PSL-week | March 3-7 2024
Lecture 2 (data mining and modeling for behavioral sciences)

Guidelines for conducting a cognitive modeling study: theory and practice (1/2)

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PSL Data Science Program

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

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Modeling guidelines

eLIFE
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REVIEW ARTICLE

Ten simple rules for the computational modeling of behavioral data

Robert C Wilson[1,2†*], Anne GE Collins[3,4†*]

[1]Department of Psychology, University of Arizona, Tucson, United States; [2]Cognitive Science Program, University of Arizona, Tucson, United States; [3]Department of Psychology, University of California, Berkeley, Berkeley, United States; [4]Helen Wills Neuroscience Institute, University of California, Berkeley, Berkeley, United States

Abstract Computational modeling of behavior has revolutionized psychology and neuroscience. By fitting models to experimental data we can probe the algorithms underlying behavior, find neural correlates of computational variables and better understand the effects of drugs, illness and interventions. But with great power comes great responsibility. Here, we offer ten simple rules to ensure that computational modeling is used with care and yields meaningful insights. In particular, we present a beginner-friendly, pragmatic and details-oriented introduction on how to relate models to data. What, exactly, can a model tell us about the mind? To answer this, we apply our rules to the simplest modeling techniques most accessible to beginning modelers and illustrate them with examples and code available online. However, most rules apply to more advanced ... researchers will avoid many pitfalls and

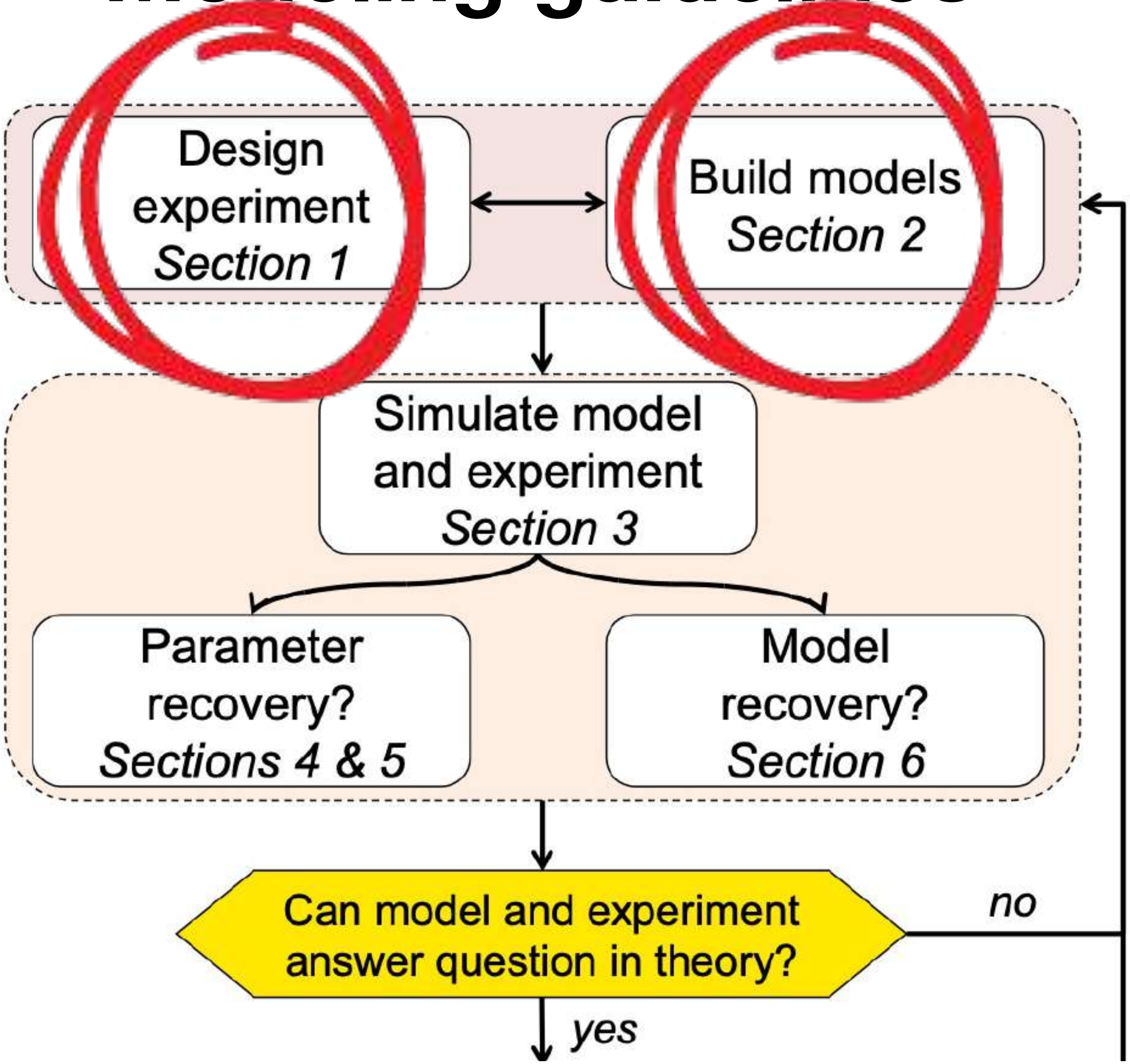
Modeling guidelines

- Goal: provide simple rules for computational cognitive modeling studies of behavior
- Why is it important to follow these rules?
- Two critical steps:
  - ✓ designing a valid cognitive modeling study
  - ✓ analyzing data using cognitive modeling
- Cognitive modeling is most powerful when used during experimental design.

Modeling guidelines

- Today: guidelines for designing a meaningful cognitive modeling study = **step 1**
- Do you remember the difference(s) between a statistical and a computational model?
- Statistical models are used to summarize and describe behavioral data.
- Computational models are used to understand how behavioral data have been generated.

Modeling guidelines



Modeling guidelines

- No data will be collected during **step 1**!
- So what will we be looking at?
- Uses of cognitive models in the same study:
  - ✓ model simulation
  - ✓ model fitting
  - ✓ model comparison
  - ✓ model parameter estimation
  - ✓ model latent variable estimation

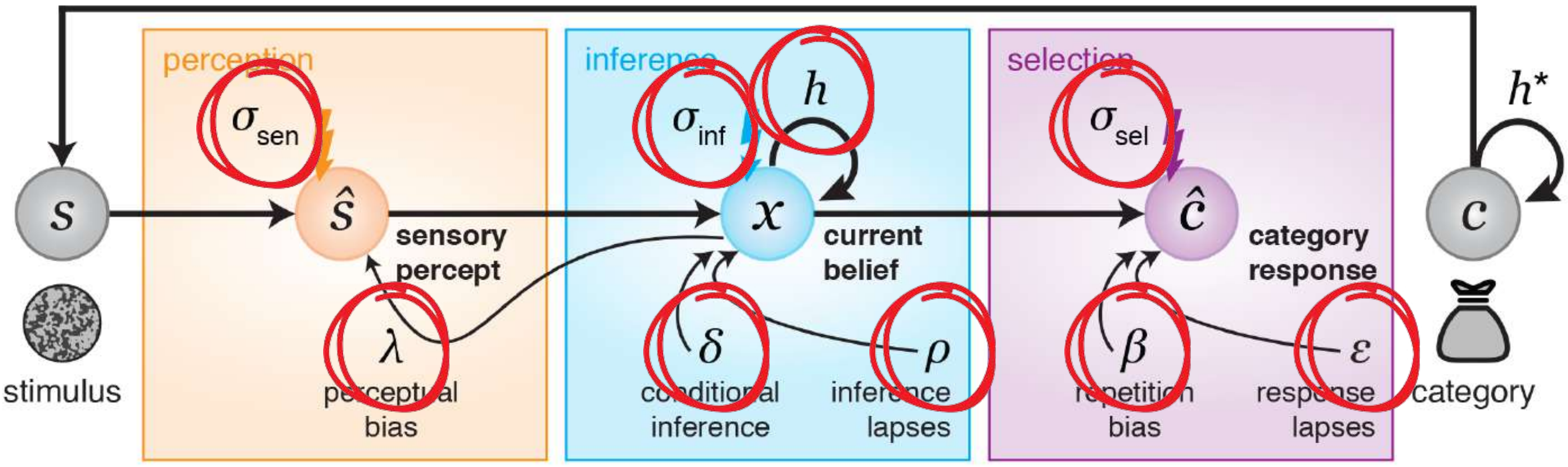
Modeling guidelines

- Difference between model parameters and model latent variables
- Model parameters: set of adjustable values θ that control specific aspects of the model
  >> behavior = $f(s, \theta)$
- Model latent variables: hidden variables x that are computed by the model
  >> $x_1 = f_1(s, \theta_1)$
  >> $x_2 = f_2(x_1, \theta_2)$
  >> behavior = $f_3(x_2, \theta_3)$

Modeling guidelines

- Difference between model parameters and model latent variables

hidden-state inference model



Modeling guidelines

- Difference between model parameters and model latent variables

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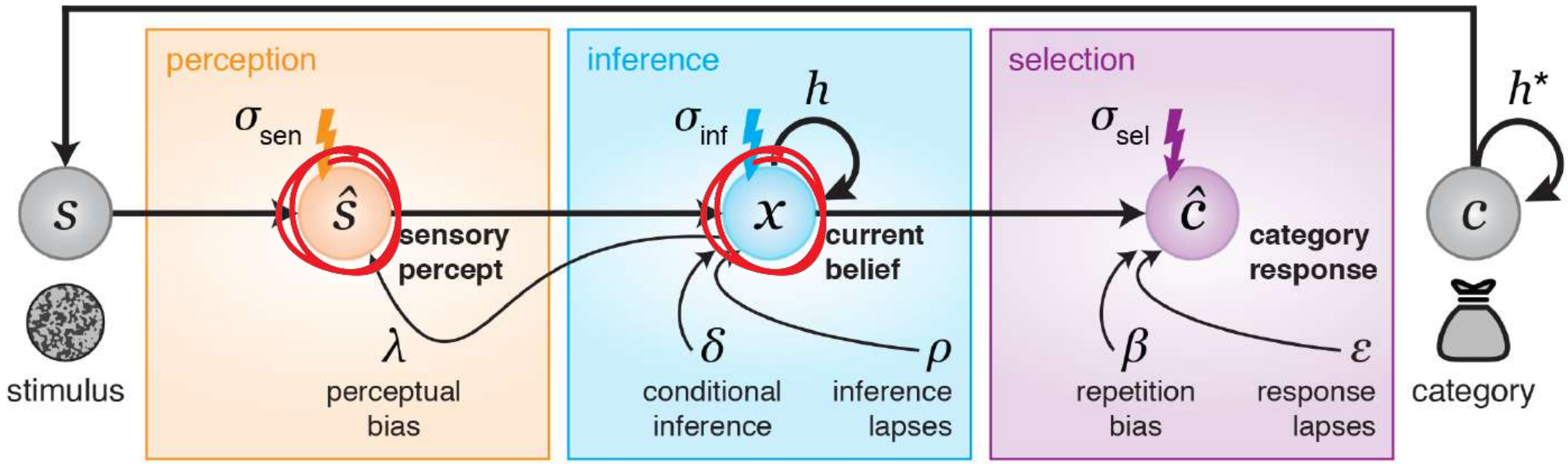


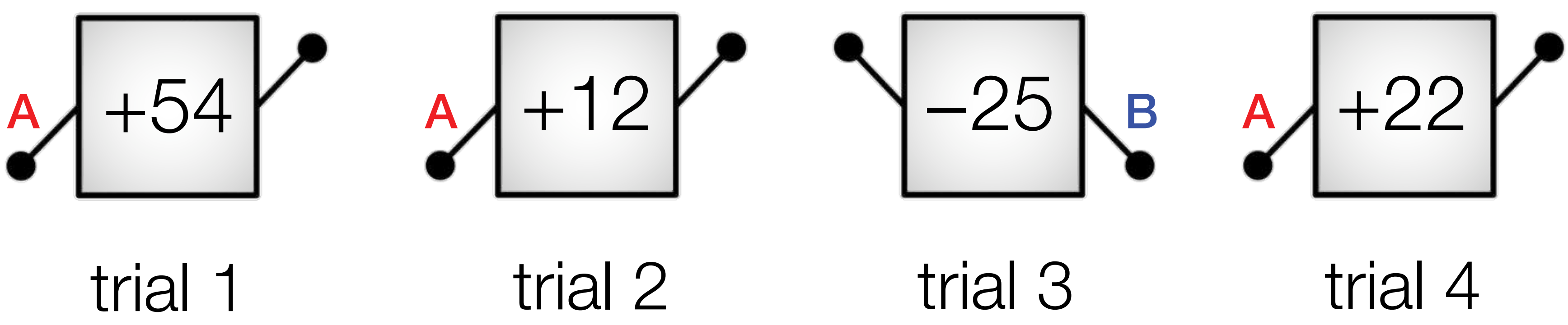
Modeling guidelines

- Difference between model parameters and model latent variables

- Example of TD-based RL:

$$Q_{1,t} = Q_{1,t-1} + \alpha\left(r_t - Q_{1,t-1}\right)$$

$$p_t = 1/\left(1 + \exp\left(-\left(Q_{1,t} - Q_{2,t}\right)/\tau\right)\right)$$



Modeling guidelines

- Difference between model parameters and model latent variables
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- α and τ are model parameters:
  - ✓ α = learning rate (Rescorla-Wagner rule)
  - ✓ τ = choice temperature (softmax policy)

Modeling guidelines

- Difference between model parameters and model latent variables

- Example of TD-based RL:

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$$p_t = 1/\left(1 + \exp\left(-\left(Q_{1,t} - Q_{2,t}\right)/\tau\right)\right)$$

- $Q_{i,t}$ and p_t are model latent variables:
  - ✓ $Q_{i,t}$ = value of option i at time t
  - ✓ p_t = choice probability of option 1 at time t

Modeling guidelines

- Model simulation: running the model with particular set of parameters θ to generate synthetic behavior (and latent variables x)
- This synthetic behavior can be analyzed exactly like human behavior to make precise, falsifiable predictions about qualitative and quantitative features of behavior.
- What does falsifiable mean?
  Difference btw qualitative and quantitative?

Modeling guidelines

Trends in Cognitive Sciences

CellPress

Opinion

The Importance of Falsification in Computational Cognitive Modeling

Stefano Palminteri,[1,2,*,‡] Valentin Wyart,[1,2,*,‡] and Etienne Koechlin[1,2,*]

In the past decade the field of cognitive sciences has seen an exponential growth in the number of computational modeling studies. Previous work has indicated why and how candidate models of cognition should be compared by trading off their ability to predict the observed data as a function of their complexity. However, the importance of falsifying candidate models in light of the observed data has been largely underestimated, leading to important drawbacks and unjustified conclusions. We argue here that the simulation of candidate models is necessary to falsify models and therefore support the

Trends

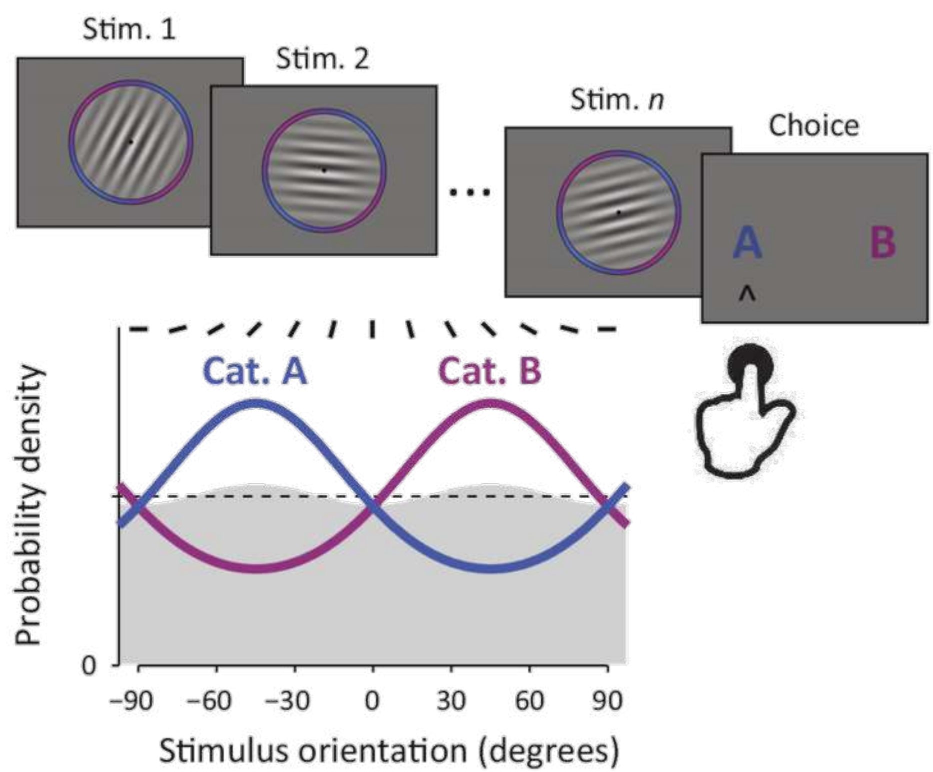
Computational modeling has grown exponentially in cognitive sciences in the past decade.

Model selection most often relies on evaluating the ability of candidate models to predict the observed data.

The ability of a candidate model to

Modeling guidelines

- Model falsification: showing through simulations that a model is not able to generate a specific behavioral effect of interest.



