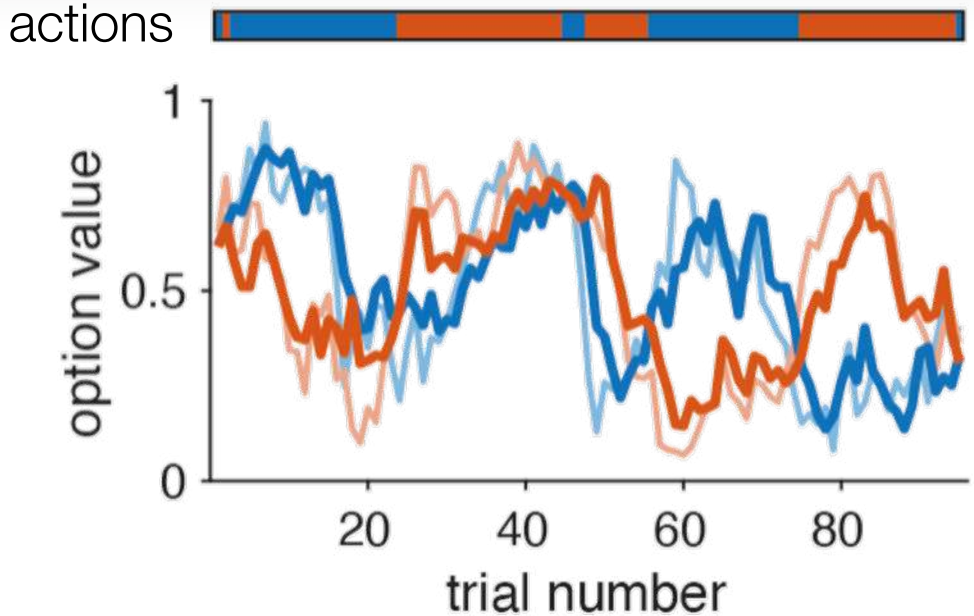
Definition:
Considering what would have happened in other circumstances

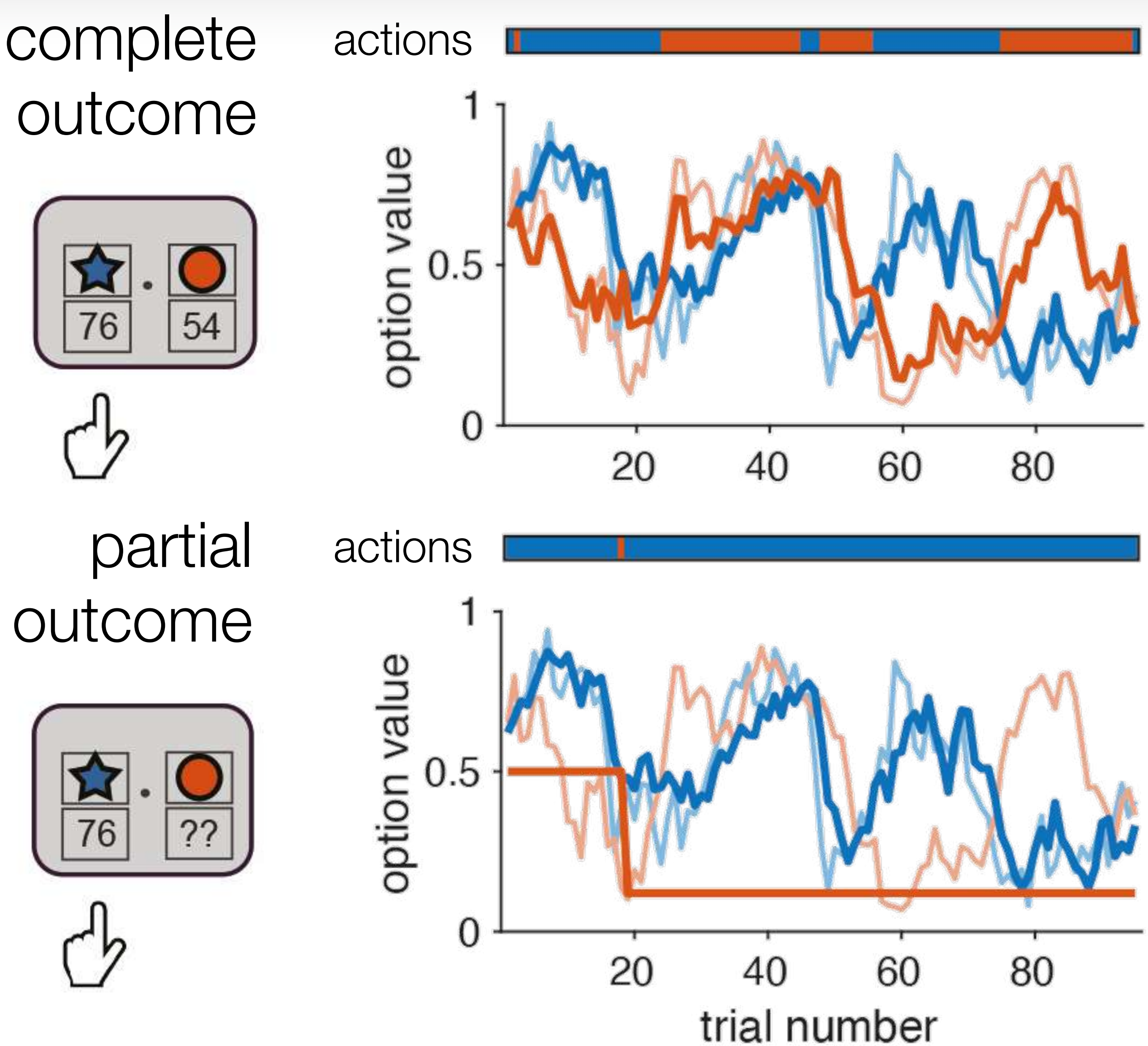
Example:
Would I have stayed dry if I had waited under that tree?



