An introduction to Reinforcement Learning

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What is reinforcement learning (RL)?

Also, why are slides in English?

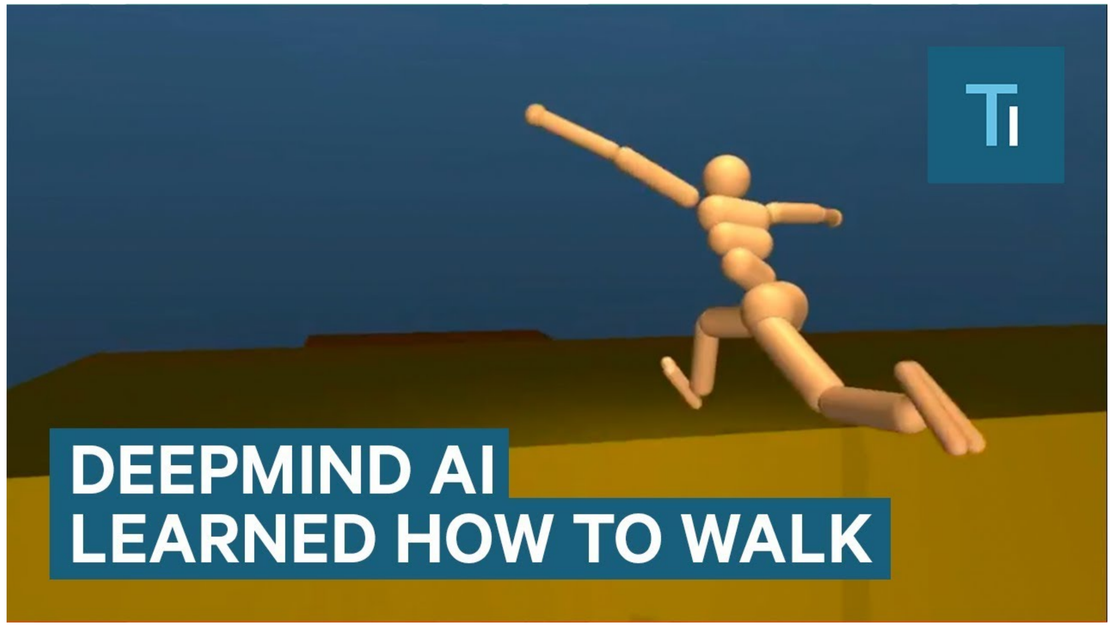
- RL is a **computational approach** to learning from **interactions** with the **environment**
  - Trial-and-error
  - Delayed reward
- Considers whole problem of **goal-directed** agent interacting with an **uncertain** environment
- RL agents
  - Have explicit goals
  - Sense aspects of their environments
  - Choose actions to influence their environments
- Very general

What is reinforcement learning (RL)?

A few hours (+a bit of evolution) after birth:

What is reinforcement learning (RL)?

This process is perhaps not too different from AI learning to walk:

