



(In)Flexible learning behavior in autism through the lens of reinforcement learning

Lei Zhang

Social, Cognitive and Affective Neuroscience Unit (SCAN-Unit)

Faculty of Psychology, University of Vienna

April 17, 2021

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



universität
wien
Fakultät für Psychologie

Outline

- The emergence of Computational Psychiatry (CP)
- A case study: flexible choice behavior in Autism
- hBayesDM: a toolbox for estimating hierarchical Bayesian models
- Summary

Outline

- The emergence of Computational Psychiatry (CP)
- A case study: flexible choice behavior in Autism
- hBayesDM: a toolbox for estimating hierarchical Bayesian models
- Summary

Three cultures of CP

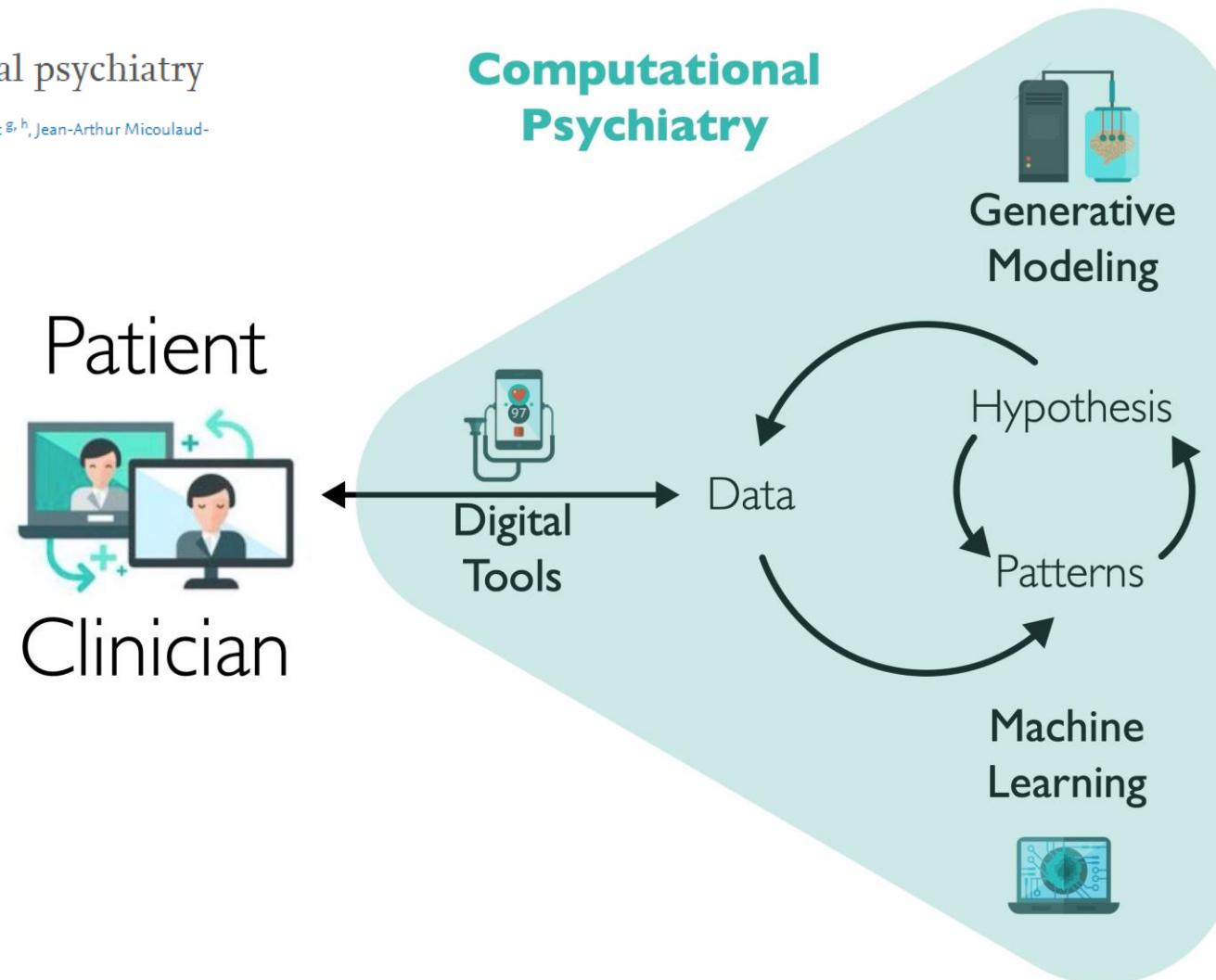
Communication

Les trois cultures de la psychiatrie computationnelle

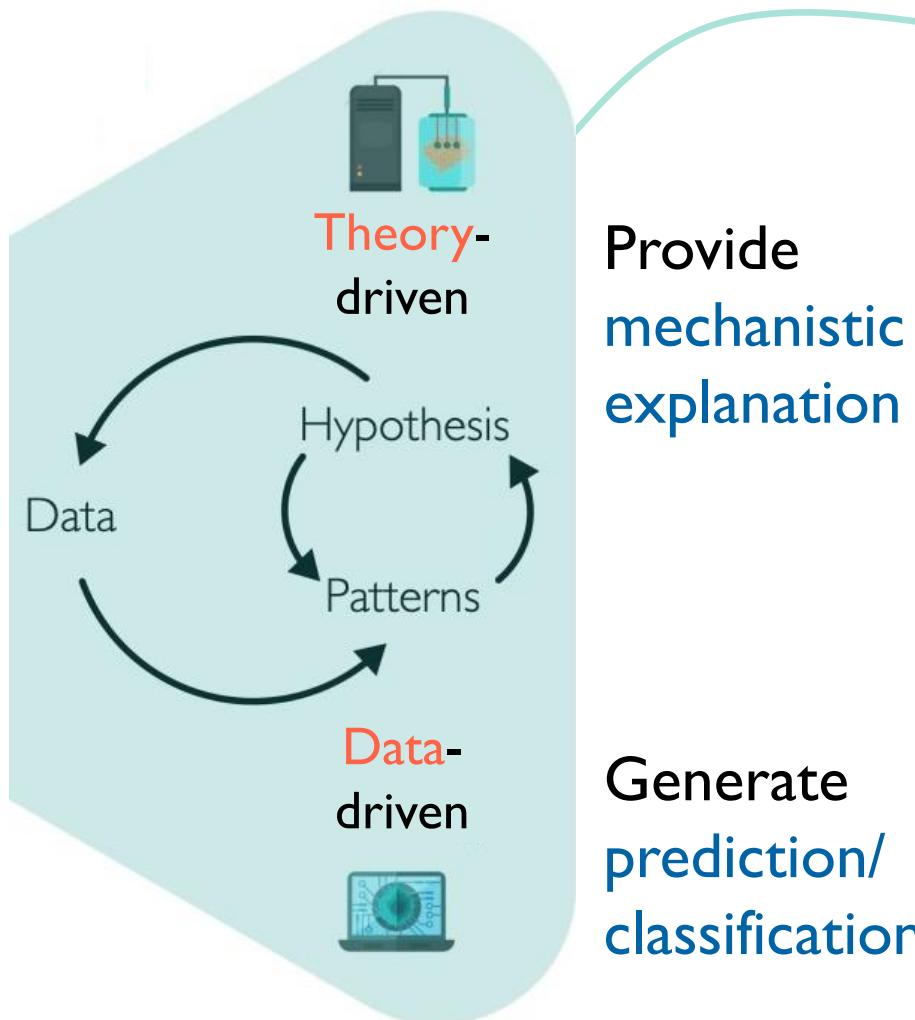
The three cultures of computational psychiatry

Christophe Gauld^{a, b, g, h}, Guillaume Dumas^{c, d}, Éric Fakra^{e, f}, Jérémie Mattout^{g, h}, Jean-Arthur Micoulaud-Franchi^{i, j}

Show more ▾



Theory-driven



Provide mechanistic explanation

Generate prediction/ classification

Construct



- Reward,
- Learning,
- Self v. Other,
- etc.

Computational modeling

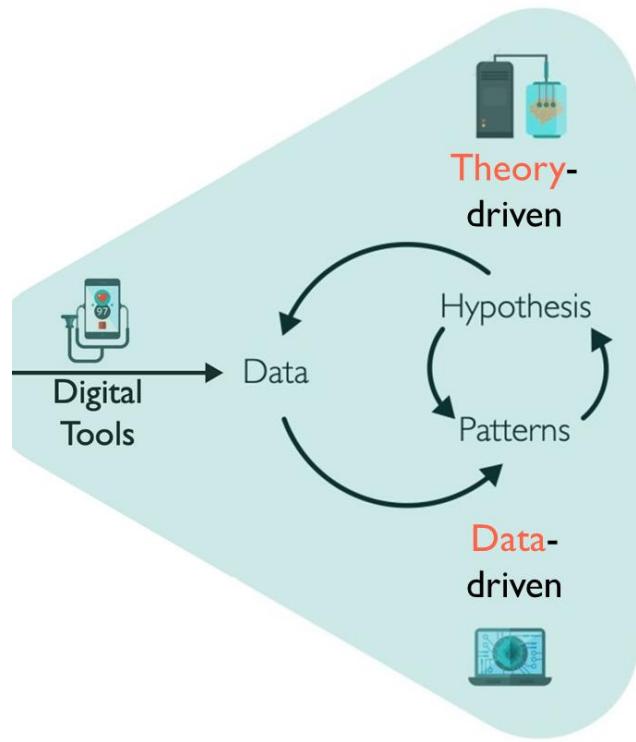
On the role of theory and modeling in neuroscience

Daniel Levenstein¹, Veronica A. Alvarez², Asohan Amarasingham¹⁴, Habiba Azab³, Richard C. Gerkin⁴, Andrea Hasenstaub⁵, Ramakrishnan Iyer⁶, Renaud B. Jolivet⁷, Sarah Marzen¹², Joseph D. Monaco⁸, Astrid A. Prinz¹³, Salma Quraishi, Fidel Santamaría⁹, Sabyasachi Shivkumar¹⁵, Matthew F. Singh¹⁰, David B. Stockton, Roger Traub¹¹, Horacio G. Rotstein^{16,*}, Farzan Nadim^{16,*}, A. David Redish^{17,*}

