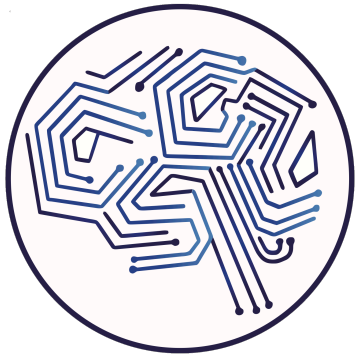
Reinforcement Learning



Woo-Young (Young) Ahn
Department of Psychology
Seoul National University
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…

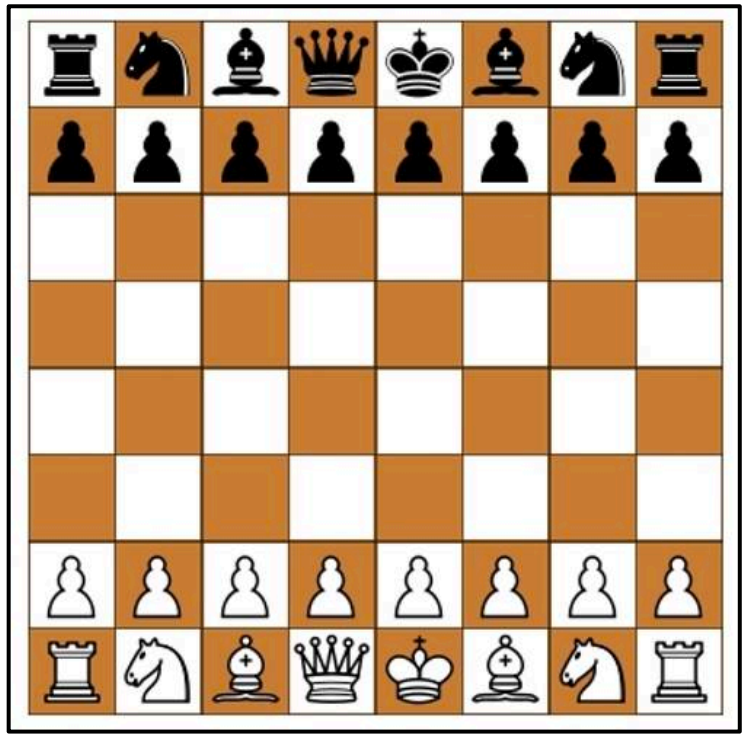
- *Understand the key concepts and notations of RL (in multiple fields)*
- *Know (some of) popular RL models (& references)*
  - *Simple to complex models*
- *Limitations of RL and some new approaches*

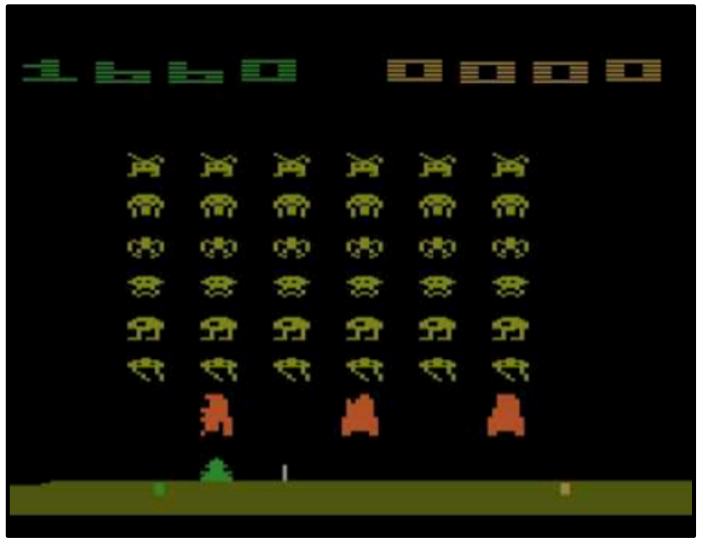
What is RL?

"Learning what to do" …
based on rewards and punishments

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

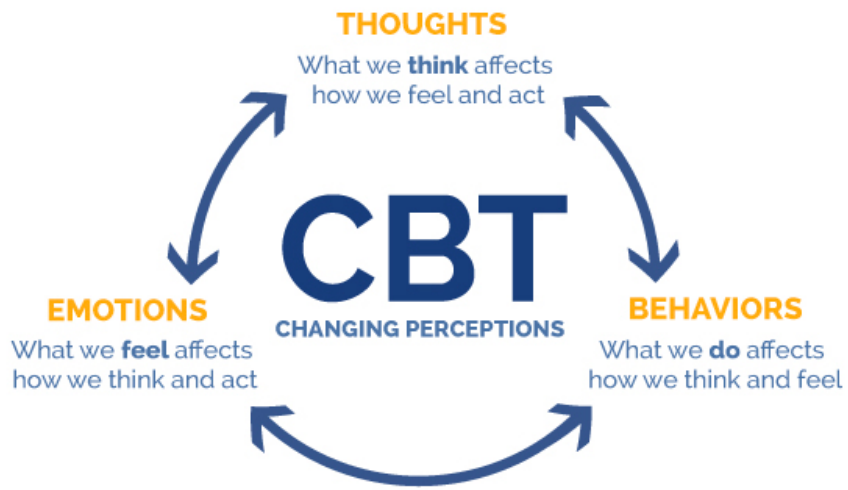
"Learn optimal ways to make decisions"
in an uncertain environment





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?

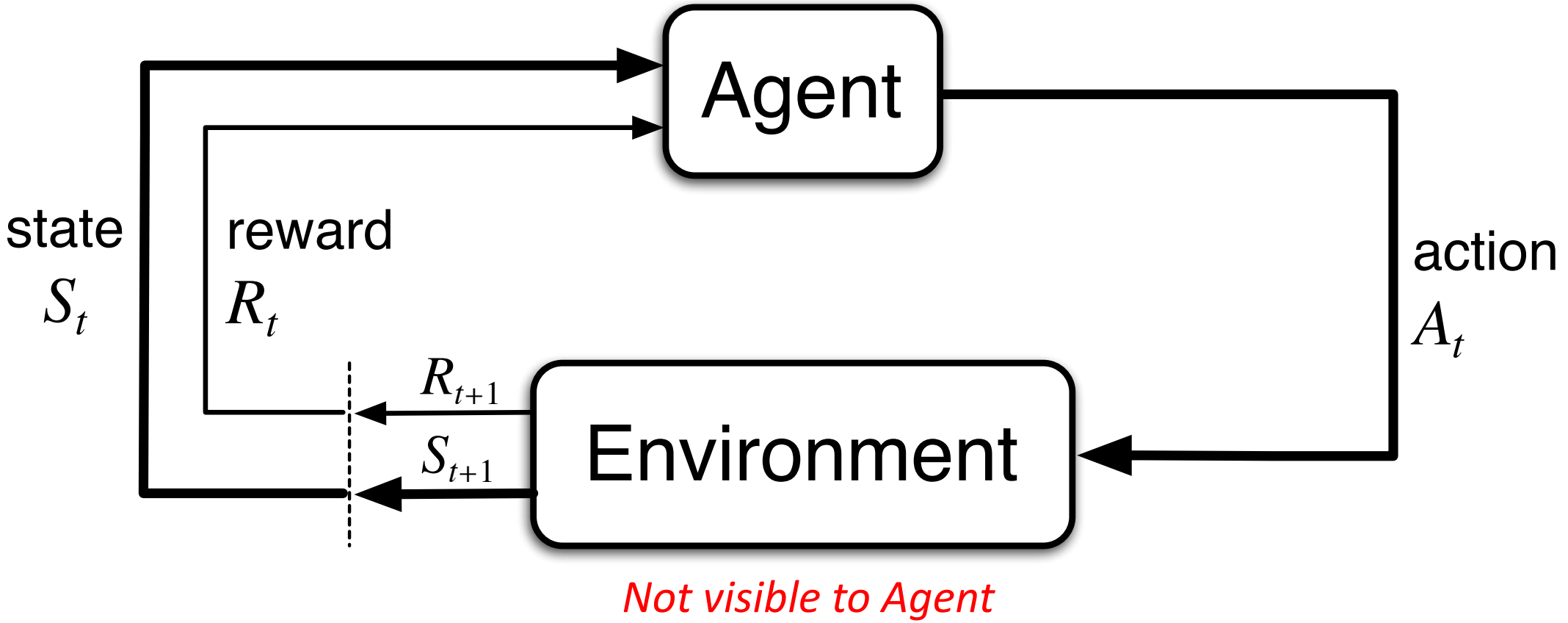
- *No external supervisor (“minimally supervised”)*
- *Reward signals (learn from trials and errors)*
- *Interaction with environment*
- *Closely tied to action selection (e.g., exploration/exploitation)*

"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

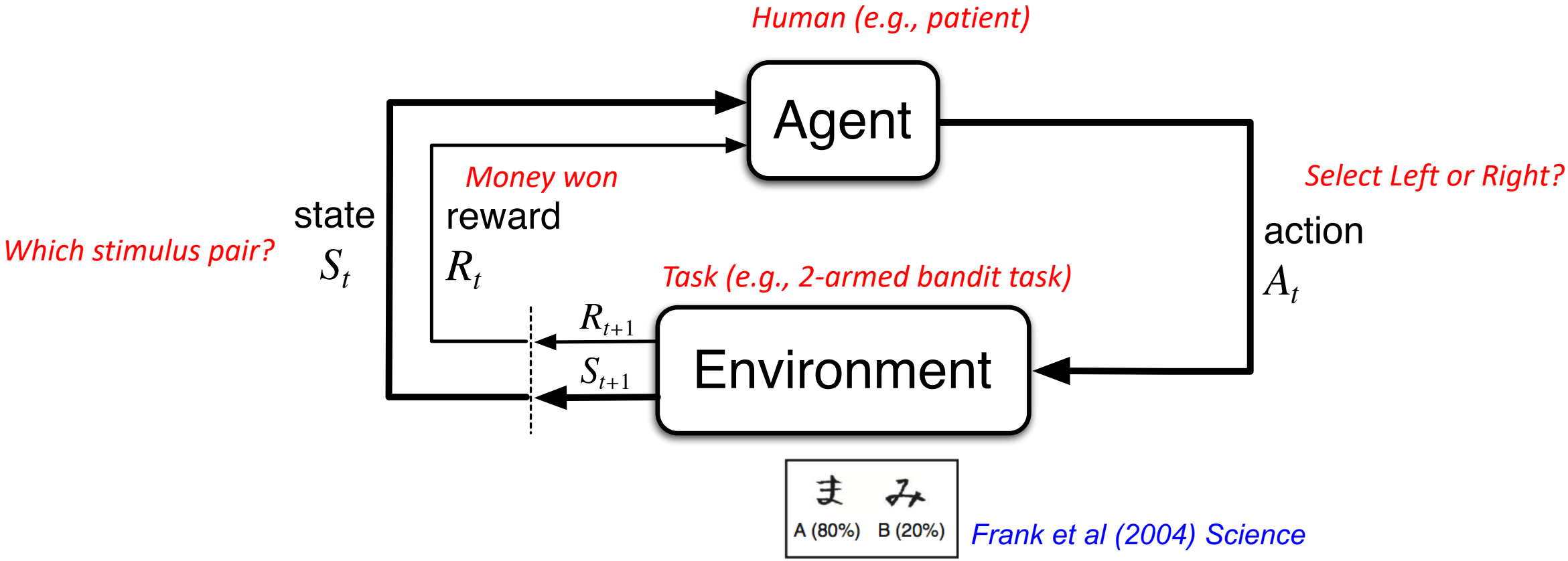
e.g., Maze task, Tree search, N-armed Bandit



Sutton & Barto (1998) Reinforcement Learning

Typically in Computational Psychiatric research settings..