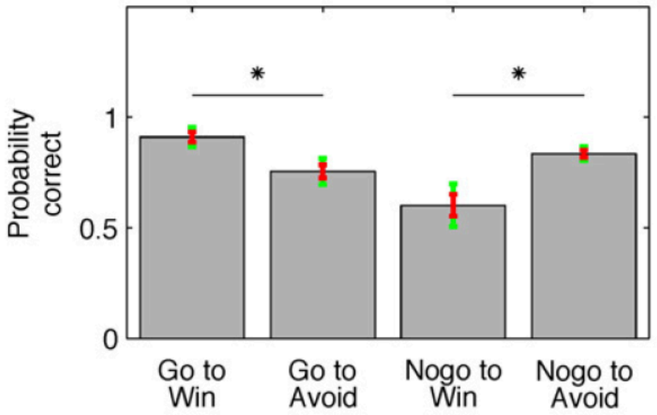


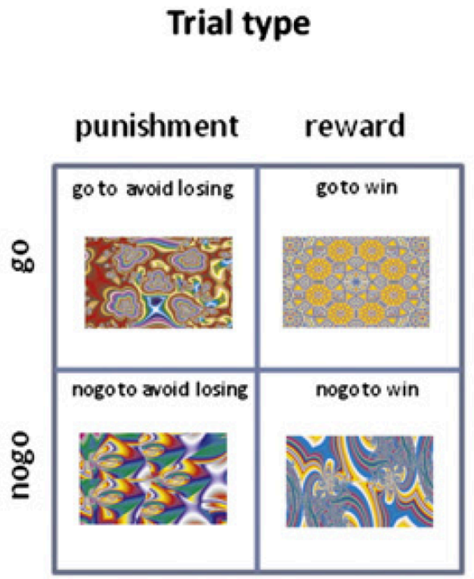
What is reinforcement learning (RL)?

Learn useful actions:

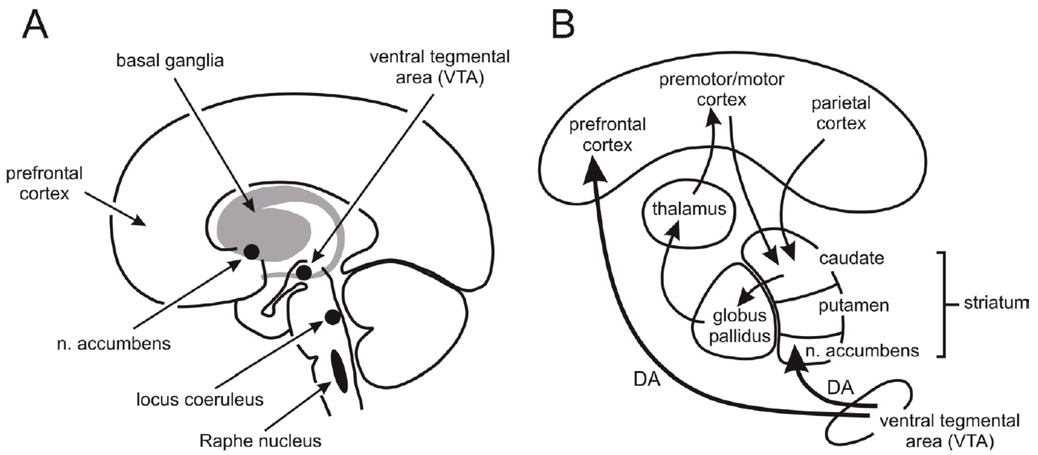
What is reinforcement learning (RL)?

RL has been tremendously successful at explaining behaviour and psychological variables
(More next session)





Guitart-Masip et al. 2011



Ludvig et al. 2011

RL has been tremendously successful at explaining neuroscience
(More in session after next)

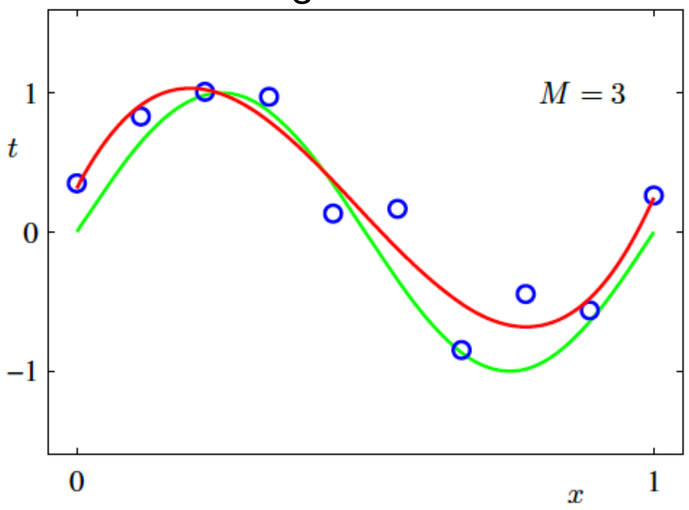
Types of (machine) learning: supervised learning

- Find correct labelling/prediction of data:

Classification

MNIST

Regression



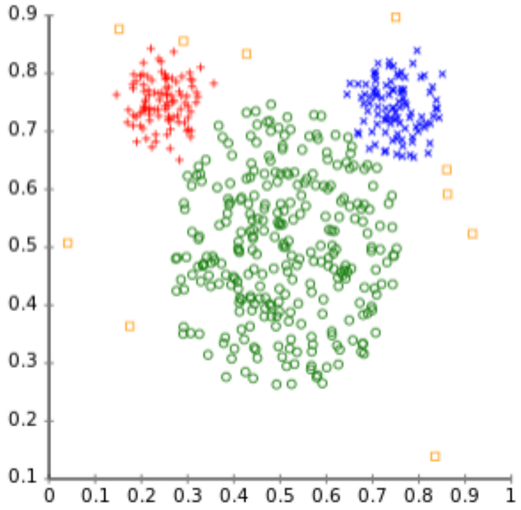
Bishop 2006

- That's not what we want though:
  - Want to learn from *own experience* by *interacting* with the world

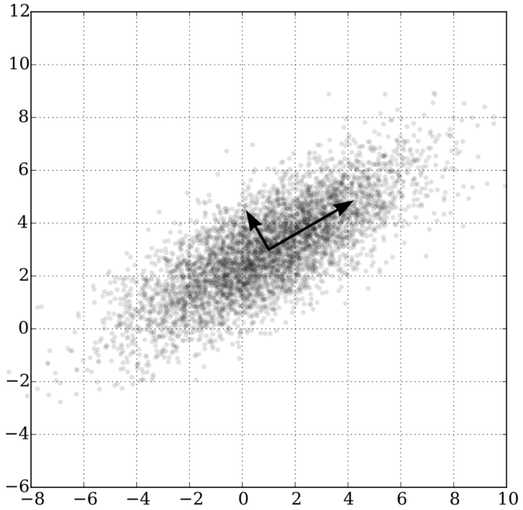
Types of (machine) learning: unsupervised learning

- Find structure in data:

