The Neuroscience of Reinforcement Learning

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ICML'09 Tutorial
Montreal

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  1. Take pride
  2. Ask: what can neuroscience do for me?
- Why are you here?
  - To learn about learning in animals and humans
  - To find out the latest about how the brain does RL
  - To find out how understanding learning in the brain can help RL research

If you are here for other reasons...

learn what is RL and how to do it

learn about the brain in general

read email

take a well-needed nap

smirk at the shoddy state of neuroscience

Outline

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- The brain coarse-grain

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Why do we have a brain?

Credits: Daniel Wolpert

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- example: sea squirt
- larval stage: primitive brain & eye, swims around, attaches to a rock
- adult stage: sits. digests brain.

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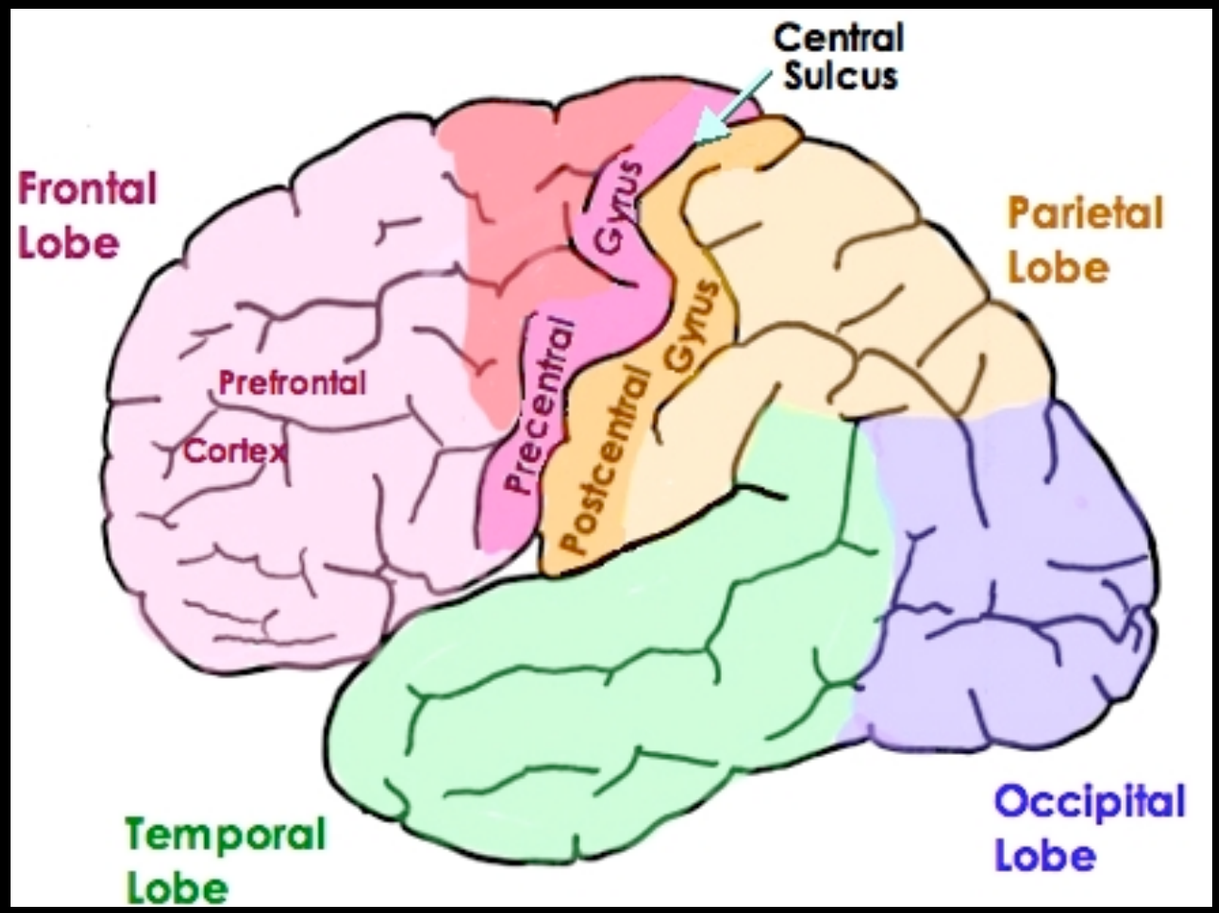
the brain in very coarse grain



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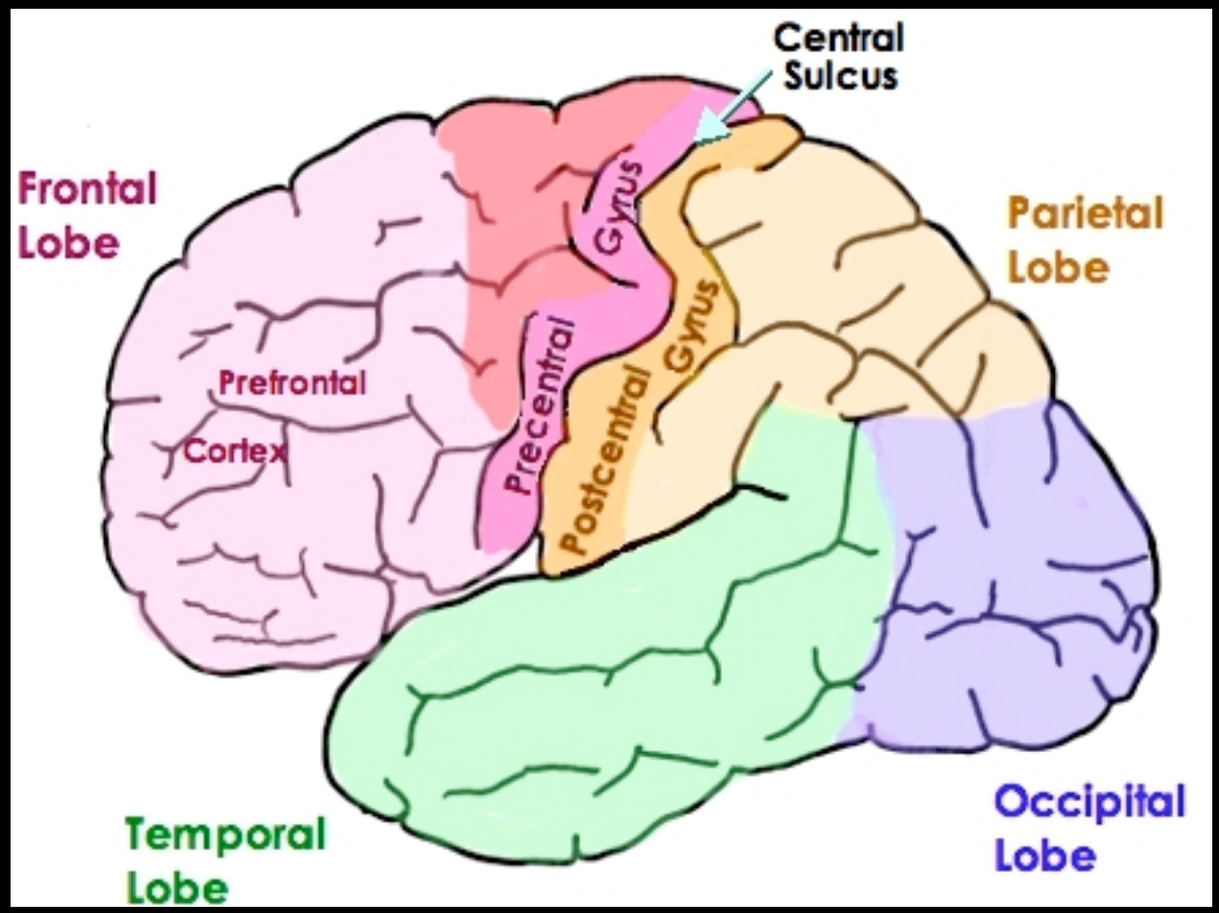
world



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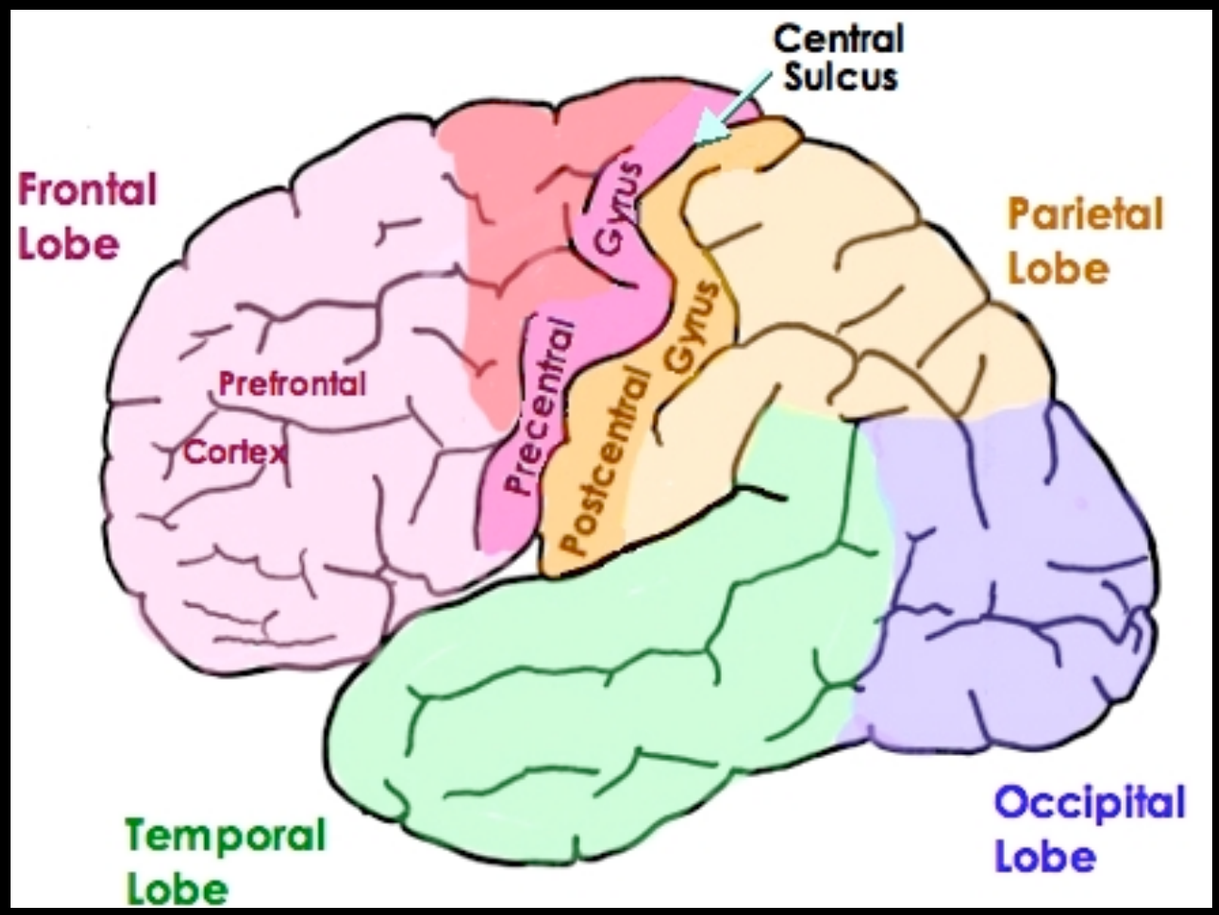
sensory processing



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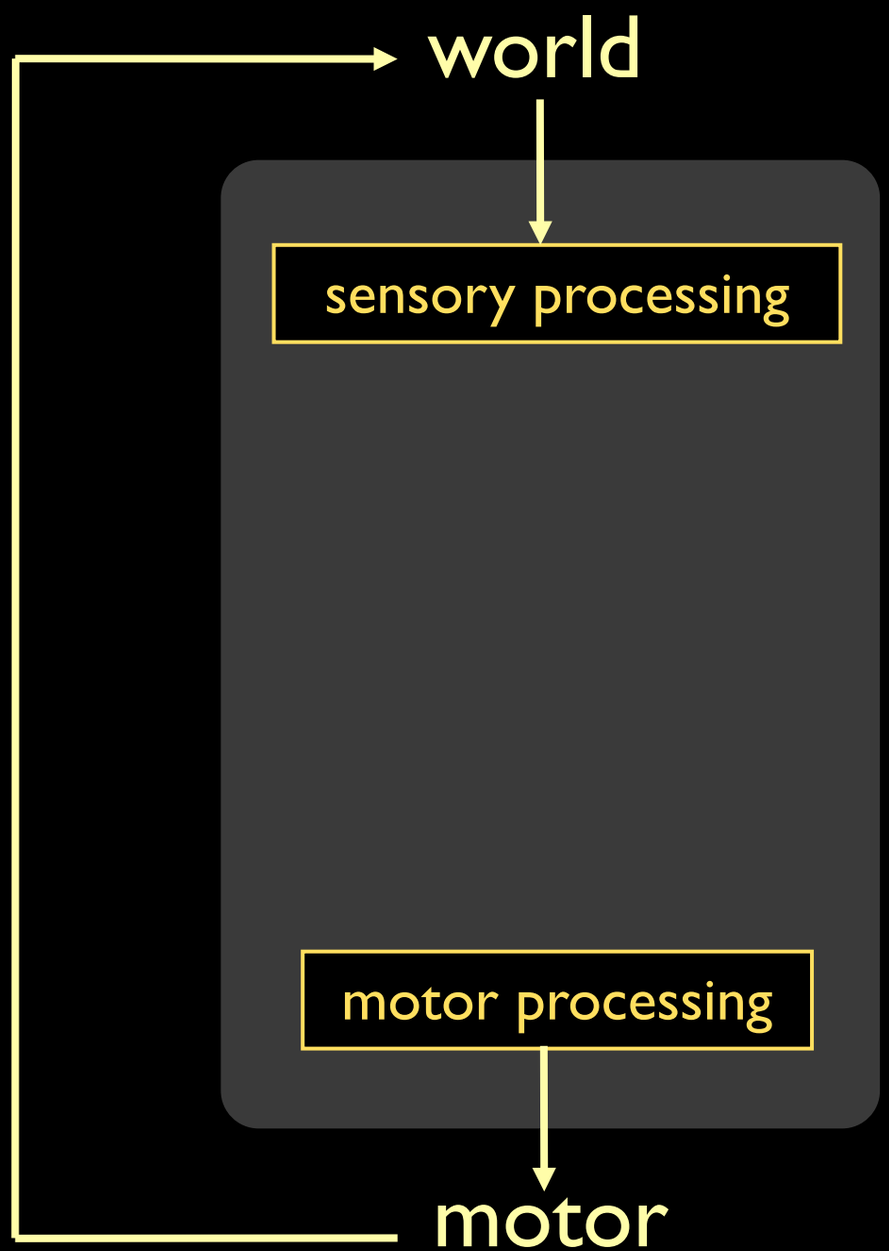

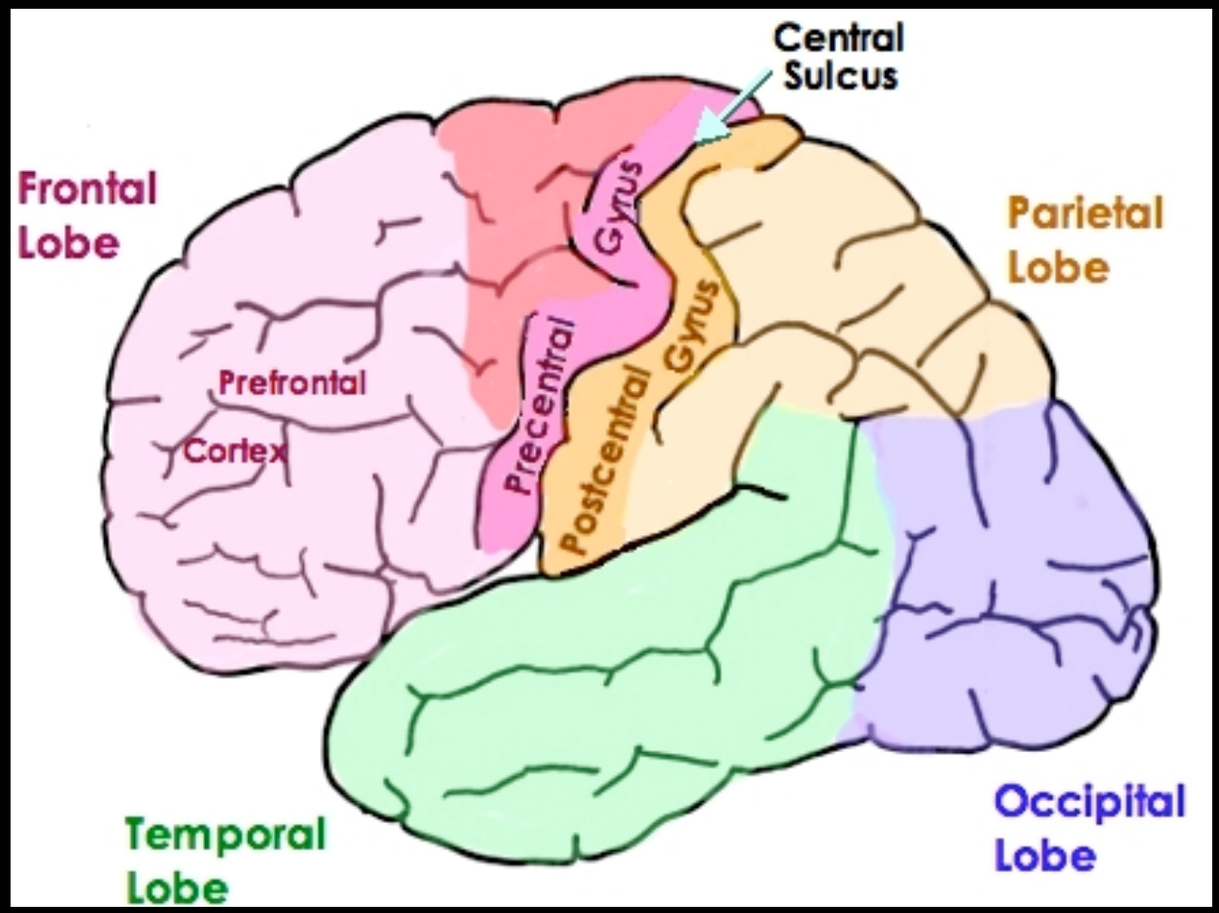

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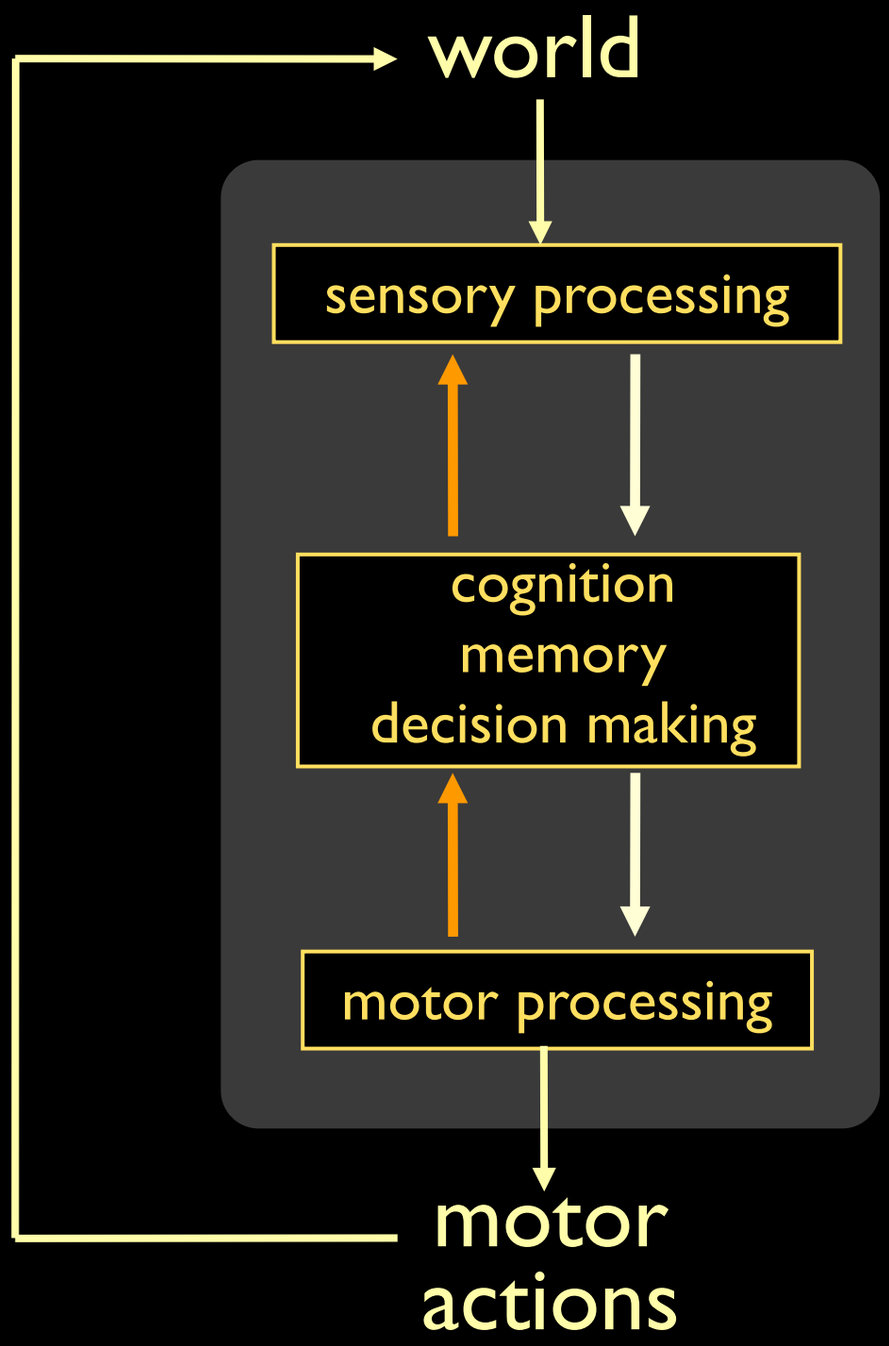

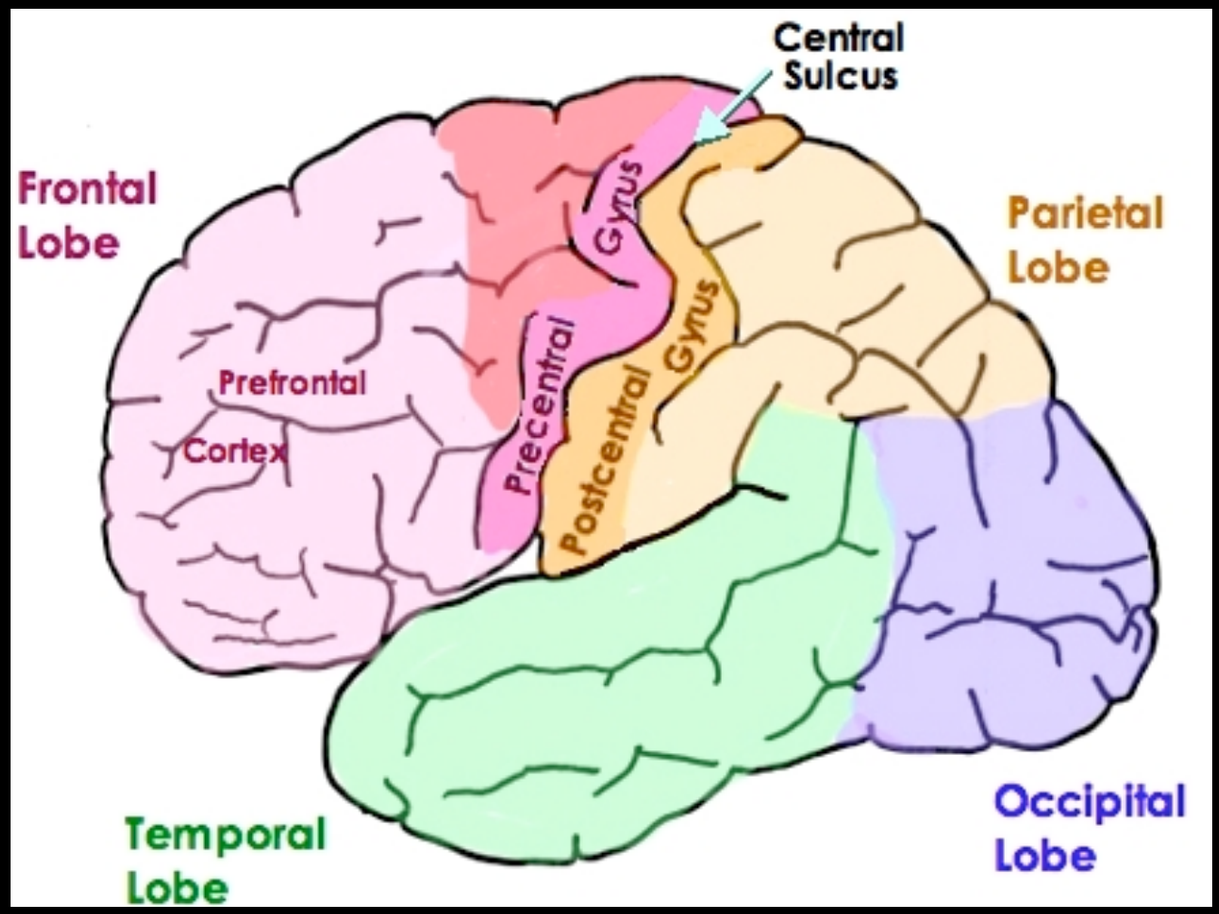

what do we know about the brain?

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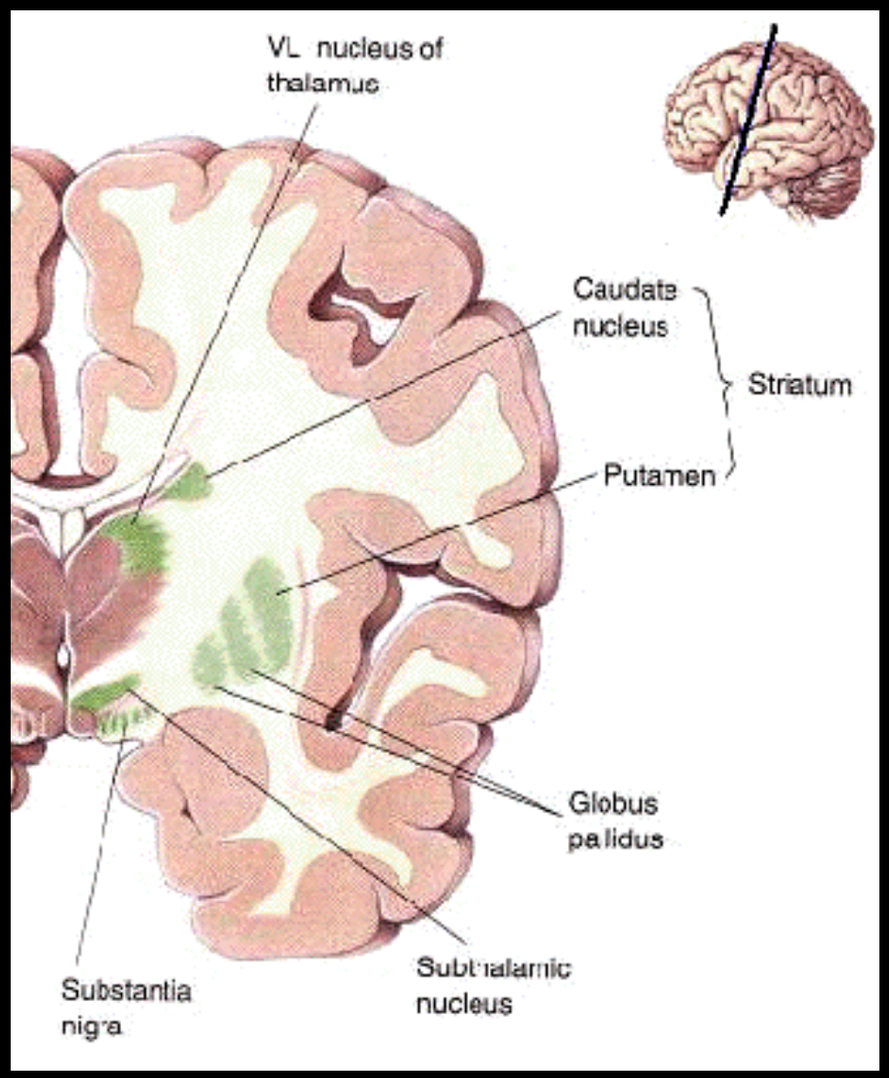

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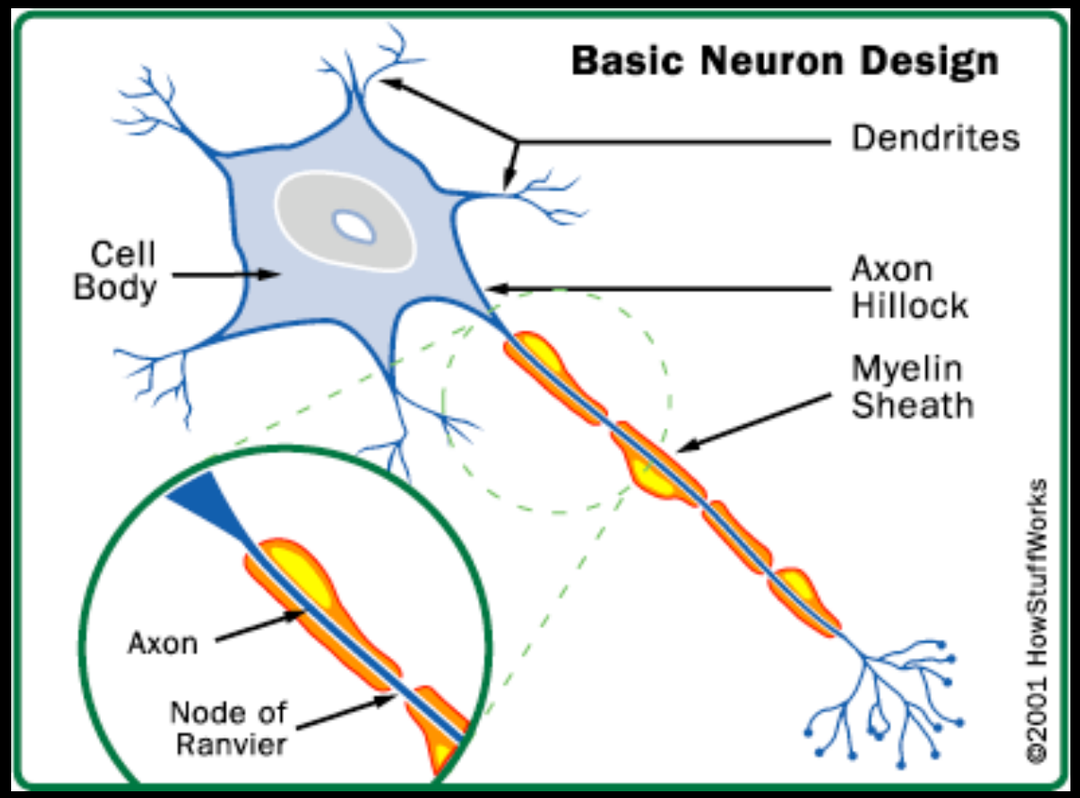

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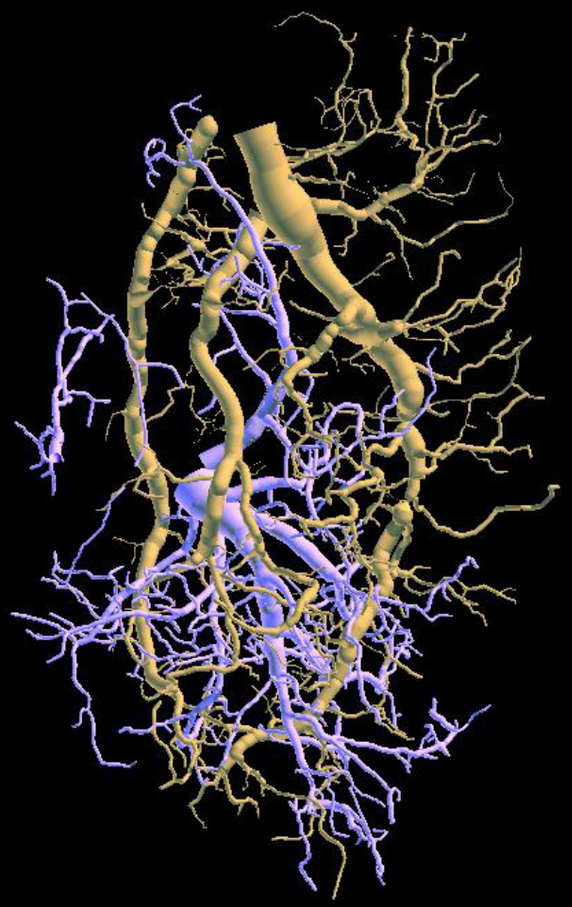

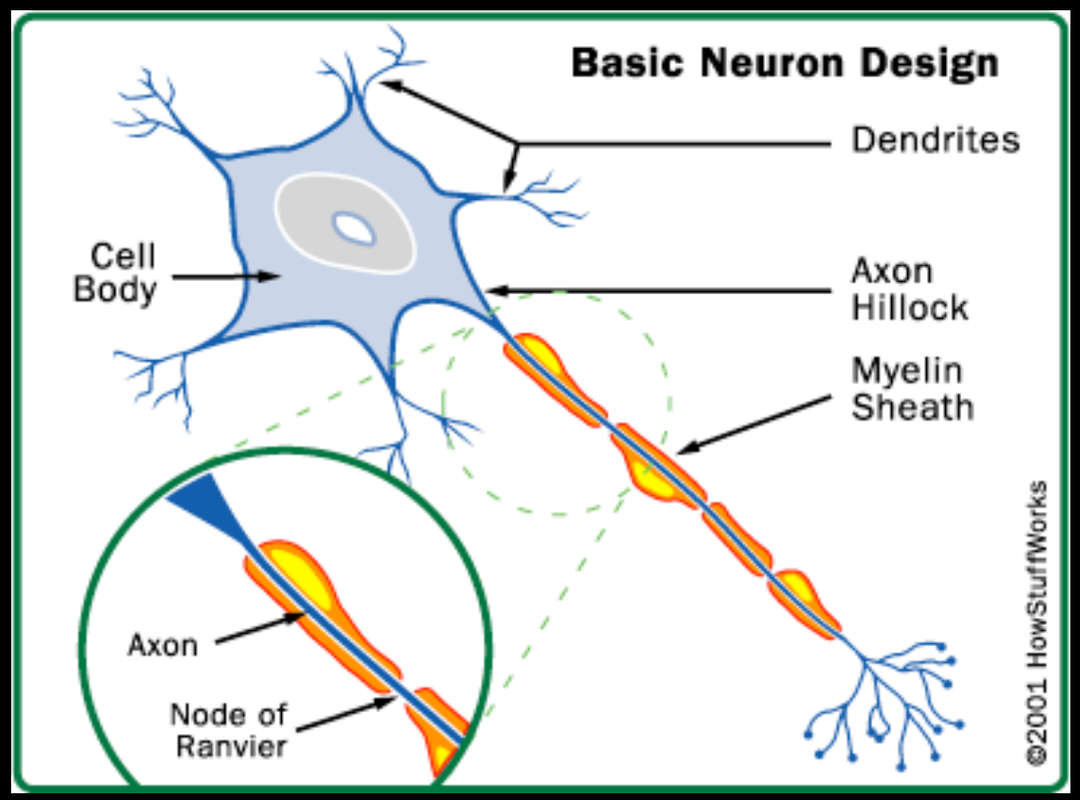

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- Function: we have pretty coarse grain knowledge of what different brain areas do (mainly sensory and motor; unclear about higher cognitive areas; much emphasis on representation rather than computation)

Summary so far...

- We have a lot of facts about the brain
- But.. we still don't understand that much about how it works
- (can ML help??)

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what do neuroscientists do all day?

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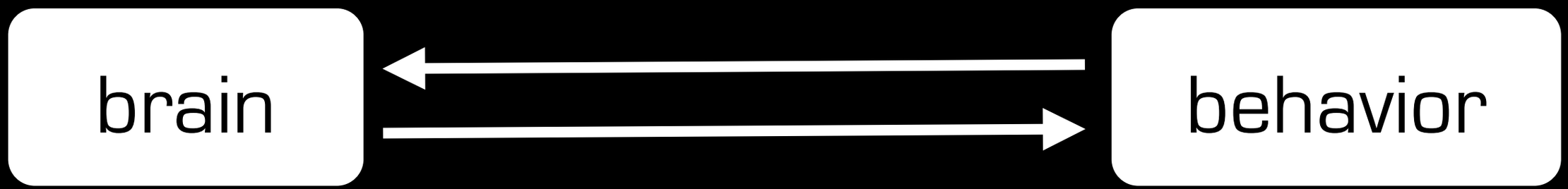
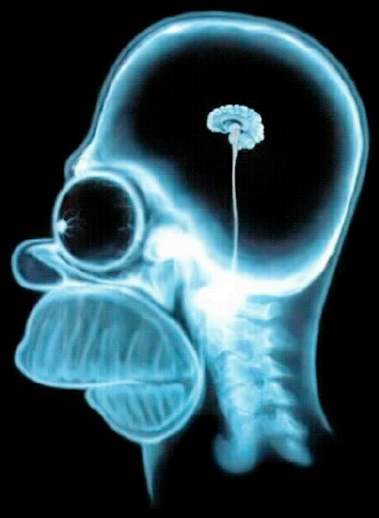
figure out how the brain generates behavior





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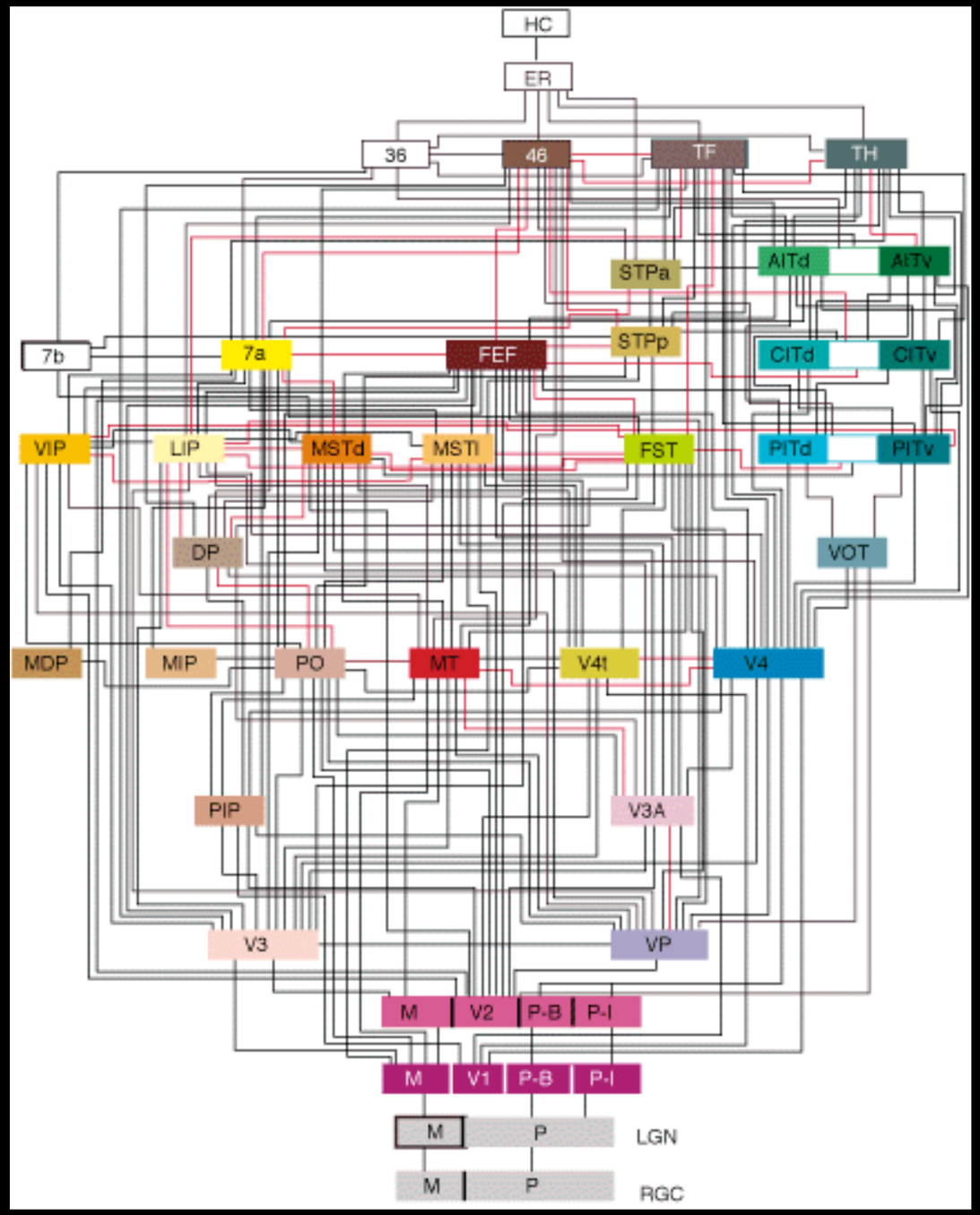

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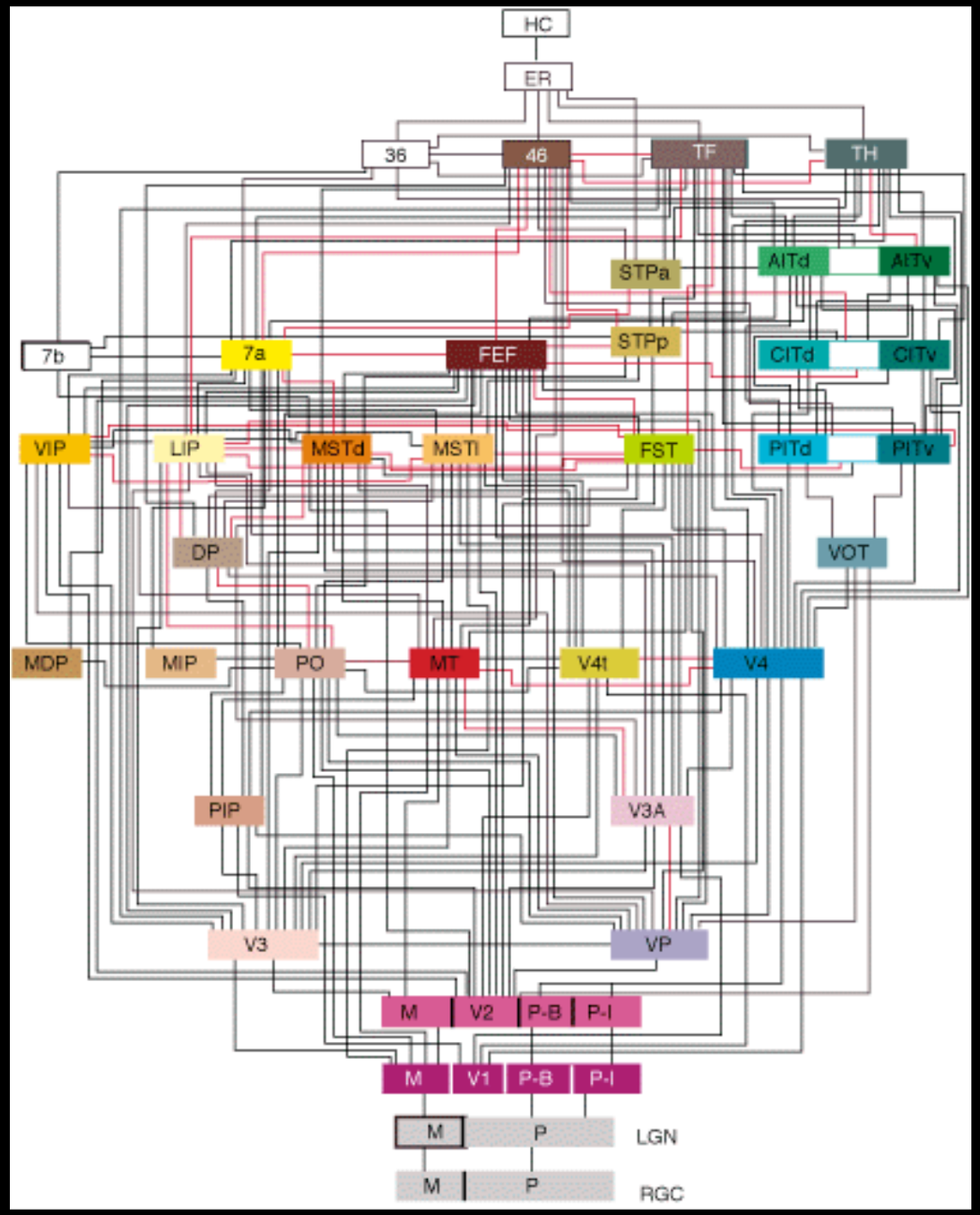

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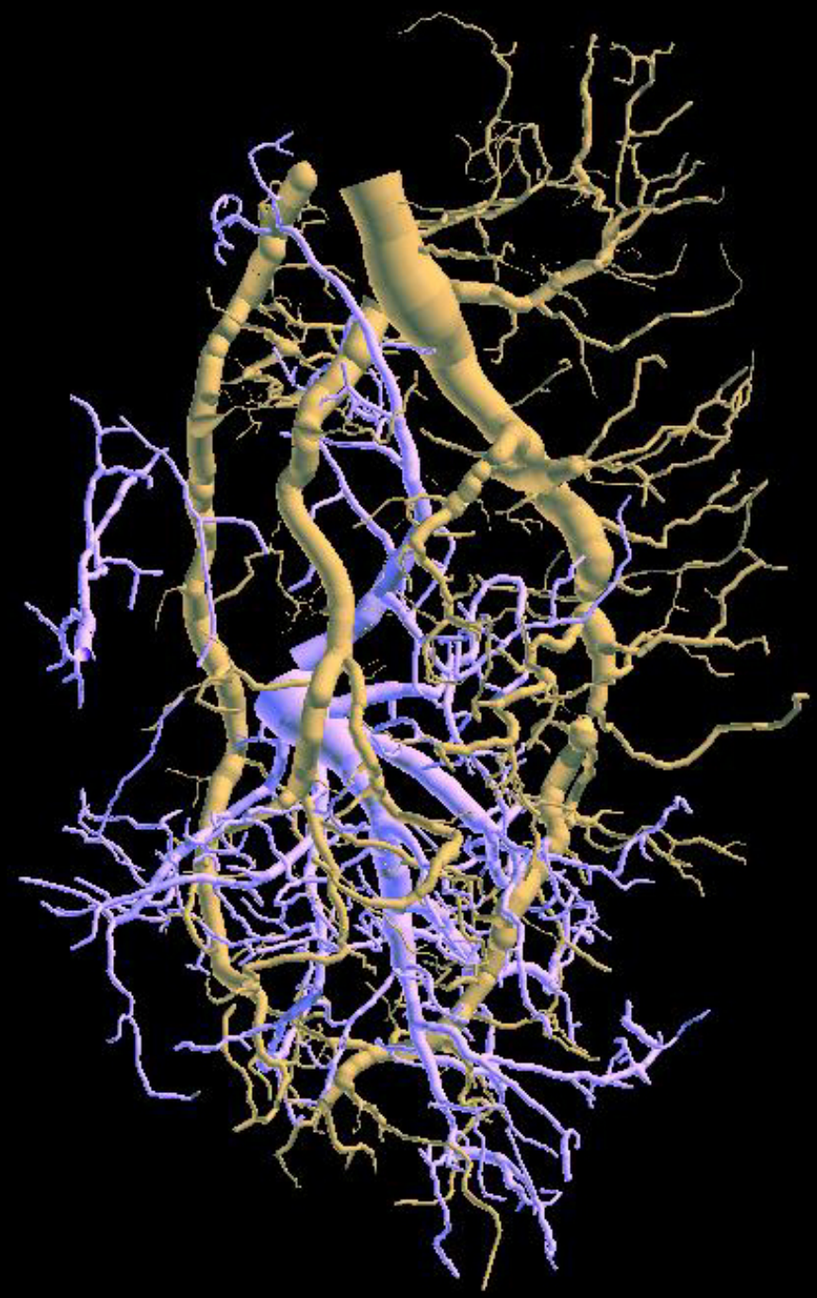

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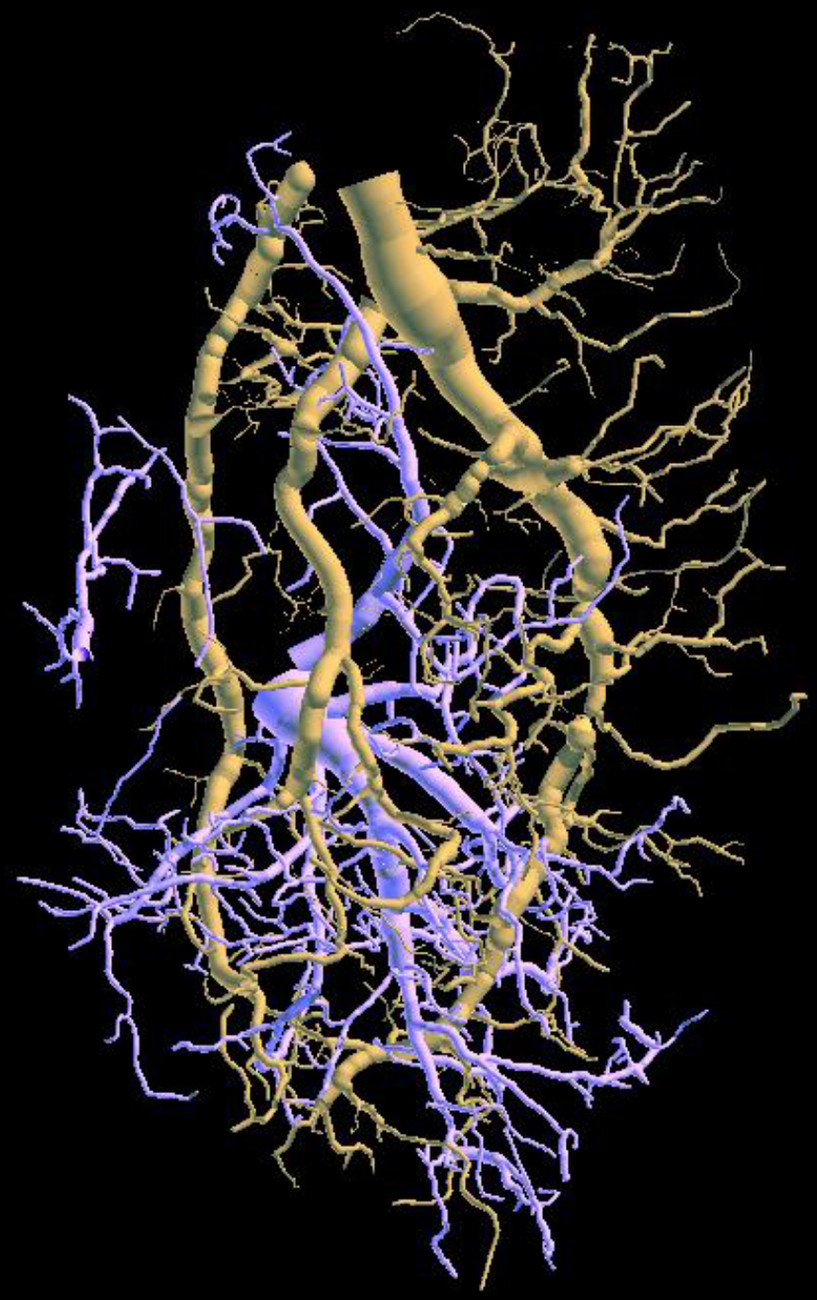

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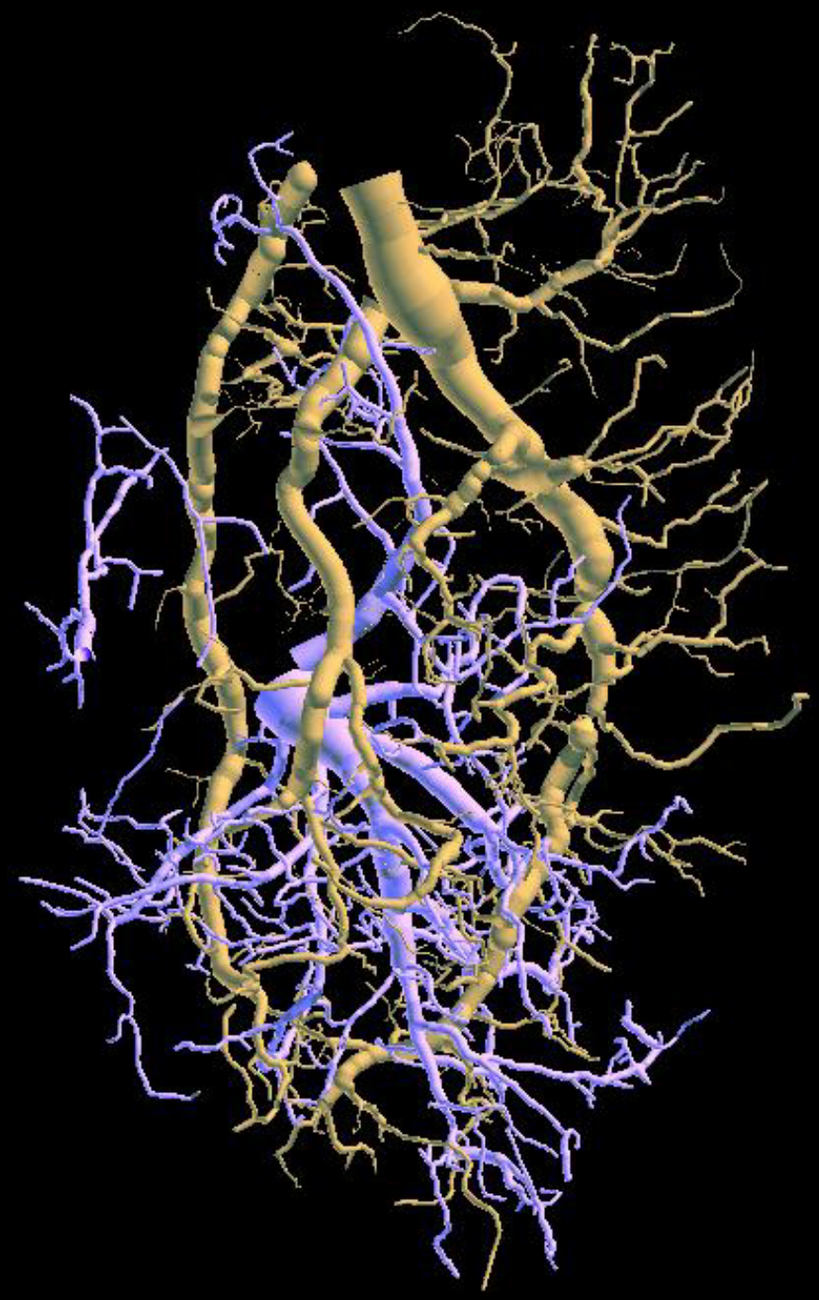

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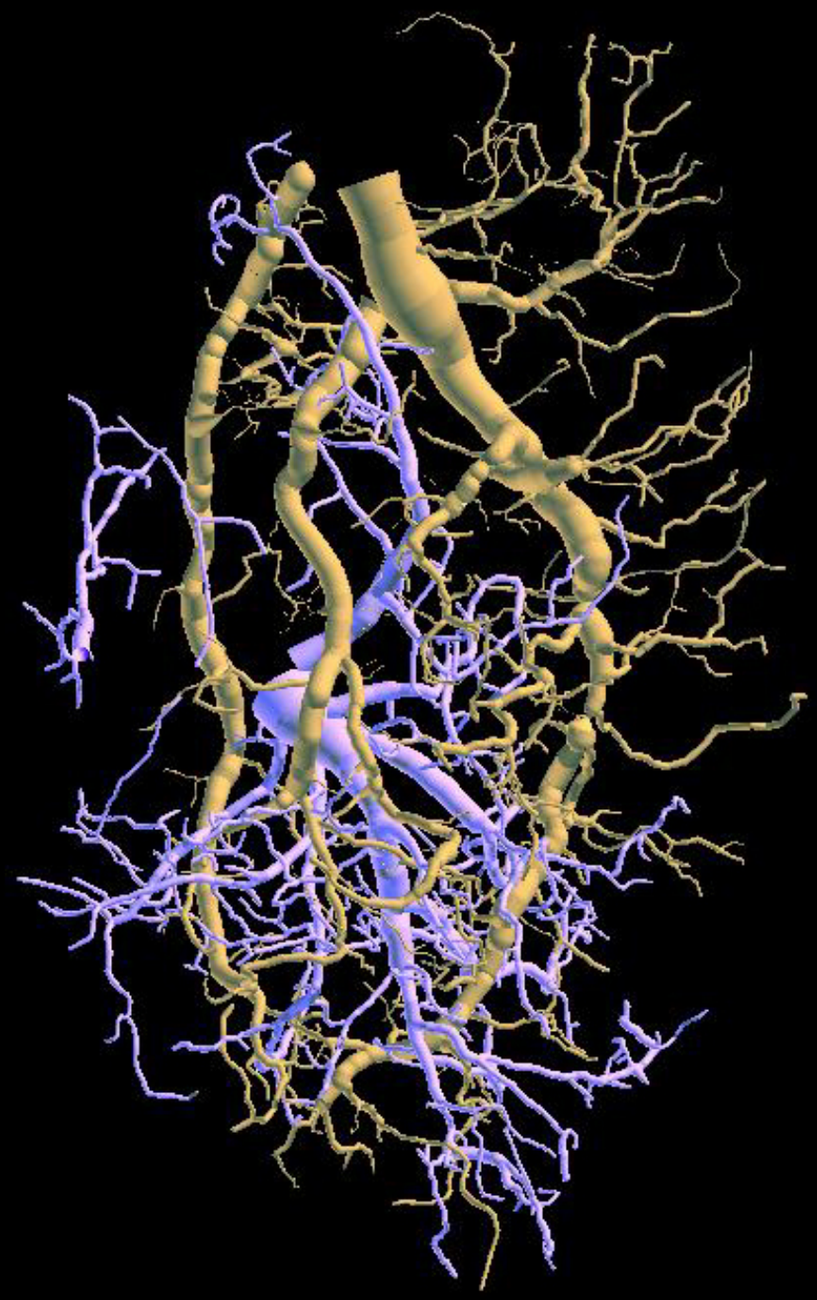
- 10^{11} neurons communicating through 10^{14} synapses
- we don’t stand a chance...



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- (relatively) New Idea:
- The brain is a computing device
- Computational models can help us talk about functions of the brain in a precise way
- Abstract and formal theory can help us organize and interpret (concrete) data

a framework for
computational neuroscience

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a framework for computational neuroscience

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1. the problem (Computational Level)
2. the strategy (Algorithmic Level)
3. how its actually done by networks of neurons (Implementational Level)

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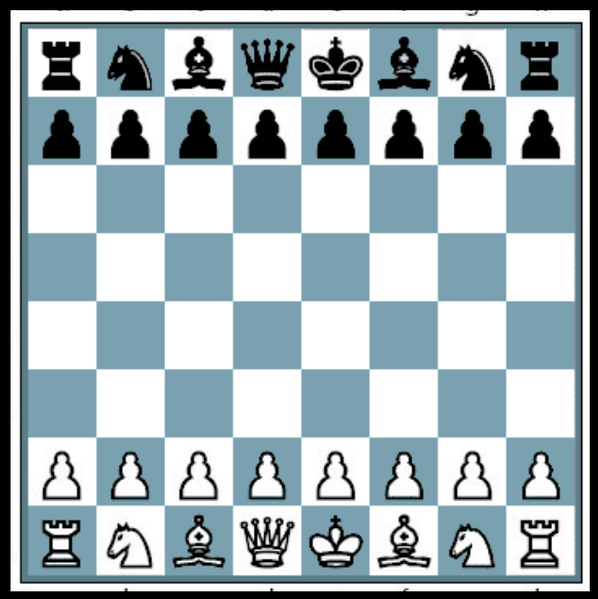

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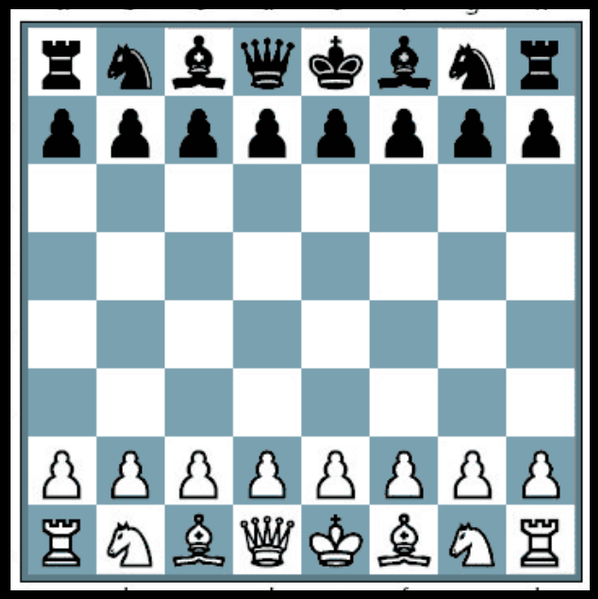

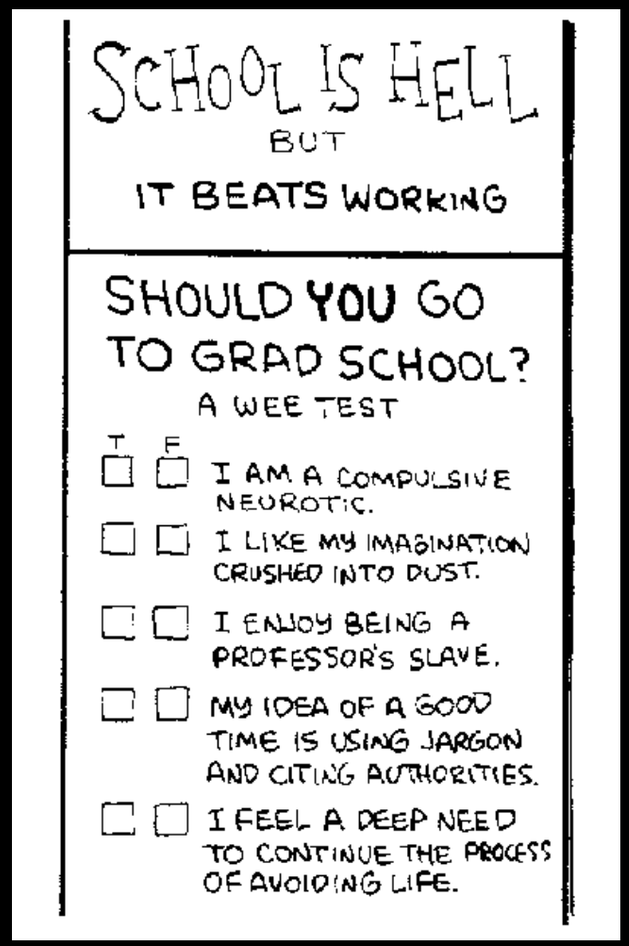

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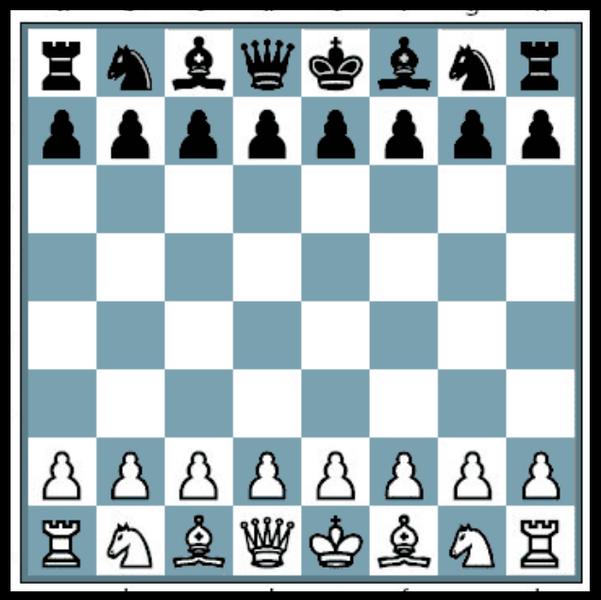
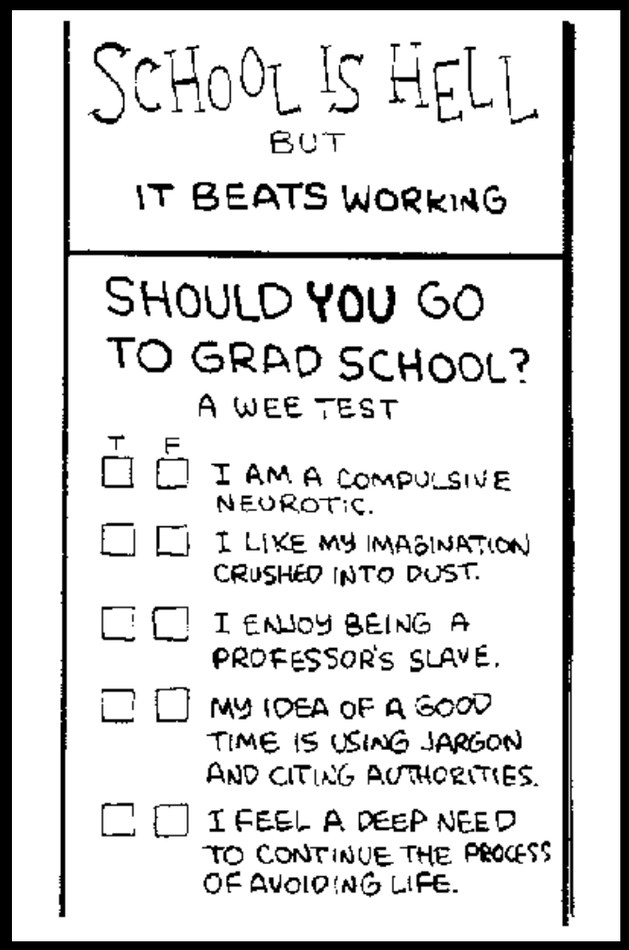
optimal decision making
(maximize reward, minimize punishment)





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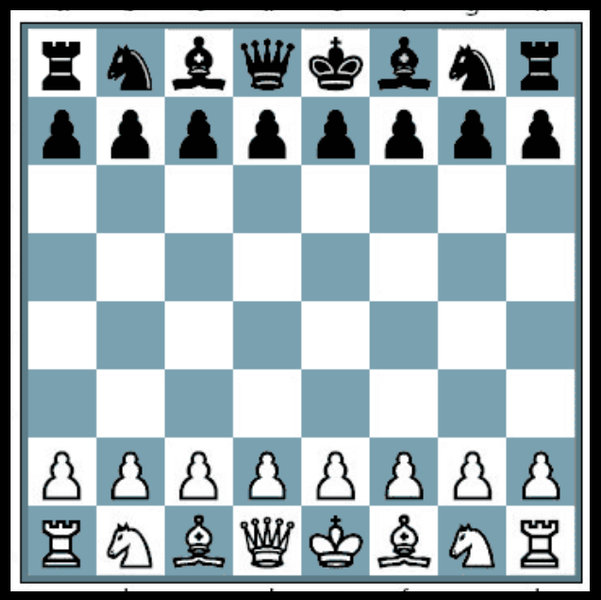

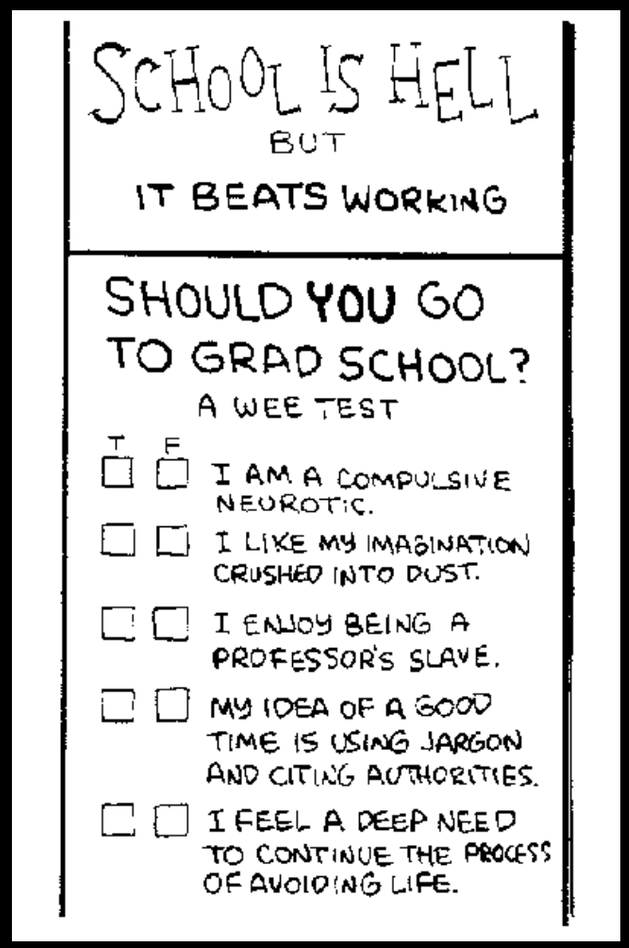

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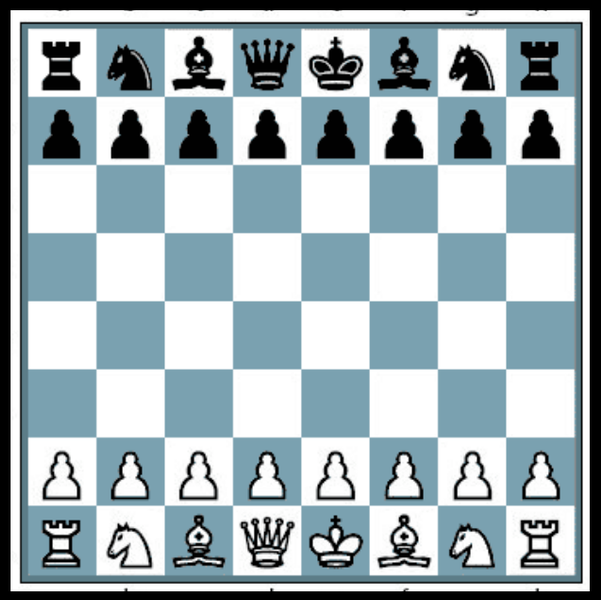

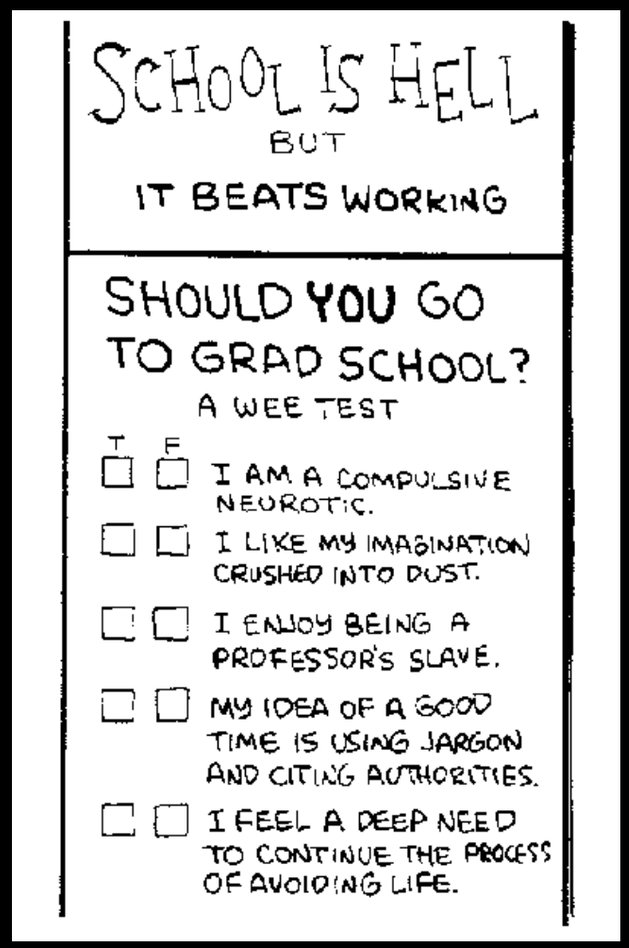

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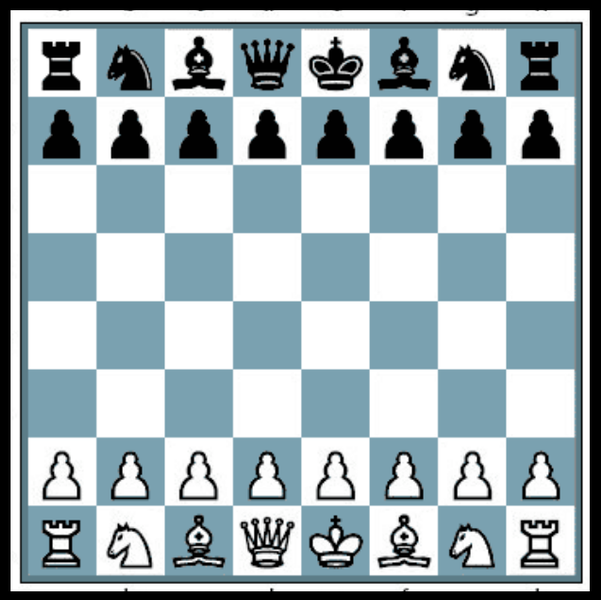

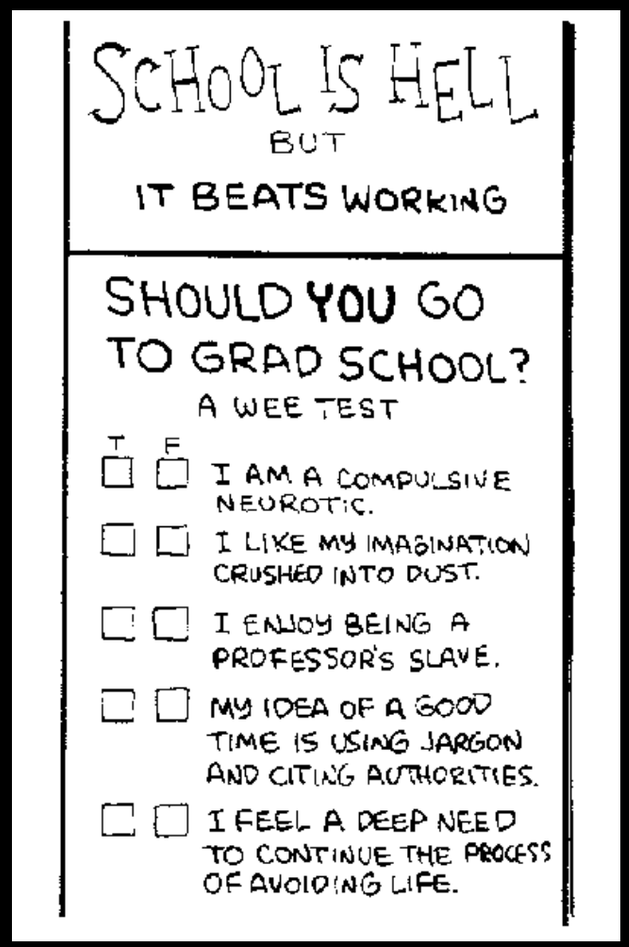

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- Outcomes may depend on a series of actions

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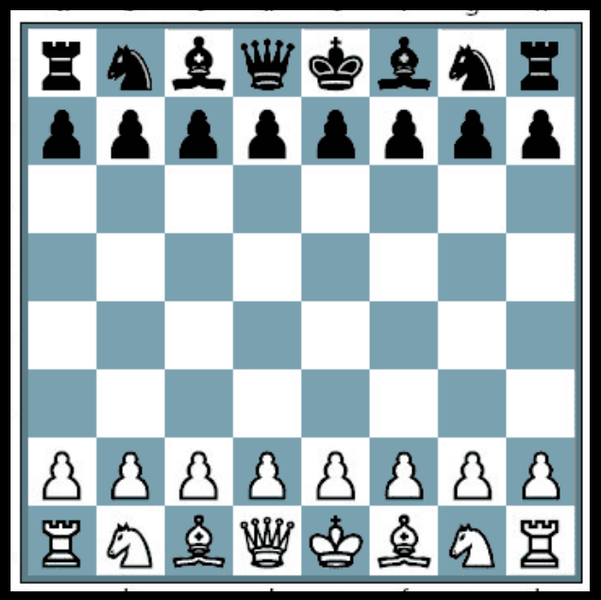

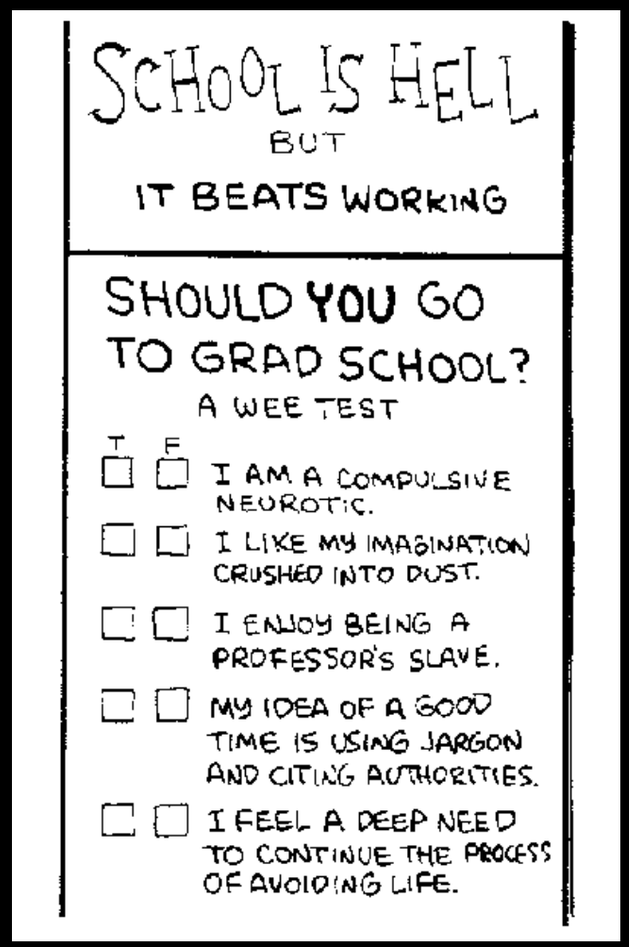

Why is this hard?