complete
outcome

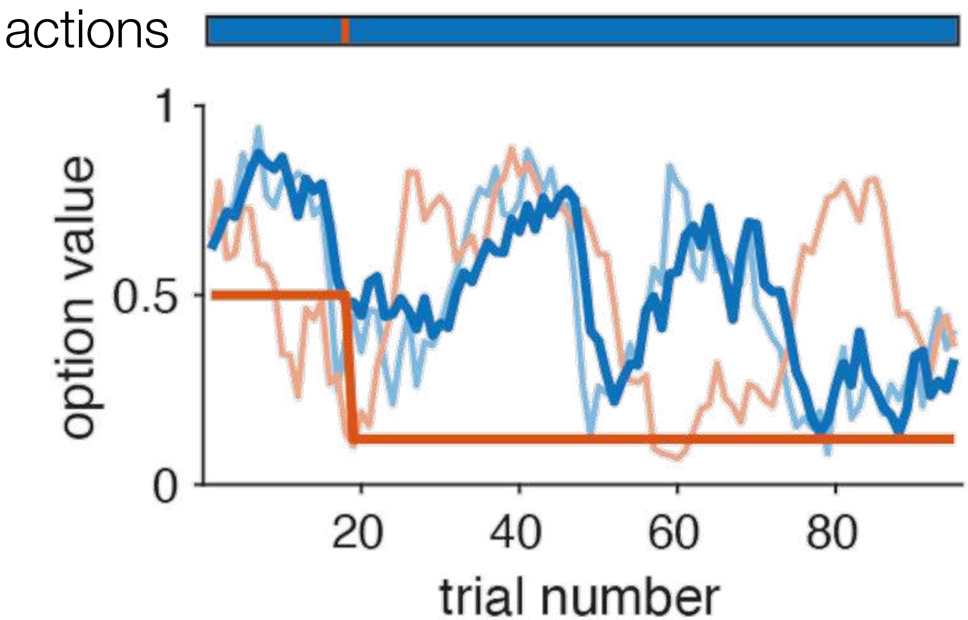





complete
outcome
76
54
actions
1
0.5
0
option value
20
40
60
80
partial
outcome
76
??
actions
1
0.5
0
option value
20
40
60
80
trial number

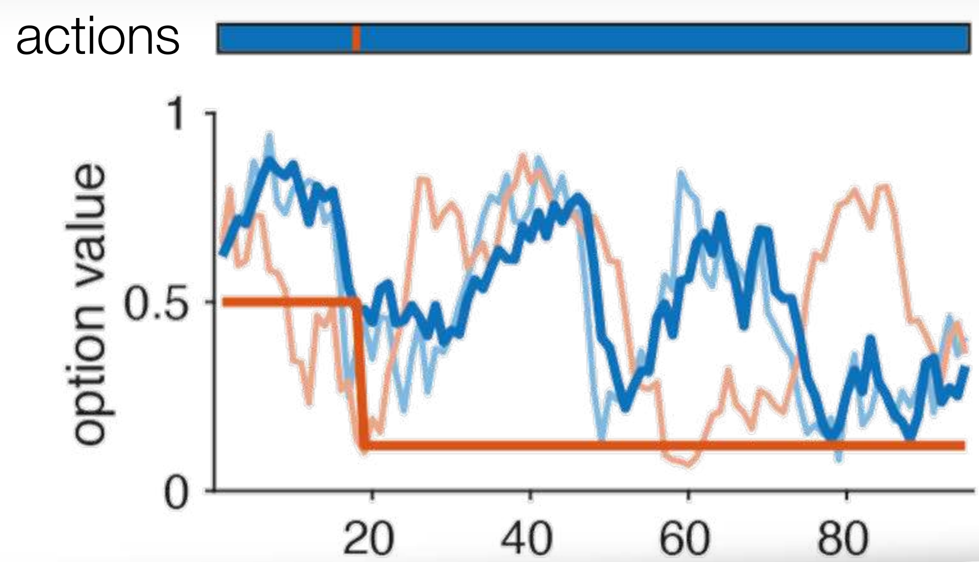
greedy
policy

without
exploration



greedy
policy

without
exploration



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Current Opinion in
Neurobiology

Check for updates

The algorithmic architecture of exploration in the human brain

Eric Schulz and Samuel J Gershman

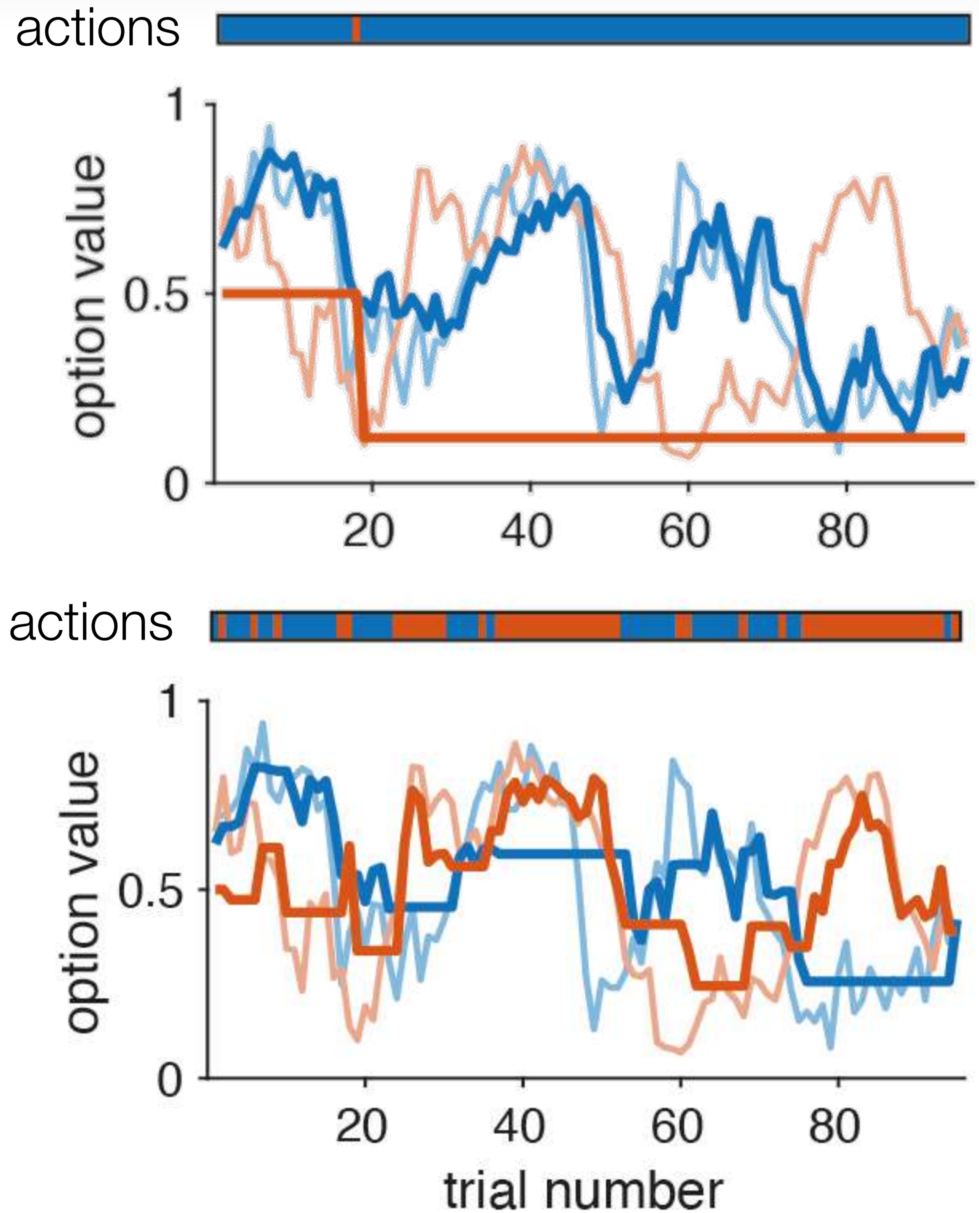
Balancing exploration and exploitation is one of the central problems in reinforcement learning. We review recent studies that have identified multiple algorithmic strategies underlying exploration. In particular, humans use a combination of random and uncertainty-directed exploration strategies, which rely on different brain systems, have different developmental

