An introduction to Reinforcement Learning

19th of July 2022

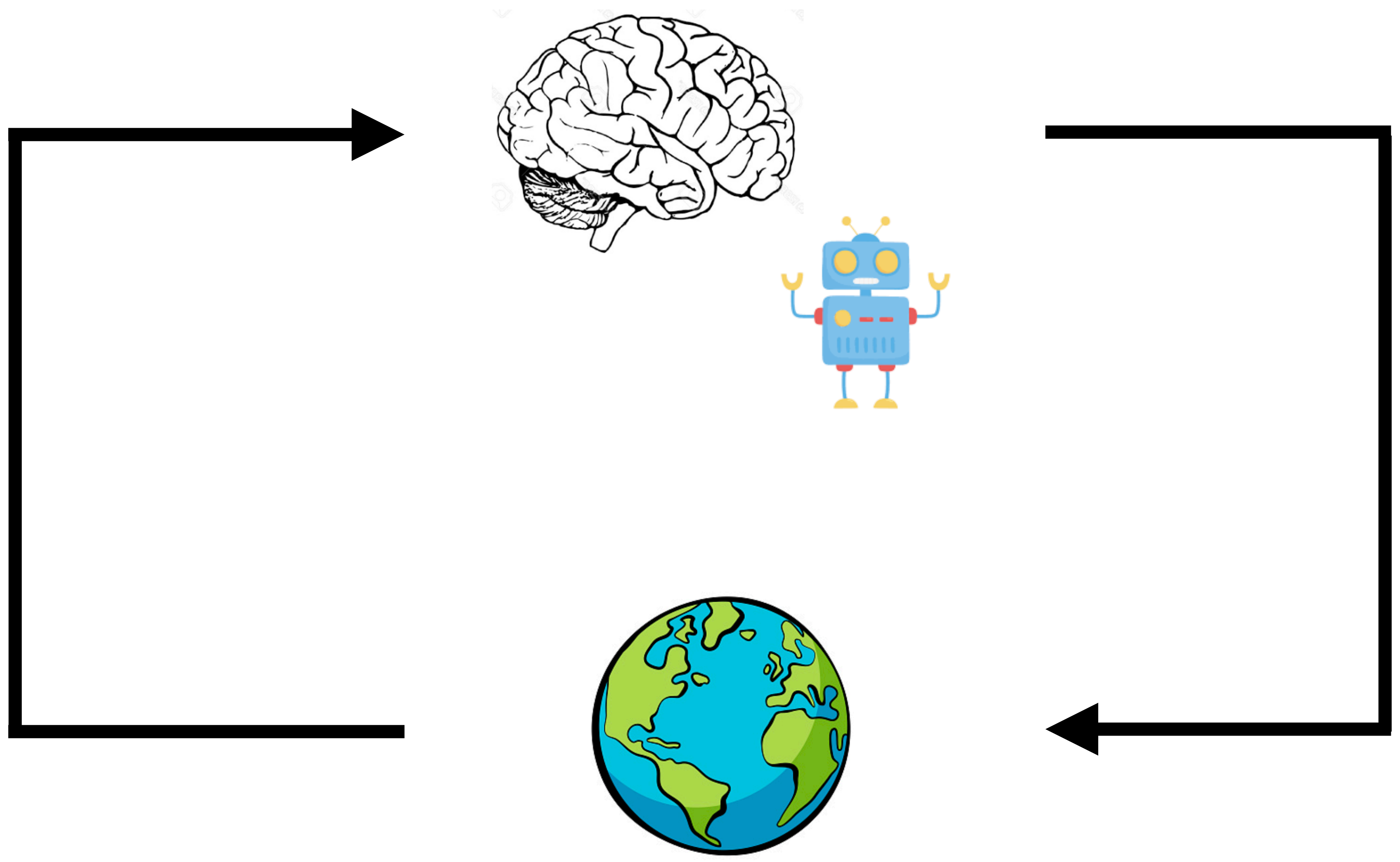
Recap: models in RL

Based on a reward signal, agents learn **values of actions/states:**

$$V_\pi(s) = \mathbb{E}_\pi[R \mid s_0 = s]$$

Action is governed by a **policy**:

$$\pi(a, s) = P(a_t = a \mid s_t = s)$$



Reward r_t

Action a_t

State s_t

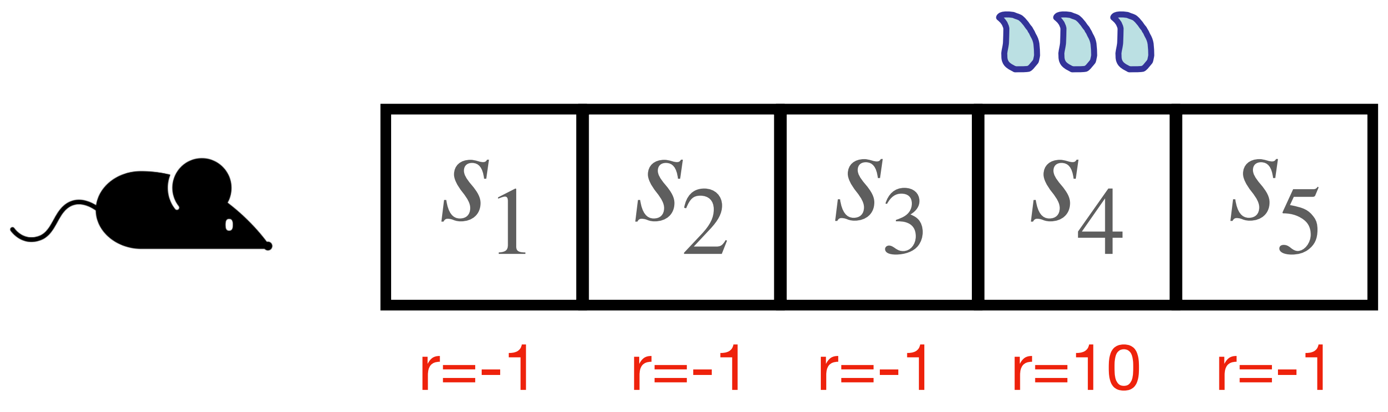
Agents can learn a **model of the environment** to make smarter decisions, e.g.:

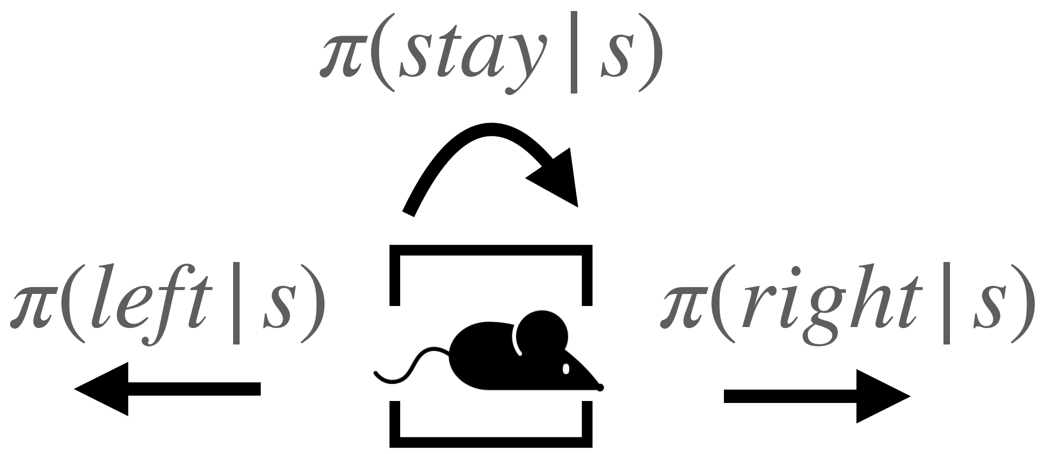
$$P(s_{t+1} = s \mid s_t = s, a_t = a)$$