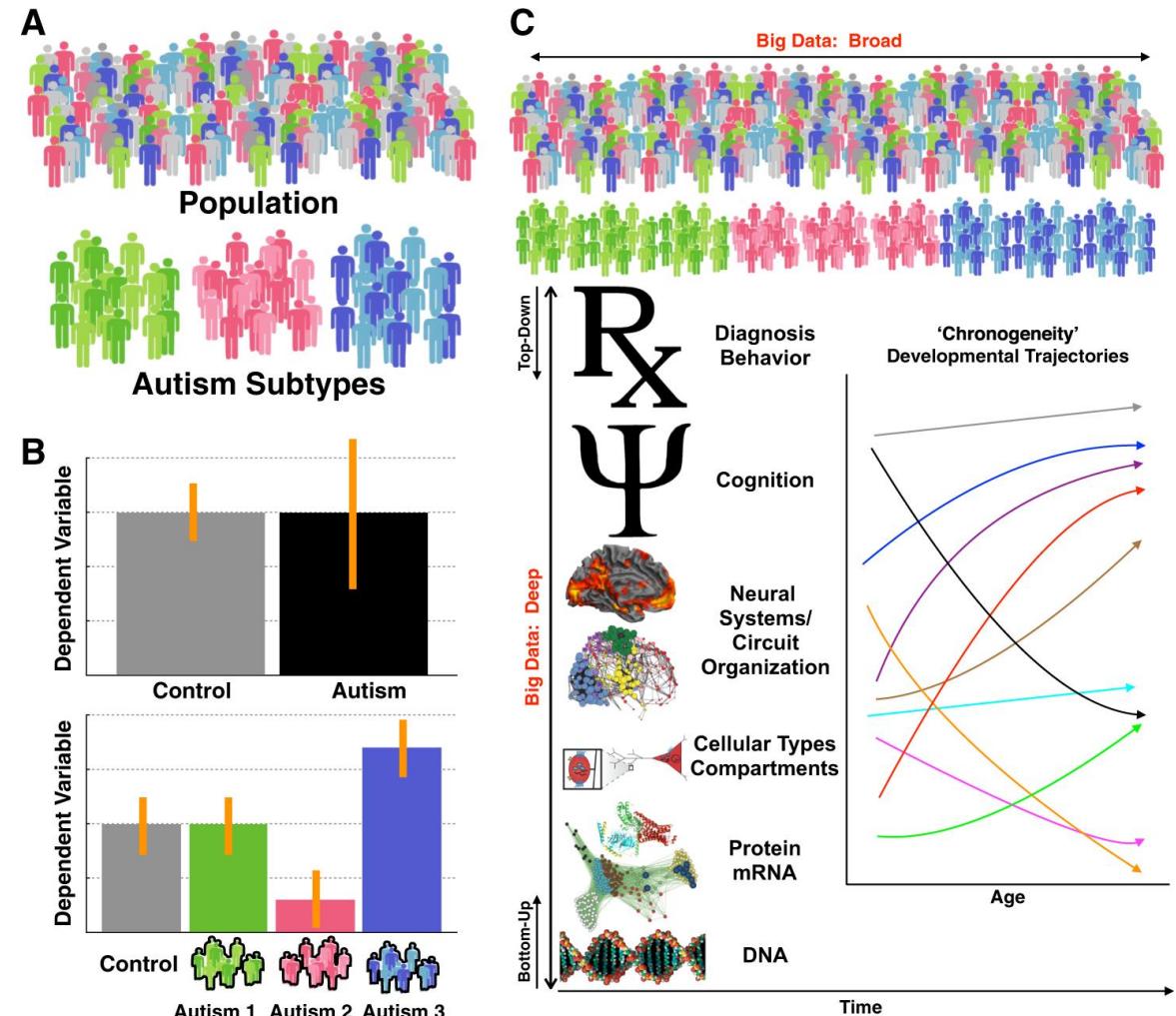
How Computational Modeling Can Force Theory Building in Psychological Science