Clustering



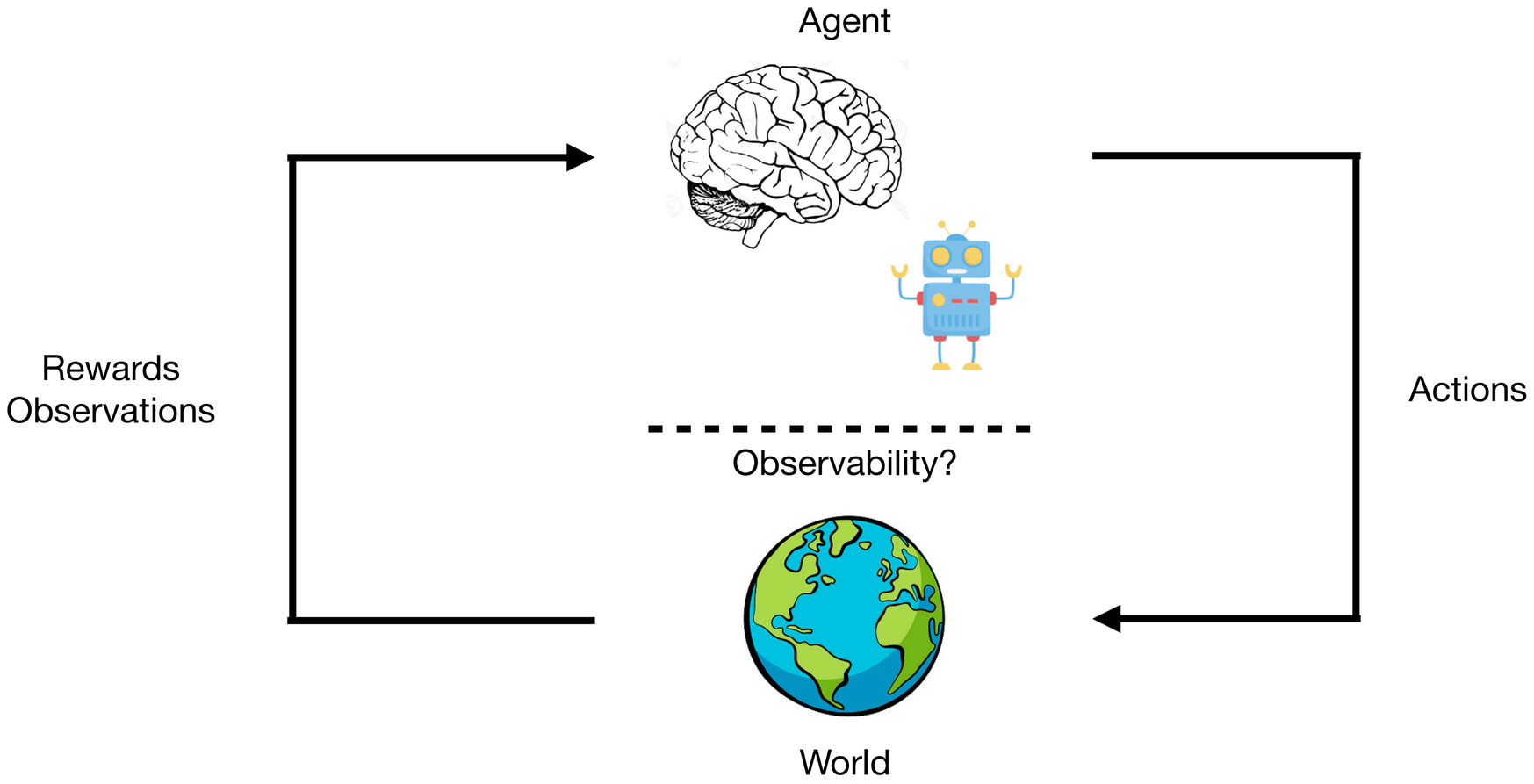
Dimensionality Reduction



- That’s also not what we want:
  - Don’t (necessarily) want to learn hidden structure, rather: maximise reward

Types of (machine) learning: Reinforcement learning

- In RL, we want to learn good actions from interactions with the world



RL as a Marrian system?

- RL has the ambition to provide a complete account of agency
  - There is much debate about that (e.g. Sliver et al. 2021: “Reward is enough”)

- Can RL account for Marr’s levels?
  - The **problem**: optimal prediction of future reward
  - The **algorithm**: temporal difference learning, Q-learning, model-based RL, …
  - Neural **implementation**: Basal ganglia, dopaminergic system, replay, …

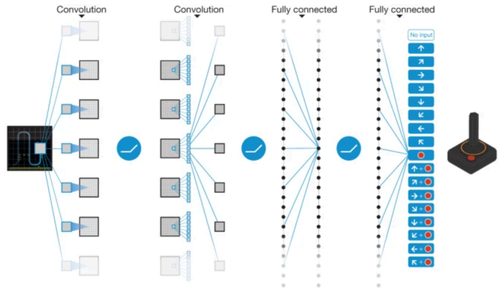
Why should we know about RL?

- Lots of reasons

- Powerful framework to understand individual differences in behaviour - individual parameters?
  - Differences in action selection (randomness, heuristics)
  - Mechanisms to find the value of states
  - Mechanisms of learning

- Exploit vs. Explore

- Interesting modern applications based on (‘deep’) RL



Mnih et al. 2015

Course Structure

This seminar: components

- Most of this is first time material - tell me if something doesn't work
  - Should be fun and open for suggestions

- Theory (key reference: Sutton & Barto, 1998)
- Research (key papers)
- Coding (Python)

Dates and topics

Options
- Just cancel
- Coding exercise
- Two sessions (coding) on 17th or 31st

Probably not around

19.04.2022
26.04.2022
03.05.2022
10.05.2022
17.05.2022
24.05.2022
31.05.2022

Basics, theory

Holiday

14.06.2022
21.06.2022
28.06.2022
05.07.2022
12.07.2022
19.07.2022
26.07.2022

Applications, other aspects

Dates and topics

Topics (some flexibility)

