Reinforcement Learning

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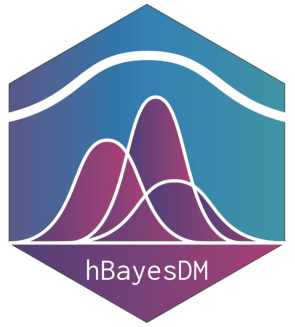
ccs-lab.github.io



Reinforcement Learning (RL)

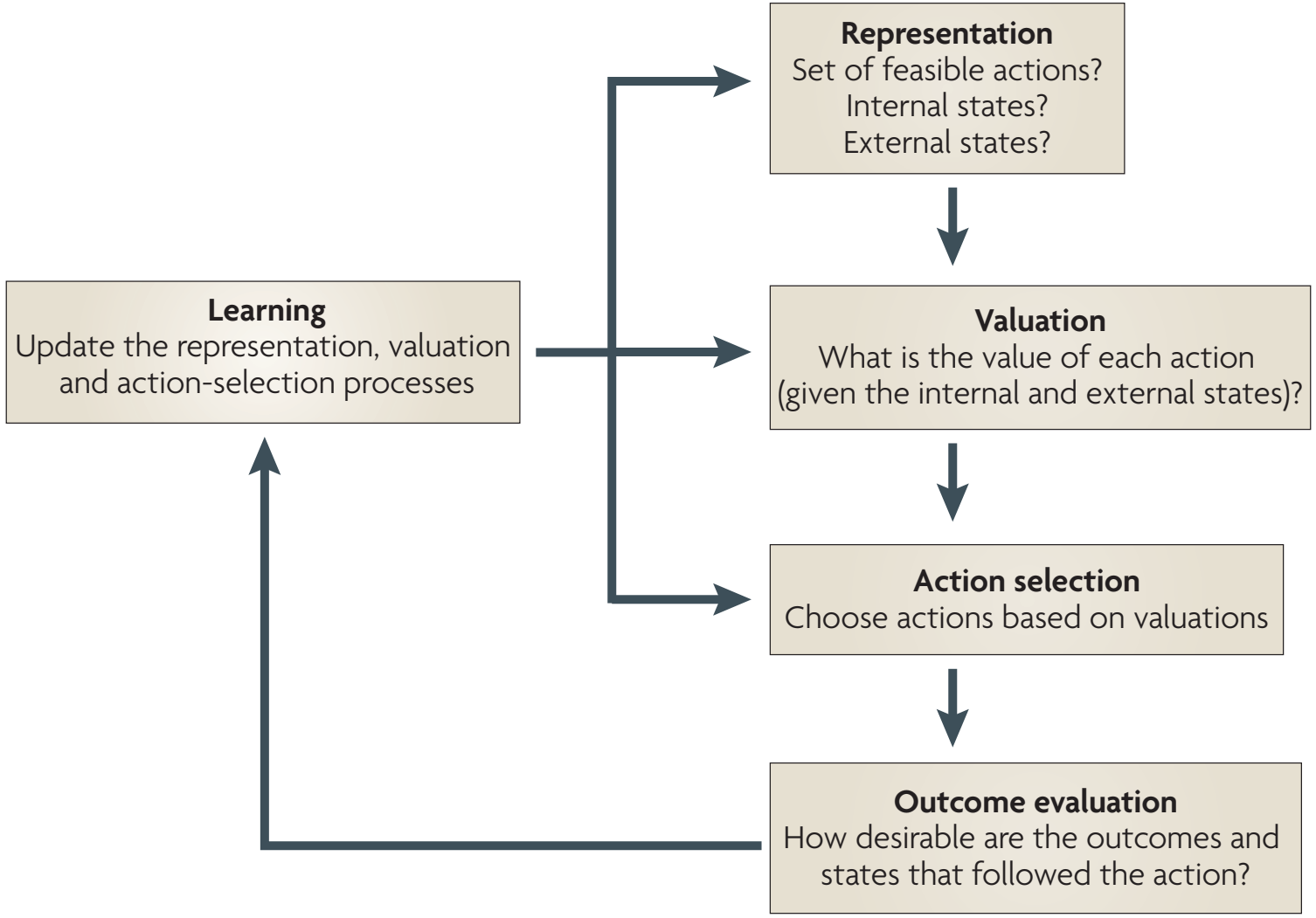
- *What is RL?*
  - *RL in human research vs RL in AI*

- *RL models (algorithms for prediction and control)*
  - *Classical conditioning*
    - *Rescorla-Wagner (R-W) model*
    - *(Bayesian or non-Bayesian) extension of R-W models*
  - *Operant (instrumental) conditioning*
    - *Model-free vs Model-based learning*
    - *Pavlovian control vs Instrumental control*
- *Adaptive Design Optimization within the RL framework*
- *Limitations & Future directions*

Learning objectives

Participants will…

- *Understand the key concepts and notations of RL (in multiple fields)*
- *Know (some of) popular RL models (& references)*
  - *Simple to complex models*
- *Limitations of RL and some new approaches*



Rangel et al (2008) Nature Reviews Neuroscience

What is RL?

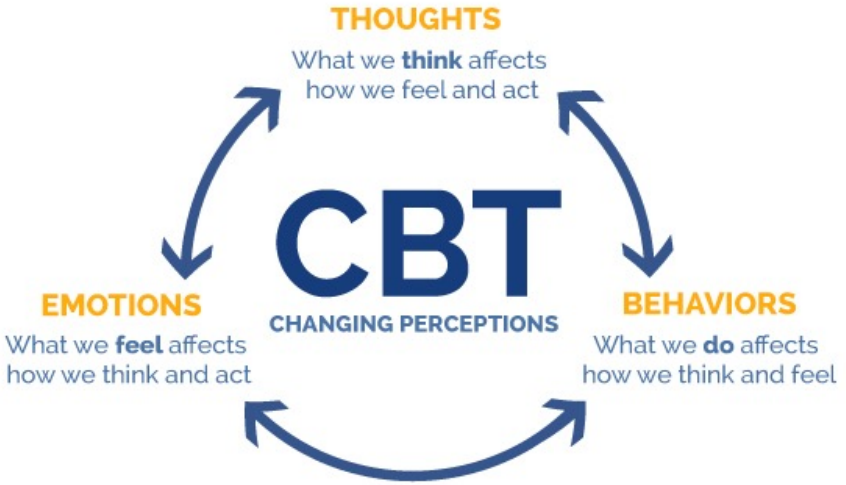
"Learning what to do" …
based on (an incomplete history of) rewards and punishments

Sutton & Barto (1998) Reinforcement Learning
Dayan & Labott (2000) Theoretical neuroscience

"Learn optimal ways to make decisions"
in an uncertain environment

Mnih et al (2015) Nature

Silver et al (2016) Nature



RL is a type of Machine Learning

- *Supervised Learning*
- *Unsupervised Learning*
- *Reinforcement Learning*

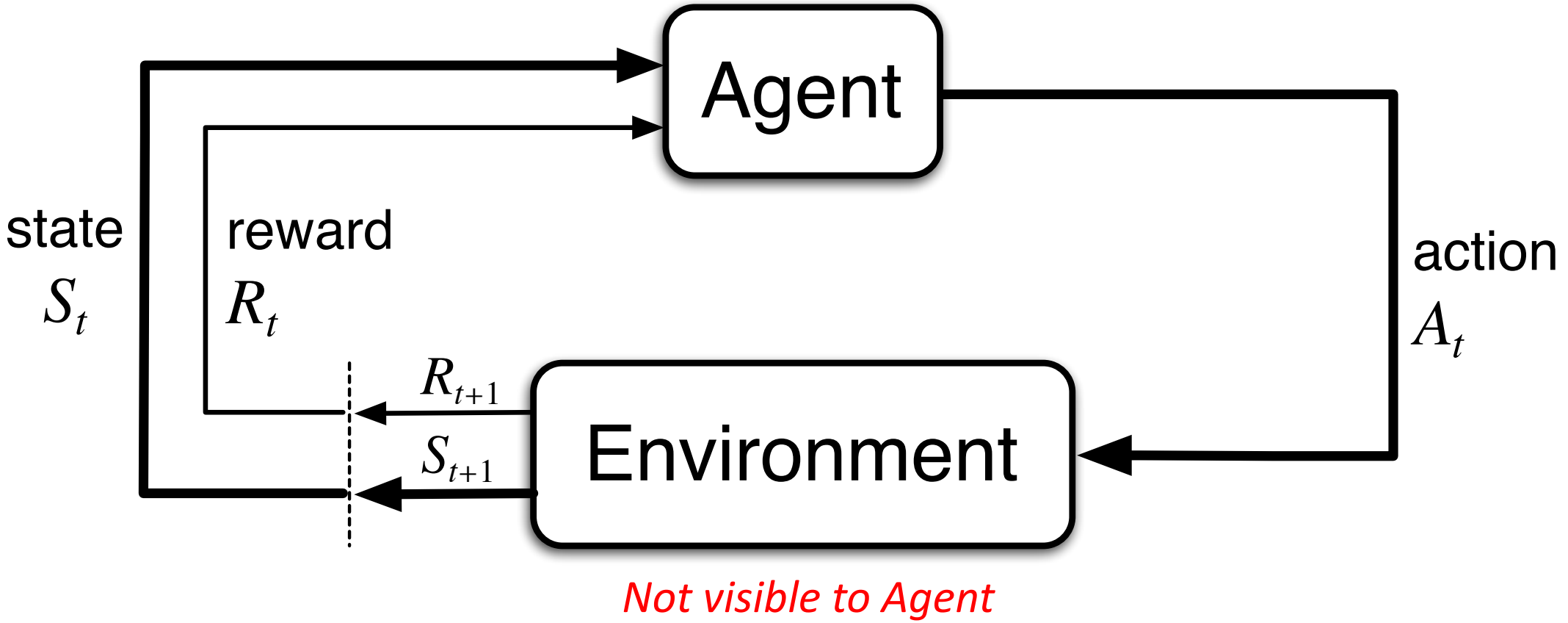
Q) How is RL different from other ML paradigms?

- *No external supervisor (“minimally supervised”)*
- *Reward signals (learn from trials and errors)*
- *Interaction with environment*
- *Closely tied to action selection (e.g., exploration/exploitation)*

"Learn optimal ways to make decisions" in an uncertain environment

	RL in human research	*RL in AI*
Goal	*Characterize individual differences*	*Generate optimal solution*
Amount of data	*Small*	*Very large*
# parameters	*Typically < 10*	*A lot*
Parameter estimation	*Important*	*Estimate? Often fixed*

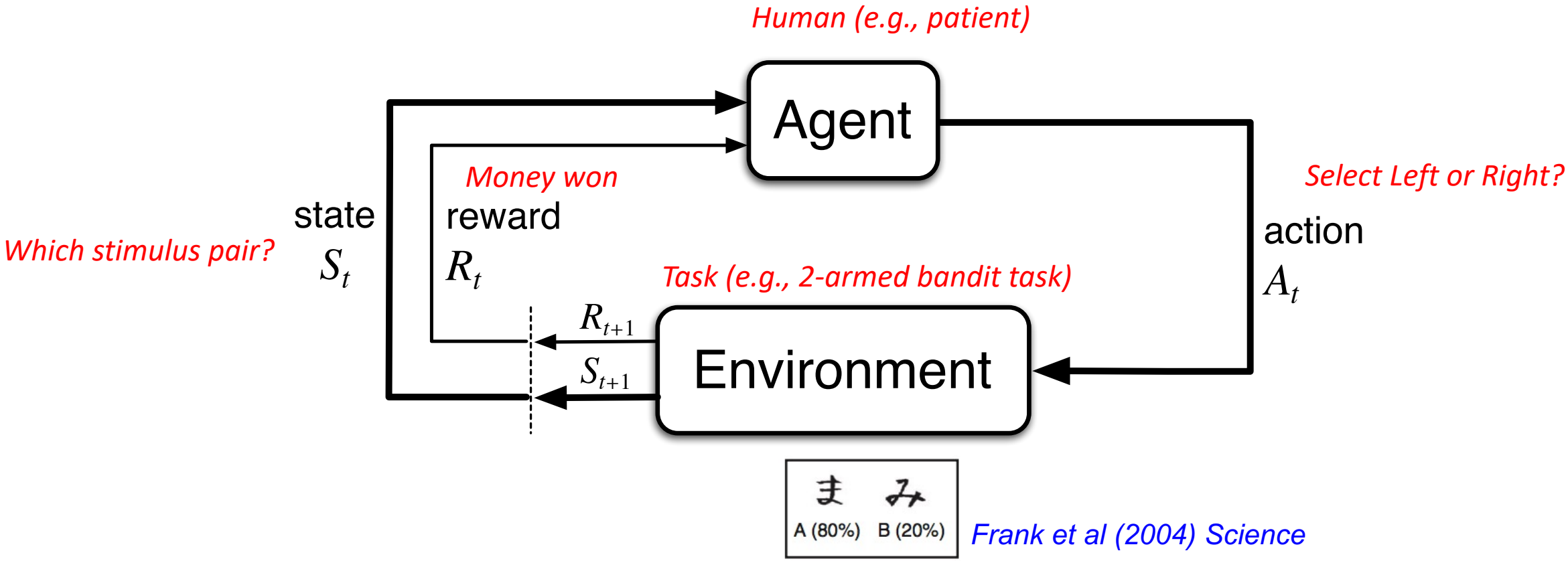
Agent-Environment Interface
(check MDP lecture)
e.g., Maze task, Tree search, N-armed Bandit



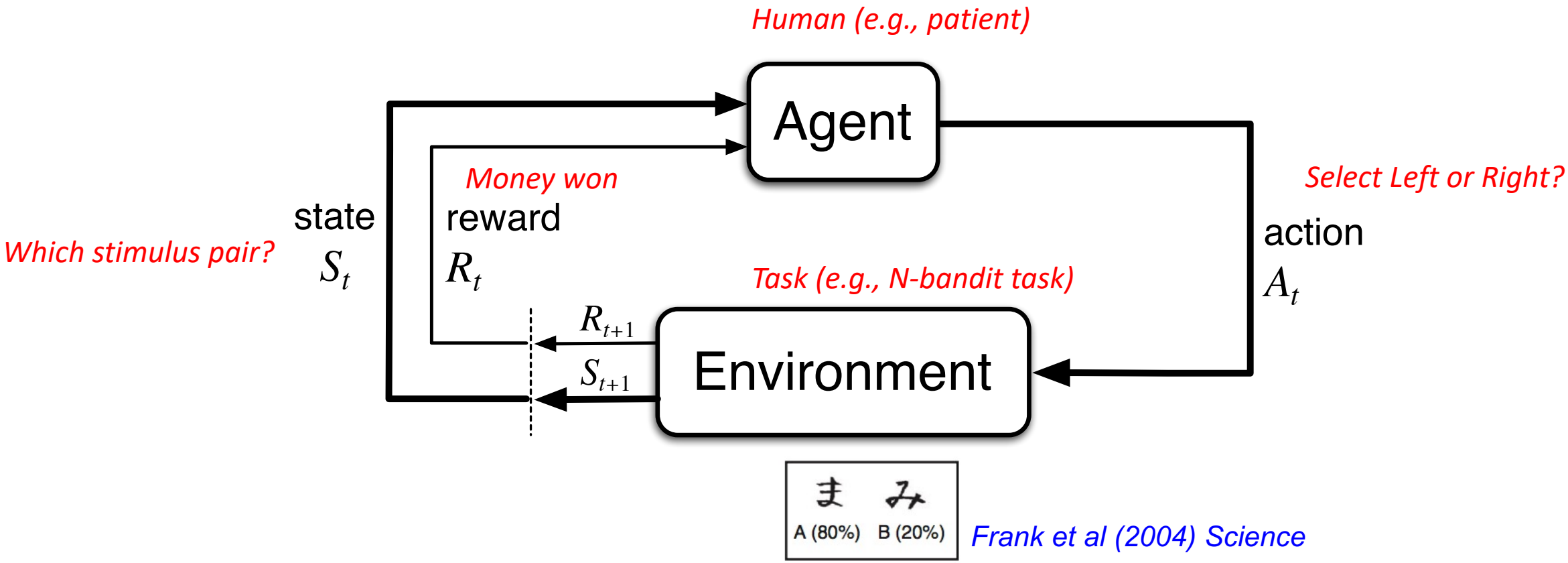
Sutton & Barto (1998) Reinforcement Learning

Typically in Computational Psychiatric research settings..

