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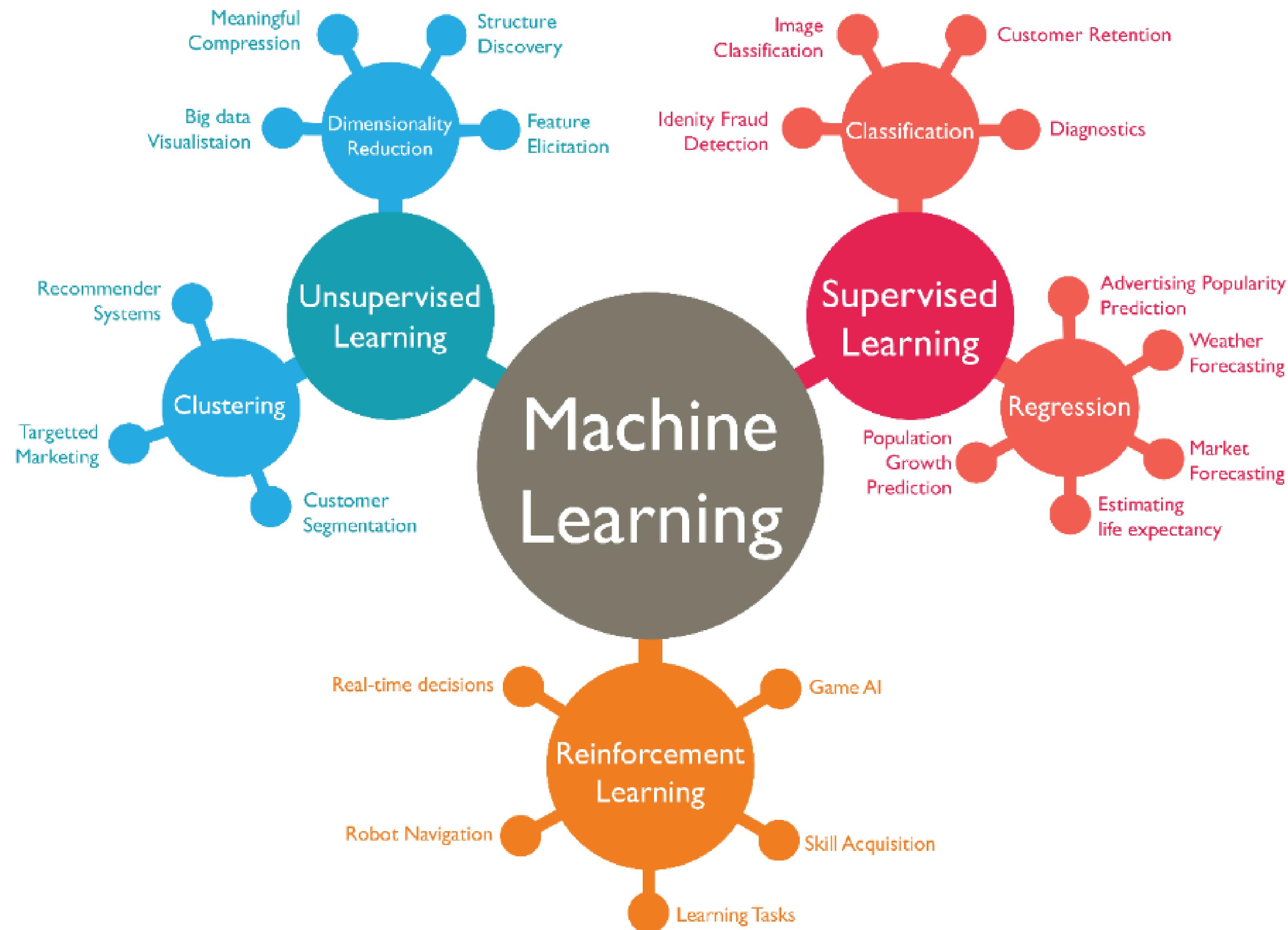
Deep Reinforcement Learning

Introduction

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<https://tu-chemnitz.de/informatik/KI/edu/deeprl>



Different types of machine learning depending on the feedback

- **Supervised learning:** the correct answer is provided to the system.
- **Unsupervised learning:** no answer is given to the system.
- **Reinforcement learning:** an estimation of the correctness of the answer is provided.

Supervised Learning

- Makes machine learn explicitly
- Data with clearly defined output is given
- Direct feedback is given
- Predicts outcome/ future
- Resolves classification & regression problems



Unsupervised Learning

- Machine understands the data (Identifies patterns/ structures)
- Evaluation is qualitative or indirect
- Does not predict / find anything specific



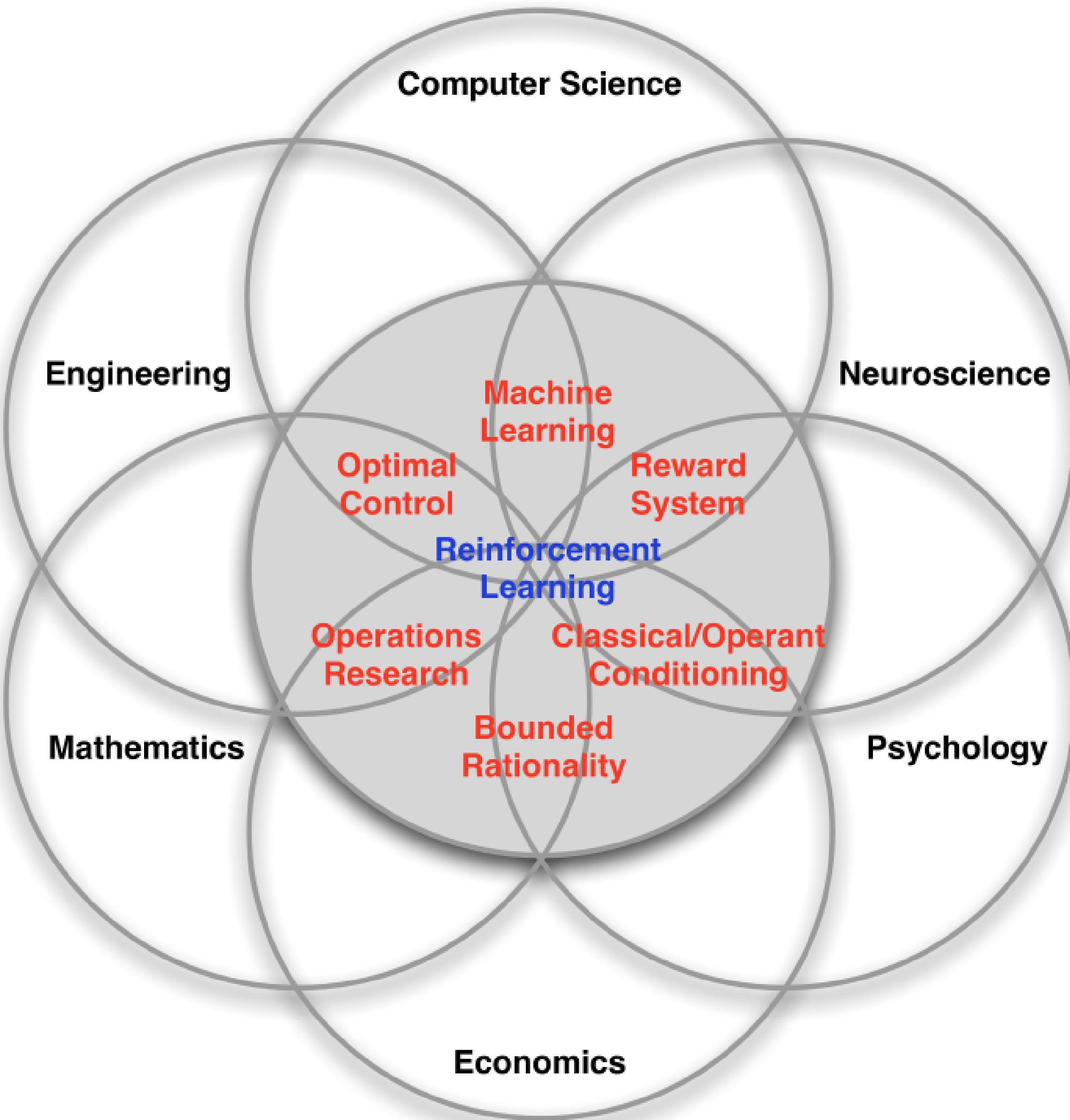
Reinforcement Learning

- An approach to AI
- Reward based learning
- Learning from +ve & -ve reinforcement
- Machine learns how to act in a certain environment
- To maximize rewards



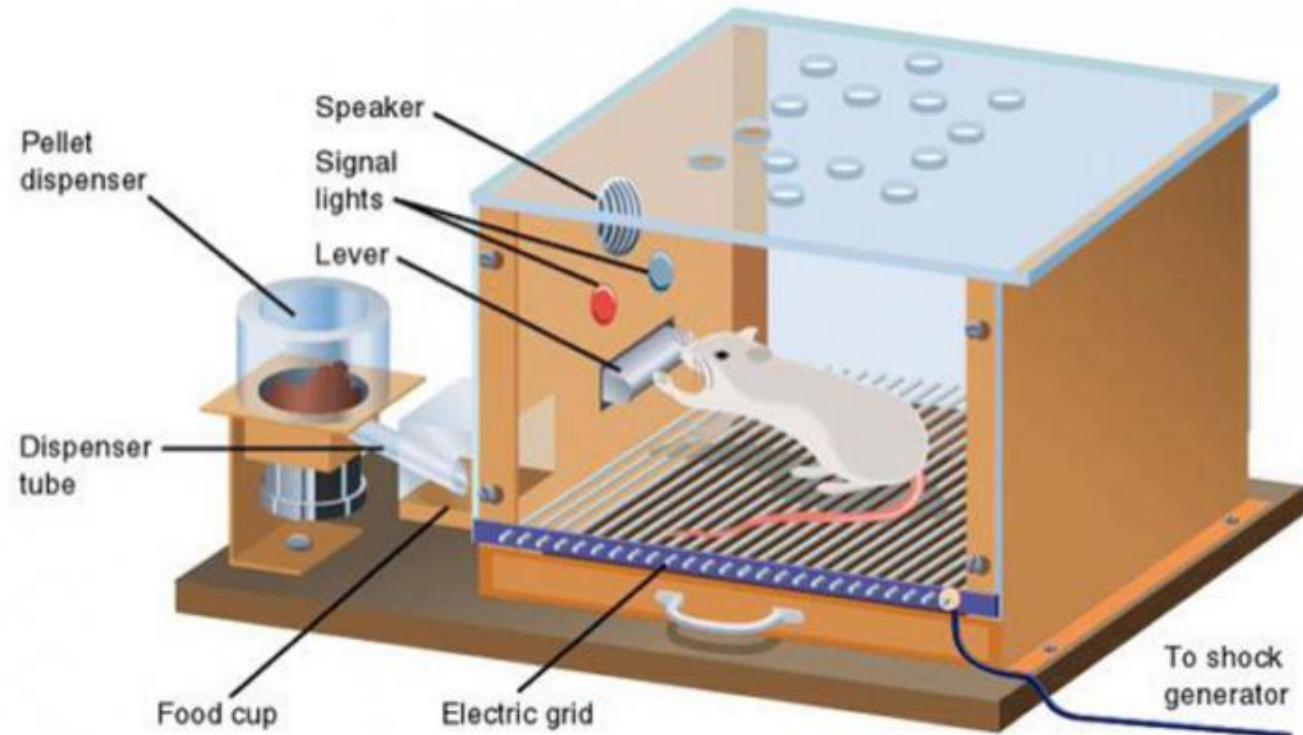
Source: <https://www.analyticsvidhya.com/blog/2016/12/artificial-intelligence-demystified/>