Model parameters → Psychologically meaningful processes/constructs

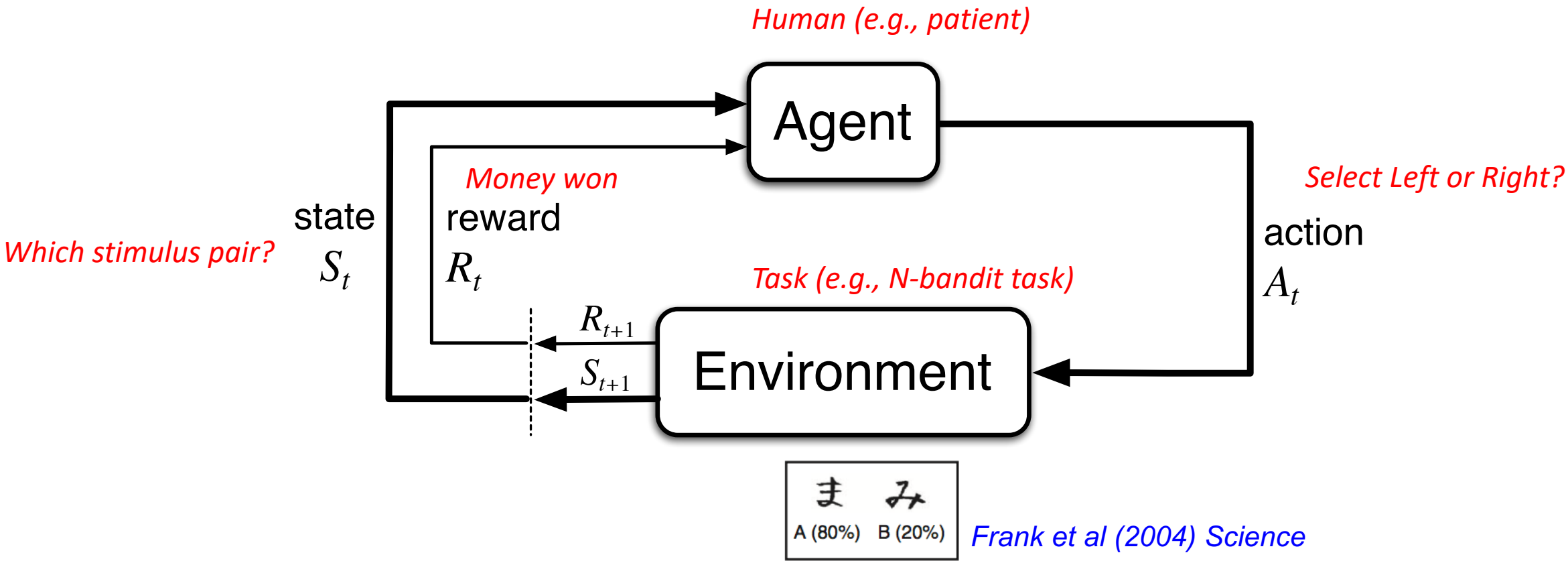


S_t: State value on time (trial) t

A_t: Action value on time (trial) t

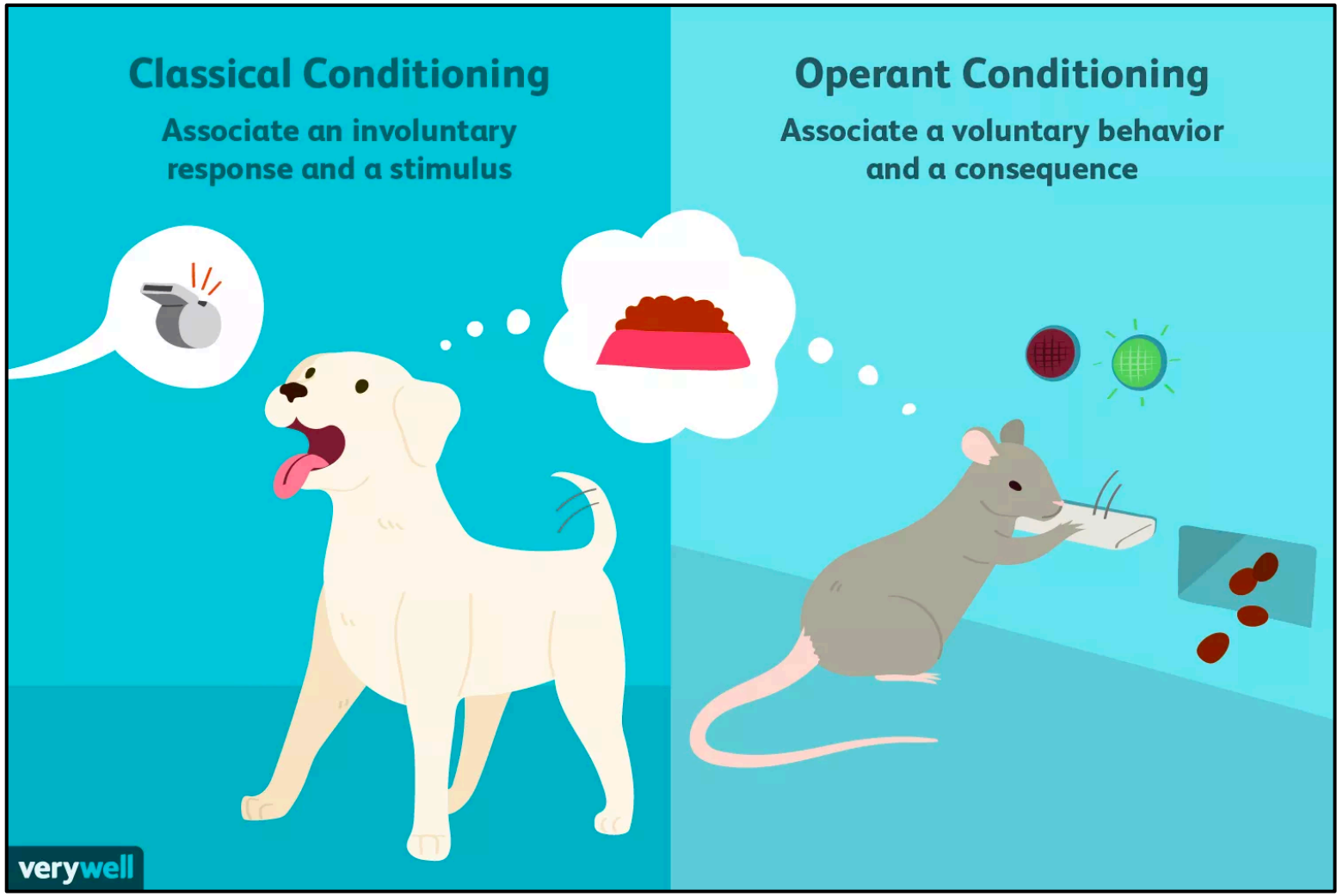
R_t: Reward on time (trial) t

$\pi_t(a_t, s_t)$: 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

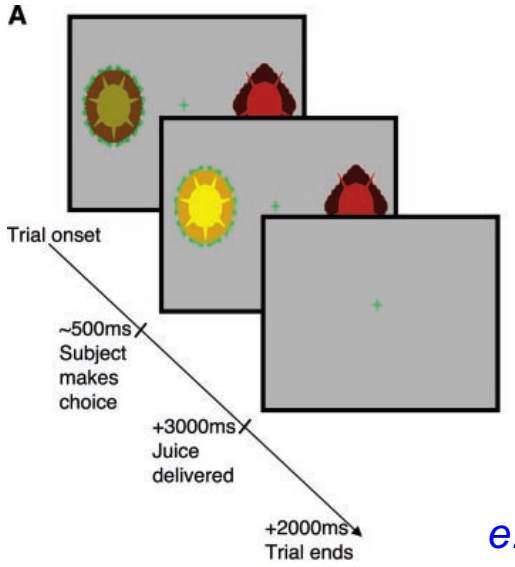
Two experimental set-ups
(Not a distinction of learning mechanisms)