Model parameters → Psychologically meaningful processes/constructs

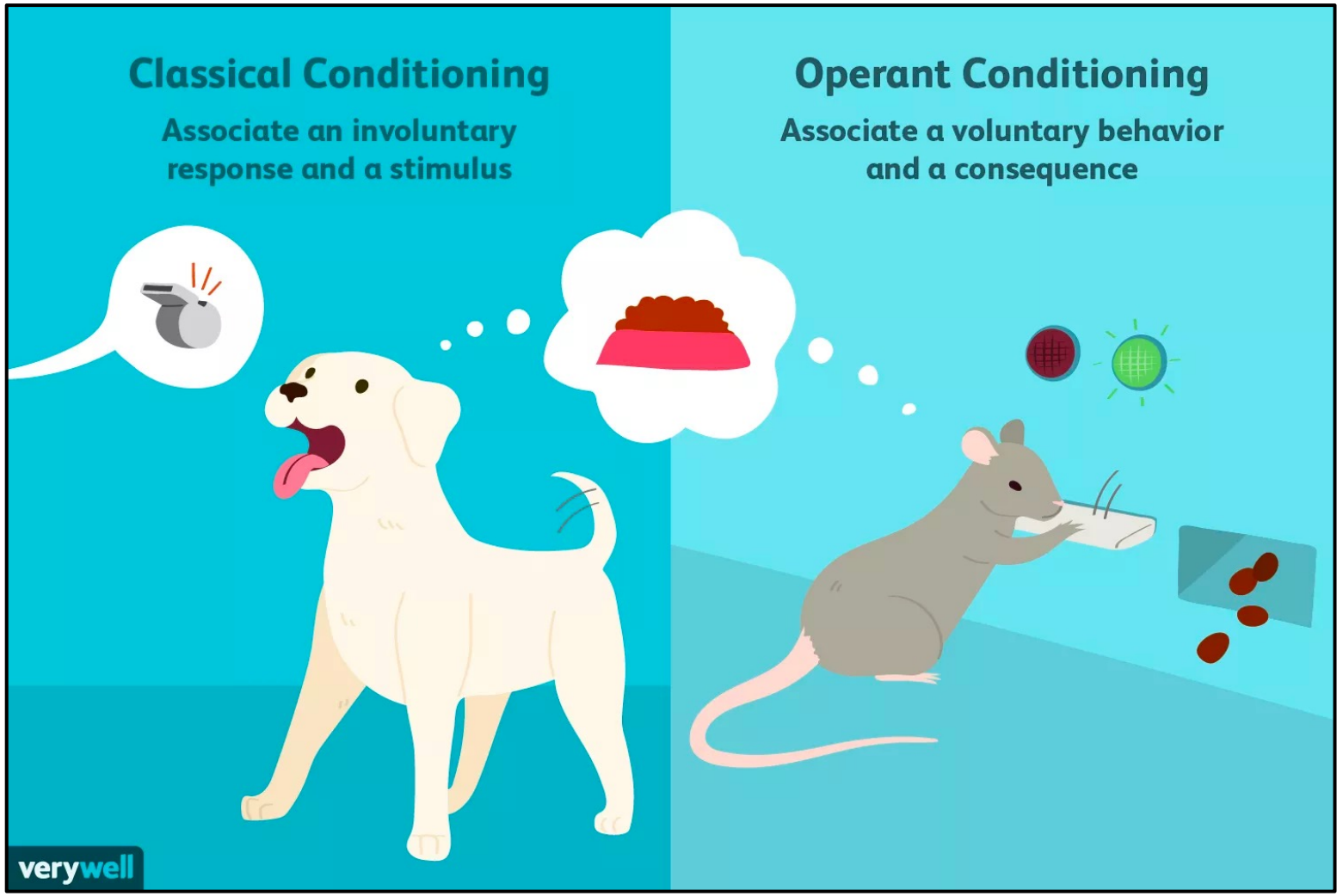


S_t: State value on time (trial) t
A_t: Action value on time (trial) t
R_t: Reward on time (trial) t
$\pi_t(a_t, s_t)$: Policy on time (trial) t → mapping from states to actions



RL models (algorithms for prediction)

Two experimental set-ups
(Not a distinction of learning mechanisms)



https://www.verywellmind.com/classical-vs-operant-conditioning-2794861

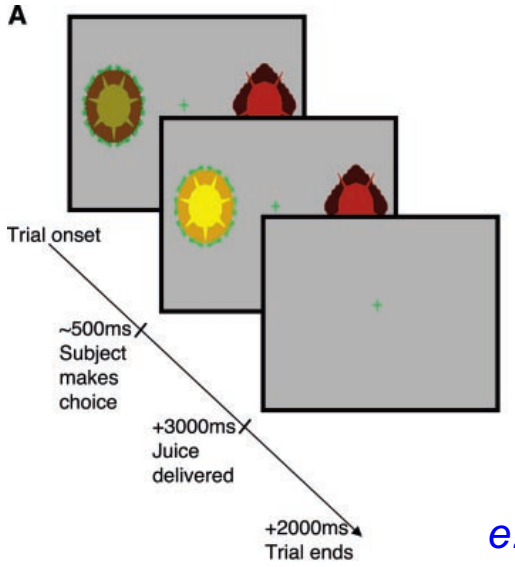
Two experimental set-ups
(Not a distinction of learning mechanisms)

Classical conditioning
(No action required)

CS+ CS- CS Neut

e.g., O'Doherty et al (2003) Neuron

Operant (Instrumental)
Conditioning (Action required)



e.g., O'Doherty et al (2004) Science

Classical conditioning

CS+ CS- CS Neut

e.g., O'Doherty et al (2003) Neuron

Rescorla-Wagner (R-W) model

→ Point estimates of V_t

$$V_t = V_{t-1} + \alpha(R_t - V_{t-1})$$

Learning rate

Stimulus value (t)

Stimulus value (t-1)

Outcome

Stimulus value (t-1)

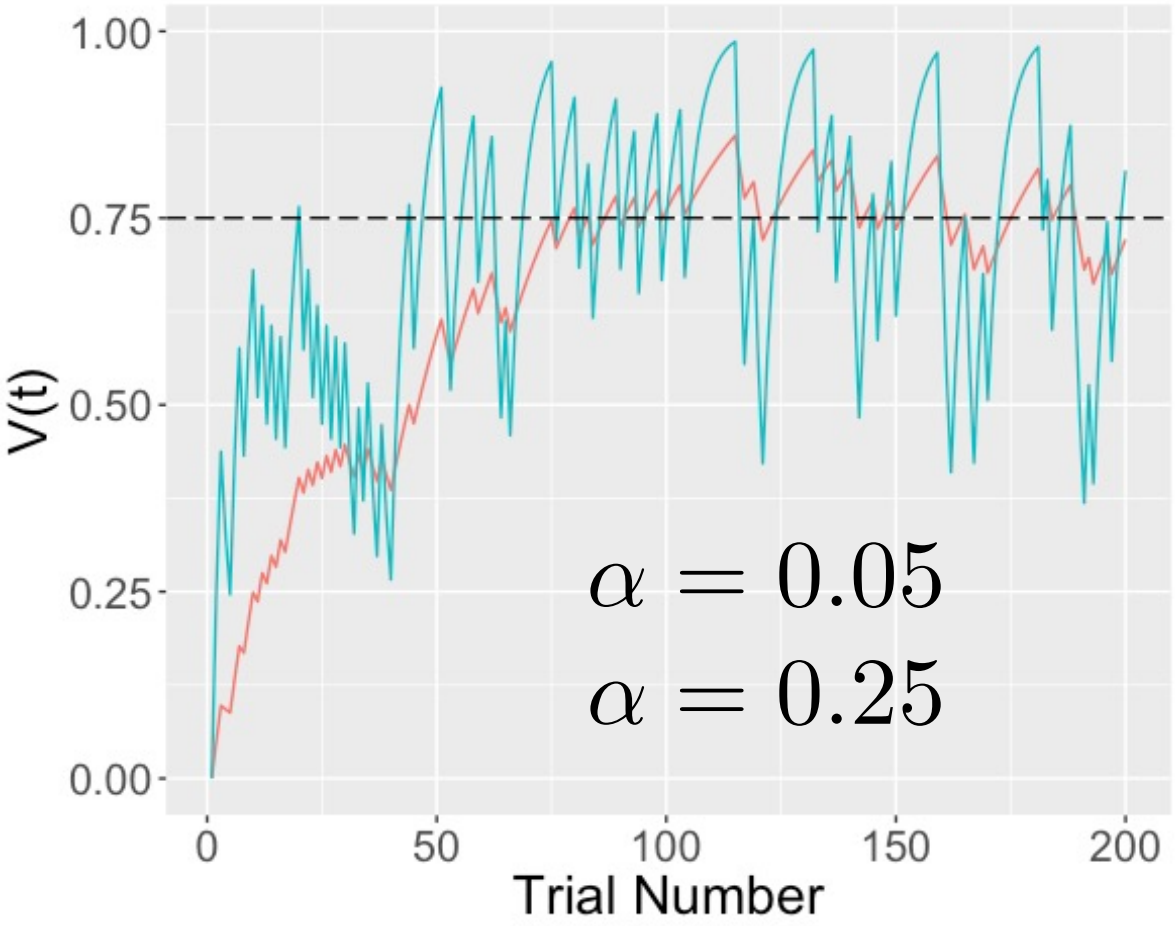
Prediction error

Classical conditioning

CS+ CS- CS Neut

e.g., O'Doherty et al (2003) Neuron

e.g., Reward rate = 0.75



http://haines-lab.com/post/2017-04-04-choice_rl_1/

* *Rescorla-Wagner (R-W) model*
→ *Point estimates of V_t*

* *Bayesian generalization of R-W*
→ *Kalman filter ➔ HGF*

Dayan et al (2000); Kakade & Dayan (2002)
Daw et al (2006); Kruschke (2008); Mathys et al (2011; 2014)

Also see Maaten Speekenbrink's blogs
https://speekenbrink-lab.github.io/blog/

Classical conditioning

CS+ CS- CS Neut

e.g., O'Doherty et al (2003) Neuron

Temporal Difference (TD) Learning model

→ *Generalization of R-W (real-time model)*
→ *To account for within-trial and between-trial relationships among stimuli*

Reward Prediction Error
TD learning model

Computational roles for dopamine in behavioural control

P. Read Montague[1,2], Steven E. Hyman[3] & Jonathan D. Cohen[4,5]

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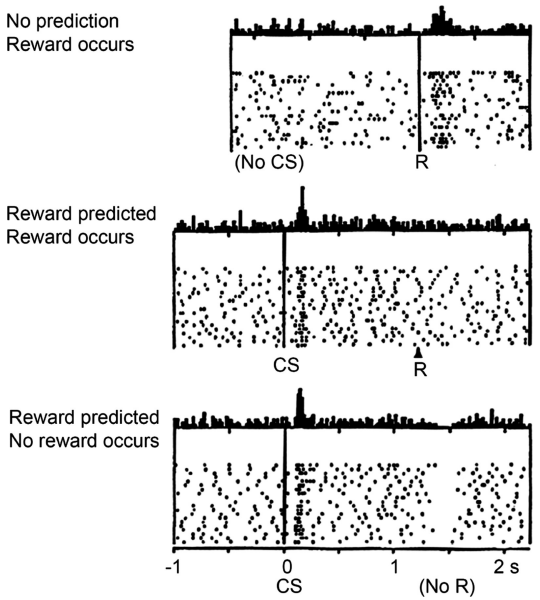
[3]*Harvard University, Cambridge, Massachusetts 02138, USA (e-mail: seh@harvard.edu)*
[4]*Department of Psychiatry, University of Pittsburgh and* [5]*Department of Psychology, Center for the Study of Brain, Mind & Behavior, Green Hall, Princeton University, Princeton, New Jersey 08544, USA (e-mail: jdc@princeton.edu)*

Montague et al (2004) Nature



Temporal difference (TD) learning model

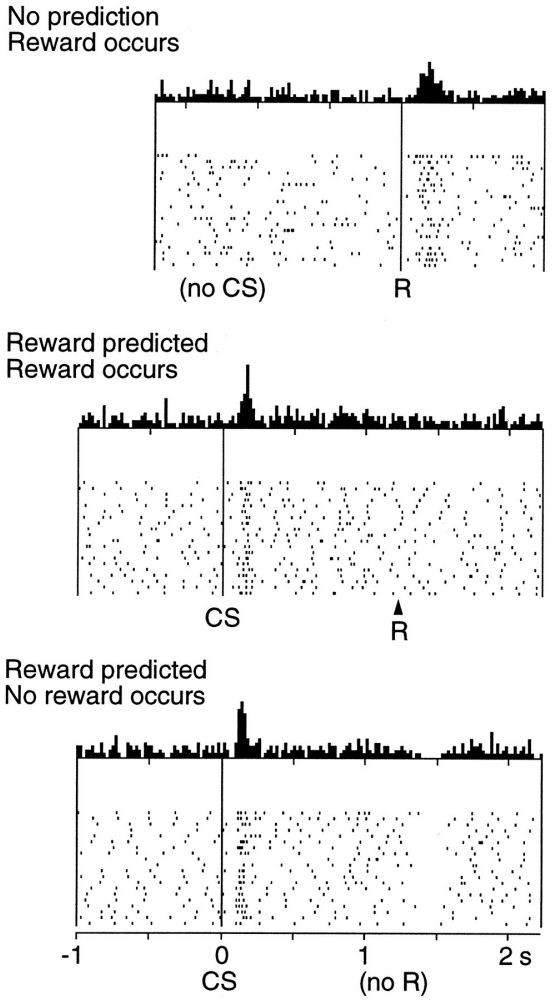
$$\delta(t) = \text{prediction error } (t) = E[r_t] + \gamma \cdot \hat{V}(s_{t+1}) - \hat{V}(s_t)$$
$$\approx \text{current reward} + \gamma \cdot \text{next prediction} - \text{current prediction}$$

Sutton & Barto (1998) Reinforcement Learning

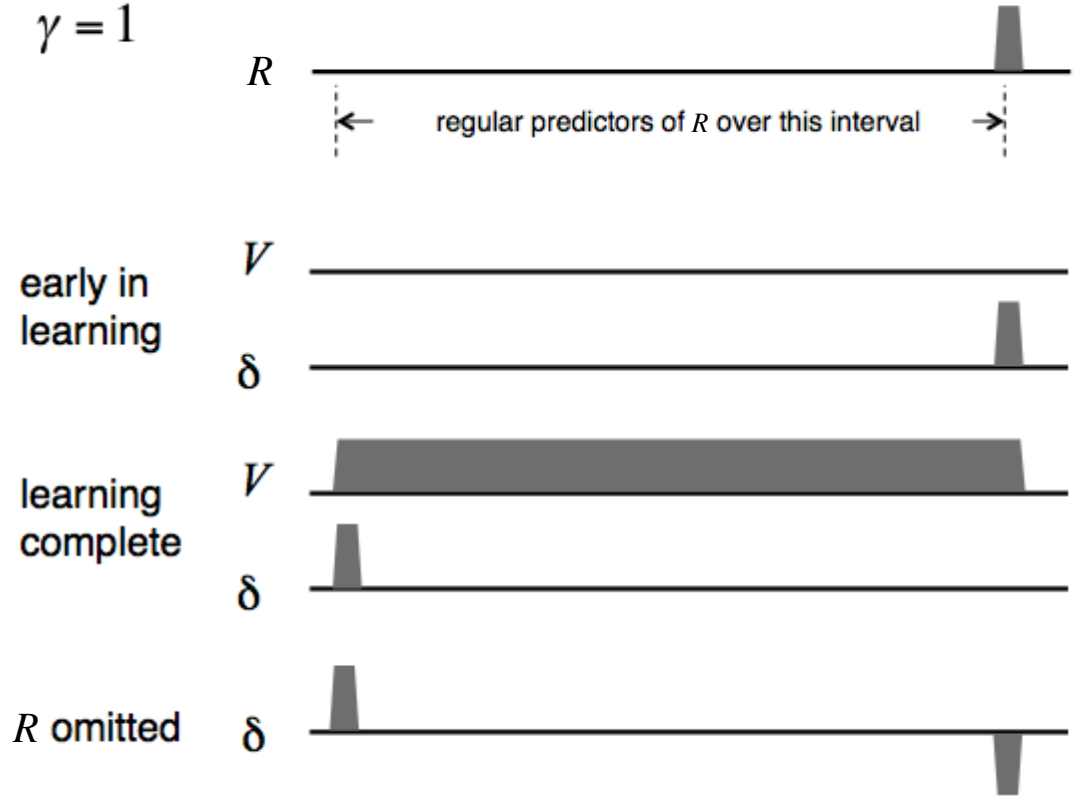
Q) How TD learning accounts for the phasic response of a dopamine neuron?