Recap: models in RL

Allows to specify all environment dynamics for RL problem:

$$P(s', r \mid s, a) = P(s_{t+1} = s', r_{t+1} = r \mid s_t = s, a_t = a)$$





Recap: models in RL

$$P(s', r \mid s, a) = P(s_{t+1} = s', r_{t+1} = r \mid s_t = s, a_t = a)$$

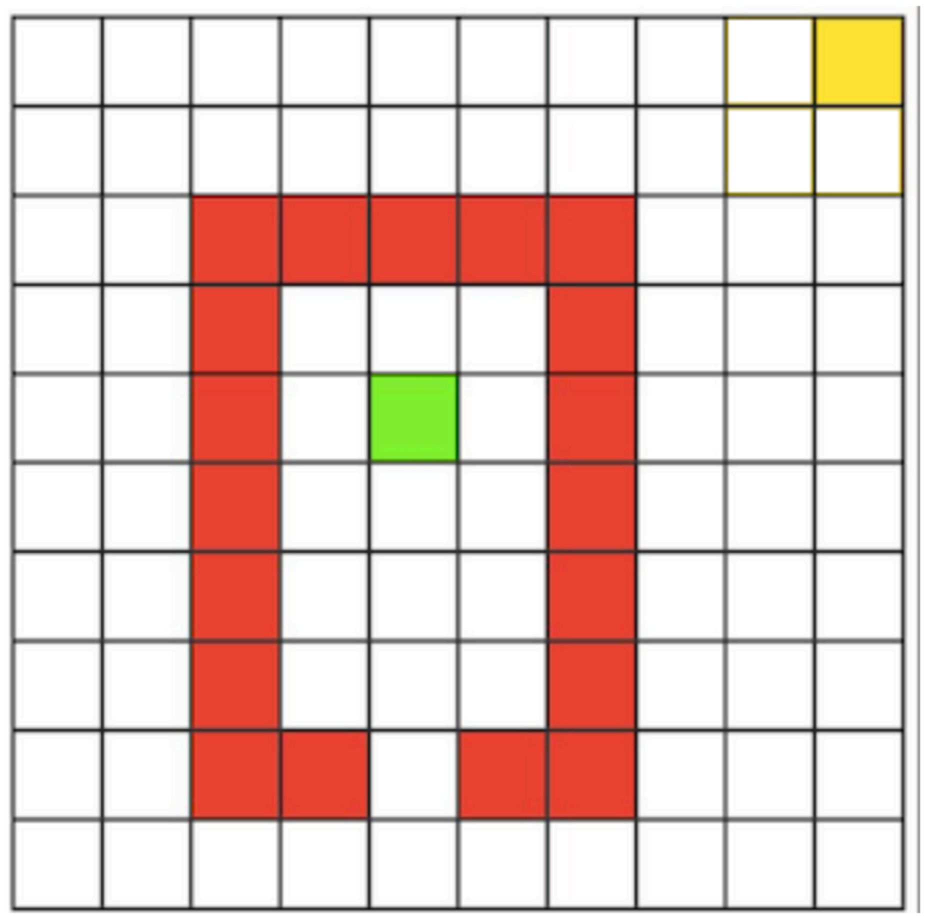
How can we make use of such models of the world?

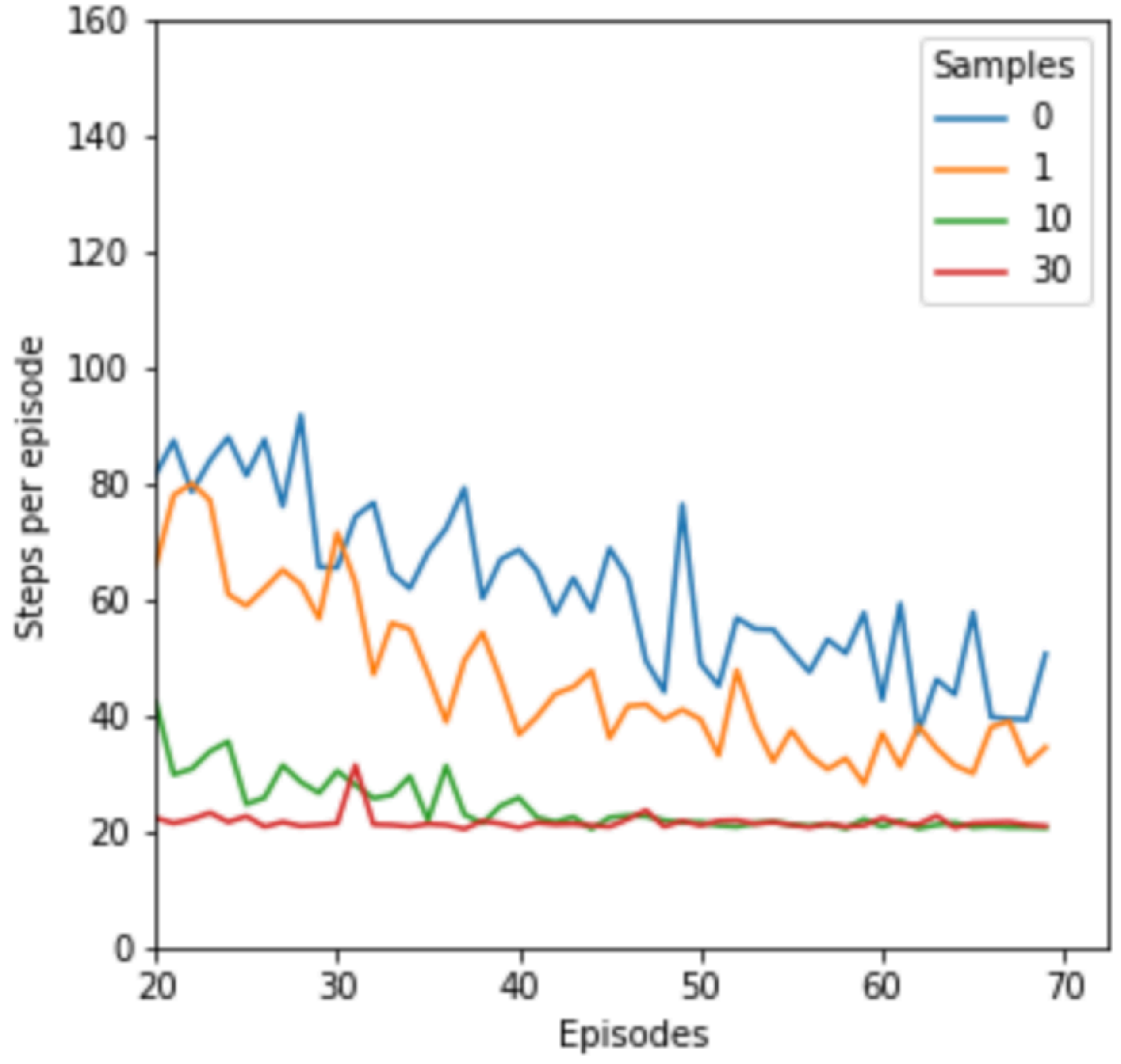
Planning and **action selection**

Learning

- Key idea: store experiences in world model $P(s', r \mid s, a)$
- Sample from this model to generate extra learning data
- This is called **DYNA-Q…**