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

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

Learning rate

Stimulus value (t) *Stimulus value (t-1)* *Outcome* *Stimulus value (t-1)*

Prediction error

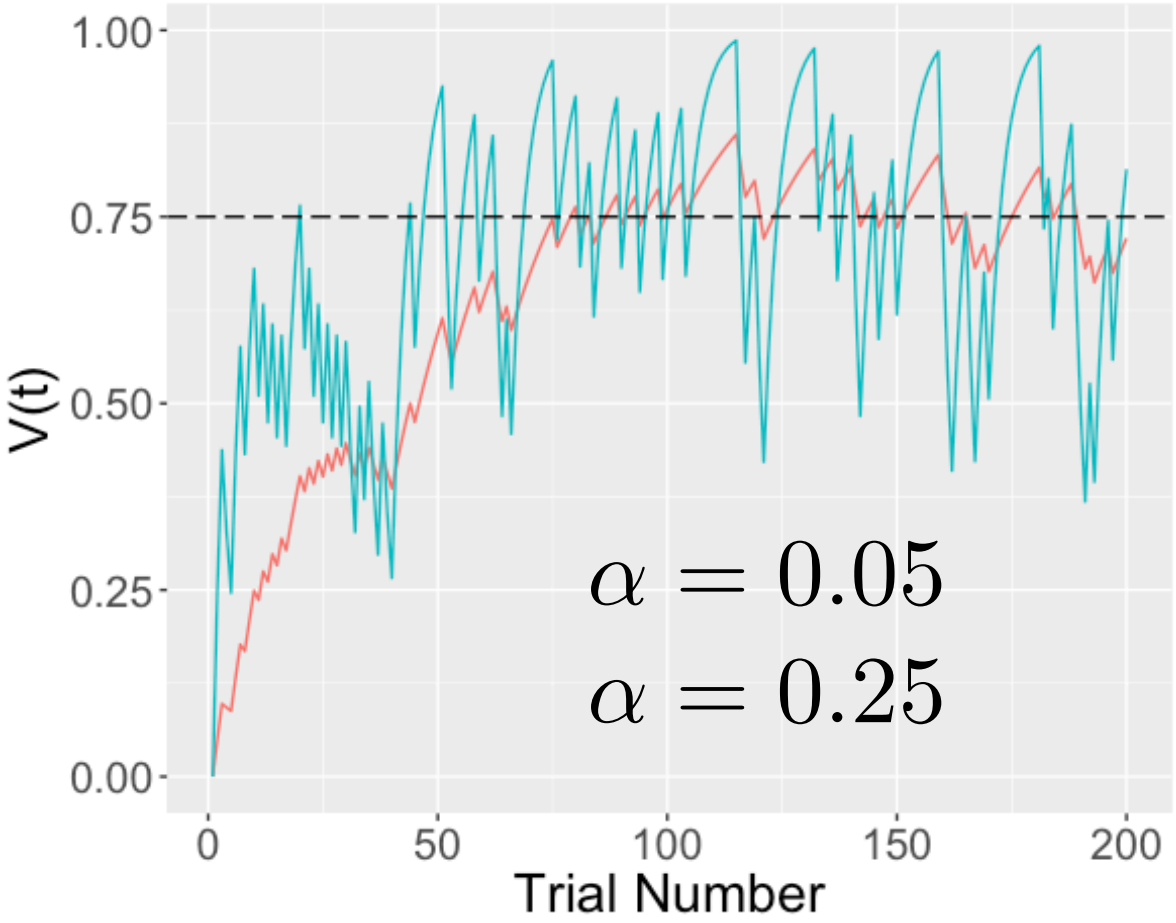
→ Point estimates of V_t

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)

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*

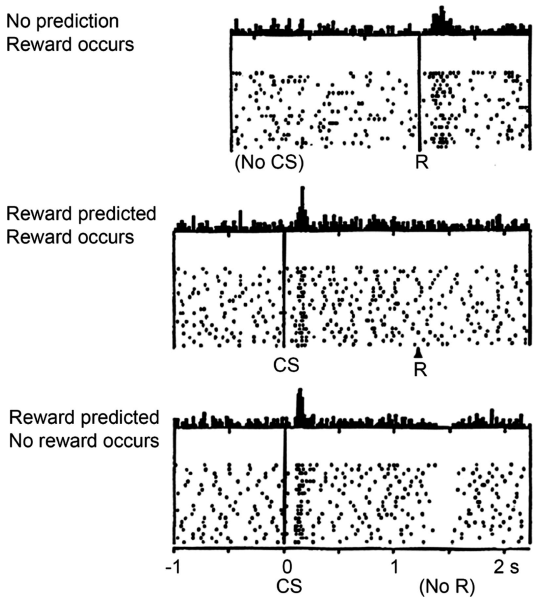
Reward Prediction Error
TD learning model

Computational roles for dopamine in behavioural control

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

[1]*Department of Neuroscience and* [2]*Menninger Department of Psychiatry and Behavioral Sciences, Baylor College of Medicine, 1 Baylor Plaza, Houston, Texas 77030, USA (e-mail: read@bcm.tmc.edu)*
[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

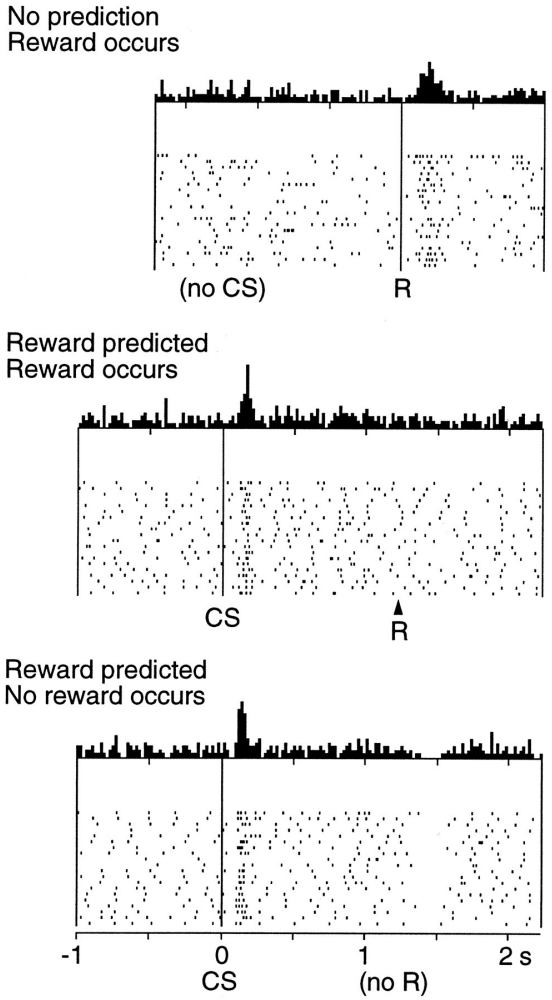
$$\delta(t) = \text{prediction error } (t) = E[r_t] + \gamma \cdot \hat{V}(s_{t+1}) - \hat{V}(s_t)$$
$$\approx \text{current reward} + \gamma \cdot \text{next prediction} - \text{current prediction}$$

Sutton & Barto (1998) Reinforcement Learning

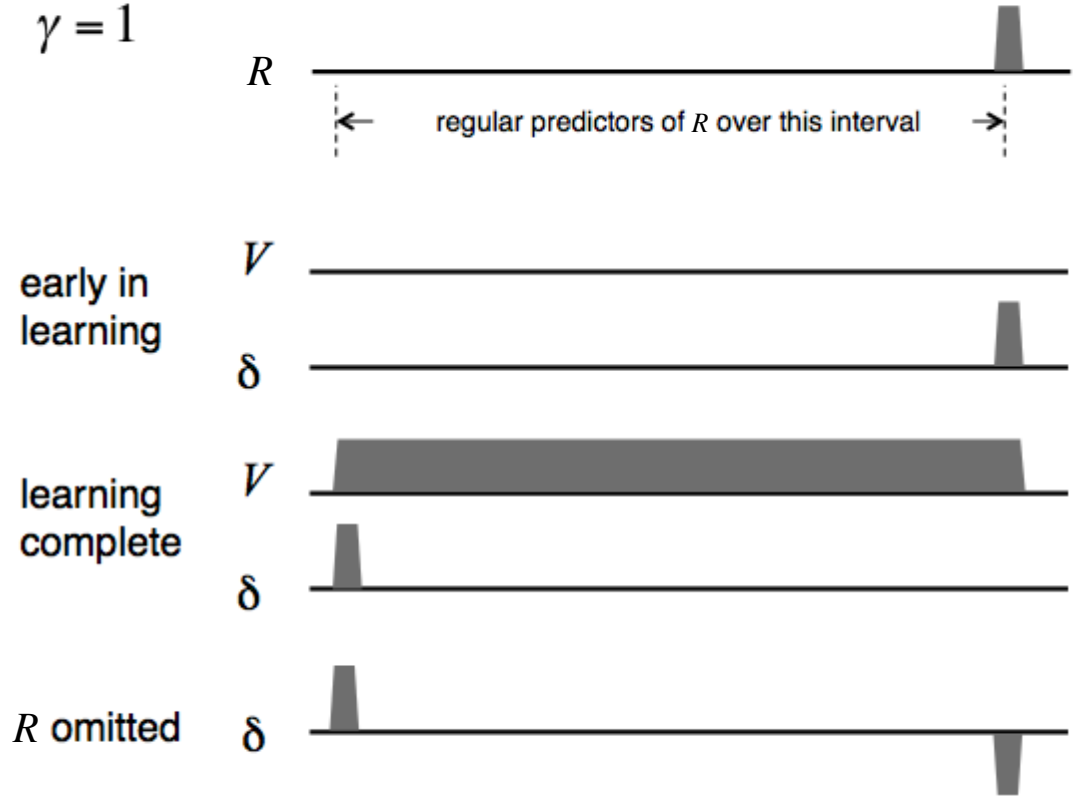
Q) How TD learning accounts for the phasic response of a dopamine neuron?