Olivia Guest^{ID}, Andrea E. Martin

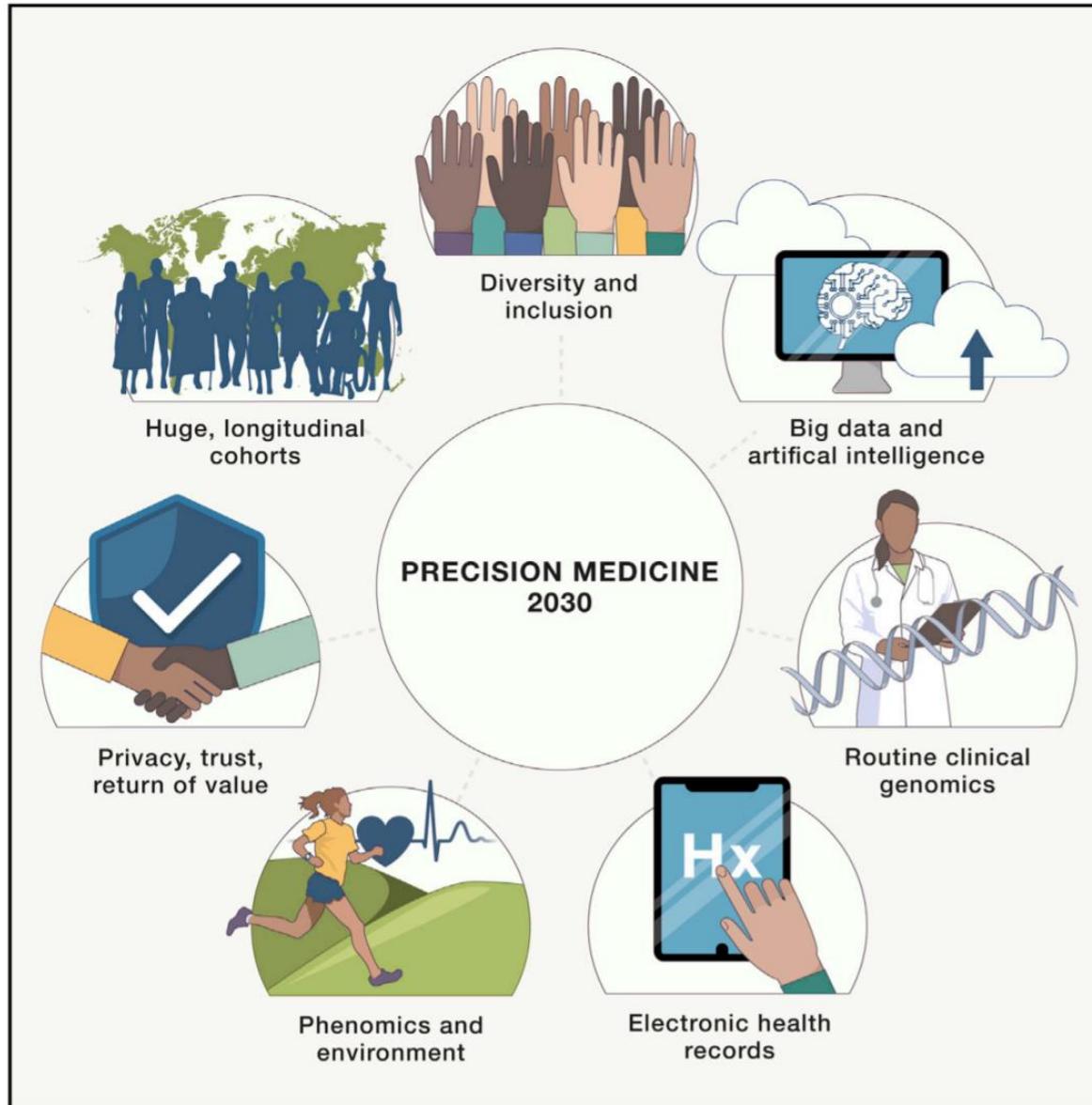
Data-Driven



- Diagnostic
- Treatment response
- Identify sub-groups
- Speech analysis

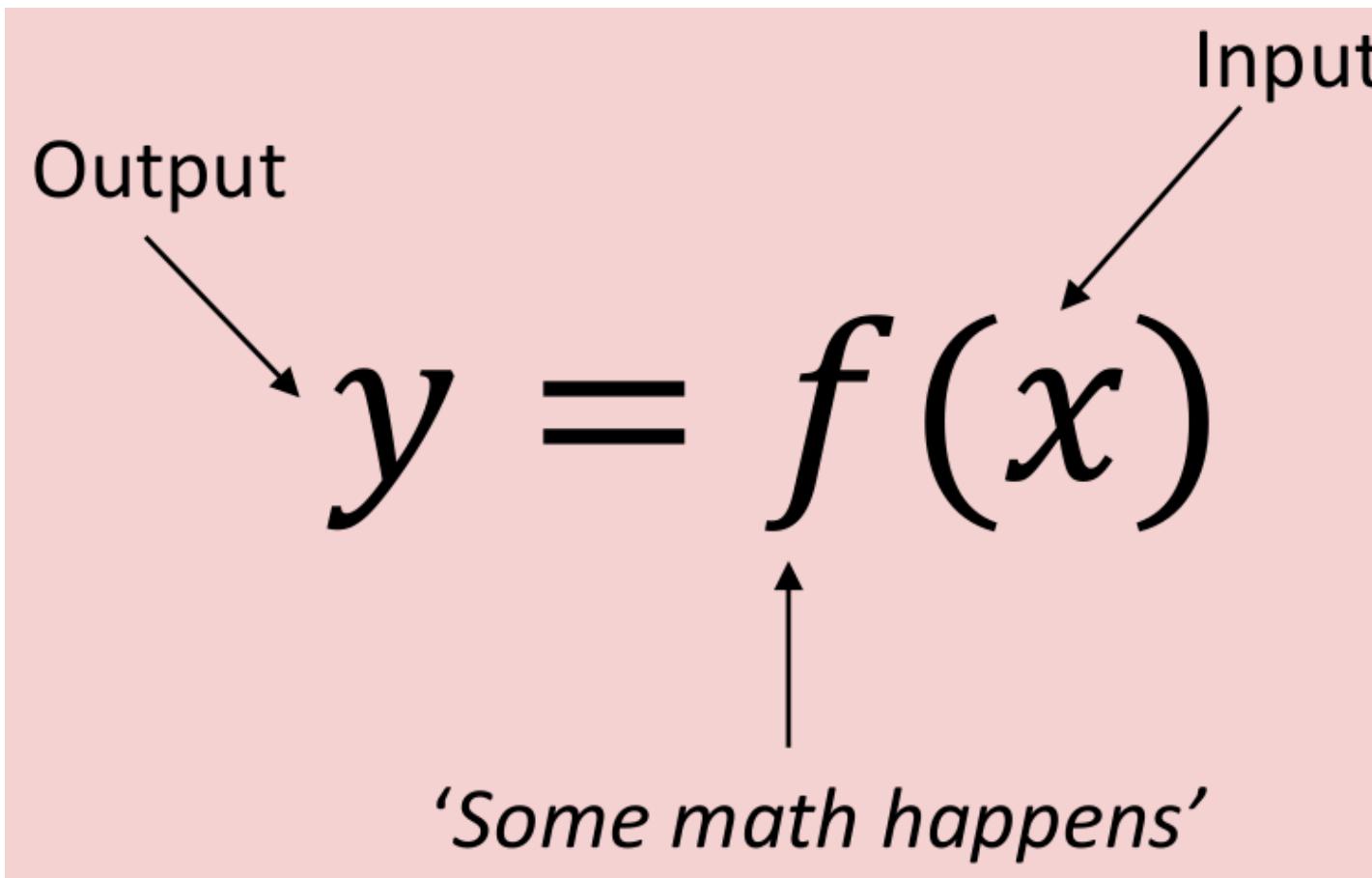


Precision medicine in 2030



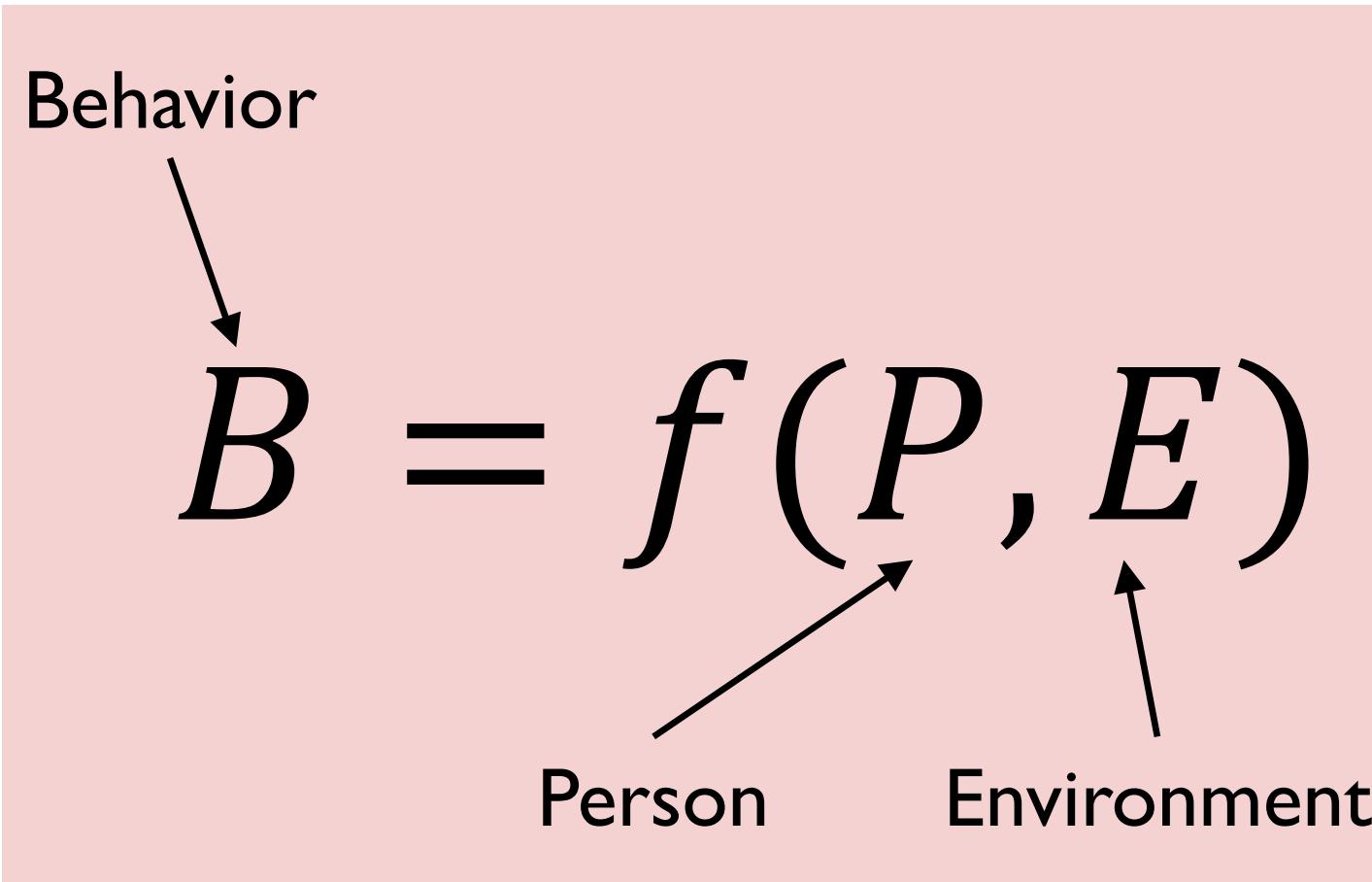
Computational modeling

Cognition as information processing



Computational modeling

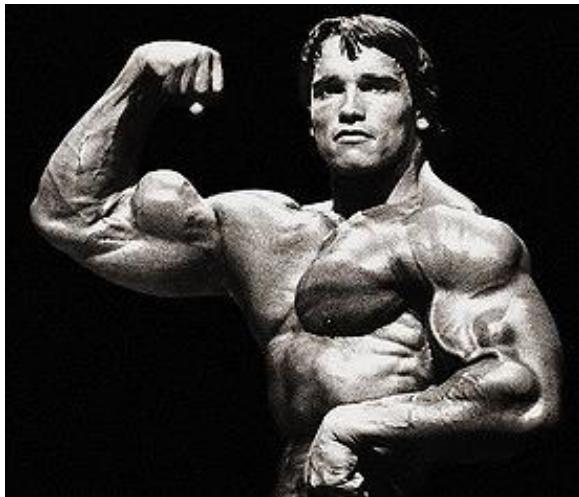
Cognition as information processing



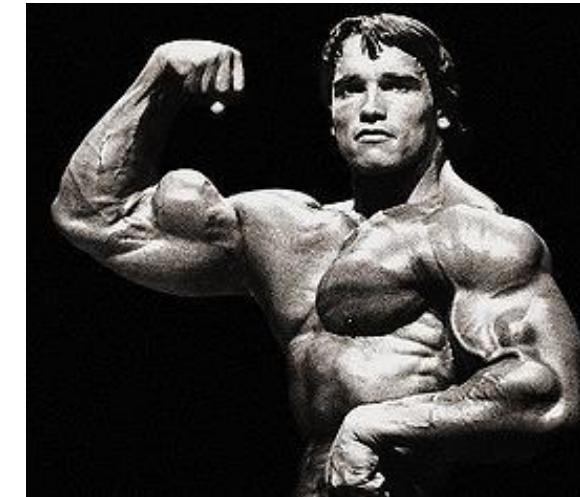
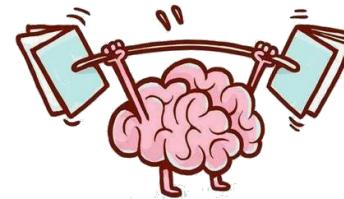
Kurt Lewin, (1936)

Computational Psychiatry

Wrong problem



Wrong solution



Wrong environment



Outline

- The emergence of Computational Psychiatry (CP)
- A case study: flexible choice behavior in Autism
- hBayesDM: a toolbox for estimating hierarchical Bayesian models
- Summary

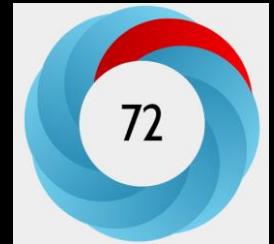
Case study

Flexible learning behavior in autism

(Crawley* & Zhang* et al., 2020, *Plos Biology*)

*: joint first author

PLOS BIOLOGY



RESEARCH ARTICLE

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

Daisy Crawley^{1‡*}, Lei Zhang^{2,3,4‡}, Emily J. H. Jones⁵, Jumana Ahmad^{1,6},
Bethany Oakley¹, Antonia San José Cáceres^{1,7}, Tony Charman^{1,8,9}, Jan
K. Buitelaar^{10,11,12}, Declan G. M. Murphy^{1,9,13}, Christopher Chatham⁴, Hanneke den
Ouden^{10‡}, Eva Loth^{1,13‡}, the EU-AIMS LEAP group¹¹

Autism spectrum disorders

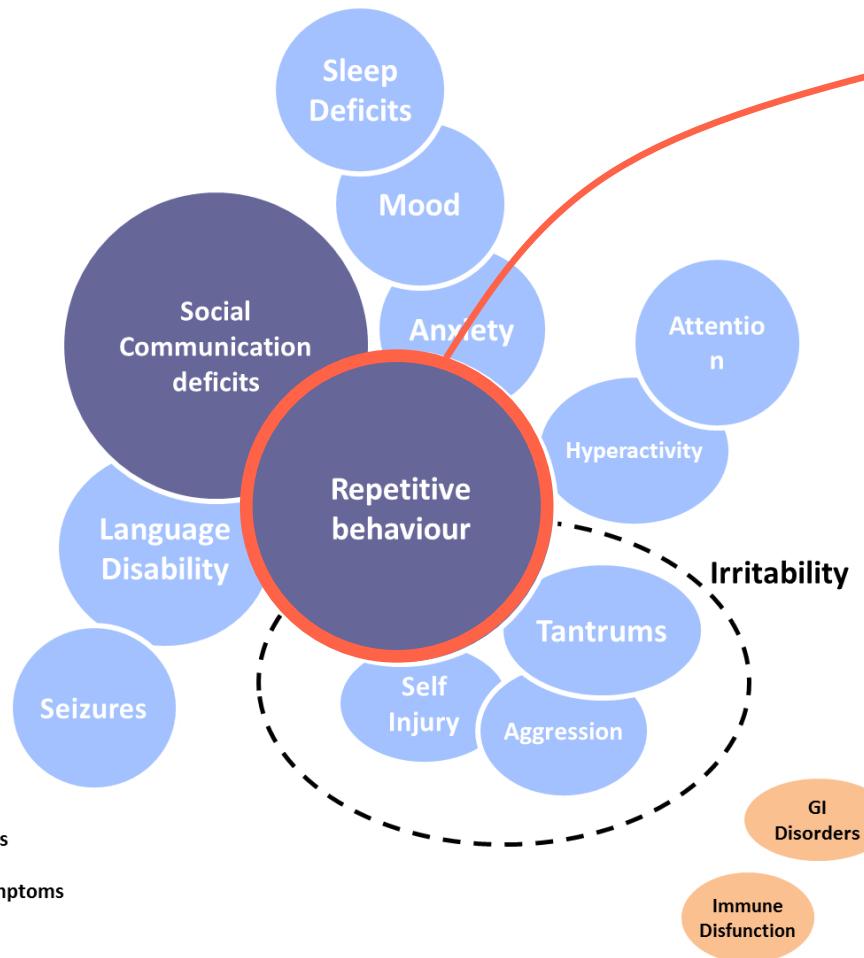
Autism is a developmental disorder characterized by difficulties with social interaction and communication, and by restricted and repetitive behavior.^[3] Parents often notice signs during the first three years of their child's life.^{[1][3]} These signs often develop gradually, though some autistic children experience regression in their communication and social skills after reaching developmental milestones at a normal pace.^[14]

- In 2020, the CDC reported that approximately 1 in 54 children in the U.S. is diagnosed with an autism spectrum disorder (ASD), according to 2016 data.
 - 1 in 34 boys identified with autism
 - 1 in 144 girls identified with autism
- Boys are four times more likely to be diagnosed with autism than girls.
- Most children were still being diagnosed after age 4, though autism can be reliably diagnosed as early as age 2.
- 31% of children with ASD have an intellectual disability (intelligence quotient [IQ] <70), 25% are in the borderline range (IQ 71–85), and 44% have IQ scores in the average to above average range (i.e., IQ >85).

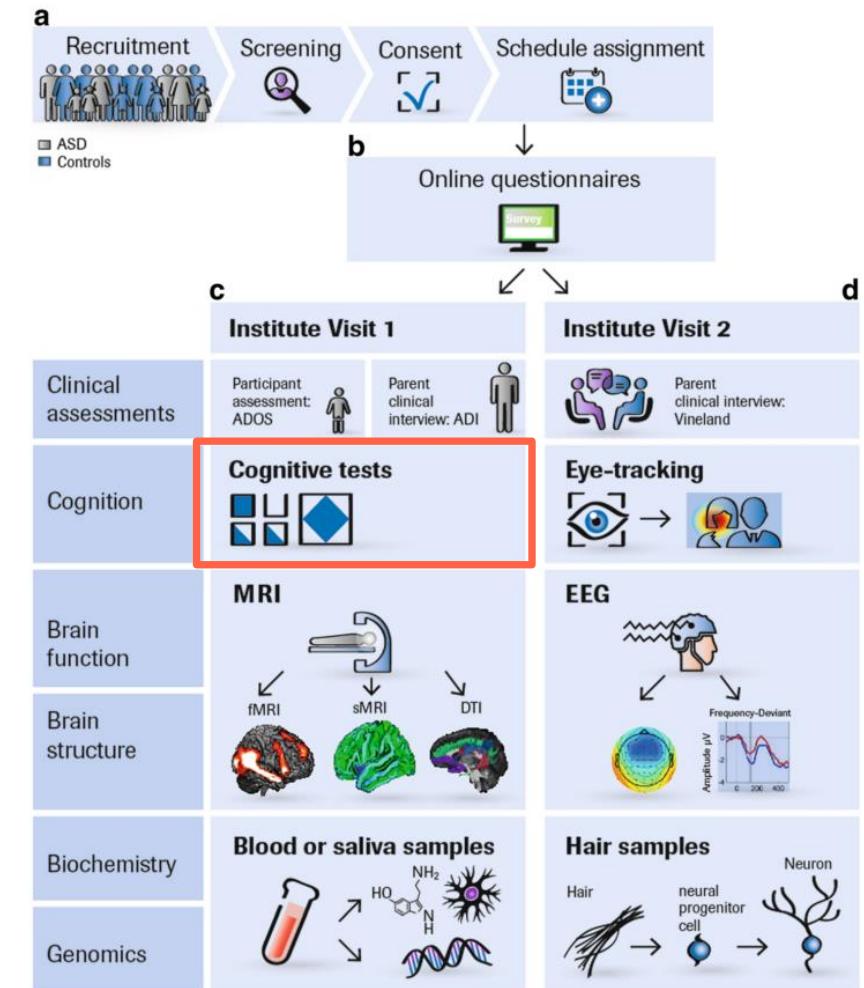


Impaired cognitive flexibility in Autism

Behavioral rigidity is underpinned by cognitive (in)flexibility



DSM-V; Loth et al., (2017)



