TEWA 1: Advanced Data Analysis

Lecture 13

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https://github.com/lei-zhang/tewa1_univie

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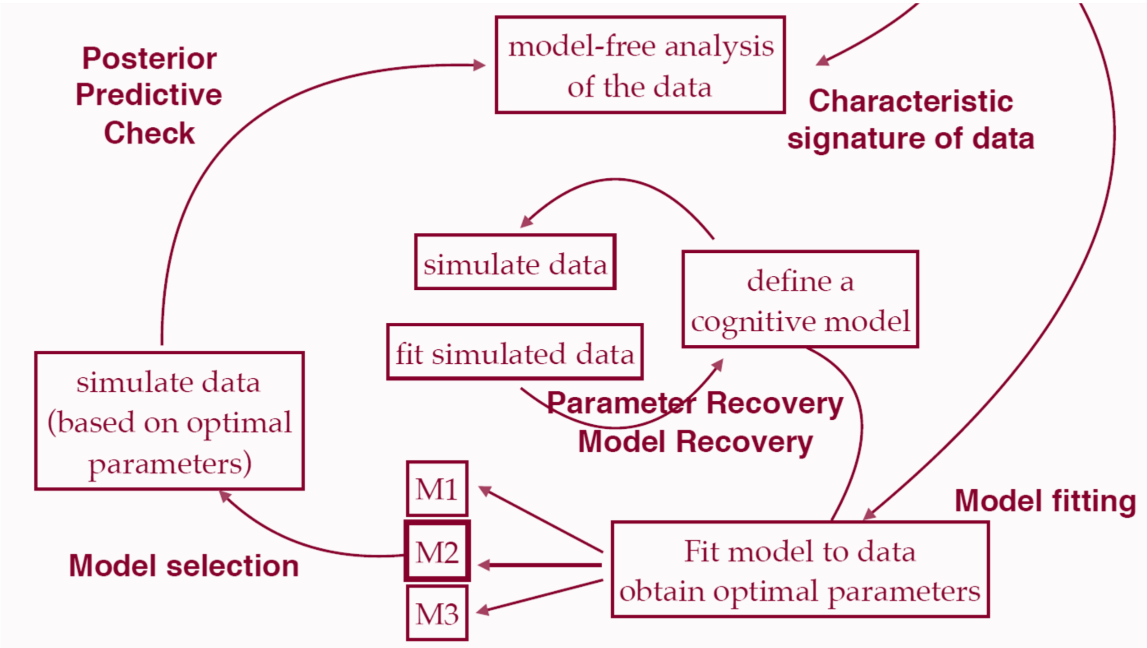

Cracking computational modelling with Stan: A principled Bayesian workflow

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Fakultät für Psychologie

Outline

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

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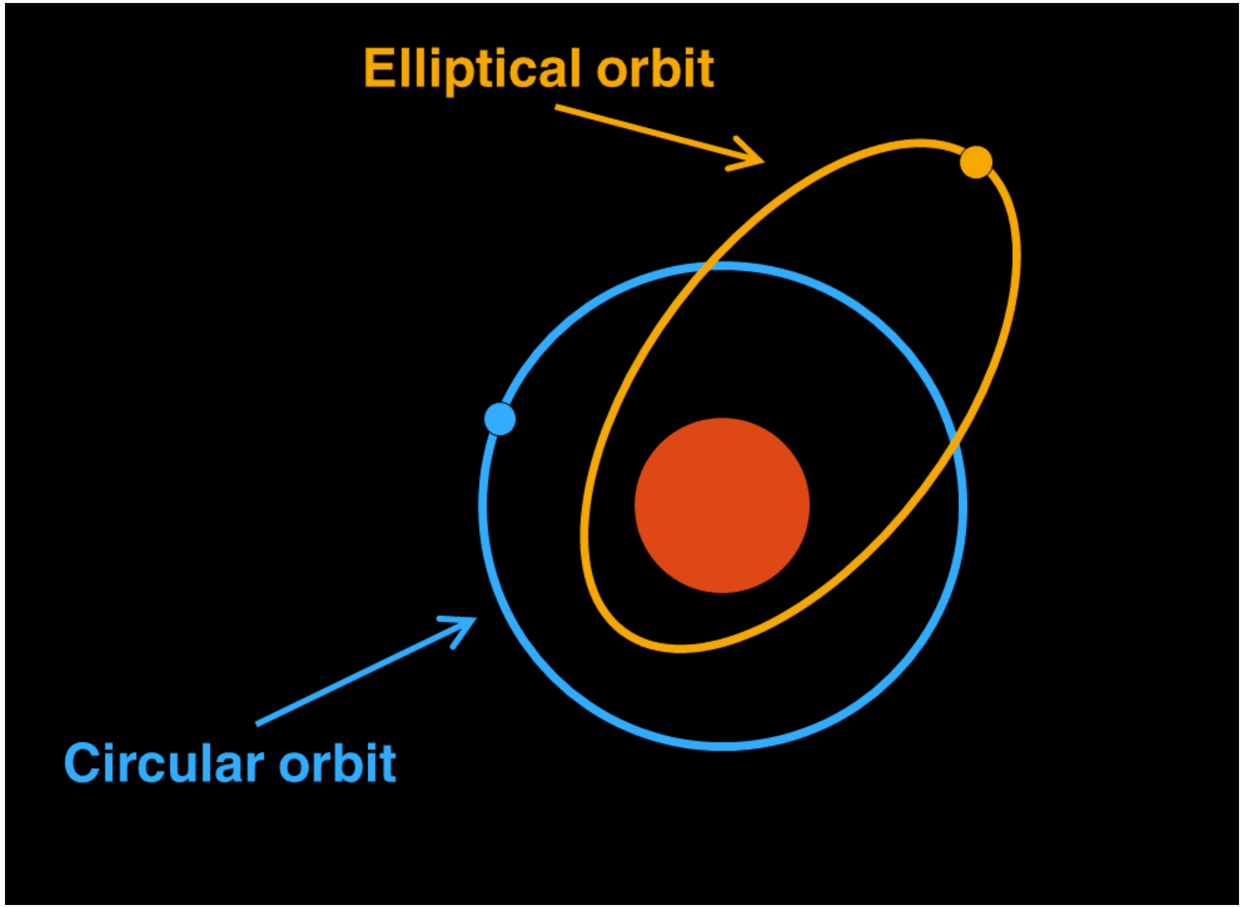
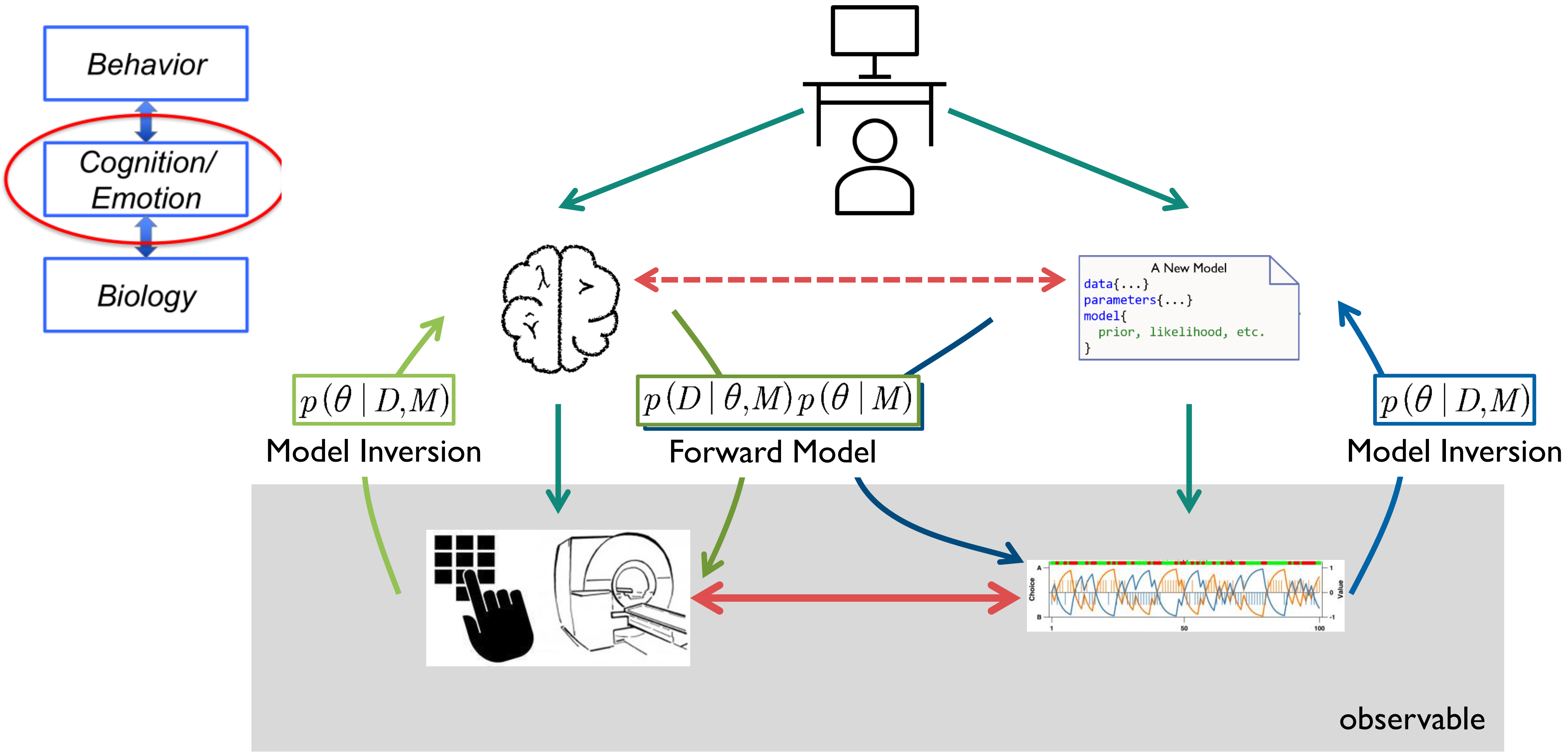
The idea of computational modeling is never new

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



Computational modeling of Cognition



Lewandowsky & Farrell (2011); Stephan et al. (2016); Ahn et al., (2017)

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

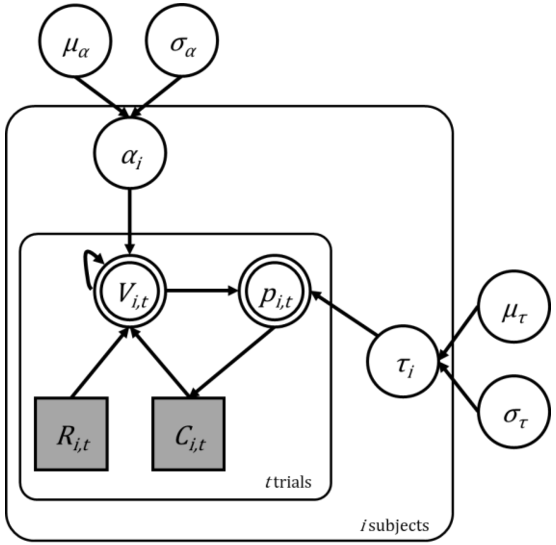
Article | Open Access | Published: 17 March 2020

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

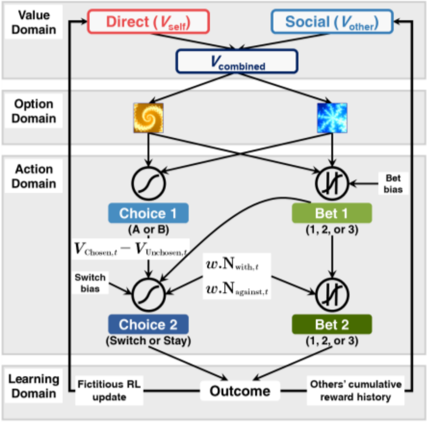
Geert-Jan Will, Michael Moutoussis, Palee M. Womack, Edward T. Bullmore, Ian M. Goodyer, Peter Fonagy, Peter B. Jones, NSPN Consortium, Robb B. Rutledge & Raymond J. Dolan

I like the idea of Modeling, ...

…but, …



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



$$
\begin{aligned}
V_{self,t} &= [V_{self,t}(A), V_{self,t}(B)] \\
V_{other,t} &= [V_{other,t}(A), V_{other,t}(B)] \\
V_t &= \beta_{vself} V_{self,t} + \beta_{vother} V_{other,t} \\
C1_t &\sim Categorical(Softmax(V_t)) \\
U_{bet1,t} &= \beta_{bias_{B1}} + \beta_{vdiff_{B1}}(V_{chosen,C1,t} - V_{unchosen,C1,t}) \\
B1_t &\sim OrderedLogistic(U_{bet1,t} \mid \theta) \\
w.N_{against,t} &= \frac{\sum_{s=1}^{K} w_{s,t}}{\sum_{s=1}^{4} w_{s,t}}, K = 0,1,\dots,4 \\
w.N_{with,t} &= \frac{\sum_{s=1}^{4-K} w_{s,t}}{\sum_{s=1}^{4} w_{s,t}} \\
V_t(\text{switch}) &= \beta_{bias_{C2}} + \beta_{vdiff_{C2}}(V_{chosen,C1,t} - V_{unchosen,C1,t}) + \beta_{against} w.N_{against,t} \\
C2 &\sim Bernoulli(V_t(\text{switch})) \\
U_{bet2,t} &= \begin{cases} U_{bet1,t} + \beta_{with_{agr}} w.N_{with,t} + \beta_{against_{agr}} w.N_{against,t} &, \text{if } C1 = C2 \\ U_{bet1,t} + \beta_{with_{dis}} w.N_{with,t} + \beta_{against_{dis}} w.N_{against,t}, &\text{if } C1 \neq C2 \end{cases} \\
B2_t &\sim OrderedLogistic(U_{bet2,t} \mid \theta) \\
\Phi(x) &= \frac{1}{1+e^{-x}} \\
\delta_{self,chosen,C2,t} &= R_{self,t} - V_{self,chosen,C2,t} \\
\delta_{self,unchosen,C2,t} &= -R_{self,t} - V_{self,unchosen,C2,t} \\
V_{self,chosen,C2,t+1} &= V_{self,chosen,C2,t} + \alpha\delta_{self,chosen,C2,t} \\
V_{self,unchosen,C2,t+1} &= V_{self,unchosen,C2,t} + \alpha\delta_{self,unchosen,C2,t}
\end{aligned}
$$

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...

