Reinforcement Learning

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hBayesDM

Reinforcement Learning (RL)

- *What is RL?*
  - *Definitions & terminology*
  - *RL in human research vs RL in AI*

- *RL models <u>(algorithms for prediction and control)</u>*
  - *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*
- *Naturalistic RL*
- *Limitations & Future directions*

Learning objectives

Participants will…

- *Understand the key concepts and notations of RL (in multiple fields)*
  - *"RL is everywhere"*

- *Know (some of) popular RL models (& references)*
  - *Simple to complex models*

- *Limitations of (current) RL in CP and some new approaches*
  - *Naturalistic paradigms for RL, new algorithms in human RL research*

What is RL?

Why RL?

What is RL?

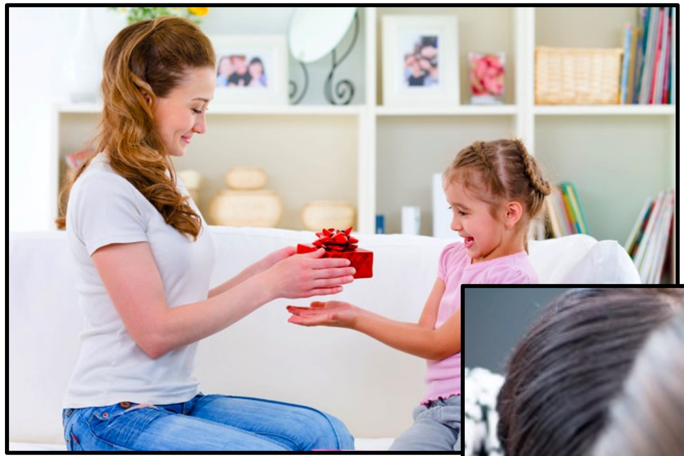
"Learning what to do" …
based on (an incomplete history of)
rewards and punishments

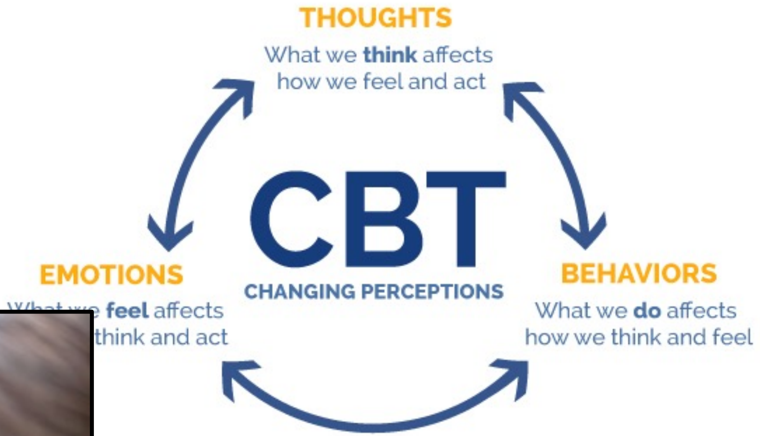
Sutton & Barto (1998) Reinforcement Learning
Dayan & Labott (2000) Theoretical neuroscience

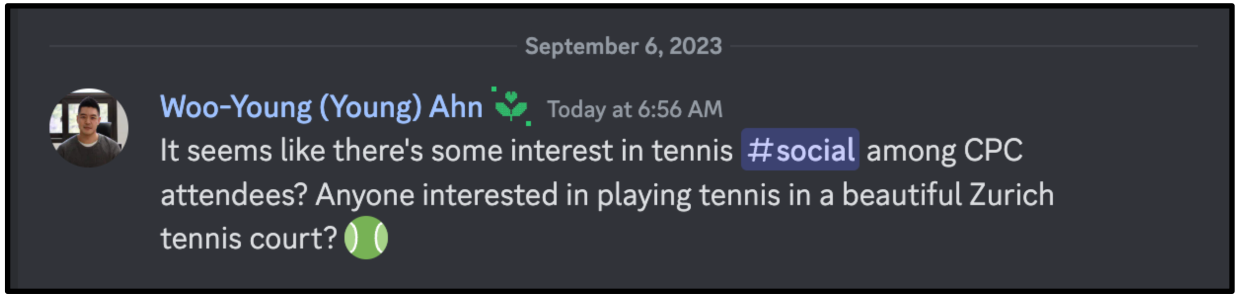
"Learn optimal ways to make decisions"
in an uncertain environment

Why RL in CP?

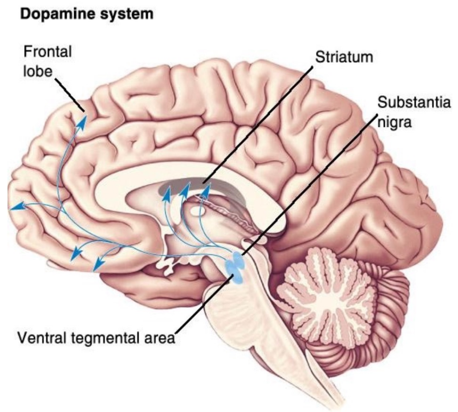
RL is everywhere & in multiple fields



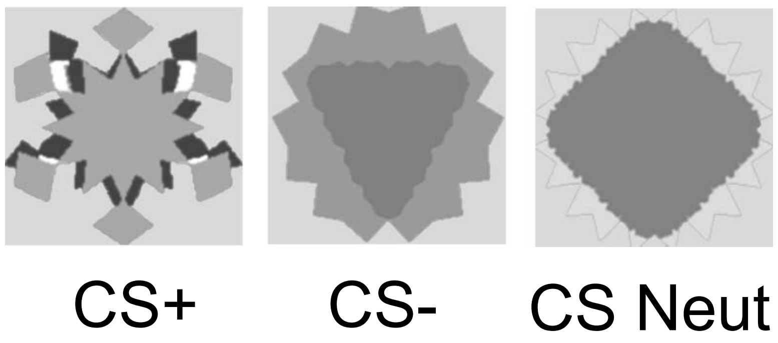




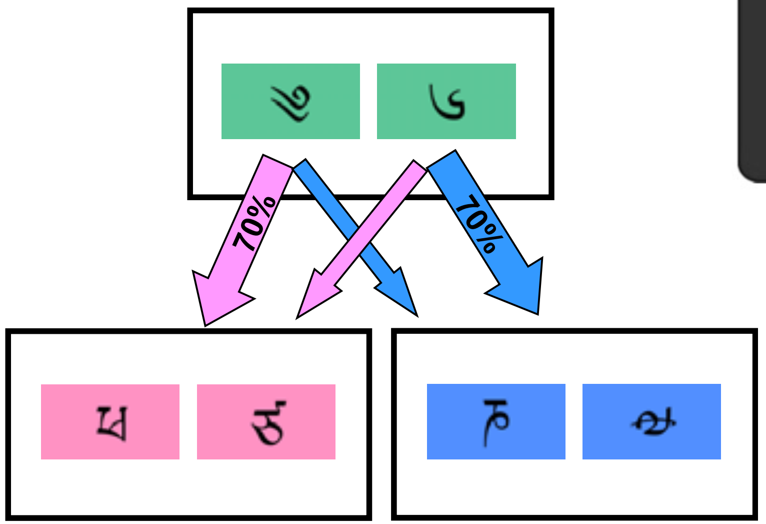
How do we study RL in humans?



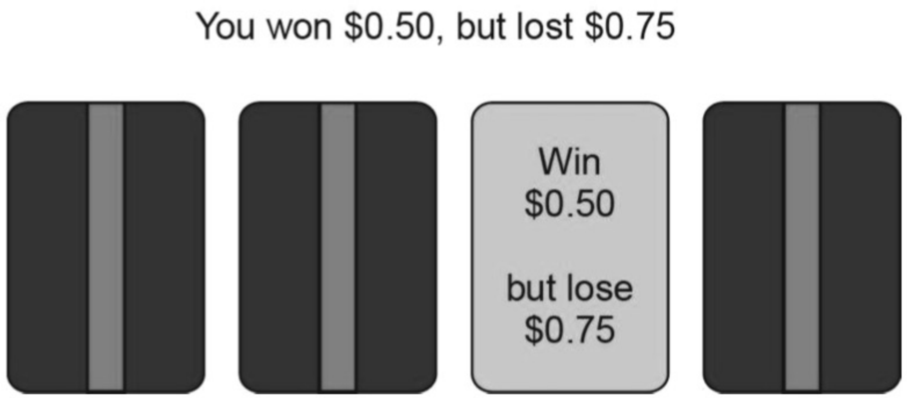
"Classical laboratory tasks"



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



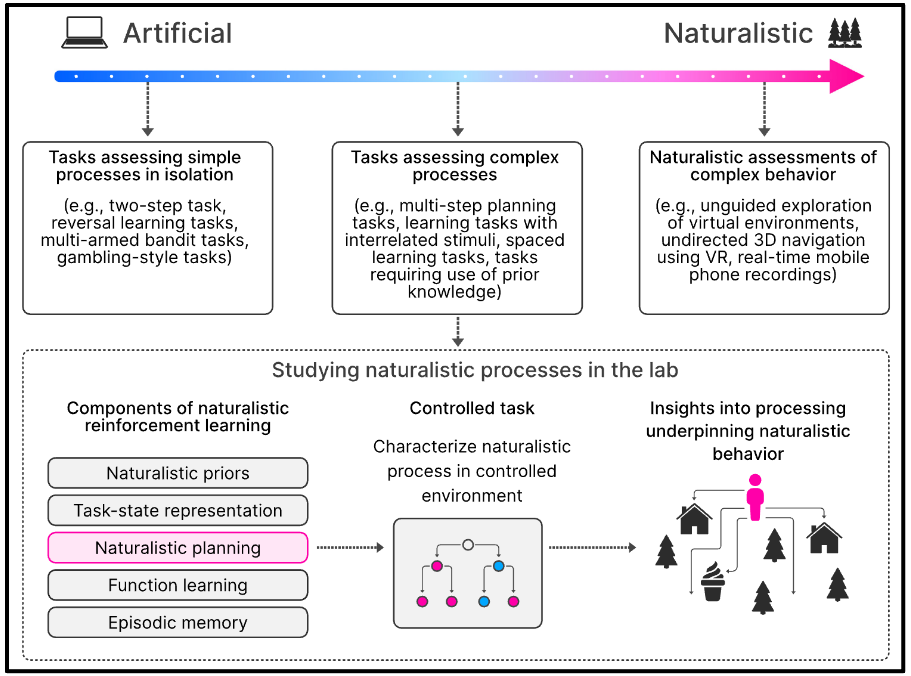
Daw et al (2011) Neuron



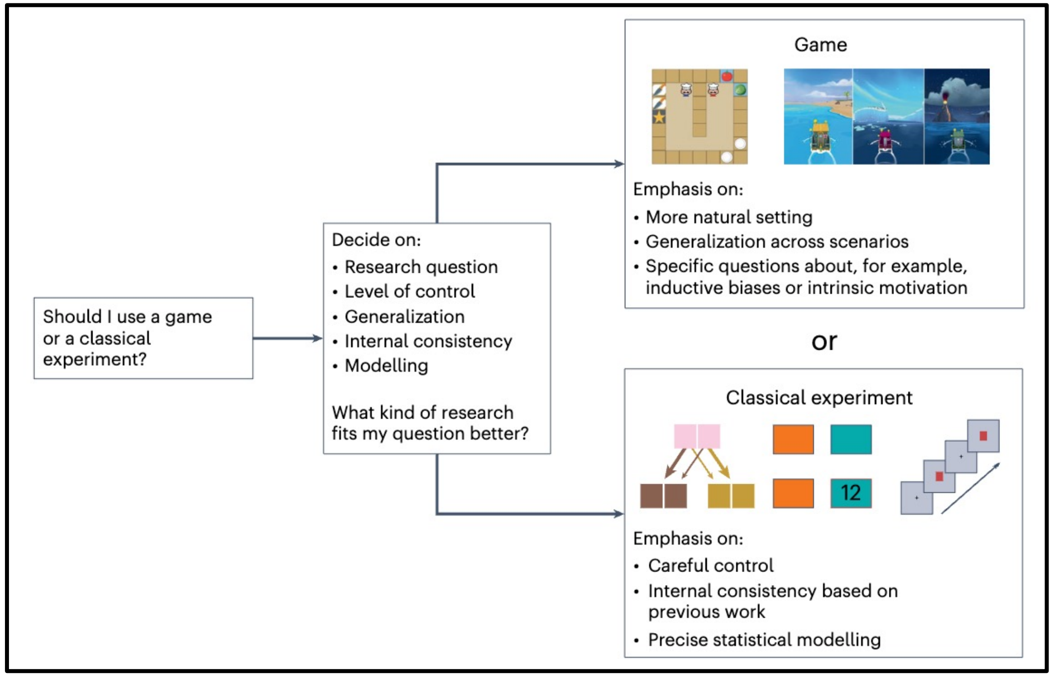
e.g., Bechara et al (1994) Cognition

How do we study RL in humans?

"Naturalistic RL tasks"



Wise et al (2023) Trends in Cog Sci



Allen et al (2024) Nature Human Behaviour

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")*
- *Data is not i.i.d.! Reward signals (learn from trials and errors)*
- *Interaction with environment*
- *Goal: "all about data" vs "all about optimization"*

What to solve with RL?

- *Maximize (cumulative) reward is not the only problem*

- *Other topics*
    - *Learning reward function from examples (inverse reinforcement learning)*
    - *Optimize environment to maximize information gain about agent (adaptive design)*
    - *Transferring knowledge between domains (transfer learning, meta-learning,*

Anguera et al (2013) Nature

Silver et al (2016) Nature

Mnih et al (2015) Nature

Machine learning / DNN in Decision Neuroscience

Neuron

CellPress

Review

Deep Reinforcement Learning and Its Neuroscientific Implications

Matthew Botvinick,[1,2,*] Jane X. Wang,[1] Will Dabney,[1] Kevin J.
[1]DeepMind, London, UK
[2]University College London, London, UK
*Correspondence: botvinick@google.com
https://doi.org/10.1016/j.neuron.2020.06.014

Article

Neuron

Using deep reinforcement learning to reveal how the brain encodes abstract state-space representations in high-dimensional environments

Molecular Psychiatry (2019) 24:1583–1598
https://doi.org/10.1038/s41380-019-0365-9

EXPERT REVIEW

Check for updates

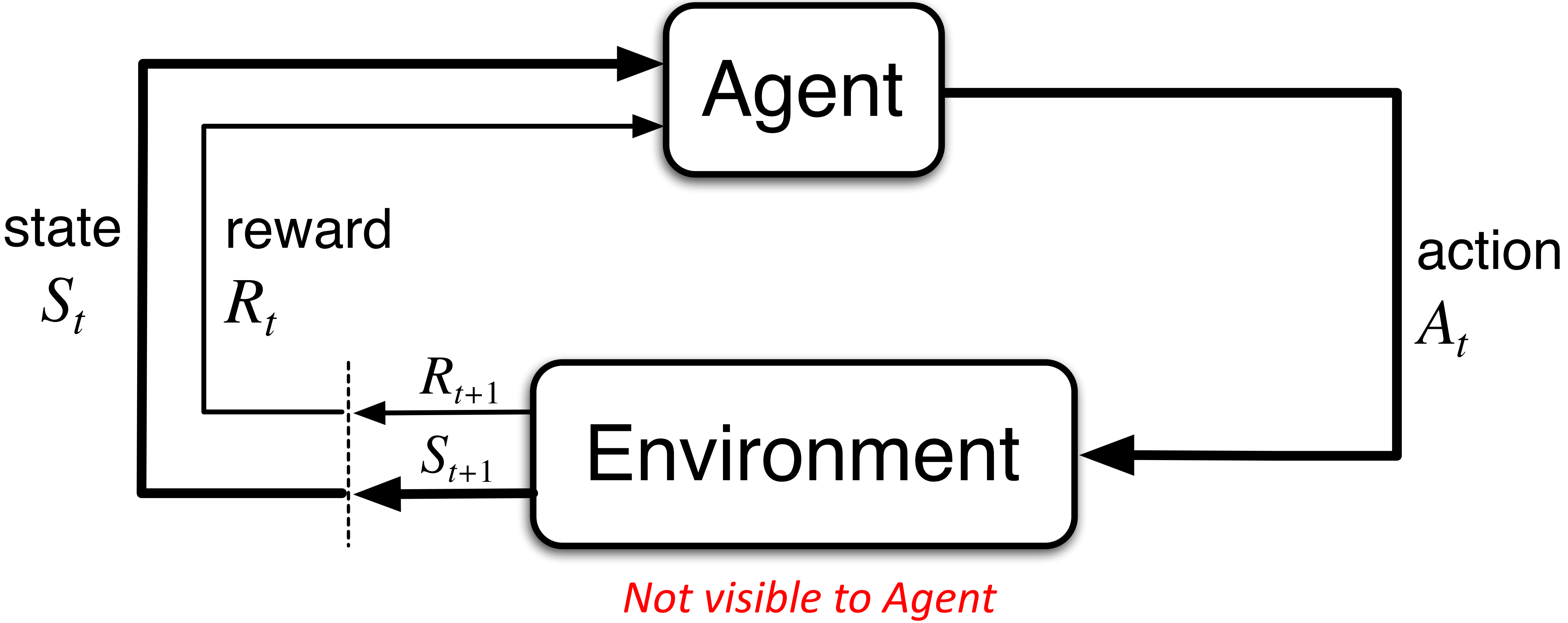
Deep neural networks in psychiatry

Daniel Durstewitz[1] · Georgia Koppe[1,2] · Andreas Meyer-Lindenberg[2]