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

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

Instrumental learning

Model-based vs Model-free

Model-based vs Model-free

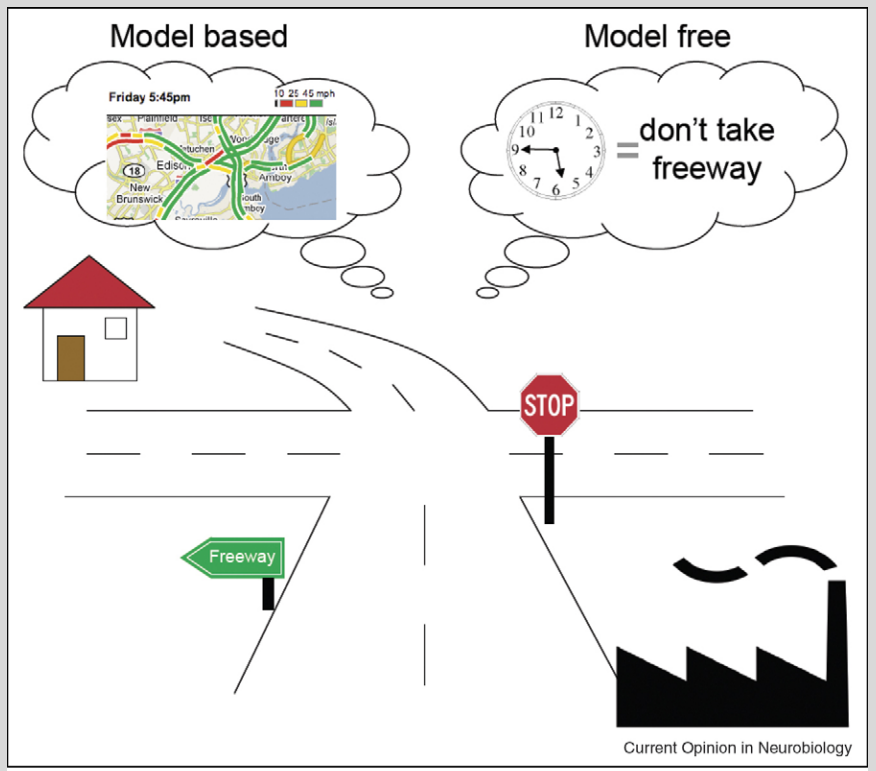


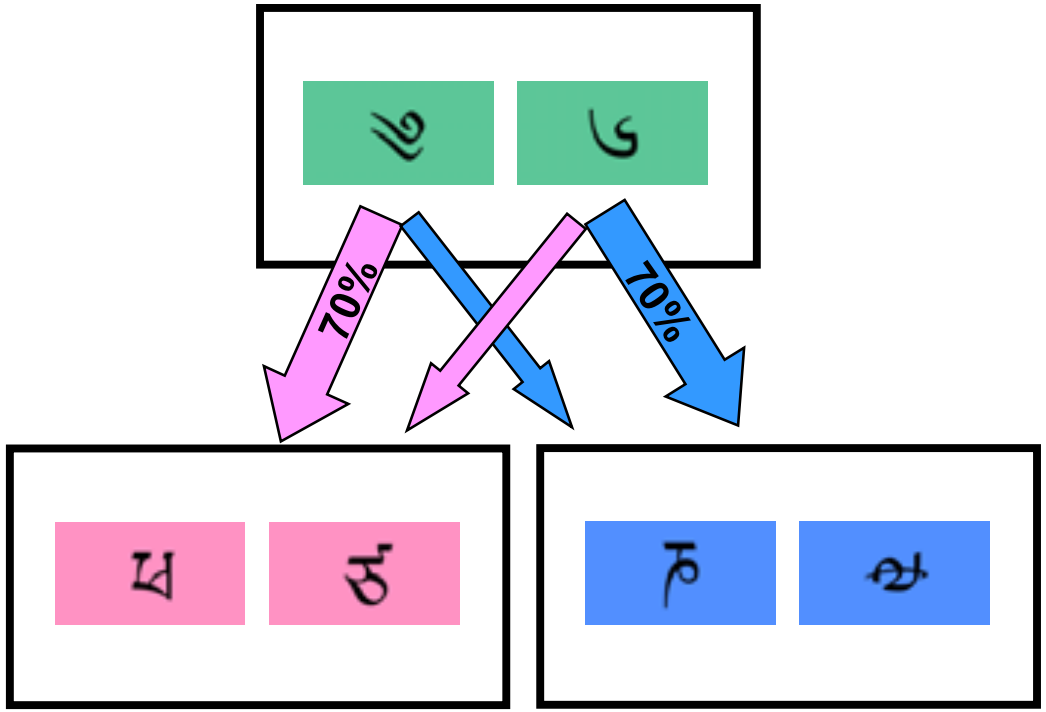
Figure 1: Two ways to choose which route to take when traveling home from work on friday evening.

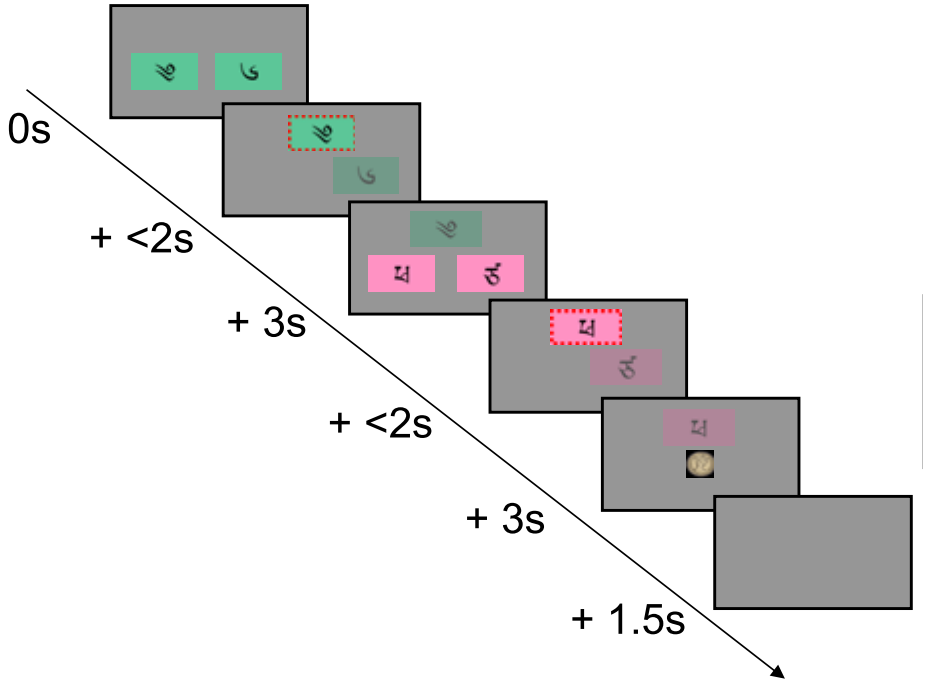
Dayan & Niv (2008)

- *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.*

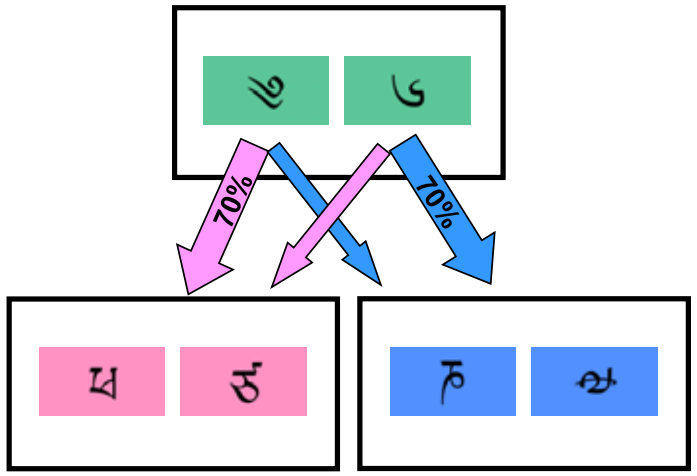
Two-Step task

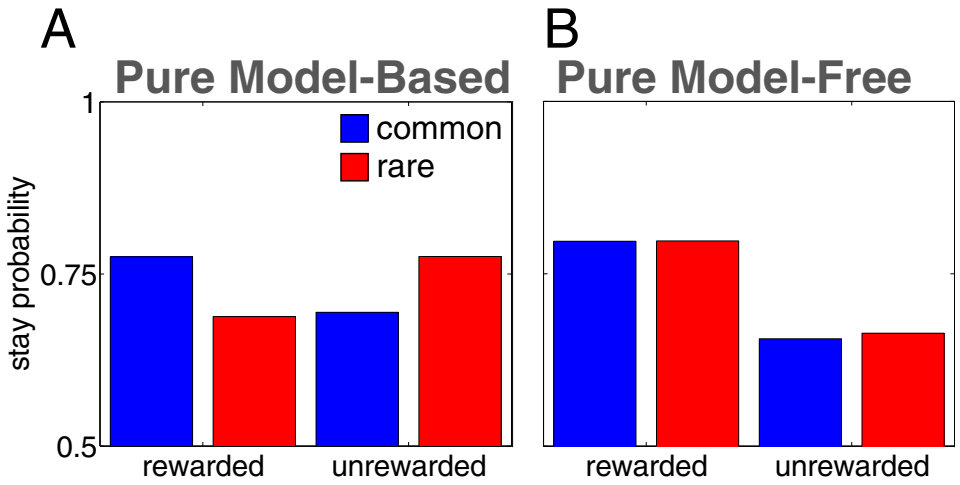
Daw et al (2011) Neuron





Competing predictions





Scenario 1 (model-based individual)

- Step1: choose Left
- Common transition (70%) to green
- Step2: choose Left and won!

Next trial

- To choose the same 2nd level stimulus,
- In Step 1, I will choose Left (=stay)

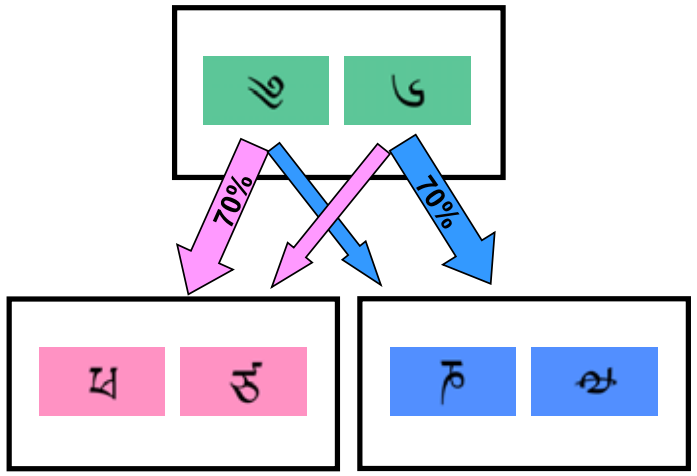
Scenario 2 (model-based individual)

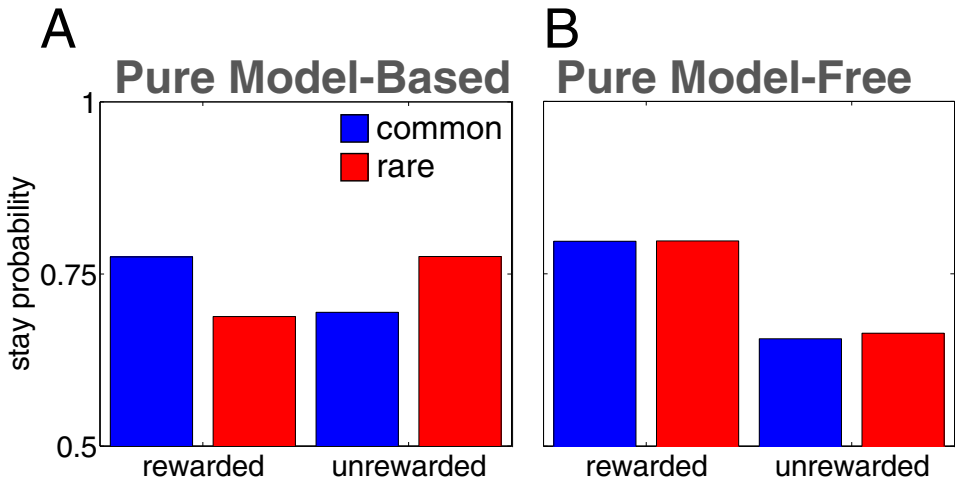
- Step1: choose Left
- Rare transition (30%) to blue
- Step2: choose Left and won!