Modeling guidelines

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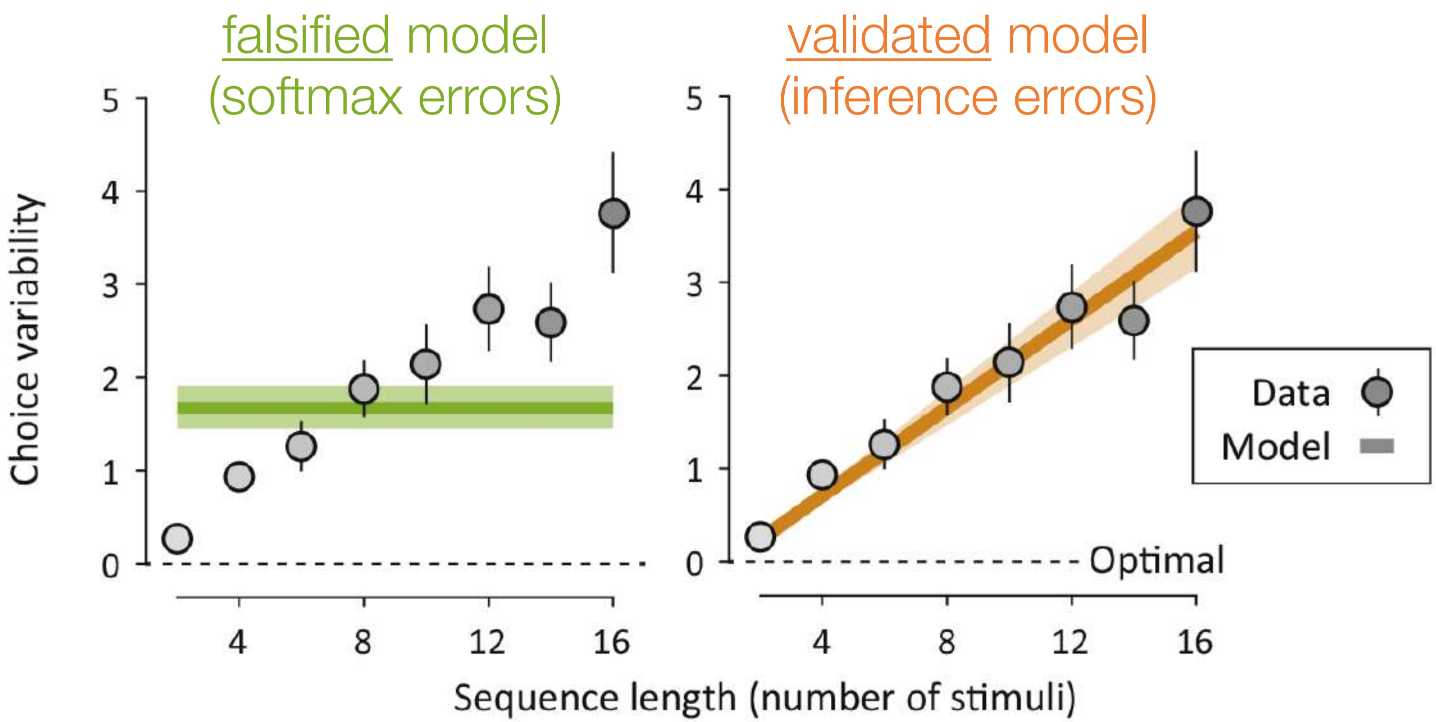

Modeling guidelines

Article

Neuron

Computational Precision of Mental Inference as Critical Source of Human Choice Suboptimality

Highlights

- Human decisions based on multiple ambiguous cues are typically suboptimal
- Sensory noise and response selection cannot explain choice suboptimality alone
- Imperfections in mental inference cause a dominant fraction of choice suboptimality
- Most of choice suboptimality arises from imprecise rather than biased computations

Authors

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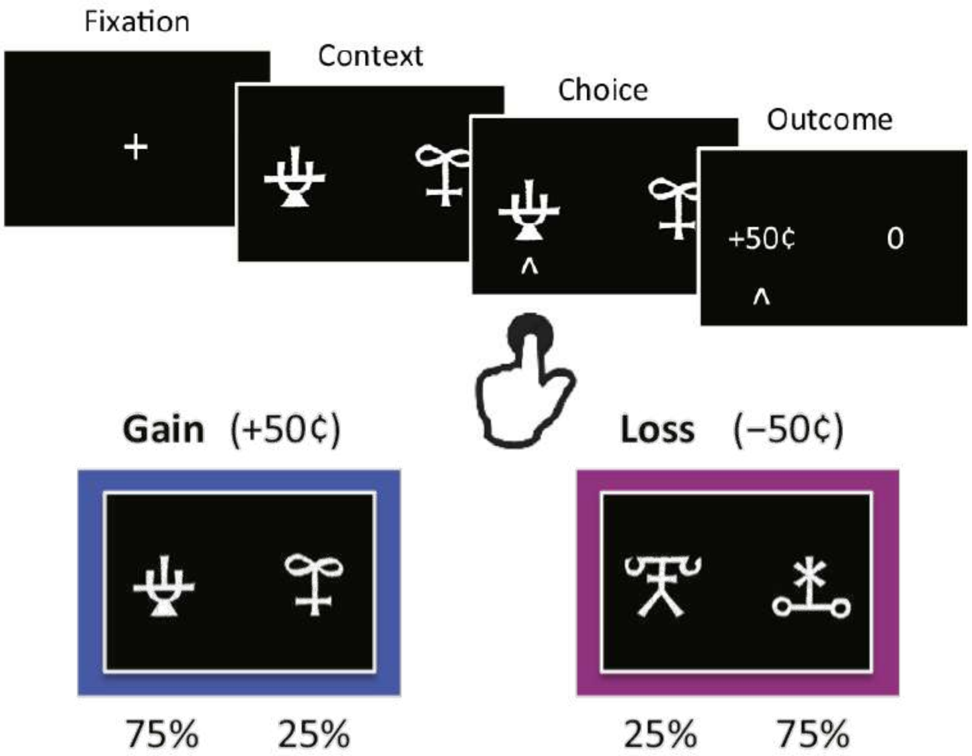
In Brief

Decisions made under uncertainty show a suboptimal variability whose origin is usually ascribed to the peripheries of the decision process. Drugowitsch et al. show that computational imprecisions in the decision process itself account for a dominant fraction of choice

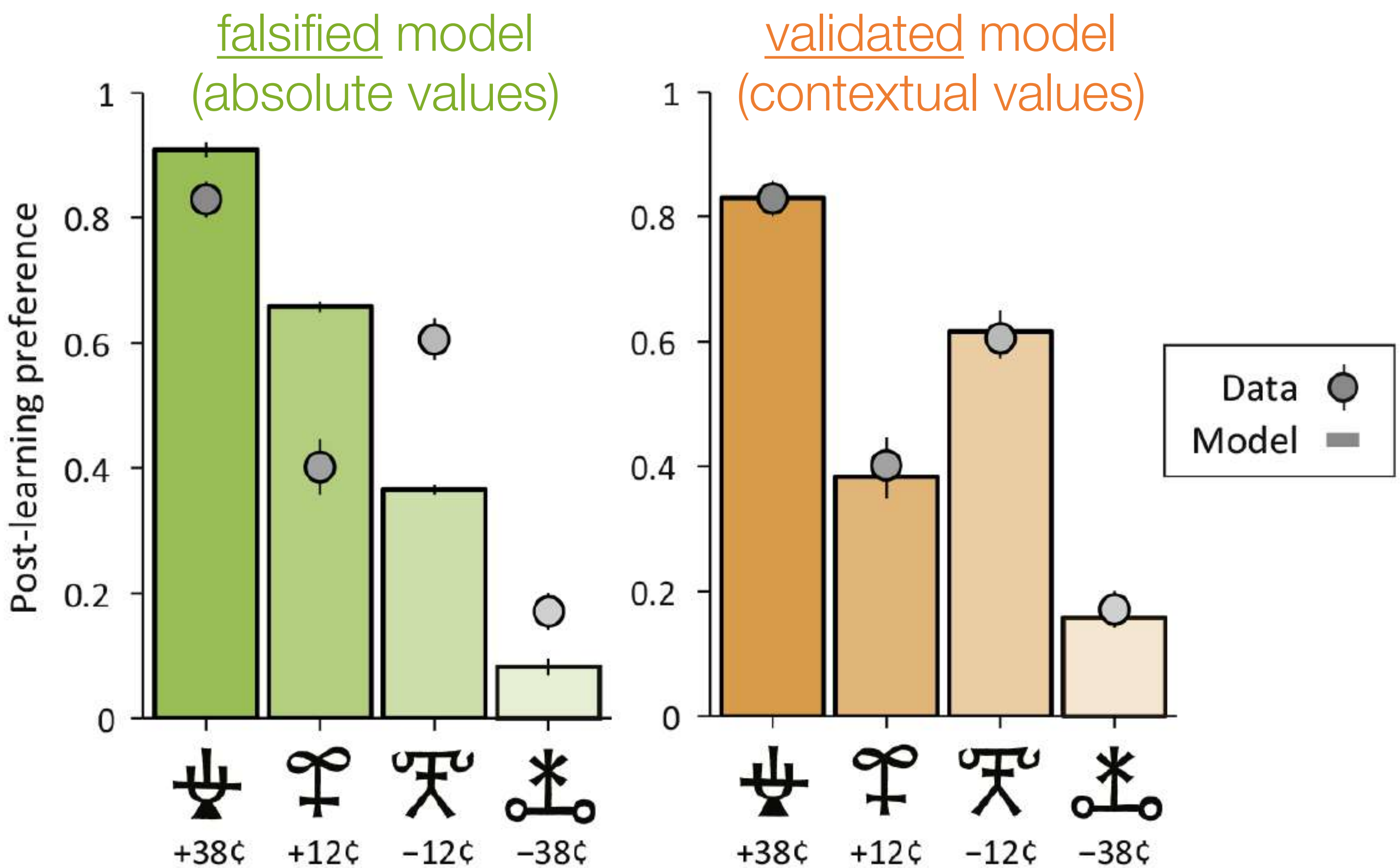
Modeling guidelines

- Model falsification: showing through simulations that a model is not able to generate a specific behavioral effect of interest.



Modeling guidelines

- Model falsification:



Modeling guidelines

nature COMMUNICATIONS

ARTICLE

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OPEN

Contextual modulation of value signals in reward and punishment learning

Stefano Palminteri[1,2], Mehdi Khamassi[3,4], Mateus Joffily[4,5] & Giorgio Coricelli[2,4,6]

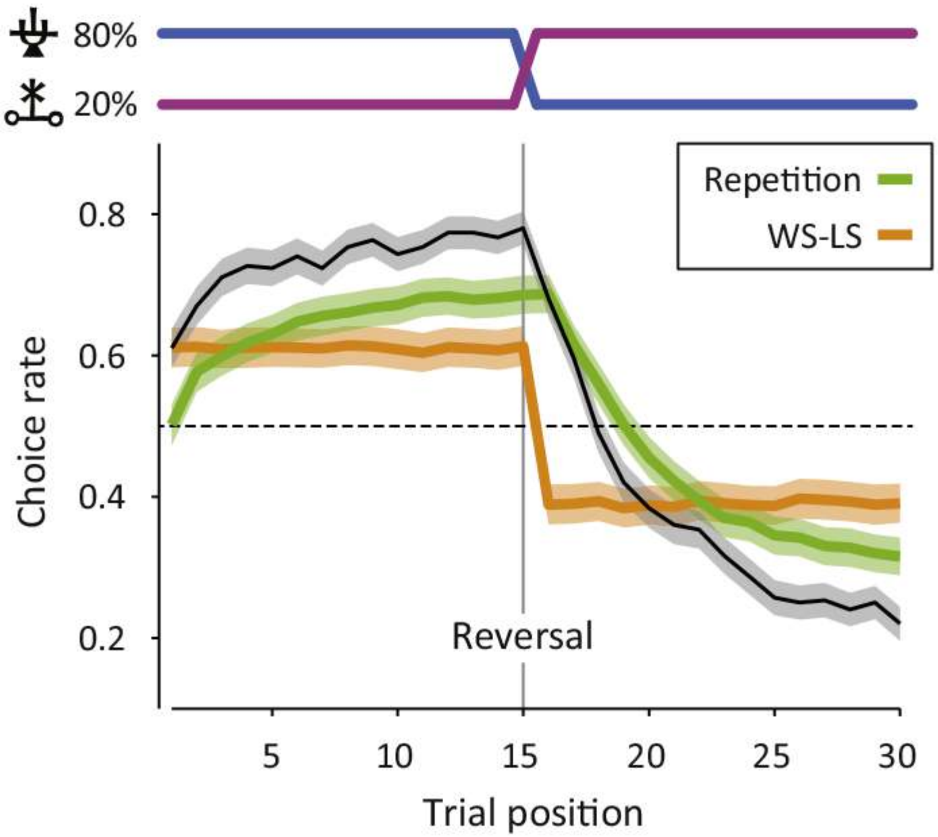
Compared with reward seeking, punishment avoidance learning is less clearly understood at both the computational and neurobiological levels. Here we demonstrate, using computational modelling and fMRI in humans, that learning option values in a relative—context-dependent—scale offers a simple computational solution for avoidance learning. The context (or state) value sets the reference point to which an outcome should be compared before updating the option value. Consequently, in contexts with an overall negative expected

Modeling guidelines

- Qualitative vs quantitative differences:
  - ✓ qualitative = specific pattern of behavior as in the last two examples
  - ✓ quantitative = magnitude of deviations btw observed and fitted behavior

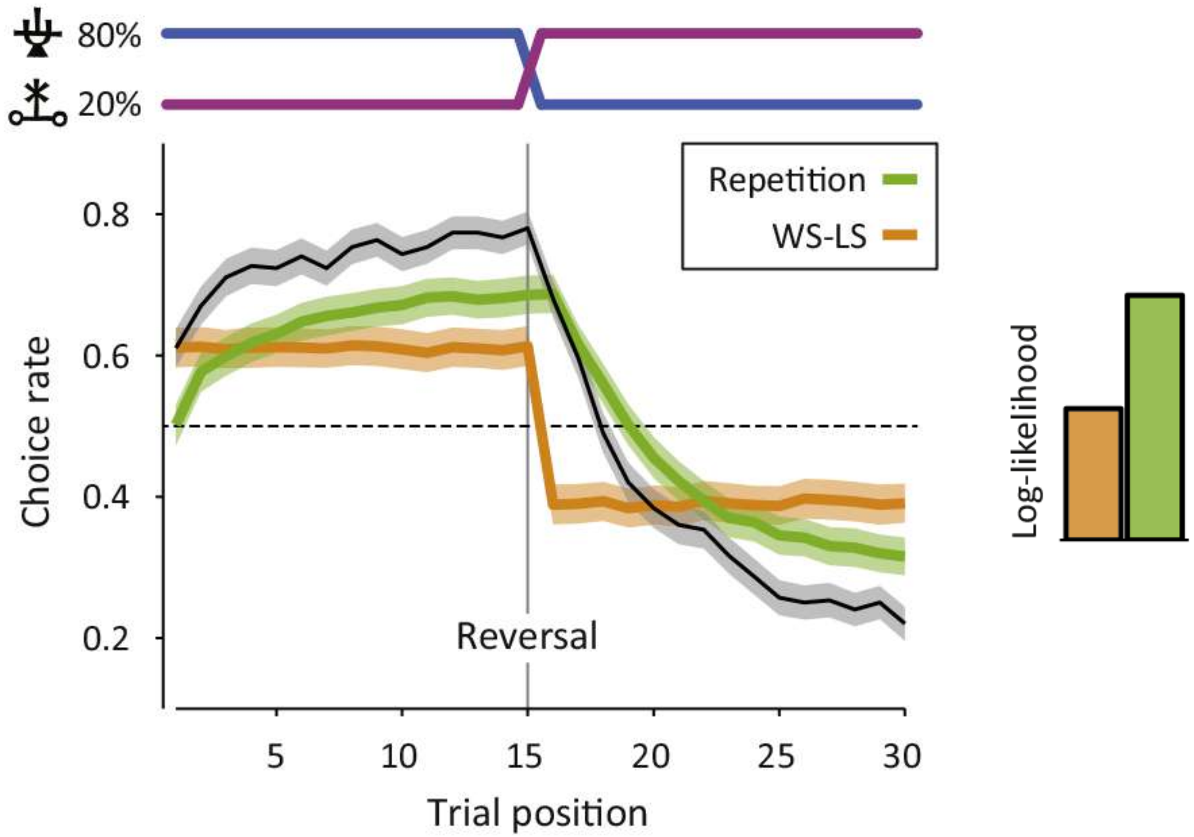
Modeling guidelines

- Qualitative vs quantitative differences:



Modeling guidelines

- Qualitative vs quantitative differences:



Modeling guidelines

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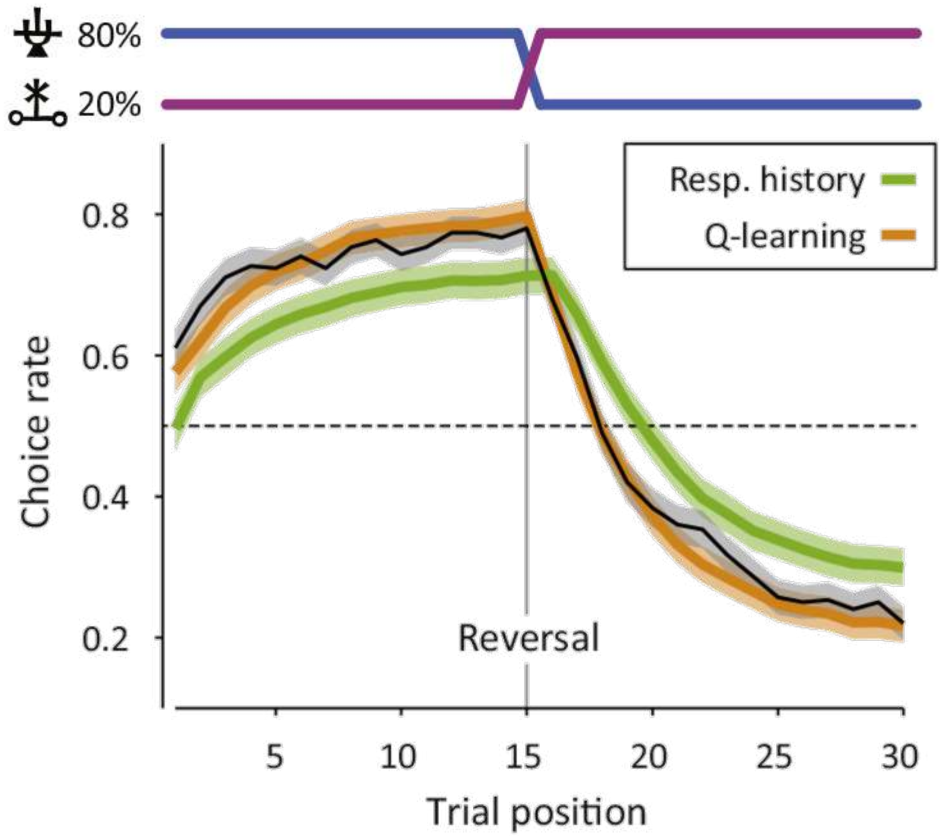
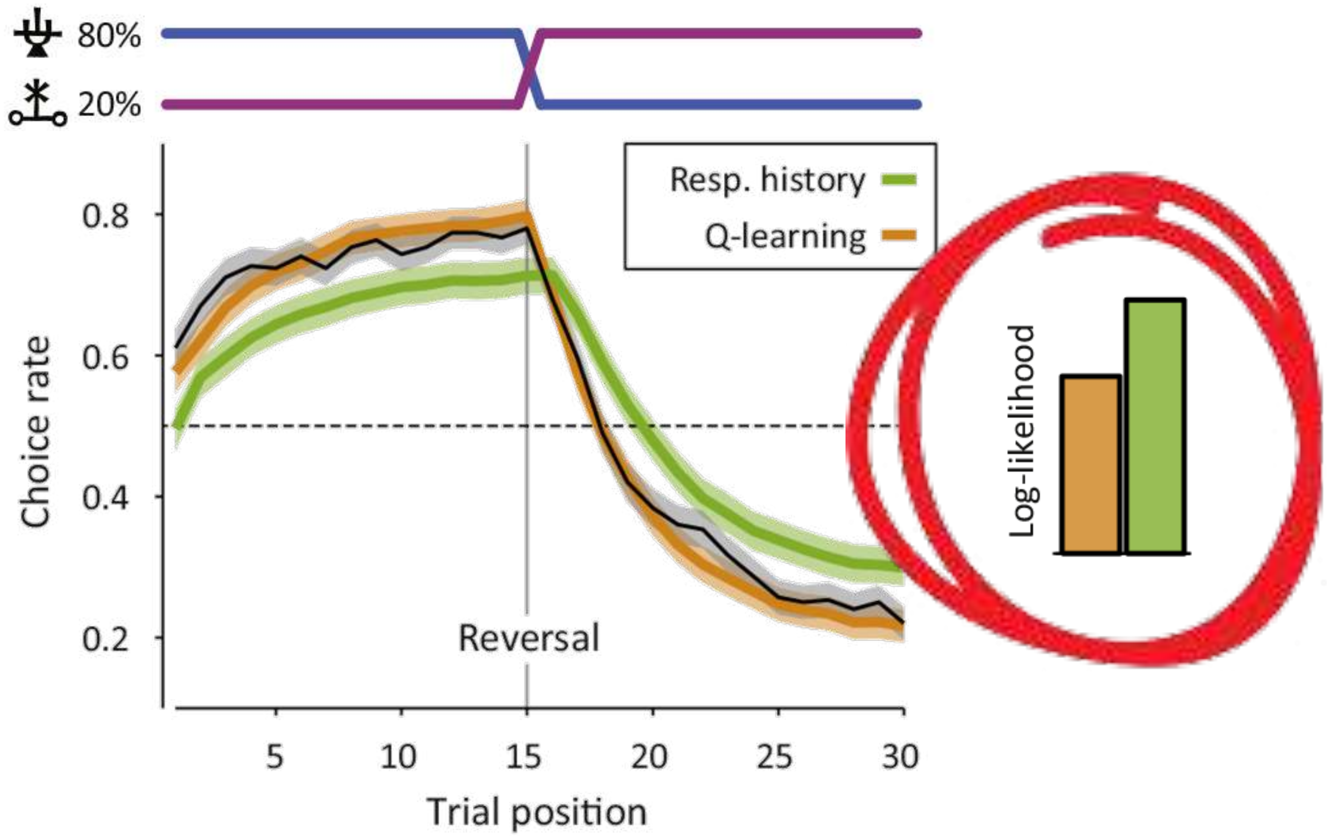


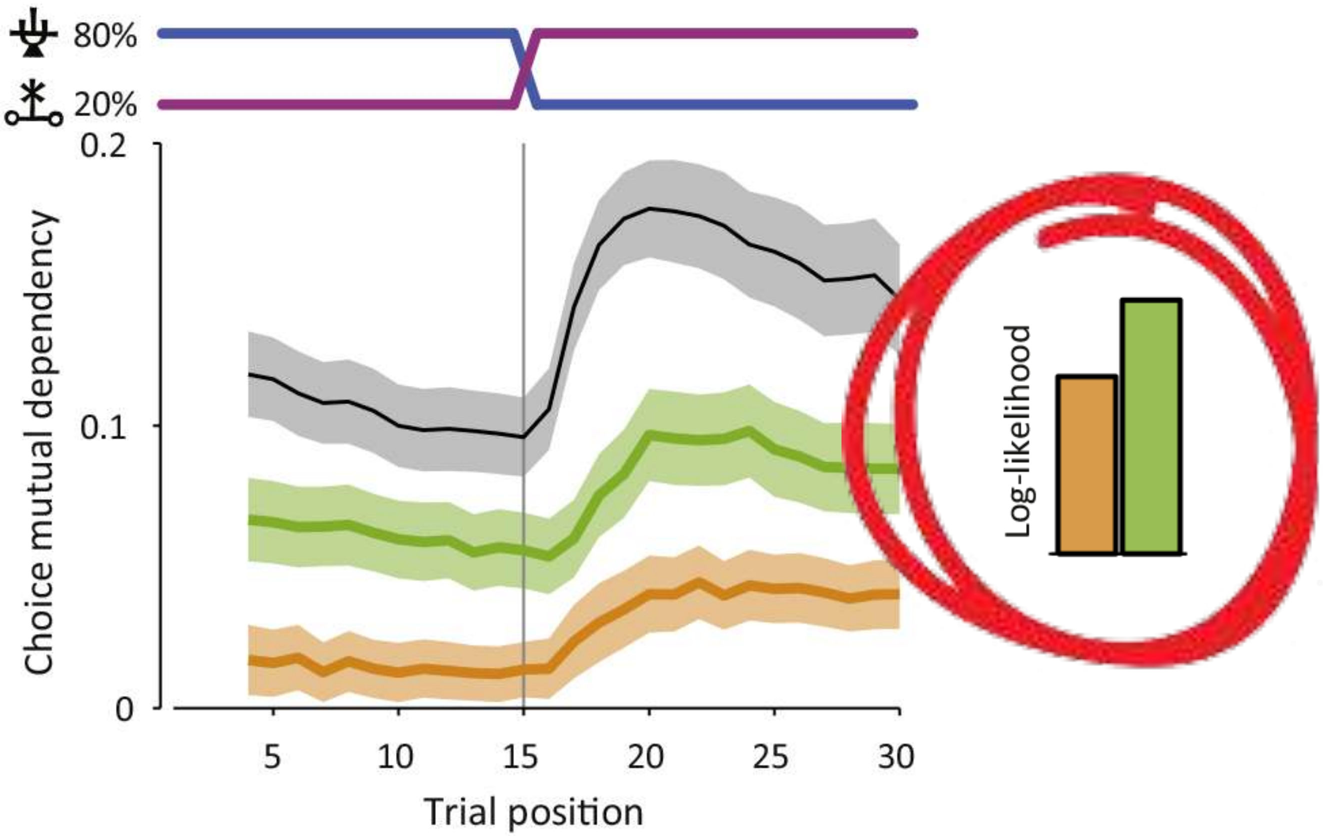
Modeling guidelines

- Qualitative vs quantitative differences:



Modeling guidelines

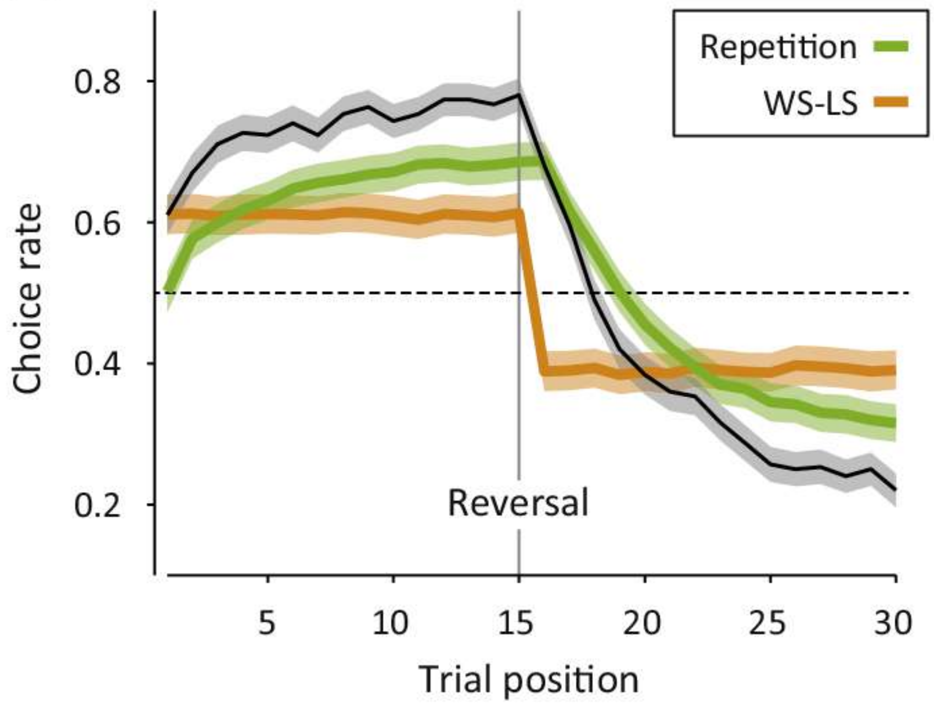
- Qualitative vs quantitative differences:



Modeling guidelines

- Qualitative vs quantitative differences:

fitted behavior
(based on model fits)

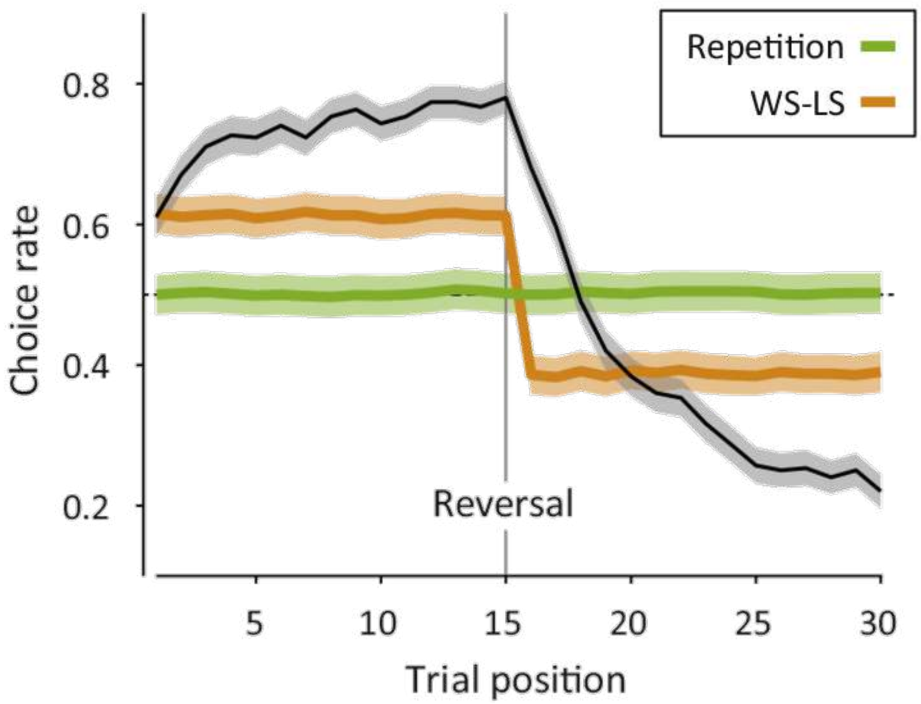


repetition better than WS-LS

Modeling guidelines

- Qualitative vs quantitative differences:

<u>simulated</u> behavior
(based on model simulations)



repetition at <u>chance level</u>

Modeling guidelines

- Take-home messages:
  - ✓ a specific behavioral effect may not explain why a certain model fits behavior better
  - ✓ a certain model may fit behavior well, but fail when simulated to perform the task

Modeling guidelines

- Model fitting: finding the set of parameters θ that best accounts for the observed behavior
- Unlike empirical metrics like task accuracy, fitted parameters account for task variables (such as task difficulty):
$$\hat{\theta}_{\mathrm{MLE}} = \mathrm{argmax}_{\theta}\left(\log\left(p(\mathrm{behavior}|\theta, s)\right)\right)$$
- MLE = Maximum Likelihood Estimate (set of parameters that maximize the likelihood of the observed behavior given task variables)

Modeling guidelines

- Model comparison: identifying which of a set of alternative models best describes the same observed behavior given task variables

- This comparison uses the log-likelihood (or the log-posterior) of alternative models as measure of model evidence:

$$\mathrm{MLE} = \max_{\theta}\left(\log\left(p(\mathrm{behavior}|\theta, s)\right)\right)$$

- BMS = Bayesian Model Selection (statistical procedure used for model comparison)

Modeling guidelines

- Model parameter estimation: often a synonym for model fitting (finding the set of parameters θ that best accounts for the observed behavior)
- Fitted parameters can be used as a algorithmic phenotype for investigating:
  - ✓ individual differences in the same task
  - ✓ effect of drugs, lesions, moods, illness
  - ✓ effect of experimental conditions
  - ✓ effect of practice

Modeling guidelines

Personality Neuroscience

cambridge.org/pen

Computational Phenotyping: Using Models to Understand Individual Differences in Personality, Development, and Mental Illness

Edward H. Patzelt[1], Catherine A. Hartley[2] and Samuel J. Gershman[1]

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[2]Department of Psychology and Center for Neural Science, New York University, New York, NY, USA

Review Paper

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Inaugural Invited Paper
Accepted: 6 June 2018

Key words:
psychopathology (general); reward/punishment; computational models; learning; decision making

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Abstract

This paper reviews progress in the application of computational models to personality, developmental, and clinical neuroscience. We first describe the concept of a computational phenotype, a collection of parameters derived from computational models fit to behavioral and neural data. This approach represents individuals as points in a continuous parameter space, complementing traditional trait and symptom measures. One key advantage of this representation is that it is mechanistic: The parameters have interpretations in terms of cognitive processes, which can be translated into quantitative predictions about future behavior and brain activity. We illustrate with several examples how this approach has led to new scientific insights into individual differences, developmental trajectories, and psychopathology. We then survey some of the challenges that lay ahead.

The study of personality has a rich history examining individual differences in how we behave, relate to ourselves and each other, and understand our experiences and environment. This work has had the significant challenge of linking multiple levels of analysis spanning complex neural and cognitive processes. Recently, computational models have provided a powerful tool to mathematically formalize this complexity, and provide rich descriptions of the processes

Modeling guidelines

nature human behaviour

Article

https://doi.org/10.1038/s41562-024-01814-x

Dynamic computational phenotyping of human cognition

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Accepted: 21 December 2023

Published online: 08 February 2024

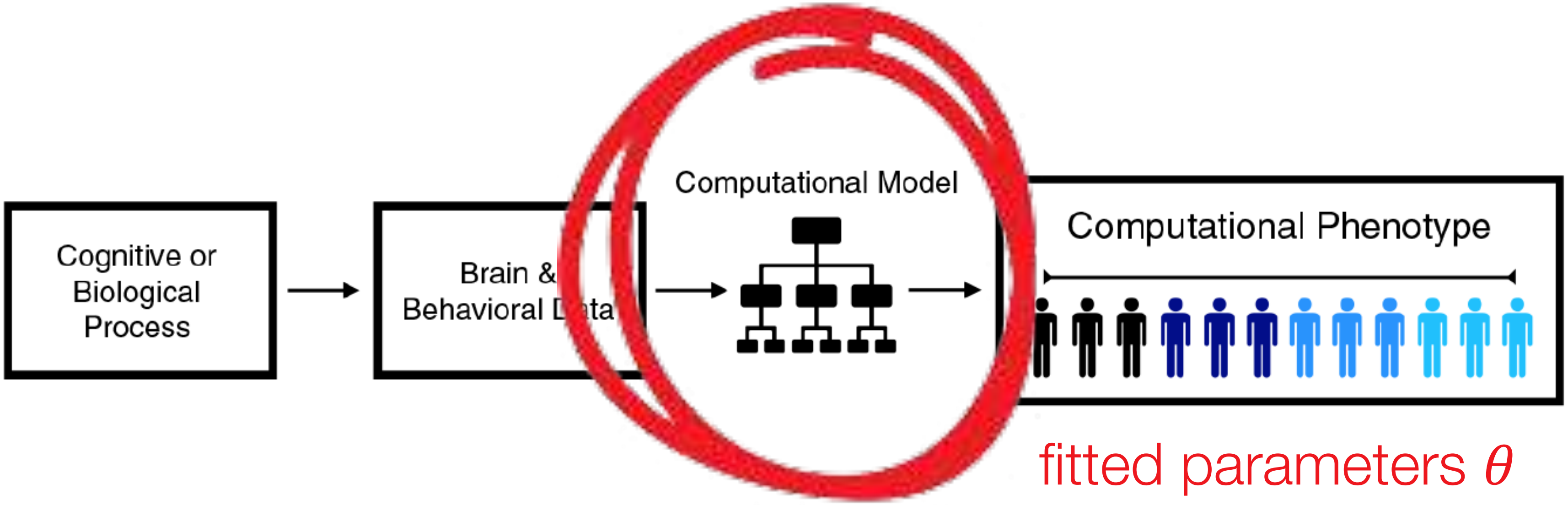
Check for updates

Roey Schurr [1,7], Daniel Reznik [2,7], Hanna Hillman [3], Rahul Bhui [4,5] & Samuel J. Gershman [1,6]

Computational phenotyping has emerged as a powerful tool for characterizing individual variability across a variety of cognitive domains. An individual's computational phenotype is defined as a set of mechanistically interpretable parameters obtained from fitting computational models to behavioural data. However, the interpretation of these parameters hinges critically on their psychometric properties, which are rarely studied. To identify the sources governing the temporal variability of the computational phenotype, we carried out a 12-week longitudinal study using a battery of seven tasks that measure aspects of human learning

Modeling guidelines

- Model parameter estimation: often a synonym for model fitting (finding the set of parameters θ that best accounts for the observed behavior)



fitted parameters θ across a group

Modeling guidelines

nature mental health

https://doi.org/10.1038/s44220-024-00364-5

Article

Compulsivity is linked to suboptimal choice variability but unaltered reinforcement learning under uncertainty

