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REINFORCEMENT LEARNING
Computational Modeling for Learning and Decision Making

Maria K. Eckstein
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BAMB summer school, 18/07/2024

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Reinforcement Learning (RL)

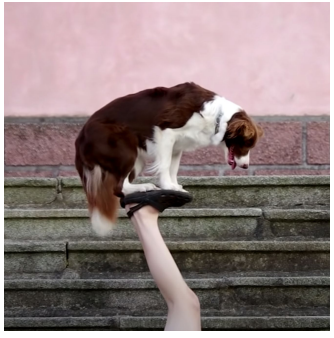
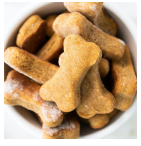
-> What do both videos have in common?

What is RL?

Learning from rewards;

and punishment.

How to Use RL (as a Cognitive Model)?

Goal	Reward	Ingredients	Algorithm
	+1	action = [→, ←] state = [] reward = [0, +1]	$Q(s,a) \leftarrow Q(s,a) + \alpha\ RPE$ $RPE = r + \gamma\ Q(s',a') - Q(s,a)$
		action = [jump, stand] state = [] reward = [0, ]	???

Questions?

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Lecture Roadmap

Reinforcement Learning (RL)

1. **Introduction**
2. RL from a psychology perspective
3. RL from an AI perspective
4. RL from a neuroscience perspective
5. Bringing it all together: RL as a cognitive model
6. Conclusion

Reinforcement Learning (RL)

1. Introduction
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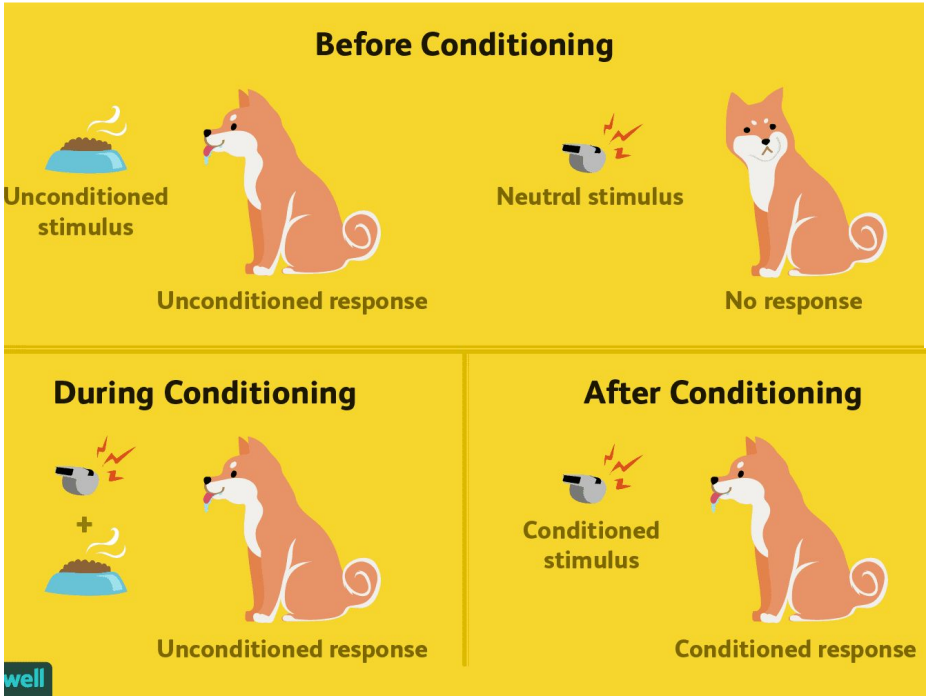
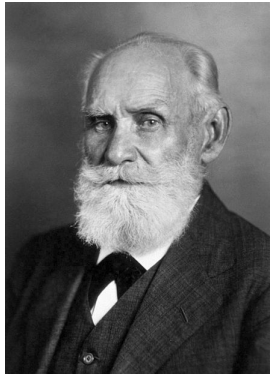
RL from a psychology perspective

Classical Conditioning

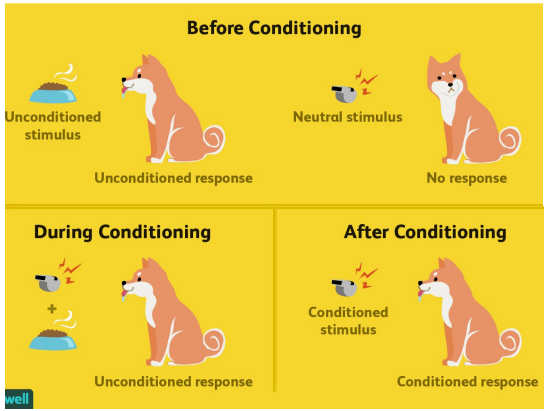




Ivan Pavlov
(1849–1936)

Animals learn associations between CS (e.g., bell) and US (e.g., food) when they reliably co-occur.

The Rescorla-Wagner Model (1972)



Combined predictive value of all present stimuli

$$RPE = reward - \Sigma[value(CS)]$$

$$\underbrace{value(CS)}_{\text{New value (after learning)}} \leftarrow \underbrace{value(CS)}_{\text{old value (before learning)}} + \alpha_{CS} * \beta_{US} * RPE$$

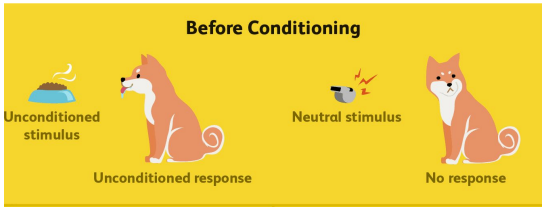
- Stimuli (CS) have "associative strength" (value)
  - Does the stimulus predict a US (reward)?
- When reward arrives, there might a "reward prediction error" (RPE)
  - Was the reward predicted by the present CS?
- RPEs trigger learning: update values to better predict reward
  - Learning speed depends on salience (α_{CS}) and "association value" (β_{US})

Rescorla-Wagner Example

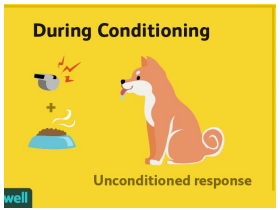
$$RPE = reward - \Sigma[value(CS)]$$

$$value(CS) <- value(CS) + \alpha_{CS} * \beta_{US} * RPE$$

[[Assume $\alpha_{CS} * \beta_{US} = 0.5$]]



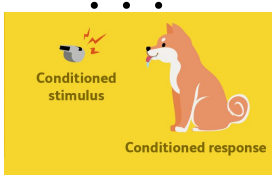

```
value(bell):          0
reward:               1
RPE:                  1
New value(bell):      0.5
```




```
value(bell):          0.5
reward:               1
RPE:                  0.5
New value(bell):      0.75
```


```
value(bell):          0.75
reward:               1
RPE:                  0.25
New value(bell):      0.865
```

???




```
value(bell):          1
```

"Conditioned response"