Recap: DYNA-Q

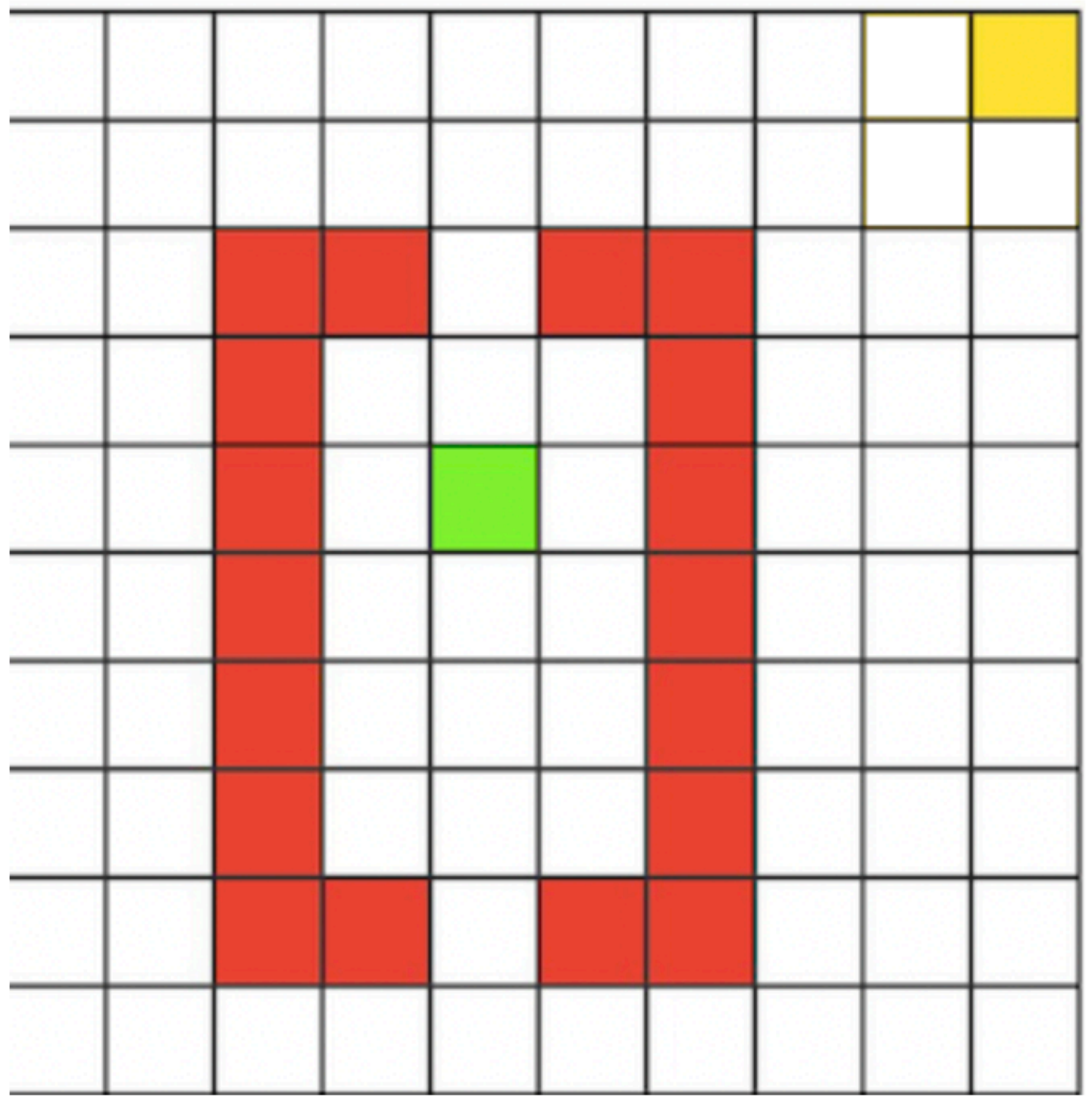


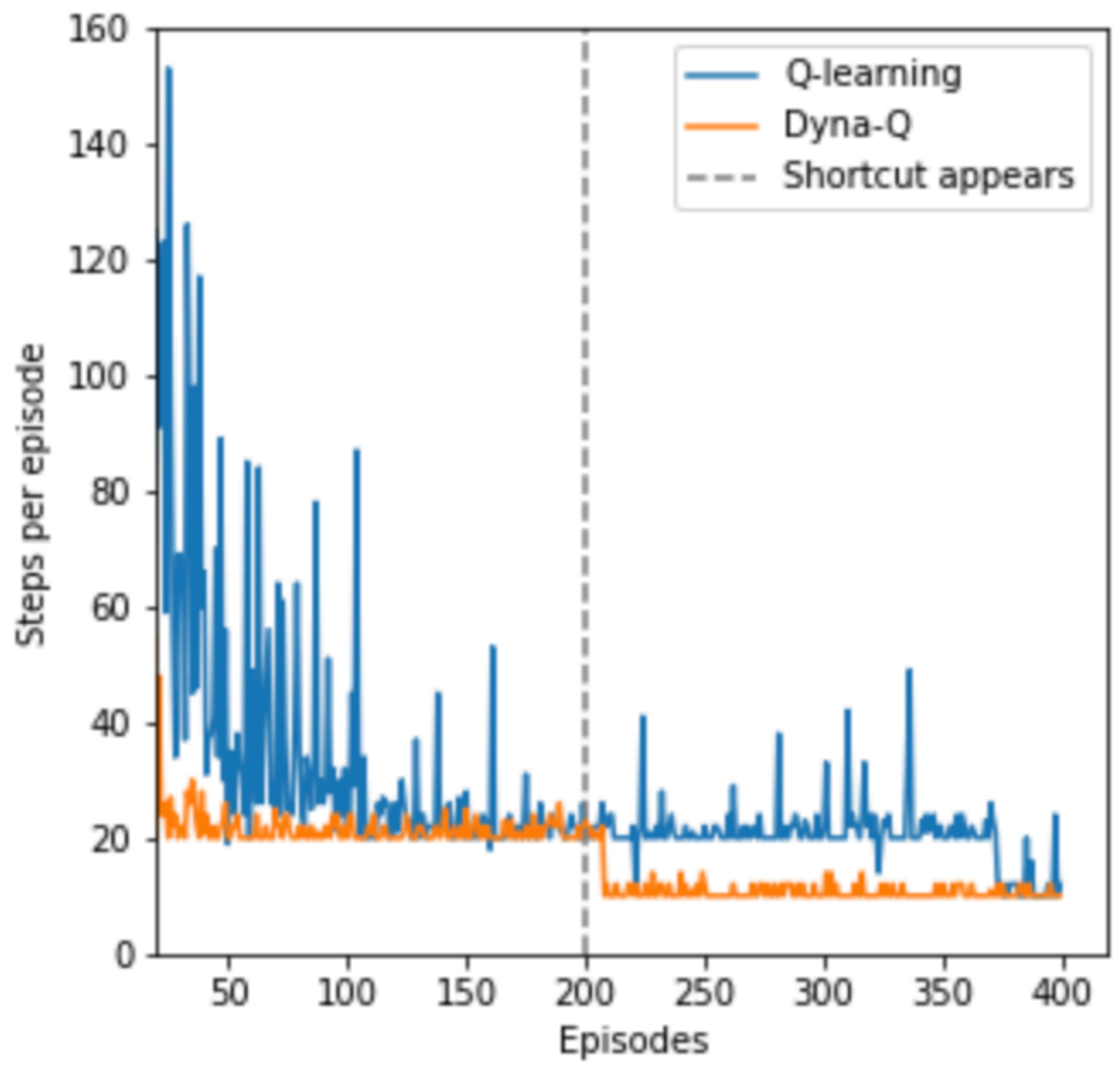


And during breaks ('offline rest'), they can sample from this experience and learn from these samples:

$S \leftarrow$ previously observed state
$A \leftarrow$ action previously taken in S
$R, S' \leftarrow Model(S, A)$
$Q(S, A) \leftarrow Q(S, A) + \alpha \left[R + \gamma \max_a Q(S', A) - Q(S, A)\right]$

Recap: DYNA-Q



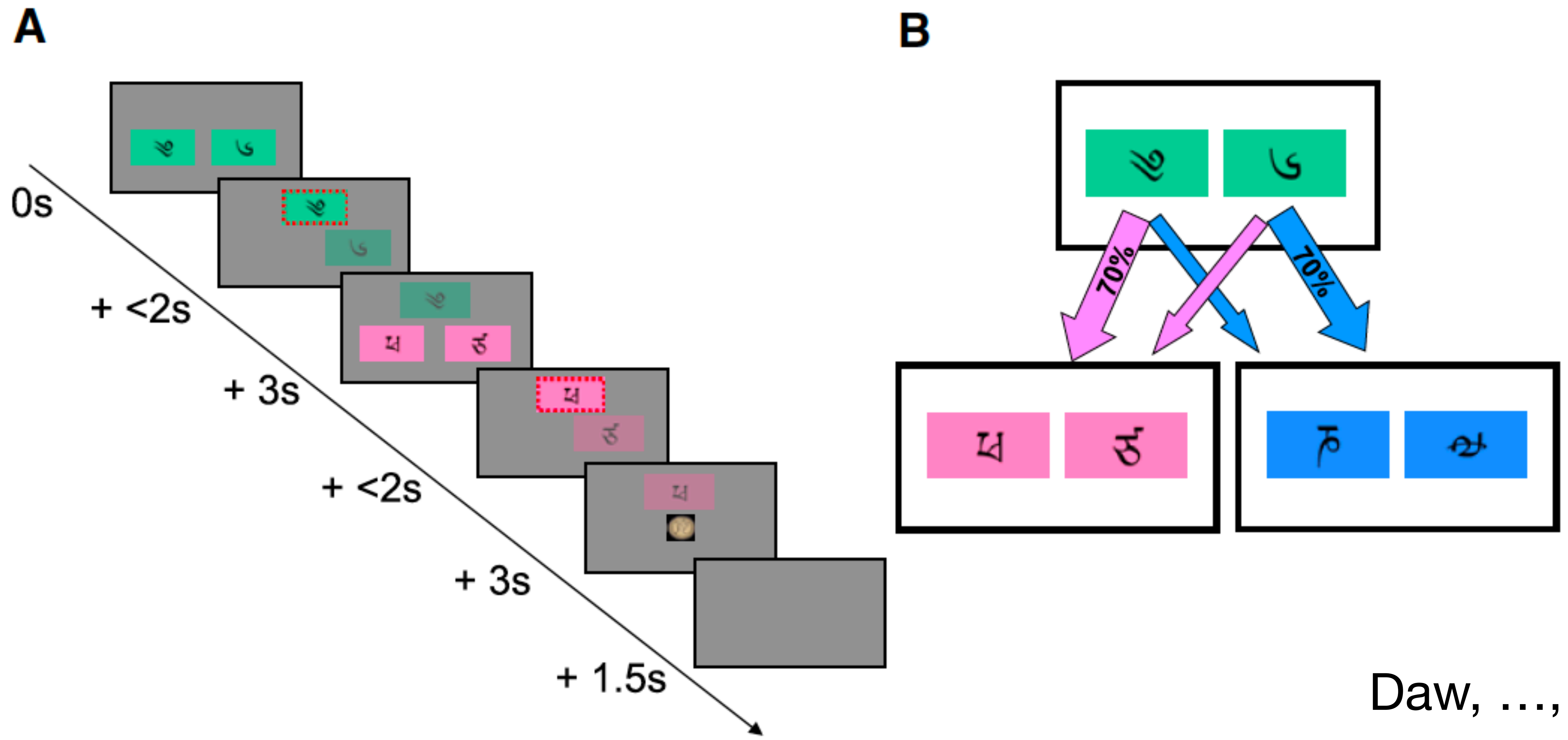


Q-learning
Dyna-Q
Shortcut appears
Steps per episode
Episodes
0
20
40
60
80
100
120
140
160
50
100
150
200
250
300
350
400