“Learn optimal ways to make decisions” in an uncertain environment

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

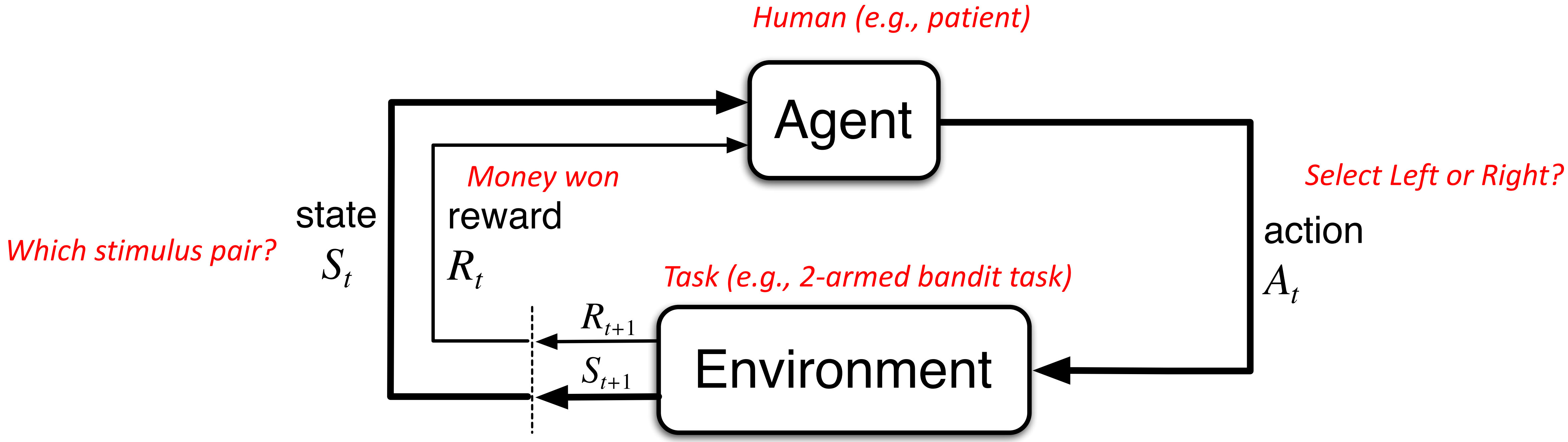
Agent-Environment Interface
(check <u>MDP lecture</u>)
e.g., Maze task, Tree search, N-armed Bandit



Sutton & Barto (1998) Reinforcement Learning

Typically in Computational Psychiatric research settings..

Model parameters → Psychologically meaningful processes/constructs



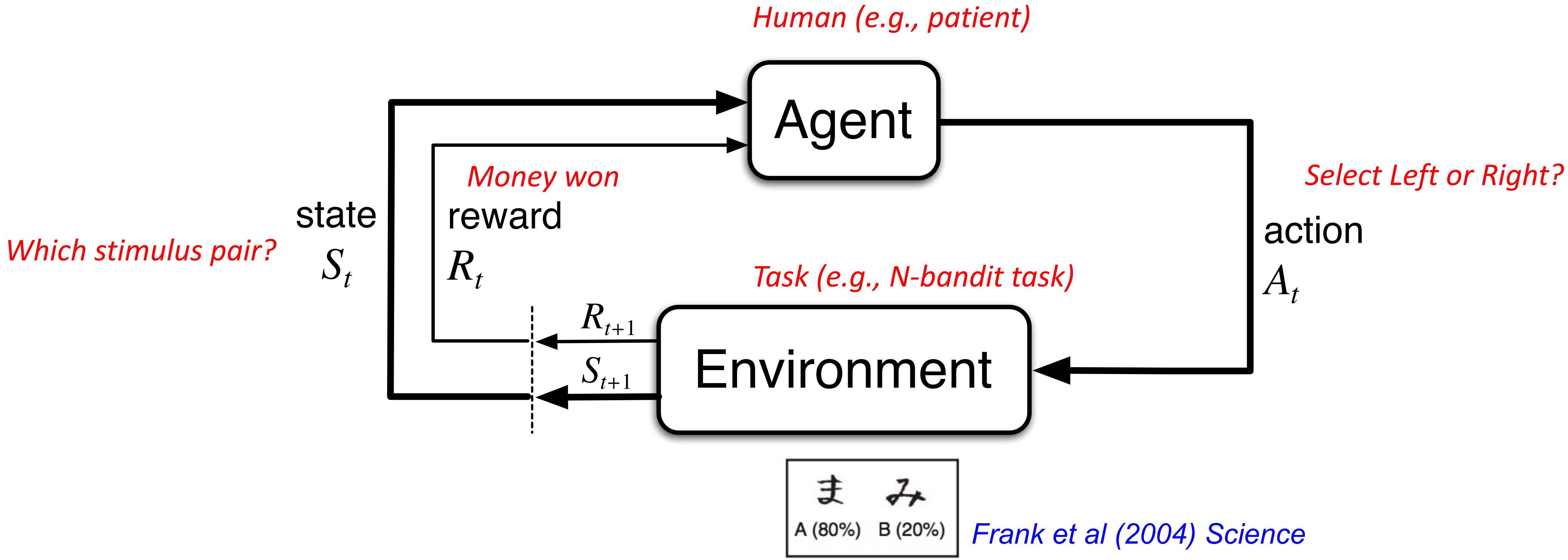
Frank et al (2004) Science

S_t: *State value on time (trial) t*

A_t: *Action value on time (trial) t*

R_t: *Reward on time (trial) t*

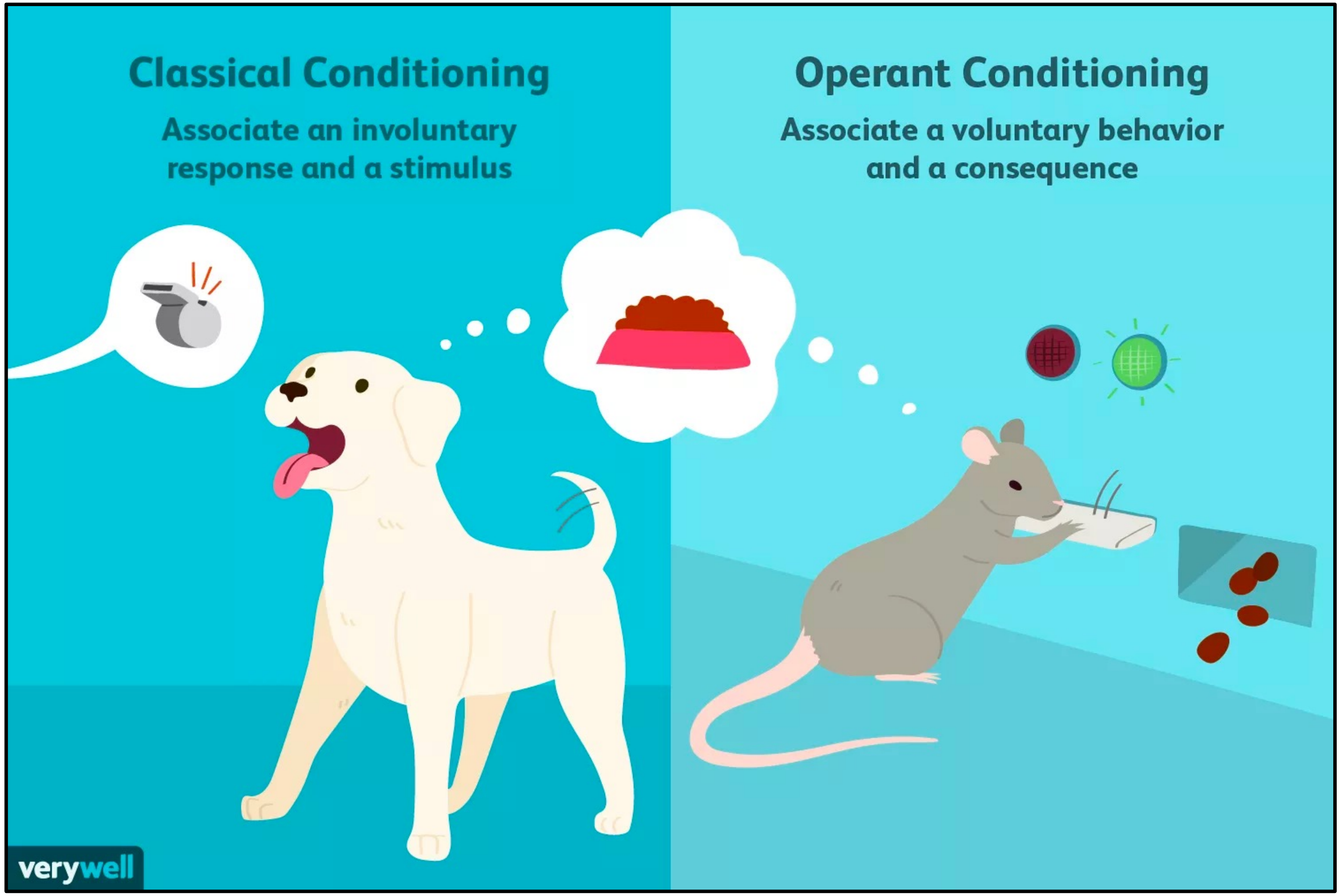
$\pi_t(a_t, s_t)$: *Policy on time (trial) t → mapping from states to actions*



Frank et al (2004) Science

RL models *(algorithms for prediction)*

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



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

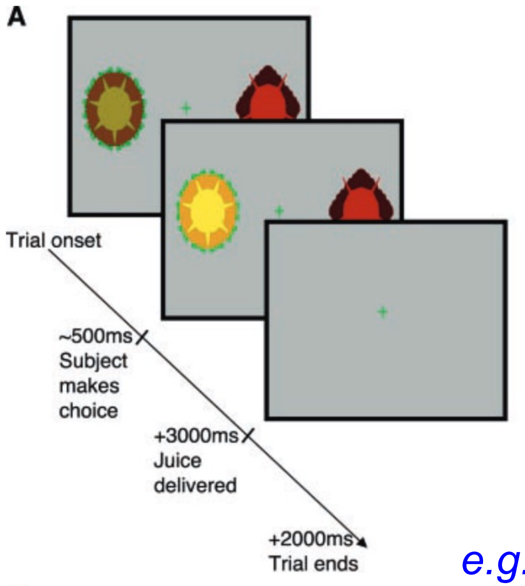
Two experimental set-ups (Not a distinction of learning mechanisms)

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

Learning rate

$$V_t = V_{t-1} + \alpha(\underbrace{R_t - V_{t-1}}_{\text{Prediction error}})$$

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

Prediction error

Classical conditioning

CS+ CS- CS Neut

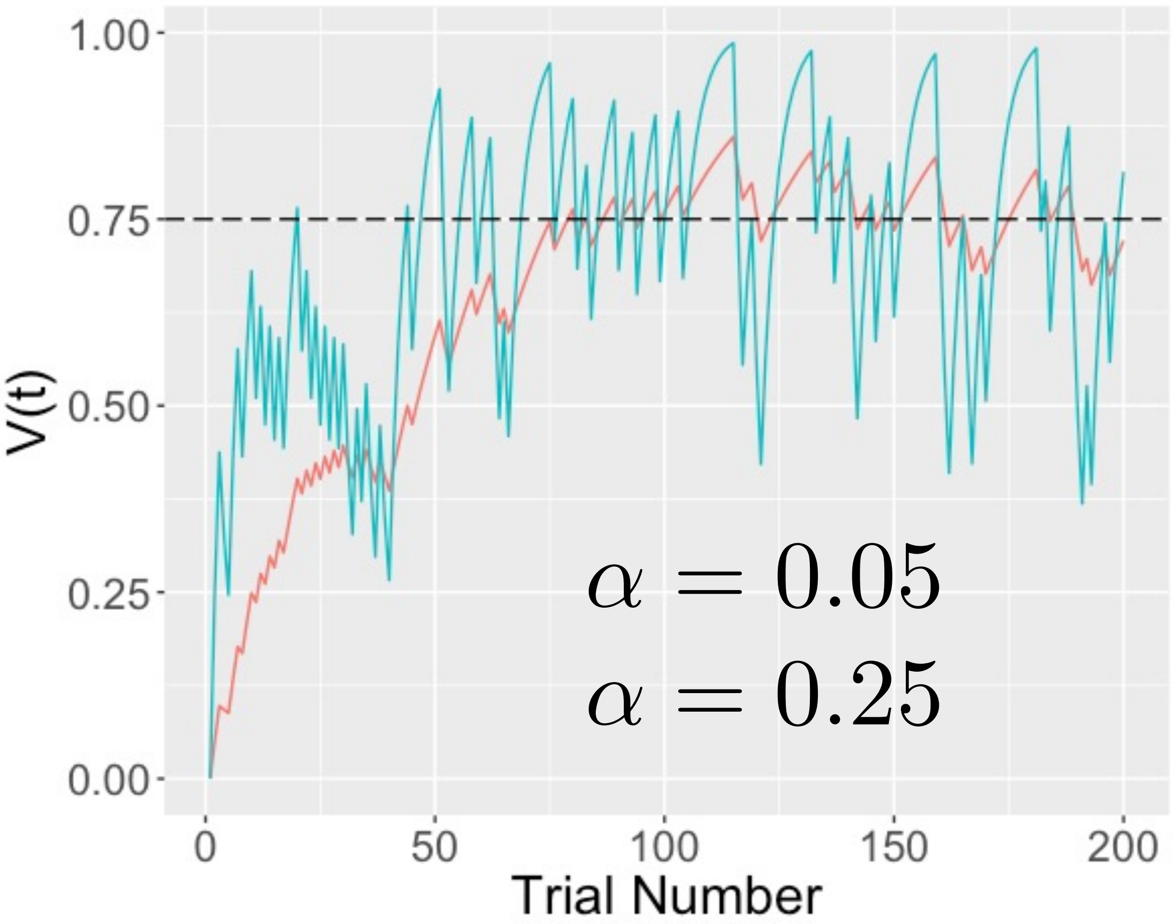
e.g., O'Doherty et al (2003) Neuron

* 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)

e.g., Reward rate = 0.75



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

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*

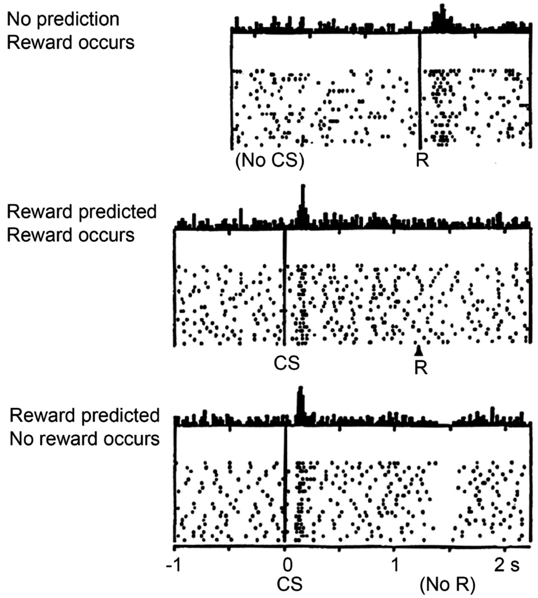
Reward Prediction Error
TD learning model

Computational roles for dopamine in behavioural control

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

[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

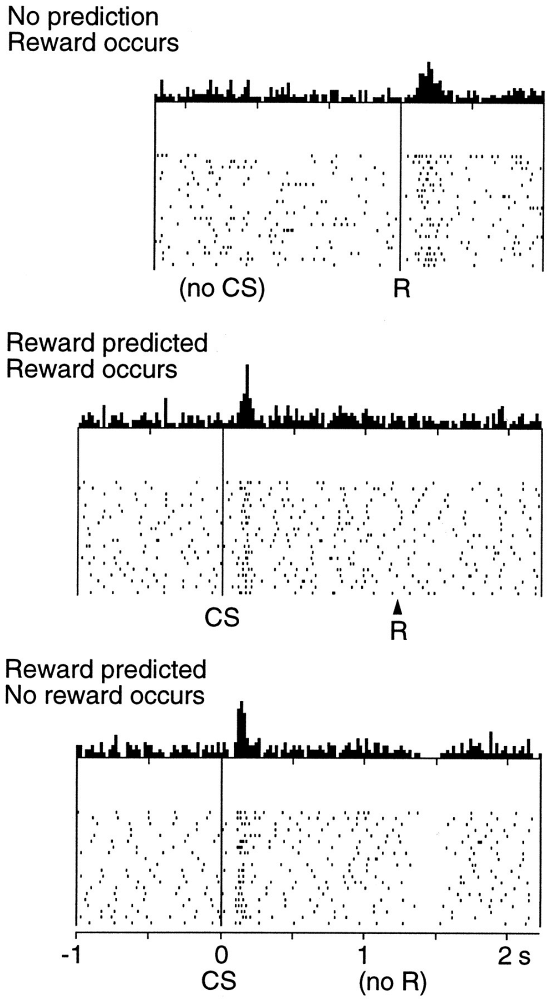
$$\delta(t) = \text{prediction error }(t) = E[r_t] + \boxed{\gamma \cdot \hat{V}(s_{t+1})} - \hat{V}(s_t)$$
$$\approx \text{current reward} + \gamma \cdot \text{next prediction} - \text{current prediction}$$