Received: 5 January 2023

Accepted: 25 October 2024

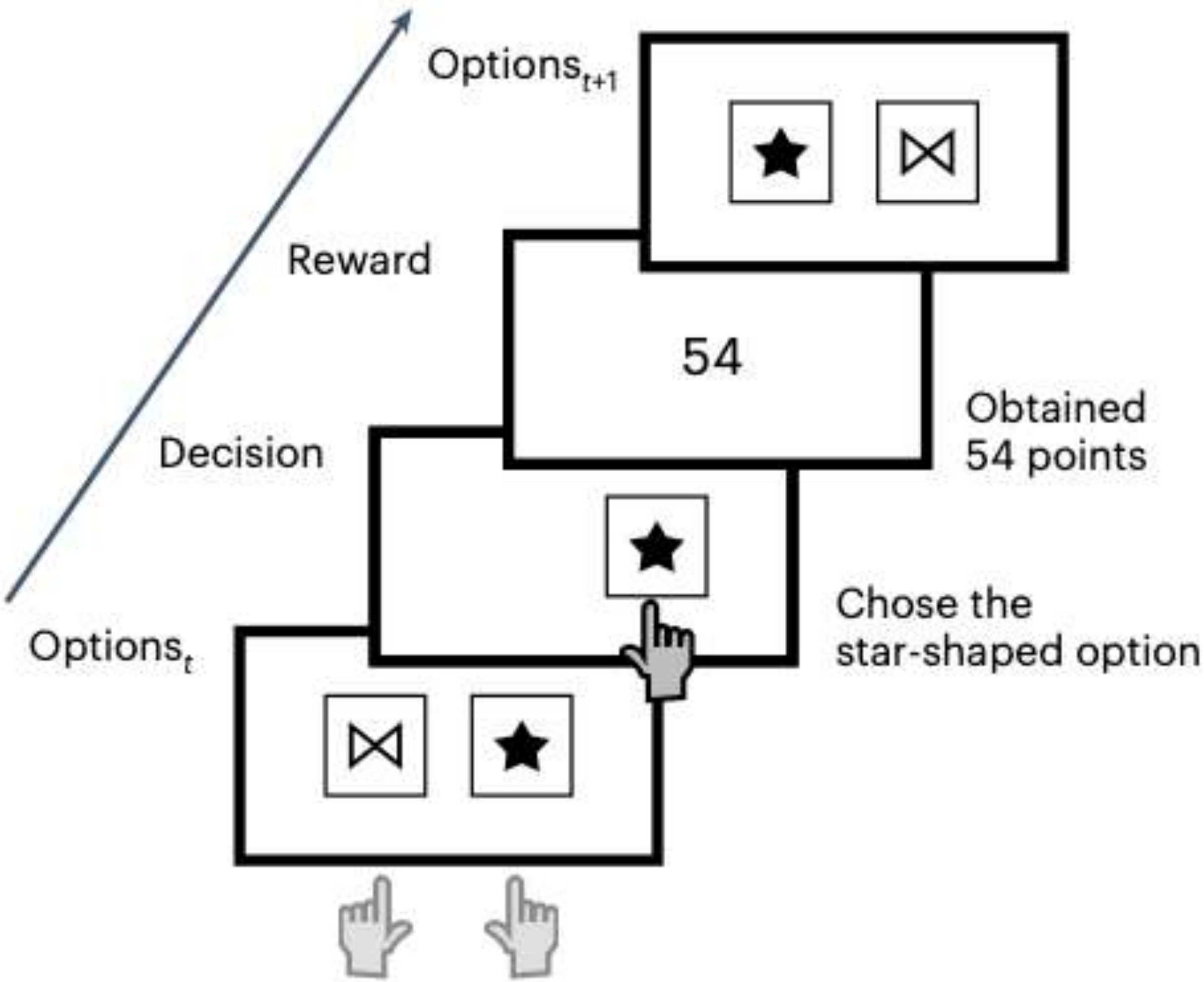
Published online: 6 January 2025

Check for updates

Junseok K. Lee [1,2], Marion Rouault [1,2,3] & Valentin Wyart [1,2,4]

Compulsivity has been associated with variable behavior under uncertainty. However, previous work has not distinguished between two main sources of behavioral variability: the stochastic selection of choice options that do not maximize expected reward (choice variability) and random noise in the reinforcement learning process that updates option values from choice outcomes (learning variability). Here we study the relation between dimensional compulsivity and behavioral variability using a computational model that dissociates its two sources. Across two independent datasets

Modeling guidelines



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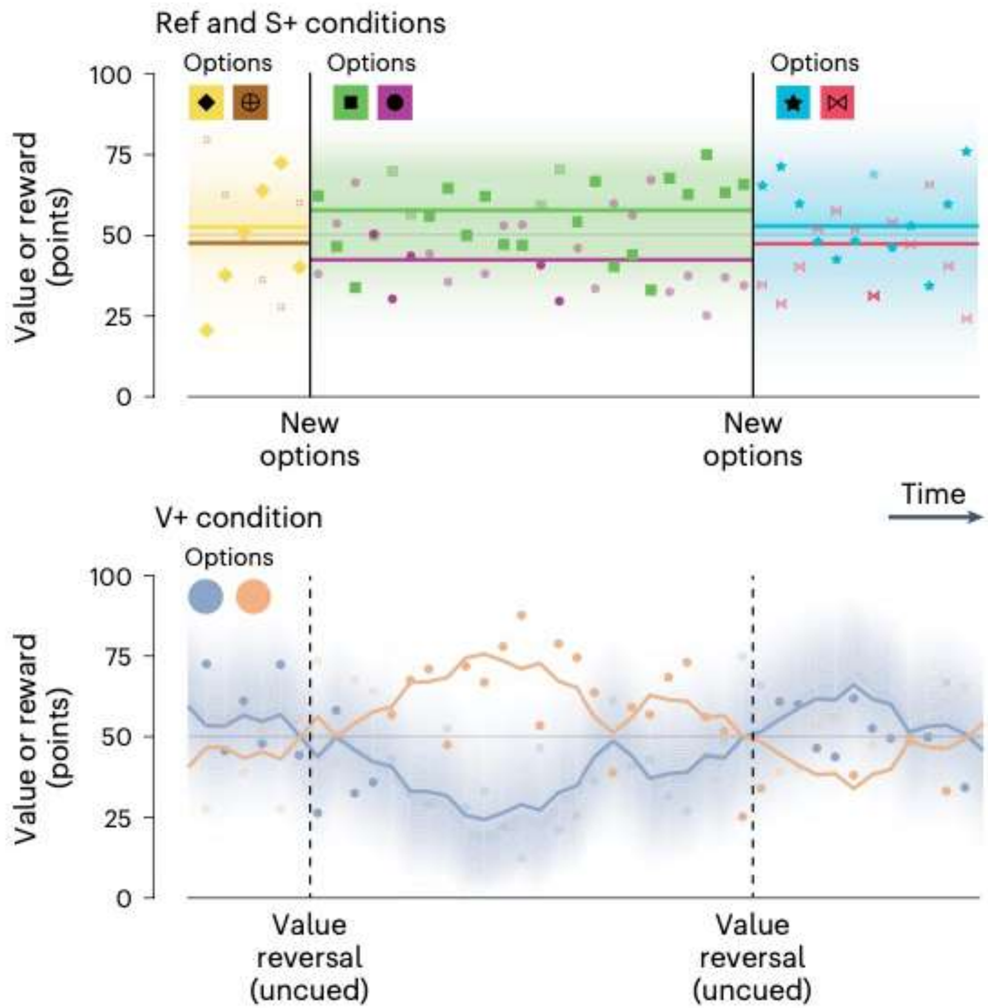

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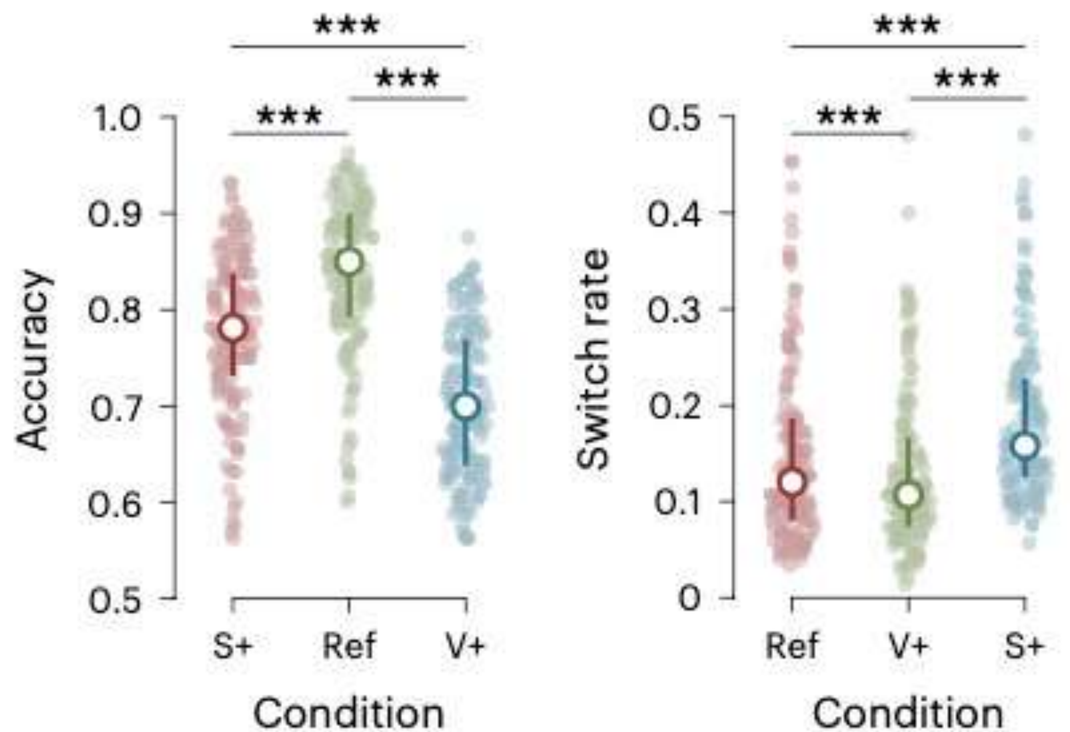
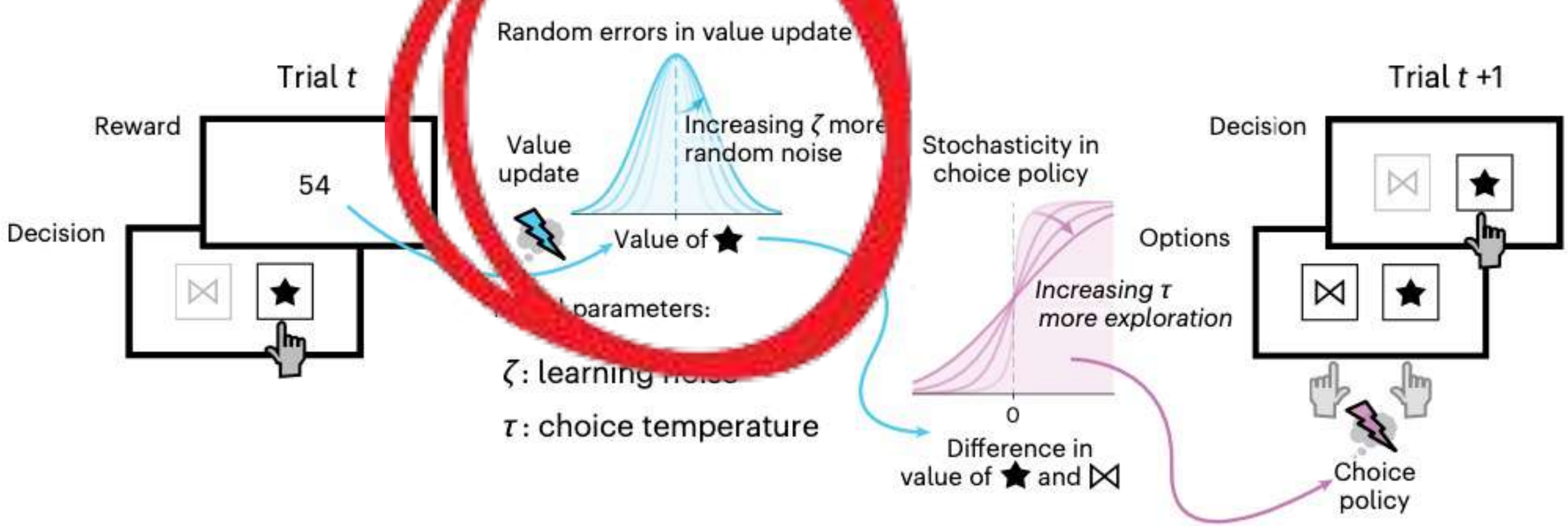


Modeling guidelines

noisy TD-RL model with softmax-based exploration



Modeling guidelines

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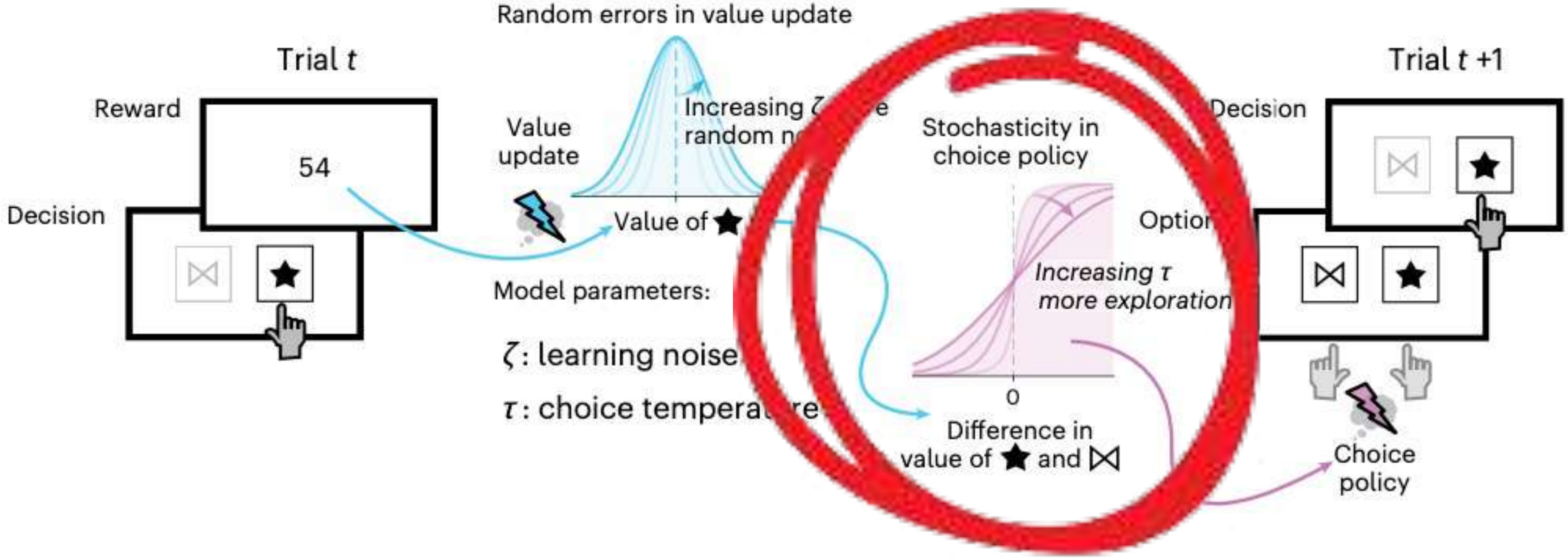
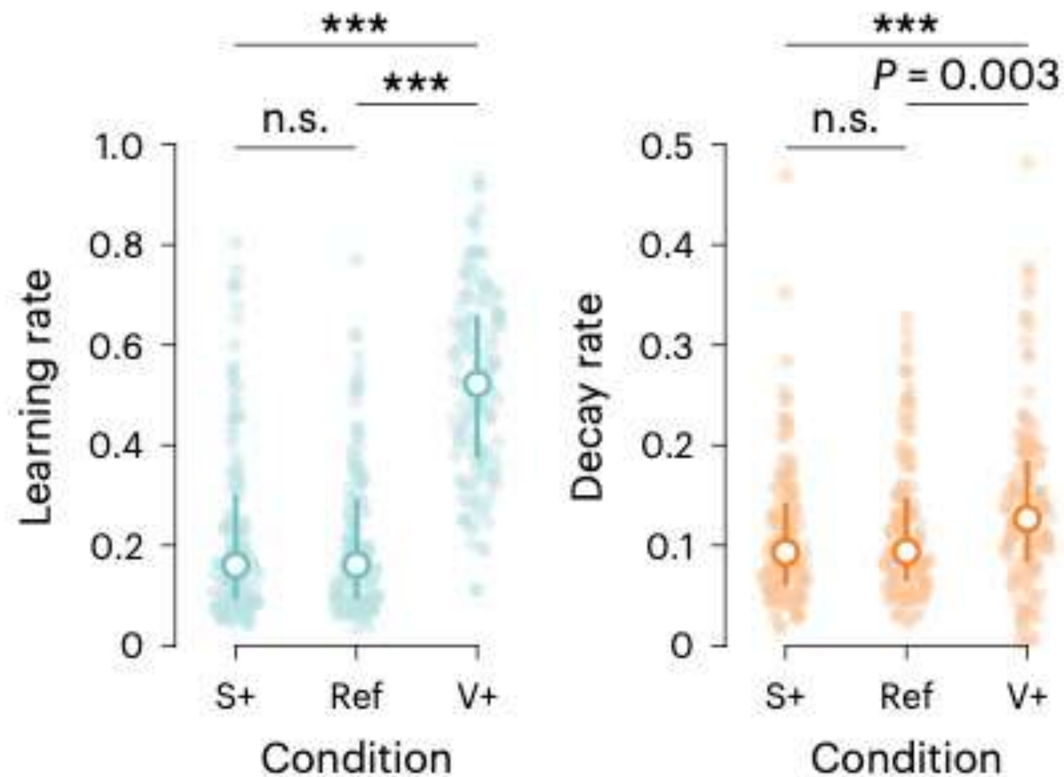
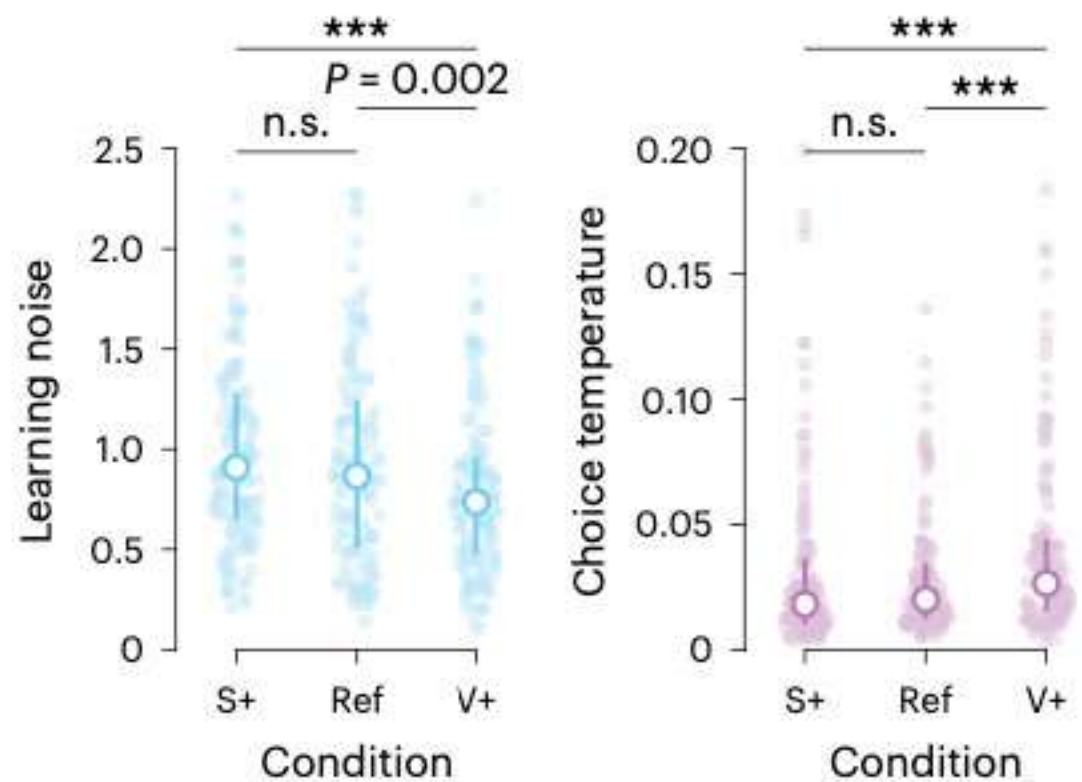