Model-free vs. Model-based control

Two-step task: one of the most iconic RL tasks

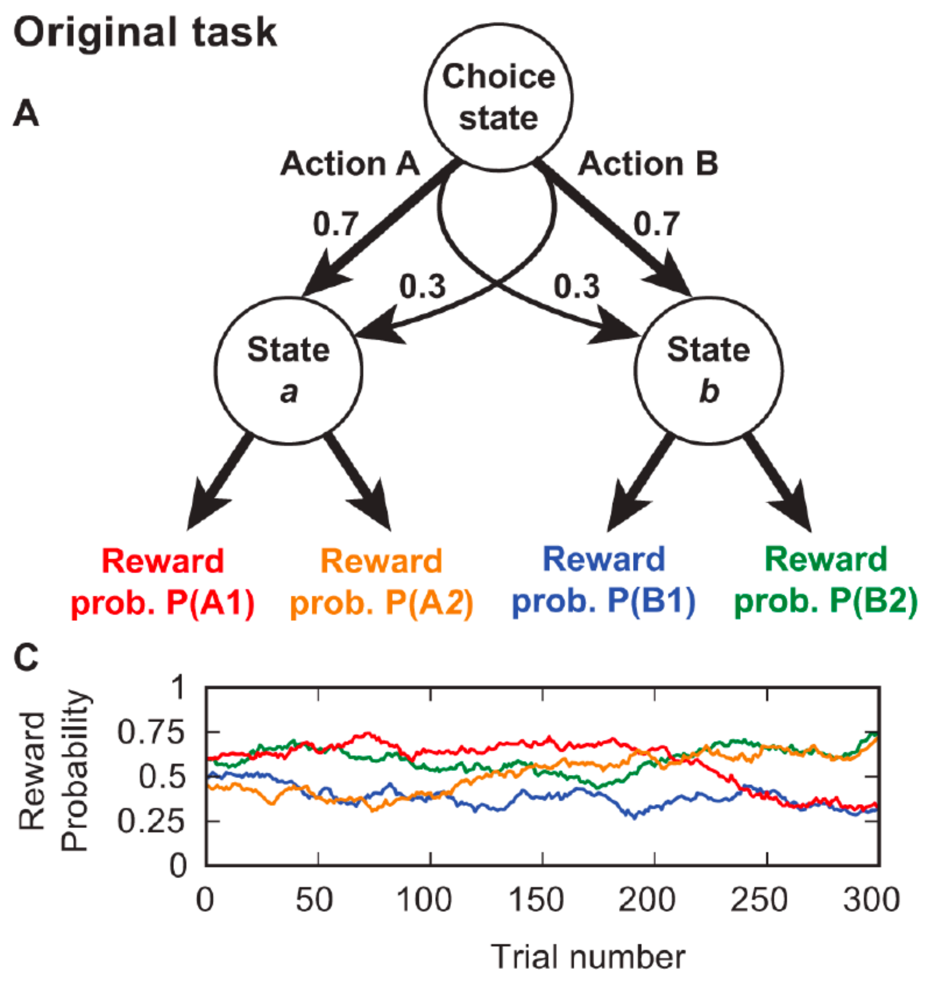
Choose twice between two options to obtain a reward



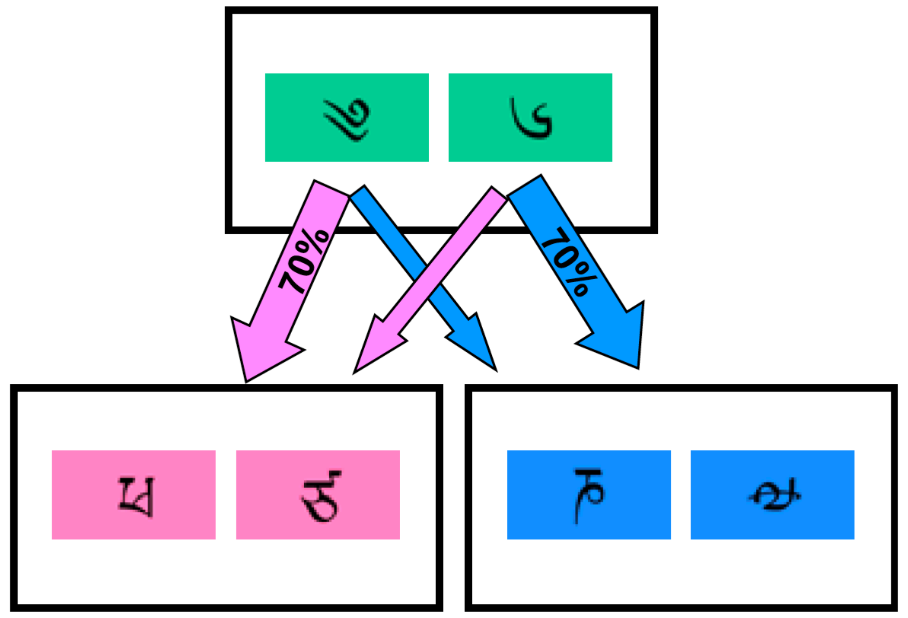
Key manipulation: **common** and **rare** transitions
- how should you update?