- Intro RL, Python
- Basics of learning theories, psychology
- Learning about different options, neuroscience
  - Primer on Temporal Difference (TD) learning
- Markov Decision Processes
- Basics of control
  - Dynamic Programming, TD learning
  - Action selection
- Other important aspects
  - Model-based vs. Model-free
  - Exploration vs. Exploitation

19.04.2022

26.04.2022

03.05.2022

10.05.2022

17.05.2022

24.05.2022

31.05.2022

Basics, theory

Dates and topics

Topics (some flexibility)

- Some coding
  - Role of different parameters
  - Model-fitting
  - If possible: parameter recovery, model comparison
- ‘Advanced’ topics and current applications
  - Planning, Dyna, replay
  - Clever ways of planning, tree-search etc
- Deep RL
- Future directions, limitations, current research

14.06.2022

21.06.2022

28.06.2022

05.07.2022

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Applications, important aspects

Key resources

- Sutton and Barto 1998 Reinforcement Learning: An Introduction
- My GitHub

- Other resources
  - David Silver's course at UCL
  - Other great courses on RL in Tuebingen with slightly different focus, e.g. by Georg Martius

Evaluation

- Some flexibility

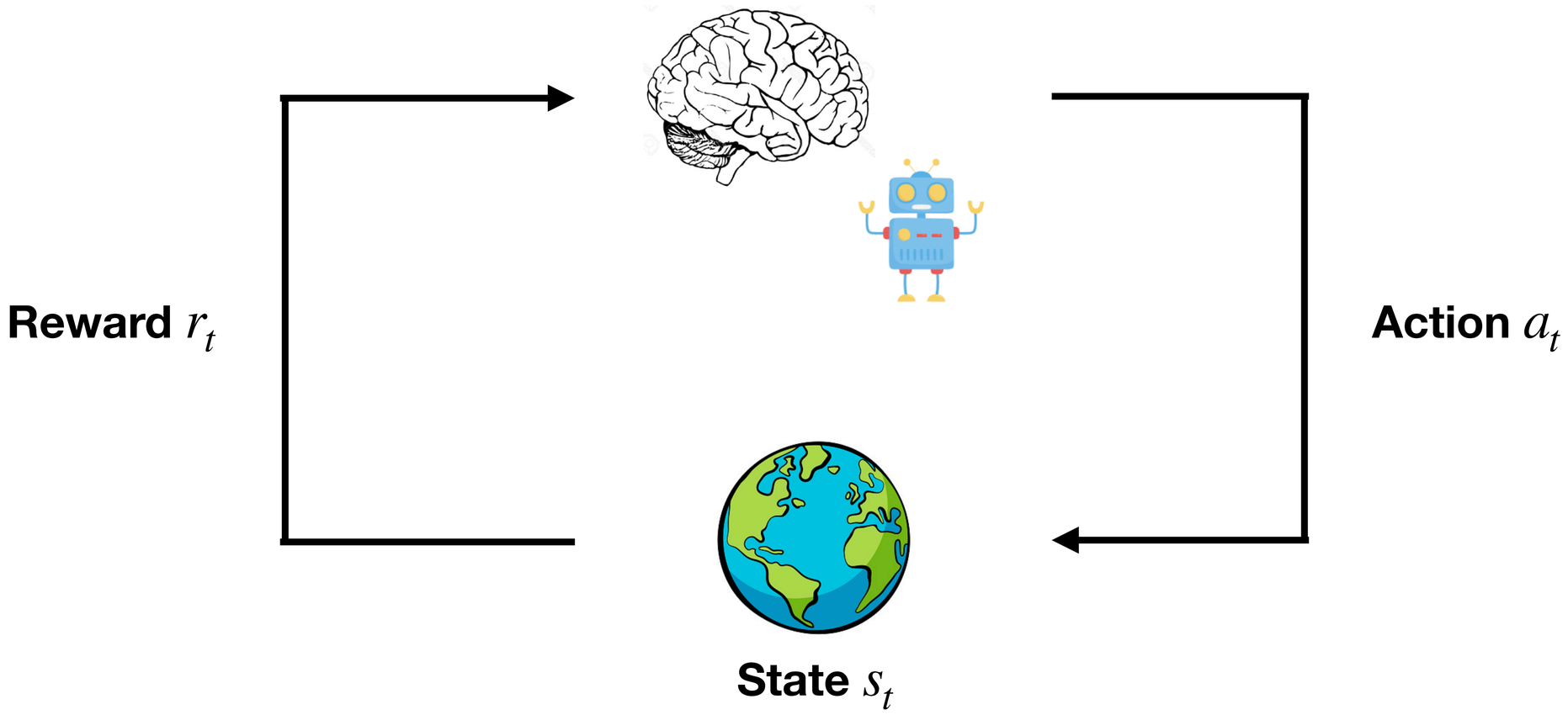
- Essay at end of the course
  - e.g. modelling of a simple task
  - Review on specific application, topic