- Reward/punishment may be delayed
- Outcomes may depend on a series of actions

⇒ "credit assignment problem" (Sutton, 1978)

in comes reinforcement learning

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- The problem: optimal decision making (maximize reward, minimize punishment)

in comes reinforcement learning

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- An algorithm: reinforcement learning

in comes reinforcement learning

- The problem: optimal decision making (maximize reward, minimize punishment)
- An algorithm: reinforcement learning
- Neural implementation: basal ganglia, dopamine

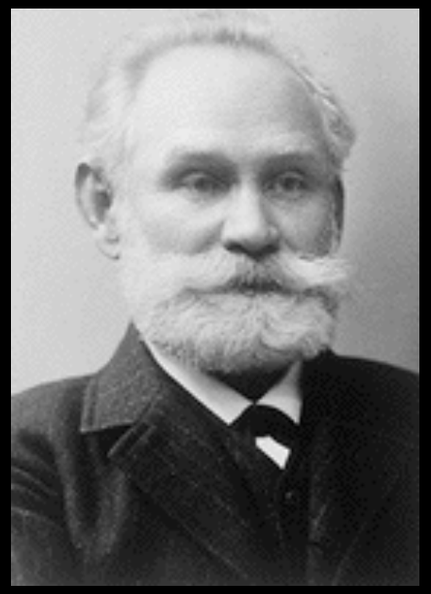
Summary so far...

- Idea: study the brain as a computing device
- Rather than look at what networks of neurons in the brain represent, look at what they compute
- What do animal's brains compute?

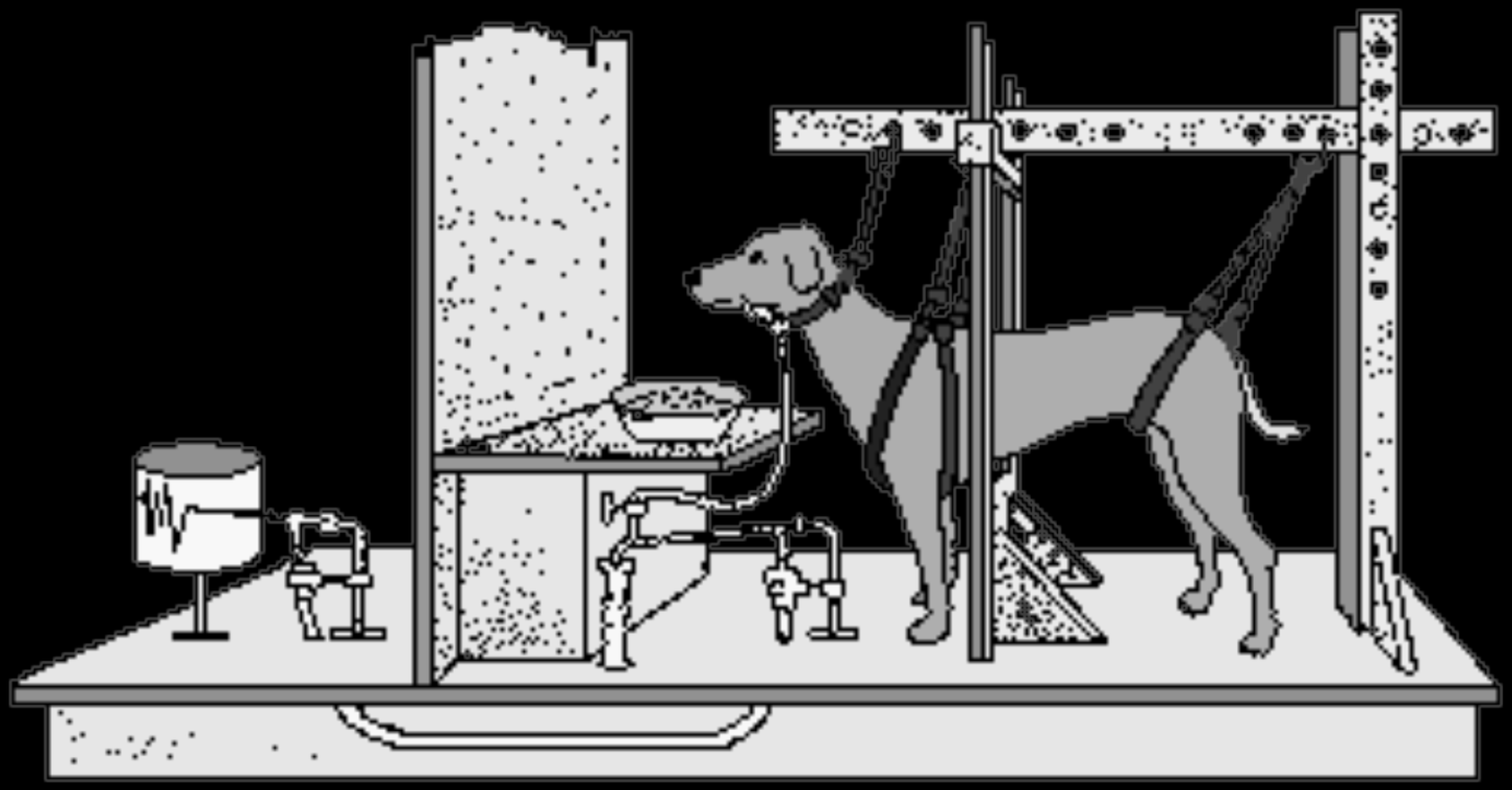
Animal Conditioning and RL

- two basic types of animal conditioning (animal learning)
- how do these relate to RL?

1. Pavlovian conditioning: animals learn predictions



Ivan Pavlov
(Nobel prize portrait)



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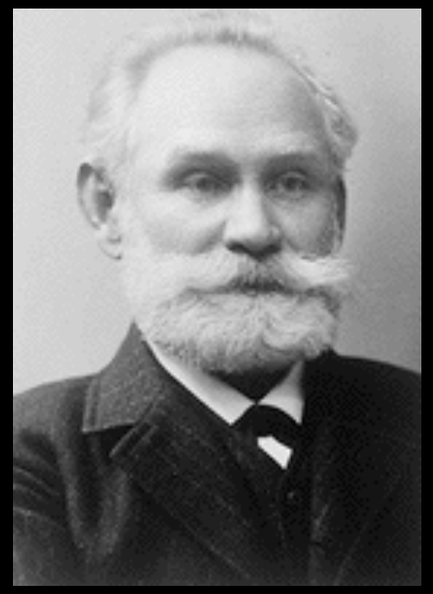

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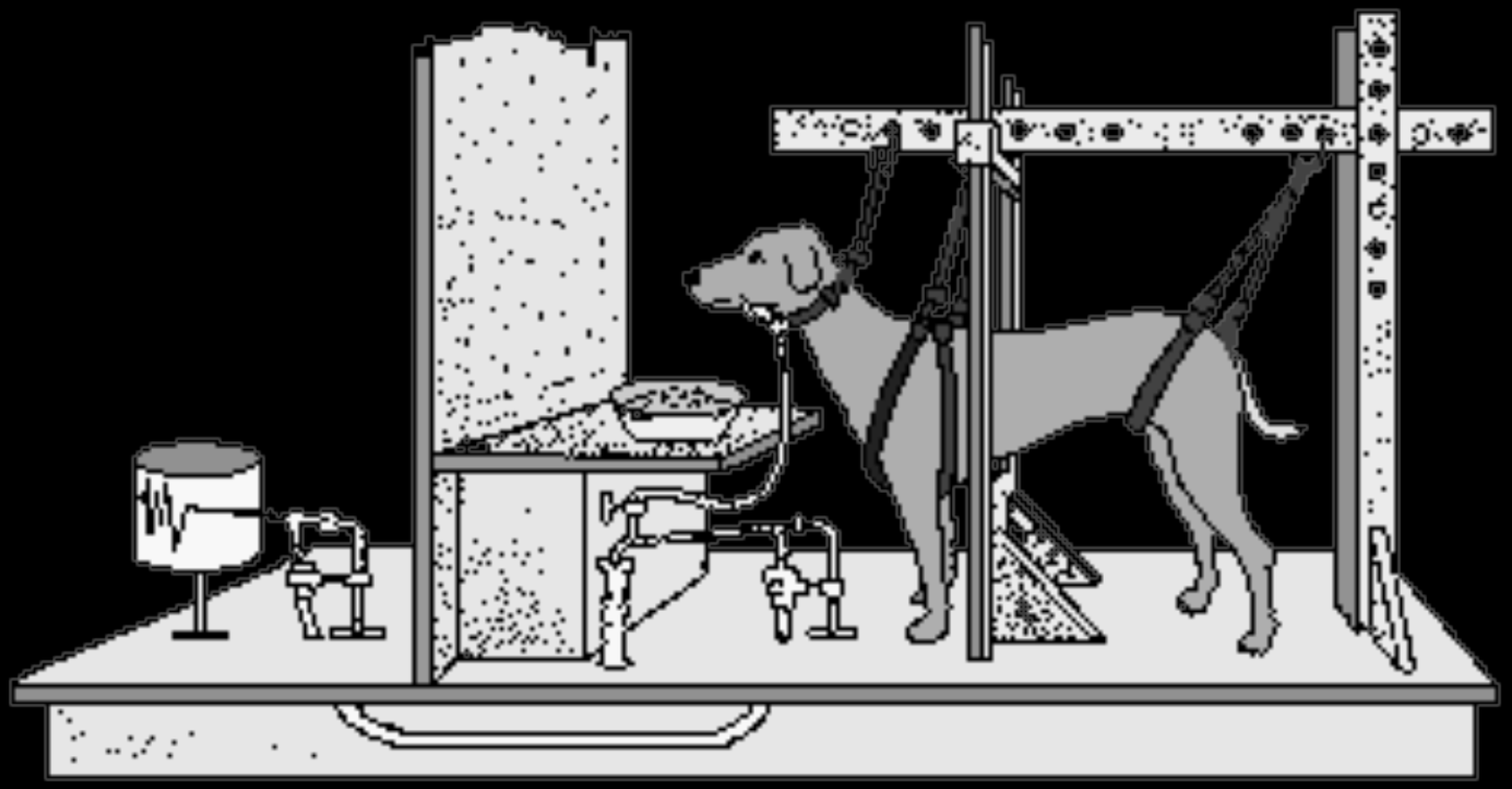

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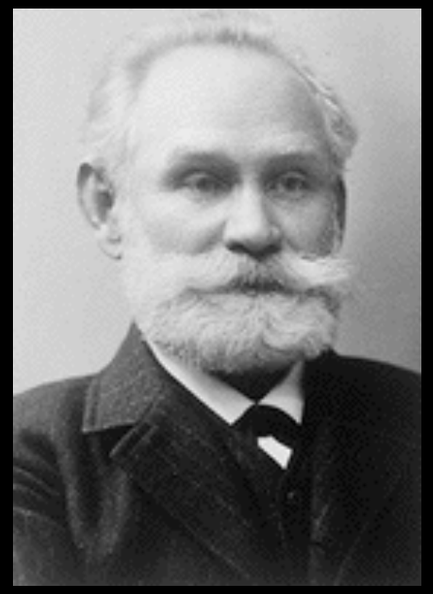

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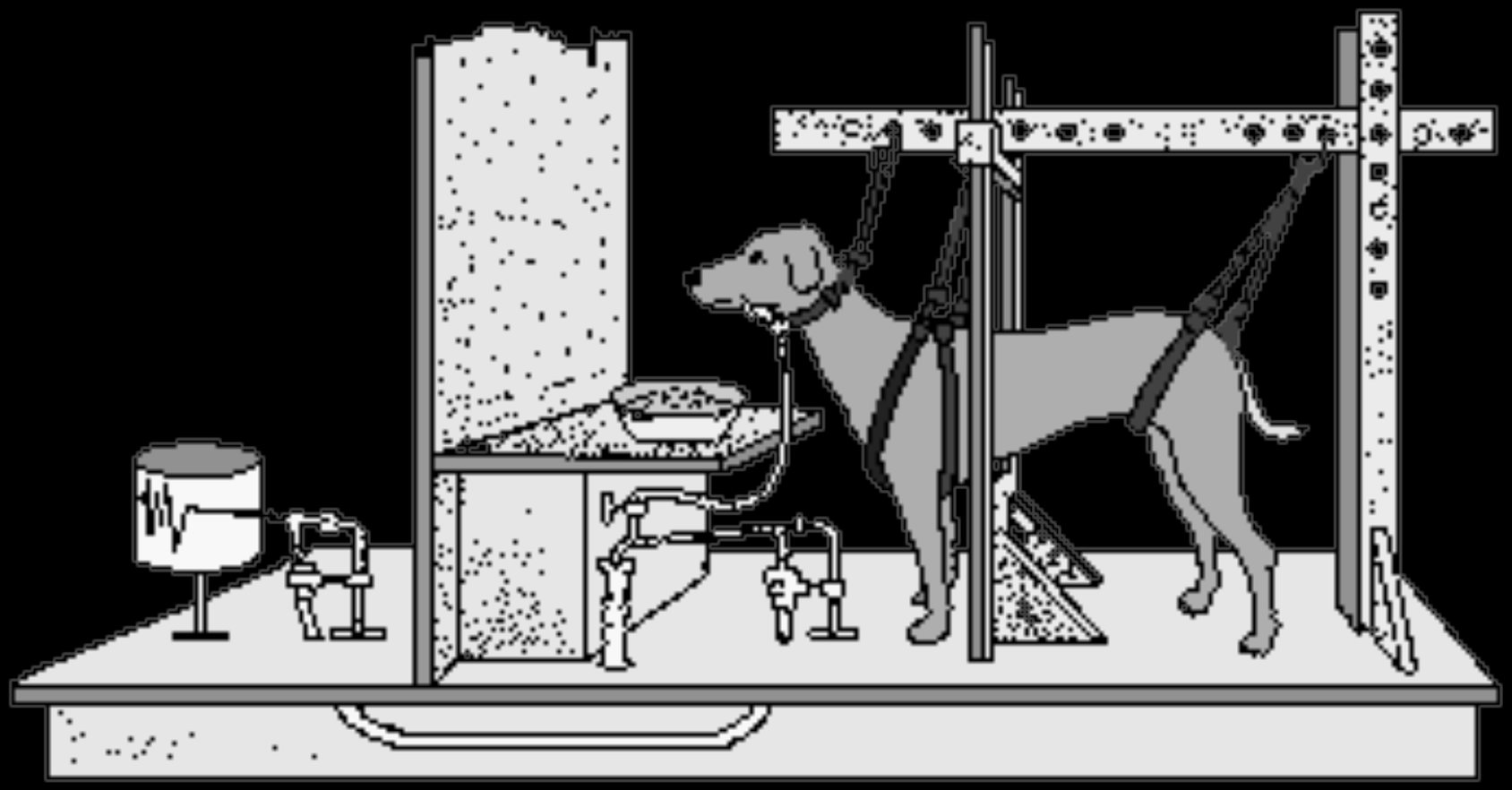

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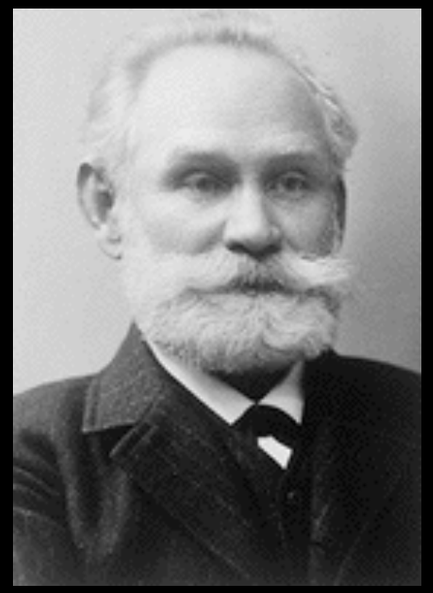

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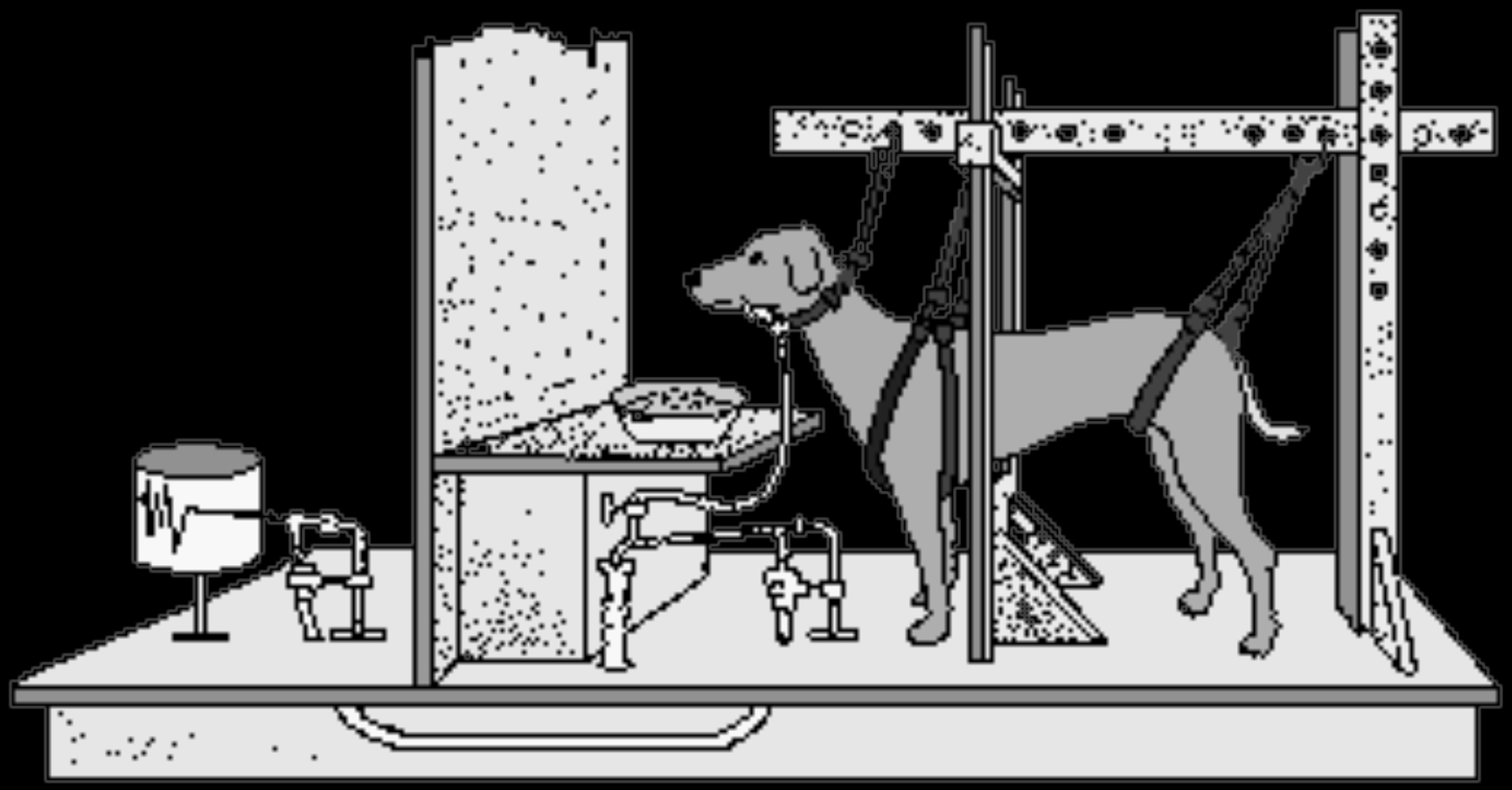

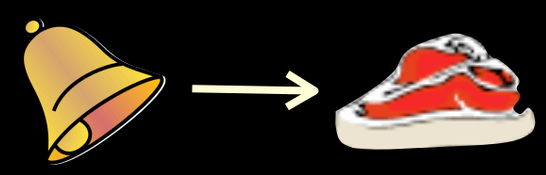

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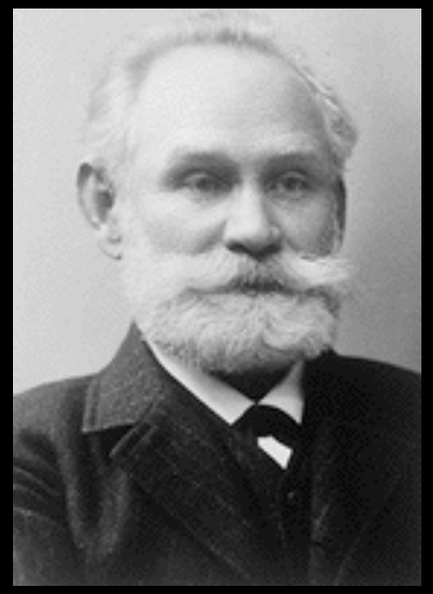

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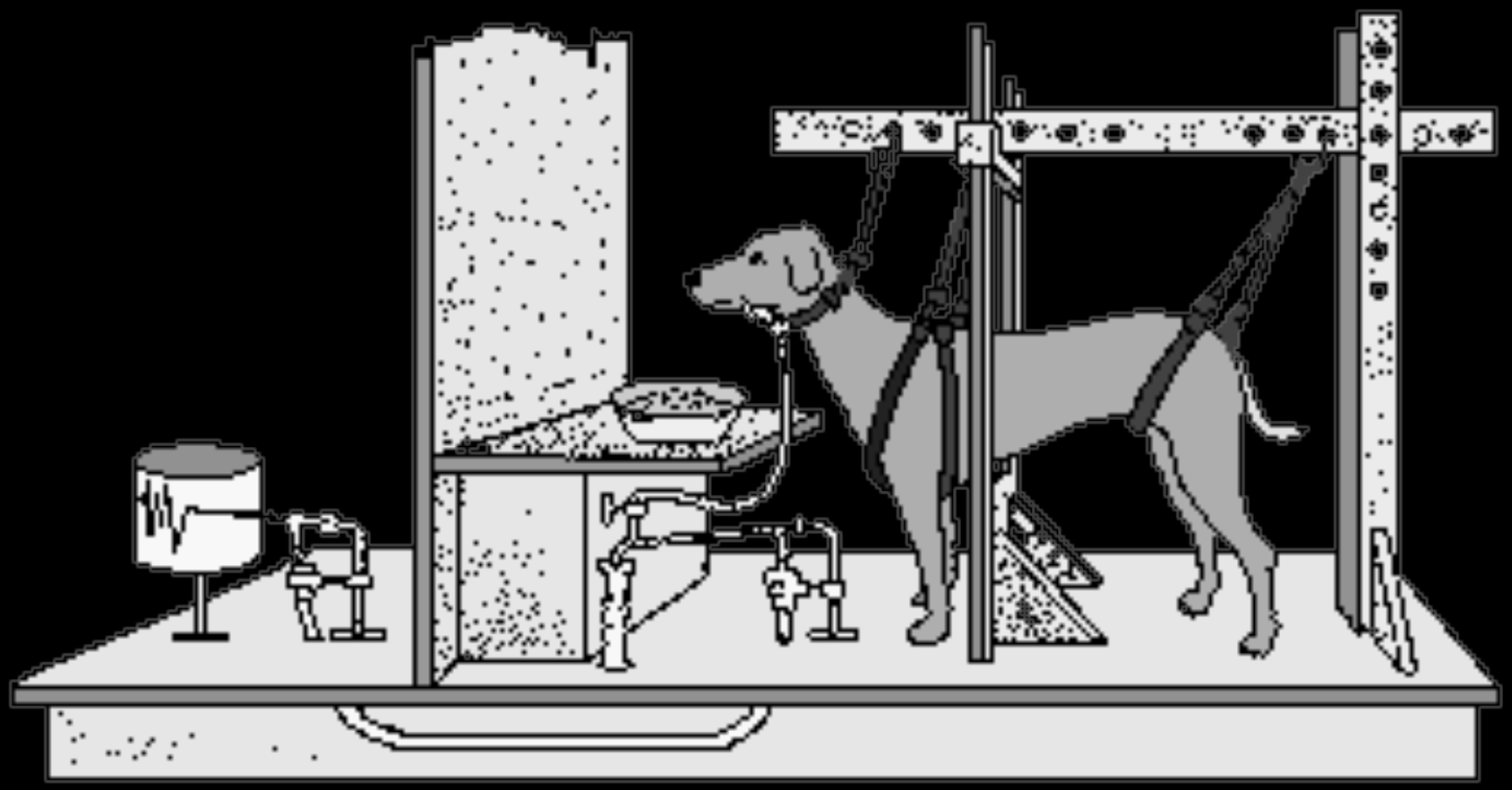

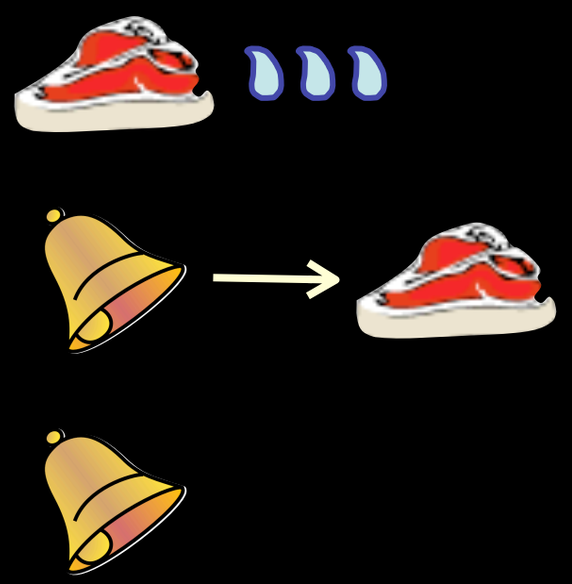

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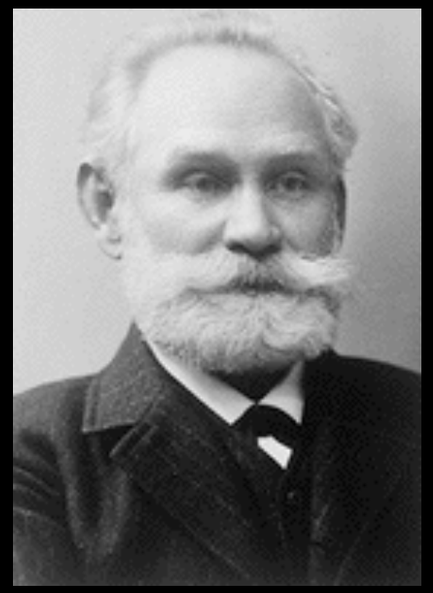

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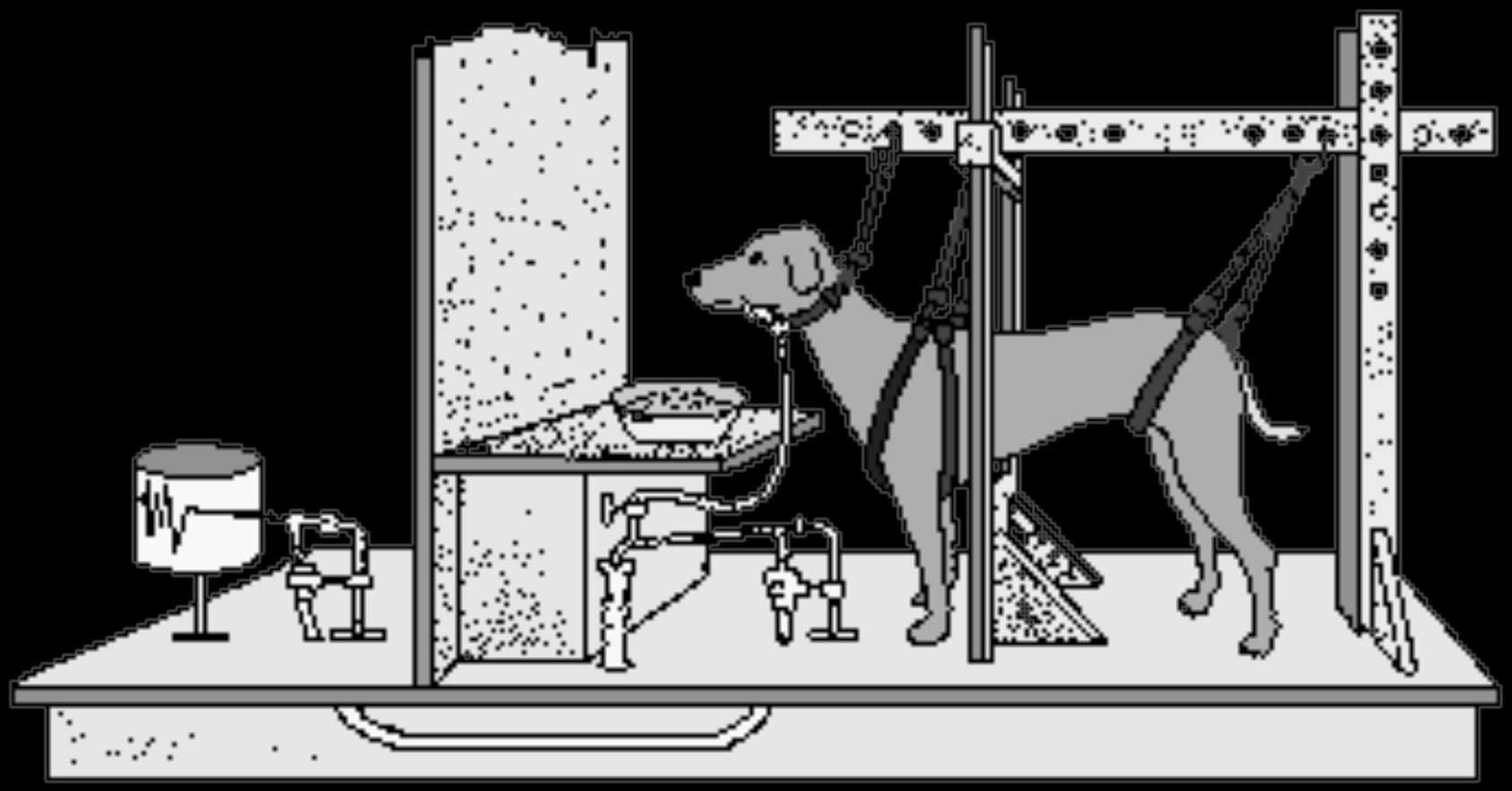

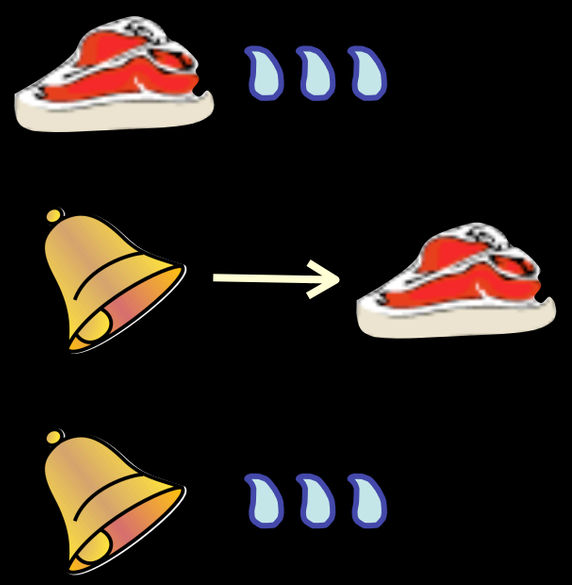

Pavlovian conditioning examples
(conditioned suppression, autoshaping)

Credits: Greg Quirk, Dale Swartzentruber

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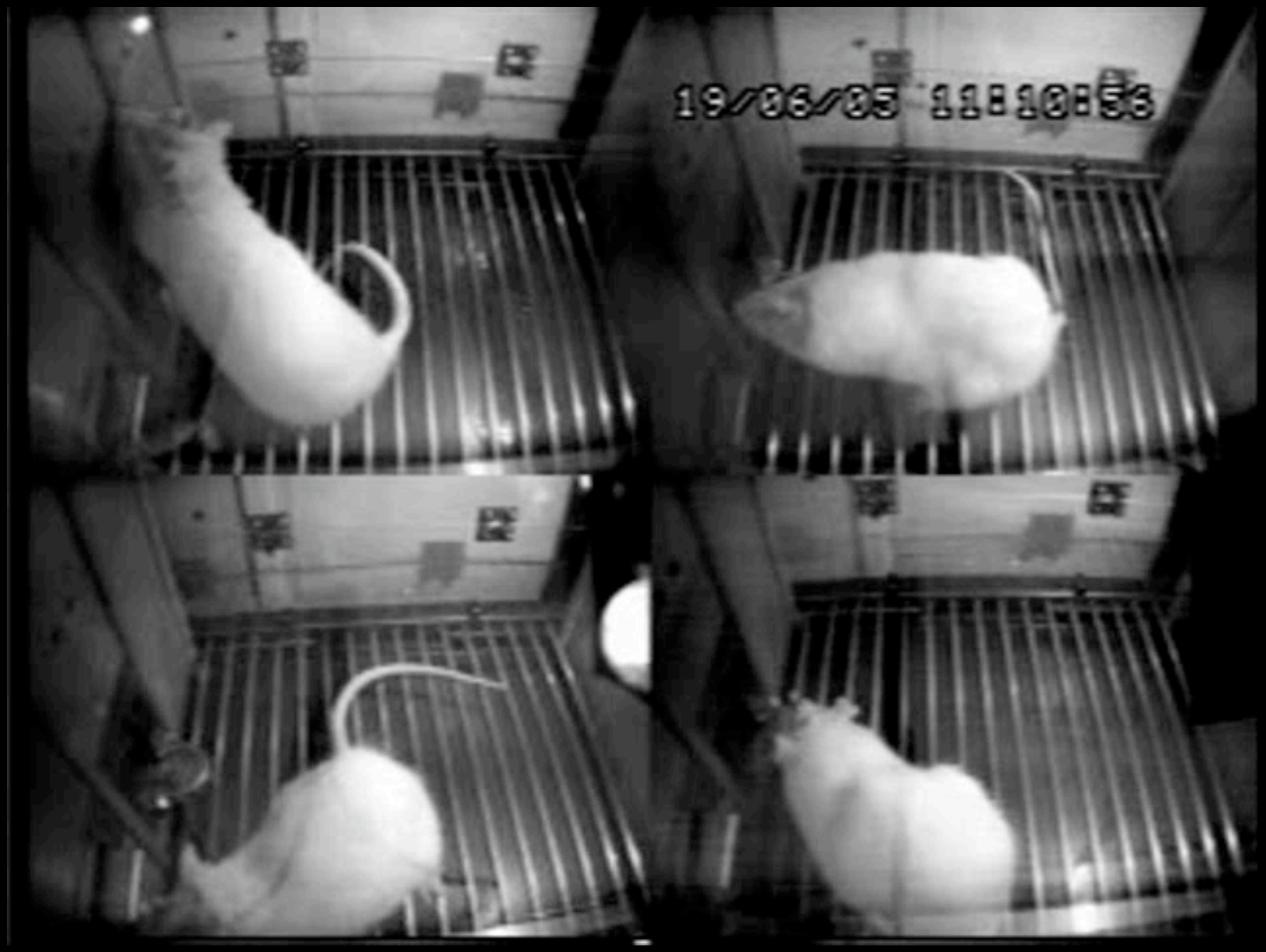

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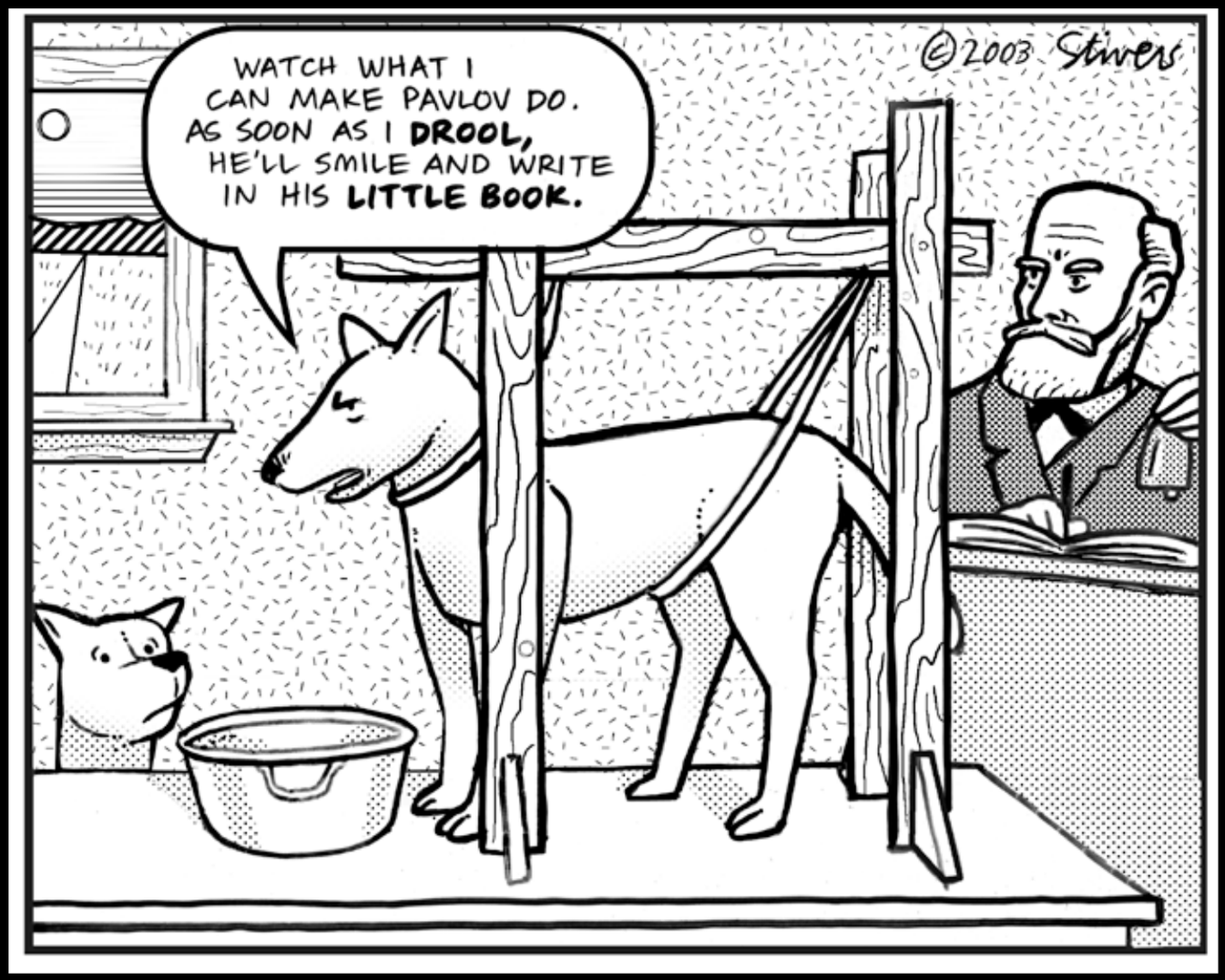
how is this related to RL?



model-free learning of values of stimuli through experience;
responding conditioned on (predictive) value of stimulus

Dayan et al. (2006) - "The Misbehavior of Value and the Discipline of the Will"

Rescorla & Wagner (1972)

The idea: error-driven learning

Change in value is proportional to the difference between actual and predicted outcome

$$\Delta V(S_i) = \eta[R - \sum_{j \in \text{trial}} V(S_j)]$$

Two assumptions/hypotheses:

(1) learning is driven by error (formalize notion of surprise)

(2) summations of predictors is linear

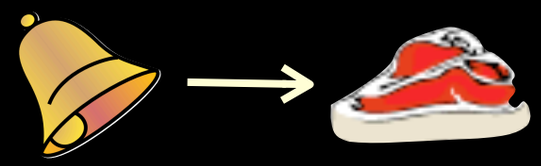
How do we know that animals use an error-correcting learning rule?

Phase I

Phase II

How do we know that animals use an error-correcting learning rule?

Phase I



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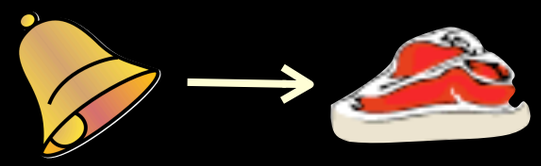

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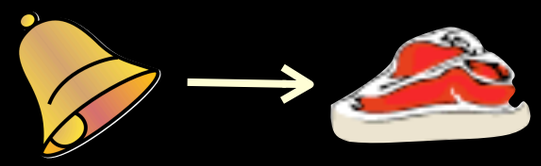

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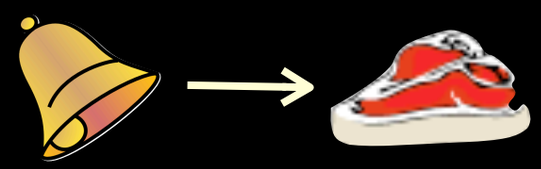

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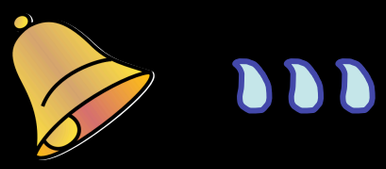

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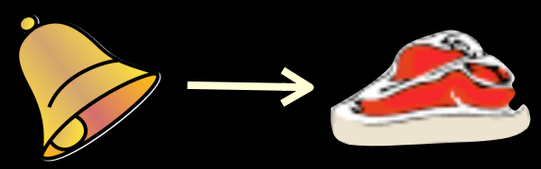

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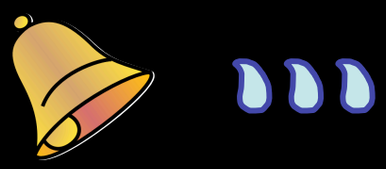

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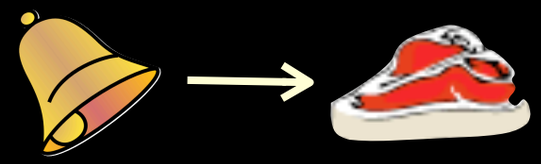

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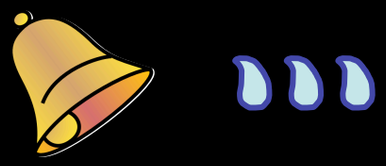

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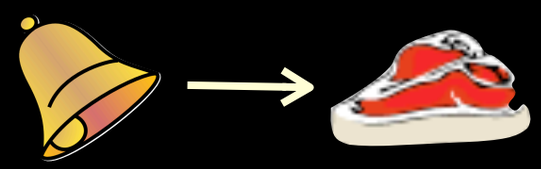

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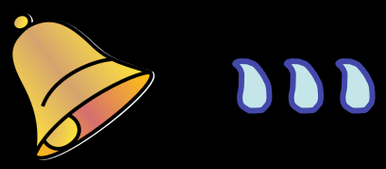

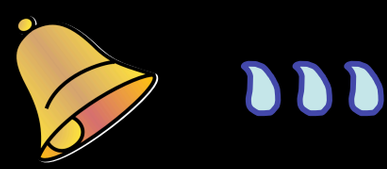

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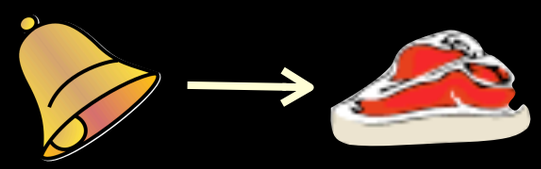

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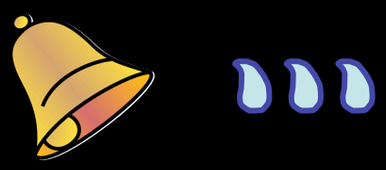

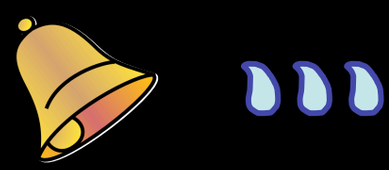

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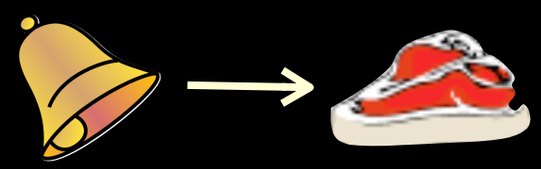

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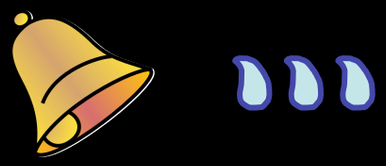

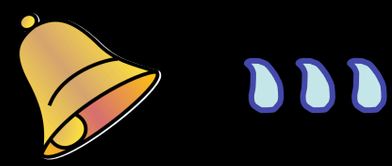

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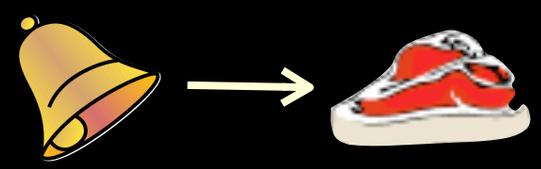

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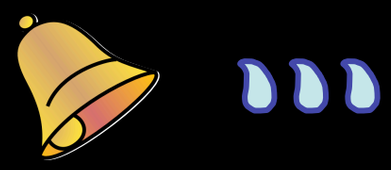

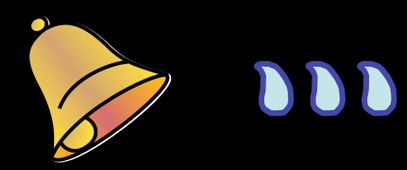

Blocking

(NB. Also in humans)

2. Instrumental conditioning: adding control

Edward Thorndike (law of effect)

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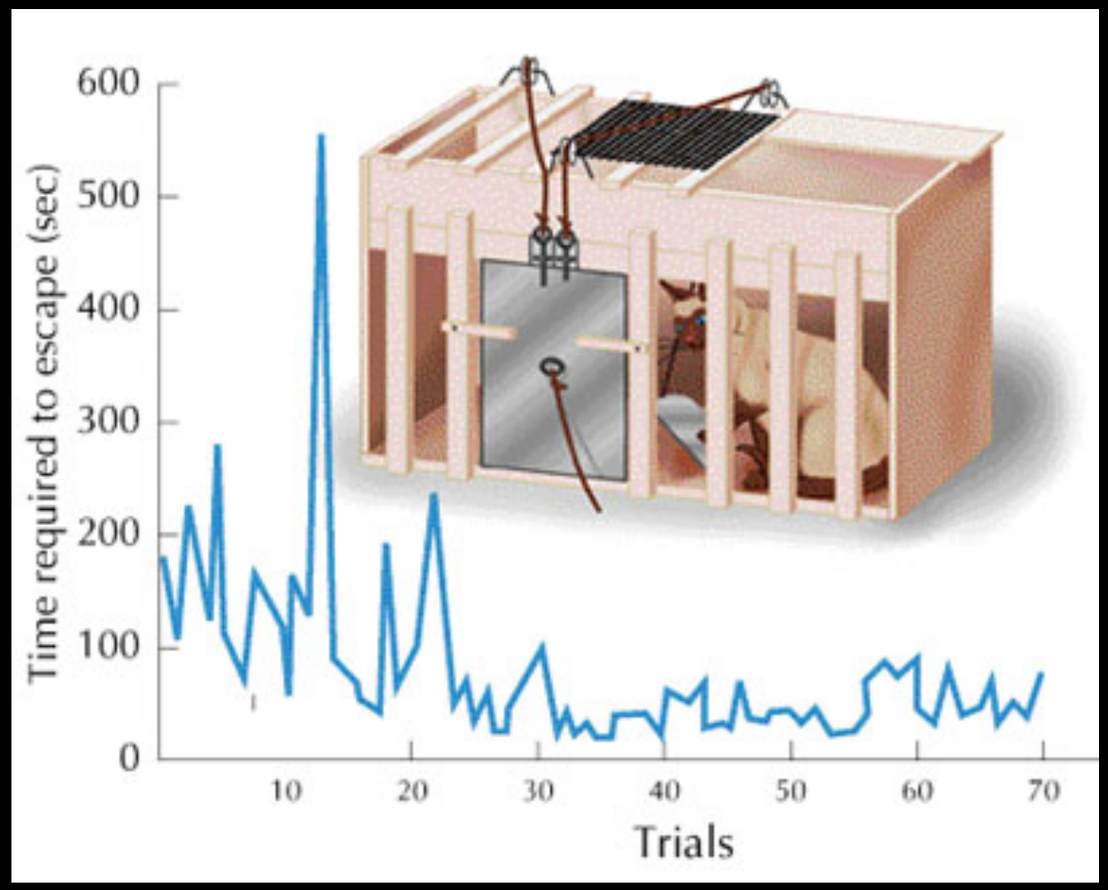

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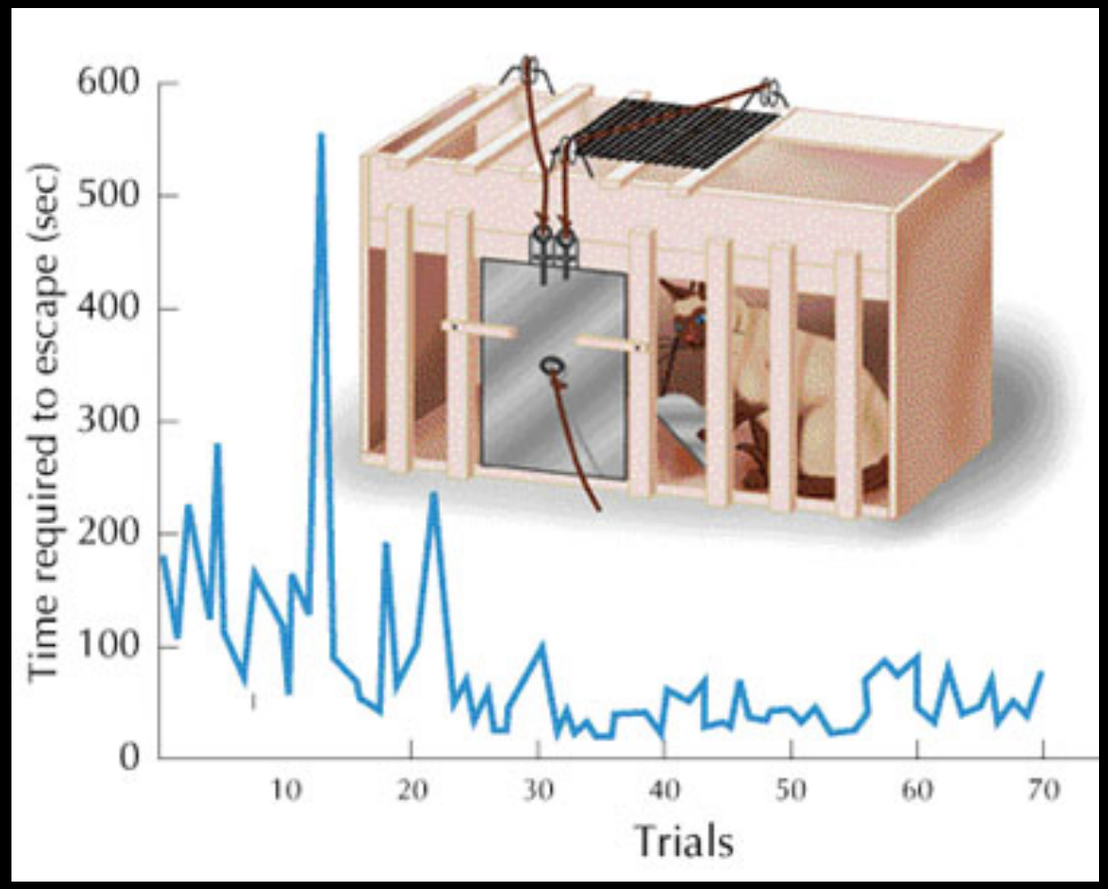

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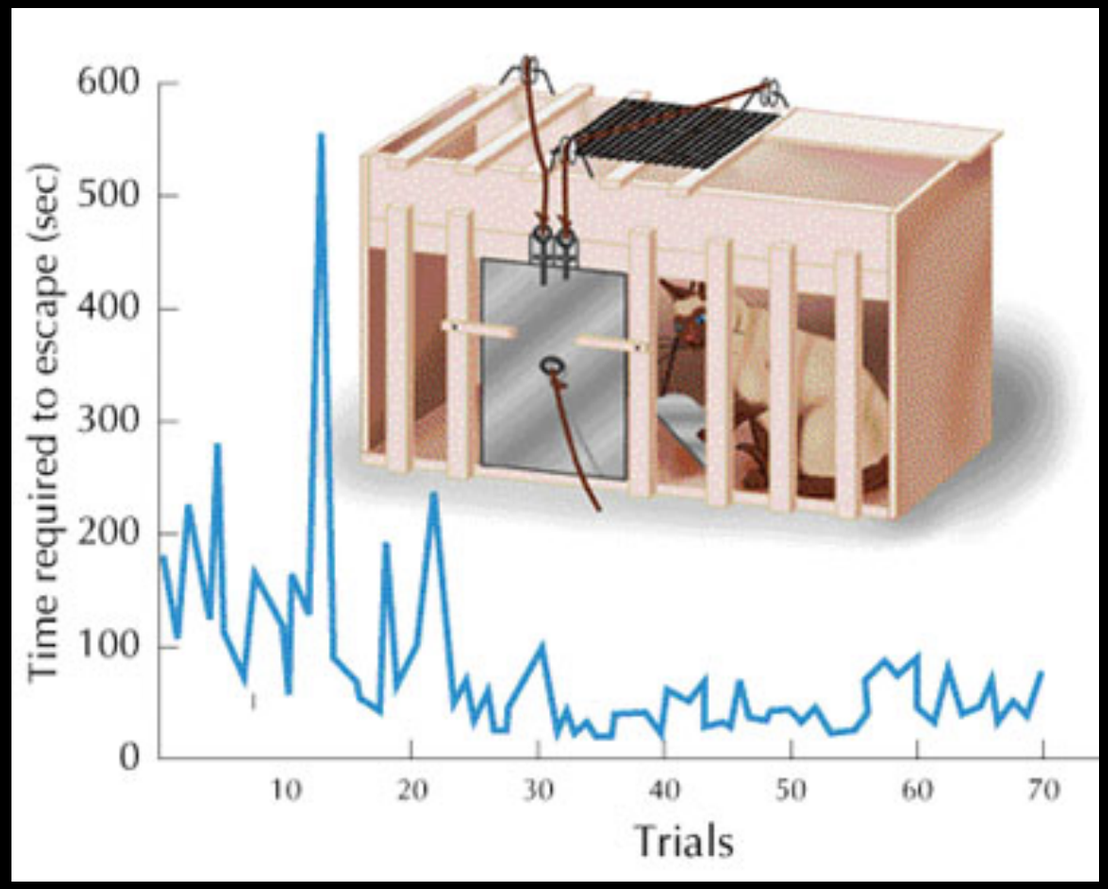
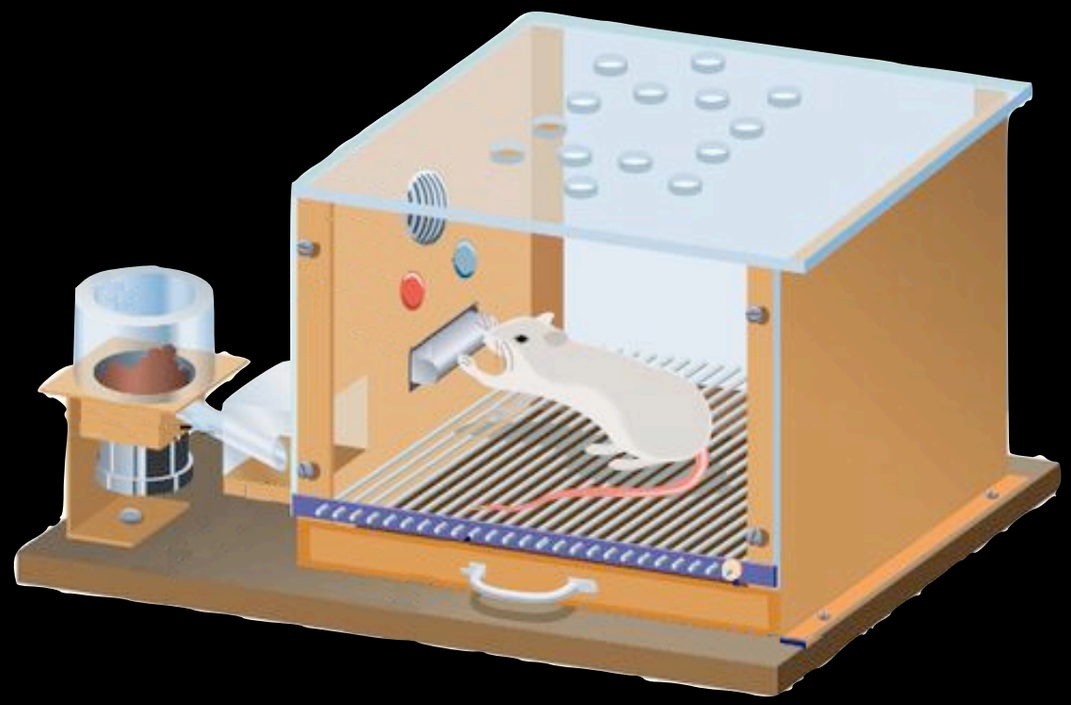
- Definition for learning: time to escape
- Gradual learning curves, did not look like 'insight' but rather trial and error



Example: Free operant conditioning (Skinner)



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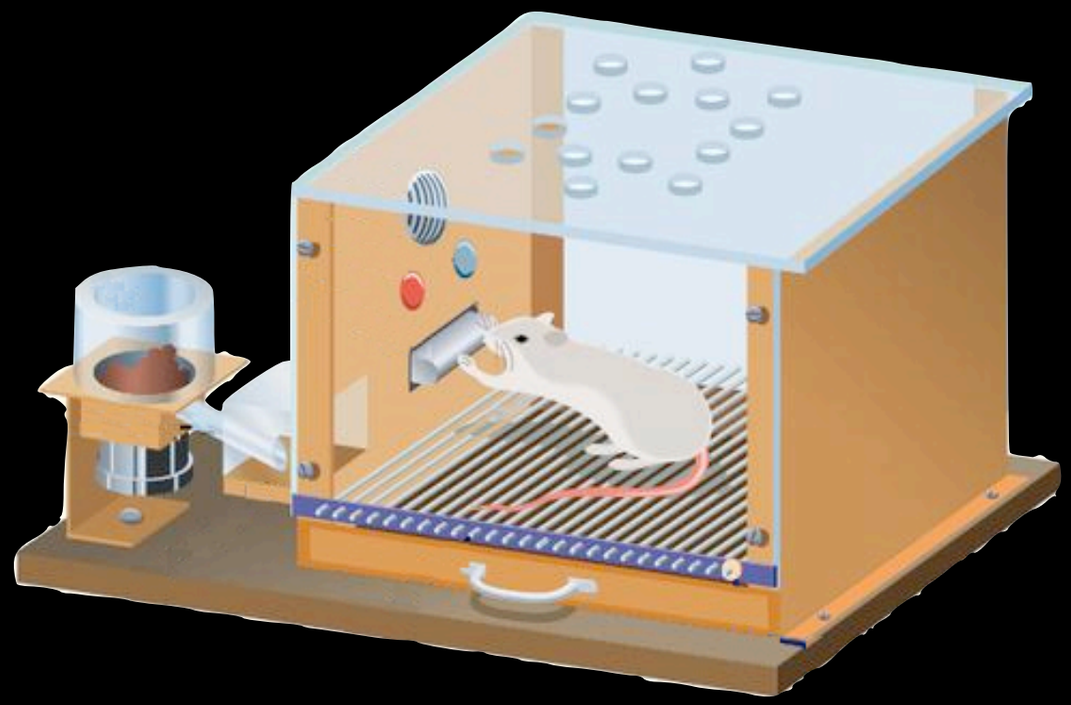


how is this related to RL?

animals can learn an arbitrary policy to obtain rewards (and avoid punishments)

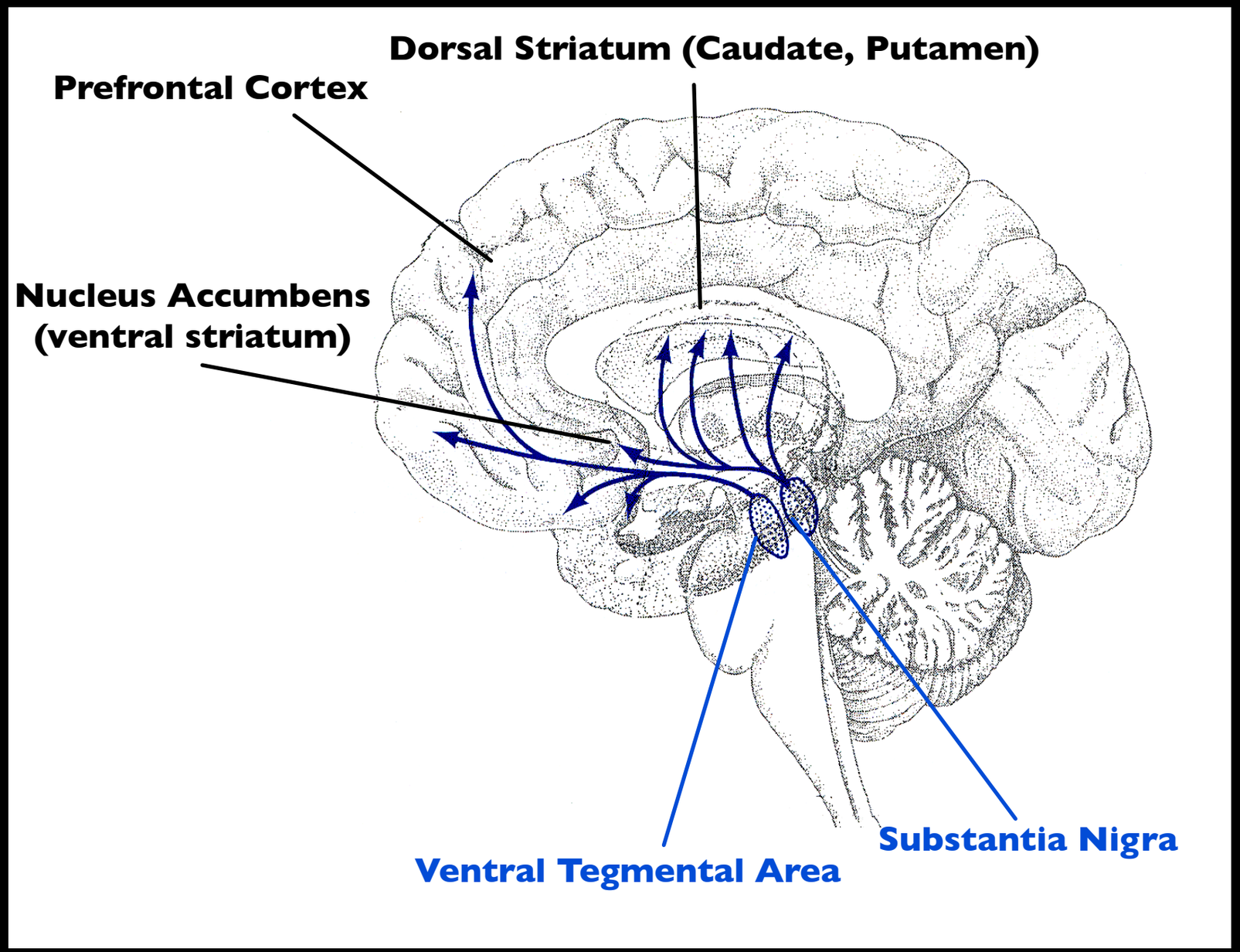
Summary so far...

- The world presents animals/humans with a huge reinforcement learning problem (or many such small problems)
- Optimal learning and behavior depend on prediction and control
- How can the brain realize these? Can RL help us understand the brain's computations?

Outline

- The brain coarse-grain
- Learning and decision making in animals and humans: what does RL have to do with it?
- A success story: Dopamine and prediction errors
- Actor/Critic architecture in basal ganglia
- SARSA vs Q-learning: can the brain teach us about ML?
- Model free and model based RL in the brain
- Average reward RL & tonic dopamine
- Risk sensitivity and RL in the brain
- Open challenges and future directions

What is dopamine and why do we care about it?