an independent payoff distribution. It is then an agents goal to maximize rewards by repeatedly selecting an arm and observing and collecting the resulting reward.

We first summarize evidence that humans use two distinct exploration strategies [4,5]: *random exploration*,

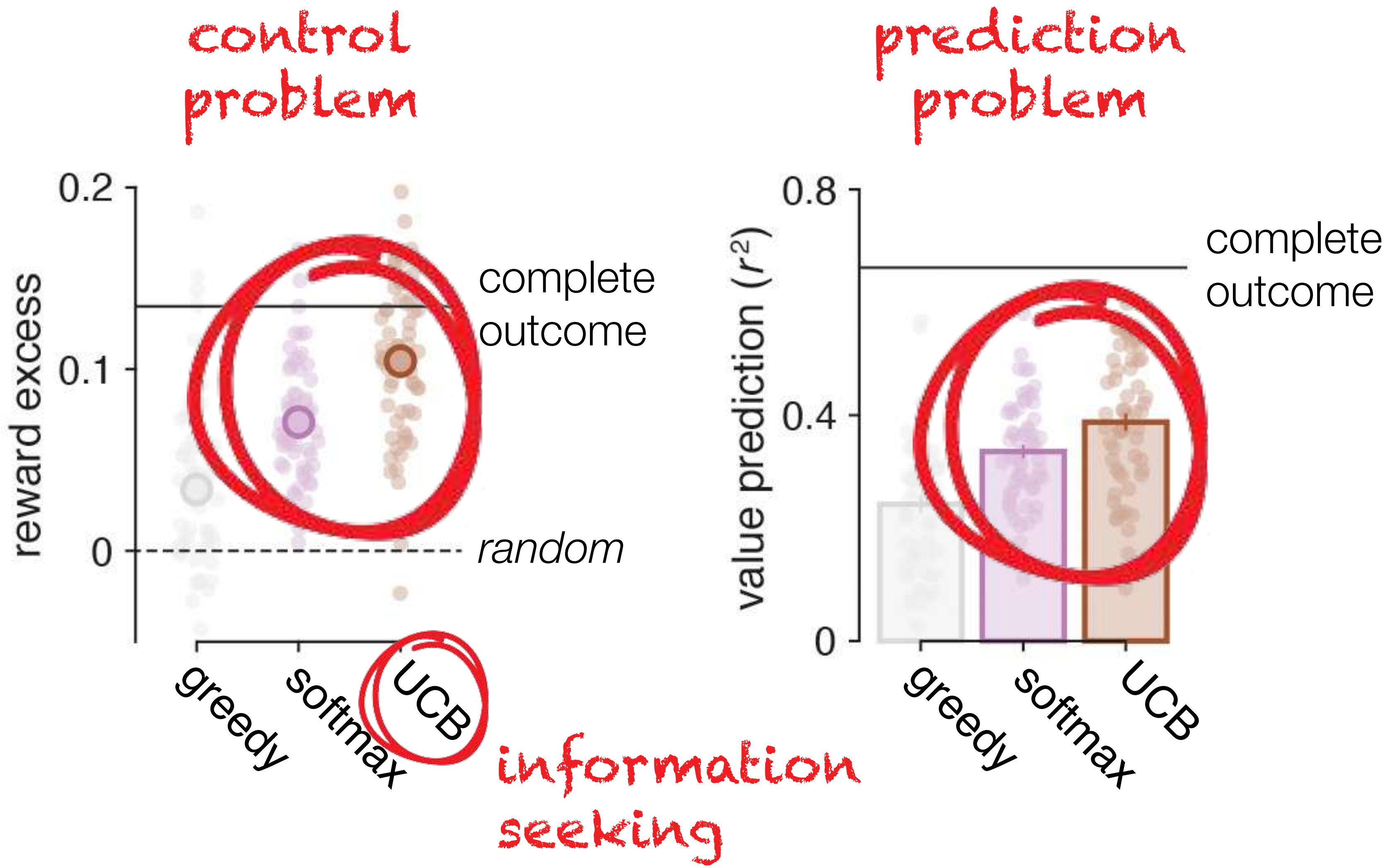
greedy
policy

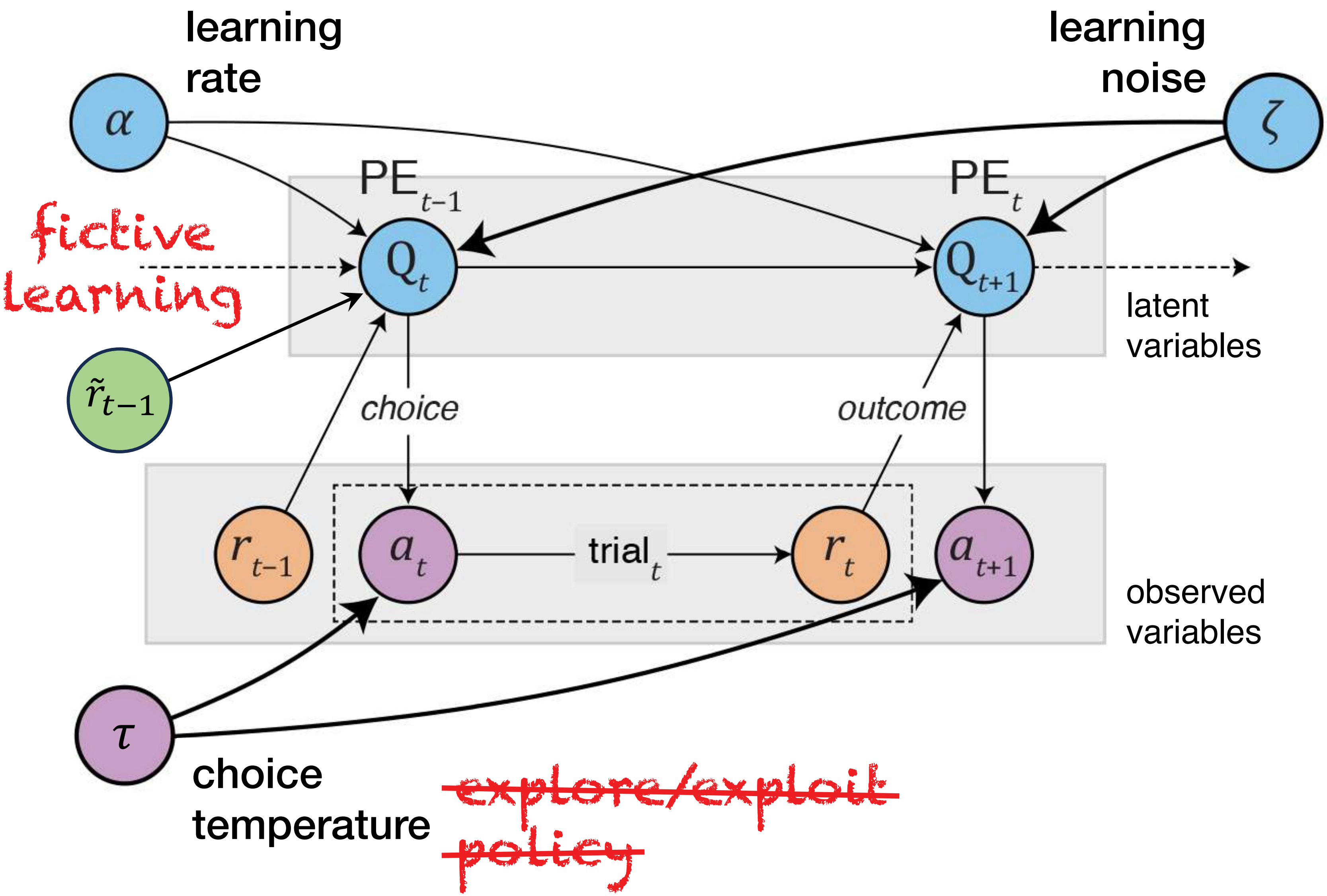
without
exploration



softmax
policy

with
exploration