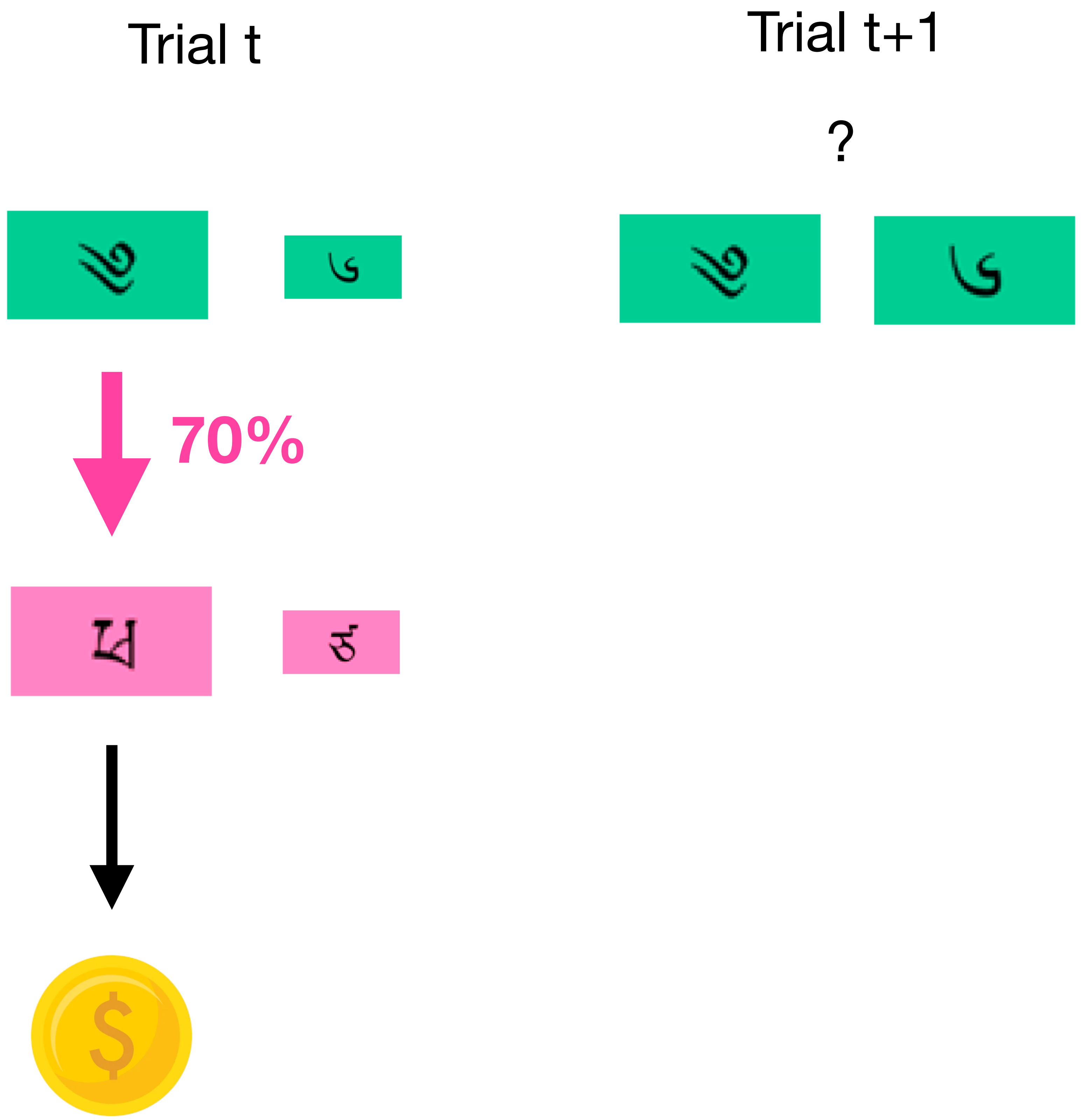
Daw, …, Dolan, Neuron, 2011

Two-step task: one of the most iconic RL tasks



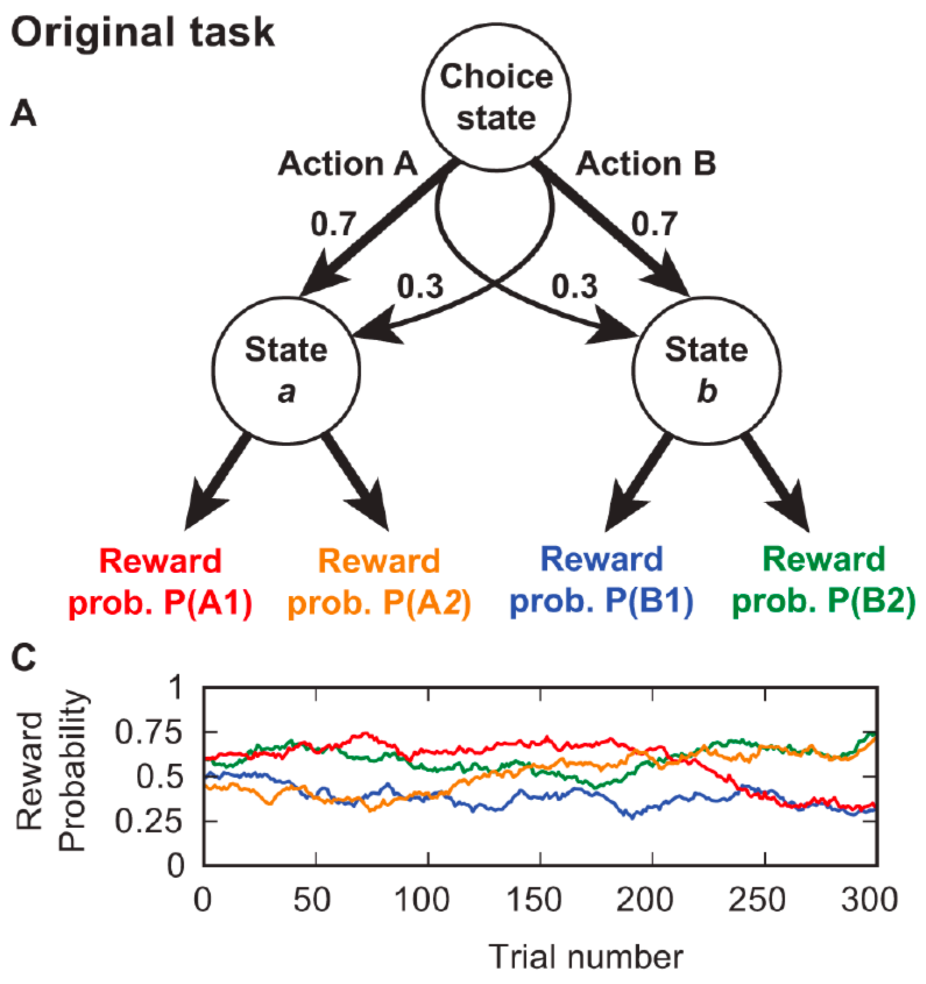
Akam, Costa, Dayan,
PLOS Computational Biology, 2015

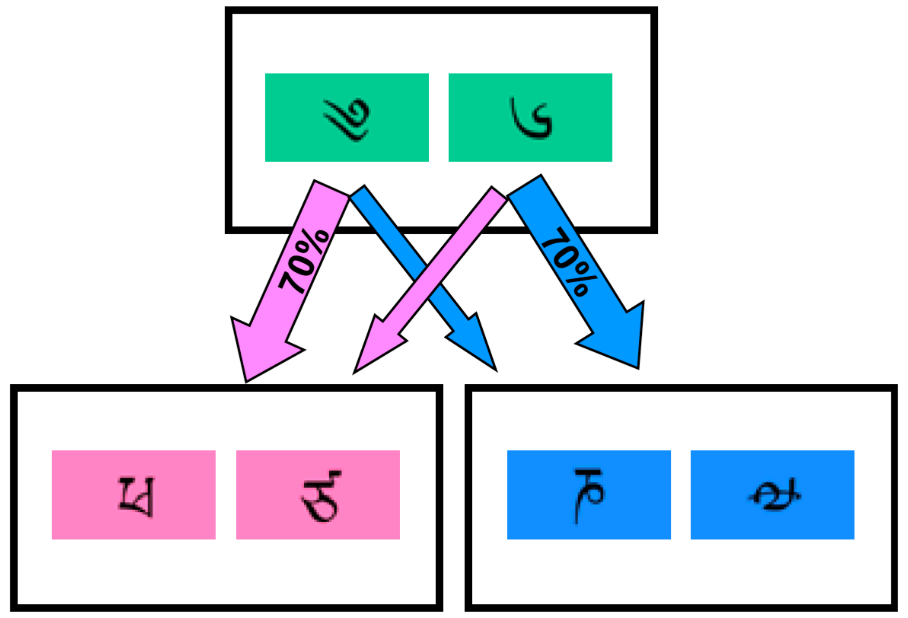




Which green option should the agent choose again at trial t+1?

Two-step task: one of the most iconic RL tasks





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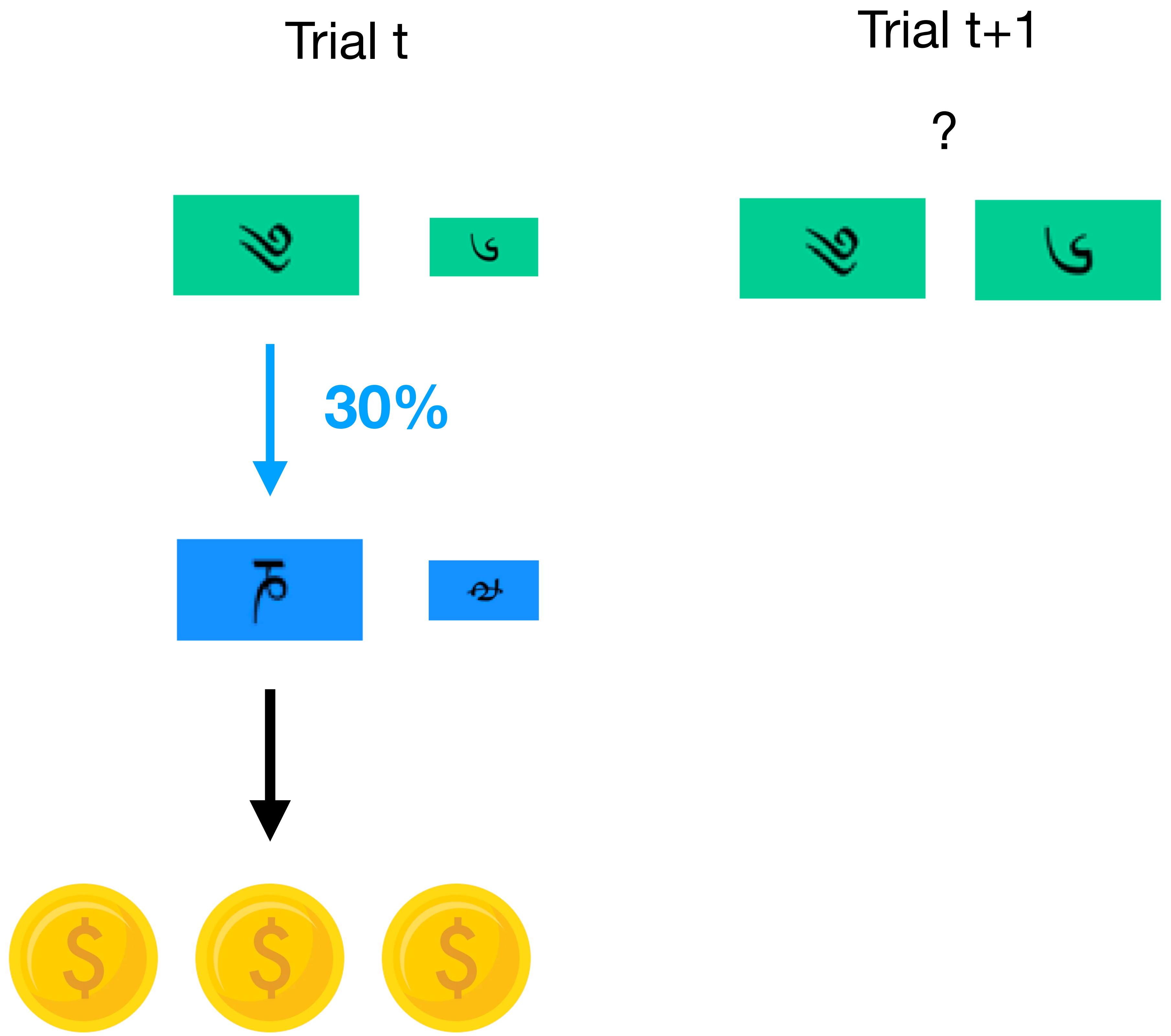