Modeling guidelines



Modeling guidelines



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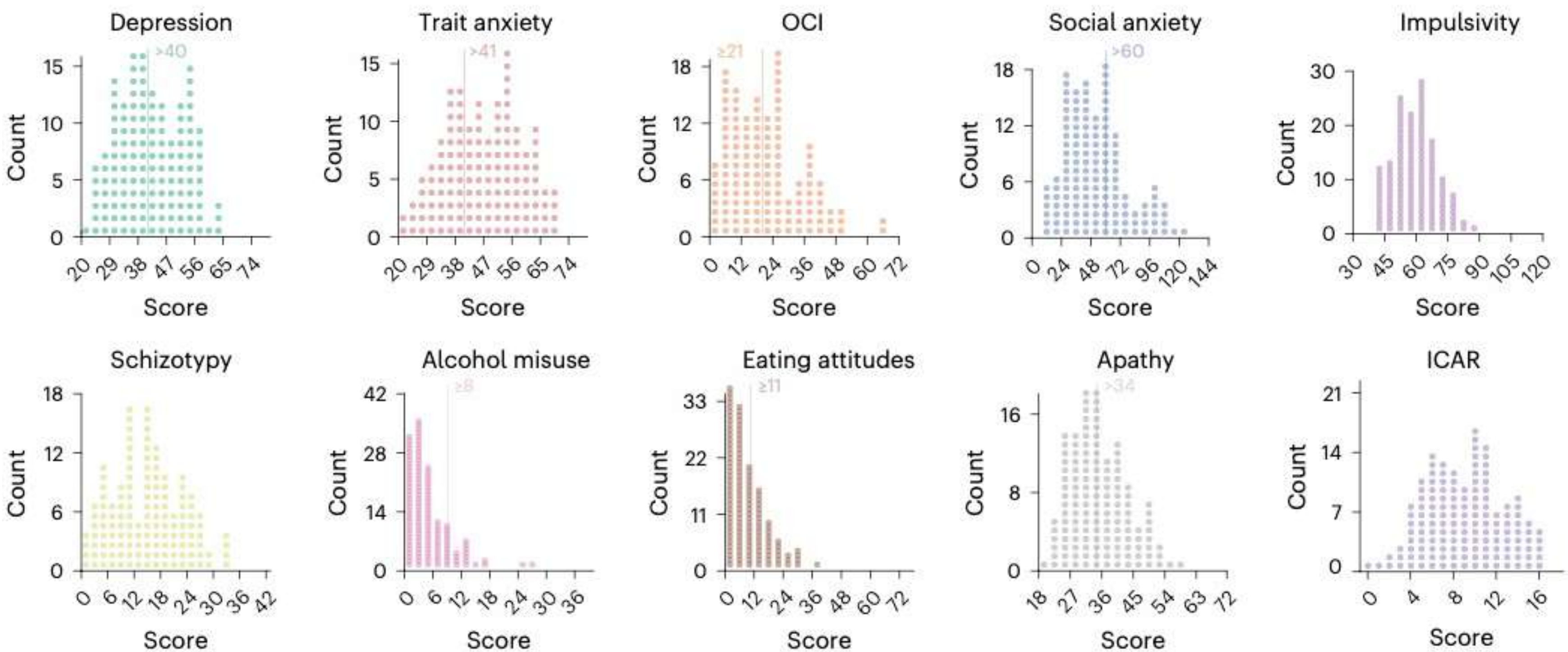
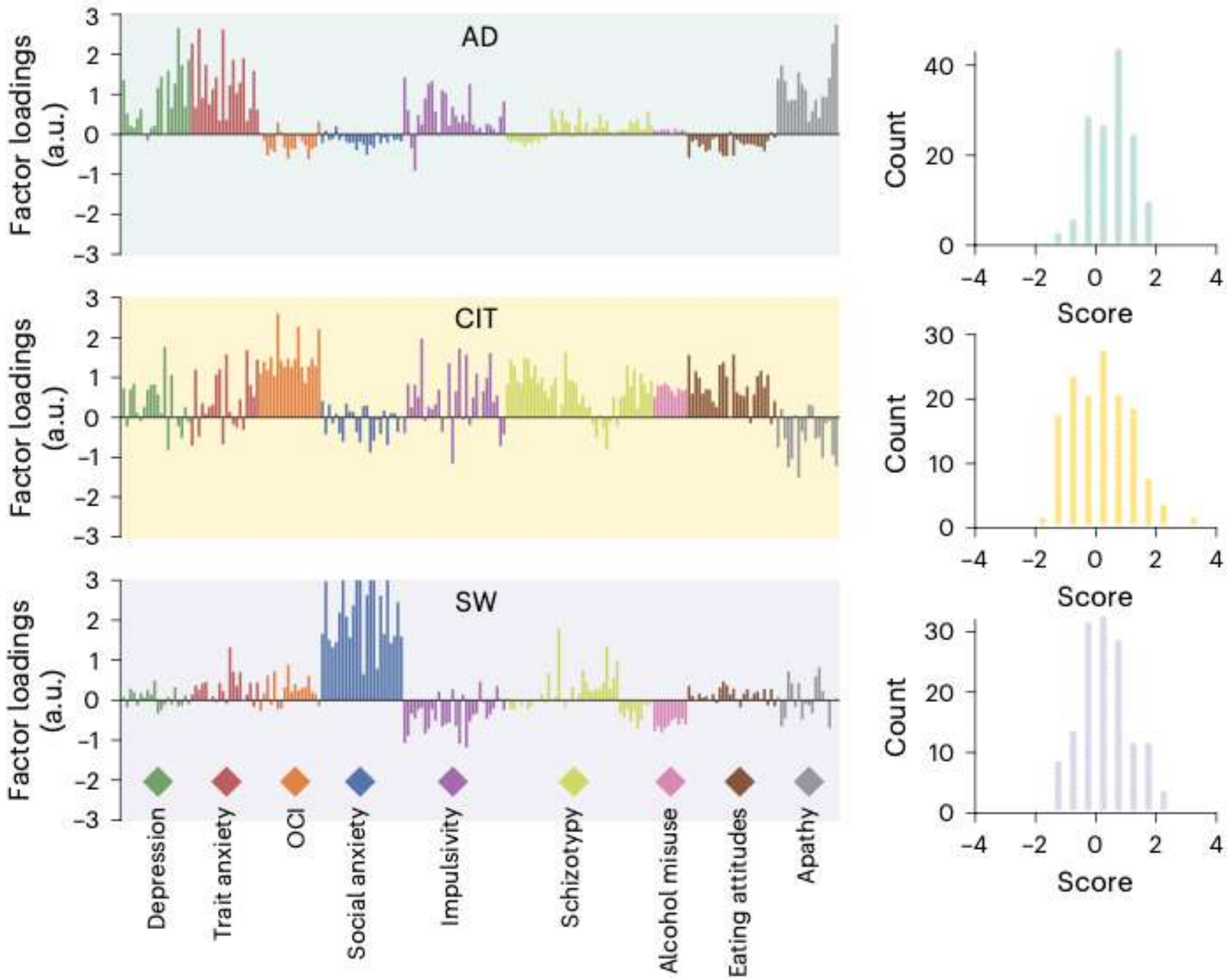
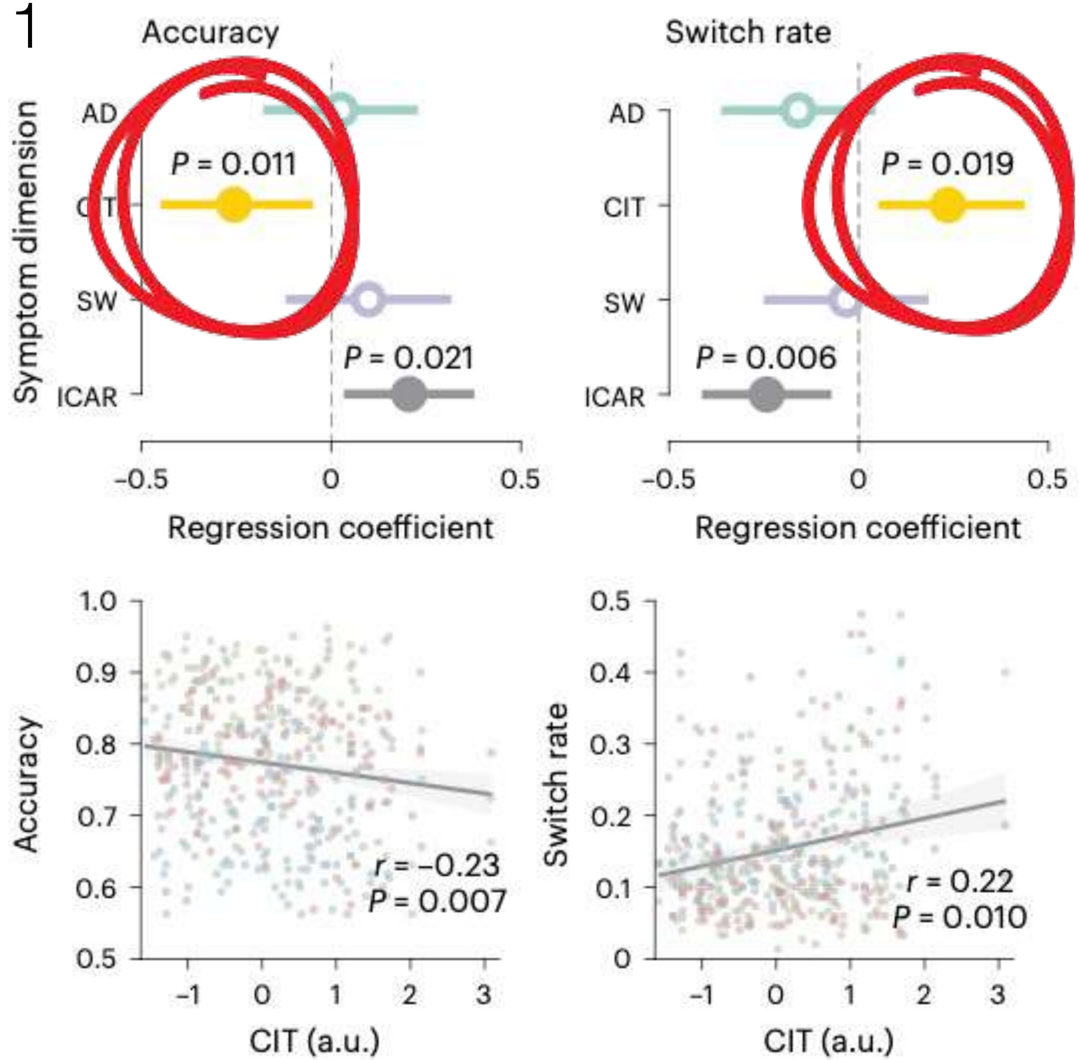


