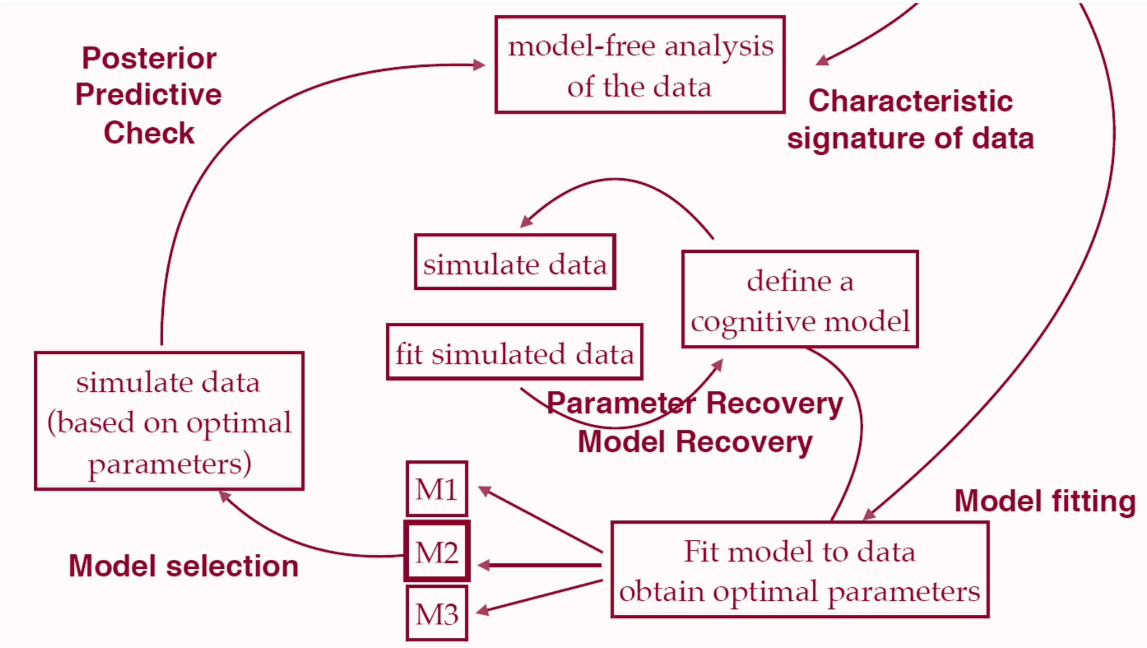


Cracking computational modelling with Stan II: A principled Bayesian workflow

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/RL_tutorial_webinar

lei.zhang@univie.ac.at

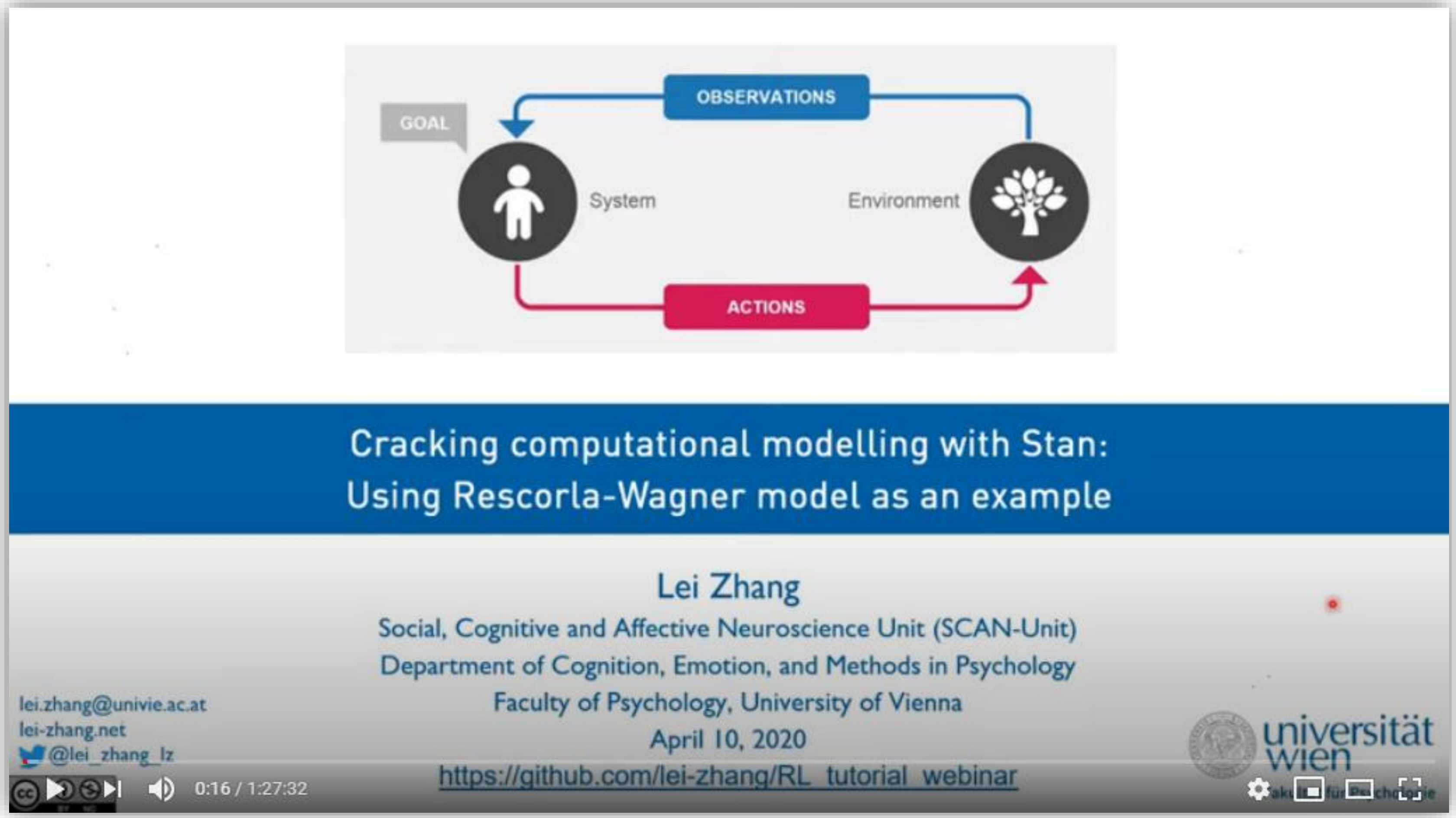
lei-zhang.net

@lei_zhang_lz

universität wien

Fakultät für Psychologie

Last time...



[直播分享：强化学习模型在Stan中的实现]()

Outline

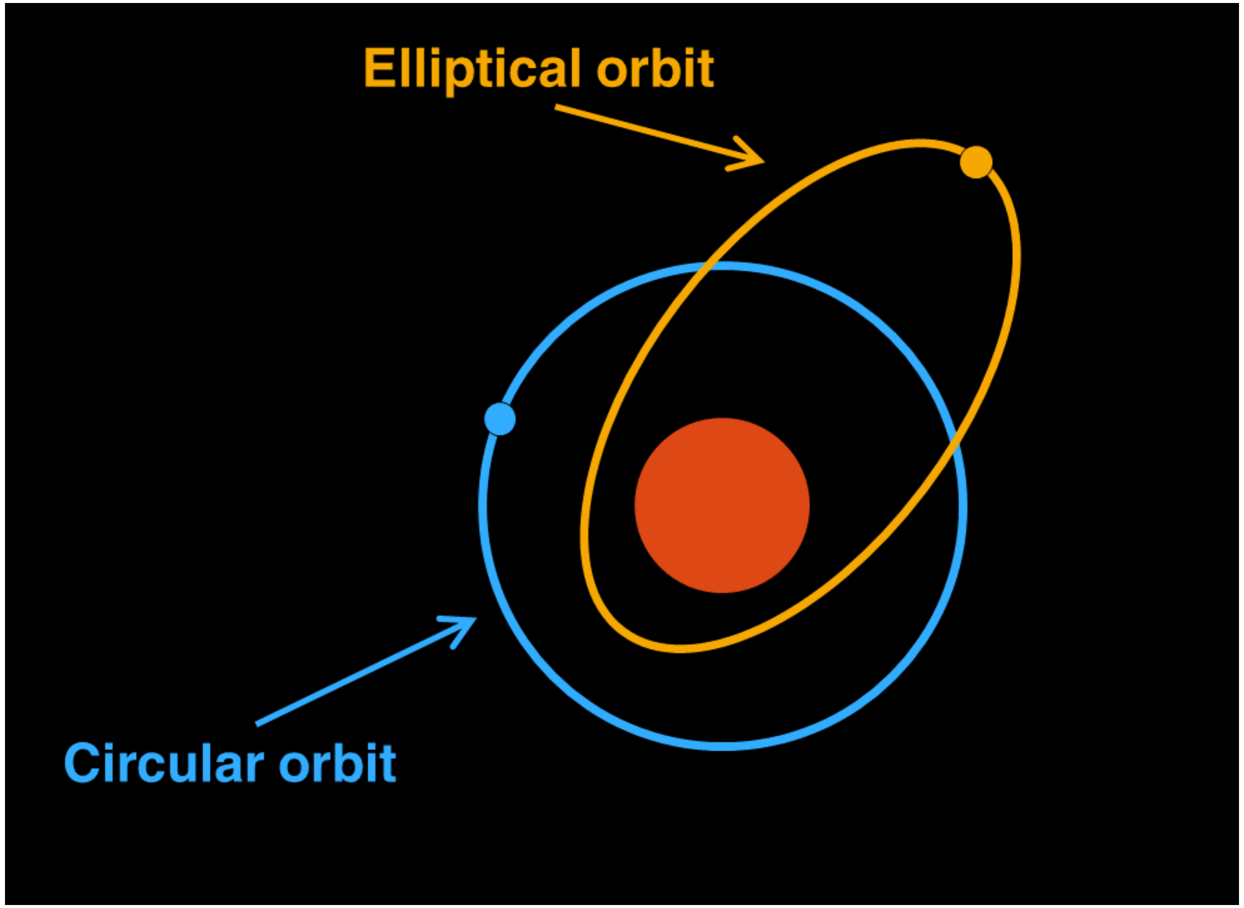
- Motivation (recap)
- A computational psychiatry example
- A Bayesian workflow (conceptual)
- A Bayesian workflow (practical)
- Summary

Outline

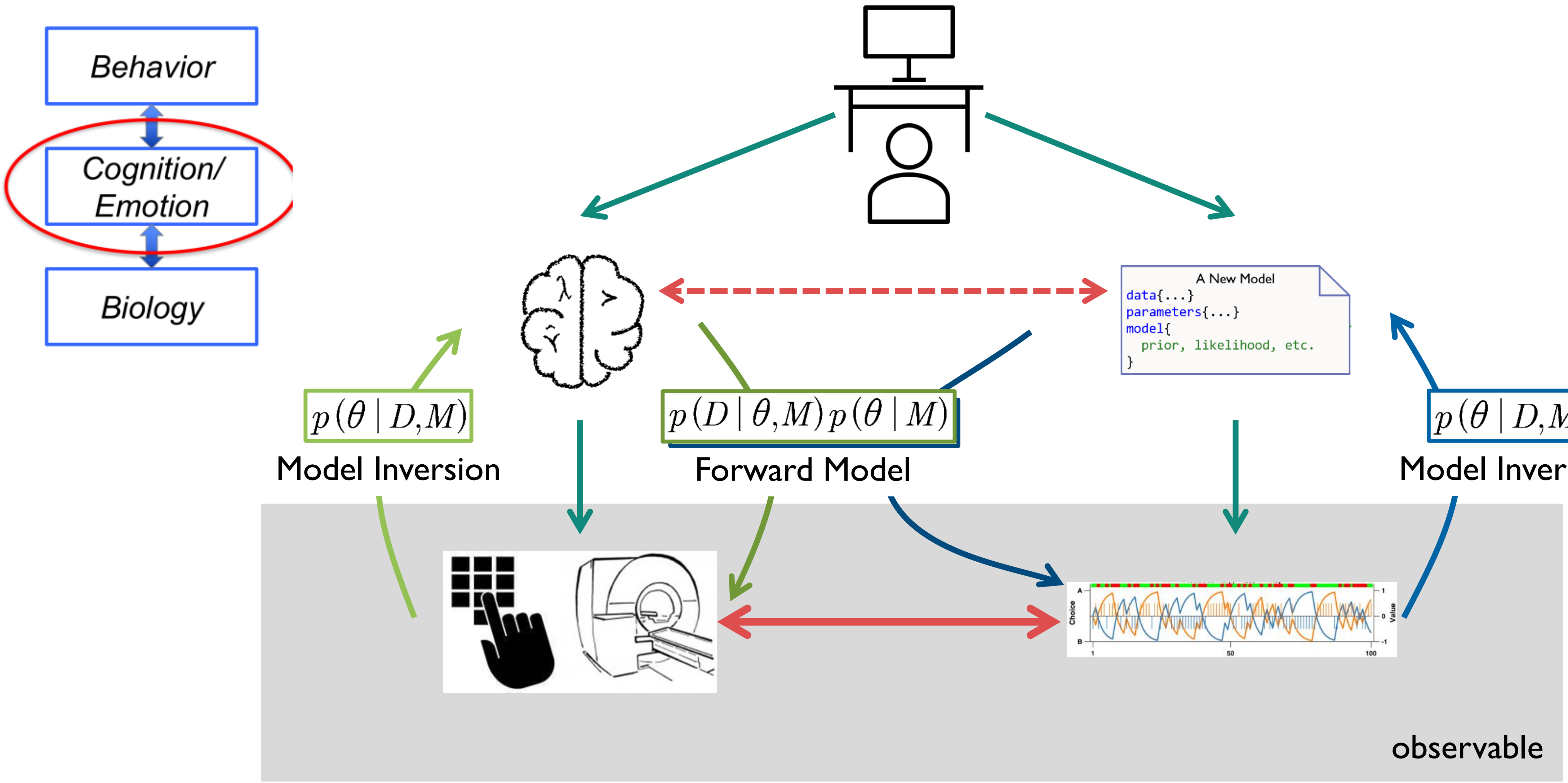
- Motivation (recap)
- A computational psychiatry example
- A Bayesian workflow (conceptual)
- A Bayesian workflow (practical)
- Summary