Sutton & Barto (2017) Reinforcement Learning, 2nd Ed., Chapter 15

$$\delta_t = R_t + \gamma V(s_t) - V(s_{t-1})$$



$\gamma = 1$



Reward onset

$$\delta_t = R_t + V_t - V_{t-1} = R_t + 0 - 0 = R_t$$

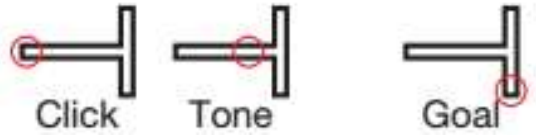
Cue onset

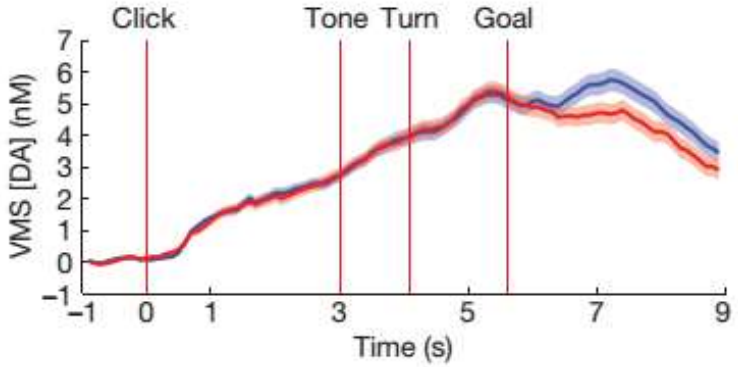
$$\delta_t = R_t + V_t - V_{t-1} = 0 + R_t - 0 = R_t$$

Reward onset

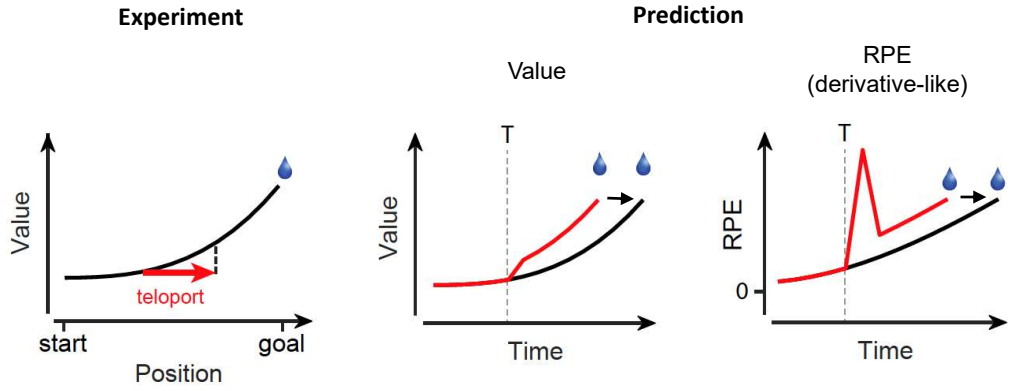
$$\delta_t = R_t + V_t - V_{t-1} = 0 + 0 - R_t = -R_t$$

Continued discussion about reward prediction error





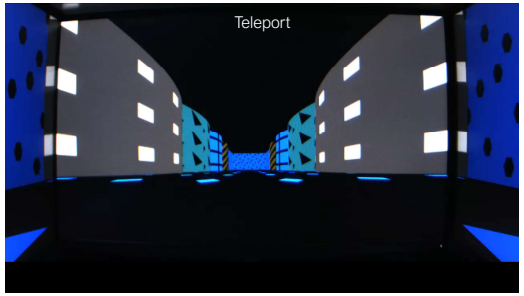
Howe et al (2013) Nature

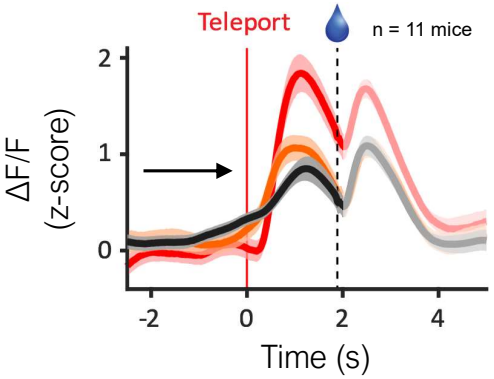


Kim et al (2020) Cell

State value V(t)?
Or moment-by-moment TD error?

Gershman (2014) Neural Computation





Instrumental learning

Model-based vs Model-free

Model-based vs Model-free

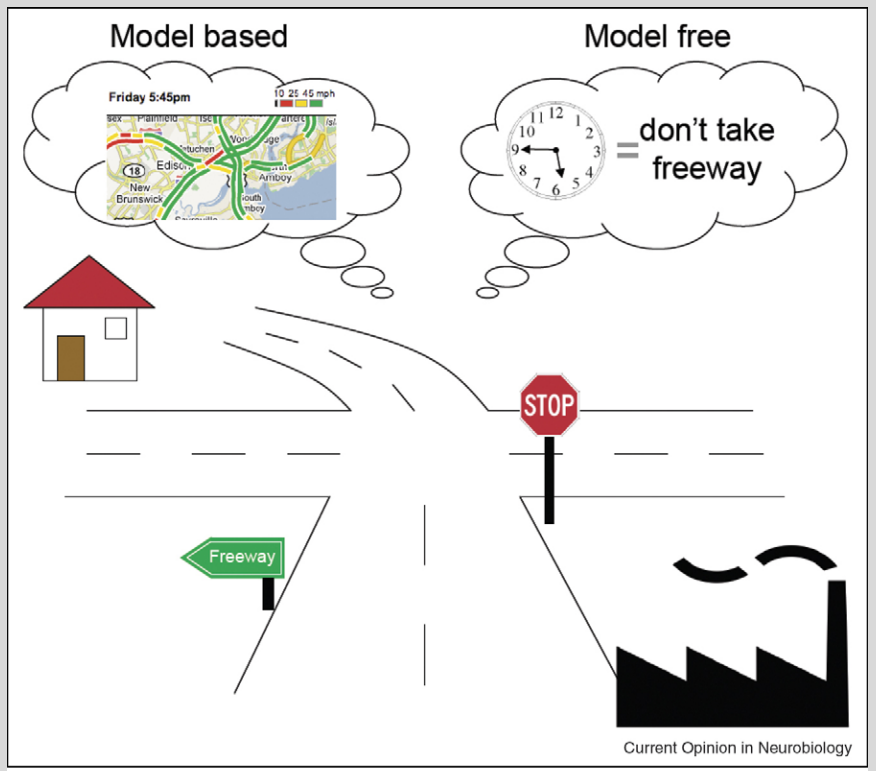


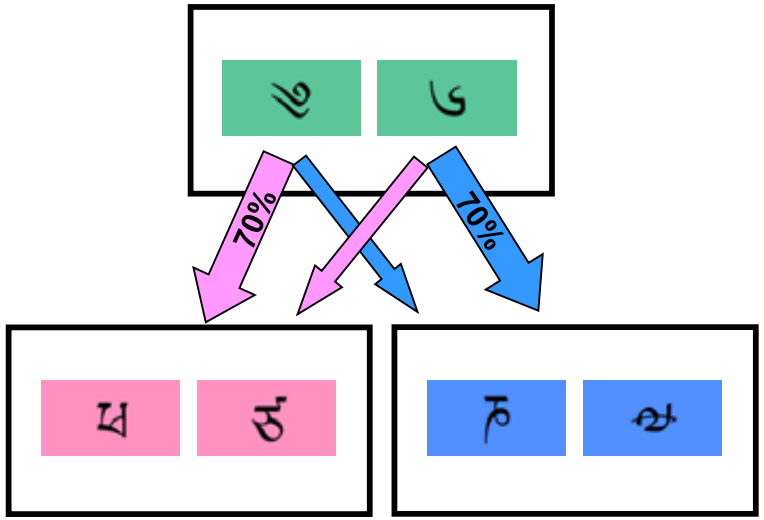
Figure 1: Two ways to choose which route to take when traveling home from work on friday evening.

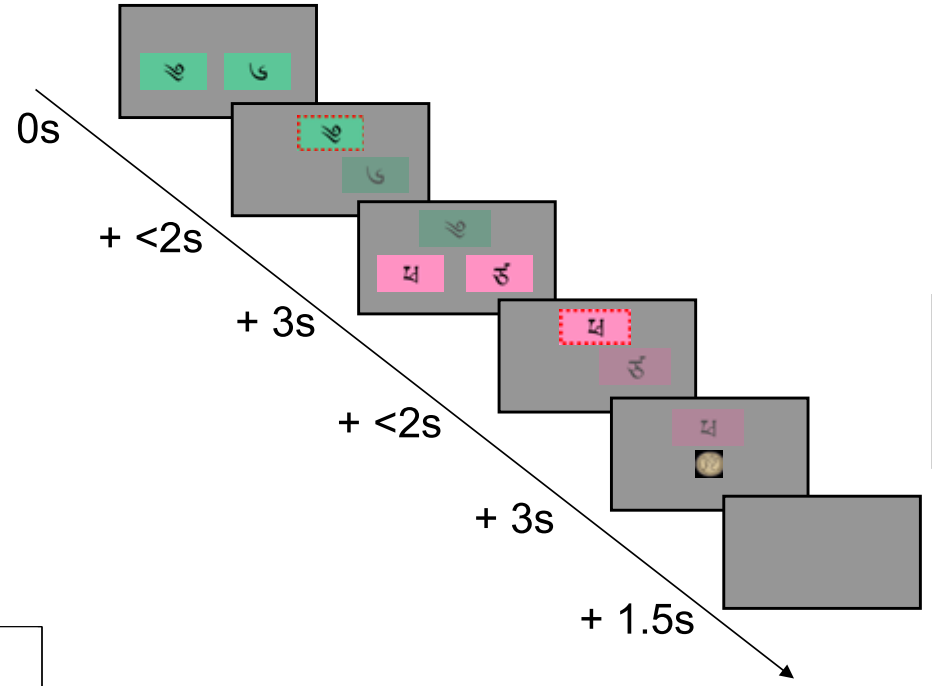
Dayan & Niv (2008)

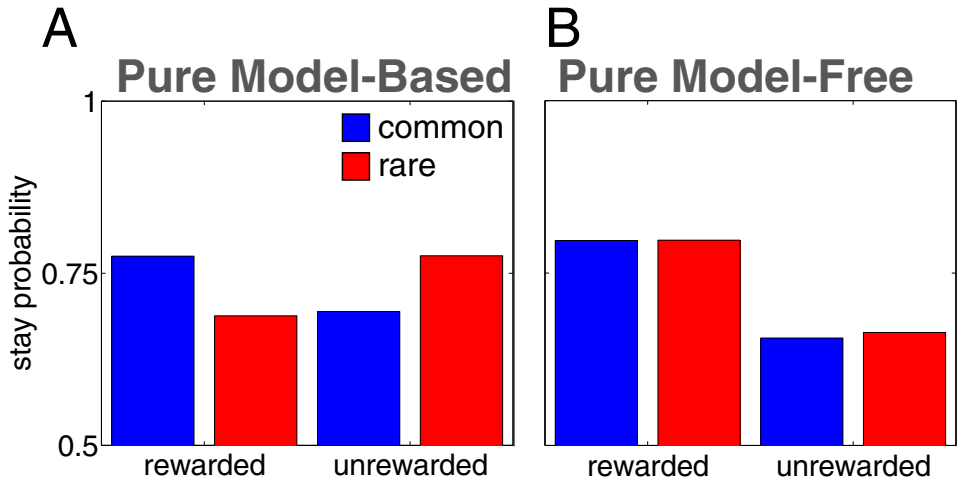
- *Model-based (goal-directed) learning: build a model of an environment. Effortful but flexible.*
- *Model-free (habitual) learning: relies on trials-and-errors. Efficient but inflexible.*
- *(Clinical) examples: compulsive behaviors, etc.*

Two-Step task

Daw et al (2011) Neuron







Computational model

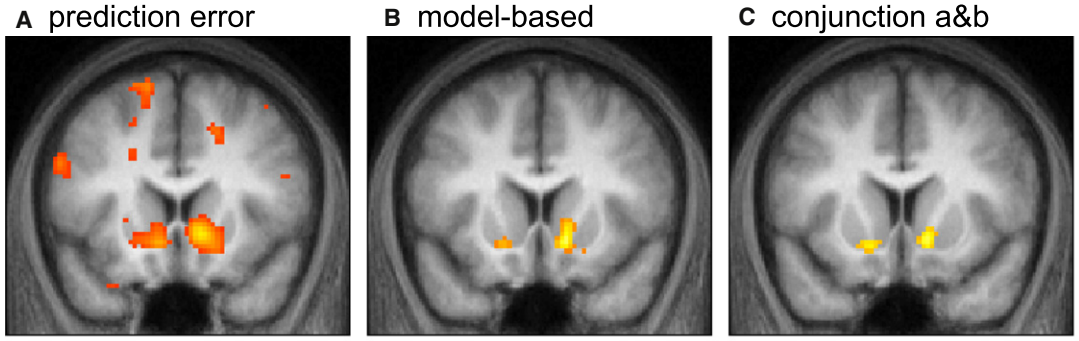
Daw et al (2011) Neuron
Wunderich et al (2012) Neuron

- *Separately calculate V^{MF} and V^{MB} (assuming full knowledge of the environment).*