Impaired cognitive flexibility

26

Review

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



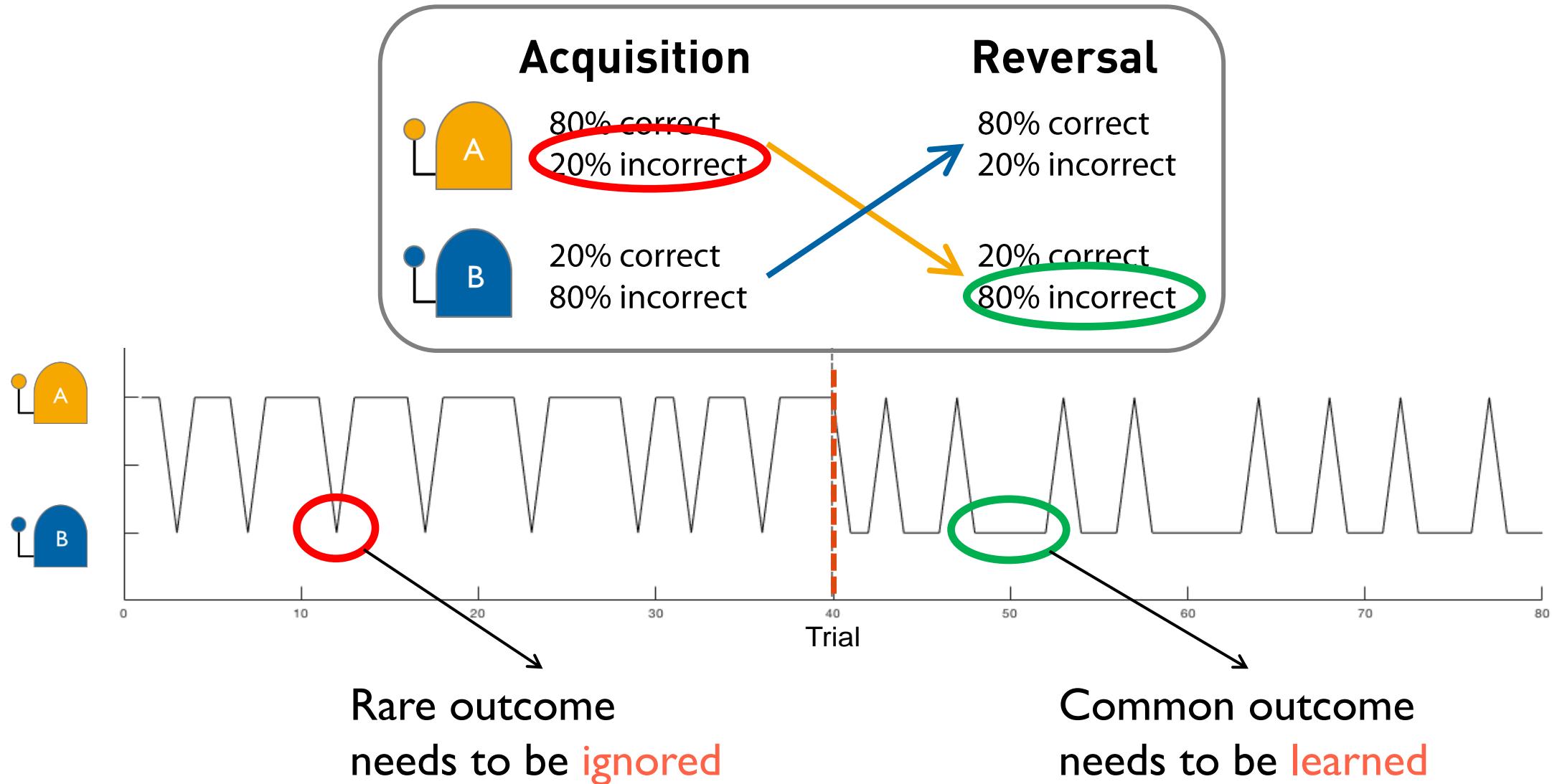
Executive dysfunction in autism[☆]

Elisabeth L. Hill

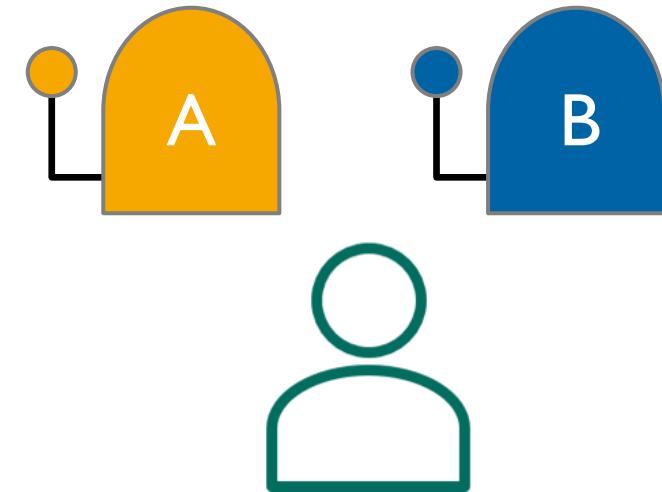
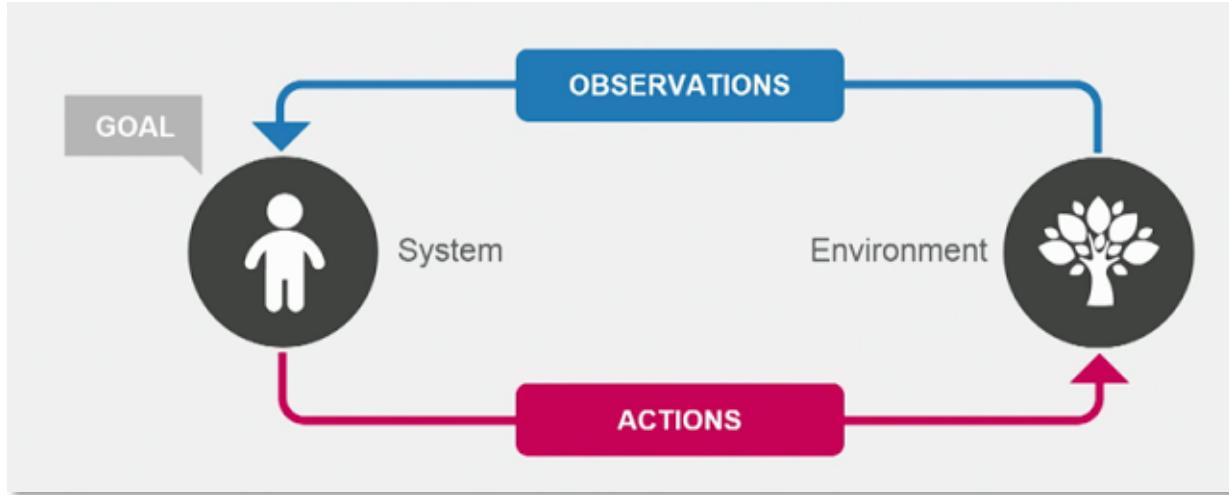
Department of Psychology, Goldsmiths College, University of London, Whitehead Building, New Cross, London, SE14 6NW, UK

- 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 in reversal learning



Computational focus



Reinforcement learning

- gain reward/avoid punishment
- feedback-driven, trial-and-error

Rescorla-Wagner Model

Value update: $V_t = V_{t-1} + \alpha * PE_{t-1}$

Prediction error: $PE_{t-1} = R_{t-1} - V_{t-1}$

*Expectations on the next trial = the expectation on the current trial + learning rate * prediction error (reward – current expectation)*

EU-AIMS LEAP

Longitudinal European Autism Project



Age group	Diagnosis		
	ASD	TD	Total
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

- ASD = Autism spectrum disorder
- TD = Typical development

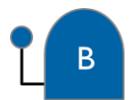


Paradigm

Acquisition



80% correct
20% incorrect



20% correct
80% incorrect

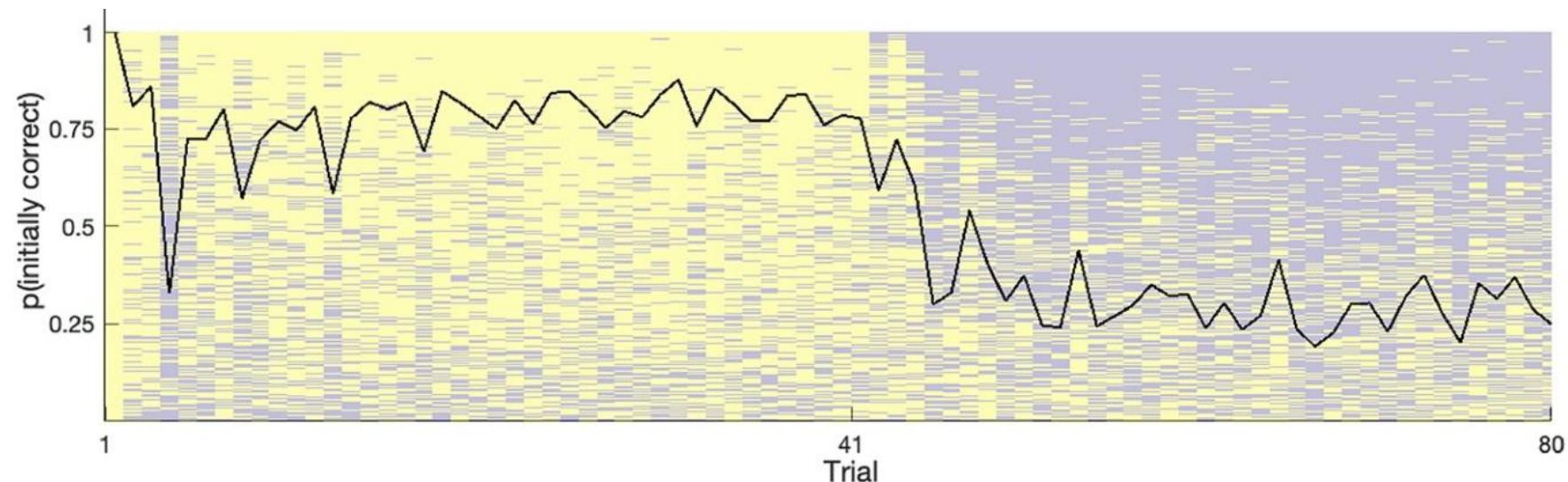
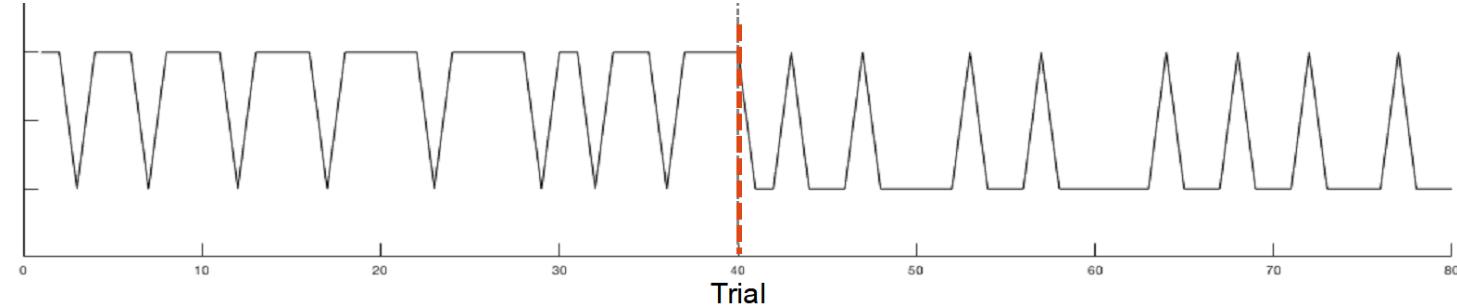
Reversal