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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. 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]

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

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]

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

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

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

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.

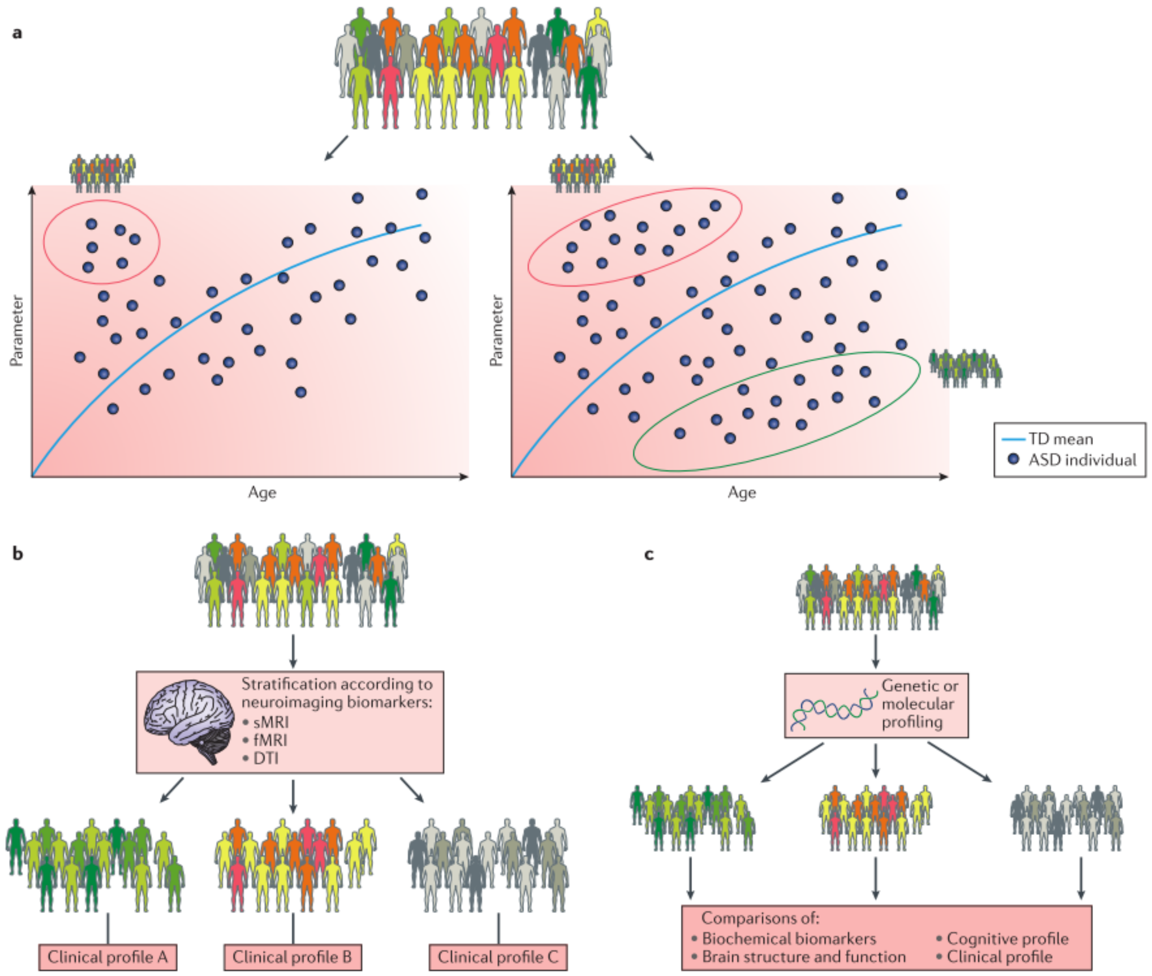
Visit computationalpsychiatry.org.

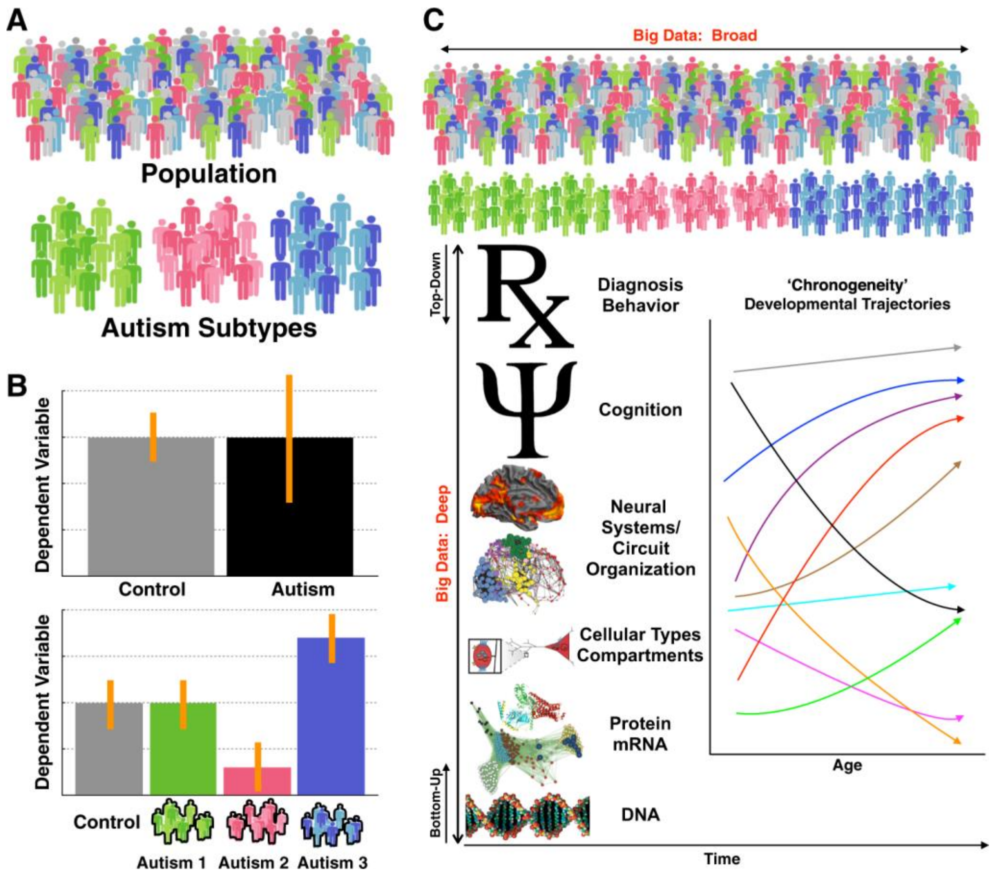
Continuous Publication
Founded: 2017
E-ISSN: 2379-6227