- *Omega (ω): weight for model-based (MB)*

  – *0 (completely model-free) ≤ ω_{MB} ≤ 1 (completely model-based)*

$$V^{Hybrid} = \omega \cdot V^{MB} + (1 - \omega) \cdot V^{MF}$$

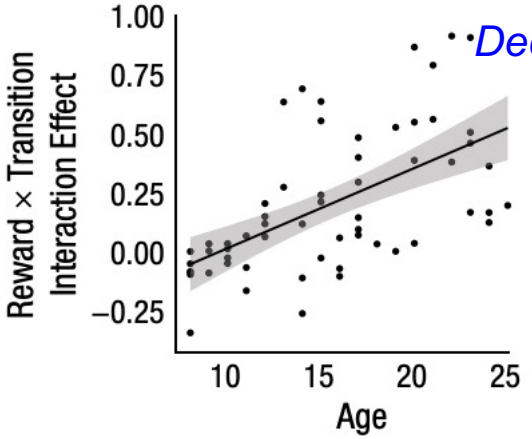


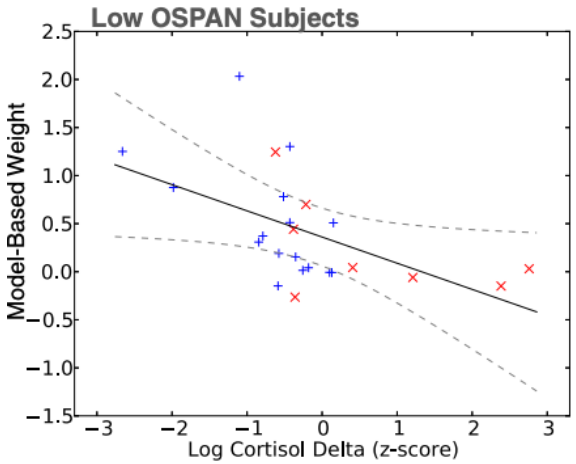
Daw et al (2011) Neuron

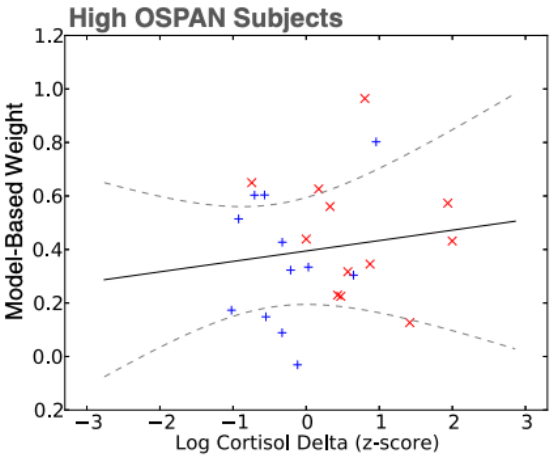
Individual differences in MB-MF

- *Age*
- *WM and stress*

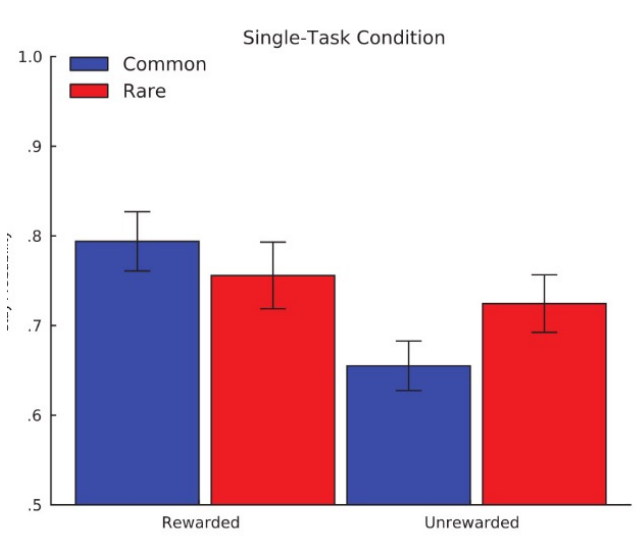
Decker et al (2016) Psych Sci

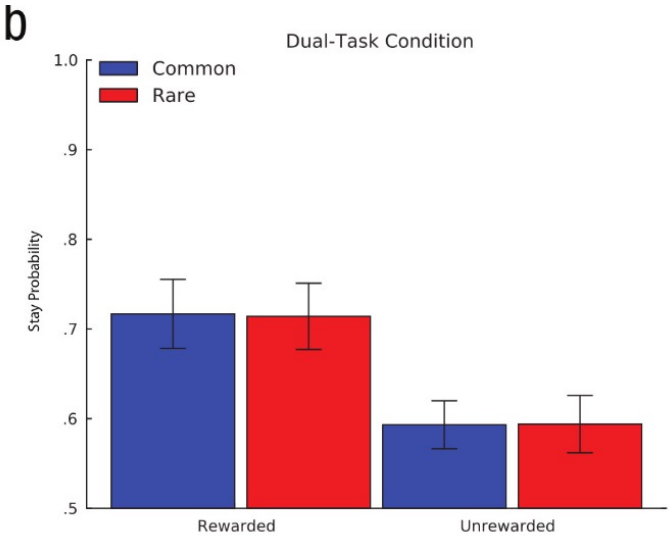






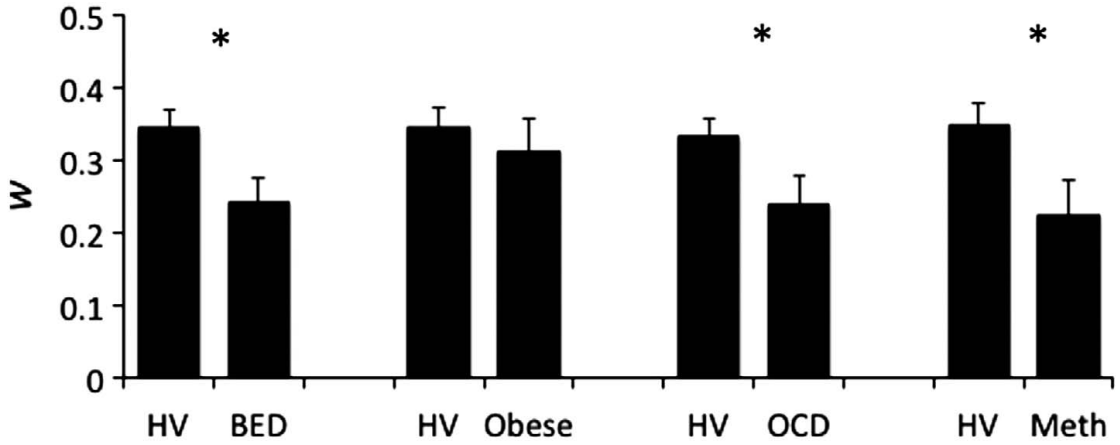
Otto et al (2013) PNAS



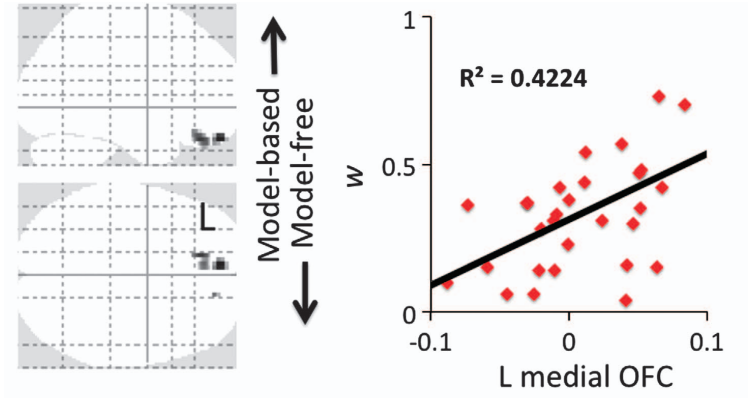


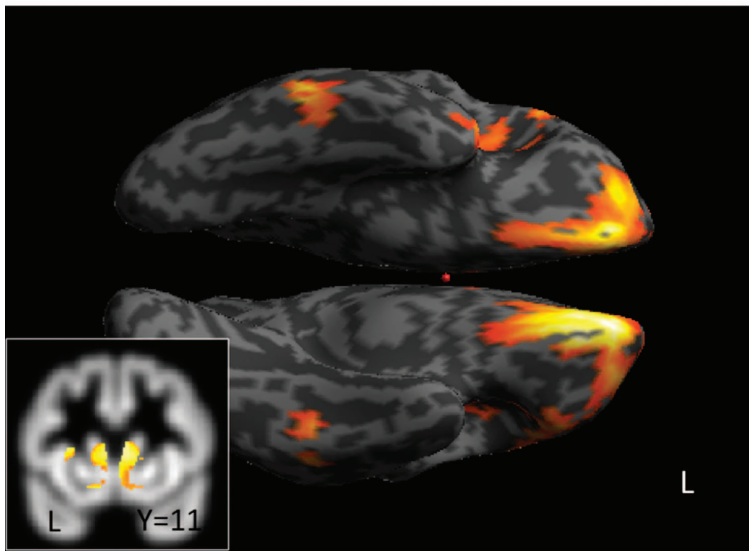
Reliance of model-based control → Disorders of compulsivity

Voon et al (2014) Molecular Psych



$$V^{Hybrid} = \omega \cdot V^{MB} + (1 - \omega) \cdot V^{MF}$$





Gray-matter volume

Correlated with model-based weight among healthy controls

PLOS COMPUTATIONAL BIOLOGY

RESEARCH ARTICLE

When Does Model-Based Control Pay Off?

Wouter Kool[1]*, Fiery A. Cushman[1☯], Samuel J. Gershman[1,2☯]

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2 Center for Brain Science, Harvard University, Cambridge, Massachusetts, United States of America

☯ These authors contributed equally to this work.
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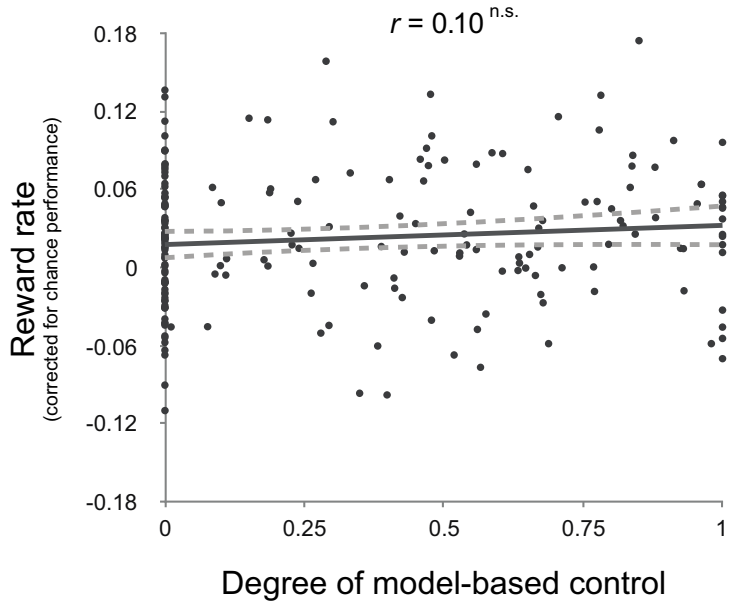
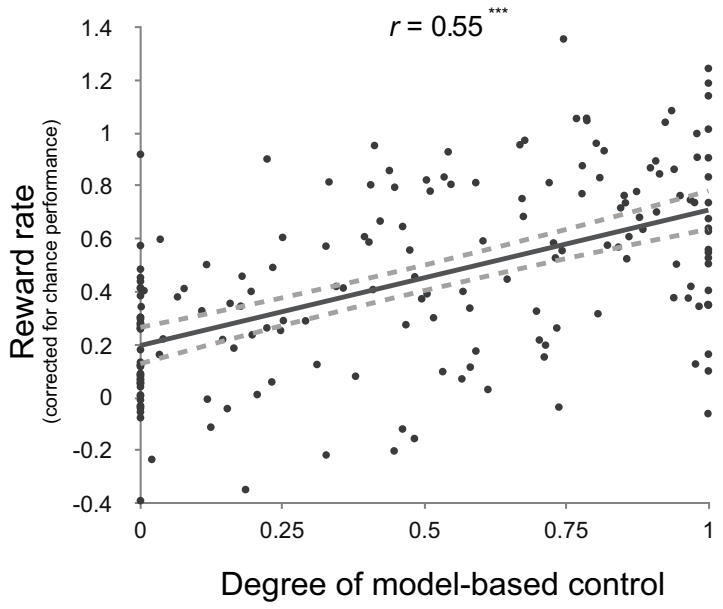
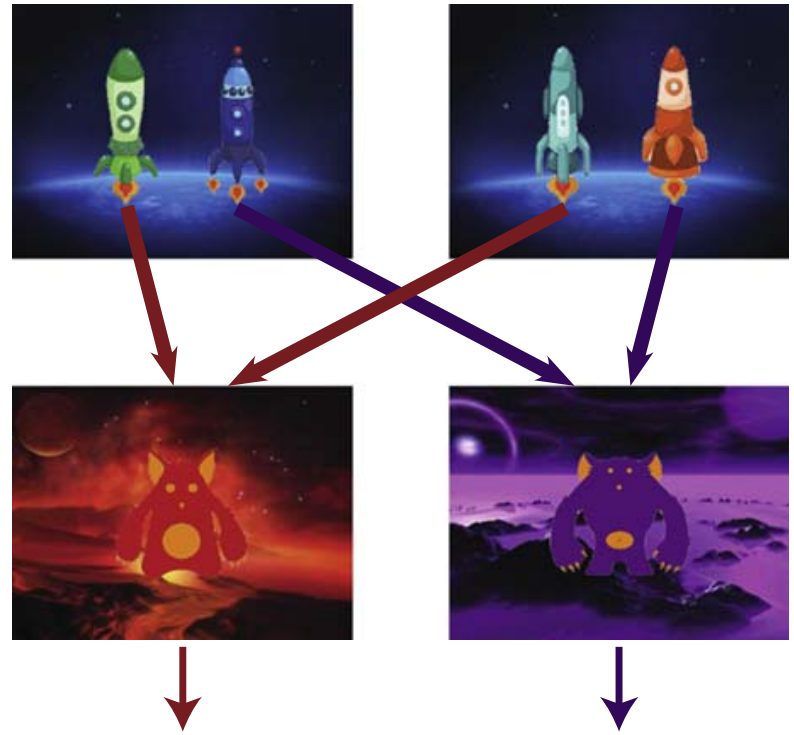