Modeling guidelines



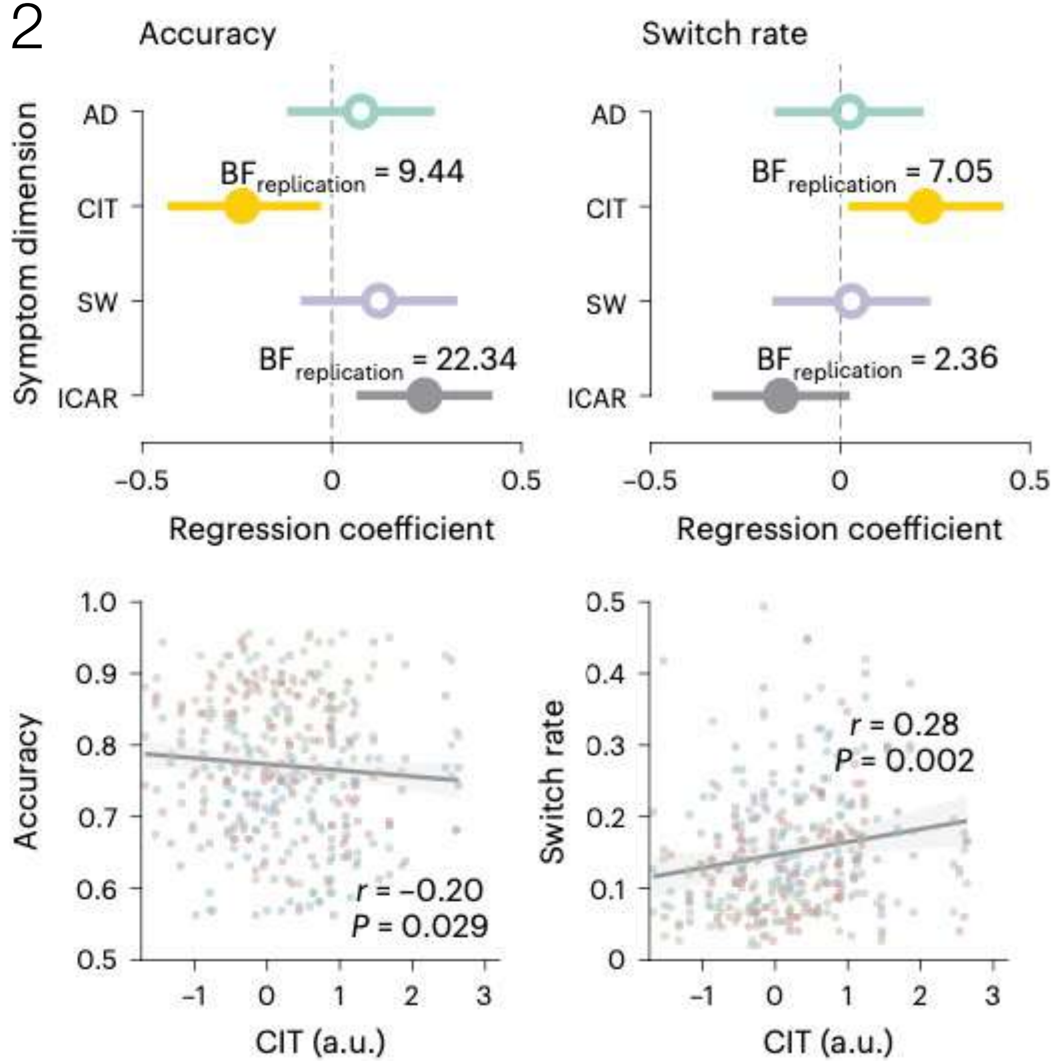
Modeling guidelines

sample 1



Modeling guidelines

sample 2



Modeling guidelines

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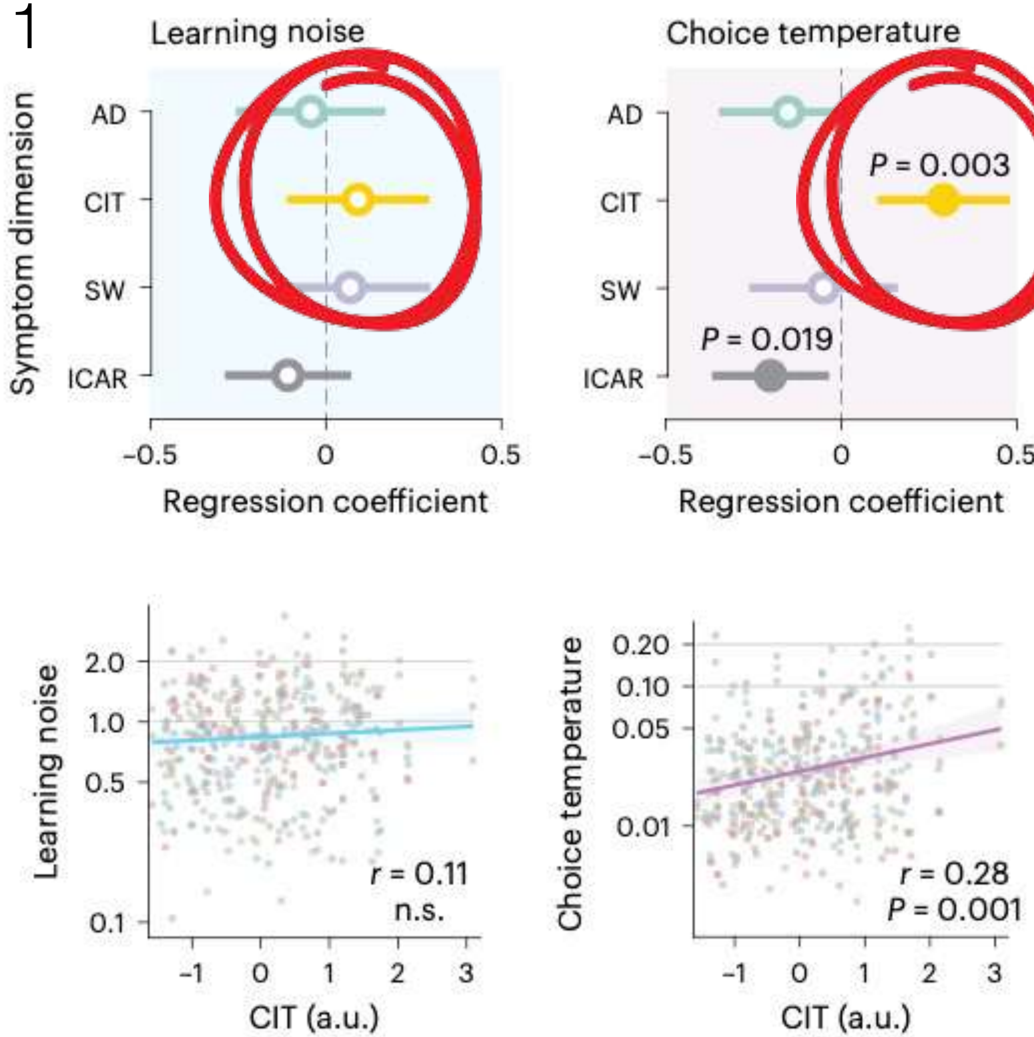
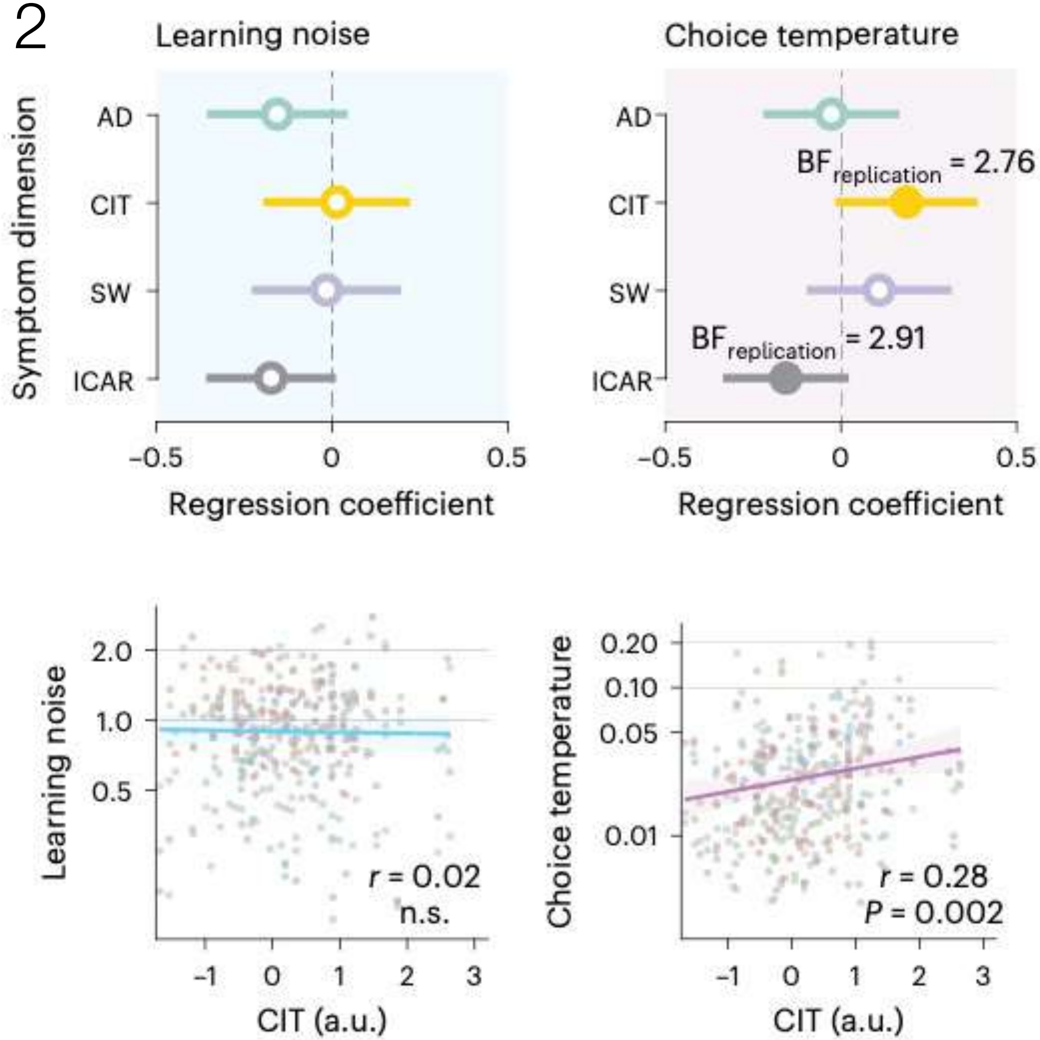
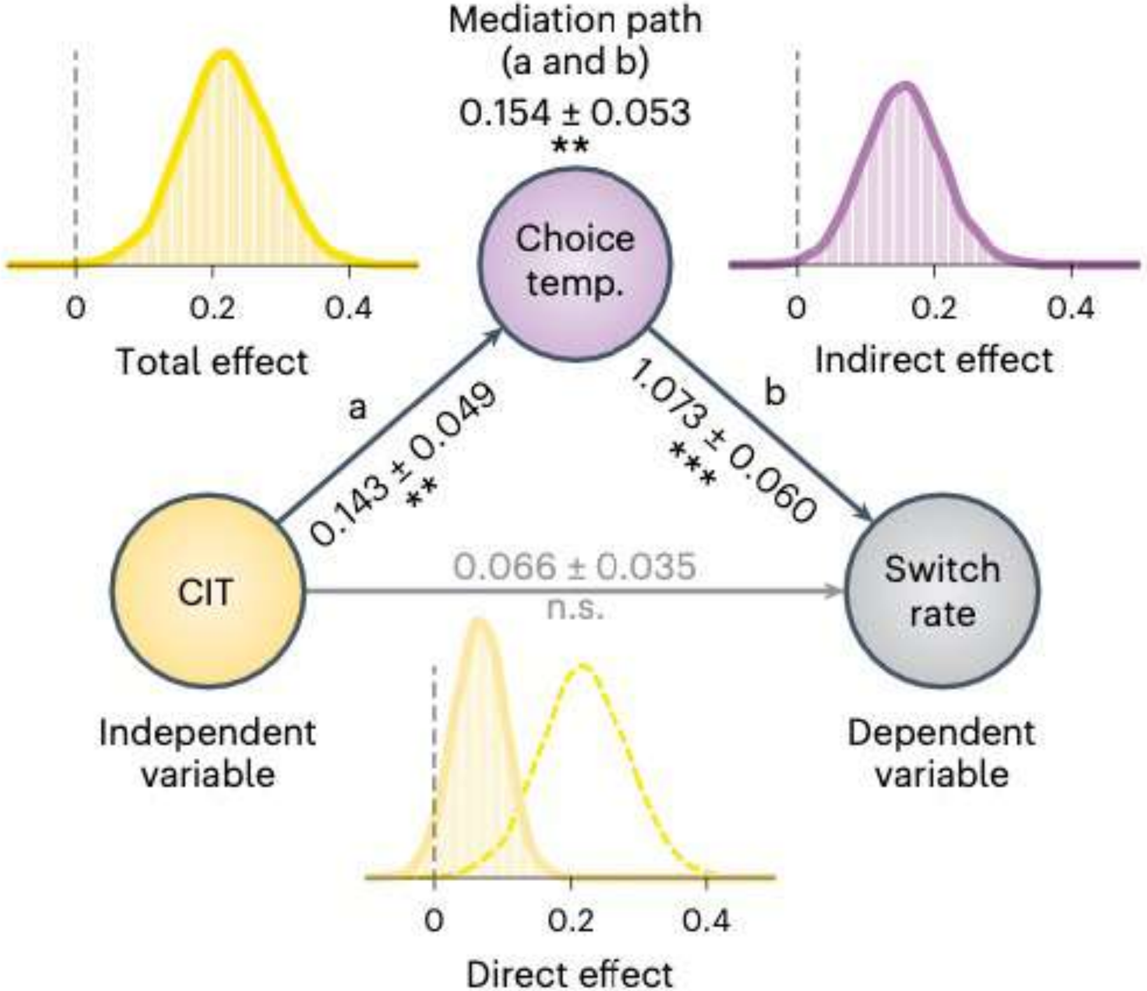


Modeling guidelines

sample 2



Modeling guidelines



Modeling guidelines

- Model latent variable estimation: finding the hidden variables x_i computed by the model that best account for the observed behavior

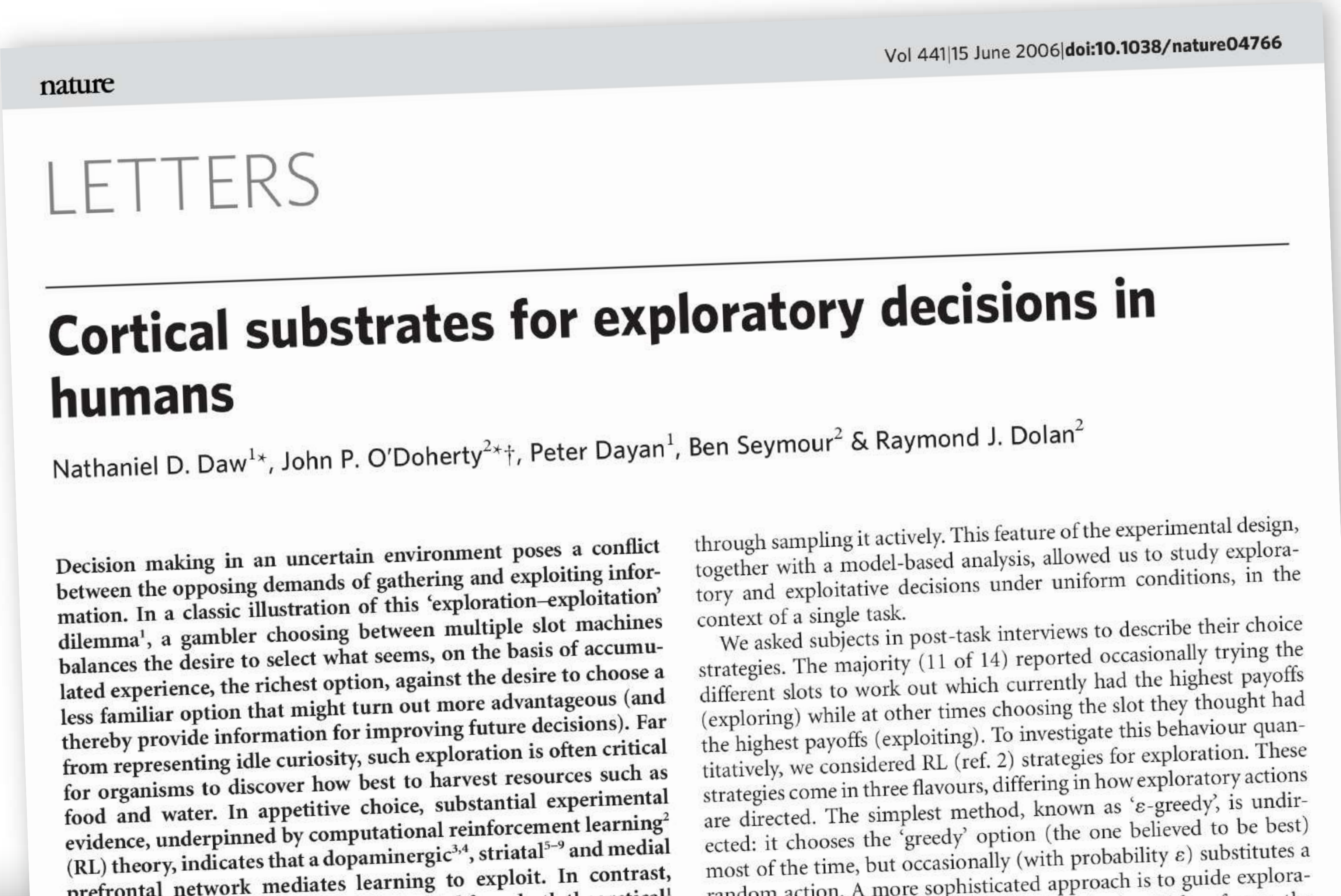
- Hidden variables x_i can be used to validate specific aspects of the model using additional observables (e.g., physiological data).

- Hidden variables x_i are often used to identify neural correlates of the model.
  Remember what <u>reverse inference</u> means?

Modeling guidelines

- Example: the multi-armed bandit task

Modeling guidelines



nature

Vol 441|15 June 2006|doi:10.1038/nature04766

LETTERS

Cortical substrates for exploratory decisions in humans

Nathaniel D. Daw[1*], John P. O'Doherty[2*†], Peter Dayan[1], Ben Seymour[2] & Raymond J. Dolan[2]

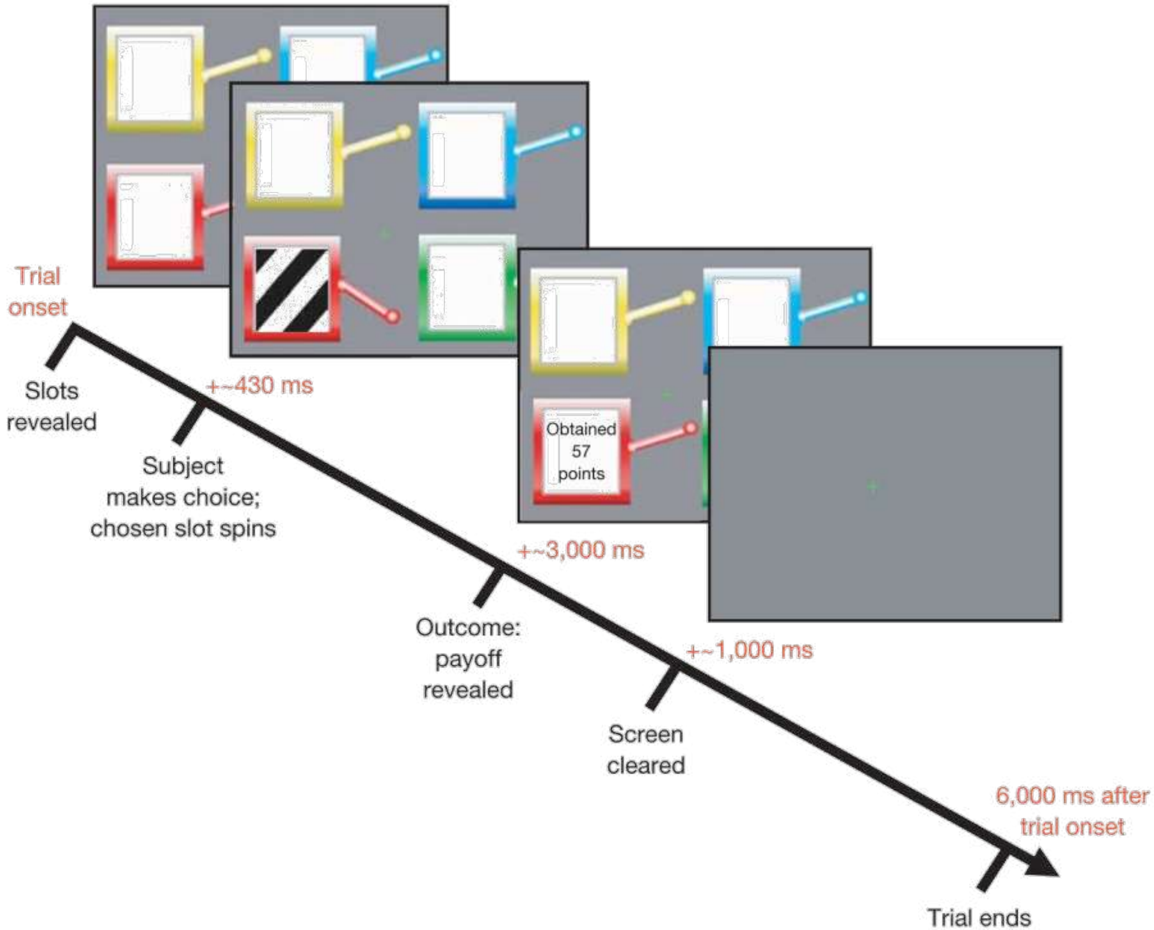
Decision making in an uncertain environment poses a conflict between the opposing demands of gathering and exploiting information. In a classic illustration of this 'exploration–exploitation' dilemma[1], a gambler choosing between multiple slot machines balances the desire to select what seems, on the basis of accumulated experience, the richest option, against the desire to choose a less familiar option that might turn out more advantageous (and thereby provide information for improving future decisions). Far from representing idle curiosity, such exploration is often critical for organisms to discover how best to harvest resources such as food and water. In appetitive choice, substantial experimental evidence, underpinned by computational reinforcement learning[2] (RL) theory, indicates that a dopaminergic[3,4], striatal[5–9] and medial prefrontal network mediates learning to exploit. In contrast,

through sampling it actively. This feature of the experimental design, together with a model-based analysis, allowed us to study exploratory and exploitative decisions under uniform conditions, in the context of a single task.

We asked subjects in post-task interviews to describe their choice strategies. The majority (11 of 14) reported occasionally trying the different slots to work out which currently had the highest payoffs (exploring) while at other times choosing the slot they thought had the highest payoffs (exploiting). To investigate this behaviour quantitatively, we considered RL (ref. 2) strategies for exploration. These strategies come in three flavours, differing in how exploratory actions are directed. The simplest method, known as 'ε-greedy', is undirected: it chooses the 'greedy' option (the one believed to be best) most of the time, but occasionally (with probability ε) substitutes a random action. A more sophisticated approach is to guide explora-

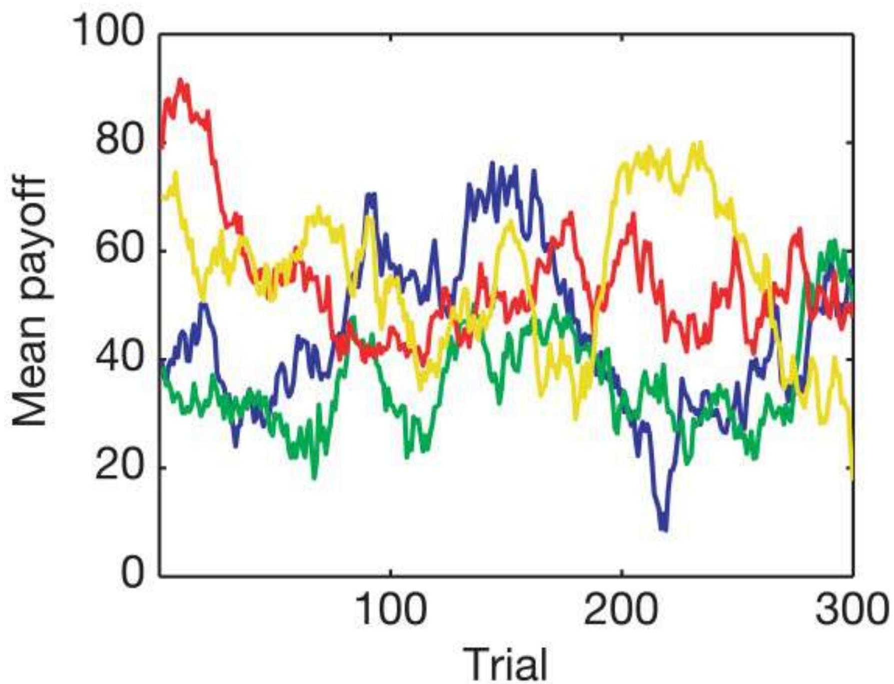
Modeling guidelines

- <u>Example:</u> the multi-armed bandit task



Modeling guidelines

- <u>Example:</u> the multi-armed bandit task



Modeling guidelines

- Example: the multi-armed bandit task

We compared the fit of three distinct RL models, embodying the aforementioned strategies, to our subjects' behavioural choices. All the models learned the values of actions with the use of a Kalman filter (see Supplementary Methods), an error-driven prediction algorithm that generalizes the temporal-difference learning algorithm (used in most RL theories of dopamine) by also tracking uncertainty about the value of each action. The models differed only in their choice rules. We compared models by using the likelihood of the subjects' choices given their experience, optimized over free parameters. This comparison (Supplementary Tables 1 and 2) revealed strong evidence for value-sensitive (softmax) over undirected (ε-greedy) exploration. There was no evidence to justify the introduction of an extra parameter that allowed exploration to be directed towards uncertainty (softmax with an uncertainty bonus): at optimal fit, the bonus was negligible, making the model equivalent to the simpler softmax. We conducted additional model fits (see Supplementary Information) to verify that these findings were not an artefact of our assumptions about the yoking of free parameters between subjects.