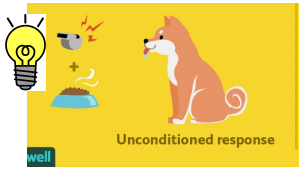
Blocking Example

$$RPE = reward - \Sigma[value(CS)]$$

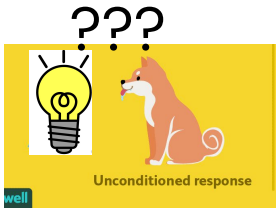
$$value(CS) \leftarrow value(CS) + \alpha_{CS} * \beta_{US} * RPE$$

[[Assume $\alpha_{CS} * \beta_{US} = 0.5$]]


```
value(bell):          1
reward:               1
RPE:                  0
New value(bell):      1  (no change)
```




```
value(bell):          1
value(light):         0
Σ[value(CS)]:         1
reward:               1
RPE:                  0
New value(bell):      1  (no change)
New value(light):     0  (no change)
```




```
value(light):         0
```

No “Conditioned response”

Operant conditioning

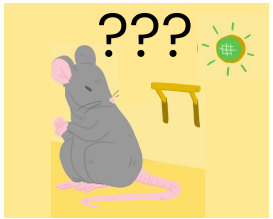
RPE = reward – value(action|state)

value(action|state) <-
value(action|state) + α * RPE


```
value(press|light):      0
reward:                  1
RPE:                     1
New value(press|lig):    0.5
```


```
value(press|light):      0.5
reward:                  1
RPE:                     0.5
New value(press|lig):    0.75
```

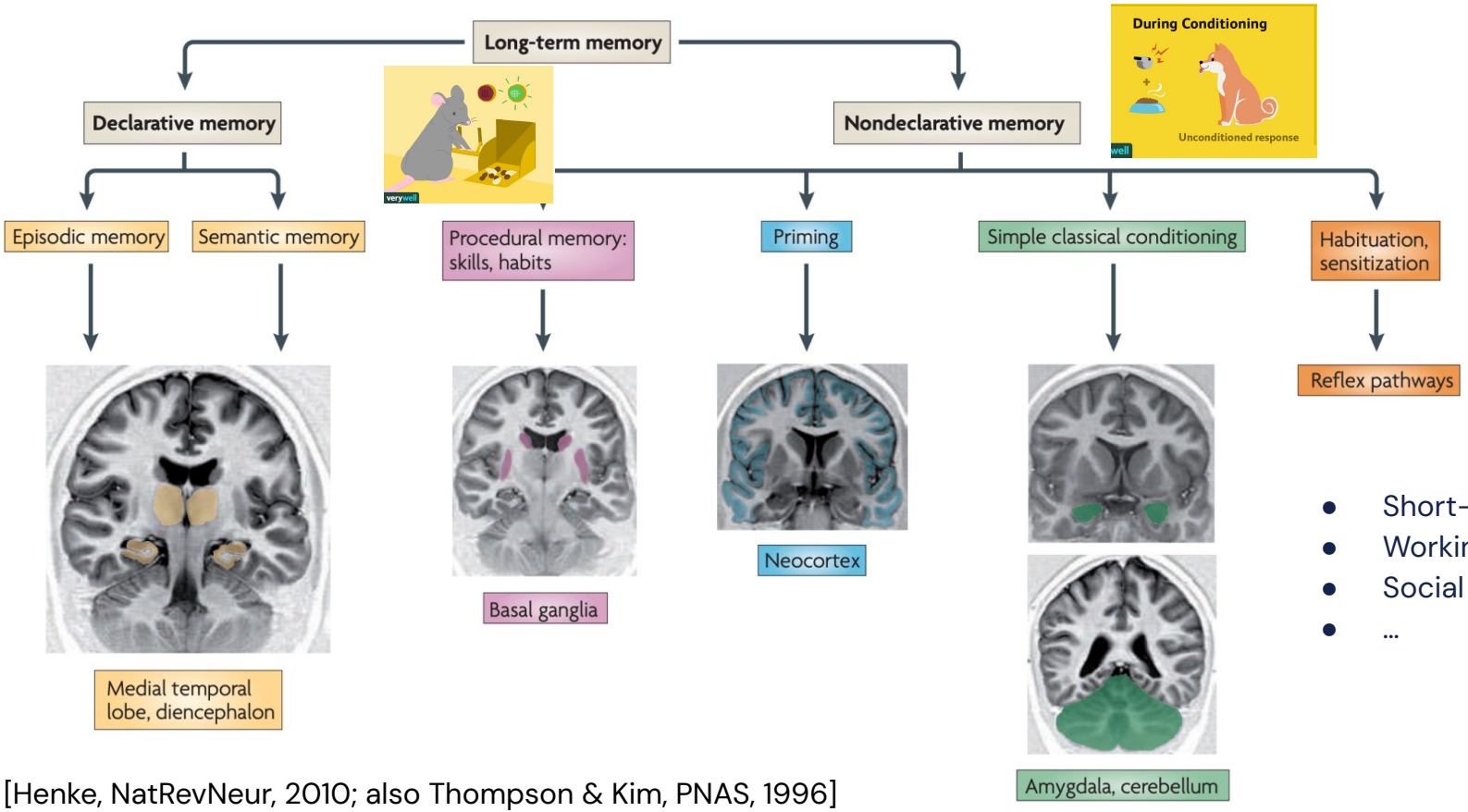
...




```
value(press|light):      1
```

“Goal-directed response” or “Habit”?

Multiple memory systems



- Short-term memory
- Working memory
- Social memory
- ...

[Henke, NatRevNeur, 2010; also Thompson & Kim, PNAS, 1996]

Questions?

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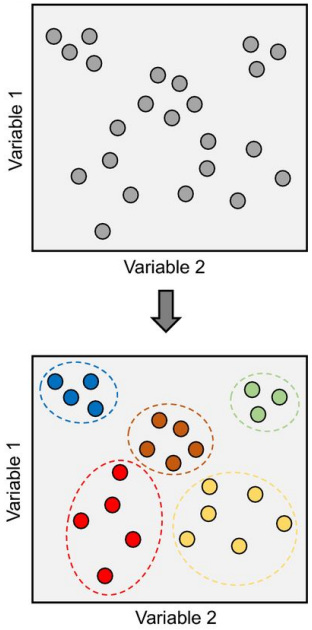
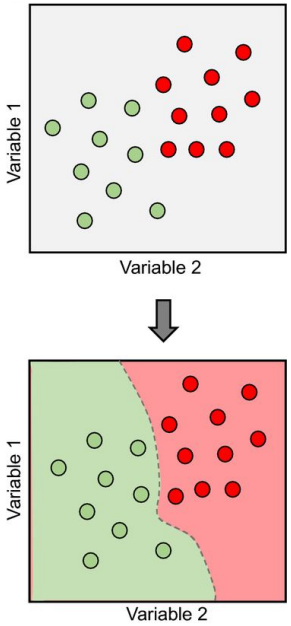
RL from an AI perspective

RL in the context of machine learning (ML)



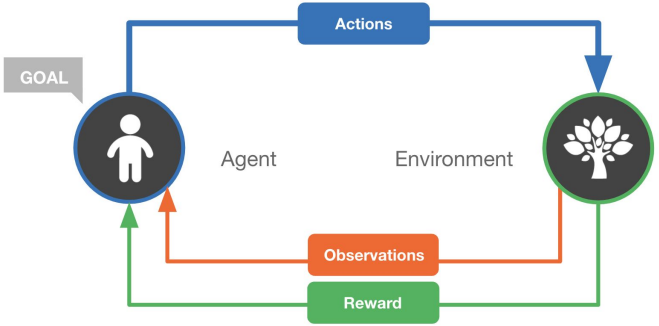
Unsupervised learning: Learn patterns or structure in data

(e.g., dimensionality reduction, clustering, ...)