Many faces of RL

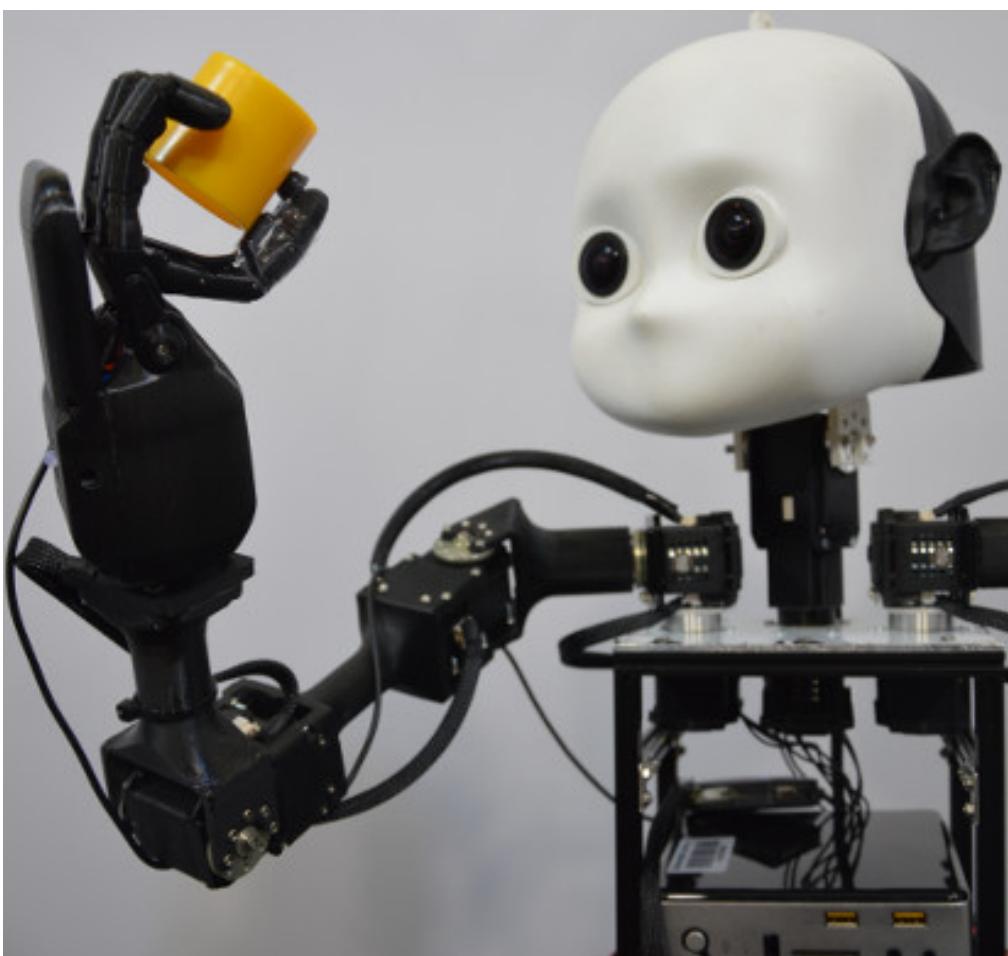


Source: David Silver. <http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html>

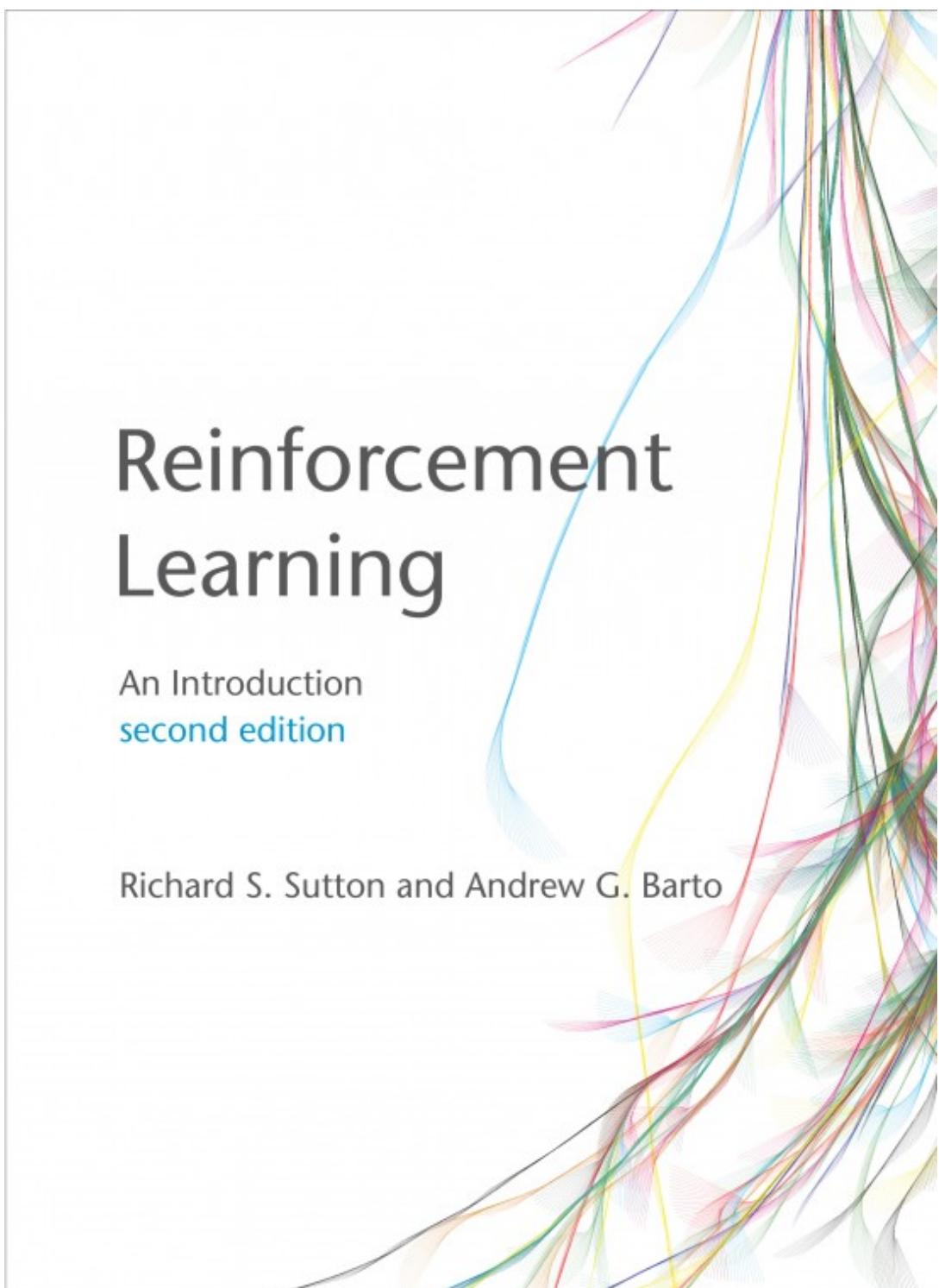
A brief history of reinforcement learning



- **Early 20th century:** animal behavior, psychology, operant conditioning
 - Ivan Pavlov, Edward Thorndike, B.F. Skinner
- **1950s:** optimal control, Markov Decision Process, dynamic programming
 - Richard Bellman, Ronald Howard
- **1970s:** trial-and-error learning
 - Marvin Minsky, Harry Klopf, Robert Rescorla, Allan Wagner
- **1980s:** temporal difference learning, Q-learning
 - Richard Sutton, Andrew Barto, Christopher Watkins, Peter Dayan
- **2013-now:** deep reinforcement learning
 - Deepmind (Mnih, Silver, Graves...)
 - OpenAI (Sutskever, Schulman...)
 - Sergey Levine (Berkeley)



The RL bible



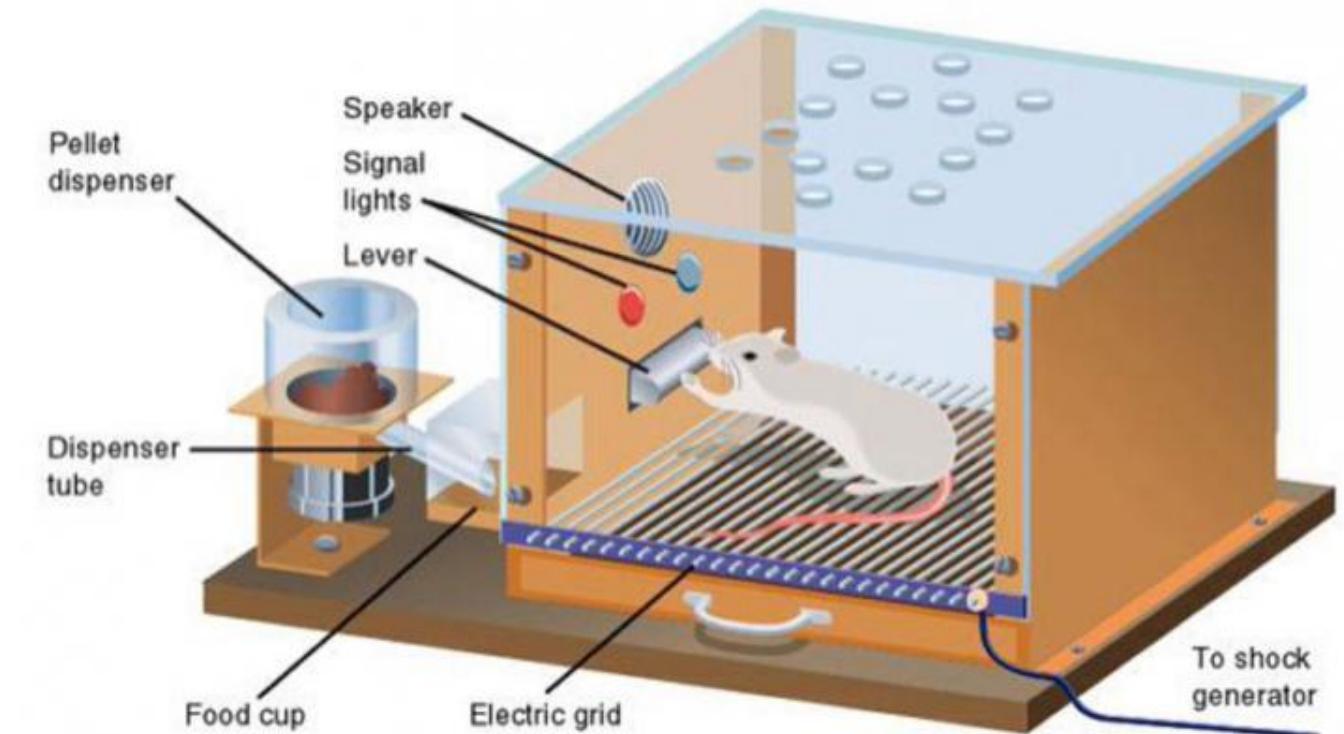
Sutton and Barto (1998). Reinforcement Learning: An Introduction. MIT Press.

Sutton and Barto (2017). Reinforcement Learning: An Introduction. MIT Press. 2nd edition.