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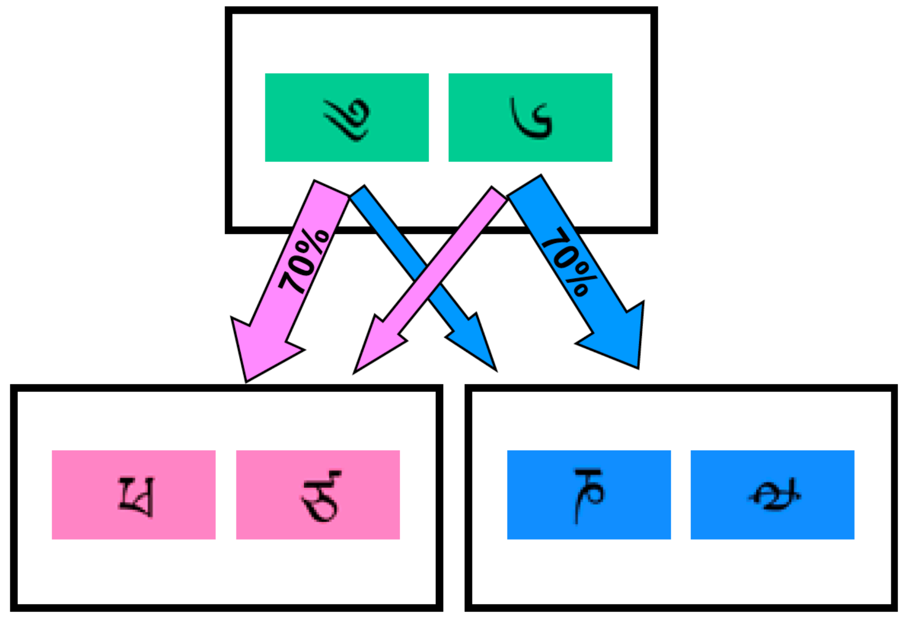
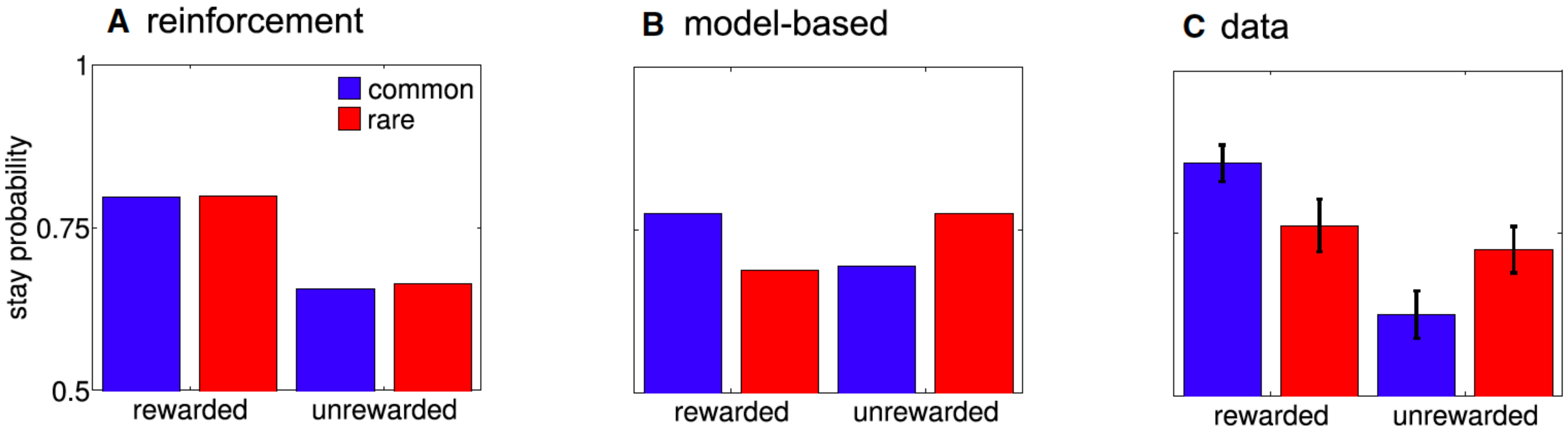
Two-step task: one of the most iconic RL tasks



Trial t+1

?



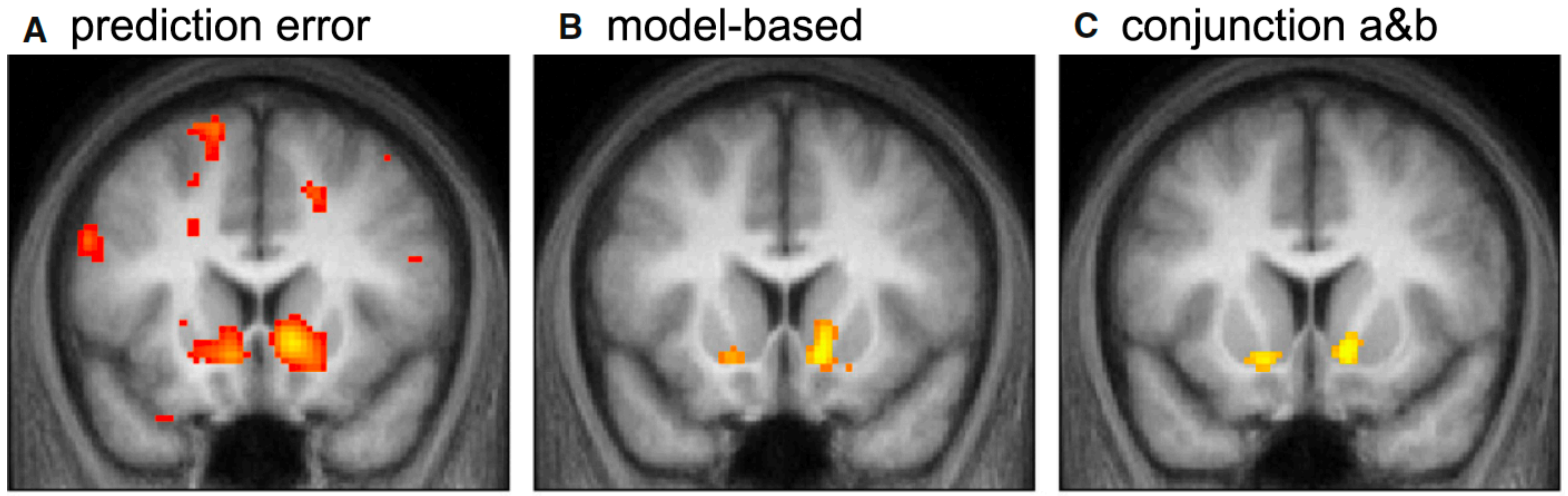
Model-free RL agent: repeat what is rewarding