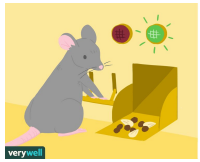
Supervised learning: Learn to predict target(s)

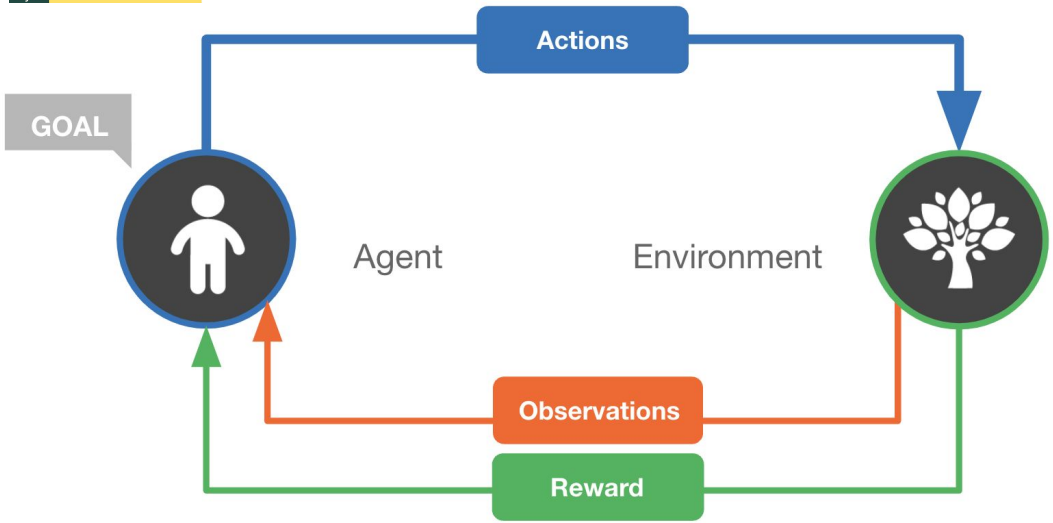
(e.g., regression, classification, ...)



Reinforcement Learning: Learn from interactions in the world, through a scalar reward signal

RL Ingredients





Agent: Learns a policy π that maps observations to actions, in order to maximize rewards.

Environment: E.g., experimental task; game (chess, Starcraft); factory (robotics); fusion reactor; …

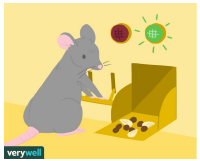
Reward: E.g., food, water, number of points / wins (*extrinsic*)

Also: *Intrinsic rewards*: E.g., curiosity, novelty, empowerment, learning progress, compression, explanation, …

[image credits: Jane Wang, Feryal Behbahani]

The Markov Decision Process (MDP)

Markov Decision Processes allow us to *formalize* and *solve* the RL problem.



Finite set of **states**

Transition function

Discount factor

$$\langle S, \mathcal{A}, P, R, \gamma \rangle$$

Finite set of **actions**

Reward function

Markov Property: The next state depends only on the current state and action, not on the entire history (e.g., chess).

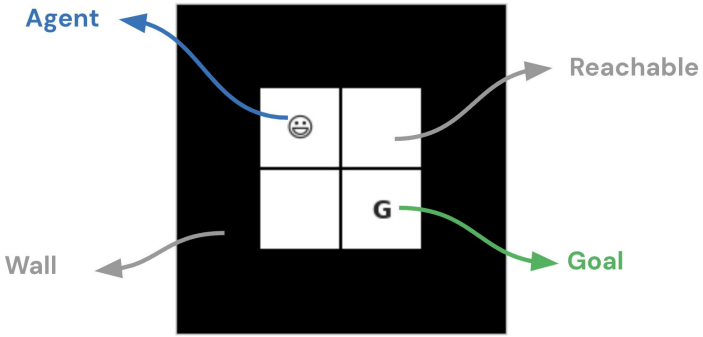
$$\mathbf{P}(s_{t+1} | s_t, a_t, s_{t-1}, a_{t-1}, \ldots, s_0) = \mathbf{P}(s_{t+1} | s_t, a_t)$$

Future Present Past — Future Present

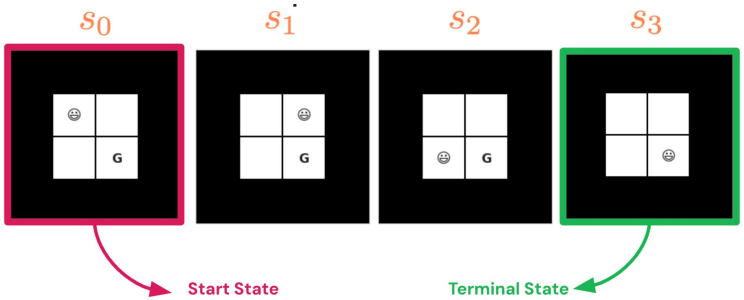
[image credits: Jane Wang, Feryal Behbahani]

Grid Worlds

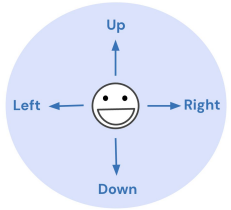
Size of the world: [2 X 2]



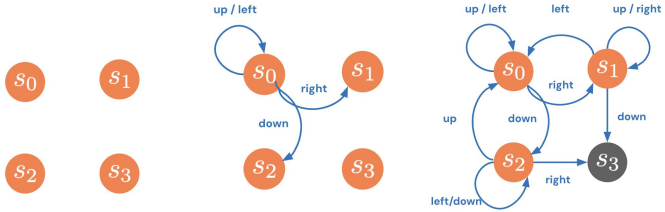
State space $\mathcal{S}$



Action Space $\mathcal{A}$



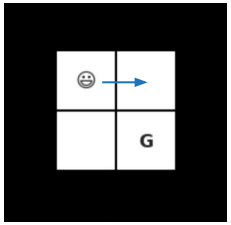
Transition model P

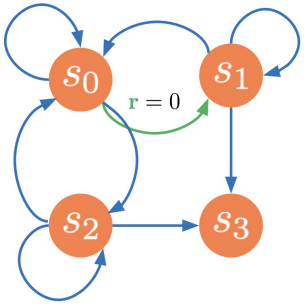


Rewards R

Empty cell: 0
Wall: -5
Goal: +10

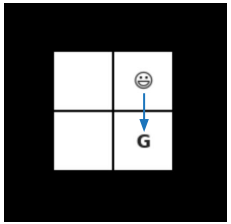
Temporal Difference (TD) Algorithms

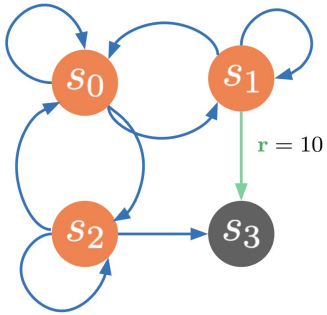




[assume γ = 0.9]

$Q^{\pi^*}(s_0, a_{right}) = 0 + 0.9 * 10 = 9$





$Q^{\pi^*}(s_1, a_{down}) = 10 + 0.9 * 0 = 10$

Agent's goal: Maximize (γ-discounted) sum of future rewards:

$$G_t = \underbrace{r_t + \gamma r_{t+1} + \gamma^2 r_{t+2}}_{\text{Return}} + \dots$$

To achieve this, the agent learns an action **policy π**:

$$a_t \sim \pi(a_t | s_t)$$

How do we find this policy?