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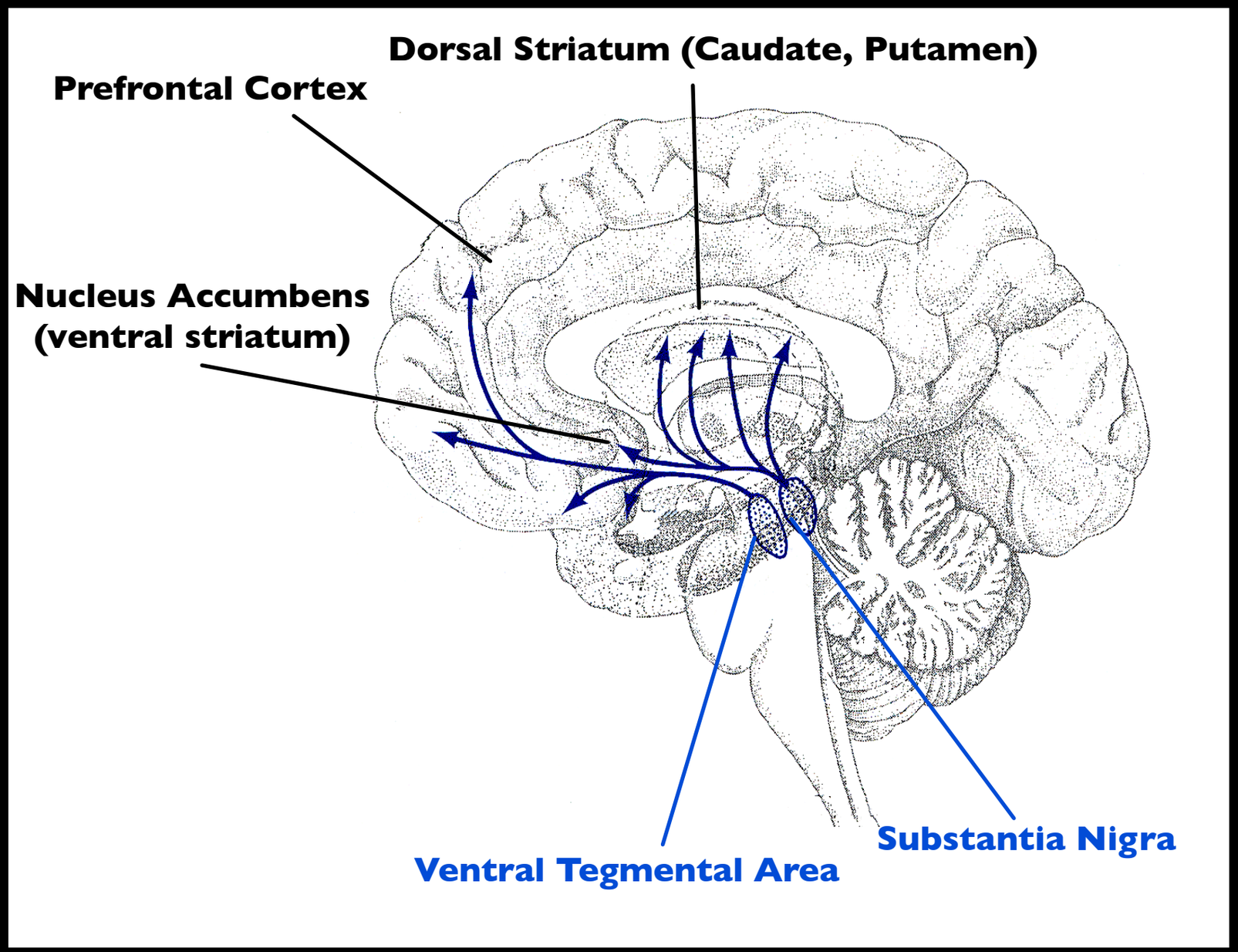

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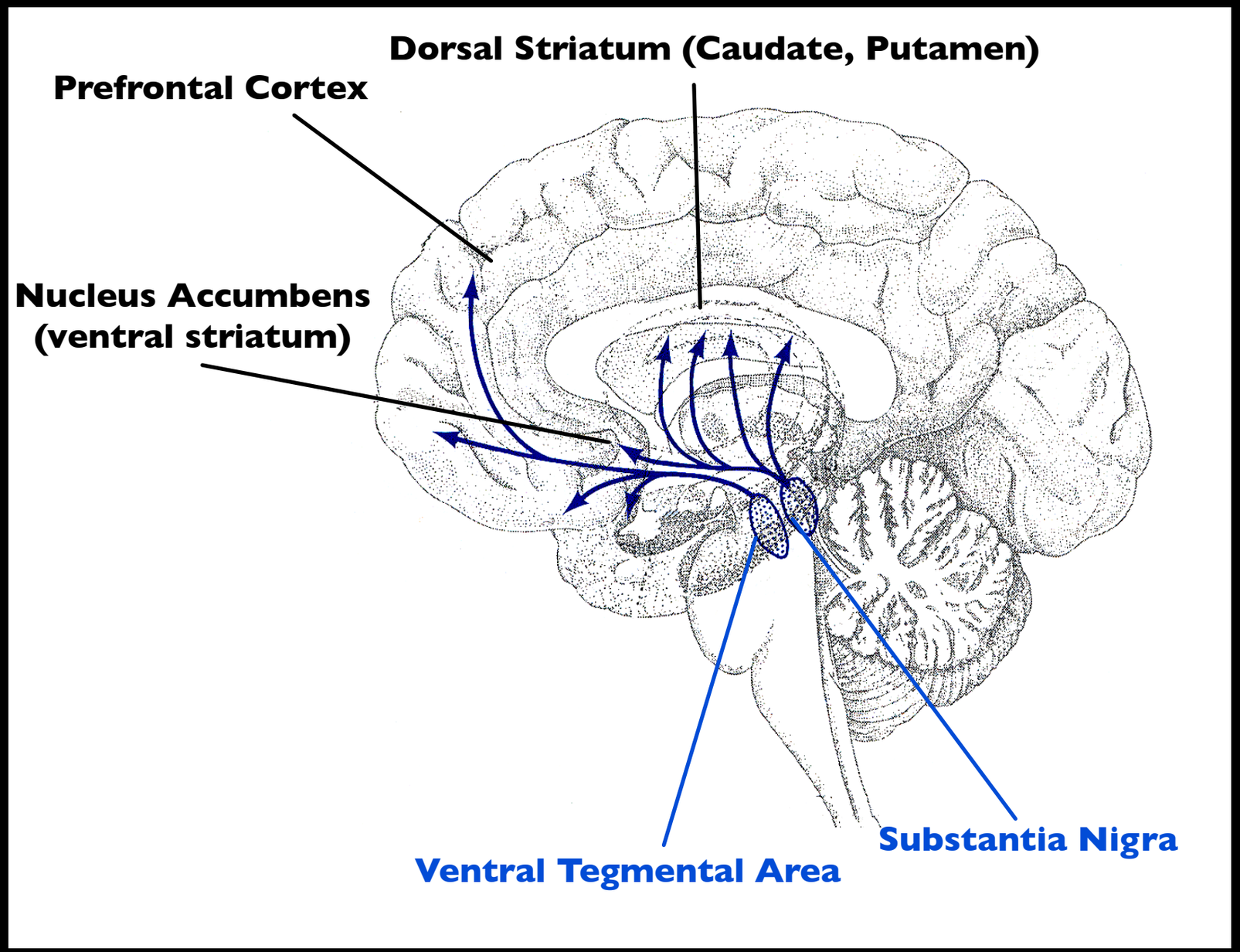

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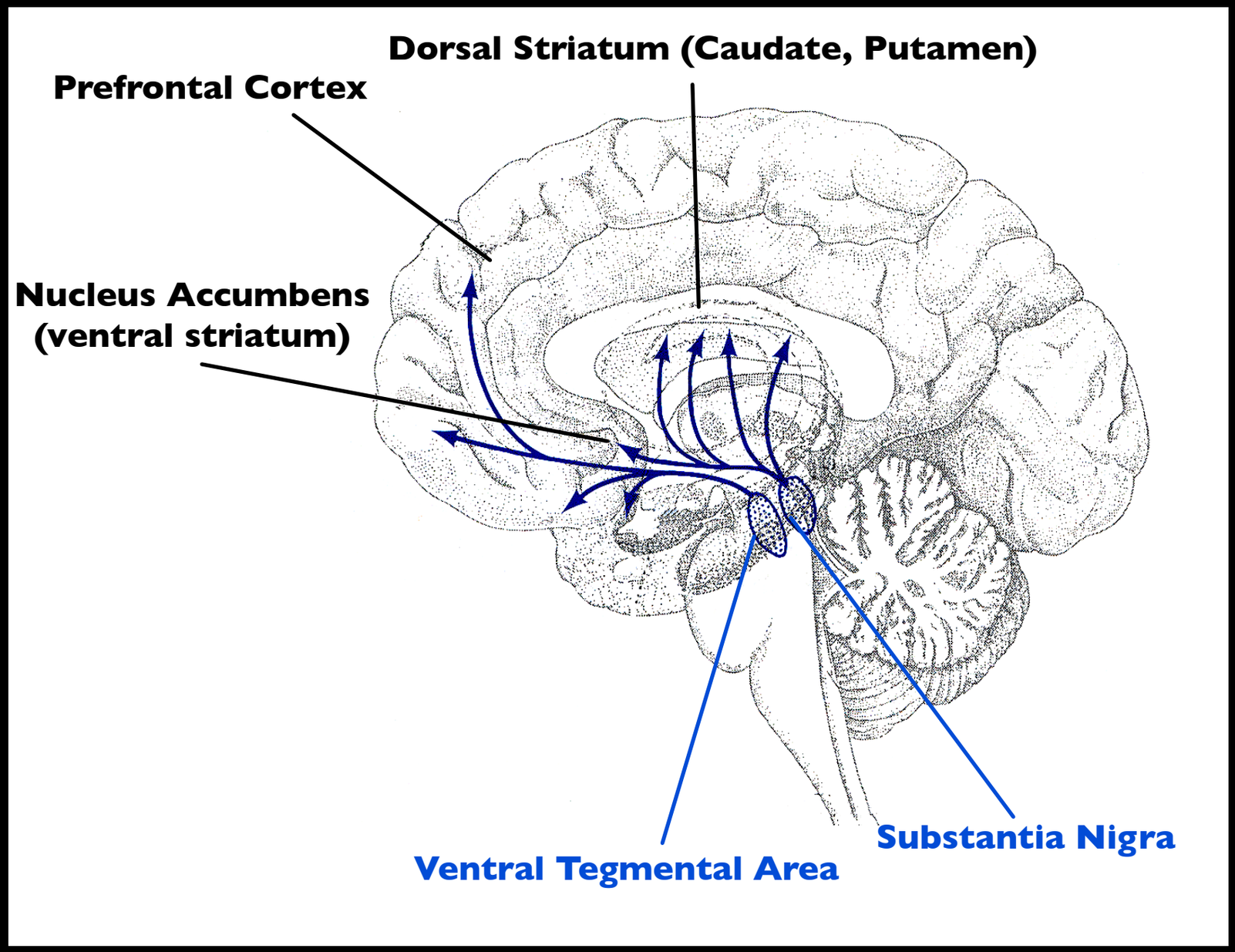

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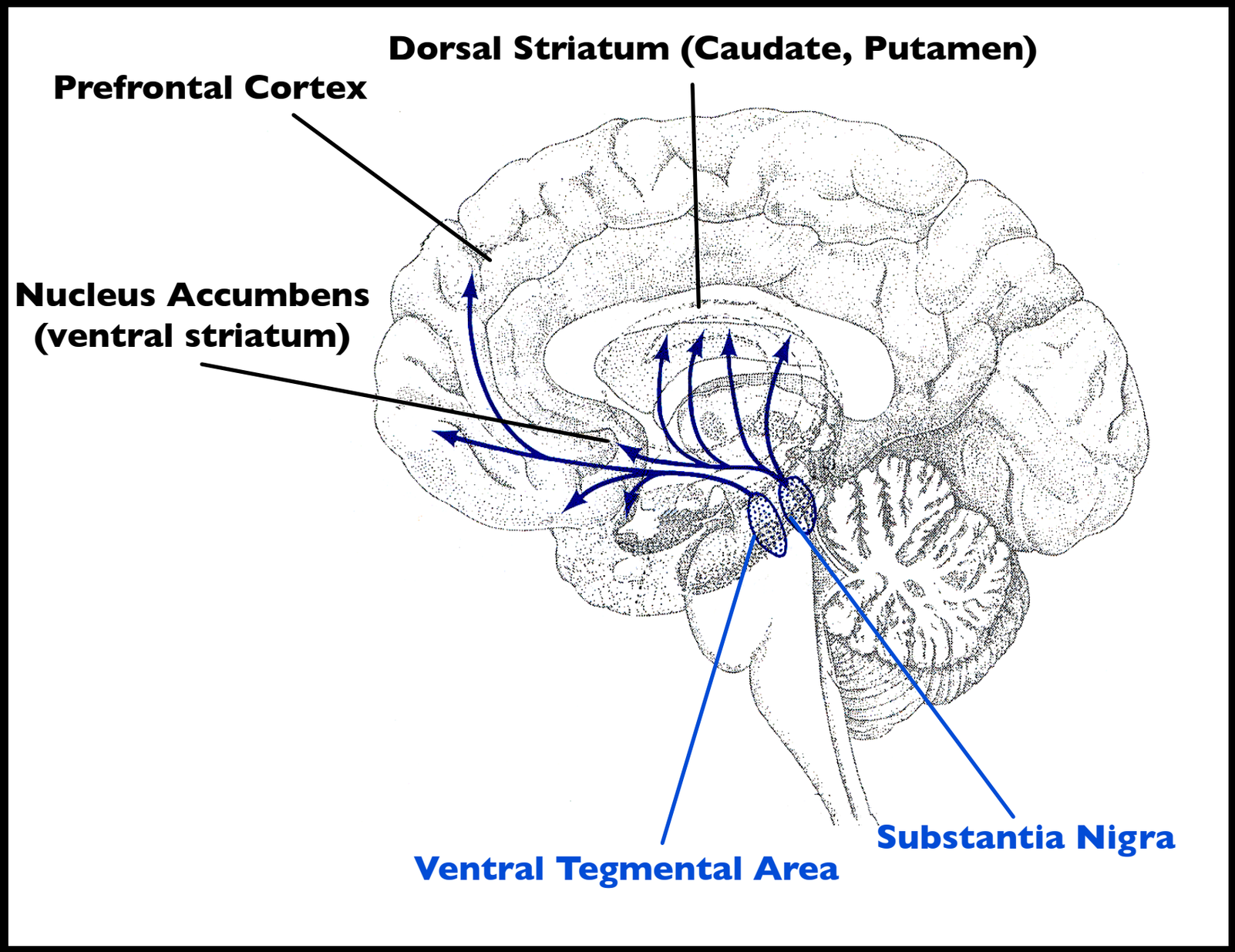

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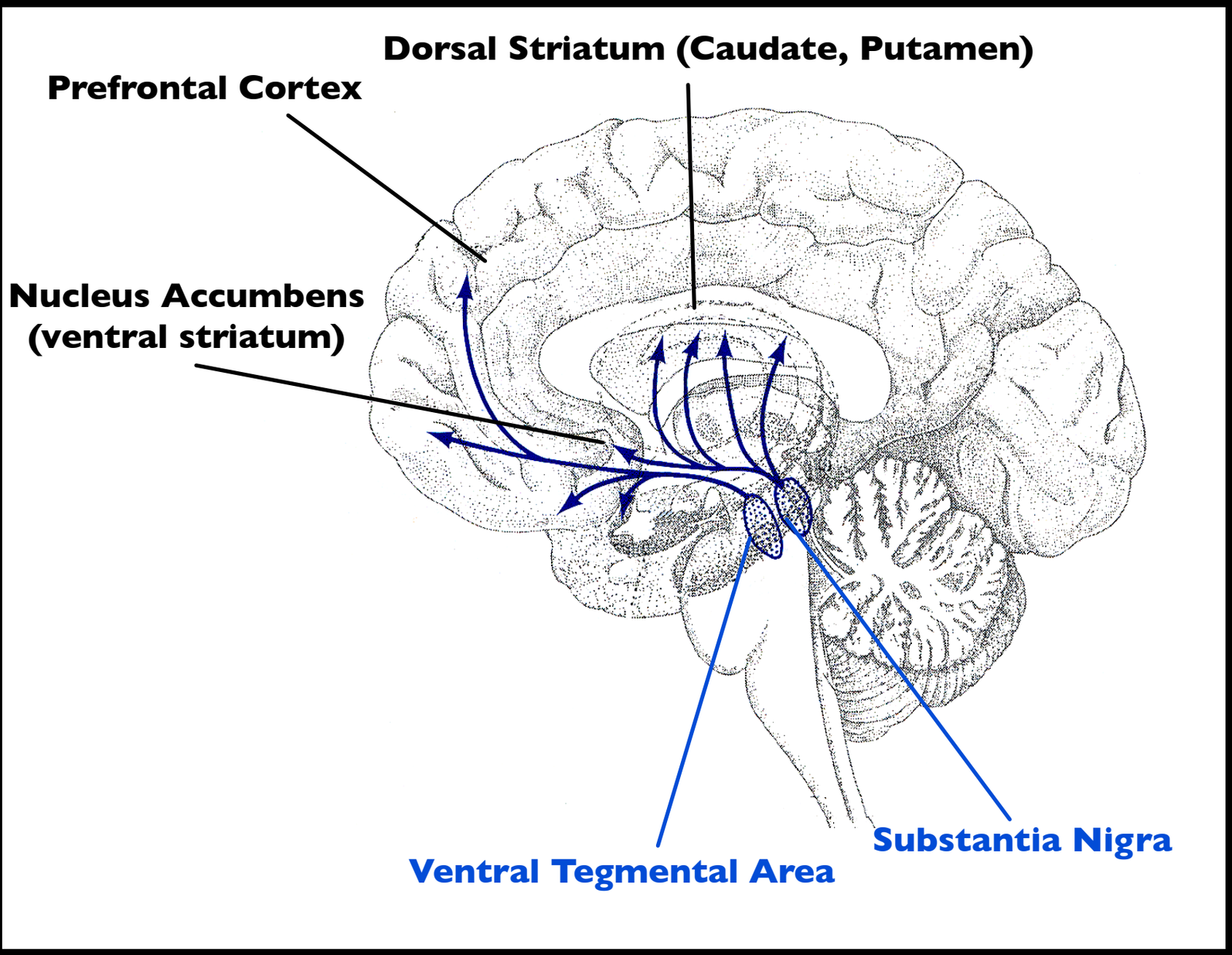

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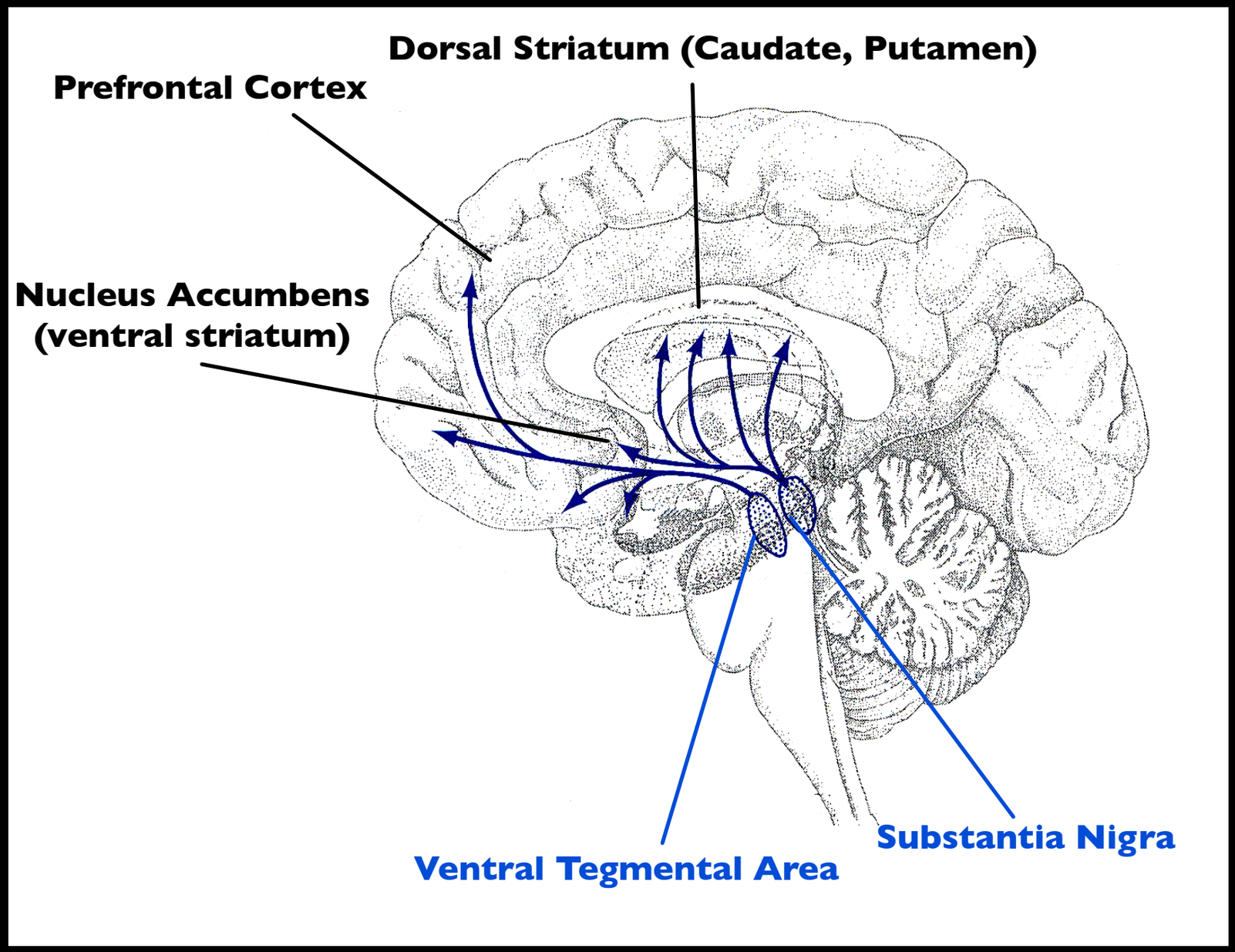

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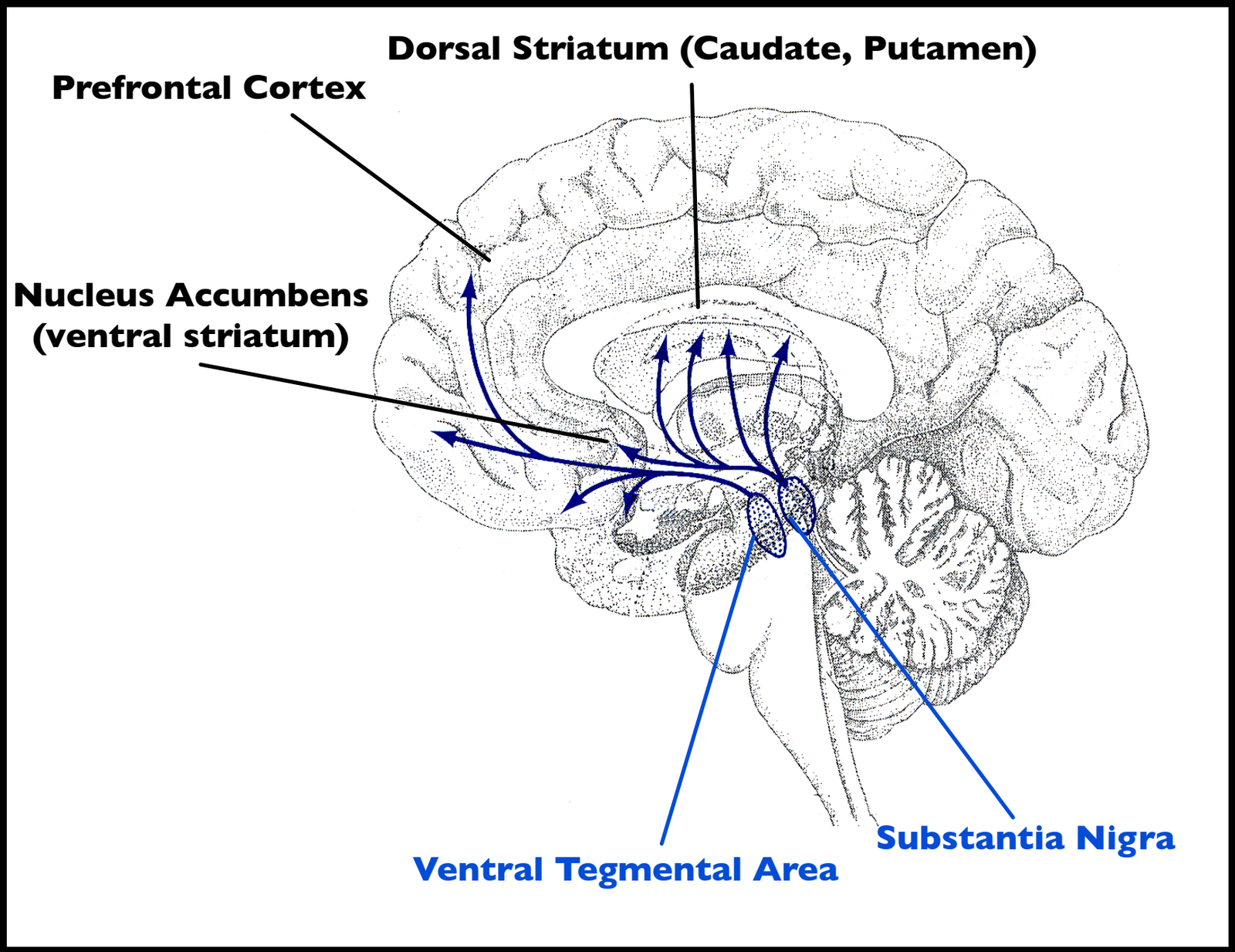

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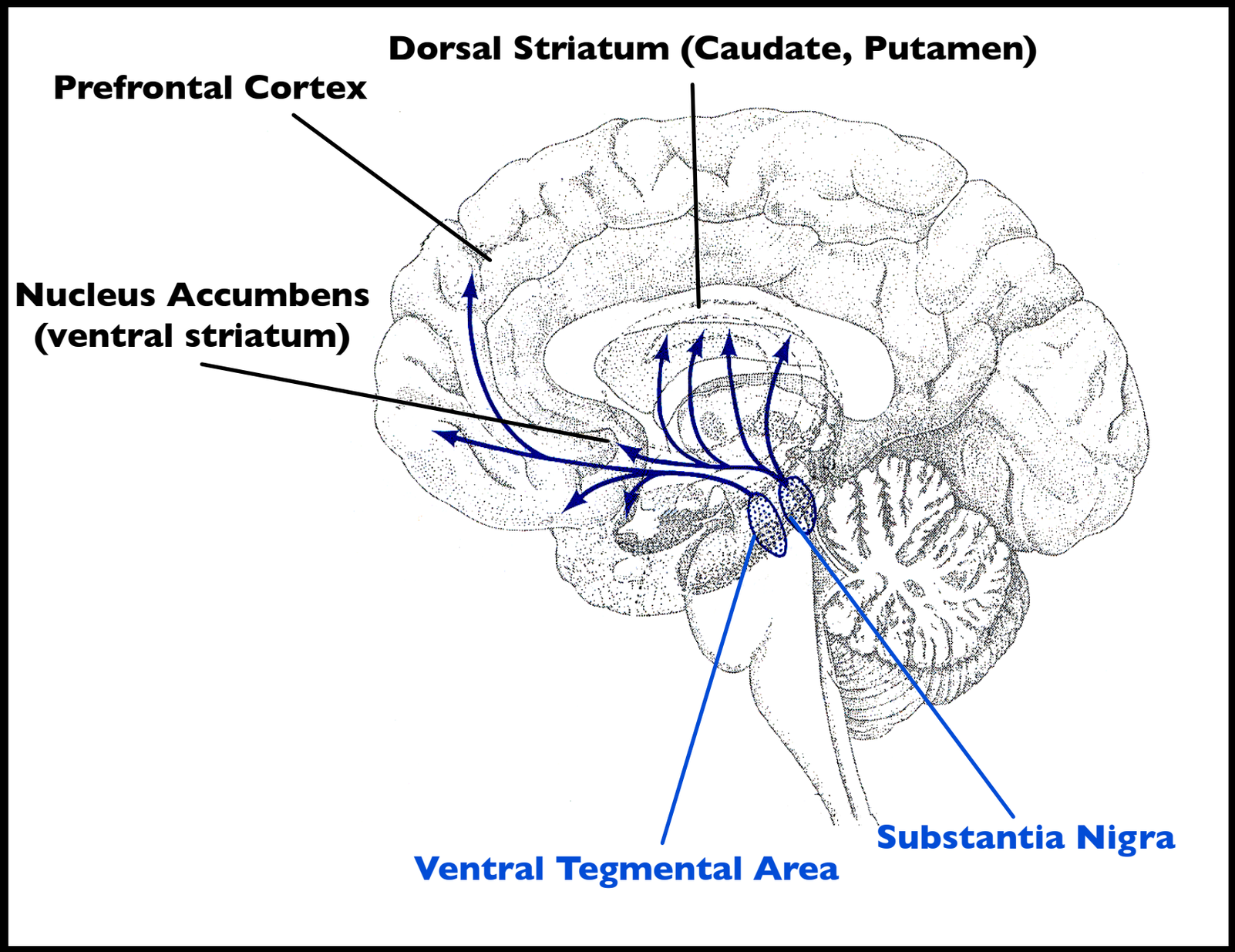

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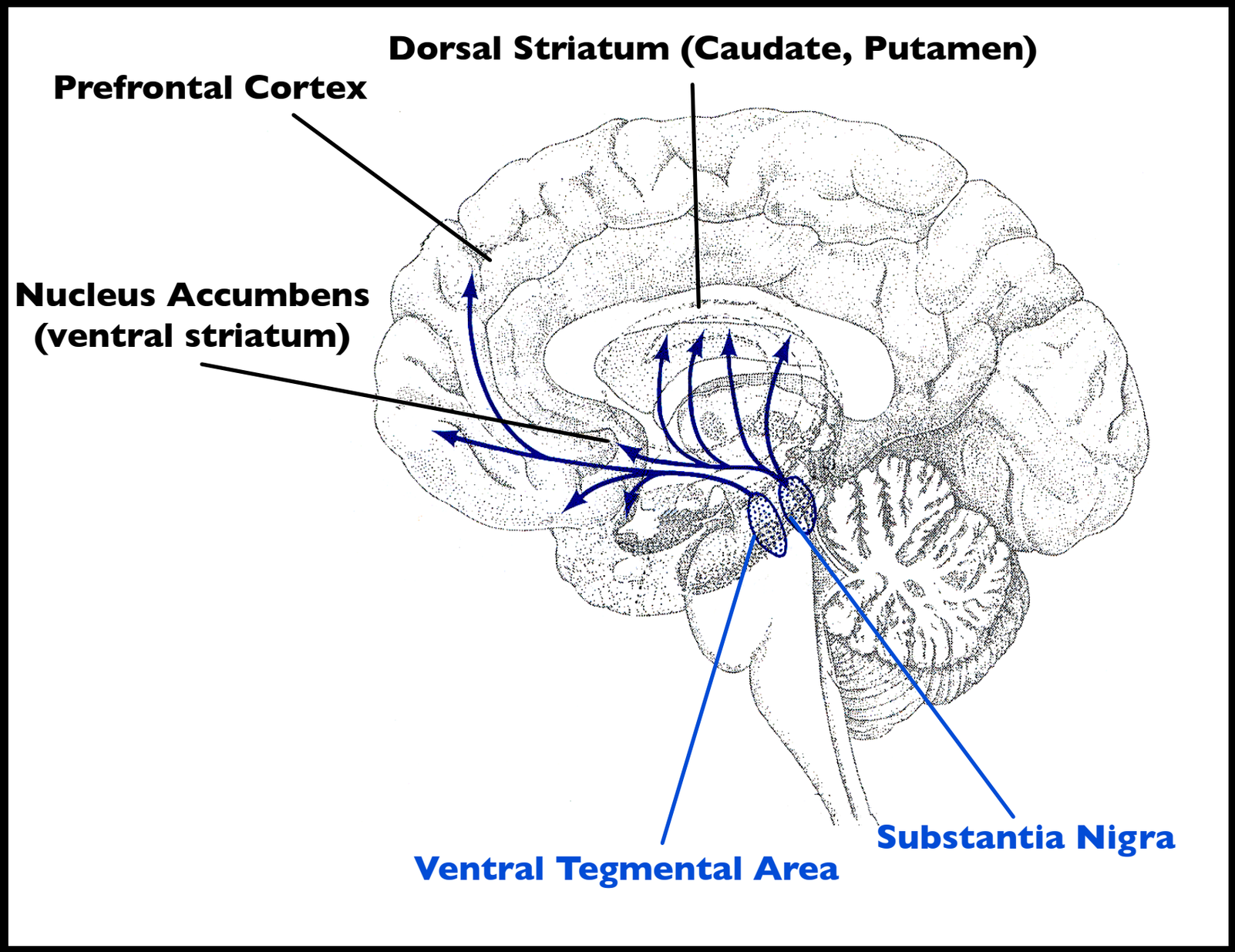

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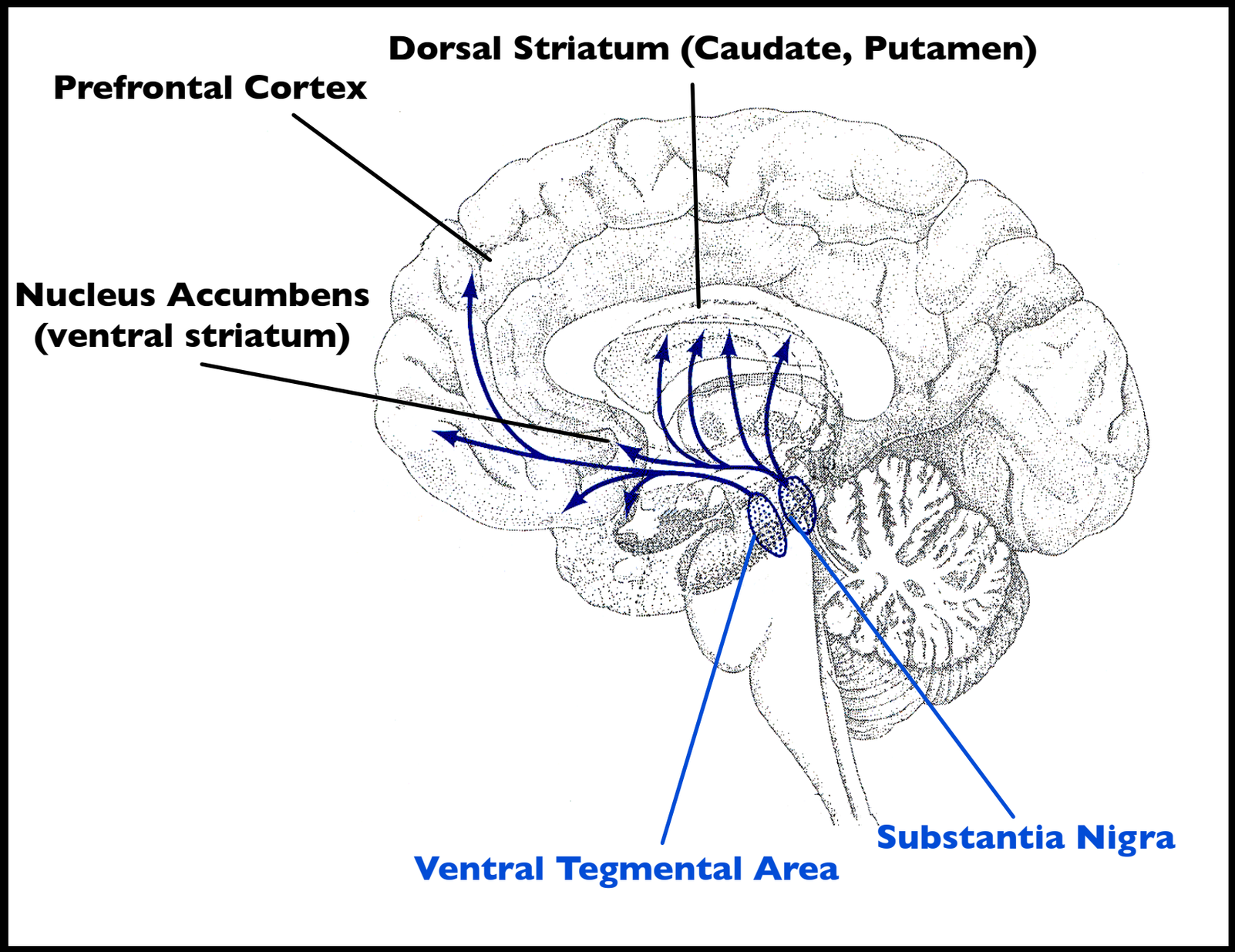

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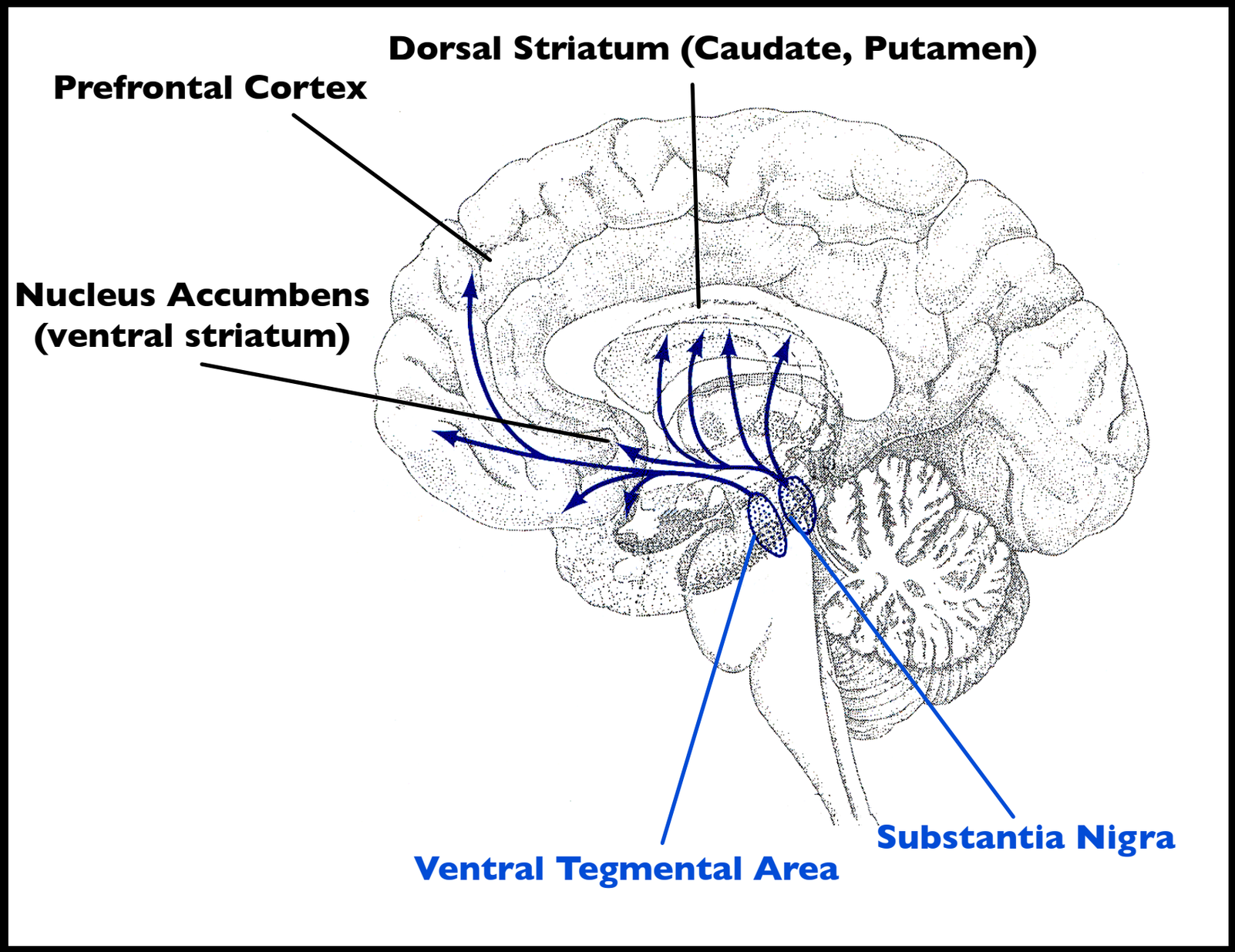

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role of dopamine: many hypotheses

- Anhedonia hypothesis
- Prediction error hypothesis
- Salience/attention
- (Uncertainty)
- Incentive salience
- Cost/benefit computation
- Energizing/motivating behavior

the anhedonia hypothesis (Wise, ’80s)

(Credits: Peter Shizgal, Concordia)

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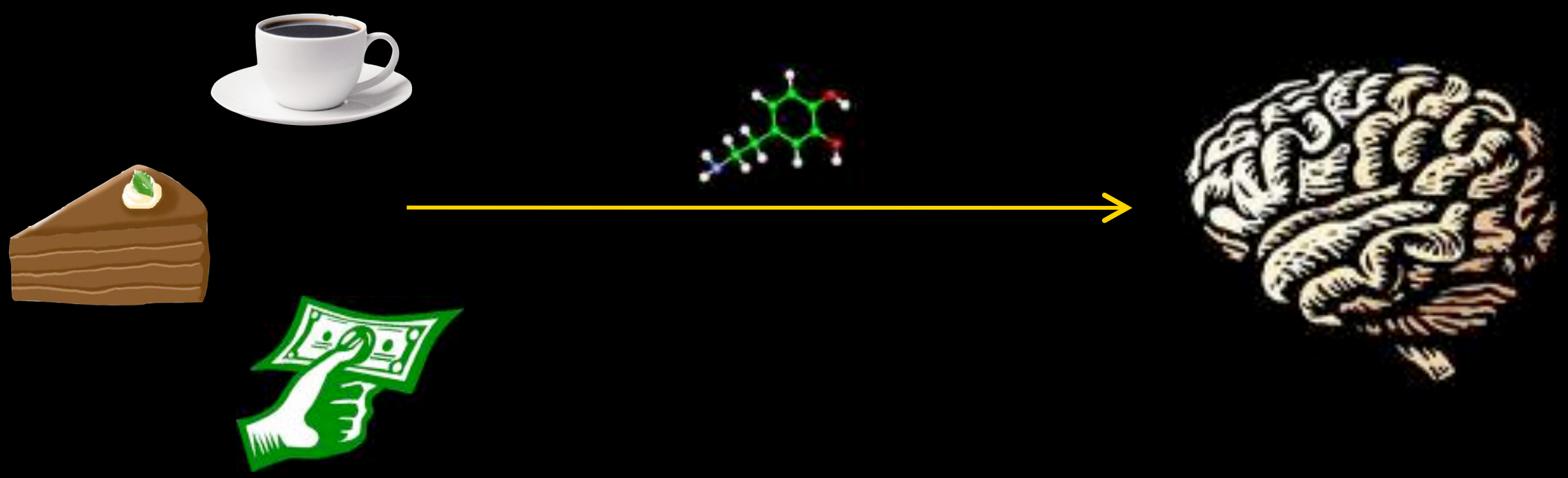

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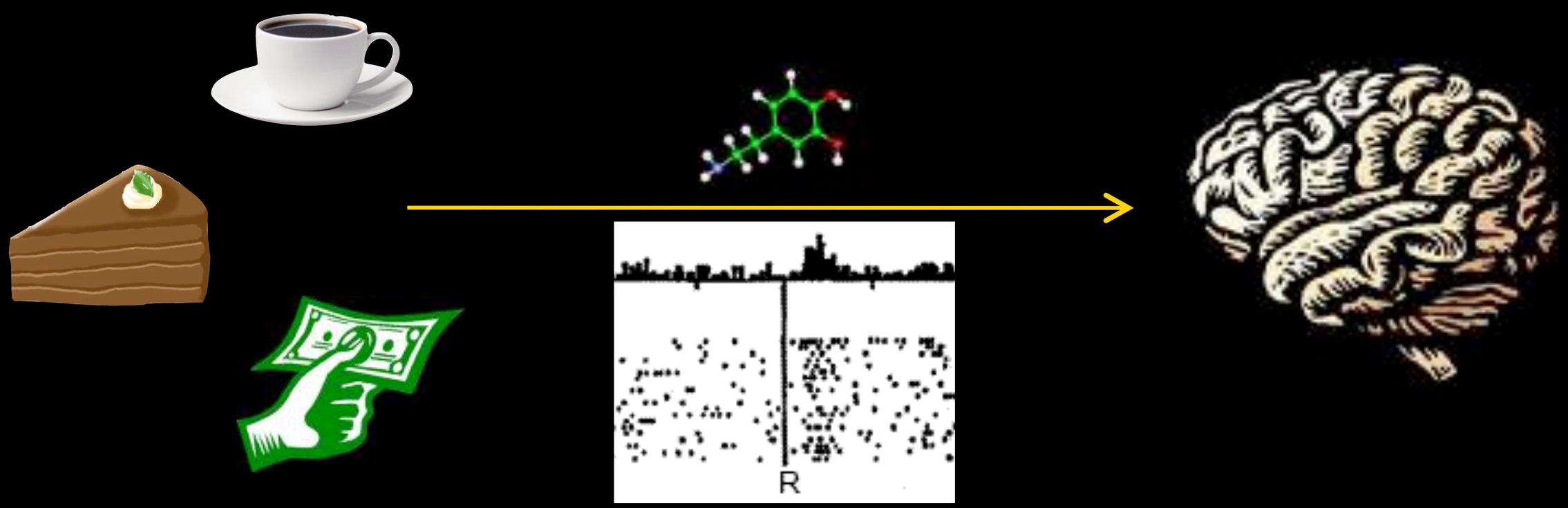

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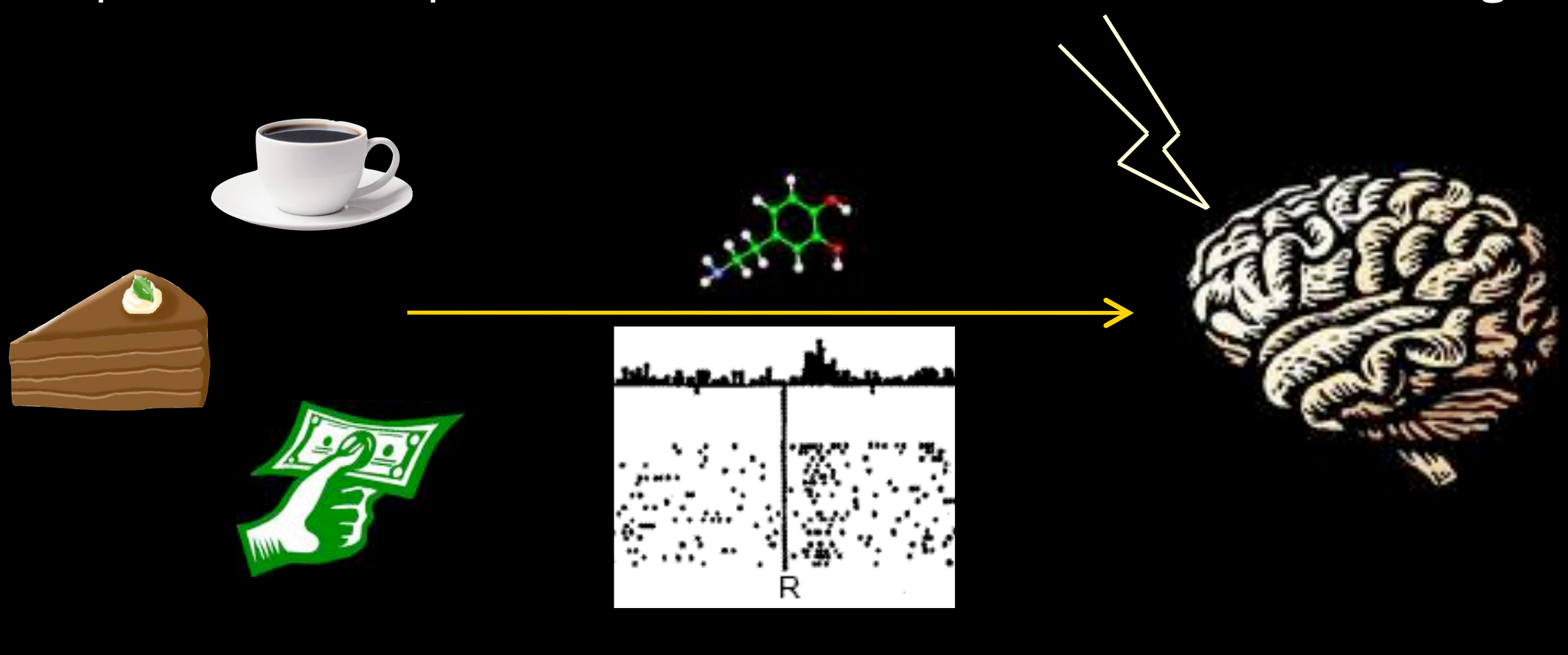

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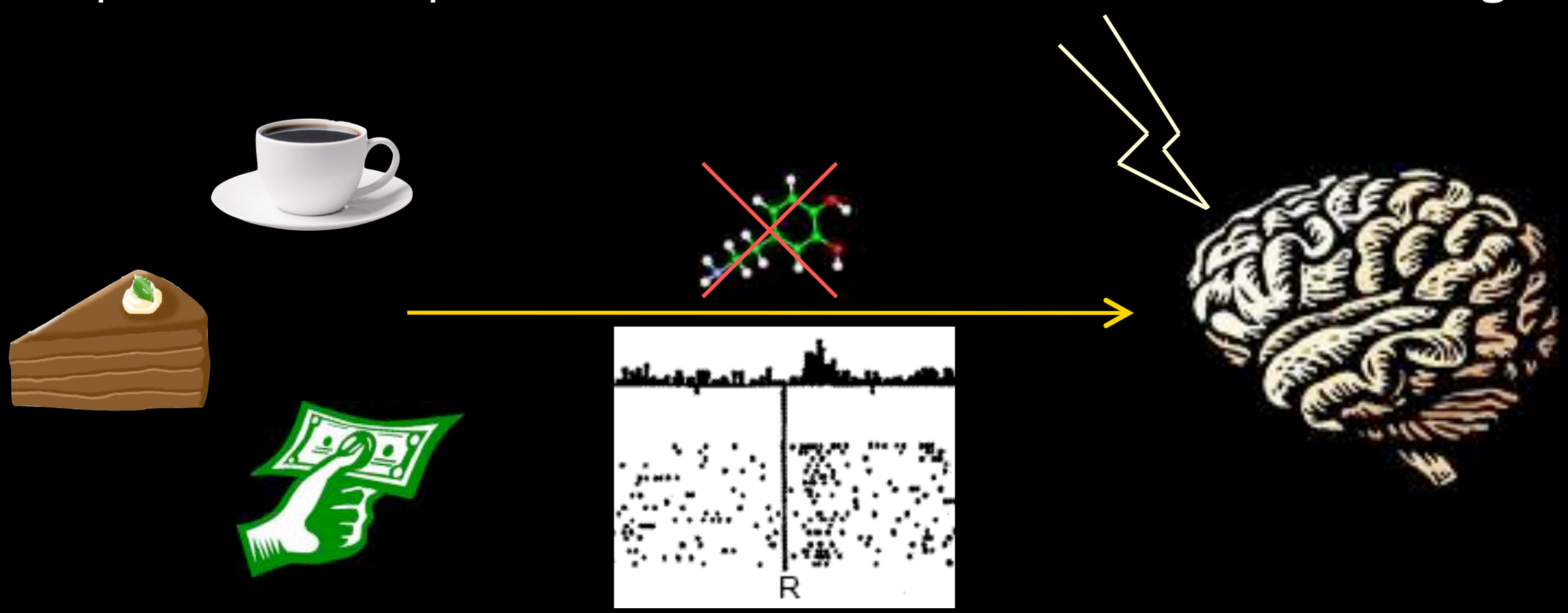

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(Schultz et al. ’90s)

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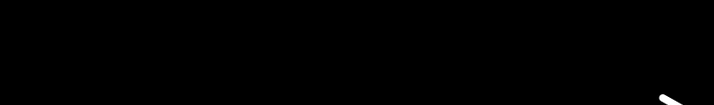

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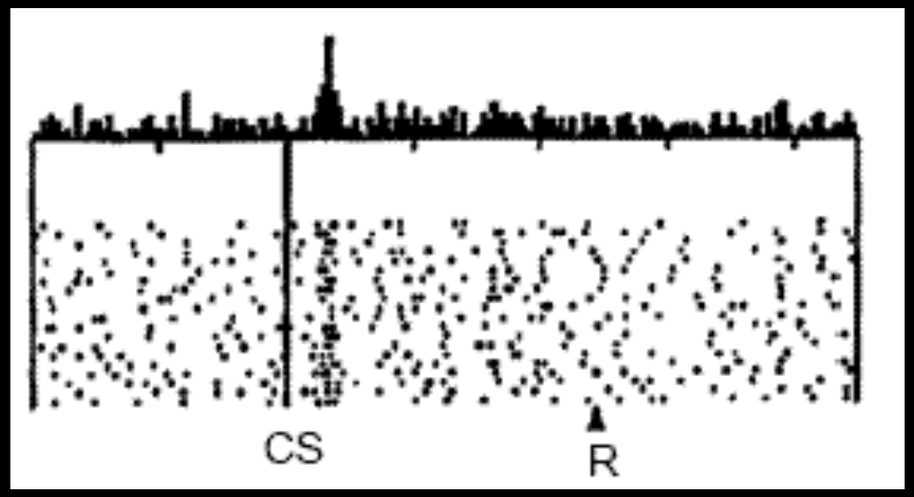

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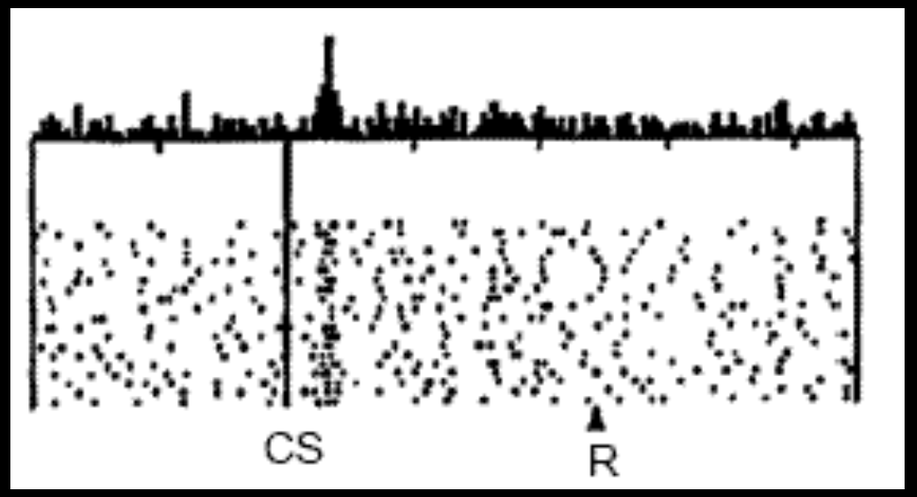

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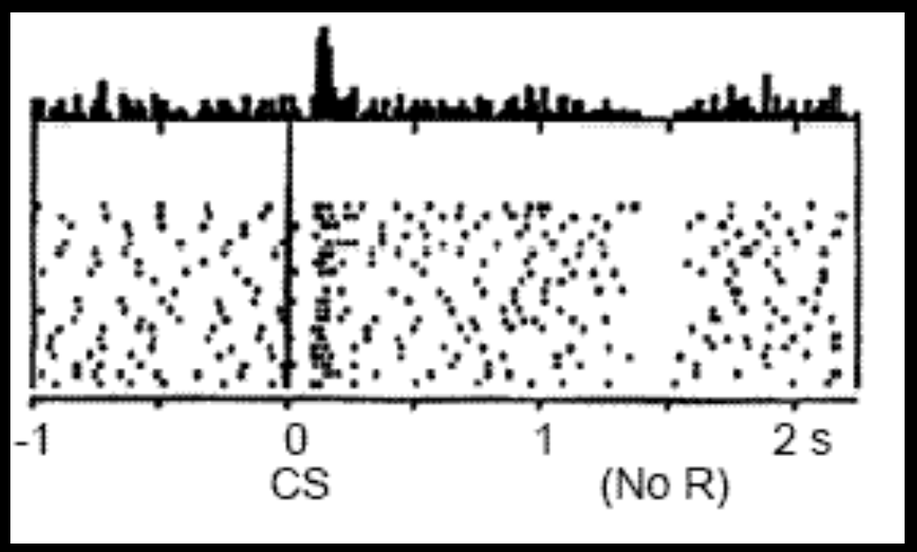

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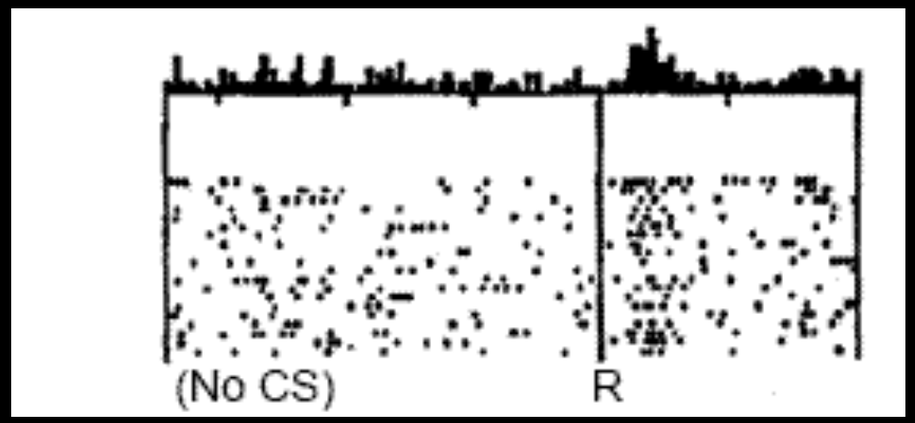

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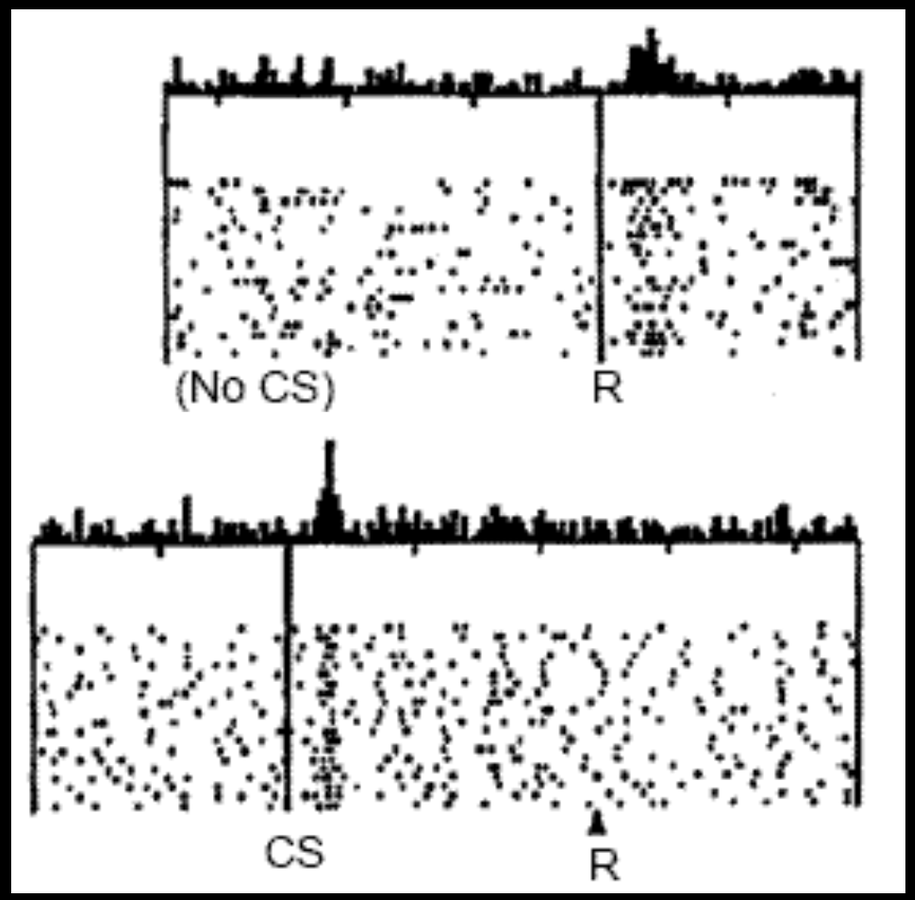

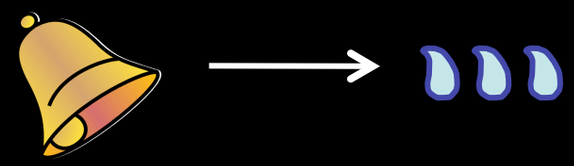

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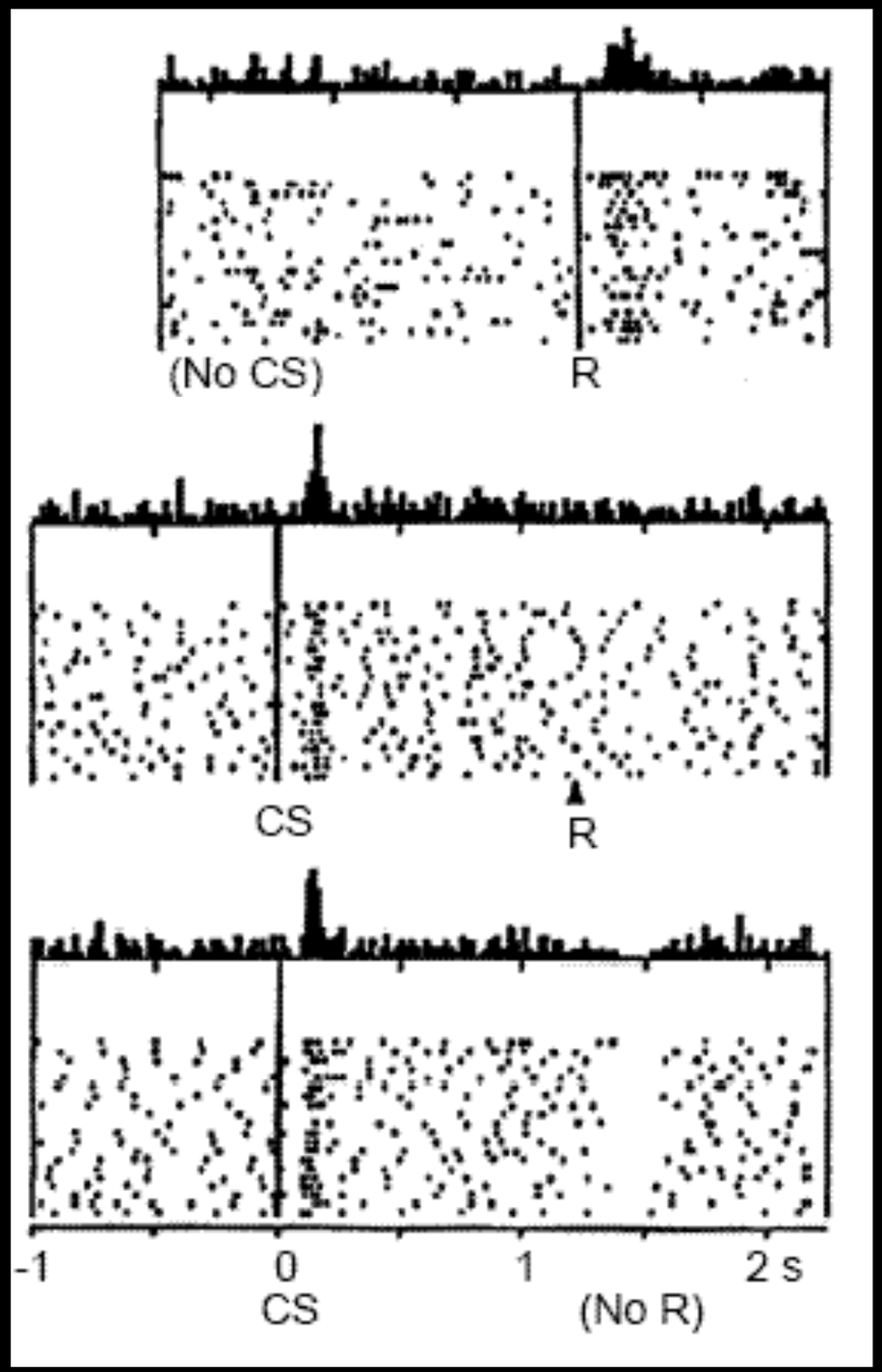

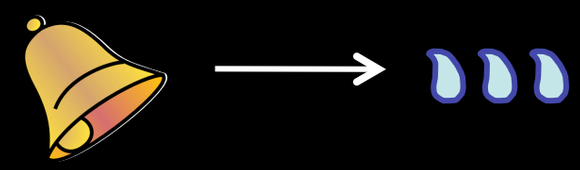

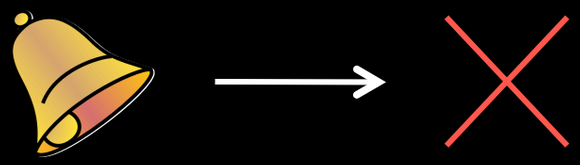

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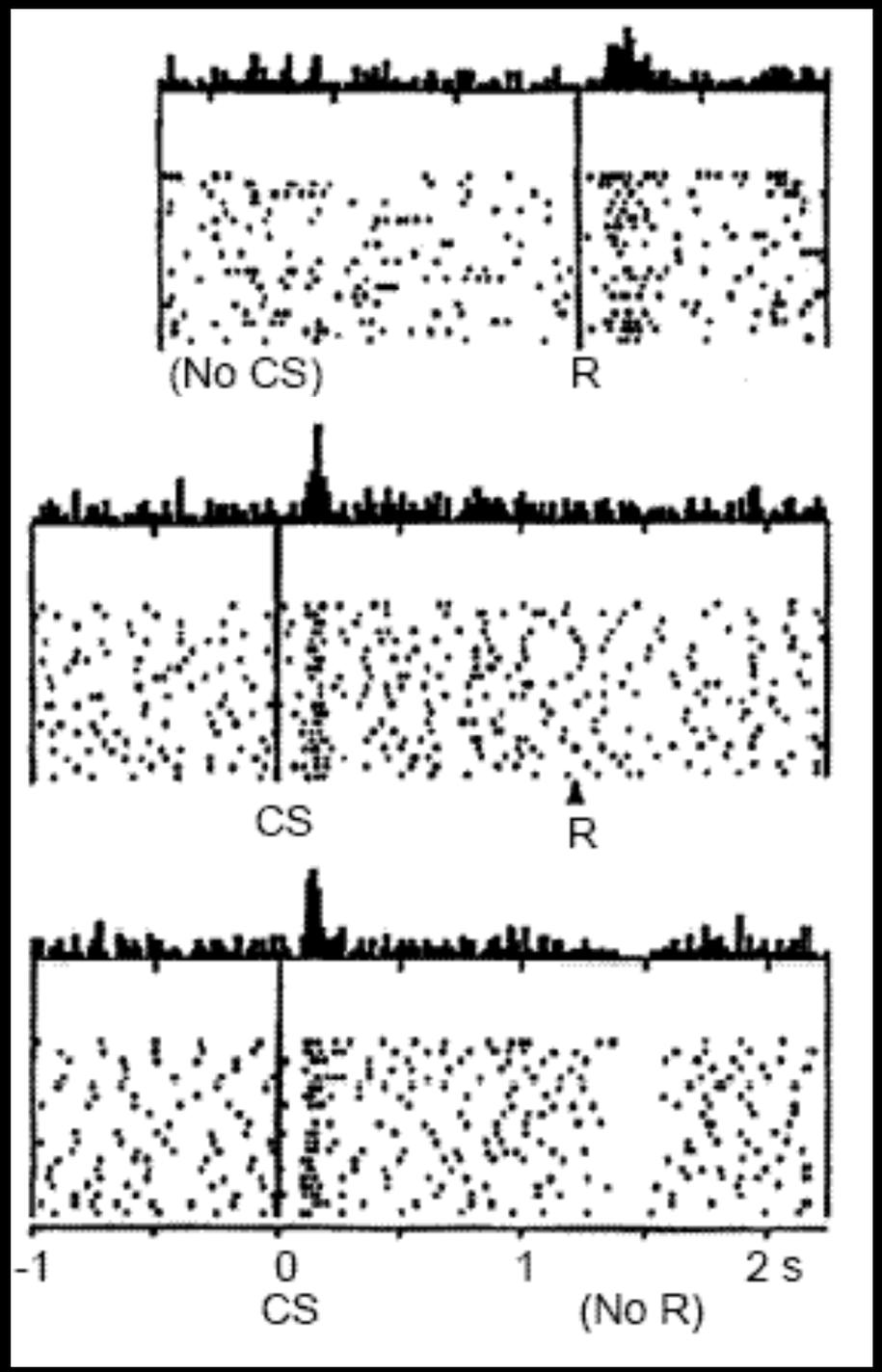

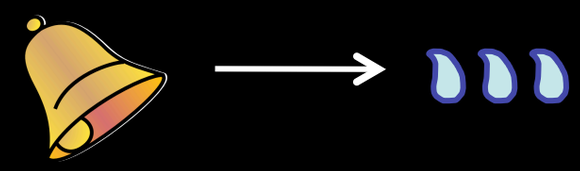

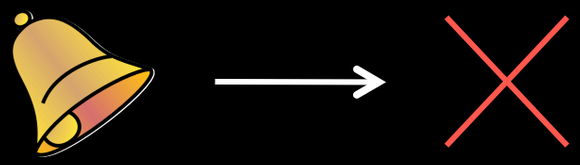

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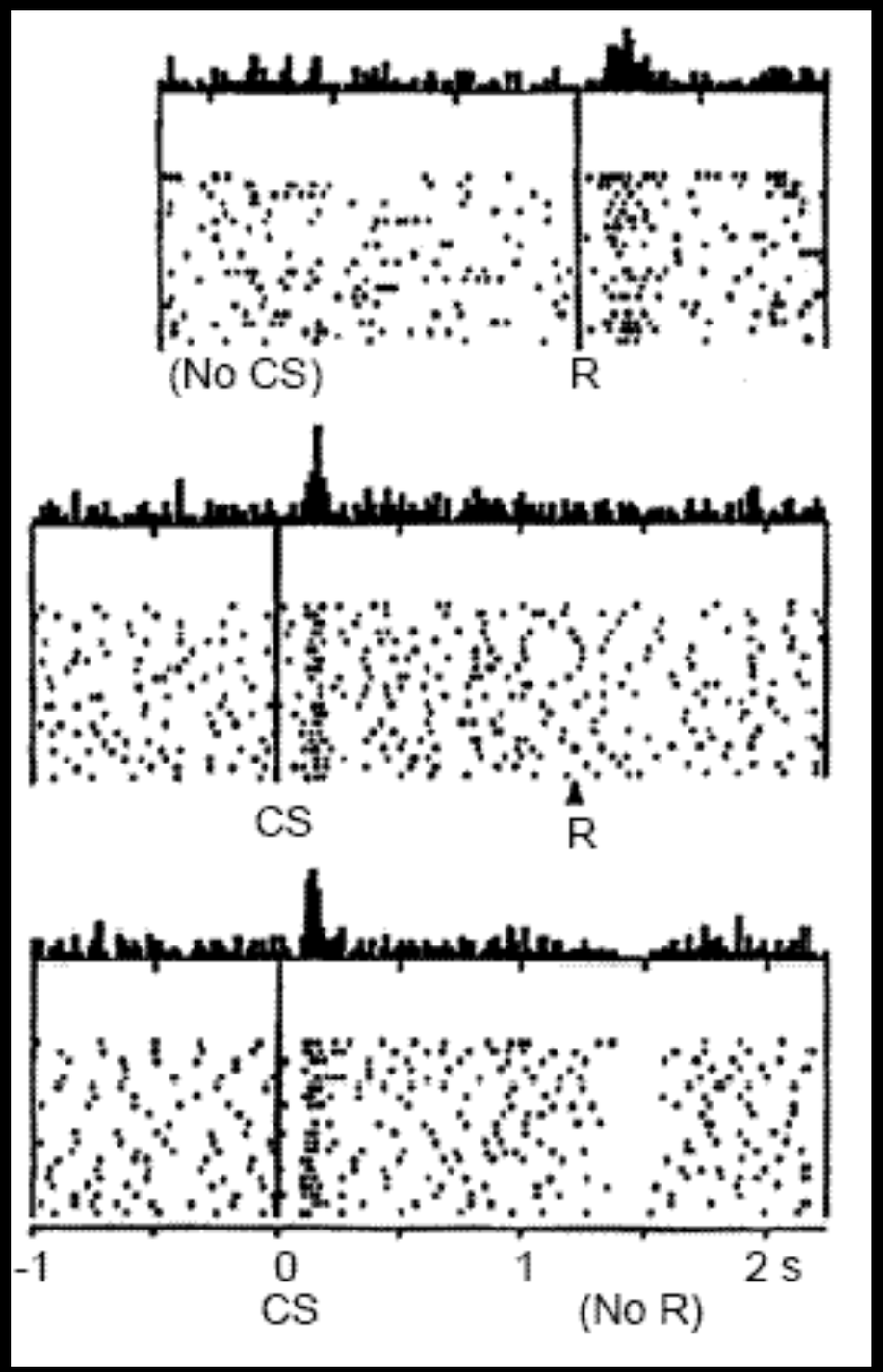

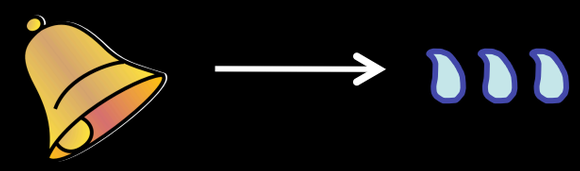

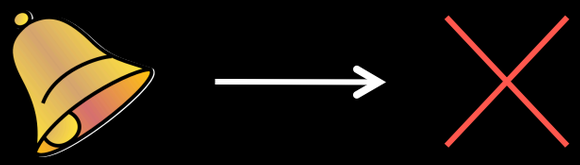

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prediction error hypothesis of dopamine

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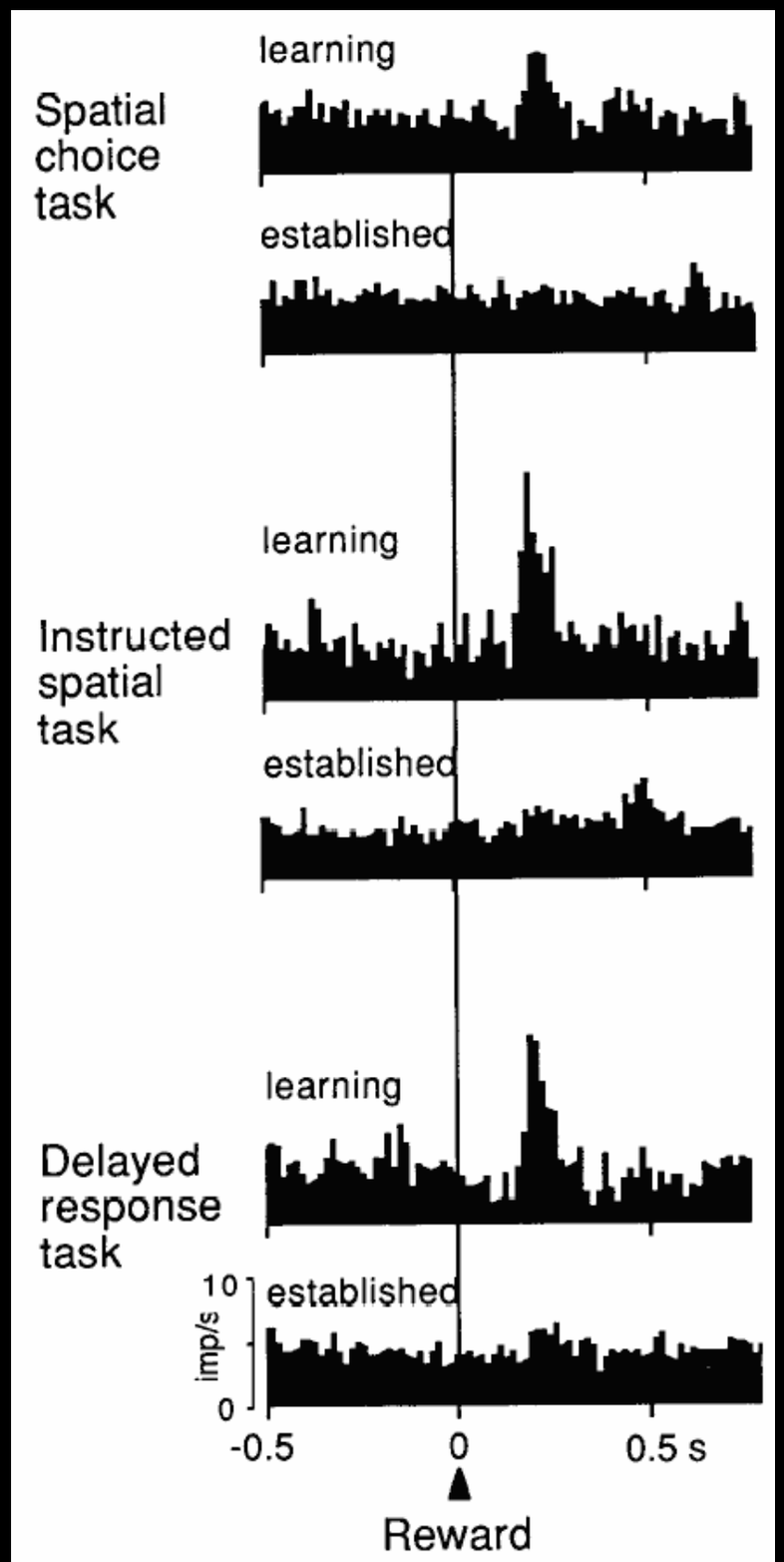

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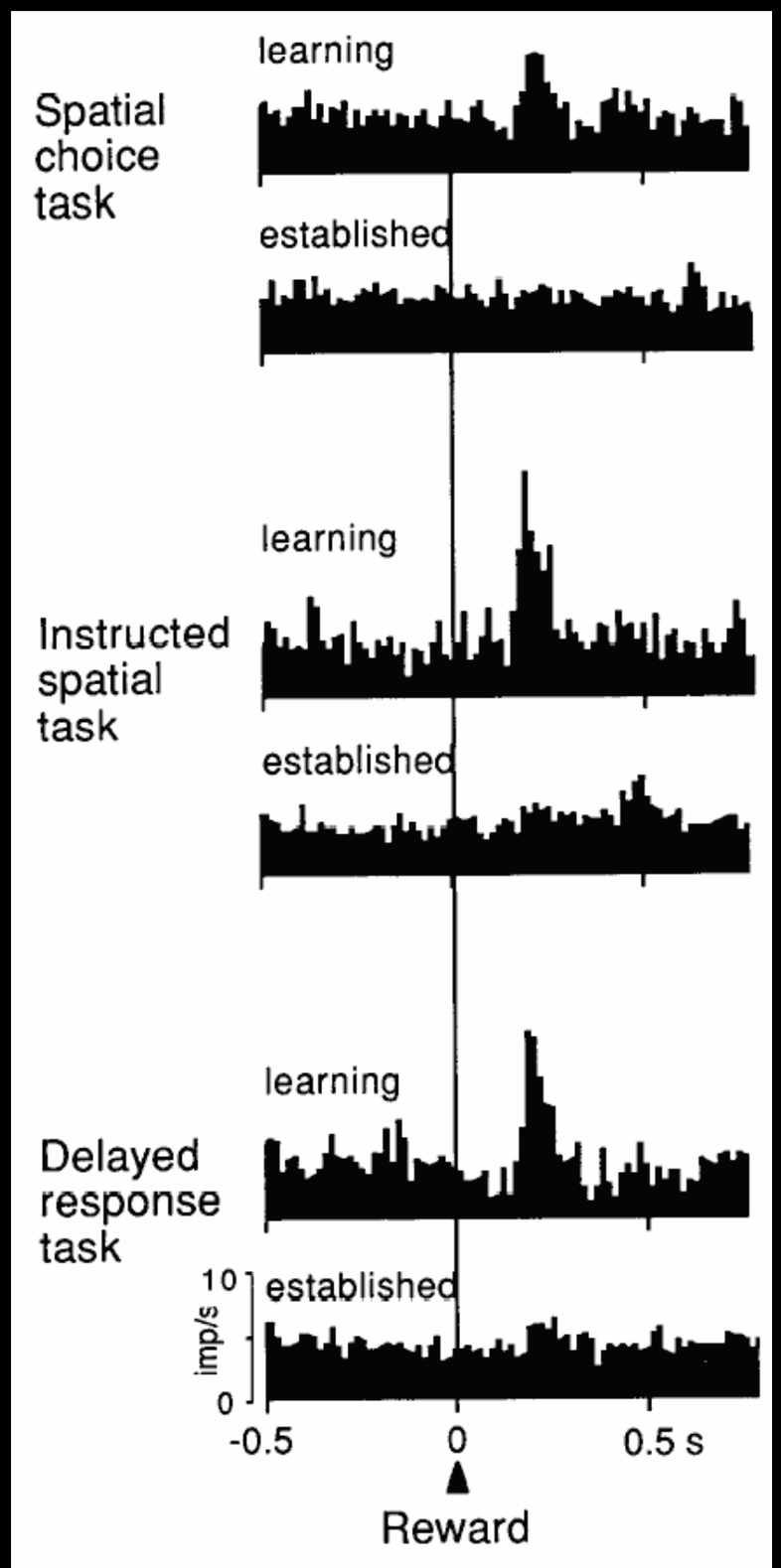