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

CellPress

Article

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

Caroline J. Charpentier [1, 2], Kiyohito Iigaya [1], John P. O'Doherty [1]

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

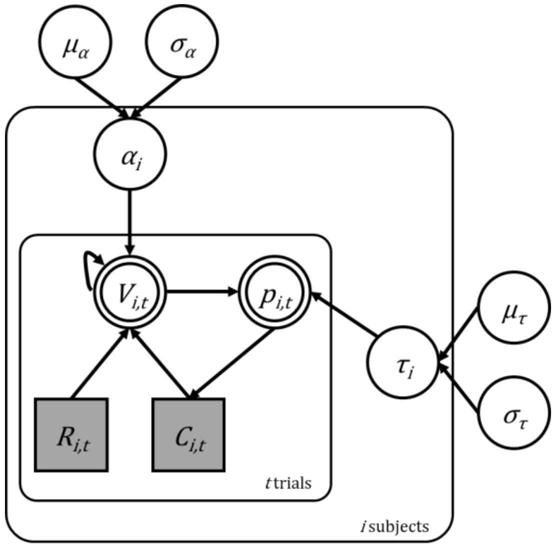
Article | Open Access | Published: 17 March 2020

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

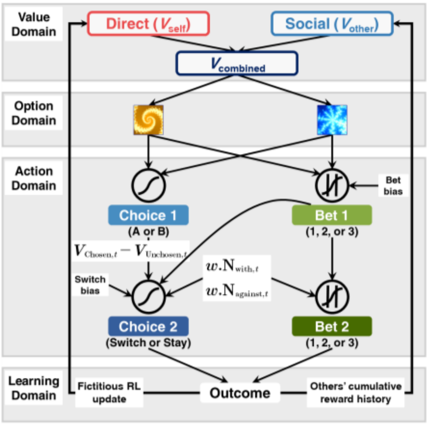
Geert-Jan Will, Michael Moutoussis, Palee M. Womack, Edward T. Bullmore, Ian M. Goodyer, Peter Fonagy, Peter B. Jones, NSPN Consortium, Robb B. Rutledge & Raymond J. Dolan

I like the idea of Modeling, ...

...but, ...



$$\mu_\alpha \sim Uniform(0,1)$$
$$\sigma_\alpha \sim halfCauchy(0,1)$$
$$\mu_\tau \sim Uniform(0,3)$$
$$\sigma_\tau \sim halfCauchy(0,3)$$
$$\alpha_i \sim Normal(\mu_\alpha, \sigma_\alpha)_{\mathcal{T}(0,1)}$$
$$\tau_i \sim Normal(\mu_\tau, \sigma_\tau)_{\mathcal{T}(0,3)}$$
$$p_{i,t}(C=A) = \frac{1}{1+e^{\tau_i(V_{i,t}(B)-V_{i,t}(A))}}$$
$$V_{i,t+1}^{c} = V_{i,t}^{C} + \alpha_i(R_{i,t} - V_{i,t}^{C})$$



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

Toward a easy-to-follow workflow

- We all are familiar with the workflow for simple factorial designs
  - e.g., a 2 x 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?


Including Bayesian
functions...

Outline

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

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. Dolan [2], Karl J. Friston [2], Peter Dayan [3]

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]

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]

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

Viewpoint

April 24, 2019

The Two Cultures of Computational Psychiatry

Daniel Bennett, PhD[1]; 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

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

2019 Computational Psychiatry Summer Course

July 29-30, 2019

The Metropolitan Museum of Art, New York, NY
Bonnie J. Sacerdote Lecture Hall (enter on 81st St and 5th Ave)

Cost (including talks, coffee/tea/snack, and lunch on both days, plus free entry to the museum):
£180 GBP (after April 1st, 2019)

cpsy

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

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.

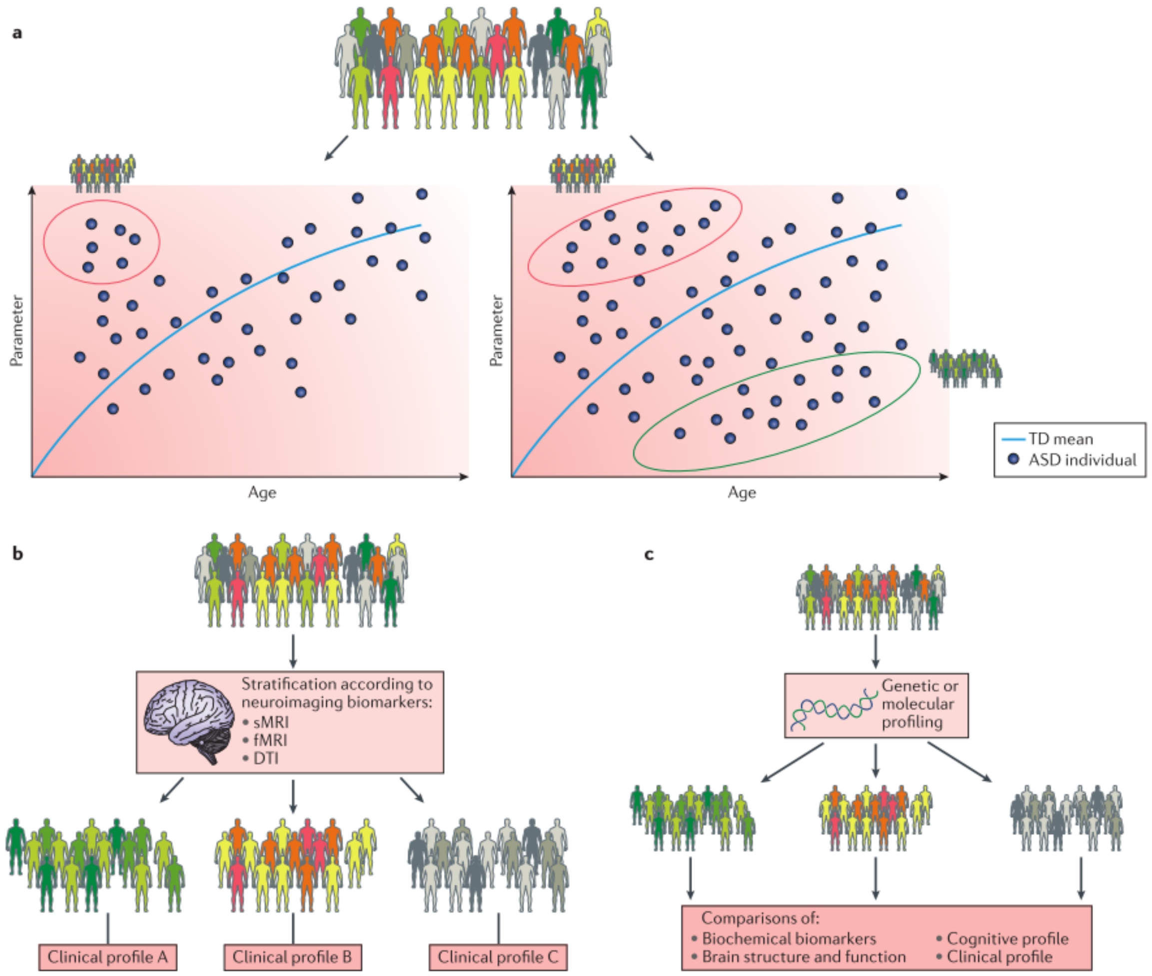
Computational Psychiatry is an Open Access journal.

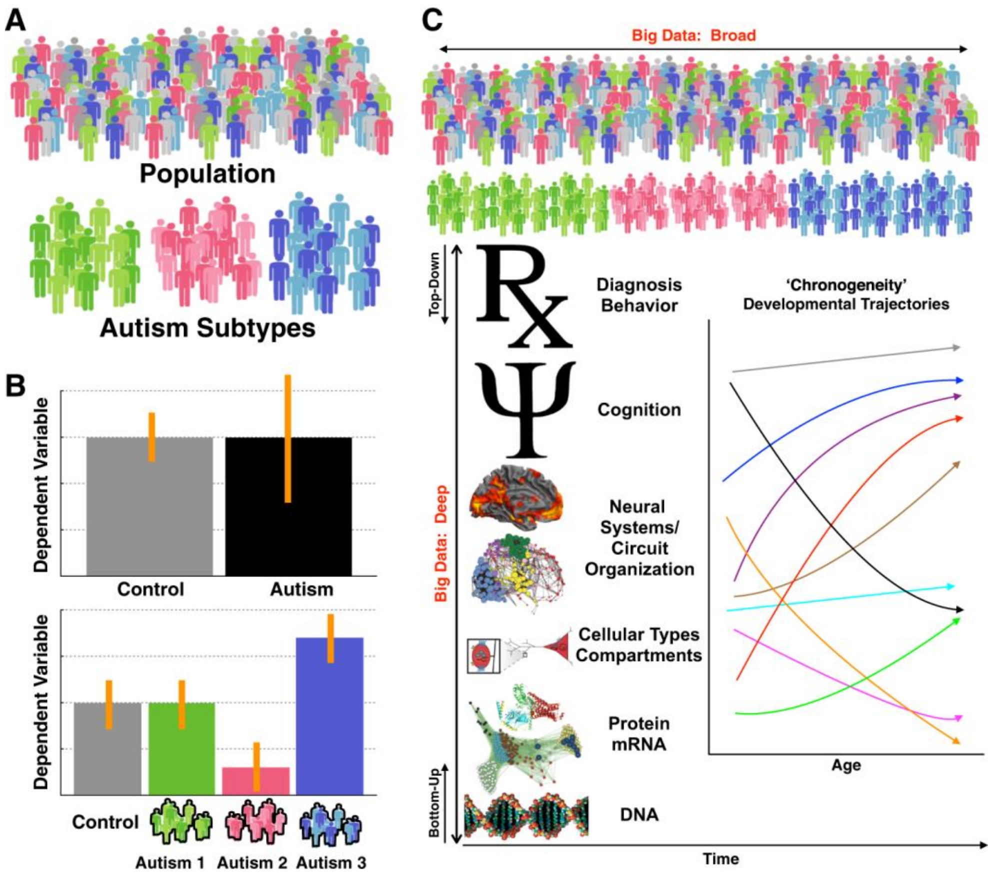
Visit computationalpsychiatry.org.