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





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

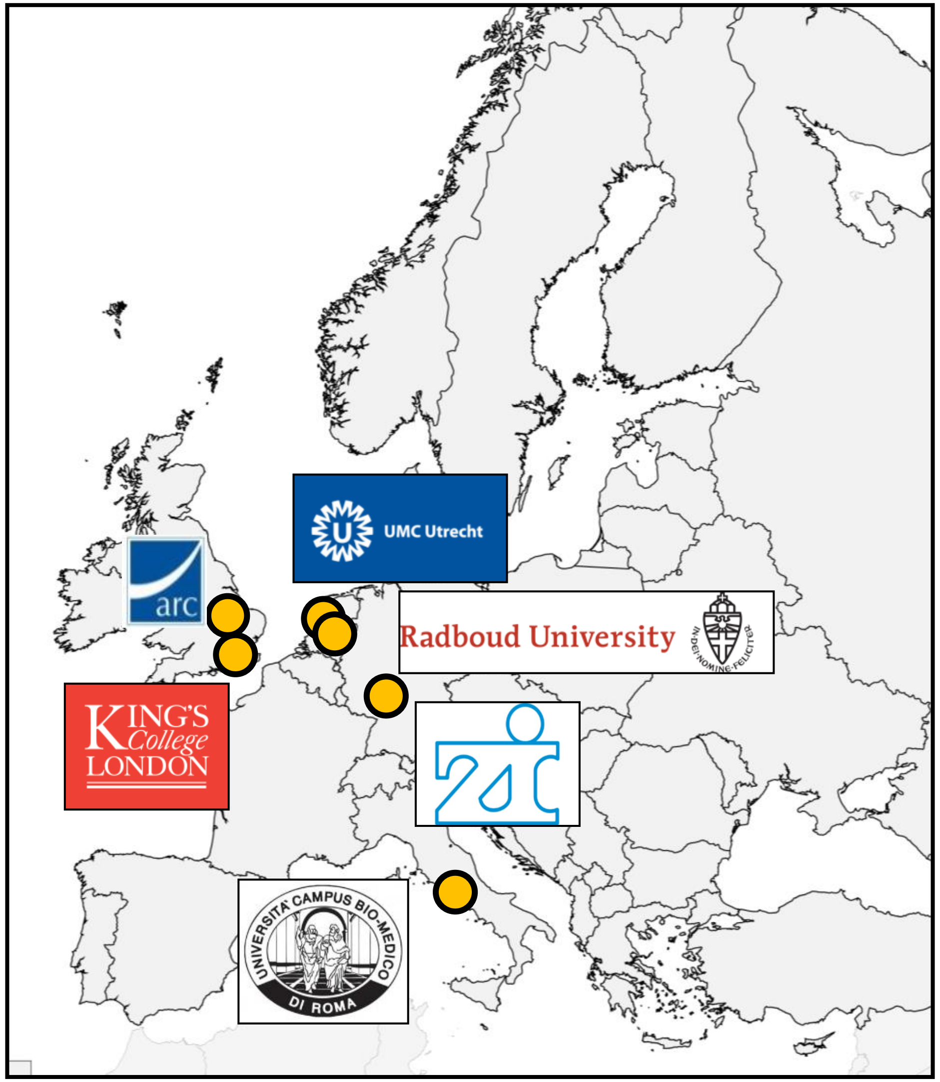
EU-AIMS

EU-AIMS
Autism Research in Europe

AIMS•2•TRIALS
AUTISM RESEARCH FOR EUROPE

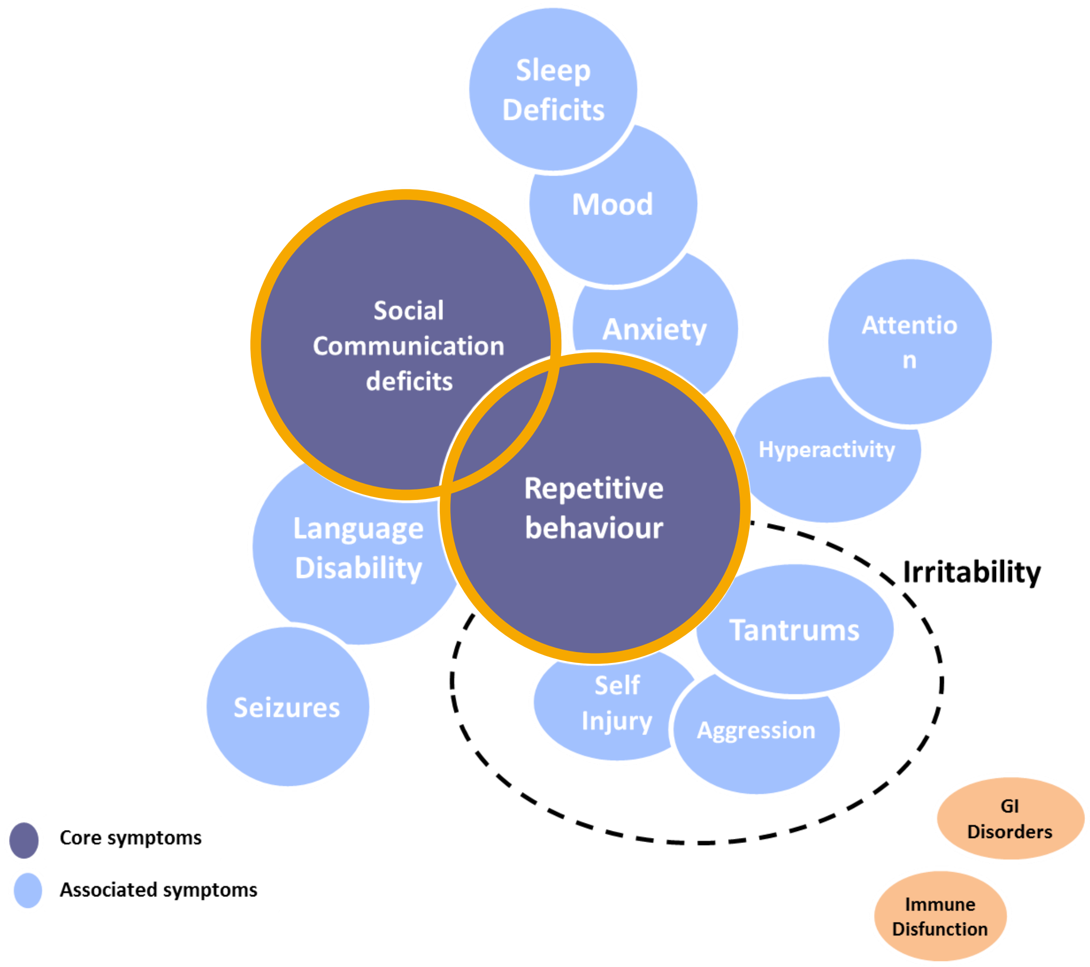
>120 scientist from 10 countries

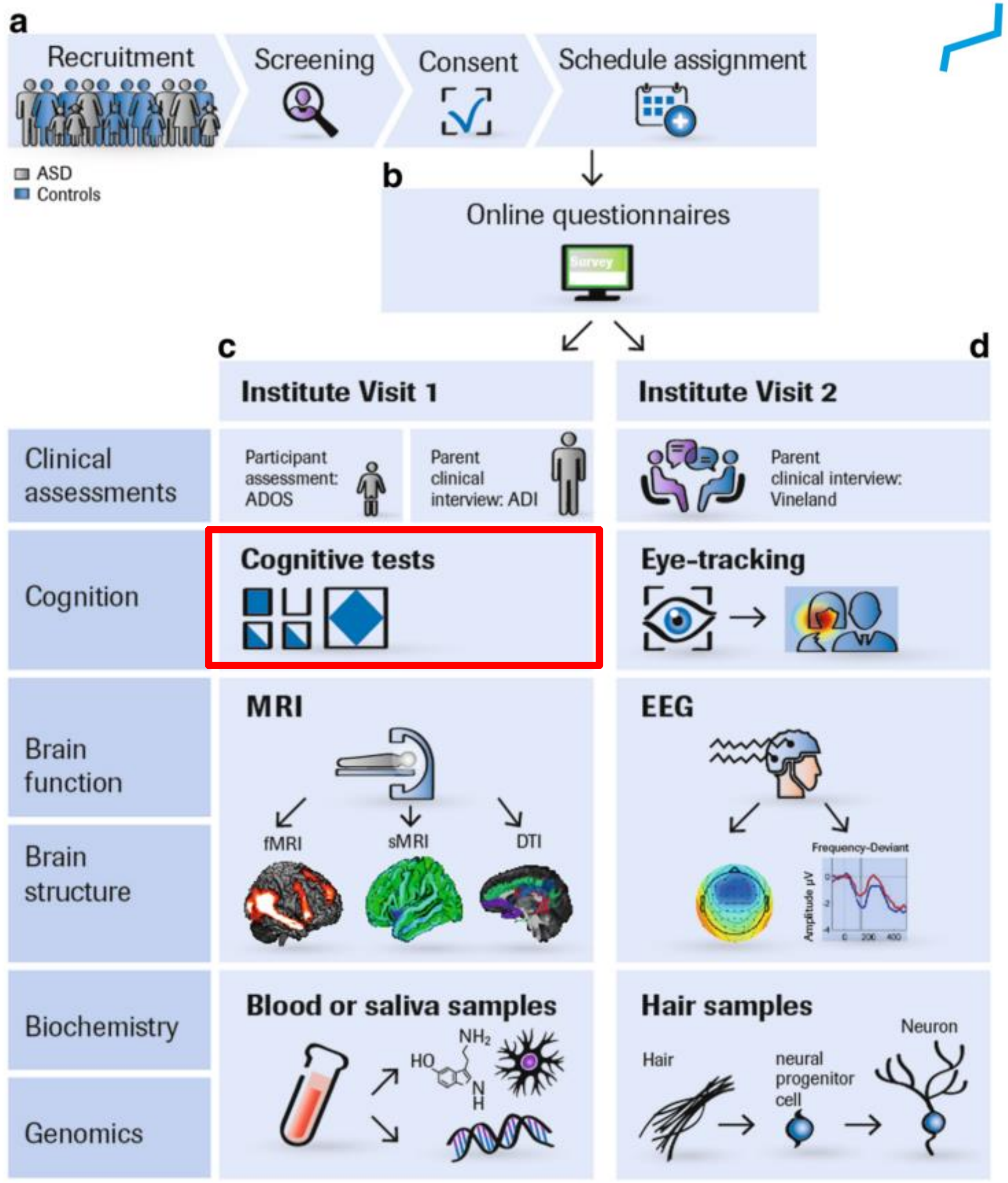
EU-AIMS LEAP
Longitudinal European Autism Project



		Diagnosis		
		ASD	TD	Total
Age group	Children (6-11 years)	81	64	145
	Adolescents (12-17 years)	114	90	204
	Adults (18-30 years)	126	97	223
	Total	321	251	572

EU-AIMS LEAP





[Loth et al. (2017)](#)

Impaired cognitive flexibility

26 Review *TRENDS in Cognitive Sciences* Vol.8 No.1 January 2004

ELSEVIER

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

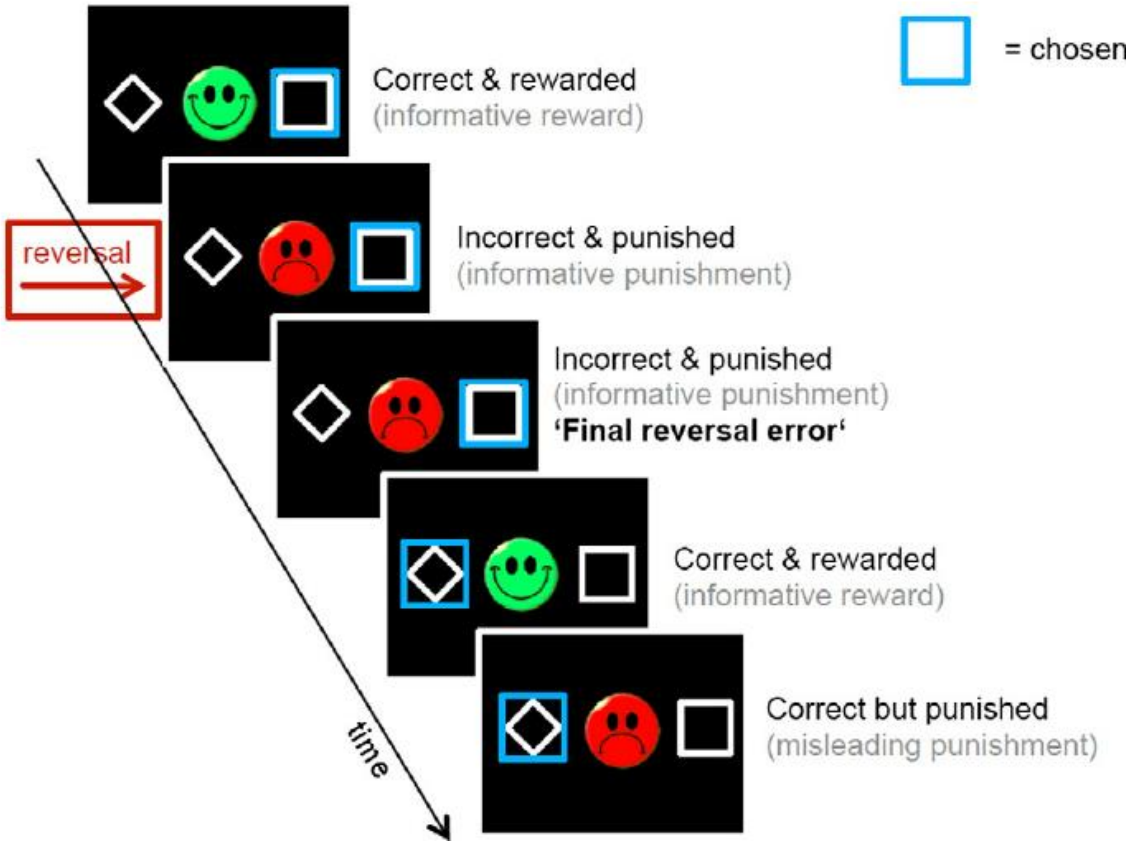
- ‘The ability to **shift between** different tasks or goals
- ‘The ability to **shift** to different thoughts or actions **depending on situational demands**’
- ‘Capacity to **adjust** one’s thoughts or actions **in response to** situational **changes**’

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

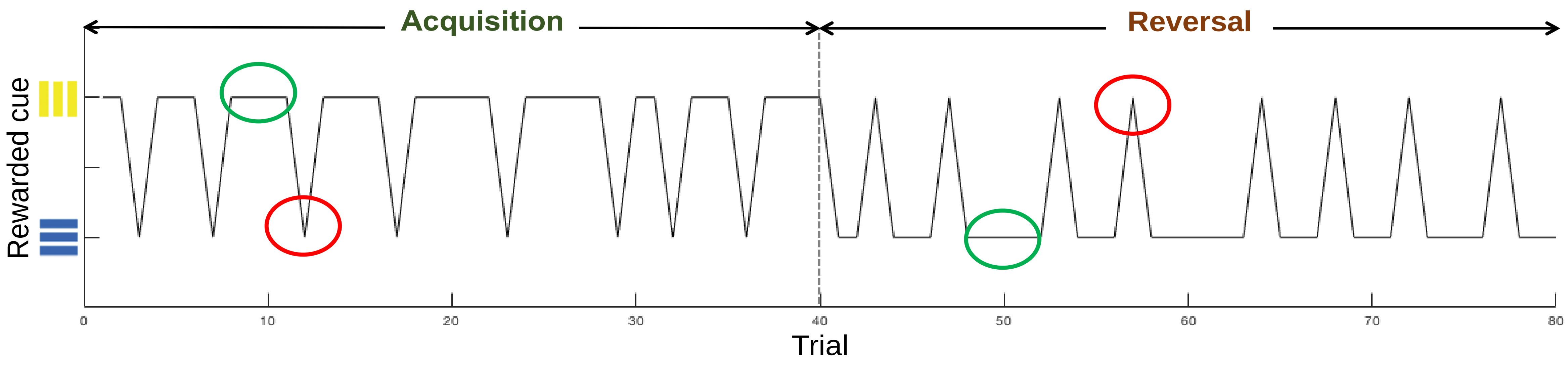
Cognitive flexibility studies

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

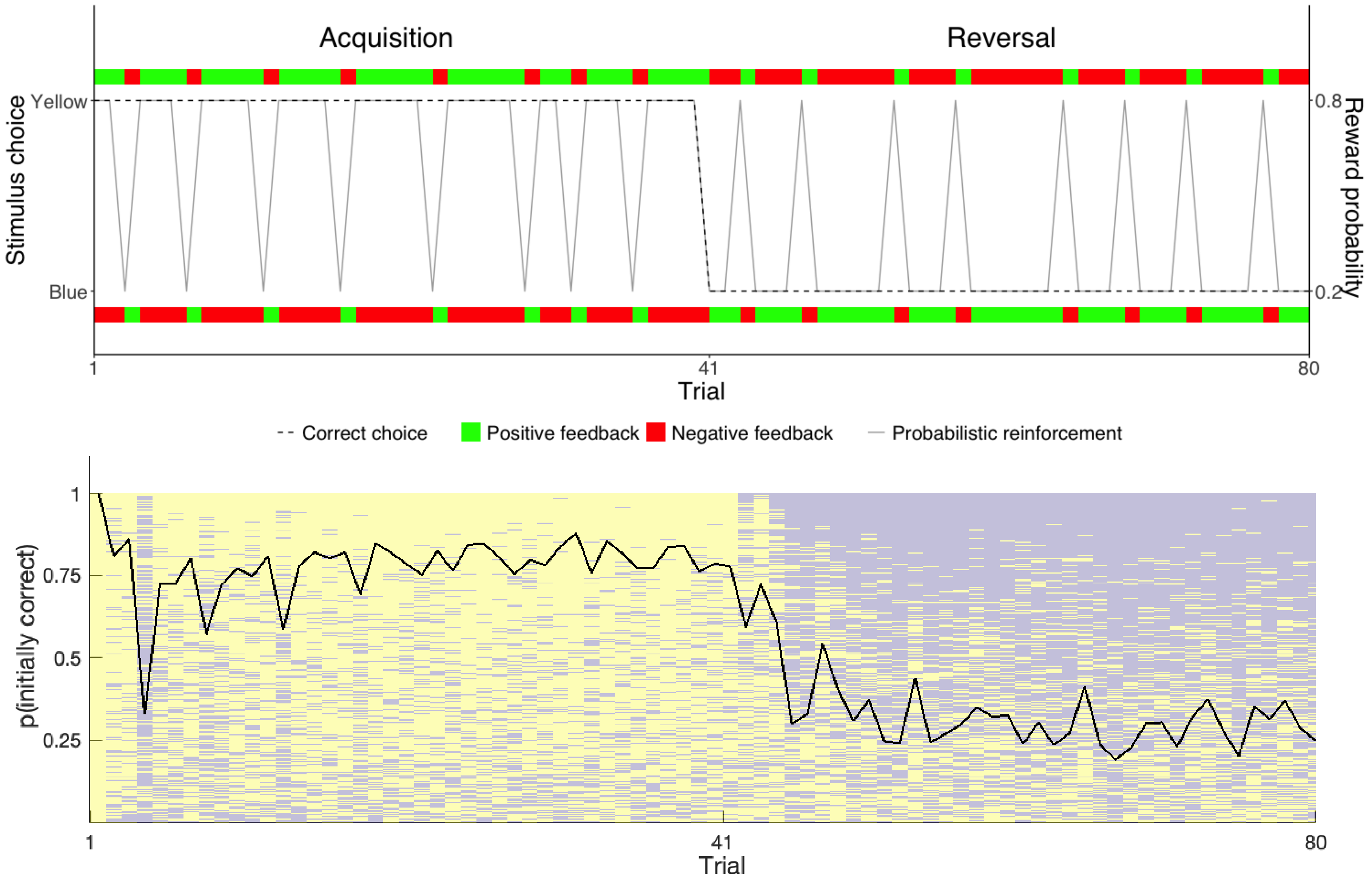


Common outcome, needs to be learnt

Rare outcome, needs to be ignored

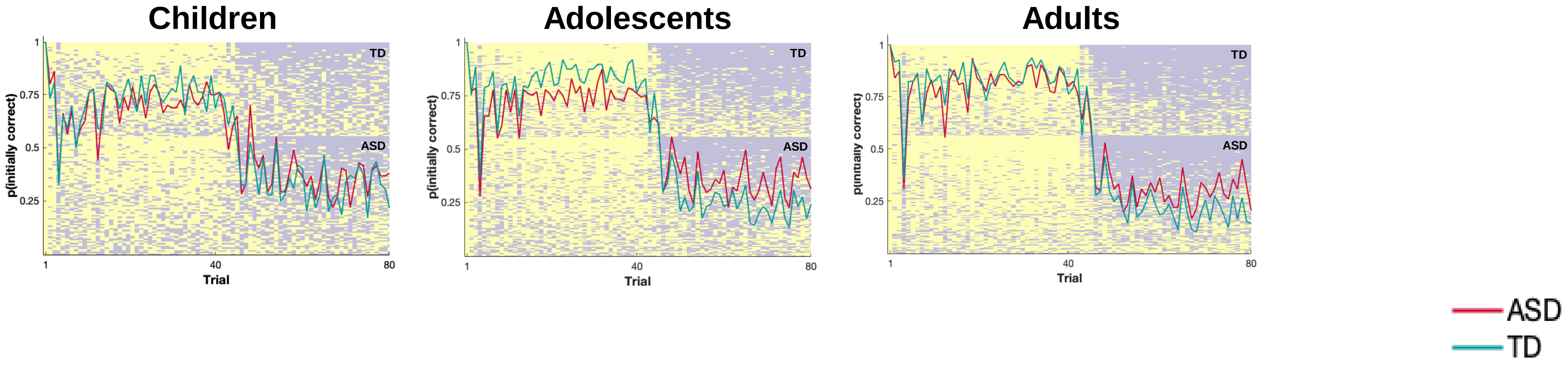
den Ouden et al. (2013)

