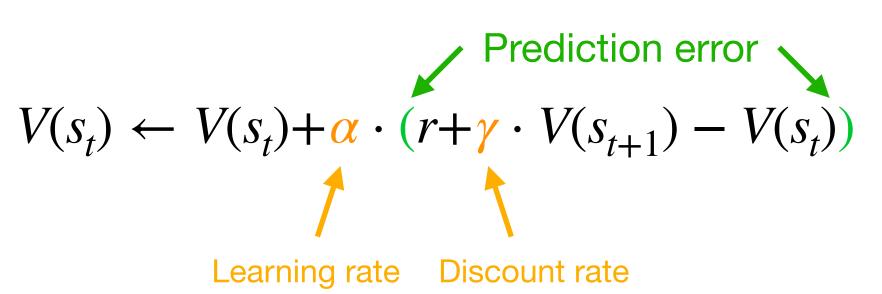
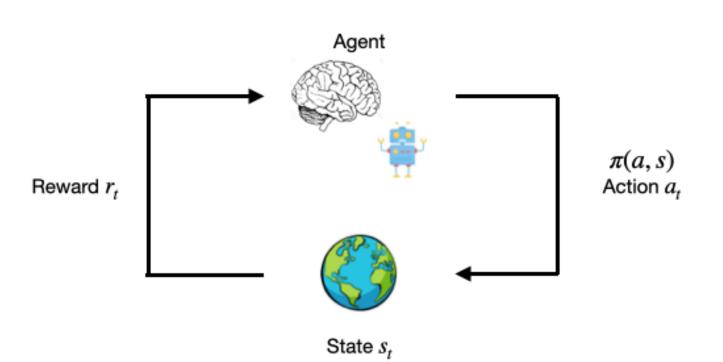
An introduction to Reinforcement Learning

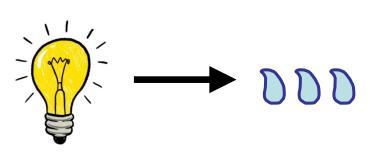
14th of June 2022

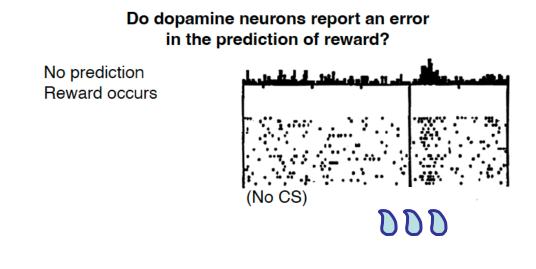
Recap: Temporal Difference Learning

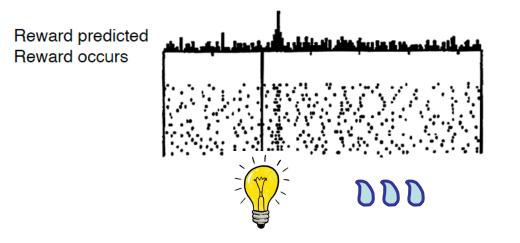
TD Learning:

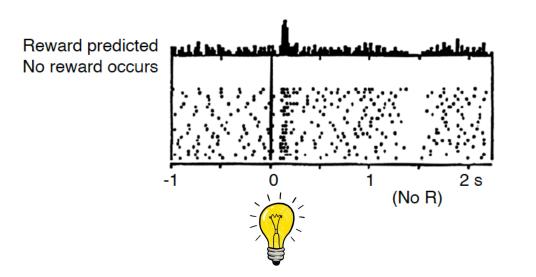


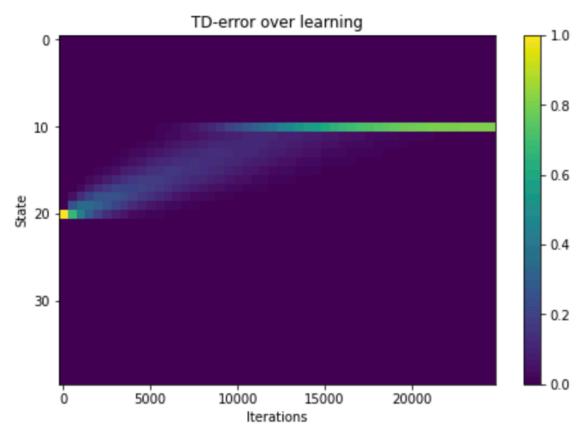


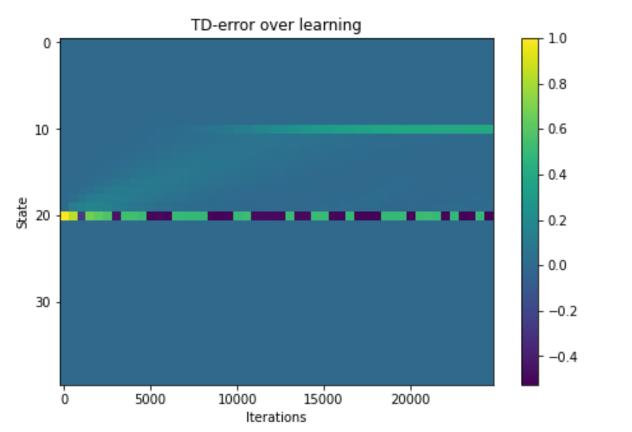












But what about actions?

