

Cracking computational modelling with Stan II: A principled Bayesian workflow

Lei Zhang

Social, Cognitive and Affective Neuroscience Unit (SCAN-Unit)
Department of Cognition, Emotion, and Methods in Psychology

Faculty of Psychology, University of Vienna

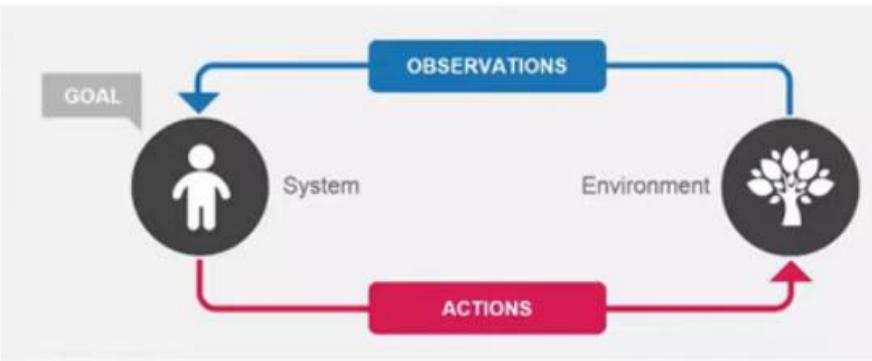
May 06, 2020

https://github.com/lei-zhang/OS_tutorial_webinar

lei.zhang@univie.ac.at
lei-zhang.net
@lei_zhang_lz



Last time...



The diagram illustrates a reinforcement learning loop. It features two main components: 'System' (represented by a person icon) and 'Environment' (represented by a tree icon). A blue arrow labeled 'OBSERVATIONS' points from the Environment to the System. A red arrow labeled 'ACTIONS' points from the System to the Environment. A grey box labeled 'GOAL' has a downward arrow pointing to the System.

Cracking computational modelling with Stan:
Using Rescorla-Wagner model as an example

Lei Zhang
Social, Cognitive and Affective Neuroscience Unit (SCAN-Unit)
Department of Cognition, Emotion, and Methods in Psychology
Faculty of Psychology, University of Vienna
April 10, 2020
https://github.com/lei-zhang/RL_tutorial_webinar

lei.zhang@univie.ac.at
lei-zhang.net
@lei_zhang_lz

0:16 / 1:27:32

universität wien

直播分享：强化学习模型在Stan中的实现

Outline

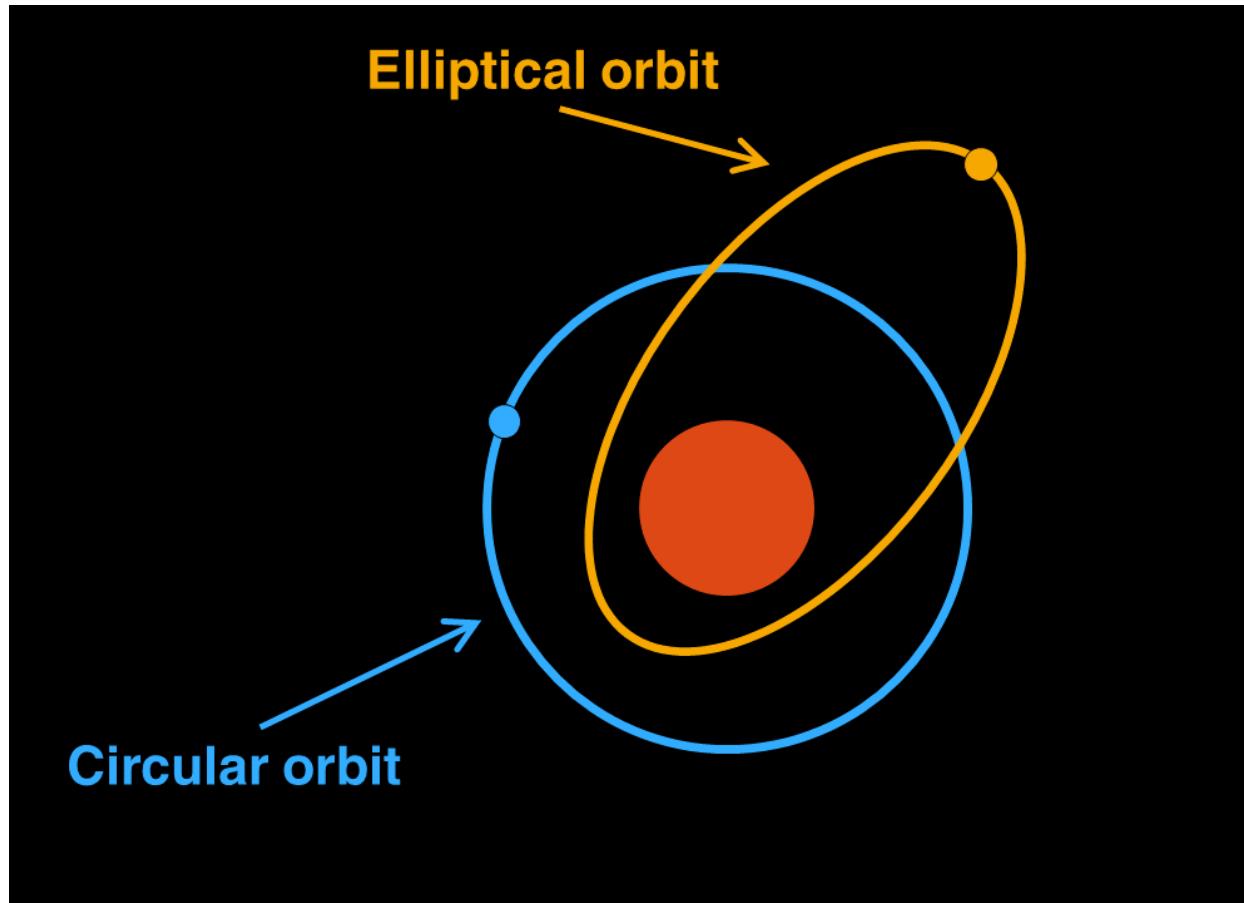
- Motivation (recap)
- A computational psychiatry example
- A Bayesian workflow (conceptual)
- A Bayesian workflow (practical)
- Summary

Outline

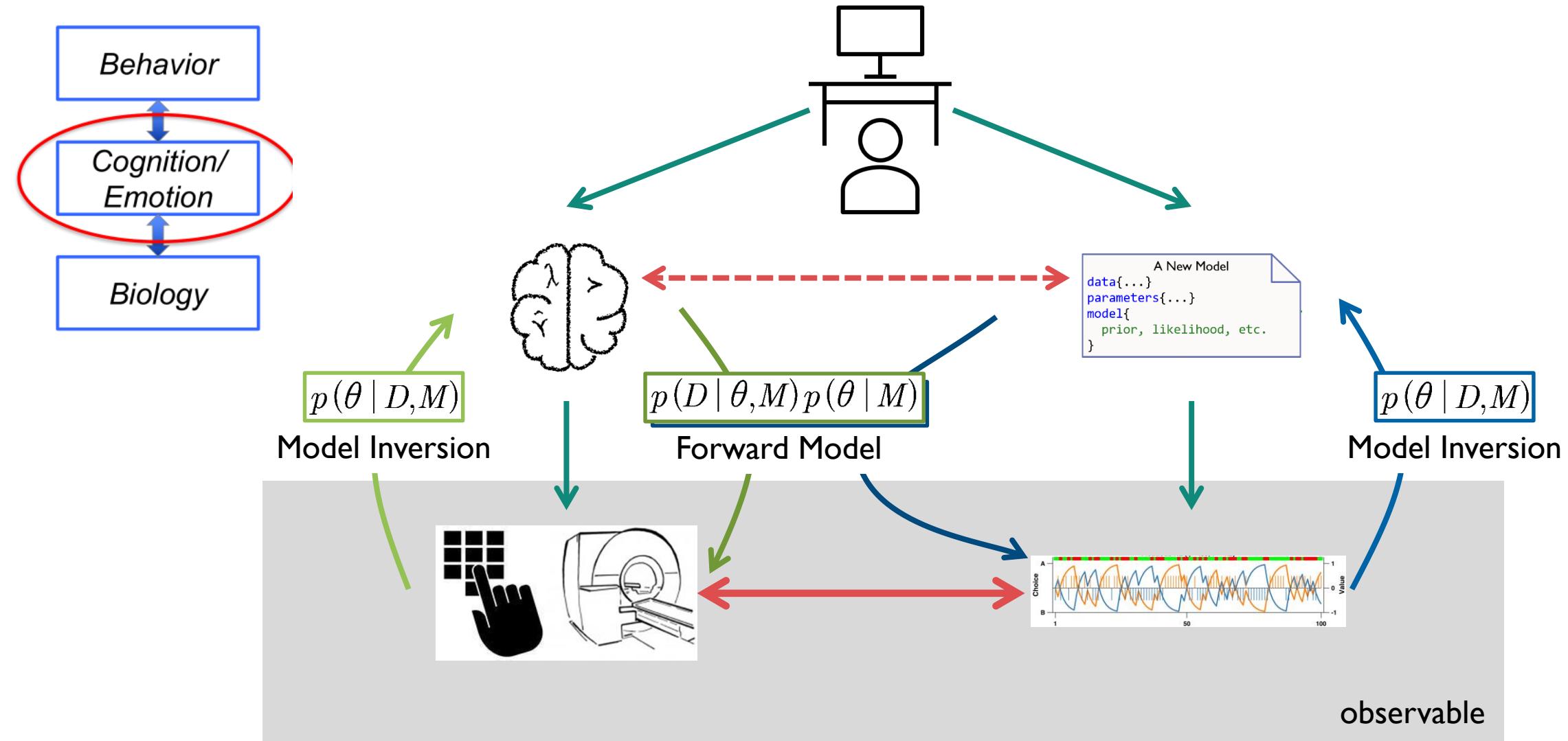
- Motivation (recap)
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The idea of computational modeling is never new

Scientists use mathematical models to approximate certain processes (physical or mental), in order to explain and to predict.



Computational modeling of Cognition



Very recent examples

REPORT

Dopamine promotes cognitive effort by biasing the benefits versus costs of cognitive work

A. Westbrook^{1,2,3,*}, R. van den Bosch^{2,3}, J. I. Määttä^{2,3}, L. Hofmans^{2,3}, D. Papadopetraki^{2,3}, R. Cools^{2,3,†}, M. J. Frank^{1,4,†}

+ See all authors and affiliations

Science 20 Mar 2020:
Vol. 367, Issue 6484, pp. 1362-1366
DOI: 10.1126/science.aaz5891

Neuron

Available online 17 March 2020
In Press, Corrected Proof 



Article

A Neuro-computational Account of Arbitration between Choice Imitation and Goal Emulation during Human Observational Learning

Caroline J. Charpentier^{1, 2}  , Kiyohito ligaya¹, John P. O'Doherty¹

3 out of 4 focused on Reinforcement Learning models!

nature reviews
neuroscience

Review Article | Published: 12 March 2020

The neural and computational systems of social learning

Andreas Olsson , Ewelina Knapska & Björn Lindström

Nature Reviews Neuroscience 21, 197–212(2020) | Cite this article

Translational
Psychiatry

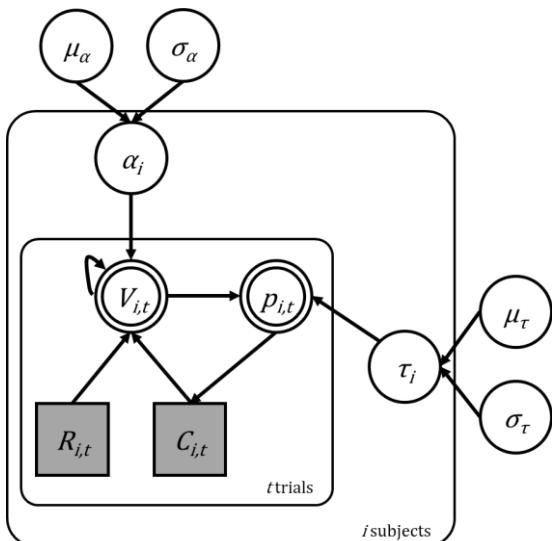
Article | Open Access | Published: 17 March 2020

Neurocomputational mechanisms underpinning aberrant social learning in young adults with low self-esteem

Geert-Jan Will , Michael Moutoussis, Palee M. Womack, Edward T. Bullmore, Ian M. Goodyer, Peter Fonagy, Peter B. Jones, NSPN Consortium, Robb B. Rutledge & Raymond J. Dolan

I like the idea of Modeling, ...

...but, ...



$$\mu_\alpha \sim Uniform(0,1)$$

$$\sigma_\alpha \sim halfCauchy(0,1)$$

$$\mu_\tau \sim Uniform(0,3)$$

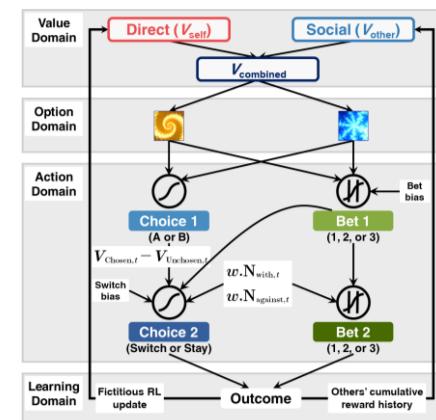
$$\sigma_\tau \sim halfCauchy(0,3)$$

$$\alpha_i \sim Normal(\mu_\alpha, \sigma_\alpha)_{\mathcal{T}(0,1)}$$

$$\tau_i \sim Normal(\mu_\tau, \sigma_\tau)_{\mathcal{T}(0,3)}$$

$$p_{i,t}(C = A) = \frac{1}{1 + e^{\tau_i(V_{i,t}(B) - V_{i,t}(A))}}$$

$$V_{i,t+1}^c = V_{i,t}^c + \alpha_i(R_{i,t} - V_{i,t}^c)$$



$V_{self,t}$	$= [V_{self,t}(A), V_{self,t}(B)]$
$V_{other,t}$	$= [V_{other,t}(A), V_{other,t}(B)]$
V_t	$= \beta_{self} V_{self,t} + \beta_{other} V_{other,t}$
$C1_t$	$\sim Categorical(Softmax(V_t))$
$U_{bet1,t}$	$= \beta_{bias_{self}} + \beta_{val_{diff}} (V_{chosen,C1,t} - V_{unchosen,C1,t})$
$B1_t$	$\sim OrderedLogistic(U_{bet1,t} \theta)$
$w.N_{against,t}$	$= \sum_{s=1}^K w_{s,t}, K = 0, 1, \dots, 4$
$w.N_{with,t}$	$= \frac{s-1}{4}, \sum_{s=1}^{4-K} w_{s,t}$
$V_t(\text{switch})$	$= \beta_{bias_{self}} + \beta_{val_{diff}} (V_{chosen,C1,t} - V_{unchosen,C1,t}) + \beta_{against} w.N_{against,t}$
$C2$	$\sim Bernoulli(V_t(\text{switch}))$
$U_{bet2,t}$	$= \begin{cases} U_{bet1,t} + \beta_{with_{self}} w.N_{with,t} + \beta_{against_{self}} w.N_{against,t}, & \text{if } C1 = C2 \\ U_{bet1,t} + \beta_{with_{self}} w.N_{with,t} + \beta_{against_{switch}} w.N_{against,t}, & \text{if } C1 \neq C2 \end{cases}$
$B2_t$	$\sim OrderedLogistic(U_{bet2,t} \theta)$
$\Phi(x)$	$= \frac{1}{1 + e^{-x}}$
$\delta_{self,chosen,C2,t}$	$= R_{self,t} - V_{self,chosen,C2,t}$
$\delta_{self,unchosen,C2,t}$	$= -R_{self,t} - V_{self,unchosen,C2,t}$
$V_{self,chosen,C2,t+1}$	$= V_{self,chosen,C2,t} + \alpha \delta_{self,chosen,C2,t}$
$V_{self,unchosen,C2,t+1}$	$= V_{self,unchosen,C2,t} + \alpha \delta_{self,unchosen,C2,t}$

Toward a easy-to-follow workflow

- We all are familiar with the workflow for simple factorial designs
 - e.g., a 2×2 design
 - run ANOVA or linear mixed model
 - examine main and interaction effects
- Is there any easy-to-use and reproducible workflow in computational modeling, under the Bayesian framework?