Daw Two-Step Task

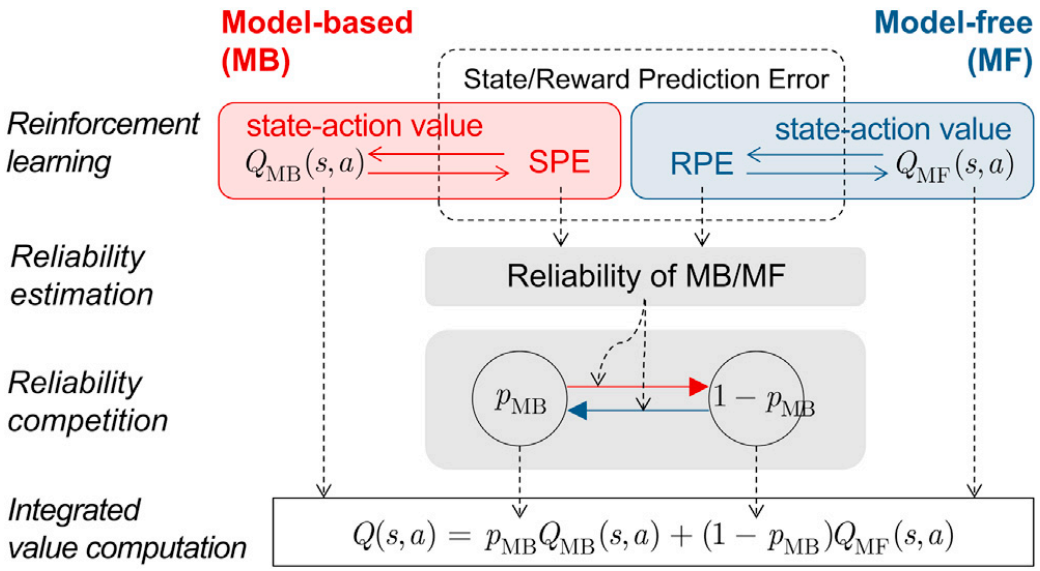


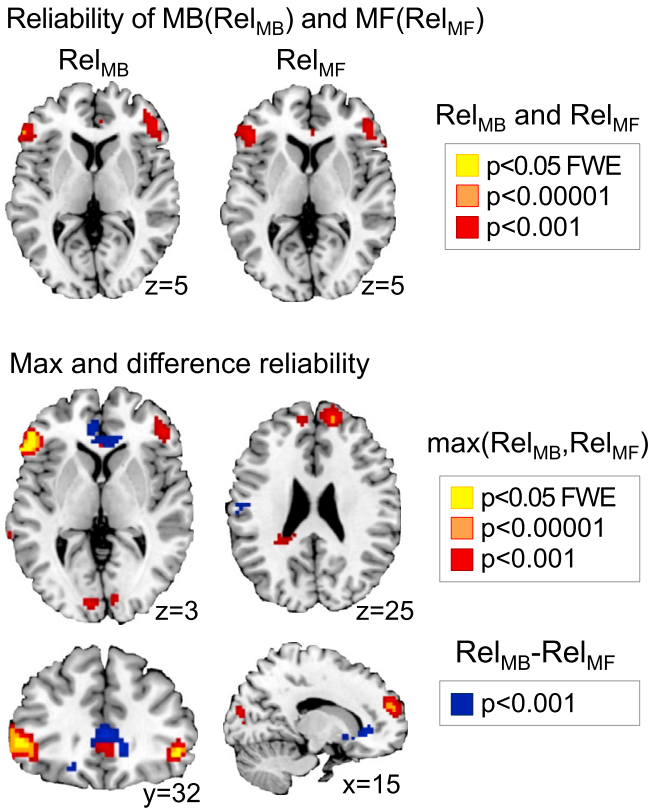
Kool Two-Step Task



Kool et al (2016) PloS Comput Biol

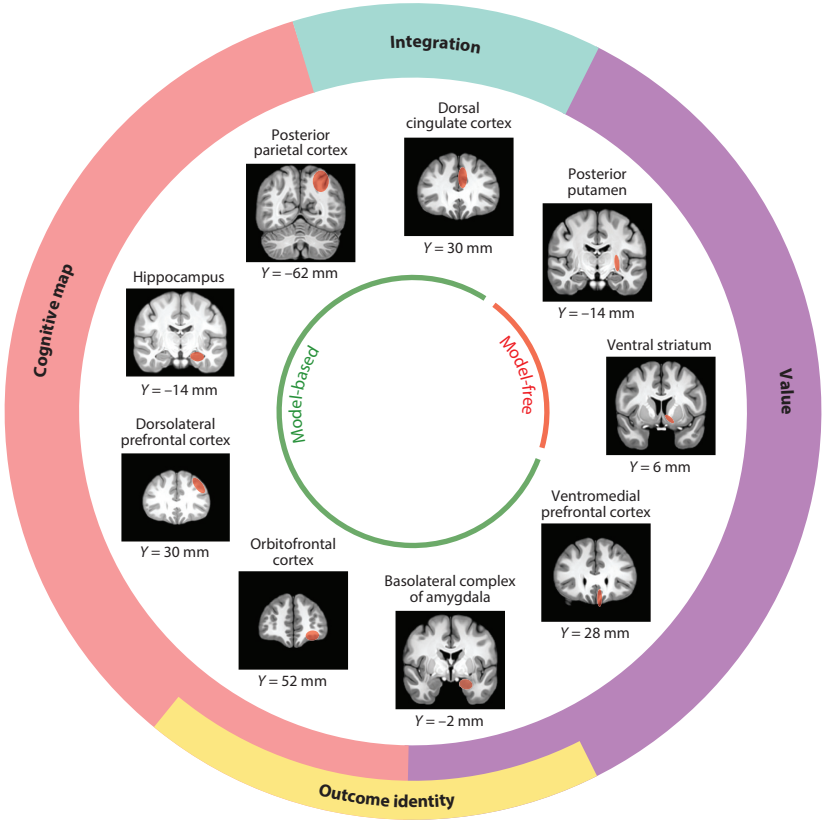
Reliability-based arbitration between model-based and model-free



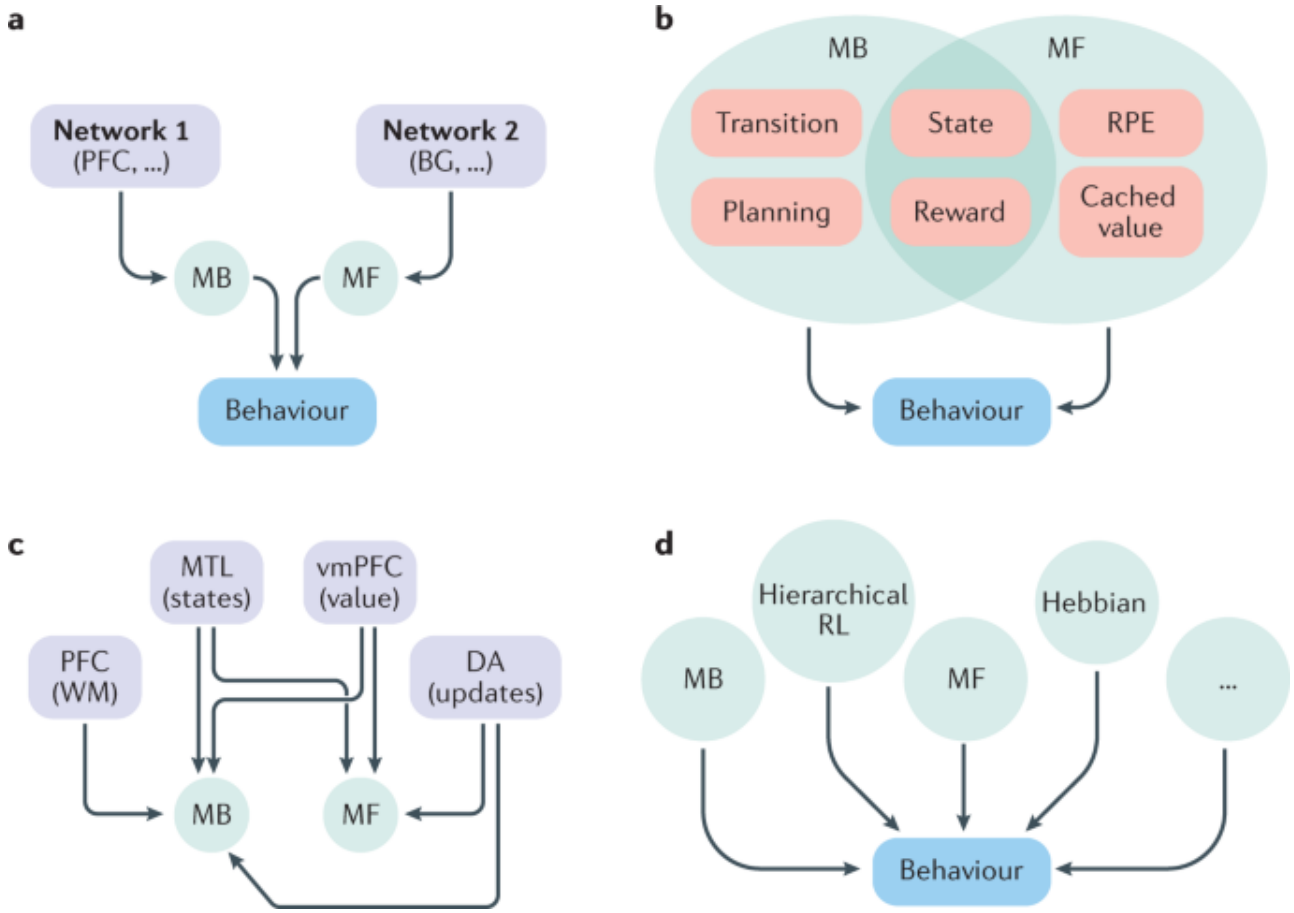


Lee et al (2014) Neuron
Daw et al (2005) Nature Neuroscience
Wang et al (2018) Brain & Neuro. Advances

Inferior lateral prefrontal and frontopolar cortex



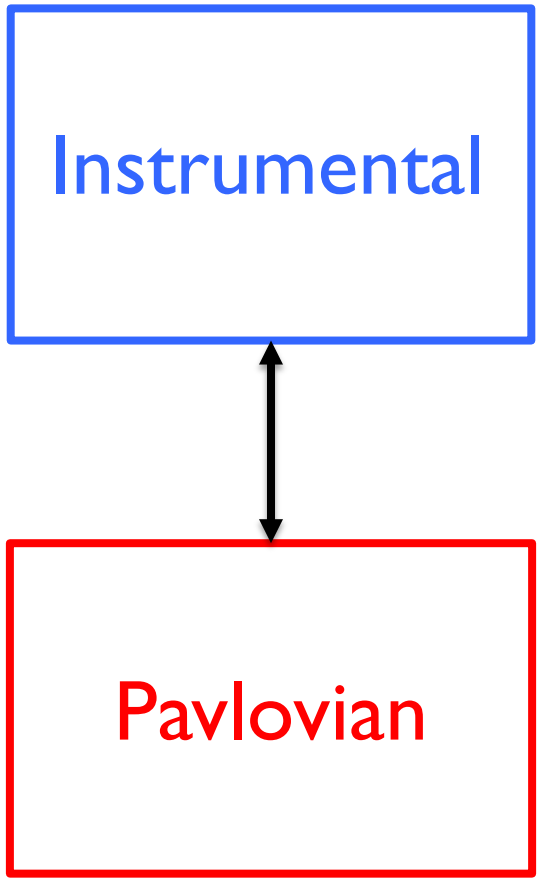
O'Doherty et al (2017) Annu. Rev. Psychology



Collins & Cockburn (2020) Nature Reviews Neuroscience

Pavlovian vs Instrumental control

Pavlovian vs Instrumental control



"Learn what's best"

Approach for (+)
Withdraw from (-)

"Pavlovian bias"

Opinion

CellPress

Action versus valence in decision making

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Balleine & O'Doherty (2010); Dayan et al (2006); Dayan (2013); Dayan & Niv (2008); Dolan & Dayan (2013); Dayan & Berridge (2014); Rangel et al (2008)

Hungry Chicken

Food!

Hershberger (1986)

Hungry Chicken

Food!

Hershberger (1986)

Pavlovian-Instrumental competition

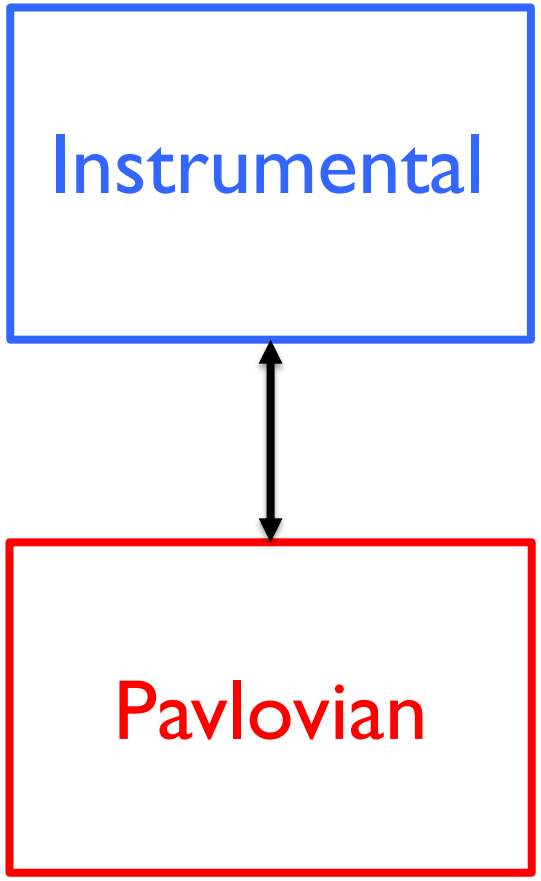
Hershberger (1986)

Impulse control

www.ignitermedia.com

Orthogonalized Go/Nogo task
Pavlovian-Instrumental competition

Guitart-Masip et al (2012) Neuroimage
Also, see Huys et al (2011) Plos Comp Biology



"Learn what's best"

Approach for (+)
Withdraw from (-)

"Pavlovian bias"

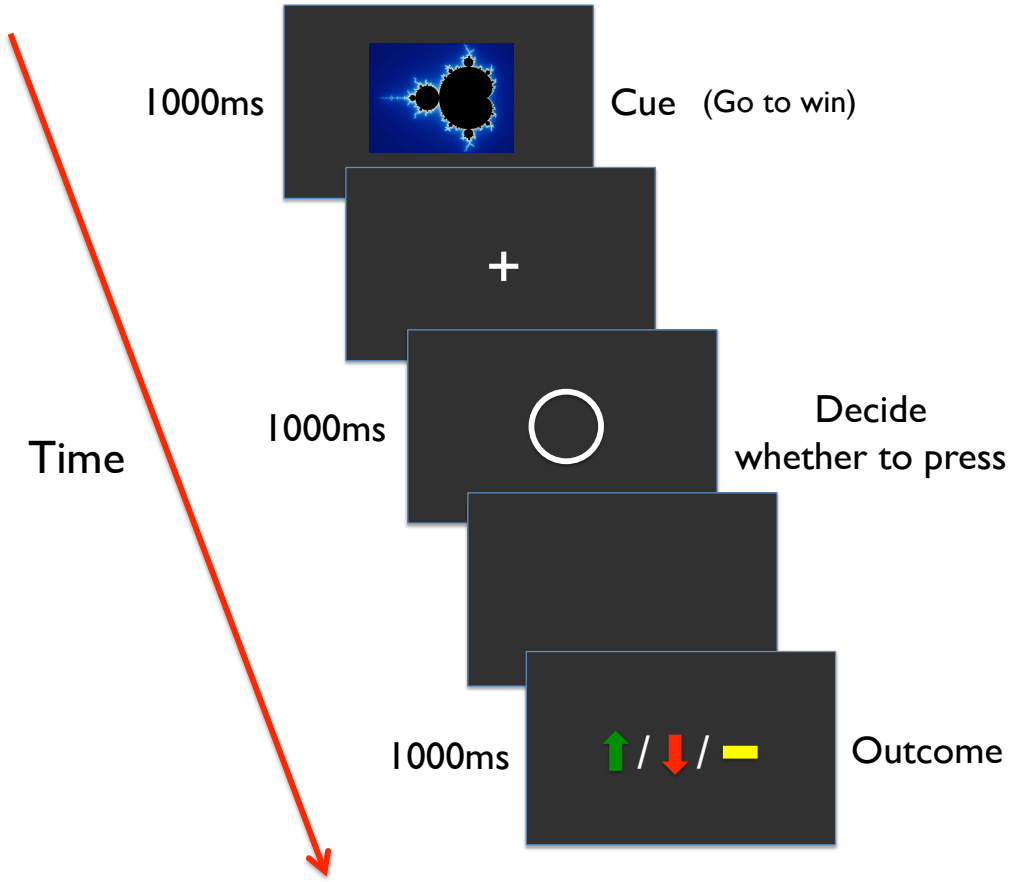
Balleine & O'Doherty (2010); Dayan et al (2006); Dayan (2013); Dayan & Niv (2008); Dolan & Dayan (2013); Dayan & Berridge (2014); Rangel et al (2008)

Orthogonalized Go/Nogo task

	Loss	Gain
Go	Go to avoid	Go to win
Nogo	Nogo to avoid	Nogo to win

Pavlovian congruent

Pavlovian incongruent



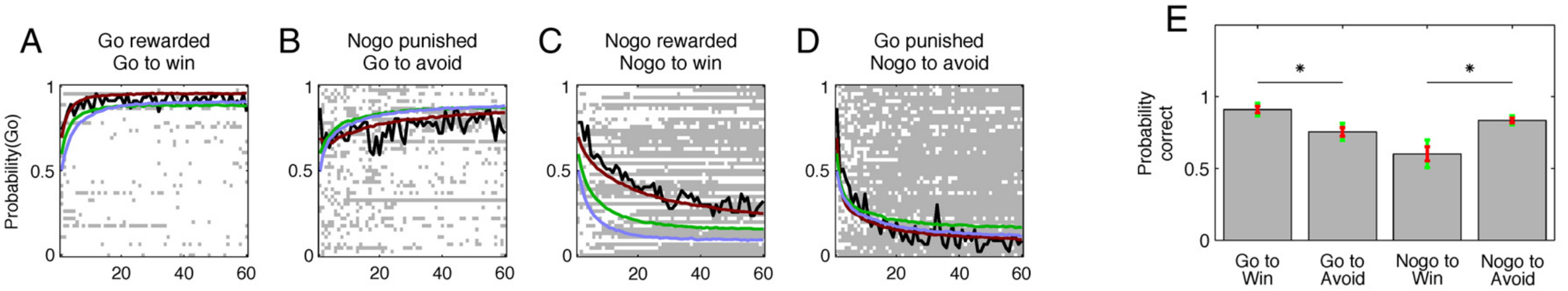
- *4 cues (conditions)*

  2 actions (Go / Nogo) x
  2 valence (Gain / Loss)

Guitart-Masip et al (2012) Neuroimage
Cavanagh et al (2013) J Neuro

Orthogonalized Go/Nogo task

Guitart-Masip et al (2012) Neuroimage



Reward sensitivity

$$Q_t(a_t, s_t) = Q_{t-1}(a_t, s_t) + \epsilon \cdot (\rho r_t - Q_{t-1}(a_t, s_t))$$