80% correct
20% incorrect

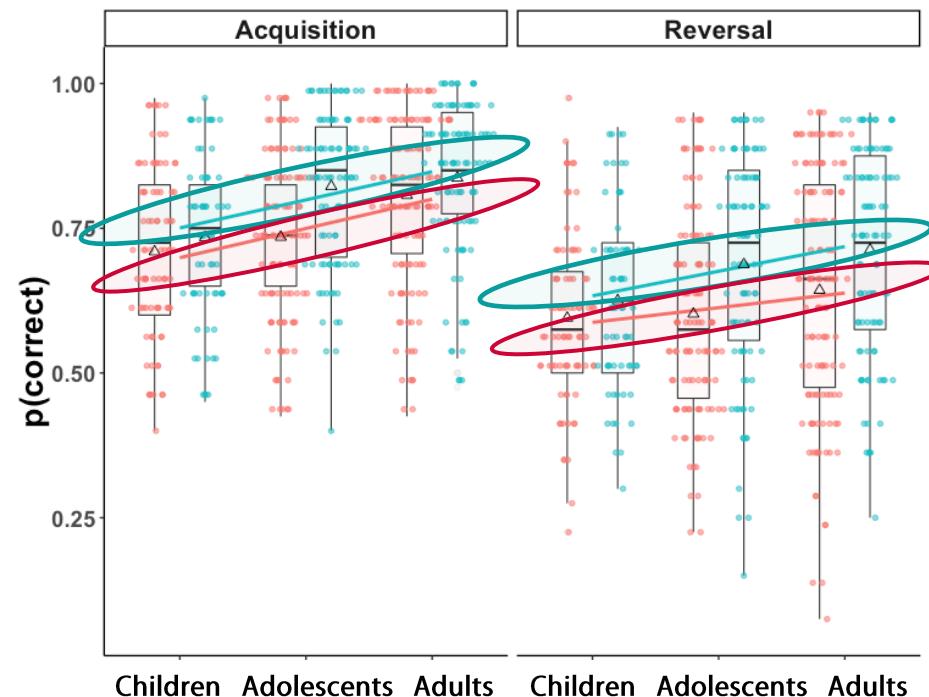


20% correct
80% incorrect

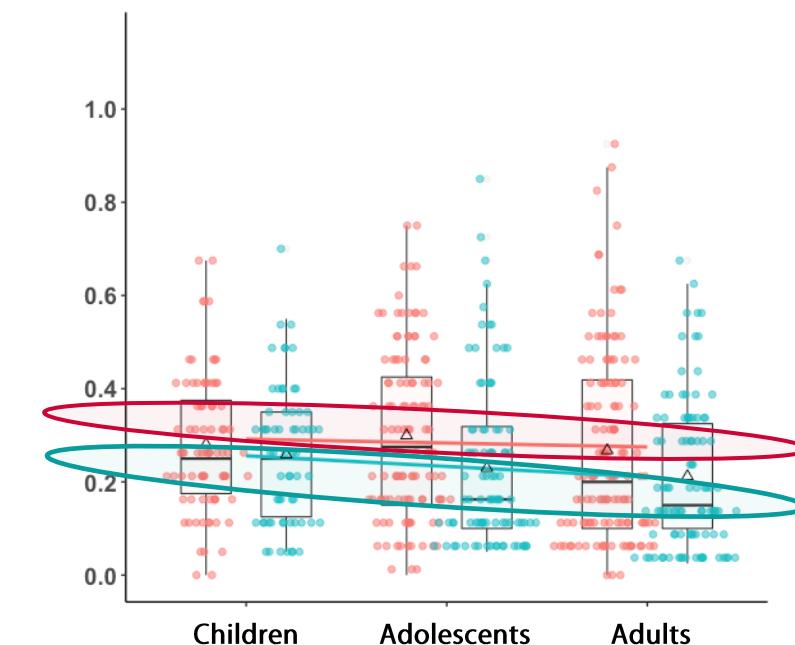


Less optimal learning performance in ASD

Choice accuracy



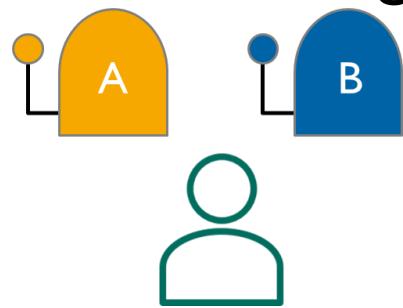
Perseverative errors (after reversal)



— ASD
— TD

What to model?

Decision-making tasks



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
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

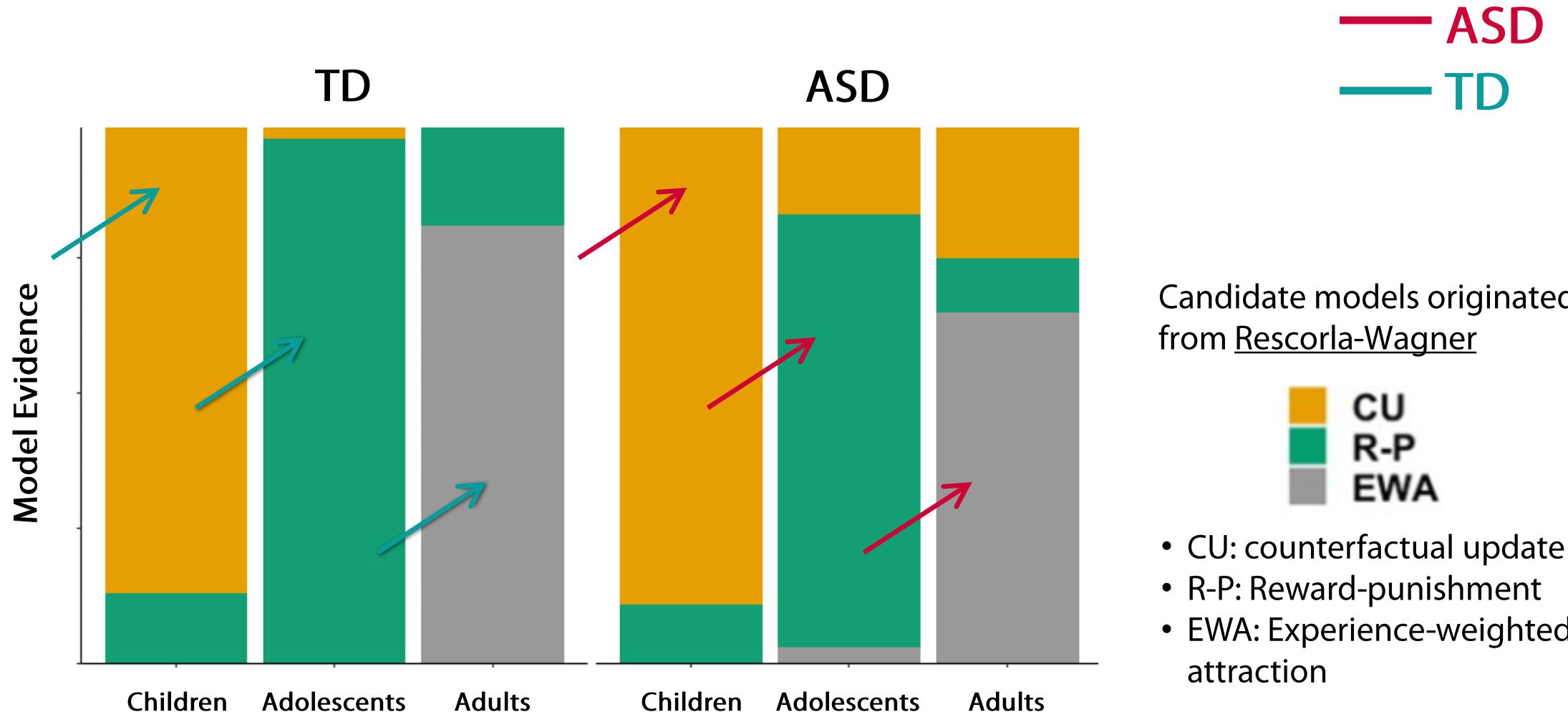
$$V_{c,t} = \begin{cases} V_{c,t-1} + \eta^{\text{rew}} (O_{t-1} - V_{c,t-1}), & \text{if } O_{t-1} > 0 \\ V_{c,t-1} + \eta^{\text{pun}} (O_{t-1} - V_{c,t-1}), & \text{if } O_{t-1} < 0 \end{cases}$$

Experience-weighted attraction

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

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

Same computational model within age group

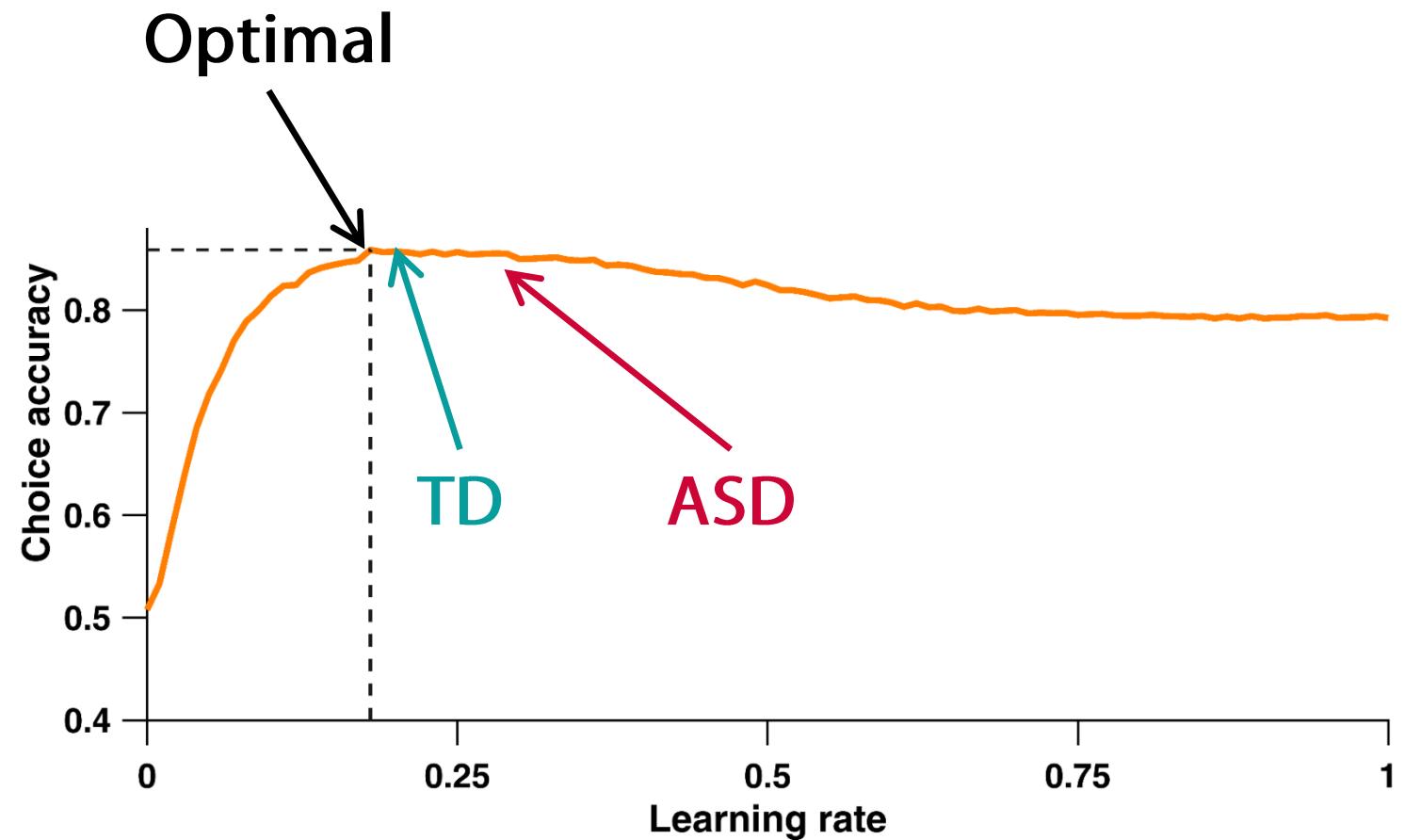
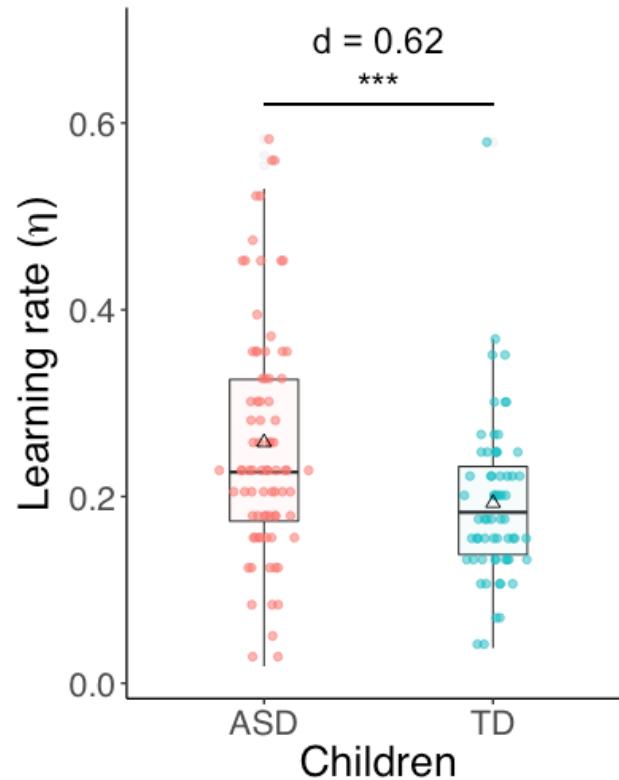