A scene from Star Trek: The Next Generation. Captain Jean-Luc Picard is seated at his console, looking towards the front of the bridge. Data, the android, stands to his right, pointing his hand towards a large, translucent projection of a starship on the main display screen. The projection shows the ship's hull, thrusters, and internal structures. The bridge is filled with various control panels and screens, typical of the Starfleet command center.

Including Bayesian
functions...

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Computational Psychiatry: a rapidly growing, highly multidisciplinary field

Trends in Cognitive Sciences

Volume 16, Issue 1, January 2012, Pages 72-80



Review

Special Issue: Cognition in Neuropsychiatric Disorders

Computational psychiatry

P. Read Montague^{1, 2}, Raymond J. Dolan², Karl J. Friston², Peter Dayan³

THE LANCET Psychiatry

Volume 1, Issue 2, July 2014, Pages 148-158



Review

Computational psychiatry: the brain as a phantastic organ

Prof Karl J Friston FRS^a, Prof Klaas Enno Stephan PhD^{a, b}, Prof Read Montague PhD^{a, c}, Prof Raymond J Dolan FRS^a

Viewpoint

April 24, 2019

The Two Cultures of Computational Psychiatry

Daniel Bennett, PhD¹; Steven M. Silverstein, PhD^{2,3}; Yael Niv, PhD^{1,4}

[» Author Affiliations](#) | [Article Information](#)

JAMA Psychiatry. 2019;76(6):563-564. doi:10.1001/jamapsychiatry.2019.0231

Neuron

Volume 84, Issue 3, 5 November 2014, Pages 638-654



Perspective

Computational Psychiatry

Xiao-Jing Wang^{1, 2, 3}, John H. Krystal^{3, 4, 5, 6}

nature neuroscience

Published: 23 February 2016

Computational psychiatry as a bridge from neuroscience to clinical applications

Quentin J M Huys[✉], Tiago V Maia & Michael J Frank

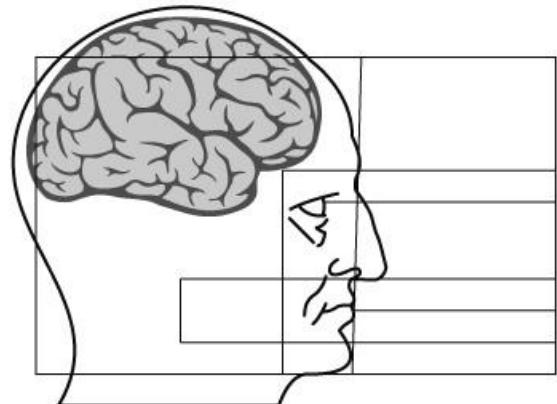
Molecular Psychiatry

News | Open Access | Published: 27 April 2018

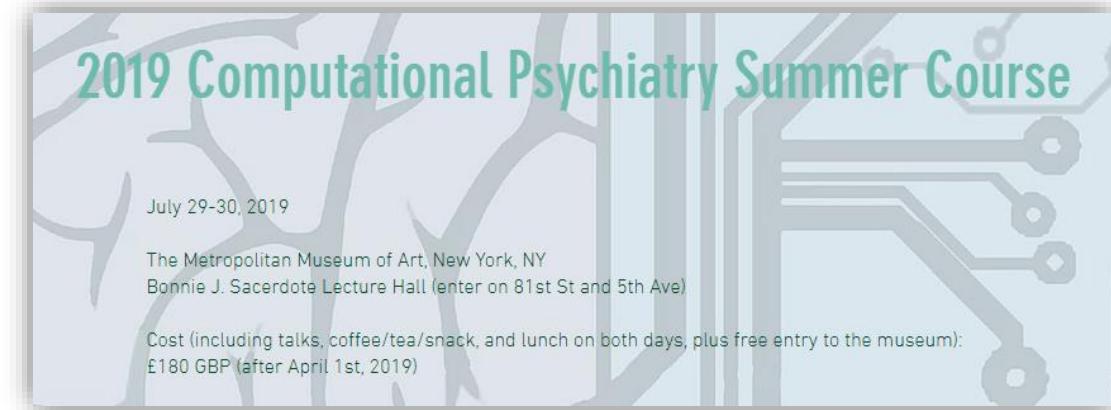
Computational psychiatry: a report from the 2017 NIMH workshop on opportunities and challenges

Michele Ferrante[✉], A. David Redish, Maria A. Oquendo, Bruno B. Averbeck, Megan E. Kinnane & Joshua A. Gordon

Computational Psychiatry



MAX PLANCK
UCL CENTRE
for Computational Psychiatry
and Ageing Research



Computational Psychiatry

Peter Dayan and Read Montague, Editors

Computational Psychiatry publishes original research articles and reviews that involve the application, analysis, or invention of theoretical, computational and statistical approaches to mental function and dysfunction. Topics include brain modeling over multiple scales and levels of analysis, and the use of these models to understand psychiatric dysfunction, its remediation, and the sustenance of healthy cognition through the lifespan. The journal also has a special interest in computational issues pertaining to related areas such as law and education.

Computational Psychiatry is an Open Access journal.

Visit computationalpsychiatry.org.

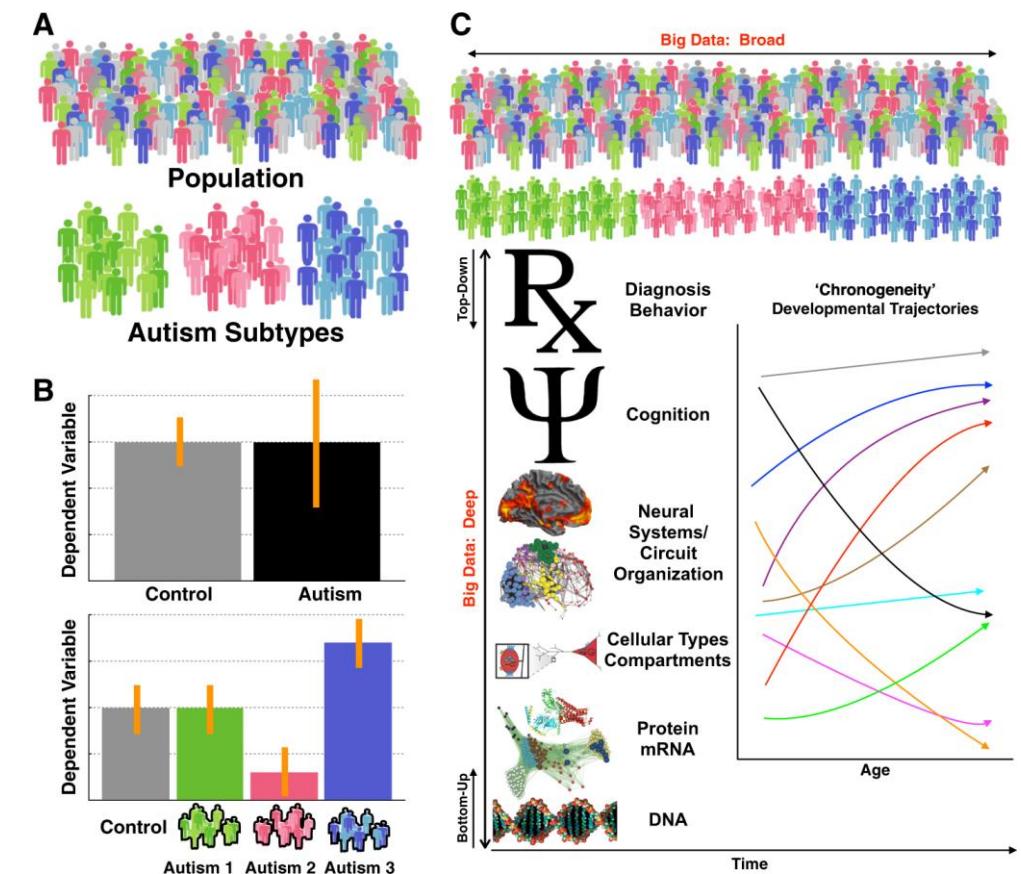
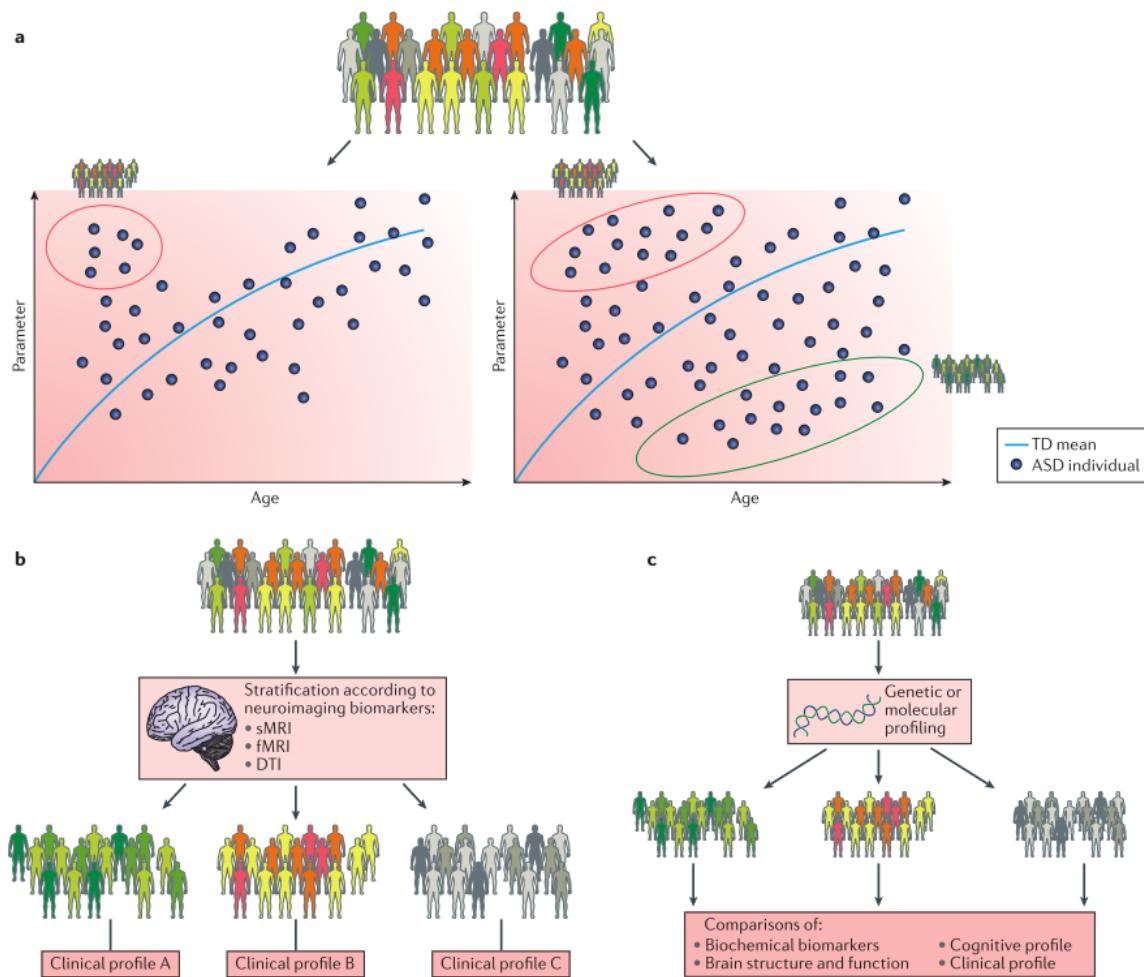
Continuous Publication
Founded: 2017
E-ISSN: 2379-6227



ABOUT THE CPC

This course is organized by the [Translational Neuromodeling Unit \(TNU\)](#), University of Zurich & ETH Zurich and is designed to provide students across fields (neuroscience, psychiatry, physics, biology, psychology....) with the necessary toolkit to master challenges in computational psychiatry research.