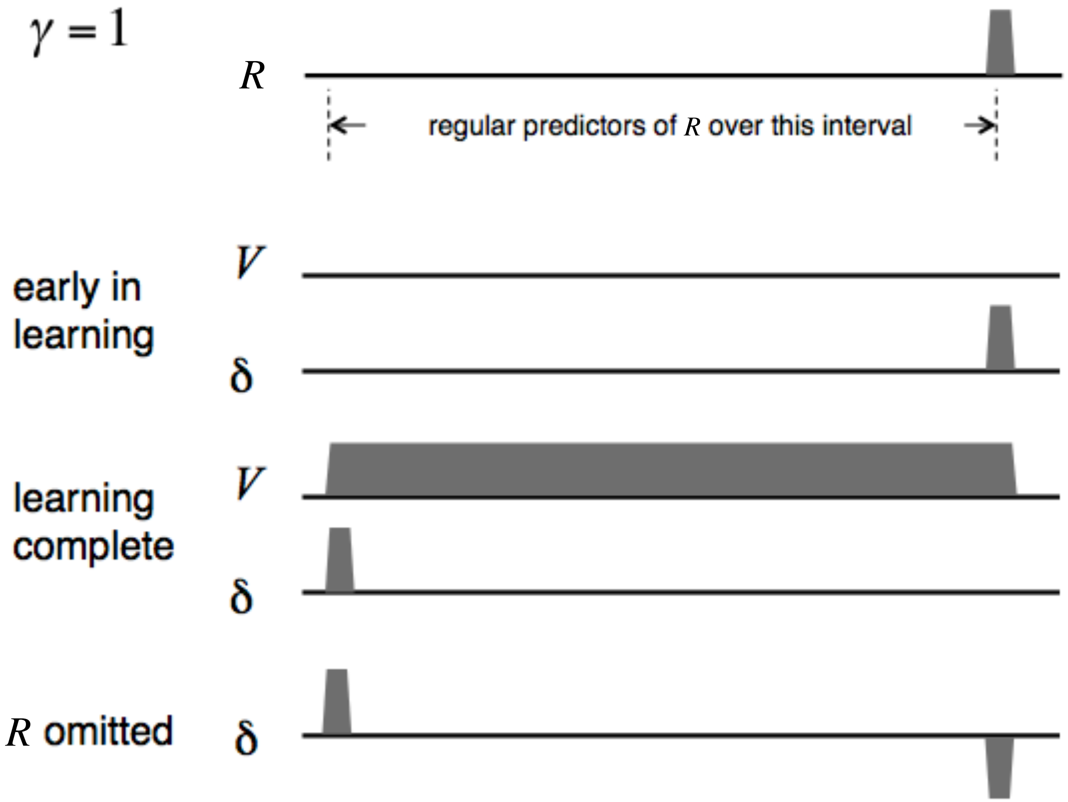
Sutton & Barto (1998) Reinforcement Learning

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

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

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





Reward onset

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

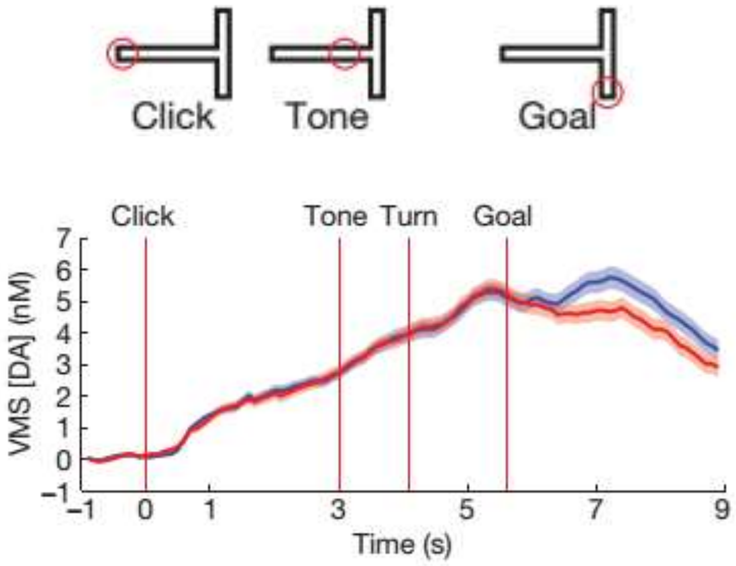
Cue onset

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

Reward onset

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

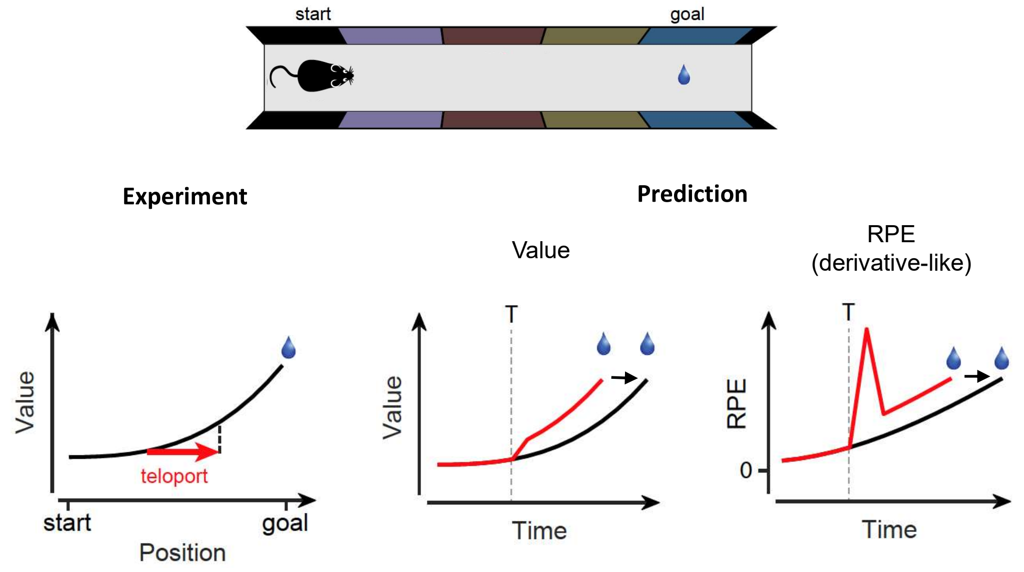
Continued discussion about reward prediction error



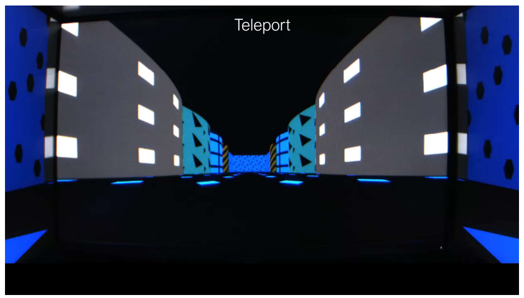
Howe et al (2013) Nature

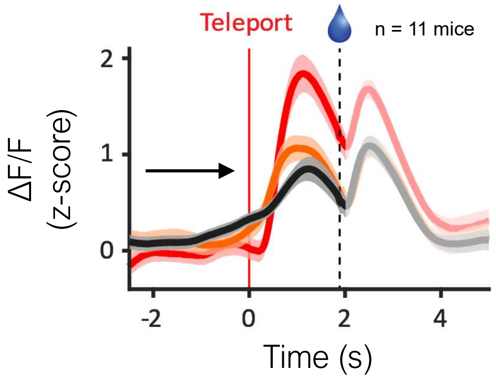
State value V(t)?
Or moment-by-moment TD error?

Gershman (2014) Neural Computation



Kim et al (2020) Cell





Instrumental learning

Model-based vs Model-free

Model-based vs Model-free

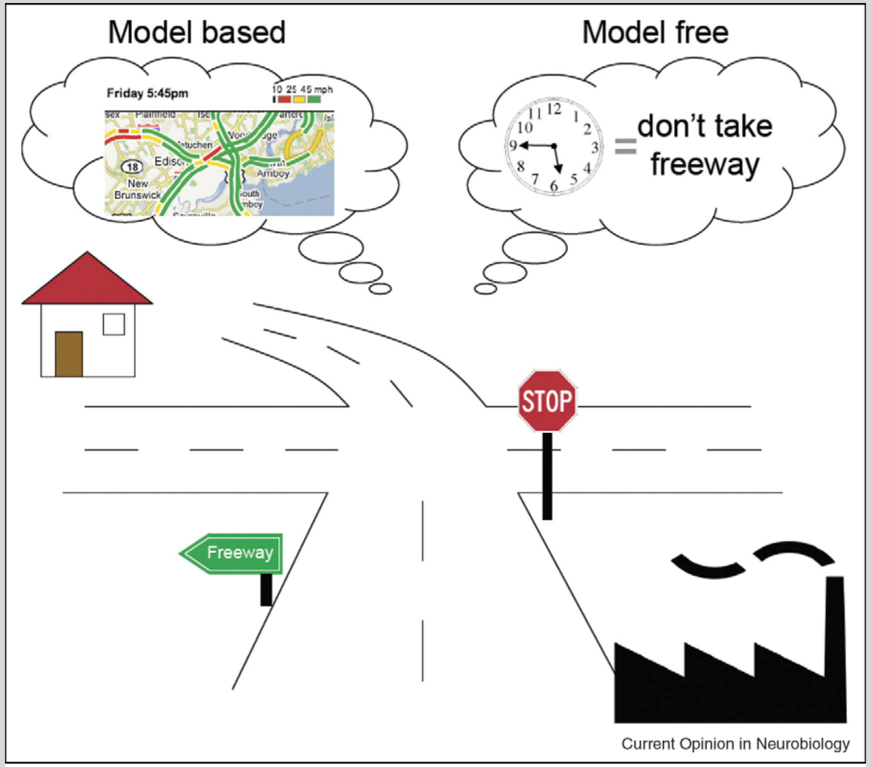


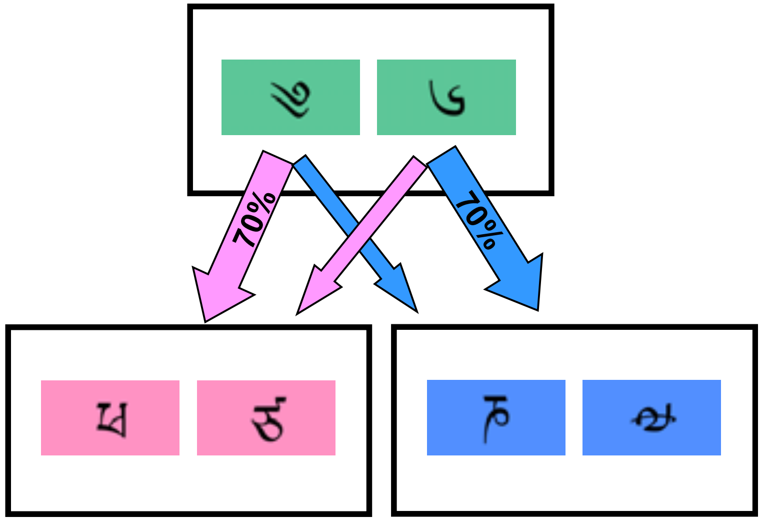
Figure 1: Two ways to choose which route to take when traveling home from work on friday evening.

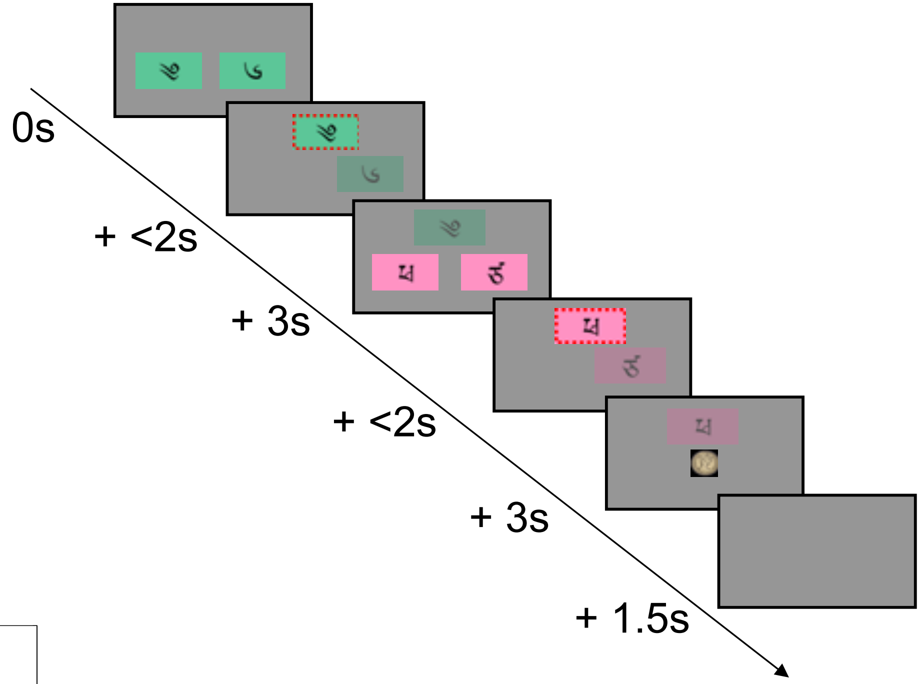
Dayan & Niv (2008)

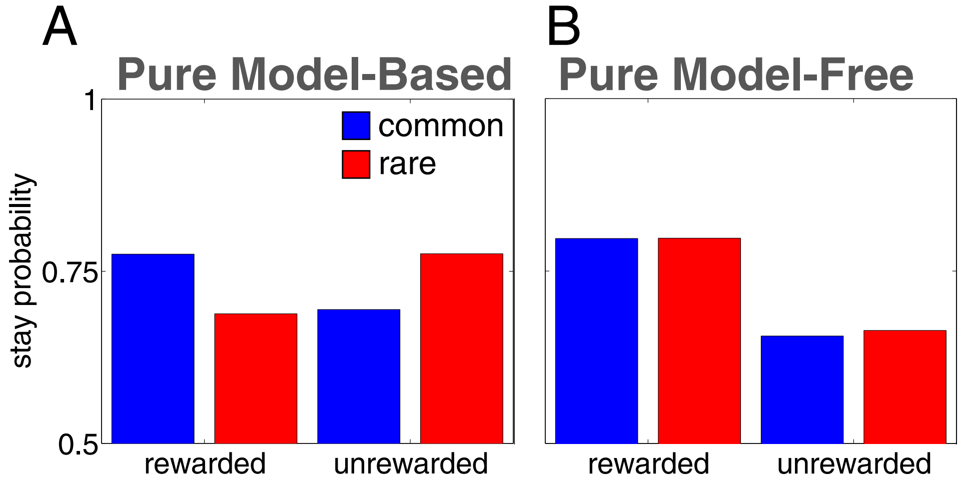
- *Model-based (goal-directed) learning: build a model of an environment. Effortful but flexible.*
- *Model-free (habitual) learning: relies on trials-and-errors. Efficient but inflexible.*
- *(Clinical) examples: compulsive behaviors, etc.*

Two-Step task

Daw et al (2011) Neuron







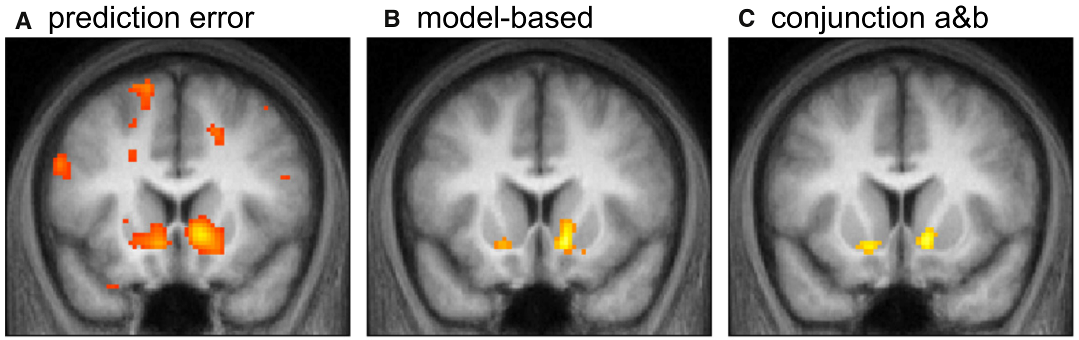
Computational model

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

PLOS | COMPUTATIONAL BIOLOGY

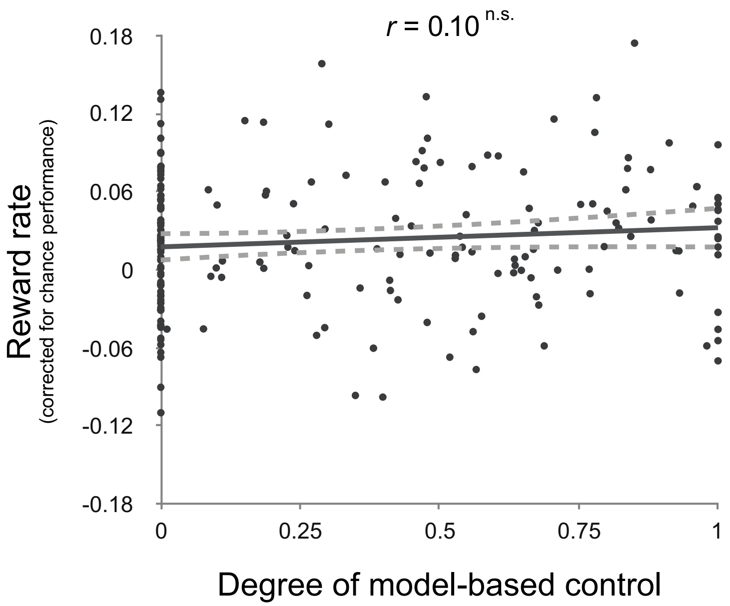
RESEARCH ARTICLE

When Does Model-Based Control Pay Off?