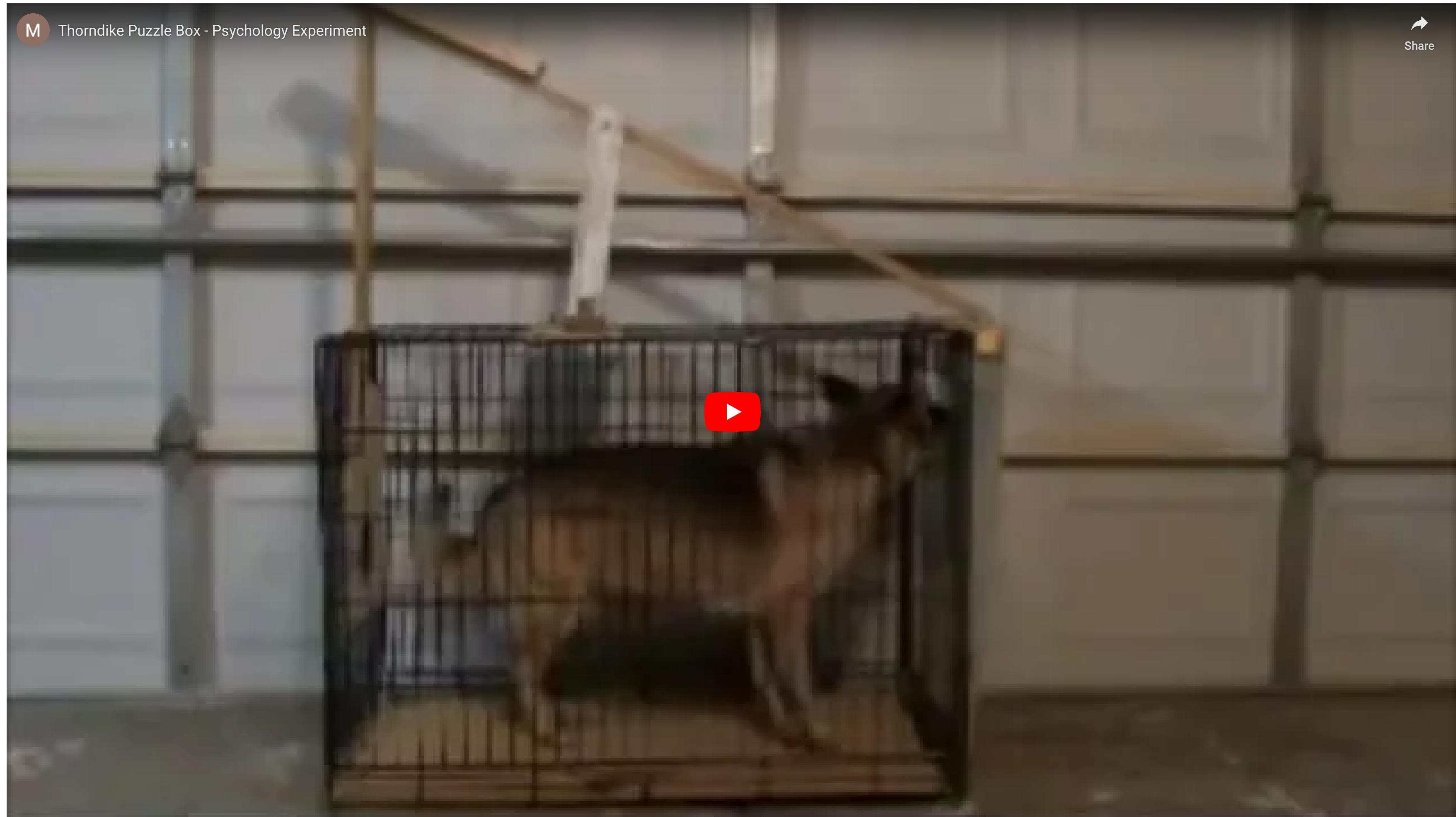
<http://incompleteideas.net/sutton/book/the-book.html>

Operant conditioning

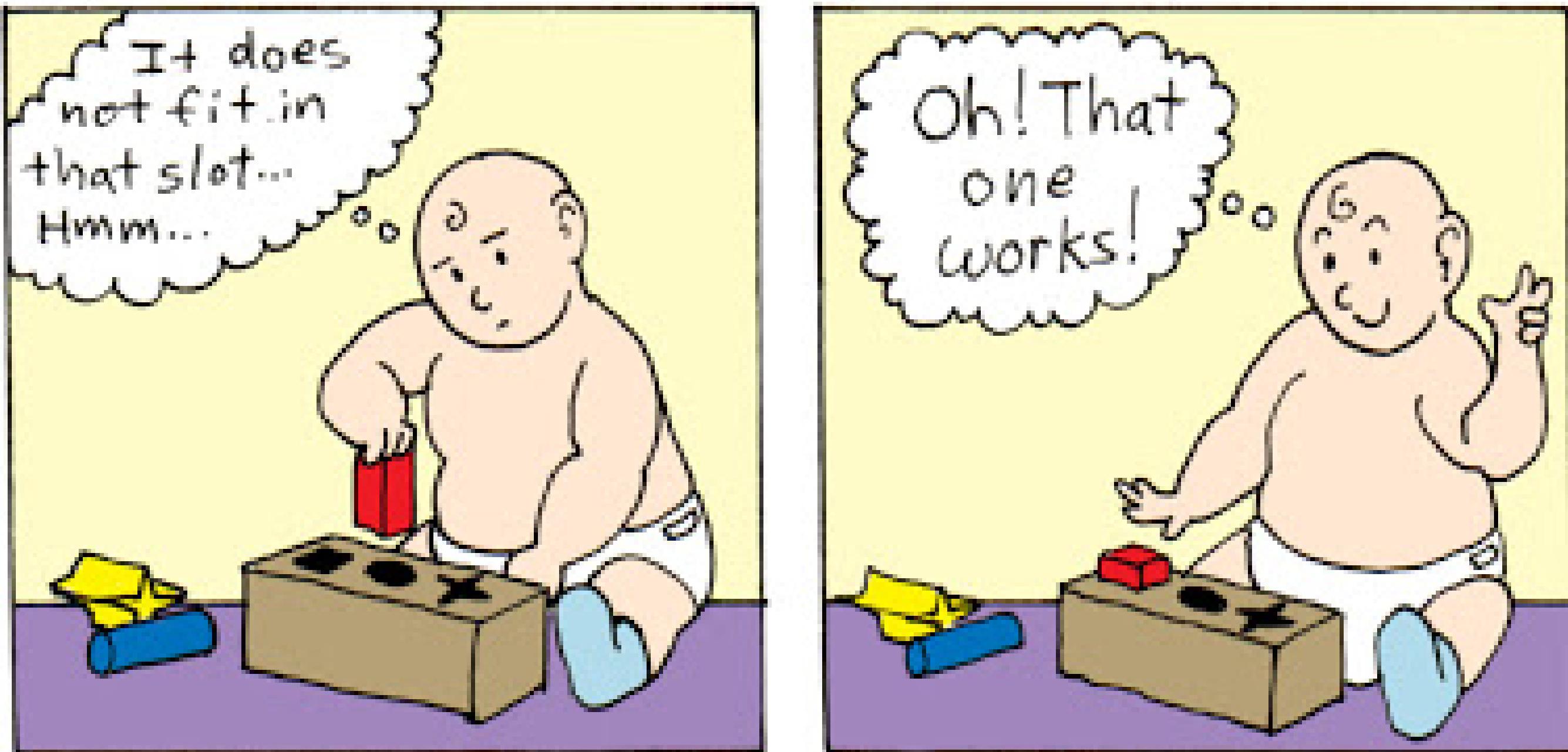
- Reinforcement learning comes from animal behavior studies, especially **operant conditioning / instrumental learning**.
- **Thorndike's Law of Effect** (1874–1949) suggested that behaviors followed by satisfying consequences tend to be repeated and those that produce unpleasant consequences are less likely to be repeated.
- Positive reinforcements (**rewards**) or negative reinforcements (**punishments**) can be used to modify behavior (**Skinner's box, 1936**).
- This form of learning applies to all animals, including humans:
 - Training (animals, children...)
 - Addiction, economics, gambling, psychological manipulation...
- **Behaviorism:** only behavior matters, not mental states.



Operant conditioning



Trial and error learning



Source: <https://sites.google.com/site/acrader4th2014/home/part-3-unity-and-diversity-of-life/trialanderrorlearning>

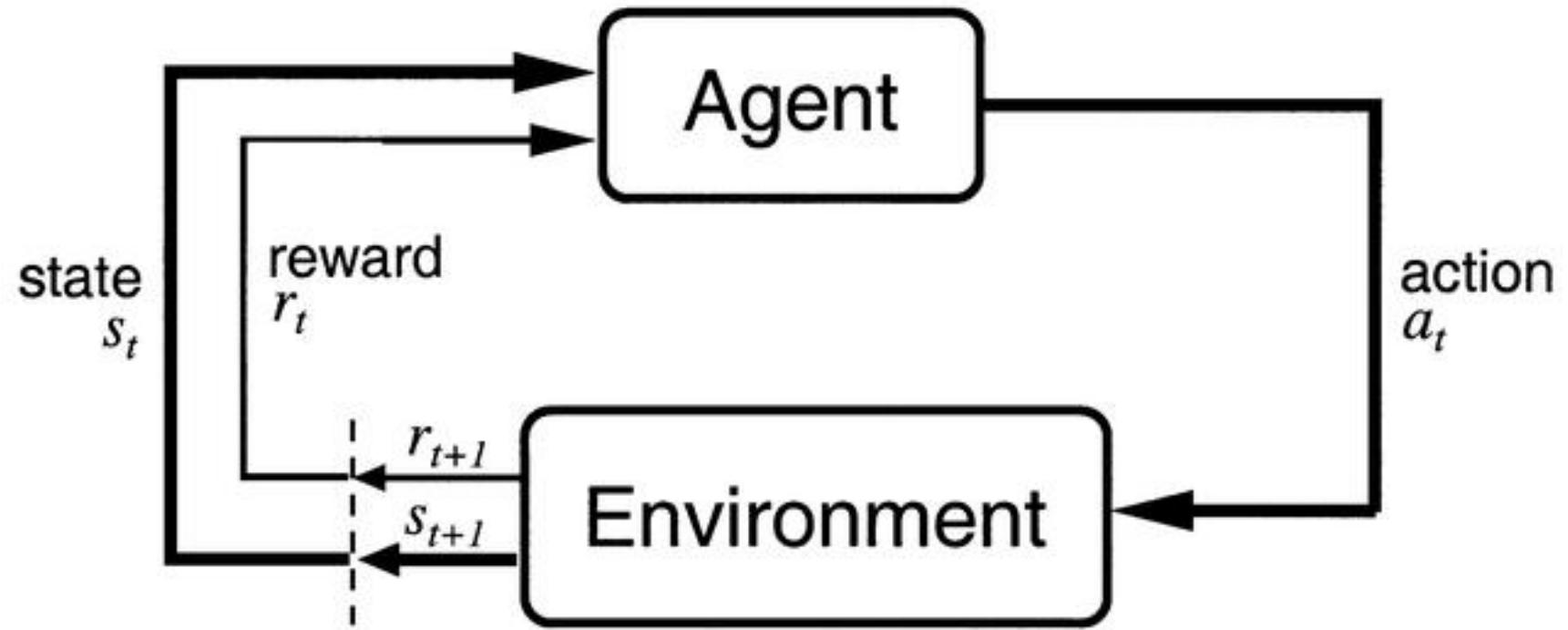
- The key concept of RL is **trial and error** learning.
- The agent (rat, robot, algorithm) tries out an **action** and observes the **outcome**.
 - If the outcome is positive (reward), the action is reinforced (more likely to occur again).
 - If the outcome is negative (punishment), the action will be avoided.
- After enough interactions, the agent has **learned** which action to perform in a given situation.

Trial and error learning



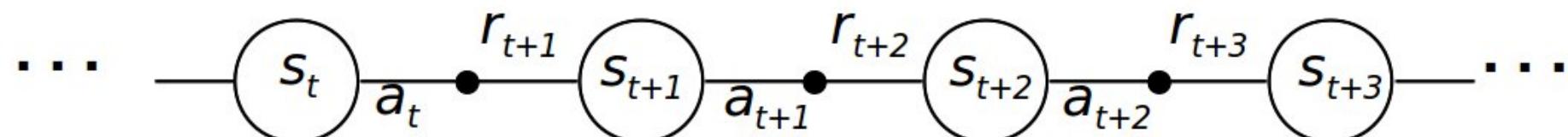
- RL is merely a formalization of the trial-and-error learning paradigm.
- The agent has to **explore** its environment via trial-and-error in order to gain knowledge.
- The biggest issue with this approach is that exploring large action spaces might necessitate a **lot** of trials (**sample complexity**).
- The modern techniques we will see in this course try to reduce the sample complexity.