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



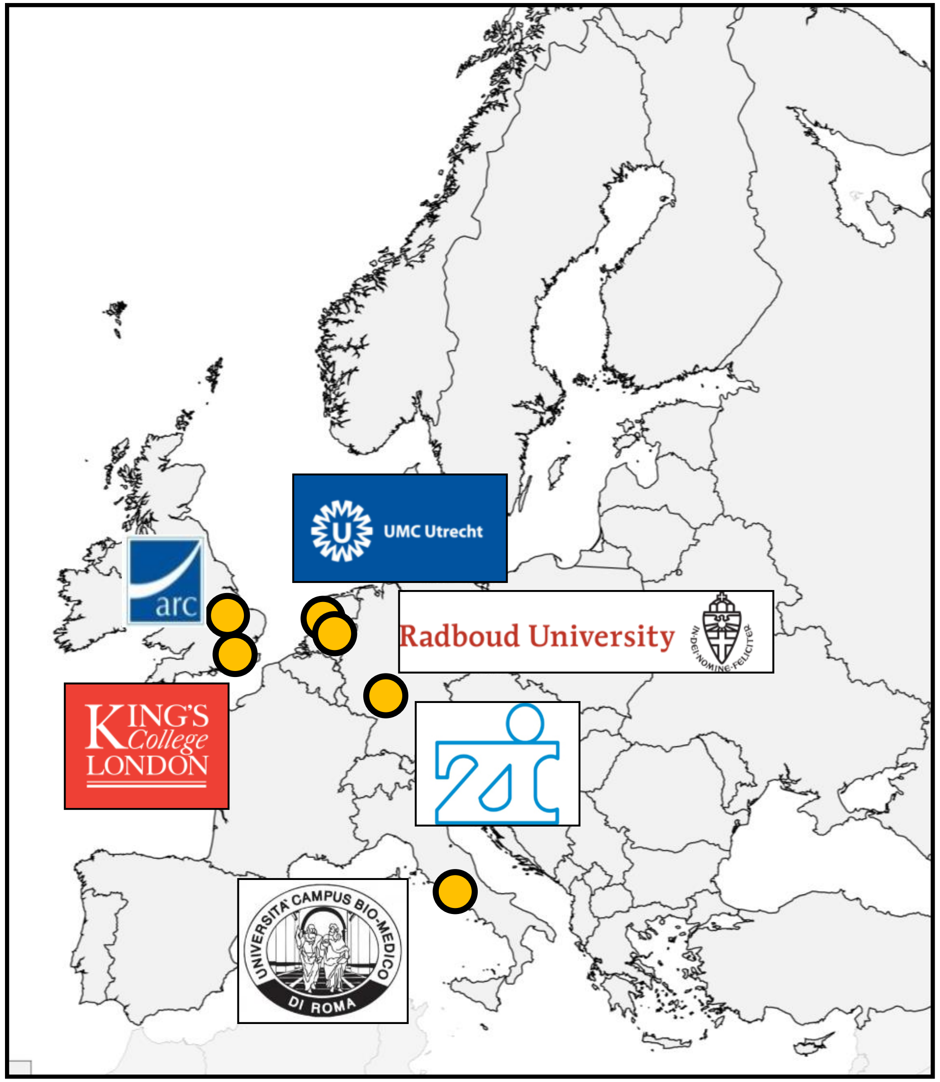


Loth (2016); Lombardo et al. (2019)

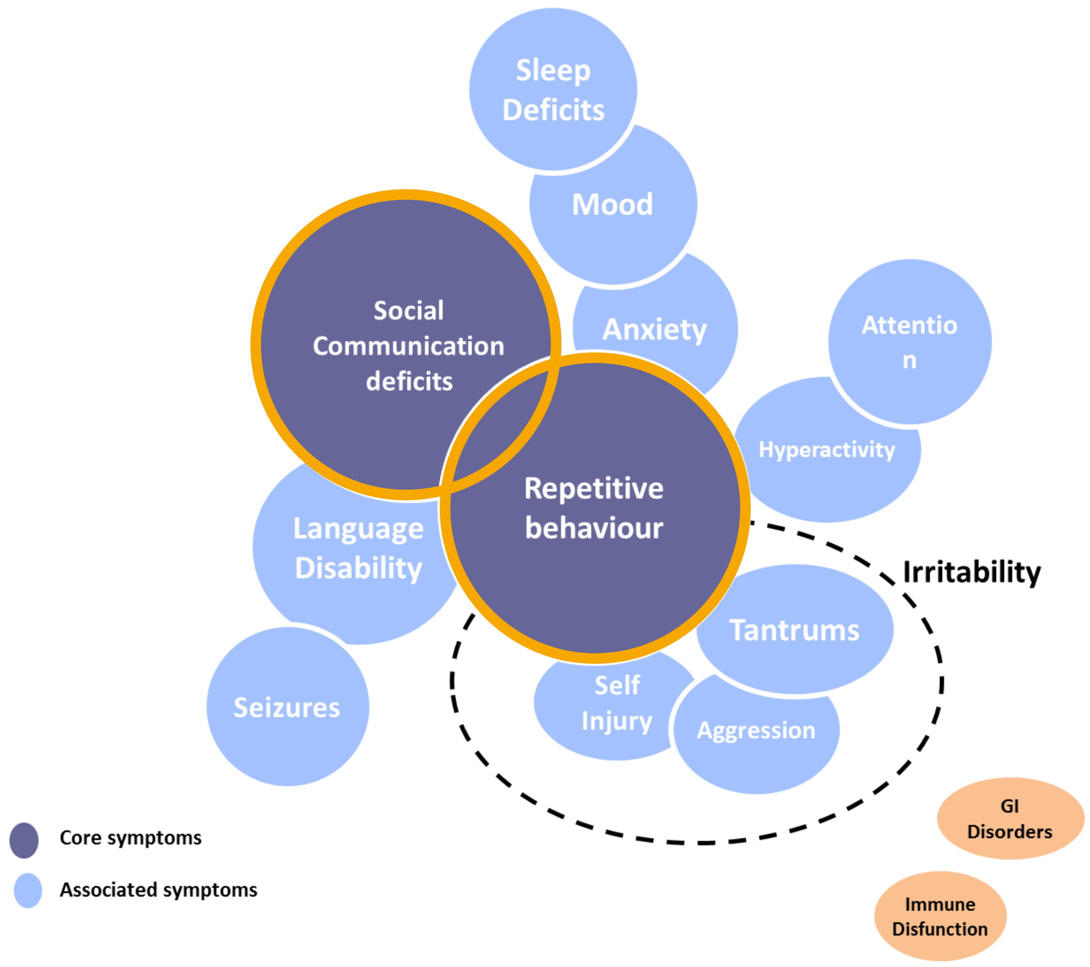
EU-AIMS

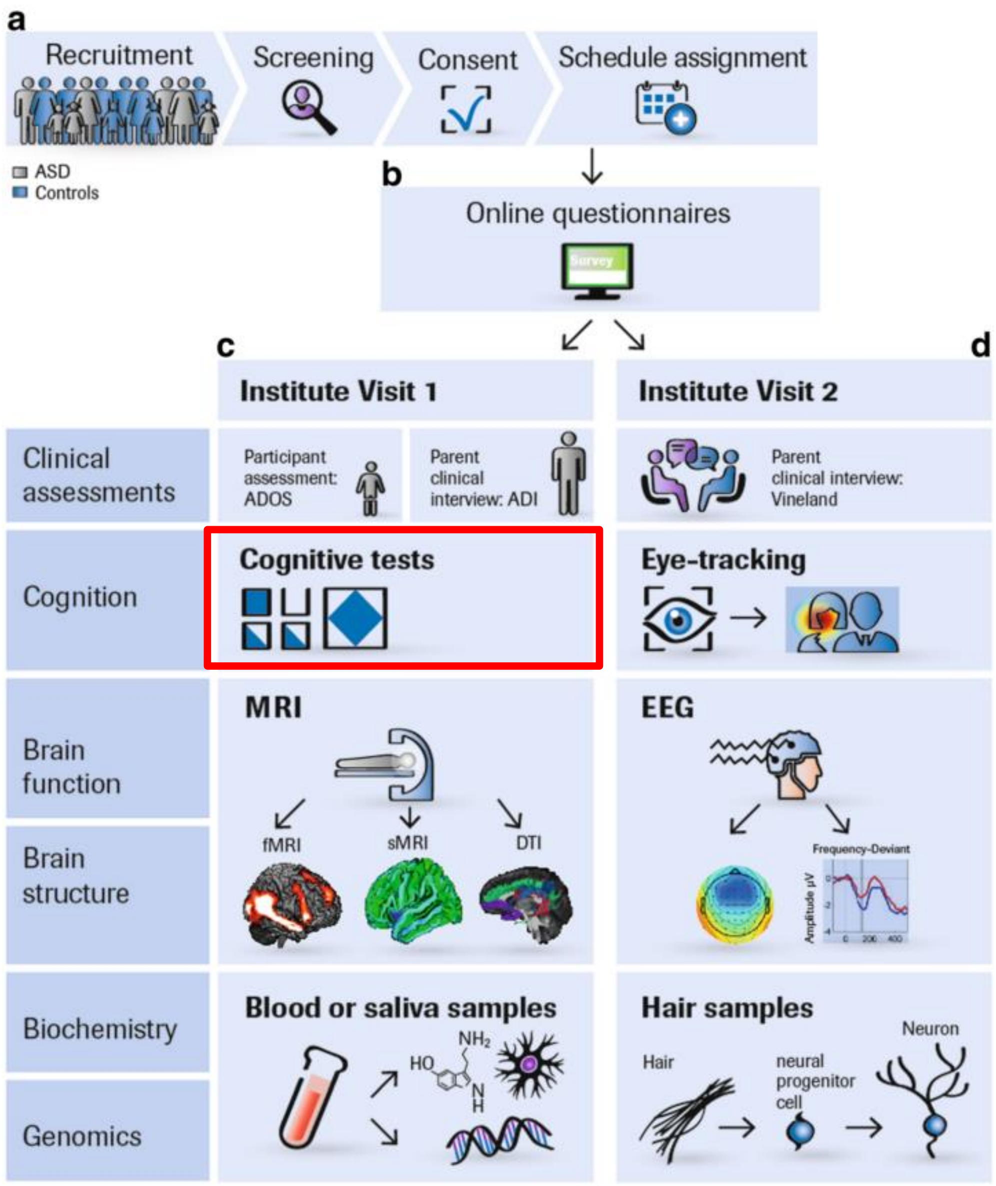
EU-AIMS
Autism Research in Europe

AIMS•2•TRIALS
AUTISM RESEARCH FOR EUROPE



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

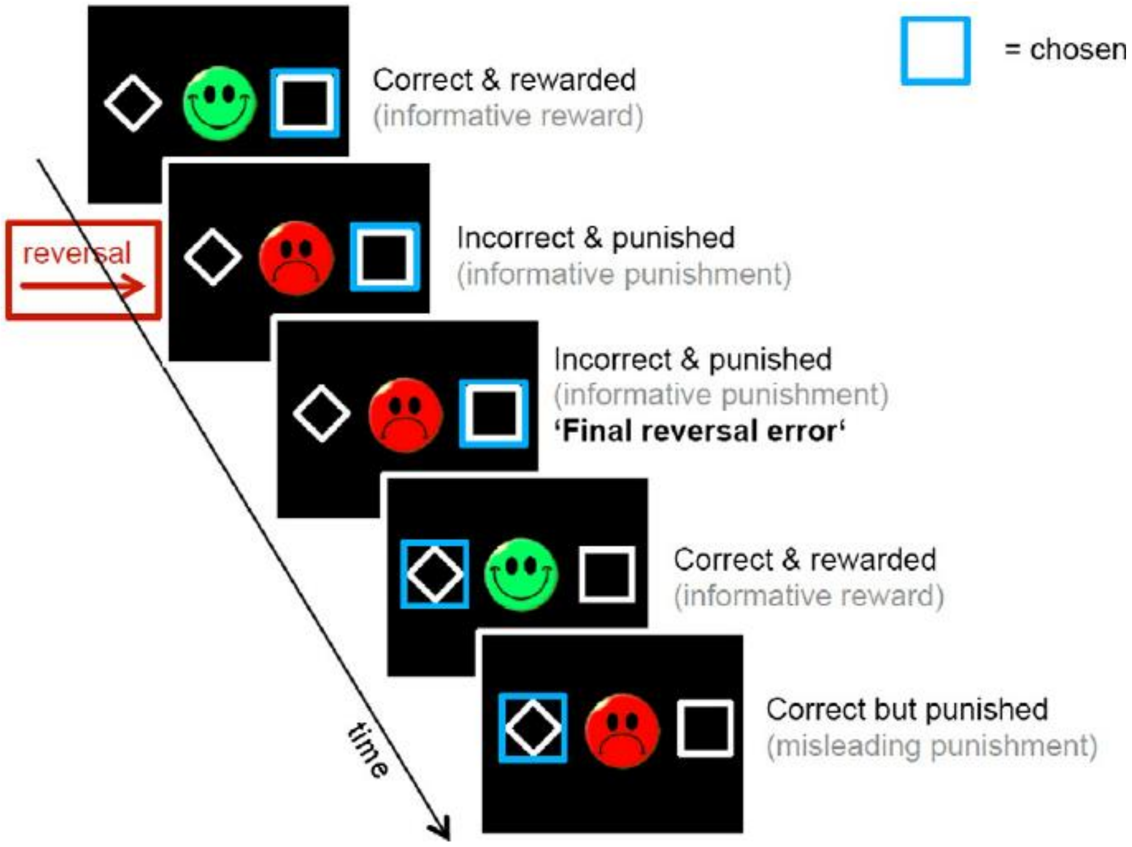
- ‘The ability to **shift between** different tasks or goals
- ‘The ability to **shift** to different thoughts or actions **depending on situational demands**’
- ‘Capacity to **adjust** one’s thoughts or actions **in response to** situational **changes**’

Miyake et al., (2000); Monsell, (2003); Geurts et al., (2009); Costescu et al., (2015)