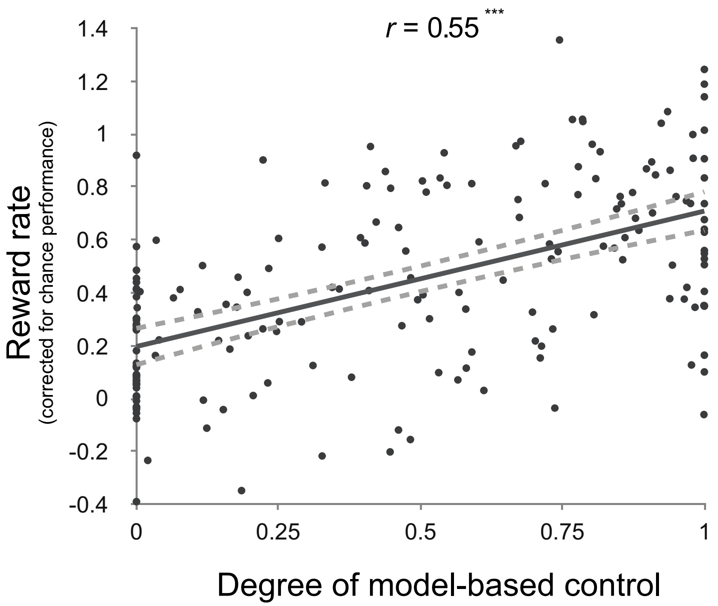
Wouter Kool[1]*, Fiery A. Cushman[1☯], Samuel J. Gershman[1,2☯]

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

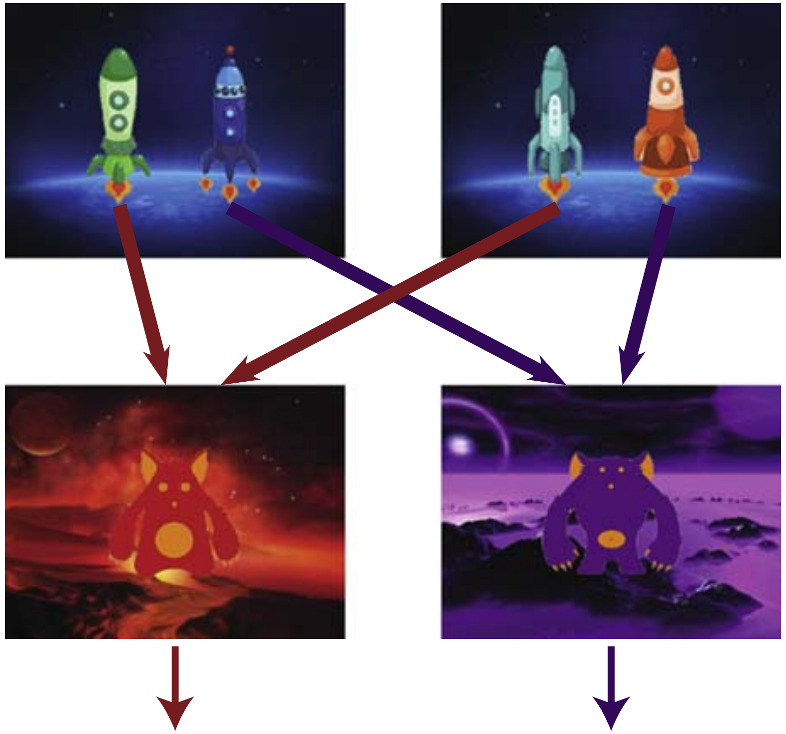
☯ These authors contributed equally to this work.
* wkool@fas.harvard.edu



Daw Two-Step Task



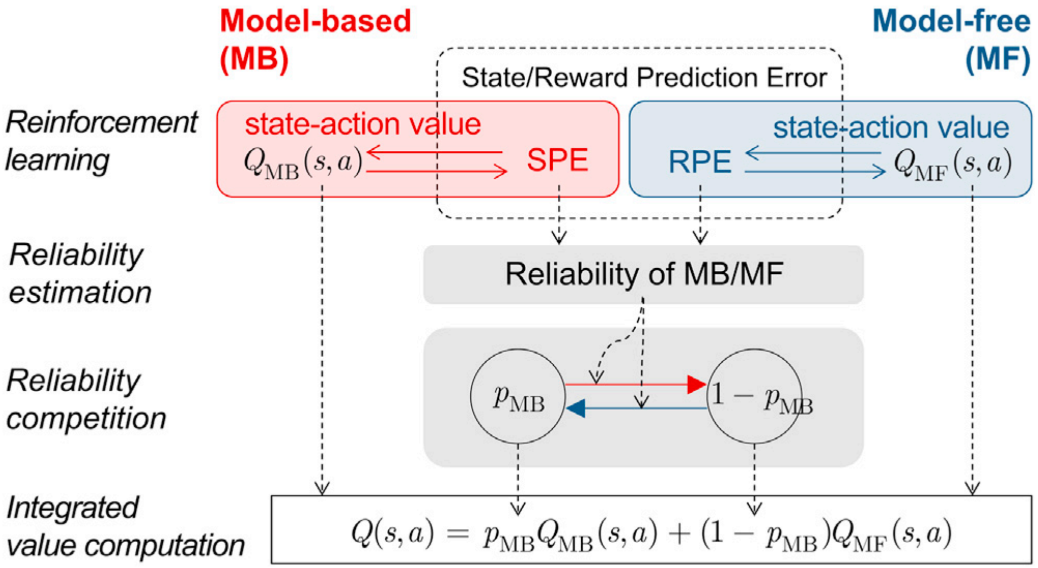
Kool Two-Step Task

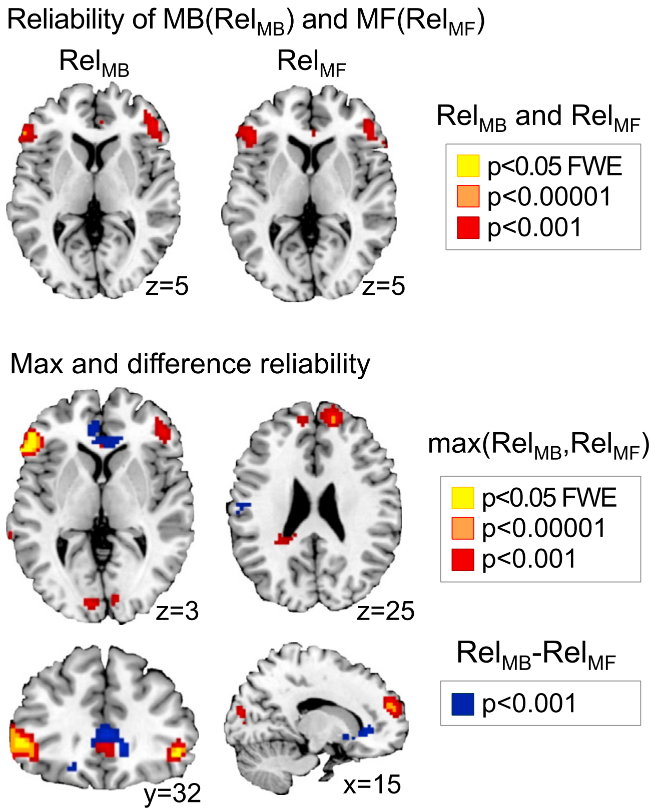


Opportunity to obtain reward (changing over time)

Kool et al (2016) PloS Comput Biol

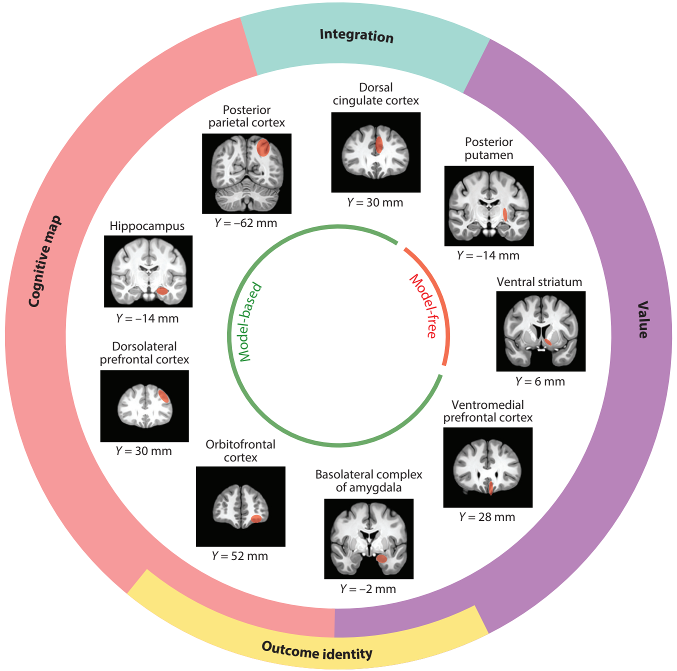
Reliability-based arbitration between model-based and model-free



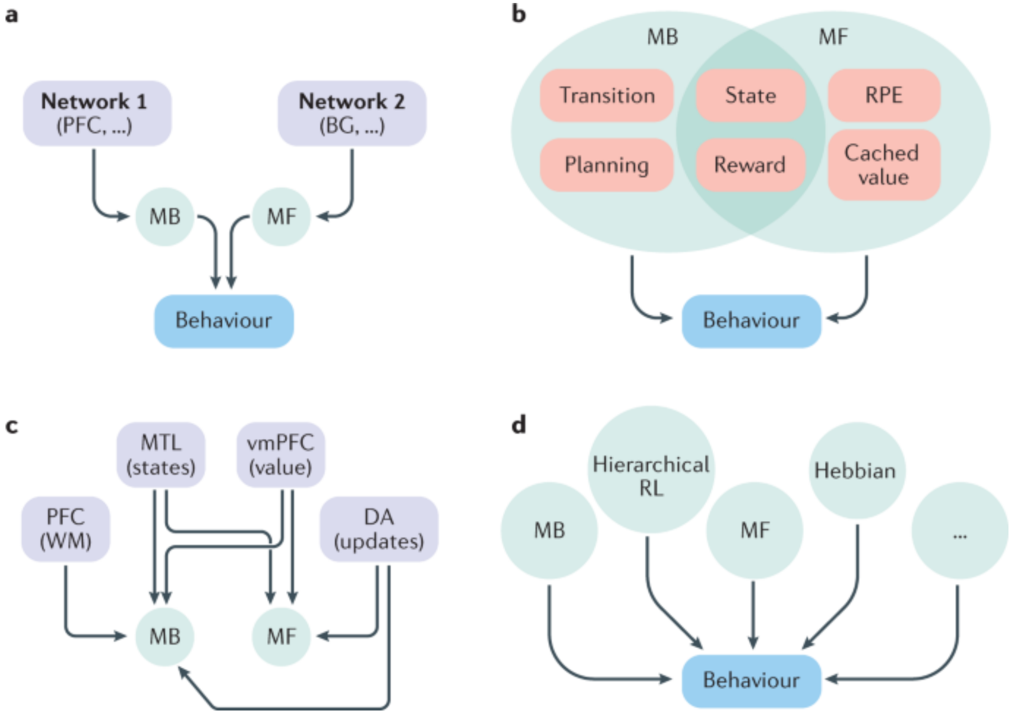


Lee et al (2014) Neuron
Daw et al (2005) Nature Neuroscience
Wang et al (2018) Brain & Neuro. Advances

Inferior lateral prefrontal and frontopolar cortex



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



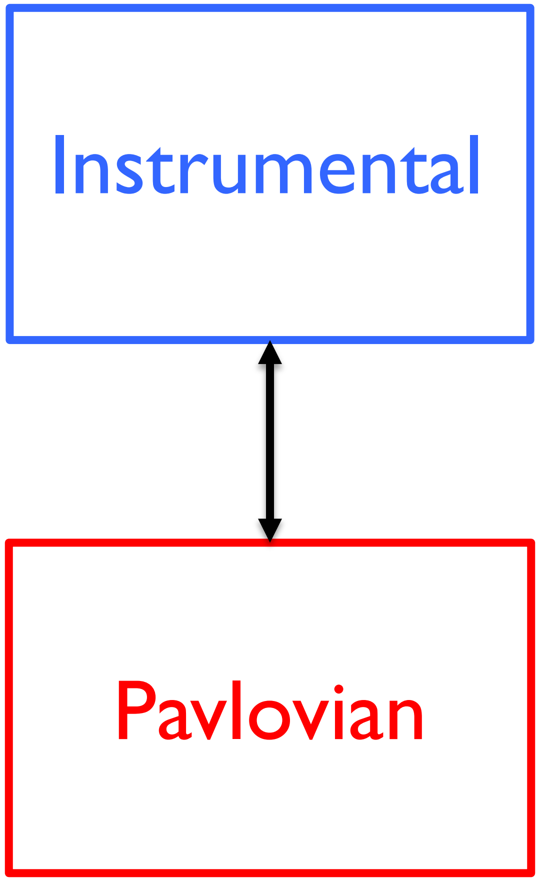
Collins & Cockburn (2020) Nature Reviews Neuroscience

Current Biology
Review

The Role of Hippocampal Replay in Memory and Planning

H. Freyja Ólafsdóttir[1], Daniel Bush[2], and Caswell Barry[1]

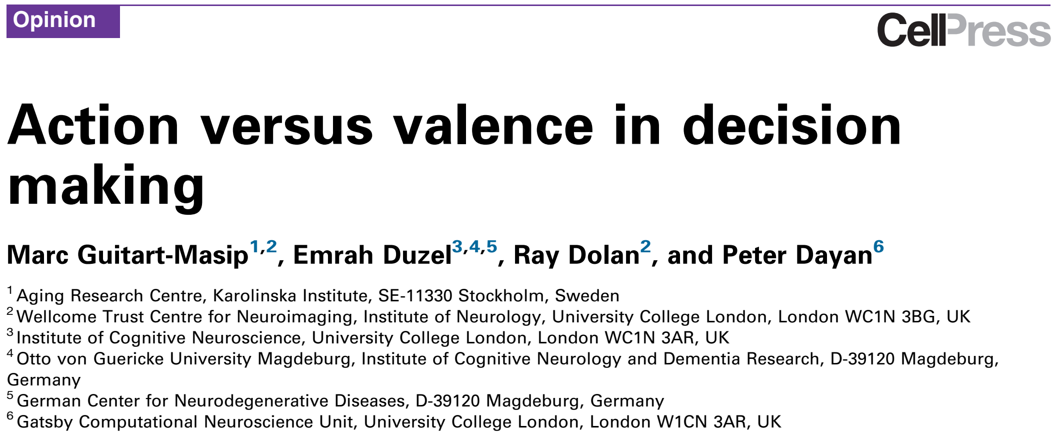
Pavlovian vs Instrumental control



"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)

Orthogonalized Go/Nogo task
Pavlovian-Instrumental competition

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

Instrumental

"Learn what's best"

Approach for (+)
Withdraw from (-)

"Pavlovian bias"

Pavlovian

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

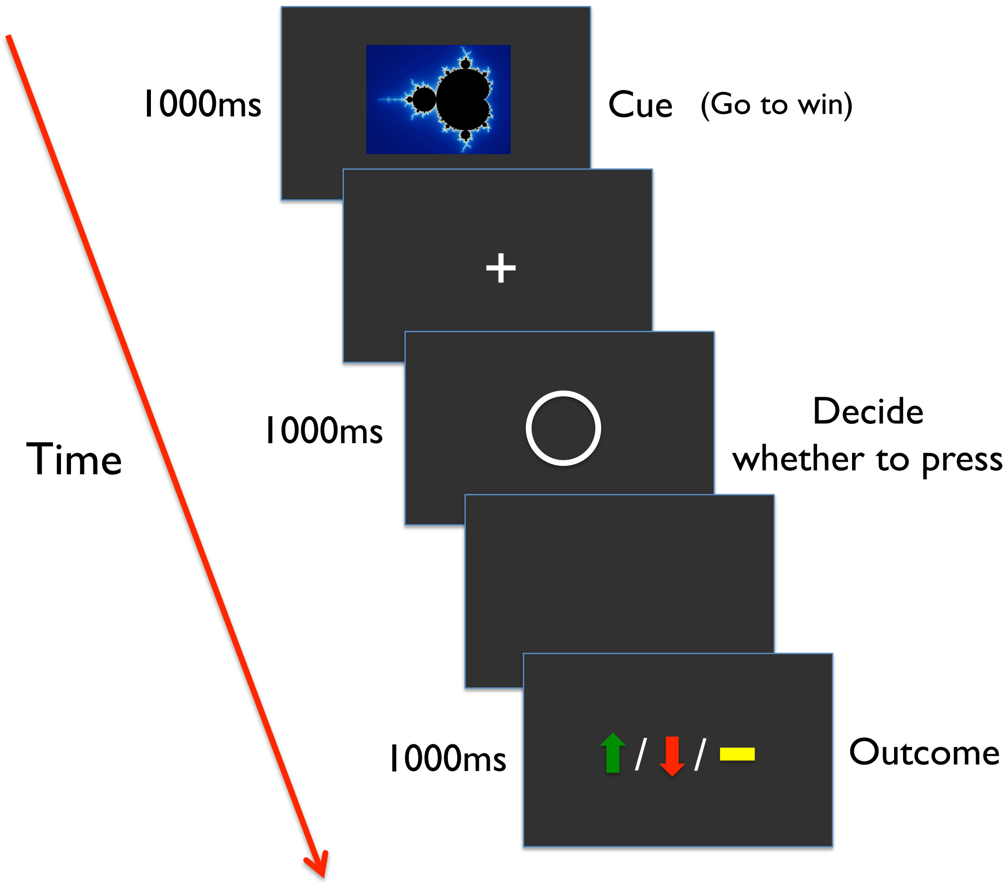
	Loss	Gain
Go	Go to avoid	Go to win
Nogo	Nogo to avoid	Nogo to win