Q value

Modified R-W rule

Go bias

$$W_t(Go_t, s_t) = Q_t(a_t, s_t) + b + \pi V_t(s_t)$$

Pavlovian bias

Effects of WM load on Pavlovian-instrumental learning

WM load on the Orthogonalized Go/Nogo task

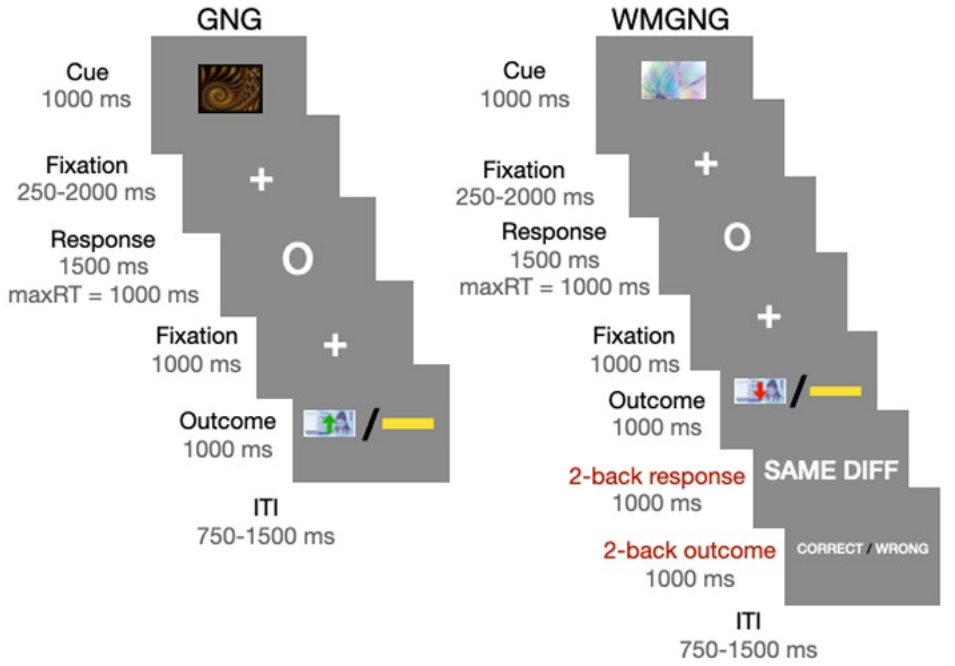
Limited resources in the WM system →

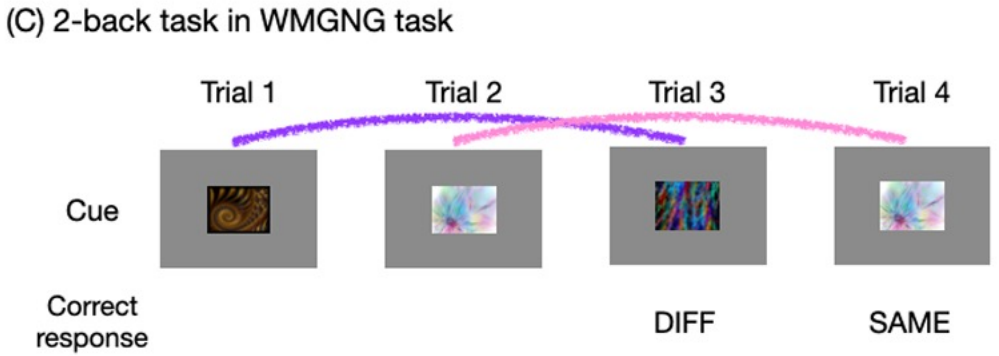
Hyp1: Affects learning and greater RPE (Collins & Frank, 2018)

Hyp2: Greater Pavlovian bias (Otto et al, 2013)

Hyp3: More random and inconsistent response

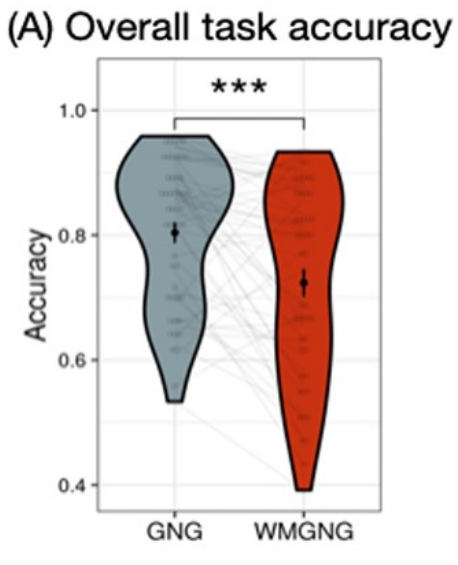
(Franco-Watkins et al, 2006; 2010)

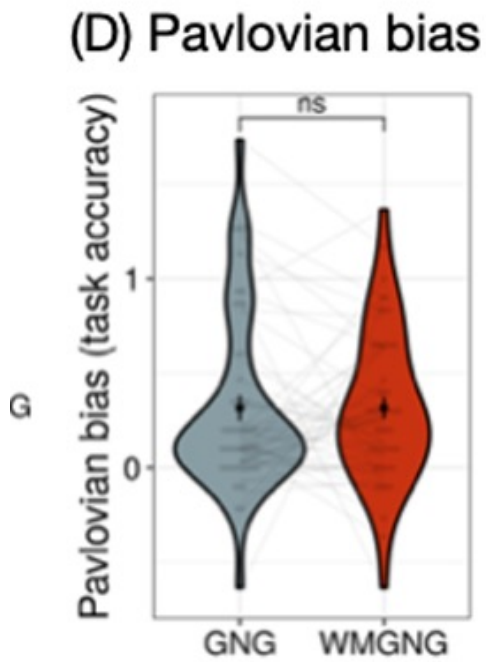


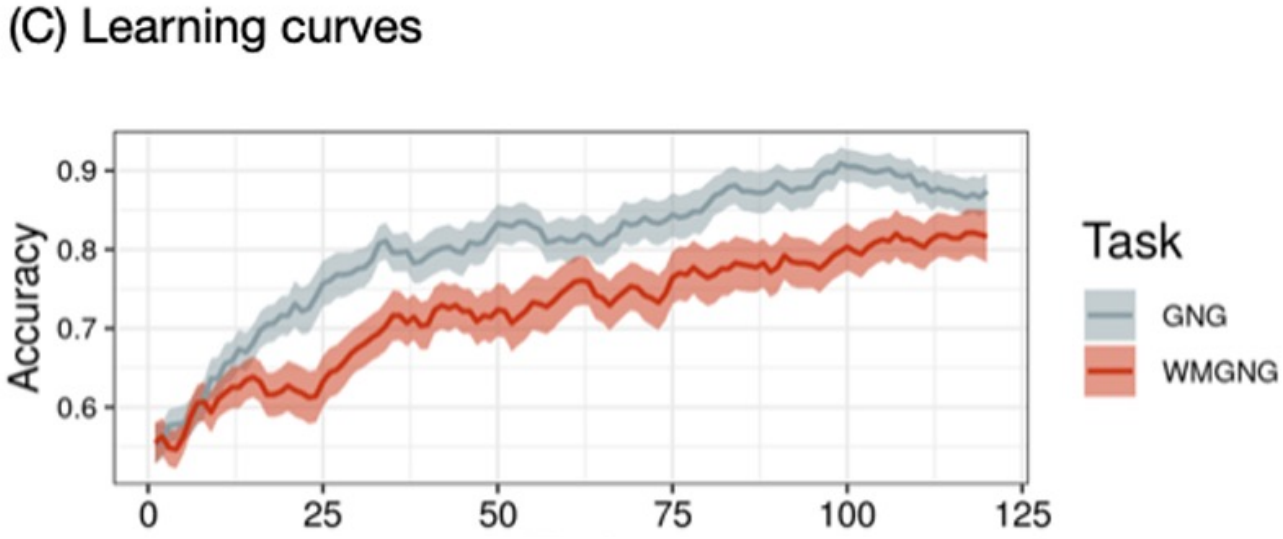


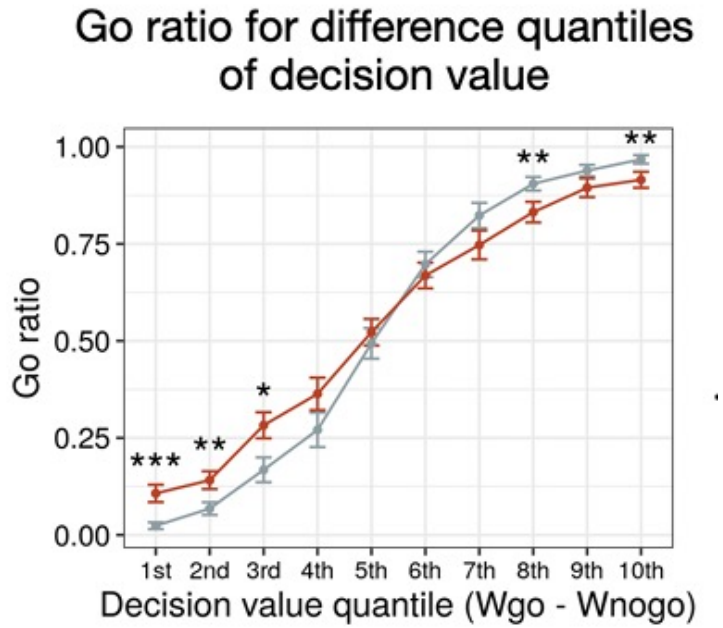
Park et al. (under review) bioRxiv
https://www.biorxiv.org/content/10.1101/2022.08.01.502269v3

Behavioral results



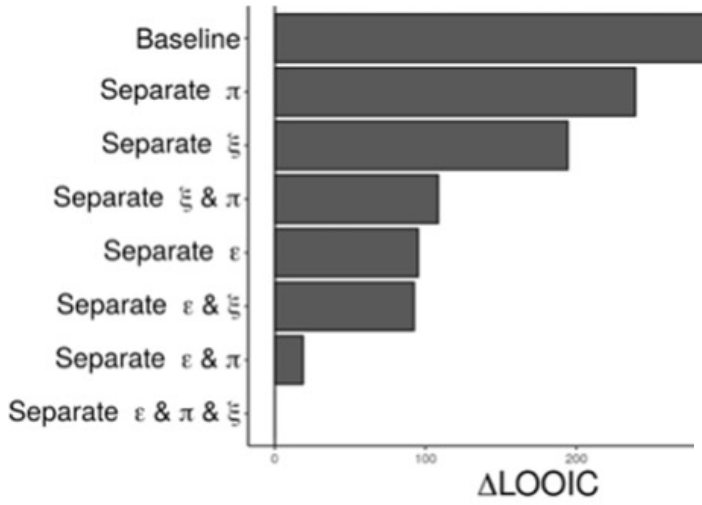




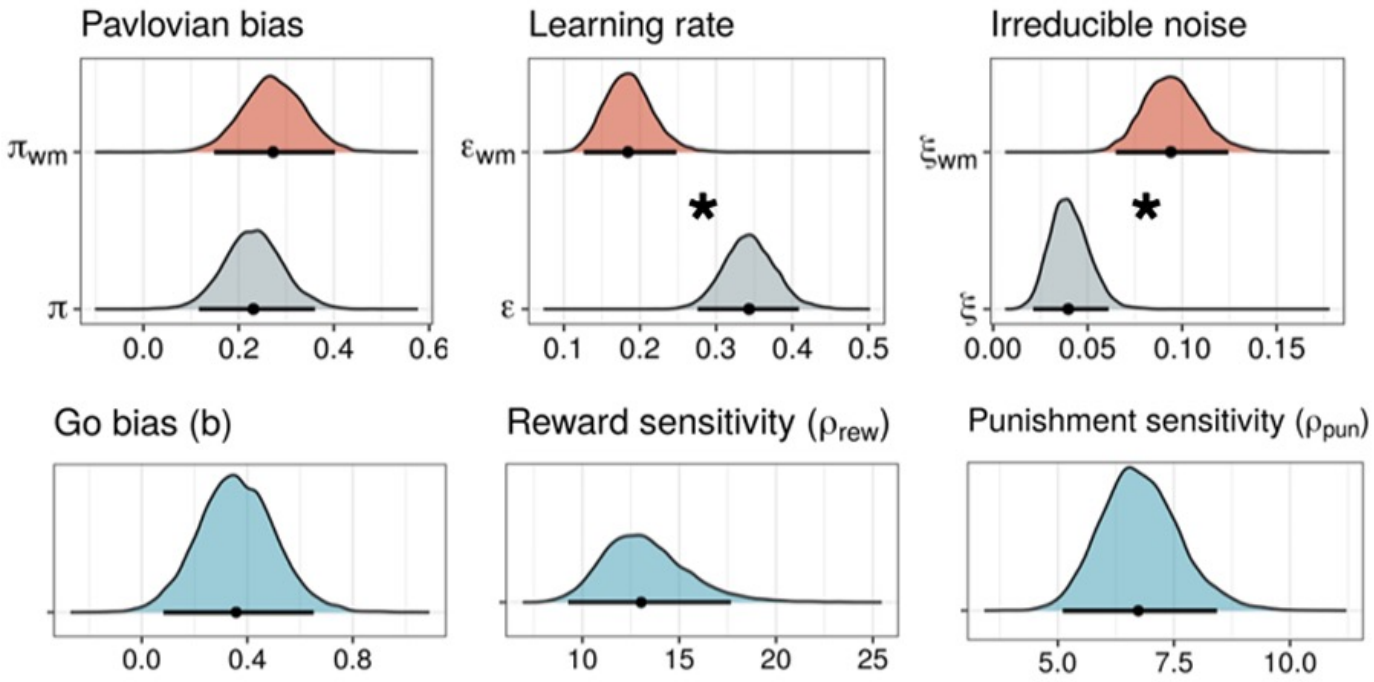


Modeling results

(A) Model comparison



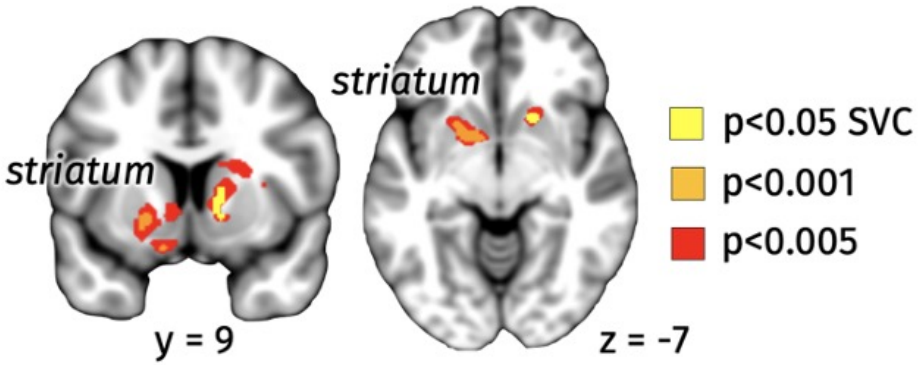
(B) Posterior distributions of the group-level parameters



fMRI results

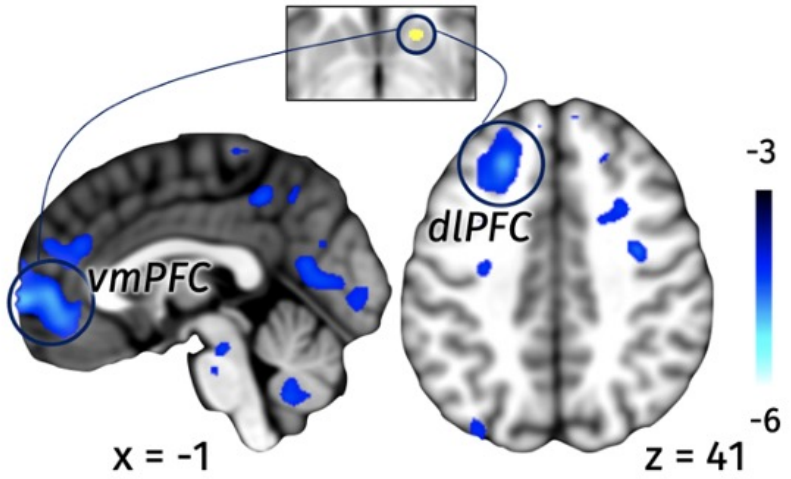
(A) Model-based fMRI result

RPE (WMGNG > GNG)