Modeling guidelines

- Example: the multi-armed bandit task
- What was done by the authors?
  - ✓ model simulation?

Modeling guidelines

- Example: the multi-armed bandit task
- What was done by the authors?
  - ✓ ~~model simulation?~~ **NO**
  - ✓ model fitting? YES
  - ✓ model comparison? YES
  - ✓ model parameter estimation? YES

Modeling guidelines

- Example: the multi-armed bandit task

Having characterized subjects' behaviour computationally, we used the best-fitting softmax model to generate regressors containing value predictions, prediction errors and choice probabilities for each subject on each trial. We used statistical parametric mapping to identify brain regions in which neural activity was significantly correlated with the model's internal signals. Consistent with previous studies[7–9] was our observation that a prediction error was correlated significantly with activity in both the ventral and dorsal striatum (see Supplementary Table 3).

Modeling guidelines

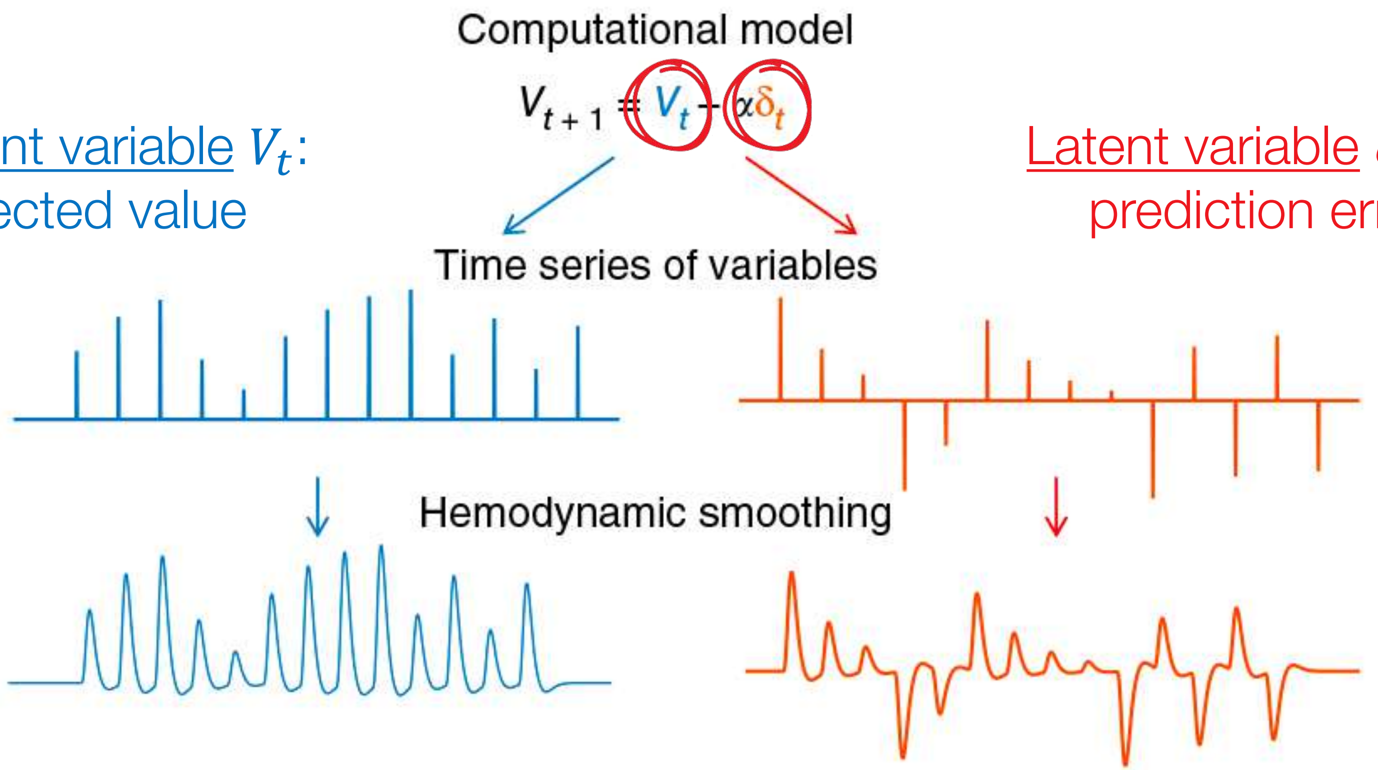
- Example: the multi-armed bandit task
- What was done by the authors?
  - ✓ ~~model simulation?~~ **NO**
  - ✓ model fitting? YES
  - ✓ model comparison? YES
  - ✓ model parameter estimation? YES
  - ✓ model latent variable estimation? YES

Modeling guidelines

- Example: the multi-armed bandit task

Latent variable V_t:
expected value

Latent variable δ_t:
prediction error



Modeling guidelines

- Example: the multi-armed bandit task

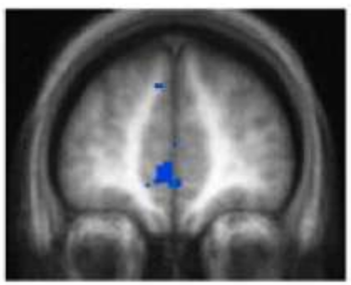
Computational model

$$V_{t+1} = V_t + \alpha\delta_t$$

Latent variable V_t: expected value

Latent variable δ_t: prediction error

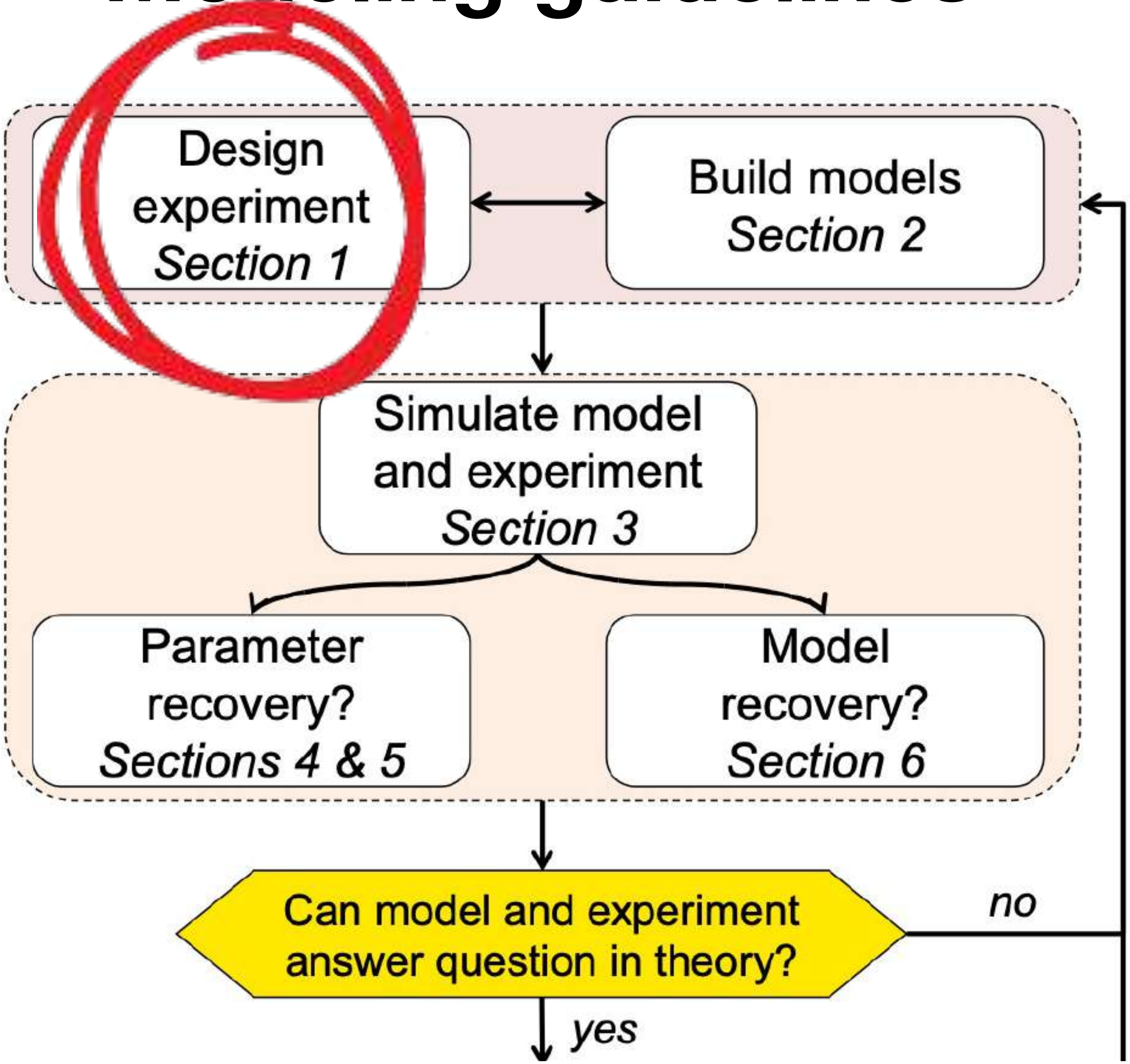
Correlated regions



ventromedial prefrontal cortex

ventral striatum

Modeling guidelines

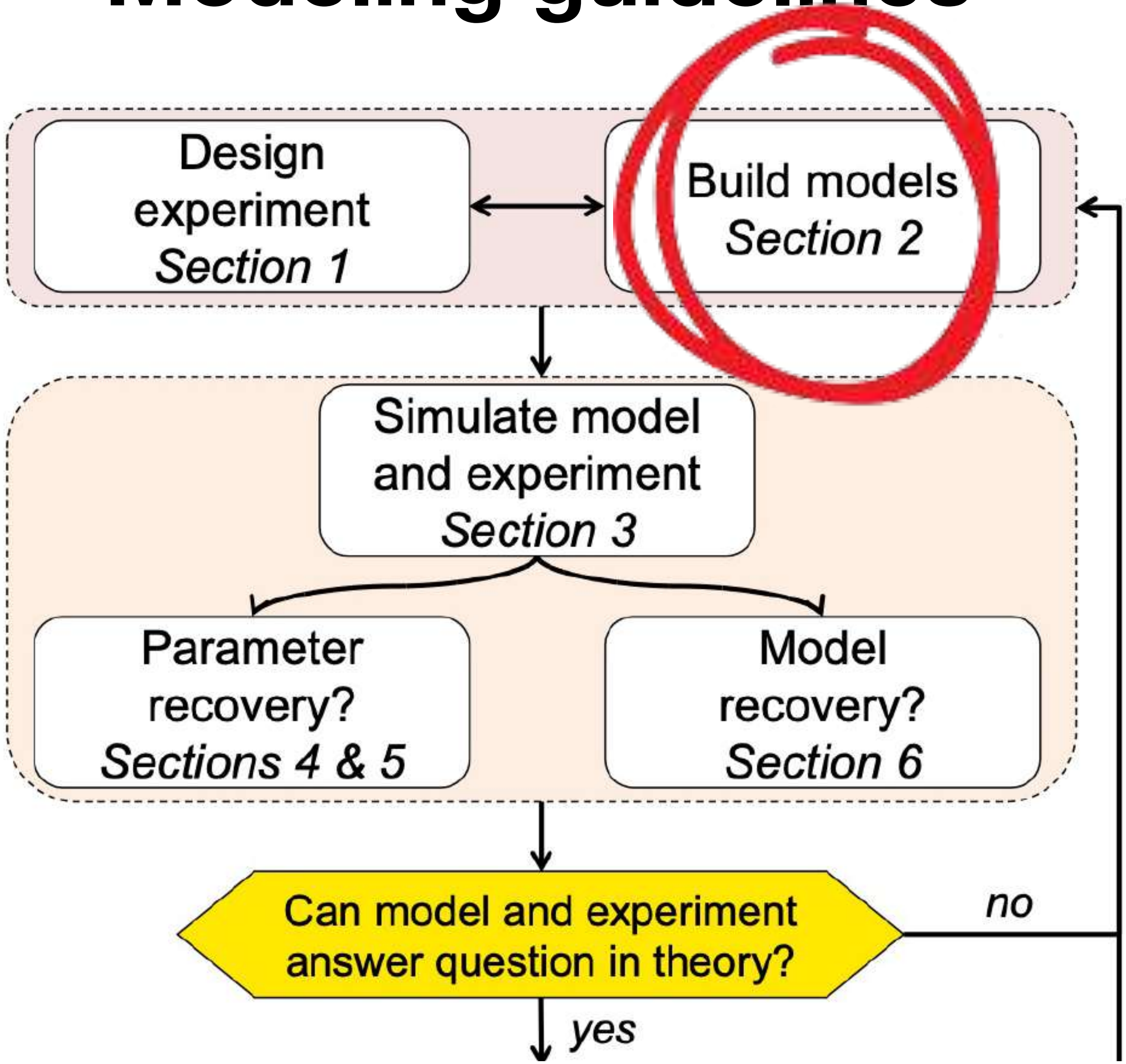


Modeling guidelines

Box 2. Example: simulating behavior in the bandit task.

To simulate behavior, we first need to define the parameters of the task. These include the total number of trials, T (=1000 in the example), as well as the number of bandits, $K (= 2)$, and the reward probability for each bandit, μ^k (0.2 and 0.8 for bandits 1 and 2, respectively). The experiment parameters, as used in the simulation, should match the actual parameters used in the experiment.

Modeling guidelines



Modeling guidelines

Box 2. Example: simulating behavior in the bandit task.

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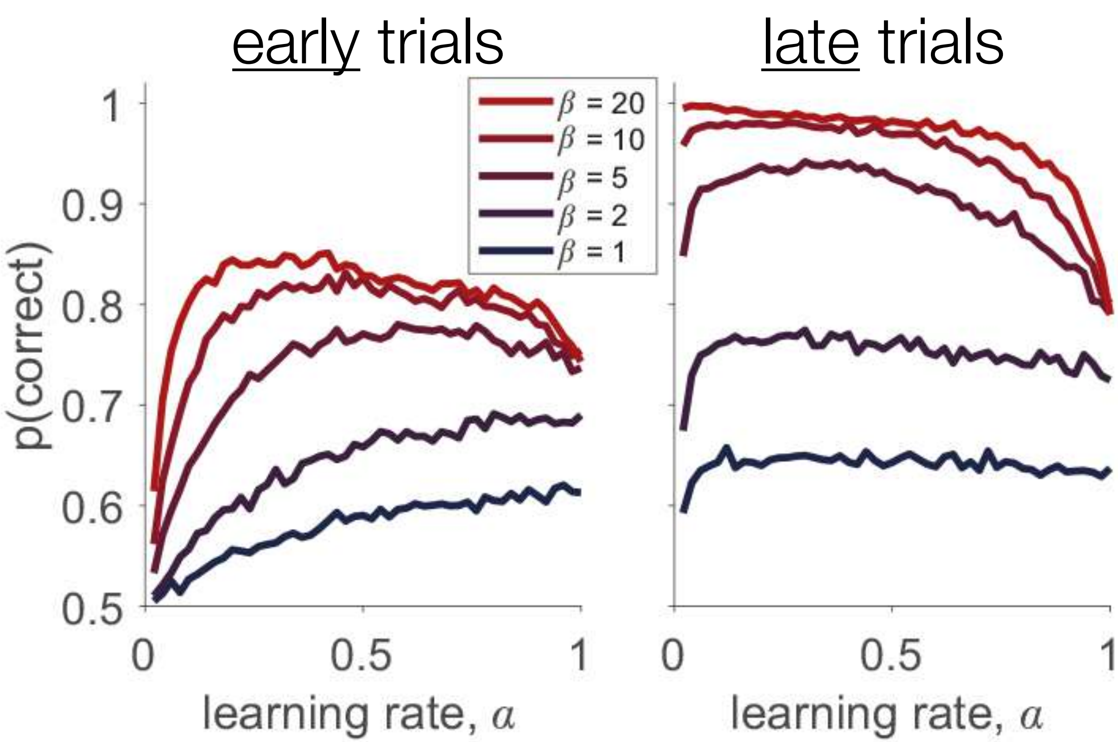
Box 1. Example: Modeling behavior in the multi-armed bandit task.

We consider five different models of how participants could behave in the multi-armed bandit task.