Pavlovian congruent

Pavlovian incongruent

- *4 cues (conditions)*

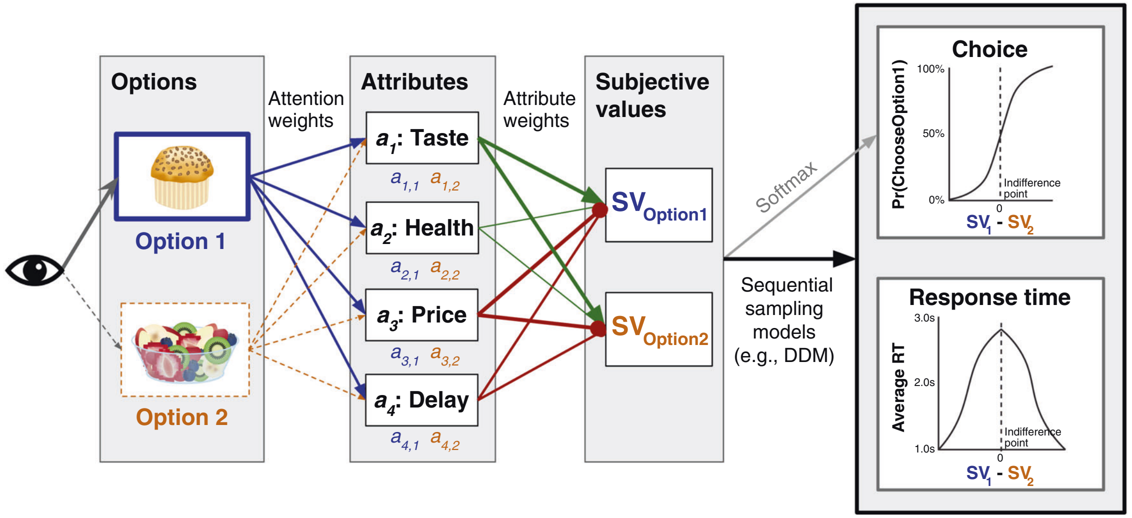
  2 actions (Go / Nogo) x
  2 valence (Gain / Loss)



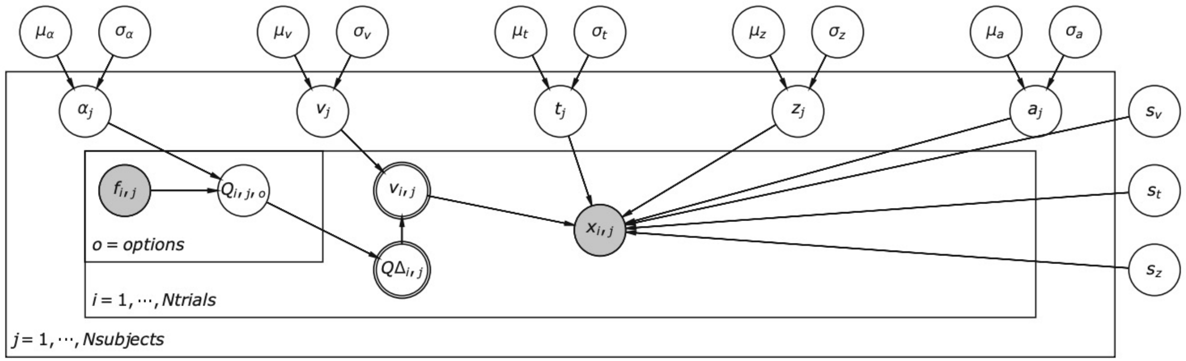
Guitart-Masip et al (2012) Neuroimage
Cavanagh et al (2013) J Neuro

More…

RL + sequential sampling models



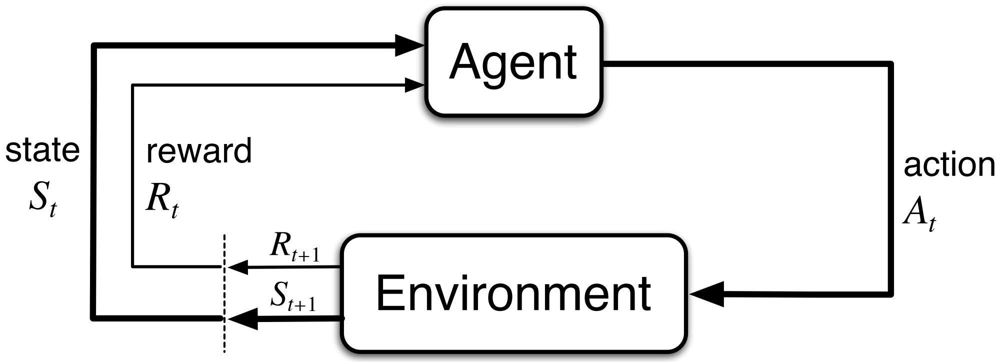
Collins & Shenhav et al (2021) Neuropsychopharmacology

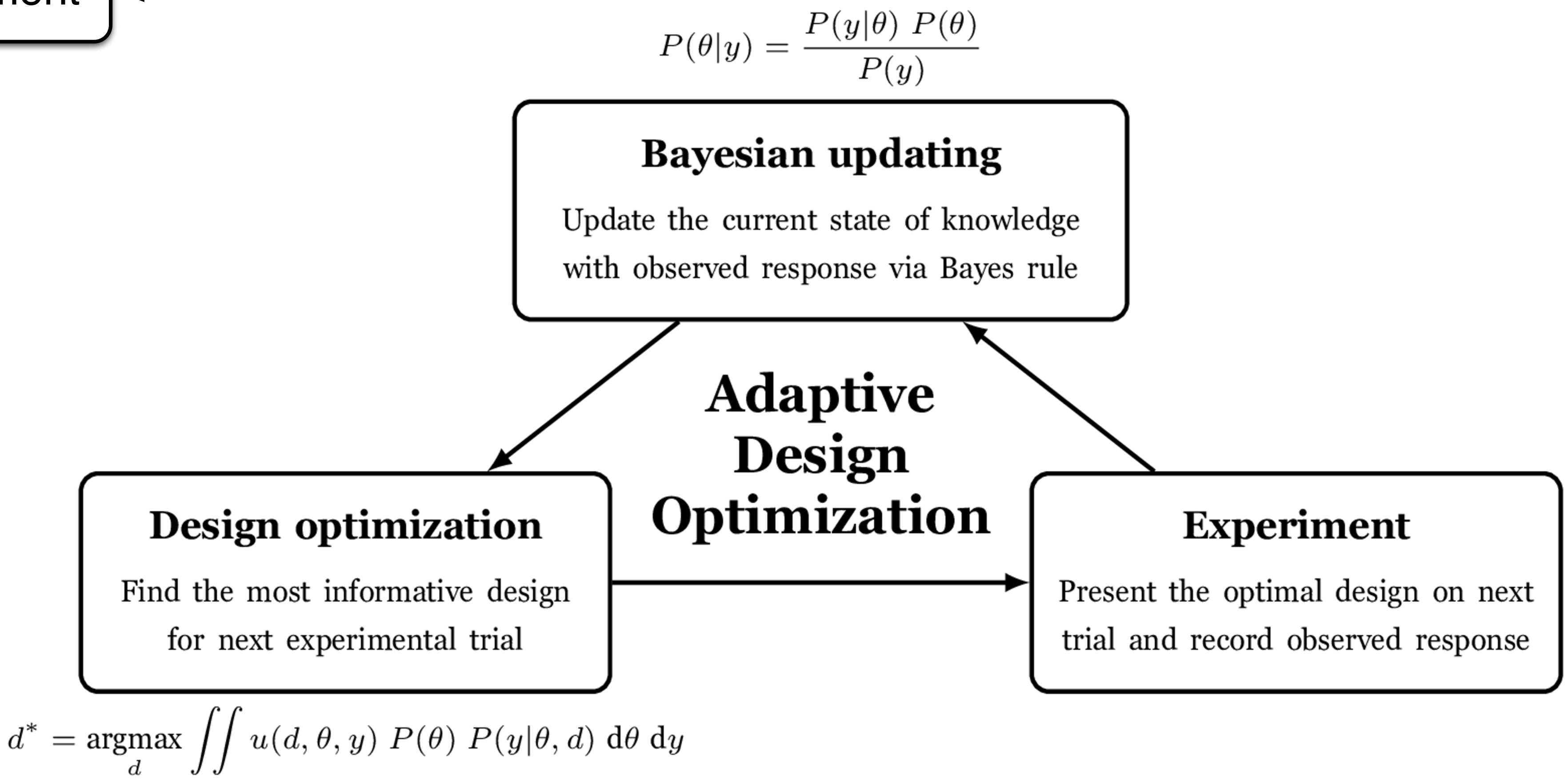


Pedersen & Frank (2020) Computational Brain & Behavior

Adaptive Design Optimization
within the RL framework

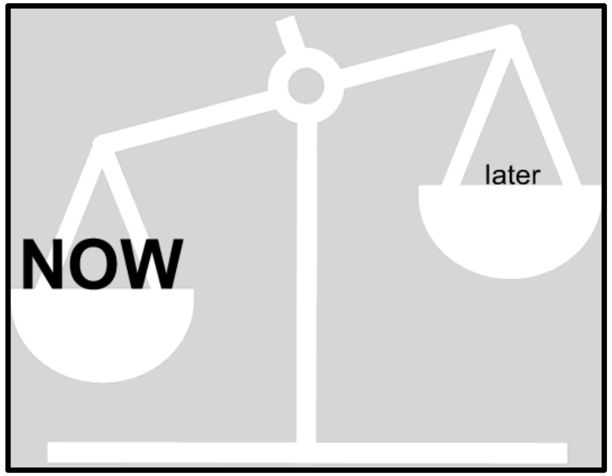
<u>Optimize experiments on the fly!</u>


Agent
state
S_t
reward
R_t
action
A_t
R_{t+1}
S_{t+1}
Environment


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

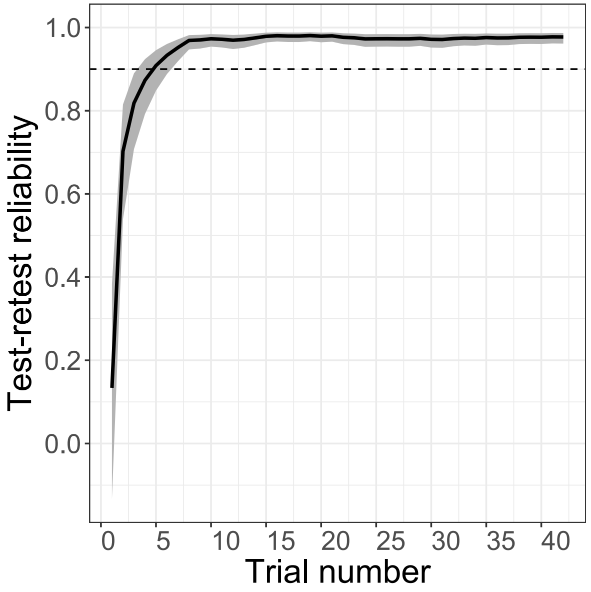
Design & Conduct a mini-experiment on every trial
“What’s the most informative design (d^*) we should use?”

e.g., <u>$320</u> now vs $800 in <u>3 years</u>

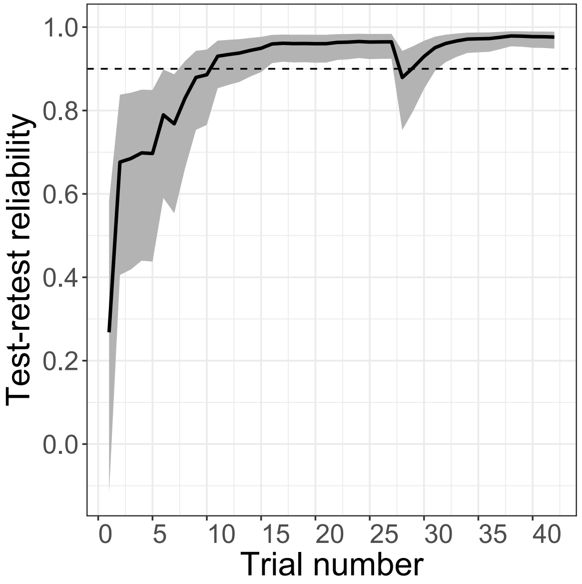
Observe Data (y)

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

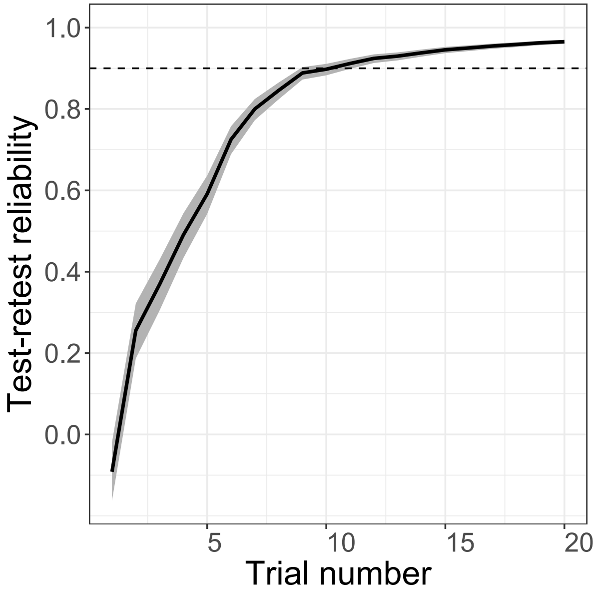
Up to 0.98 test-retest reliability within ~10 trials



College students

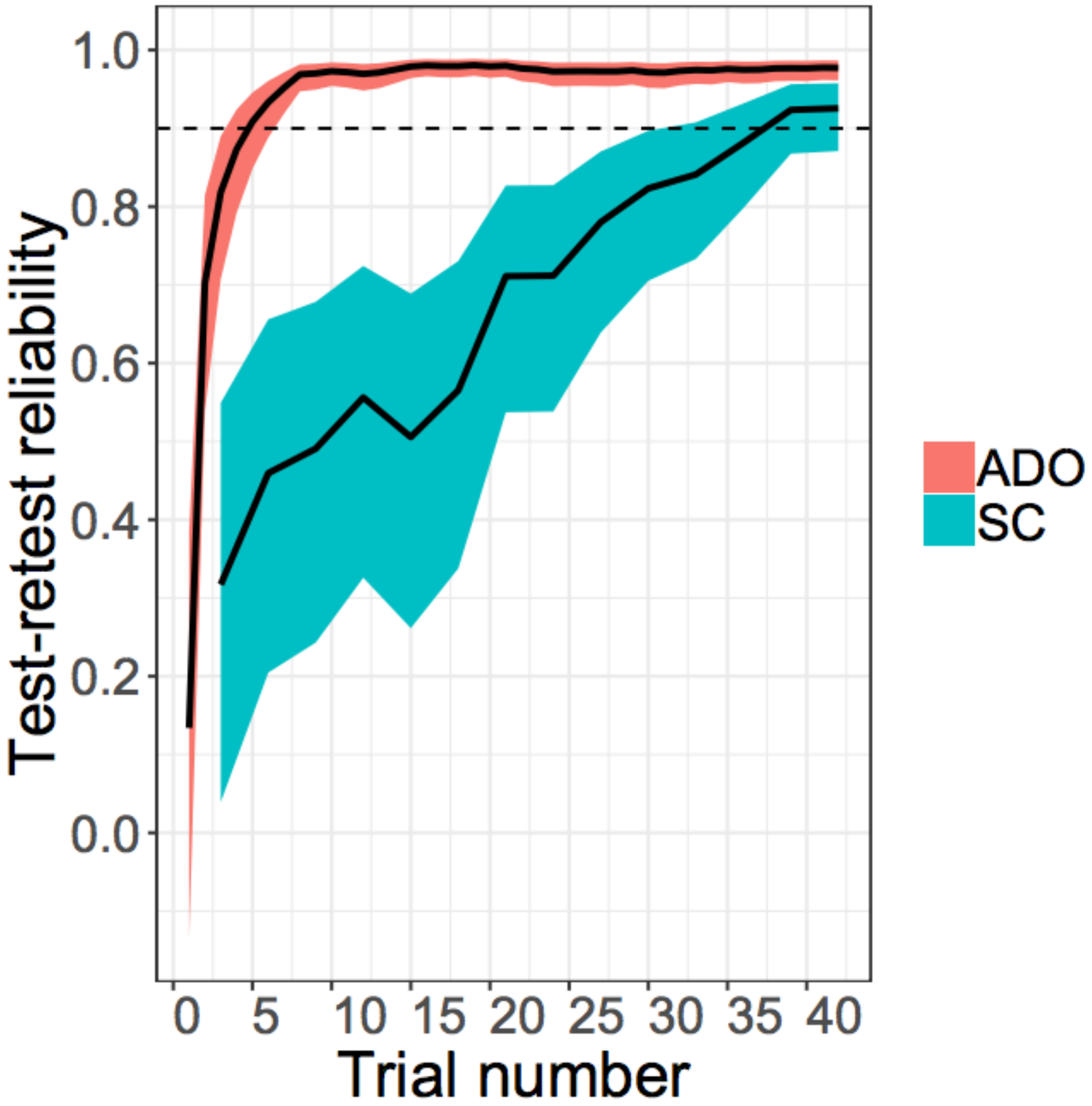


Patients with SUDs



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
Adaptive Design Optimization for Experimental Tasks

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**

Yang, Pitt, Ahn, Myung (2020) Behavior Research Methods https://github.com/adopy/adopy

ADOpy

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

ADOpy

Adaptive Design Optimization for Experimental Tasks

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.