The agent-environment interface



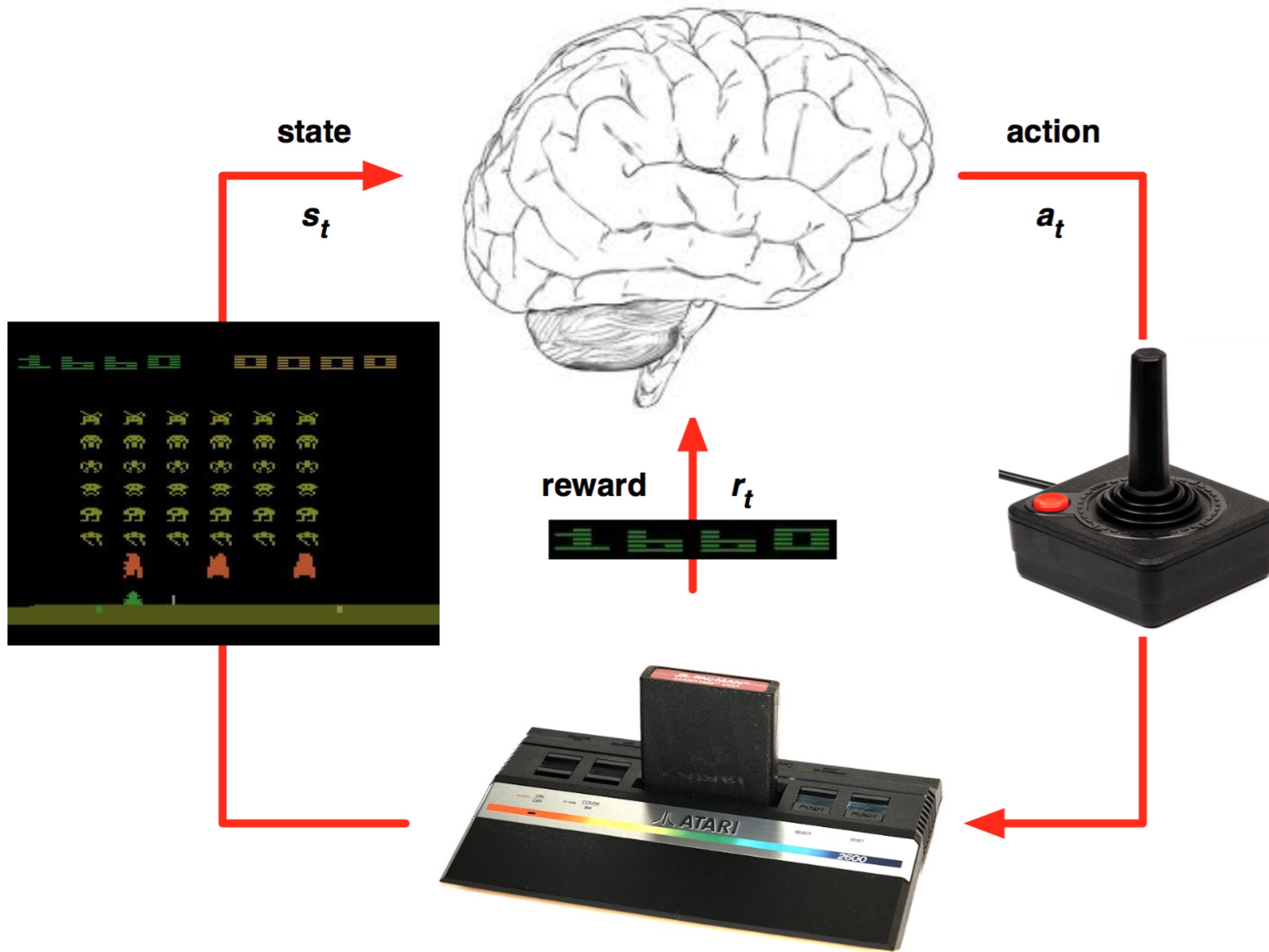
Source: Sutton and Barto (1998).

- The agent and the environment interact at discrete time steps: $t=0, 1, \dots$
 - The agent observes its state at time t : $s_t \in \mathcal{S}$
 - It produces an action at time t , depending on the available actions in the current state: $a_t \in \mathcal{A}(s_t)$
 - It receives a reward according to this action at time $t+1$: $r_{t+1} \in \mathbb{R}$
 - It updates its state: $s_{t+1} \in \mathcal{S}$
- The behavior of the agent is therefore is a sequence of **state-action-reward-state** (s, a, r, s') transitions.



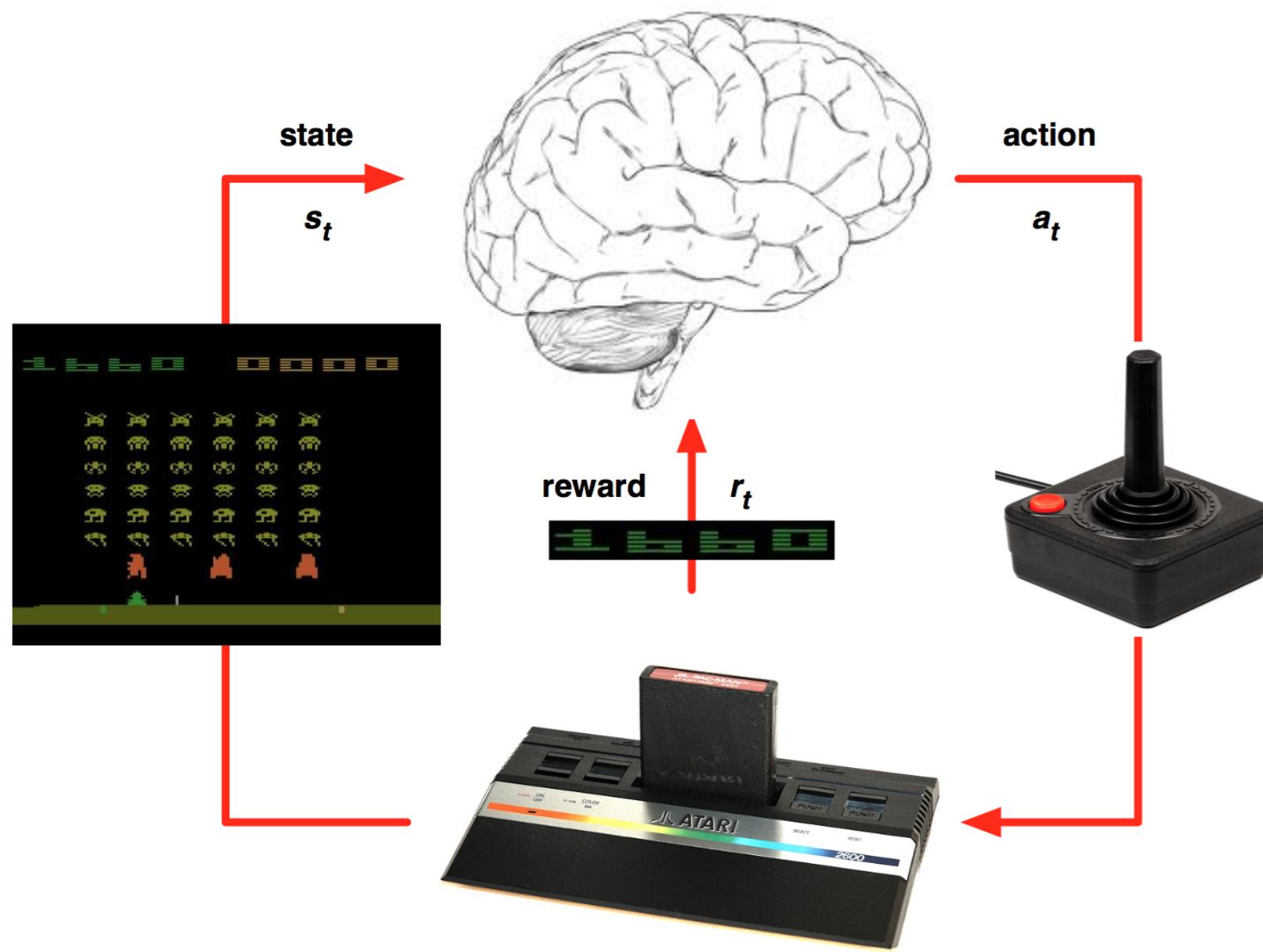
- Sequences $\tau = (s_0, a_0, r_1, s_1, a_1, \dots, s_T)$ are called **episodes, trajectories, histories or rollouts**.

The agent-environment interface



Source: David Silver. <http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html>

Environment and agent states



- The state s_t can relate to:
 - the **environment state**, i.e. all information external to the agent (position of objects, other agents, etc).
 - the **internal state**, information about the agent itself (needs, joint positions, etc).
- Generally, the state represents all the information necessary to solve the task.
- The agent generally has no access to the states directly, but to **observations** o_t :

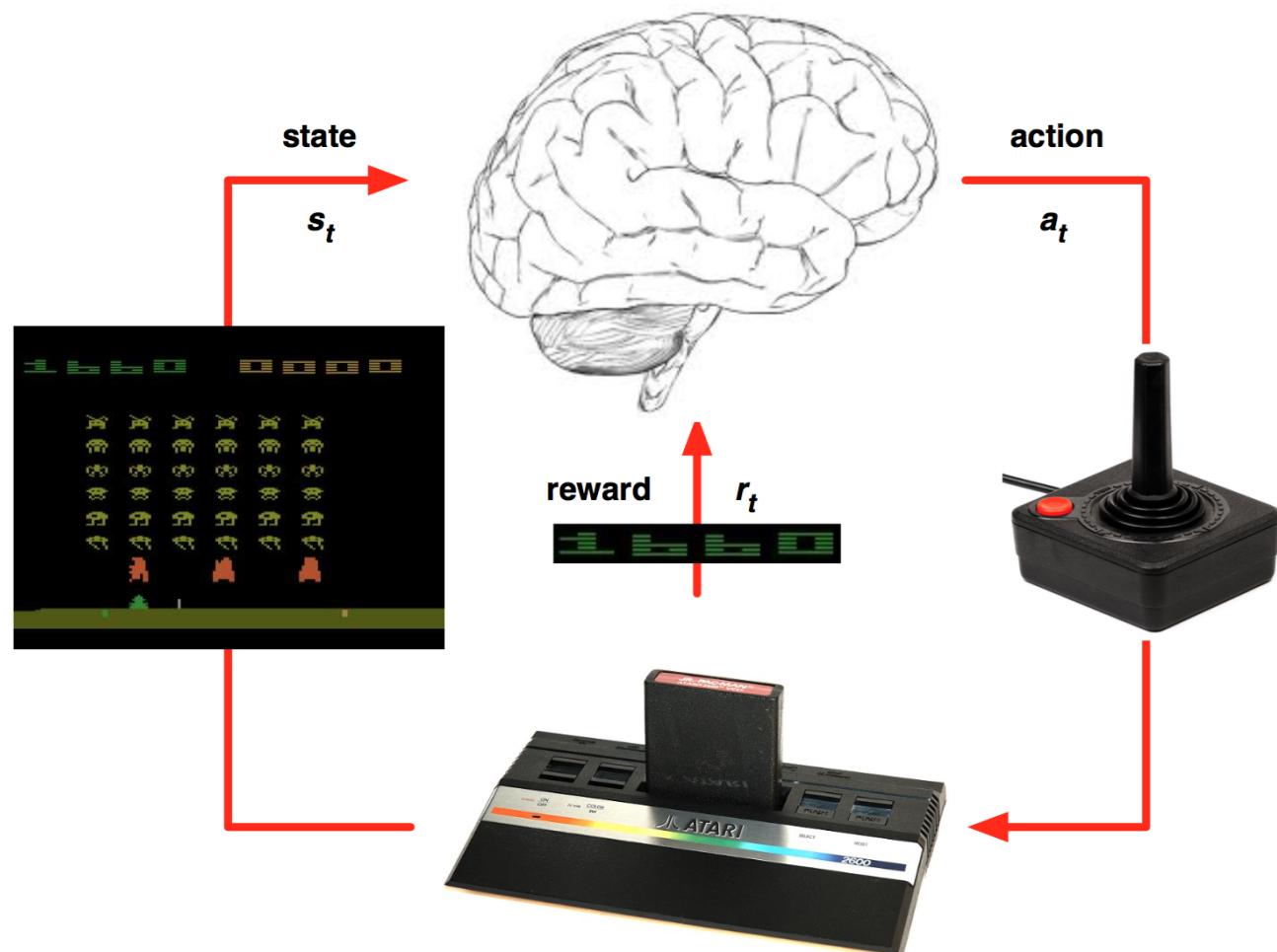
Source: David Silver.
<http://www.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html>

$$o_t = f(s_t)$$

- Example: camera inputs do not contain all the necessary information such as the agent's position.
- Imperfect information define **partially observable problems**.