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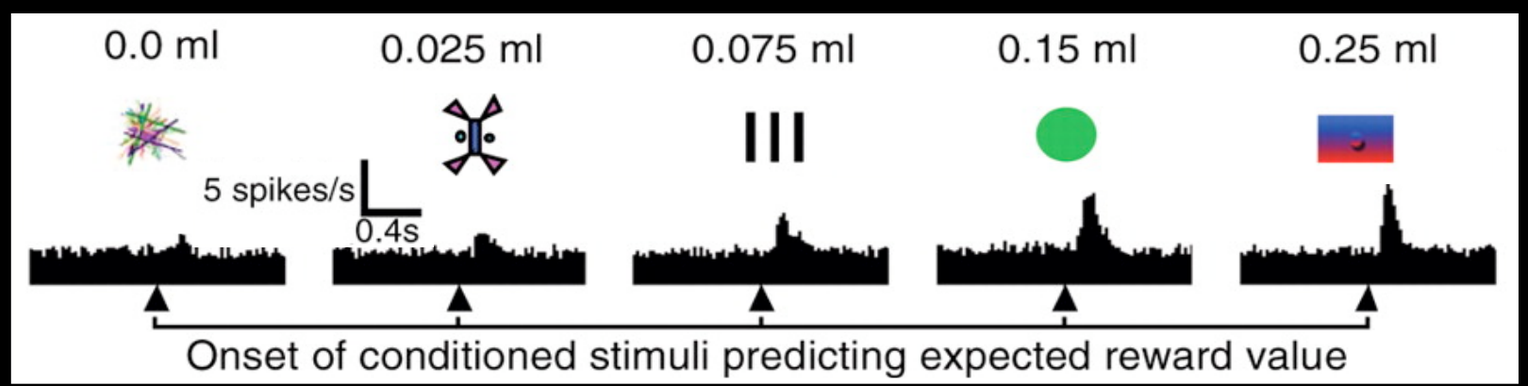

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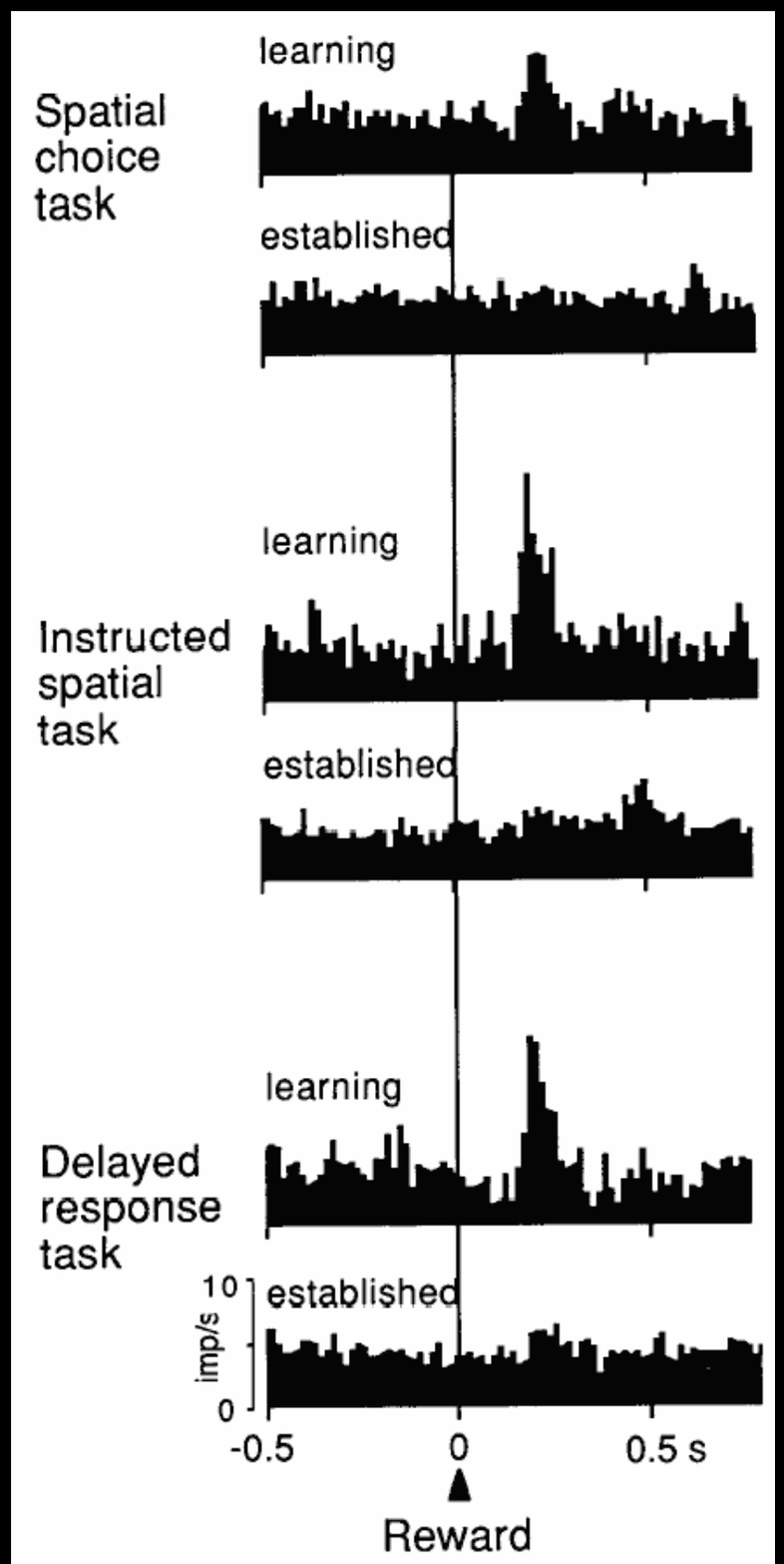

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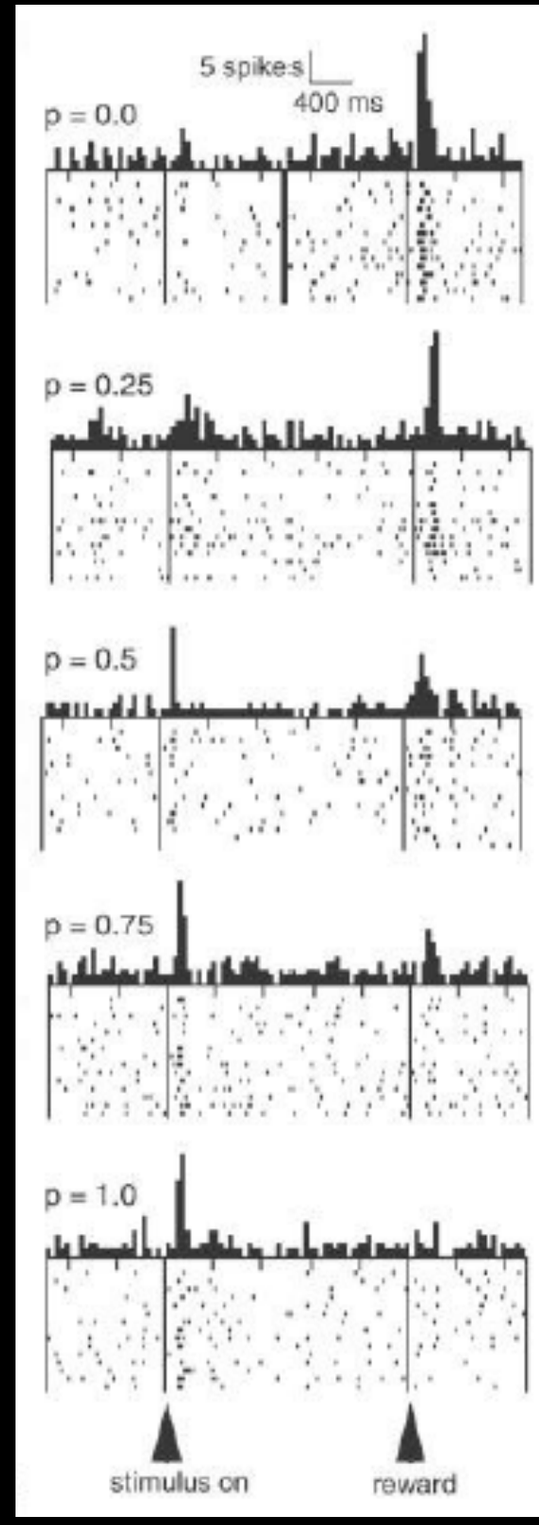

Fiorillo et al, 2003

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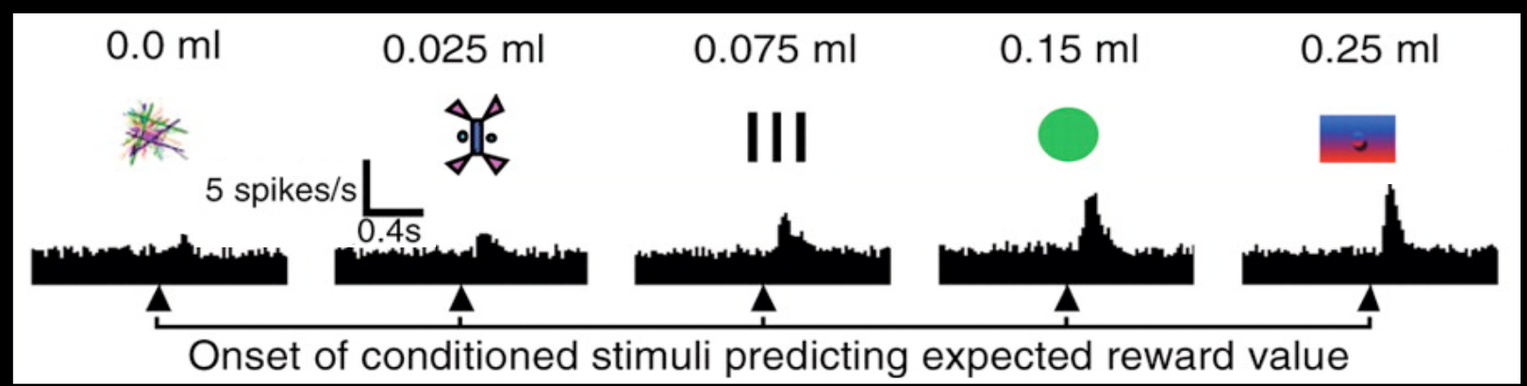

prediction error hypothesis of dopamine: stringent tests

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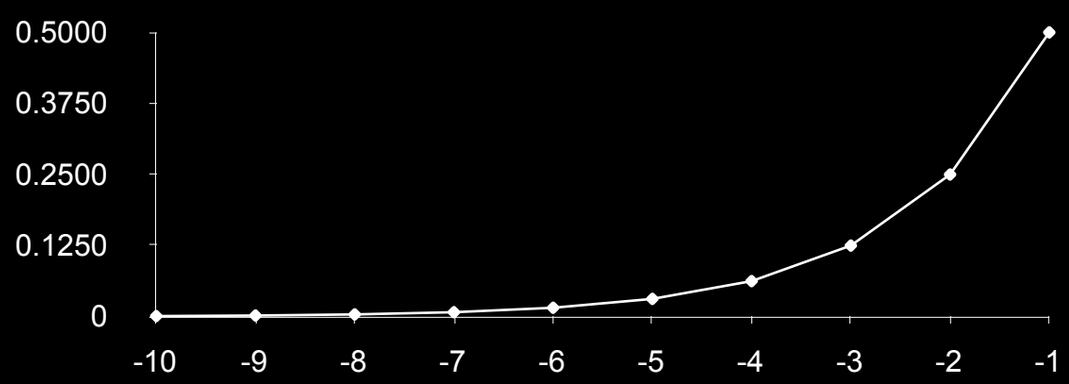

Bayer & Glimcher (2005)

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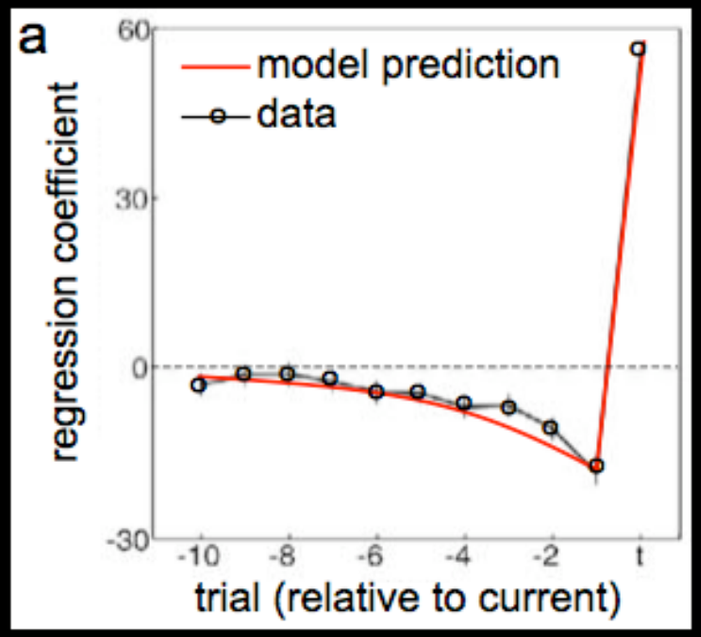

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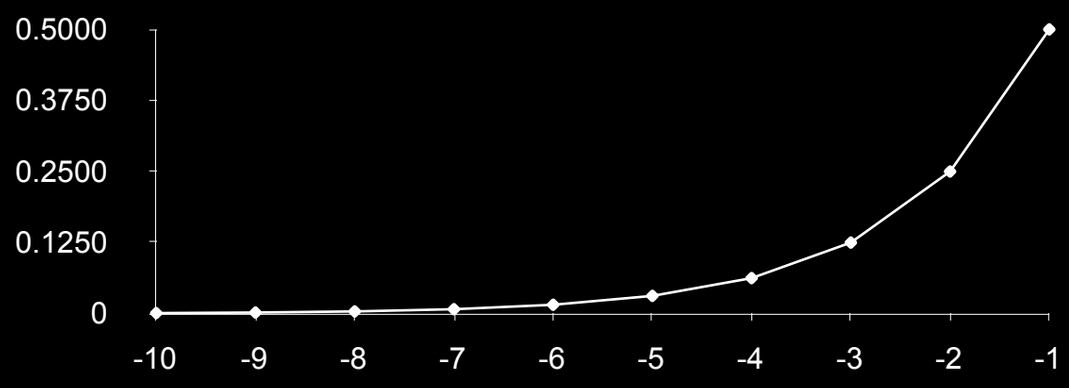

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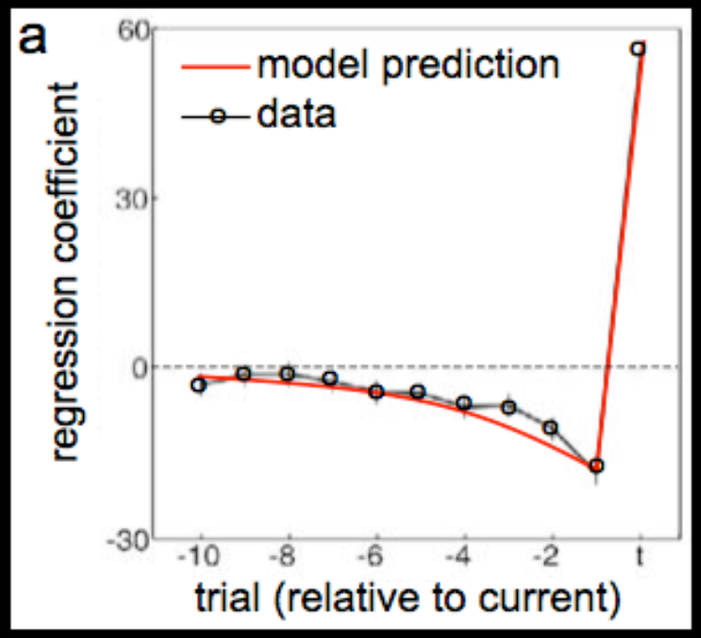
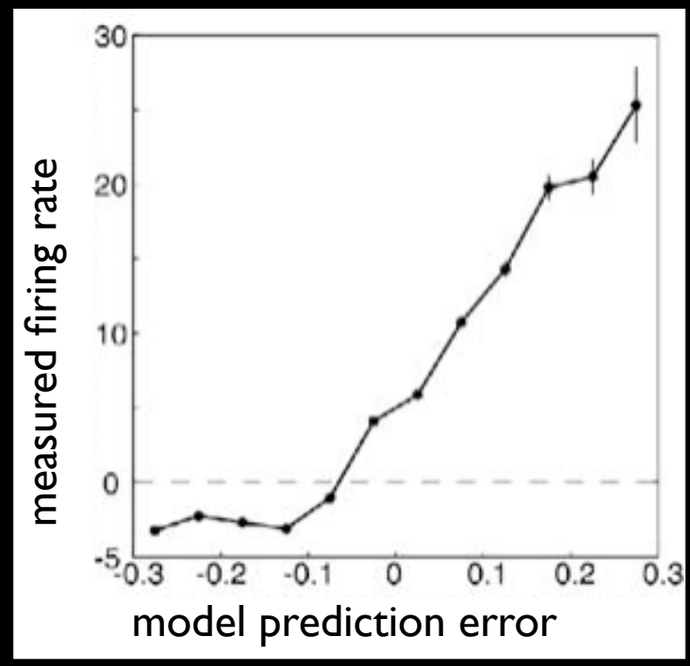
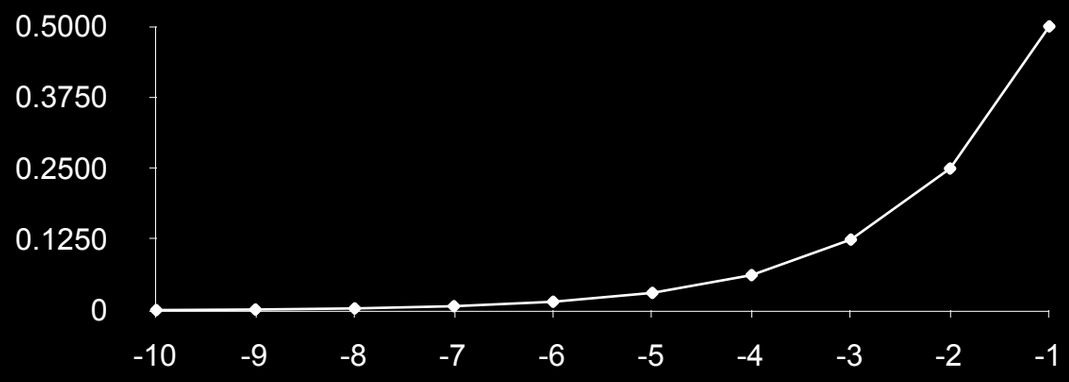
prediction error hypothesis of dopamine: stringent tests





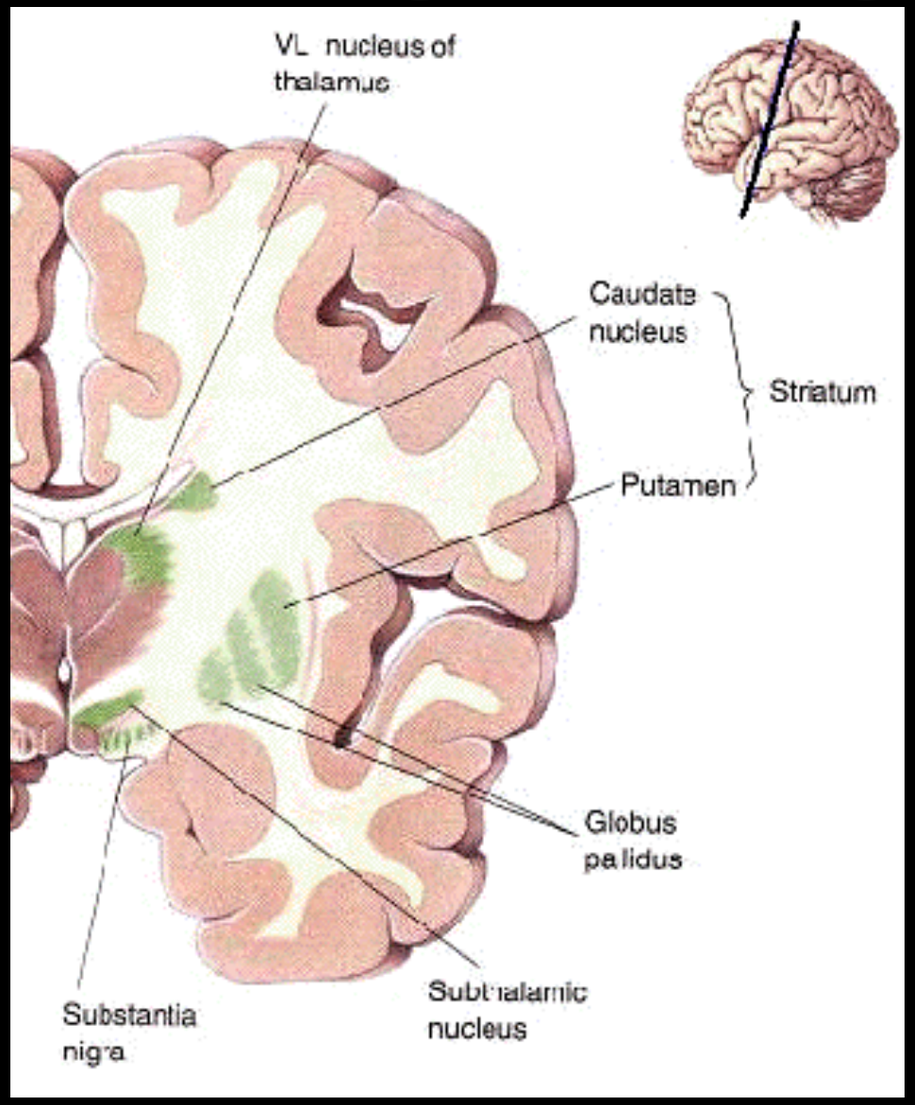
$$V_t = \eta \sum_{i=1}^{t} (1-\eta)^{t-i} r_i$$

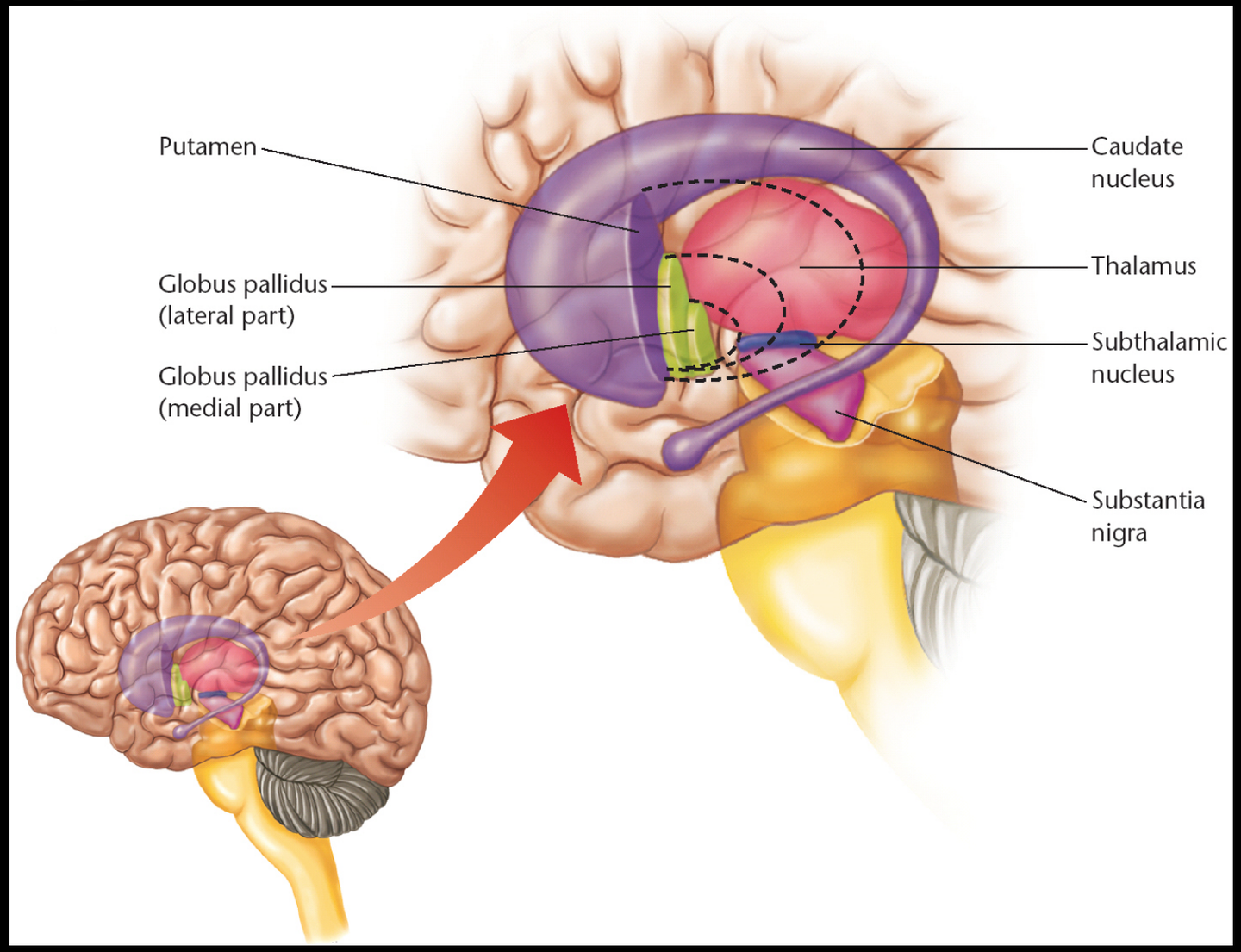


Bayer & Glimcher (2005)

where does dopamine project to?

main target: basal ganglia





dopamine and synaptic plasticity

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Wickens et al, 1996

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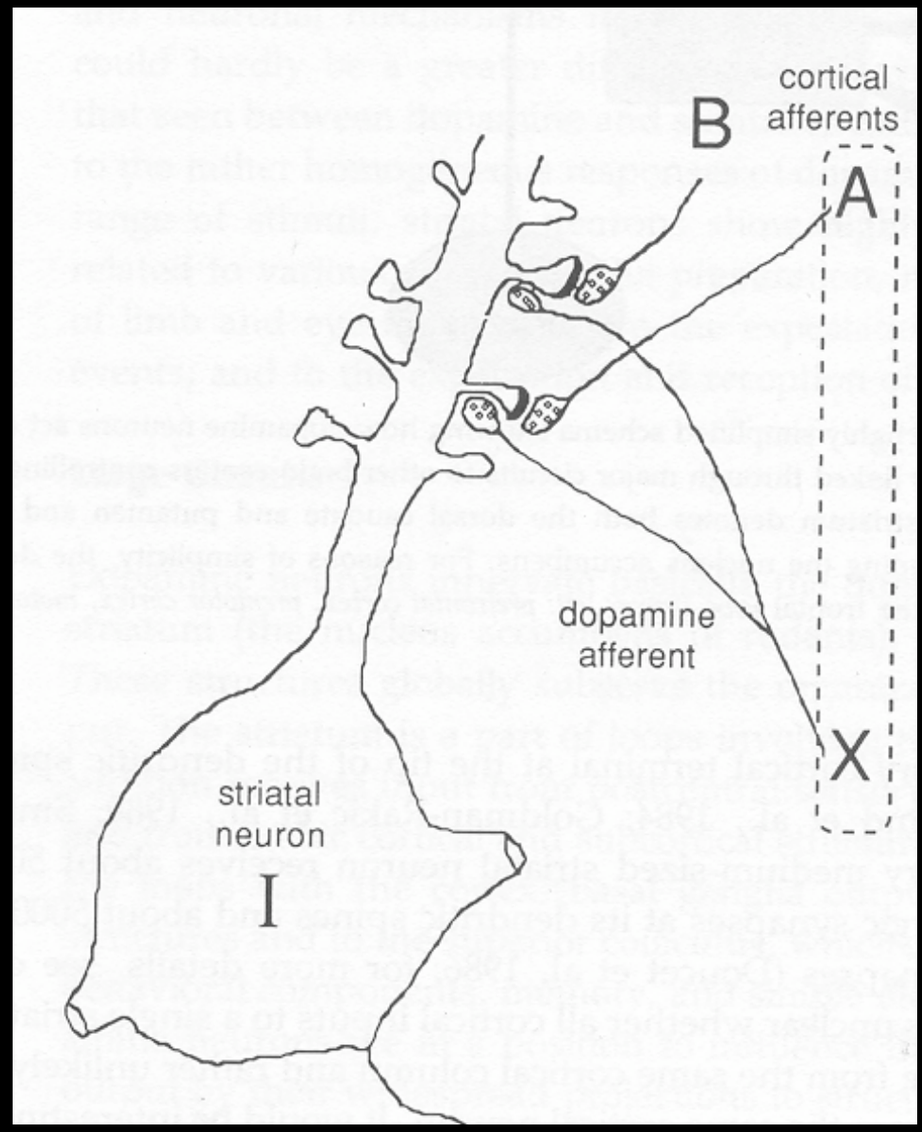

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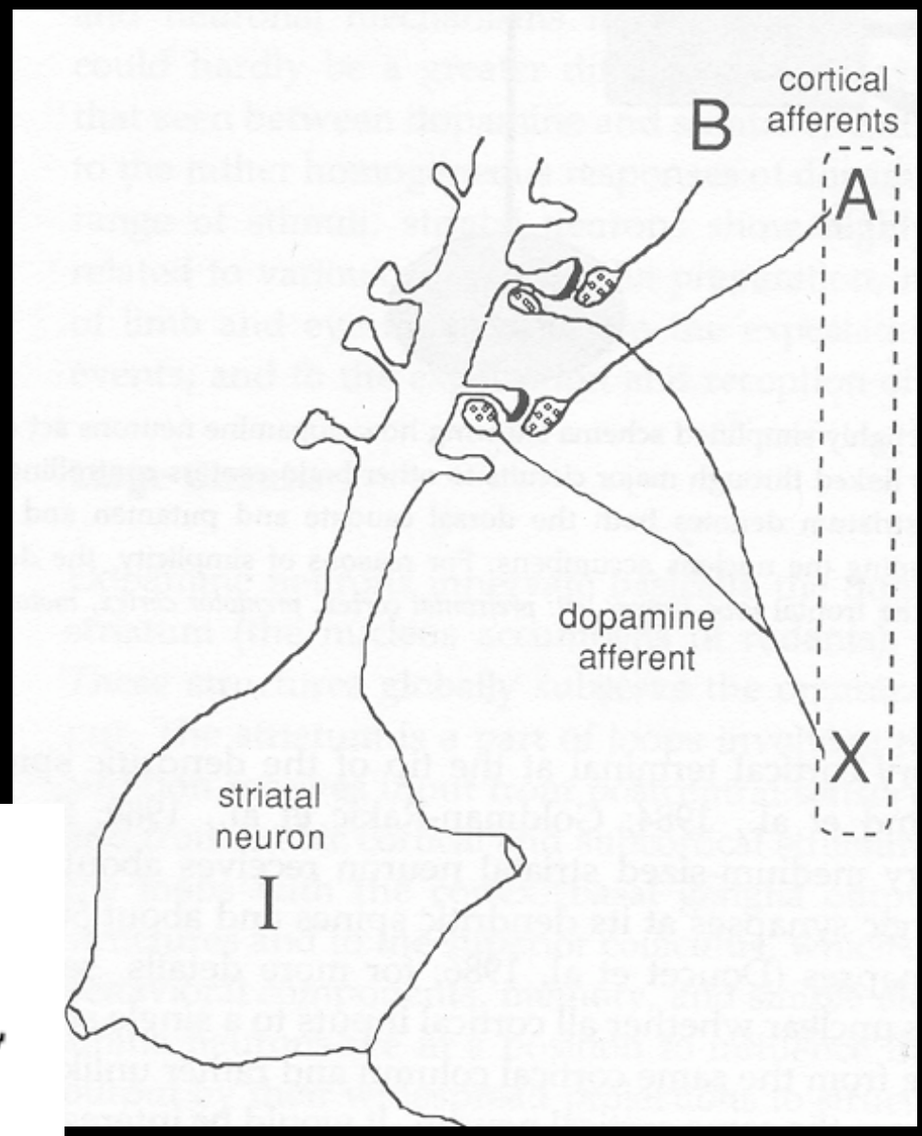

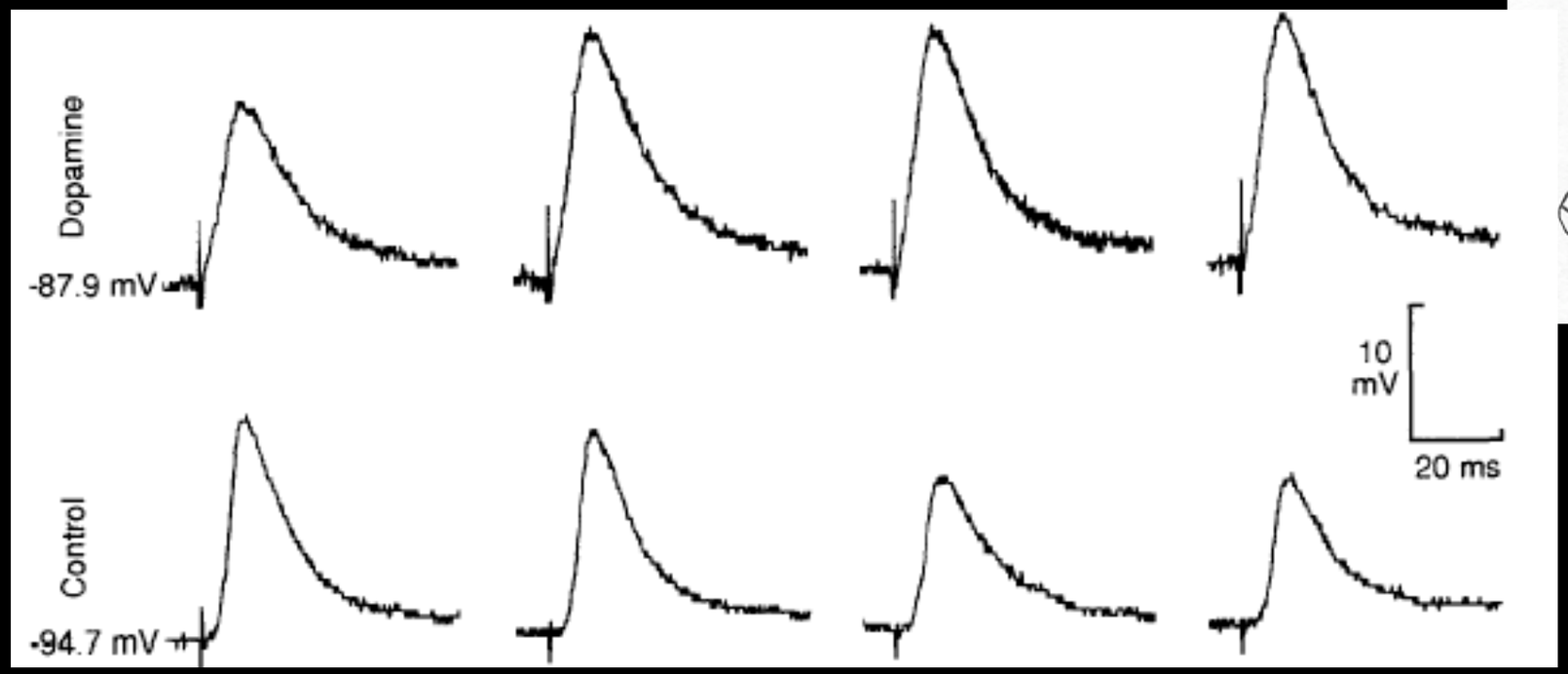

Wickens et al, 1996

dopamine and synaptic plasticity

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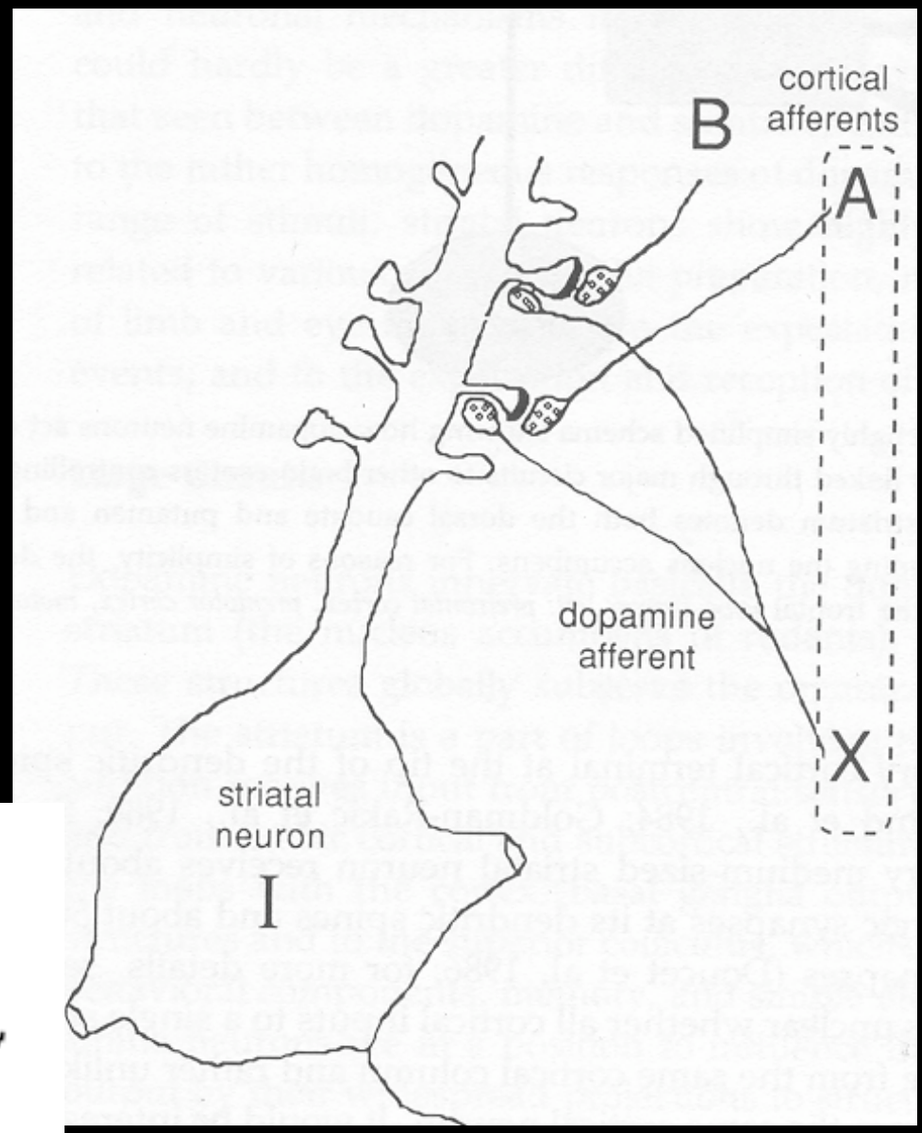
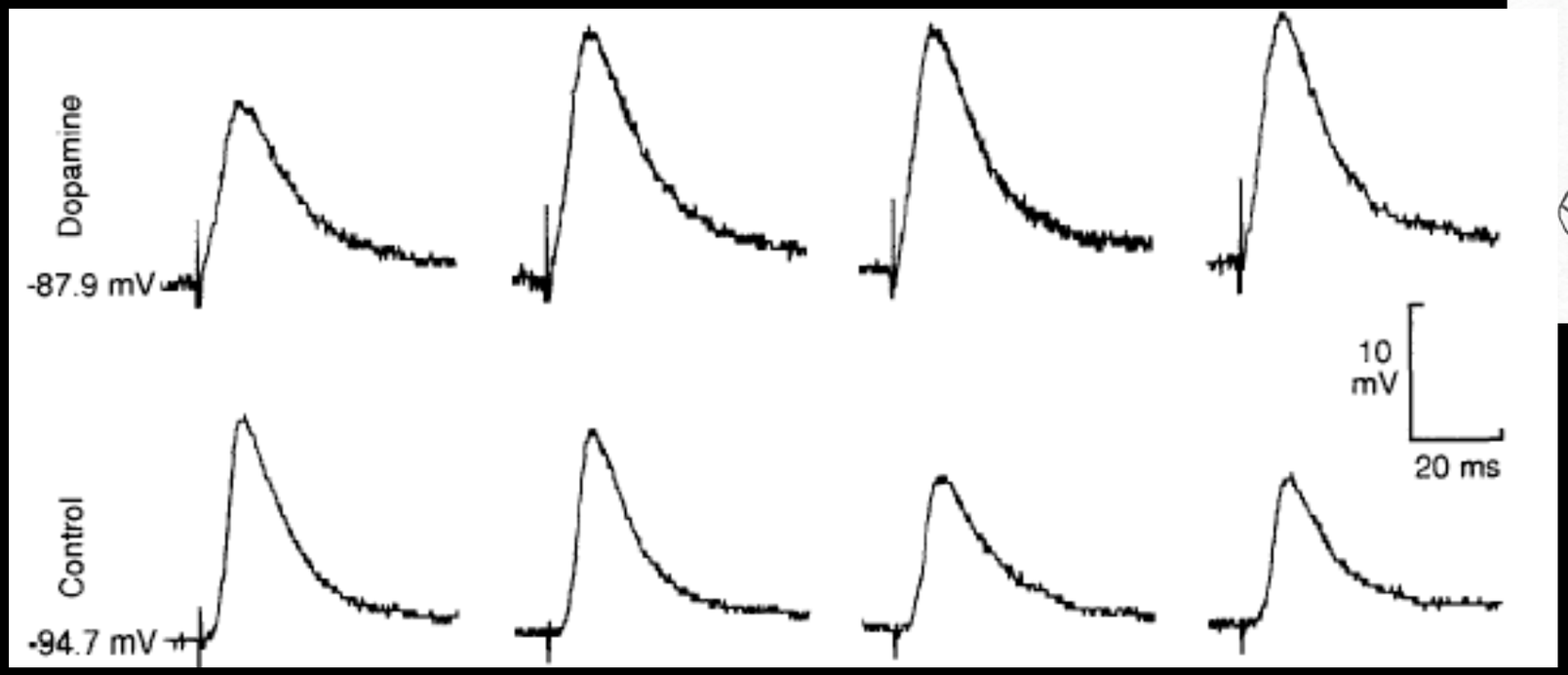
- cortico-striatal synapses show dopamine-dependent plasticity
- three-factor learning rule: need presynaptic+postsynaptic+dopamine





Wickens et al, 1996

Summary so far...

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⇒ Precise (normative!) theory for generation of dopamine firing patterns

⇒ A computational model of learning allows us to look in the brain for "hidden variables" postulated by the model

Outline

- The brain coarse-grain
- Learning and decision making in animals and humans: what does RL have to do with it?
- A success story: Dopamine and prediction errors
- Actor/Critic architecture in basal ganglia
- SARSA vs Q-learning: can the brain teach us about ML?
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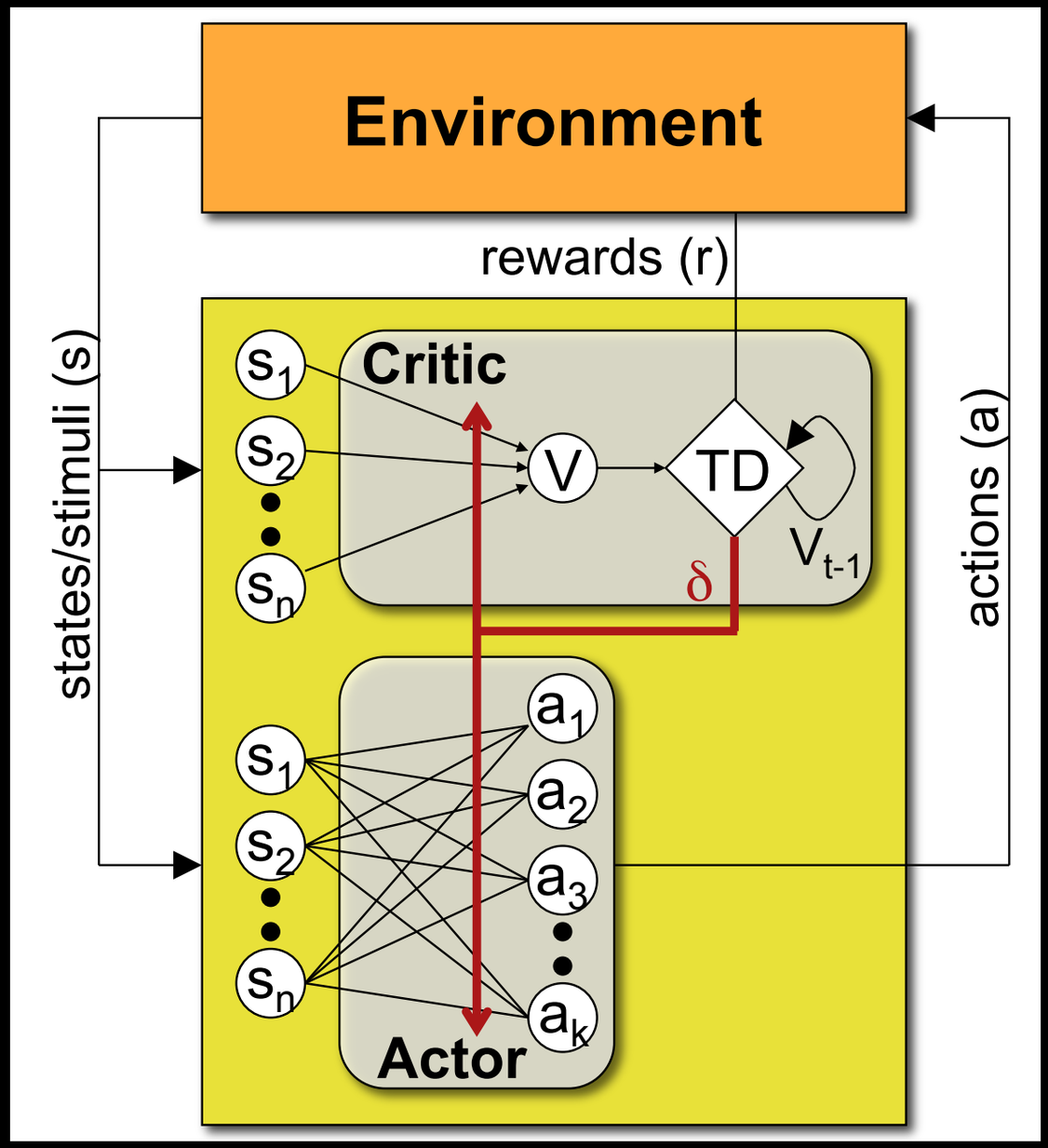
3 model-free learning algorithms

Actor/Critic

Q learning

SARSA

Actor/Critic in the brain?



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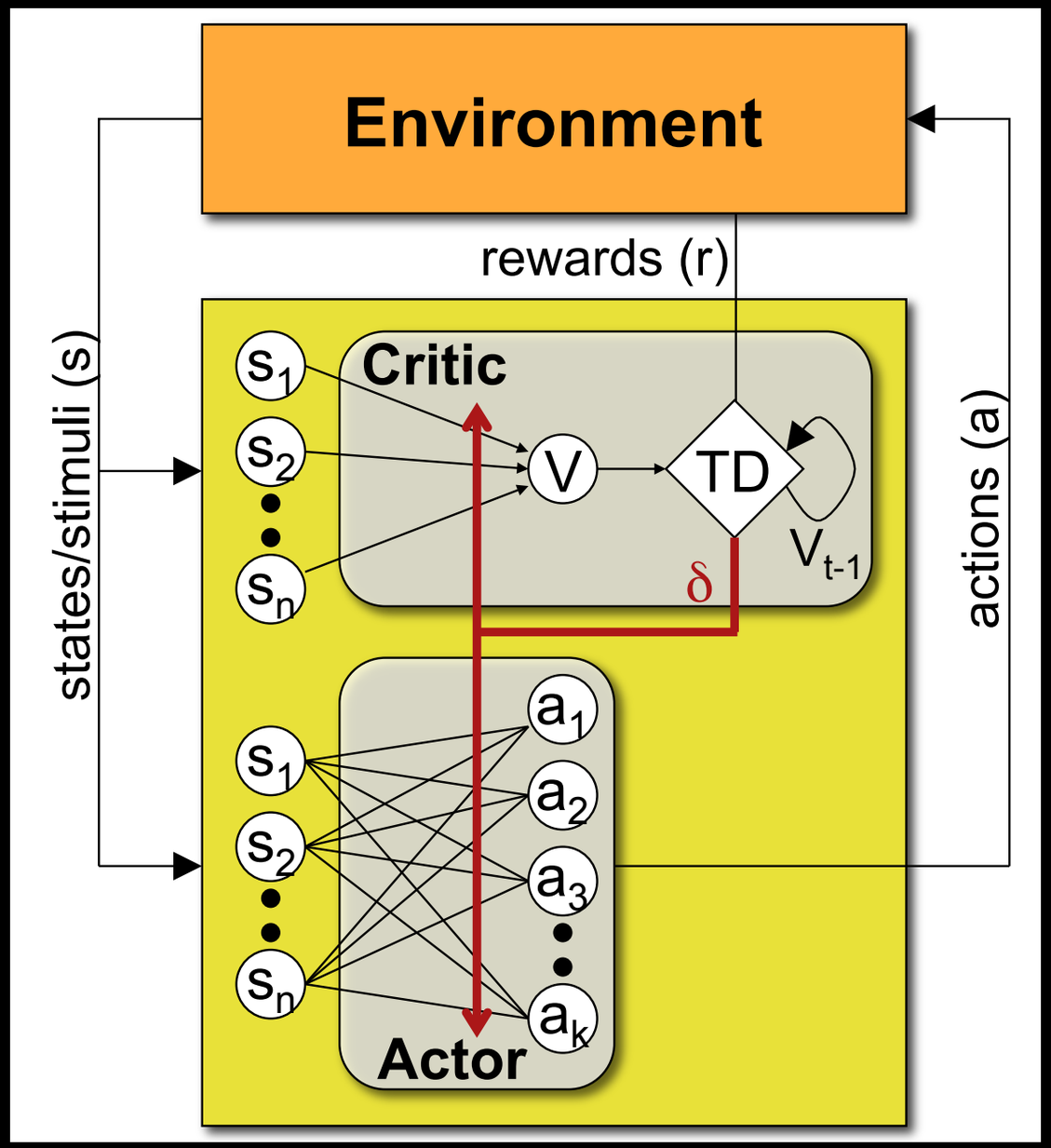

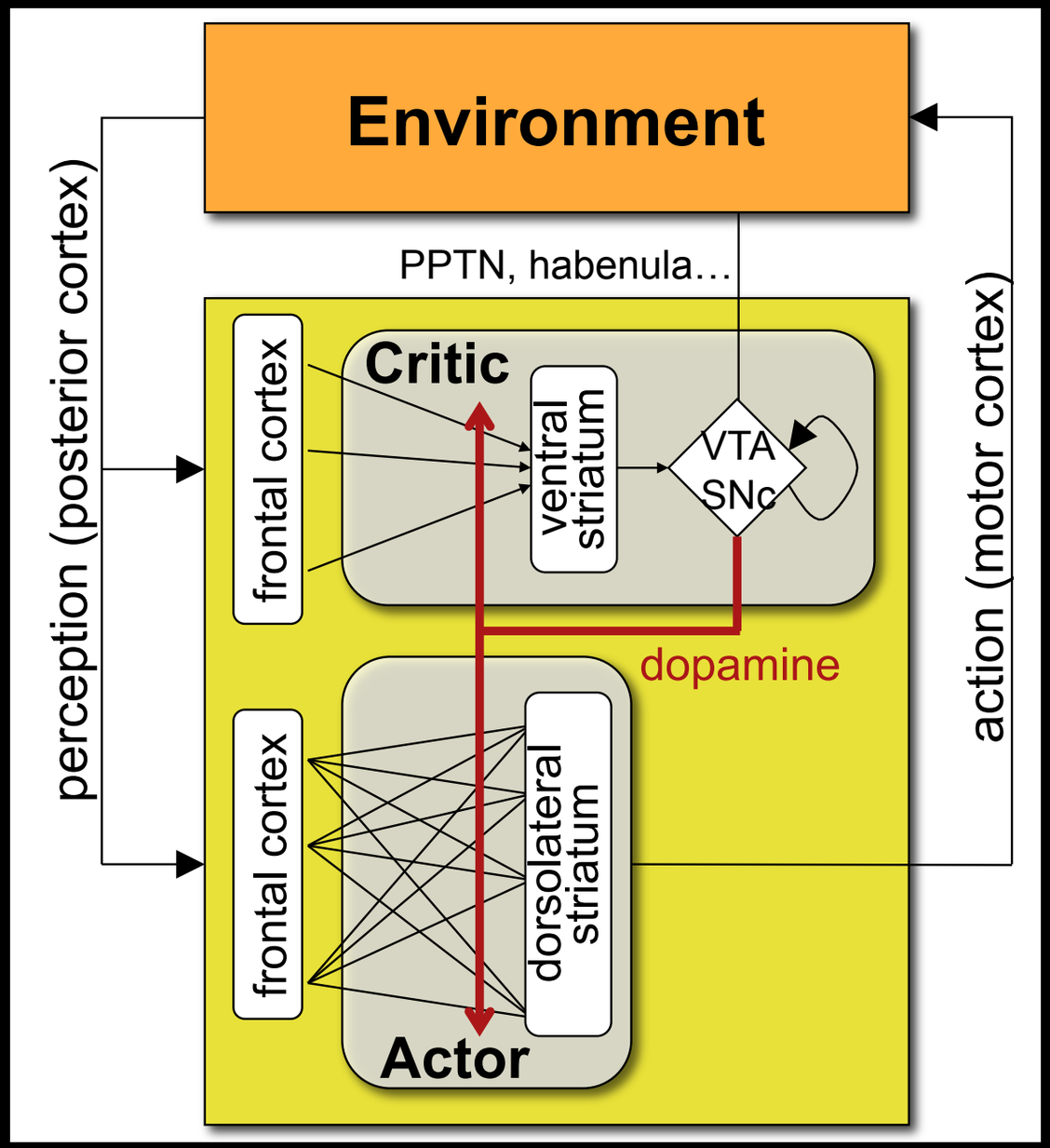

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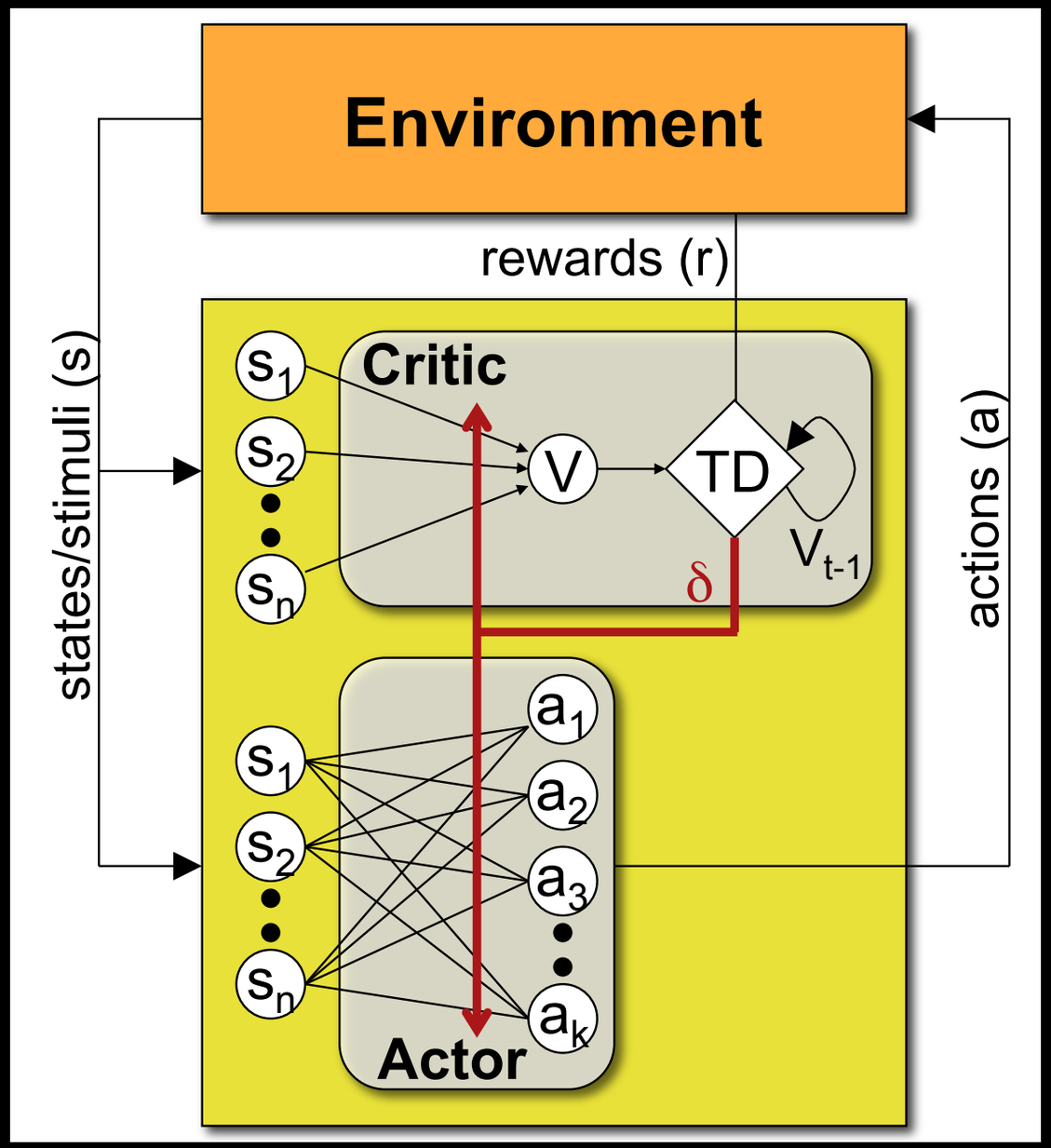

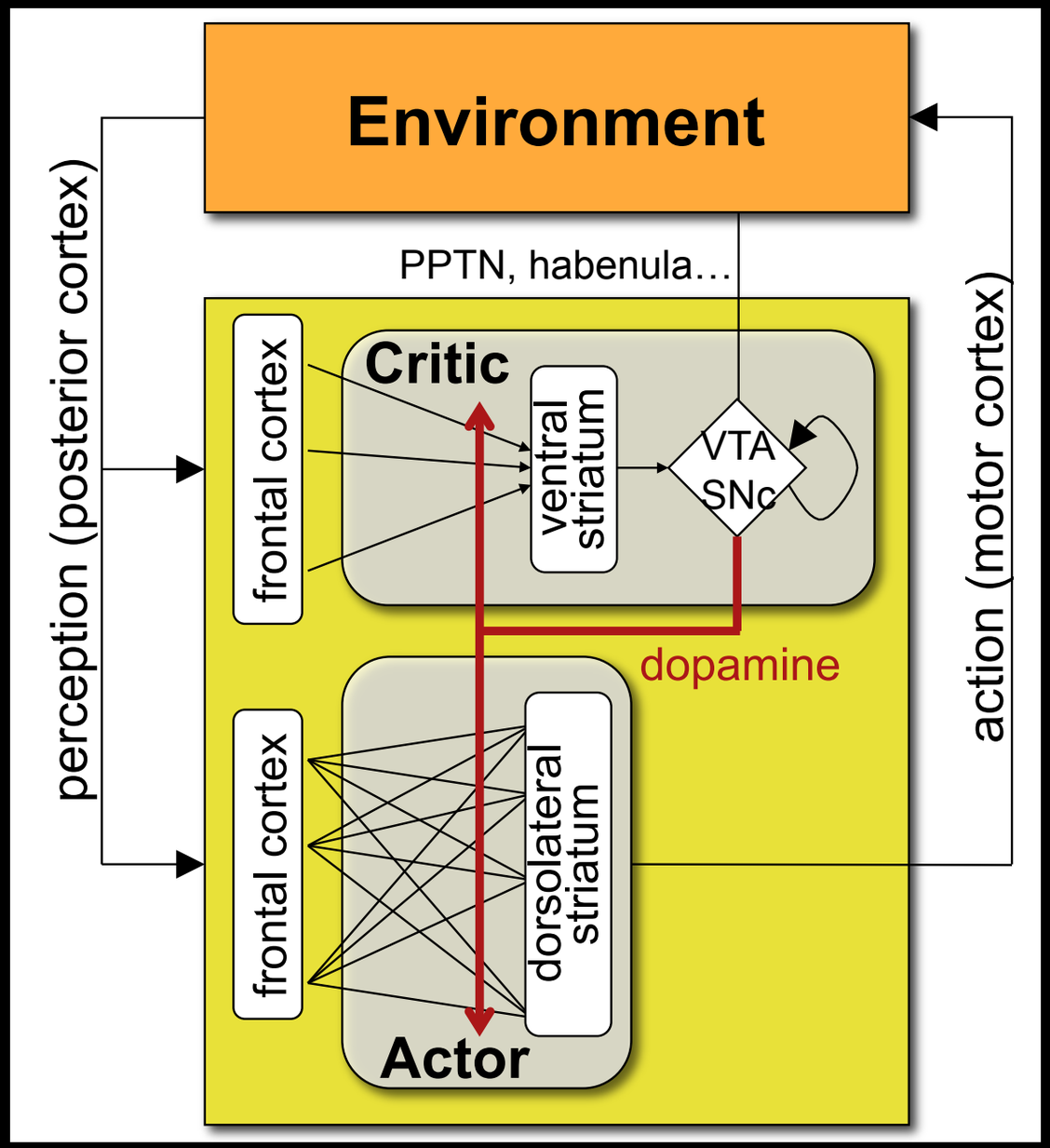

evidence for this?

short aside: functional magnetic resonance imaging (fMRI)

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- measure BOLD ("blood oxygenation level dependent") signal

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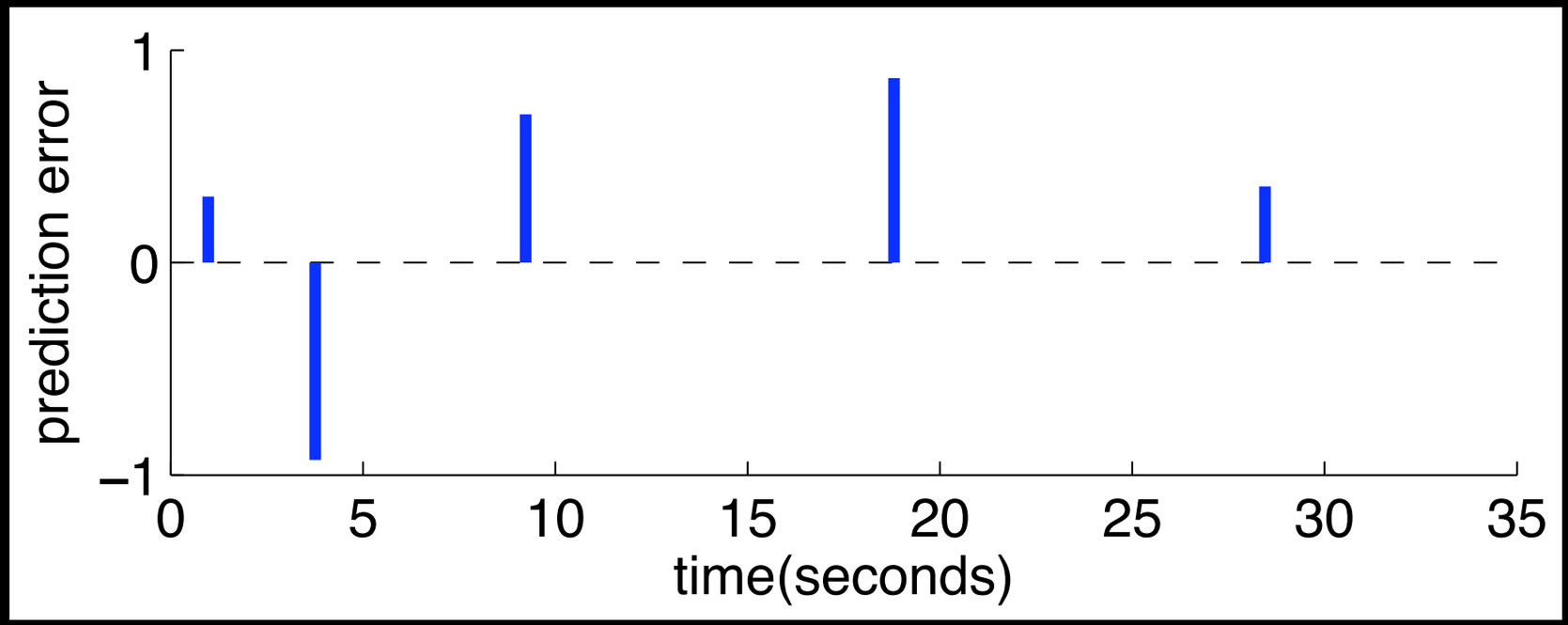

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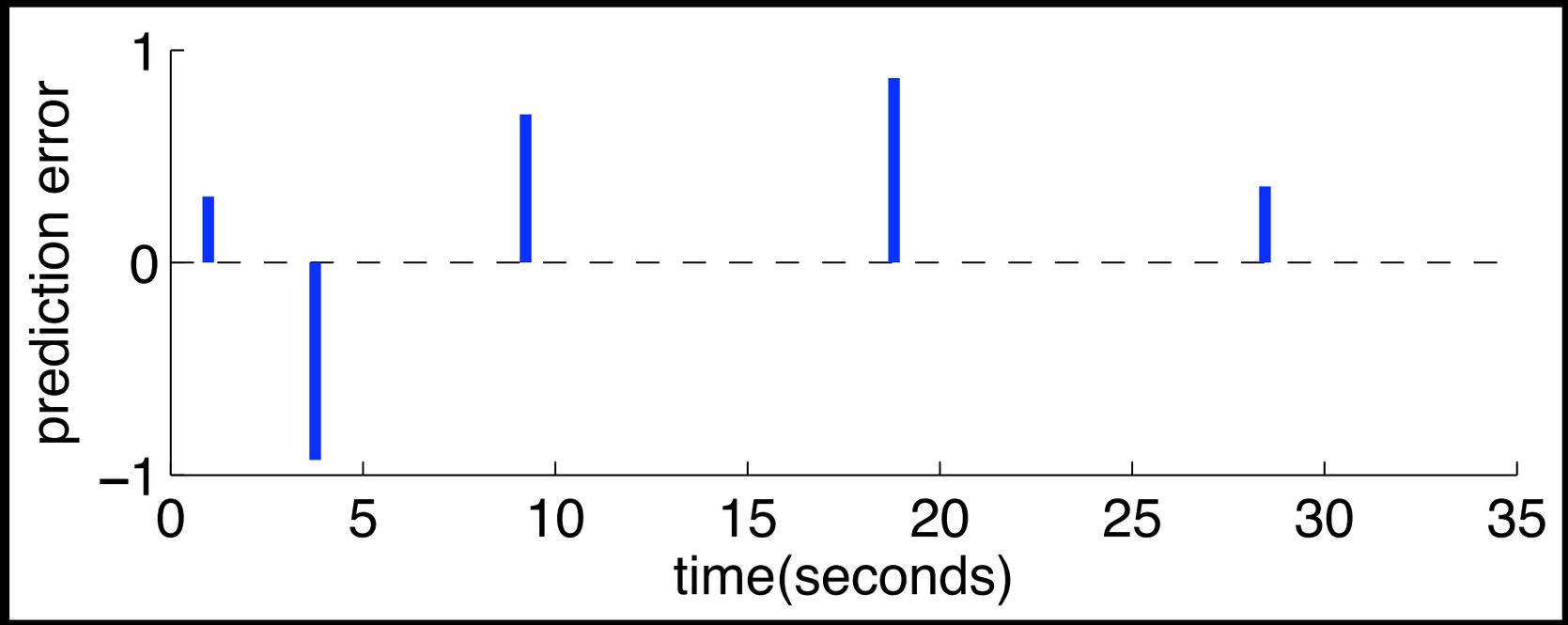

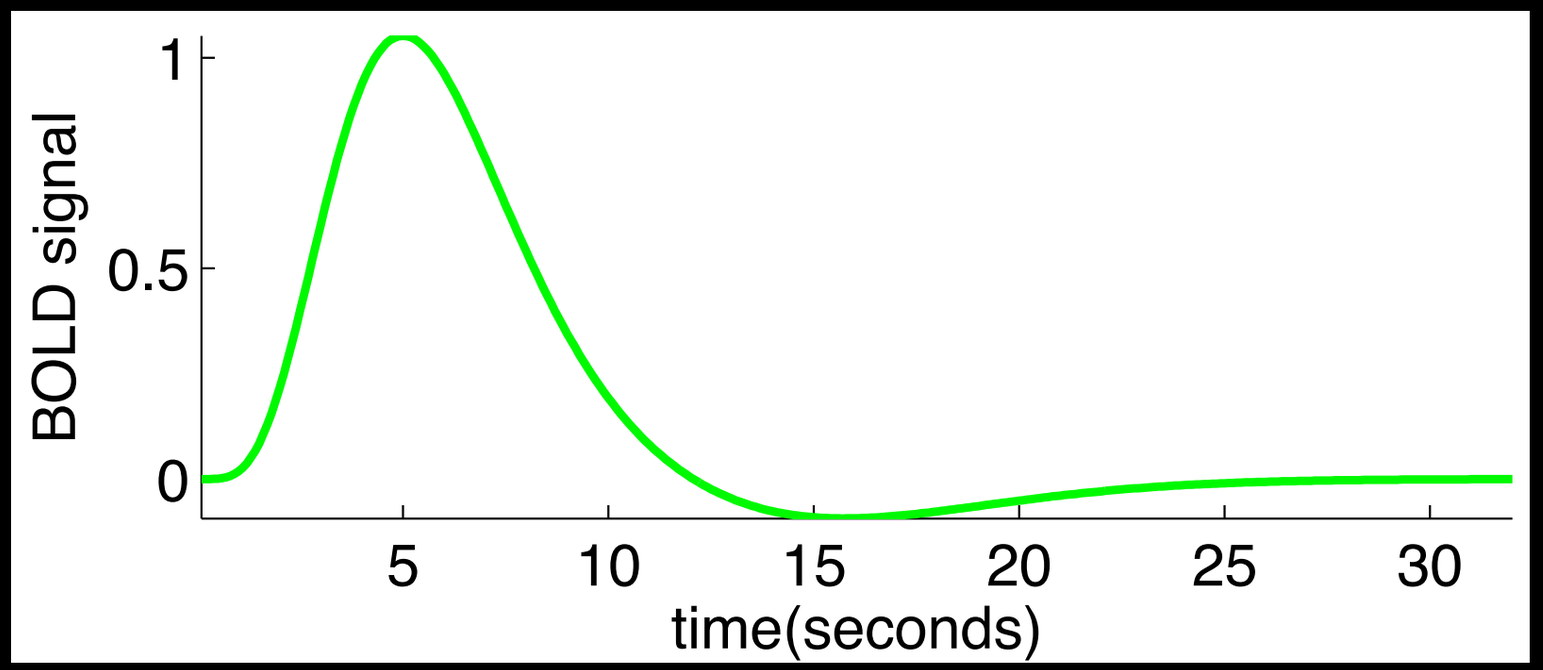

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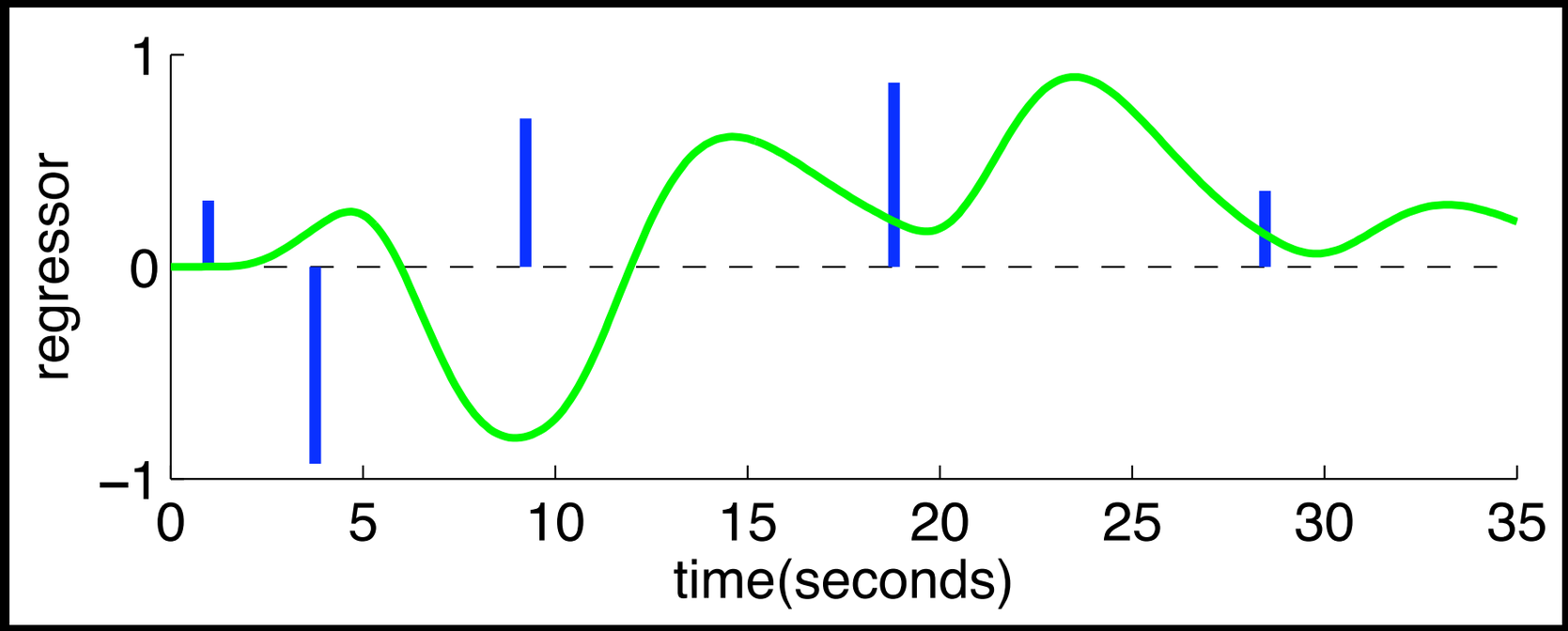