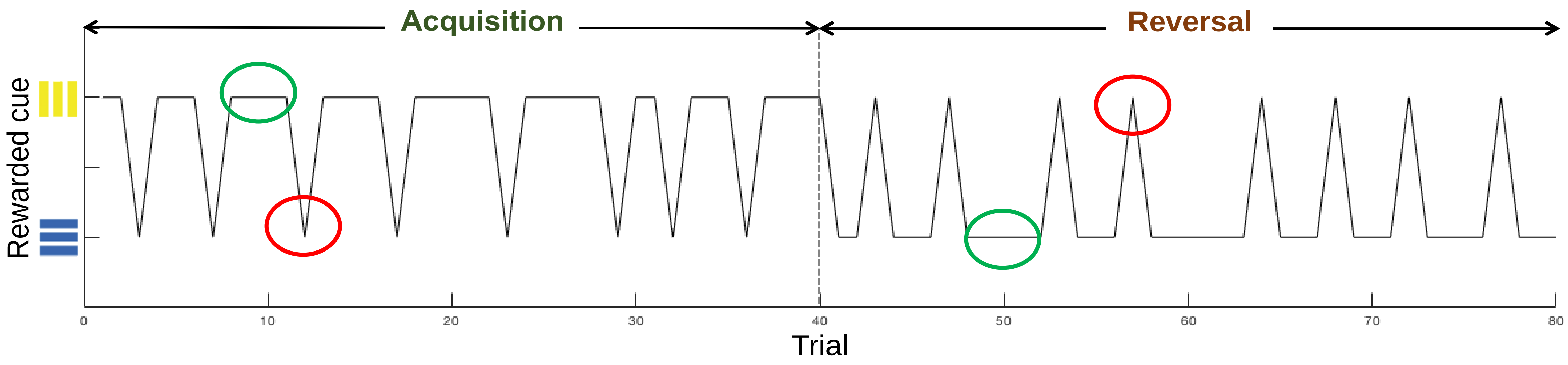
Cognitive flexibility studies

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

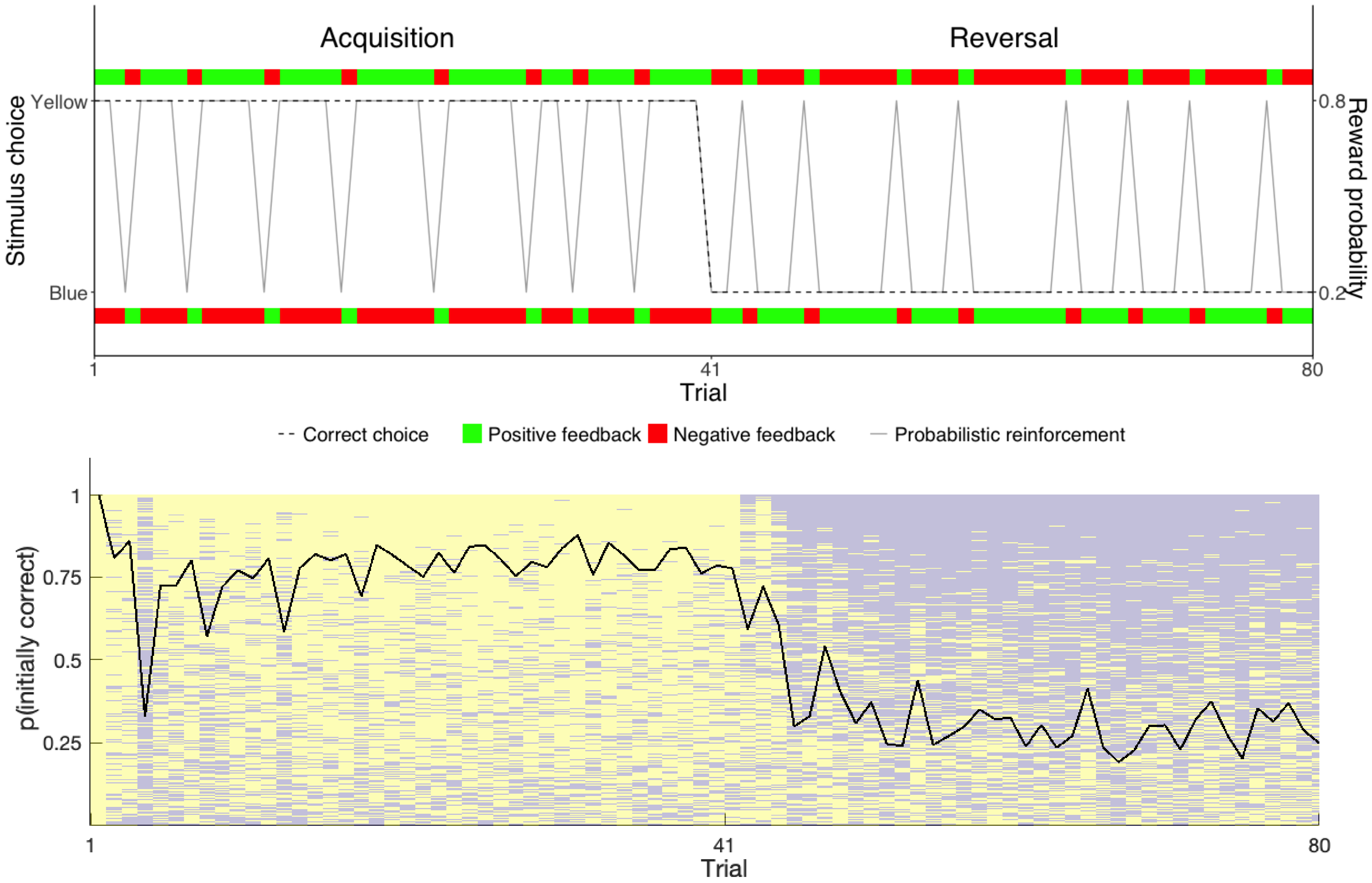


Common outcome, needs to be learnt

Rare outcome, needs to be ignored

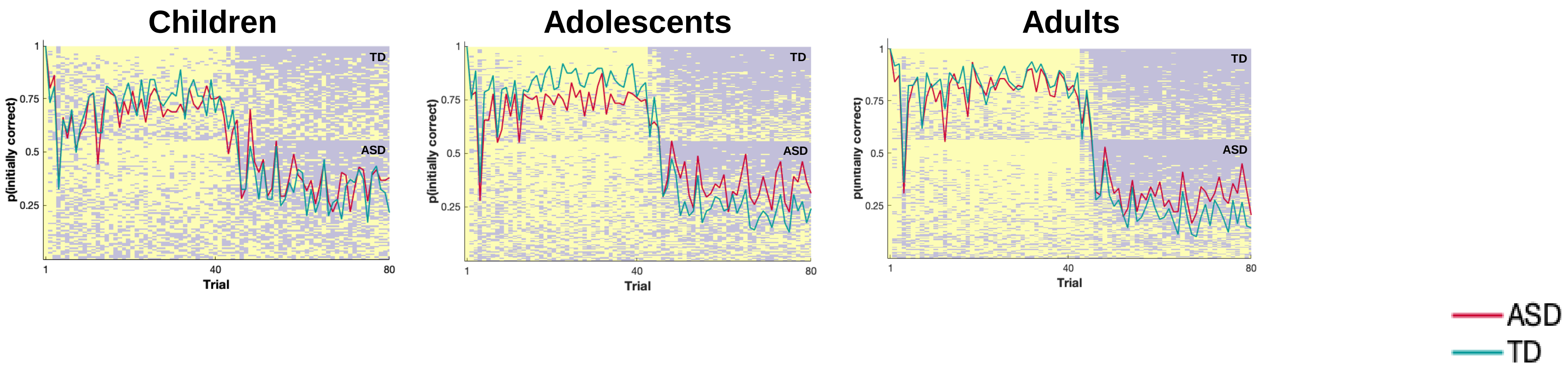
den Ouden et al. (2013)

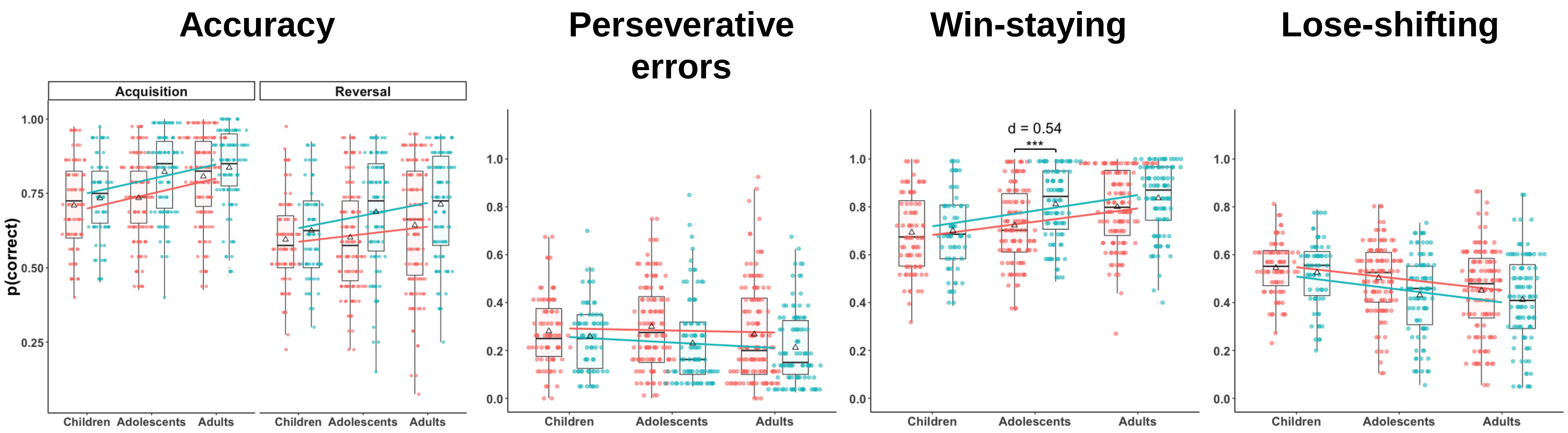
Overall trial-wise performance



Crawley & Zhang et al. (2019)

age group x diagnostic

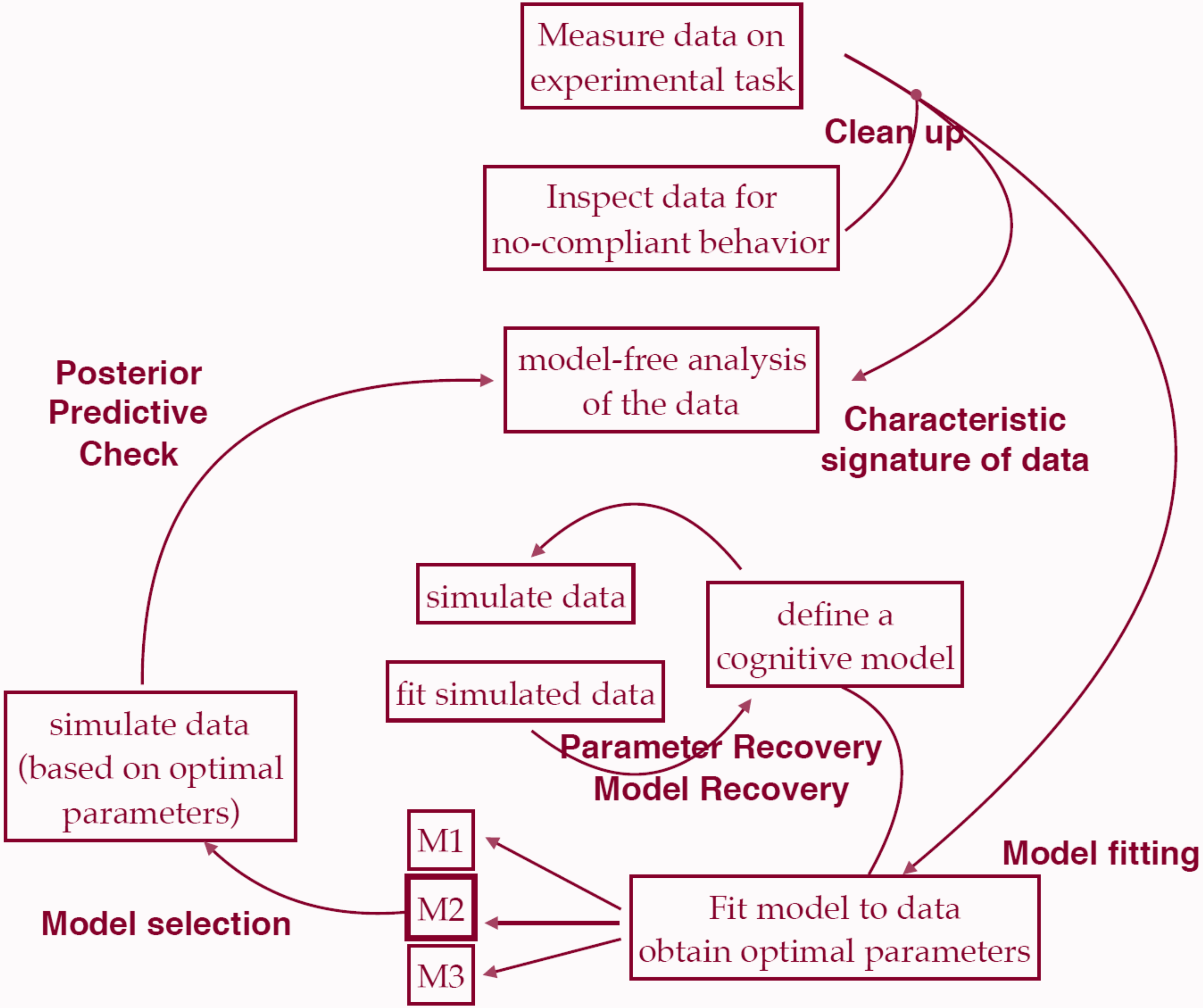




Crawley & Zhang et al. (2019)