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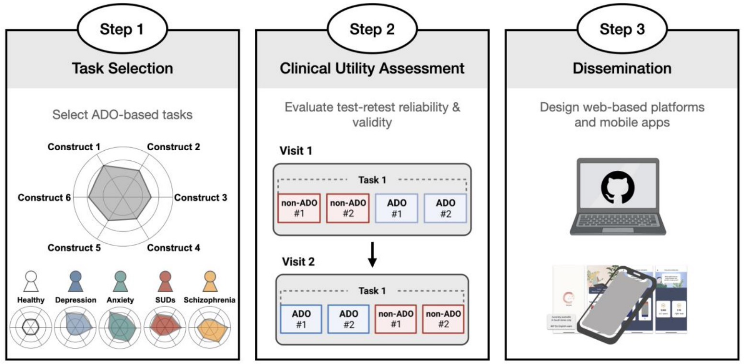
Resources

- Getting s
- Documen
- Bug repo



Utility of adaptive design optimization for developing rapid and reliable behavioral paradigms for substance use disorders

Project Number	Contact PI/Project Leader	Awardee Organization
1R01DA058038-01	VASSILEVA, JASMIN LOther PIs	VIRGINIA COMMONWEALTH UNIVERSITY

Contact PI/ Project Leader

Name
VASSILEVA, JASMIN L

Title
ASSOCIATE PROFESSOR

Contact
View Email

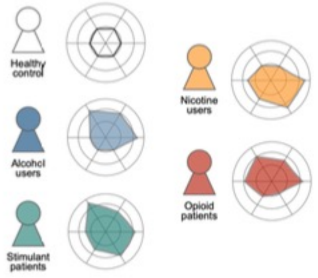
Other PIs

Name
AHN, WOO-YOUNG

Program Official

Name
PARIYADATH, VANI

Contact
View Email

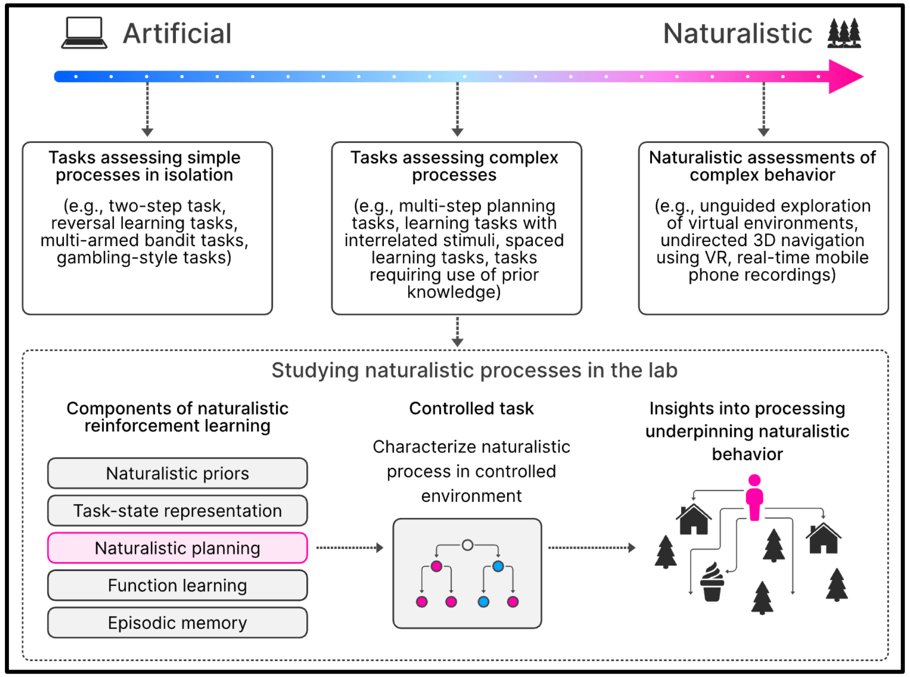


NIH / NIDA R01 (2023-2028)
MPI: Vassileva & __Ahn__

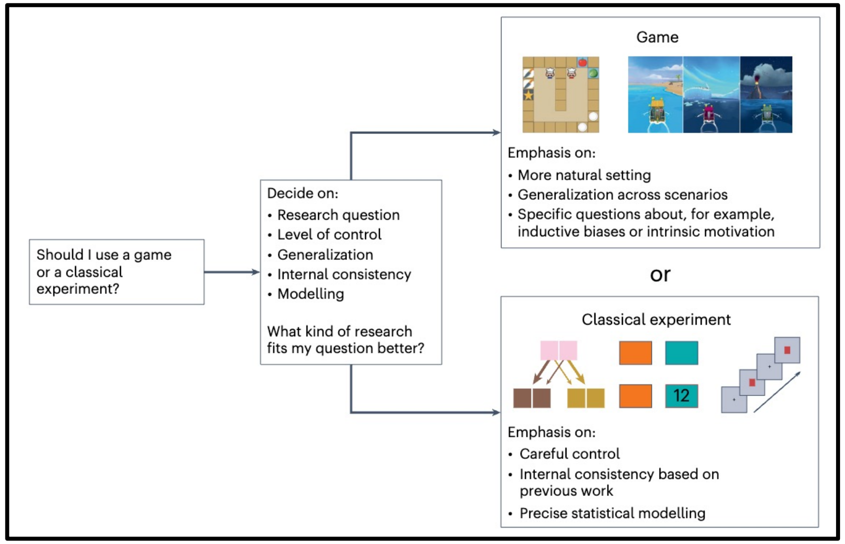
Yang, Pitt, Ahn, Myung (2020) Behavior Research Methods
Kwon, Lee, & Ahn (2023) Biol. Psychiatry: CNNI
Vassileva, Lee, Psederska & Ahn (2023) Computational Neuroscience

Last but not the least major limitation

Overly simplified "toy" problems/tasks



Wise et al (2023) Trends in Cog Sci



Allen et al (2024) Nature Human Behaviour

Overly simplified "toy" problems/tasks

Current gap

"Snap shots" of real-life tasks

"Toy" tasks overly simplify real-life problems

Empirical studies limited to secondary reward

Computational psychiatry

EMA
Digital phenotyping

Real-time, real-world
High-dimension

Utilize primary reward jointly with neuroimaging tools

Overall goal

Predictability and reliable measures to better understand psychiatric disorders

Ahn, Lee, & Kim (invited review) Current Directions in Psychological Science

Real-time Driving task


Sang-Ho Lee


Min-hwan Oh

"Real" reward (nicotine)


Josh Brown


Jeung-Hyun Lee

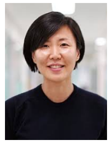

Eunhwi Lee

Naturalistic (movie) paradigm


Monica Rosenberg


Mina Kwon

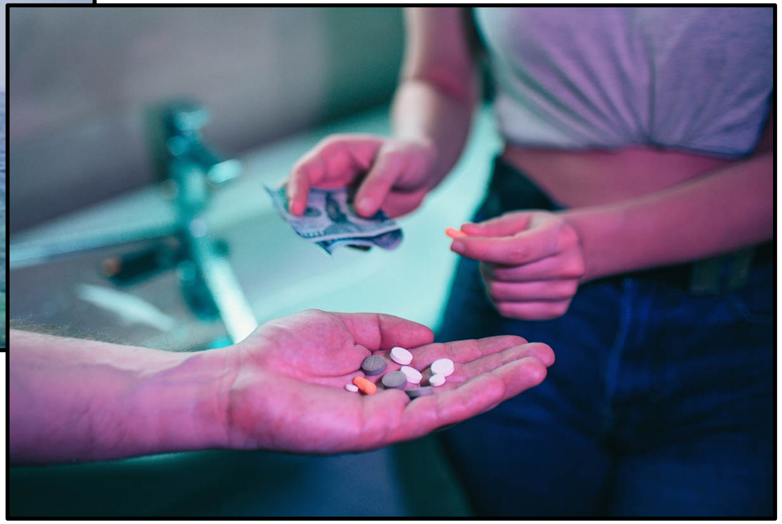
Real-time Minecraft

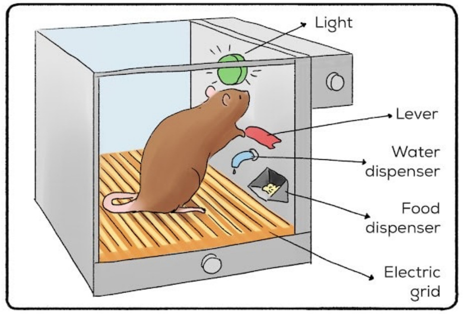

Wonmok Shim


Hyeonmin Lee

Overly simplified "toy" problems/tasks → Real-time/real-world tasks

Sang-Ho Lee





Lee, Song, Oh, & Ahn (2024) Psychological Science

Measures of Impulsivity

- ***Self-report measures*** *and* ***Behavioral measures*** *are the two most widely used methods to assess impulsivity.*

Self-report measures

- *Barratt Impulsiveness Scale*
- *UPPS Impulsive Behavior Scale*
- *Eysenck Impulsivity Scale*

Impulsivity

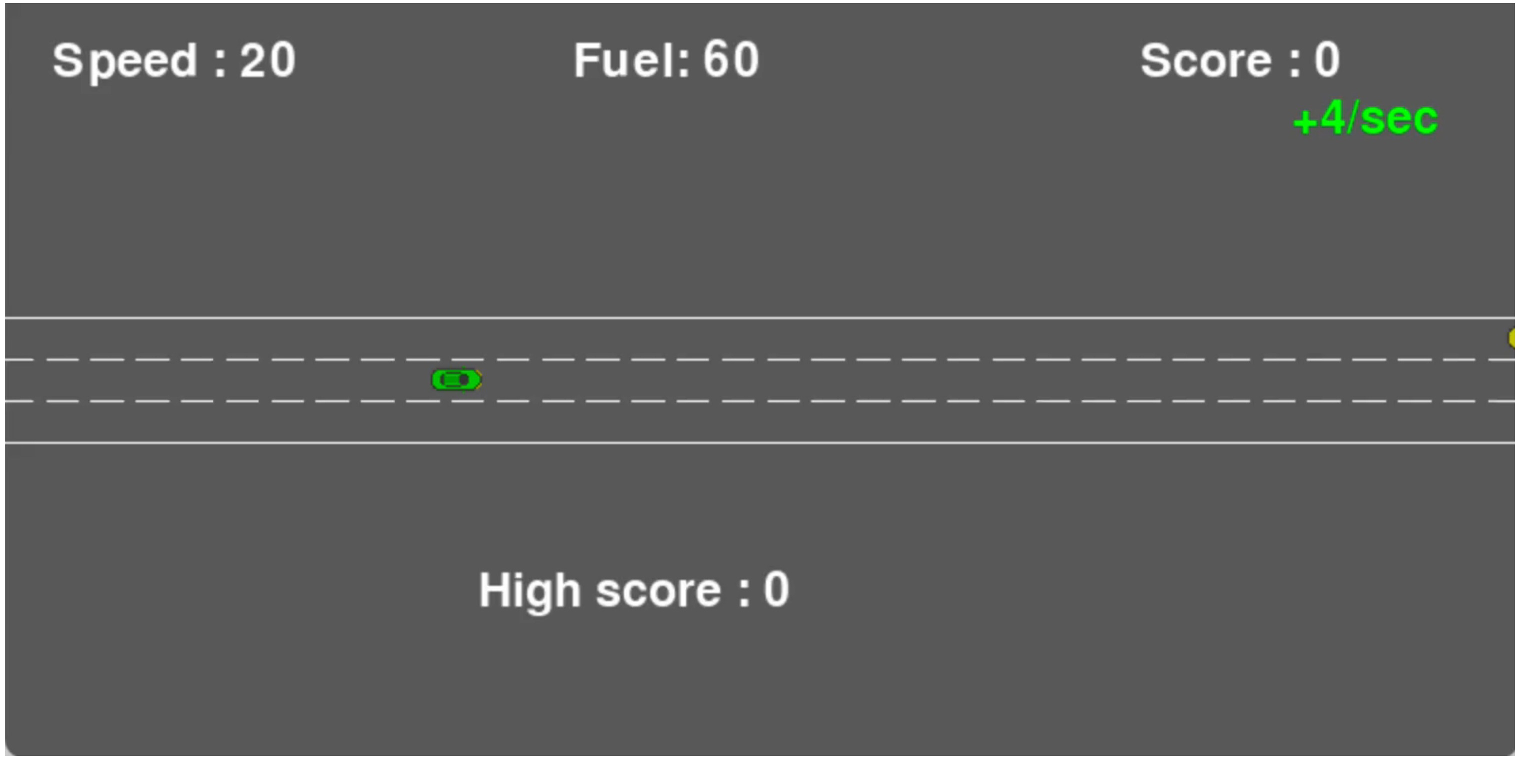
Behavioral measures

- *Go/no-go task*
- *Stop signal task*
- *Delay discounting task*
- *Balloon Analogue Risk Task*
- *Stroop task*

- ***A Challenge:*** *Self-report measures and behavioral measures often show weak correlations with each other.*

Sharma et al (2014), Saunders et al. (2018), Murphy et al (2016), Frey et al. (2017), Dang et al (2020)

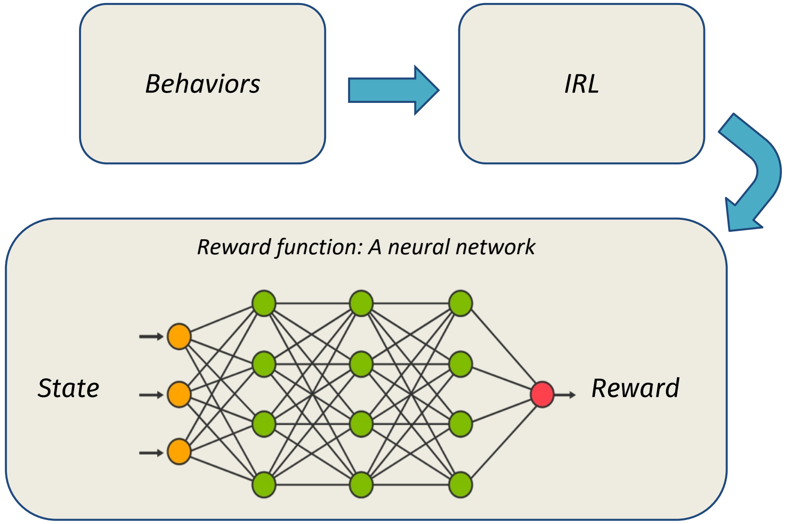
(Real-time) "Highway Task"



Lee, Song, Oh, & Ahn (2024) Psychological Science

Inverse Reinforcement Learning

Arora, Doshi (2021)
Fu et al (2017)



To model complex behaviors in a real-time task, we harness deep neural networks + inverse reinforcement learning (IRL).