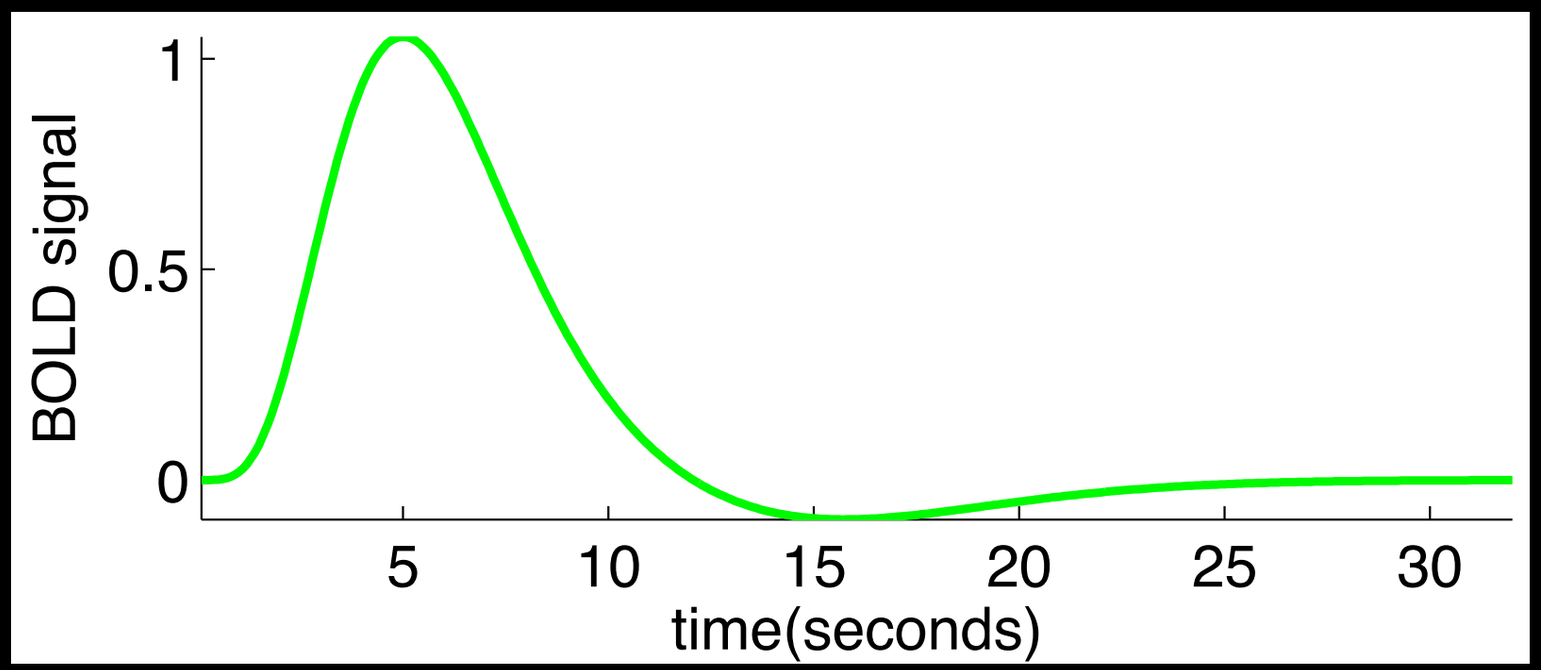

Back to Actor/Critic: Evidence from fMRI

O'Doherty et al. 2004

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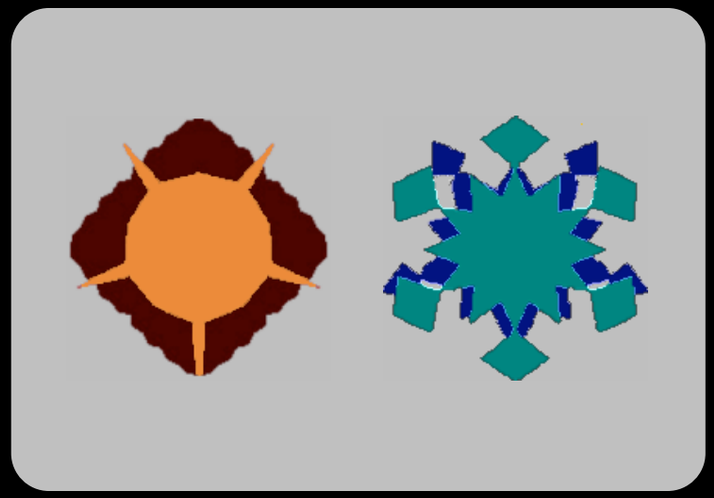

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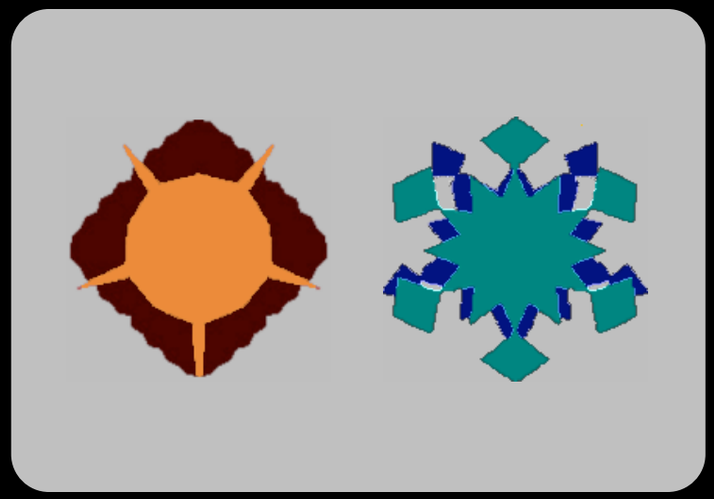

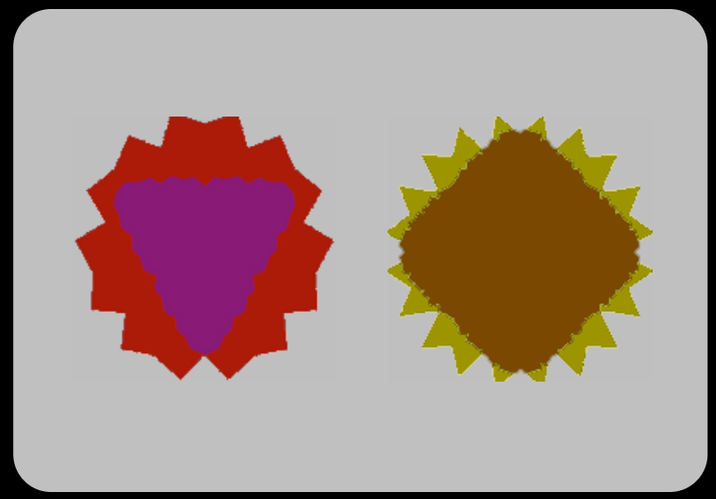

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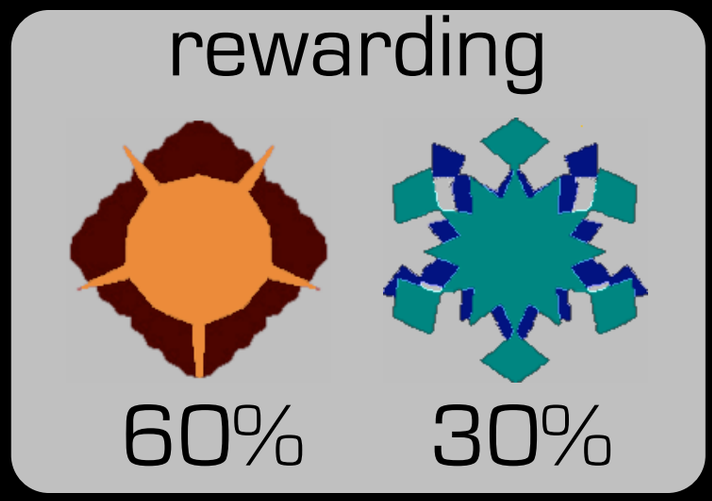
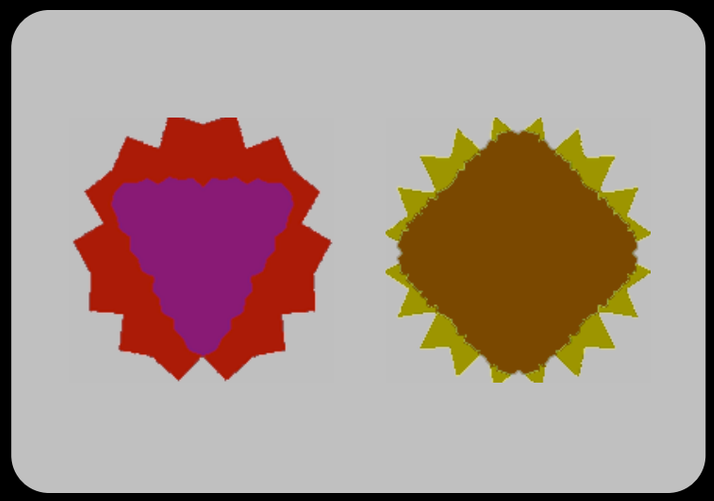
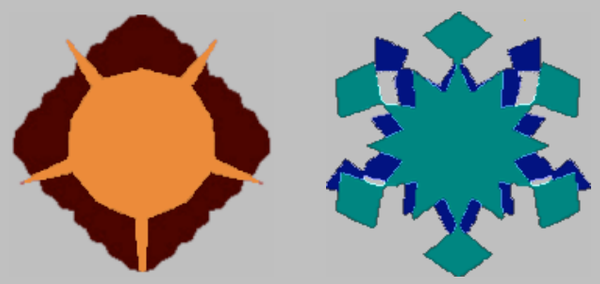




O'Doherty et al. 2004

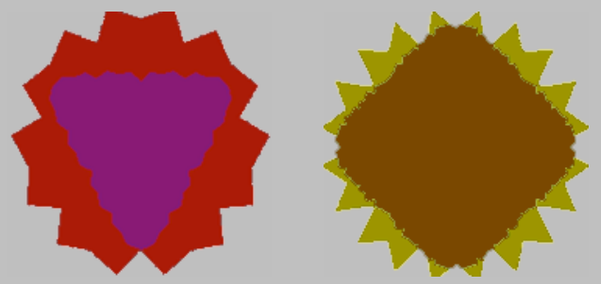
Back to Actor/Critic: Evidence from fMRI

rewarding



60% 30%

neutral



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O'Doherty et al. 2004

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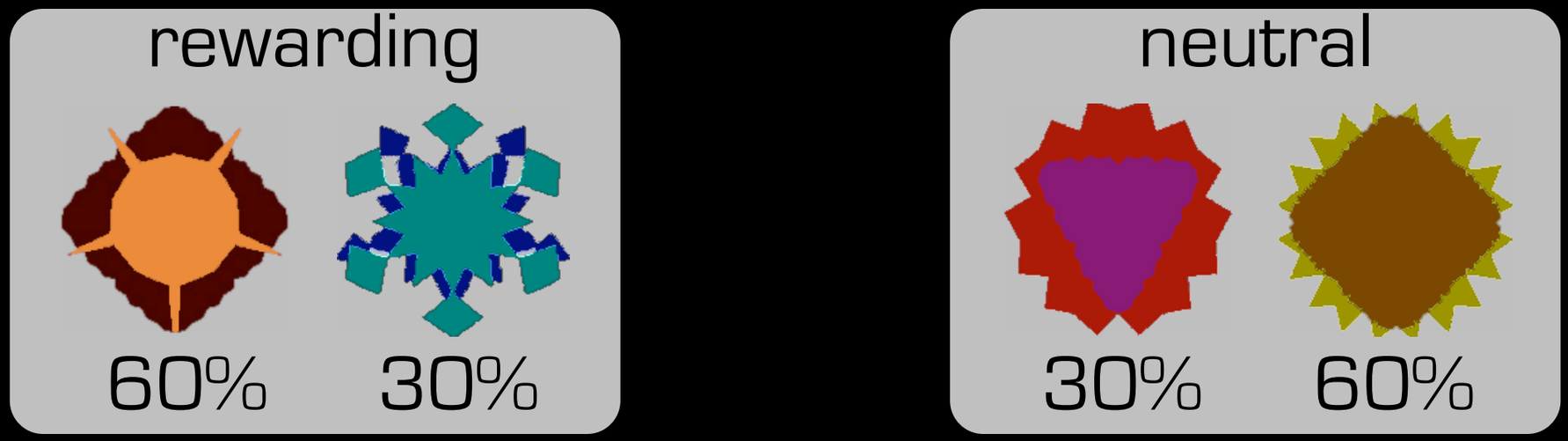

- cond 1: instrumental (choose stimuli) - show preference for high probability stimulus in rewarding but not neutral trials

O'Doherty et al. 2004

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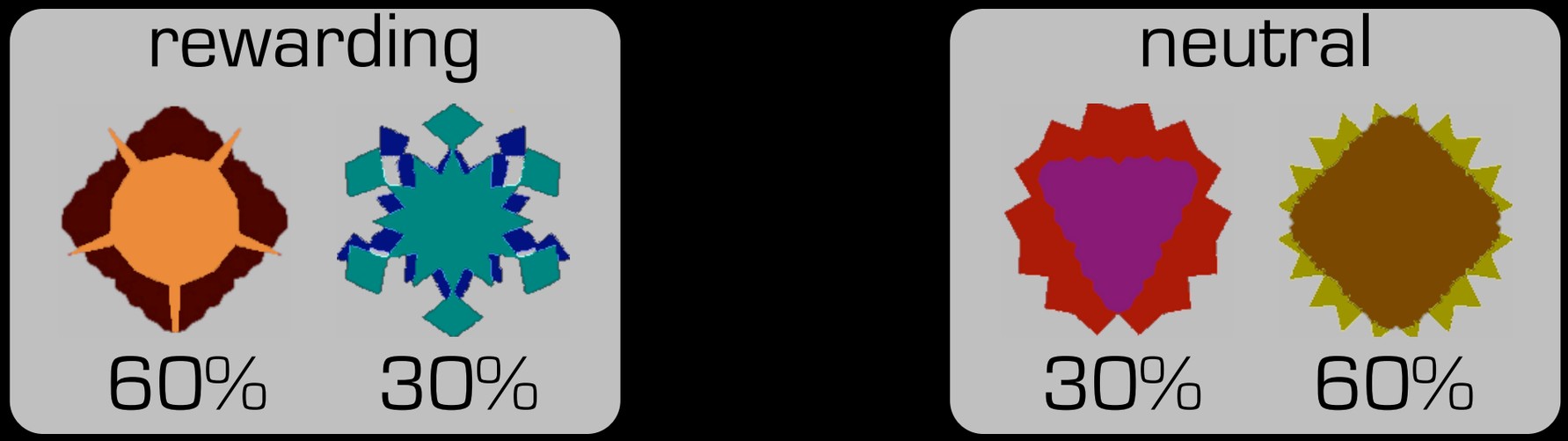

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O'Doherty et al. 2004

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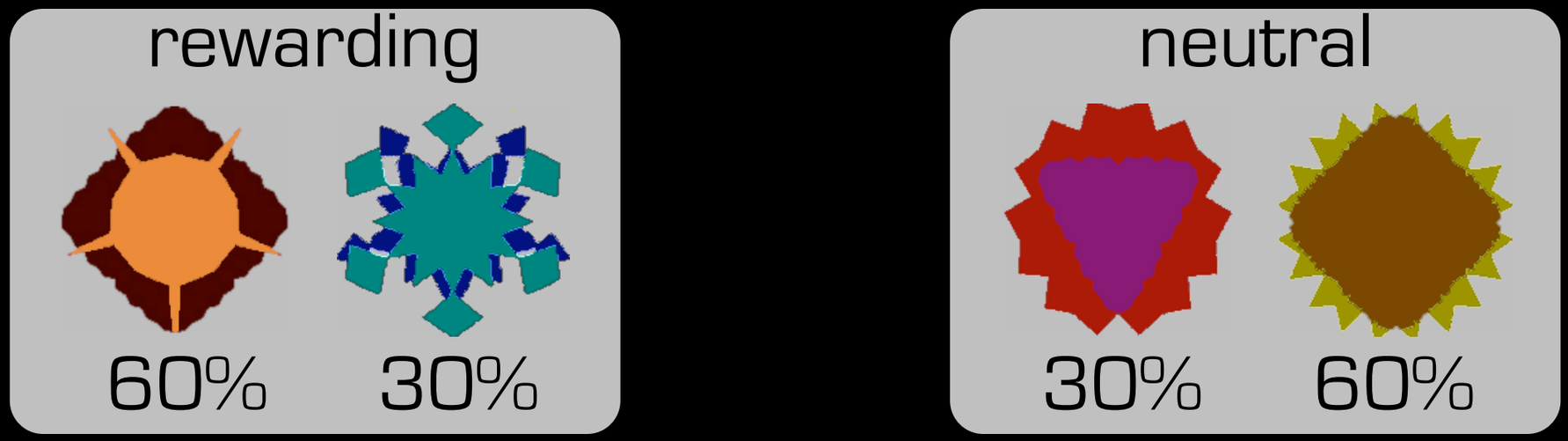
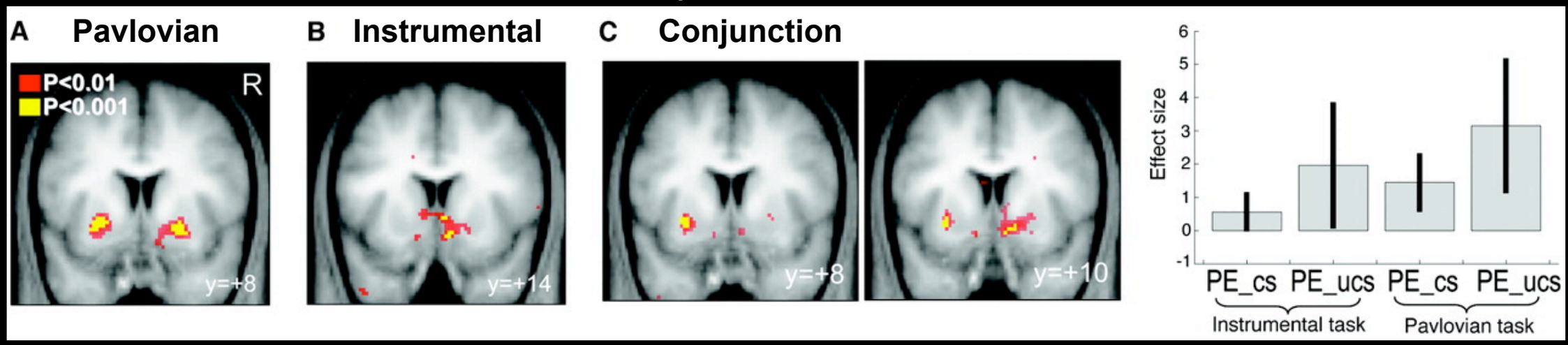


- cond 1: instrumental (choose stimuli) - show preference for high probability stimulus in rewarding but not neutral trials
- cond 2: Pavlovian - only indicate the side the 'computer' has selected (RTs as measure of learning)
- why was the experiment designed this way (hint: think of prediction errors)

O'Doherty et al. 2004

Back to Actor/Critic: Evidence from fMRI

ventral striatum: correlated with prediction error in both conditions



O'Doherty et al. 2004

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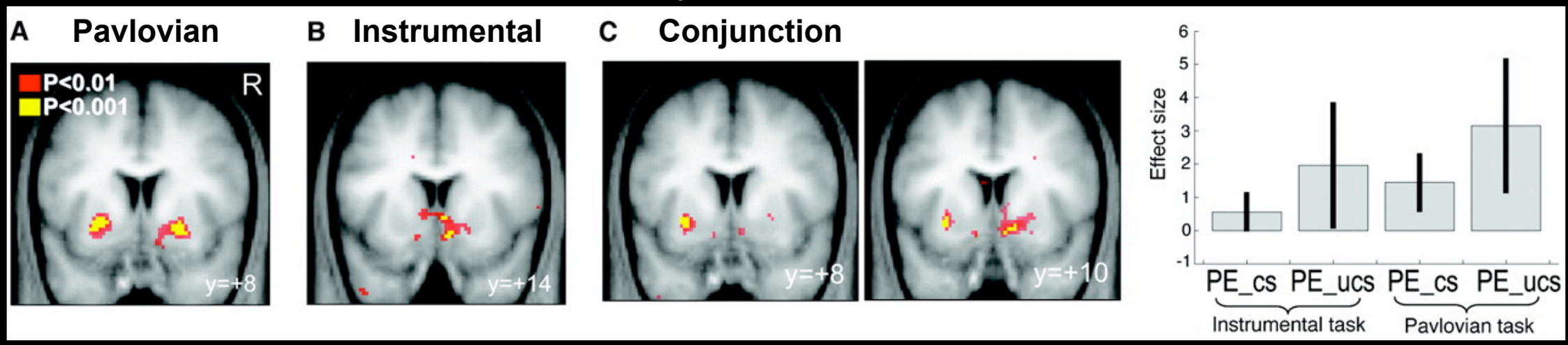
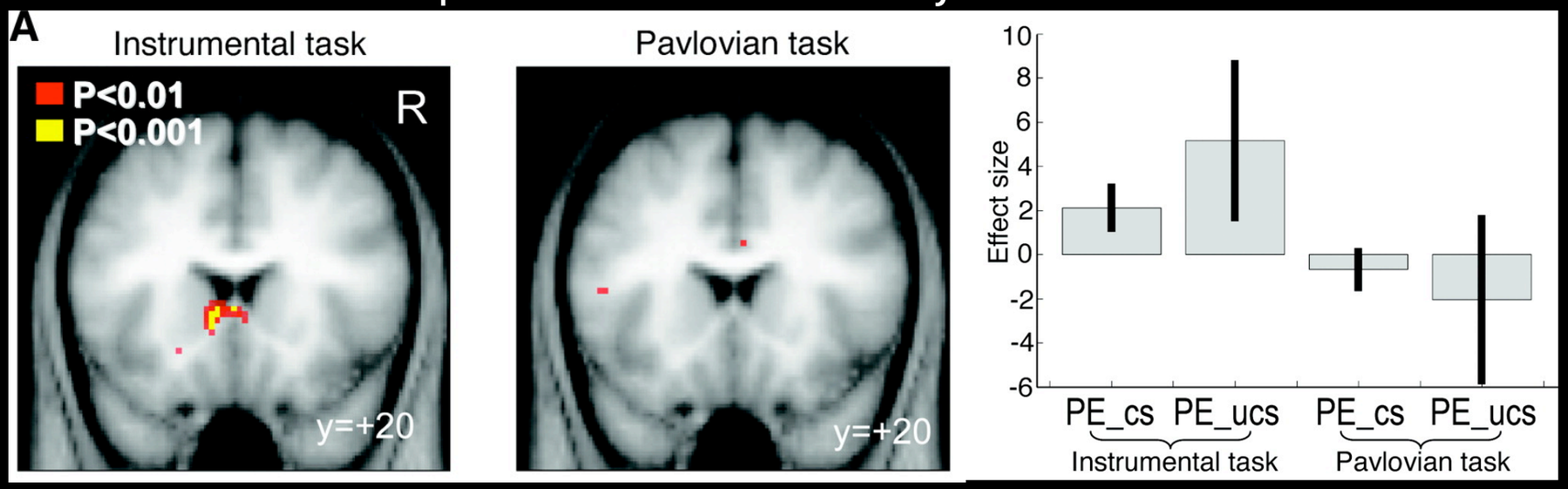
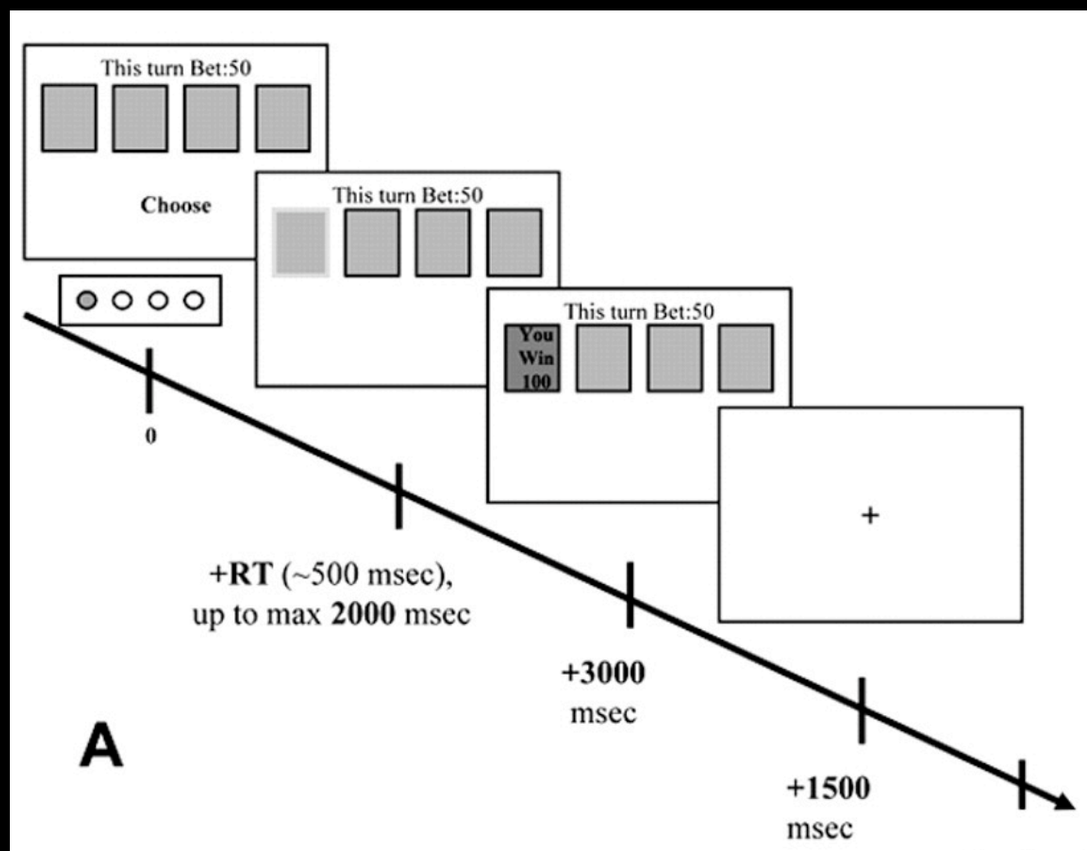


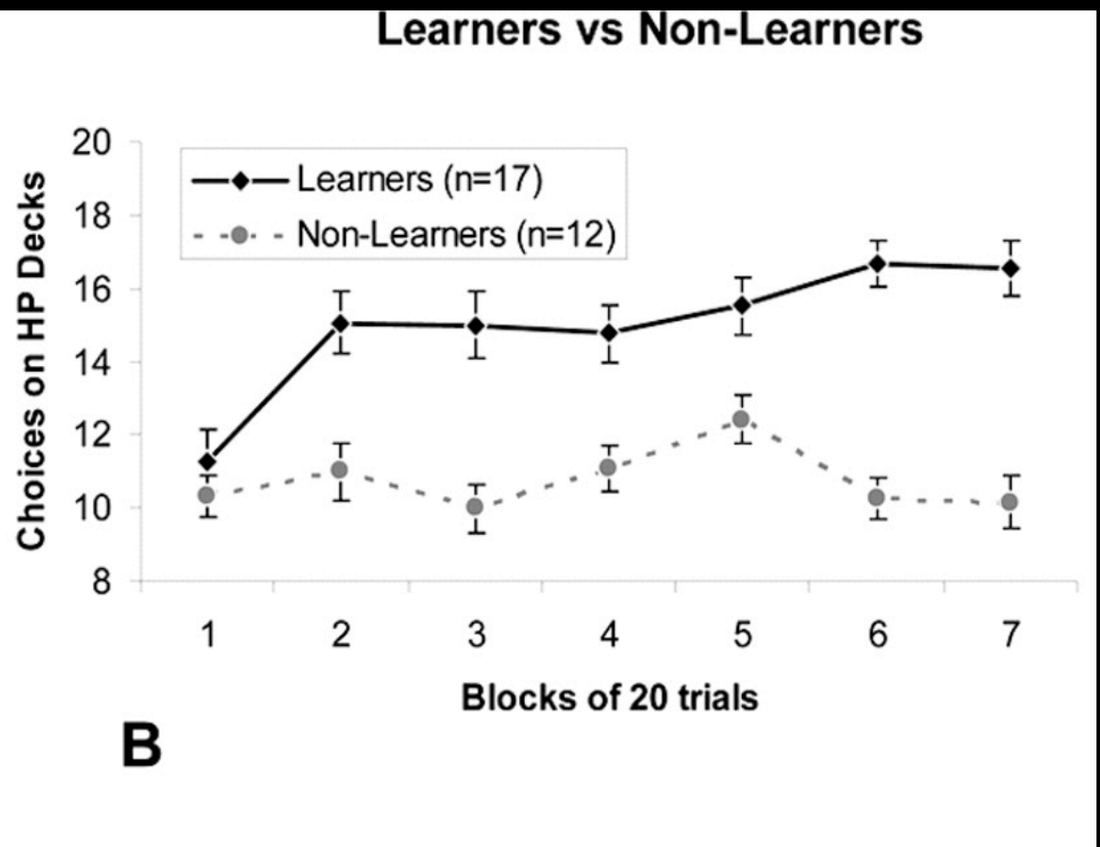
Dorsal striatum: prediction error only in instrumental task



O'Doherty et al. 2004

do prediction errors really influence learning?





Schonberg et al. 2007

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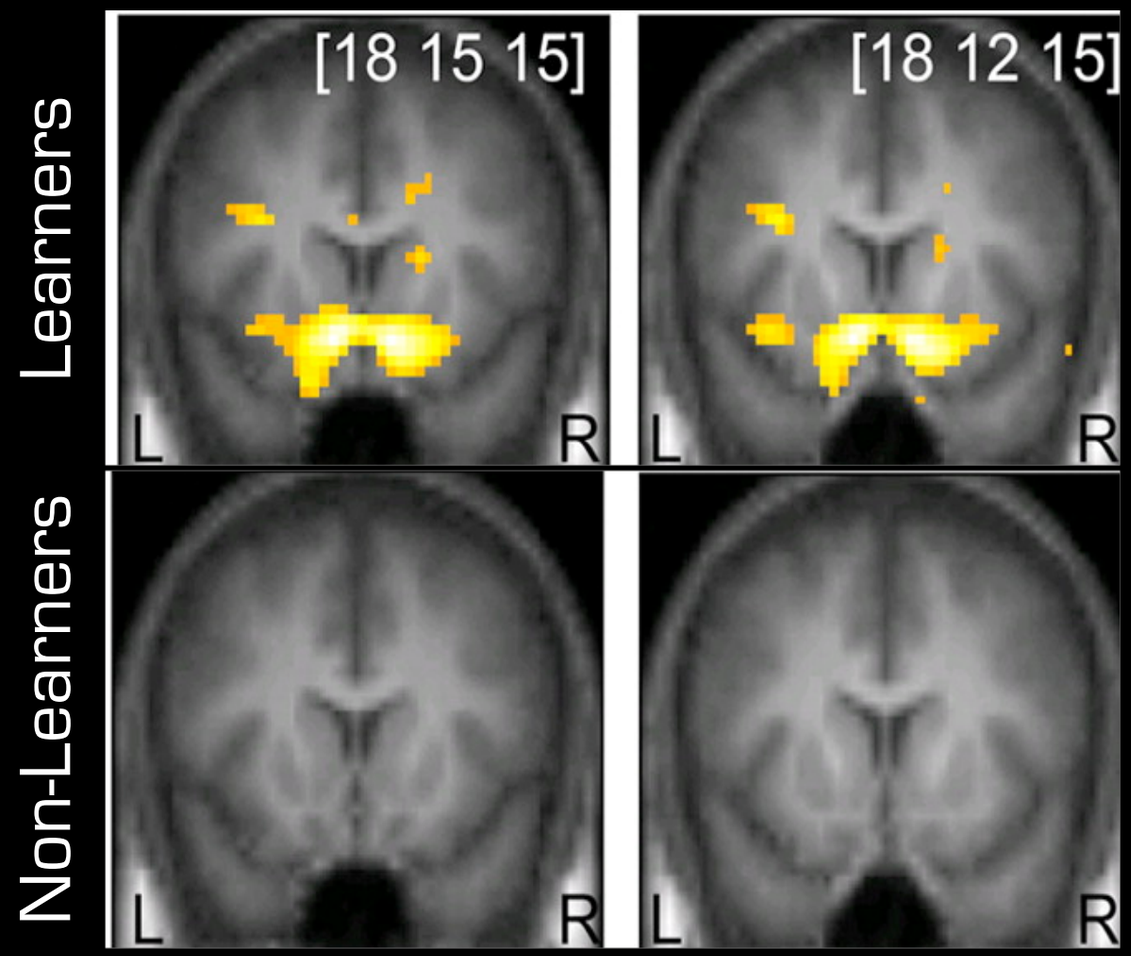

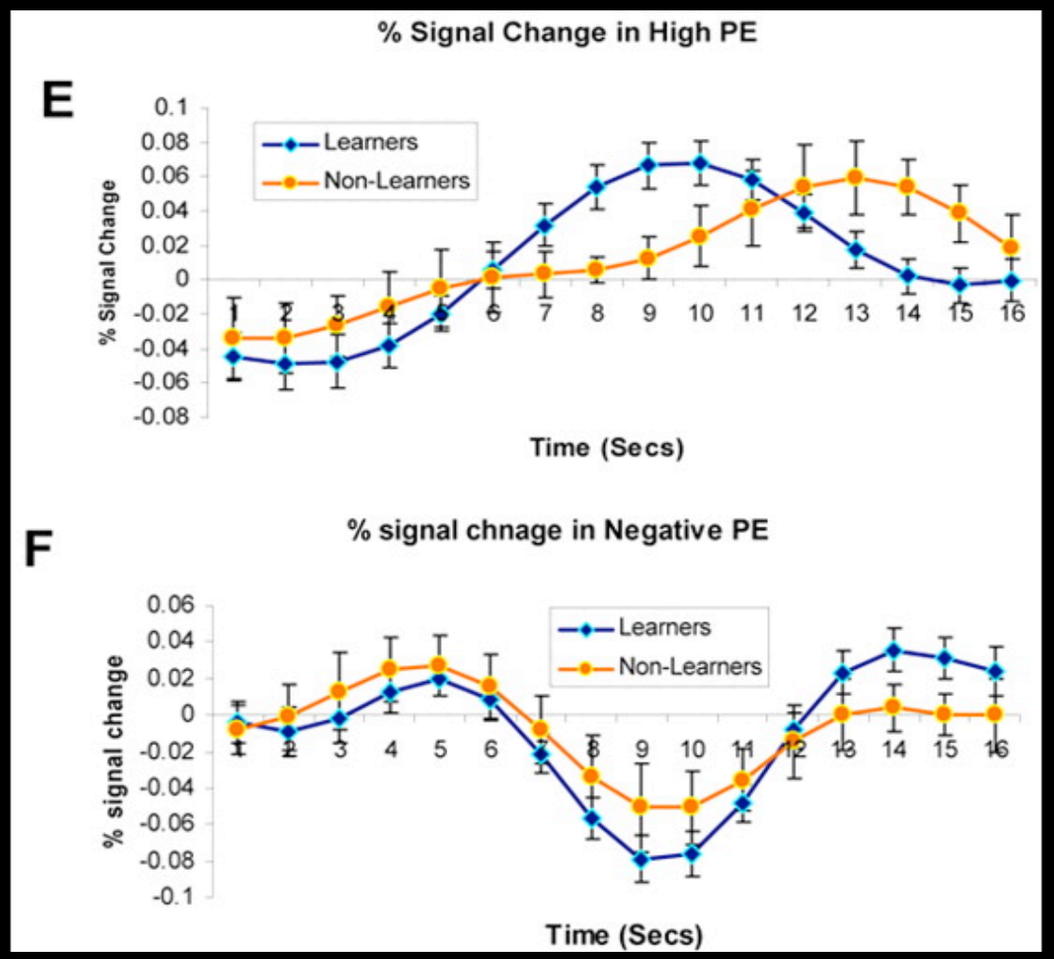

Schonberg et al. 2007 [50]

Summary so far...

- Some evidence for an Actor/Critic architecture in the brain
- Links predictions (Critic) to control (Actor) in very specific way; assumes no Q values

- (Not at all conclusive evidence)

Outline

- The brain coarse-grain
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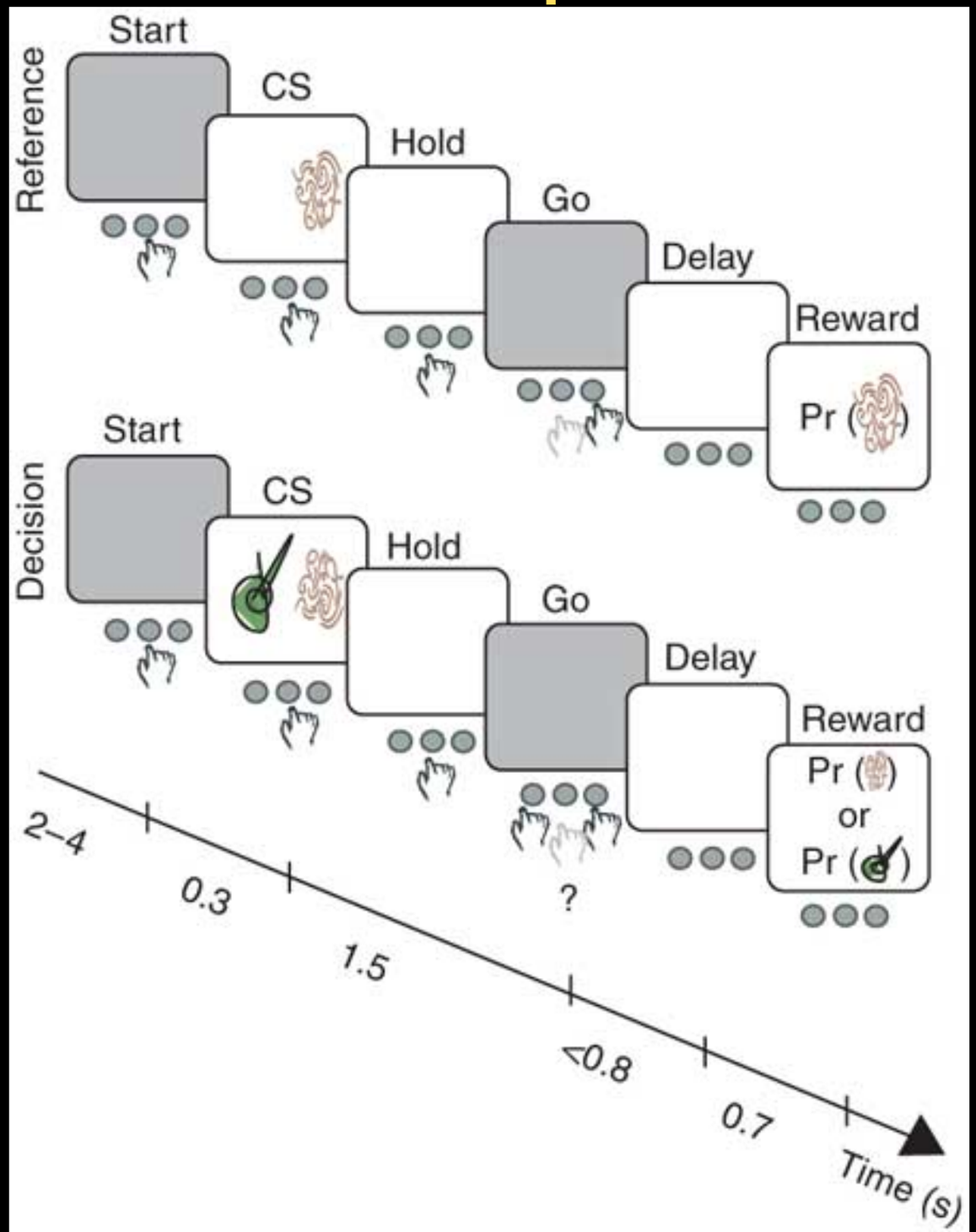

Morris et al. 2005

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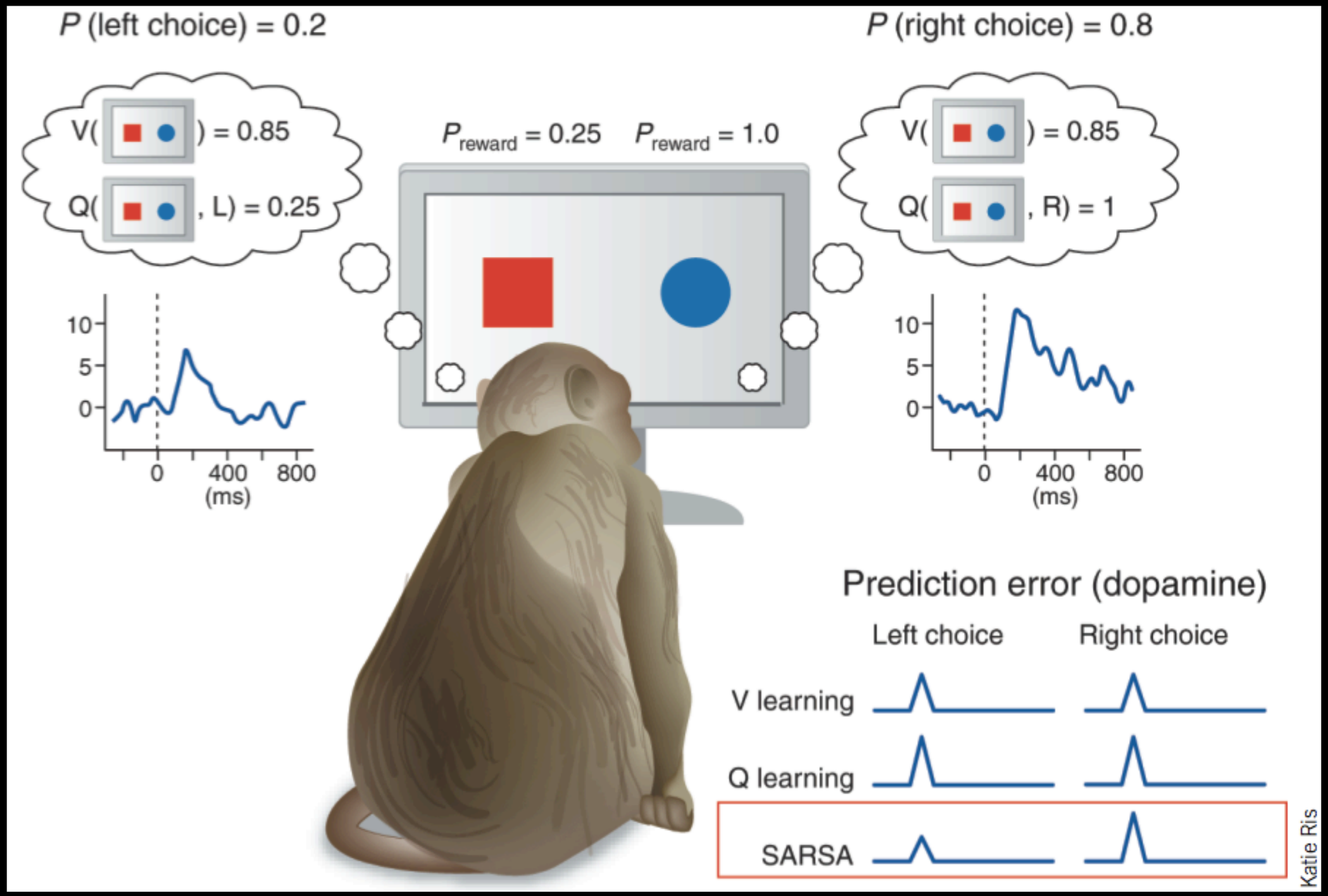

Morris et al. 2005

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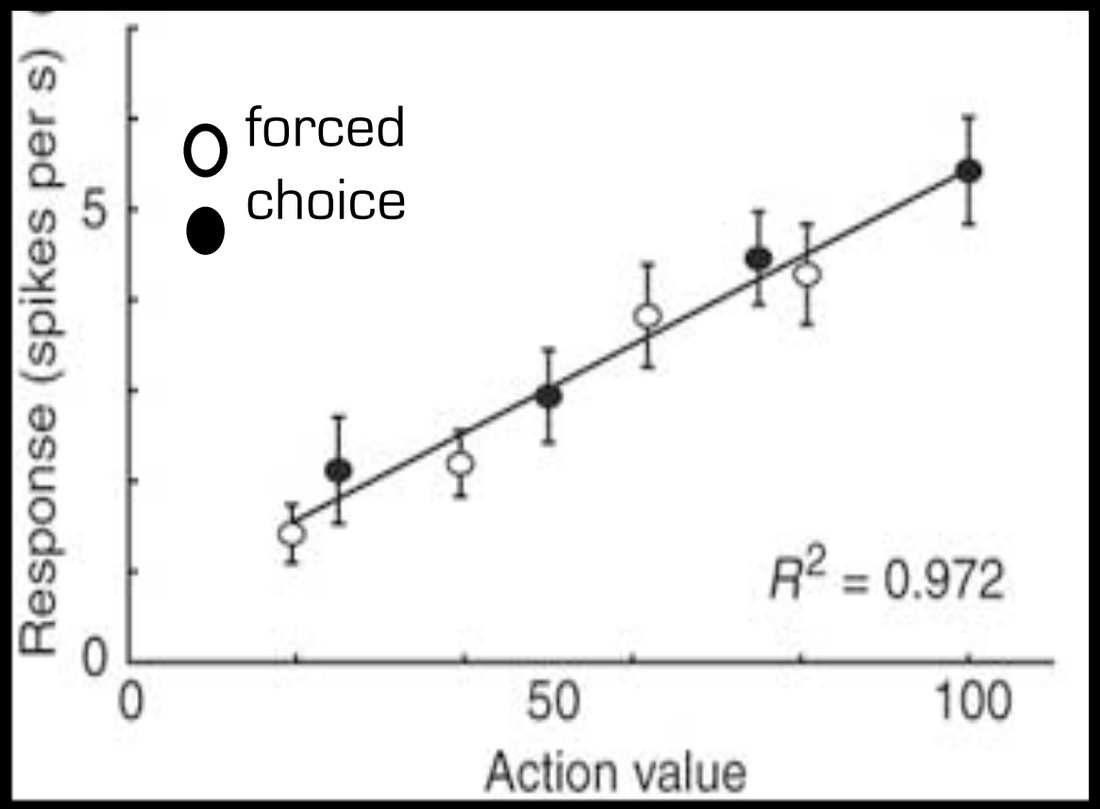
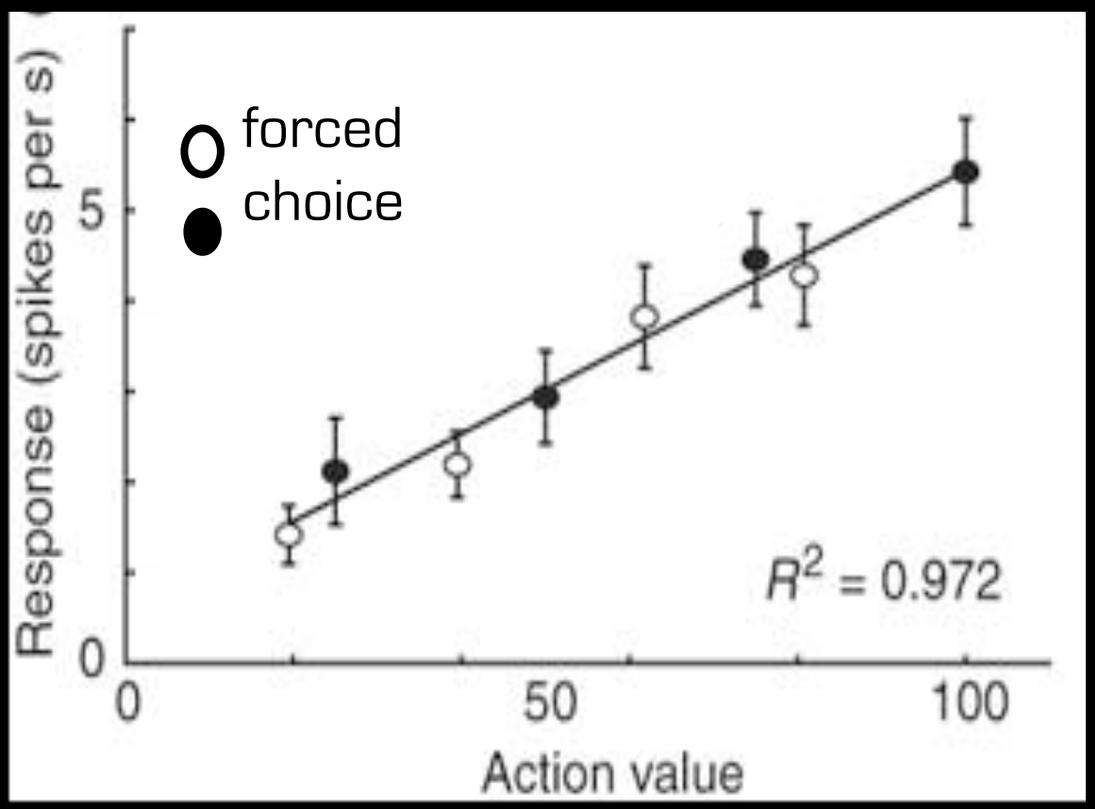
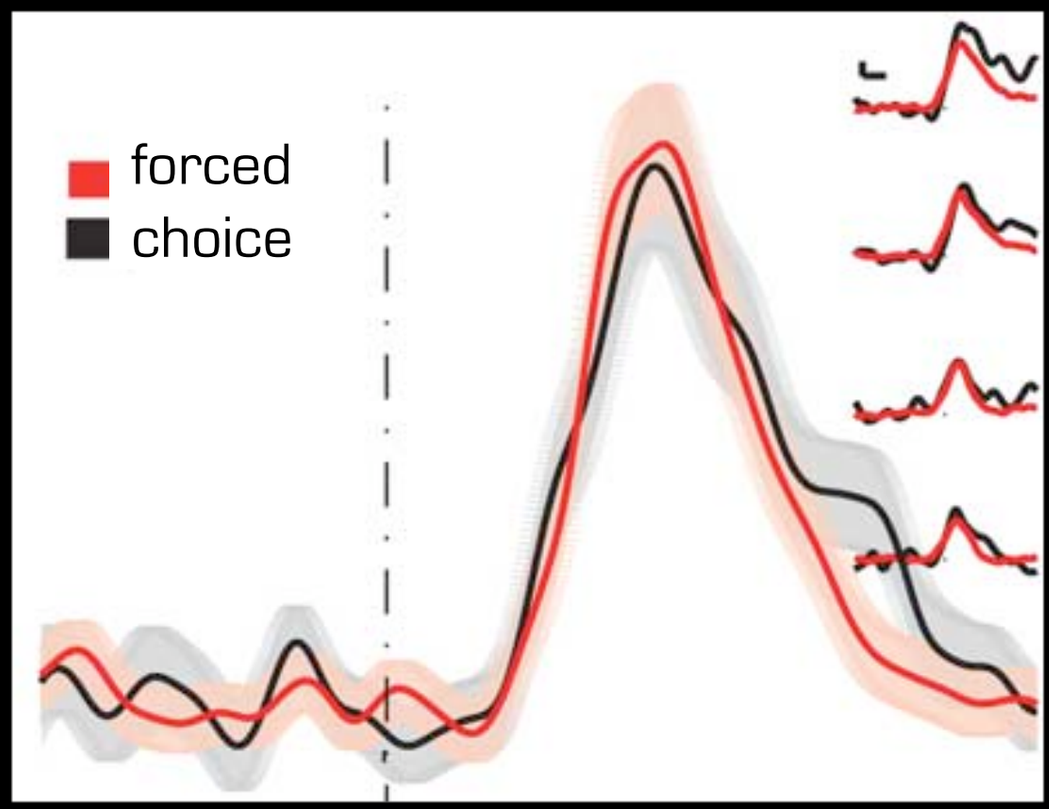


Morris et al. 2005 [55]

do dopamine prediction errors at trial onset represent V(S)?

stimulus on





Morris et al. 2005 [55]

but... another study suggests otherwise

Roesch et al. 2007

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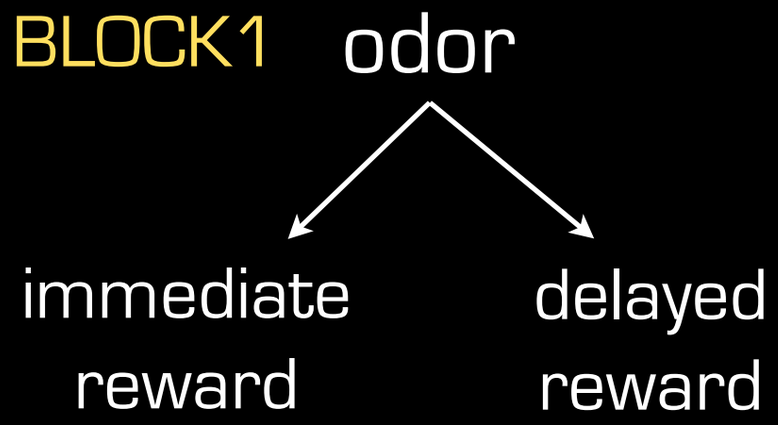

Roesch et al. 2007

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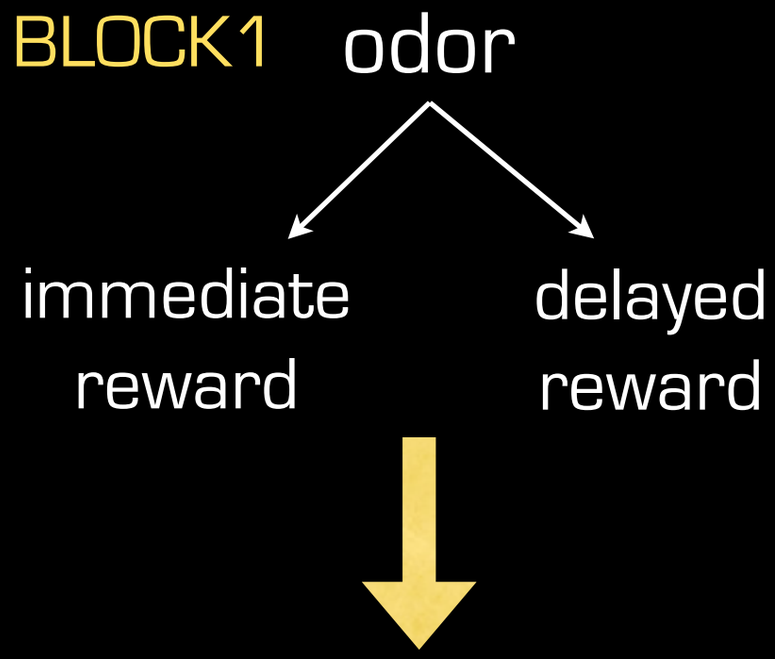

Roesch et al. 2007

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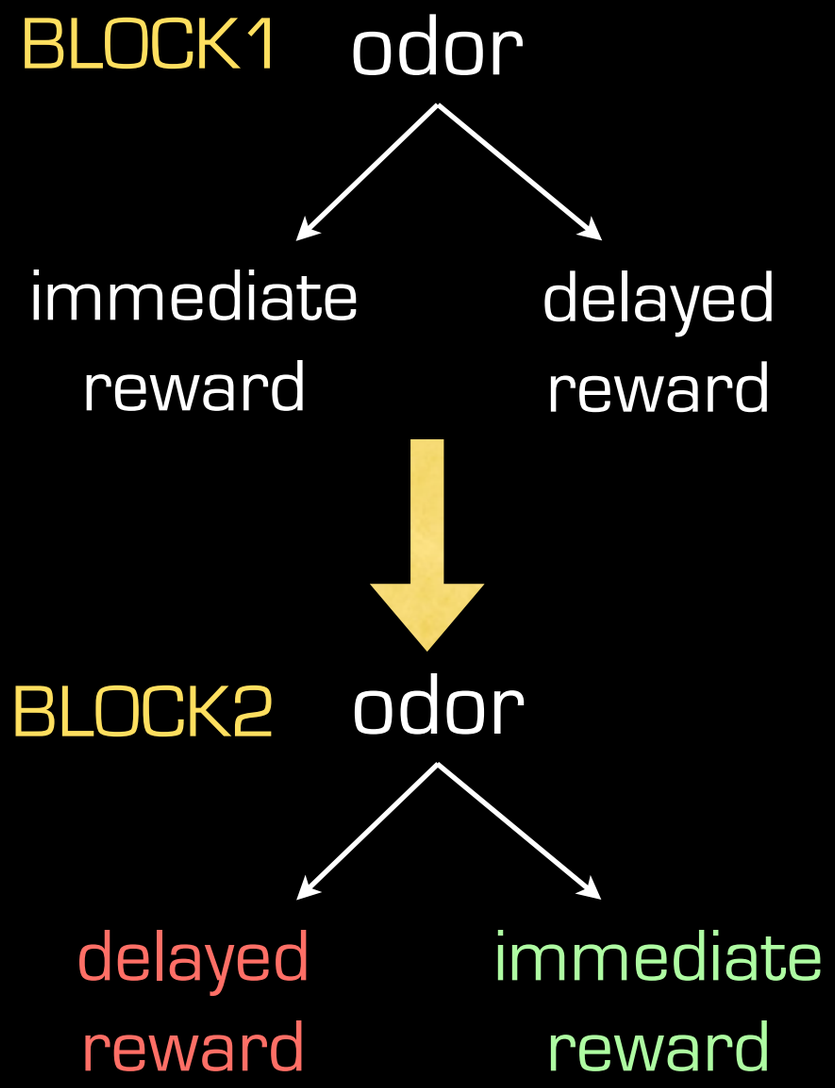

Roesch et al. 2007

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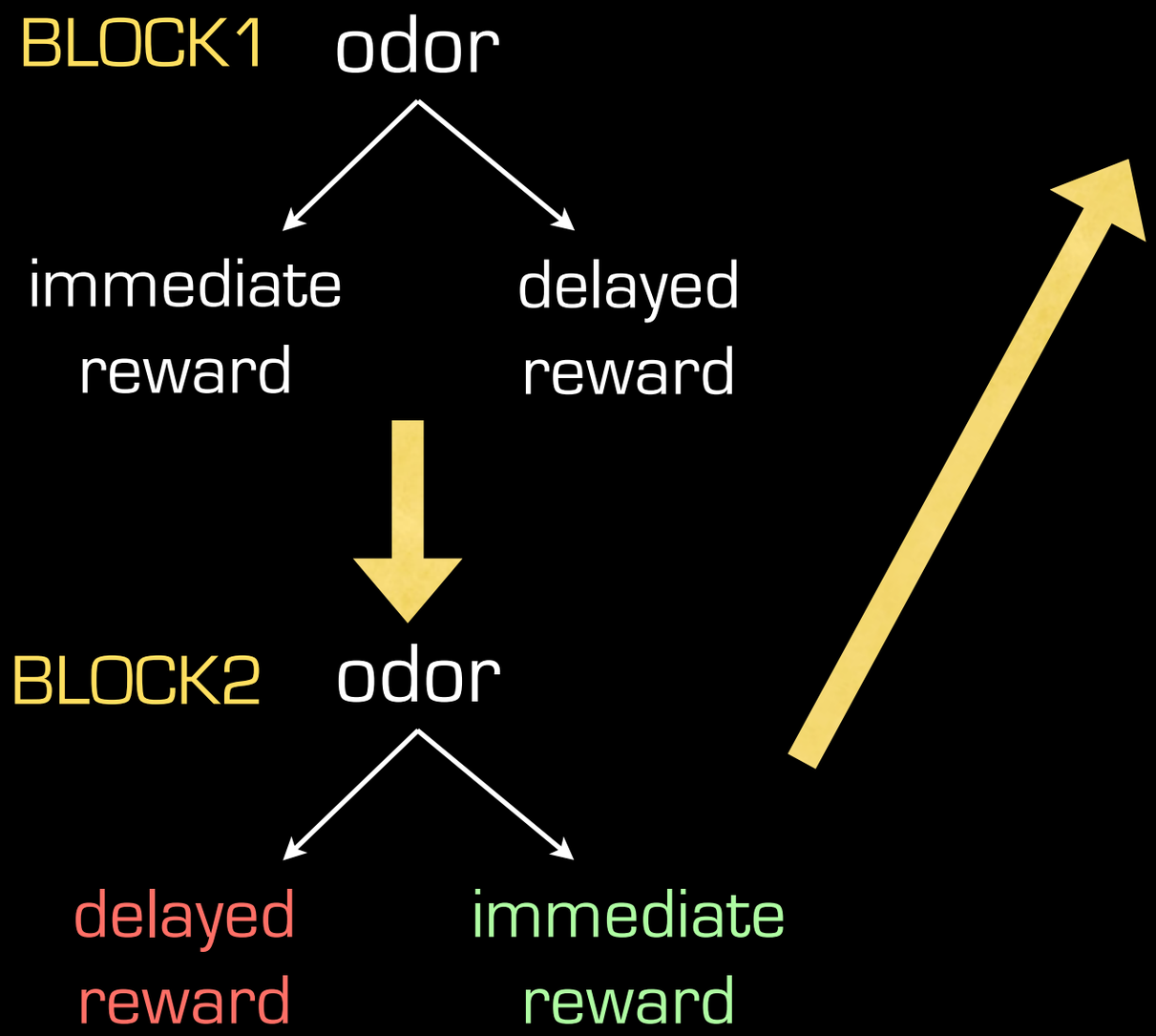

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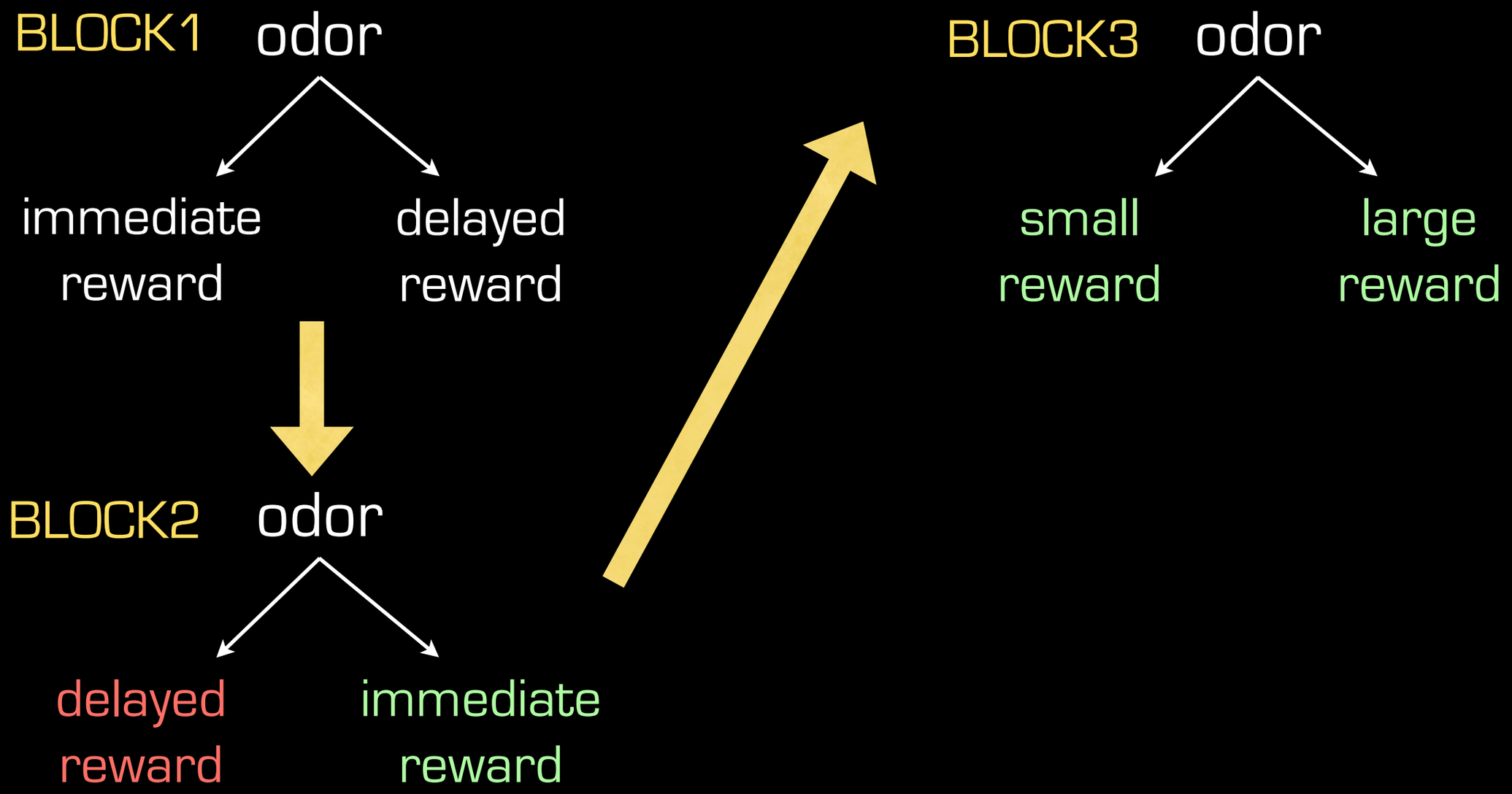

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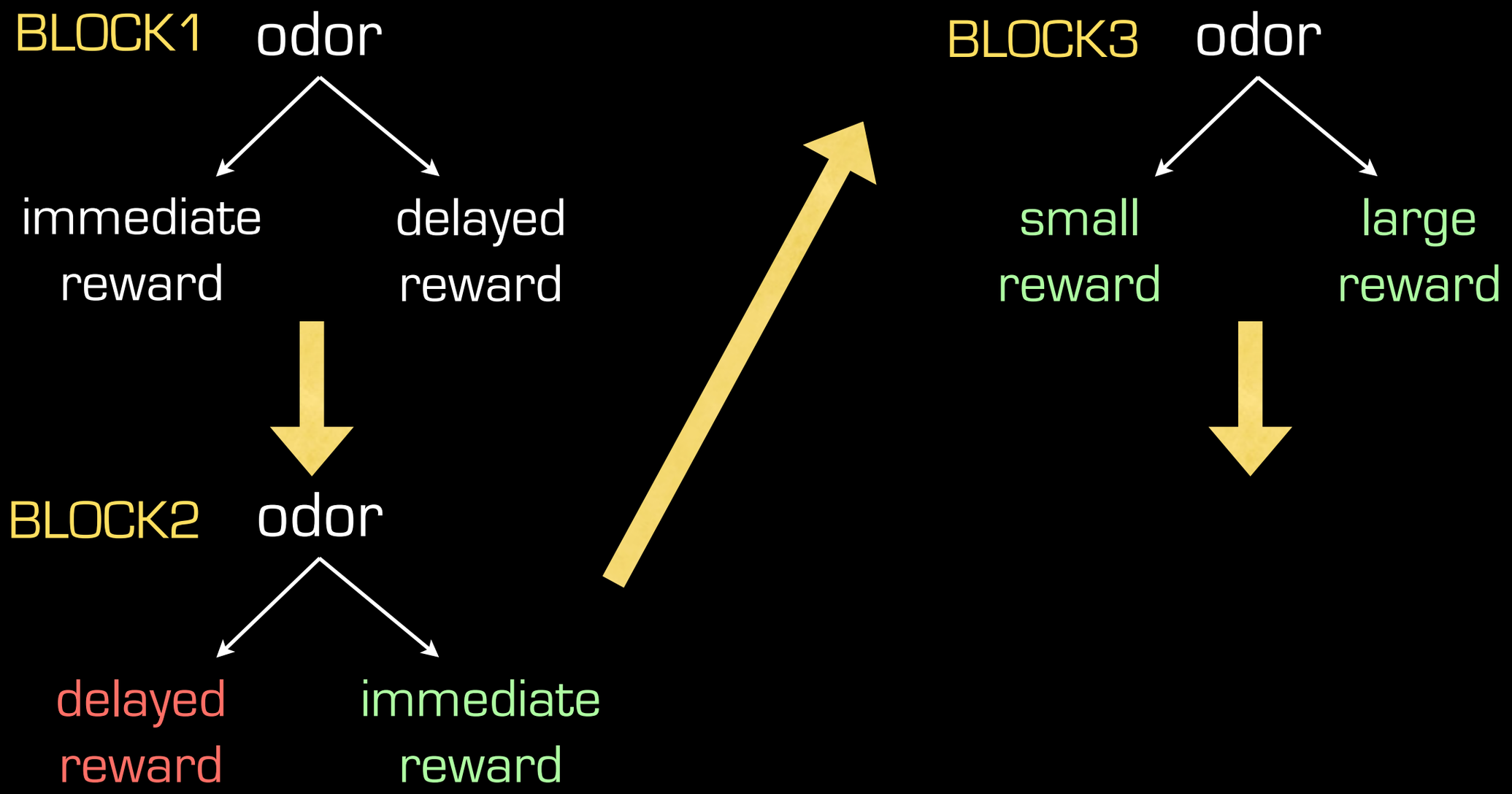

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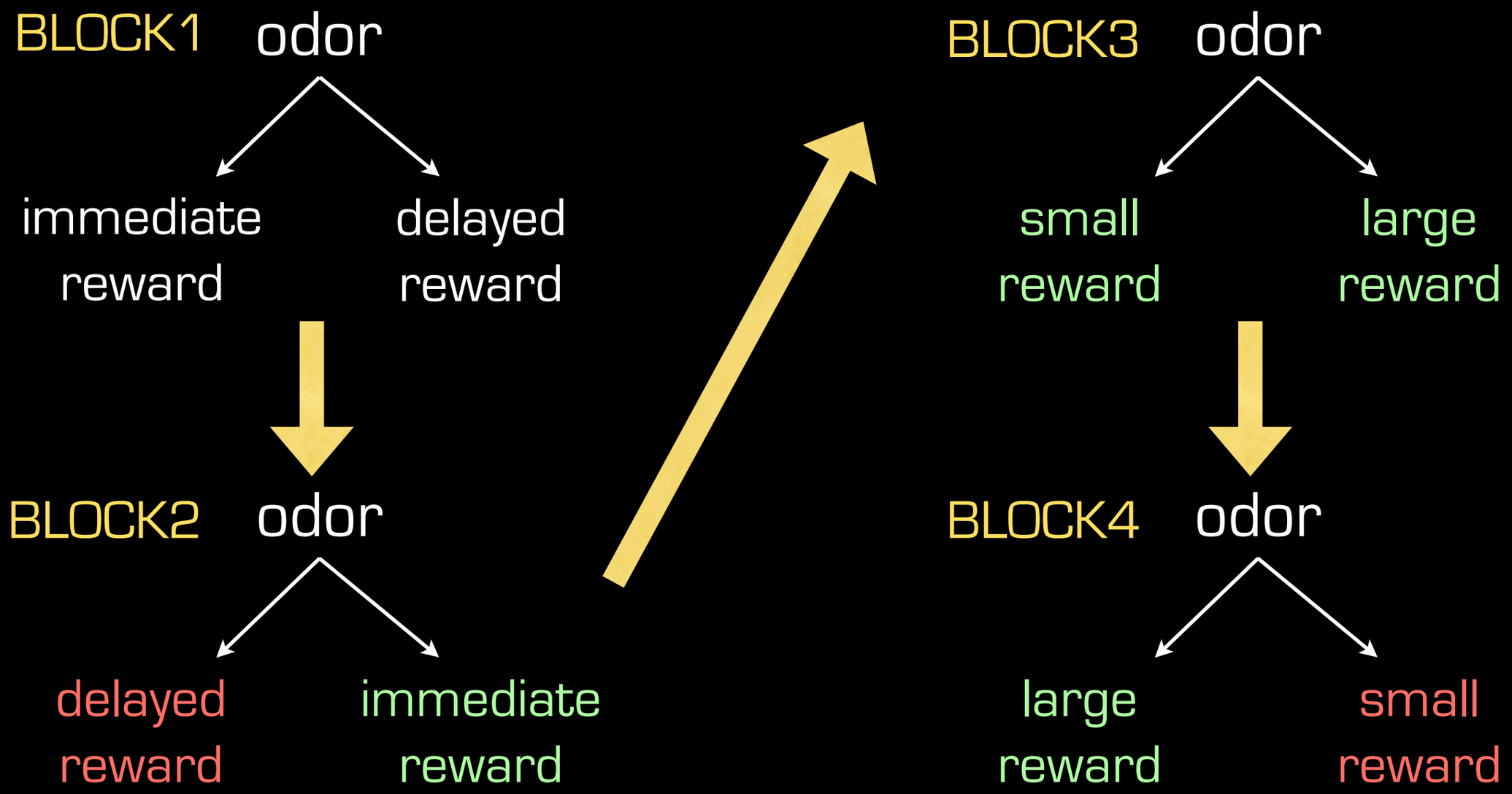