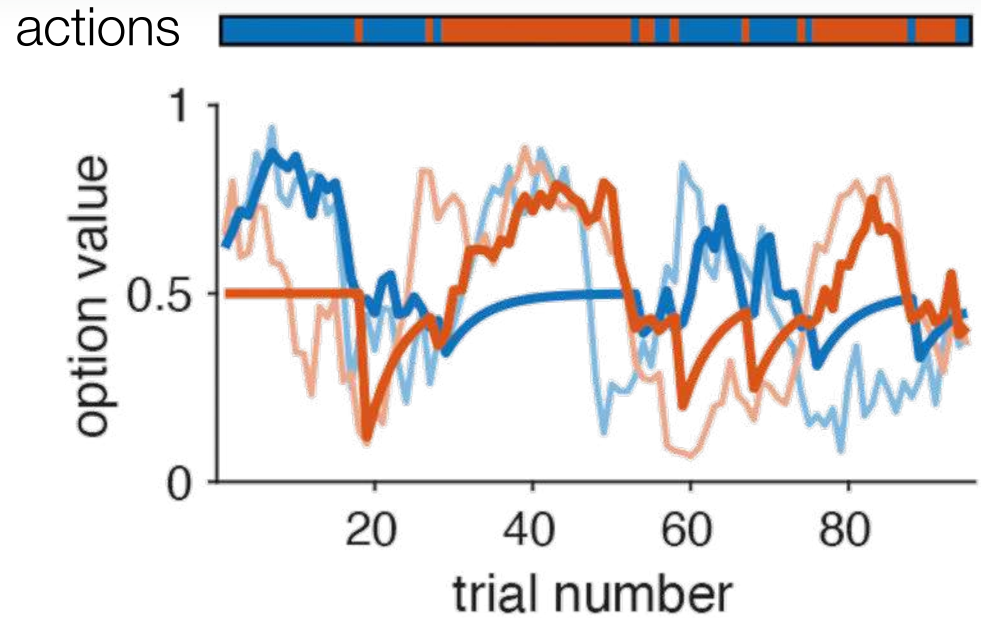

control problem
prediction problem
0.2
0.1
0
reward excess
complete outcome
random
greedy
softmax
UCB
information seeking
0.8
0.4
0
value prediction (r^2)
complete outcome
greedy
softmax
UCB



learning rate
learning noise
α
ζ
PE_{t-1}
PE_t
fictive learning
Q_t
Q_{t+1}
$\tilde{r}_{t-1}$
latent variables
choice
outcome
r_{t-1}
a_t
trial$_t$
r_t
a_{t+1}
observed variables
τ
choice temperature
~~explore/exploit policy~~