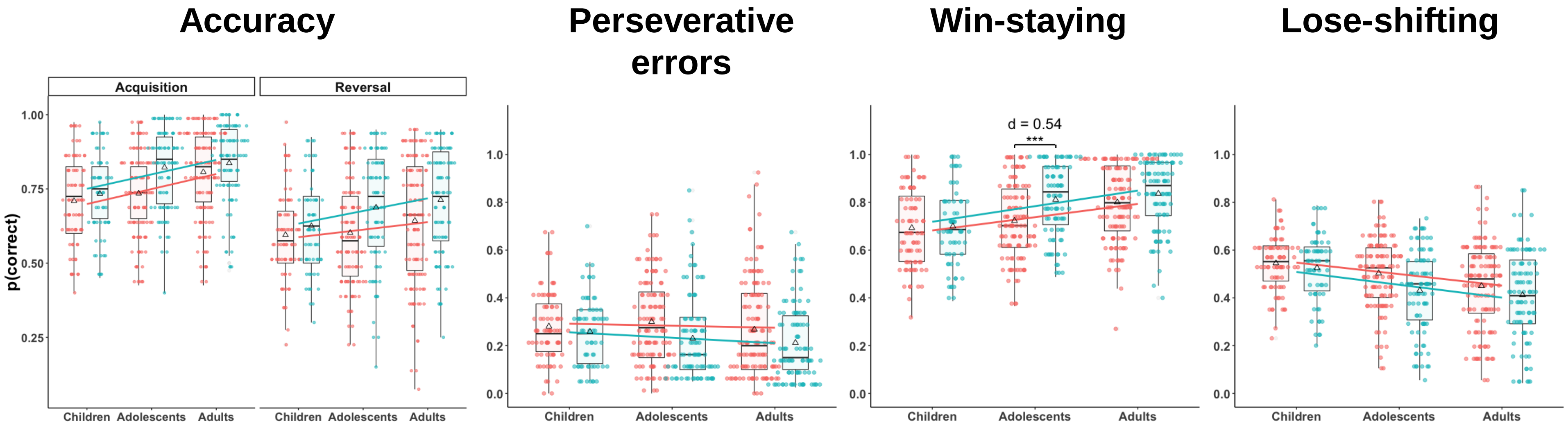
Overall trial-wise performance



Crawley & Zhang et al. (2020)

age group x diagnostic





Crawley & Zhang et al. (2020)

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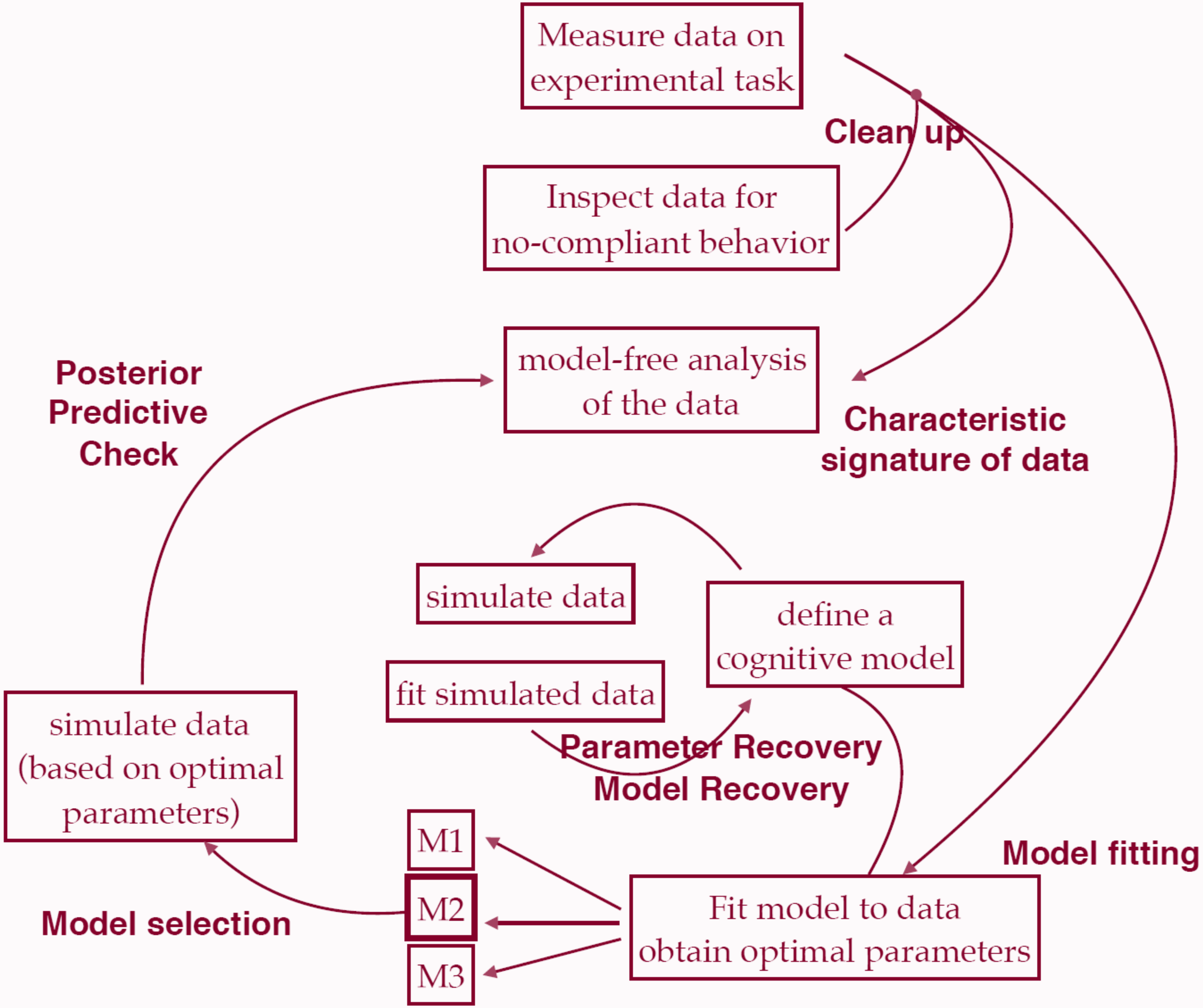
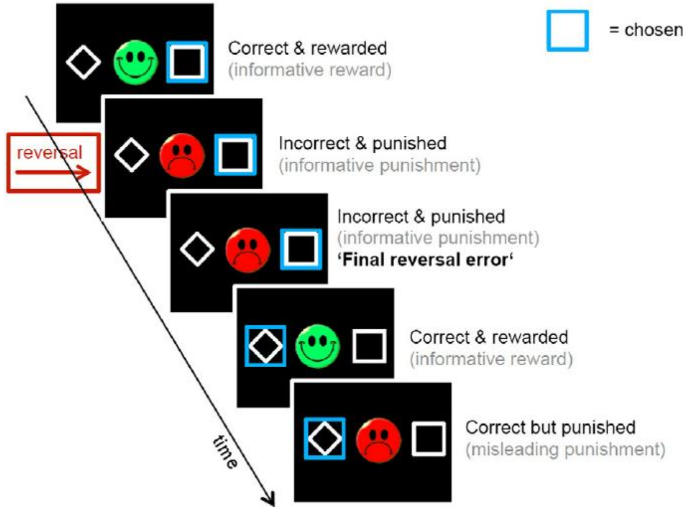
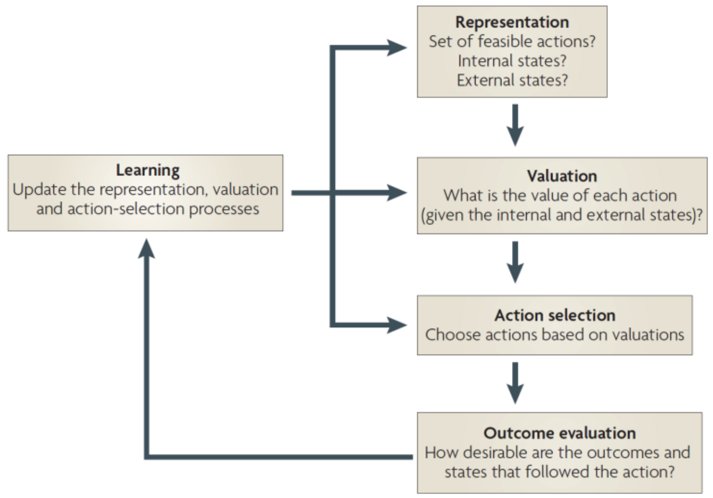

Measure data on experimental task
Clean up
Inspect data for no-compliant behavior
model-free analysis of the data
Characteristic signature of data
Posterior Predictive Check
simulate data
define a cognitive model
fit simulated data
Parameter Recovery
Model Recovery
simulate data (based on optimal parameters)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

What to model?





what do we know? — choice & outcome

what can we measure? — choice accuracy

what do we not know? — 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

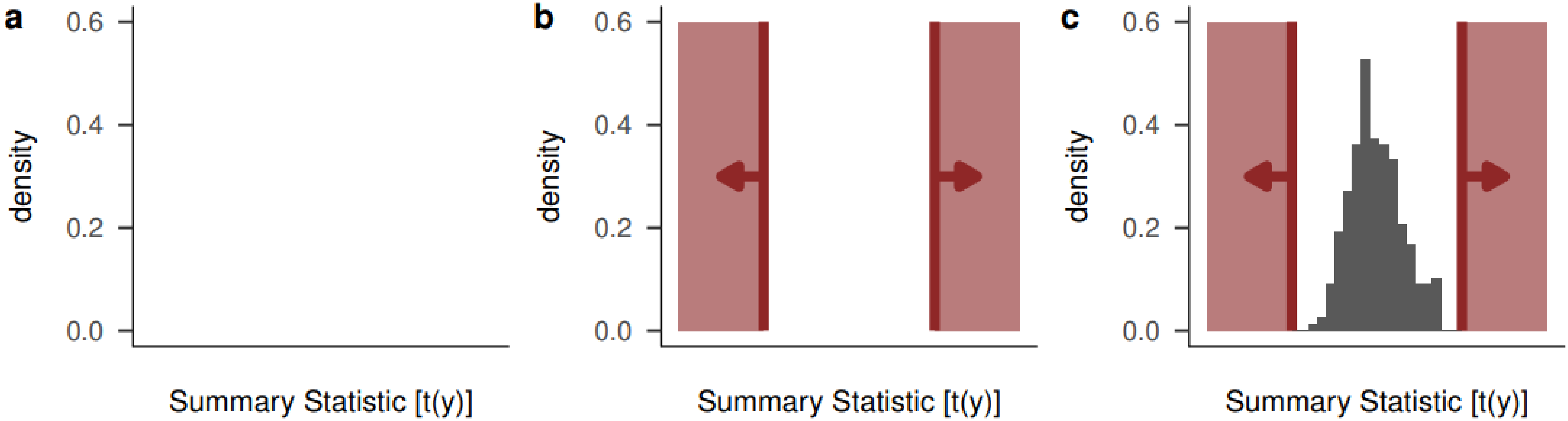
$$n_{c,t} = n_{c,t-1} \times \rho + 1$$
$$V_{c,t} = \left(V_{c,t-1} \times \varphi \times n_{c,t-1} + O_{t-1}\right) / n_{c,t}$$