Next trial

- To choose the same 2nd level stimulus,
- In Step 1, I will choose Right (=switch)

More scenarios





Scenario 1 (model-free individual)

- Step1: choose Left
- Common transition (70%) to green
- Step2: choose Left and won!

Next trial

- To choose the same 2nd level stimulus,
- In Step 1, I will choose Left (=stay)

Scenario 2 (model-free individual)

- Step1: choose Left
- Rare transition (30%) to blue
- Step2: choose Left and won!

Next trial

- To choose the same 2nd level stimulus,
- In Step 1, I will choose **Left (=stay)**

Computational model

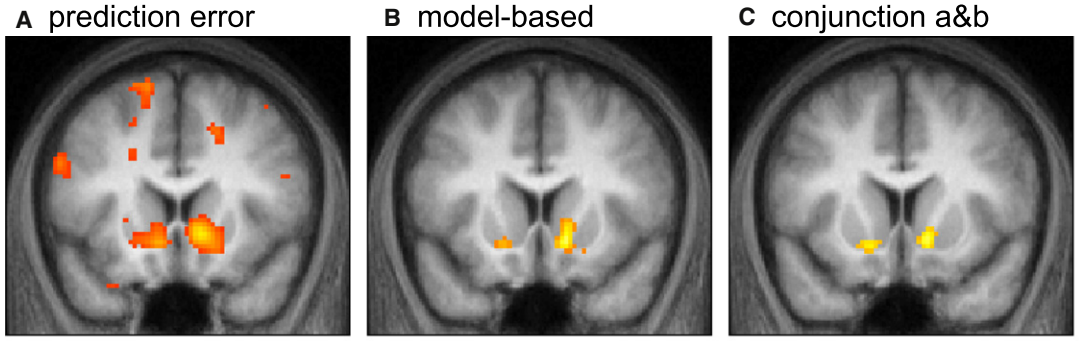
Daw et al (2011) Neuron
Wunderich et al (2012) Neuron

- *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)*

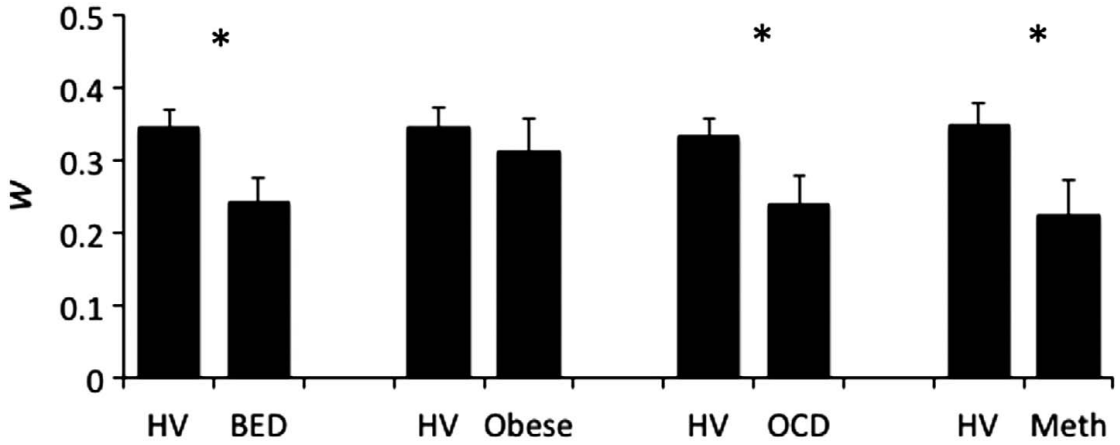
$$V^{Hybrid} = \omega \cdot V^{MB} + (1 - \omega) \cdot V^{MF}$$



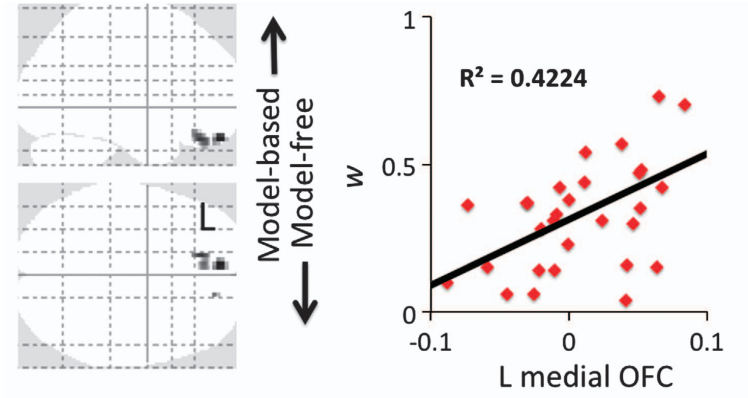
Daw et al (2011) Neuron

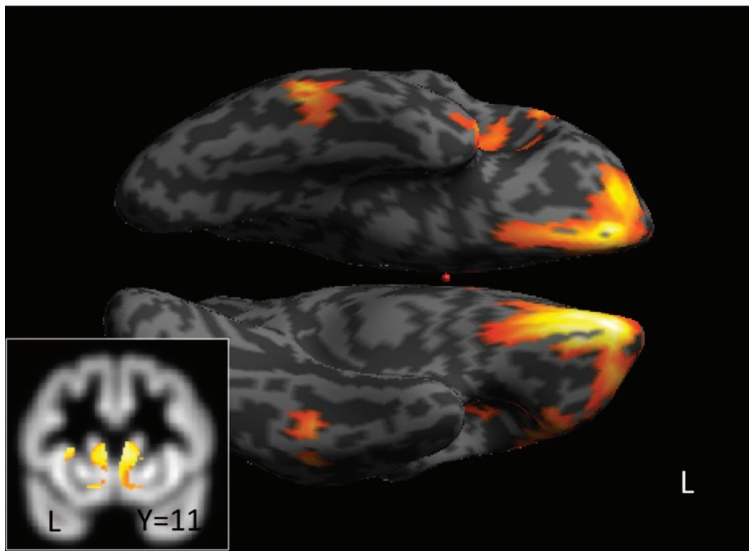
Reliance of model-based control → Disorders of compulsivity

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☯]

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

☯ These authors contributed equally to this work.
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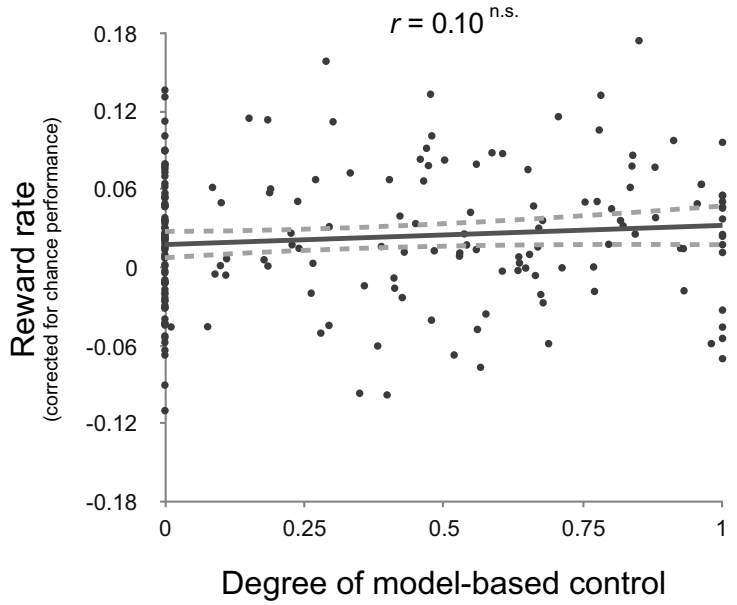
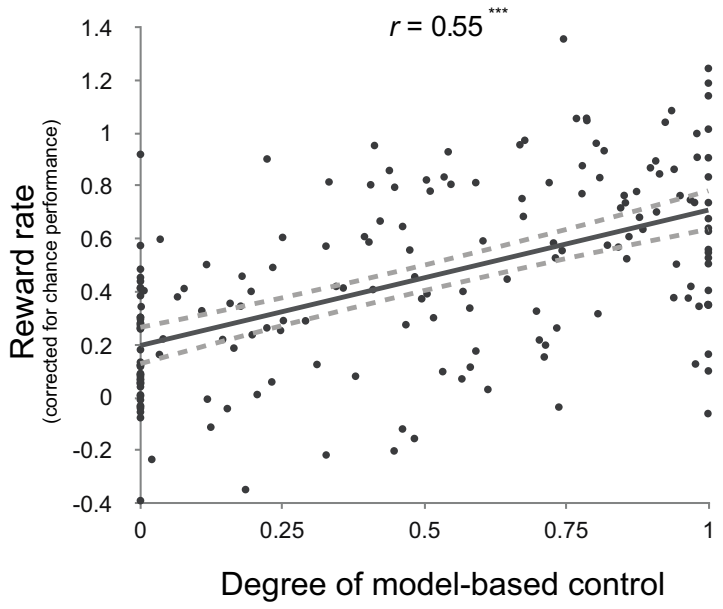
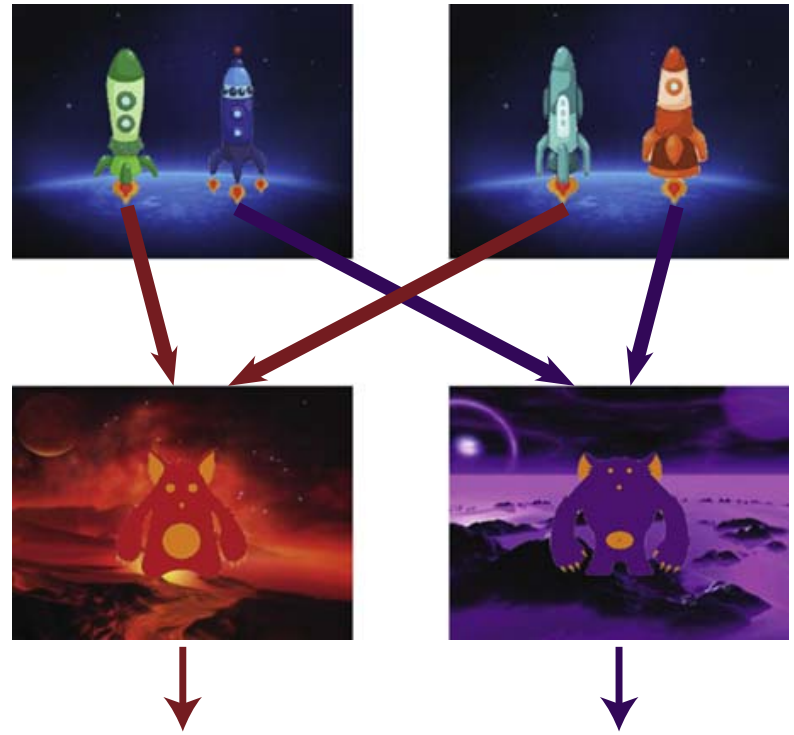