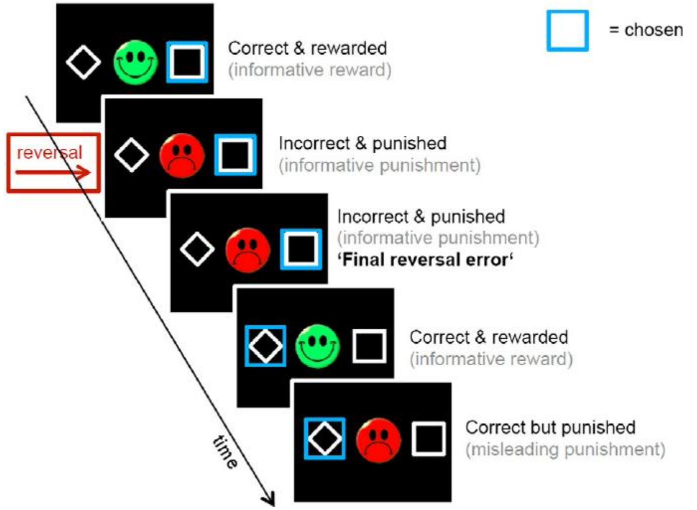
Outline

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



Measure data on experimental task
Clean up
Inspect data for no-compliant behavior
Posterior Predictive Check
model-free analysis of the data
Characteristic signature of data
simulate data
define a cognitive model
fit simulated data
Parameter Recovery
Model Recovery
simulate data (based on optimal parameters)
M1
M2
M3
Model selection
Model fitting
Fit model to data obtain optimal parameters

What to model?



what do we know?

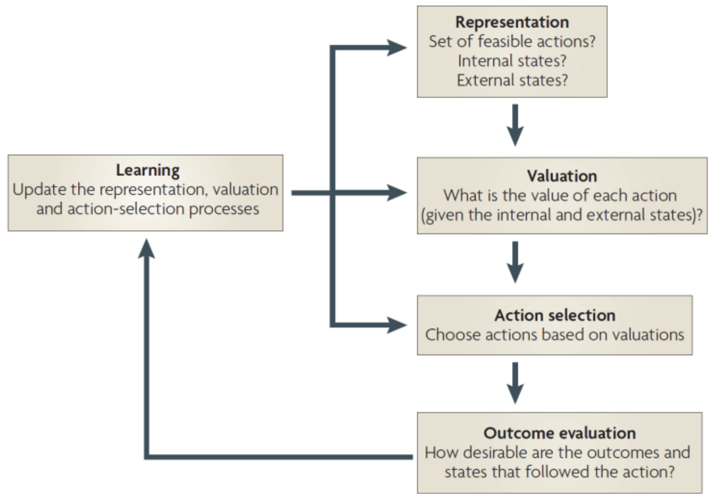
what can we measure?

what do we not know?

choice & outcome

choice accuracy

computational processed



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

Rangel et al (2008)

Model space

Counterfactual update RL

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

Reward-punishment RL

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

Experience-weighted attraction

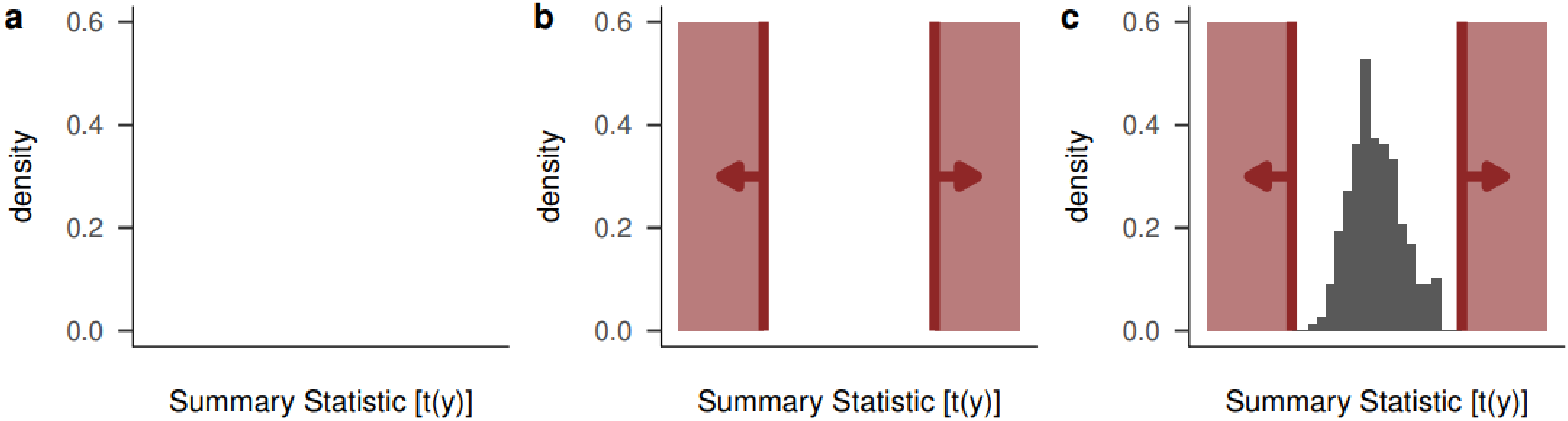
$$n_{c,t} = n_{c,t-1} \times \rho + 1$$
$$V_{c,t} = \left(V_{c,t-1} \times \varphi \times n_{c,t-1} + O_{t-1}\right) / n_{c,t}$$

Hampton et al. (2007); den Ouden et al. (2013)

Common cognitive models in decision-making

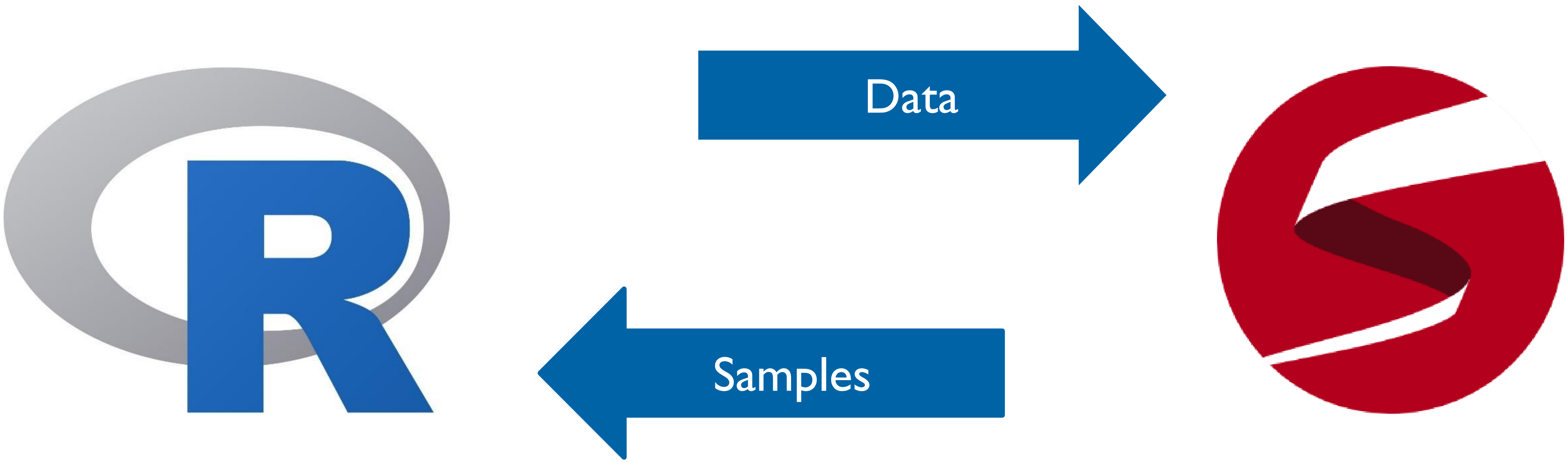
- Reinforcement learning model
- Bayesian learning model
- Risk-aversion model
- Hyperbolic delay discounting model
- Fehr-Schmidt inequity aversion model
- Sequential sampling model
- Experience-weighted attraction model
- …

Prior predictive checks: *domain expertise consistency*



[Schad et al. (2019)](#)

Model fitting



Model fitting

cpsy

an open access journal

RESEARCH

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

Woo-Young Ahn[1], Nathaniel Haines[1], and Lei Zhang[2]

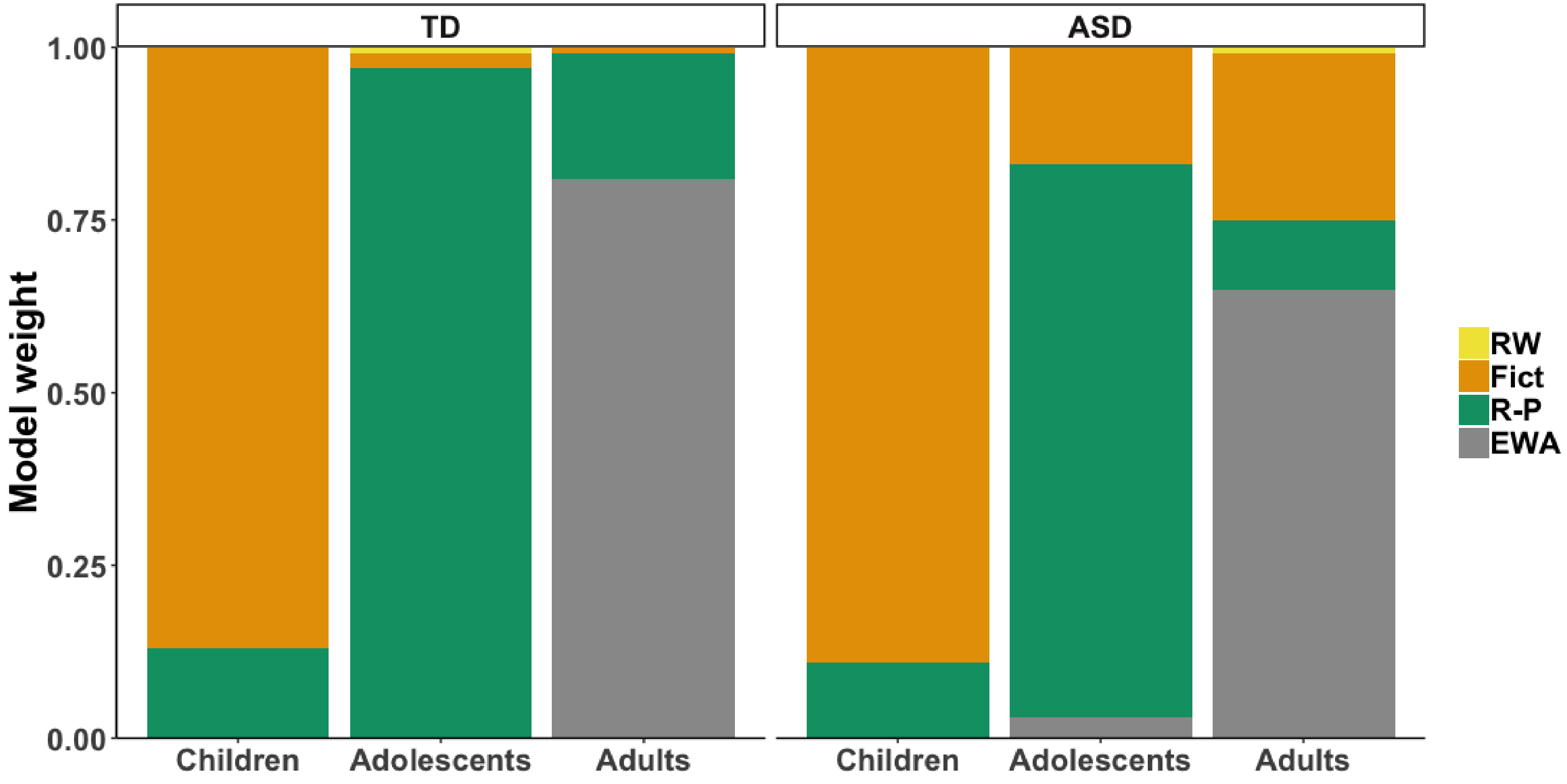
[1]Department of Psychology, The Ohio State University, Columbus, OH