Model-based RL agent: repeat what is rewarding, but be clever

Really data: a mix of both

Two-step task: one of the most iconic RL tasks

Model-free and model-based prediction errors in ventral striatum



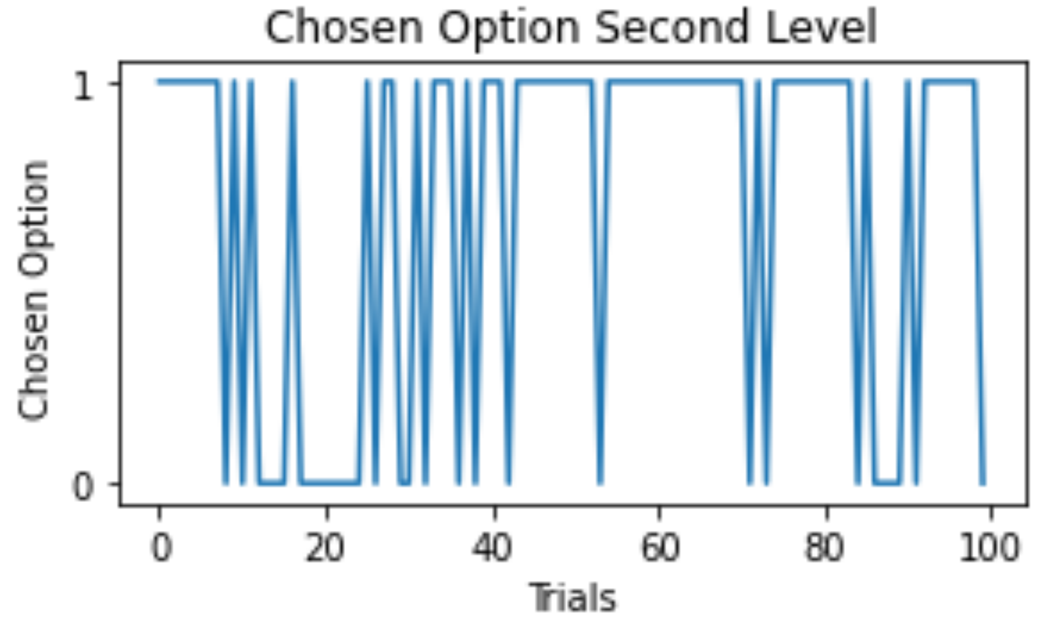
Coding: 2-Step

https://github.com/schwartenbeckph/RL-Course/tree/main/2022_07_19

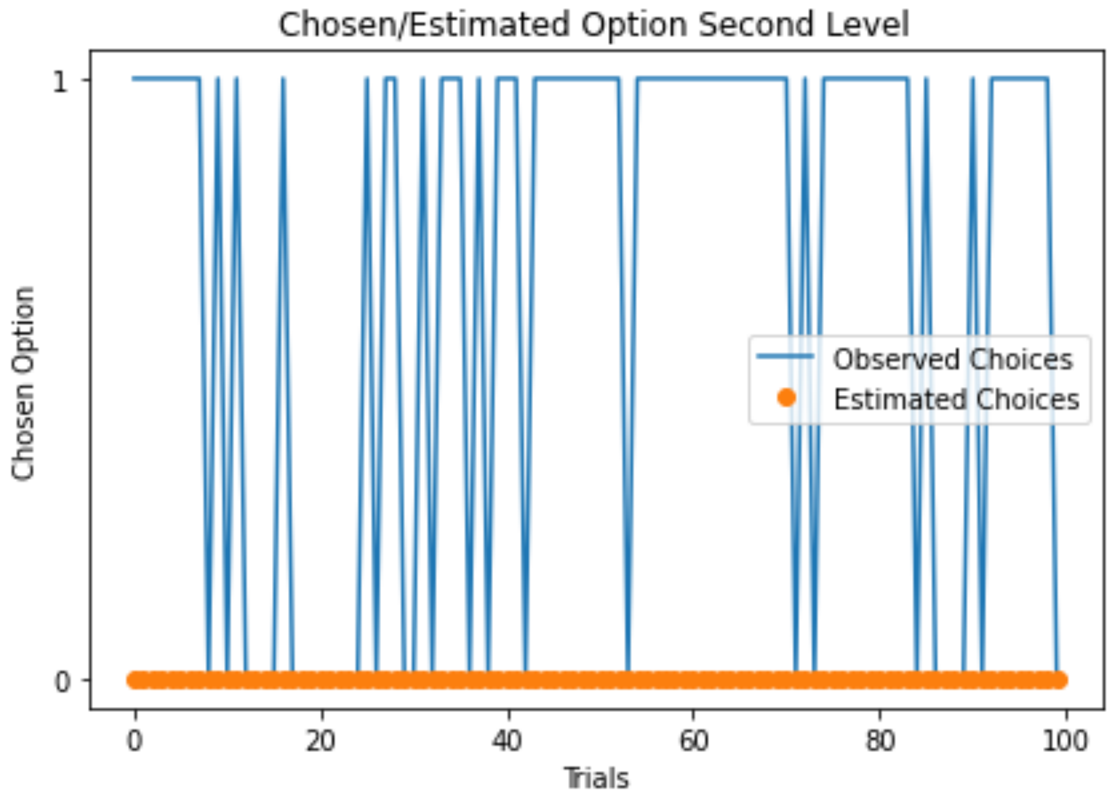
Model-fitting (a crash course)

Problem: how do we find the best parameters for a given model?

Assume your participant behaves like this:



(Here: data generated with $\alpha = 0.5$ and $\beta = 5$)



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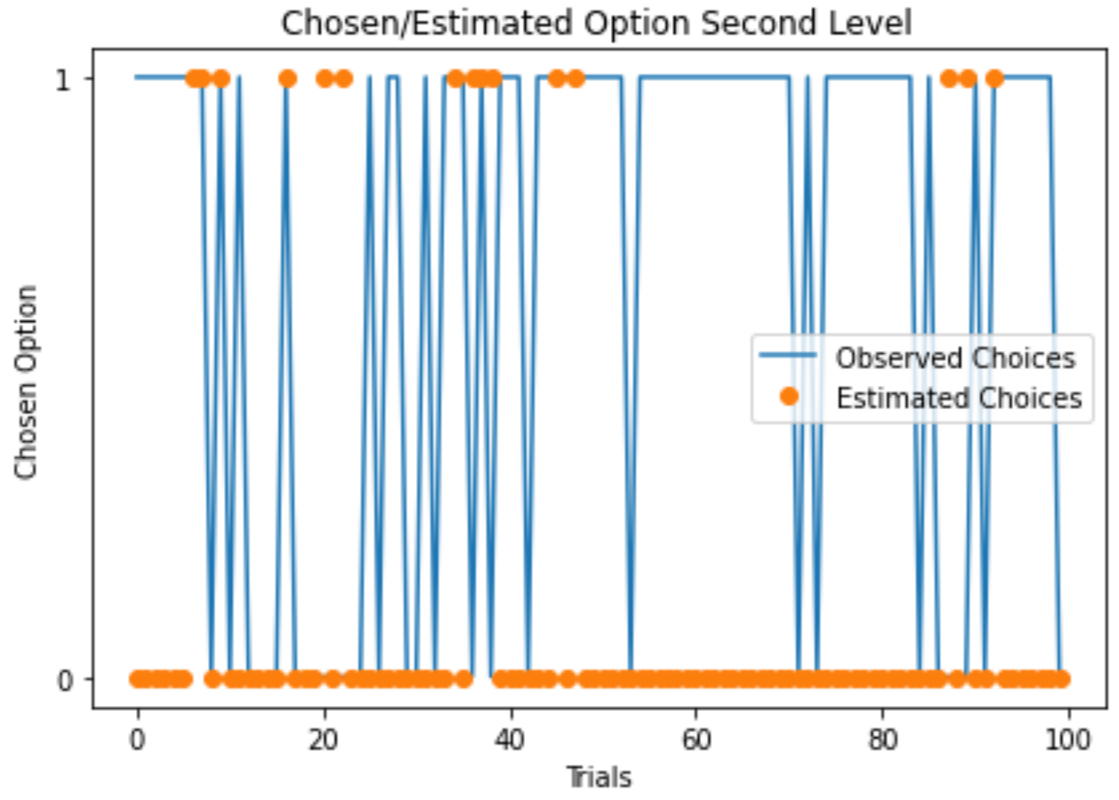
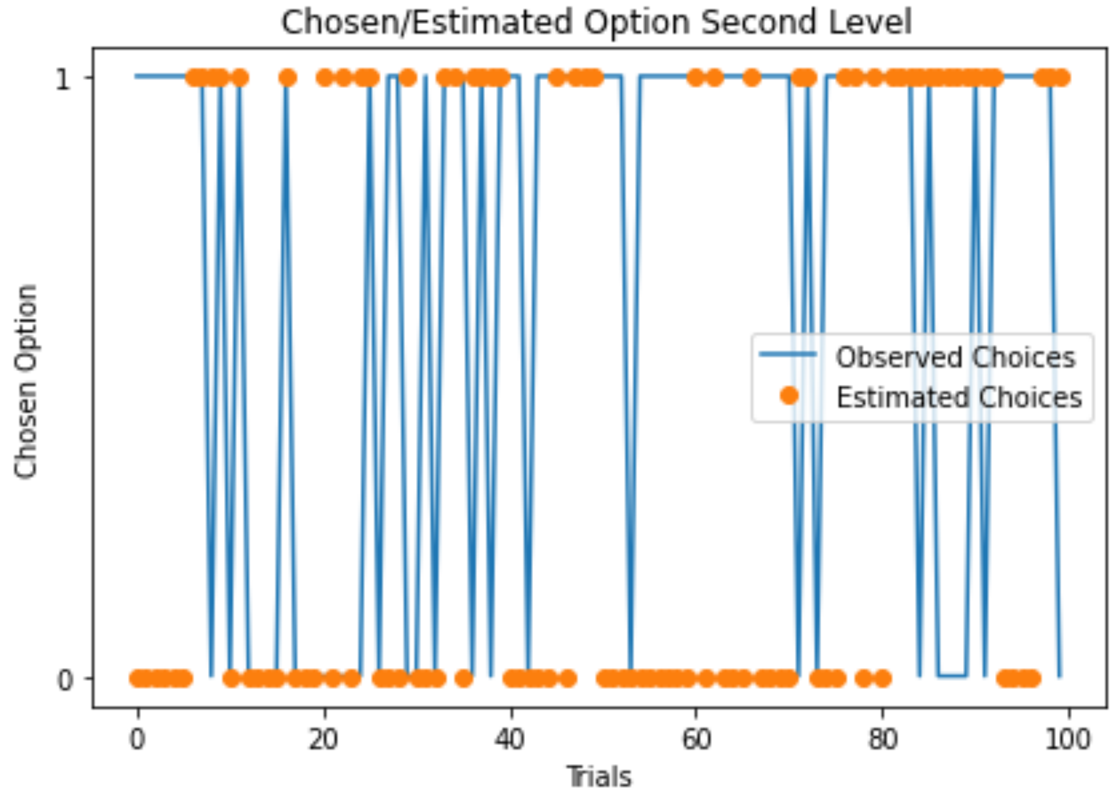
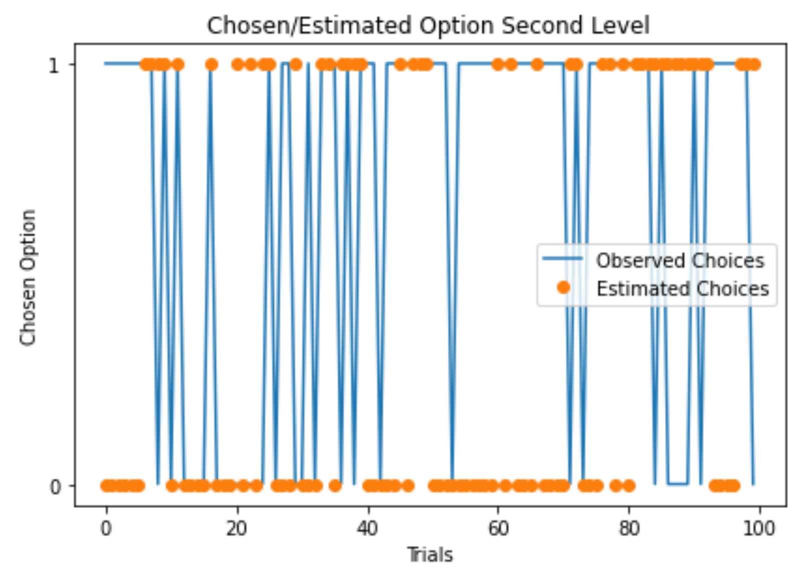