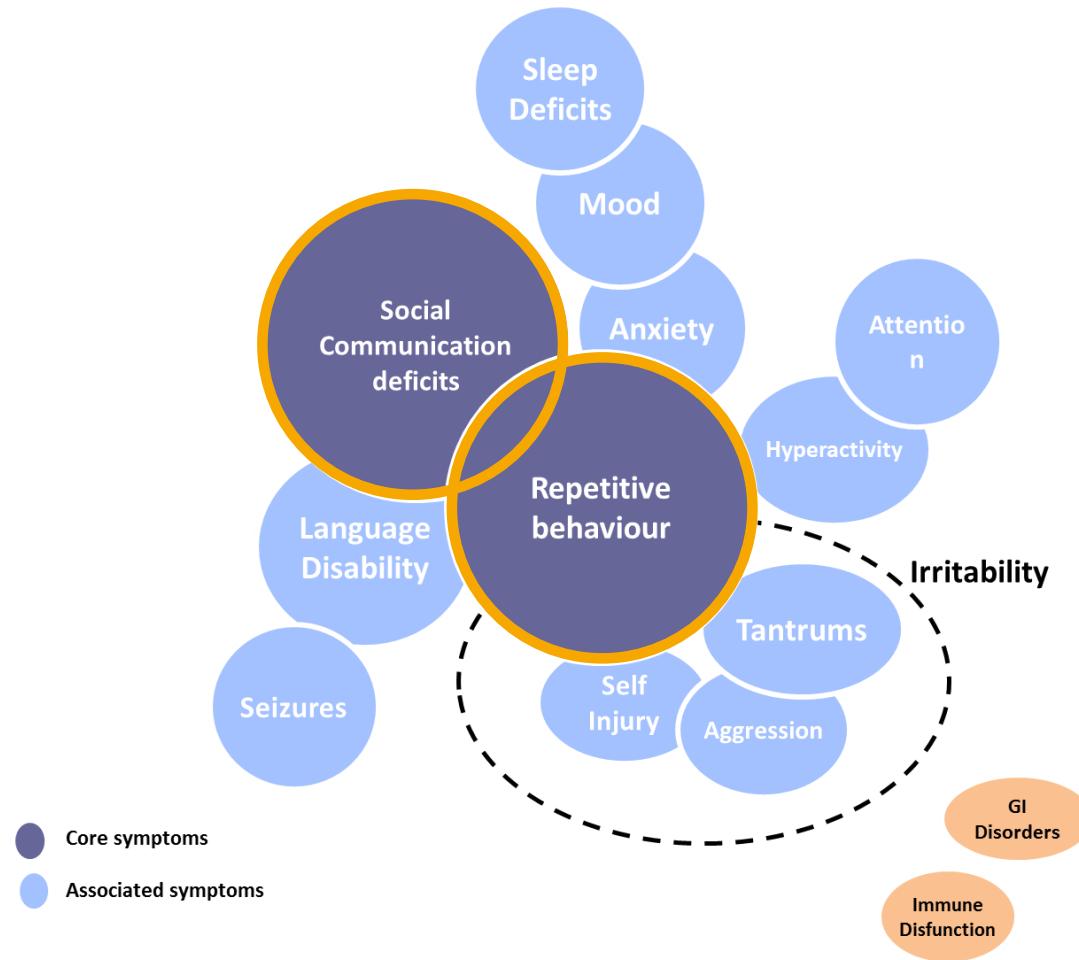
Autism spectrum disorder (ASD) as one example



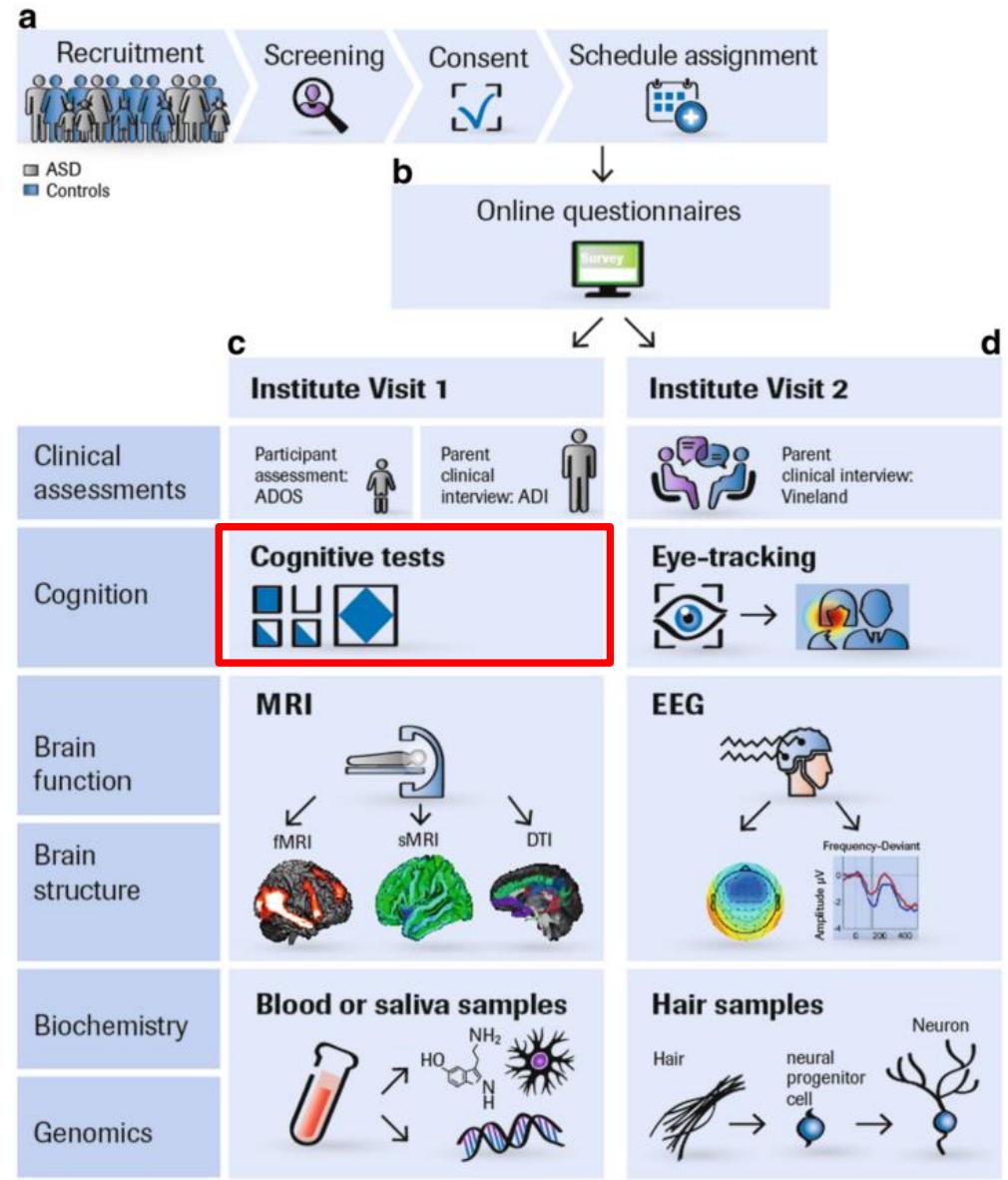
EU-AIMS



EU-AIMS



Loth et al. (2017)



Impaired cognitive flexibility

26

Review

TRENDS in Cognitive Sciences Vol.8 No.1 January 2004



Executive dysfunction in autism[☆]

Elisabeth L. Hill

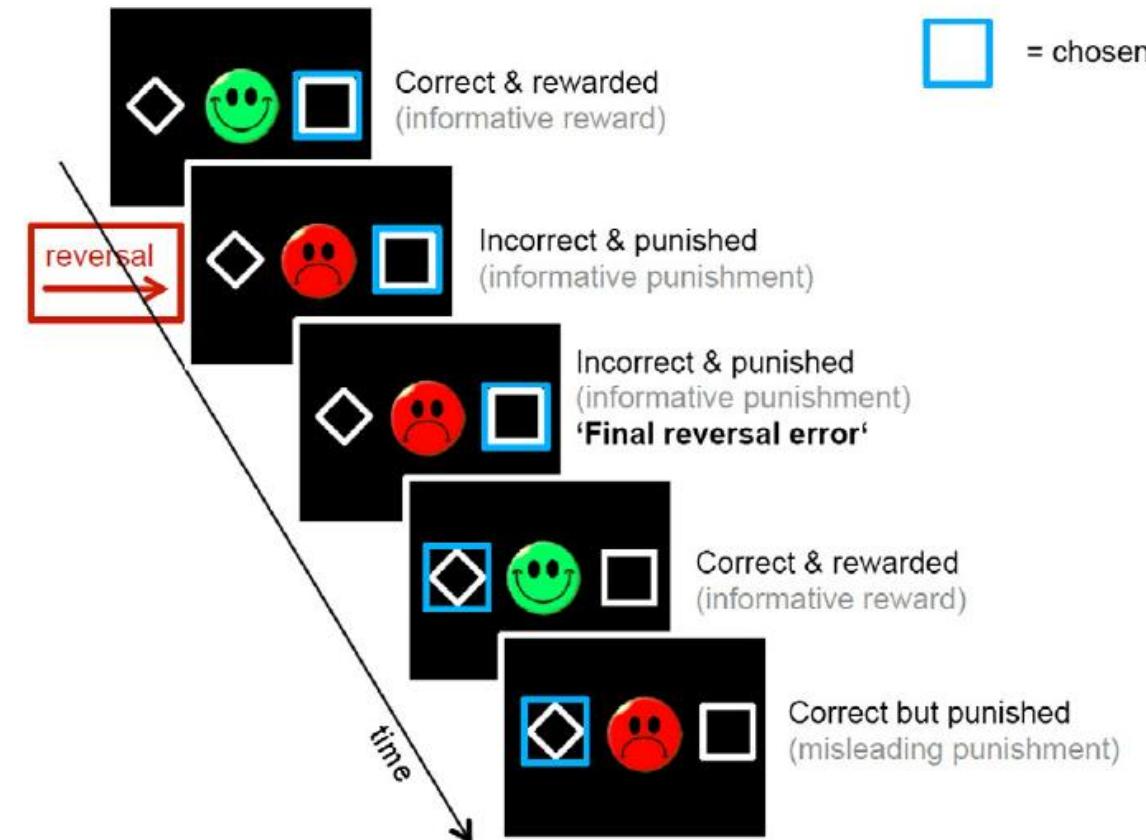
Department of Psychology, Goldsmiths College, University of London, Whitehead Building, New Cross, London, SE14 6NW, UK

- Behavioural rigidity may be underpinned by cognitive (in)flexibility
 - Repetitive motor movements
 - Insistence on **sameness**
 - **Inflexible** adherence to routines
 - Ritualised patterns of behaviour
 - **Difficulties with transitions**
 - **Rigid thinking patterns**
 - Restricted play
 - Circumscribed interests
- 'The ability to **shift between** different tasks or goals'
 - 'The ability to **shift** to different thoughts or actions **depending on situational demands**'
 - 'Capacity to **adjust** one's thoughts or actions **in response to** situational **changes**'

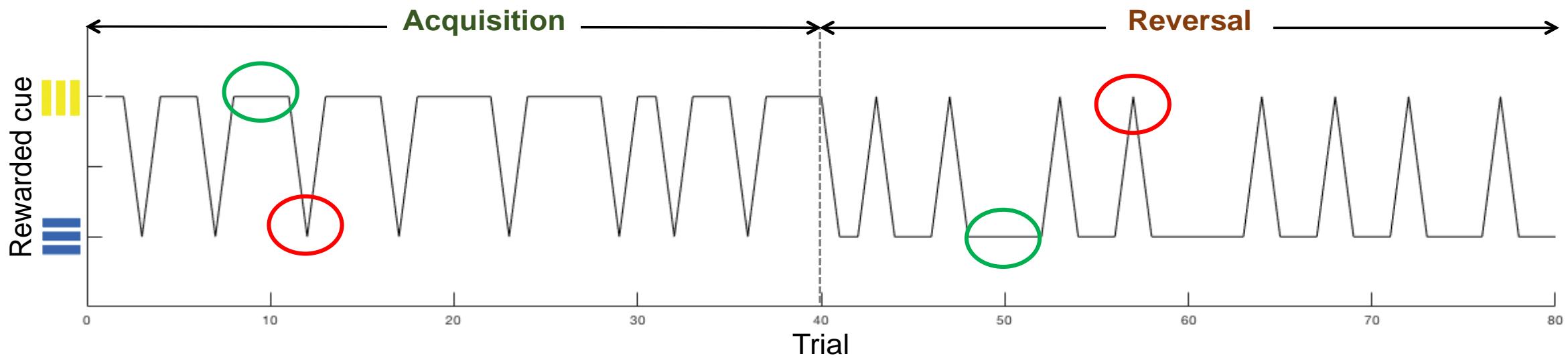
Cognitive flexibility studies

Probabilistic reversal learning (PRL) tasks

- Adapting behavior in response to changes in stimulus-reward contingencies (Cools et al., 2002)
 - Direct approach to assessing flexible choice behavior
- Varied error definitions & different age groups