Daw Two-Step Task

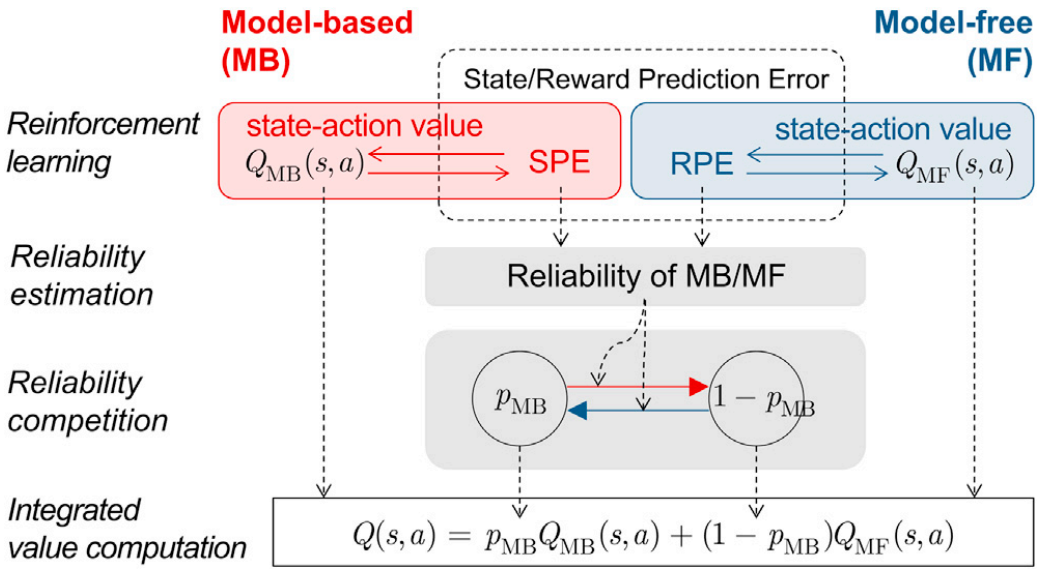


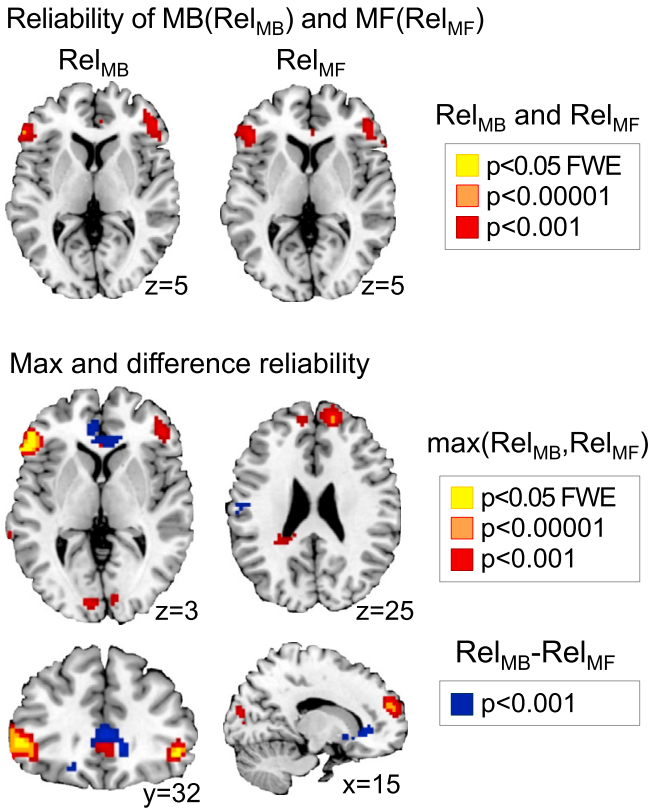
Kool Two-Step Task



Kool et al (2016) PloS Comput Biol

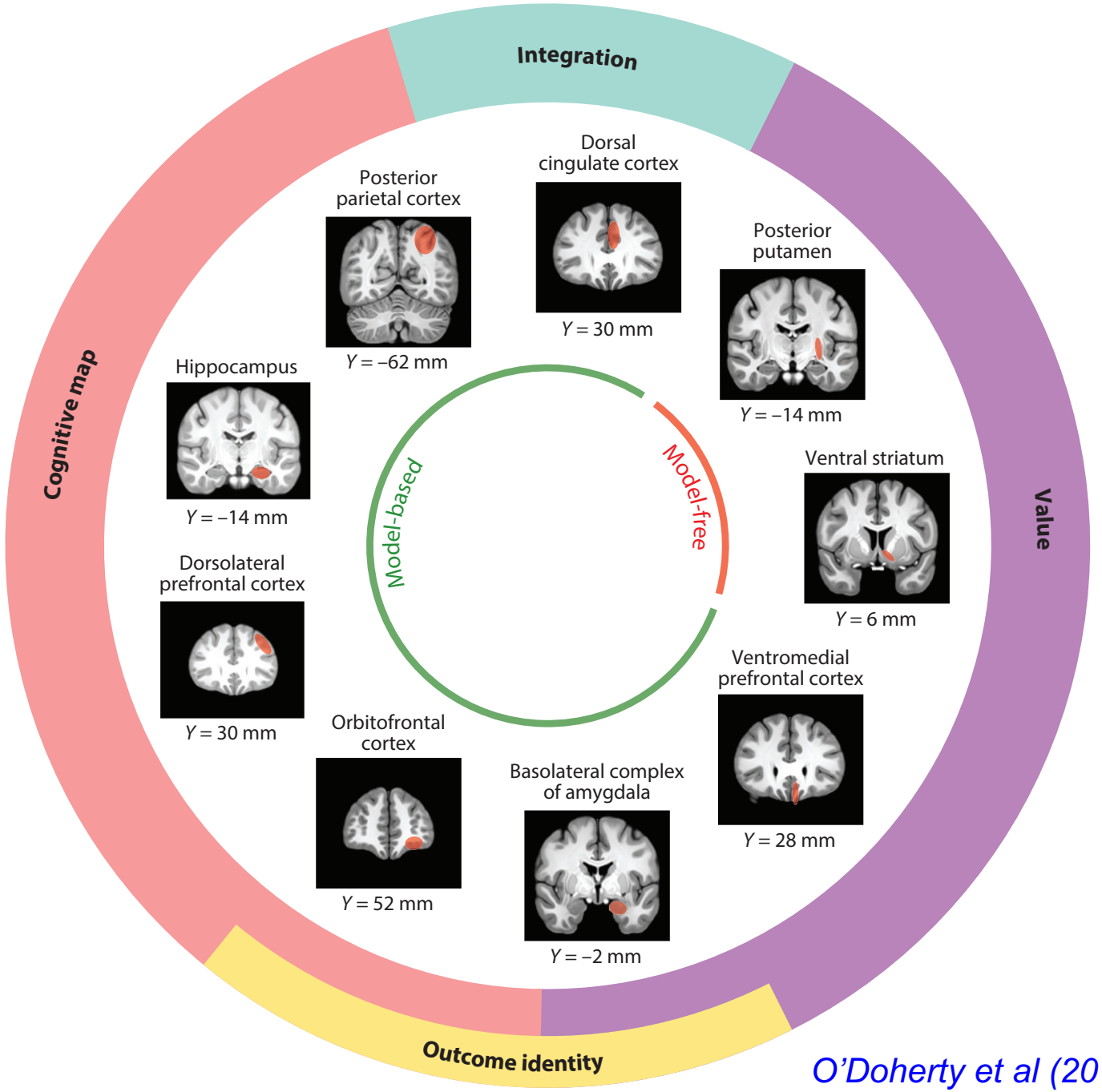
Reliability-based arbitration between model-based and model-free





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

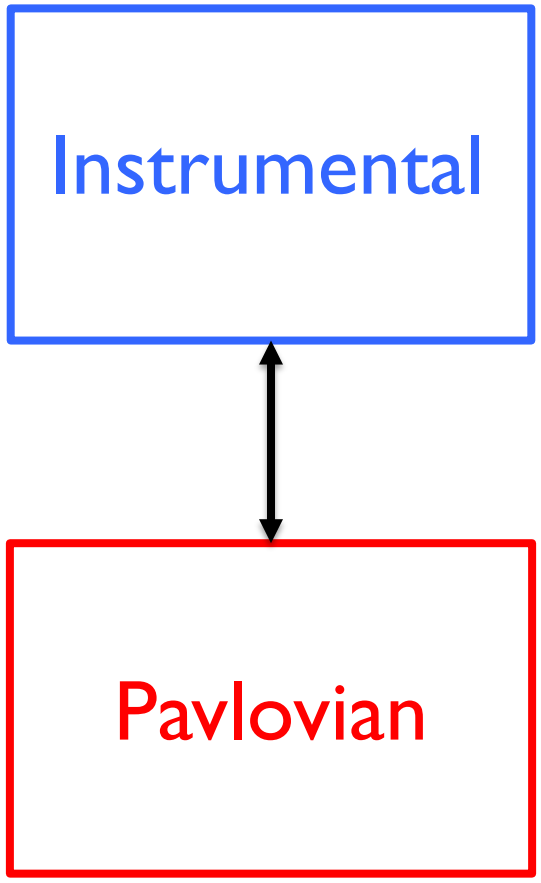
Inferior lateral prefrontal and frontopolar cortex



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

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

Marc Guitart-Masip[1,2], Emrah Duzel[3,4,5], Ray Dolan[2], and Peter Dayan[6]

[1] Aging Research Centre, Karolinska Institute, SE-11330 Stockholm, Sweden
[2] Wellcome Trust Centre for Neuroimaging, Institute of Neurology, University College London, London WC1N 3BG, UK
[3] Institute of Cognitive Neuroscience, University College London, London WC1N 3AR, UK
[4] Otto von Guericke University Magdeburg, Institute of Cognitive Neurology and Dementia Research, D-39120 Magdeburg, Germany
[5] German Center for Neurodegenerative Diseases, D-39120 Magdeburg, Germany
[6] Gatsby Computational Neuroscience Unit, University College London, London W1CN 3AR, UK