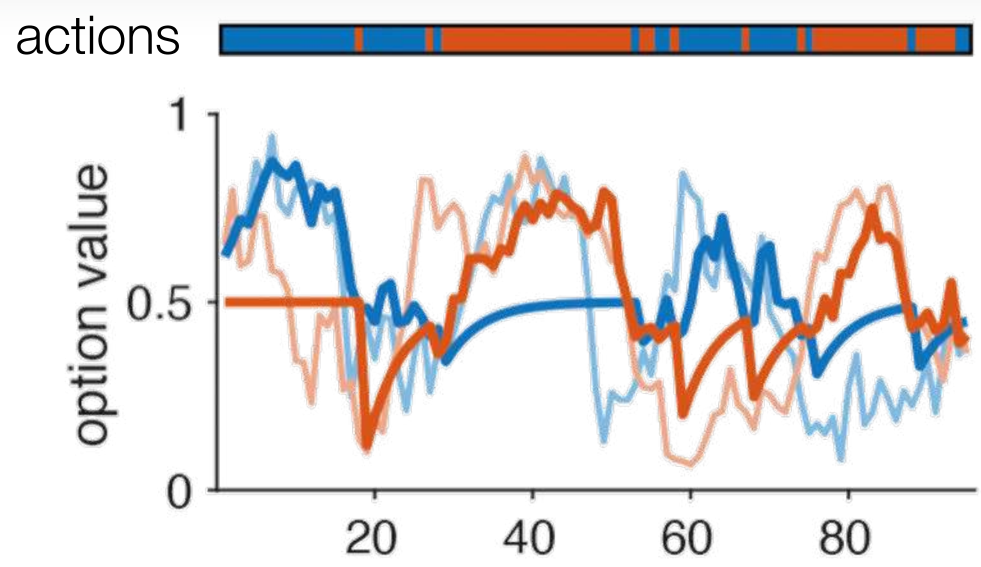
regression
to the mean

$\tilde{r}_t = E[r_{1..t}]$



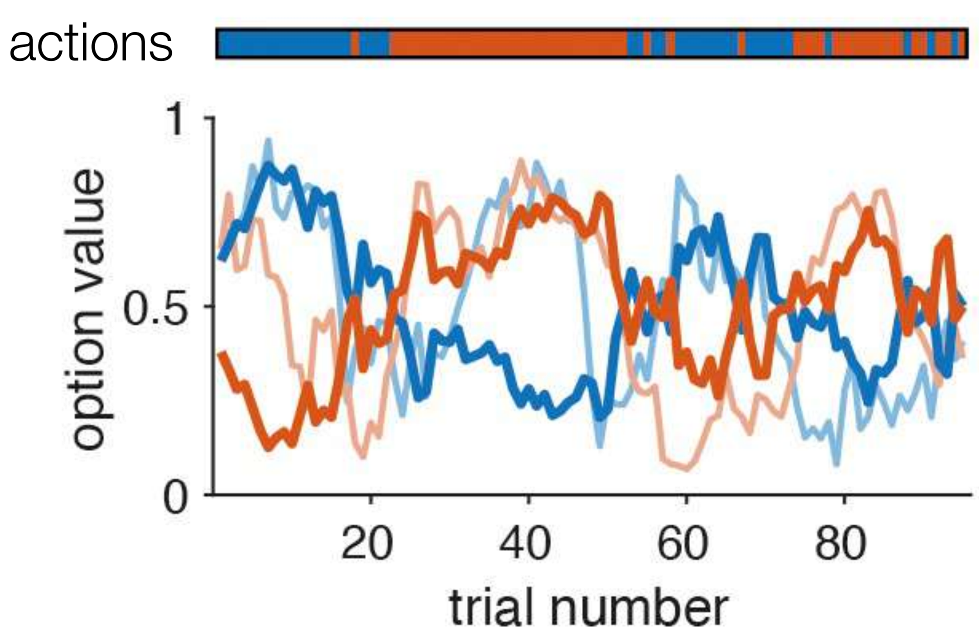
regression
to the mean

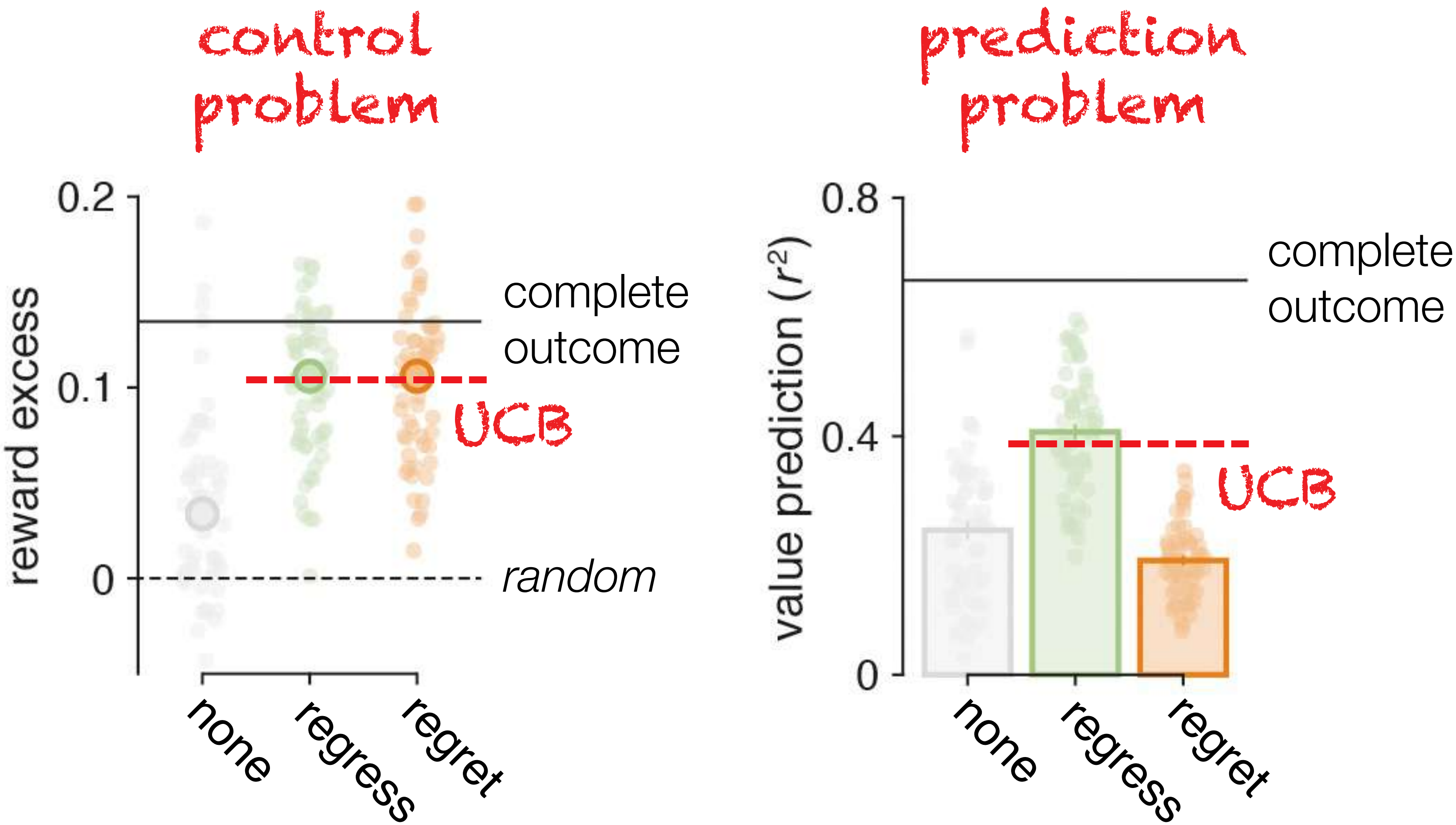
$\tilde{r}_t = E[r_{1..t}]$



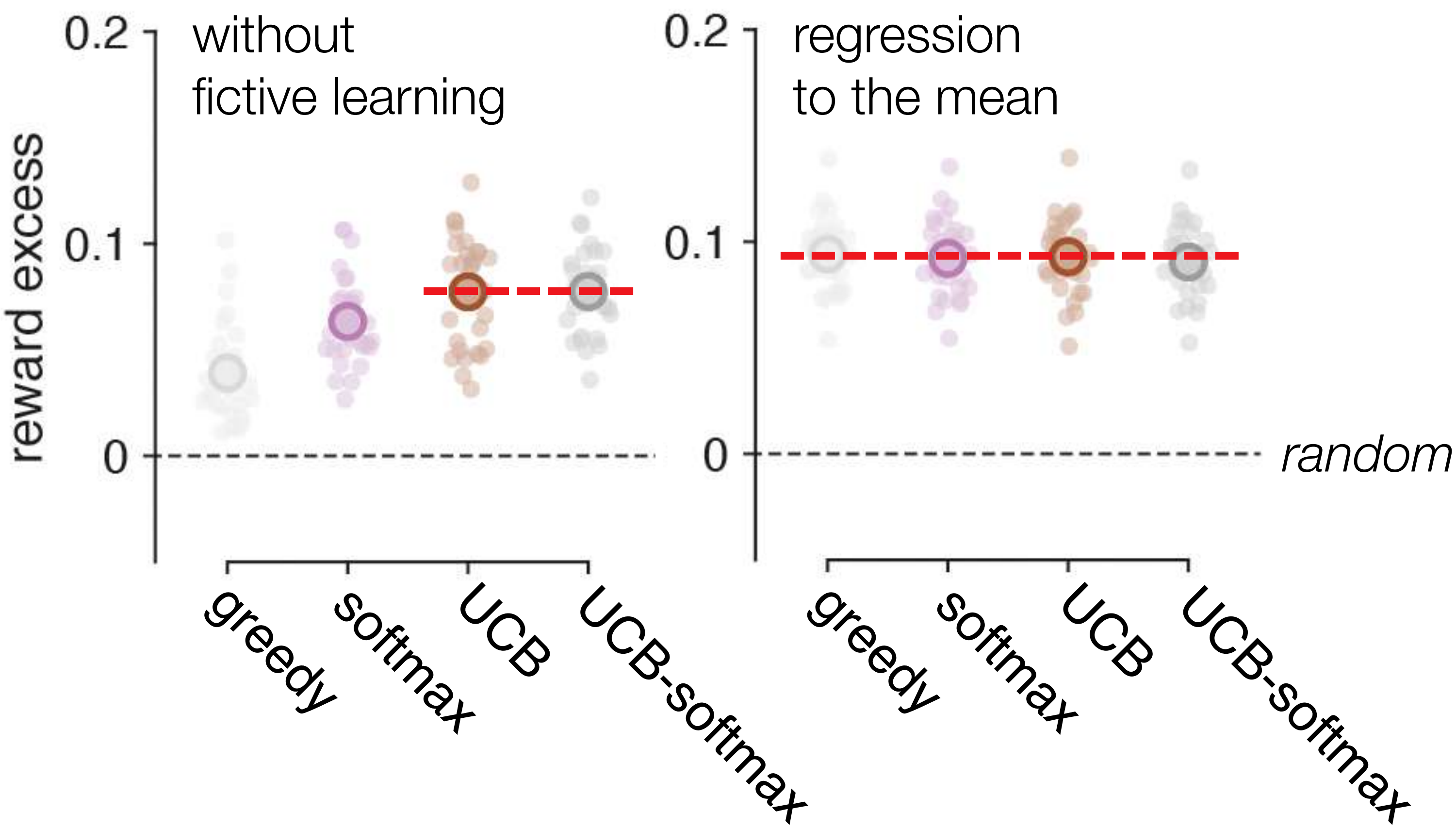
fictive
regret

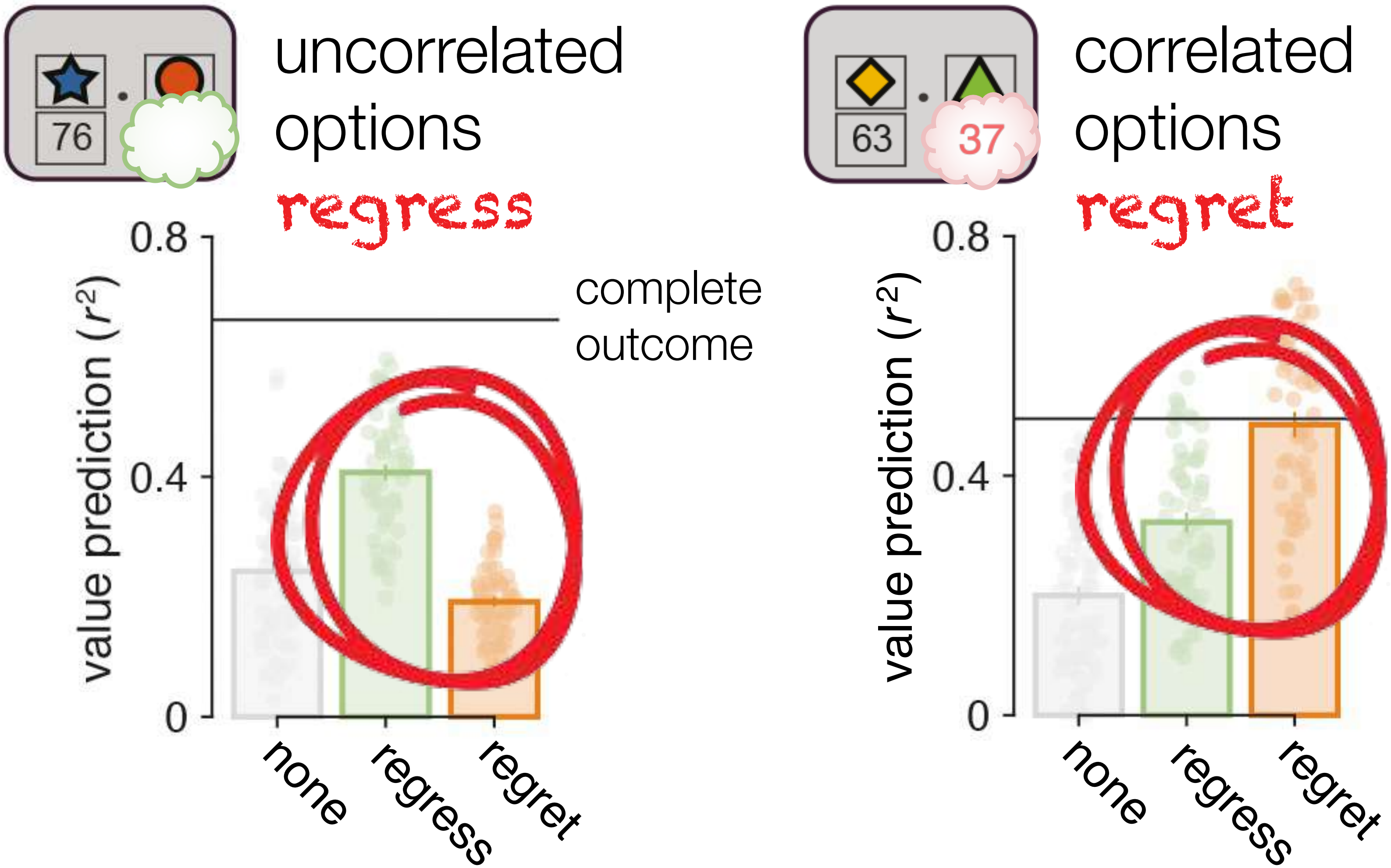
$\tilde{r}_t = 1 - r_t$