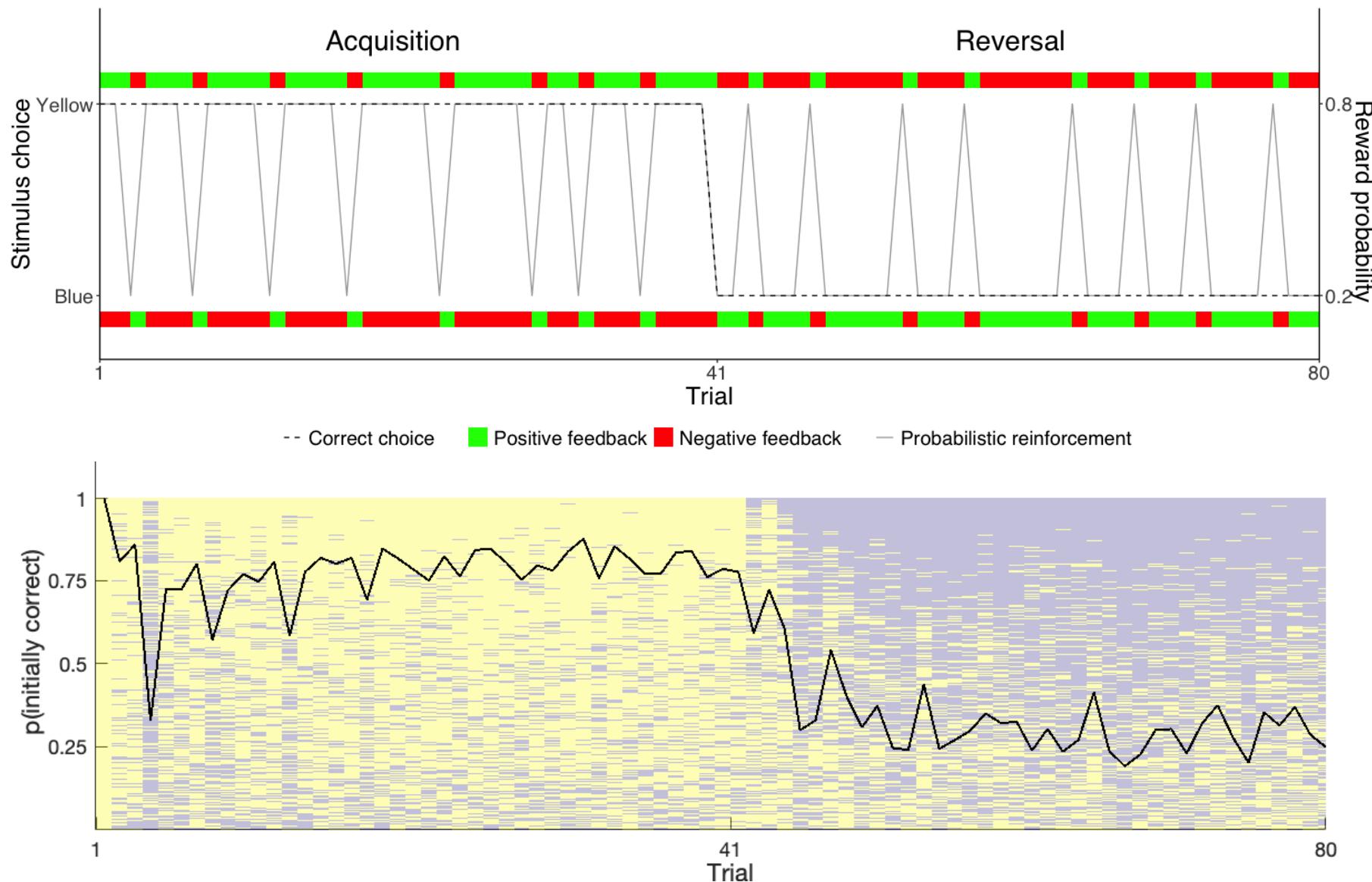


PRL task structure

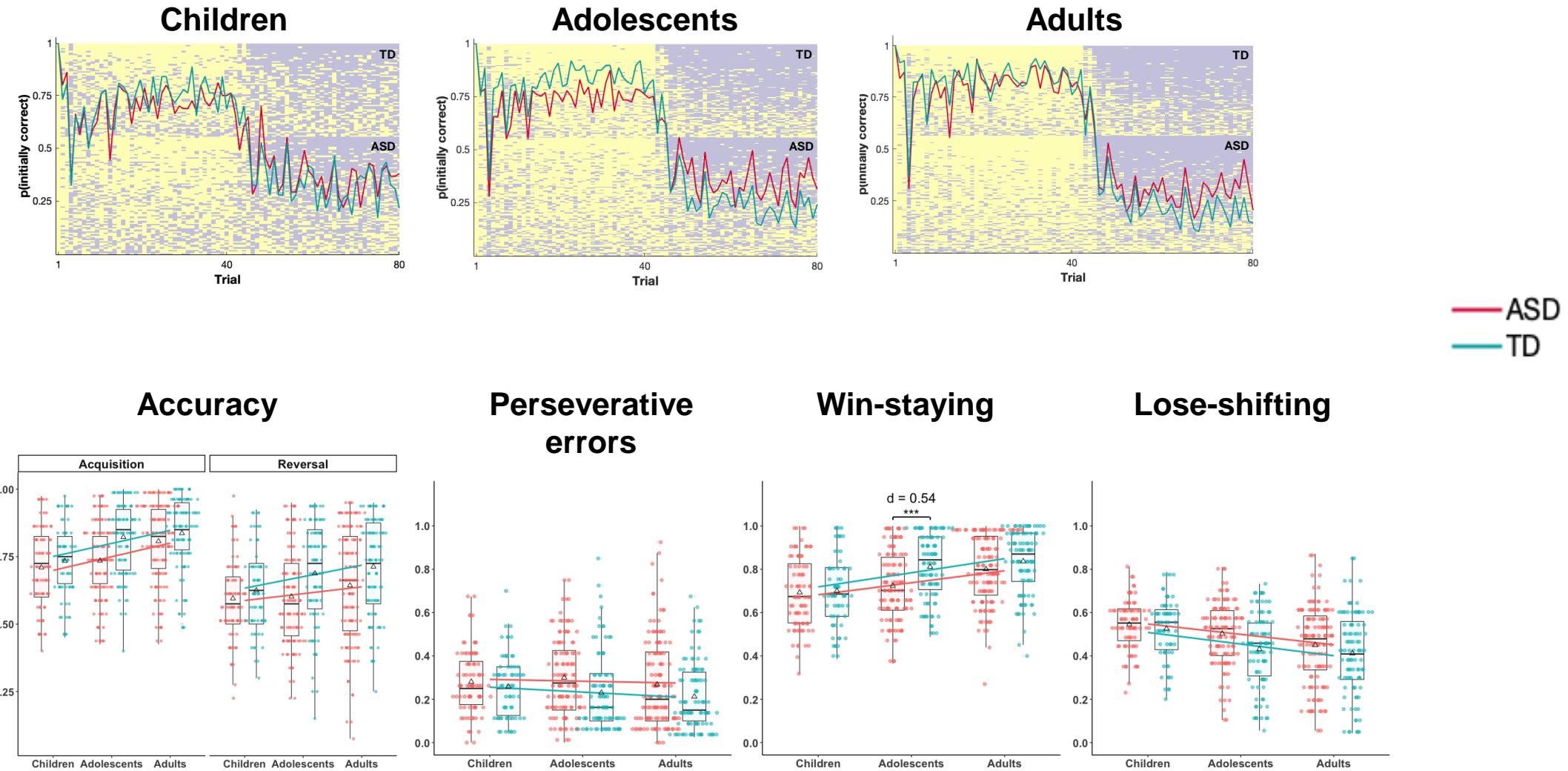


- Common outcome, needs to be learnt
- Rare outcome, needs to be ignored

Overall trial-wise performance

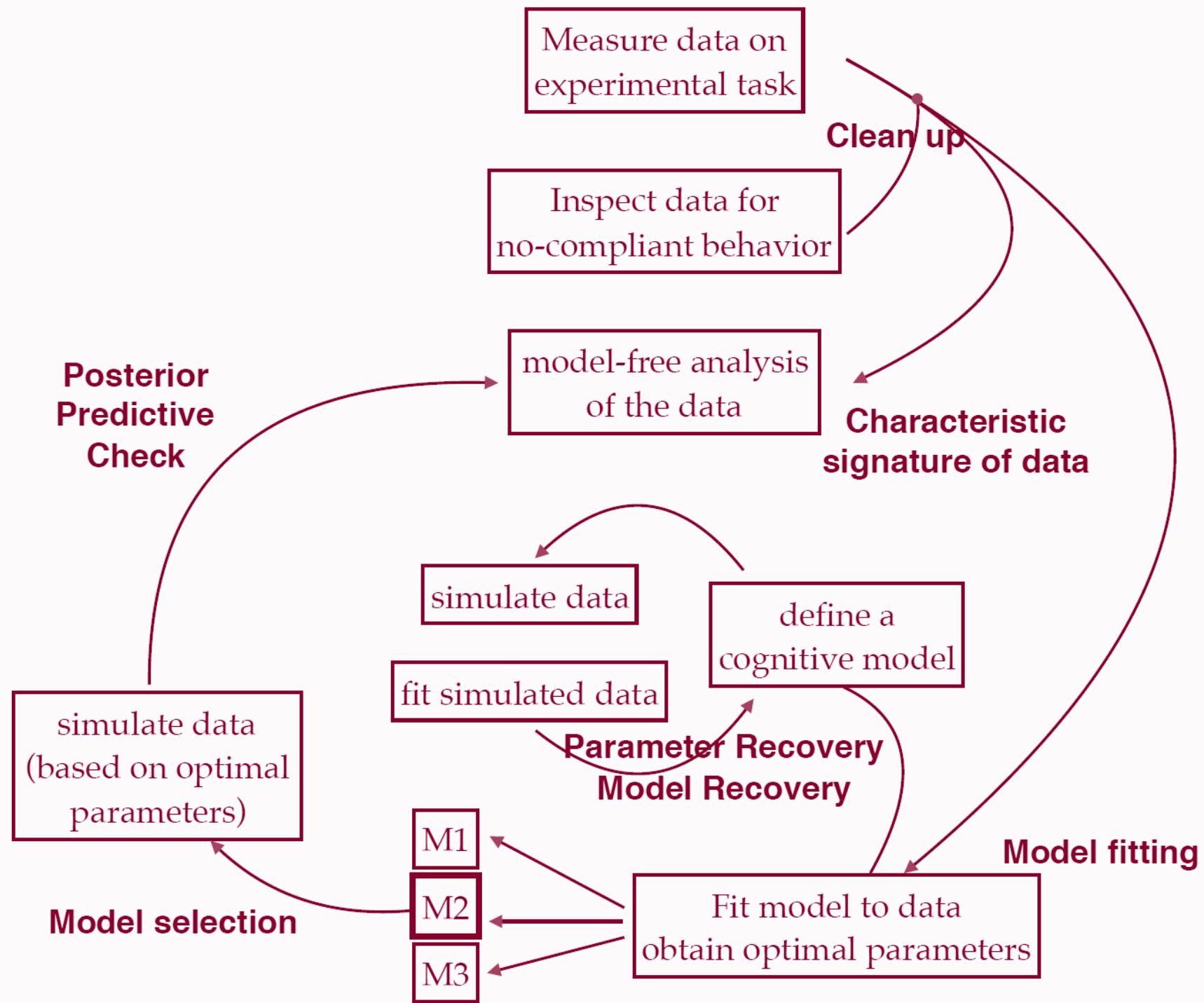


age group x diagnostic

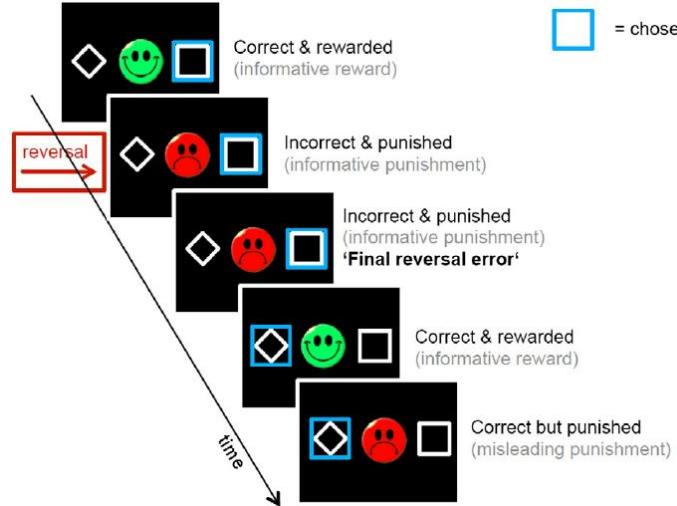


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What to model?



what do we know?

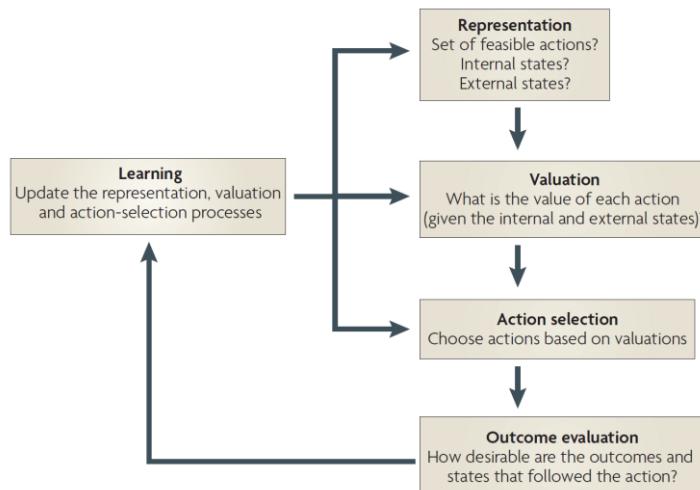
what can we measure?

what do we not know?

choice & outcome

choice accuracy

computational
processes



subjID	trialID	choice	outcome
1	1	1	1
2	1	2	1
3	1	3	1

Model space

Counterfactual update RL

$$V_{c,t} = V_{c,t-1} + \eta (O_{t-1} - V_{c,t-1})$$

$$V_{nc,t} = V_{nc,t-1} + \eta (-O_{t-1} - V_{nc,t-1})$$

Reward-punishment RL

$$V_{c,t} = \begin{cases} V_{c,t-1} + \eta^{\text{rew}} (O_{t-1} - V_{c,t-1}), & \text{if } O_{t-1} > 0 \\ V_{c,t-1} + \eta^{\text{pun}} (O_{t-1} - V_{c,t-1}), & \text{if } O_{t-1} < 0 \end{cases}$$