Policy

- What we search in RL is the optimal **policy**: which action a should the agent perform in a state s ?
- The policy π maps states into actions.



- It is defined as a **probability distribution** over states and actions:

$$\pi : \mathcal{S} \times \mathcal{A} \rightarrow P(\mathcal{S})$$

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

- $\pi(s, a)$ is the probability of selecting the action a in s . We have of course:

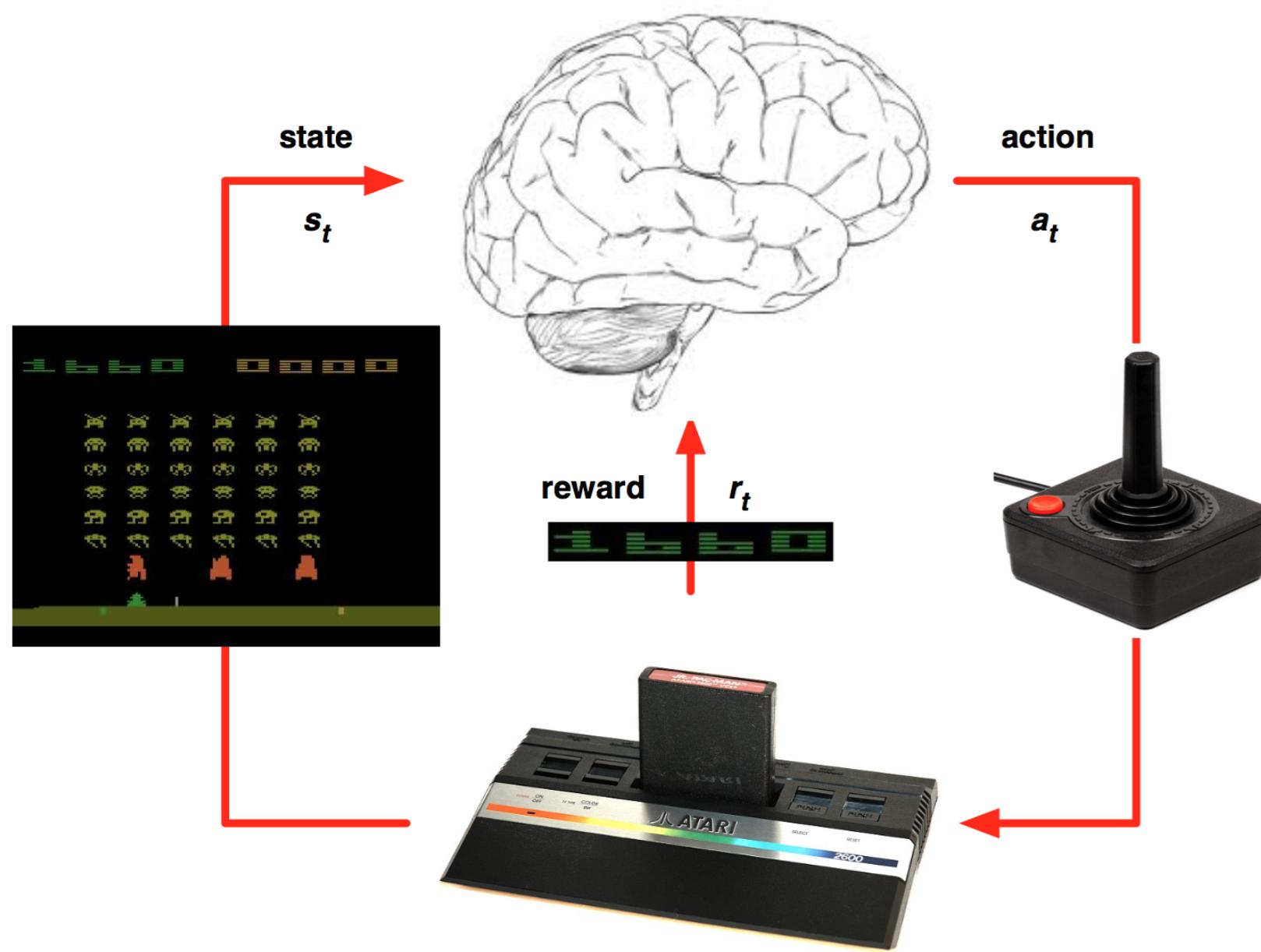
$$\sum_{a \in \mathcal{A}(s)} \pi(s, a) = 1$$

Source: David Silver.
<http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html>

- Policies can be **probabilistic / stochastic**. **Deterministic policies** select a single action a^* in s :

$$\pi(s, a) = \begin{cases} 1 & \text{if } a = a^* \\ 0 & \text{if } a \neq a^* \end{cases}$$

Reward function



- The only teaching signal in RL is the **reward function**.
- The reward is a scalar value r_{t+1} provided to the system after each transition (s_t, a_t, s_{t+1}) .
- Rewards can also be probabilistic (casino).
- The mathematical expectation of these rewards defines the **expected reward** of a transition:

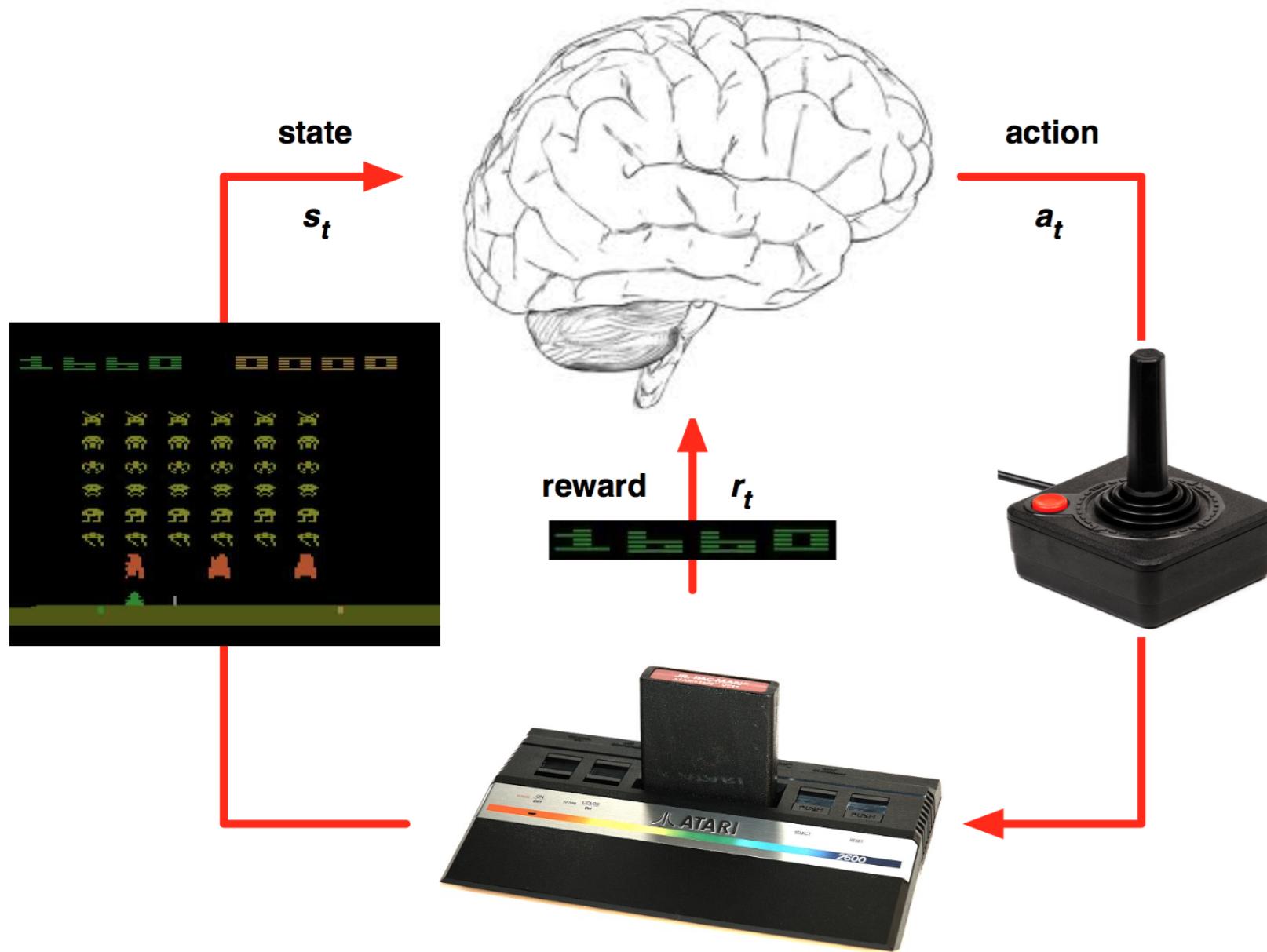
$$r(s, a, s') = \mathbb{E}_t[r_{t+1} | s_t = s, a_t = a, s_{t+1} = s']$$

- Rewards can be:
 - **dense**: a non-zero value is provided after each time step (easy).
 - **sparse**: non-zero rewards are given very seldom (difficult).

Source: David Silver.

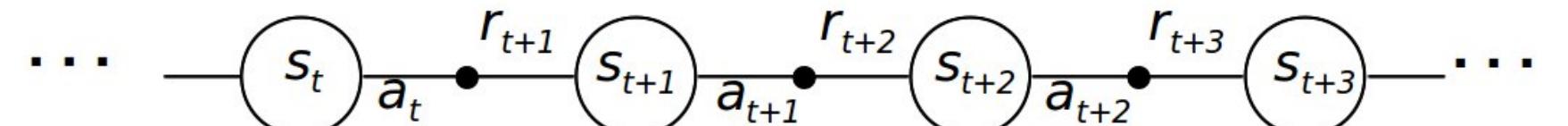
<http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html>

Returns



- The goal of the agent is to find a policy that **maximizes** the sum of future rewards at each timestep.
- The discounted sum of future rewards is called the **return**:

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$$

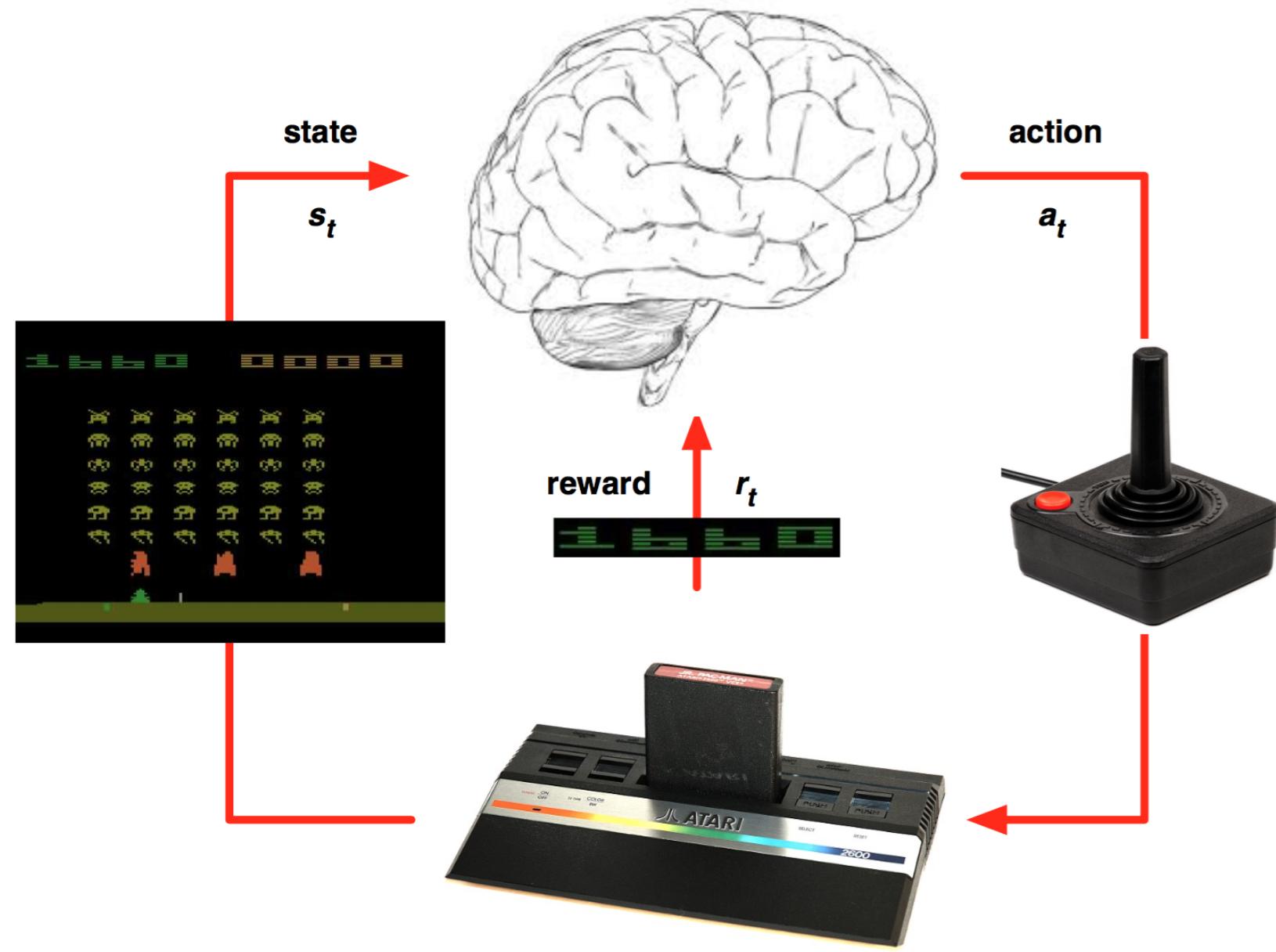


Source: David Silver.

<http://www.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html>

- Rewards can be delayed w.r.t to an action: we care about all future rewards to select an action, not only the immediate ones.
- Example: in chess, the first moves are as important as the last ones in order to win, but they do not receive reward.

Value functions



- The **expected return** in a state s is called its **value**:

$$V^\pi(s) = \mathbb{E}_\pi(R_t | s_t = s)$$

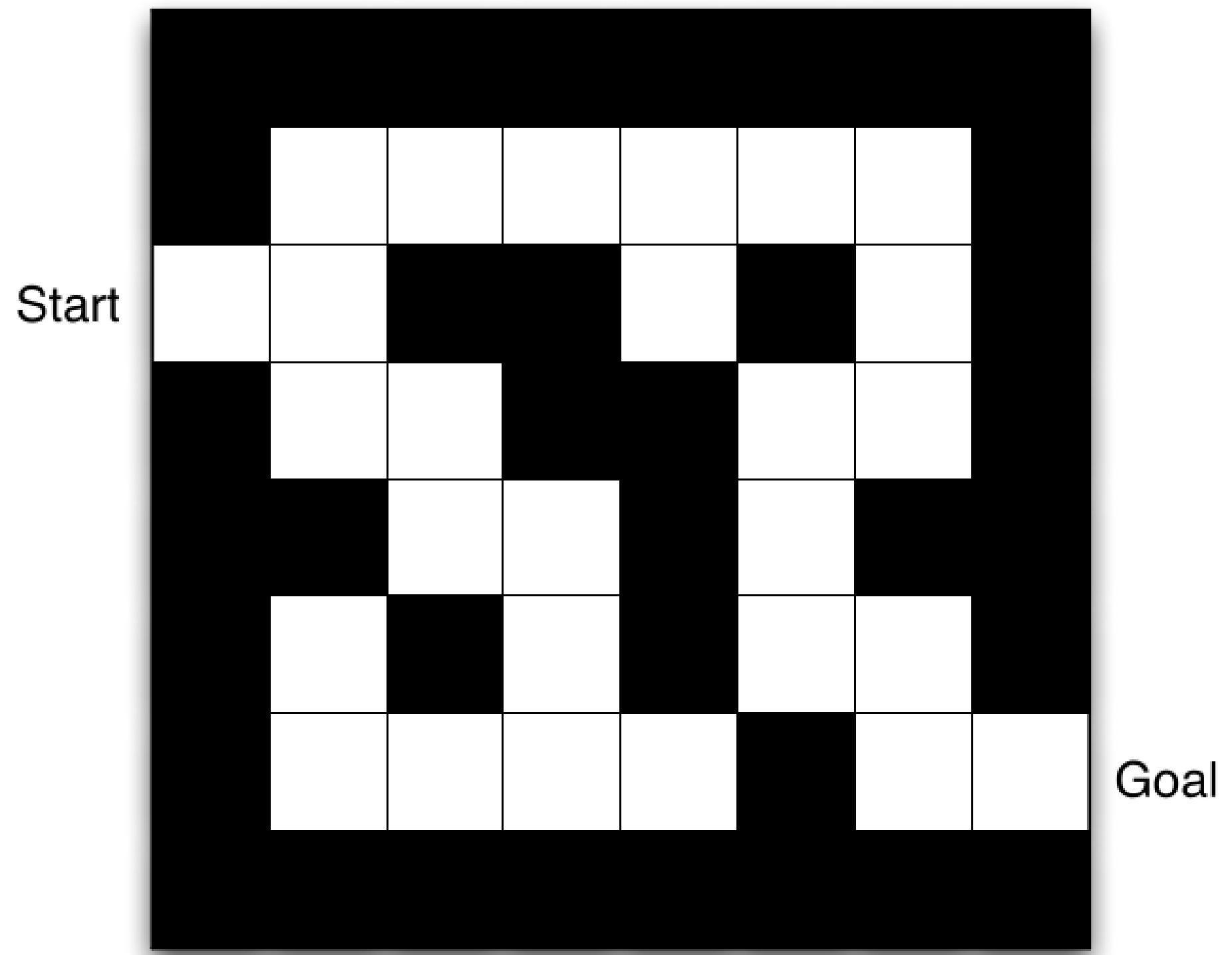
- The value of a state defines how good it is to be in that state.
- If a state has a high value, it means we will be able to collect a lot of rewards **on the long term** and **on average**.

Source: David Silver.

<http://www.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html>

- Value functions are central to RL: if we know the value of all states, we can infer the policy.
- The optimal action is the one that leads to the state with the highest value.
- Most RL methods deal with estimating the value function from experience (trial and error).

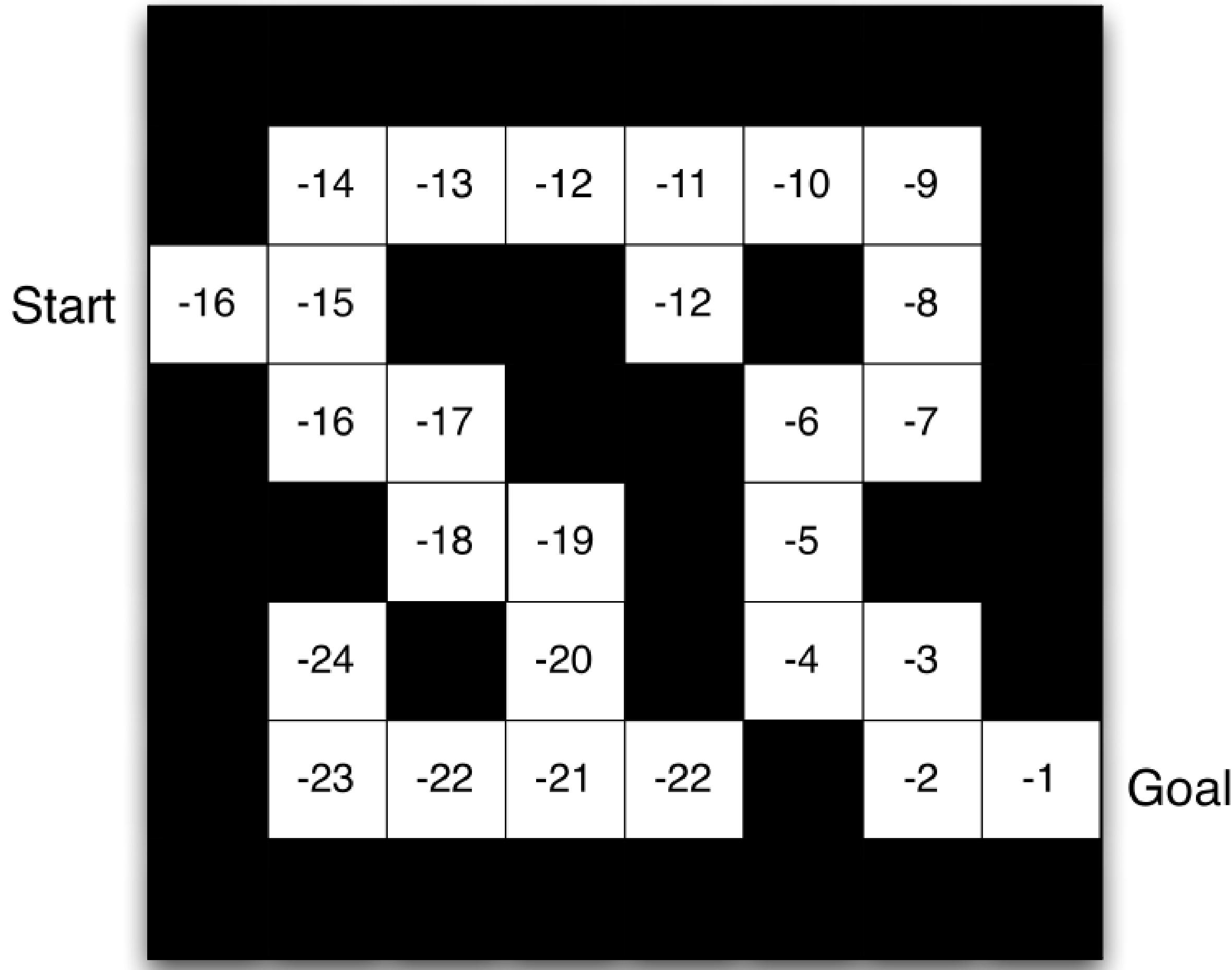
Simple maze



Goal: finding the exit as soon as possible.