- Additional possibilities
  - Smaller coding exercises
  - Presentation

What are you most interested in? Any other Ideas?

Intro to intro to RL

Basic setup



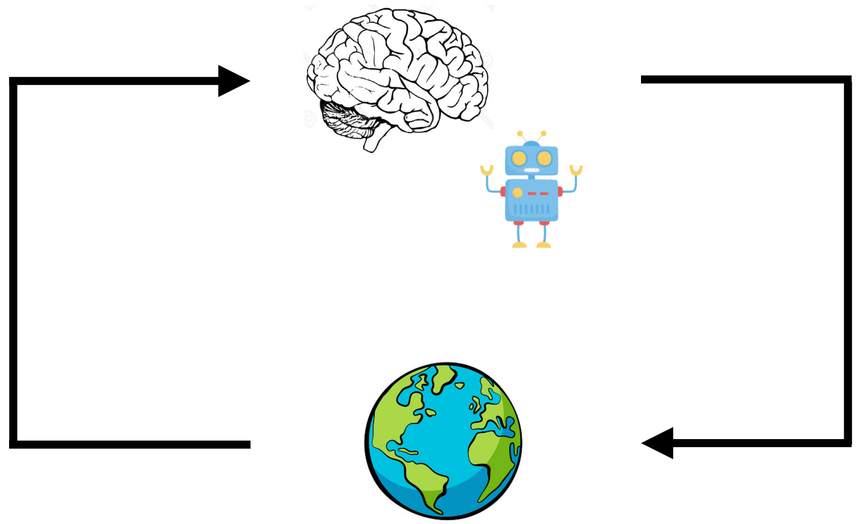
Basic setup: how to agents learn to act?

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

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

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

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



Values can be **learnt** (Note: highly simplified!!):

$$V(s) \leftarrow V(s) + \alpha \cdot (r - V(s))$$

Learning rate

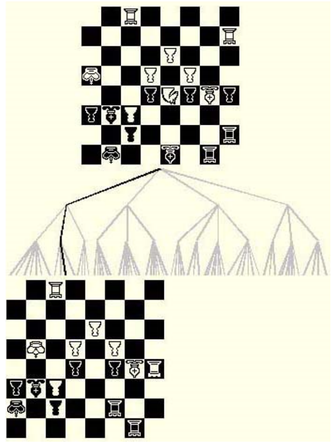
Prediction error

Action is governed by a **policy**:

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

More Examples

- **Chess**: what is…
  - The state?
  - An action?
  - A reward?



- How can values be learned over time?
- How could a model of the environment be useful?

Other relevant components:

- tree search
- position evaluation
- situation memory

Taken from Peter Dayan

Examples extended..

- **Learn how to walk**: what is…
  - The state?
  - An action?
  - A reward?

- How can values be learned over time?
- How could a model of the environment be useful?

Examples extended..

- Other examples (see Sutton & Barto, pp 4-5):

- Adaptive controller adjusts parameters of a petroleum refinery’s operation in real time
  - Optimise yield/cost/quality trade-off
  - Objective: specified marginal costs
  - Without sticking strictly to pre-defined set points

- Mobile robot decides to search for trash to collect or find its way back to battery recharging station
  - Decision based on current charge level of battery and how quickly recharger has been found in the past.