Experience-weighted attraction

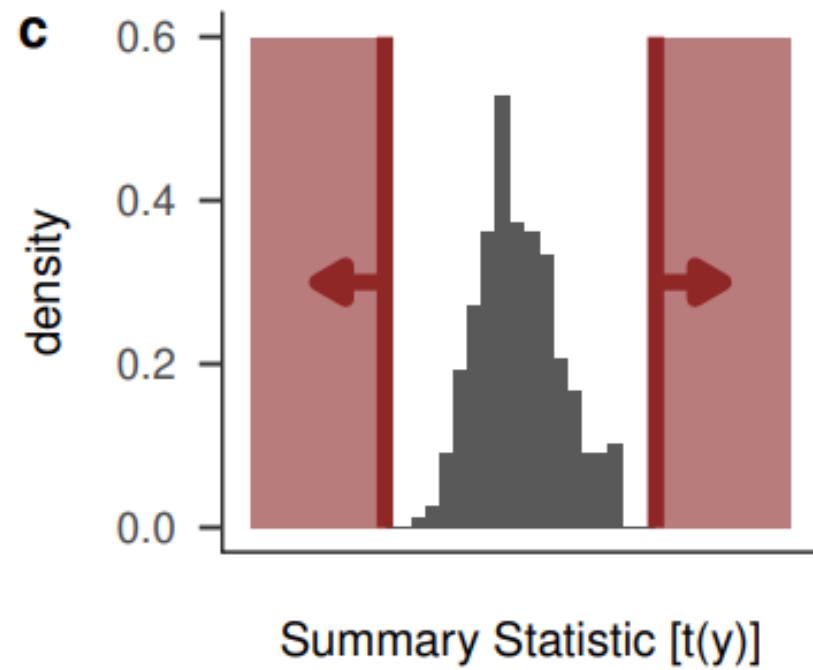
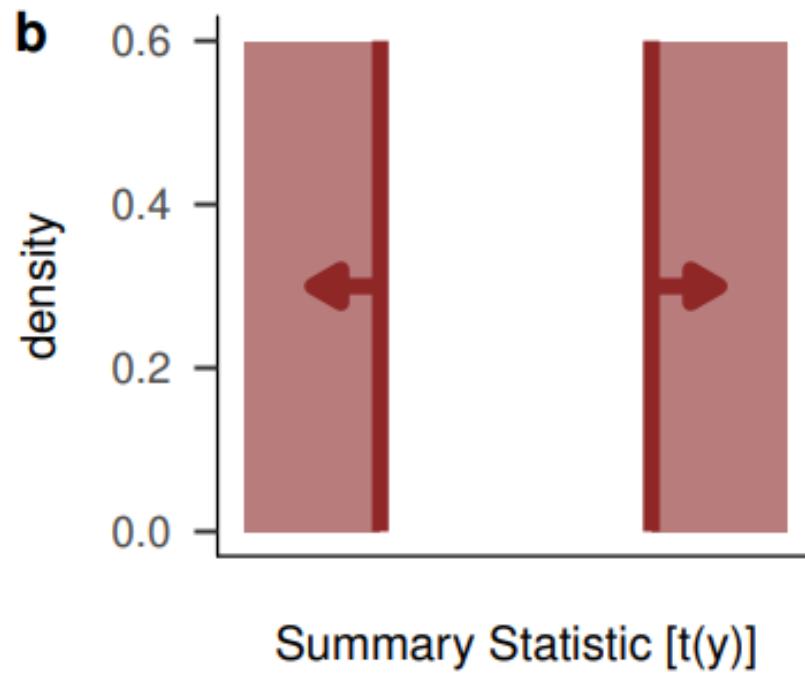
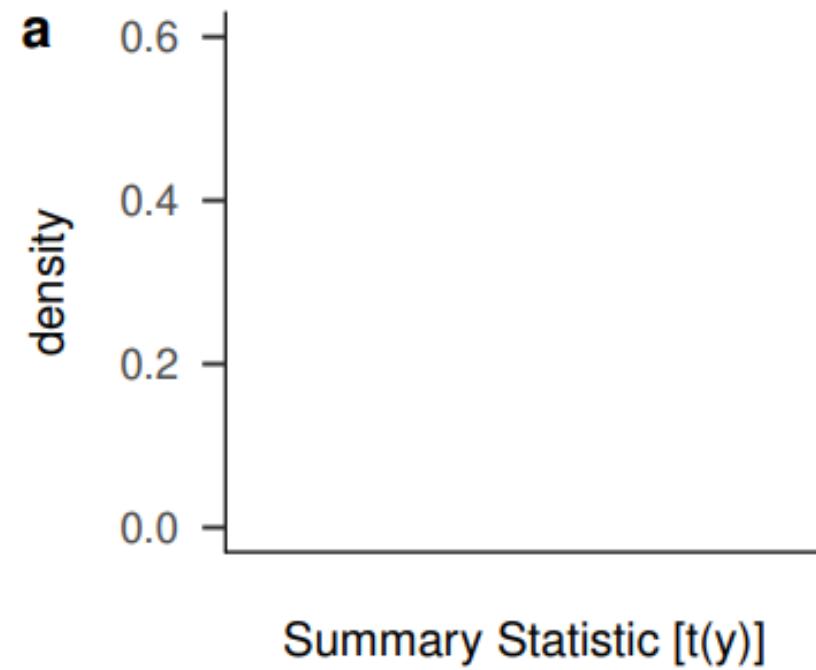
$$n_{c,t} = n_{c,t-1} \times \rho + 1$$

$$V_{c,t} = (V_{c,t-1} \times \varphi \times n_{c,t-1} + O_{t-1}) / n_{c,t}$$

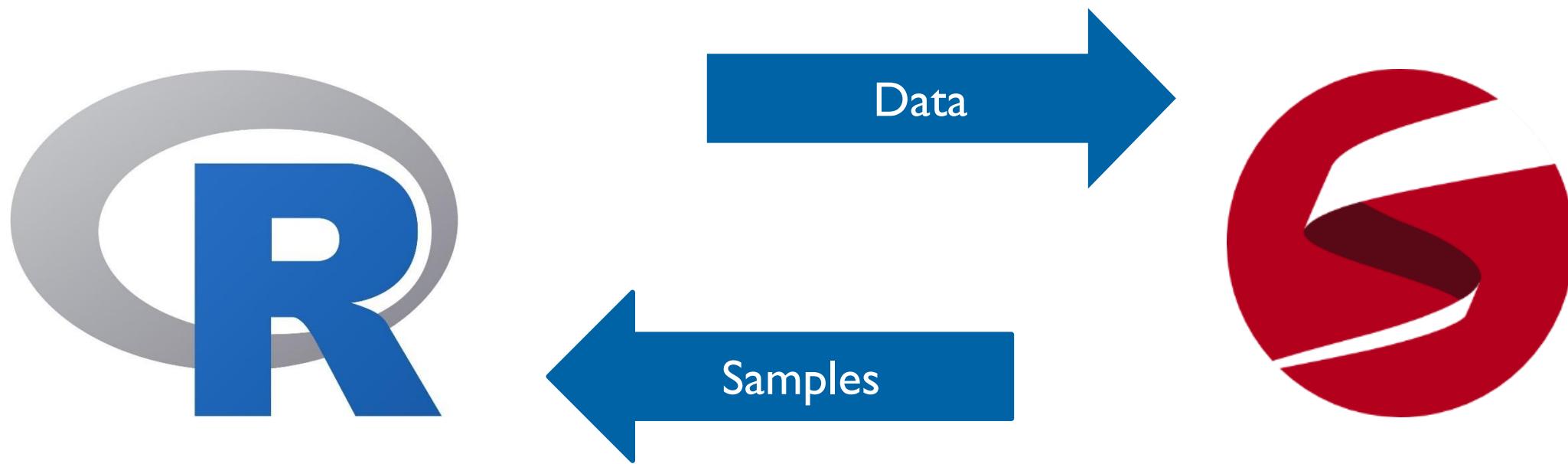
Common cognitive models in decision-making

- Reinforcement learning model
- Bayesian learning model
- Risk-aversion model
- Hyperbolic delay discounting model
- Fehr-Schmidt inequity aversion model
- Sequential sampling model
- Experience-weighted attraction model
- ...

Prior predictive checks: *domain expertise consistency*



Model fitting



Model fitting

The image shows a journal cover for 'cpsy' (Computational Psychiatry). The journal logo 'cpsy' is in large blue and grey letters on a grey background. Below it, a light blue vertical bar contains the text 'an open access journal'. The main title of the article is 'RESEARCH Revealing Neurocomputational Mechanisms of Reinforcement Learning and Decision-Making With the hBayesDM Package' by Woo-Young Ahn¹, Nathaniel Haines¹, and Lei Zhang². The authors' names are listed below the title. Footnotes indicate that ¹Department of Psychology, The Ohio State University, Columbus, OH and ²Institute for Systems Neuroscience, University Medical Center Hamburg-Eppendorf, Hamburg, Germany. The text 'Keywords: reinforcement learning, decision-making, hierarchical Bayesian modeling, model-based fMRI' is also present.

RESEARCH

Revealing Neurocomputational Mechanisms of Reinforcement Learning and Decision-Making With the hBayesDM Package

Woo-Young Ahn¹, Nathaniel Haines¹, and Lei Zhang²

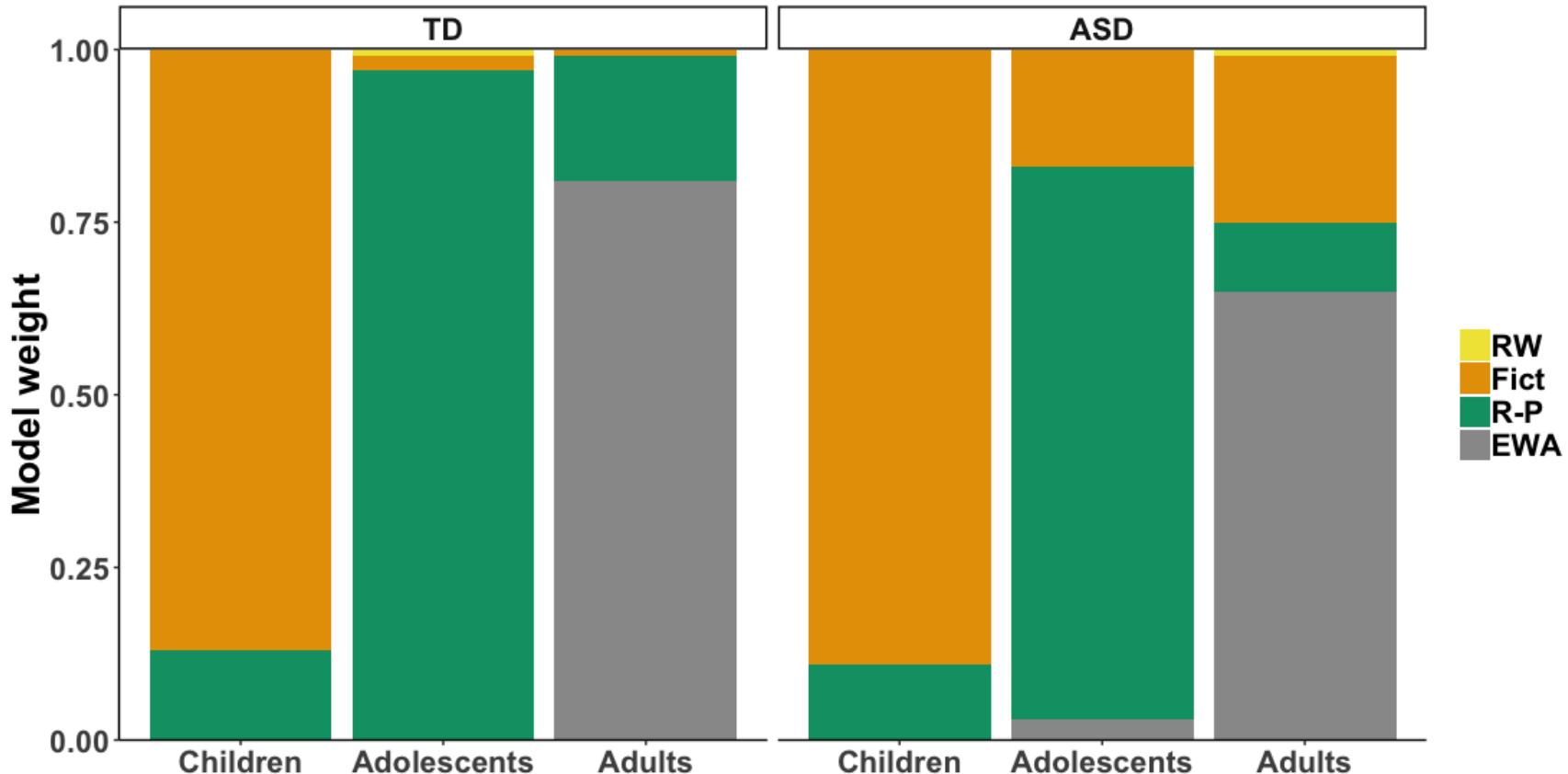
¹Department of Psychology, The Ohio State University, Columbus, OH

²Institute for Systems Neuroscience, University Medical Center Hamburg-Eppendorf, Hamburg, Germany

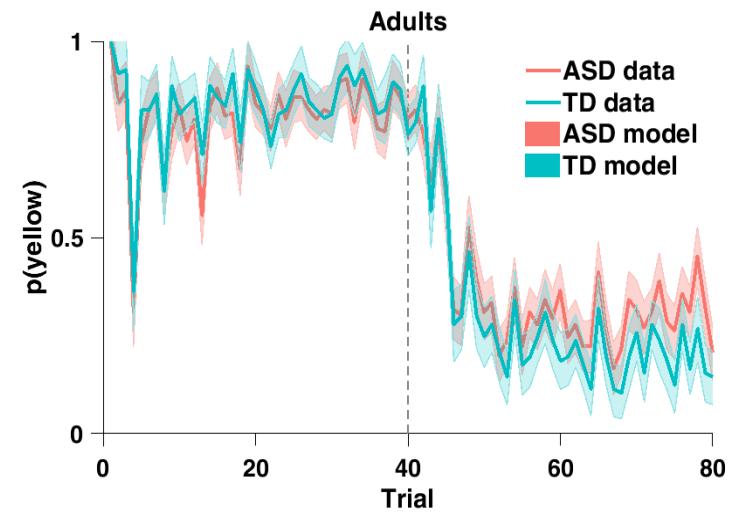
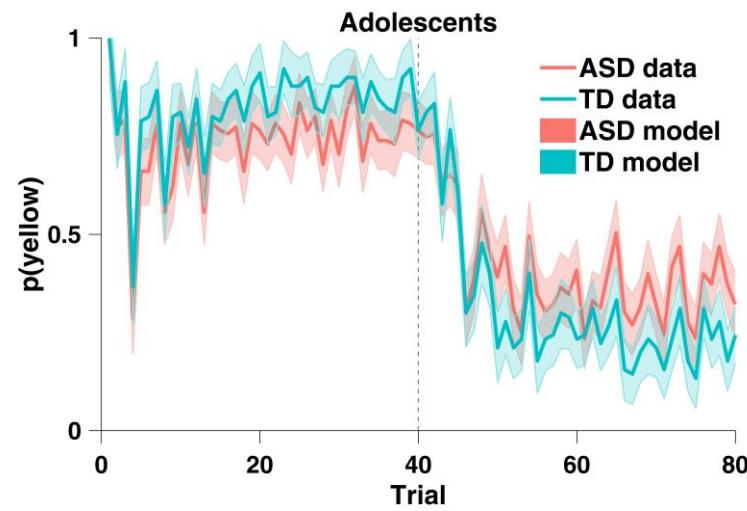
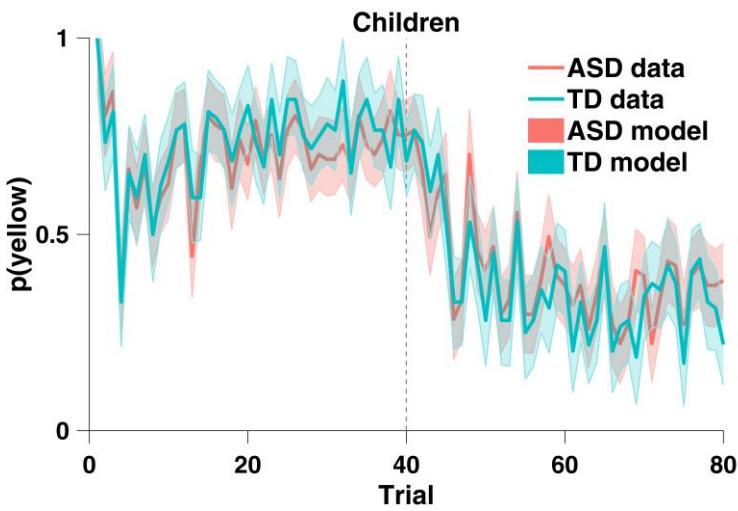
Keywords: reinforcement learning, decision-making, hierarchical Bayesian modeling, model-based fMRI