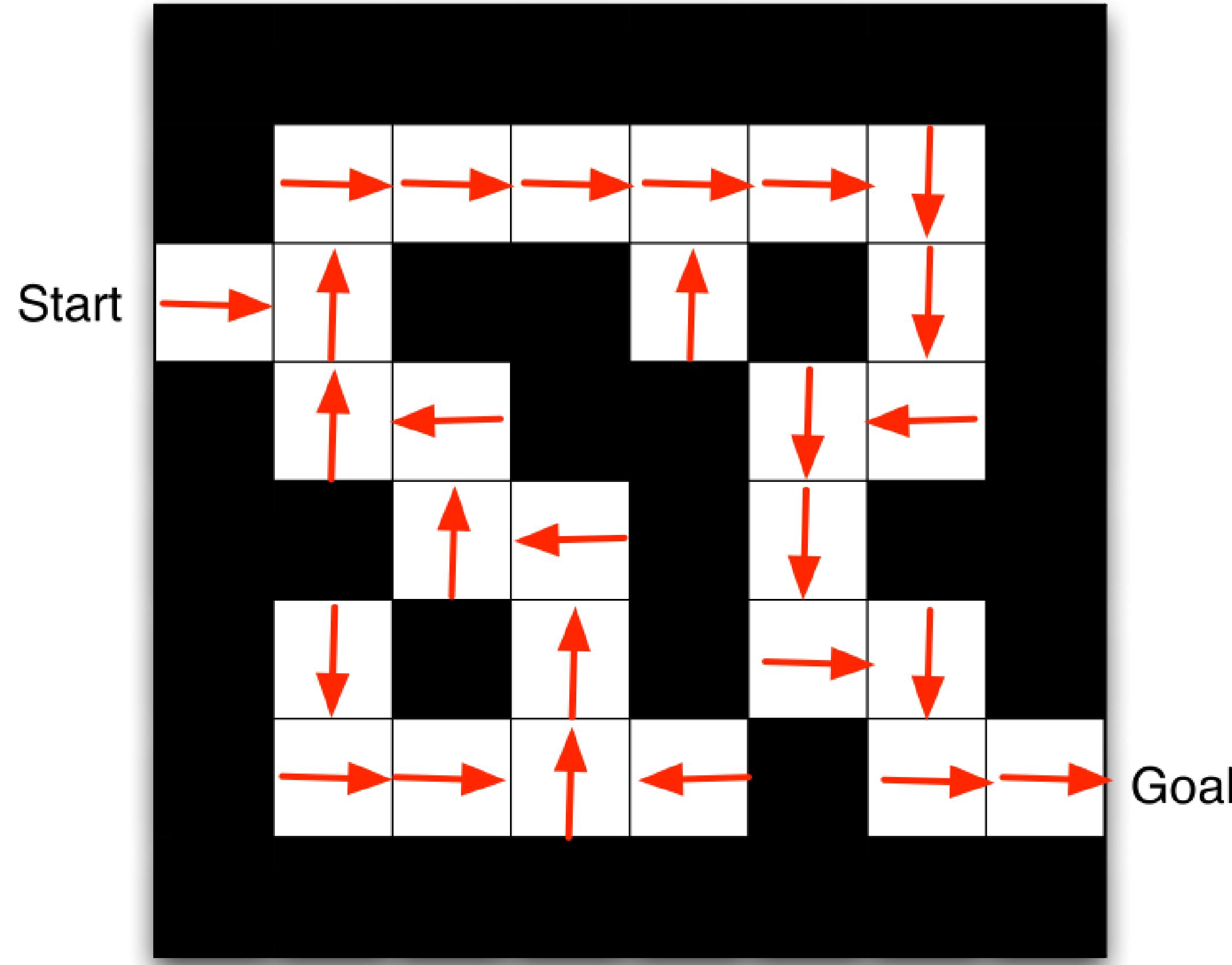
- **States:** position in the maze (1, 2, 3...).
- **Actions:** up, down, left, right.
- **Rewards:** -1 for each step until the exit.

Simple maze



- The value of each state indicates how good it is to be in that state.
- It can be learned by trial-and-error given a policy.

Simple maze

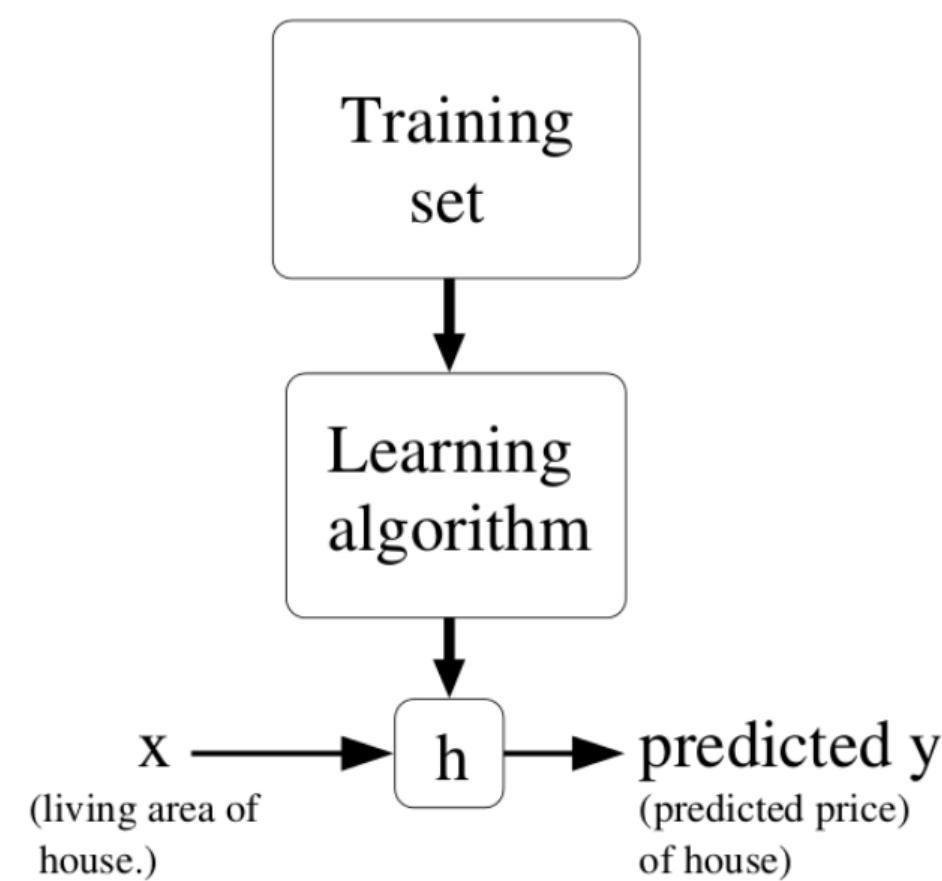


- When the value of all states is known, we can infer the optimal policy by choosing actions leading to the states with the highest value.

Note: the story is actually much more complicated...

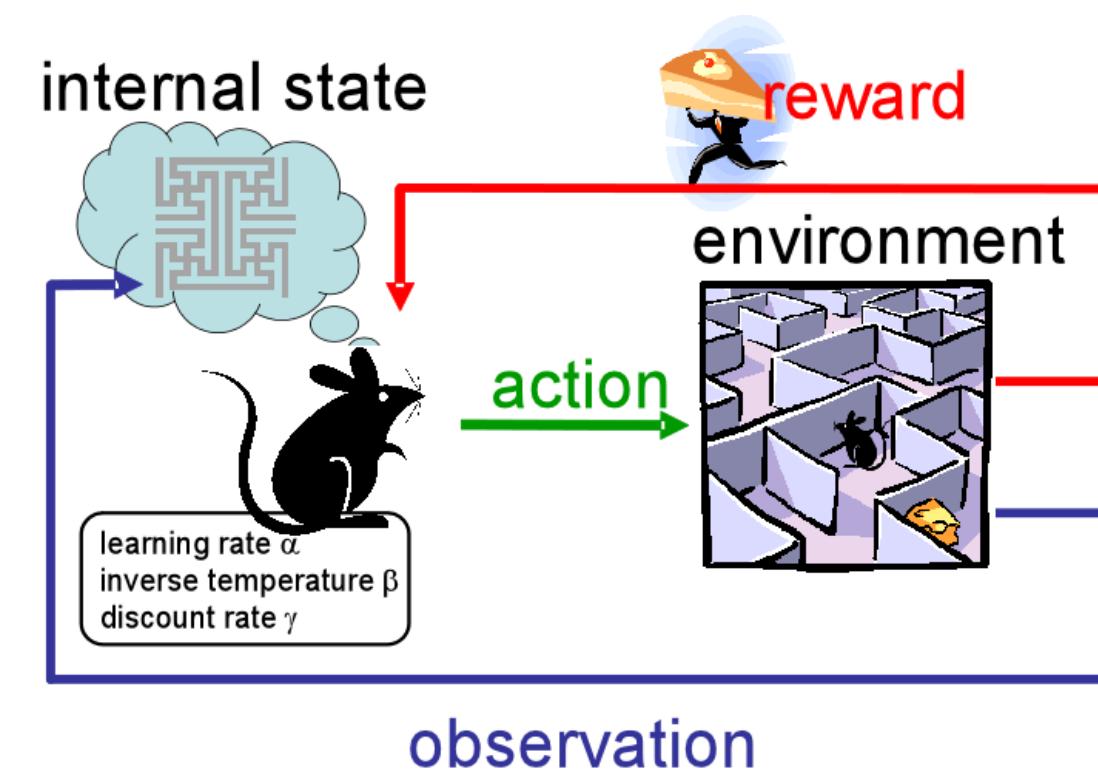
Supervised learning

- Correct input/output samples are provided by a **supervisor** (training set).
- Learning is driven by **prediction errors**, the difference between the prediction and the target.
- Feedback is **instantaneous**: the target is immediately known.
- **Time** does not matter: training samples are randomly sampled from the training set.



Reinforcement learning

- Behavior is acquired through **trial and error**, no supervision.
- **Reinforcements** (rewards or punishments) change the probability of selecting particular actions.
- Feedback is **delayed**: which action caused the reward? Credit assignment.
- **Time** matters: as behavior gets better, the observed data changes.



Applications of RL : Optimal control

Pendulum

Goal: maintaining the pendulum vertical.



- **States:** angle and velocity of the pendulum.
- **Actions:** left and right torques.
- **Rewards:** cosine distance to the vertical.

Applications of RL : Optimal control

Cartpole

Goal: maintaining the pole vertical by moving the cart left or right.