control problem
prediction problem
0.2
0.1
0
reward excess
complete outcome
UCB
random
none
regress
regret
0.8
0.4
0
value prediction (r^2)
complete outcome
UCB
none
regress
regret

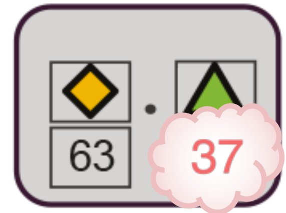
benefits of explicit exploration wiped out by fictive learning





76
uncorrelated options
regress
complete outcome
value prediction (r^2)
0.8
0.4
0
none
regress
regret
63
37
correlated options
regret
value prediction (r^2)
0.8
0.4
0
none
regress
regret

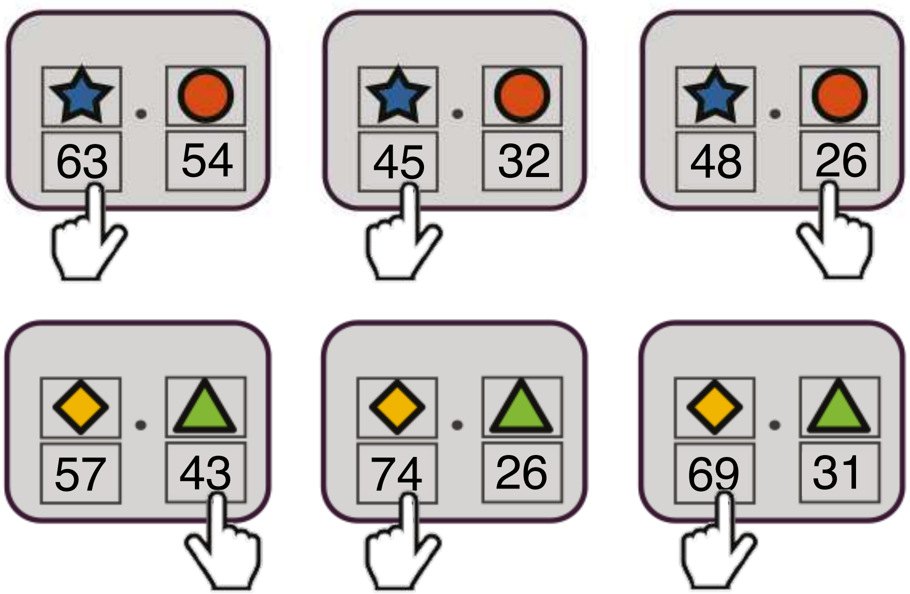
uncorrelated options



correlated options

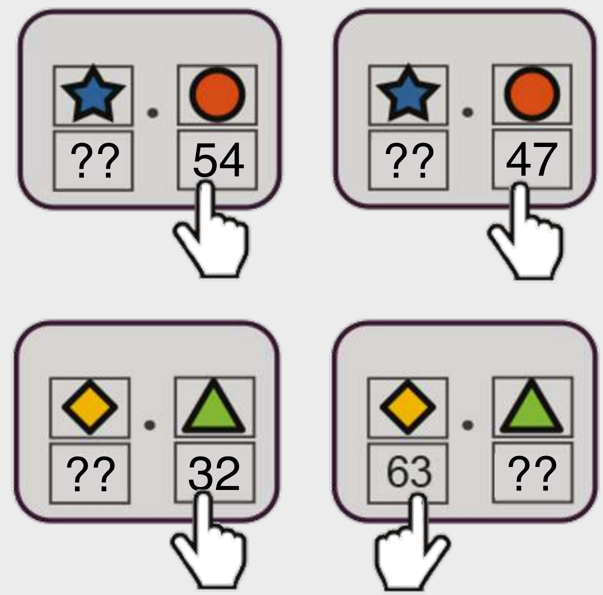
1. complete outcome

correlation structure exposure

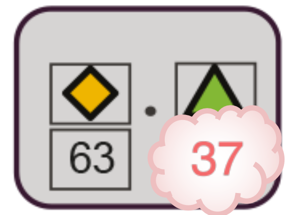


2. partial outcome

fictive learning?