https://ccs-lab.github.io/hBayesDM/articles/getting_started.html

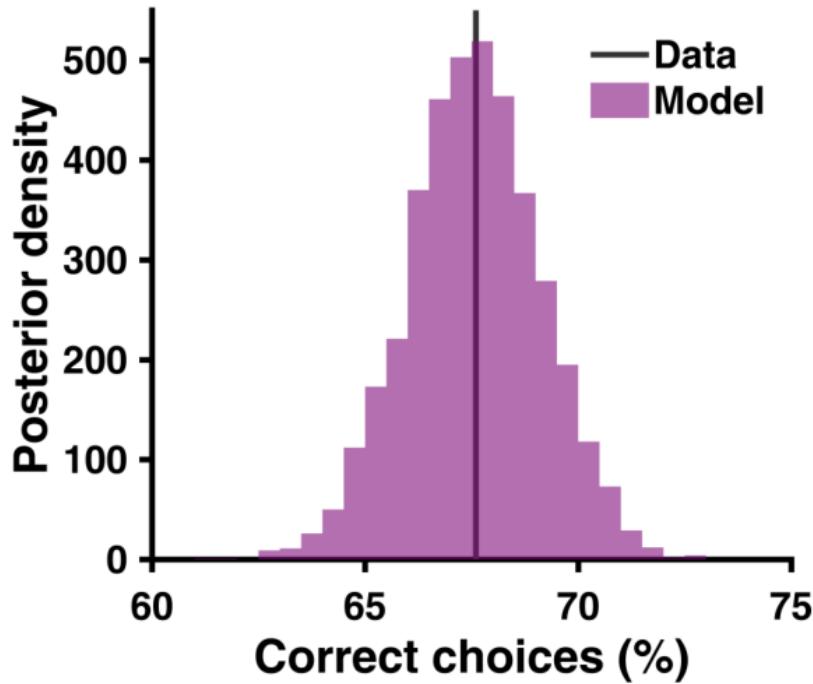
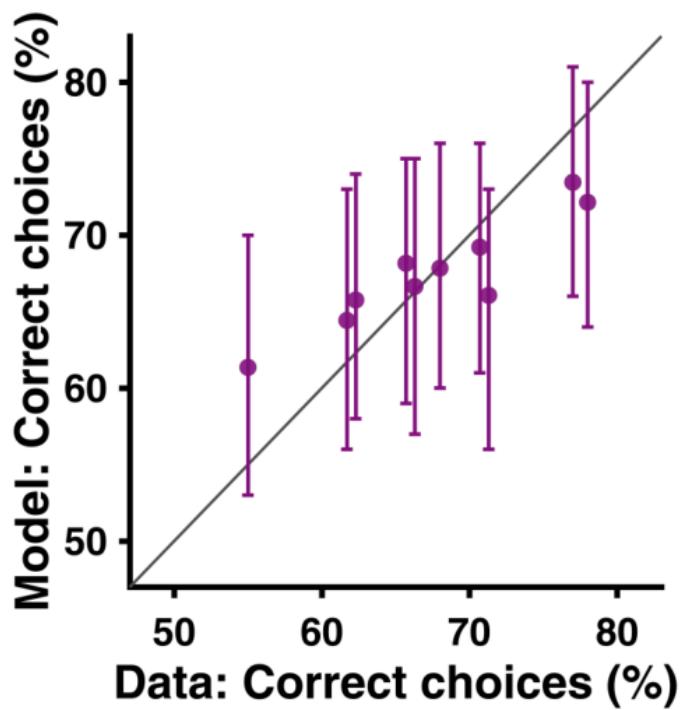
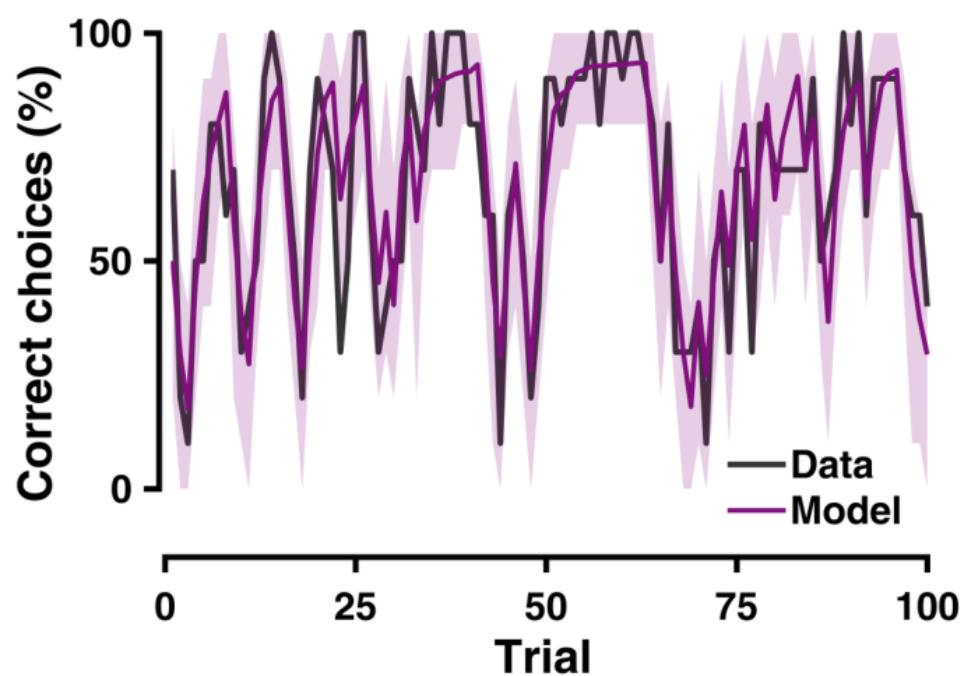
Model comparison



Model validation with posterior predictive checks (PPC)



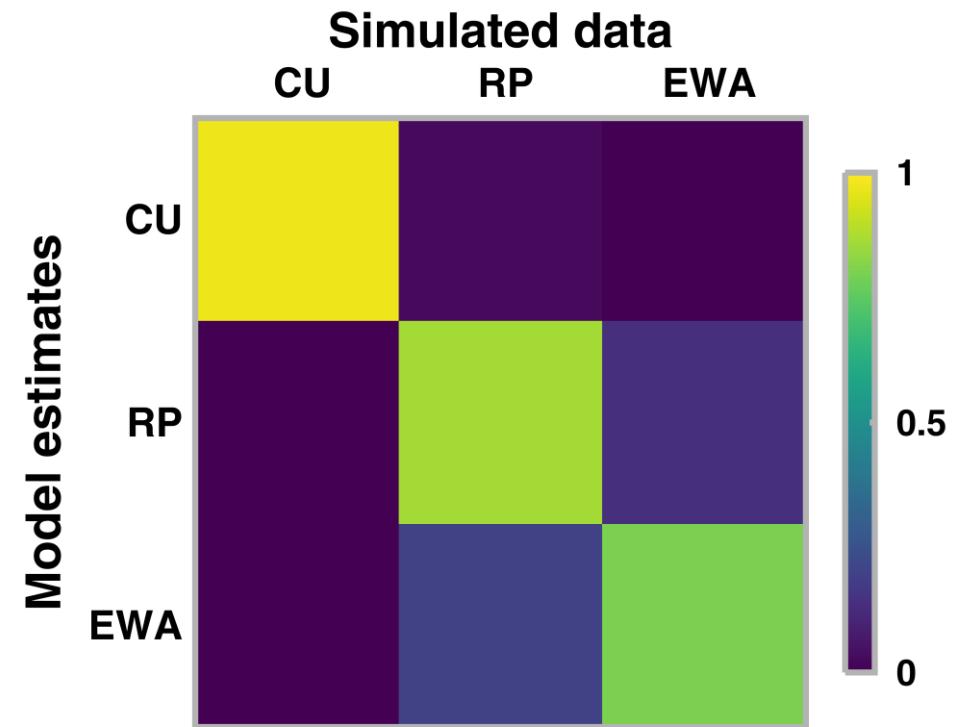
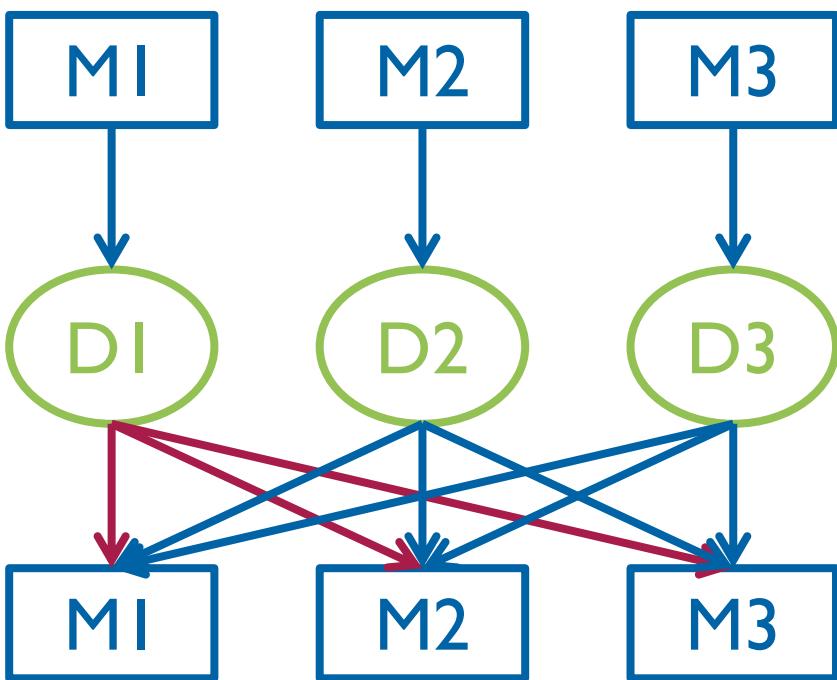
More on PPC