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

Common cognitive models in decision-making

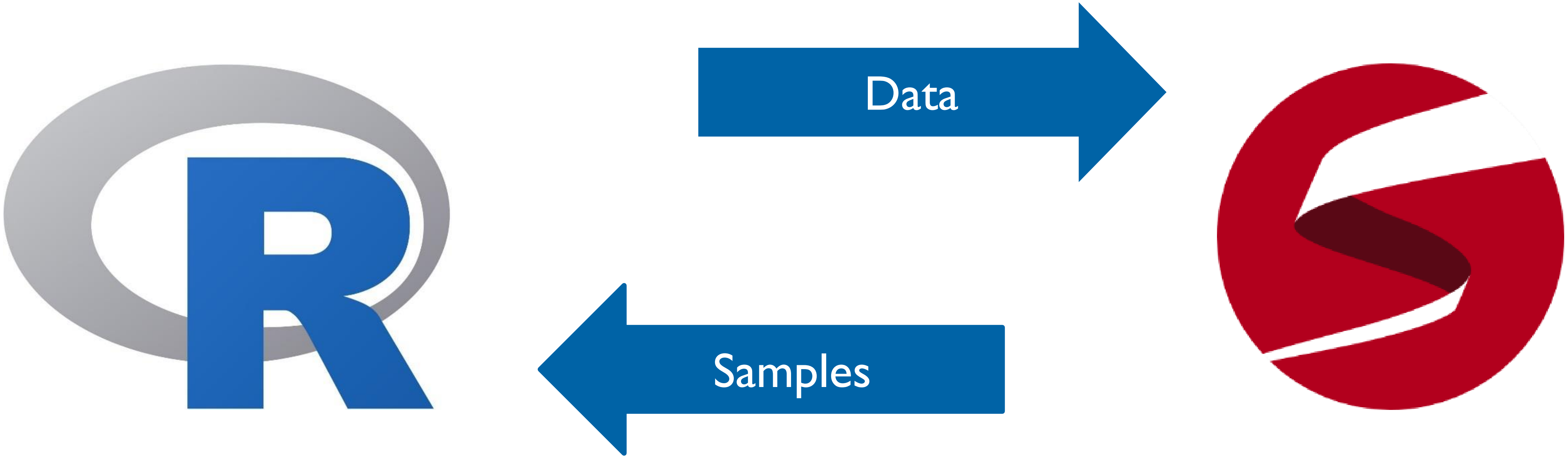
- Reinforcement learning model
- Bayesian learning model
- Risk-aversion model
- Hyperbolic delay discounting model
- Fehr-Schmidt inequity aversion model
- Sequential sampling model
- Experience-weighted attraction model
- …

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]

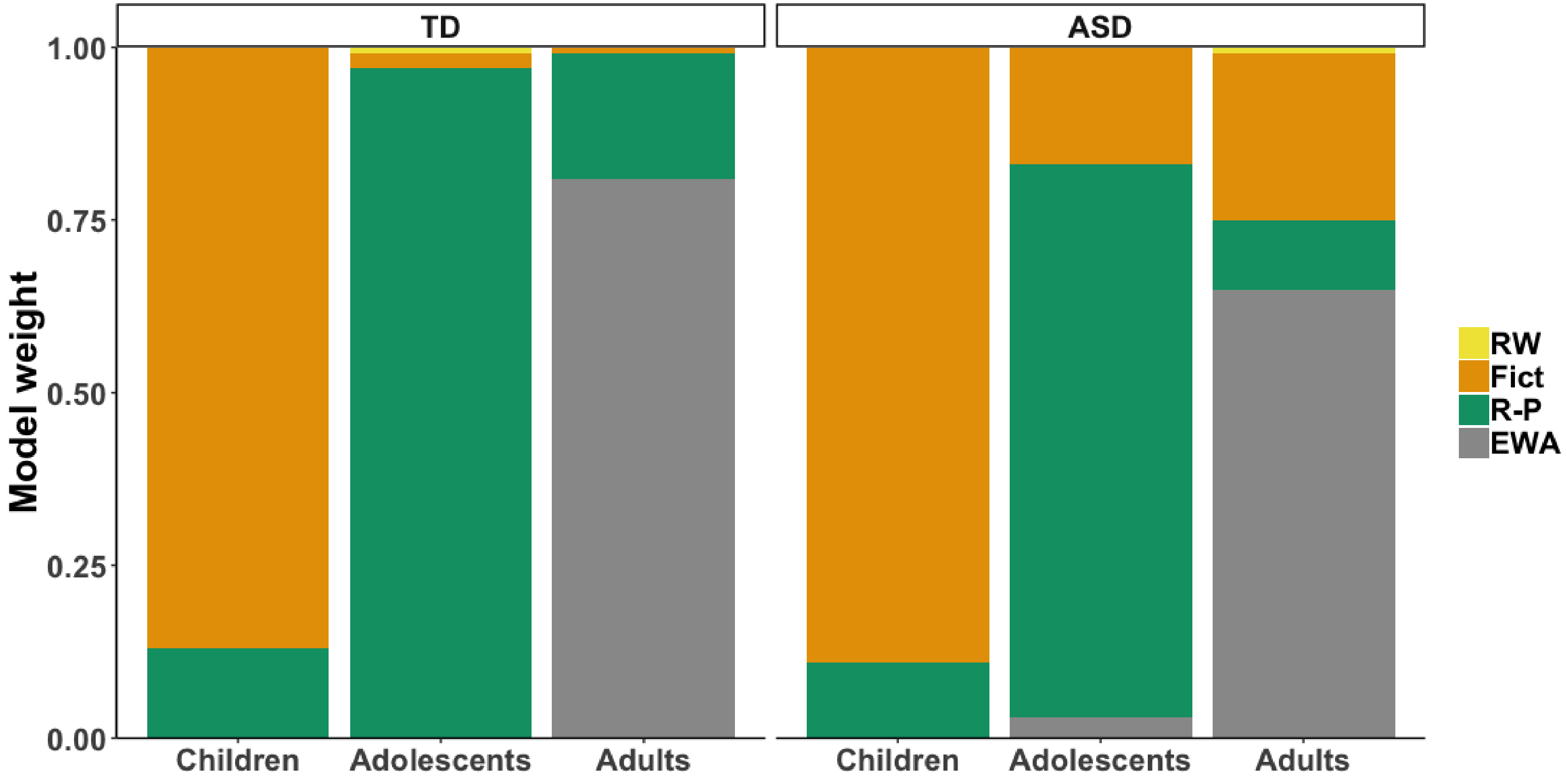
[1]Department of Psychology, The Ohio State University, Columbus, OH

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

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

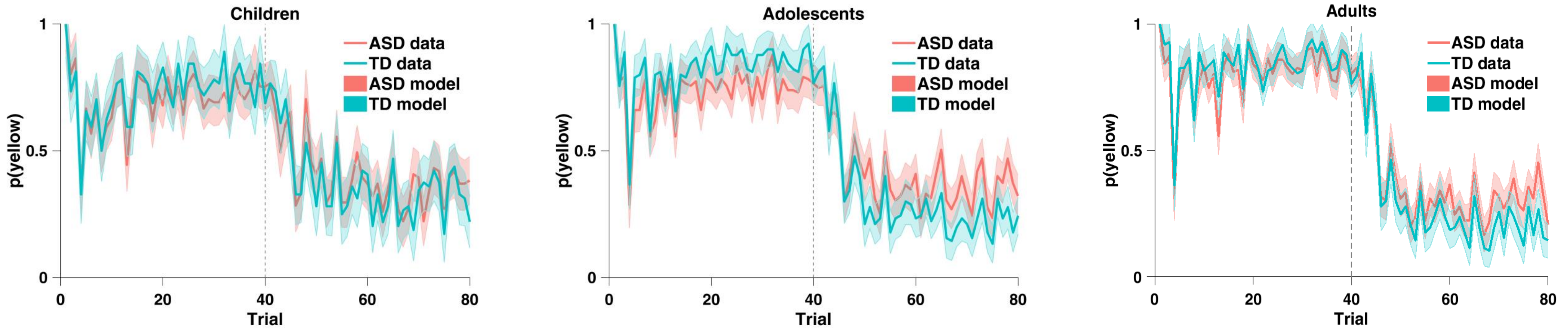
https://ccs-lab.github.io/hBayesDM/articles/getting_started.html

Model comparison



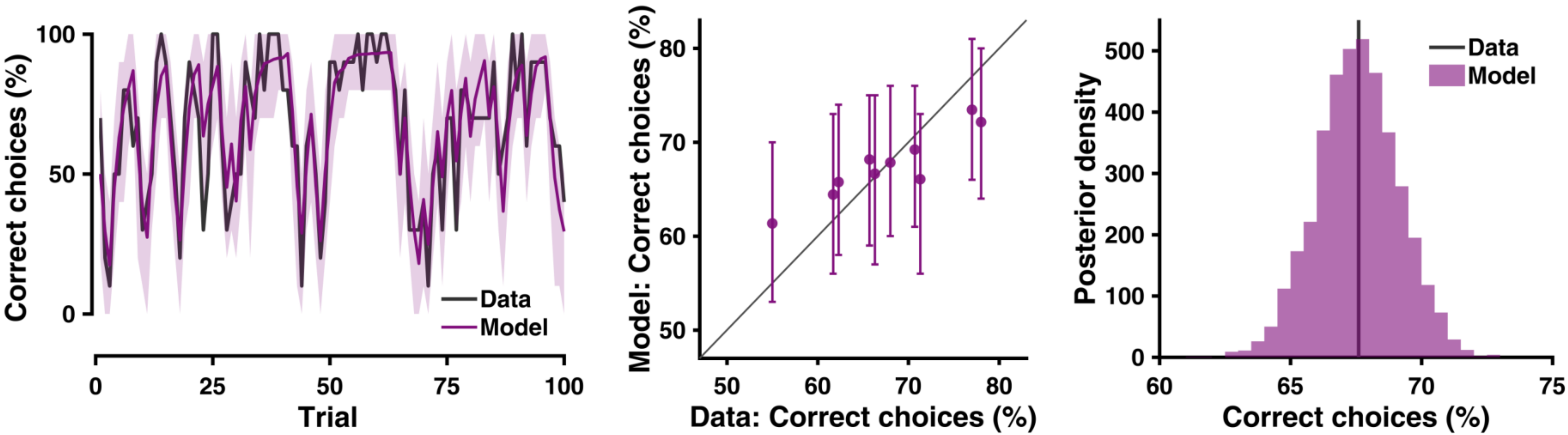
Crawley & Zhang et al. (2020)

Model validation with posterior predictive checks (PPC)



Crawley & Zhang et al. (2020)

More on PPC

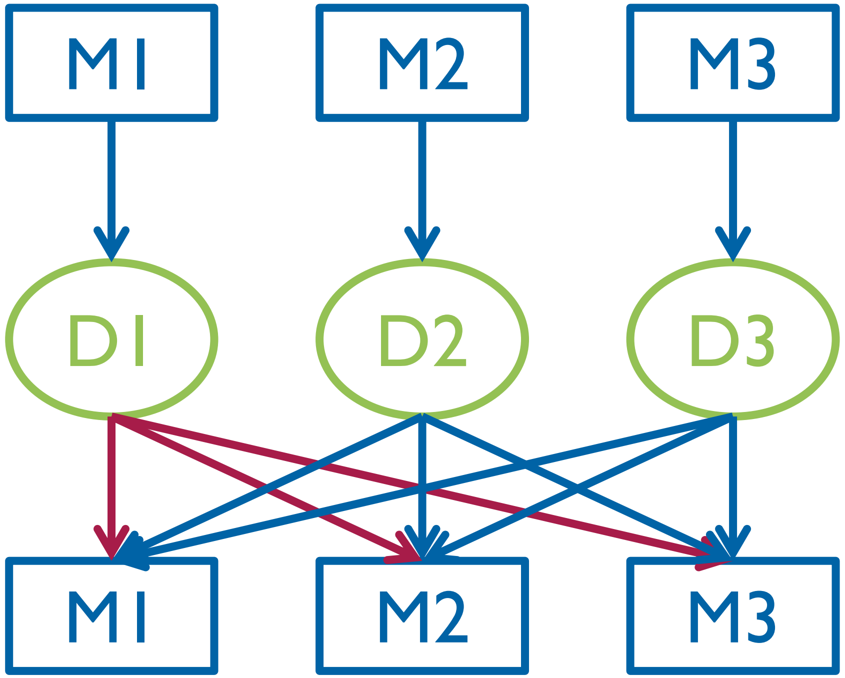


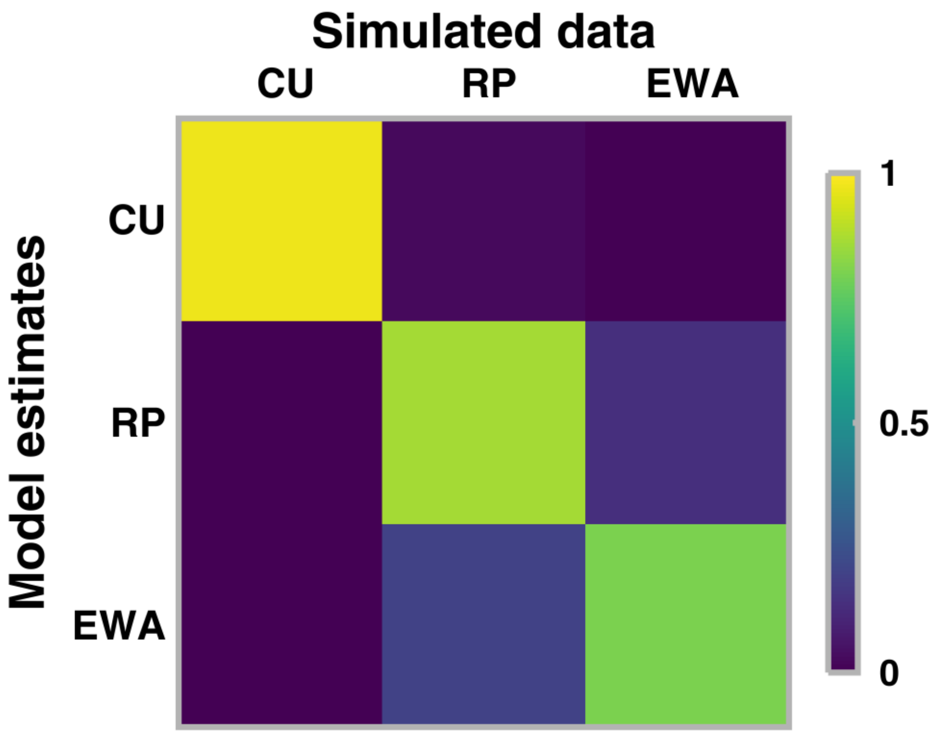
[Zhang & Lengersdorff et al. (2020)]

Model recovery:
are models identifiable?