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

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

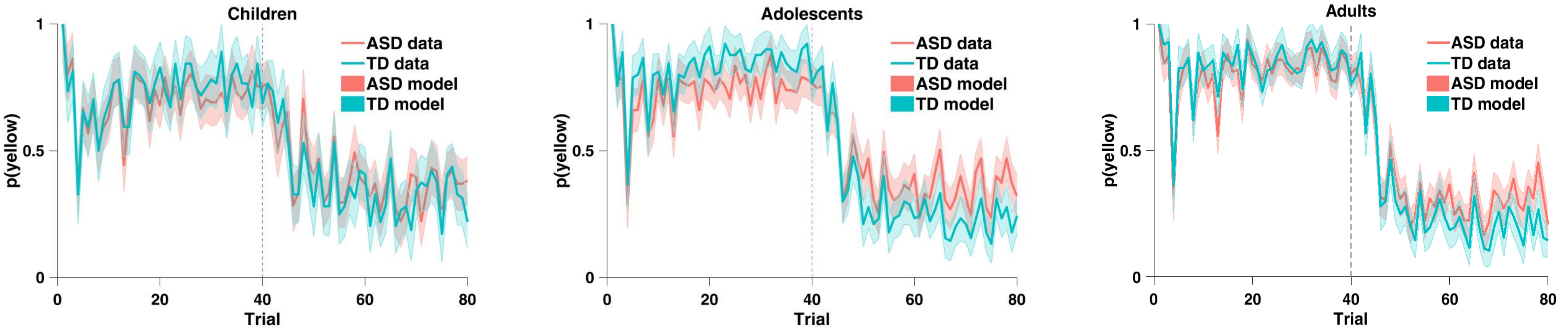
https://ccs-lab.github.io/hBayesDM/articles/getting_started.html

Model comparison



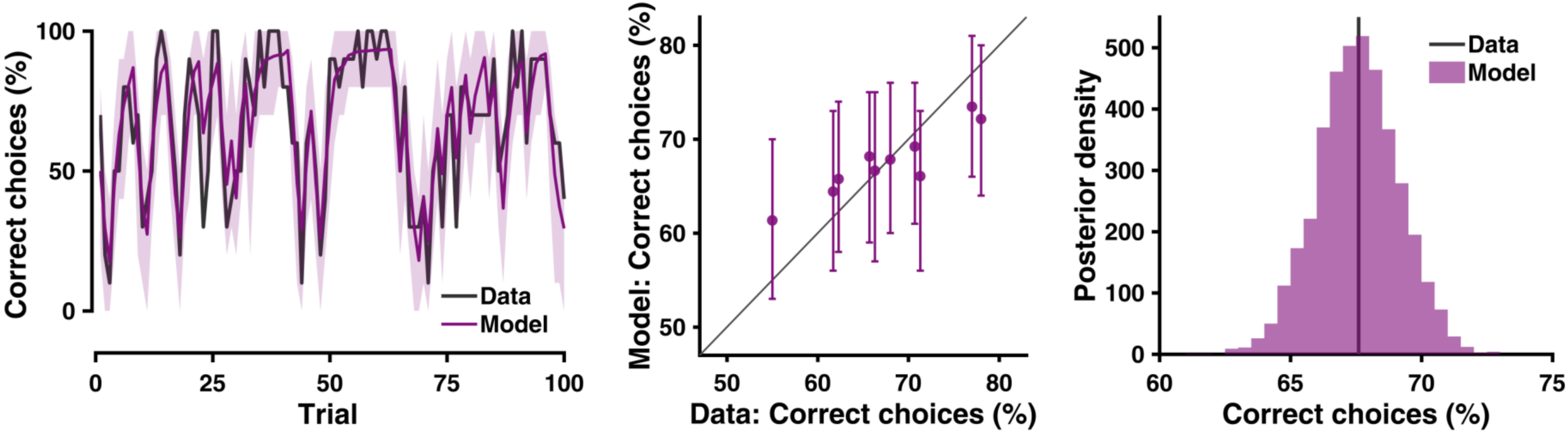
Crawley & Zhang et al. (2019)

Model validation with posterior predictive checks (PPC)



Crawley & Zhang et al. (2019)

More on PPC

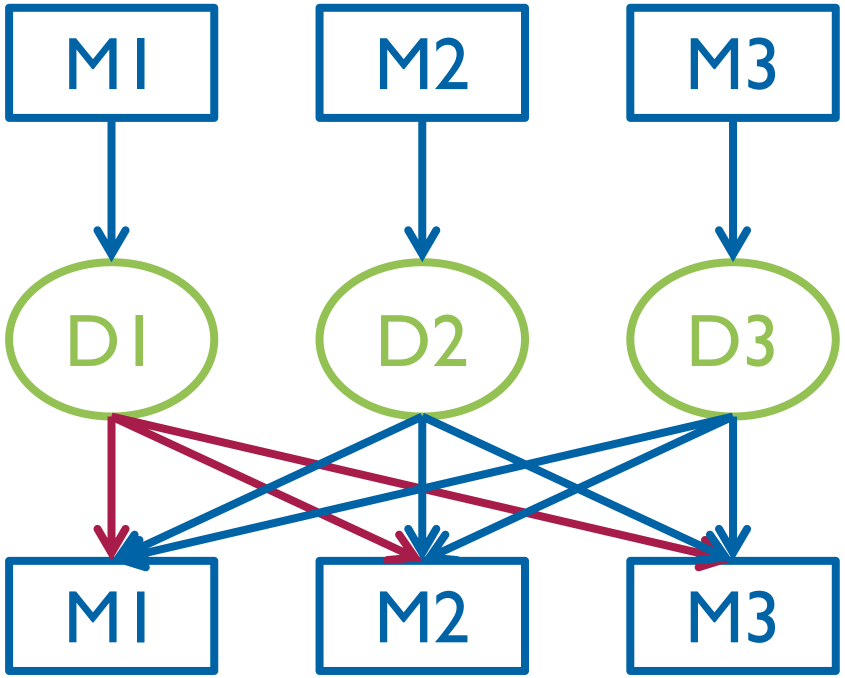


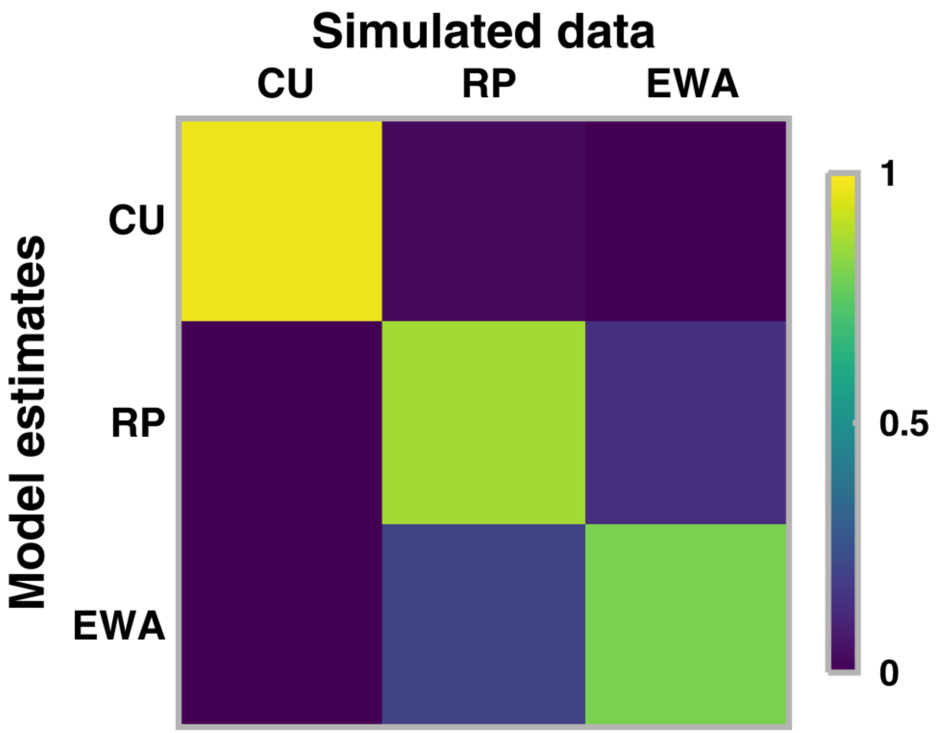
Zhang & Lengersdorff et al. (2019)