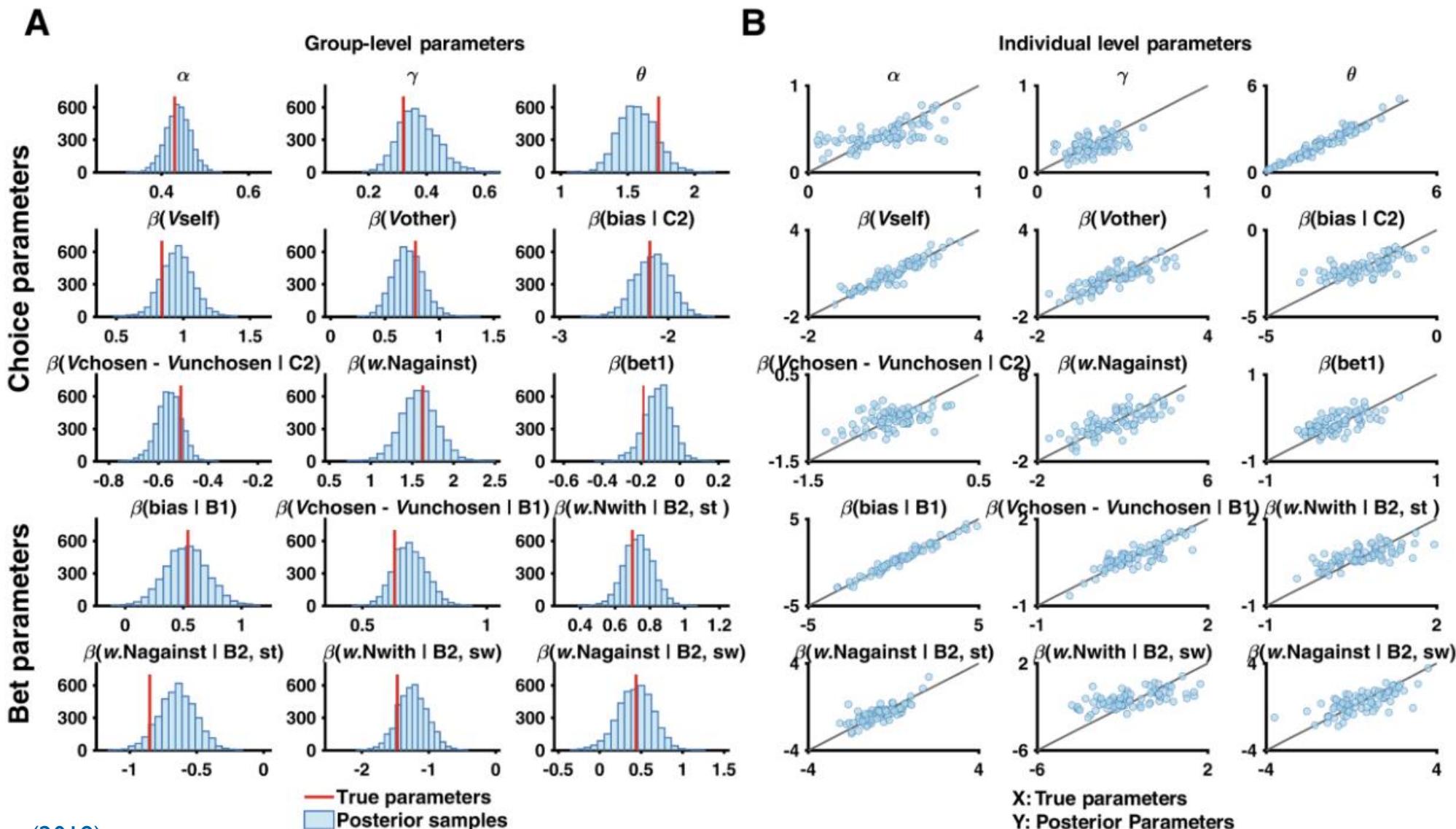
Model recovery: are models identifiable

generative
process

fitting
process

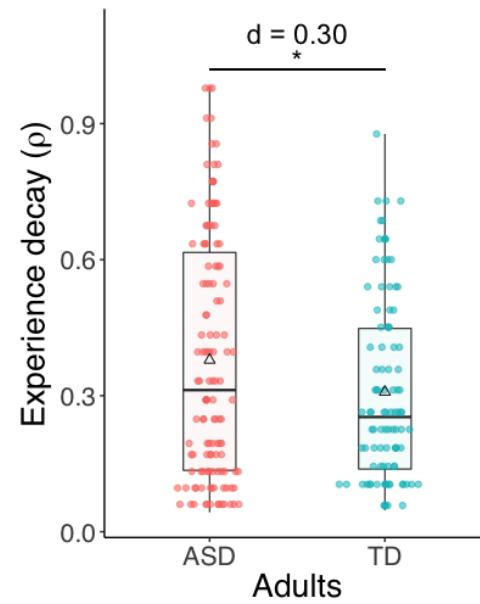
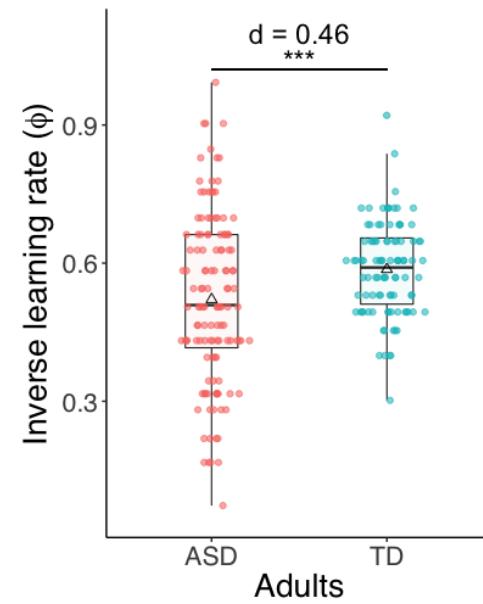
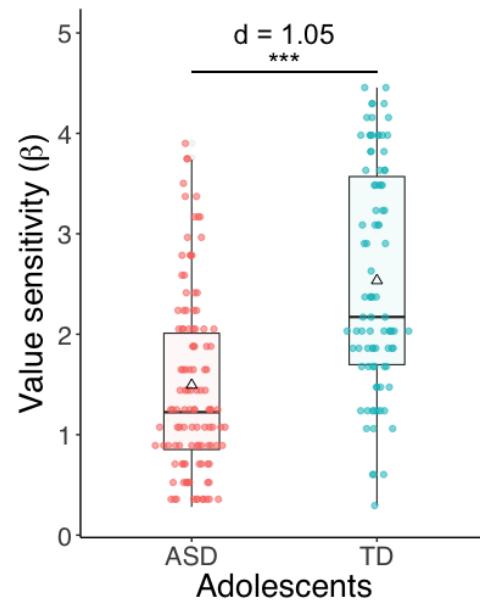
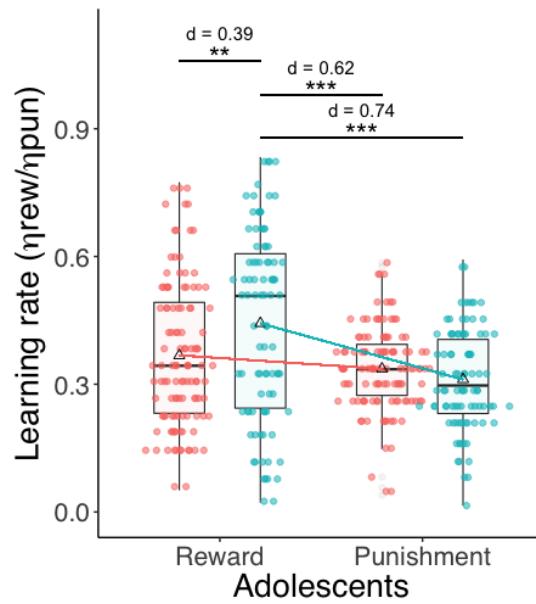
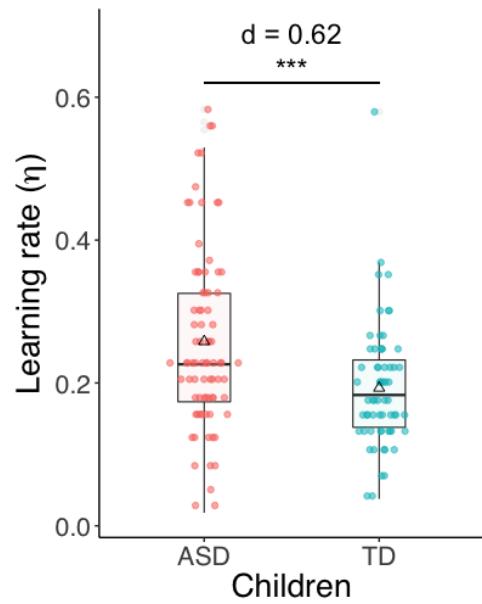


Parameter recovery: are parameters identifiable



Parameter results

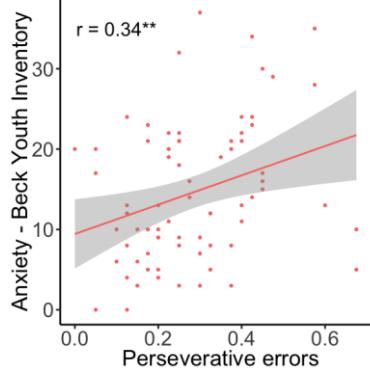
— ASD
— TD



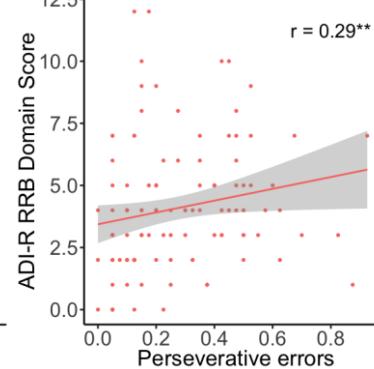
Parameter ~ clinical scales

Task behaviour

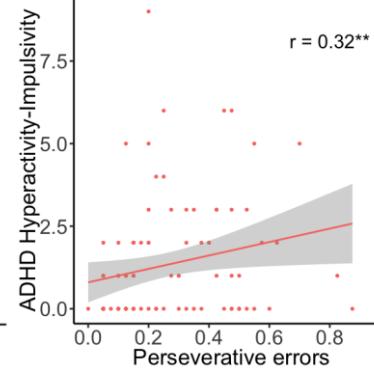
A. Children



B.

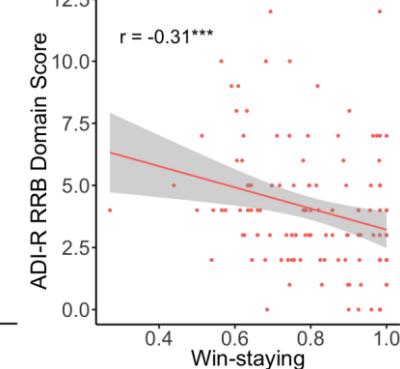


C.

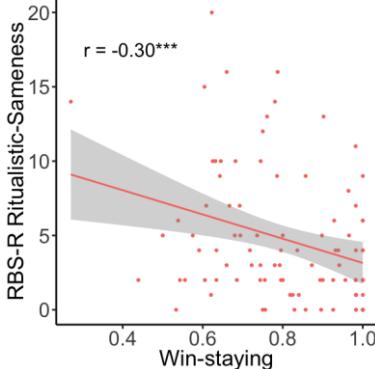


Adults

D.

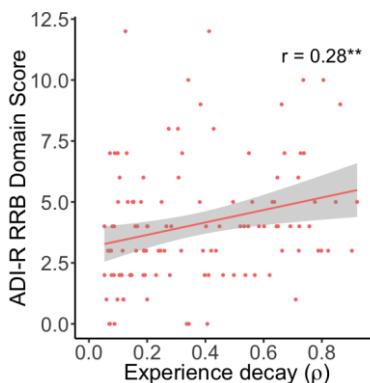


E.

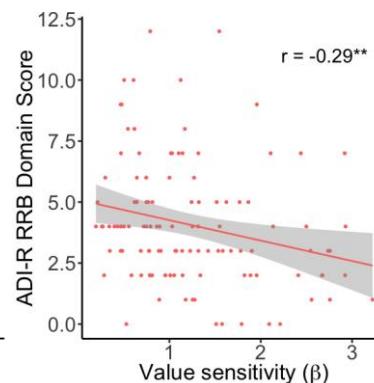


Model parameters

F.

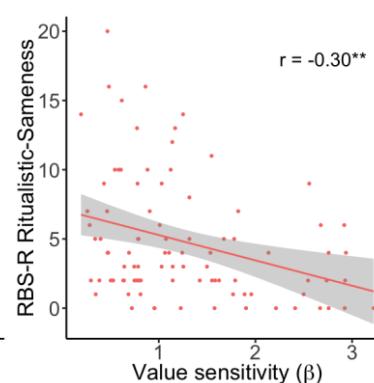


G.

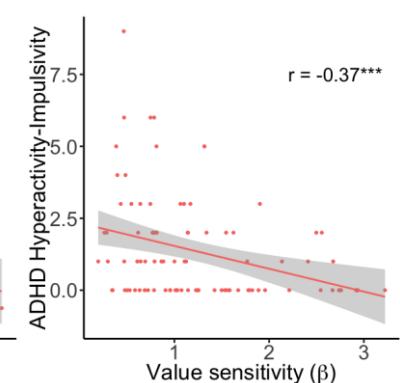


Adults

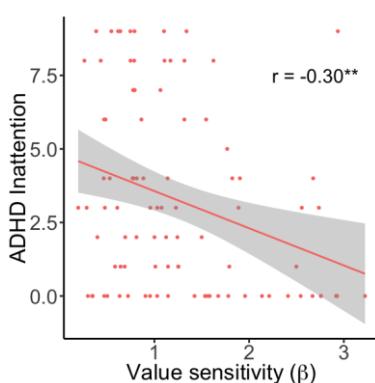
H.



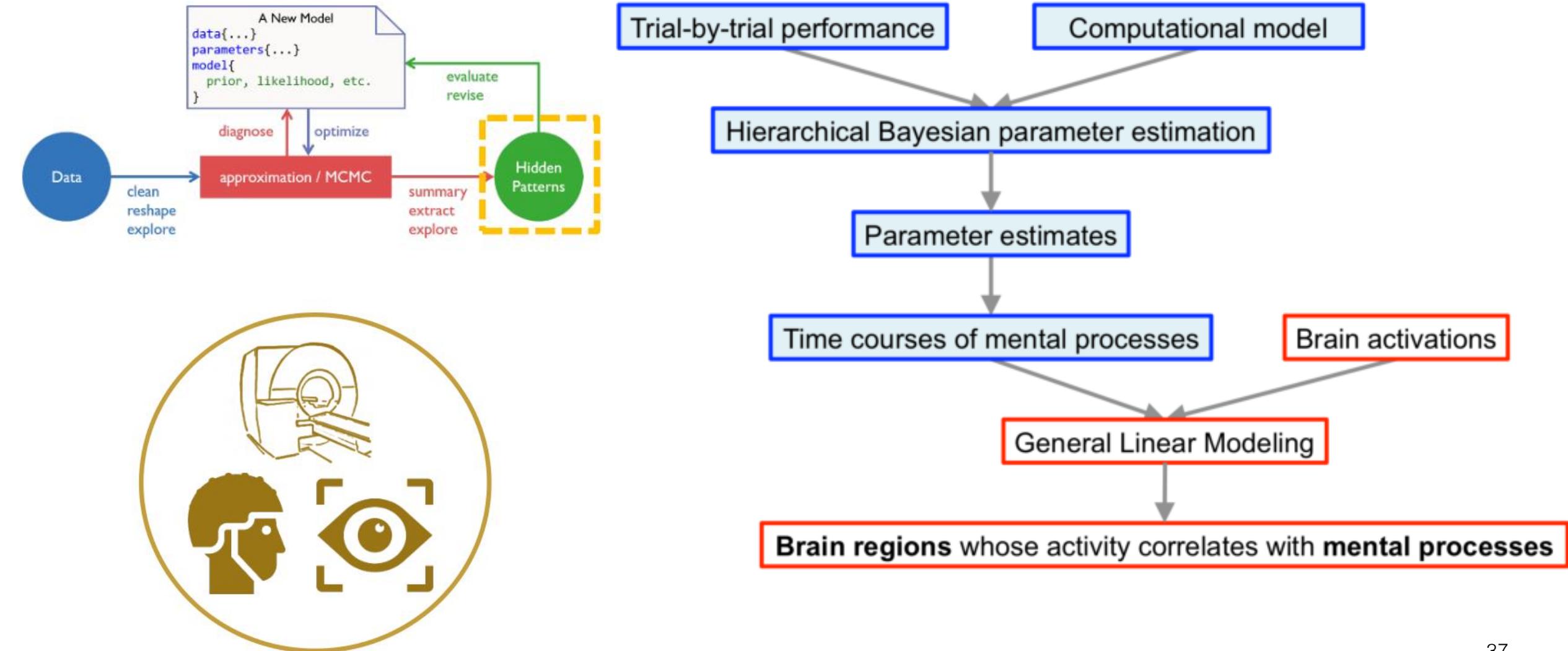
I.