Dates and topics

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14.06.2022 • Models of Action Selection, Exploration
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21.06.2022 • Combine Learning and action selection: Q-learning, SARSA

28.06.2022 • Model-based RL

05.07.2022 • Applications

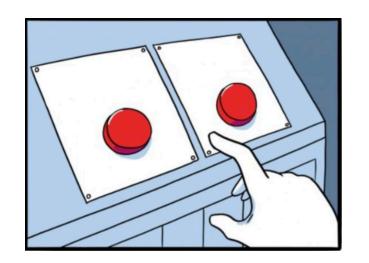
Model fitting, testing psych hypotheses

12.07.2022 • Deep RL (maybe)

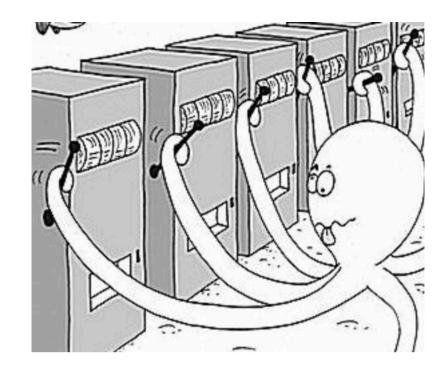
Current research (maybe)

19.07.2022

26.07.2022 • Recap and talk about essay/project ideas



Multi-armed bandits



- Problems where agents are faced with different options
 - Have to find out which of these are good or bad via trial-and-error
- Key problem: exploitation vs. exploration
 - Random vs. goal-directed exploration
- At the heart of many modern RL studies
 - Ideal testbed for different models of action selection
- Still in simplified RL setting
 - Stationary environment
 - Only consider immediate reward (for now)
 - Non-contextual
 - Tabular

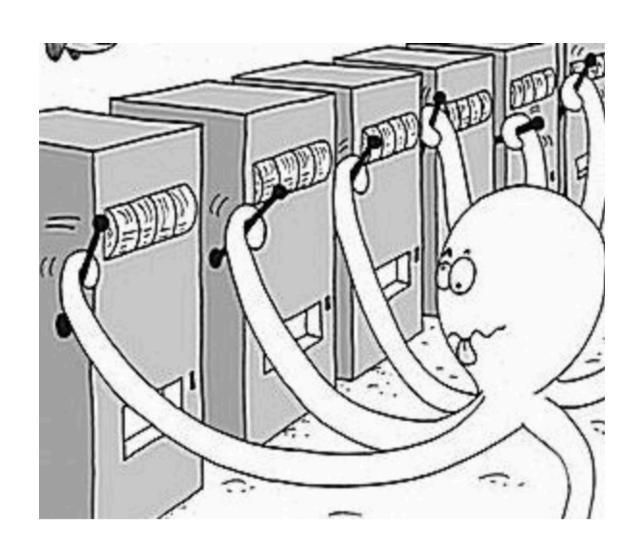
Multi-armed bandits

Greedy action selection:

$$P(a_t = a) = \begin{cases} 1 & \text{if } a_t = \operatorname{argmax}_a V_t(a) \\ 0 & \text{otherwise} \end{cases}$$

Softmax action selection:

$$P(a_t = a) = \frac{e^{V_t(a) \cdot \beta}}{\sum_{i=1}^{N} e^{V_t(a_i) \cdot \beta}}$$



Action is governed by a **policy**:

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

Epsilon-greedy action selection:

$$P(a_t = a) = \begin{cases} 1 - \epsilon & \text{if } a_t = \operatorname{argmax}_a V_t(a) \\ \epsilon / N & \text{otherwise} \end{cases}$$

Upper-confidence-bound

(UCB) action selection:

$$P(a_t = a) = \operatorname{argmax}_a [V_t(a) + c \cdot \sqrt{\frac{\ln t}{N_t(a)}}]$$

Coding: Multi-Armed Bandits

https://github.com/schwartenbeckph/RL-Course/tree/main/2022_06_14