Using values!

$$Q^{\pi}(s_t, a_t) = \mathop{\mathbb{E}}_{\pi}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \dots | s_t, a_t\right]$$

With values, finding the optimal actions is easy:

$$\pi^*(s) = \max_a Q^*(s, a)$$

Temporal Difference (TD) Learning

```
Value(s) += α * RPE
RPE = r - Value(s)
```

Learning rate

$$V_{t+1}(s_t) \leftarrow V_t(s_t) + \eta\delta_t$$

Reward prediction error

New estimate of value of current state

Old estimate of value of current state

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

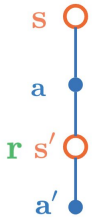
Reward prediction error

Actual observed value of current state (written the recursive way)

Old estimate of value of current state

TD Learning the value function

Problem: We can't predict the future! (And we don't want to…)

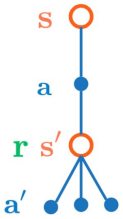


SARSA (on-policy control)

- Bootstrapping value estimates Q(s,a) based on "on-policy" (actual) experience

$$\underbrace{Q(s,a)}_{\text{new value}} \leftarrow \underbrace{Q(s,a)}_{\text{old value}} + \alpha(\overbrace{\underbrace{r}_{\text{lr reward}} + \underbrace{\gamma Q(s',a')}_{\text{Value next s-a pair}}}^{\text{RPE}} - \underbrace{Q(s,a)}_{\text{Old value}})$$

$$P(s_{t+1}|s_t, a_t, s_{t-1}, a_{t-1}, \ldots, s_0) = P(s_{t+1}|s_t, a_t)$$

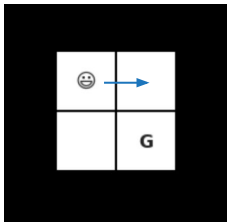


Q-learning (off-policy control)

- Bootstrapping value estimates Q(s,a) based on "off-policy" (hypothetical) experience

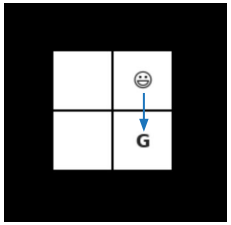
$$Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma \overbrace{\max_{a'} Q(s',a')}^{\text{Best avail. action}} - Q(s,a))$$

$$\pi^*(s) = \max_a Q^*(s,a)$$

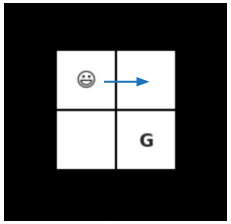


All Q's=0

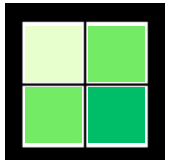
Q(s0,right) <- 0+α
(0+γ*0-0) = 0



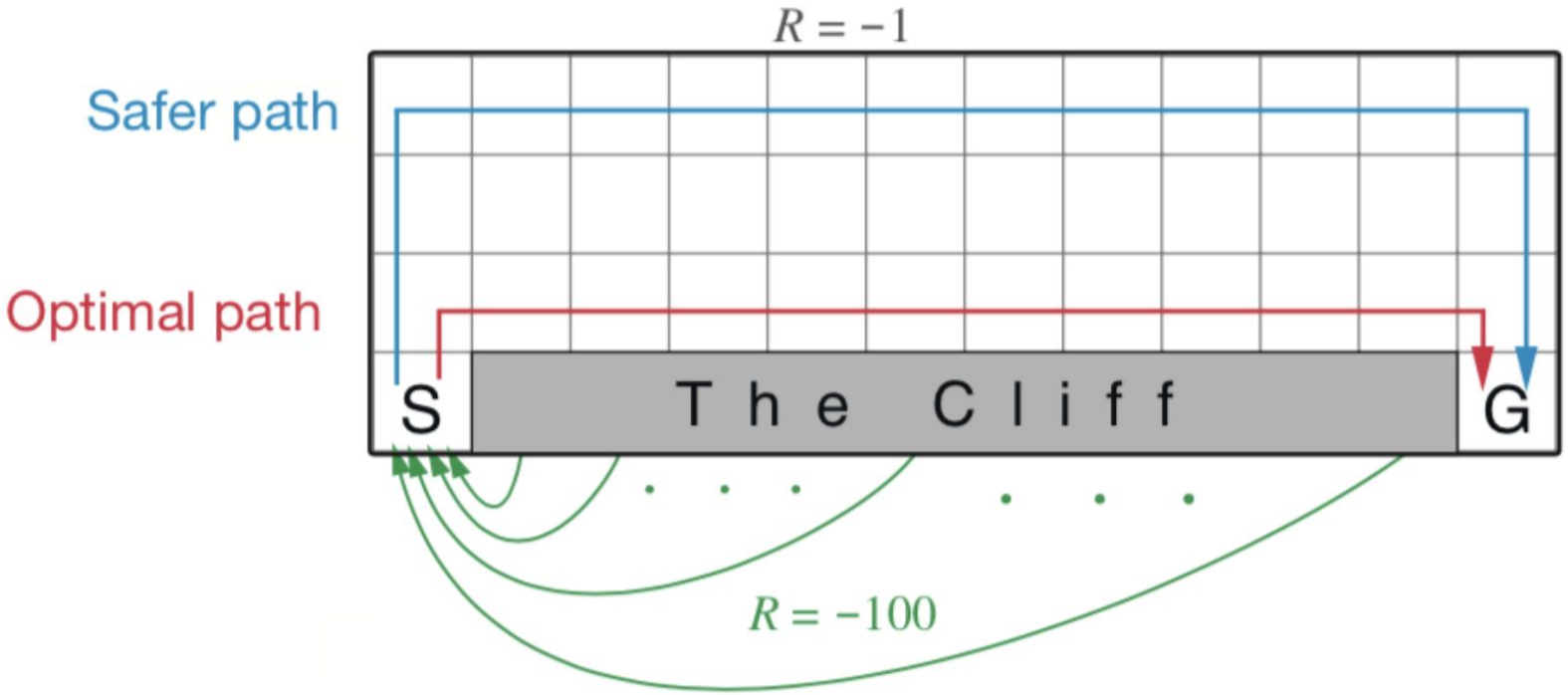
Q(s1,down) <- 0+α
(10+γ*0-0) = 5



Q(s0,right) <- 0+α
(0+γ*5-0) = 2.25



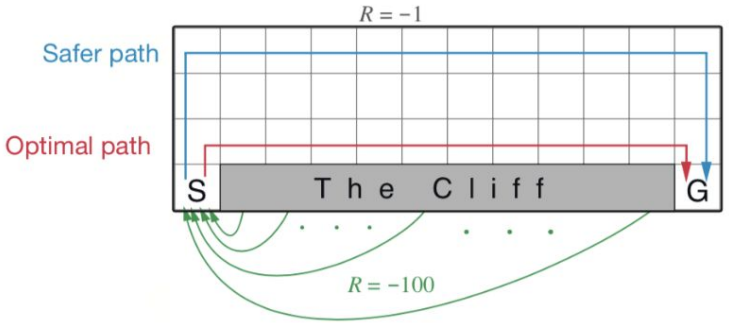
SARSA vs Q-Learning: The Cliff-walking Example