- Prepare breakfast
  - Subgoals, hierarchies
  - Conditional behaviour
  - Sense/access bodily states

Key features of all these examples

- (Danger of repeating myself): **Interaction** between active decision-making agent and its environment
  - Agent seeks to achieve a **goal**
  - **Uncertainty** about its environment

- Take into account **indirect, delayed consequences** of actions
  - Requires foresight or planning

- Need to **monitor** environment frequently

- **Judge progress** toward goal based on what can be sensed directly

- Use experience to **improve performance** over time (online vs. offline learning)
  - Basis for adjusting behaviour to exploit specific features of the task

Key Elements (more details later): Policy

- Defines agent's **way of behaving** at a given time
  - Sufficiently determines behaviour
  - Often stochastic (determine probabilities for each action)

Action is governed by a **policy**:

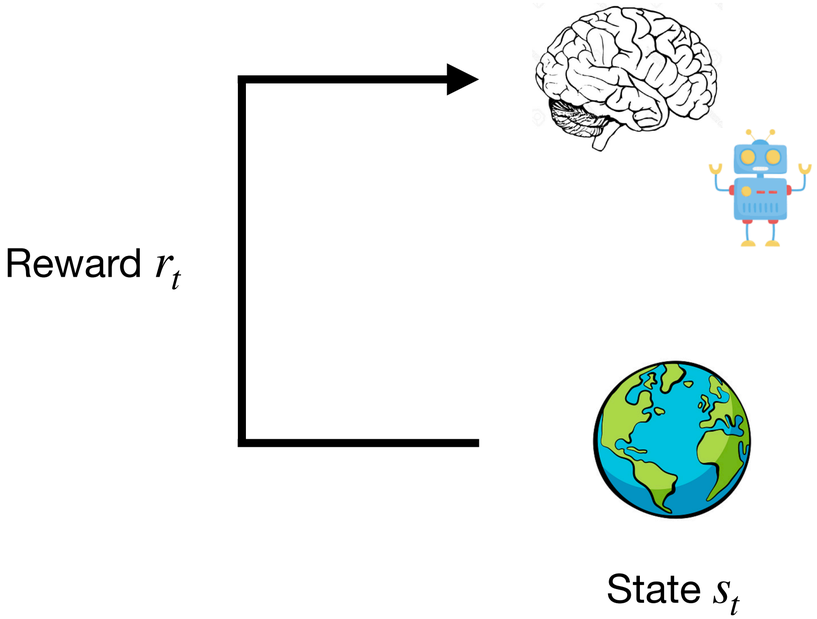
$$\pi(a, s) = P(a_t = a \mid s_t = s)$$

- Mapping from perceived states of the environment to actions to be taken when in those states
  - Cf., stimulus–response rules or associations

- Can be simple or difficult
  - Lookup table vs. extensive search

Key Elements (more details later): Reward signal

- = **goal** of a reinforcement learning problem
  - Single number from environment on each time-step



- SOLE objective is to maximise the total reward over the long run
- Primary basis for altering the policy
  - If action is followed by low reward, then the policy may be changed
- Often: stochastic function of state of environment and actions taken

Key Elements (more details later): Value function

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

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

- = what is good in the **long run**

- Total amount of reward an agent can expect to accumulate over the future, starting from a given state
  - Long-term desirability of states
  - Taking into account states that are likely to follow and rewards available in those states

- A state might yield a low immediate reward but can still have a high value (because regularly followed by other states that yield high rewards)

Reward vs. Value

Reward r_t

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

- Rewards = primary, values = secondary
  - Rewards are the basis for estimating value
- BUT action selection is based on value, not immediate reward - why?
- It is more difficult to determine value than reward
  - Methods for value estimation are a central problem in RL