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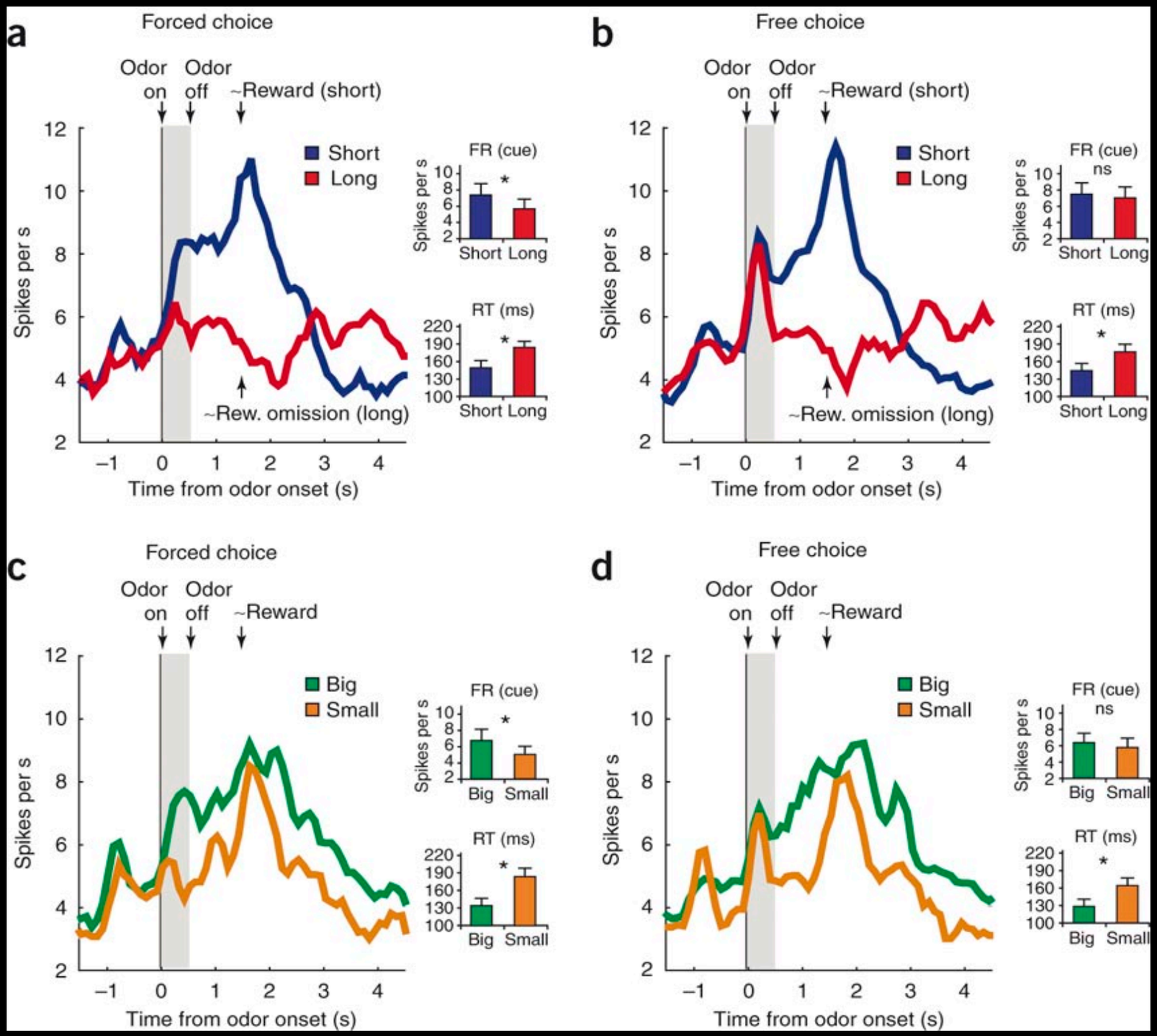

Roesch et al. 2007 57

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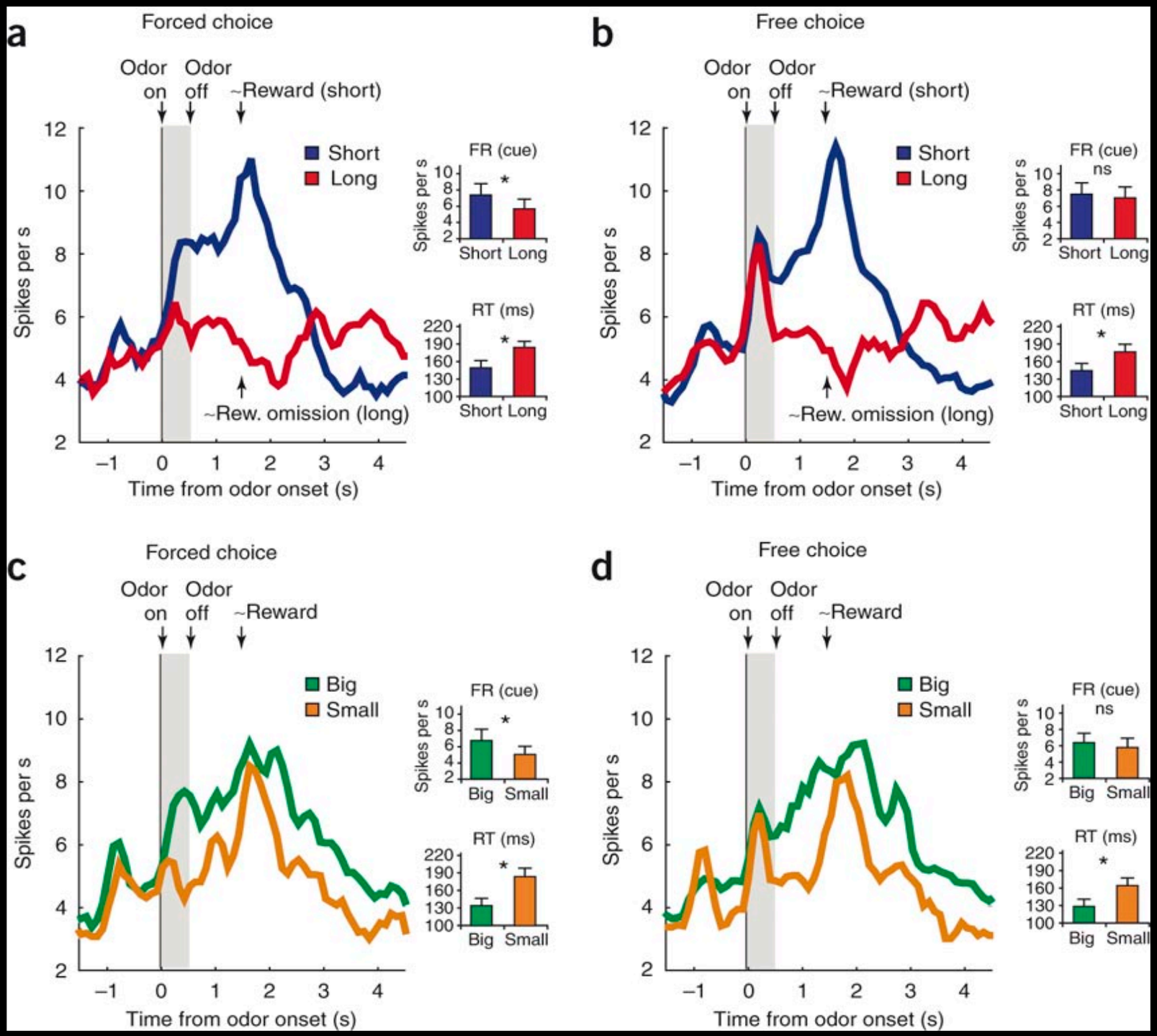

Differences from Morris et al. (2005):

Roesch et al. 2007

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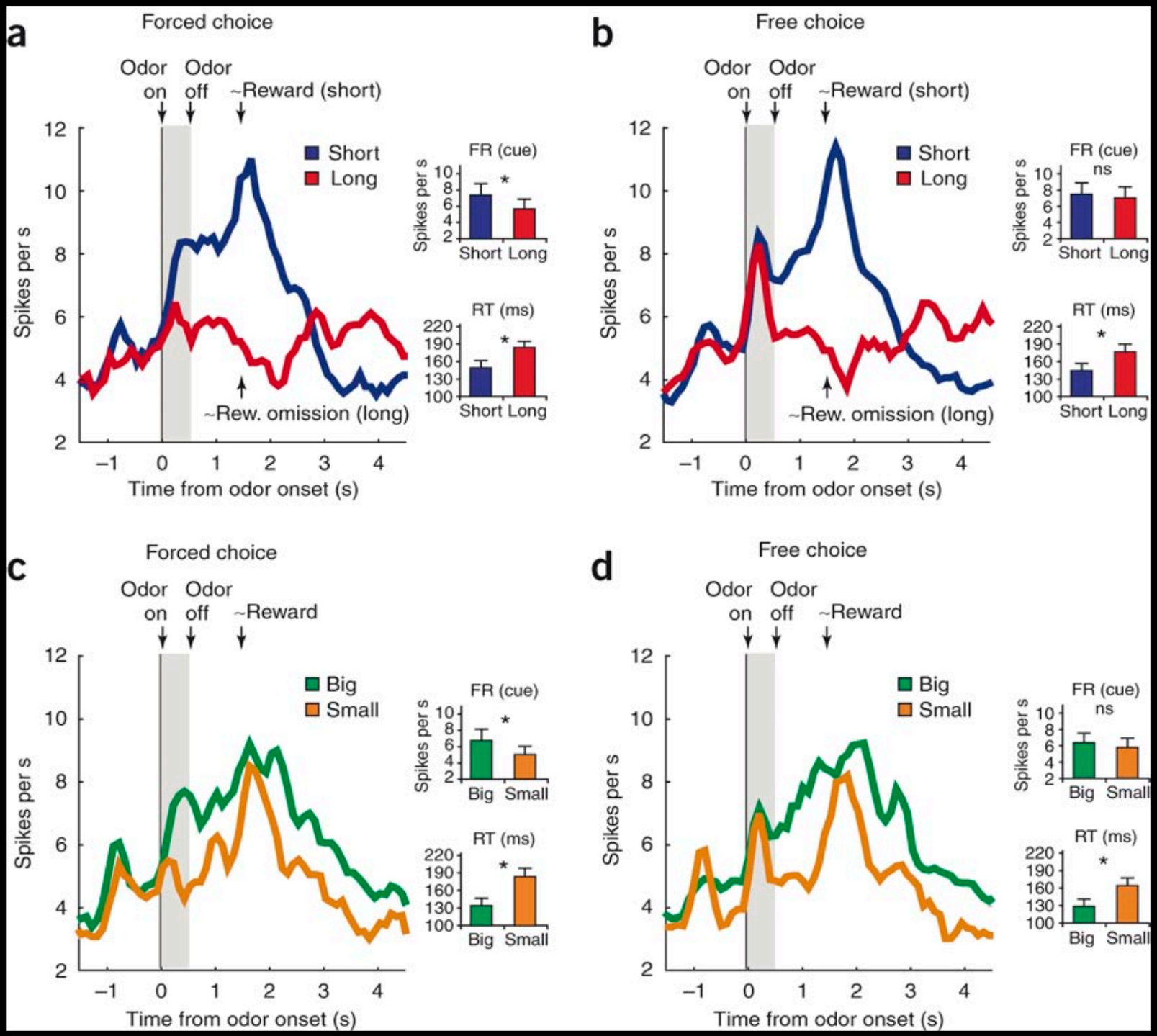

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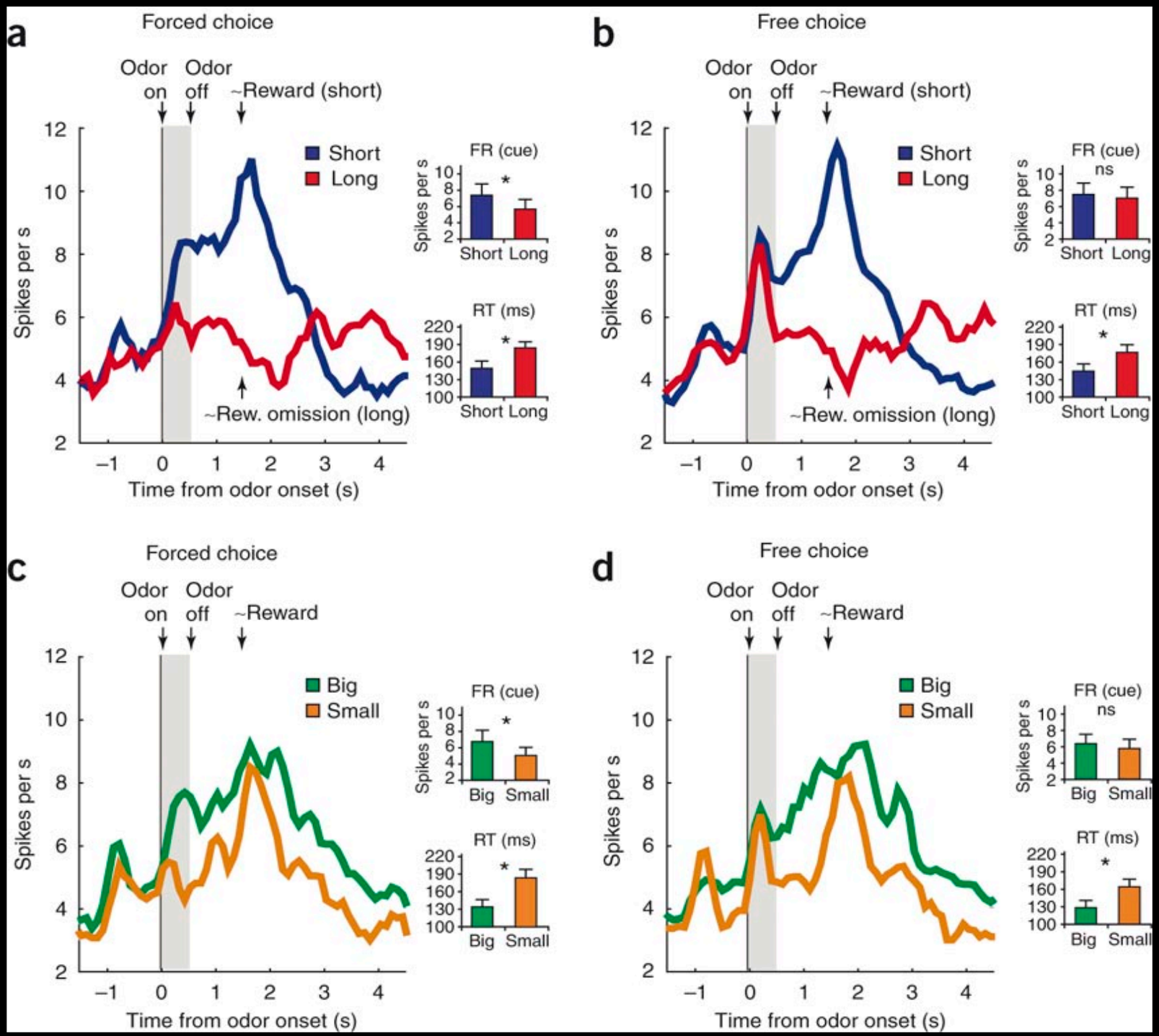

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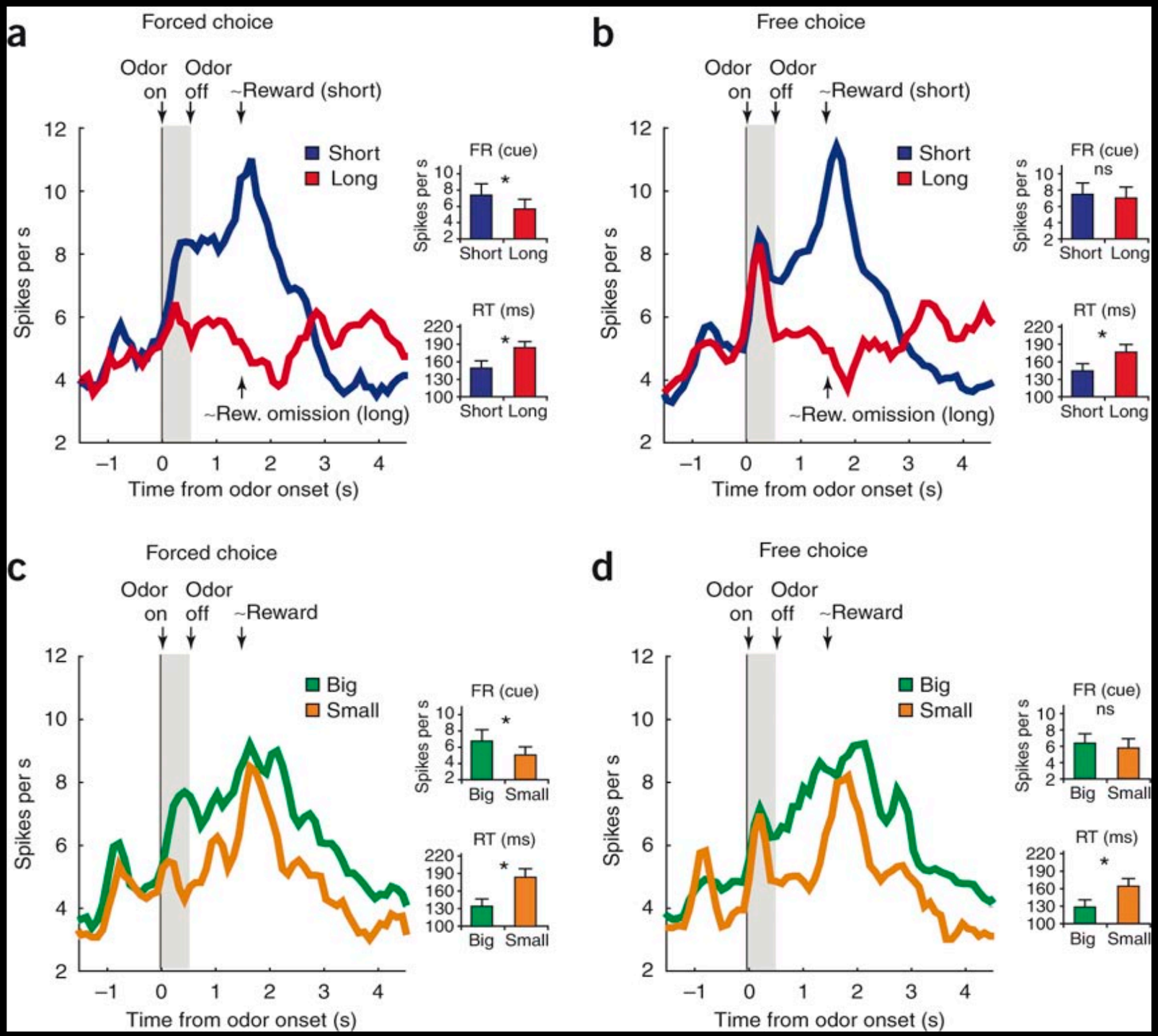

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Roesch et al. 2007

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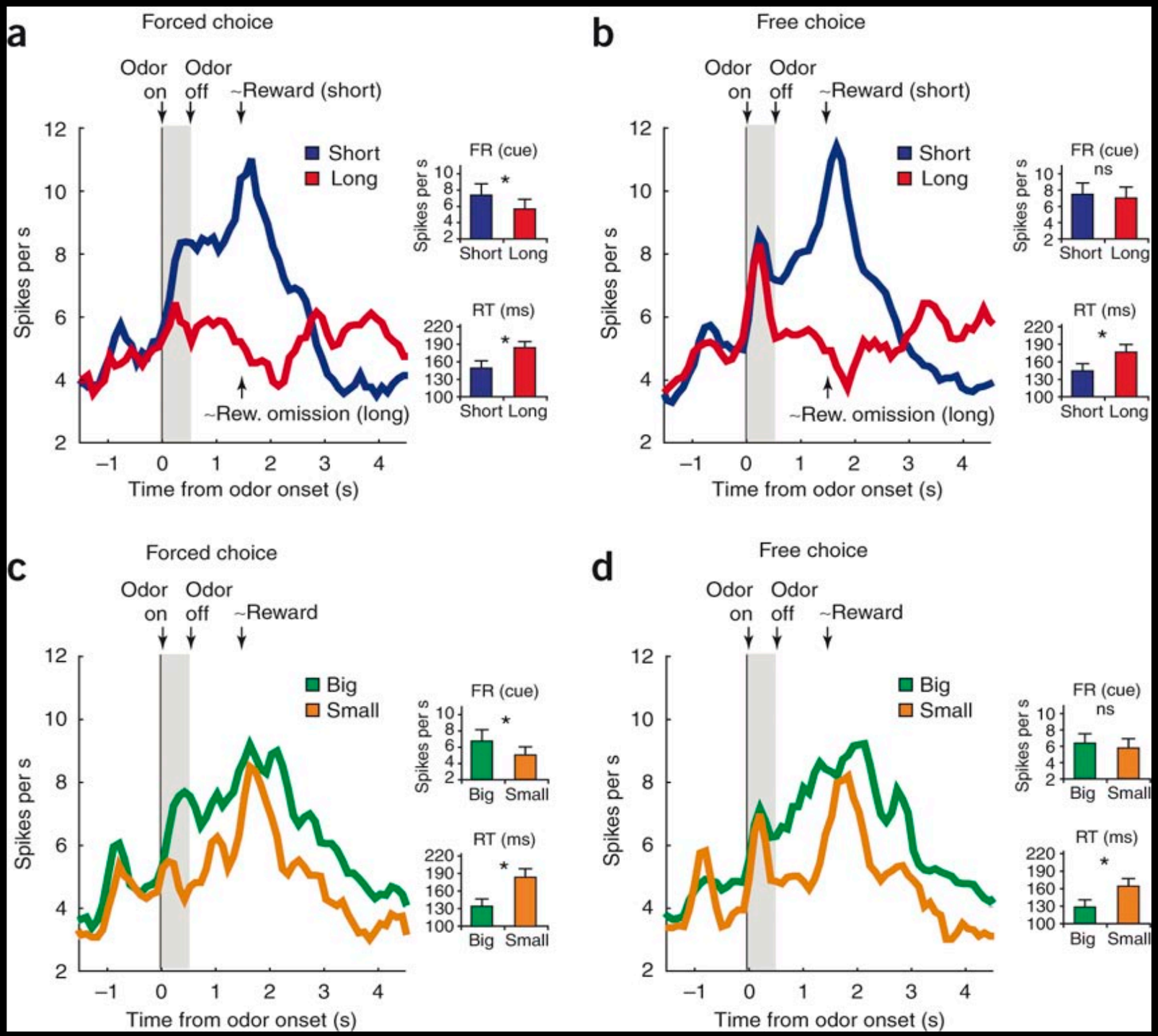

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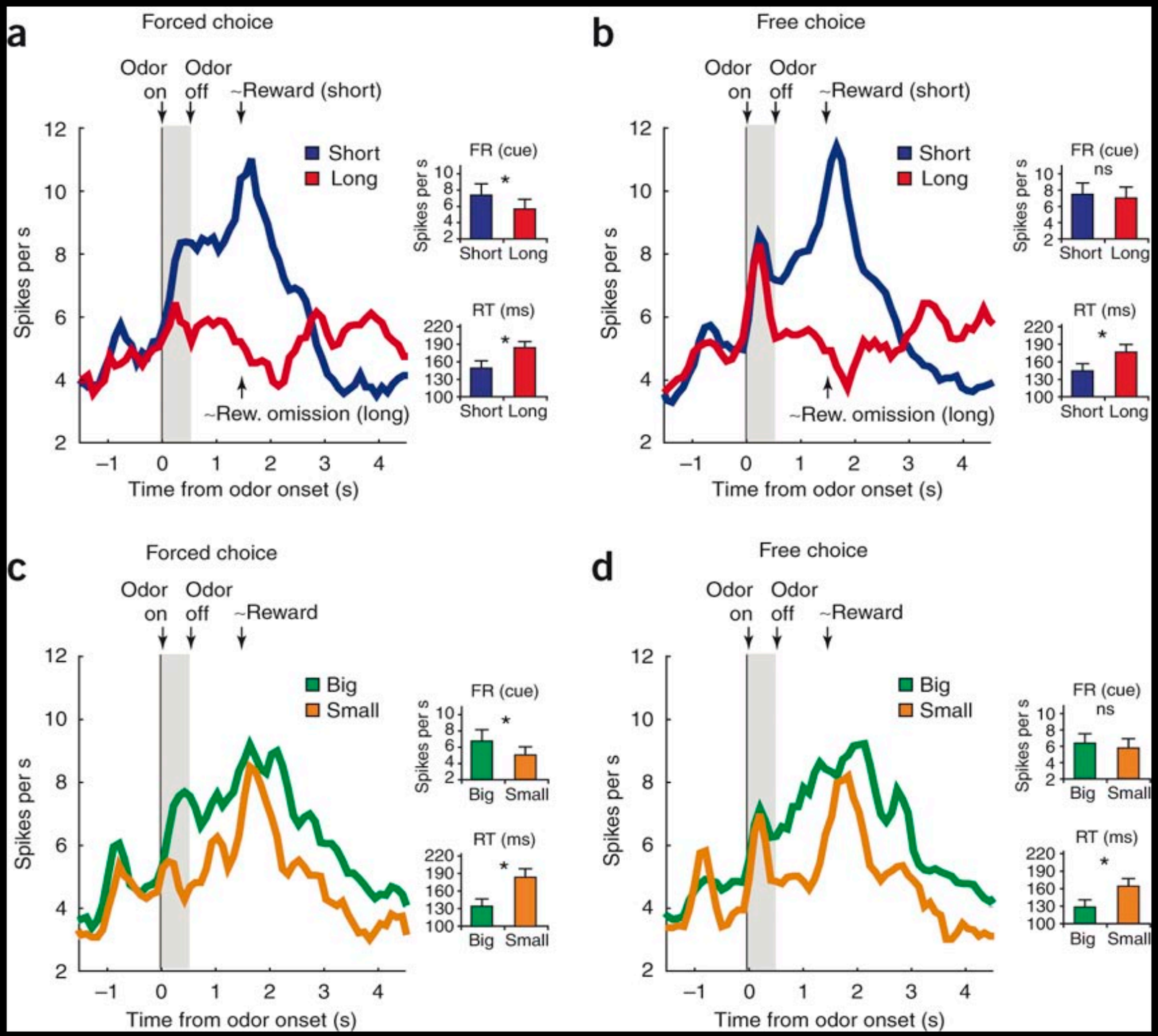

Differences from Morris et al. (2005):

- rats not monkeys
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- amount of training
- task (representation of stimuli?)

(notice the messy signal... due to measurement or is it that way in the brain?)

Roesch et al. 2007

Summary so far...

- SARSA or Q-learning? The jury is still out
- What needs to be done: more experiments recording from dopamine in telltale tasks
- The brain (dopamine) can inform RL: how does it learn in real time, with real noise, in real problems?

Outline

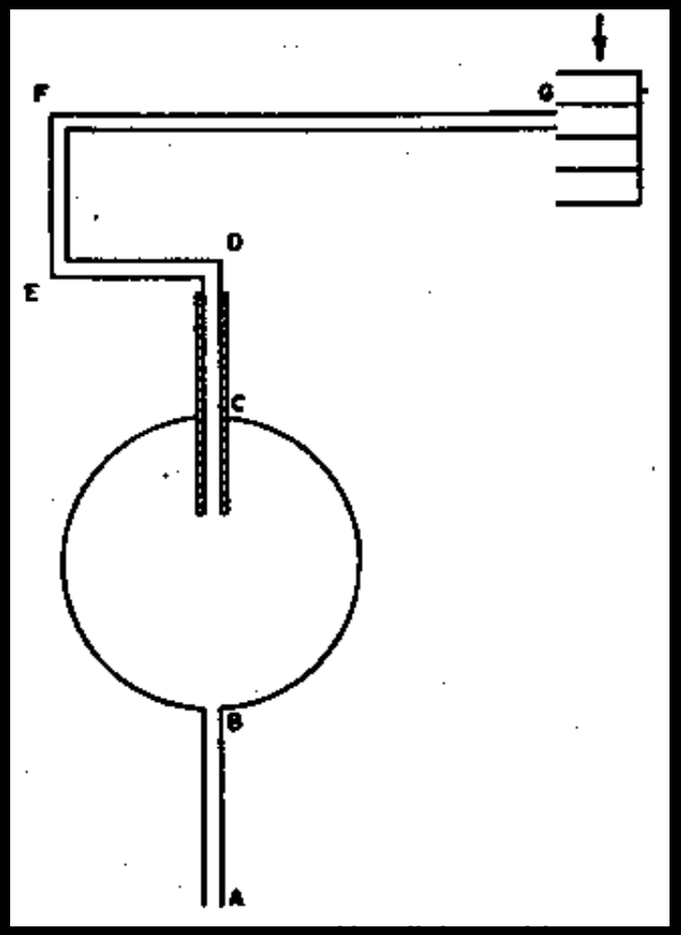
- The brain coarse-grain
- Learning and decision making in animals and humans: what does RL have to do with it?
- A success story: Dopamine and prediction errors
- Actor/Critic architecture in basal ganglia
- SARSA vs Q-learning: can the brain teach us about ML?
- Model free and model based RL in the brain
- Average reward RL & tonic dopamine
- Risk sensitivity and RL in the brain
- Open challenges and future directions

do animals only learn action policies?

Tolman et al (1946)

do animals only learn action policies?

training:



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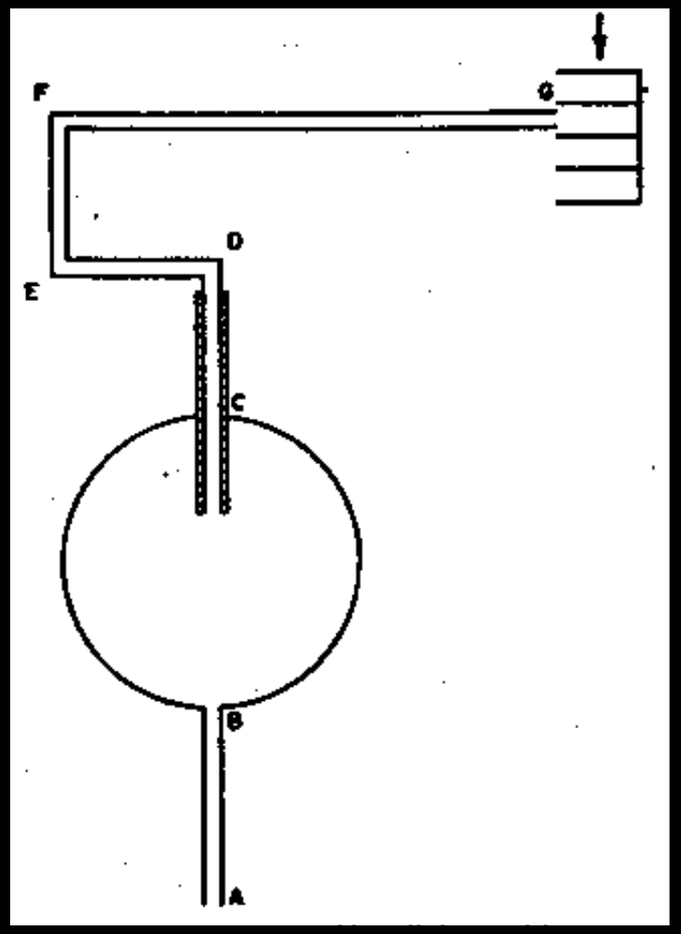

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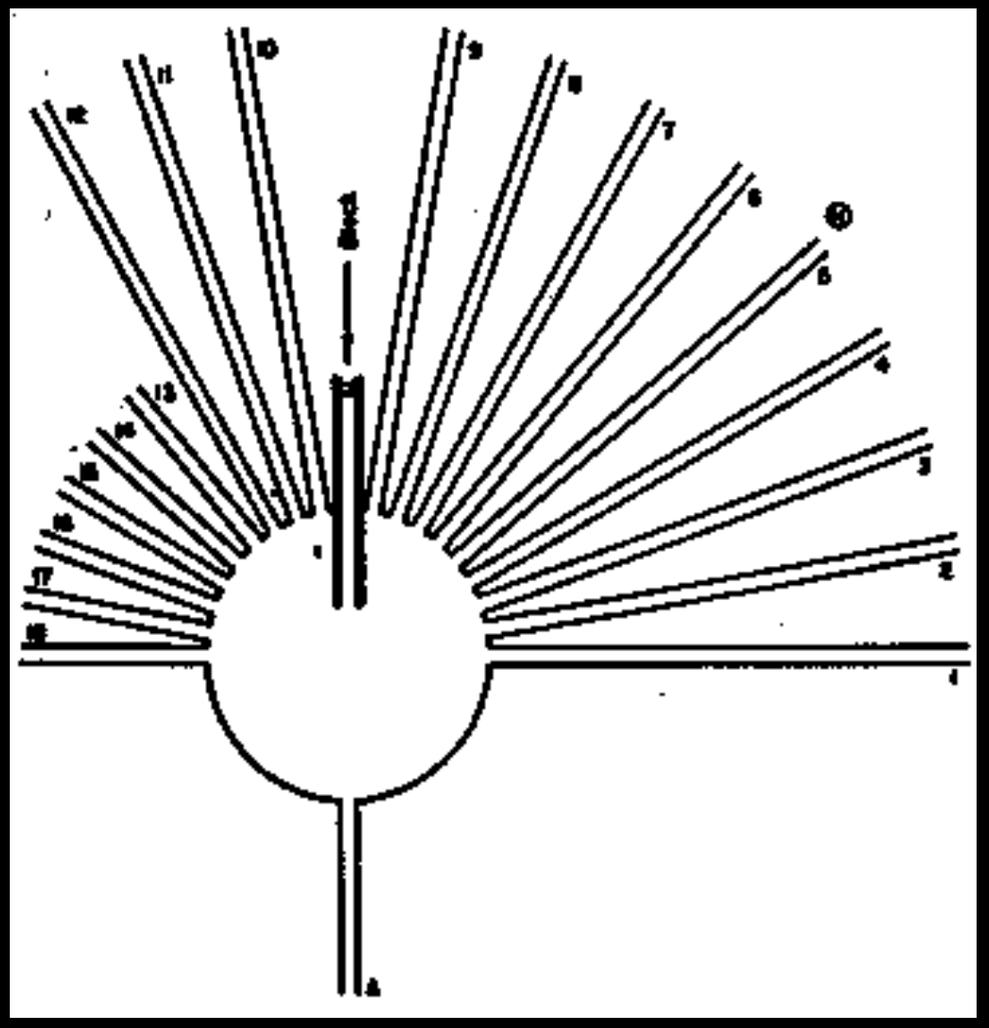

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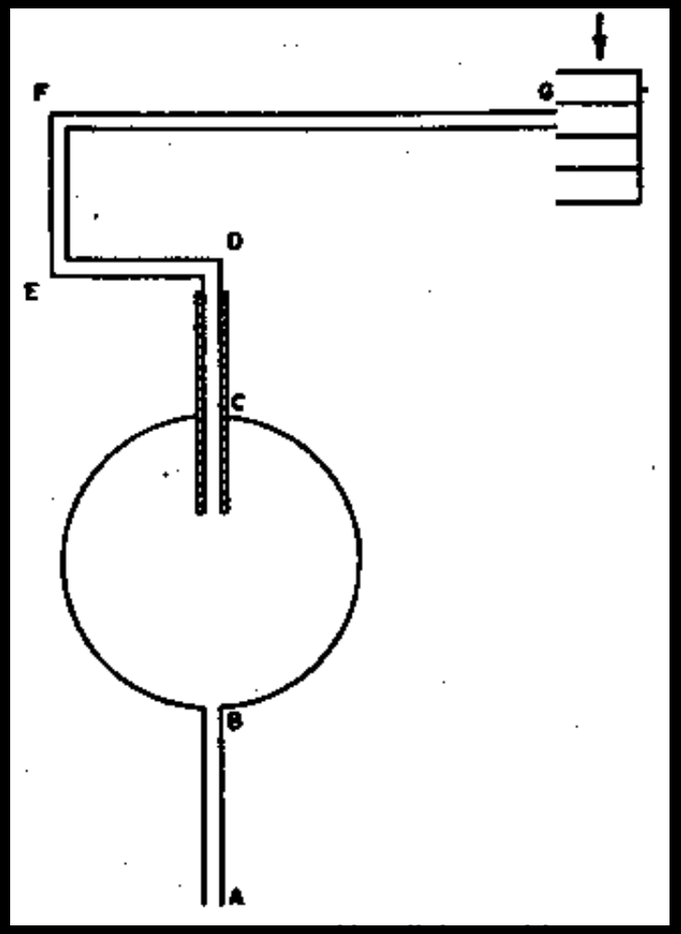

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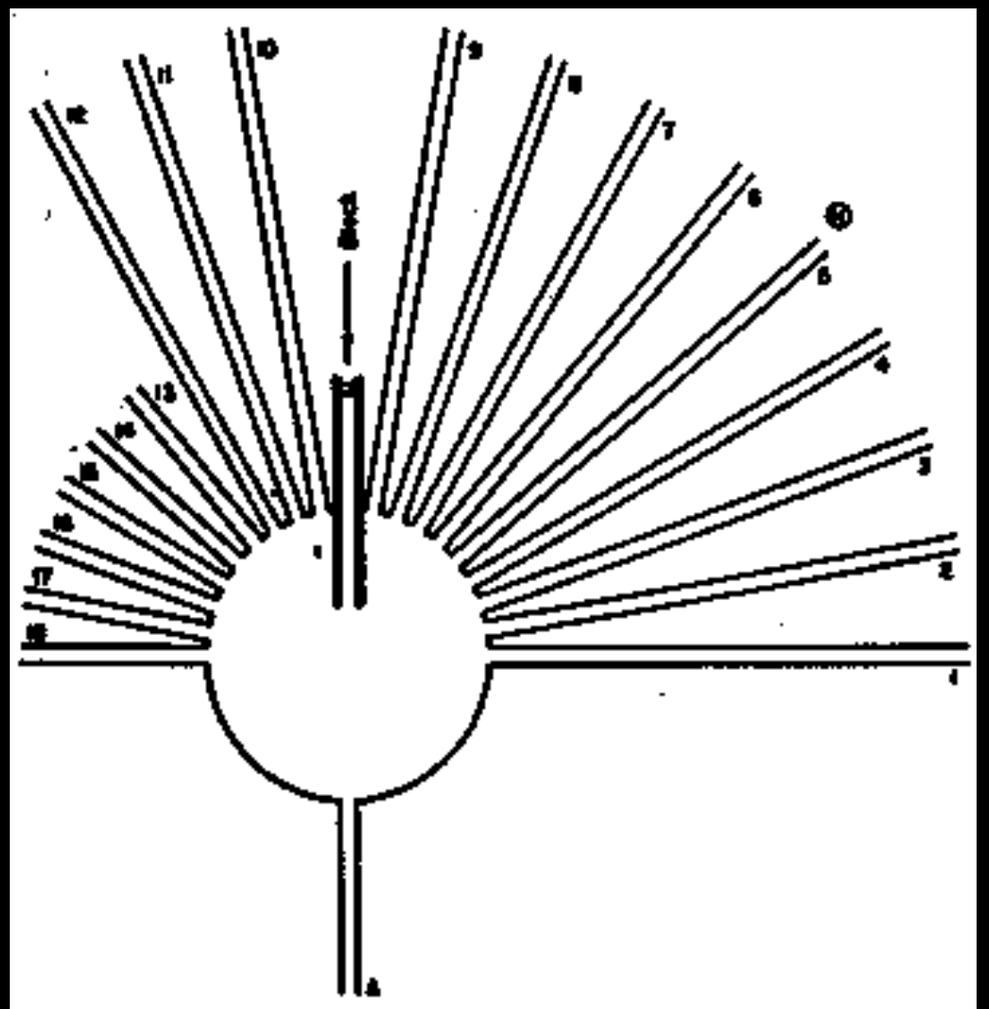
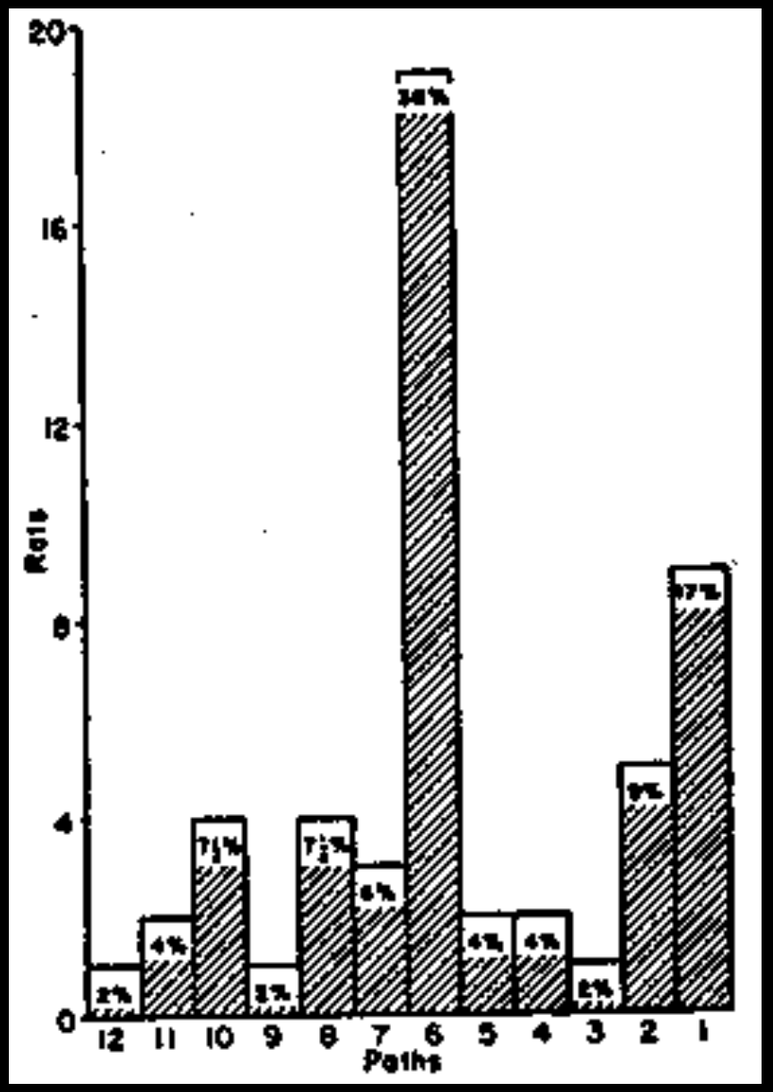


result:



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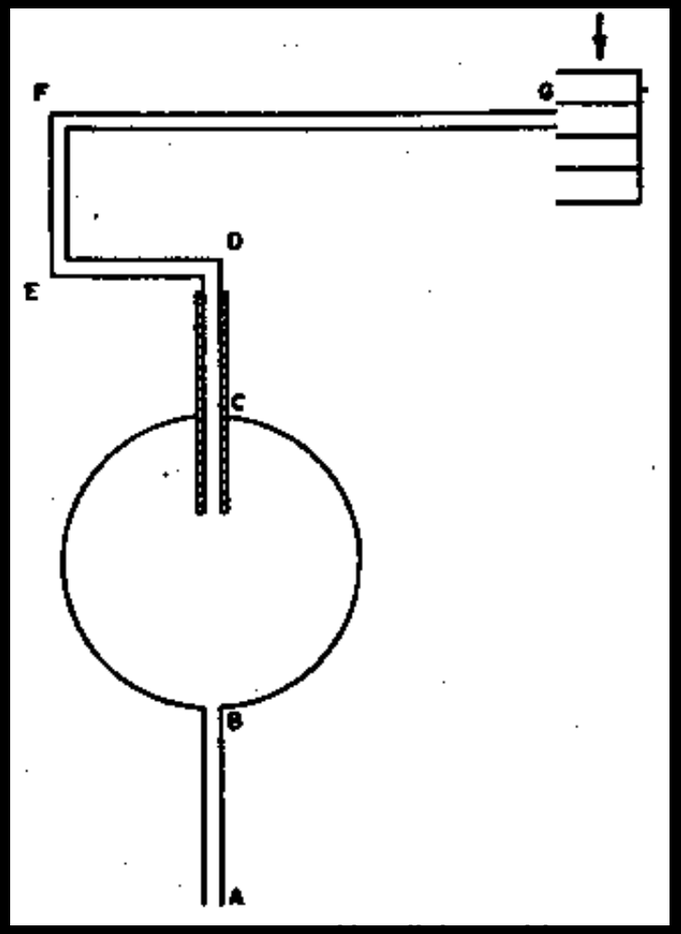

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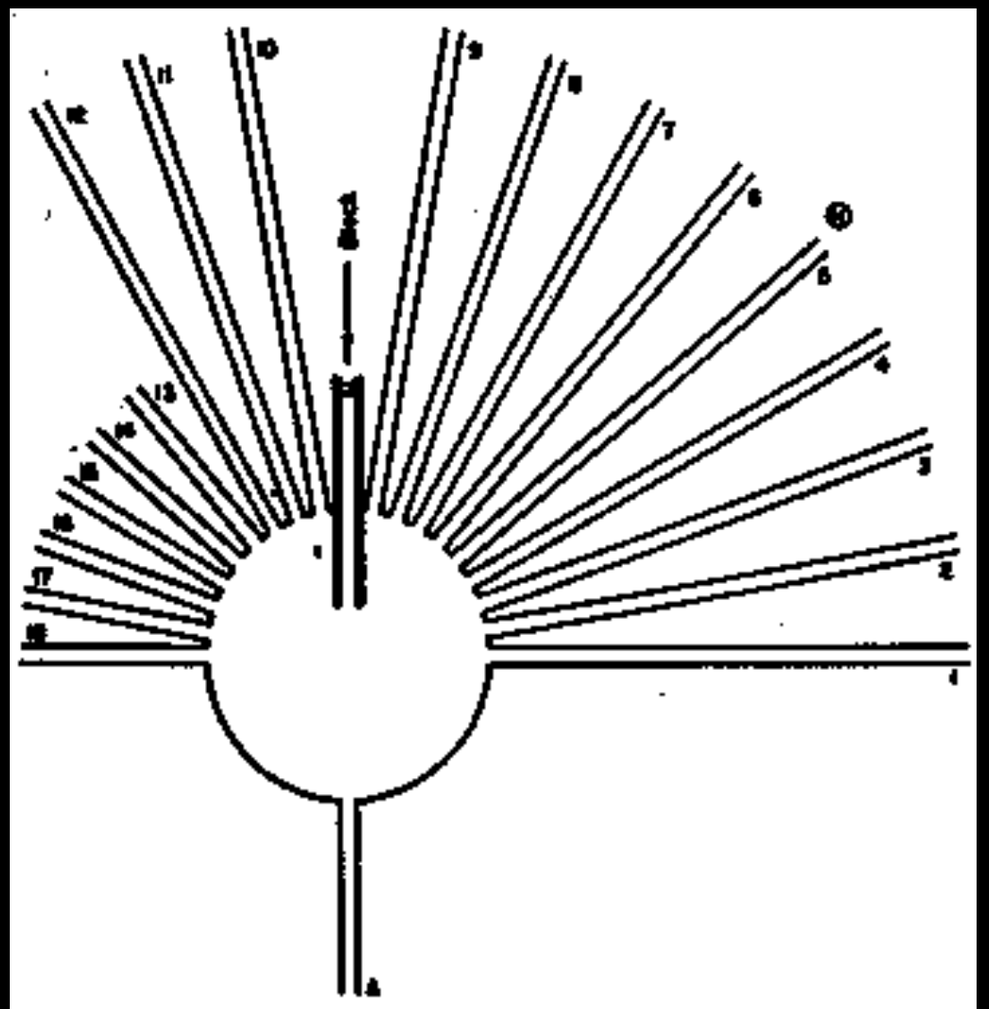

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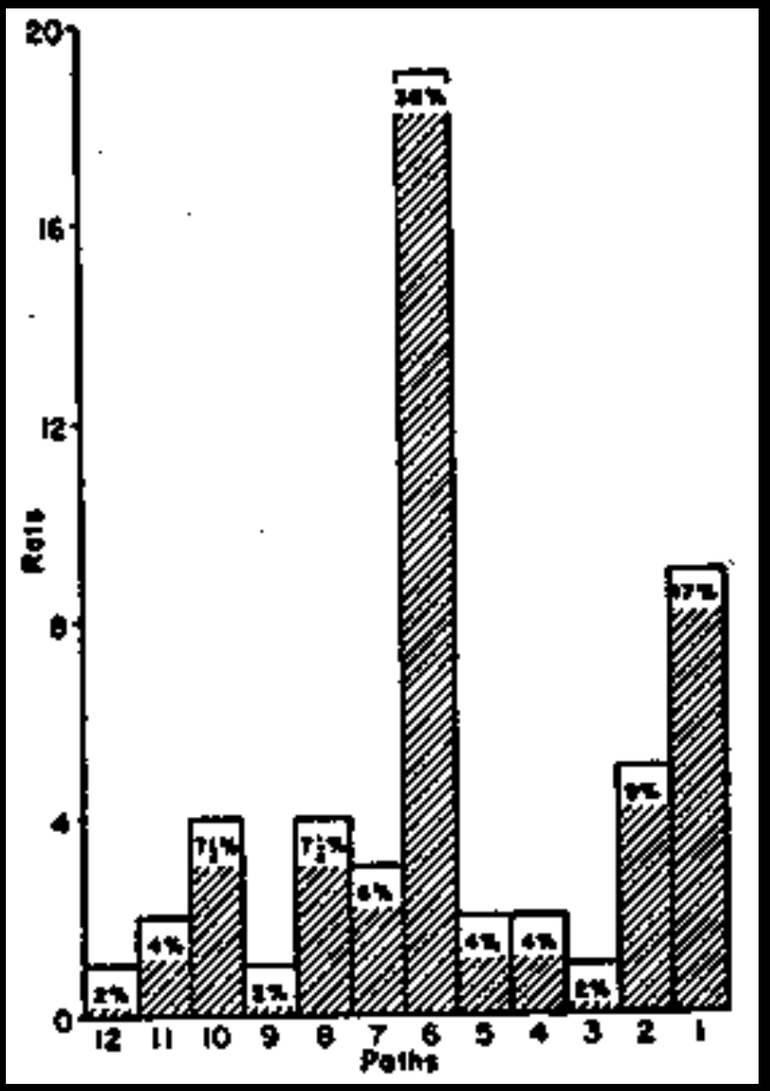

Even the humble rat can can learn spatial structure, and use it to plan flexibly

Tolman et al (1946)

another test: outcome devaluation

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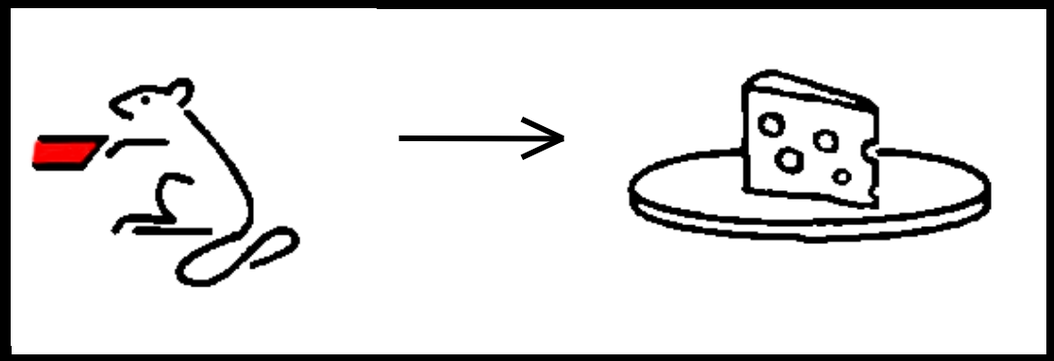
1 - Training:



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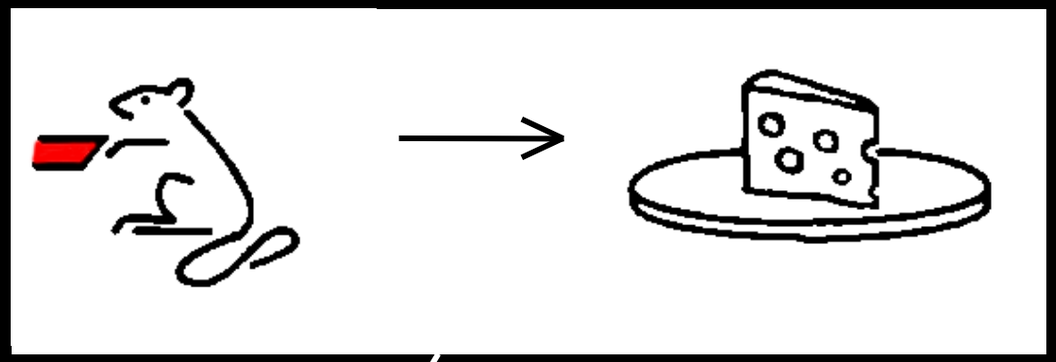
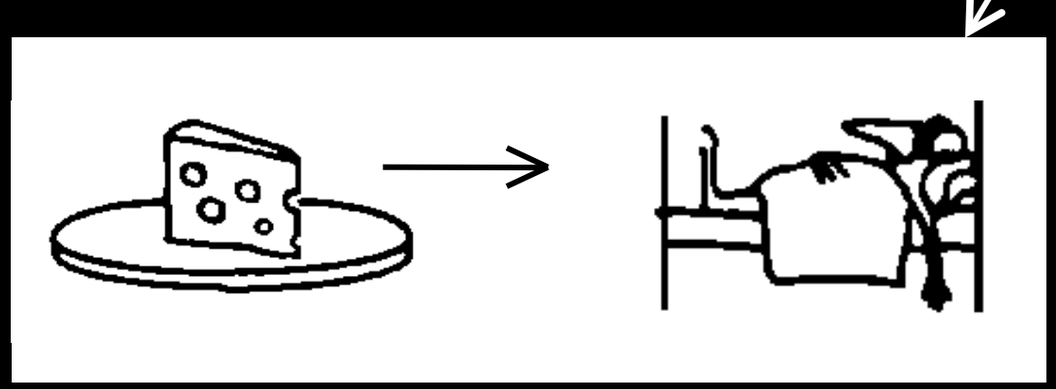


2 – Pairing with illness:



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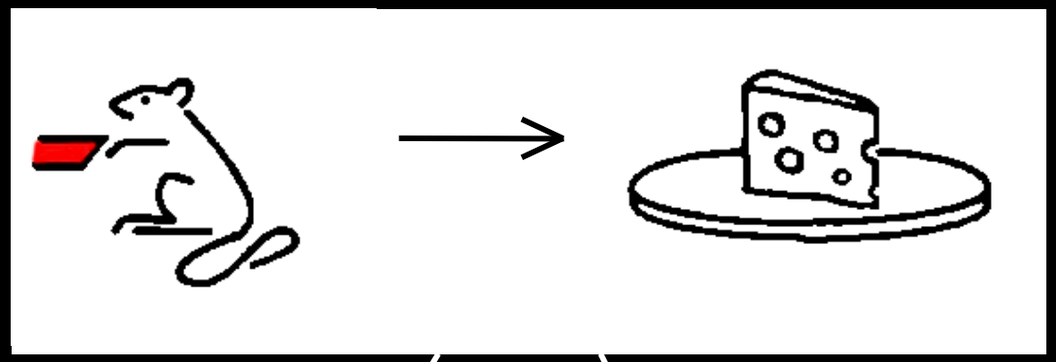

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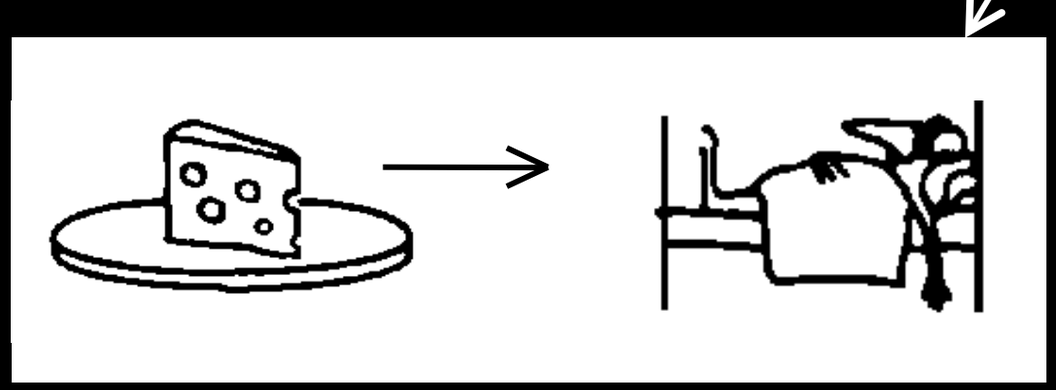
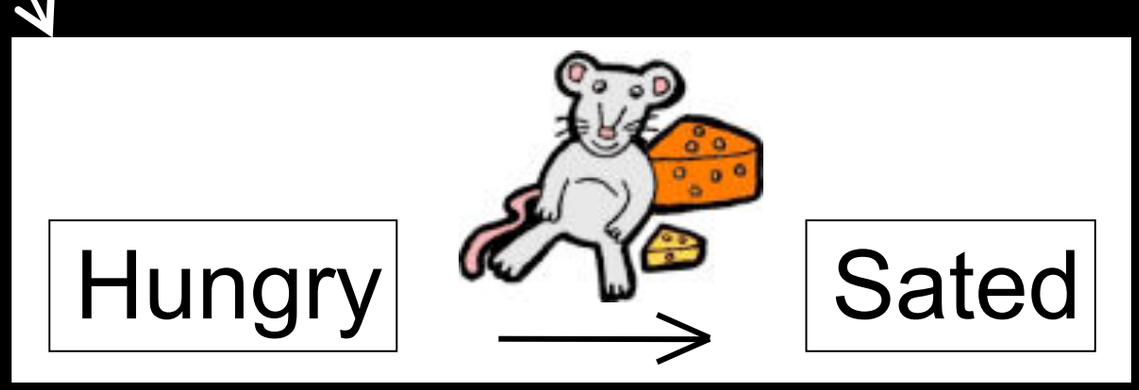


2 – Motivational shift:



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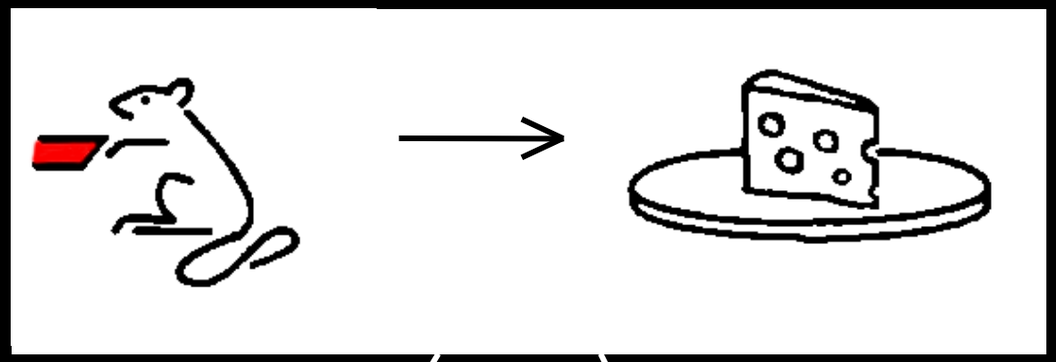

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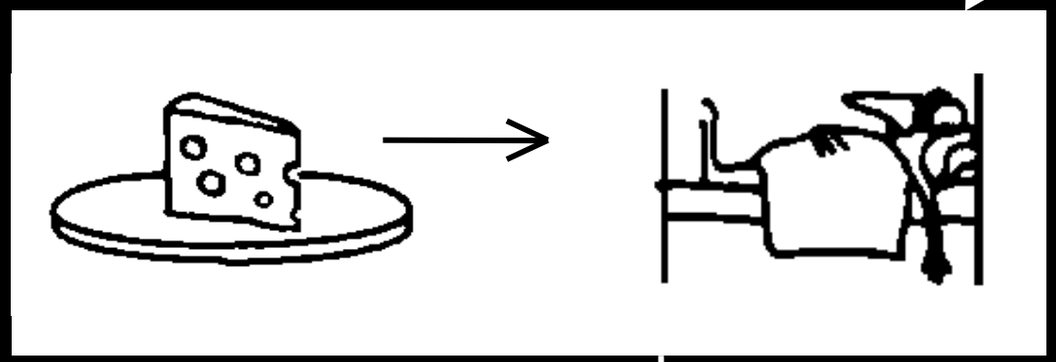

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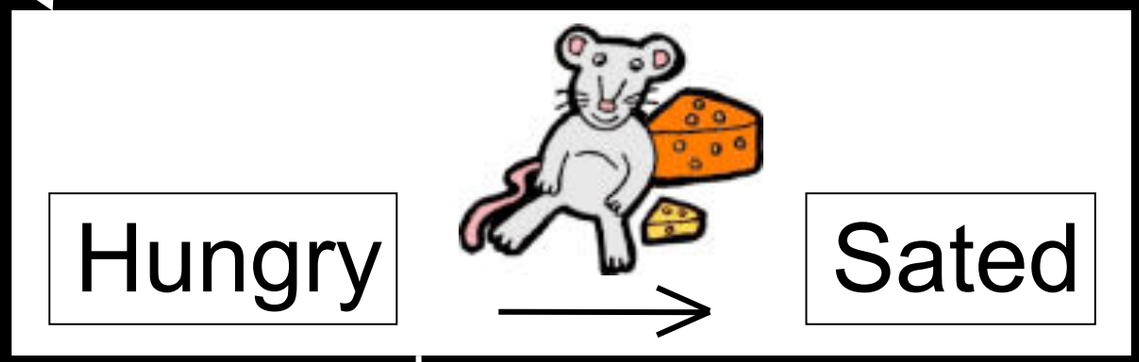
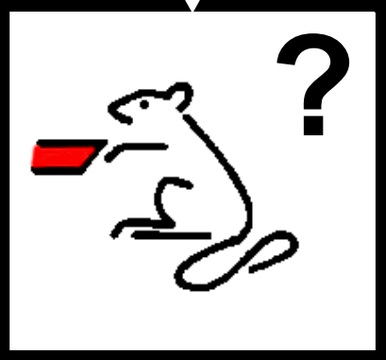
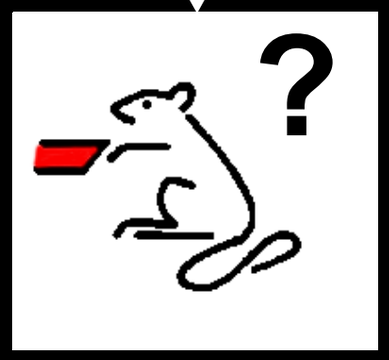


3 – Test:

(no rewards)





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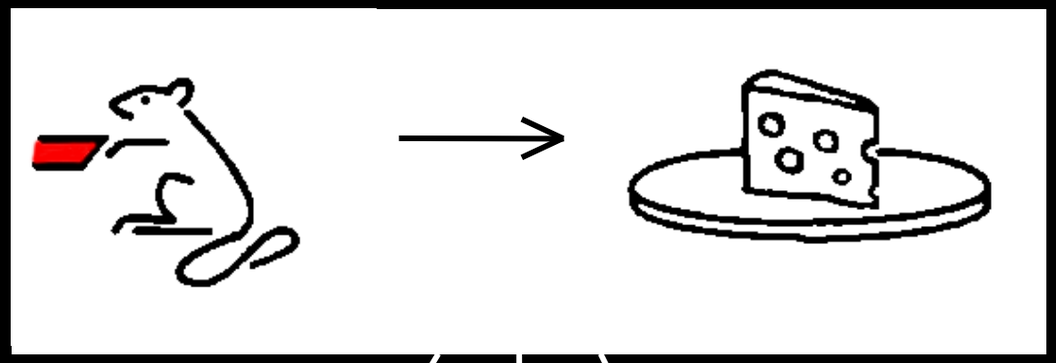

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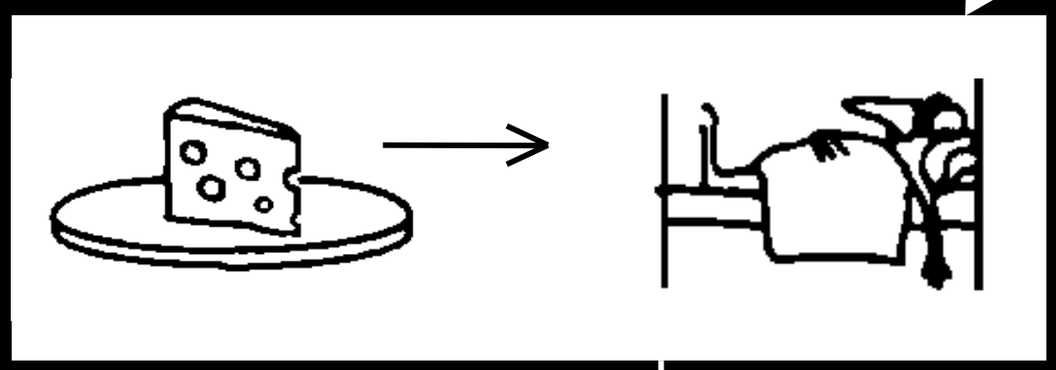

Non-devalued

Unshifted

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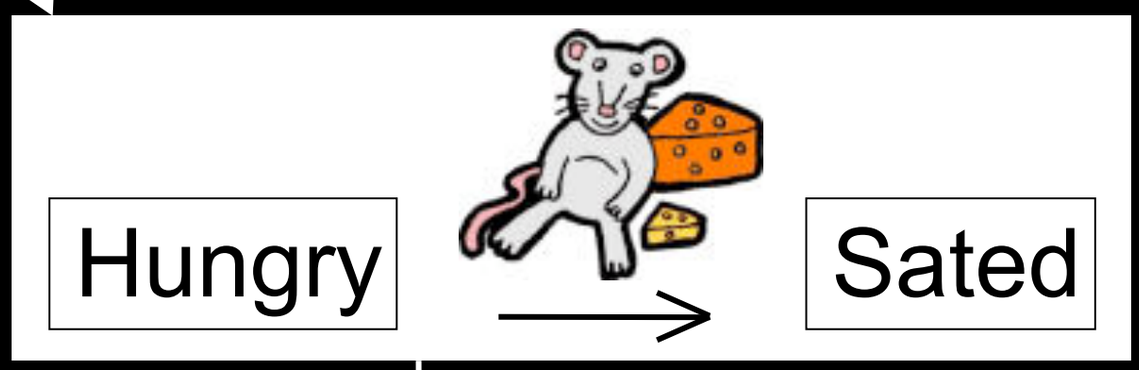

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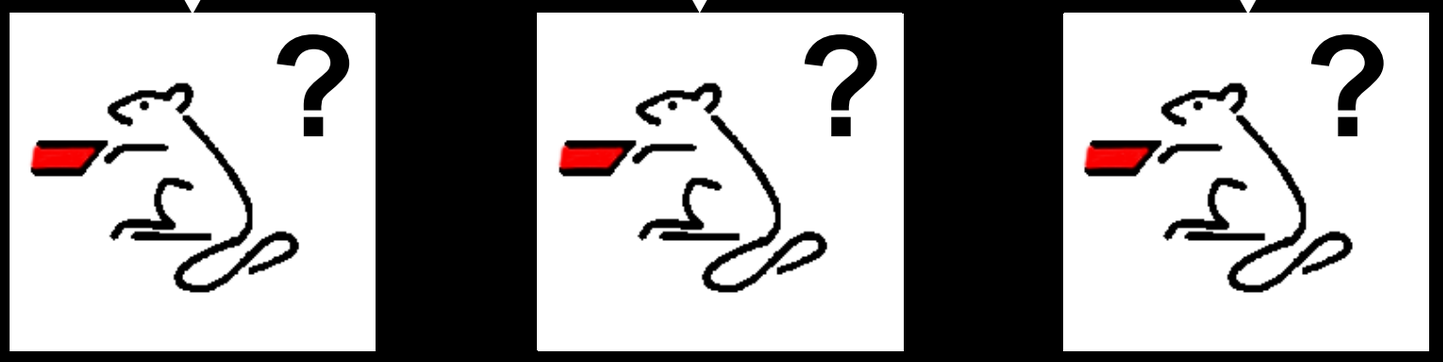

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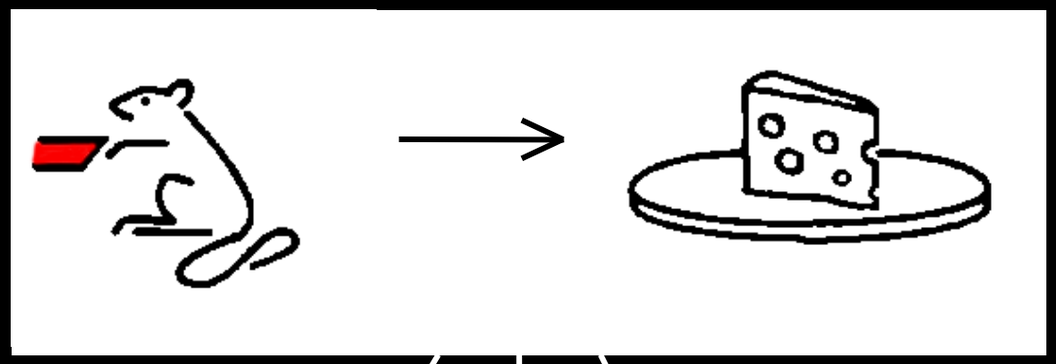

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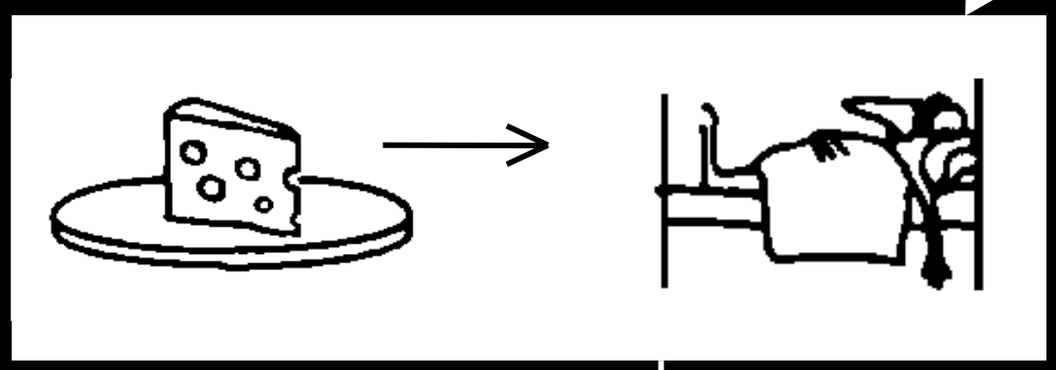

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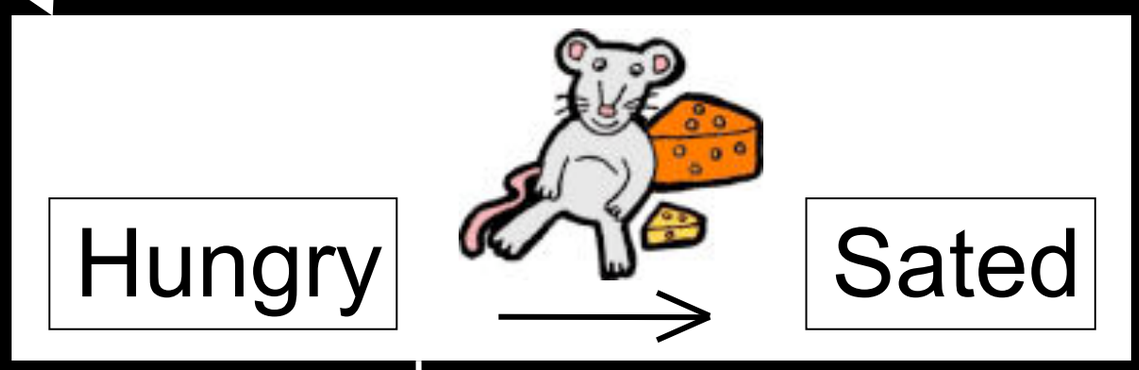