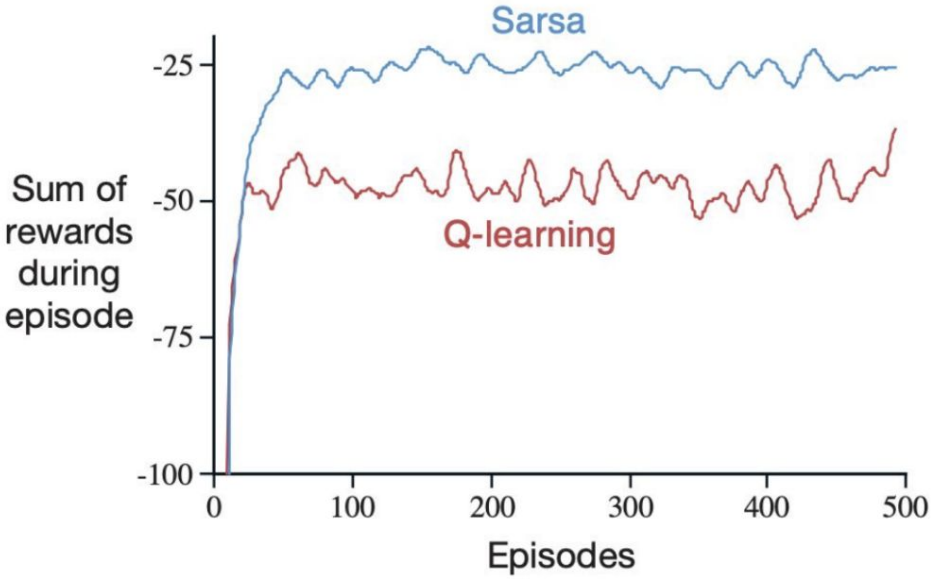


Sutton & Barto. Reinforcement Learning: An Introduction. (Chapter 6)

SARSA vs Q-Learning: The Cliff-walking Example

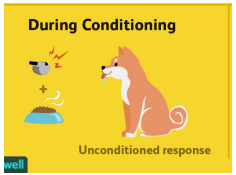
- **Q-learning** learns the **optimal path** while its online performance is worse than **SARSA**.
- **SARSA** learns the **safer path**.



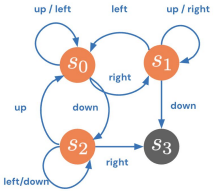


Cheat Sheet

Rescorla Wagner: keep track of reward expectations

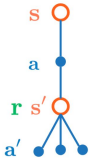


TD Learning: +over time



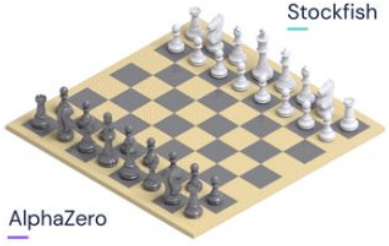
SARSA: on-policy

Q-Learning: off-policy



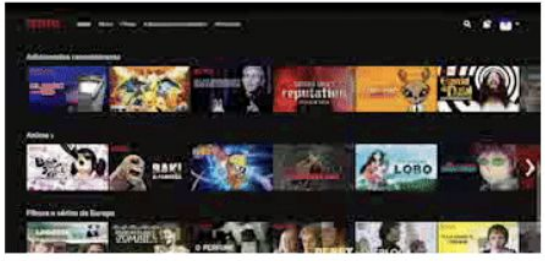
Real-world Reinforcement Learning: Examples

Game playing



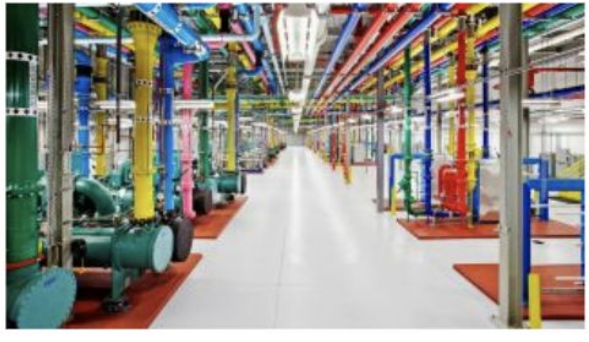
Robotics / Manipulation

User personalization



Self-driving cars

Managing energy usage



Questions?

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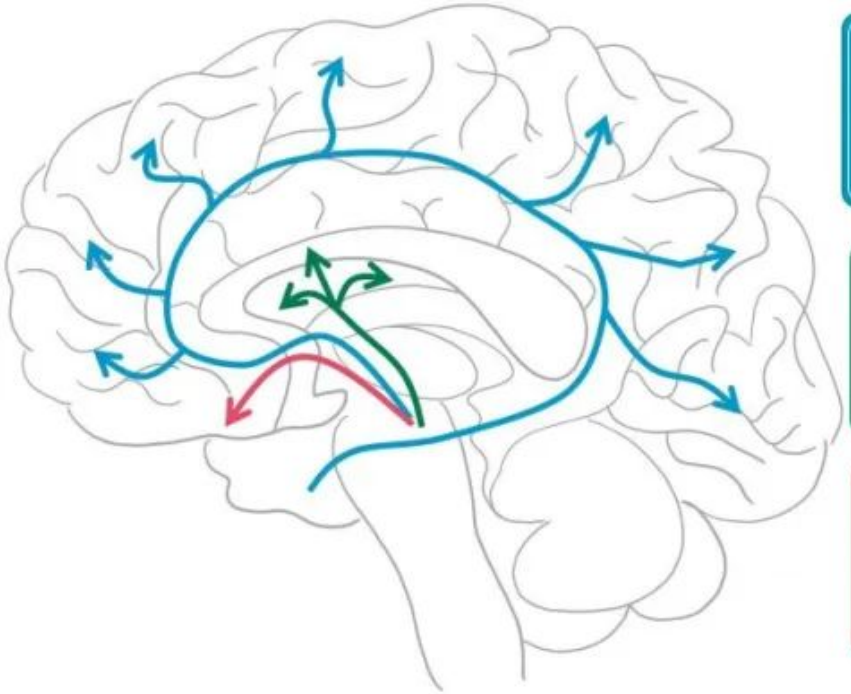
RL in neuroscience