Candidate models originated from Rescorla-Wagner



- CU: counterfactual update
- R-P: Reward-punishment
- EWA: Experience-weighted attraction

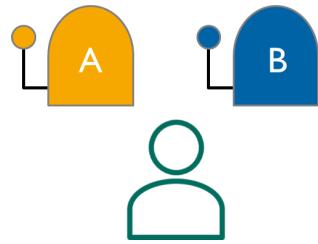
Suboptimal learning parameters in ASD



Understand the learning rate

Value update: $V_t = V_{t-1} + \alpha * PE_{t-1}$

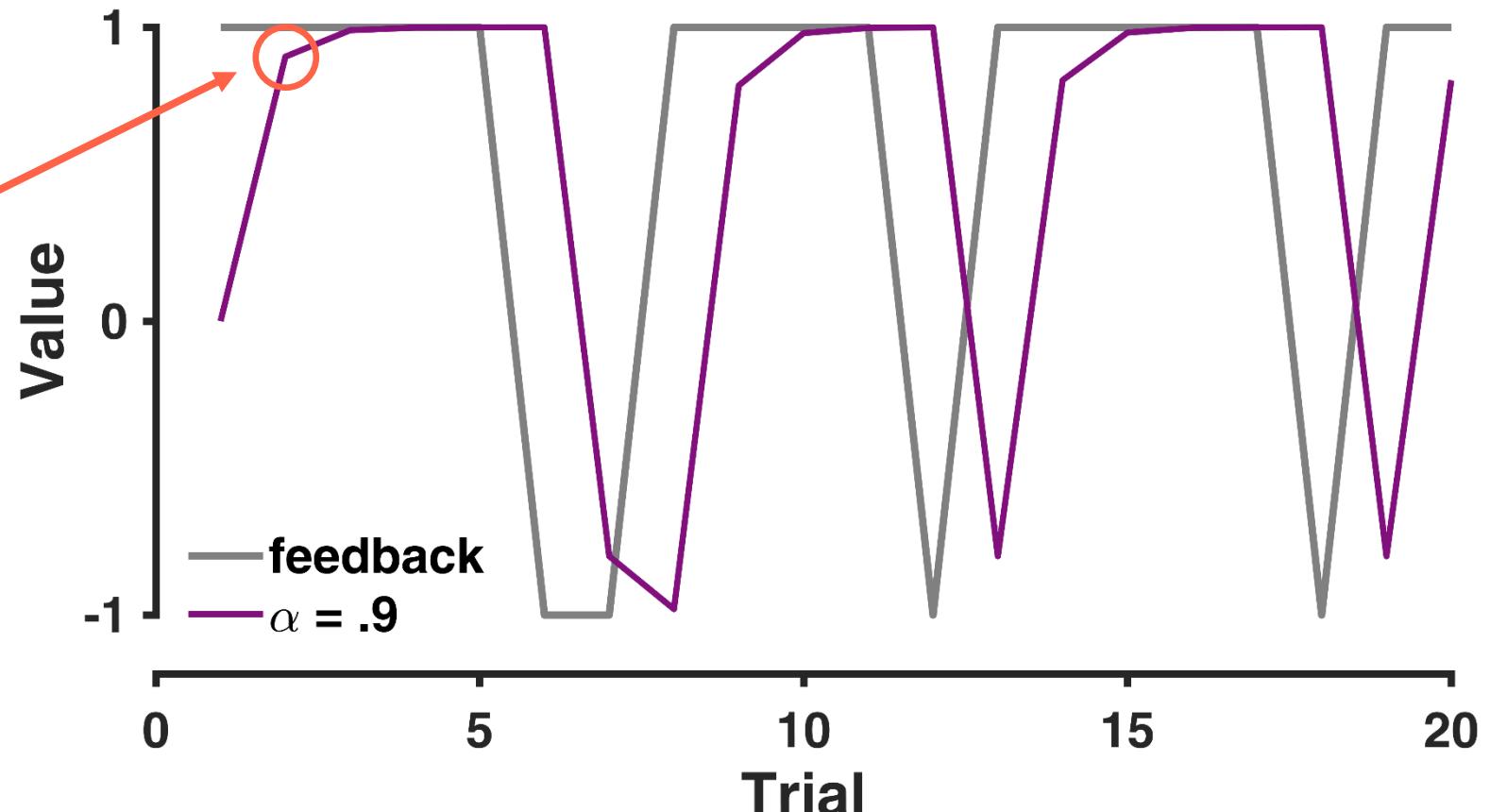
Prediction error: $PE_{t-1} = R_{t-1} - V_{t-1}$



if $\alpha = 0.9$

$$V_1 = 0$$

$$\begin{aligned} V_2 &= V_1 + 0.9 * (1 - V_1) \\ &= 0 + 0.9 * (1 - 0) \\ &= 0.9 \end{aligned}$$



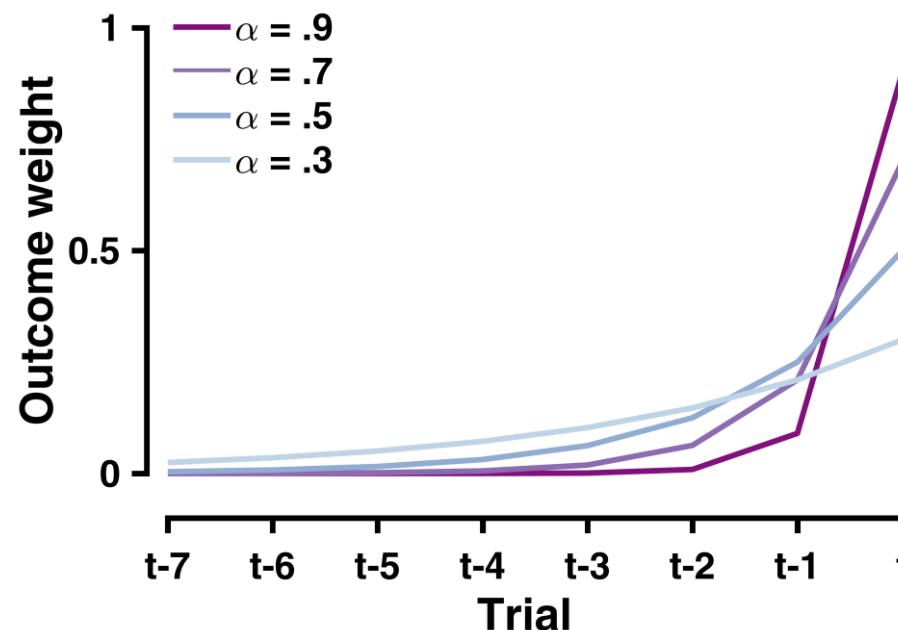
reward contingency – 80:20

Understand the learning rate

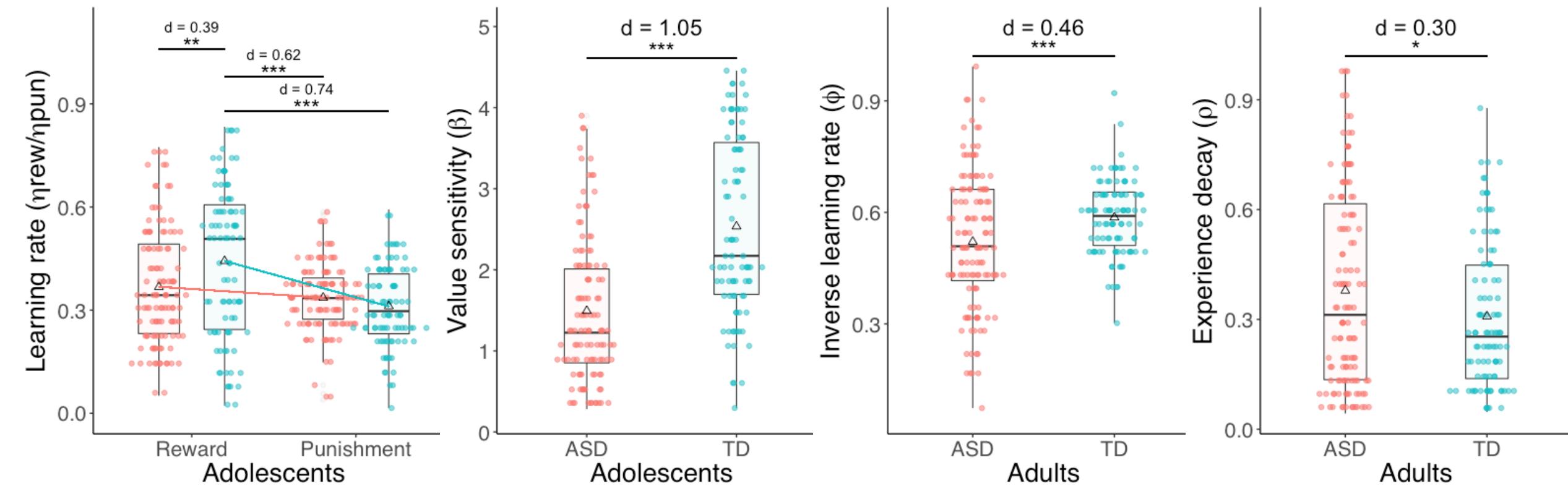
Value update: $V_t = V_{t-1} + \alpha * PE_{t-1}$

Prediction error: $PE_{t-1} = R_{t-1} - V_{t-1}$

$$\begin{aligned}V_t &= (1 - \alpha) V_{t-1} + \alpha R_{t-1} \\&= (1 - \alpha)(V_{t-2} + \alpha(R_{t-2} - V_{t-2})) + \alpha R_{t-1} \\&= (1 - \alpha)^t V_0 + \sum_{i=1}^t (1 - \alpha)^{t-i} \alpha R_i\end{aligned}$$