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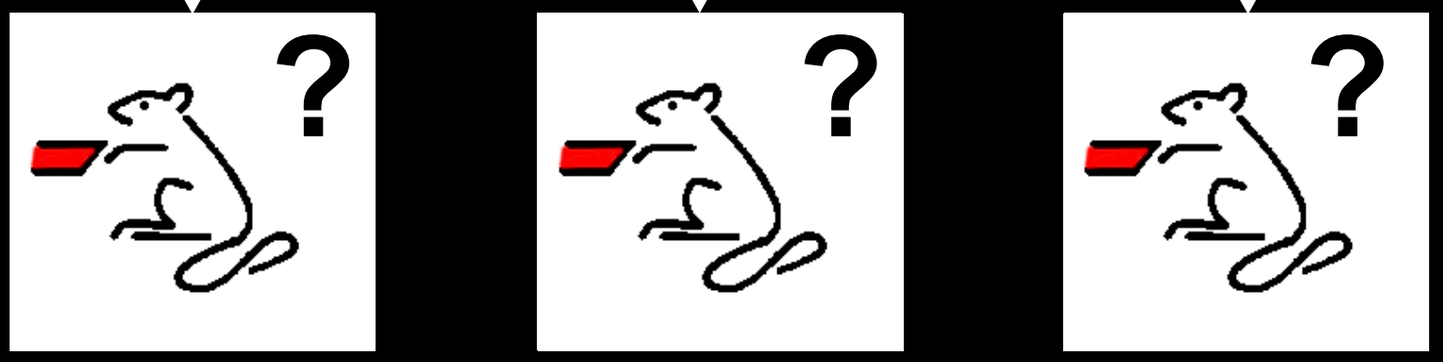
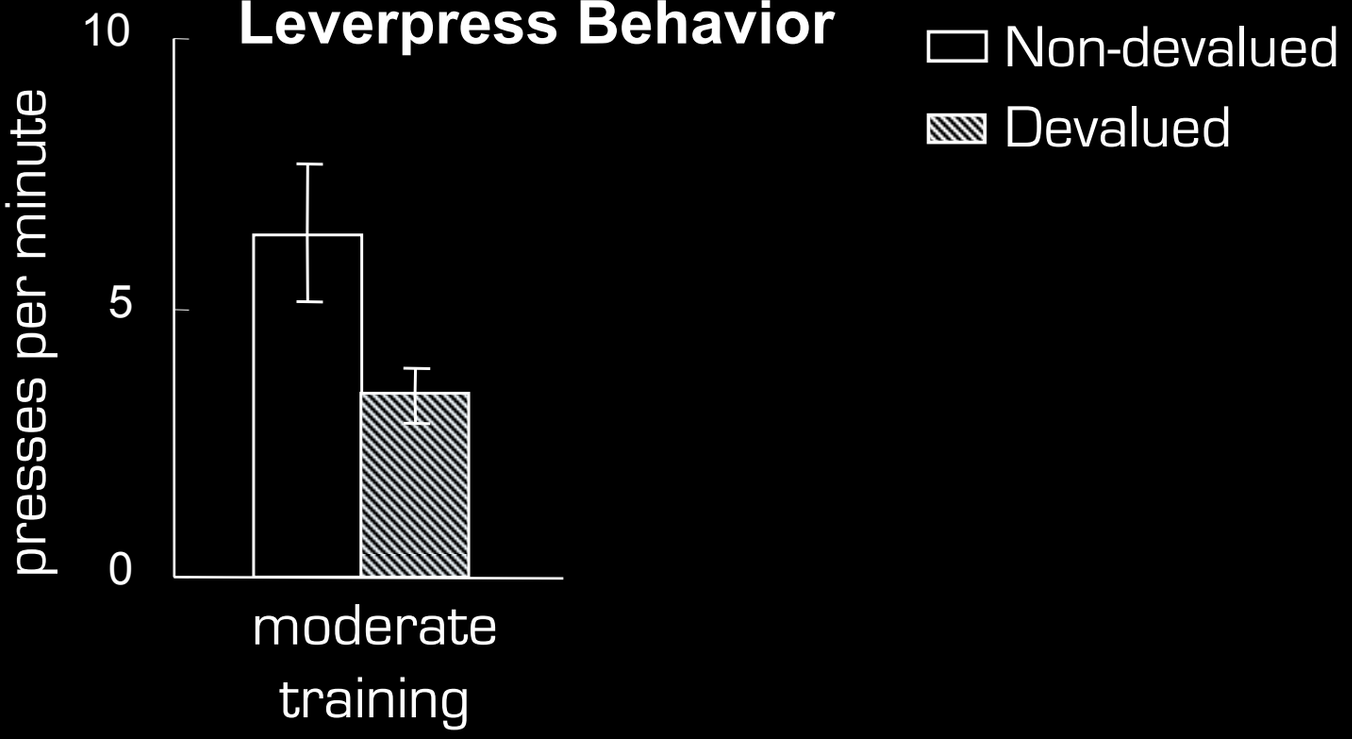


will animals work for food they don't want?

devaluation: results

Holland (2004), Kilcross & Coutureau (2003)

devaluation: results



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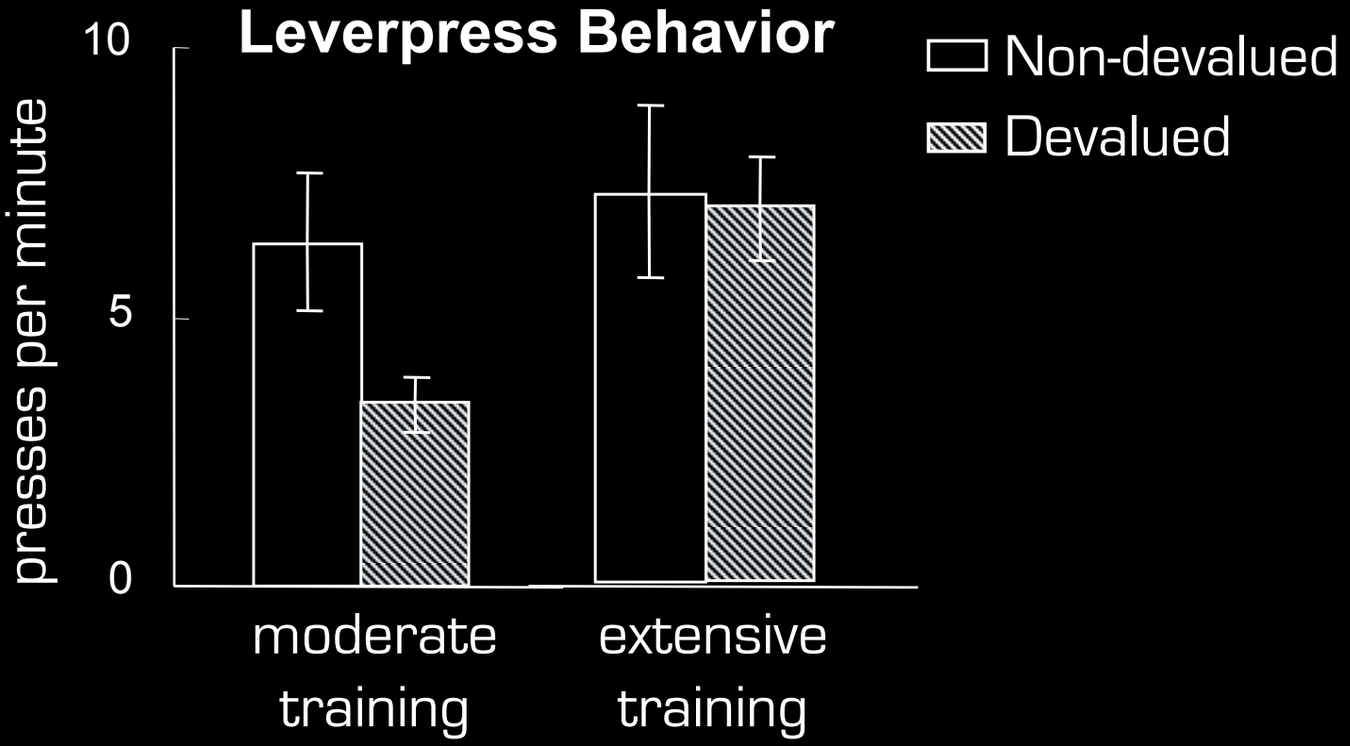

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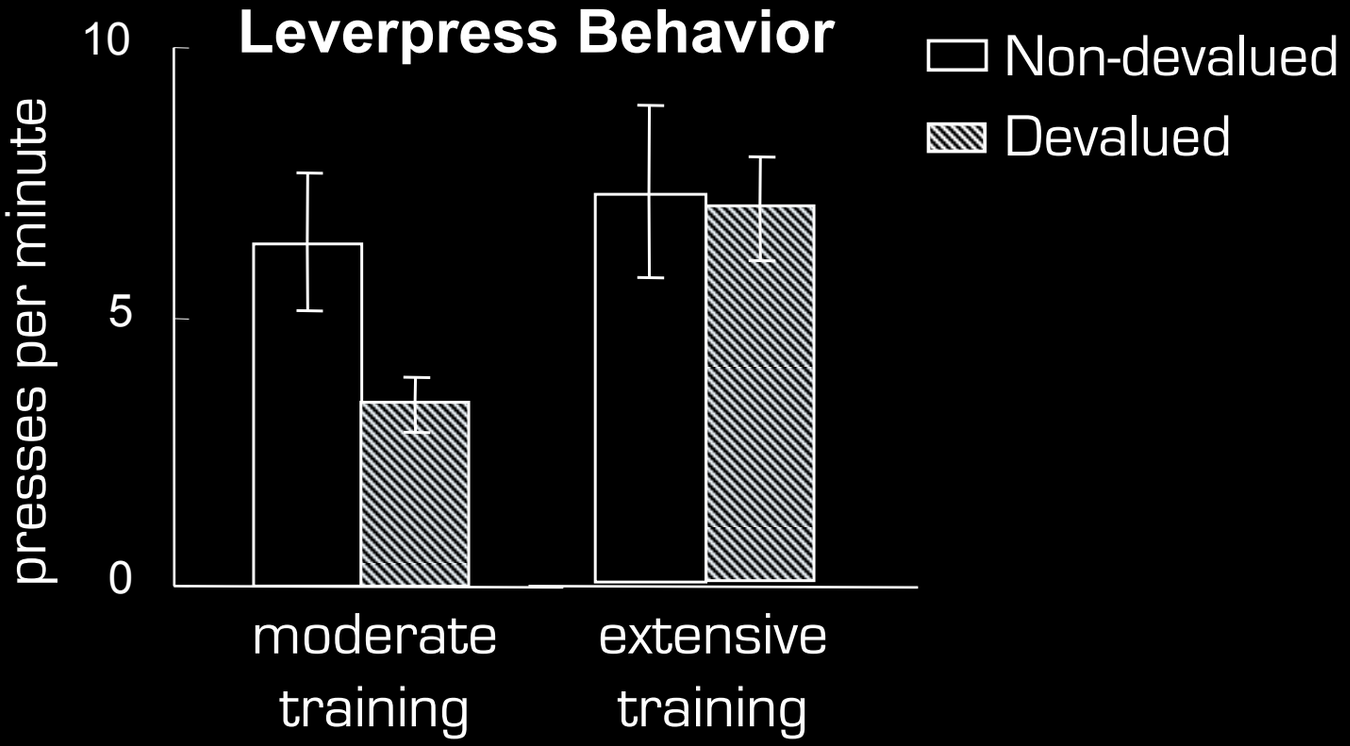

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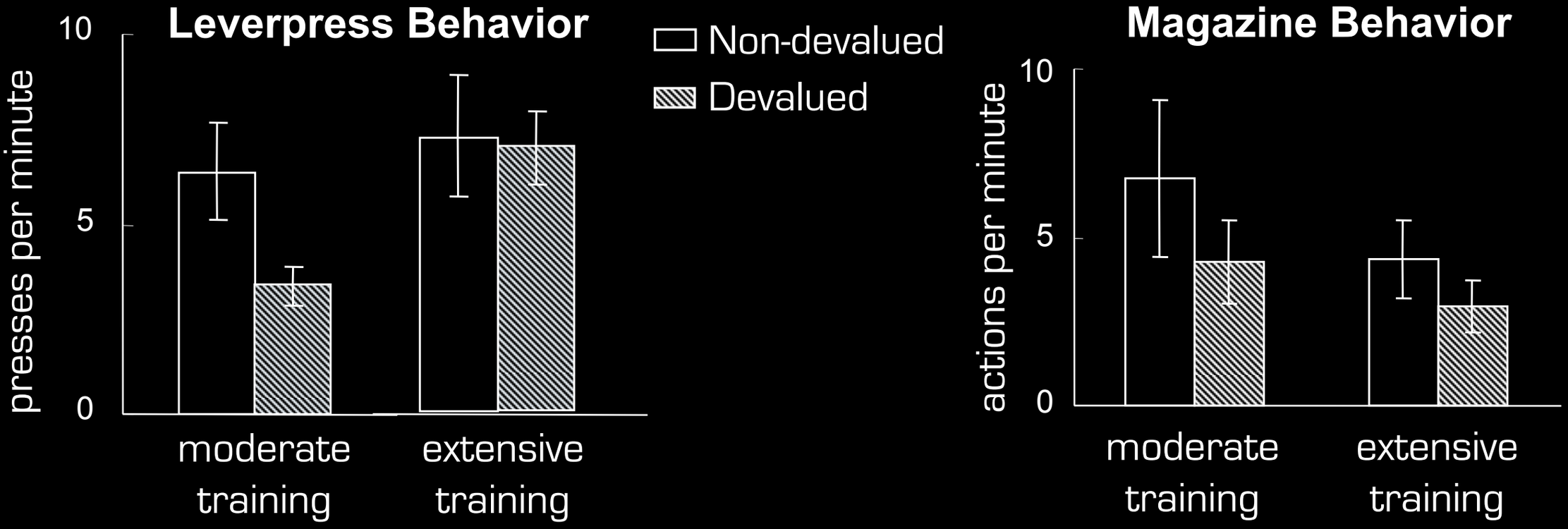

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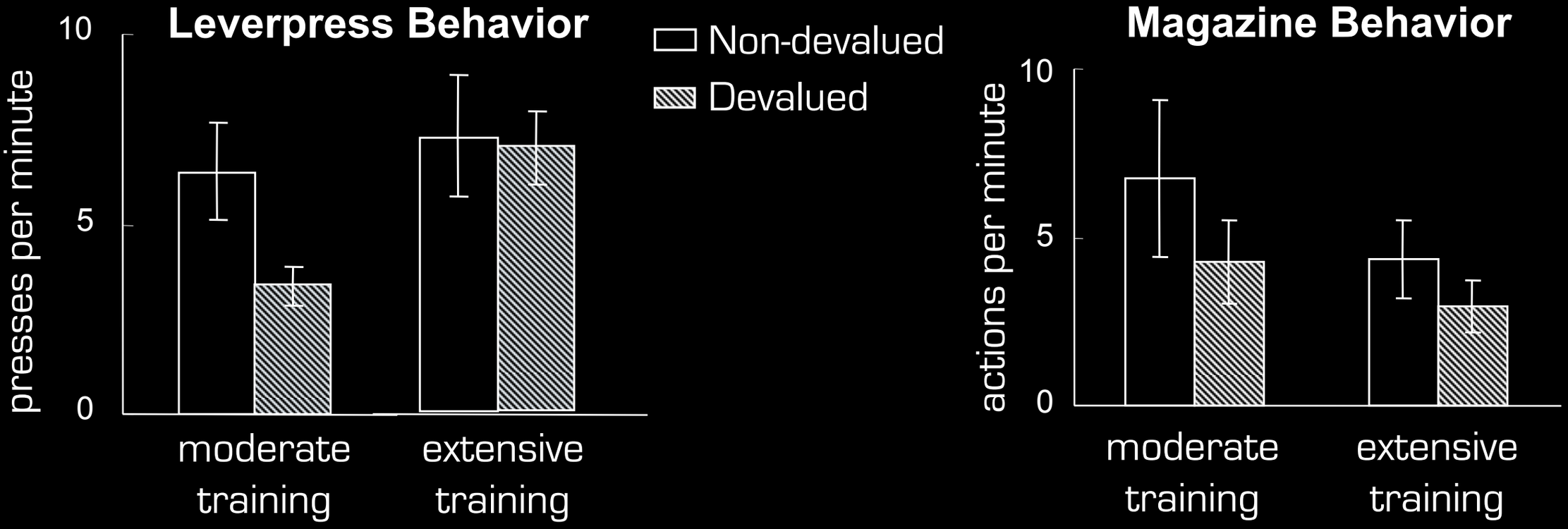

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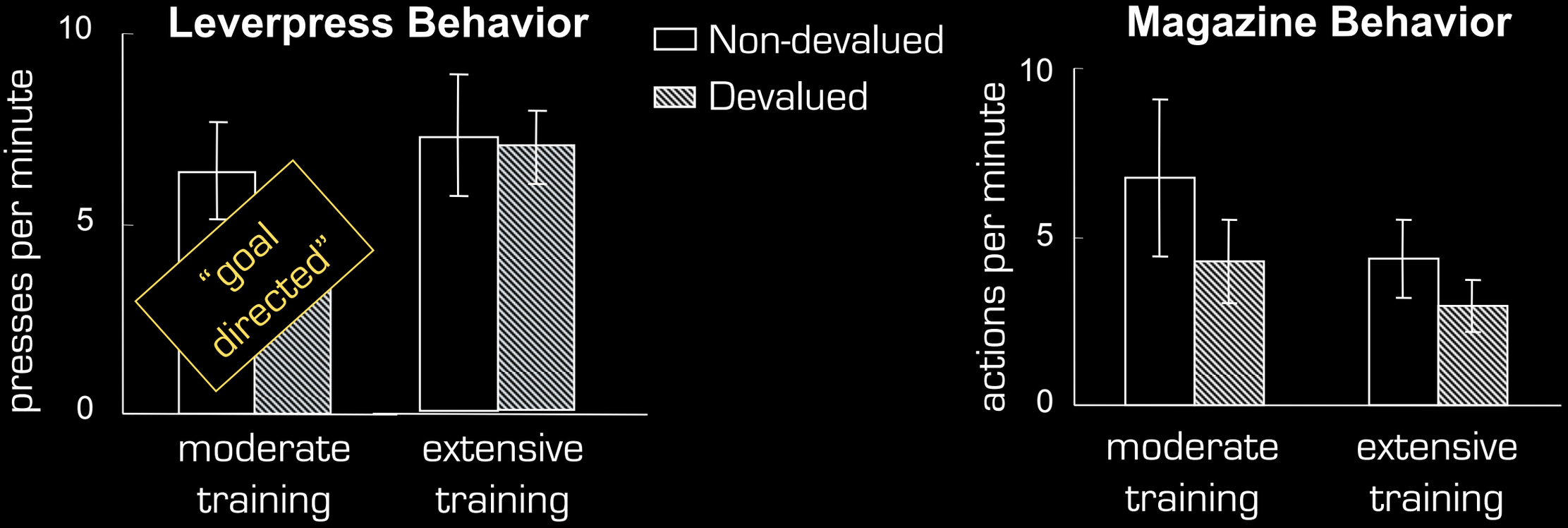

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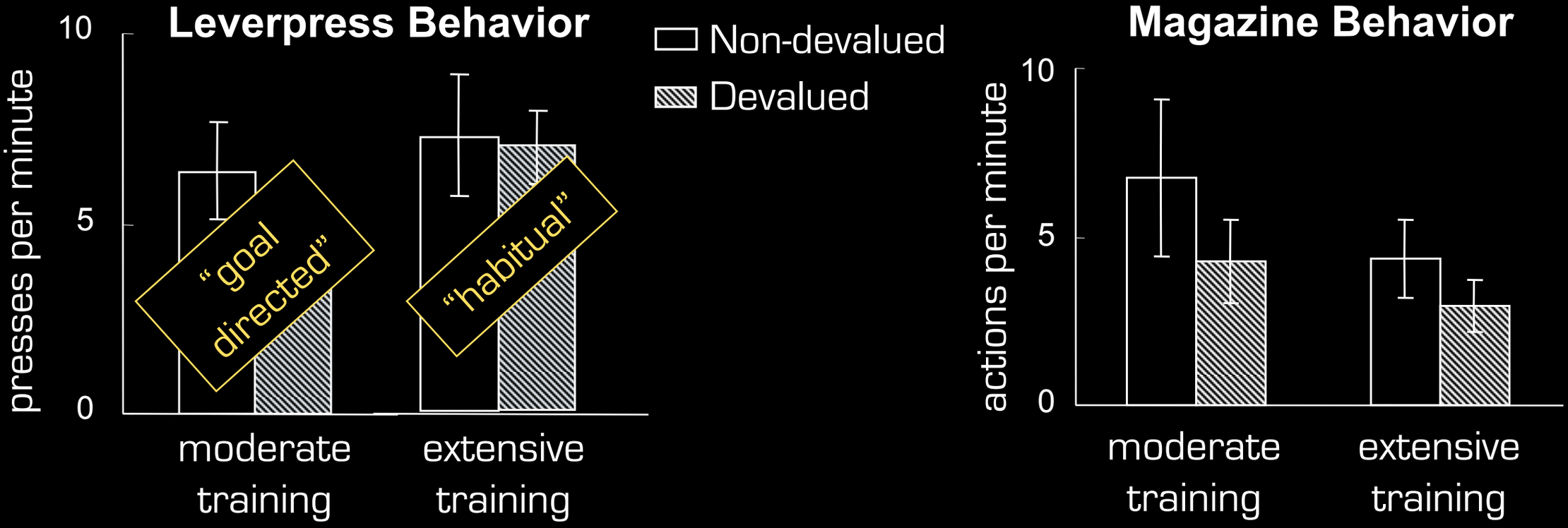

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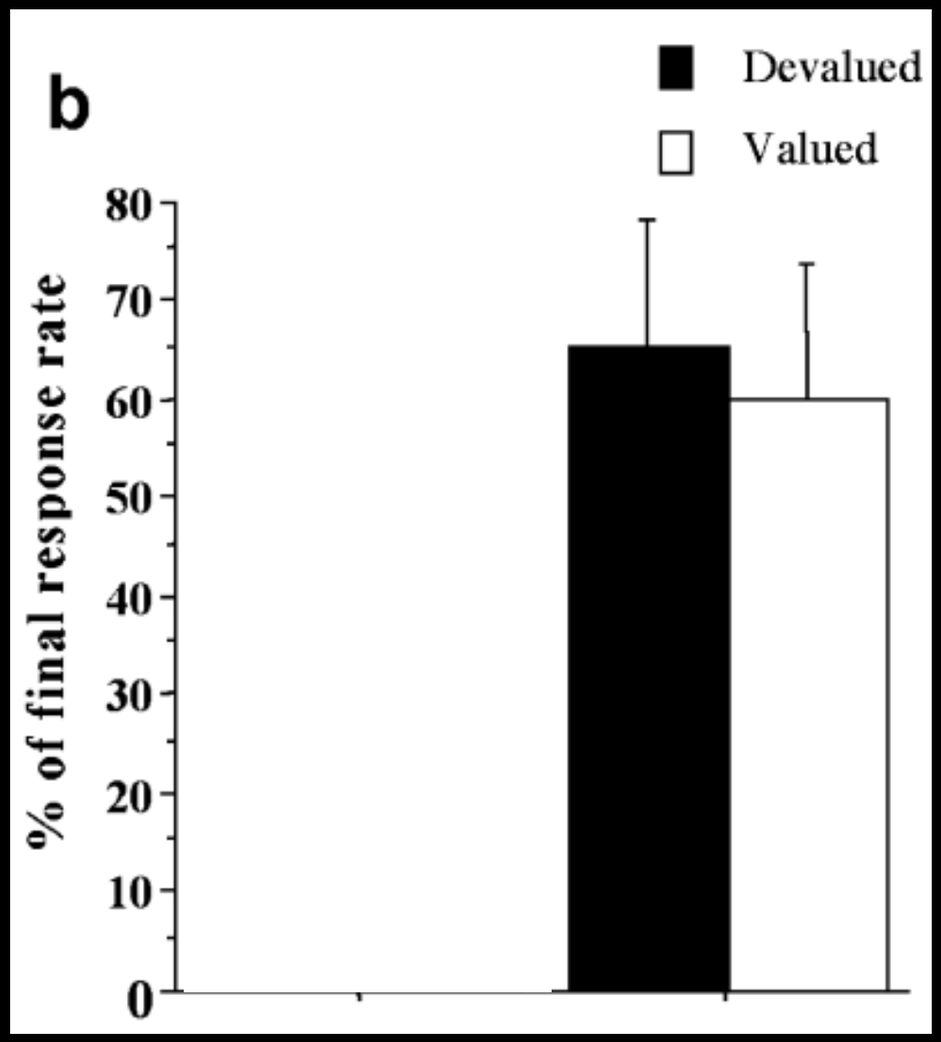

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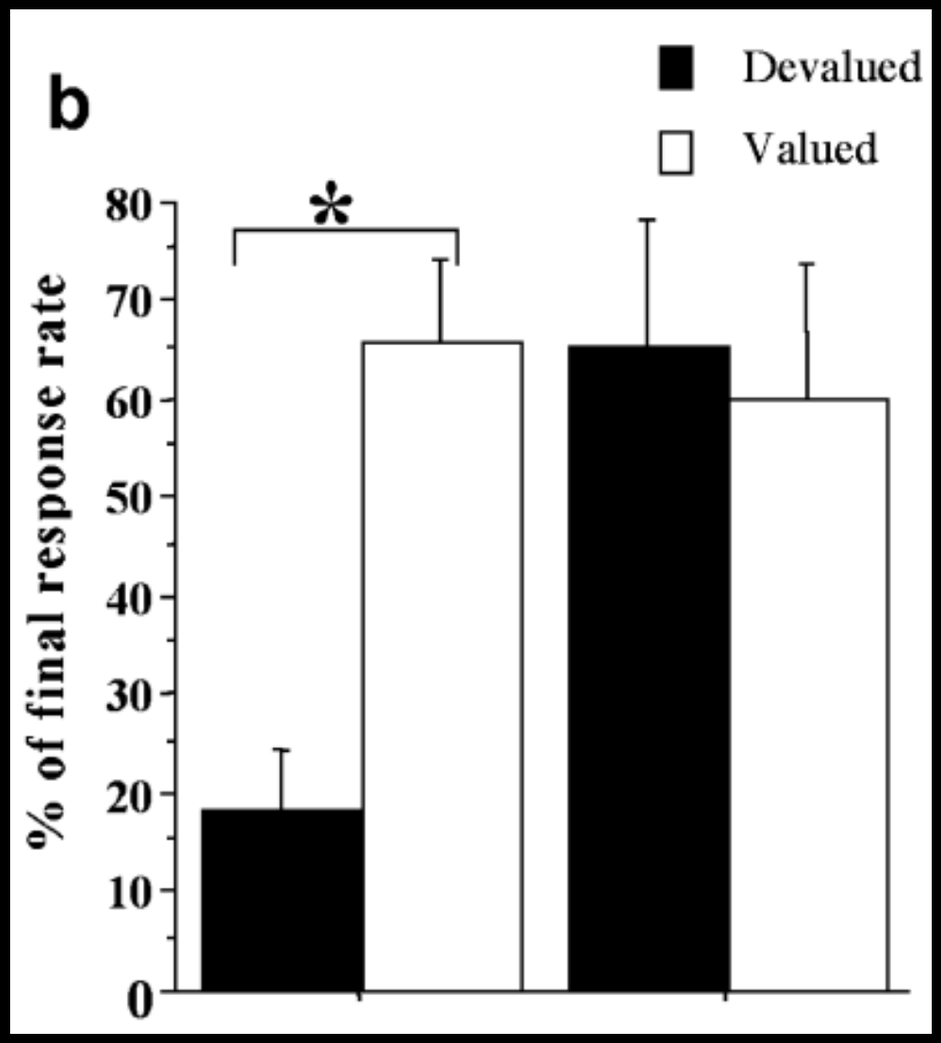

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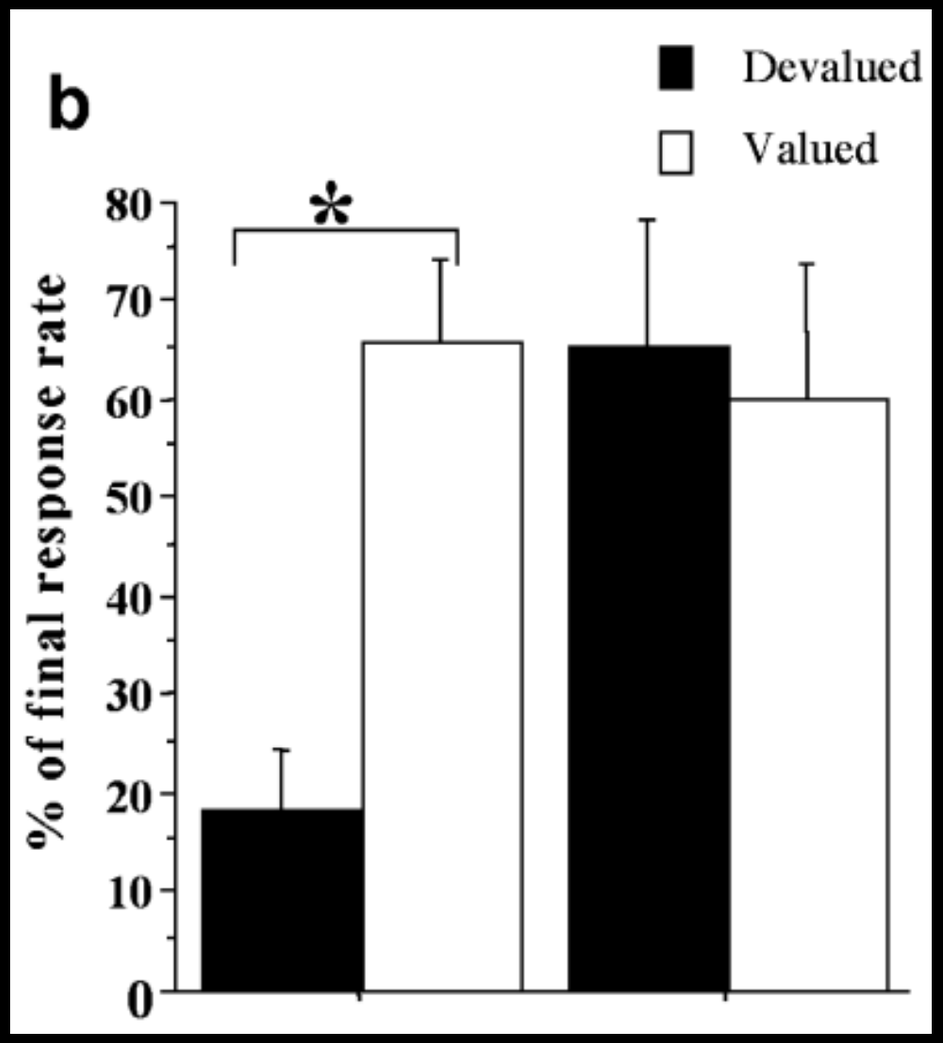

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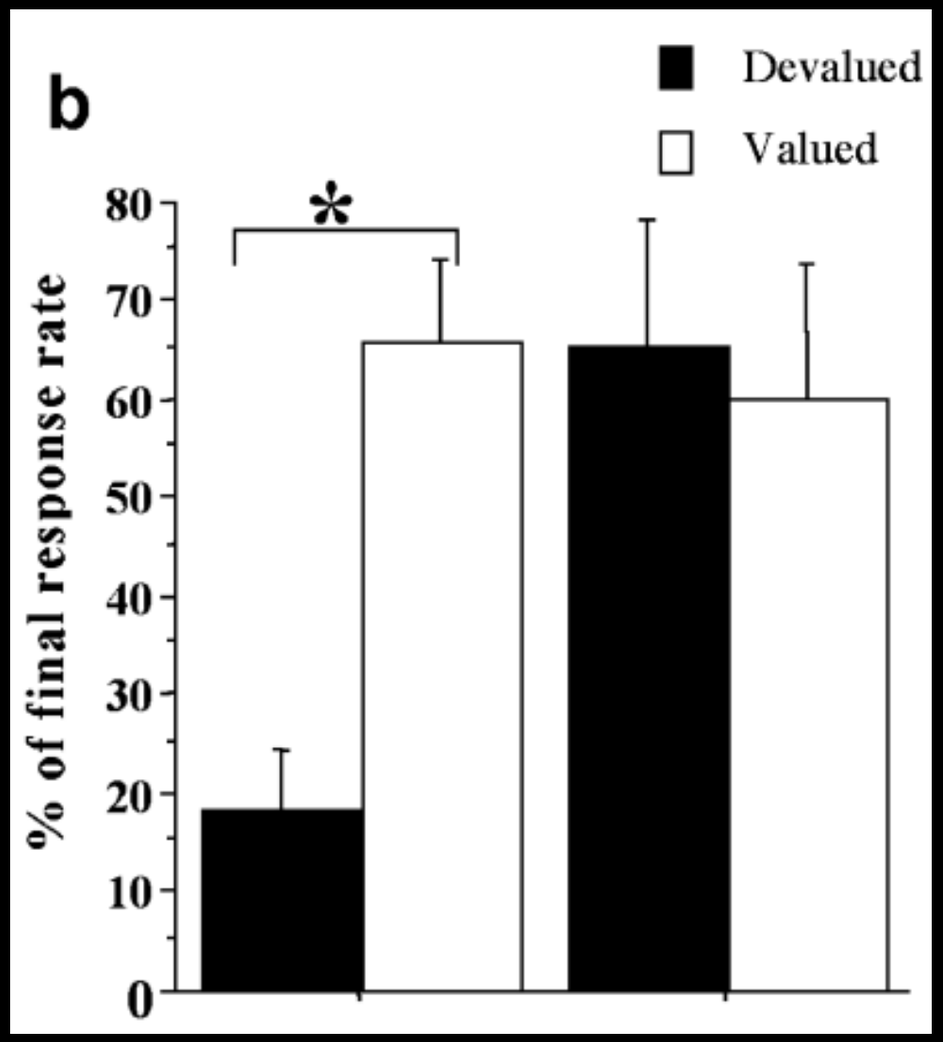

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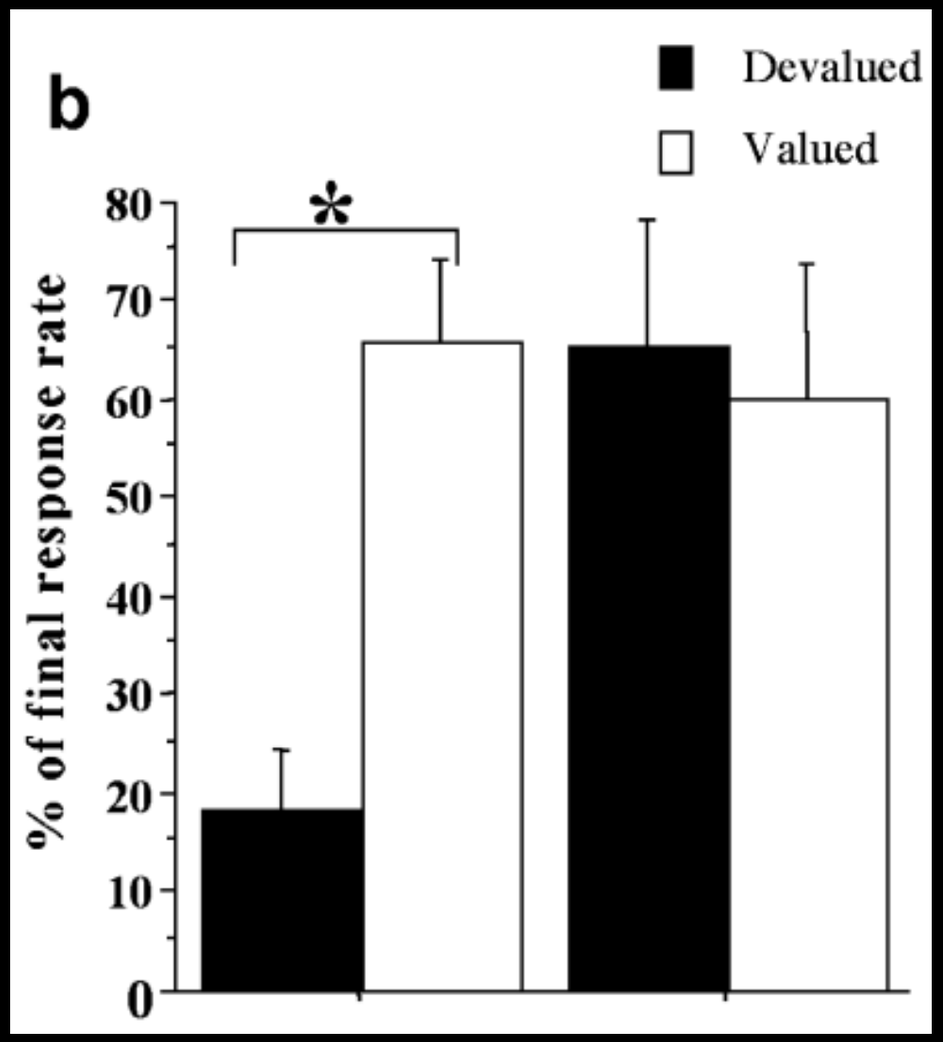

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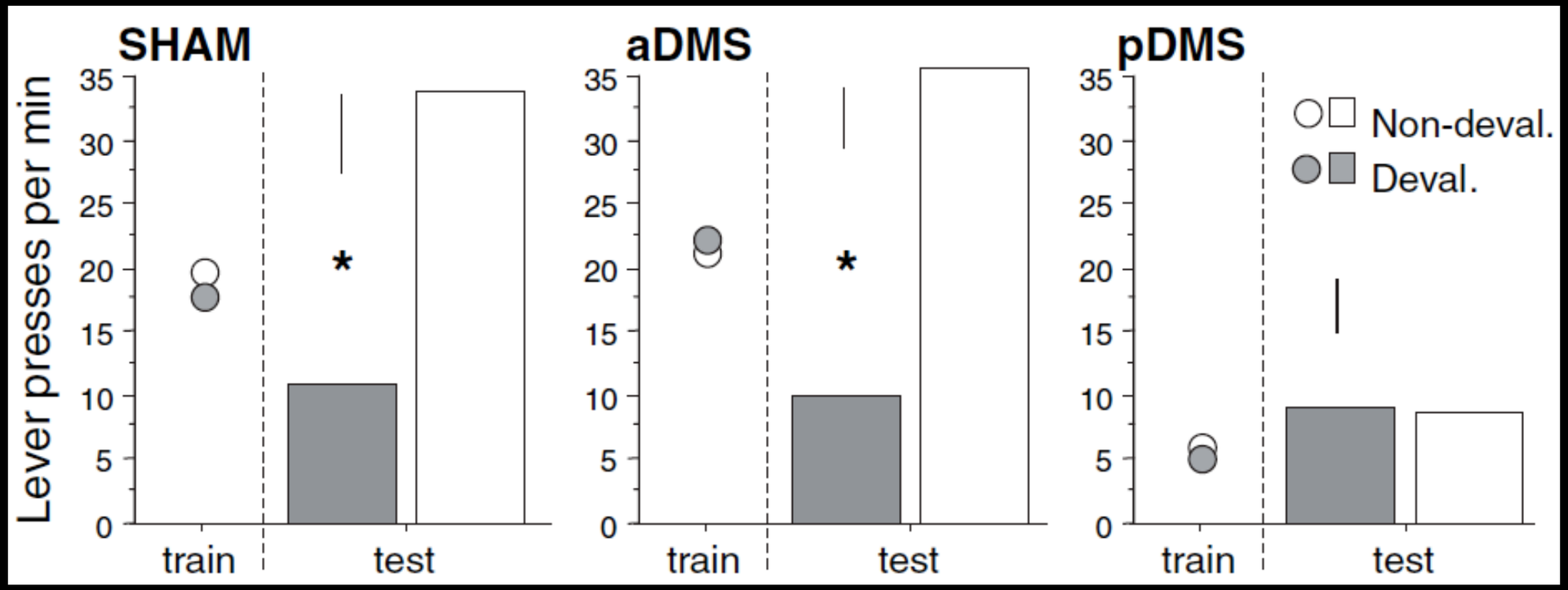
devaluation: results from lesions II



Yin, Ostlund, Knowlton & Balleine (2005)

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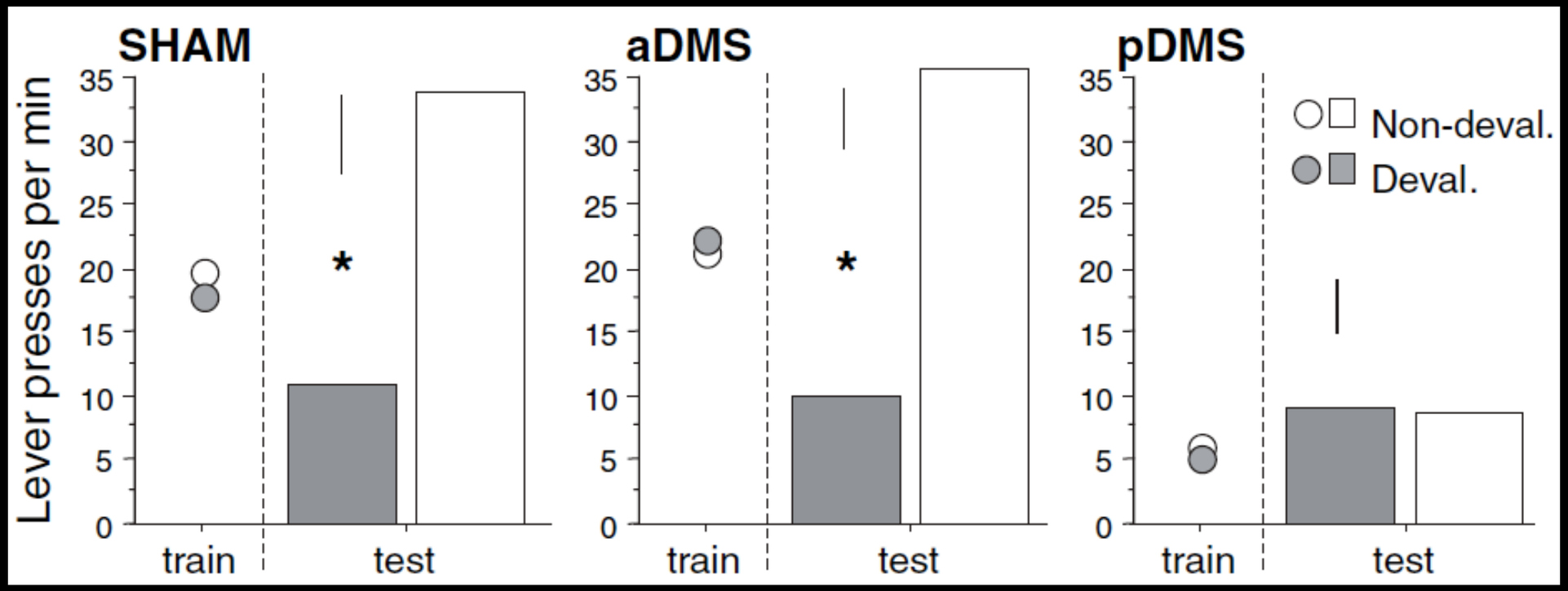

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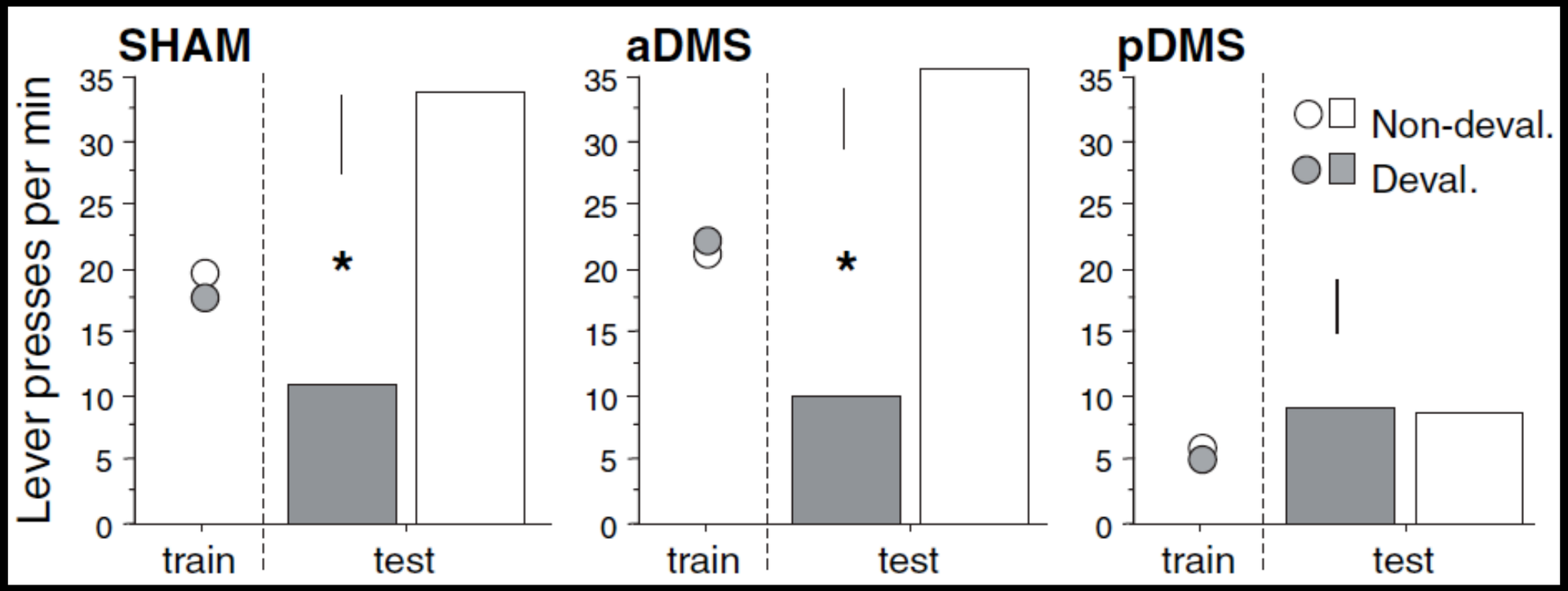

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(also.. pre-limbic PFC, dorsomedial thalamus)

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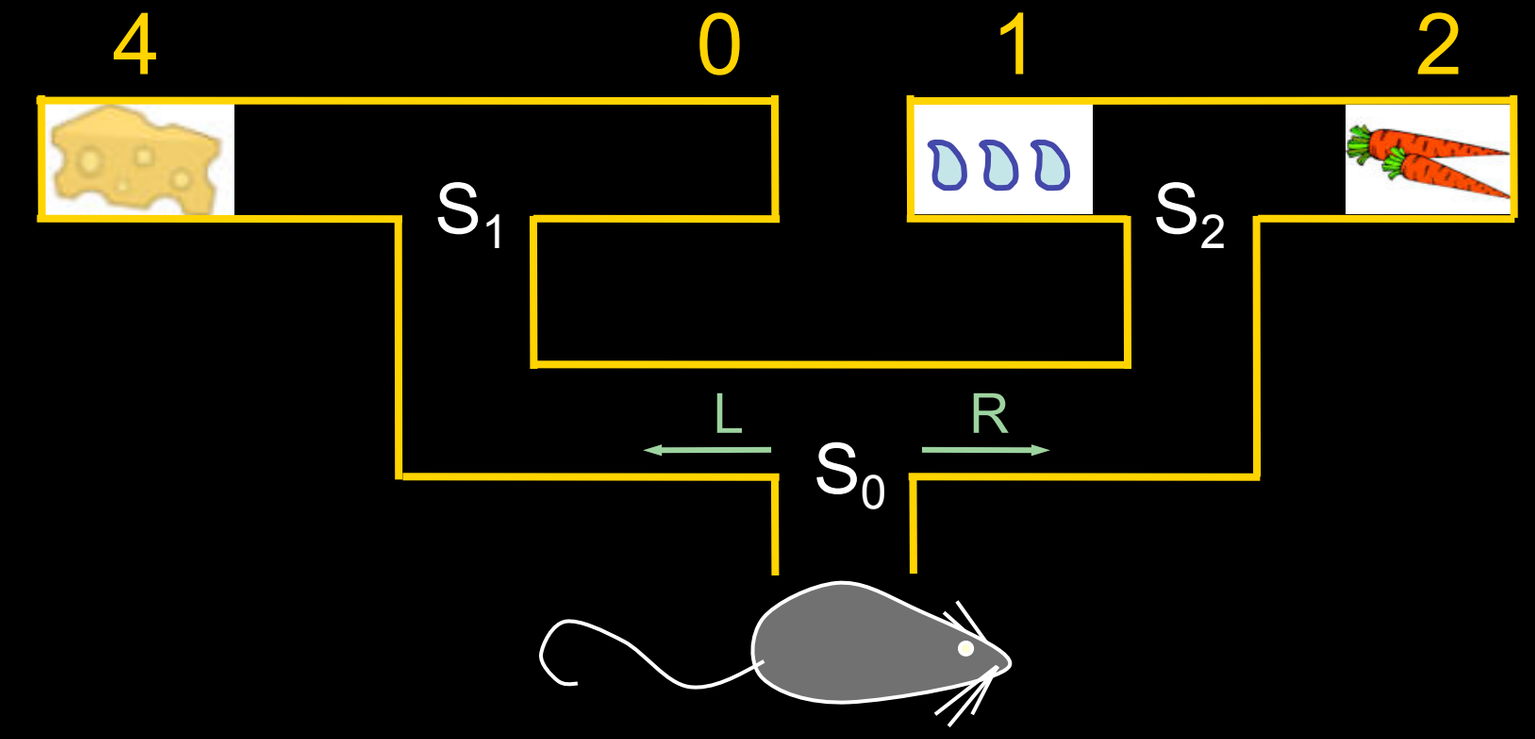
- Can RL help us make sense of this mess?

strategy 1: model based RL



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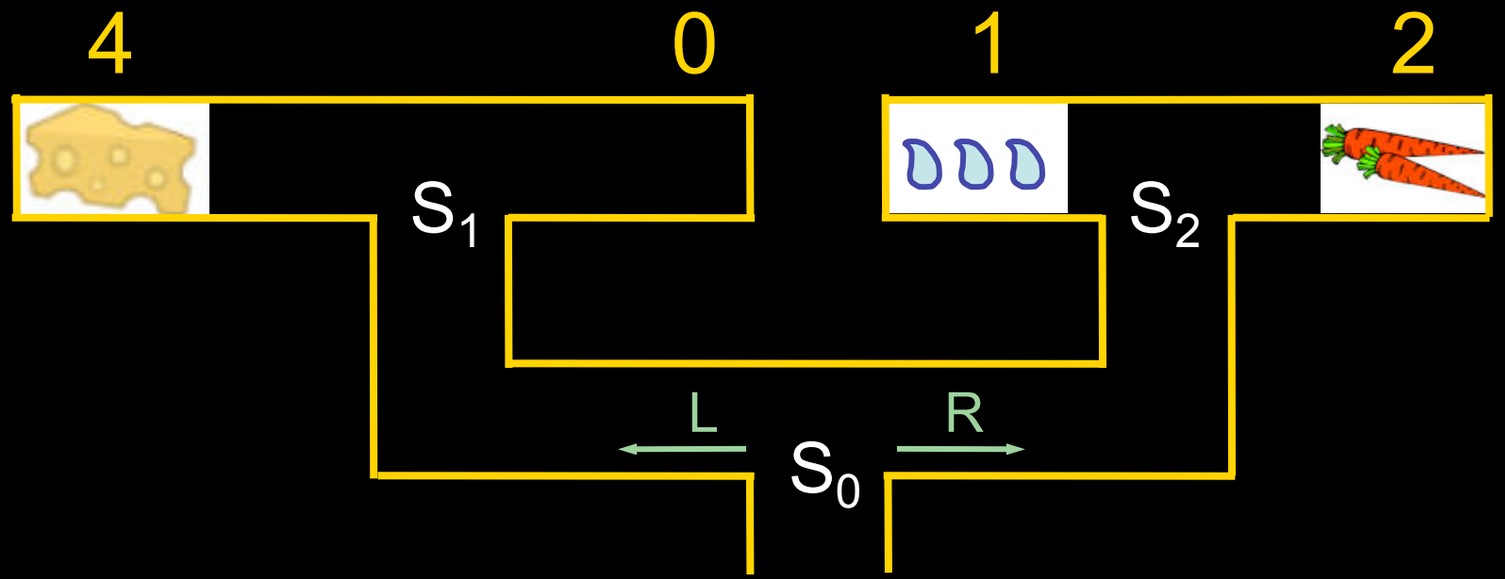

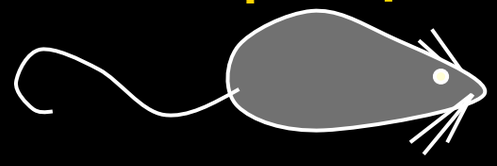

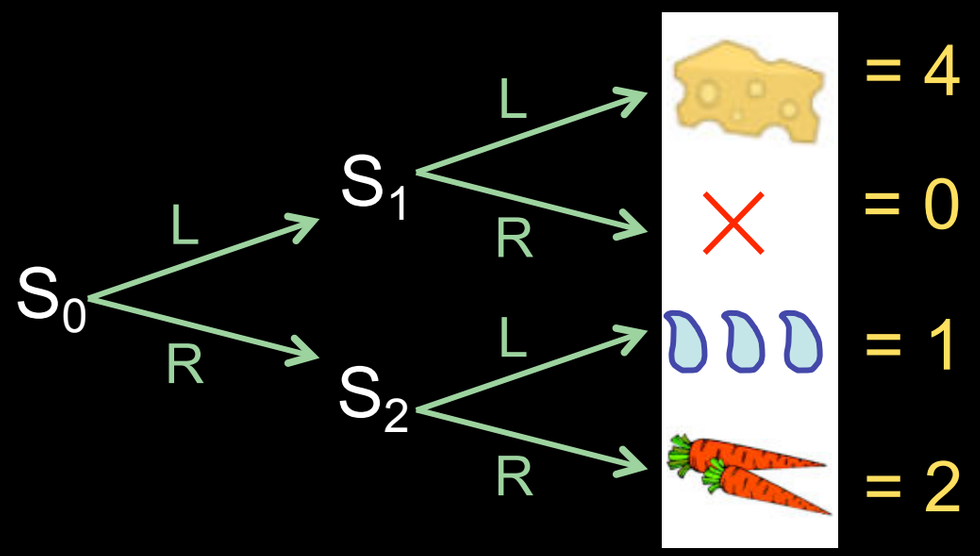

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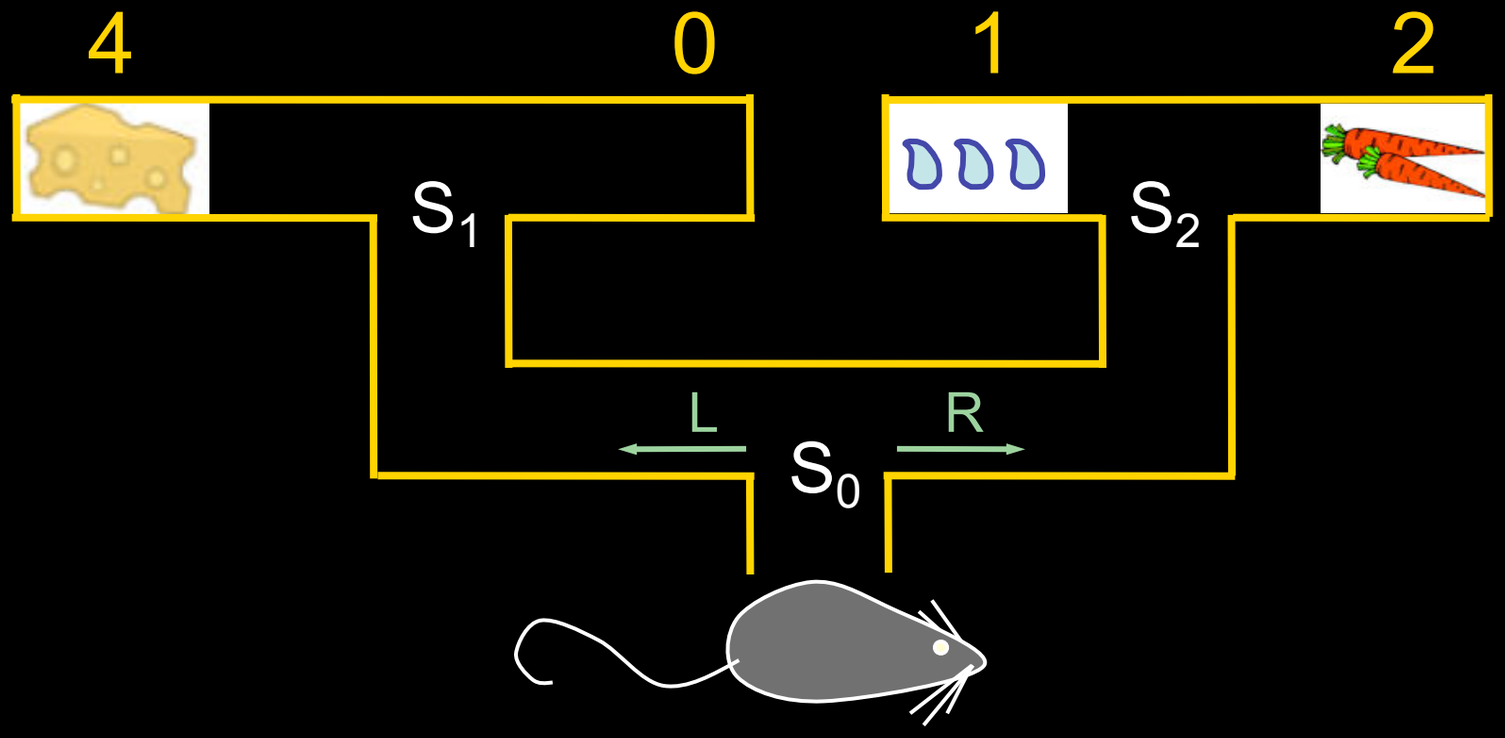

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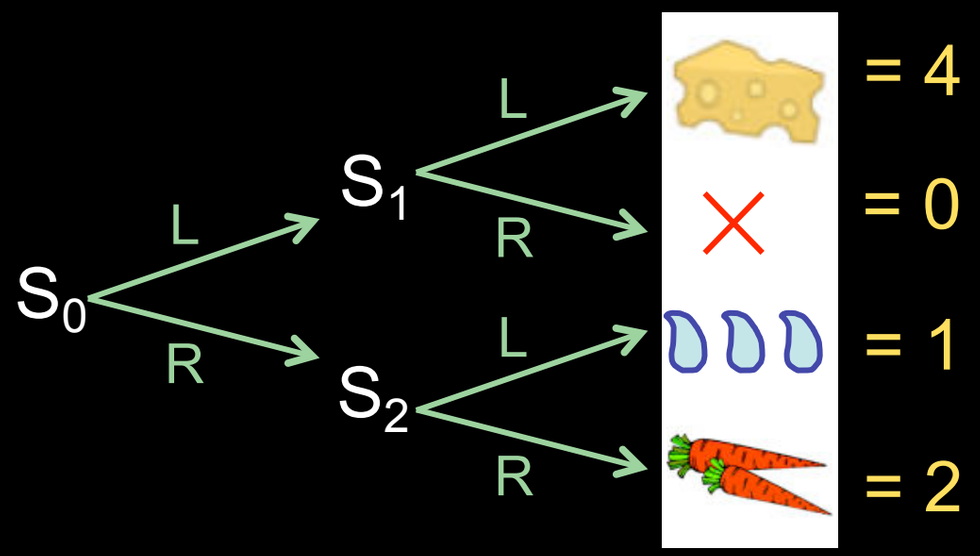

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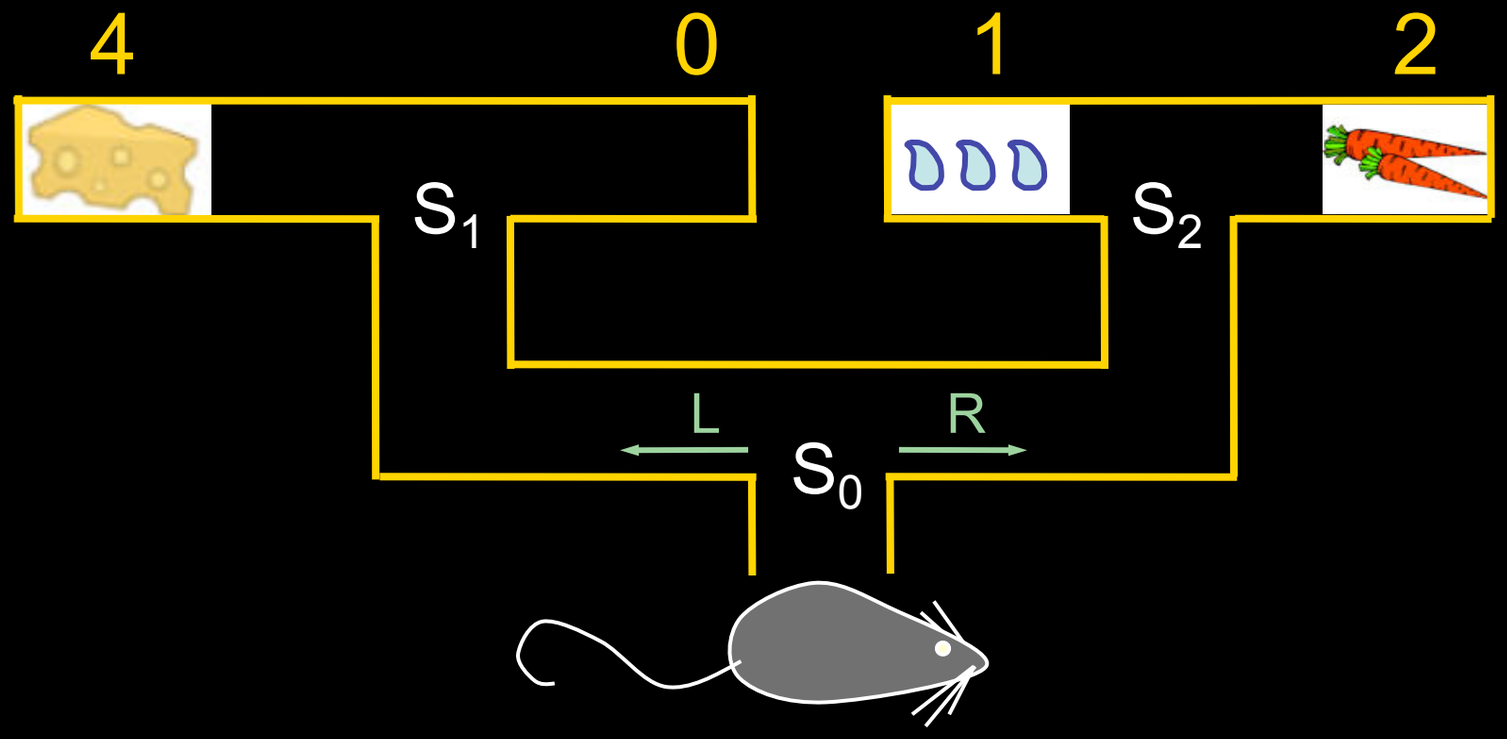

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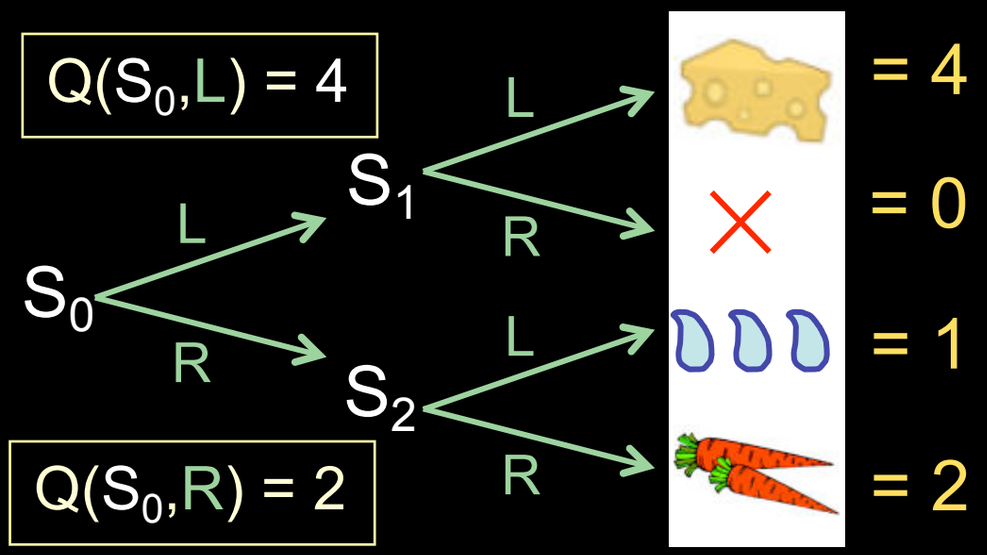

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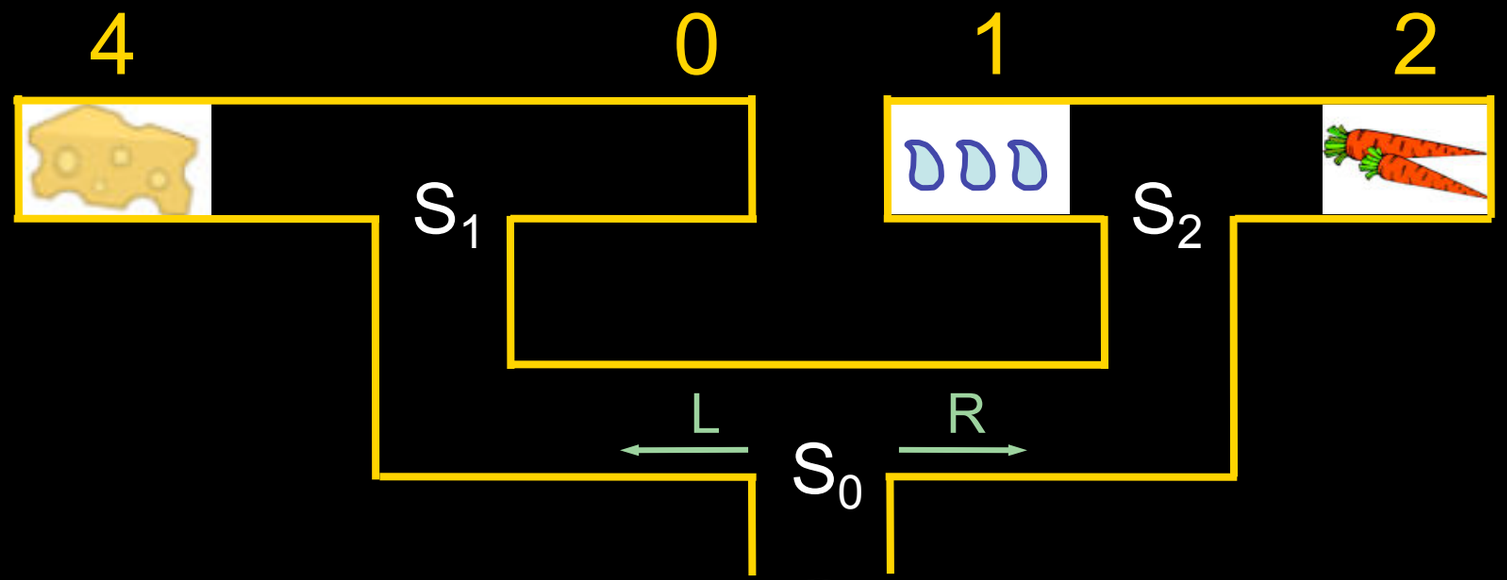

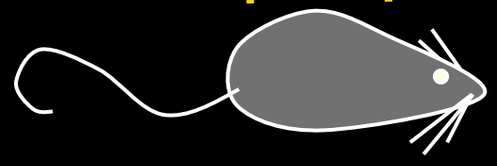

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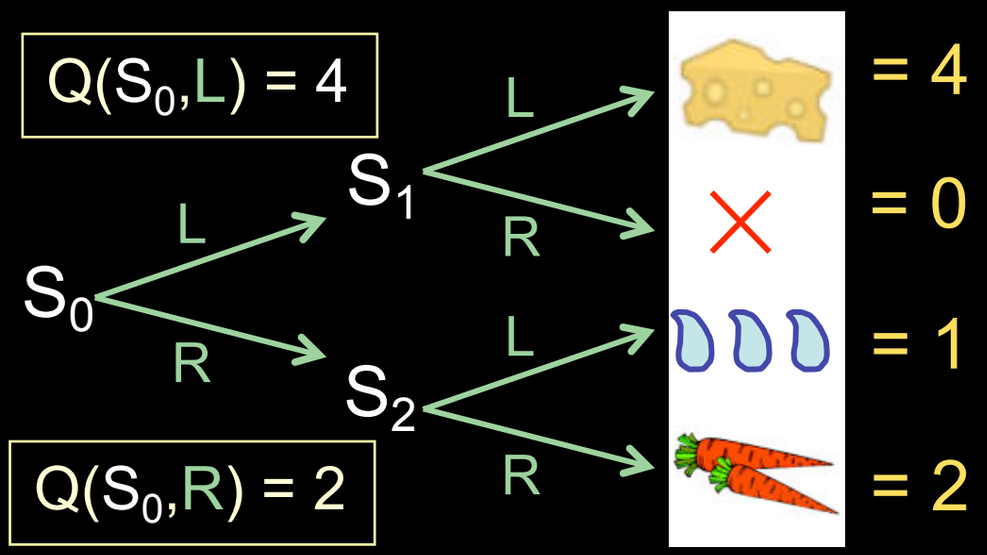

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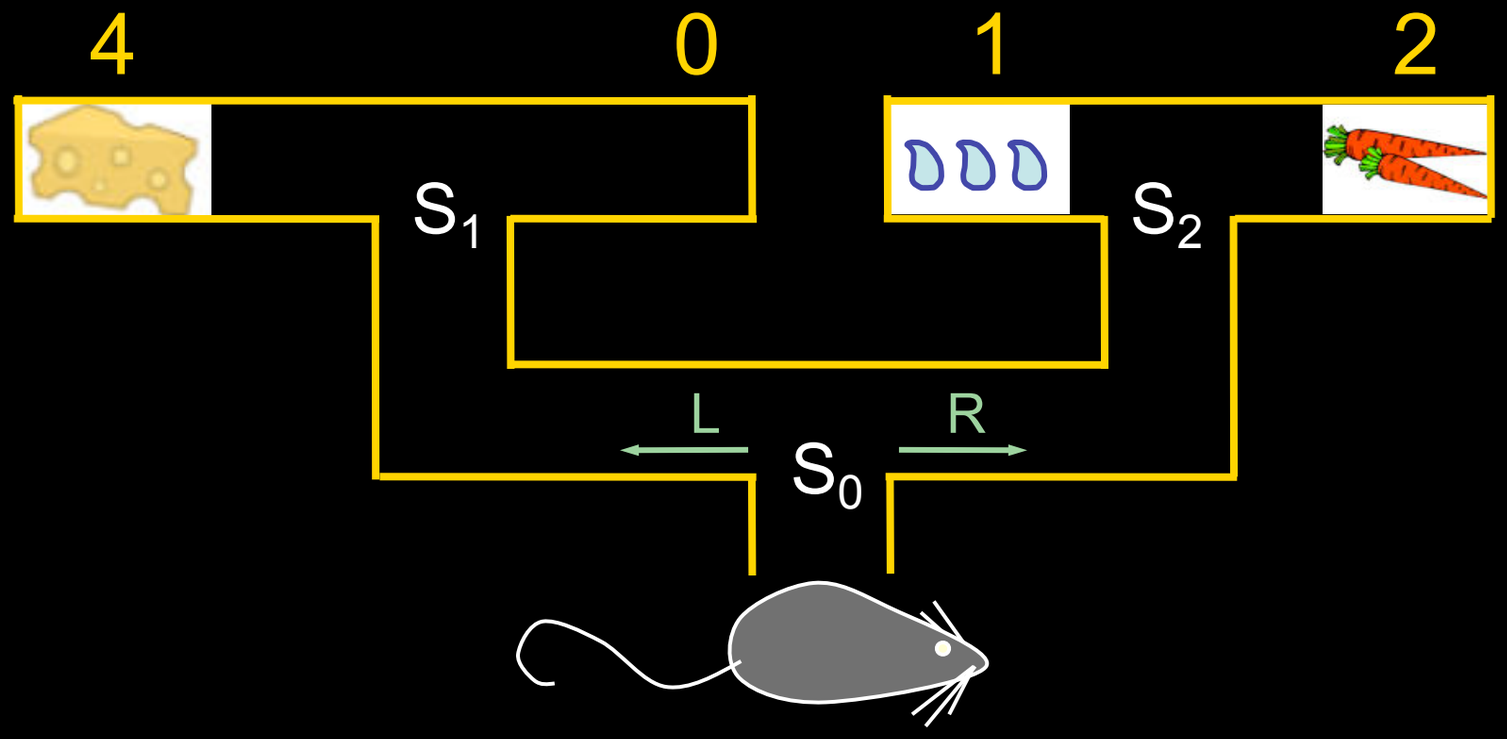

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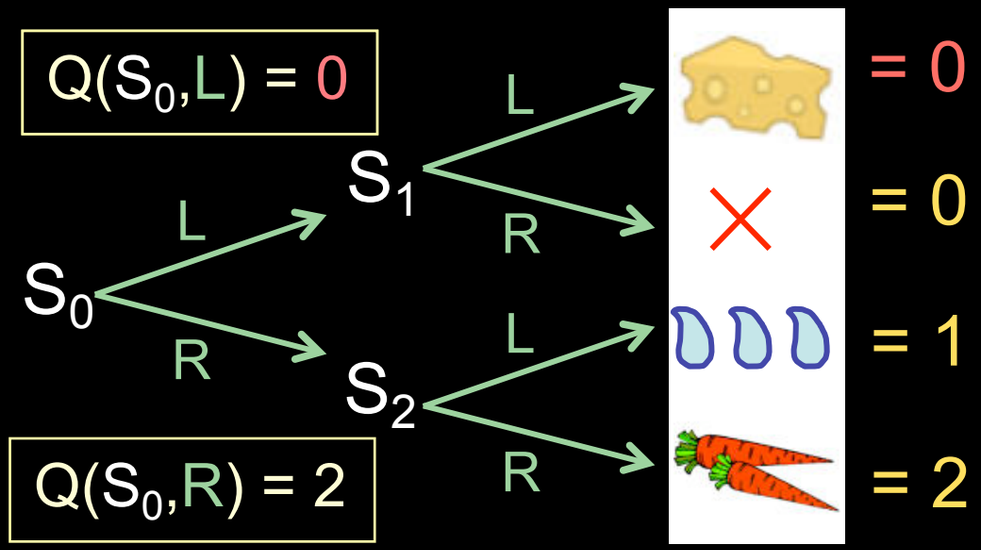