Model 1: Random responding
Model 2: Noisy win-stay-lose-shift
Model 3: Rescorla Wagner
Model 4: Choice kernel
Model 5: Rescorla Wagner + choice kernel

Modeling guidelines

- Simulate TD-based RL in the bandit task with K = 2 arms and fixed reward probabilities



Modeling guidelines

- Simulate TD-based RL in the bandit task with $K = 2$ arms and fixed reward probabilities

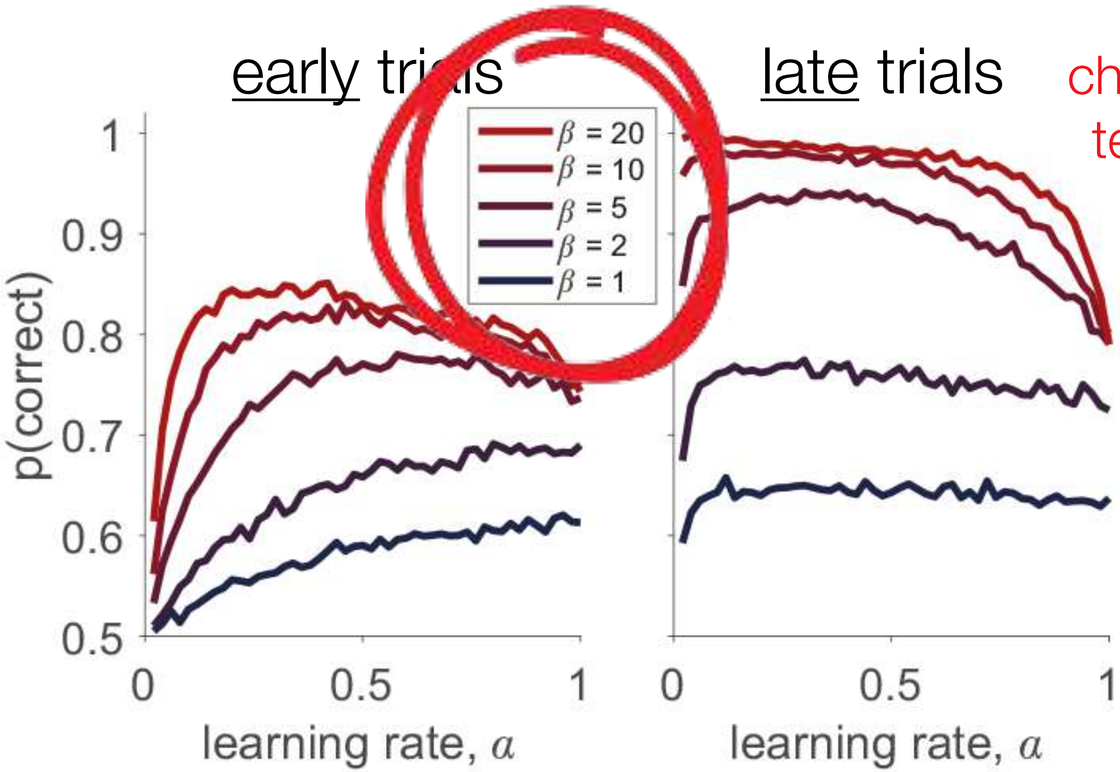
- Questions:
  1/ what behavioral feature?
  2/ what are the axes and the different curves?
  3/ what are the two panels showing?

- What is the relation between model parameters and performance in this bandit task?

Modeling guidelines

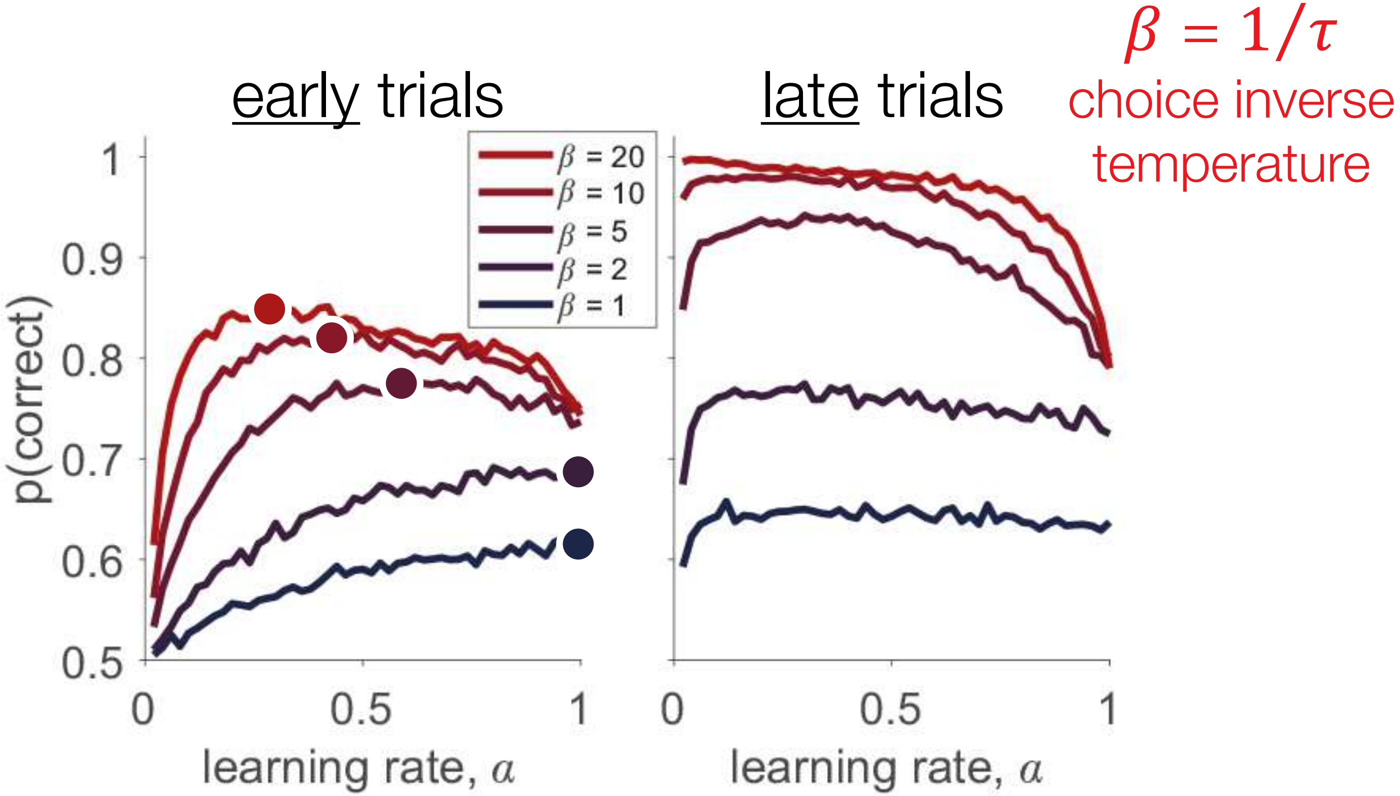
- Simulate TD-based RL in the bandit task with $K = 2$ arms and fixed reward probabilities

$\beta = 1/\tau$
choice inverse temperature



Modeling guidelines

- Simulate TD-based RL in the bandit task with K = 2 arms and fixed reward probabilities



Modeling guidelines

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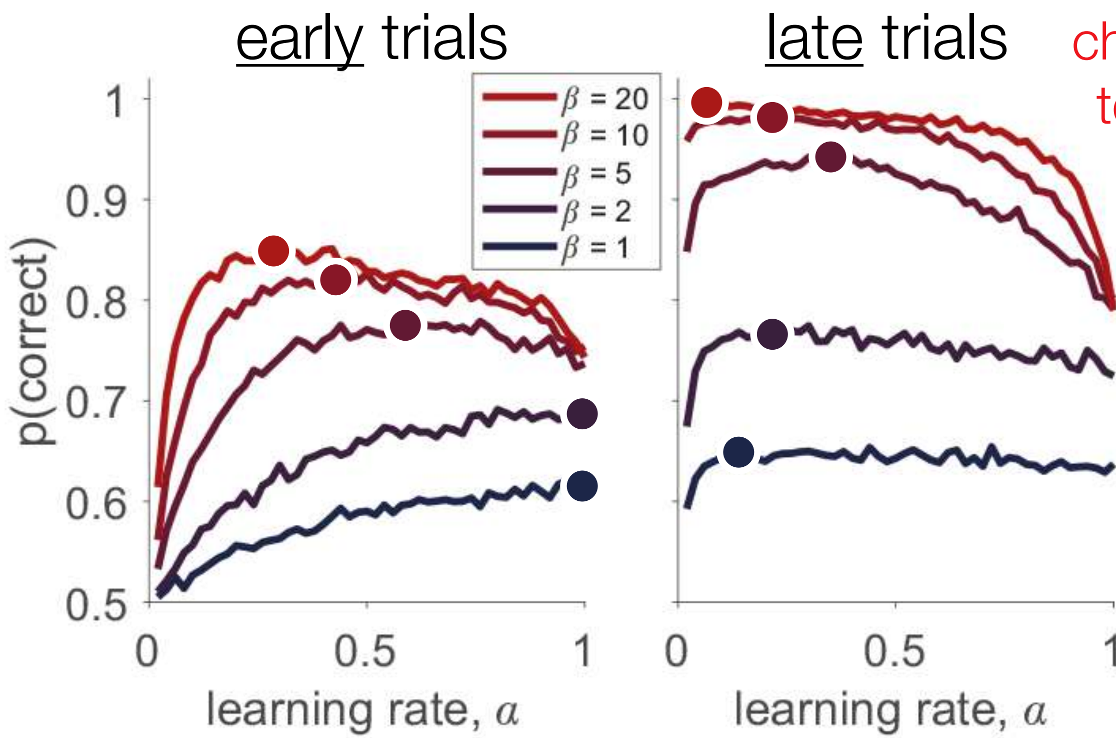


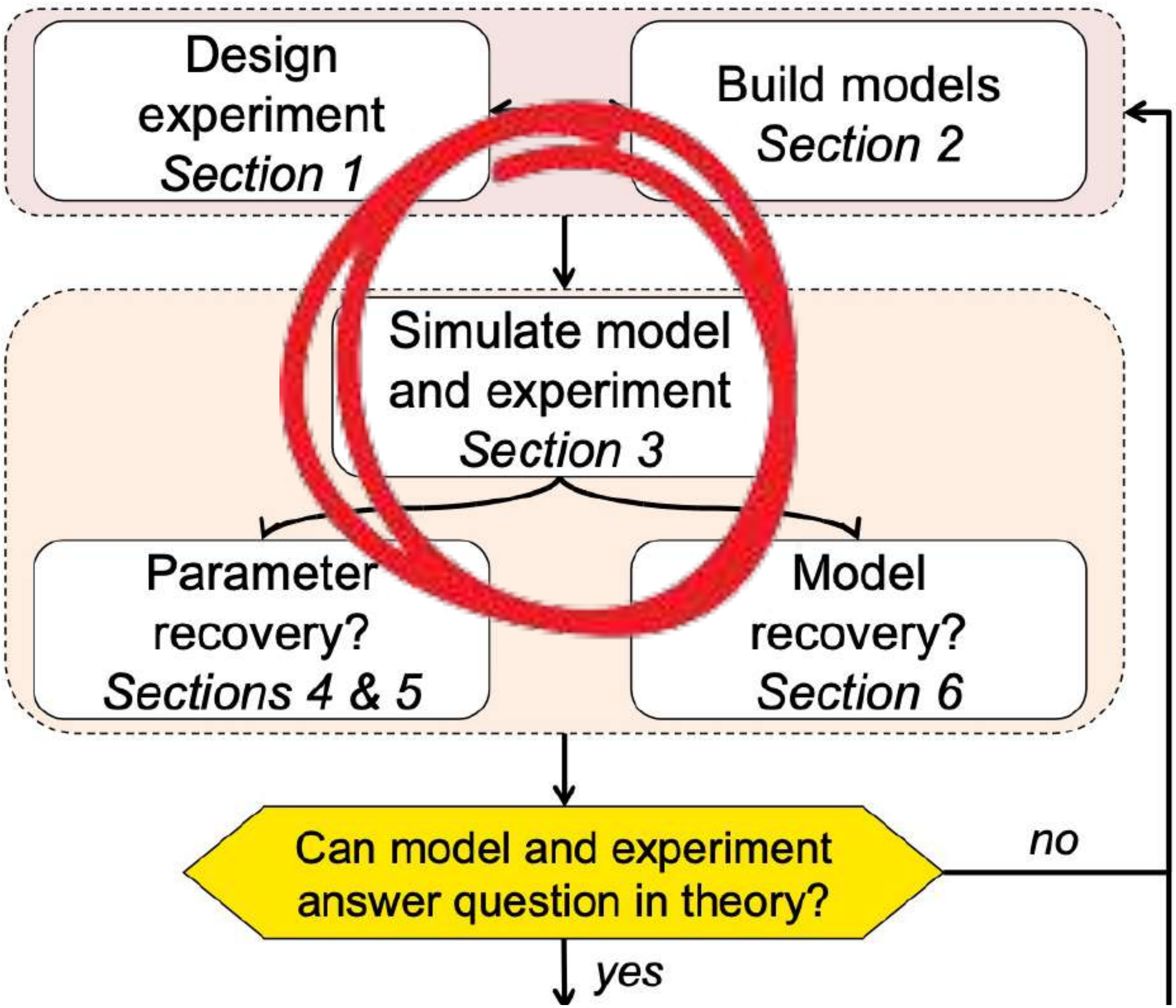
Modeling guidelines

- Simulate TD-based RL in the bandit task with $K = 2$ arms and fixed reward probabilities

- p(correct) increases monotonically with β
  Conclusion: a 'greedy' policy ($\beta \rightarrow \infty$) yields better performance in this bandit task.

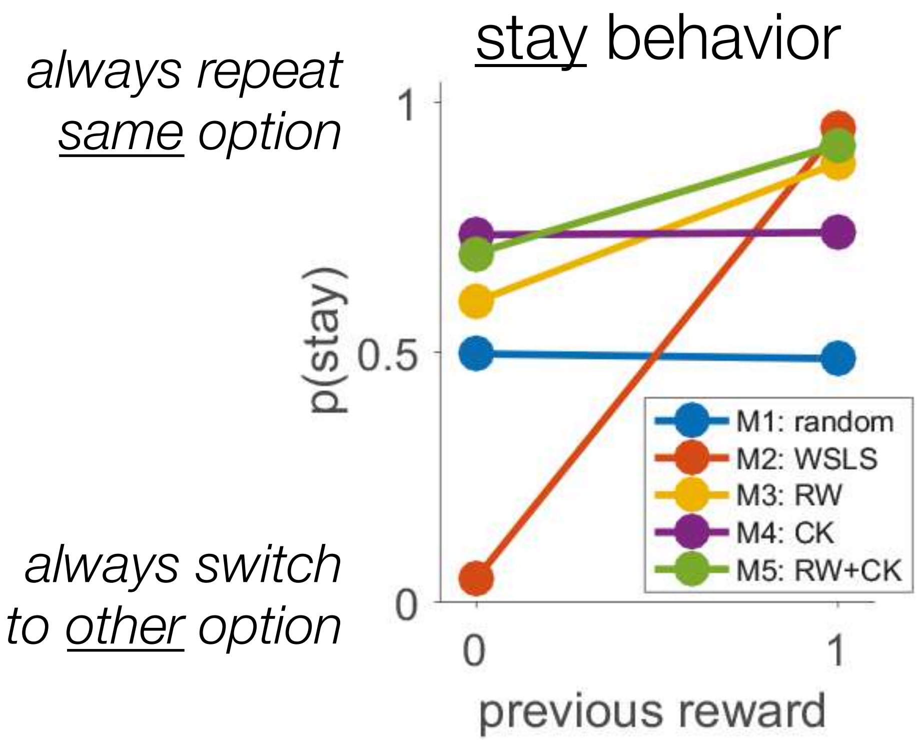
- The best learning rate α depends on β, and differently so, in early vs late trials!
  Conclusion: greedy agents should learn differently than exploratory agents in this bandit task.

Modeling guidelines



Modeling guidelines

- Simulate TD-based RL in the bandit task with K = 2 arms and fixed reward probabilities



Modeling guidelines

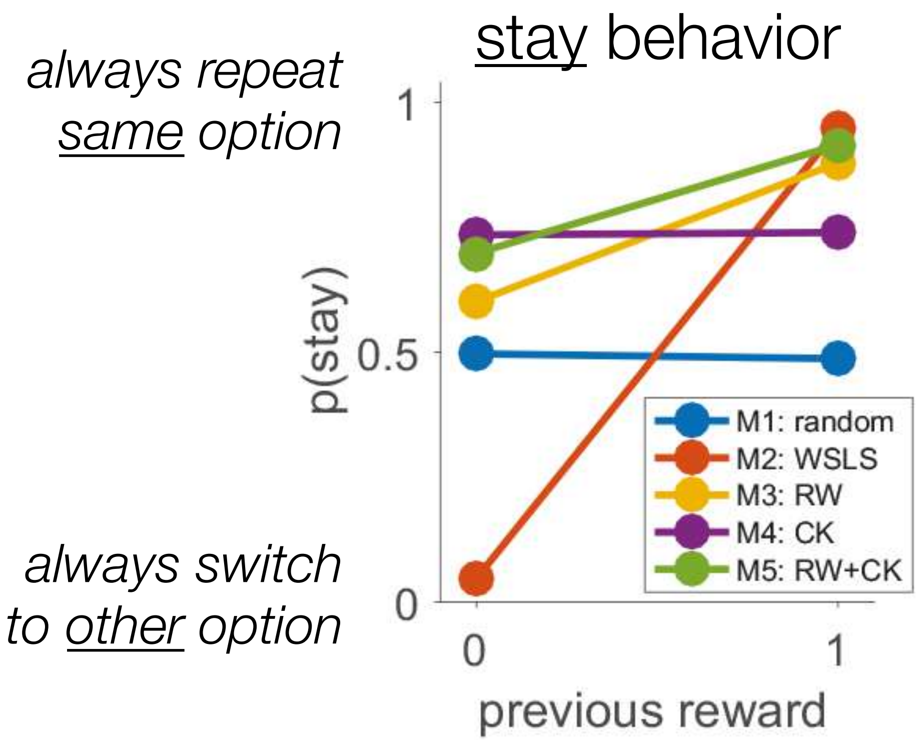
- Simulate TD-based RL in the bandit task with $K = 2$ arms and fixed reward probabilities

- Questions:
  1/ do models differ? how?
  2/ are all models influenced by reward? why?
  3/ what is set arbitrarily to make this figure?

- How is M1 (random responding) related to all other models? How is M5 related to M3/M4?

Modeling guidelines

- Simulate TD-based RL in the bandit task with $K = 2$ arms and fixed reward probabilities



Modeling guidelines

- Model simulations are useful to:
  - ✓ check that candidate models make different predictions in the same task
  - ✓ choose task variables (e.g., difficulty)
- What controls difficulty in <u>this</u> bandit task?
- Why is it important that <u>all</u> model parameters affect behavioral predictions?
- Why is it important that <u>all</u> candidate models make different behavioral predictions?

Coming next

- Practical session: today, 2.00pm, same room

- Paper to read:
  Peterson et al. (2021) Using large-scale experiments and machine learning to discover theories of human decision-making. *Science*
  https://doi.org/10.1126/science.abe2629 (open-access)

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