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

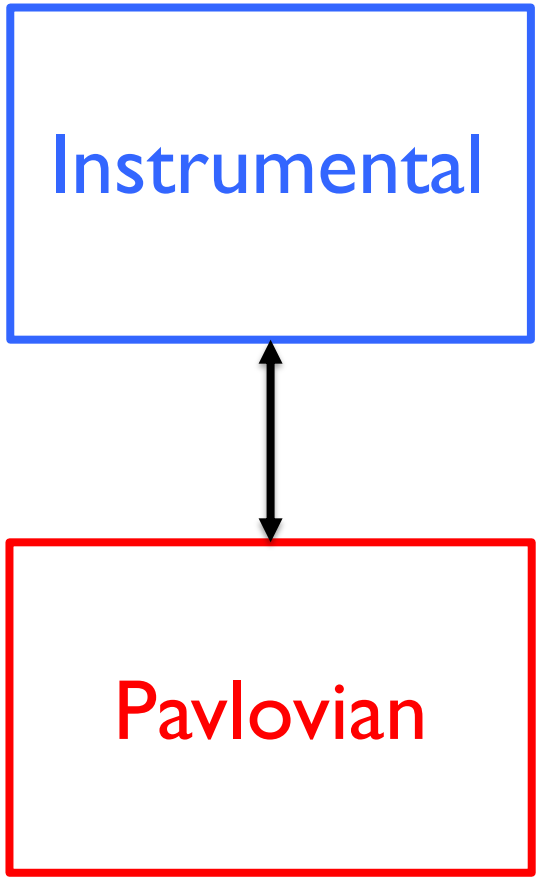
Hershberger (1986)

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"

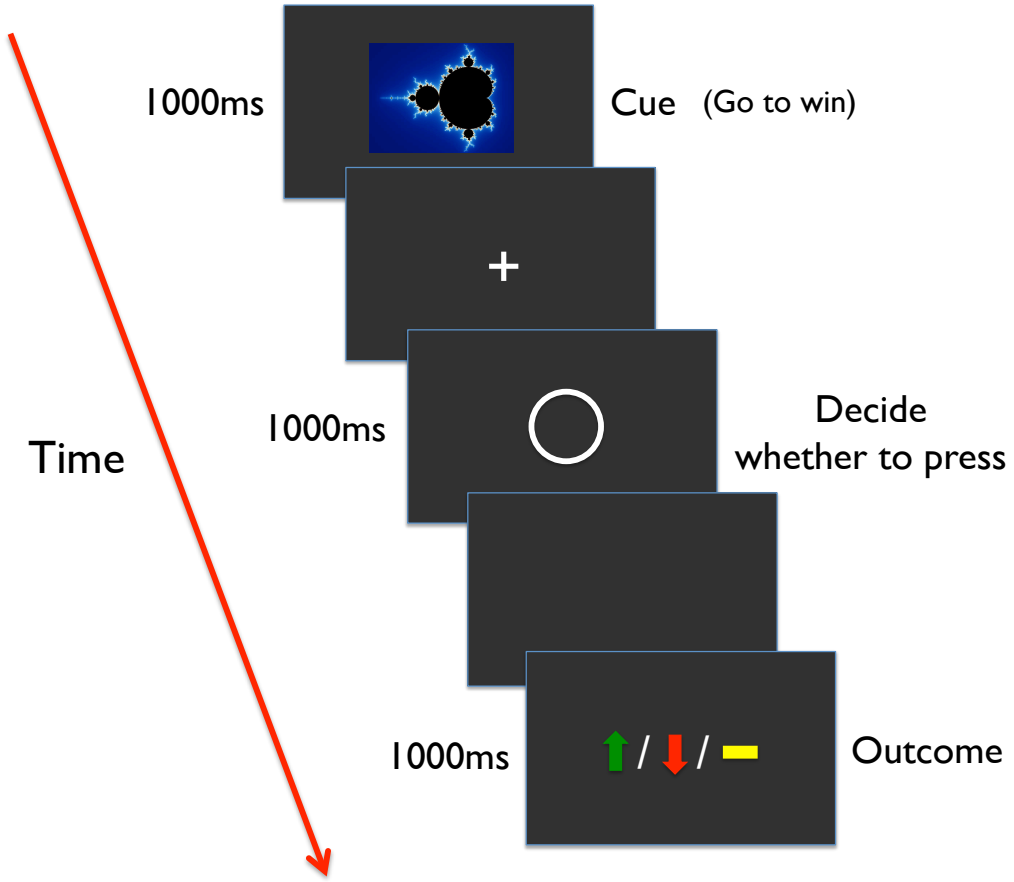
Balleine & O'Doherty (2010); Dayan et al (2006); Dayan (2013); Dayan & Niv (2008); Dolan & Dayan (2013); Dayan & Berridge (2014); Rangel et al (2008)

Orthogonalized Go/Nogo task

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

Pavlovian congruent

Pavlovian incongruent



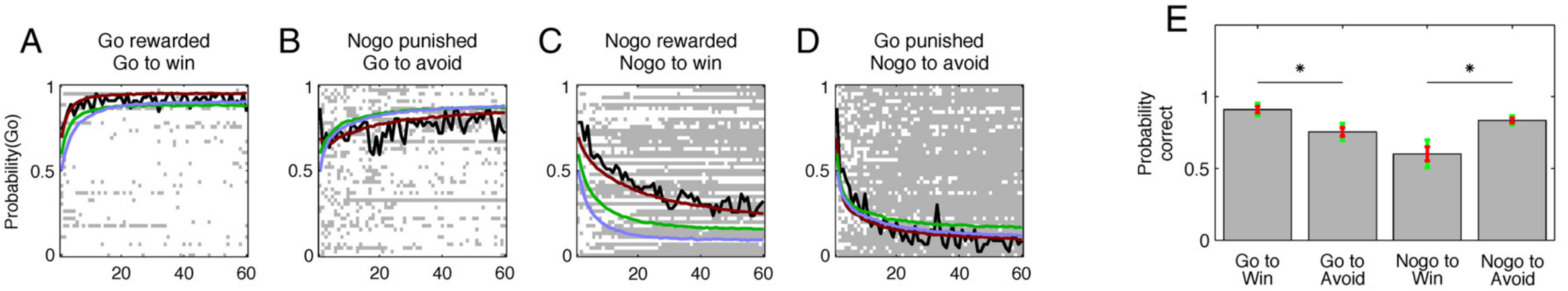
- *4 cues (conditions)*

  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

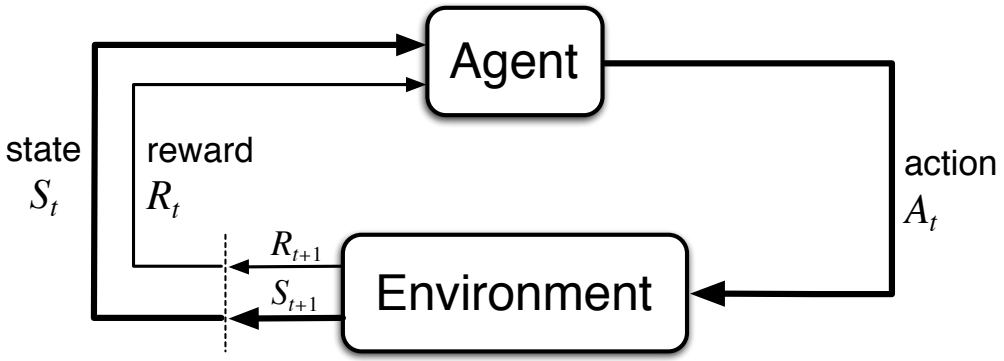
Modified R-W rule

Go bias

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

Pavlovian bias

Adaptive Design Optimization within the RL framework



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

Bayesian updating

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

Adaptive Design Optimization

Design optimization

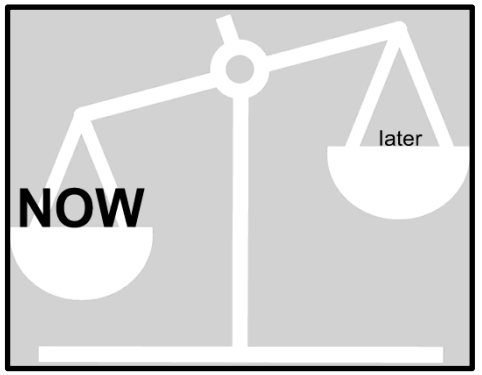
Find the most informative design for next experimental trial

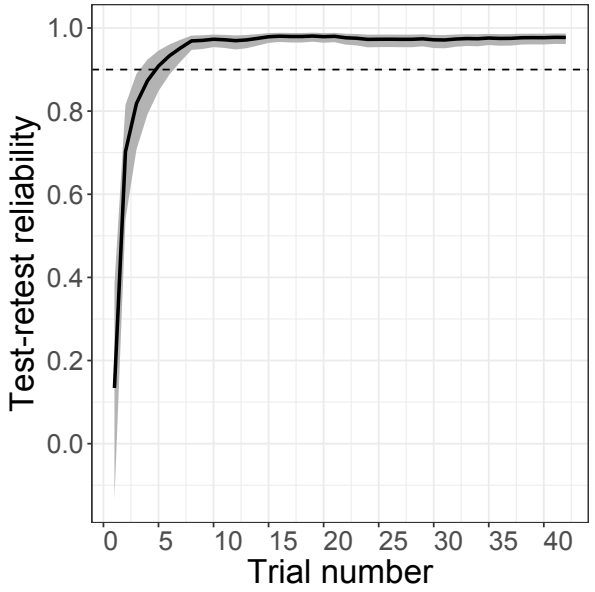
Experiment

Present the optimal design on next trial and record observed response

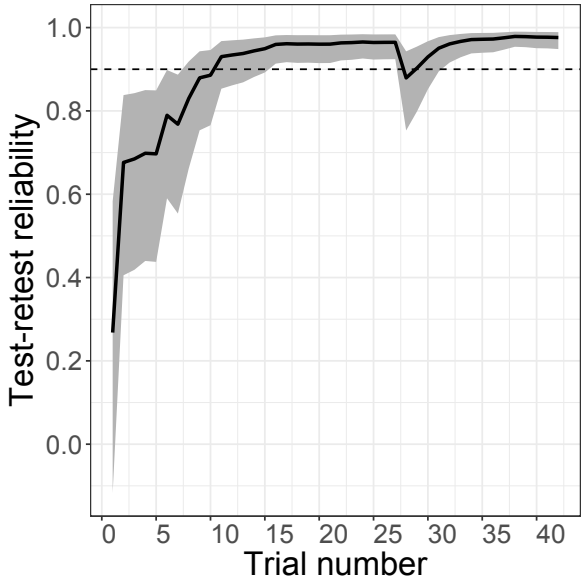
$$d^* = \underset{d}{\text{argmax}} \iint u(d, \theta, y)\ P(\theta)\ P(y|\theta, d)\ \mathrm{d}\theta\ \mathrm{d}y$$