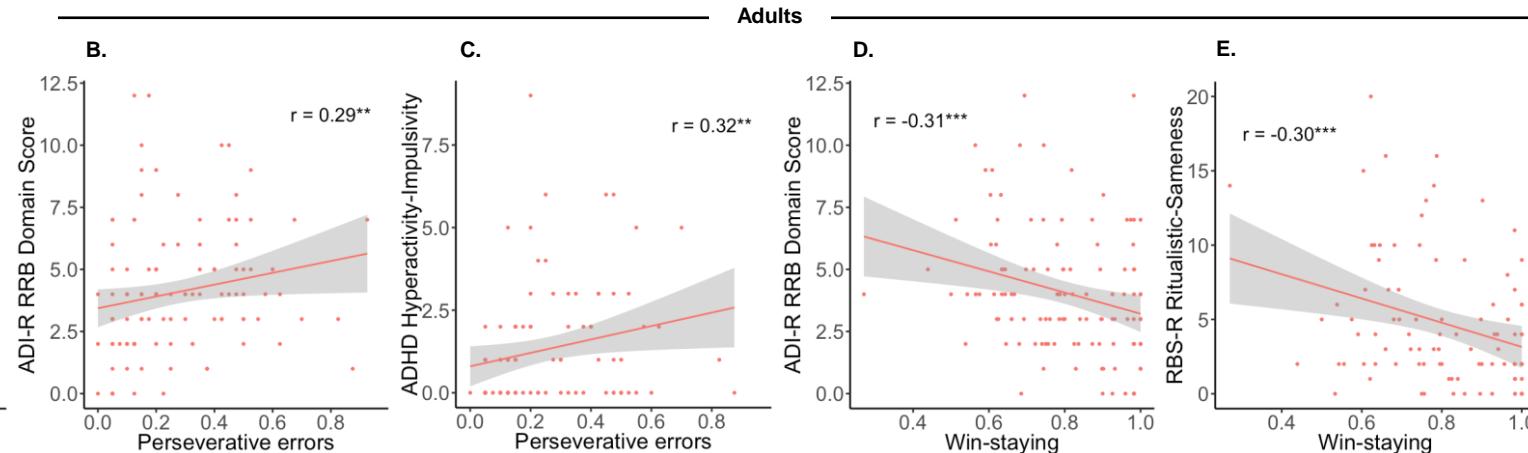
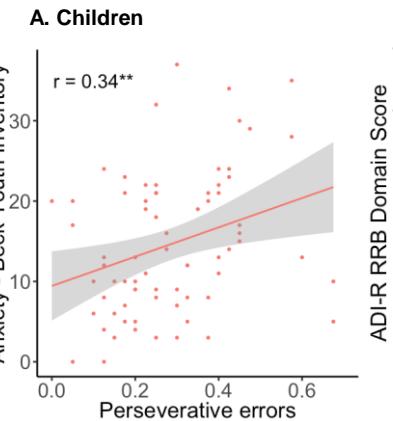


Parameter results: less optimal learning

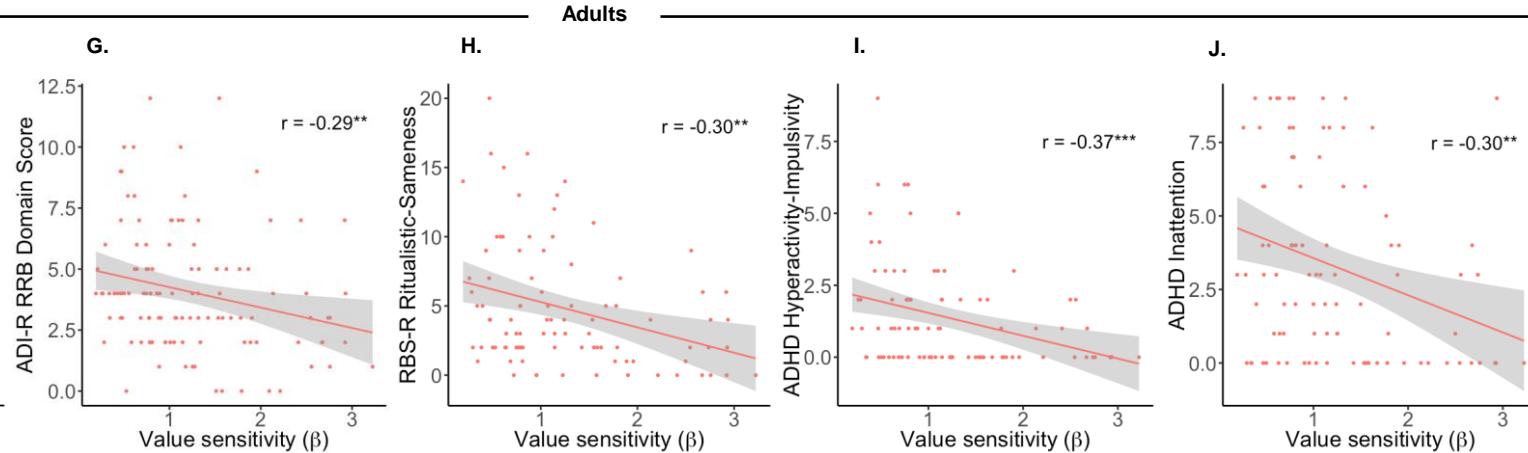
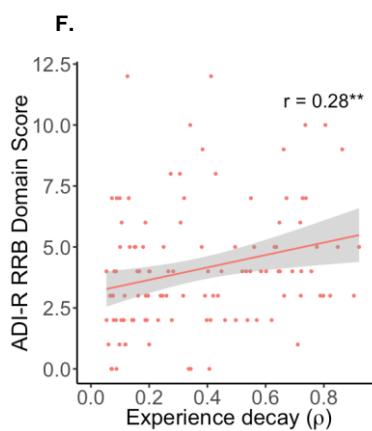


Parameter ~ clinical scales

Task behaviour



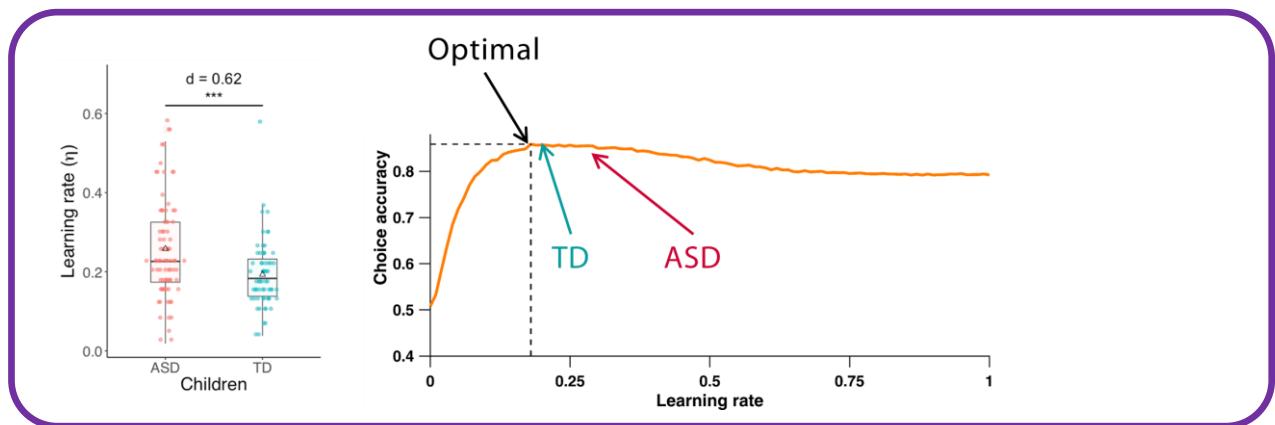
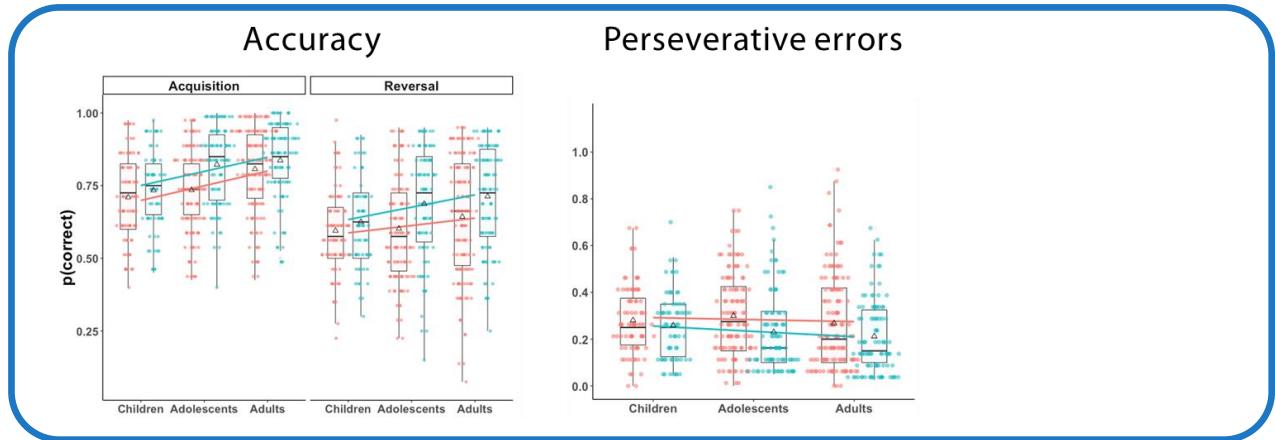
Model parameters



Summary

Computation
(why/goal)

Algorithm
(what/rules)



Outline

- The emergence of Computational Psychiatry (CP)
- A case study: flexible choice behavior in Autism
- **hBayesDM: a toolbox for estimating hierarchical Bayesian models**
- Summary

hBayesDM package

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

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

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

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

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



$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

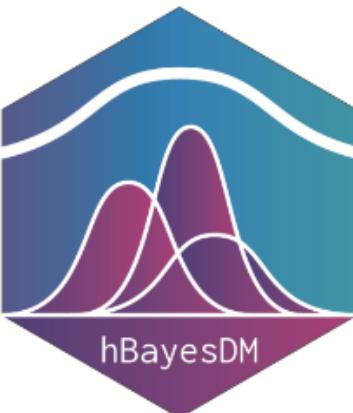
hBayesDM package

hBayesDM

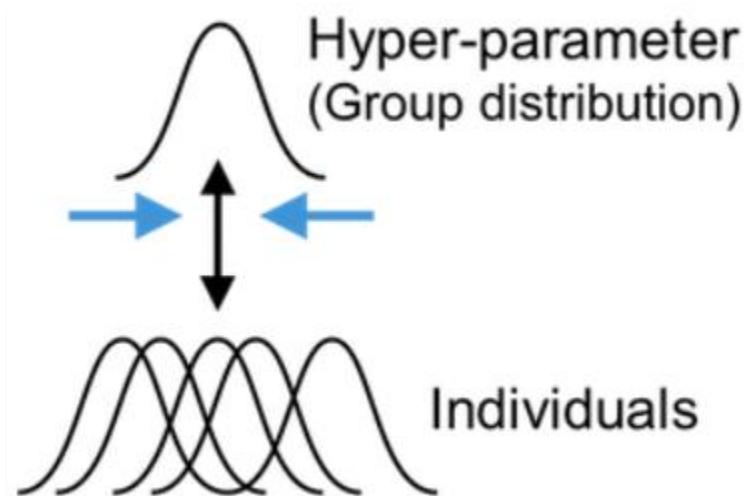
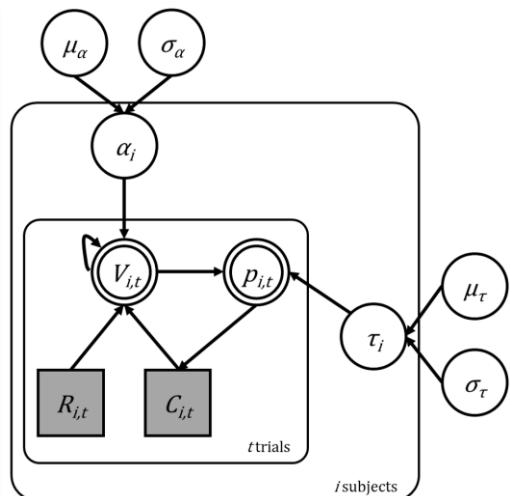
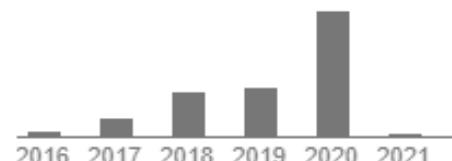
repo status Active build passing CRAN 1.0.2 – 2019-11-13 downloads 33K

DOI 10.1162/CPSY_a_00002

hBayesDM (hierarchical Bayesian modeling of Decision-Making tasks) is a user-friendly package that offers hierarchical Bayesian analysis of various computational models on an array of decision-making tasks. hBayesDM uses Stan for Bayesian inference.