(B) PPI result

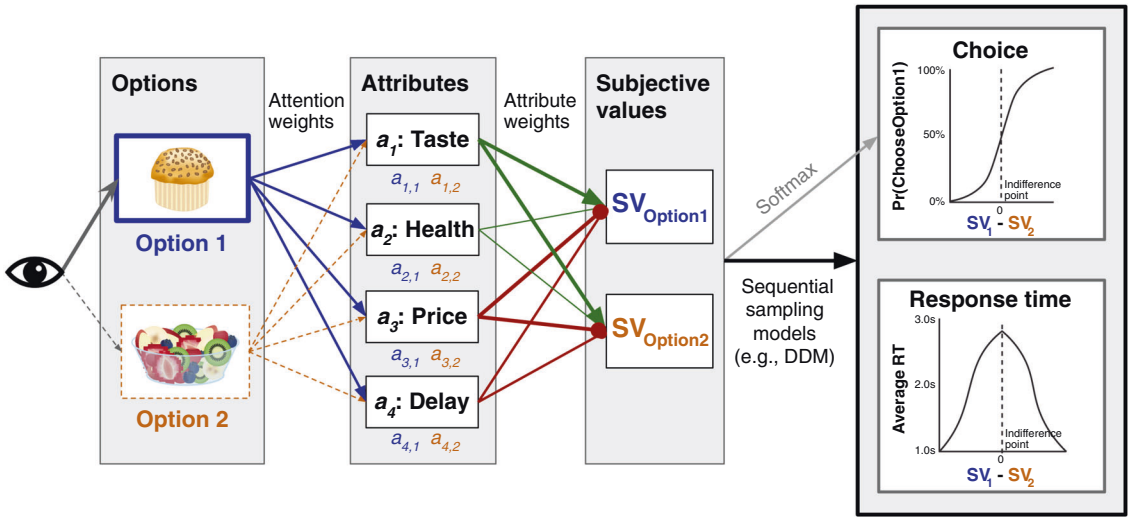
Anticipation phase (WMGNG > GNG)
Seed: striatum



Park et al. (under review) bioRxiv

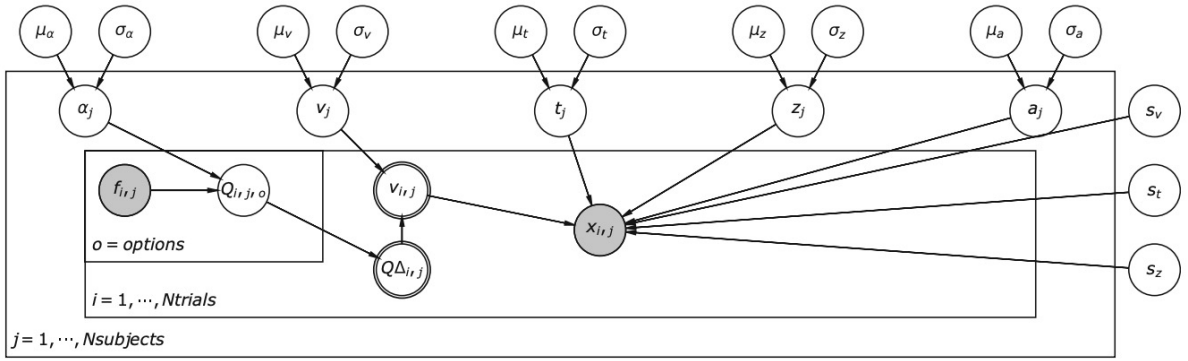
WM load compromises overall learning without affecting the balance between Pavlovian and instrumental systems

More…



Collins & Shenhav et al (2021) Neuropsychopharmacology

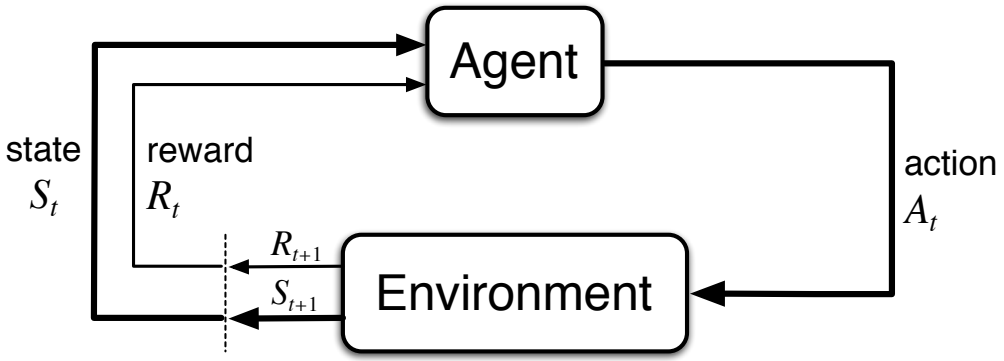
RL + sequential sampling models



Pedersen & Frank (2020) Computational Brain & Behavior

Adaptive Design Optimization within the RL framework

Optimize experiments on the fly!



$$P(\theta|y) = \frac{P(y|\theta)\ P(\theta)}{P(y)}$$

Bayesian updating

Update the current state of knowledge with observed response via Bayes rule

Adaptive Design Optimization

Design optimization

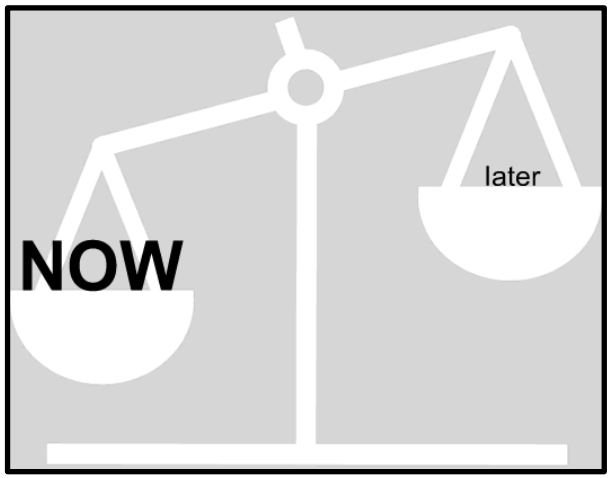
Find the most informative design for next experimental trial

Experiment

Present the optimal design on next trial and record observed response

$$d^* = \underset{d}{\operatorname{argmax}} \iint u(d, \theta, y)\ P(\theta)\ P(y|\theta, d)\ \mathrm{d}\theta\ \mathrm{d}y$$

$$p(\theta|y,d) = \frac{p(y|\theta,d)p(\theta)}{p(y|d)}$$



Bayesian updating of model parameters (θ)

Find optimal design (d^*)

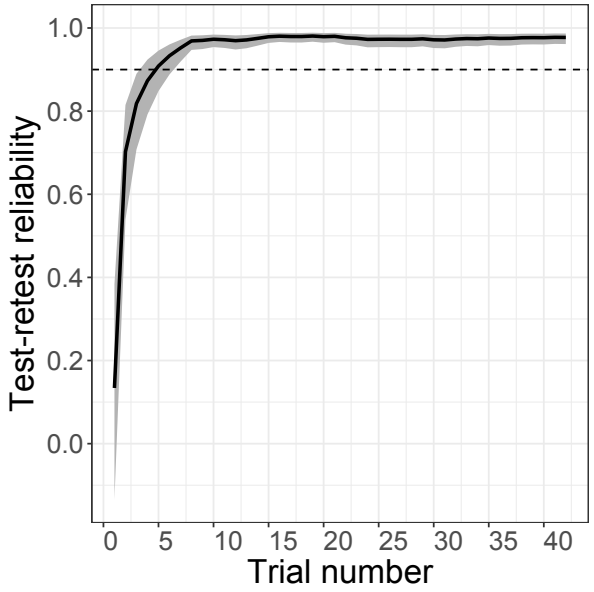
Design & Conduct a mini-experiment on every trial
"What's the most informative design (d^*) we should use?"

e.g., $320 now vs $800 in 3 years

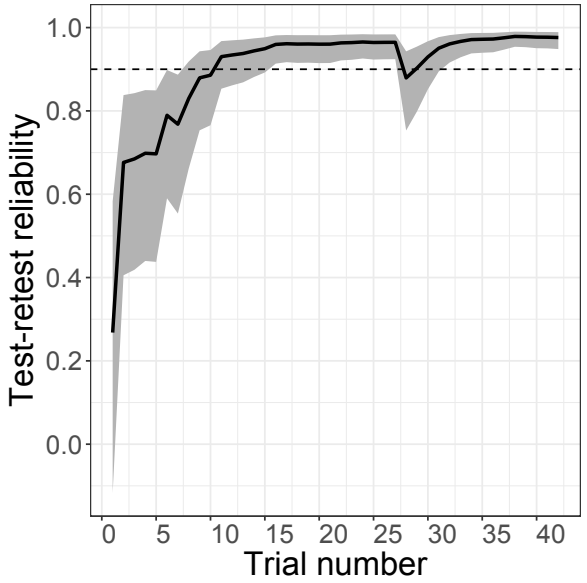
Observe Data (y)

$$d^* = \underset{d}{\operatorname{argmax}} \int \int u(d,\theta,y)p(y|\theta,d)p(\theta)dyd\theta$$

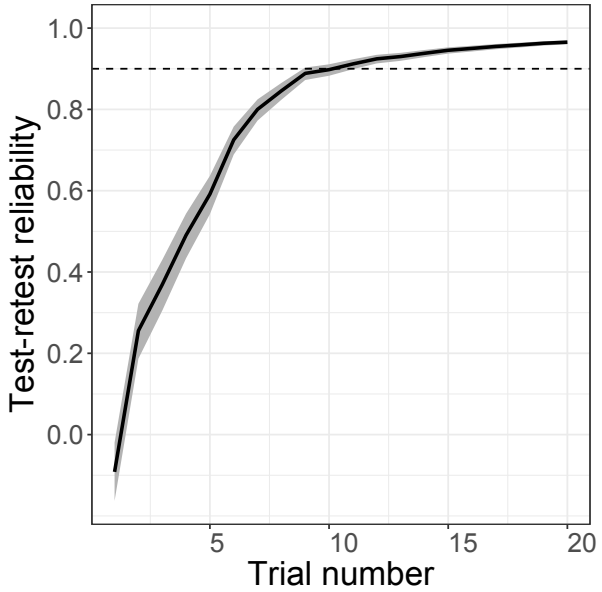
Up to 0.98 test-retest reliability within ~10 trials



College students

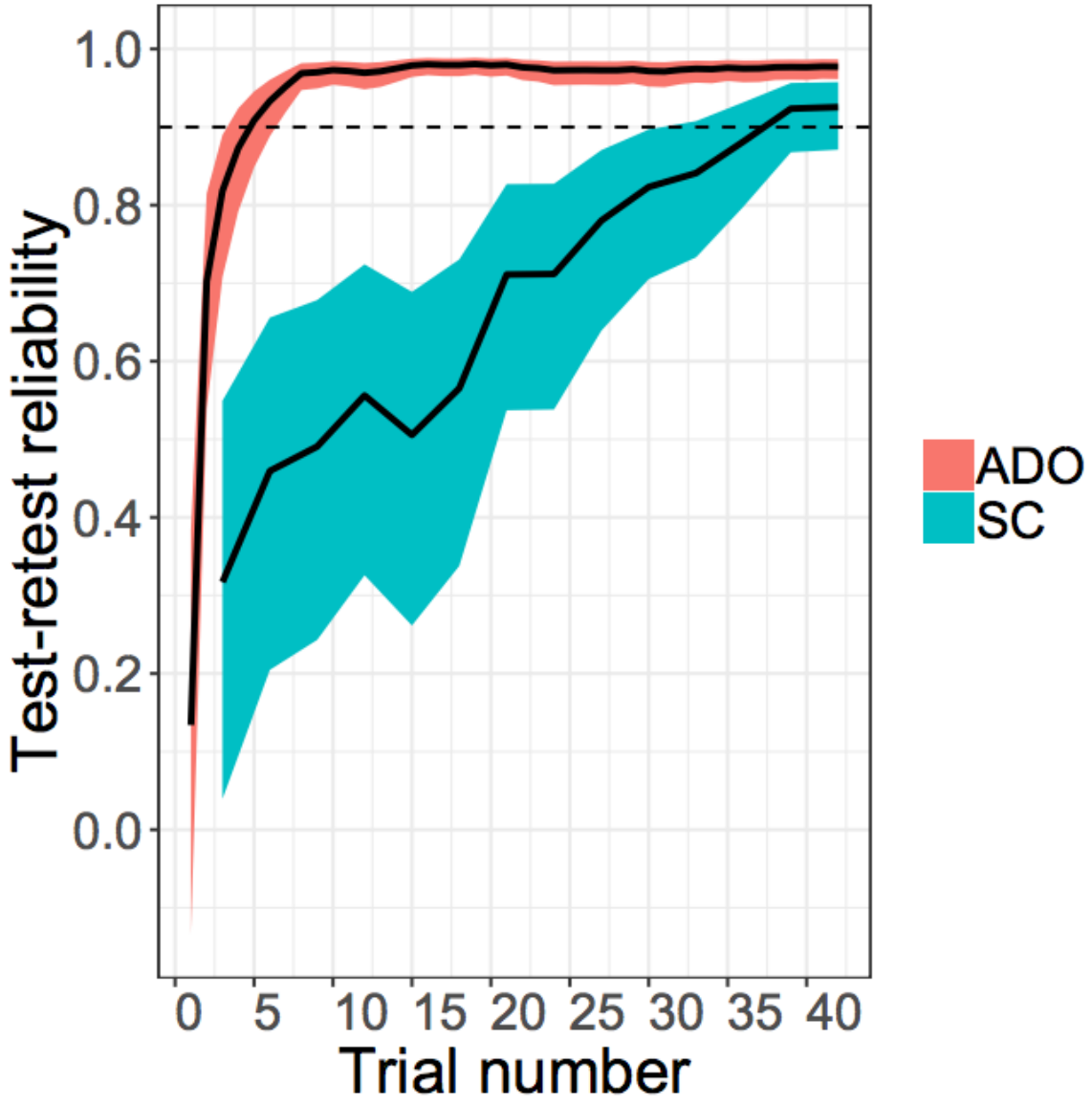


Patients with SUDs



Online Amazon MTurk

Ahn et al (2020) Scientific Reports



3-5 times more precise

3-8 times more efficient

Ahn et al (2020) Scientific Reports

Lowering the barrier to ADO

Yang, Pitt, Ahn, Myung (2020) Behavior Research Methods

- *ADOpy (https://adopy.org/)*
- *A Python package for easily implementing ADO for any (modellable) tasks*
- *Workshop at CogSci 2019 (Montreal, Canada)*

ADOpy

Adaptive Design Optimization for Psychological Tasks

repo status WIP | build passing | codecov 81% | codefactor A

Jaeyeong Yang

Jay Myung

Mark Pitt

https://github.com/adopy/adopy https://adopy.org/

ADOpy

pypi v0.3.1 | repo status Active | build passing | codecov 93%

ADOpy is a Python implementation of Adaptive Design Optimization (ADO; Myung, Cavagnaro, & Pitt, 2013), which computes optimal designs dynamically in an experiment. Its modular structure permit easy integration into existing experimentation code.

ADOpy supports Python 3.5 or above and relies on NumPy, SciPy, and Pandas.