- *IRL infers reward structures underlying observed behaviors.*

Min-hwan Oh

Algorithm 1 Adversarial inverse reinforcement learning

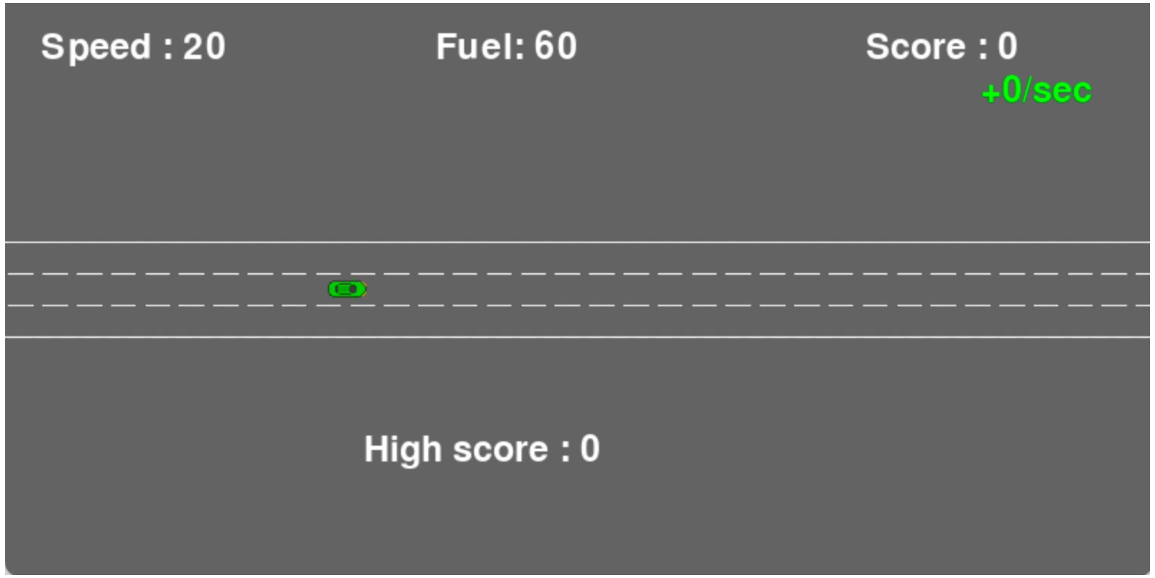
for iteration i in {1,..., N} **do**
  Obtain observed trajectories τ_i^O from the data.
  Initialize discriminator $D_{\theta,\phi}(s,a,s')$ and policy π.
  for step t in {1,..., T} **do**
    Sample trajectories τ_i using the policy function π.
    Train $D_{\theta,\phi}$ to classify the data τ_i^O from samples τ_i.
    Update reward $r(s,a,s') \leftarrow \log\left(D_{\theta,\phi}(s,a,s')\right) - \log\left(1 - D_{\theta,\phi}(s,a,s')\right)$.
    Update policy π with respect to $r(s,a,s')$.
  end for
end for

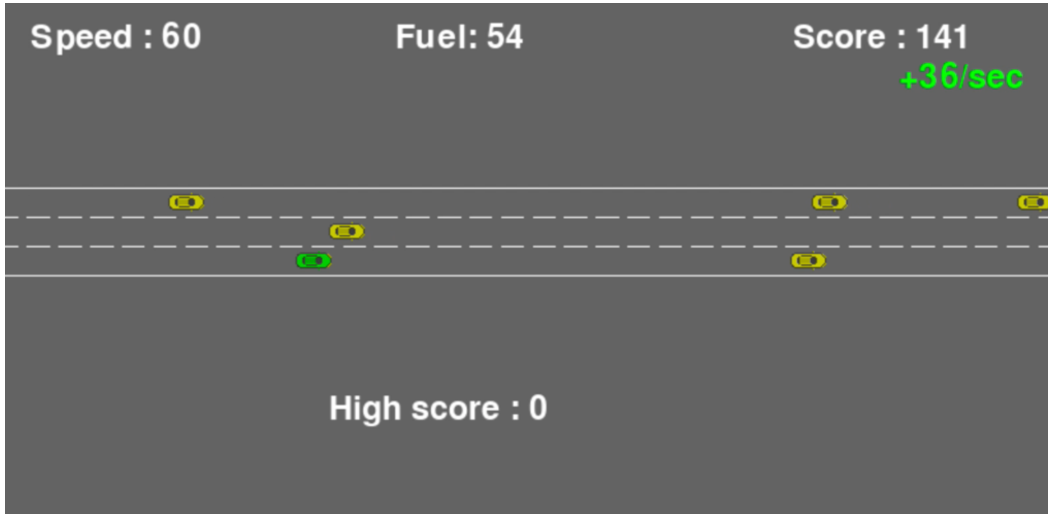
We aim to explore individual differences in impulsivity by comparing individual reward structures inferred by IRL.

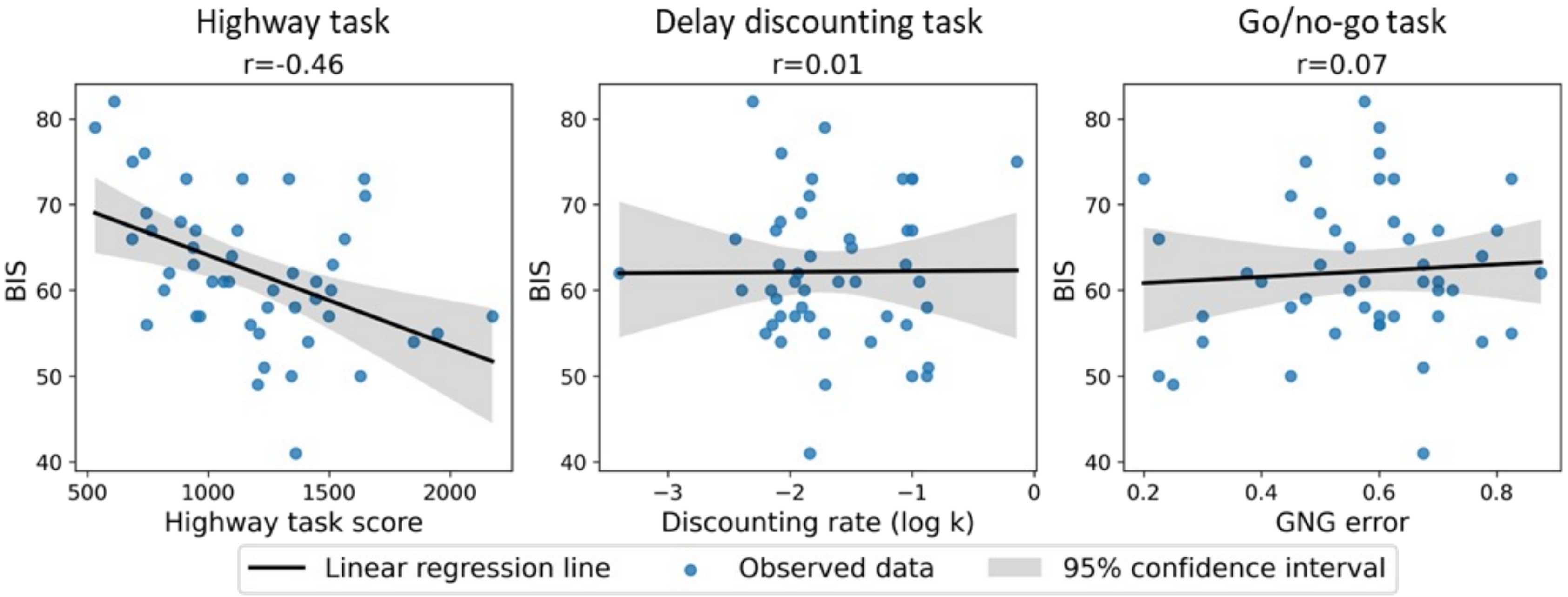
Lee, Song, Oh, & Ahn (2024) Psychological Science

Task Performance Example

- *This is an agent trained by deep Q-learning.*





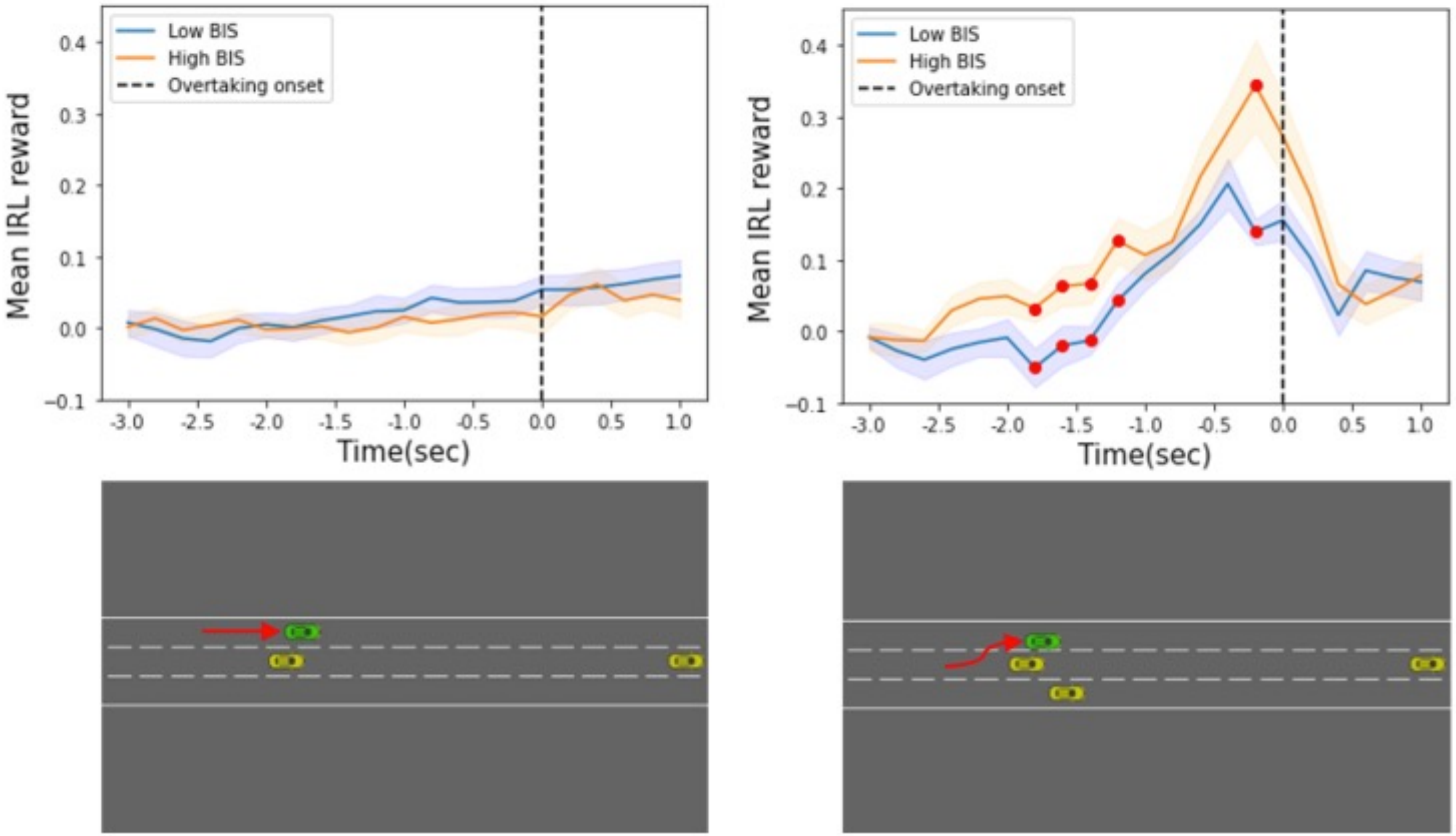


Lee, Song, Oh, & Ahn (2024) Psychological Science

Lee, Song, Oh, & Ahn (2024) Psychological Science

a) Passive overtaking

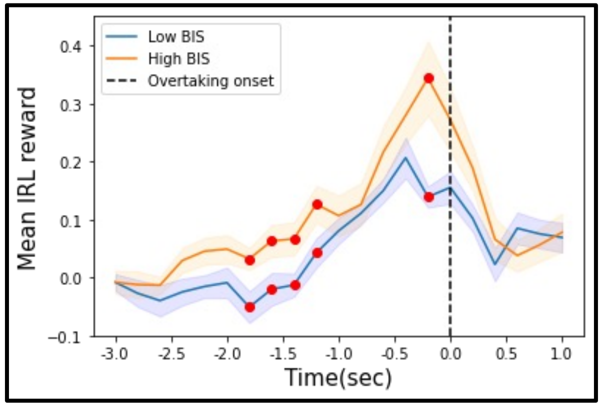
b) Active overtaking



Next Questions

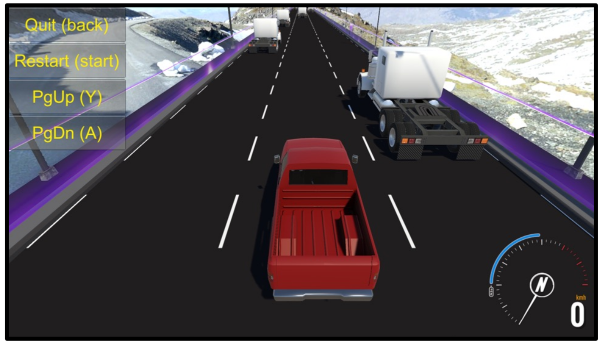
- *Will the reward-related brain activity correlate with the IRL reward values?*

  - fMRI experiments to compare BOLD signals with IRL rewards



- *Do we need more realistic tasks?*

  - 3D version of the Highway task using Unity.



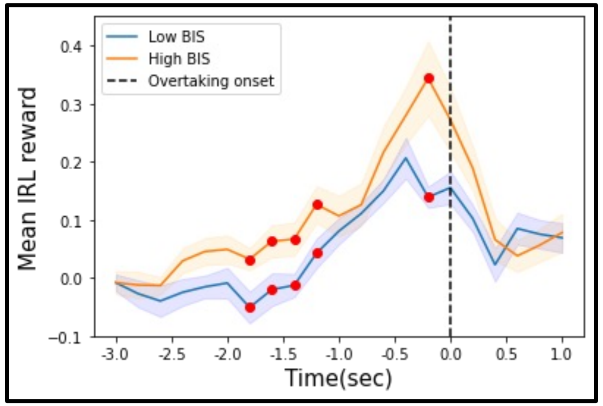
- *With clinical populations (e.g., SUDs)*

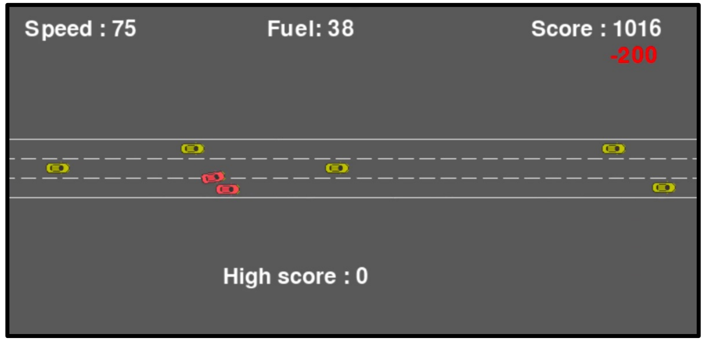
- *Can we assess other psychological constructs using the current framework?*

w/ Robert Whelan (TCD)

(Preliminary) fMRI Study w/ Highway task

- *fMRI Study w/ healthy controls (N=30)*
- *Focus on two events*
  - *"Overtaking"*
  - *"Crash"*