($\alpha = 1$ and $\beta = 5$)



($\alpha = 0.55$ and $\beta = 5.06$)

How will we do this?



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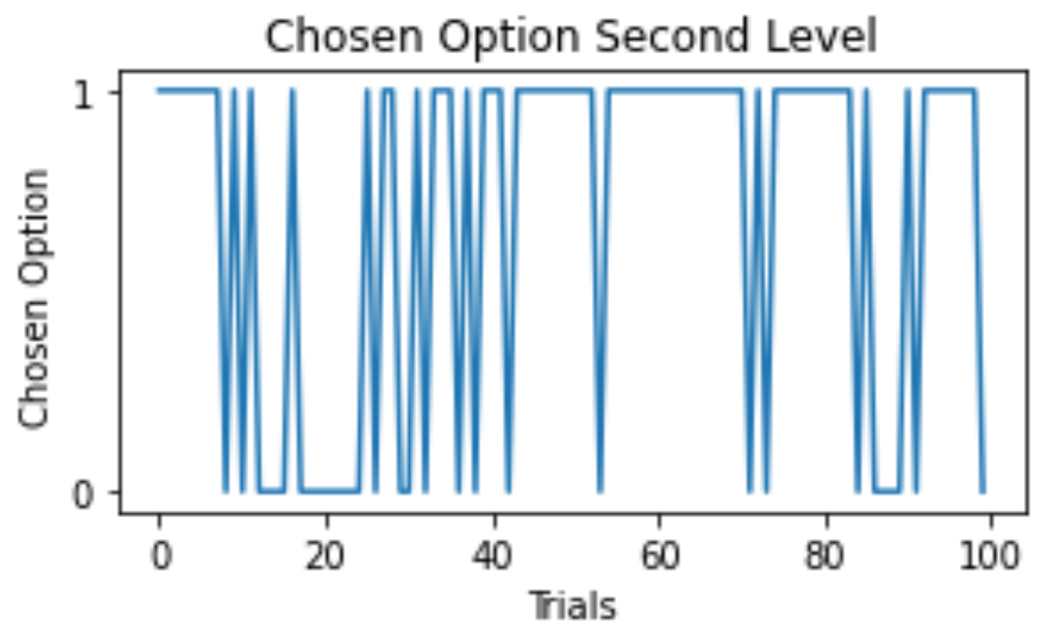


(Here: data generated with $\alpha = 0.5$ and $\beta = 5$)

Idea (grossly simplified!):

i) start with some initial params, e.g. α_1, β_1

ii) simulate behaviour using α_1, β_1

iii) assess the difference between real and simulated behaviour

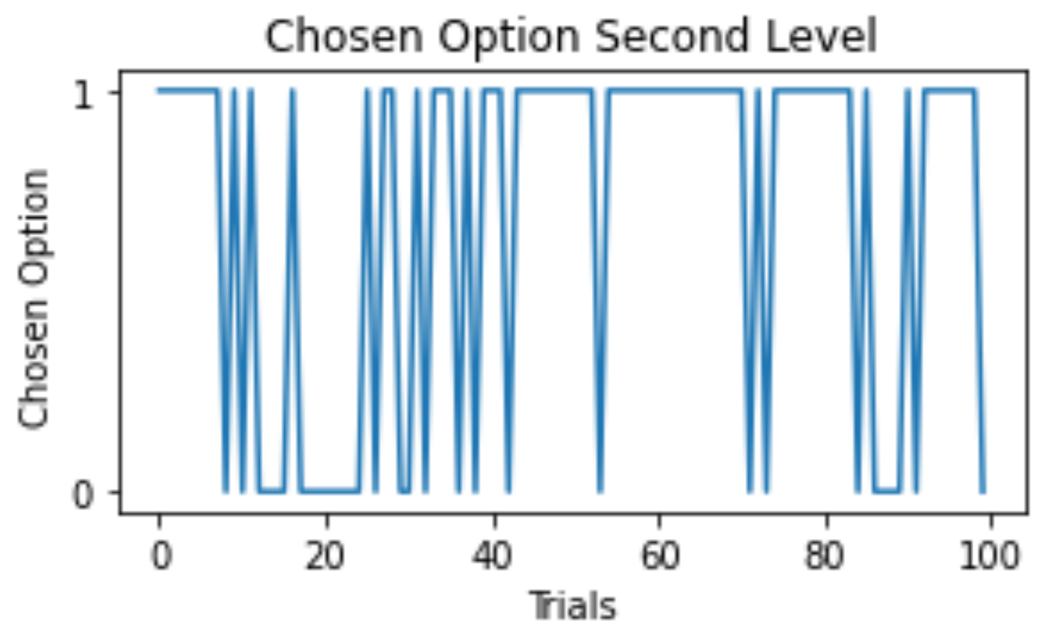
iv) Move α_1, β_1 around a bit to match real behaviour better

iv) Do this often, until you can't really improve any more

In essence: find parameters that **maximise the probability of observing** every single choice

How will we do this?

Assume your participant behaves like this:



(Here: data generated with $\alpha = 0.5$ and $\beta = 5$)

Formally (don't take too seriously!):

$$argmax_{\hat{\alpha},\hat{\beta}} P(data \mid \hat{\alpha}, \hat{\beta})$$

Often it is convenient to work in log-space:

$$argmax_{\hat{\alpha},\hat{\beta}} \sum_i logP(data_i \mid \hat{\alpha}, \hat{\beta})$$

In essence: find parameters that **maximise the probability of observing** every single choice

Coding: 2-Step

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