Model recovery:
are models identifiable

generative process

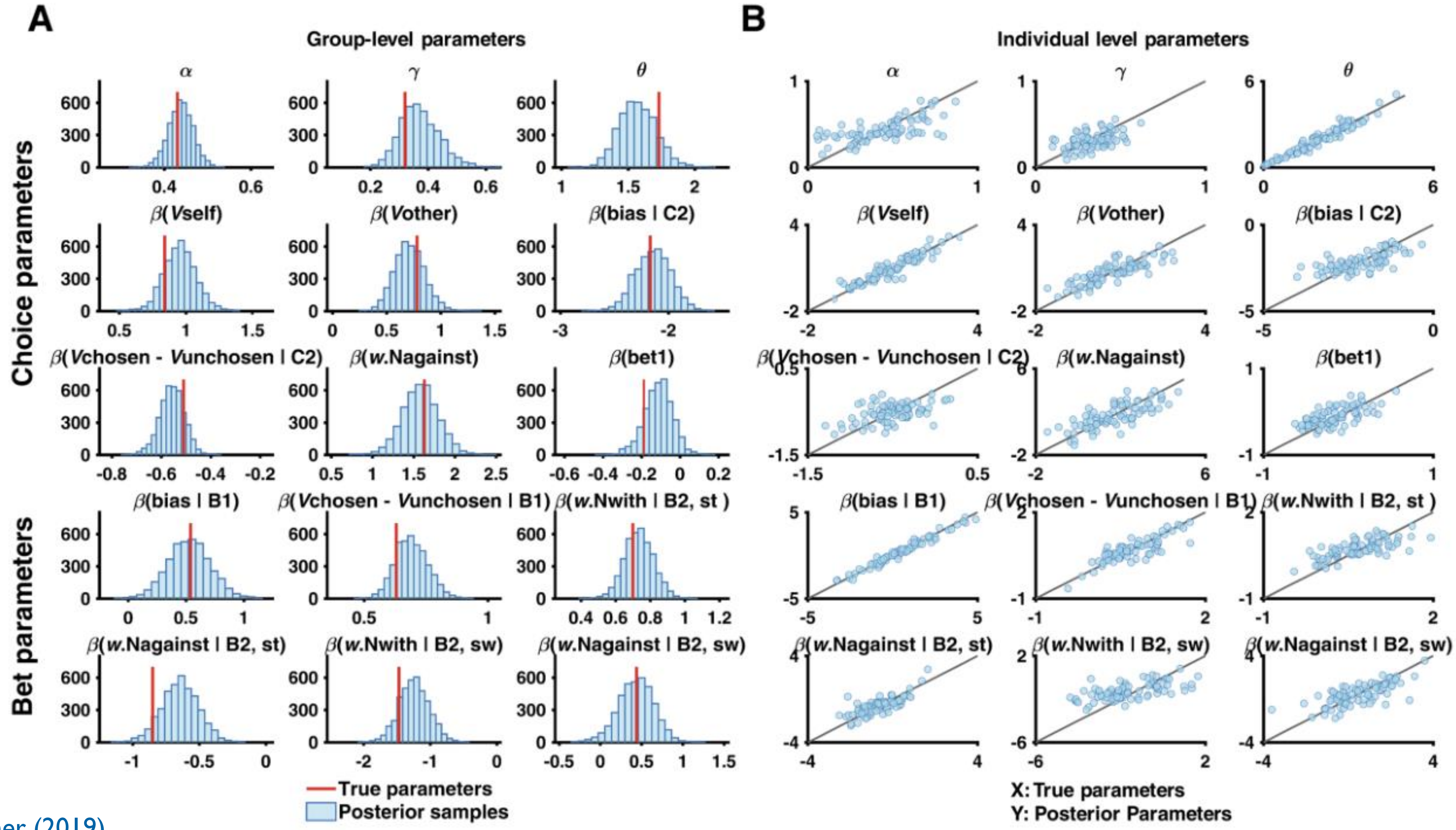
fitting process





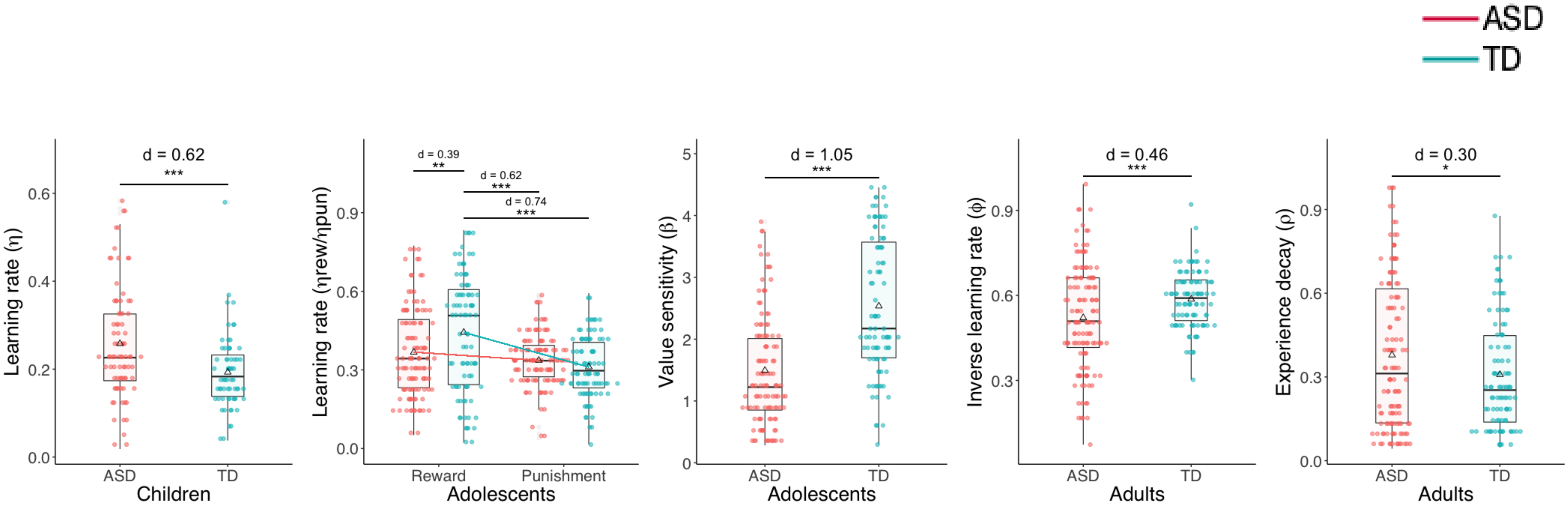
Crawley & Zhang et al. (2019)

Parameter recovery:
are parameters identifiable



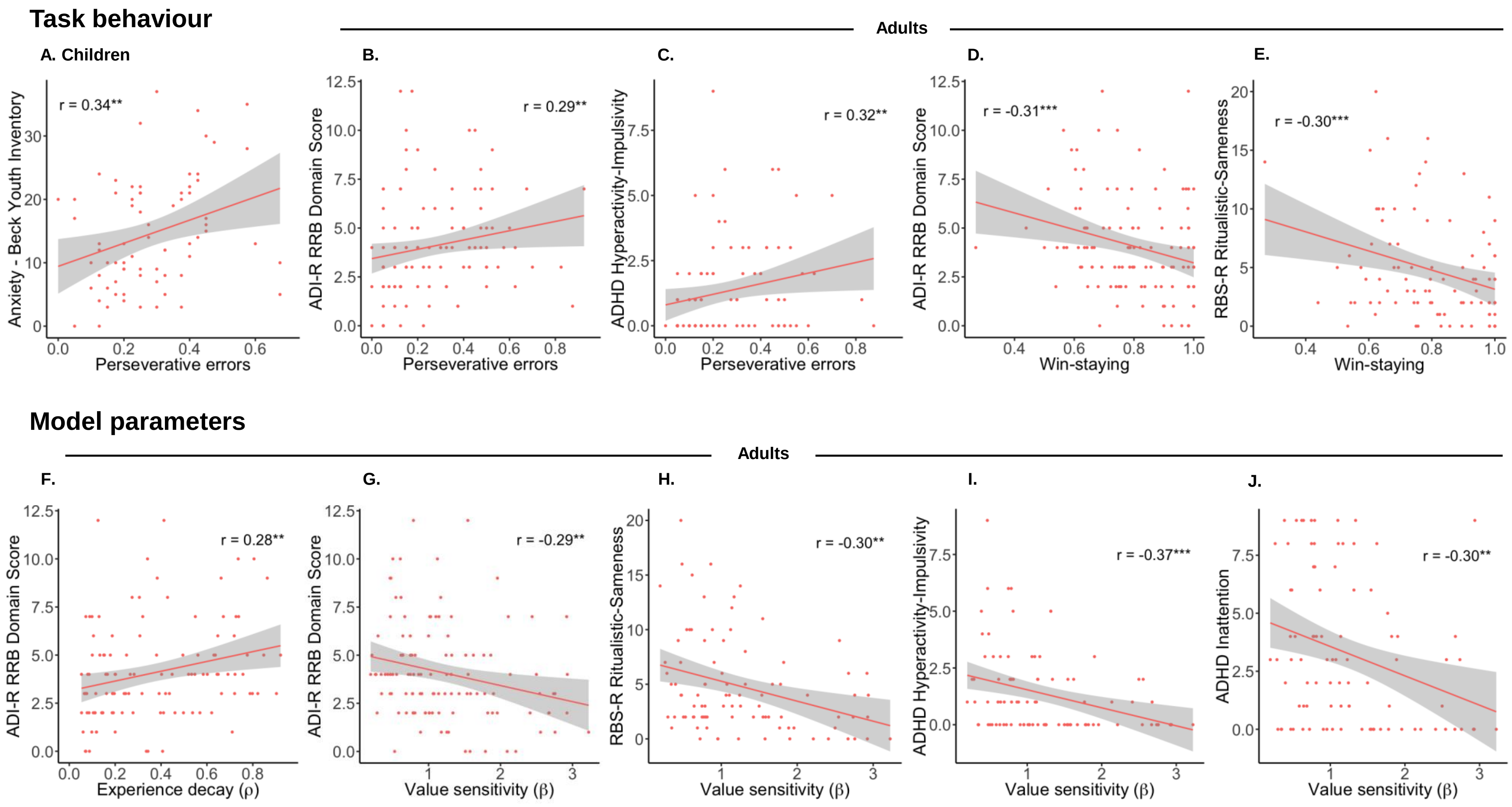
Zhang & Gläscher (2019)

Parameter results



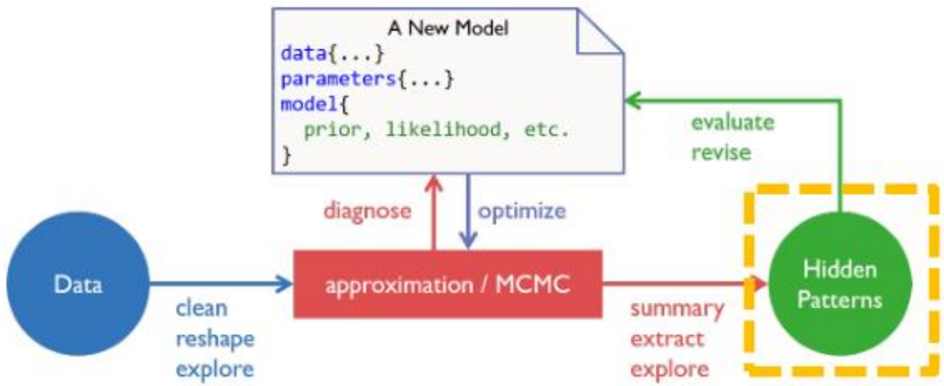
Crawley & Zhang et al. (2019); Zhang & Lengersdorff et al. (2019) for more on interpreting parameters in simple RL models