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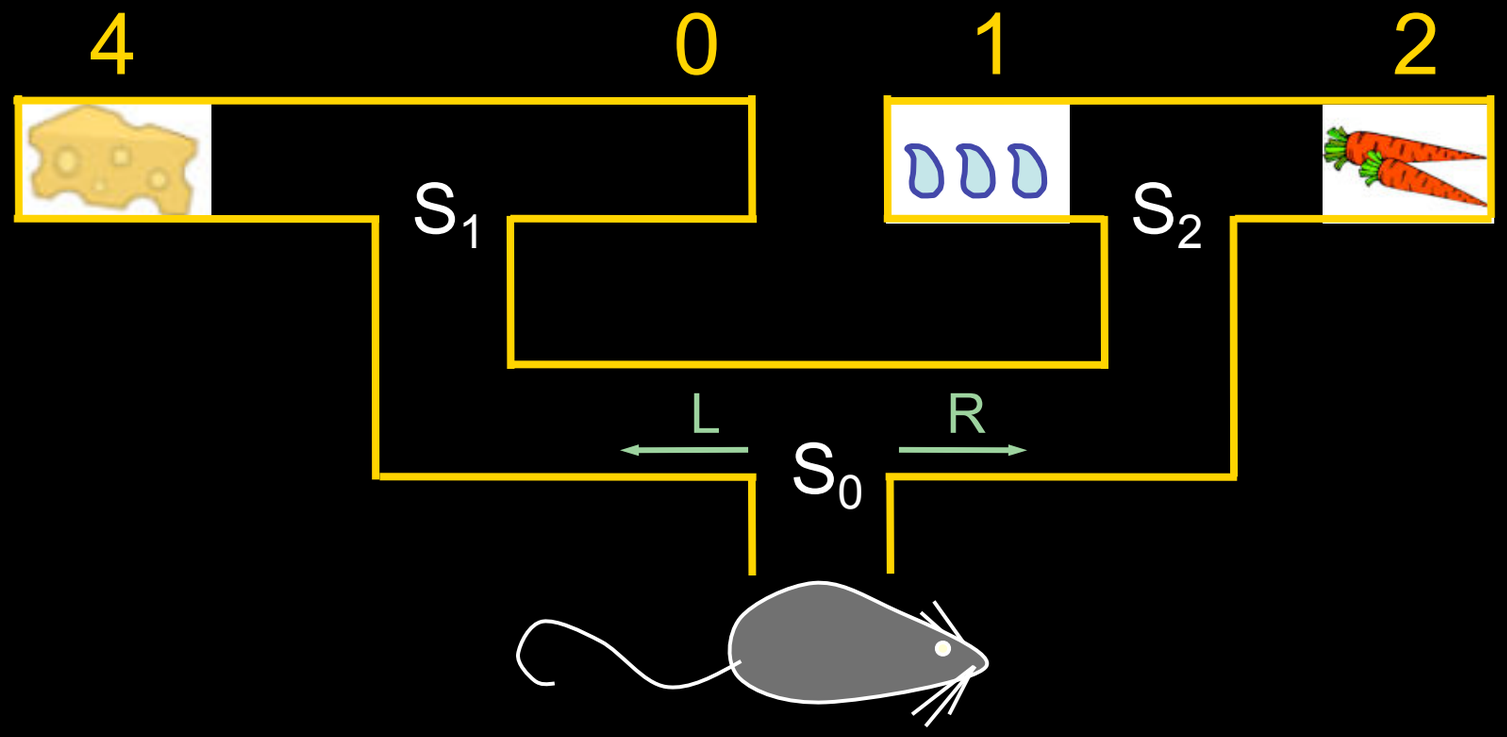
strategy II: model free RL



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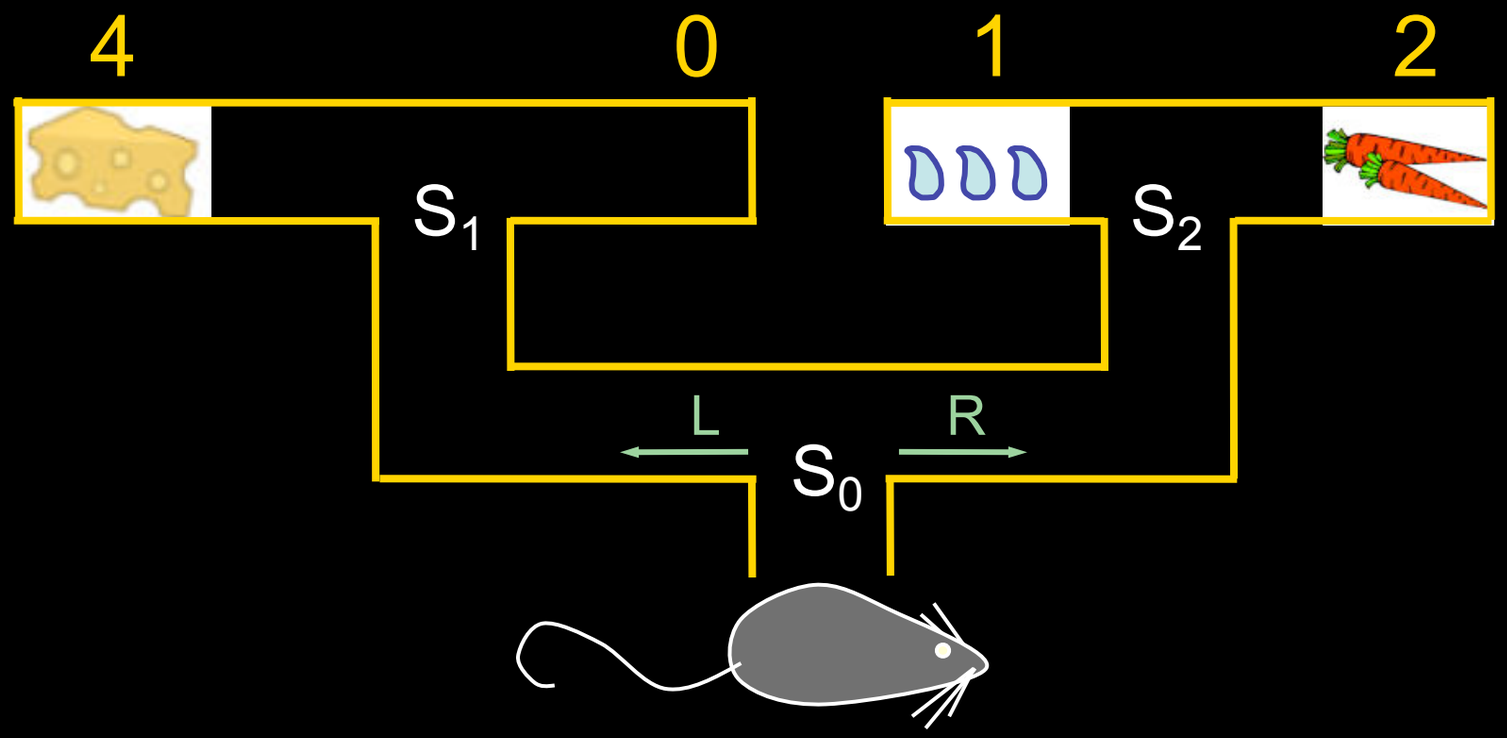

Stored:

$Q(S_0,L) = 4$	$Q(S_1,L) = 4$
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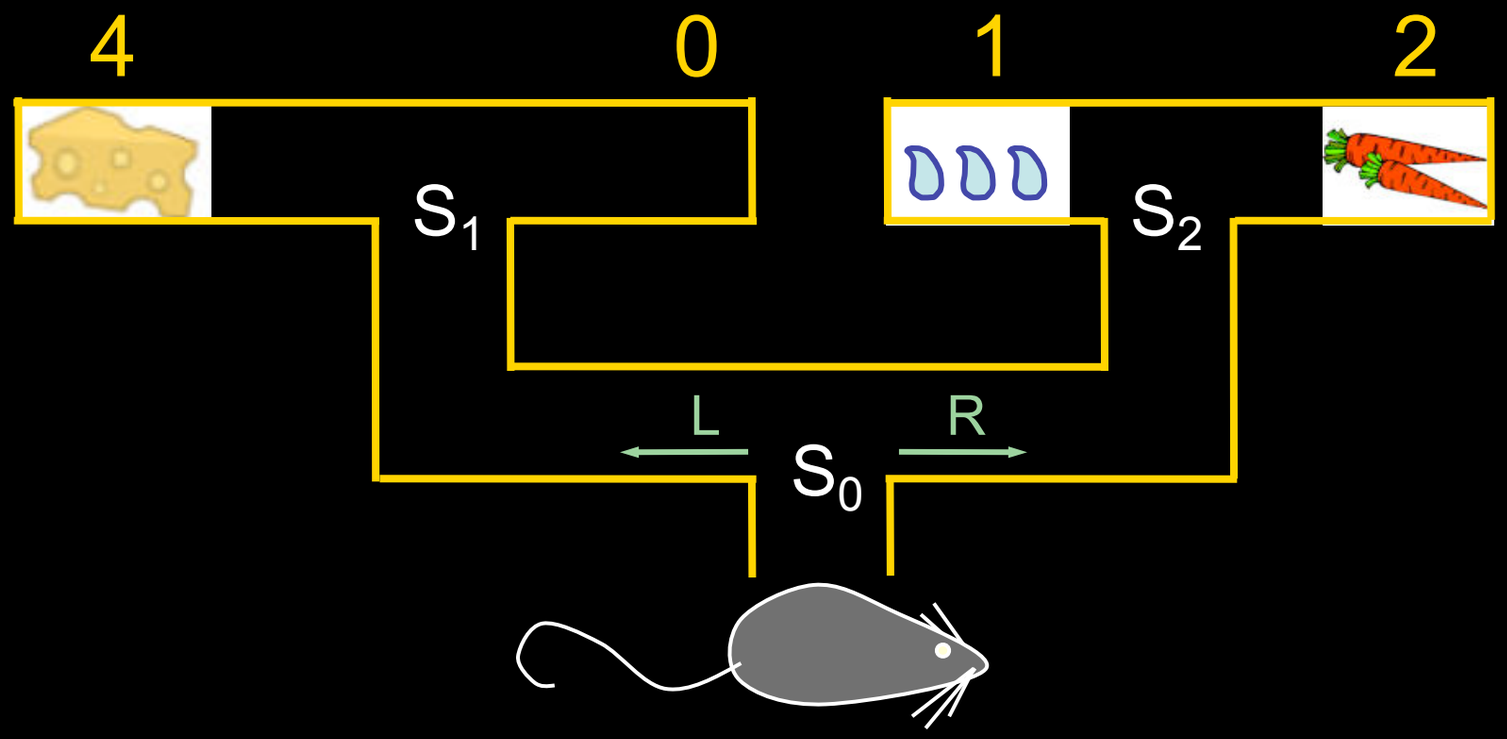

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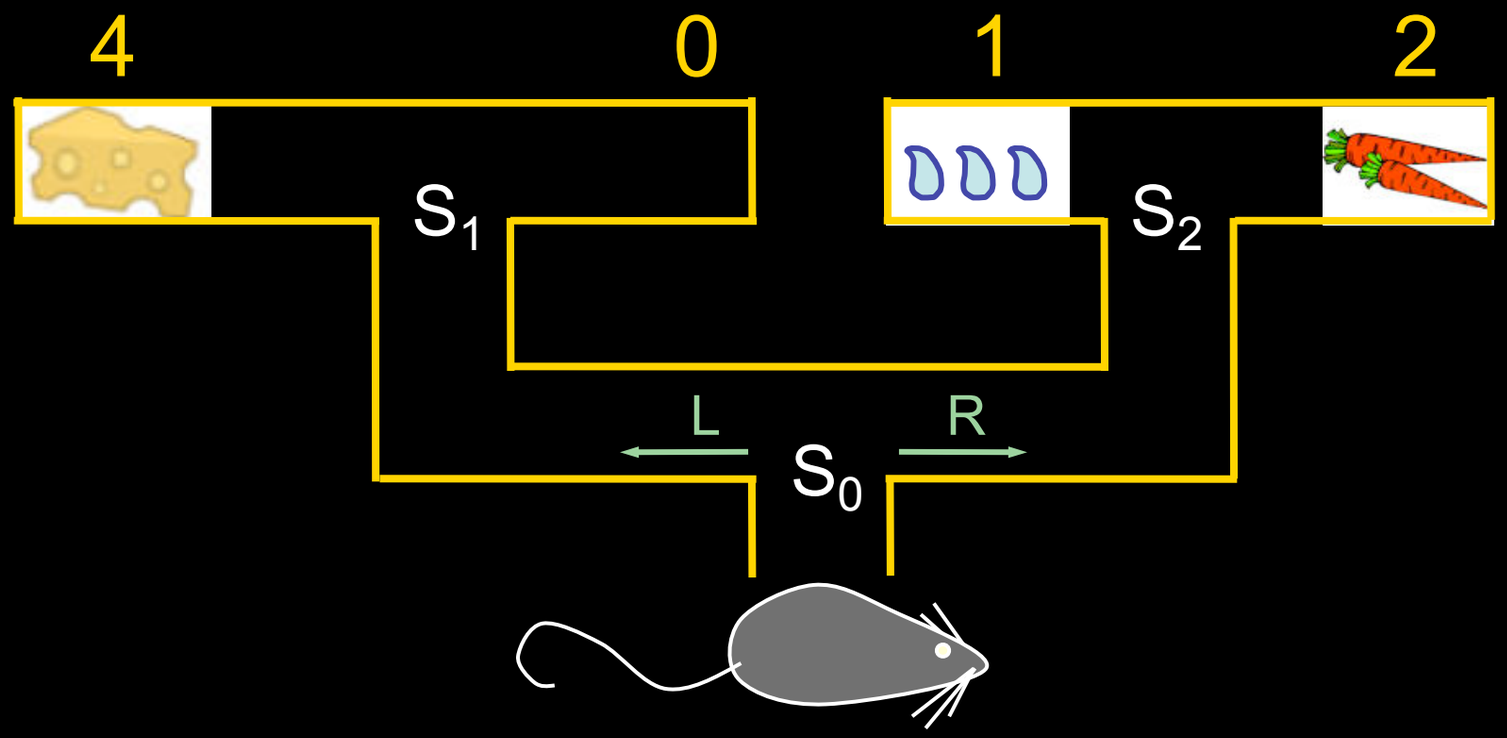

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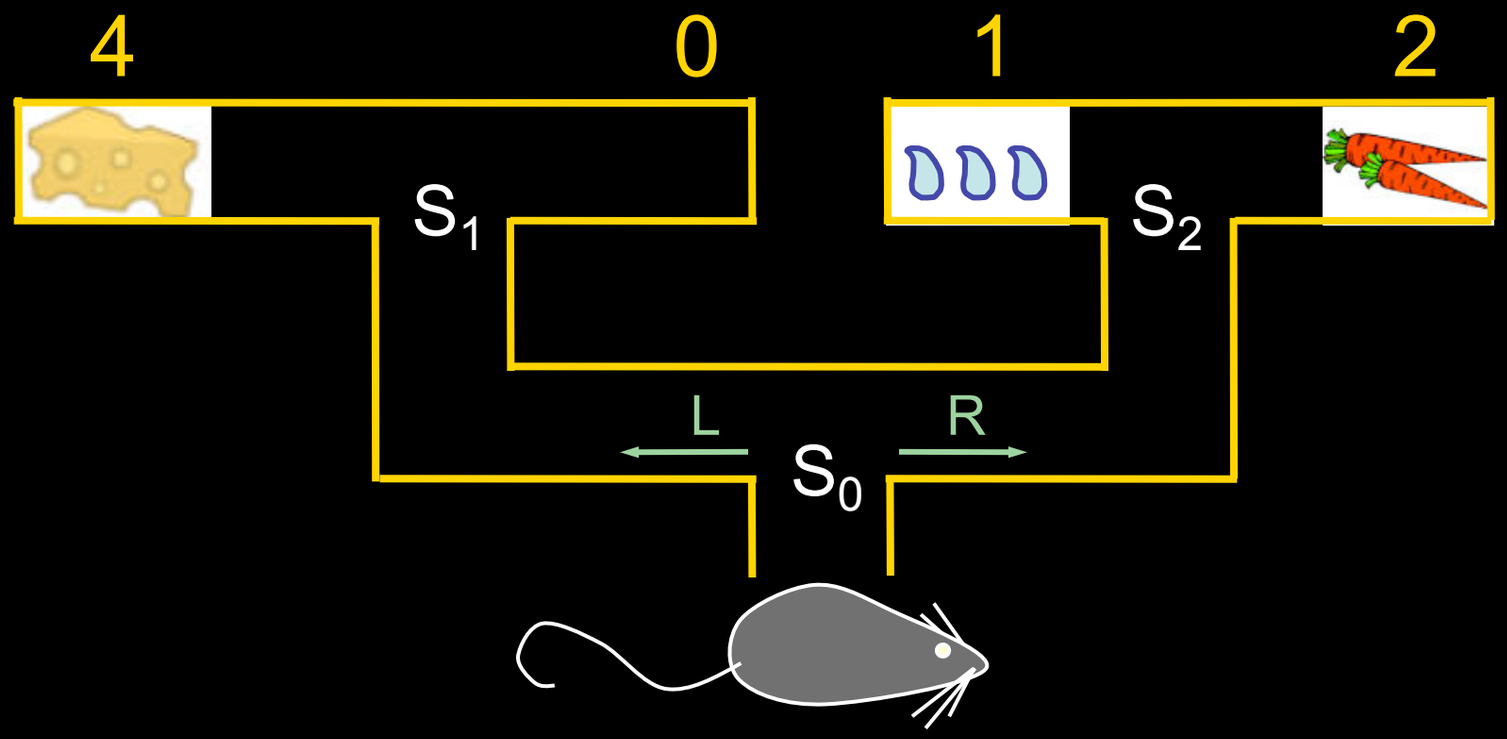

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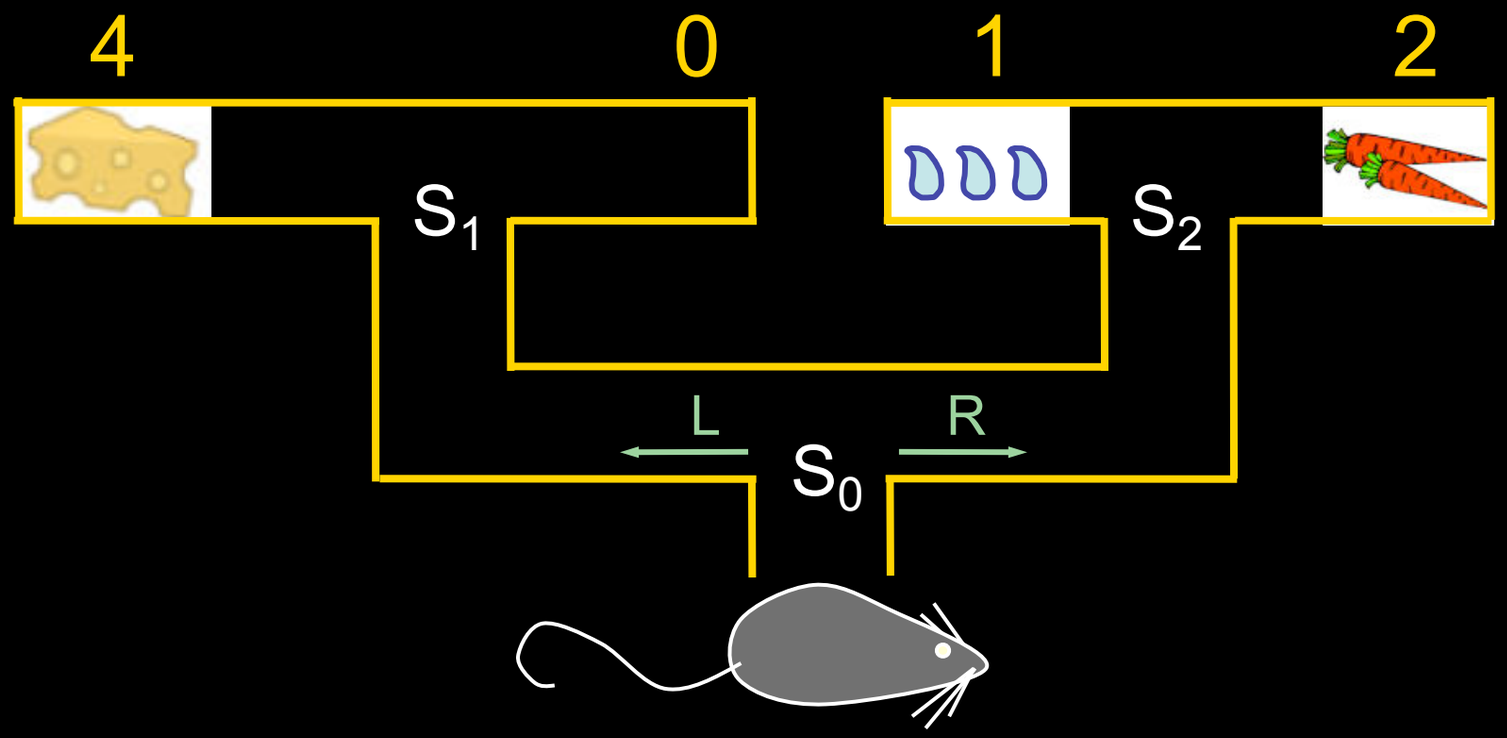

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- and inflexible, need relearning to adapt to any change (habitual)

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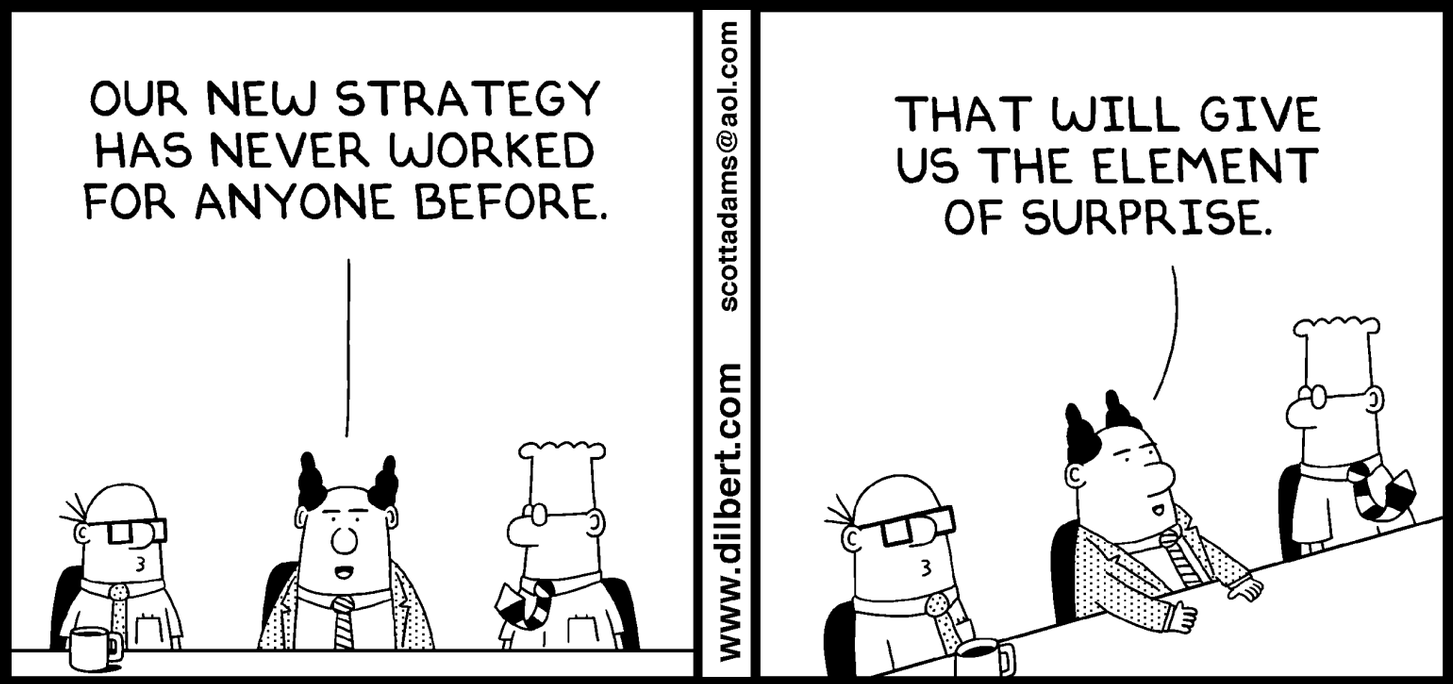

Daw, Niv, Dayan (2005)

this answer raises two questions:

- Why should the brain use two different strategies/ controllers in parallel?
- If it uses two: how can it arbitrate between the two when they disagree (new decision making problem...)

Daw, Niv, Dayan (2005)

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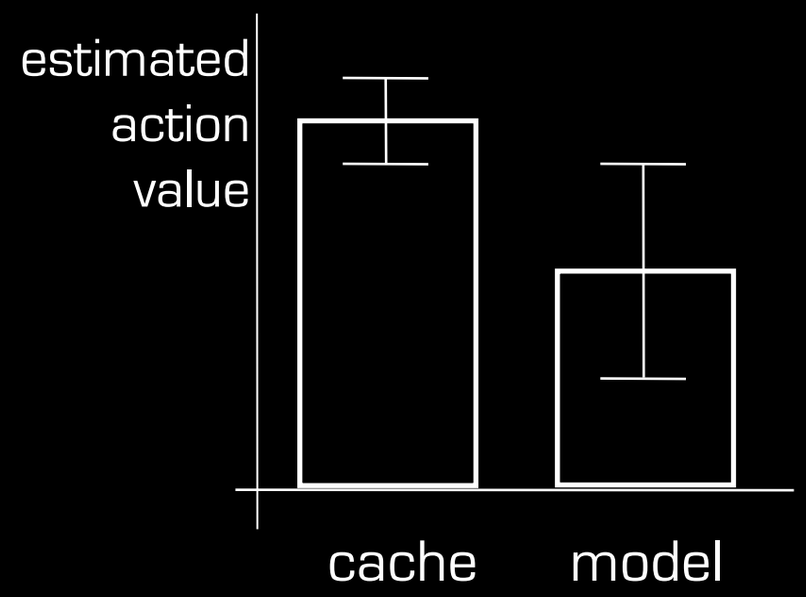

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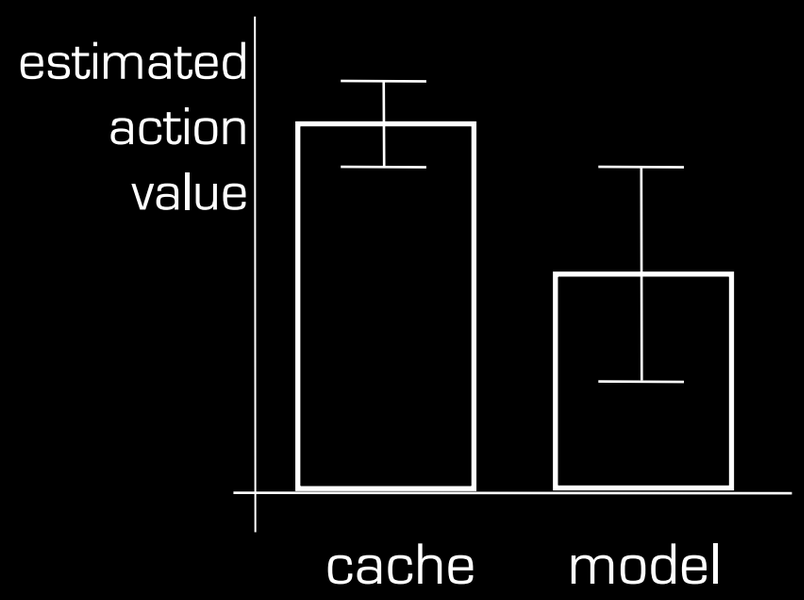

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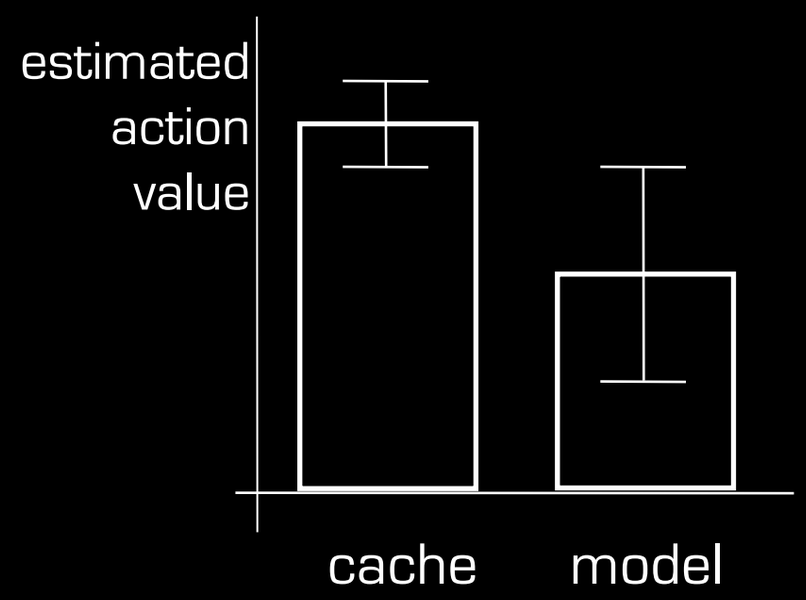
   - different sources of uncertainty in the two systems



Daw, Niv, Dayan (2005)

Summary so far...

- animal conditioned behavior is not a simple unitary phenomenon: the same response can result from different neural and computational origins
- different neural mechanisms work in parallel to support behavior: cooperation and competition
- RL provides clues as to why this should be so, and what each system does

Outline

- The brain coarse-grain
- Learning and decision making in animals and humans: what does RL have to do with it?
- A success story: Dopamine and prediction errors
- Actor/Critic architecture in basal ganglia
- SARSA vs Q-learning: can the brain teach us about ML?
- Model free and model based RL in the brain
- Average reward RL & tonic dopamine (skipped for lack of time)
- Risk sensitivity and RL in the brain *NEW*
- Open challenges and future directions

a question:

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sure $20

Niv, Edlund, Dayan, O'Doherty (not yet published)

a question:

sure $20

or

risky $40/$0

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2. RL (expected) values ignore risk

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3. BOLD signals in nucleus accumbens correlate with prediction errors (can infer value of options from these)

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Will the neural value of a sure 20¢ be the same as that of a 50% chance risky 40¢ ?

Niv, Edlund, Dayan, O'Doherty (not yet published)

sure 20¢ vs. risky 40¢/0¢

same neural values

different neural values

sure 20¢ vs. risky 40¢/0¢

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risk-sensitive decisions due to other mechanism that tracks risk

“decision value”

$= E(r) + \alpha V(r)$

Kuhnen & Knutson(2005)
Preuschoff, Bossaerts & Quartz (2006)

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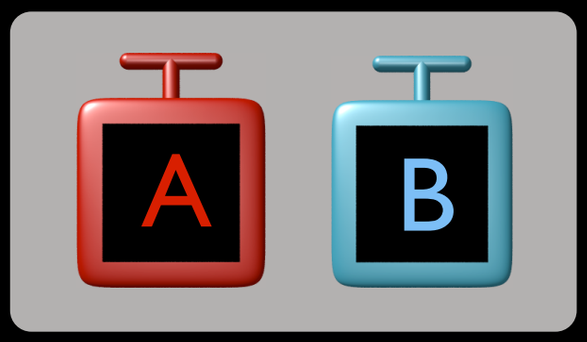

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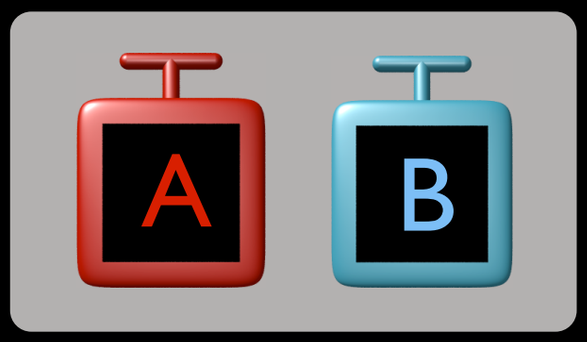

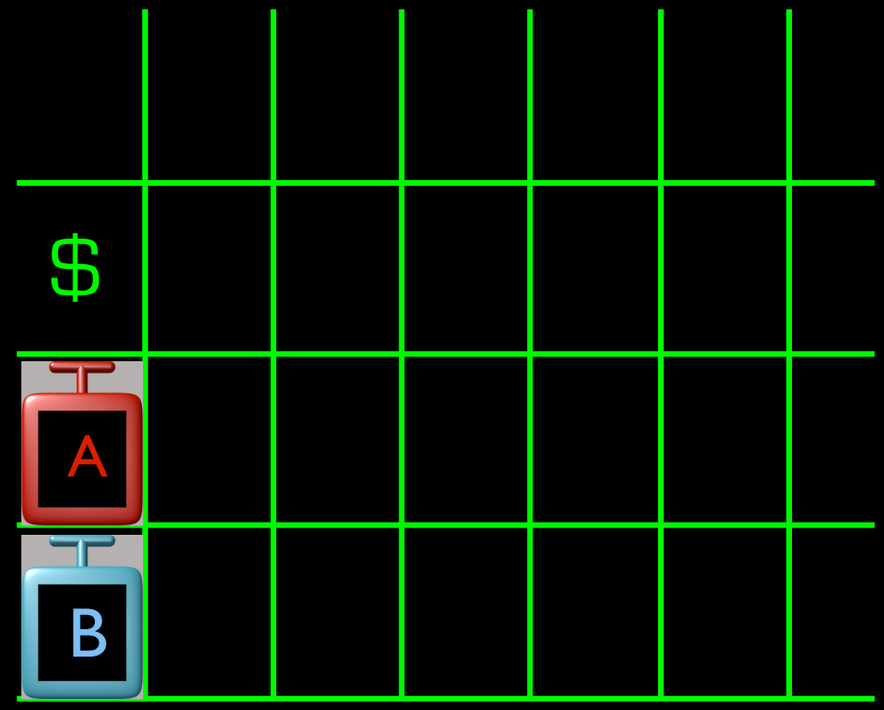

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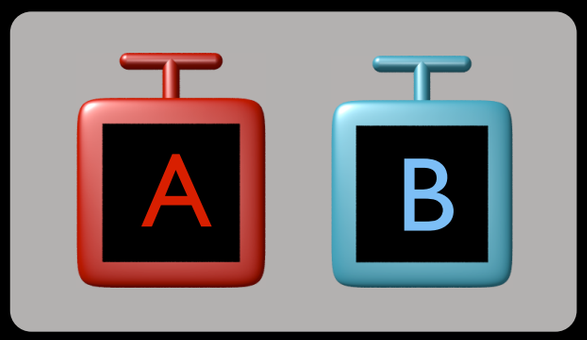

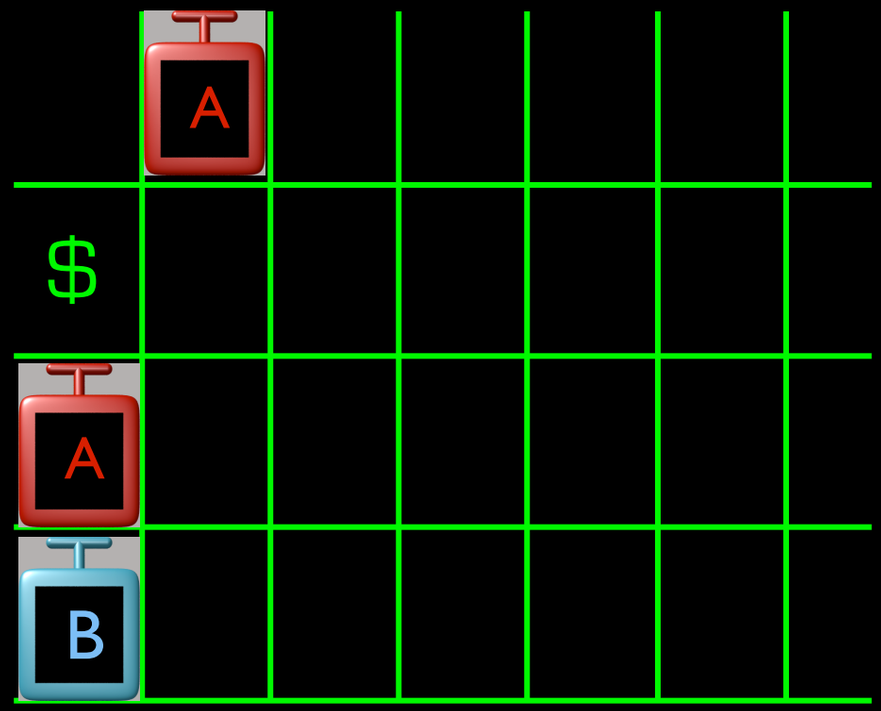

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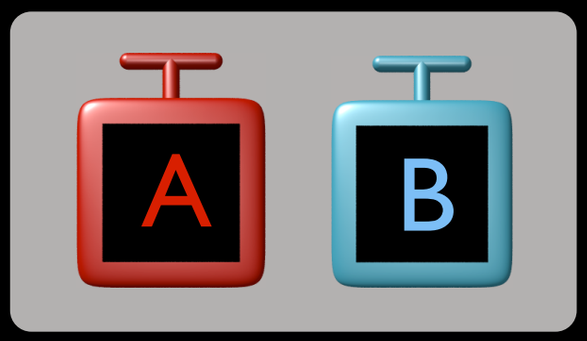

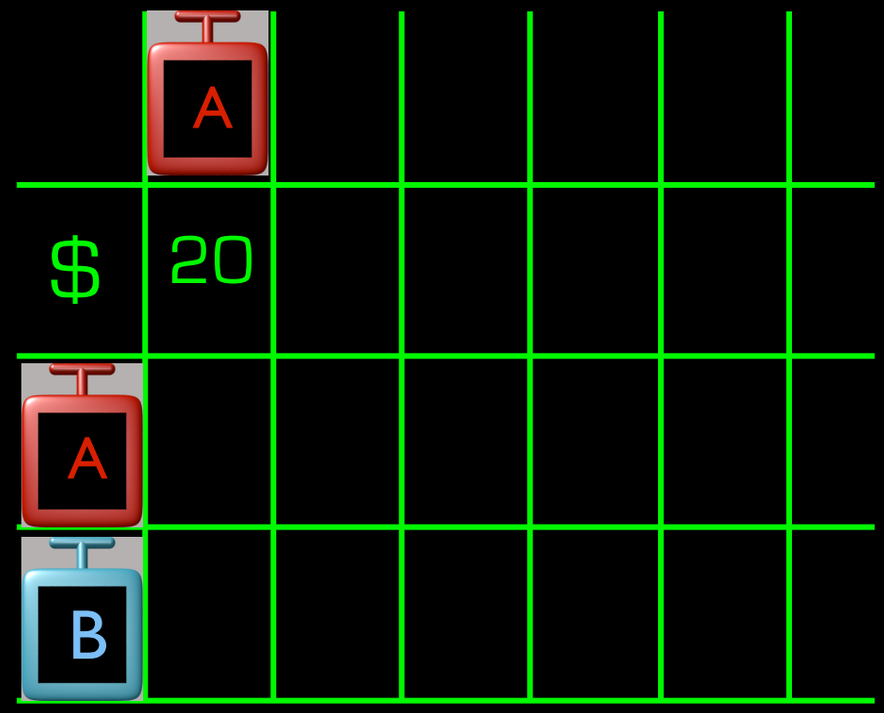

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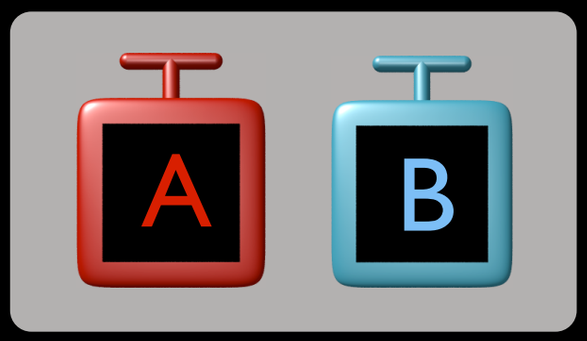

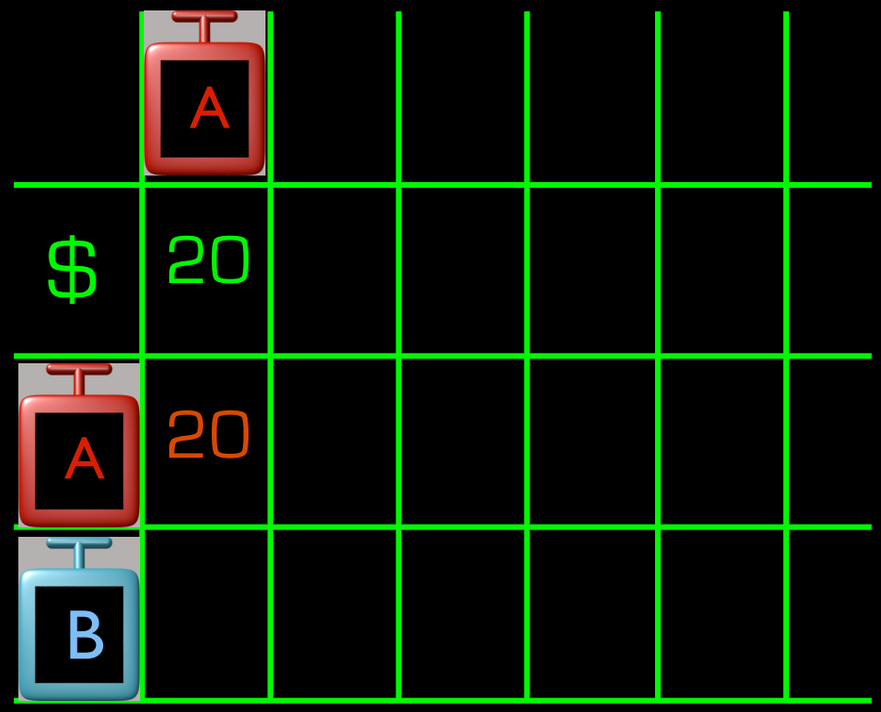

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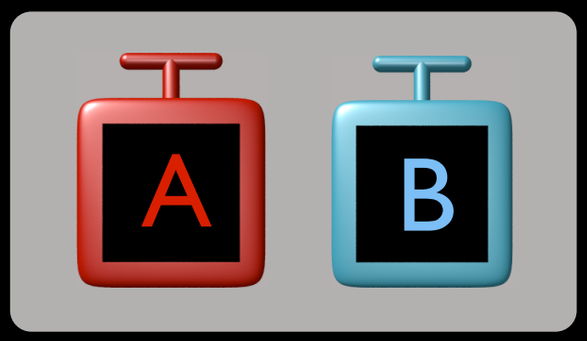

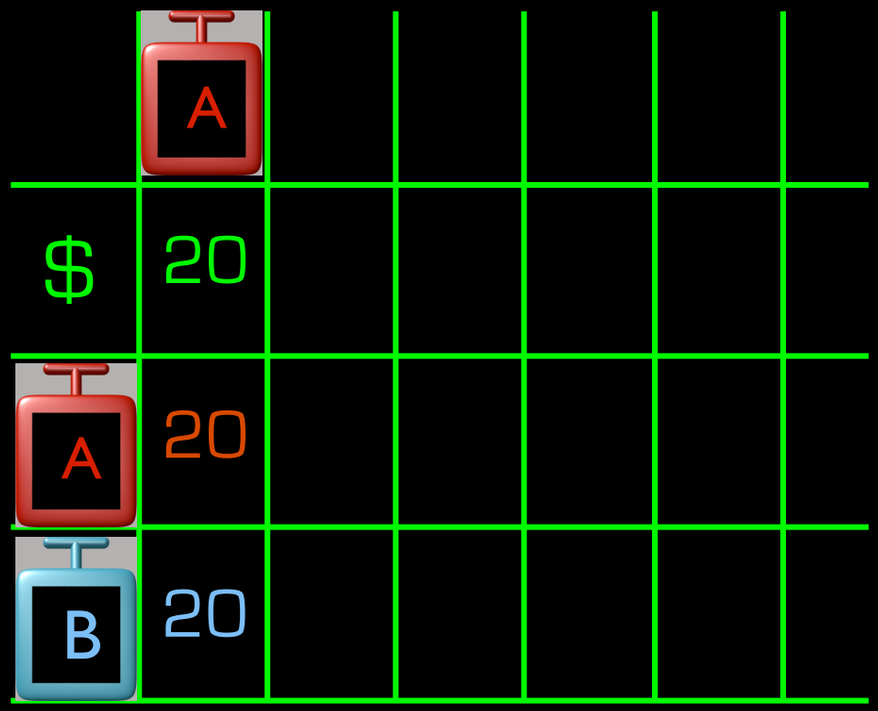

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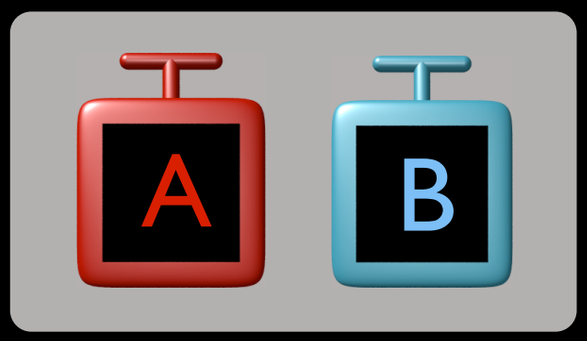

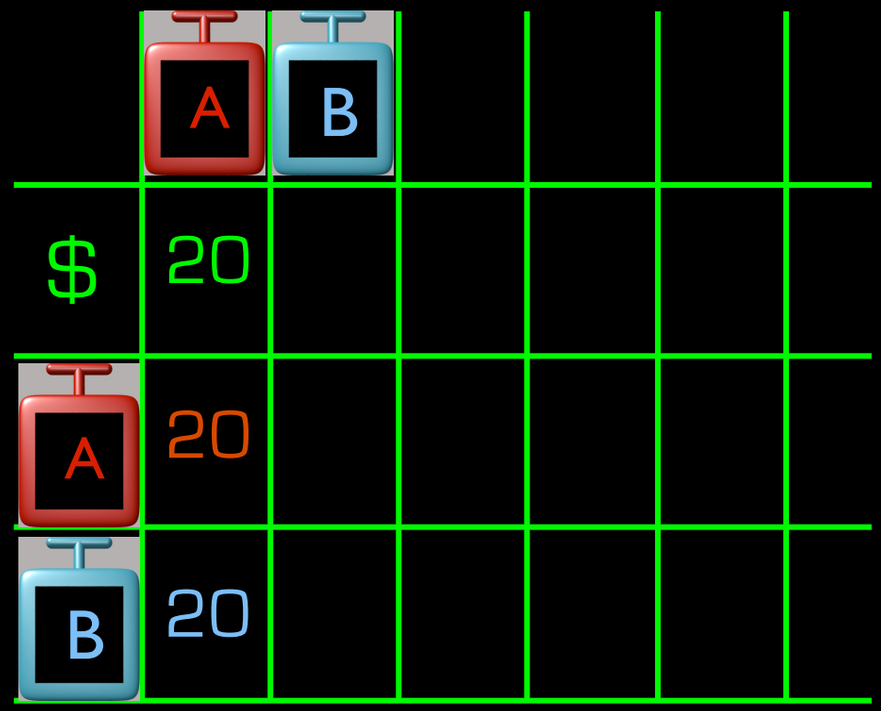

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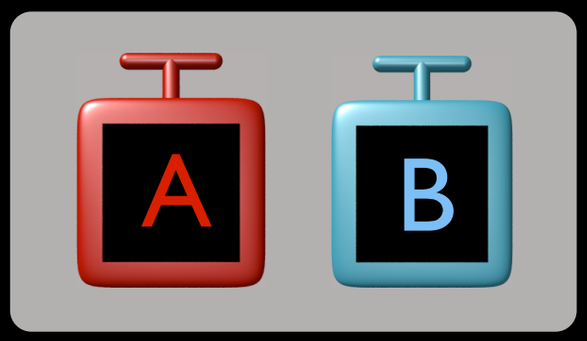

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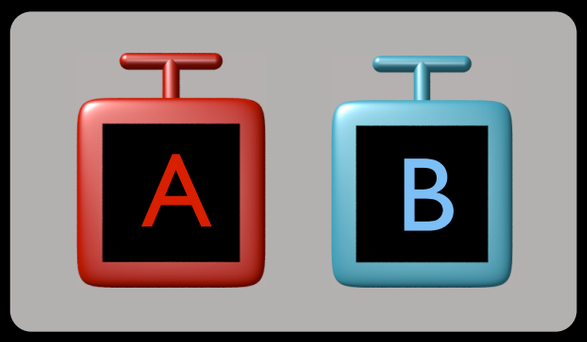

	A	B				
$	20	40				
A	20					
B	20	30				

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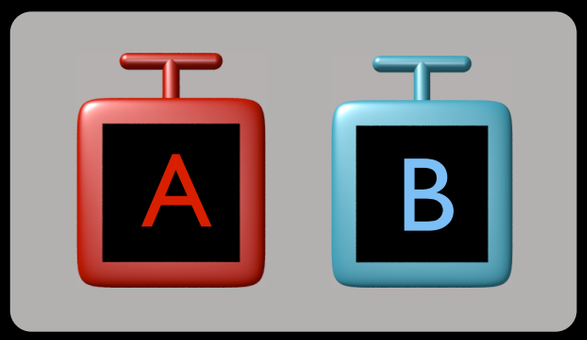

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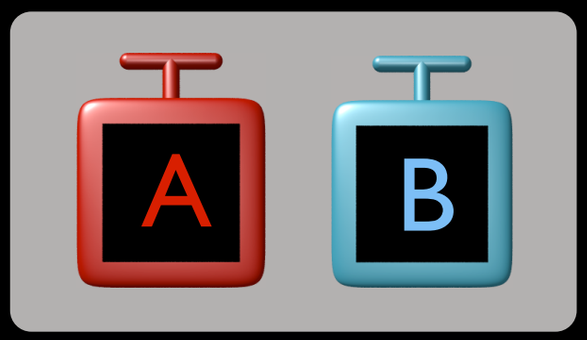

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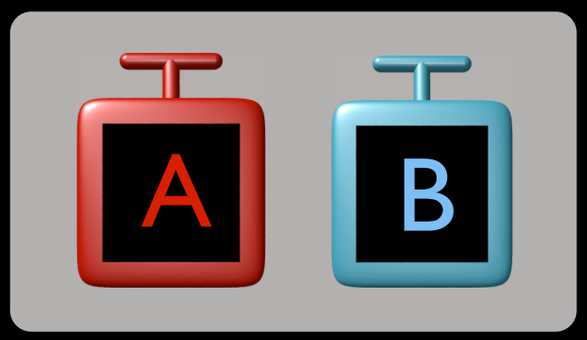

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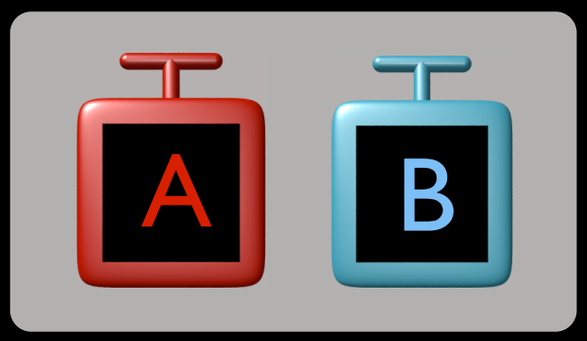

	A	B	B			
$	20	40	0			
A	20	20				
B	20	30	15			

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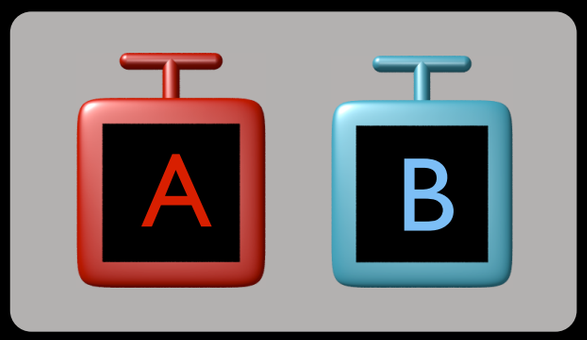

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$	20	40	0
A	20	20	20
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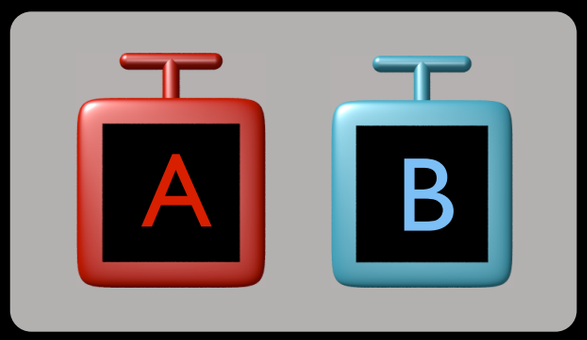

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A	20	20	20				
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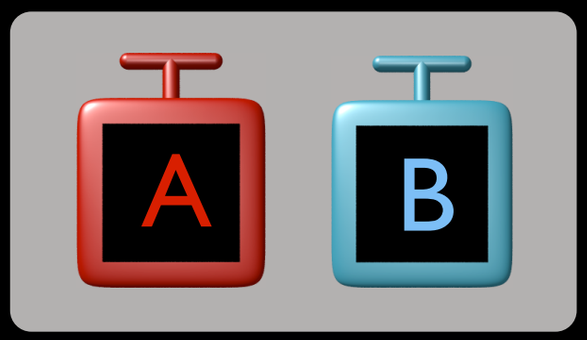

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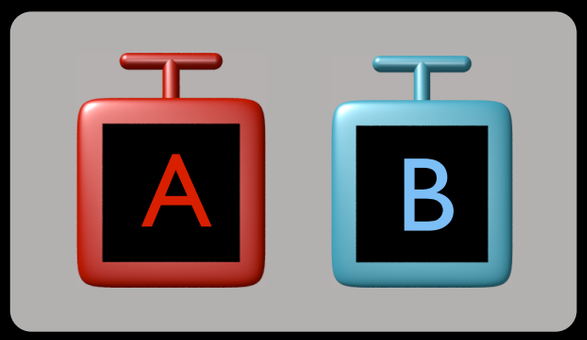

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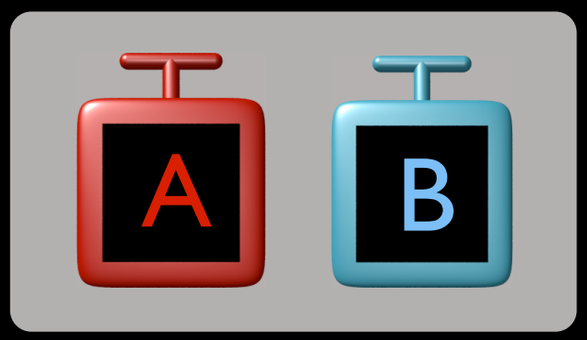

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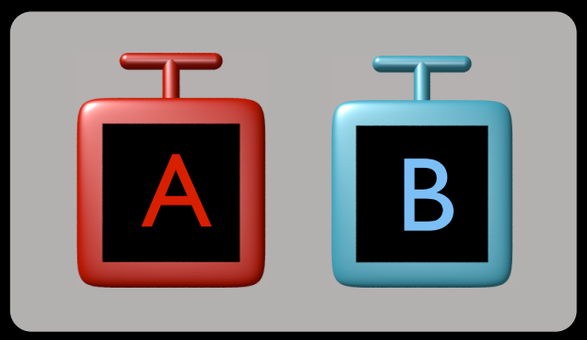

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$	20	40	0	20			
A	20	20	20	20			
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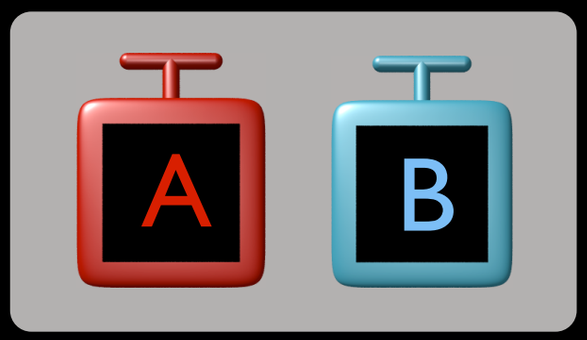

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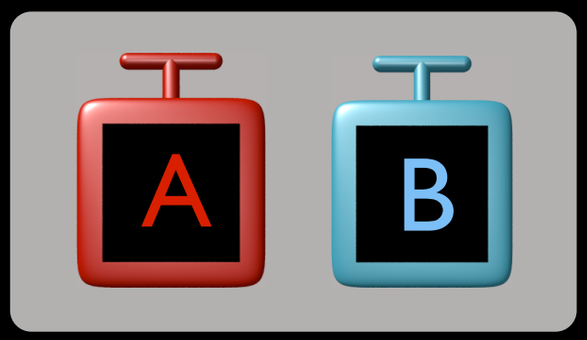

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$	20	40	0	20	20	...
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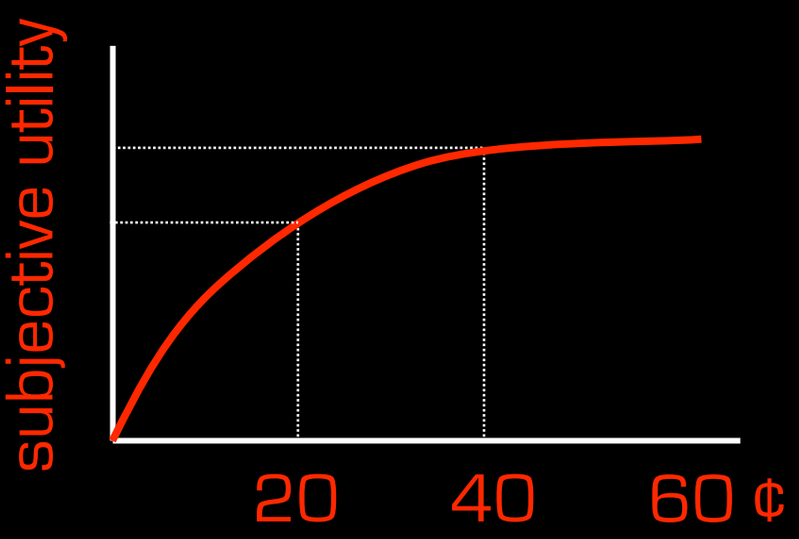

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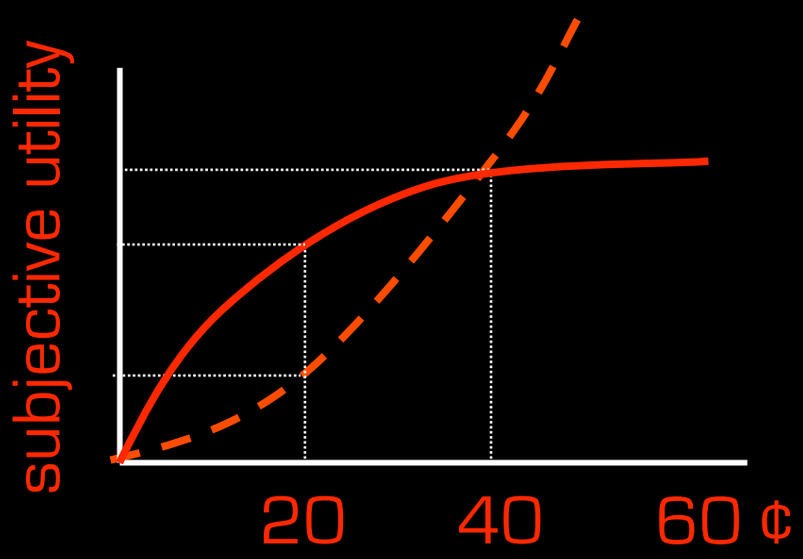

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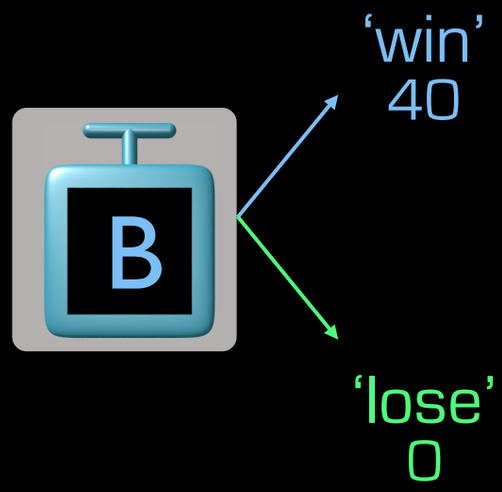

Mihatsch & Neuneier (2002)

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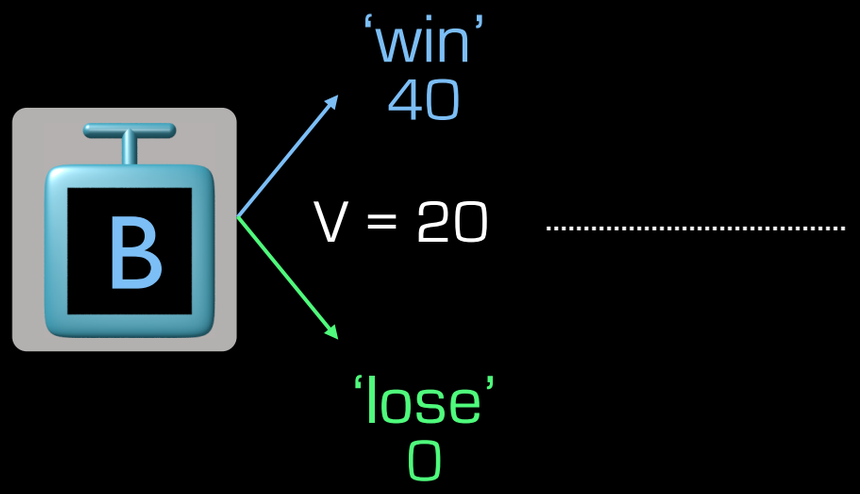

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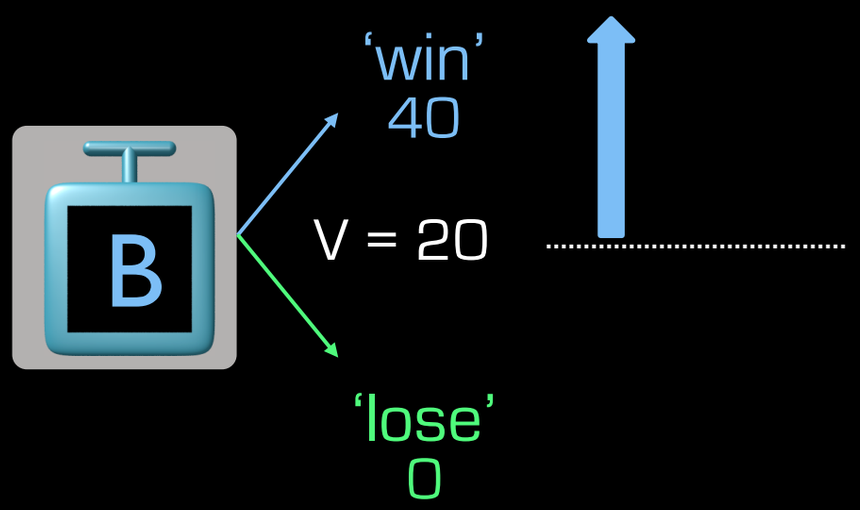

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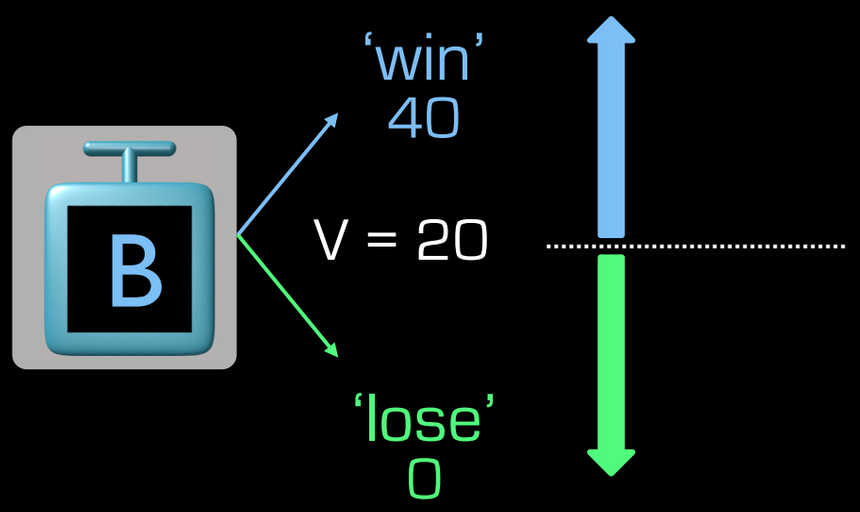

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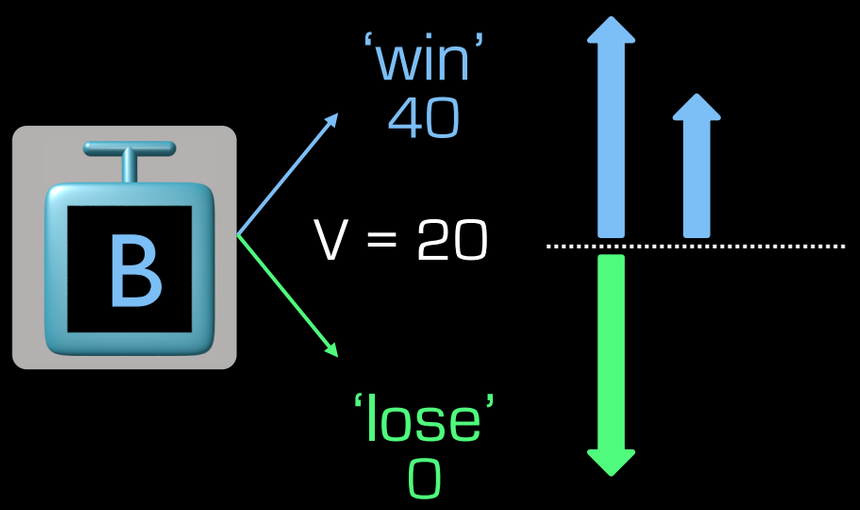

Mihatsch & Neuneier (2002)

sure 20¢ vs. risky 40¢/0¢

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different neural values

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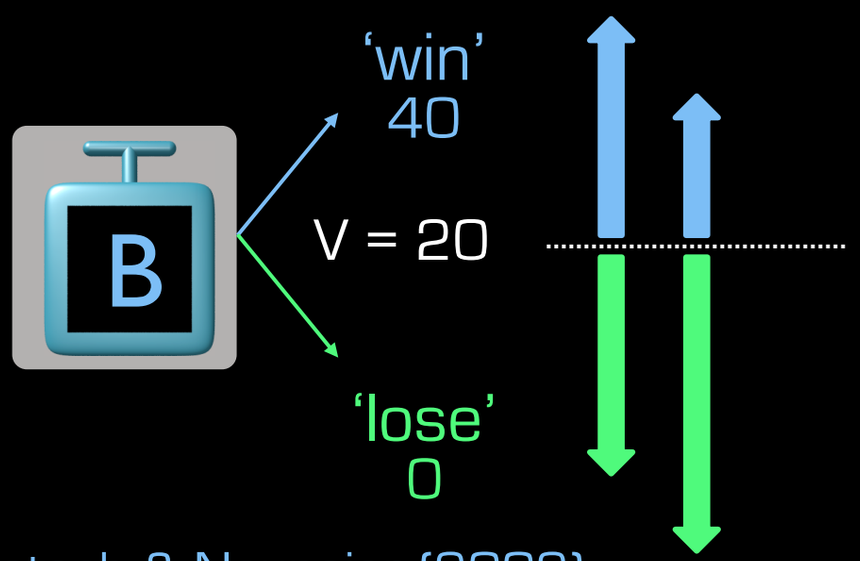

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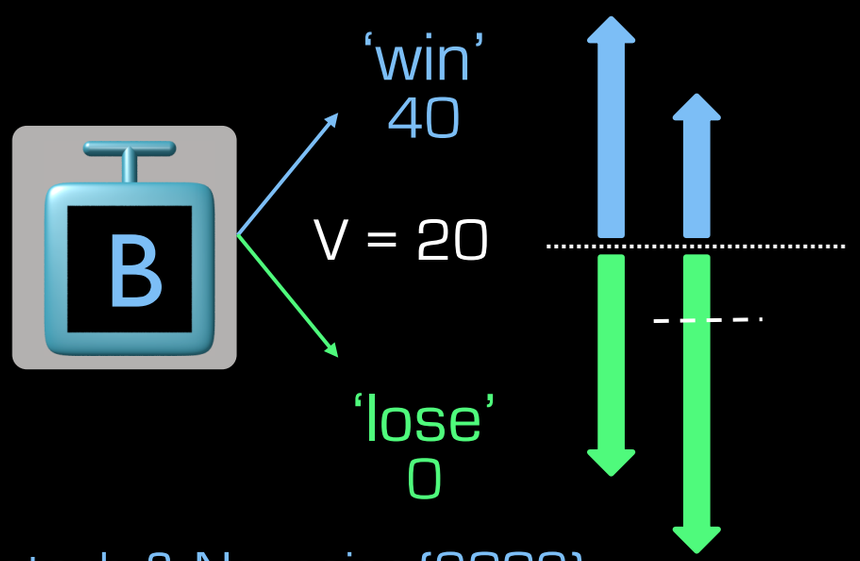

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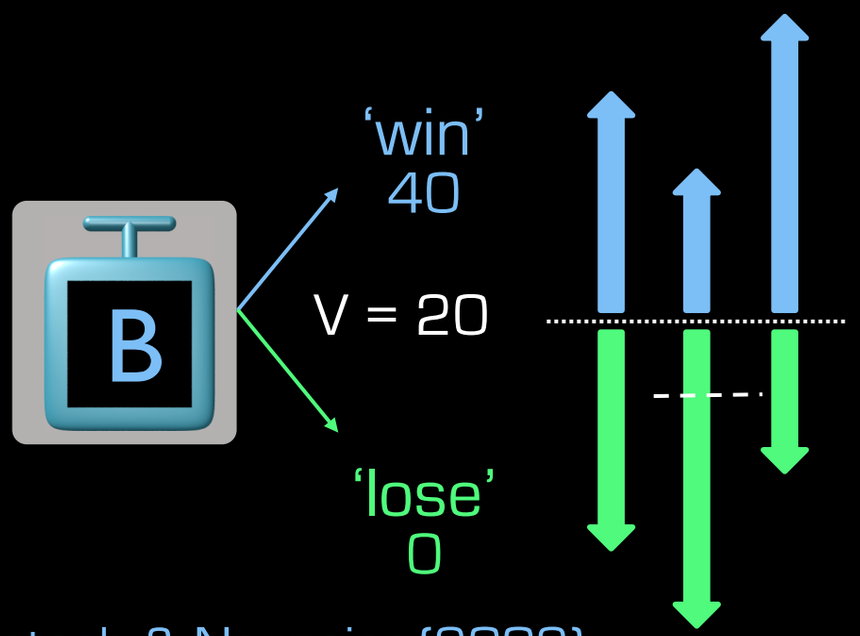

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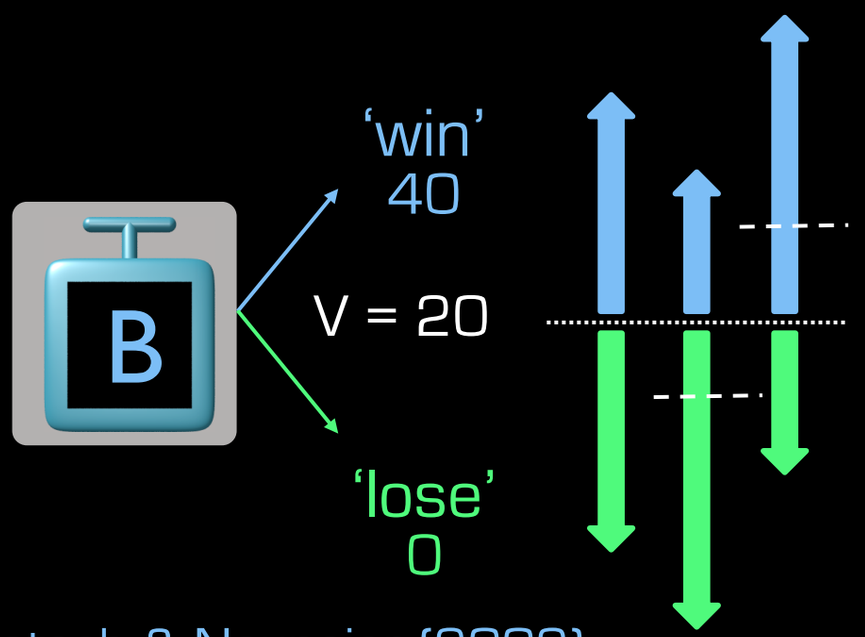

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two systems: expectation, risk

expected values + sampling biases

expected values + nonlinear utility

risk-sensitive value learning

V(20) = V(40/0)

V(20) ≠ V(40/0)

Sorry...

- This is of yet unpublished material so I hesitate to put the rest of this study online
- If you would like a copy of these slides or of the paper, feel free to email me at yael@princeton.edu

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- Can this help RL applications?

Outline

- The brain coarse-grain
- Learning and decision making in animals and humans: what does RL have to do with it?
- A success story: Dopamine and prediction errors
- Actor/Critic architecture in basal ganglia
- SARSA vs Q-learning: can the brain teach us about ML?
- Model free and model based RL in the brain
- Average reward RL & tonic dopamine
- Risk sensitivity and RL in the brain
- Open challenges and future directions

Neural RL: Open challenges

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Summary: What have we learned here?

- RL has revolutionized how we think about learning in the brain
- Theoretical, but also practical (even clinical?) implications for neuroscience
- Neuroscience continues to be a "consumer" of ML theory/algorithms
- This does not have to be a one-way street: humans solve some problems so well that it is silly not to use human learning as an inspiration for new RL methods

THANK YOU!


RED WINE MAKES THEM LIVE LONGER, BUT THEY GET TO BE A REAL PAIN.
IT HAS A TIMID NOSE WITH THE USUAL NOTES OF OAK AND VANILLA.
I CAN'T BELIEVE YOU'RE DRINKING MERLOT.

interested in reading more?
some recent reviews of neural RL

- Y Niv (2009) - Reinforcement learning in the brain - The Journal of Mathematical Psychology
- P Dayan & Y Niv (2008) - Reinforcement learning and the brain: The Good, The Bad and The Ugly - Current Opinion in Neurobiology, 18(2), 185-196
- MM Botvinick, Y Niv & A Barto (2008) - Hierarchically organized behavior and its neural foundations: A reinforcement learning perspective - Cognition (online prepublication)
- K Doya (2008) - Modulators of decision making - Nature Neuroscience 11,410-416
- MFS Rushworth & TEJ Behrens (2008) - Choice, uncertainty and value in prefrontal and cingulate cortex - Nature Neuroscience 11, 389-397
- A Johnson, MA van der Meer & AD Redish (2007) - Integrating hippocampus and striatum in decision-making - Current Opinion in Neurobiology, 17, 692-697
- JP O'Doherty, A Hampton & H Kim (2007) - Model-based fMRI and its application to reward learning and decision making - Annals of the New York Academy of Science, 1104, 35-53
- ND Daw & K Doya (2006) - The computational neurobiology of learning and reward - Current Opinion in Neurobiology, 6, 199-204