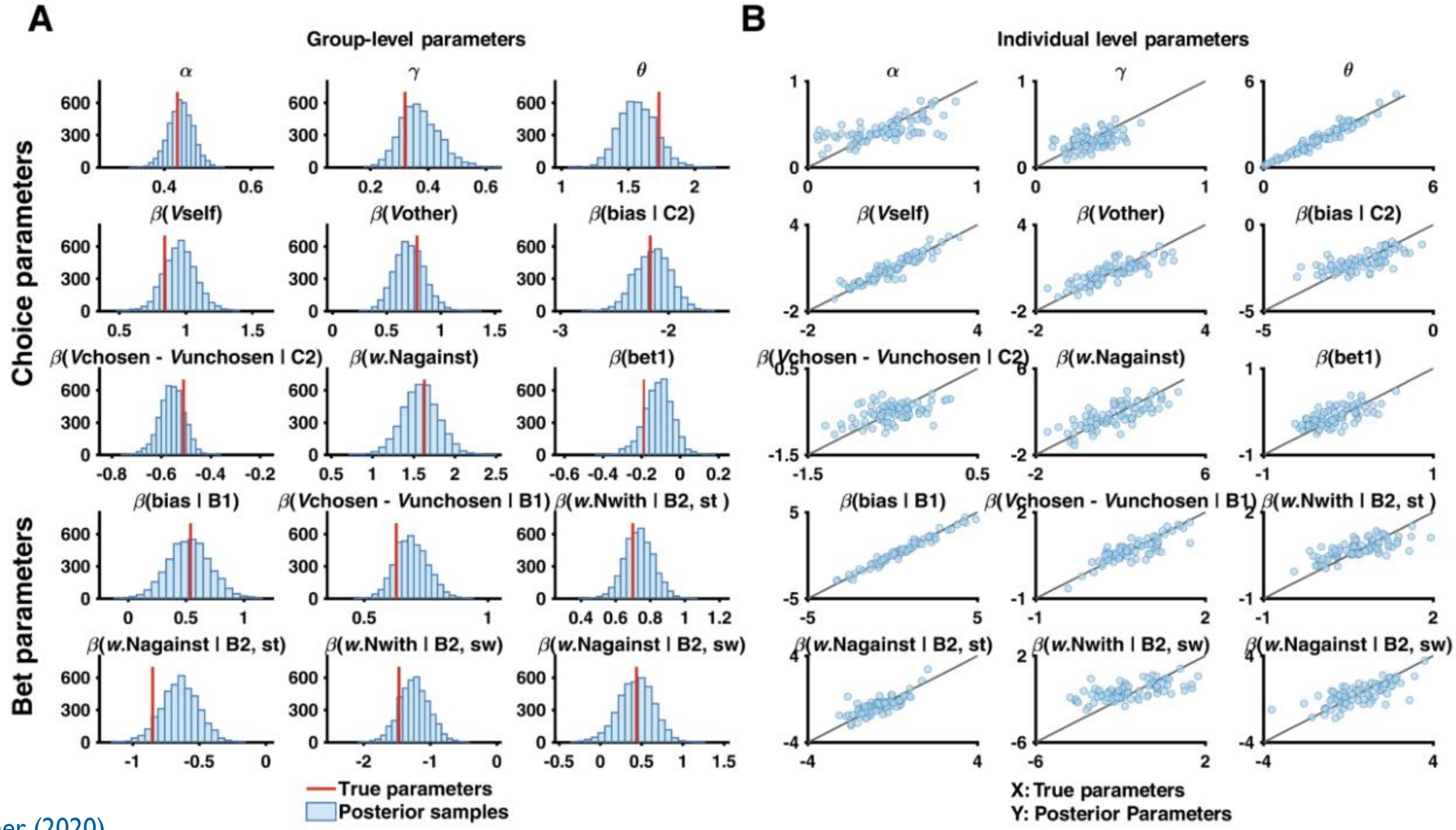
generative process

fitting process



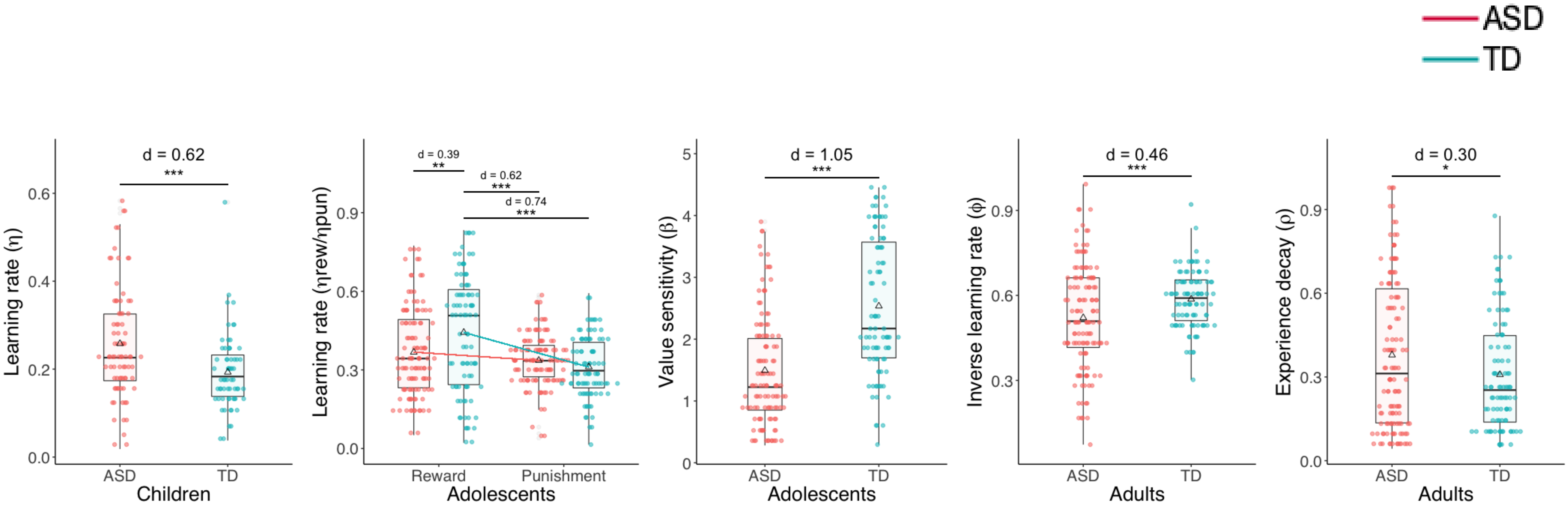


Parameter recovery:
are parameters identifiable?



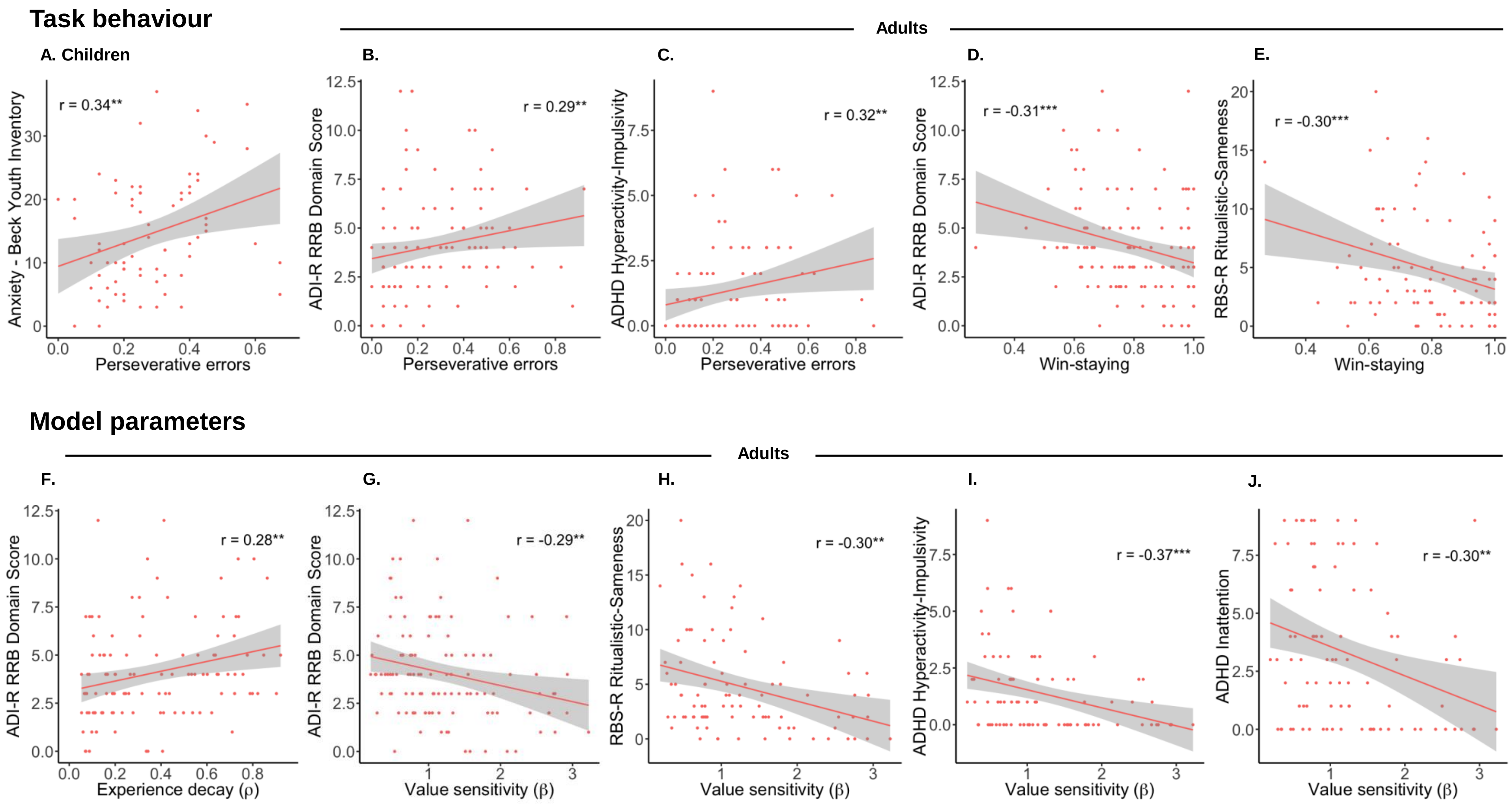
Zhang & Gläscher (2020)

Parameter results



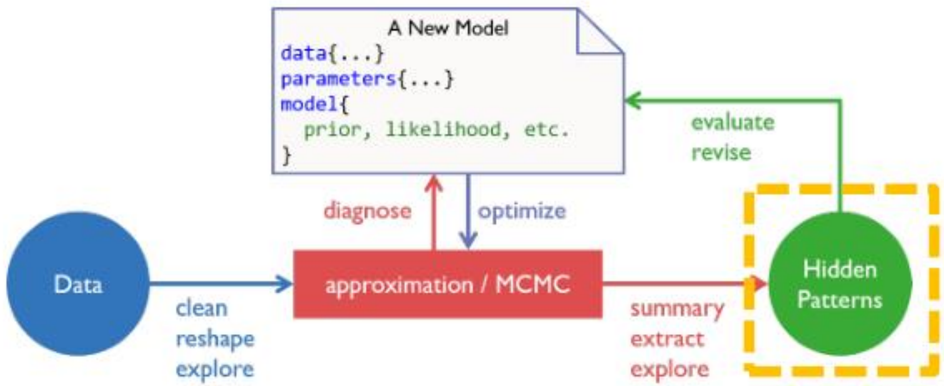
[Crawley & Zhang et al. (2020)]; [Zhang & Lengersdorff et al. (2020)] for more on interpreting parameters in simple RL models