Key Elements (more details later): Model of Environment

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

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

- Mimics **behaviour of environment**
  - Allows to predict how the environment will behave
- E.g.: given a state and action, model can predict the resultant next state and next reward
- Models are used for planning
  - Considering possible future situations before they are actually experienced
- Methods for solving reinforcement learning problems that use models and planning are called model-based methods
  - Simpler model-free methods are explicitly trial-and-error learners (opposite of planning)

‘Multiple Systems’ in RL

- **Model-based RL**
  - Build a forward model of the task and outcomes
  - Search in the forward model
    - Optimal use of information
    - Computationally ruinous

- **Model-free RL**
  - learn values, which summarise future worth
    - computationally trivial
    - bootstrap-based; so statistically inefficient

- learn both – select according to uncertainty

Slide from Peter Dayan

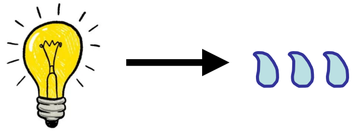
What are the limits of RL?

- How do we define a state? Are all states perceivable?
- What about problems that cannot be solved via learning (e.g. inference)?
- Is reward to explain behaviour/cognition/brains?

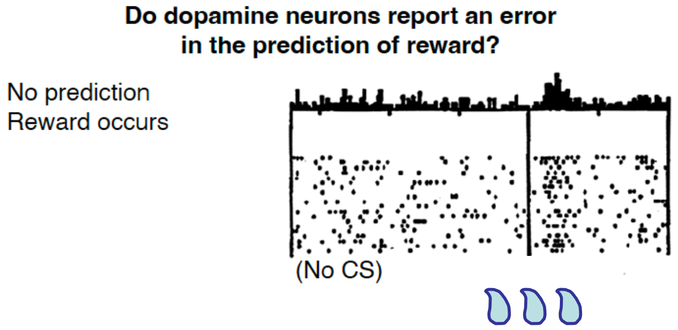
RL success story: Dopamine (a primer)

Can RL tell us anything about the brain?

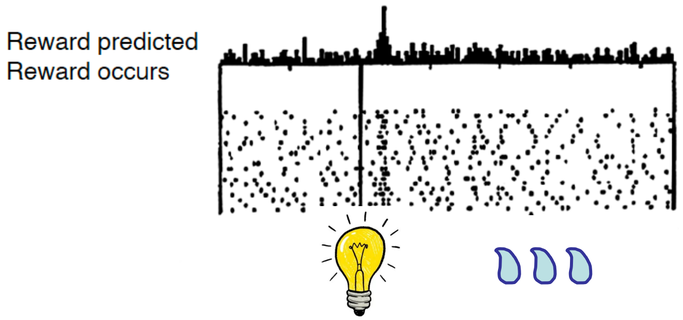
- Yes, quite a lot.
- Particularly, it looks like dopamine (DA) is a key neurotransmitter for reward learning
  - Schultz, Dayan & Montague (1997):



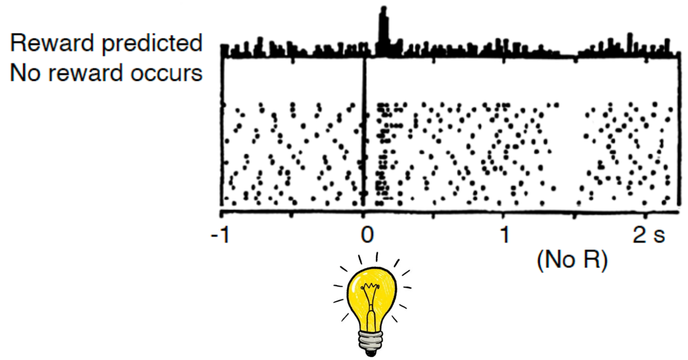
Dopamine neurons signal immediate reward



BUT: after training…
- DA signal reward prediction
- But not correctly predicted reward!



AND: it signals the unexpected omission of a reward!



This provides strong evidence that DA signals a **reward prediction error**

(Note: it is $r + V_{t+1} - V_t$ rather than $r - V_t$ though..)

Coding: Python, Google Collab

https://github.com/schwartenbeckph/RL-Course/tree/main/2022_04_19