Up to 0.98 test-retest reliability within ~10 trials

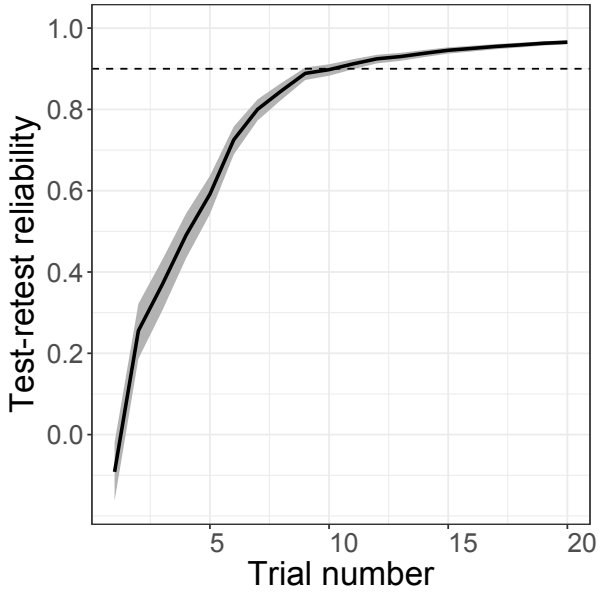




College students

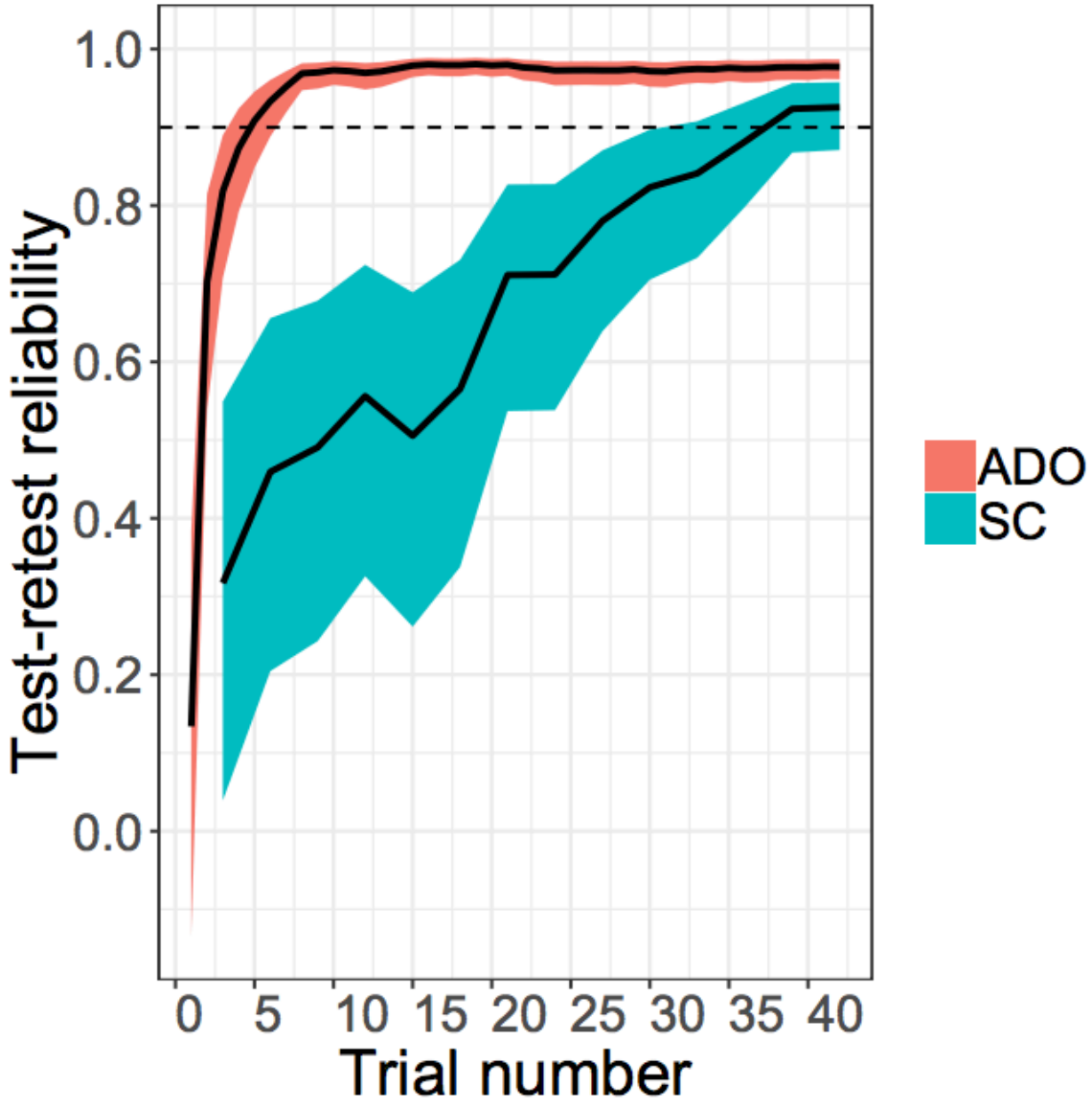


Patients with SUDs



Online Amazon MTurk

Ahn et al (in revision) bioRxiv



3-5 times more precise

3-8 times more efficient

Ahn et al (in revision) bioRxiv

Tips for RL (in human research?)

- *Several other DM variables (effort, uncertainty)*
- *Stimulus value vs. Action value*

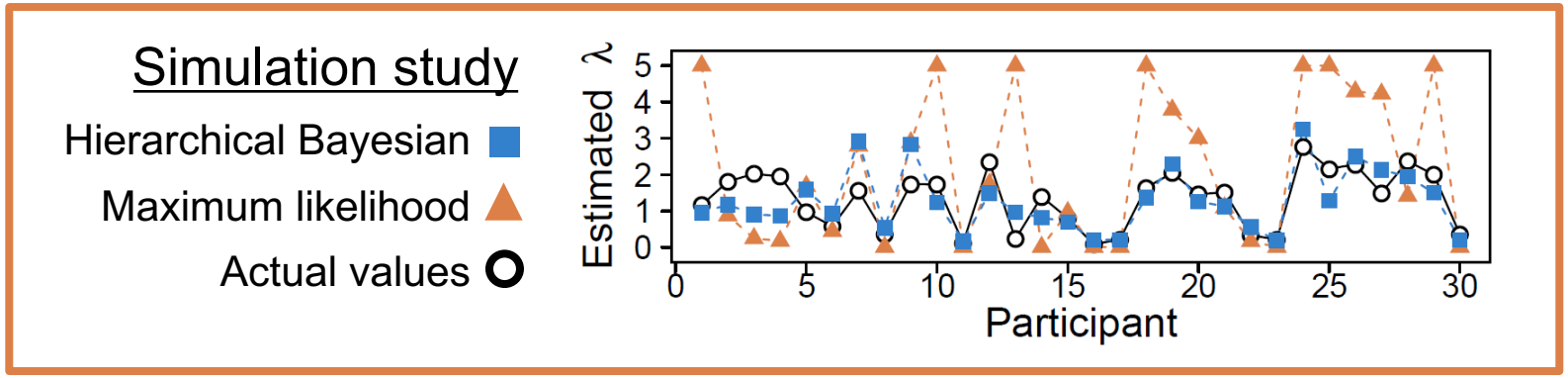
- *Only 1 action for each stimulus*

  → Stimulus value = action value

- No within-trial events → TD model is not necessary

Use a hierarchical approach across subjects when estimating model parameters

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



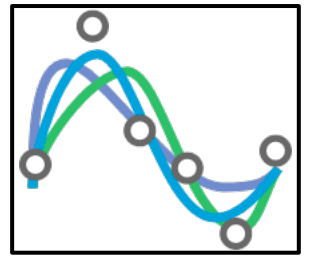
Ahn et al. (2011, JNPE)

Limitations

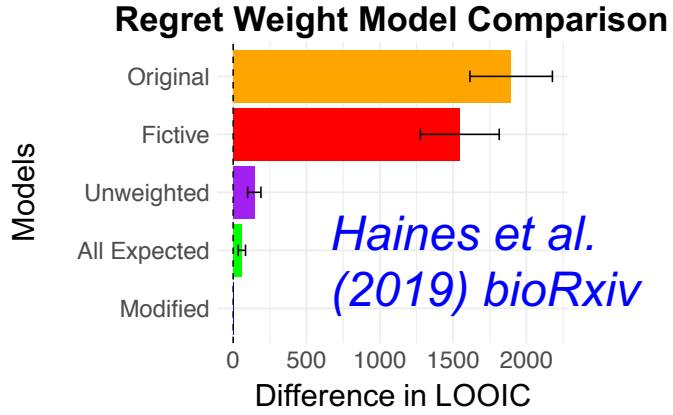
- *Overly simplified "toy" problems*
  - *Violated assumptions (e.g., discrete space/action & Markov..) , (Gershman & Daw, 2016, Annu Rev Psych)*
- *One-shot learning with sparse data*
  - *Episodic memory (hippocampus) (Gabrieli, 1998; Eichenbaum et al., 1999)*
- *Modeling of even toy problems is hard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

Future directions

TAPAS



- *Incorporating multi-modal inputs into computational models* *(Haines et al., in revision, bioRxiv 2019)*



Haines et al. (2019) bioRxiv

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

- *Lowering the barrier to RL and computational modeling*

hBayesDM
(hierarchical Bayesian modeling of Decision-Making tasks) Package

Ahn et al. (2017) Computational Psychiatry

ADOpy
Adaptive Design Optimization for Experimental Tasks

Yang et al. (2019) PsyArxiv

Thank you!

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Jaeyeong (Jayce) Yang

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https://ccs-lab.github.io