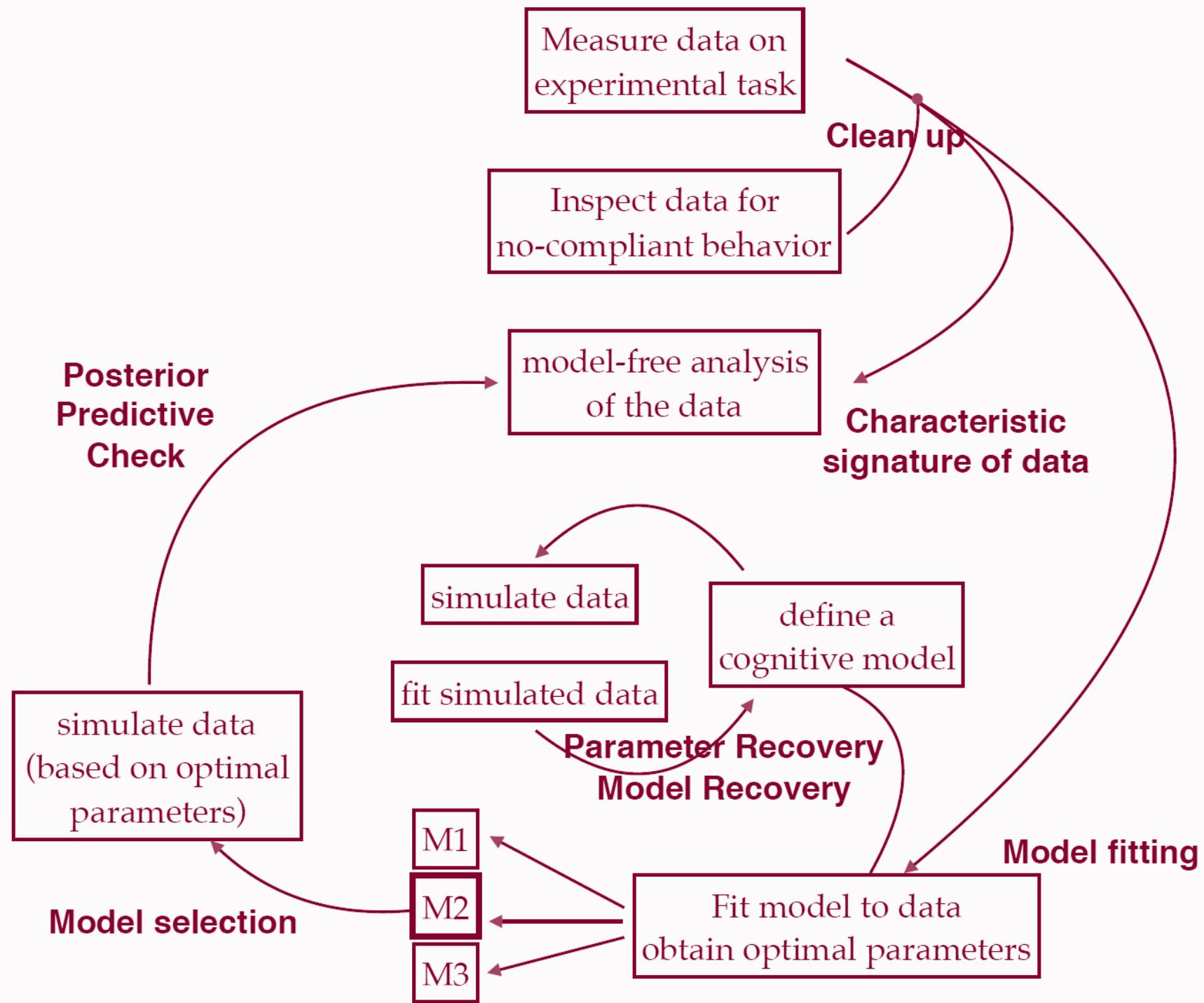


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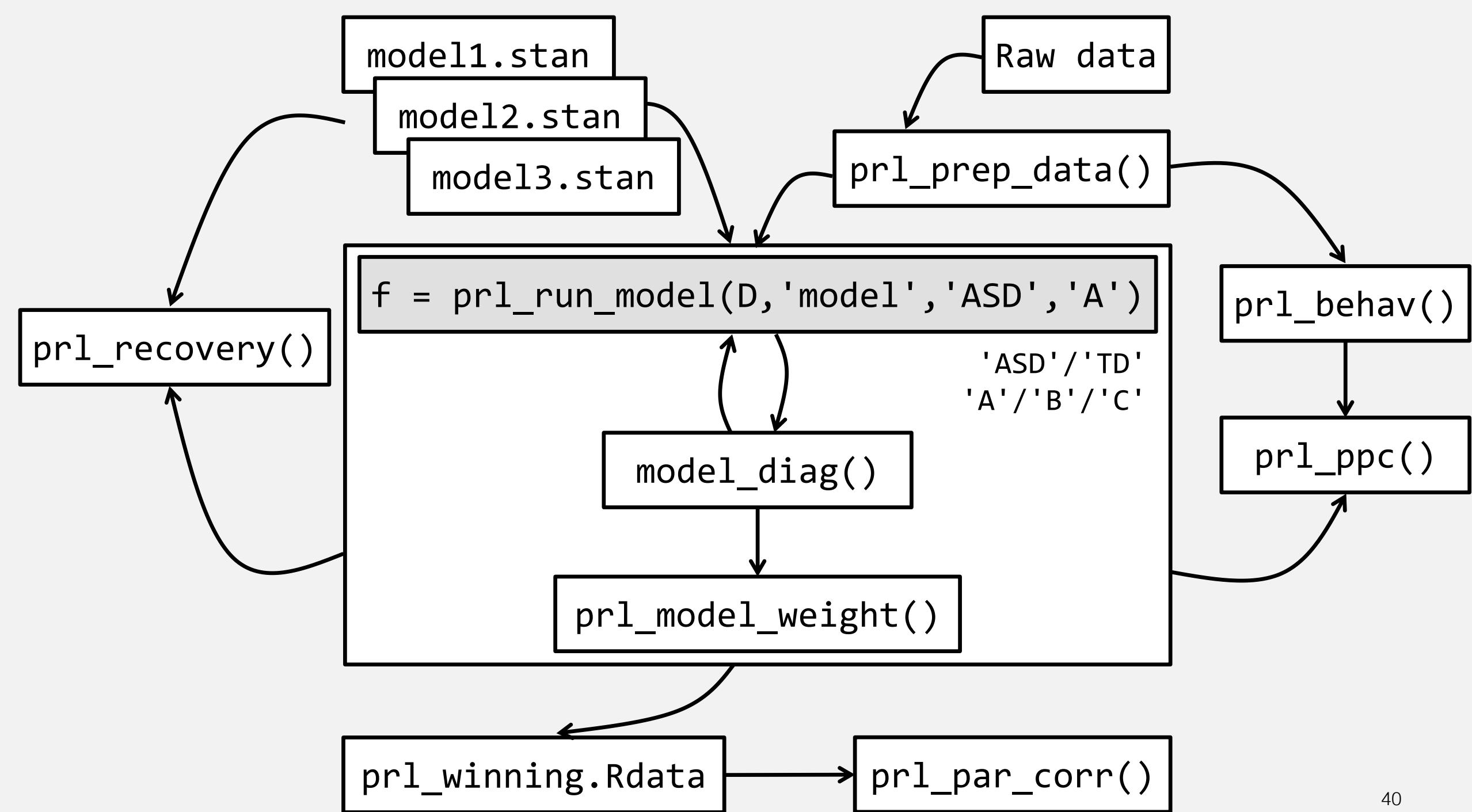
Model-based analysis





Outline

- Motivation (recap)
- A computational psychiatry example
- A Bayesian workflow (conceptual)
- **A Bayesian workflow (practical)**
- Summary



Summary

- Computational modeling is never new → don't let it fear you!
- Employ the Bayesian workflow
- Read classic works → improve theoretical thinking
- Learn to seek external help (e.g., existing packages)
- Learn in pairs; practice makes perfect!



Recommended reading: tutorial

Using reinforcement learning models in social neuroscience: frameworks, pitfalls, and suggestions of best practices

AUTHORS

Lei Zhang, Lukas Lengersdorff, Nace Mikus, Jan Gläscher, Claus Lamm

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<https://psyarxiv.com/uthw2>

ACCEPTED MANUSCRIPT

Computational modelling of social cognition and behaviour—a reinforcement learning primer 

Patricia L Lockwood , Miriam Klein-Flügge 

Social Cognitive and Affective Neuroscience, nsaa040, <https://doi.org/10.1093/scan/nsaa040>

Published: 30 March 2020 [Article history](#) ▾

<https://academic.oup.com/scan/advance-article/doi/10.1093/scan/nsaa040/5813717>

Ten simple rules for the computational modeling of behavioral data



Robert C Wilson , Anne GE Collins 

University of Arizona, United States; University of California, Berkeley, United States

<https://elifesciences.org/articles/49547>

The Importance of Falsification in Computational Cognitive Modeling

Stefano Palminteri,^{1,2,*‡} Valentin Wyart,^{1,2,*‡} and Etienne Koechlin^{1,2,*}

<https://doi.org/10.1016/j.tics.2017.03.011>

Recommended reading: empirical work

Catecholaminergic challenge uncovers distinct Pavlovian and instrumental mechanisms of motivated (in)action



Jennifer C Swart^a, Monja I Froböse, Jennifer L Cook, Dirk EM Geurts, Michael J Frank, Roshan Cools, Hanneke EM den Ouden^a
Radboud University, The Netherlands; University of Birmingham, United Kingdom; Radboud University Medical Center, The Netherlands; Linguistic and Psychological
Sciences, Brown University, United States; Brown University, United States

<https://elifesciences.org/articles/22169>

Social threat learning transfers to decision making in humans

Björn Lindström^{a,b,c,1}, Armita Golkar^{c,d}, Simon Jangard^c, Philippe N. Tobler^b, and Andreas Olsson^c

^aDepartment of Social Psychology, University of Amsterdam, 1018 WT Amsterdam, The Netherlands; ^bLaboratory for Social and Neural Systems Research, Department of Economics, University of Zürich, 8001 Zürich, Switzerland; ^cSection for Psychology, Department of Clinical Neuroscience, Karolinska Institutet, 171 77 Stockholm, Sweden; and ^dDepartment of Clinical Psychology, University of Amsterdam, 1018 WT Amsterdam, The Netherlands

<https://www.pnas.org/content/116/10/4732.abstract>

New Results

[Comment on this paper](#)

A brain network supporting social influences in human decision-making

Lei Zhang, Jan P. Gläscher

doi: <https://doi.org/10.1101/551614>

<https://www.biorxiv.org/content/10.1101/551614v3>

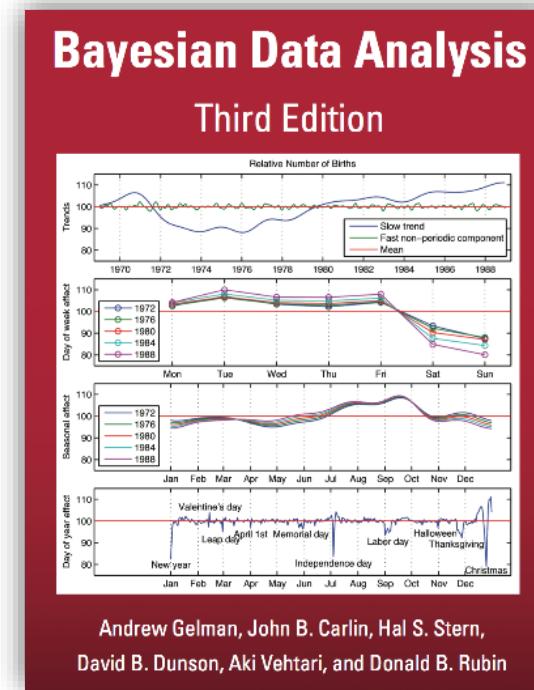
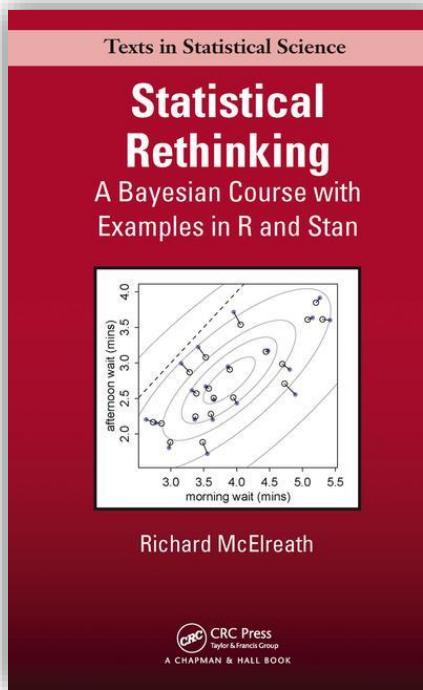
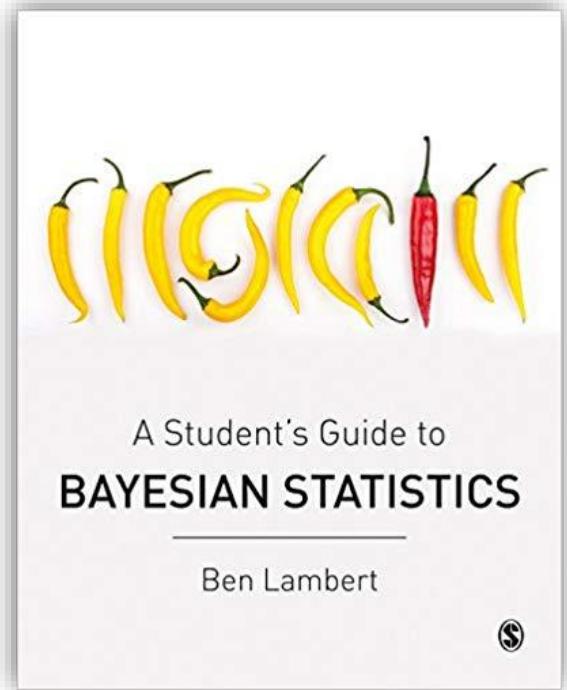
Article

Primate Amygdala Neurons Simulate Decision Processes of Social Partners

Fabian Grabenhorst^{1,5} , Raymundo Báez-Mendoza^{1,4}, Wilfried Genest¹, Gustavo Deco^{2,3}, Wolfram Schultz¹

<https://www.sciencedirect.com/science/article/pii/S0092867419302259>

Recommended reading: book



Contact



lei.zhang@univie.ac.at



<https://lei-zhang.net/>



[@lei_zhang_lz](#)



[@zhang-lei-44-62](#)



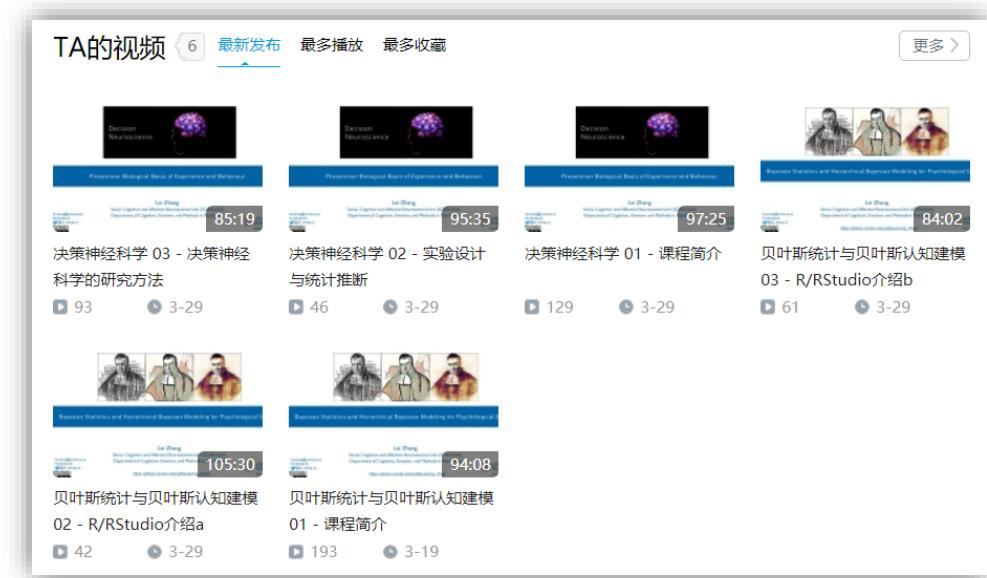
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Happy Computing!