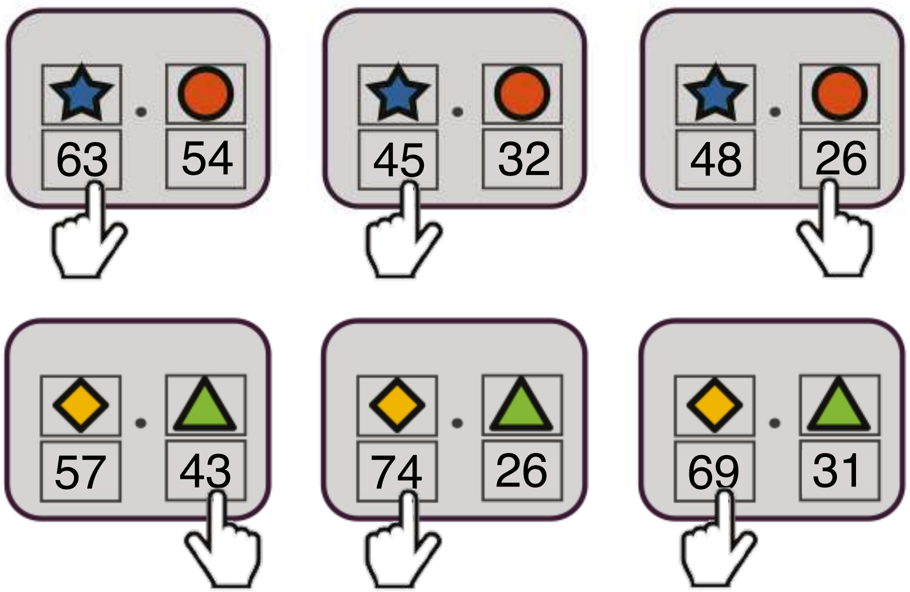


uncorrelated options

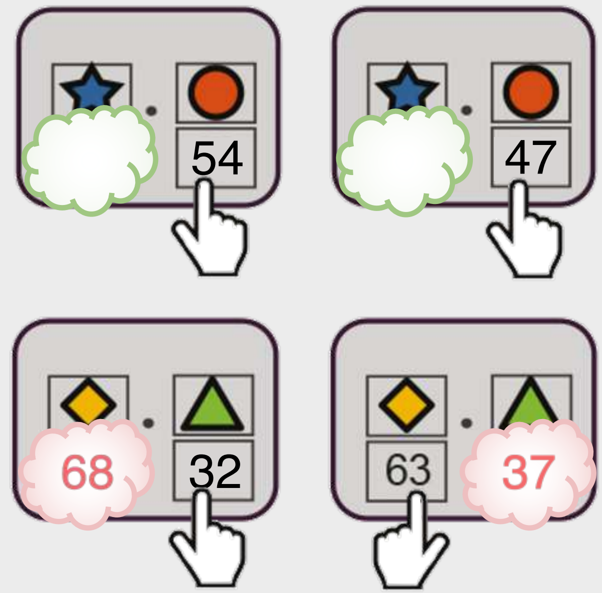


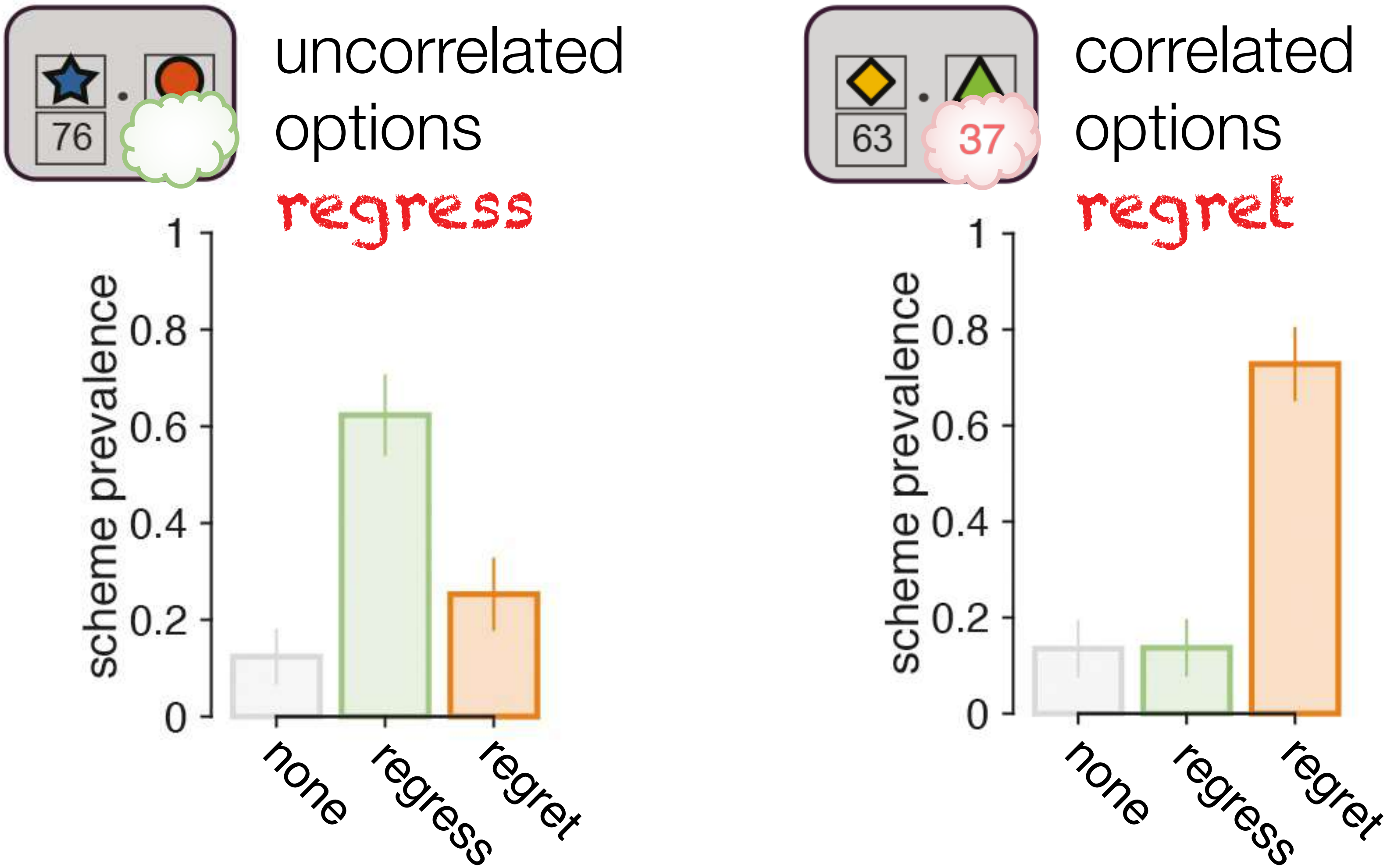
correlated options

1. complete outcome
correlation structure exposure



2. partial outcome
fictive learning?




76
uncorrelated
options
regress
1
0.8
0.6
0.4
0.2
0
scheme prevalence
none
regress
regret
63
37
correlated
options
regret
1
0.8
0.6
0.4
0.2
0
scheme prevalence
none
regress
regret

The ‘why?’ of fictive learning

- Thinking in terms of counterfactuals (what if I had done… ?) is specific to humans.
- Using a context-matched fictive learning scheme does not increase reward rate, but improves reward prediction.
- The fact that humans use such a scheme says that they care about reward prediction beyond reward rate.

Coming next

- Practical session: 2.00pm, DEC seminar room (ground floor) & LNC² seminar room (1st floor)

- Not a regular practical session (TD), but time to work on your group projects.

- Contact:

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Lucas Benjamin lucas.benjamin78@gmail.com

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Institut National de la Santé et de la Recherche Médicale
Ecole Normale Supérieure, Université PSL