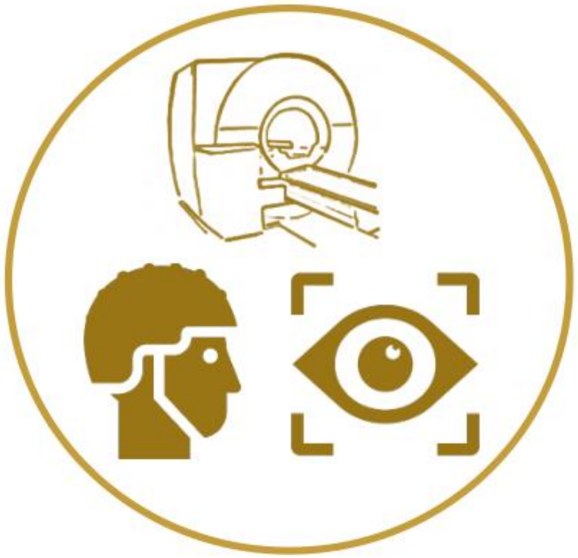
Parameter ~ clinical scales

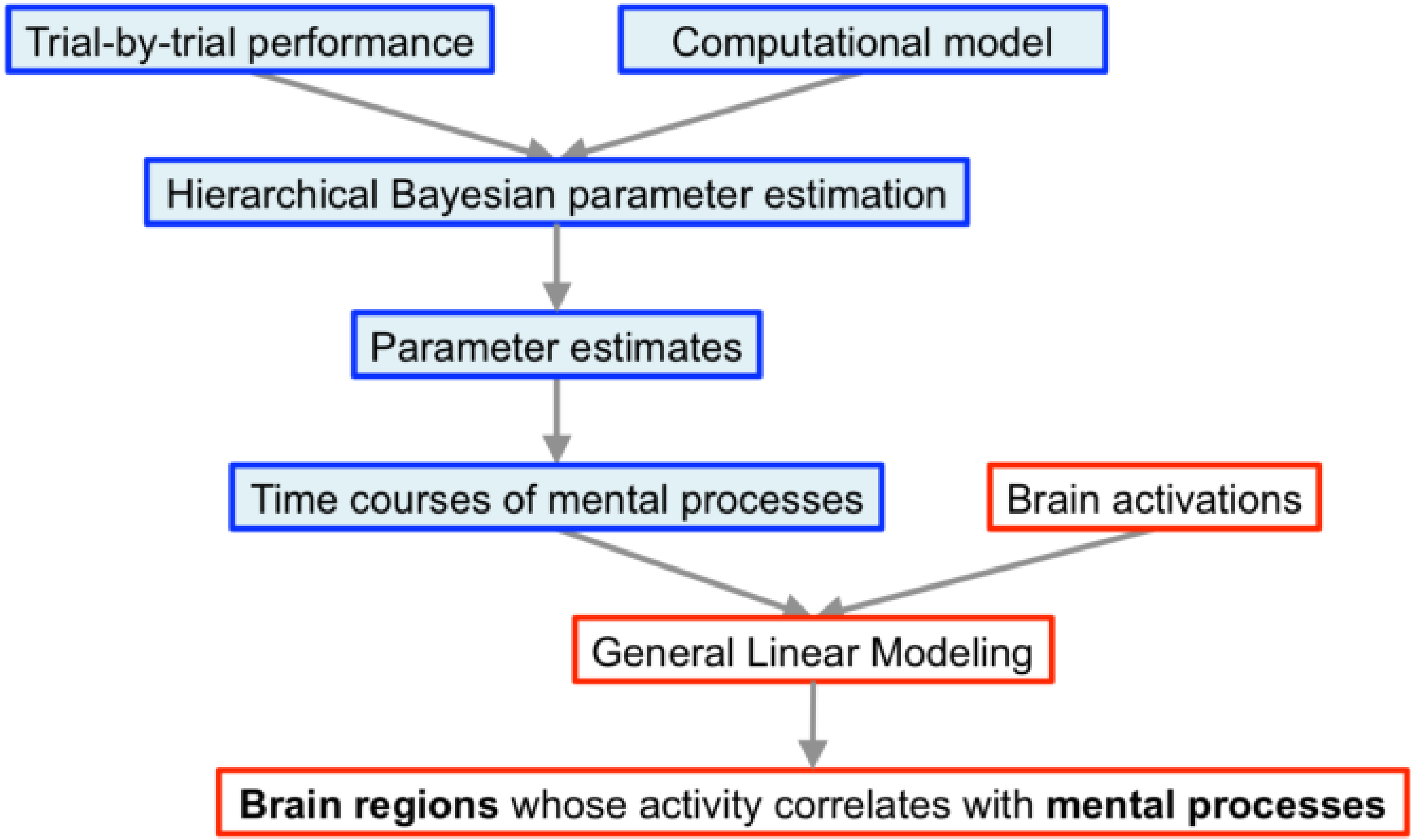


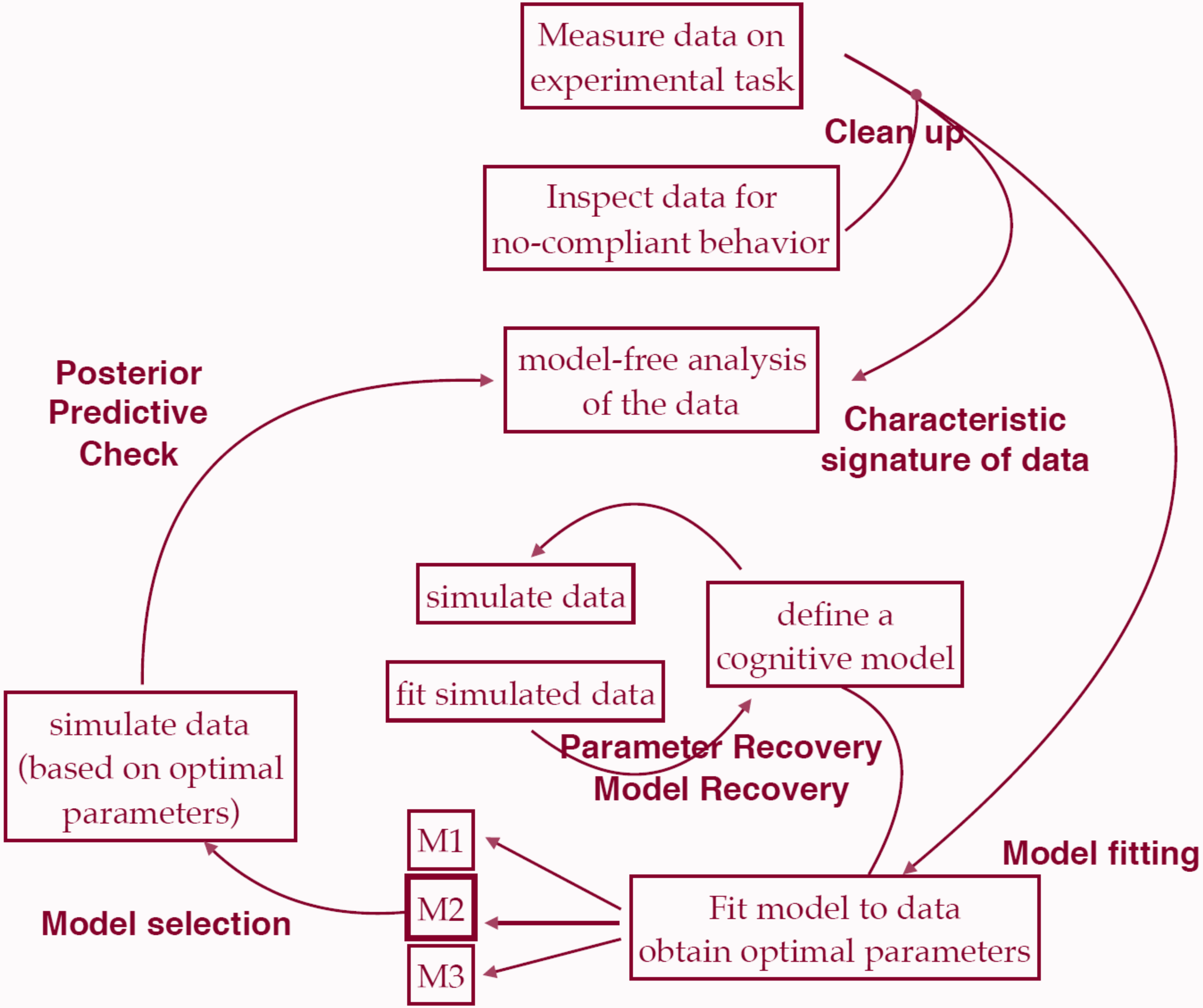
Crawley & Zhang et al. (2020)

Model-based analysis









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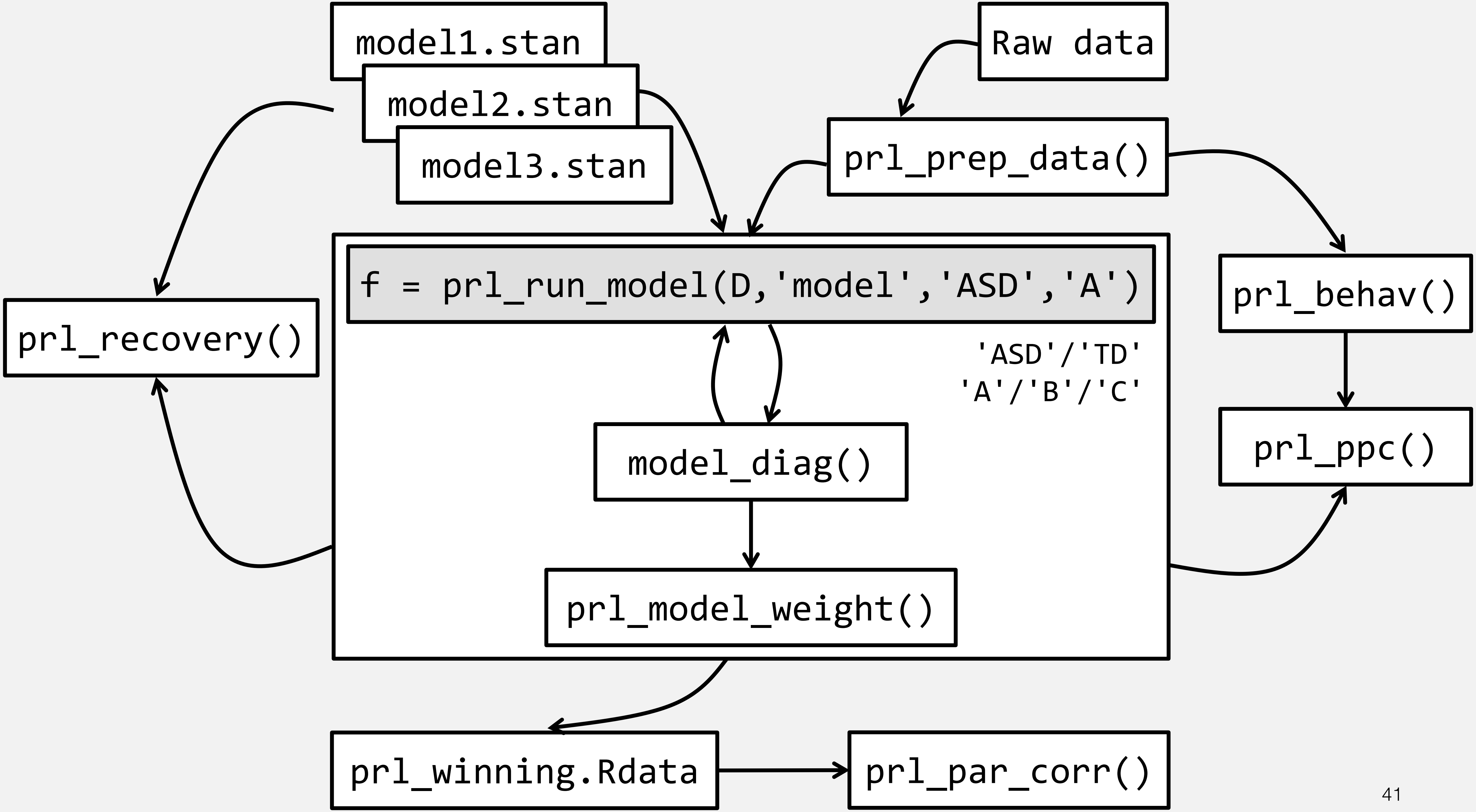
model1.stan
model2.stan
model3.stan
Raw data
prl_prep_data()
f = prl_run_model(D,'model','ASD','A')
'ASD'/'TD'
'A'/'B'/'C'
model_diag()
prl_model_weight()
prl_recovery()
prl_behav()
prl_ppc()
prl_winning.Rdata
prl_par_corr()

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

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

Social Cognitive and Affective Neuroscience, Volume 15, Issue 6, June 2020, Pages 695–707,

https://doi.org/10.1093/scan/nsaa089

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

RESEARCH ARTICLE | COGNITIVE NEUROSCIENCE

A brain network supporting social influences in human decision-making

Lei Zhang[1,2,*] and Jan Gläscher[1,*,†]
+ See all authors and affiliations

Science Advances 19 Aug 2020:
Vol. 6, no. 34, eabb4159
DOI: 10.1126/sciadv.abb4159

https://advances.sciencemag.org/content/6/34/eabb4159

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

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- Eva Loth
- Hanneke den Ouden
- Chris Chatham

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- Jan Gläscher
- Woo-Young Ahn
- Nate Haine

Modeling flexible behavior in childhood to adulthood shows age-dependent learning mechanisms and less optimal learning in autism in each age group

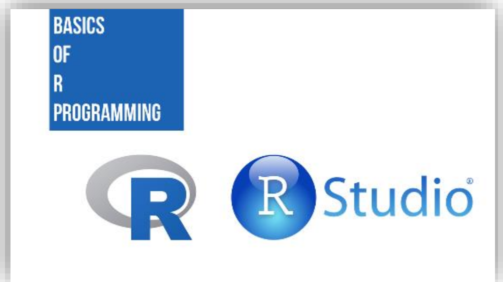
Daisy Crawley, Lei Zhang, Emily J. H. Jones, Jumana Ahmad, Bethany Oakley, Antonia San José Cáceres, Tony Charman, Jan K. Buitelaar, Declan G. M. Murphy, Christopher Chatham, Hanneke den Ouden, Eva Loth, the EU-AIMS LEAP group

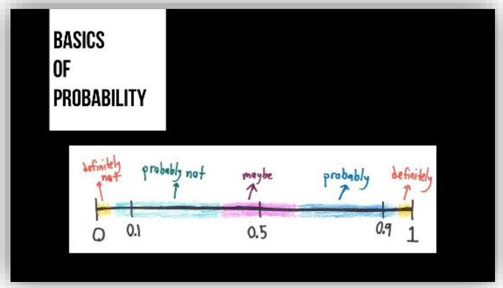
Published: October 27, 2020 • https://doi.org/10.1371/journal.pbio.3000908

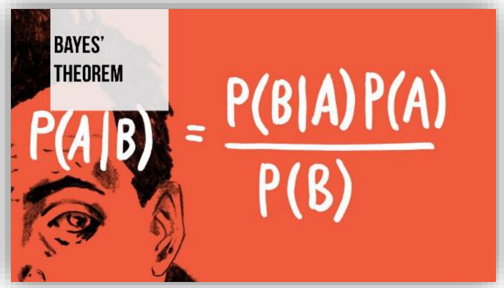
https://journals.plos.org/plosbiology/article?id=10.1371/journal.pbio.3000908