Cited by 115



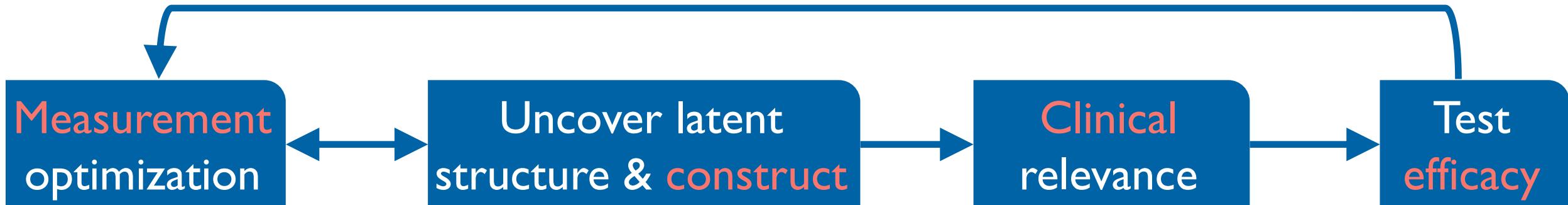
Outline

- The emergence of Computational Psychiatry (CP)
- A case study: flexible choice behavior in Autism
- hBayesDM: a toolbox for estimating hierarchical Bayesian models
- **Summary**

Current challenges in Computational psychiatry

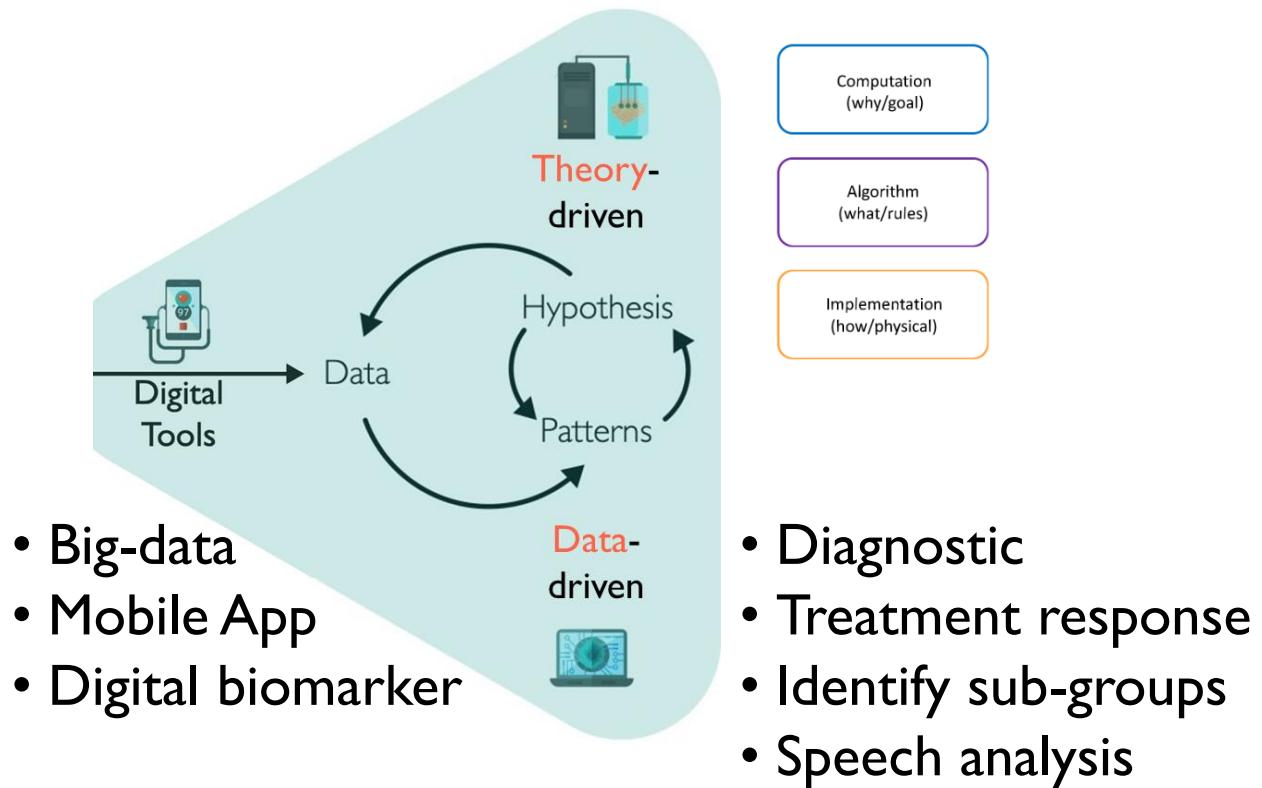
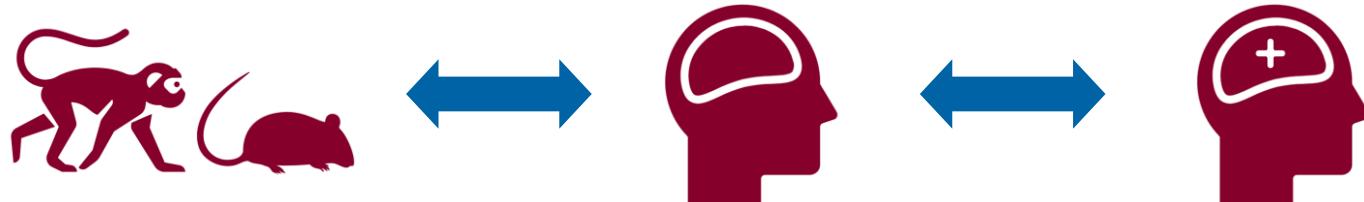
- Structured initiative, laboratory → clinic?
- Test constructs within unselected samples (e.g., online/mobile/wearable)?
- Establish causality: pharmacological manipulation, (deep) brain stimulation?

Principled Roadmap



Future CP

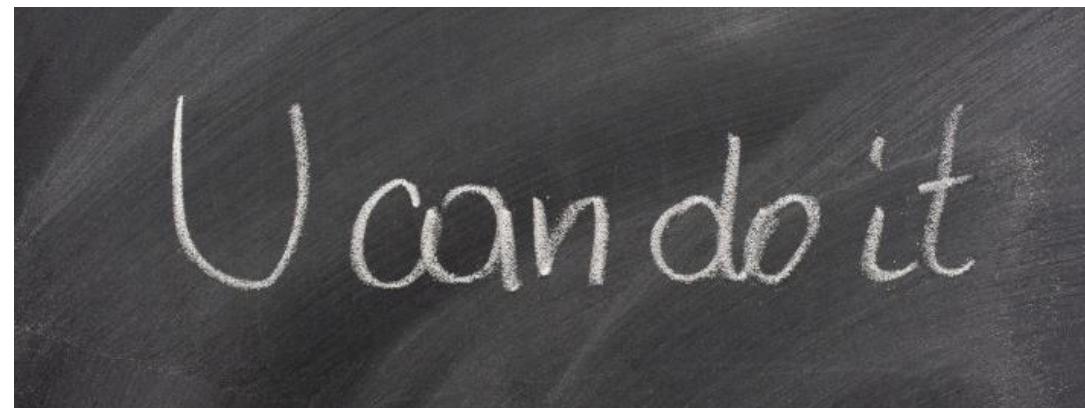
Theory-driven
+
Ethological relevance



Computational model as a link across species and cultures in CP allowing translation from fundamental discoveries to clinical practice

Summary

- CP is newly emerging and rapidly growing → embrace the opportunity!
- Computational modeling is never new → don't let it fear you!
- Improve theoretical thinking → read classic works
- Learn in pairs; no one can do everything → **seek for cooperation!**
- Learn to seek external help → existing packages! e.g., hBayesDM
- Be open minded, be aware of research landscape → use Twitter!



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](#)

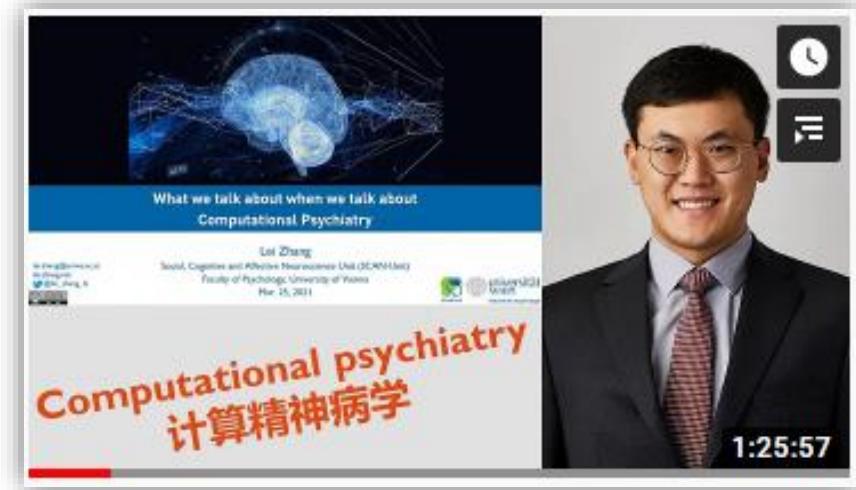
TA的视频 6 最新发布 最多播放 最多收藏 更多 >

Decision Neuroscience
Presentation: Biological Basis of Experience and Behavior
Lei Zhang
85:19
决策神经科学 03 - 决策神经
科学的研究方法
93 3-29

Decision Neuroscience
Presentation: Biological Basis of Experience and Behavior
Lei Zhang
95:35
决策神经科学 02 - 实验设计
与统计推断
46 3-29

Decision Neuroscience
Presentation: Biological Basis of Experience and Behavior
Lei Zhang
97:25
决策神经科学 01 - 课程简介
129 3-29

Bayesian Statistics and Hierarchical Bayesian Modeling for Psychologists
Introduction
Lei Zhang
84:02
贝叶斯统计与贝叶斯认知建模
03 - R/RStudio介绍b
61 3-29



SUBSCRIBE



Acknowledgement

Funding:

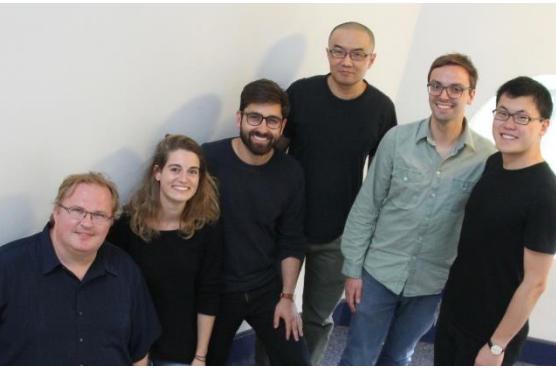


Supervisors:

Jan Gläscher (Hamburg)
Claus Lamm (Vienna)
Chris Chatham (Roche)

Collaborators:

Woo-Young Ahn (Seoul)
Laura A. Berner (Mount Sinai)
Christian Büchel (Hamburg)
Daisy Crawley (KCL)
Hanneke den Ouden (Donders)
Jean-Claude Dreher (CNRS)
Claus C. Hilgetag (Hamburg)
Farid I. Kandil (Berlin)
Eva Loth (KCL)
Gerit Pfuhl (Tromsø)
Andrea Reiter (Würzburg)
Tobias Sommer (Hamburg)



Thank you!



@lei_zhang_lz
www.lei-zhang.net

ANY
QUESTIONS
?

Happy Computing!