The Neurotransmitter Dopamine



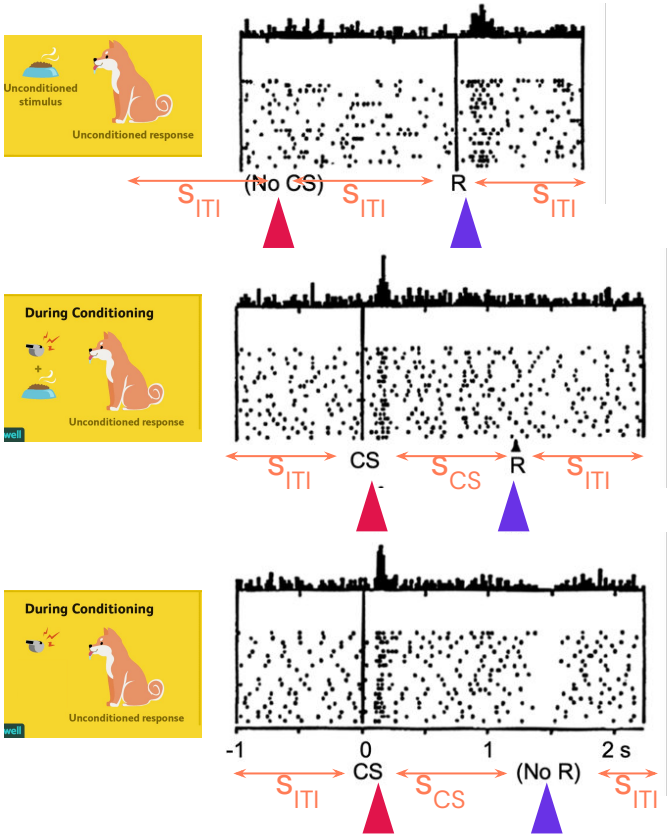
MESOCORTICAL
Cognition, Memory, Attention, Emotional Behavior, & Learning

NIGROSTRIATAL
Movement & Sensory Stimuli

MESOLIMBIC
Pleasure & Reward Seeking Behaviors; Addiction, Emotion, Perception

Dopamine Reward Prediction Errors

$$\text{RPE} = r + \gamma\, \text{Value}(s') - \text{Value}(s)$$



$$\text{RPE} = r + \gamma\, V(s_{ITI}) - V(s_{ITI}) = 0 + \gamma\, 0 - 0 = 0$$

$$\text{RPE} = r + \gamma\, V(s_{ITI}) - V(s_{ITI}) = 1 + \gamma\, 0 - 0 = 1$$

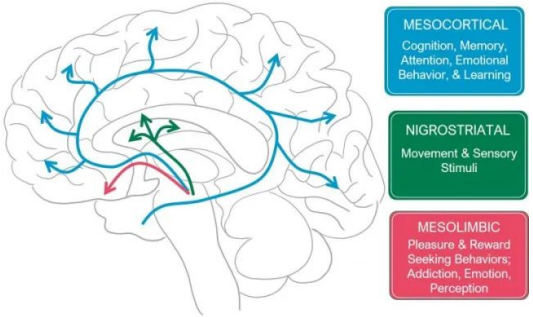
$$\text{RPE} = r + \gamma\, V(s_{CS}) - V(s_{ITI}) = 0 + \gamma\, 1 - 0 = 0.9$$

$$\text{RPE} = r + \gamma\, V(s_{ITI}) - V(s_{CS}) = 1 + \gamma\, 0 - 1 = 0$$

$$\text{RPE} = r + \gamma\, V(s_{CS}) - V(s_{ITI}) = 0 + \gamma\, 1 - 0 = 0.9$$

$$\text{RPE} = r + \gamma\, V(s_{ITI}) - V(s_{CS}) = 0 + \gamma\, 0 - 1 = -1$$

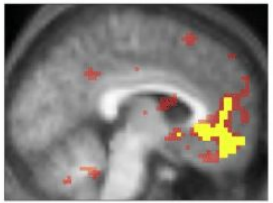
[Montague et al., 1996; Schultz et al., 1997]



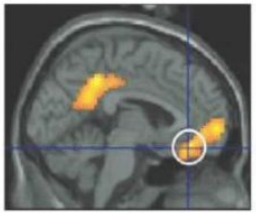
- Converging evidence across studies and species
- Mostly in simple conditioning paradigms

[Niv, 2009]

Human fMRI

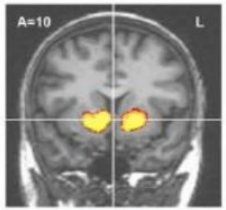


money
value predicted
(Daw et al 2006)

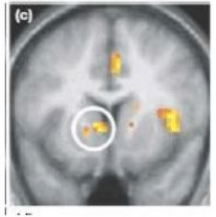


faces
attractiveness
(O' Doherty et al 2003)

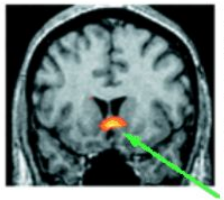
Coke or Pepsi
degree favored
(McClure et al. 2004)



money
gain vs loss
(Kuhnen & Knutson
2005)



food odors
valued vs devalued
(Gottfreid et al 2003)



juice
unpredictable vs
predictable
(Berns et al 2001)

Rewards / reward anticipation activate:

- Ventromedial prefrontal cortex
- Orbitofrontal cortex
- Striatum

➢ *Generalized appetitive function?*

Questions?

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RL for Cognitive Modeling

What is Cognitive Modeling?

Goal: Understand behavior, cognitive process

RL

$$RPE = r + \gamma\, Q(s',a') - Q(s,a)$$

$$Q(s,a) \leftarrow Q(s,a) + \alpha * RPE$$

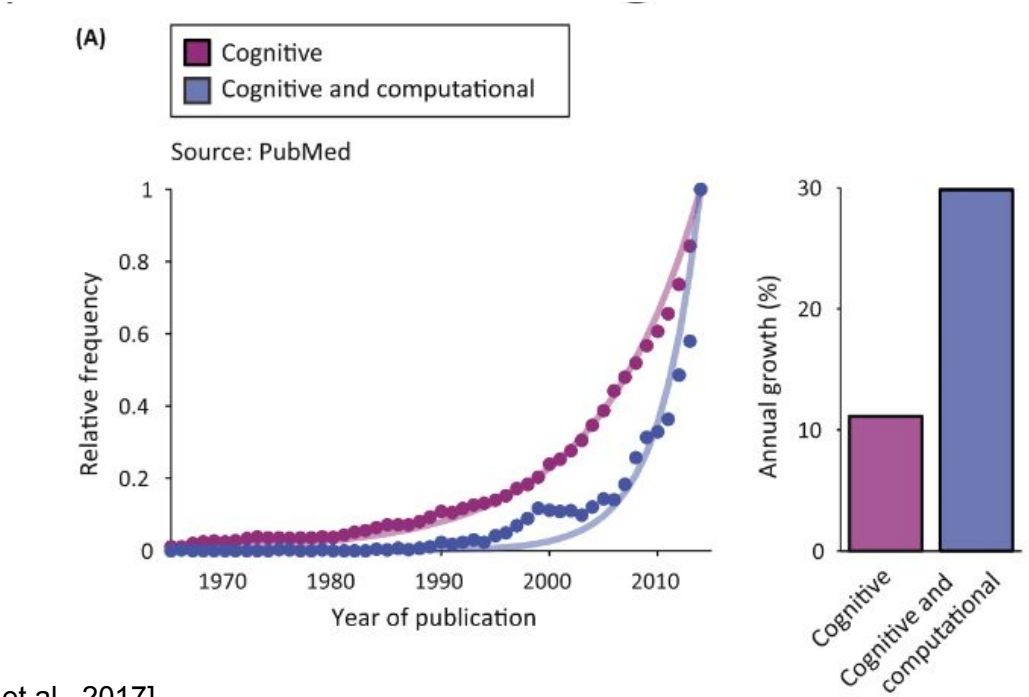
Method:

- Find model (e.g., RL, Regression, DDM, …)
- "Fit" model (find best parameters)
- Expand model
  - e.g., reward vs punishment [Frank et al., 2004]; WM [Collins & Frank, 2012]; counterfactuals [Boorman et al., 2011]; …
- Model comparison (AIC, BIC, WAIC, …)

Result:

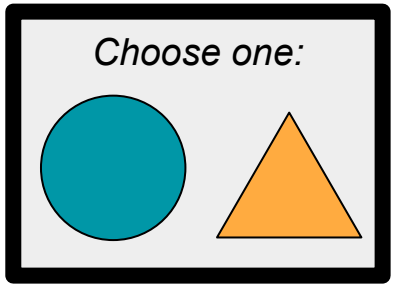
- "Cognitive process"
- Fitted parameters (individual differences)
- Normative understanding (optimality)
- Quantitative methods, statistics
- Complex, multi-step processes
- Precise prediction

Computational modeling is on the rise!

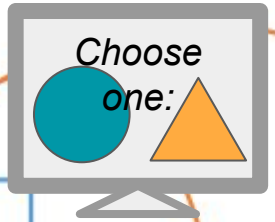


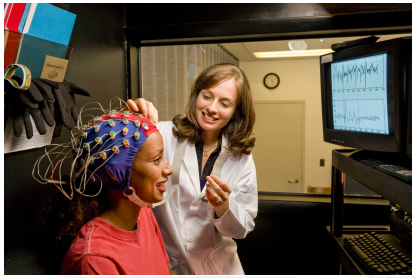
[Palminteri et al., 2017]

What is RL Modeling?

Goal	Reward	Ingredients	Algorithm
	+1	action = [→, ←] state = [] reward = [0, +1]	$RPE = r + \gamma Q(s',a') - Q(s,a)$ $Q(s,a) \leftarrow Q(s,a) + \alpha * RPE$
	+1	action = [F H] state = [] reward = [0, +1]	$RPE = r + \gamma Q(s',a') - Q(s,a)$ $Q(s,a) \leftarrow Q(s,a) + \alpha * RPE$

A Recipe for Cognitive Modeling





Scientific question

Design an experiment

Build competing models

Model predictions: Simulations

Model fitting Validate the procedure

Collect Data, Fit the models

Validate the models

RL

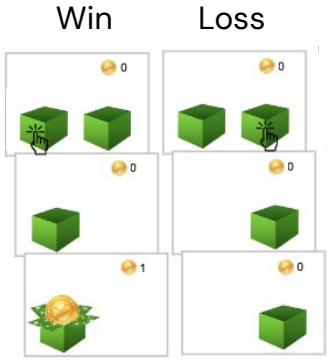
[Wilson & Collins, 2019. *eLife*]

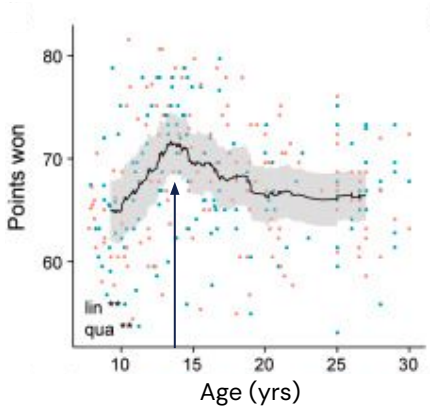
Learning to Reversal Learn

Goal: Understand age trajectory of reversal learning

$$RPE = r - Q(s,a)$$

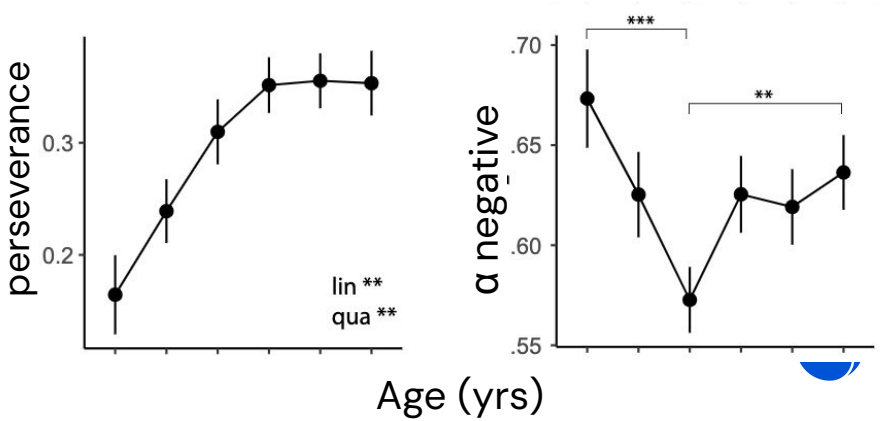
$$Q(s,a) \leftarrow Q(s,a) + \alpha * RPE$$





- Best performance at ~13-15

Why? Cognitive mechanism?



[Eckstein, Master, Dahl, Wilbrecht & Collins, 2022. *DCN*]

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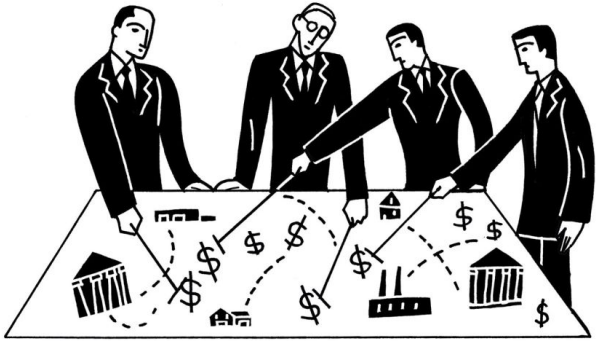
Conclusion

Where do rewards come from?