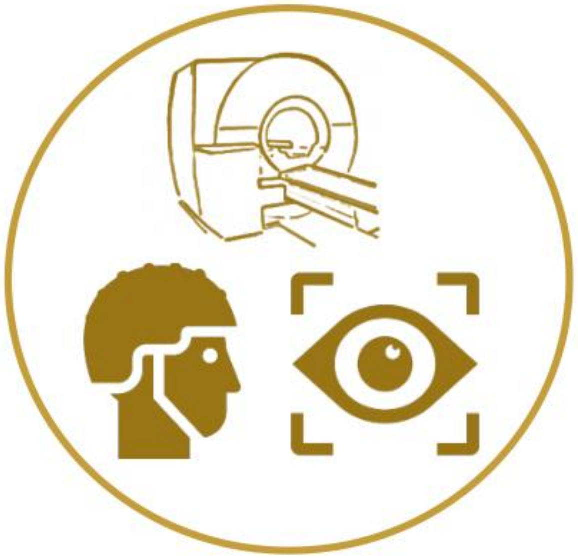
Parameter ~ clinical scales

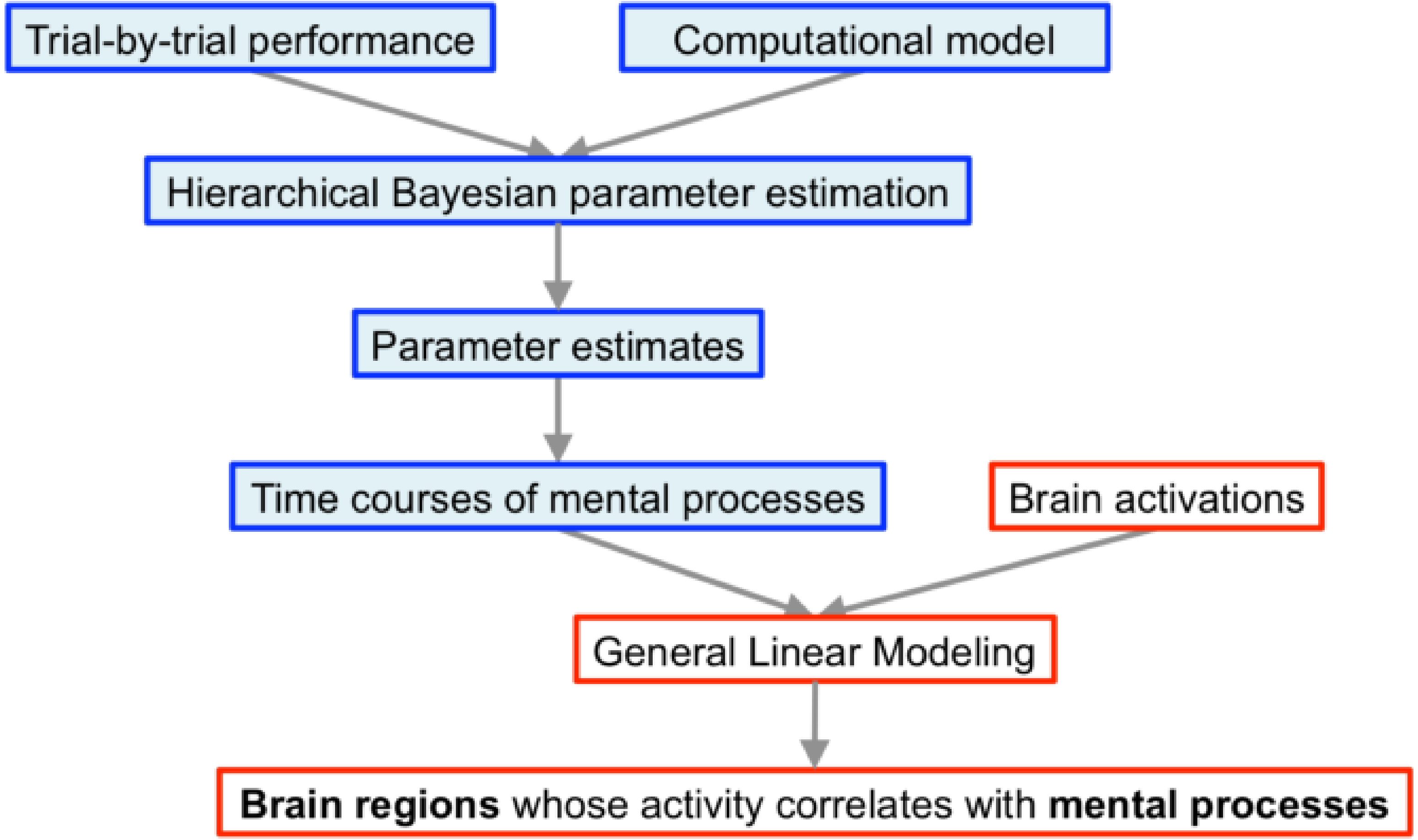


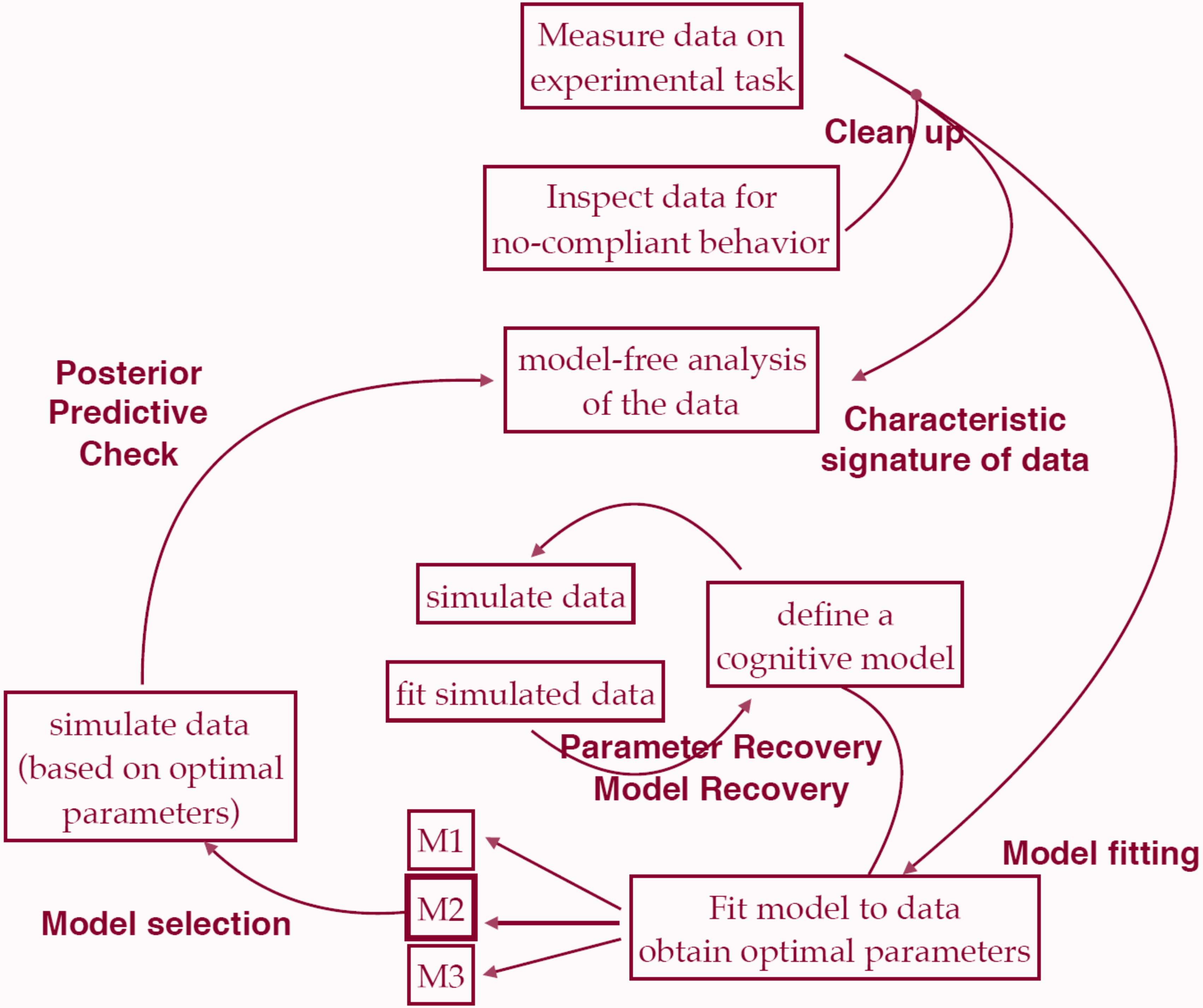
Crawley & Zhang et al. (2019)

Model-based analysis



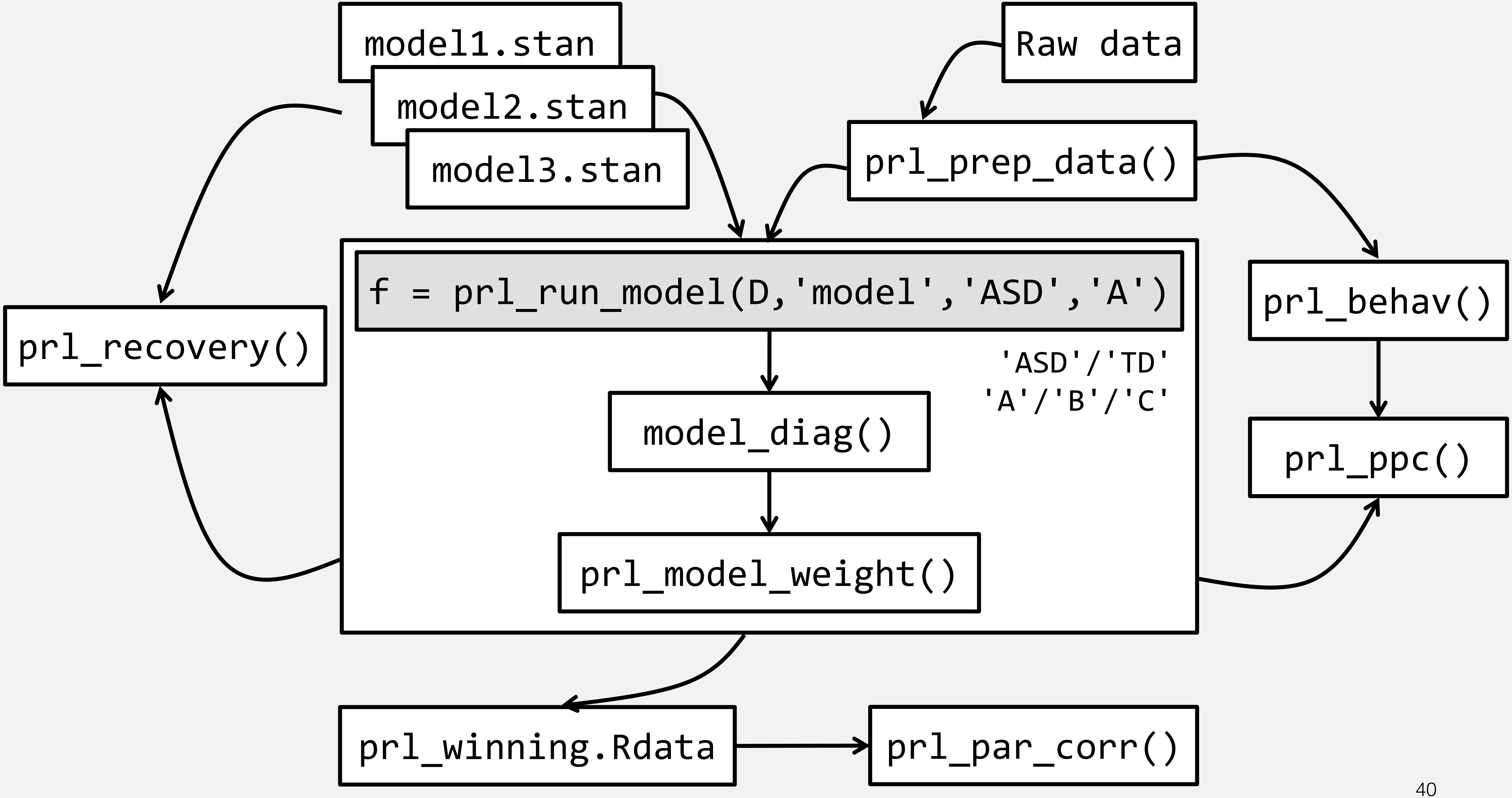





Measure data on experimental task
Clean up
Inspect data for no-compliant behavior
Posterior Predictive Check
model-free analysis of the data
Characteristic signature of data
simulate data
define a cognitive model
fit simulated data
Parameter Recovery
Model Recovery
simulate data (based on optimal parameters)
M1
M2
M3
Model fitting
Model selection
Fit model to data obtain optimal parameters

Outline

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


model1.stan
model2.stan
model3.stan
Raw data
prl_prep_data()
prl_recovery()
f = prl_run_model(D,'model','ASD','A')
'ASD'/'TD'
'A'/'B'/'C'
model_diag()
prl_model_weight()
prl_behav()
prl_ppc()
prl_winning.Rdata
prl_par_corr()

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

CREATED ON November 06, 2019 LAST EDITED March 19, 2020

https://psyarxiv.com/uthw2

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

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

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, Monja I Froböse, Jennifer L Cook, Dirk EM Geurts, Michael J Frank, Roshan Cools, Hanneke EM den Ouden
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

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

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]

[a]Department of Social Psychology, University of Amsterdam, 1018 WT Amsterdam, The Netherlands; [b]Laboratory for Social and Neural Systems Research, Department of Economics, University of Zürich, 8001 Zürich, Switzerland; [c]Section for Psychology, Department of Clinical Neuroscience, Karolinska Institutet, 171 77 Stockholm, Sweden; and [d]Department of Clinical Psychology, University of Amsterdam, 1018 WT Amsterdam, The Netherlands

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

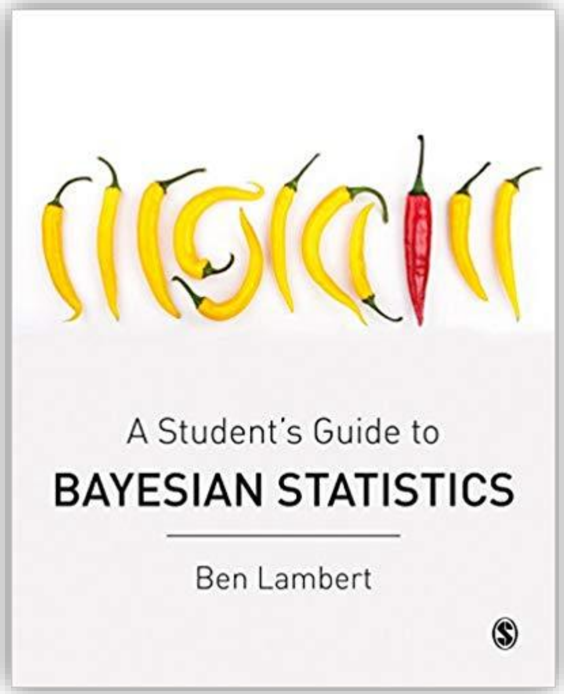
Article

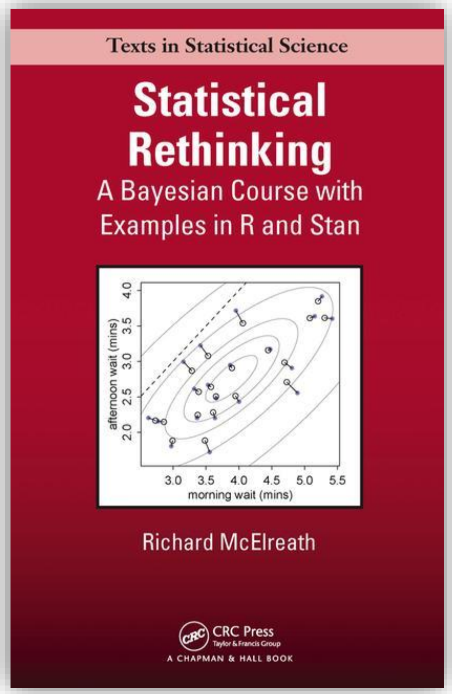
Primate Amygdala Neurons Simulate Decision Processes of Social Partners

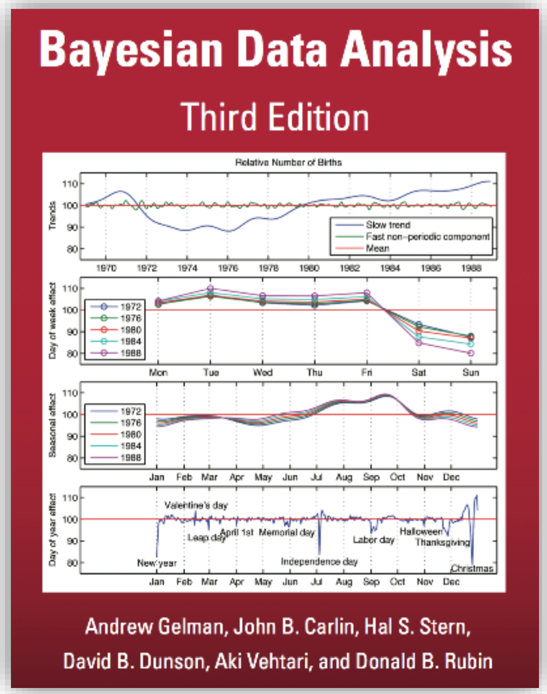
Fabian Grabenhorst [1, 5], Raymundo Báez-Mendoza [1, 4], Wilfried Genest [1], Gustavo Deco [2, 3], Wolfram Schultz [1]

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

@leizhang认知神经科学

@LeiZhang

@lei-zhang

SUBSCRIBE


ANY QUESTIONS ?

Happy Computing!