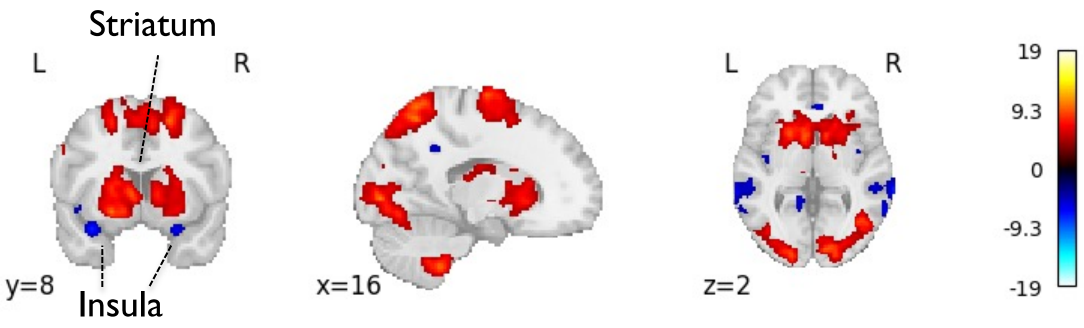


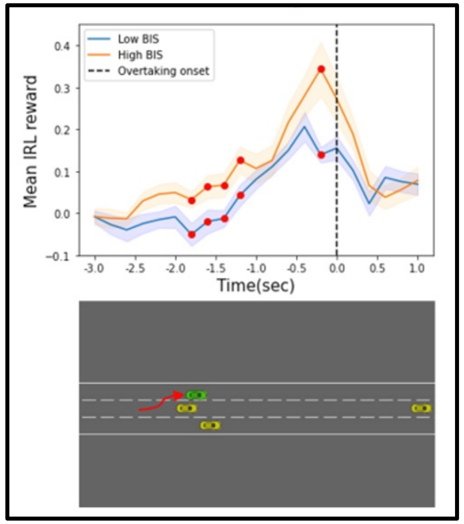


Lee, Oh, & Ahn (2024) CCN2024

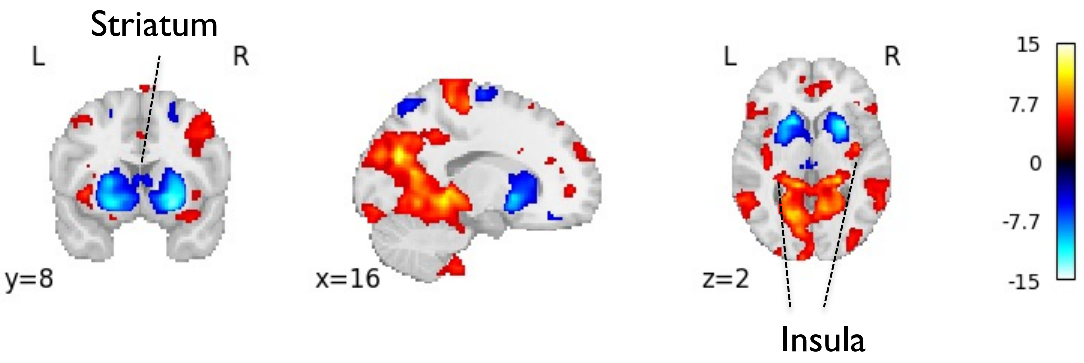
GLM analysis

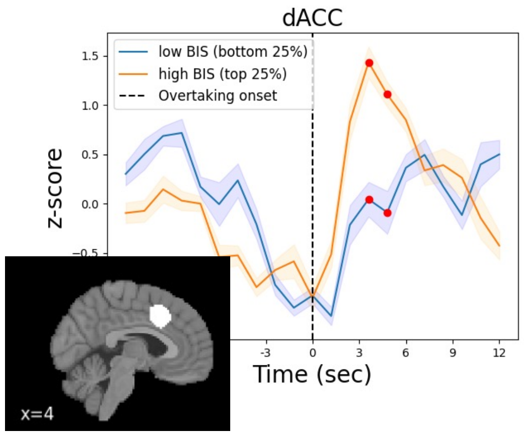
Overtake onset





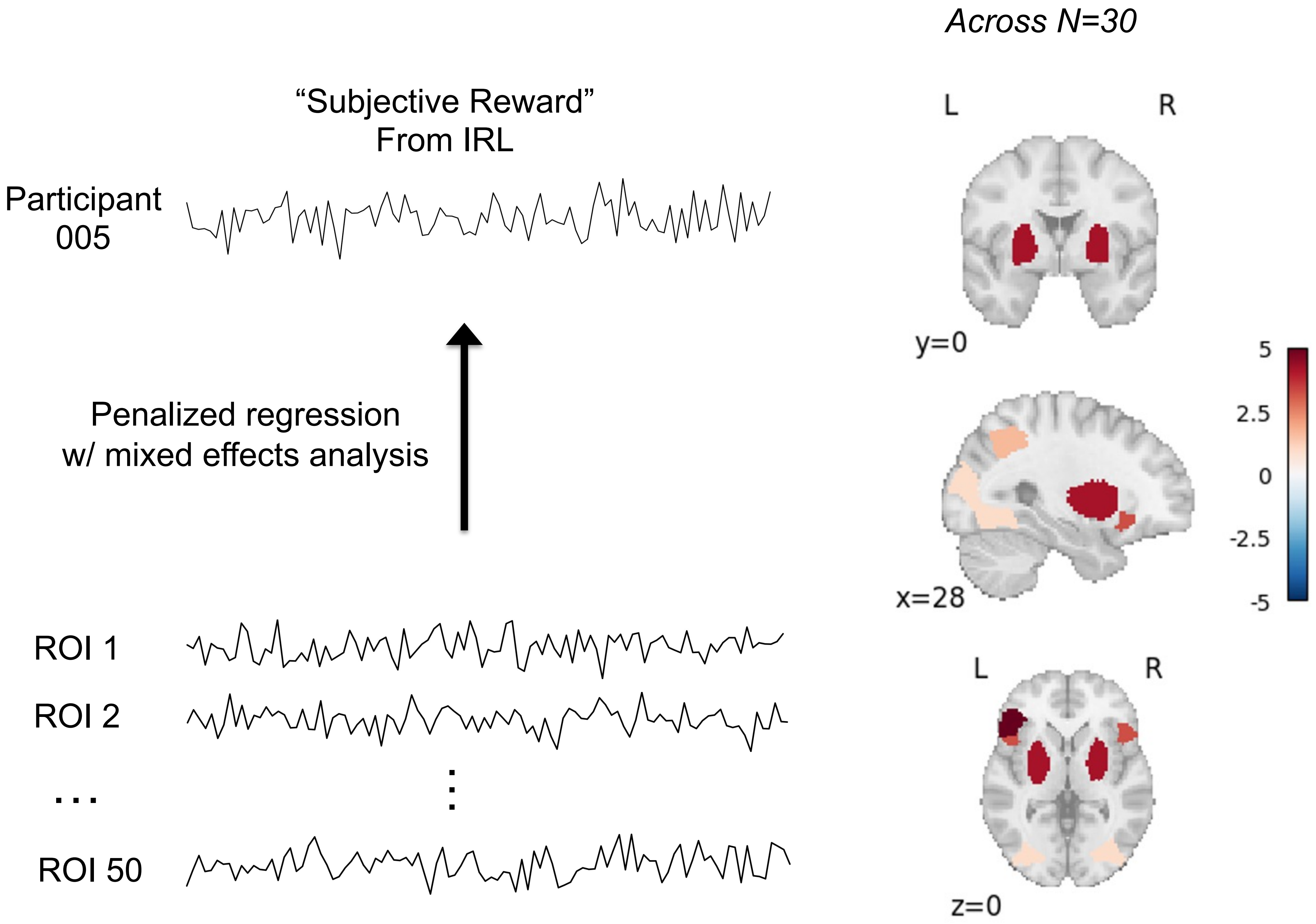
Crash onset





P value threshold = 0.001 (corrected p< 0.05, FDR corrected)

Lee, Oh, & Ahn (2024) CCN2024



Across N=30
"Subjective Reward"
From IRL
Participant
005
Penalized regression
w/ mixed effects analysis
ROI 1
ROI 2
...
ROI 50
L
R
y=0
x=28
z=0
5
2.5
0
-2.5
-5

“Real” rewards in the magnet

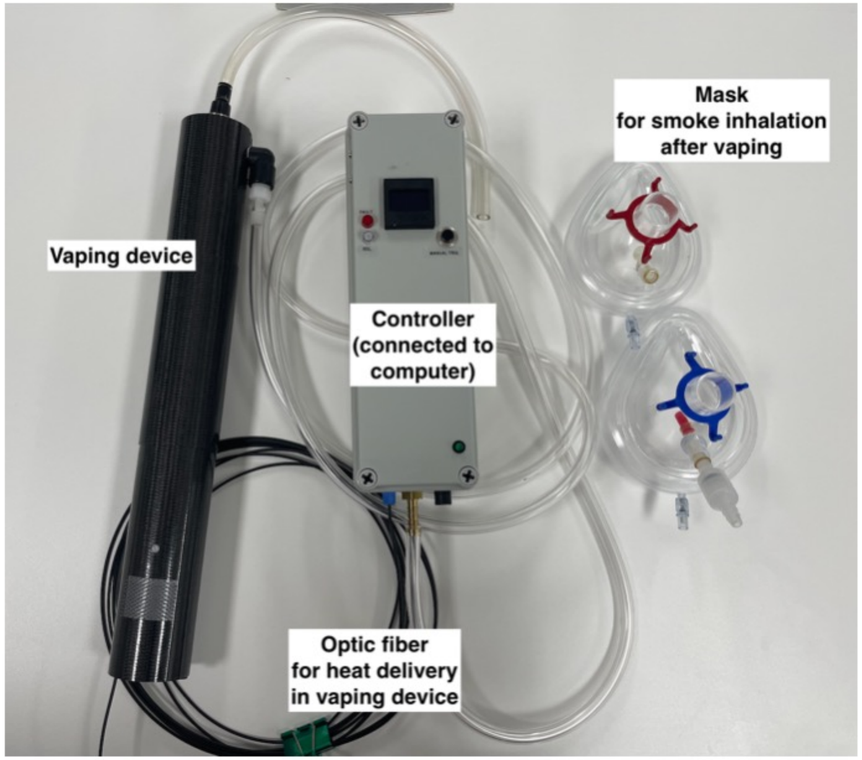
VS

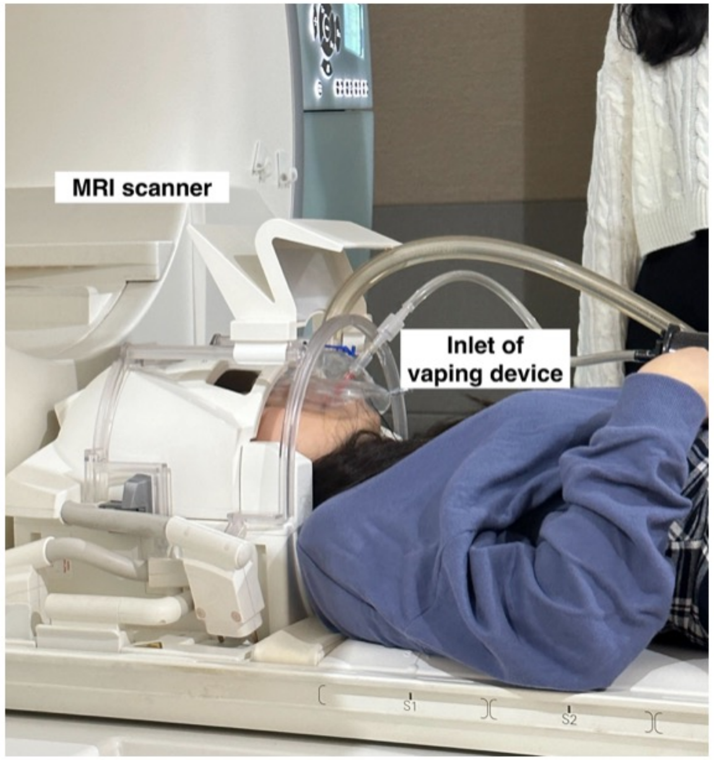
Jeung-Hyun Lee

Eun-Hwi Lee

Joshua Brown, Indiana Univ.

Modak et al. (2021) Neuroimage: Clinical
Lim et al (2020) BP: CNNI

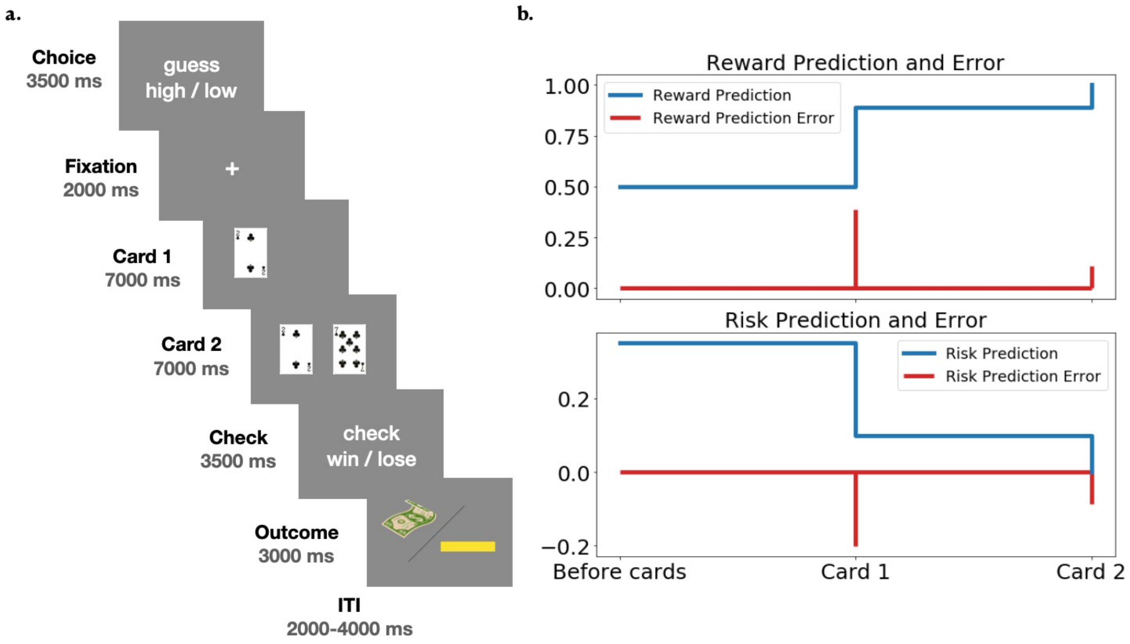




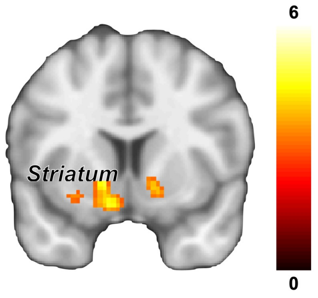
Joshua Brown, Indiana Univ.

Neural correlates of reward and risk w/ monetary and nicotine rewards

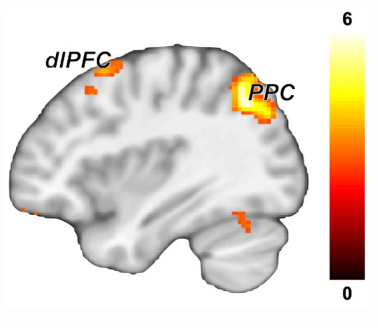
Mean-Variance model



Reward PE



Risk PE



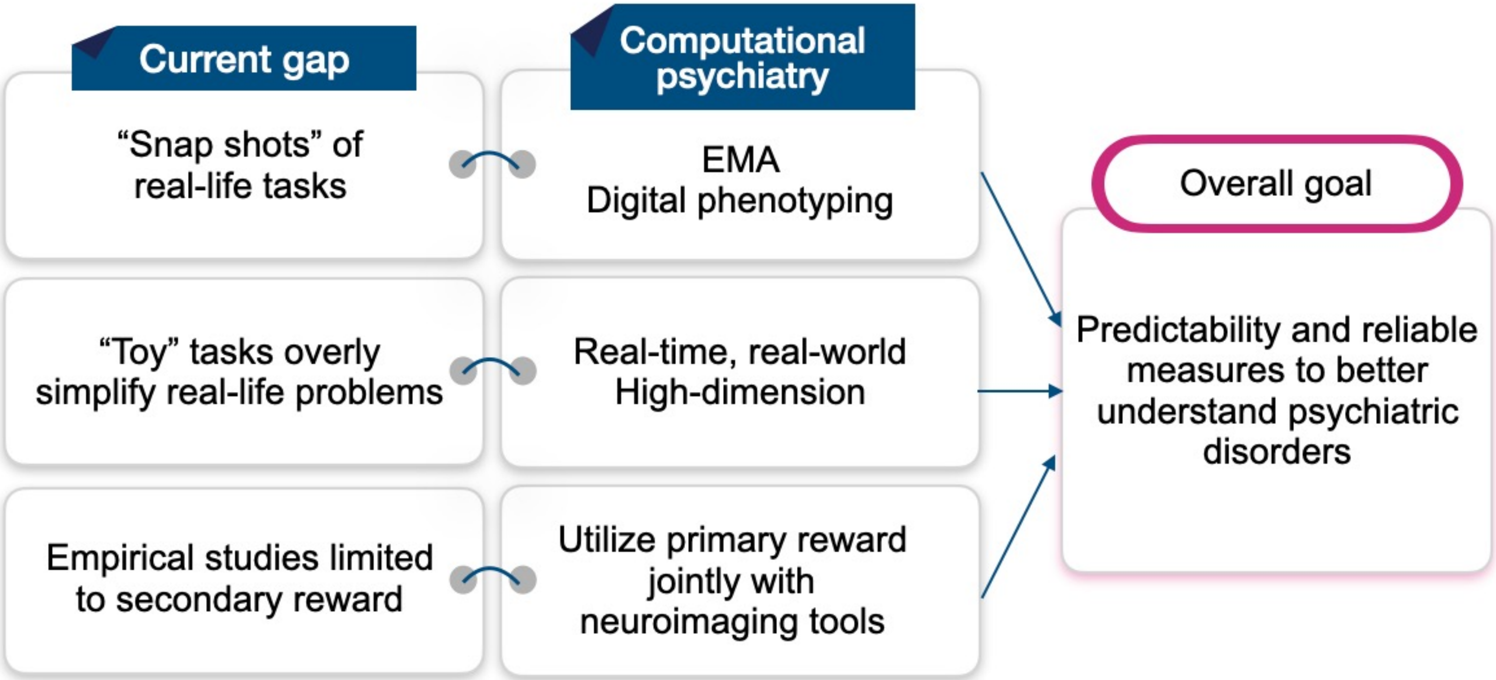
Eun-Hwi Lee

Poster on Fri!

Preuschoff et al (2008) Journal of Neuroscience
Preuschoff et al (2006) Neuron

Lee, Lee, Brown, & Ahn (2024) CCN2024

Toward building a decision-making paradigm
for dynamic and real-world addictive behaviors



Ahn, Lee, & Kim (invited review) Current Directions in Psychological Science

Challenges ahead of us

- *(Simple) computational modeling is hard*
- *Phenotypes/(bio)markers are not reliable*
- *Dynamic nature of the human mind*
- *Overly simplified "toy" problems/tasks*
- *"Good" mathematical models for "the mind"*

SATURDAY Tutorials

Tutorial C: Reinforcement Learning Using the hBayesDM Package

When: AM: 08:15 – 11:45 [CEST]
PM: 13:00 – 16:30 [CEST]

Where: Zurich

Who: Woo-Young Ahn, Jeongyeon Shin, Eunhwi Lee

Programming Language:

Materials:

In this tutorial, participants will learn how to use a Bayesian package called hBayesDM (supporting R and Python) for modeling various reinforcement learning and decision making (RLDM) tasks. A short overview of (hierarchical) Bayesian modeling will be also provided. Participants will also learn important steps and issues to check when reporting modeling results in publications.

Computational Clinical Science Laboratory

Thanks!

ccs-lab.github.io / happylaboratory.org