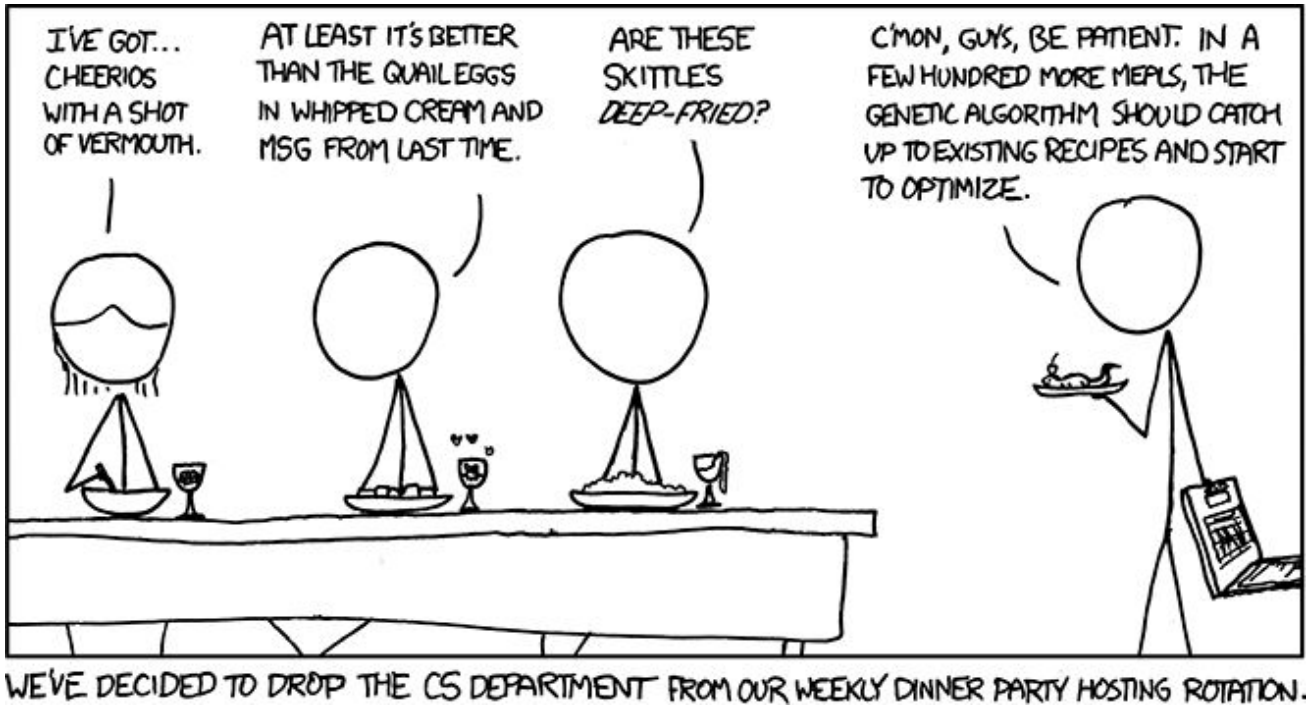
Evolution?



Economists?

- Intrinsic / extrinsic?
- Innate / learned?
- Context-dependent?
- Individual differences?

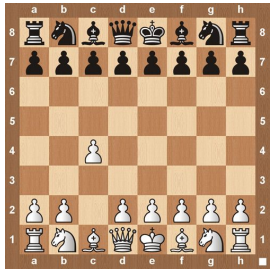
Exploration



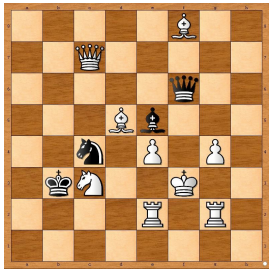
- Epsilon-greedy / softmax?
- Structured exploration?
- Intrinsic goals?
- Sparse rewards

Credit Assignment

Beginning



End

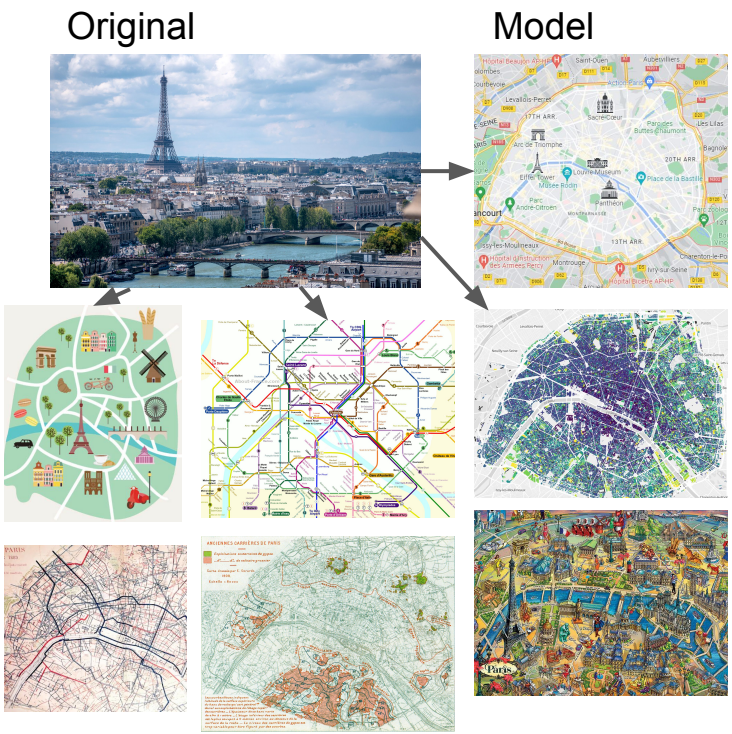


How to link distal outcomes to earlier causes despite many intervening events?

How to generalize over similar + different instances?

How to use knowledge of structure inform credit assignment?

Models as Maps



- Cognitive model = map
  - Smaller, more abstract
  - Loose information
- Different maps
  - Depending on the purpose
  - No one “true” map

Questions?

Want to Learn More?

Books

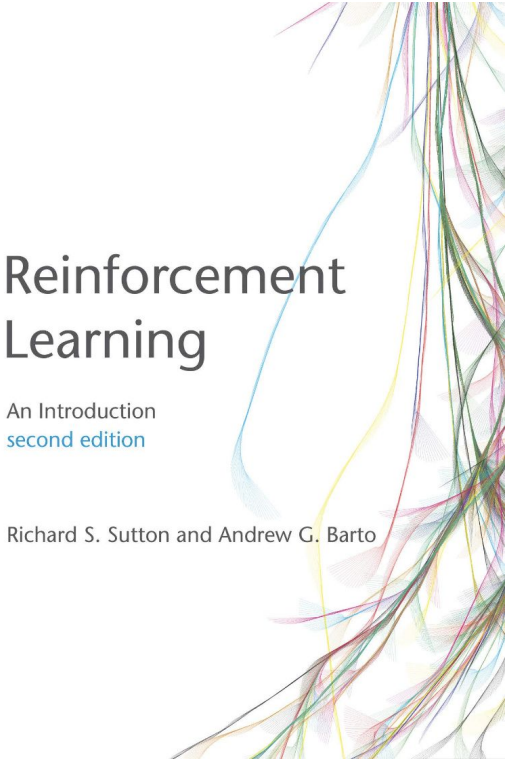
- Reinforcement Learning: an Introduction by Sutton & Barto
- Algorithms for Reinforcement Learning by Csaba Szepesvari

Lectures and course

- Neuromatch Lecture on RL by Jane Wang and Feryal Behbahani
- RL Course by David Silver
- Reinforcement Learning Course | UCL & DeepMind
- Emma Brunskill Stanford RL Course
- RL Course on Coursera by Martha White & Adam White

More practical

- Spinning Up in Deep RL by Josh Achiam
- Acme white paper & Colab tutorial
- OpenAI Gym



Acknowledgements

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Kevin Miller


Nathaniel Daw


Chris Summerfield


Dog
tricks
by
Justy