Features

- **Grid-based computation of optimal designs using only three classes:** `adopy.Task`, `adopy.Model`, and `adopy.Engine`.
- **Easily customizable for your own tasks and models**
- **Pre-implemented Task and Model classes including**:
  - Psychometric function estimation for 2AFC tasks (`adopy.tasks.psi`)
  - Delay discounting task (`adopy.tasks.ddt`)
  - Choice under risk and ambiguity task (`adopy.tasks.cra`)
- **Example code for experiments using PsychoPy** (link)

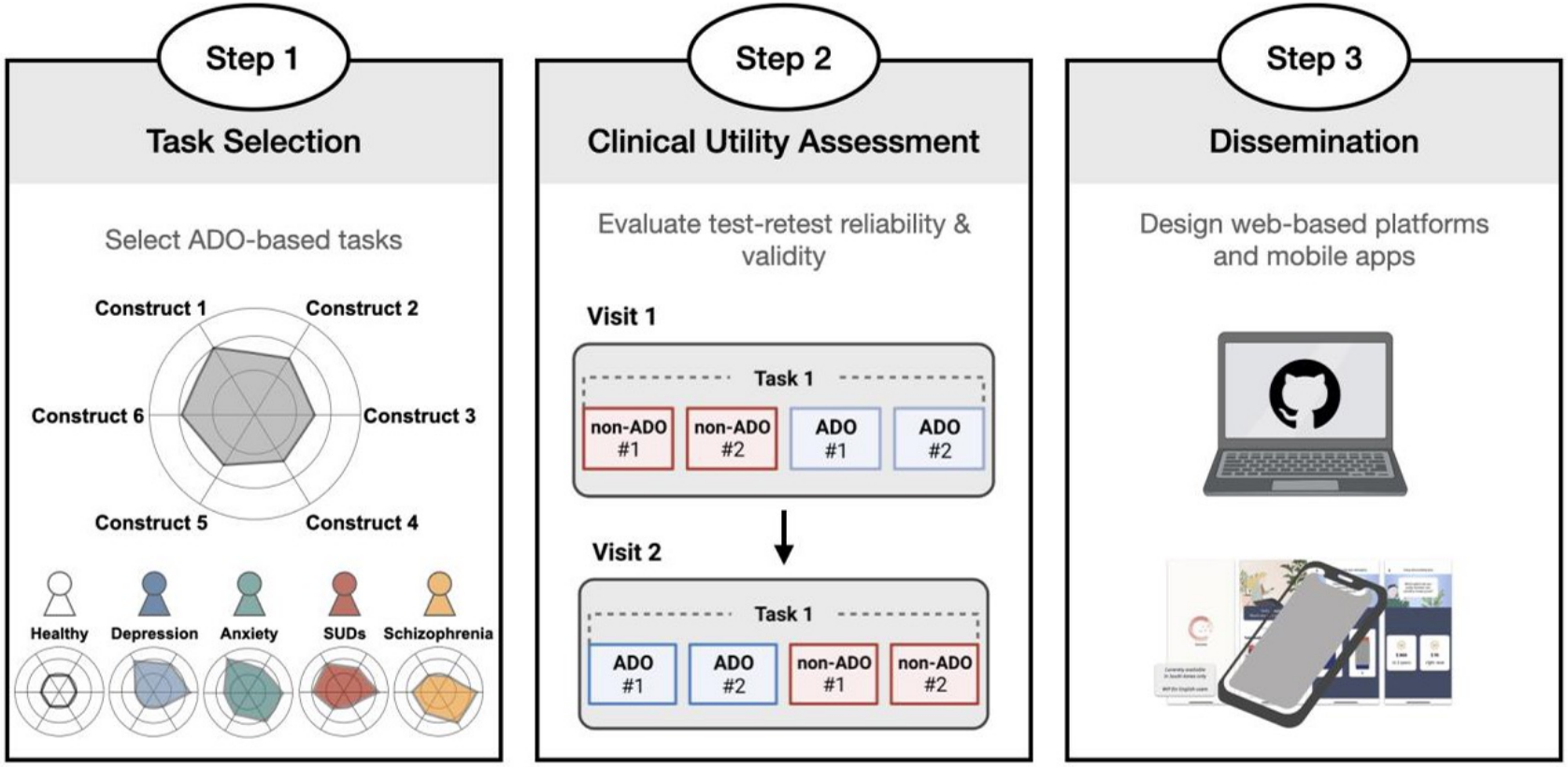
Resources

- **Getting started**
- **Documentation**
- **Bug reports**

ADOpy
Adaptive Design Optimization for Experimental Tasks

Yang, Pitt, Ahn, Myung (2020) Behavior Research Methods

ADO for reliable and efficient computational fingerprinting

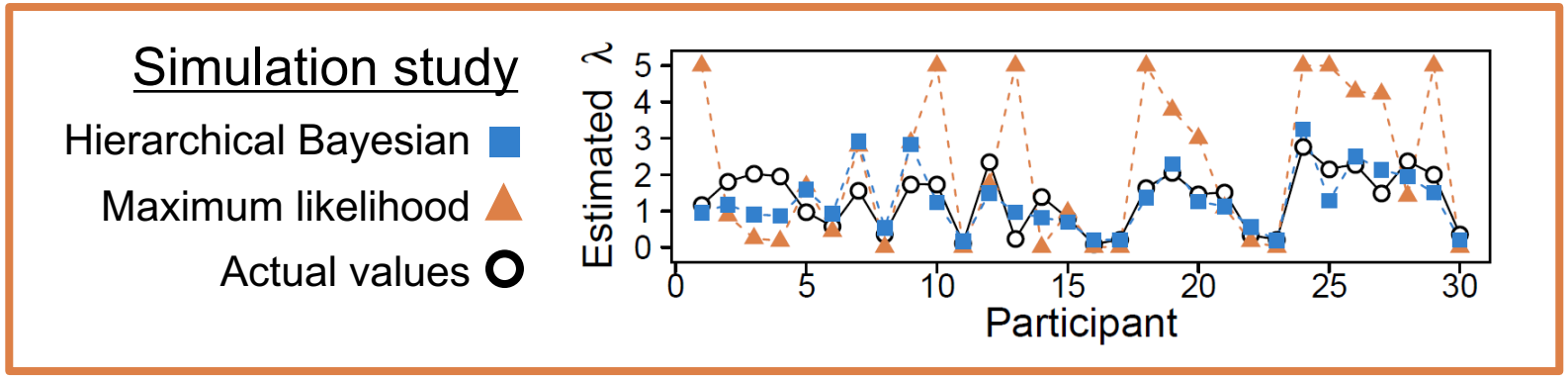


Kwon et al. (invited review) PsyArxiv
https://psyarxiv.com/8emcu/

Tips for RL (in human research?)

Use a hierarchical approach across subjects when estimating model parameters

- *Human data are noisy*
- *Hierarchical approaches lead to more reliable estimates*



Ahn et al. (2011, JNPE)

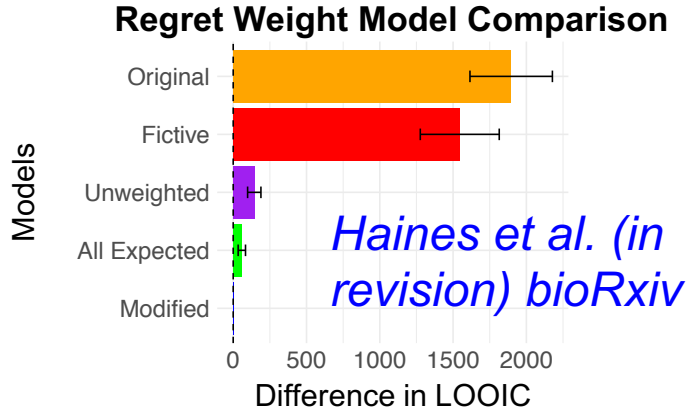
Limitations

- *Overly simplified "toy" problems*
  - *Violated assumptions (e.g., discrete space/action & Markov..) , (Gershman & Daw, 2016, Annu Rev Psych)*
- *One-shot learning with sparse data*
  - *Episodic memory (hippocampus) (Gabrieli, 1998; Eichenbaum et al., 1999)*
- *Modeling of even toy problems is hard for many people*

Future directions

TAPAS

- *Incorporating multi-modal inputs into computational models* *(Haines et al., in revision, bioRxiv 2020)*



Haines et al. (in revision) bioRxiv

- *Predict real-life DM?* *(Mobb et al., 2018, Nat Rev Neuro)*

hBayesDM

Ahn et al. (2017) Computational Psychiatry

- *Lowering the barrier to RL and computational modeling*

ADOpy
Adaptive Design Optimization for Experimental Tasks

Yang et al. (2020) Behavior Research Methods

Inverse Reinforcement Learning

Reward structure

(state, action) -> reward

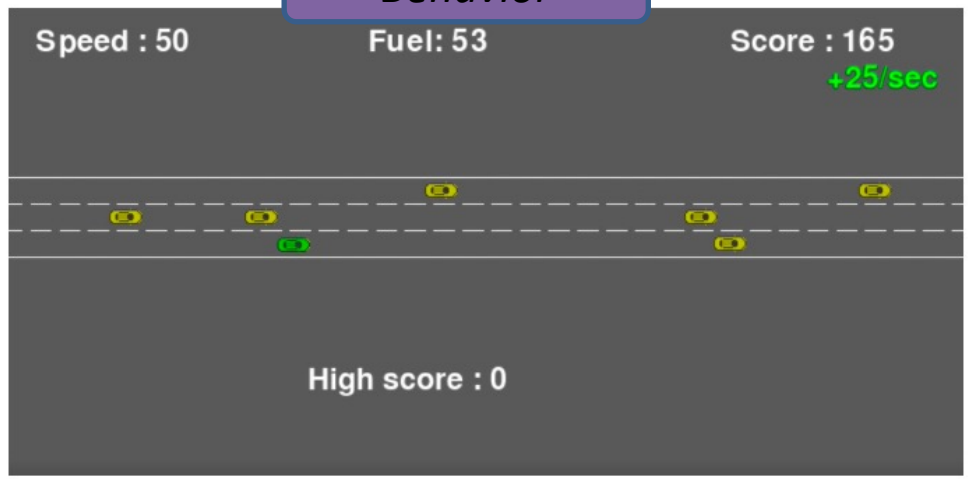
Examples (Highway task)

- *+ score if you accelerate without crashing*
- *- score and game over if you crash*

Reinforcement learning (RL)

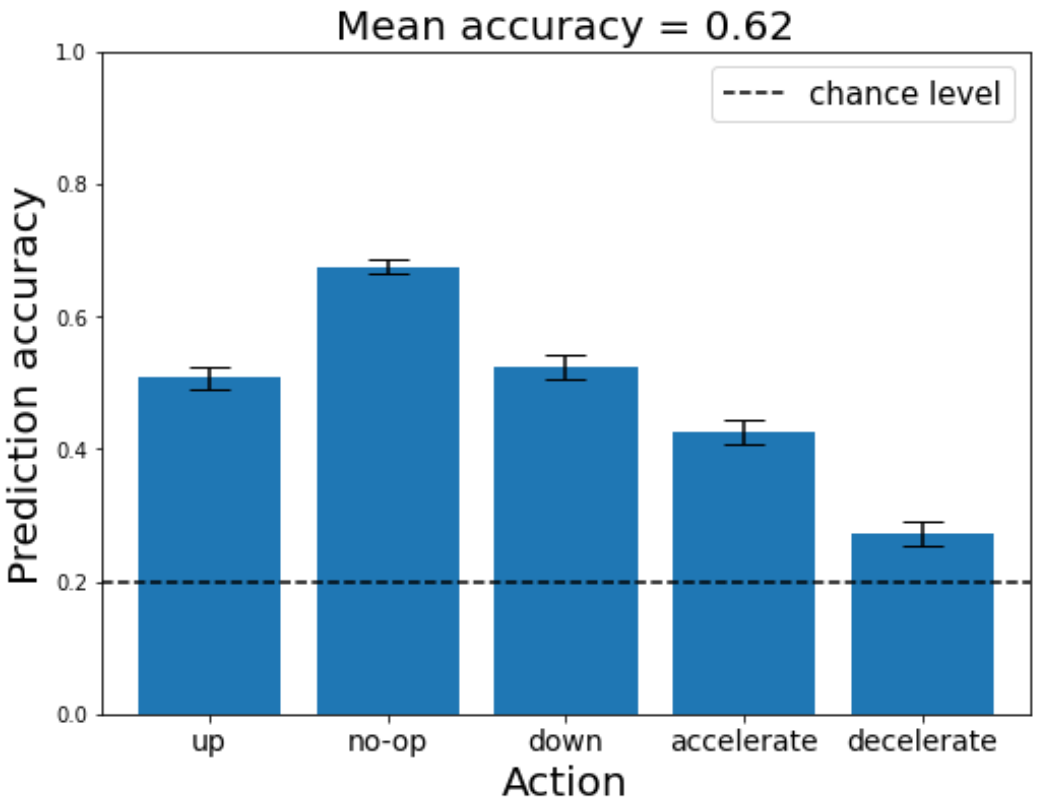
Inverse reinforcement learning (IRL)

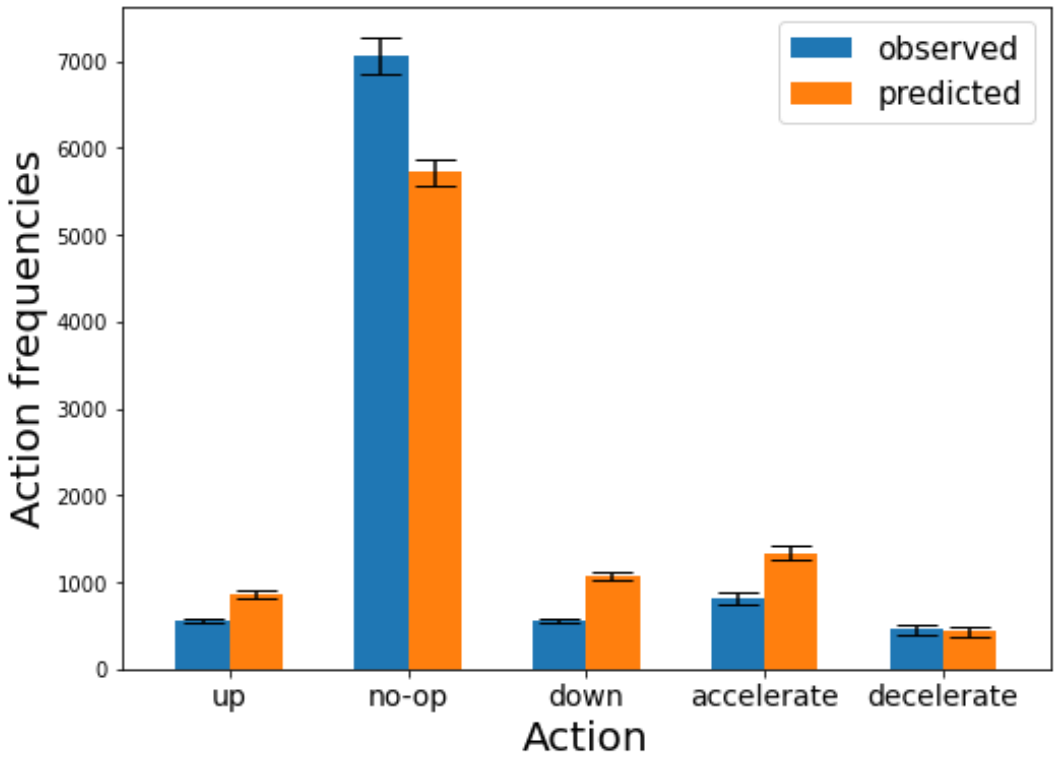
Behavior



- *Inverse reinforcement learning (IRL) is a method to learn a reward structure from observed trajectory of behaviors.*

Lee et al. (2022) RLDM


Mean accuracy = 0.62
chance level
Prediction accuracy
1.0
0.8
0.6
0.4
0.2
0.0
up
no-op
down
accelerate
decelerate
Action


observed
predicted
Action frequencies
7000
6000
5000
4000
3000
2000
1000
0
up
no-op
down
accelerate
decelerate
Action

Thank you!

Jay Myung

Mark Pitt

Jaeyeong (Jayce) Yang

Nate Haines

Sangho Lee

Mina Kwon

Computational Clinical Science Laboratory

https://ccs-lab.github.io