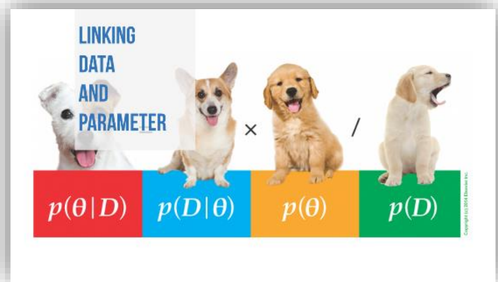

Summary

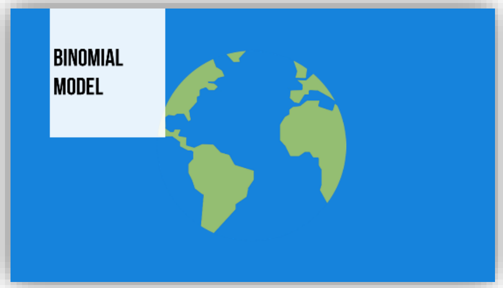
Summary of Topics

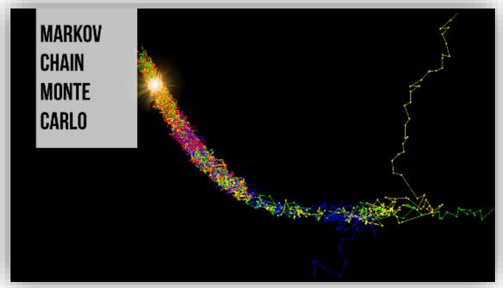


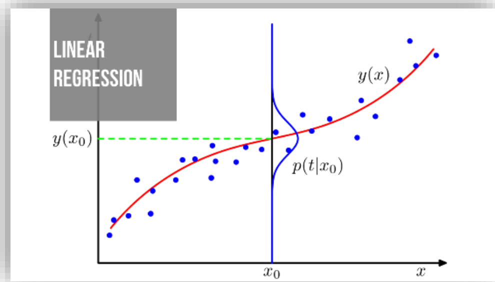


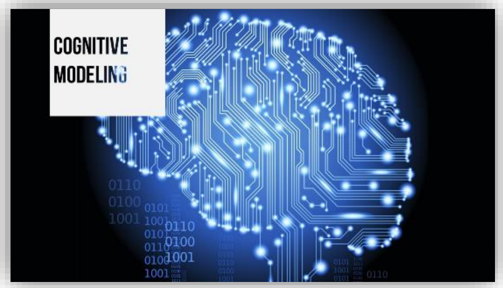


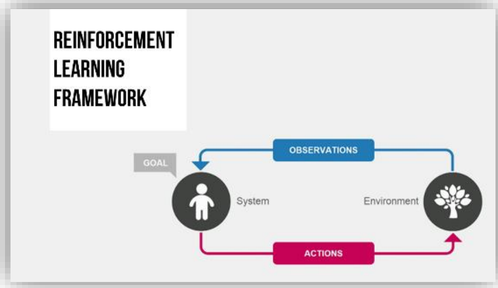


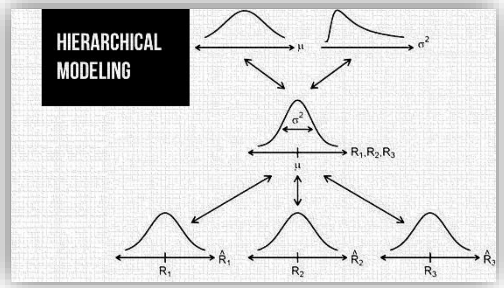


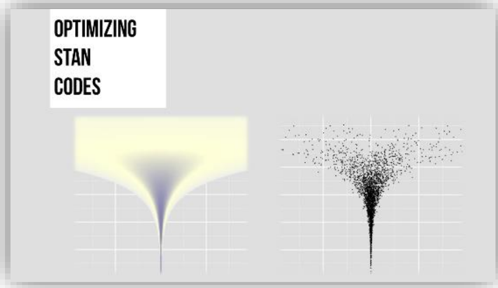


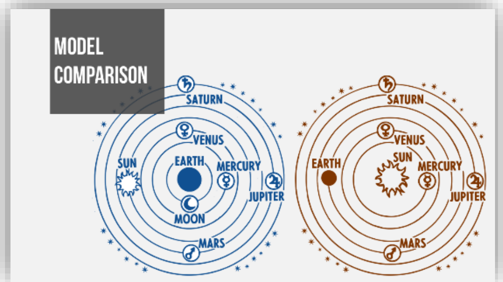


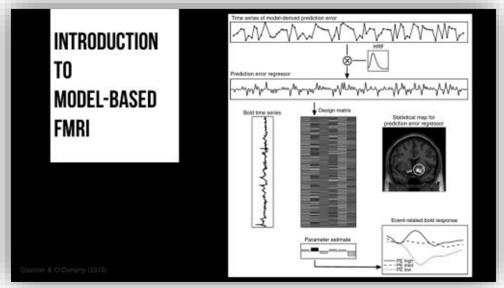












Summary of Examples/Exercises

FOLDER	TASK	MODEL
01.R_basics	NA	NA
02.binomial_globe	Globe toss	Binomial Model
03.bernoulli_coin	Coin flip	Bernoulli Model
04.regression_height 05.regression_height_poly	Observed weight and height	Linear regression model
06.reinforcement_learning 07.optm_rl	2-armed bandit task	Simple reinforcement learning (RL) model
08.compare_models	Probabilistic reversal learning task	Simple and fictitious RL models
09.debugging	Memory Retention	Exponential decay model
10.model_based	2-armed bandit task	Simple RL model
11.delay_discounting	Delay discounting task	Hyperbolic and exponential discounting model

After the Workshop, you...

…are able to implement your own model

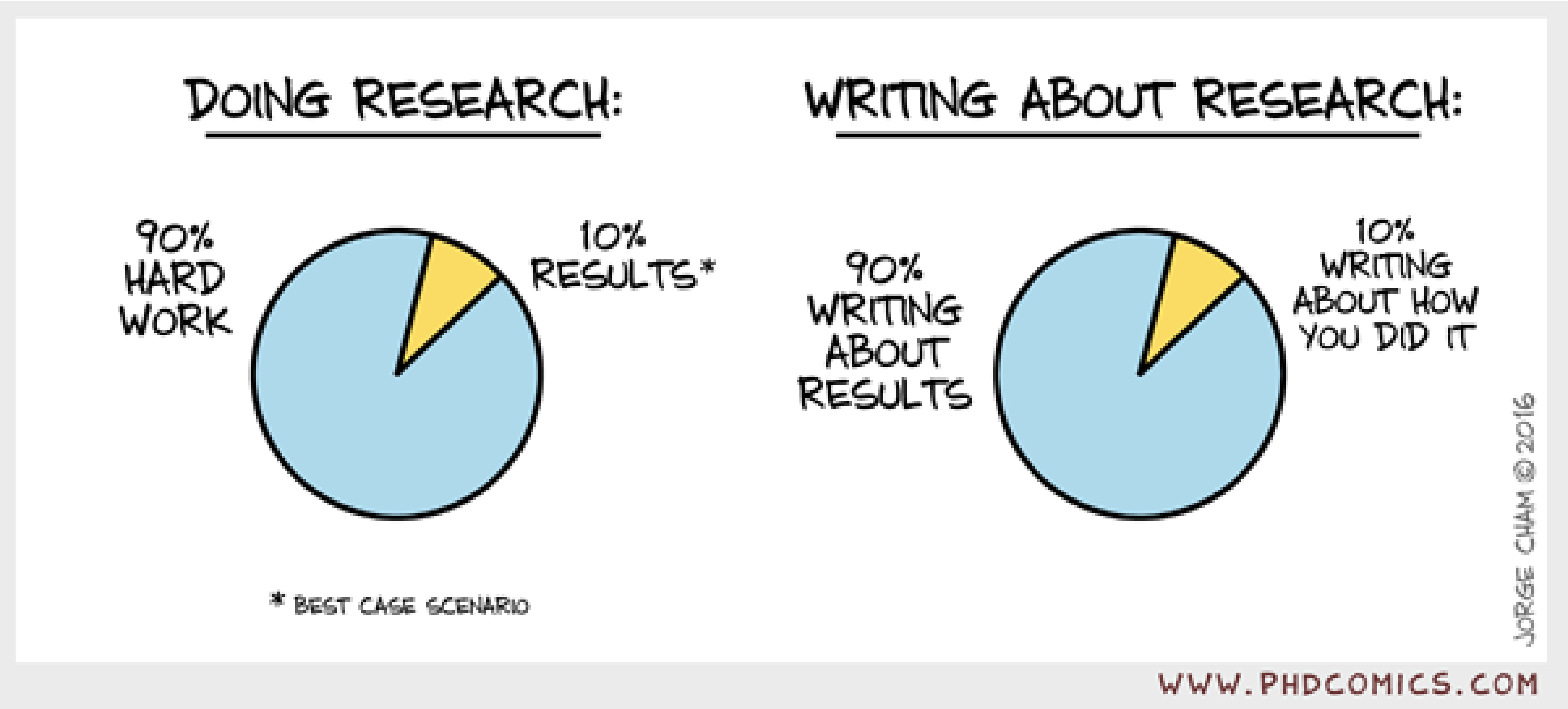
…feel comfortable with reading mathematical equations

…consider the implementation of the "computational modeling" section

…gain insightful understanding of Bayesian stats and modeling

…take it as a good start and work on it later

Remember: practice makes perfect!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10% RESULTS*
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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

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RESEARCH

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

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Keywords: Reinforcement learning; Decision-making; Hierarchical Bayesian modeling; Model-based fMRI

Task (alphabetical order)	Model name	hBayesDM function	References (see below for full citations)
Balloon Analogue Risk Task	4 parameter model	bart_4par	Wallsten et al. (2005)
Choice reaction time Task	Drift diffusion model Linear Ballistic Accumulator model	choiceRT_ddm choiceRT_lba	Ratcliff (1978) S. Brown & Heathcote (2008) Annis et al. (2017)
Choice under Risk and Ambiguity (CRA) Task	Linear model Exponential model	cra_linear cra_exp	Levy et al. (2009)
Delay Discounting Task	Constant-Sensitivity (CS) model Exponential model Hyperbolic model	dd_cs dd_exp dd_hyp	Ebert & Prelec (2007) Samuelson (1937) Mazur (1987)
Iowa Gambling Task (IGT)	Prospect Valence Learning-DecayRI Prospect Valence Learning-Delta Value-Plus-Perseverance (VPP) Outcome-Represent. Learning (ORL)	igt_pvl_decay igt_pvl_delta igt_vpp igt_orl	Ahn et al. (2011; 2014) Ahn et al. (2008) Worthy et al. (2013) Haines et al. (in press)
Orthogonalized Go/Nogo Task	RW+noise RW+noise+go bias RW+noise+go bias+Pav. bias M5 (see Table 1 of the reference)	gng_m1 gng_m2 gng_m3 gng_m4	Guitart-Masip et al. (2012) Guitart-Masip et al. (2012) Guitart-Masip et al. (2012) Cavanagh et al. (2013)
Peer influence task	Other-conferred utility (OCU)	peer_ocu	Chung et al. (2015)
Probabilistic Reversal Learning (PRL) Task	Experience-Weighted Attraction Fictitious update Reward-Punishment (Rew.-Pun.) Fictitious + Rew.-Pun. Fictitious + Rew.-Pun. w/o alpha Fictitious w/o alpha	prl_ewa prl_fictitious prl_rp prl_fictitious_rp prl_fictitious_rp_woa prl_fictitious_woa	Ouden et al. (2013) Gläscher et al. (2009) Ouden et al. (2013)
Probabilistic Selection Task	Q-learning with two learning rates	pst_gainloss_Q	M. J. Frank et al. (2007)
Risk-Aversion Task	Prospect Theory (PT) PT without loss aversion (LA) PT without risk aversion (RA)	ra_prospect ra_noLA ra_noRA	Sokol-Hessner et al. (2009) Tom et al. (2007)
Risky Decision Task	Happiness model	rdt_happiness	Rutledge et al. (2014)
Two-Armed Bandit (Experience-based) Task	Rescorla-Wagner (delta) model	bandit2arm_delta	Erev et al. (2010) Hertwig et al. (2004)
Two Step (TS) Task	7 parameter model 6 parameter model 4 parameter model	ts_7par ts_6par ts_4par	Daw et al. (2011) Wunderlich et al. (2012)
Four-Armed Bandit (Experience-based) Task	Fictive upd.+rew/pun sens. Fictive upd.+rew/pun sens.+lapse	bandit4arm_4par bandit4arm_lapse	Seymour et al. (2012) Seymour et al. (2012)
Ultimatum Game	Ideal Bayesian observer model Rescorla-Wagner (delta) model	ug_bayes ug_delta	Xiang et al. (2013) Gu et al. (2015)
Wisconsin Card Sorting Task	Sequential learning model	wcs_sql	A. J. Bishara et al. (2010)

cognitive model

statistics

computing

*hBayesDM

Workshops / Summer schools

cognitive model

statistics

computing

- JAGS and WinBUGS Workshop @ Amsterdam, NL (annual)
- Model-based Neuroscience Summer School @ Amsterdam, NL (annual)
- European Summer School on Computational and Mathematical Modeling of Cognition @ multiple EU sites (biannual)
- Computational Psychiatry Course @ Zürich, CH (annual)
- London Computational Psychiatry Course @ London, UK (annual?)
- Methods in Neuroscience at Dartmouth Computational Summer School @ Dartmouth, USA (annual)
- Brains, Minds & Machines Summer Course @ MIT, USA (annual)
- Kavli Summer Institute in Cognitive Neuroscience @UCSB, USA (annual)
- Neuromatch Academy on Computational Neuroscience @online! (annual)

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ANY
QUESTIONS
?

Happy Computing!