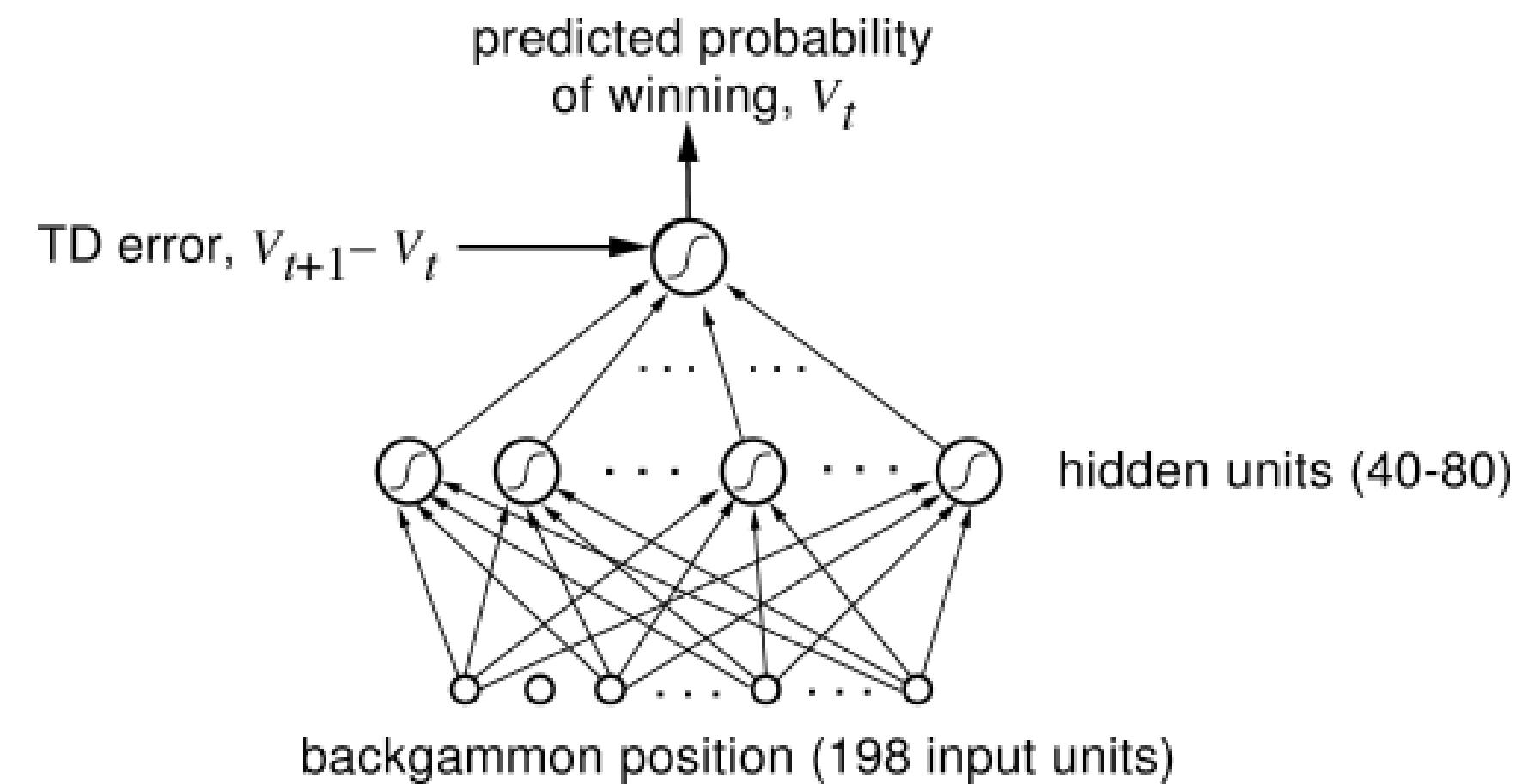
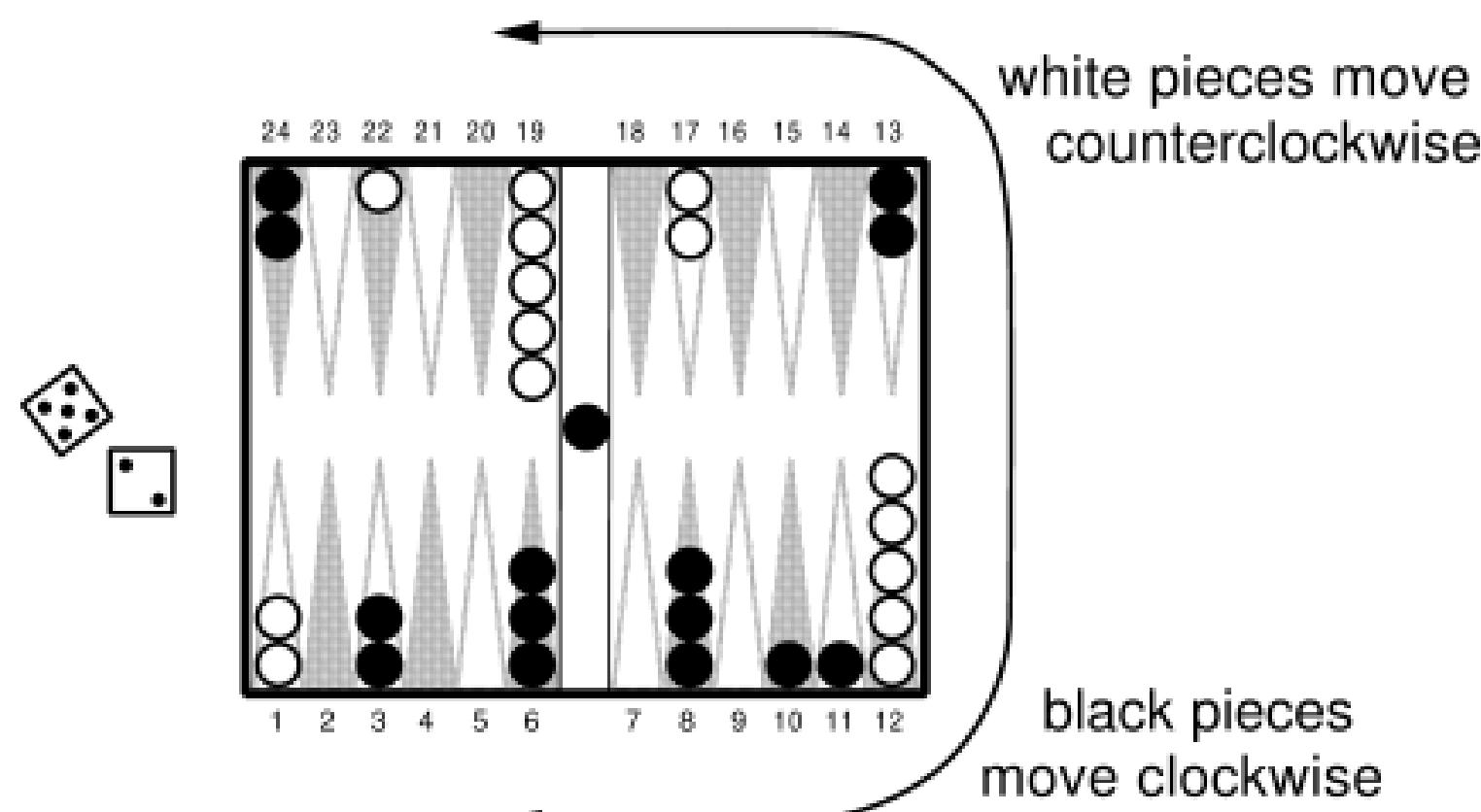
- **States:** position and speed of the cart, angle and velocity of the pole.
- **Actions:** left and right movements.
- **Rewards:** +1 for each step until failure.

Applications of RL : Optimal control



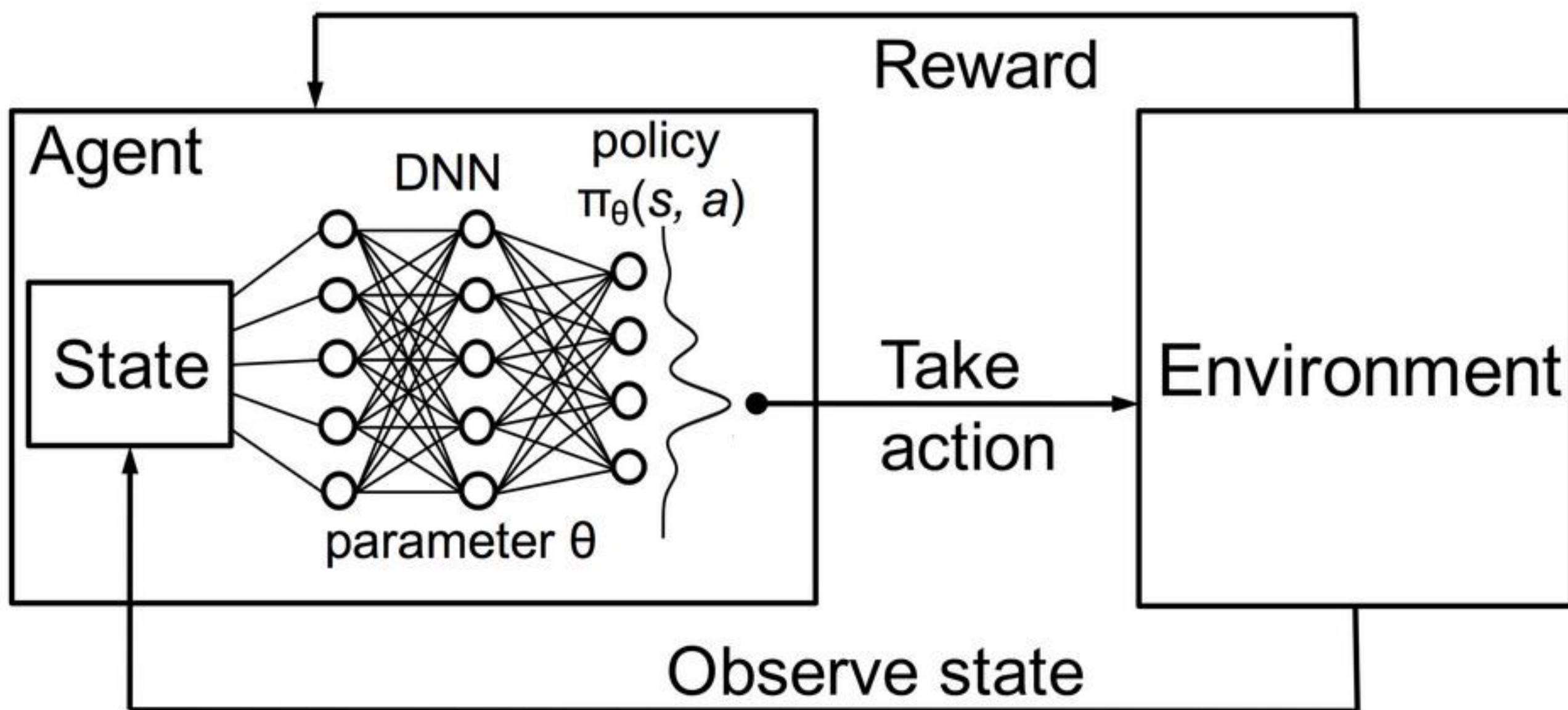
Applications of RL : Board games (Backgammon, Chess, Go, etc)

TD-Gammon (Tesauro, 1992) was one of the first AI to beat human experts at a complex game, Backgammon.



- **States:** board configurations.
- **Actions:** piece displacements.
- **Rewards:** +1 for game won, -1 for game lost, 0 otherwise. **sparse rewards**

Deep Reinforcement Learning (DRL)



- Classical tabular RL was limited to toy problems, with few states and actions.
- It is only when coupled with **deep neural networks** that interesting applications of RL became possible.
- Deepmind (now Google) started the deep RL hype in 2013 by learning to solve 50+ Atari games with a CNN.

Applications of RL : Atari games

- **States:**

pixel frames.

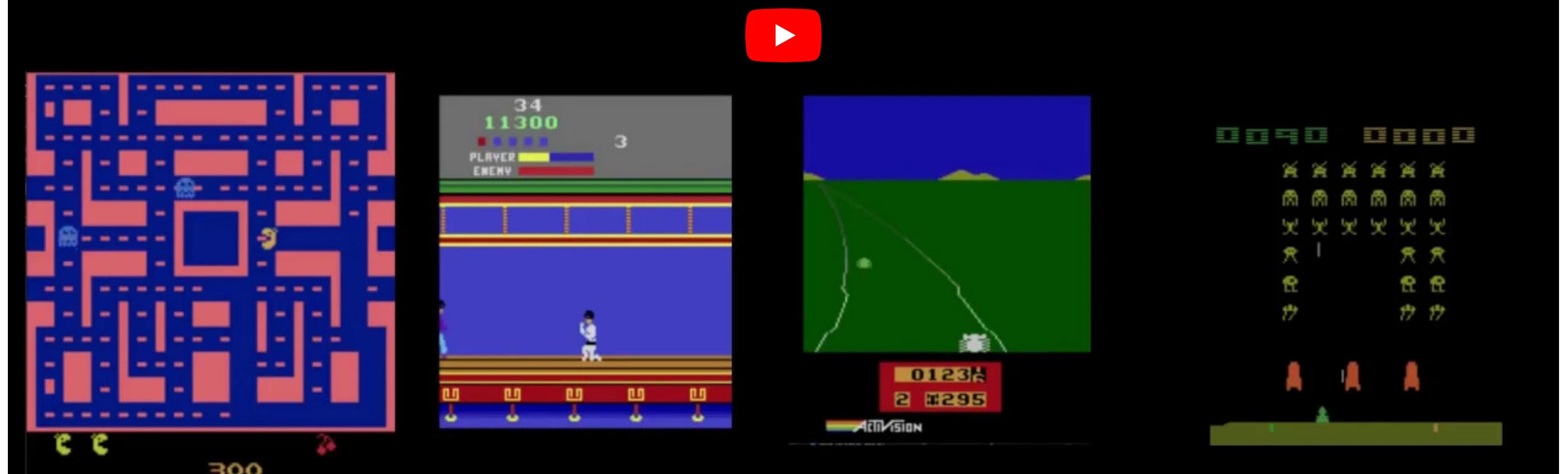


- **Actions:**

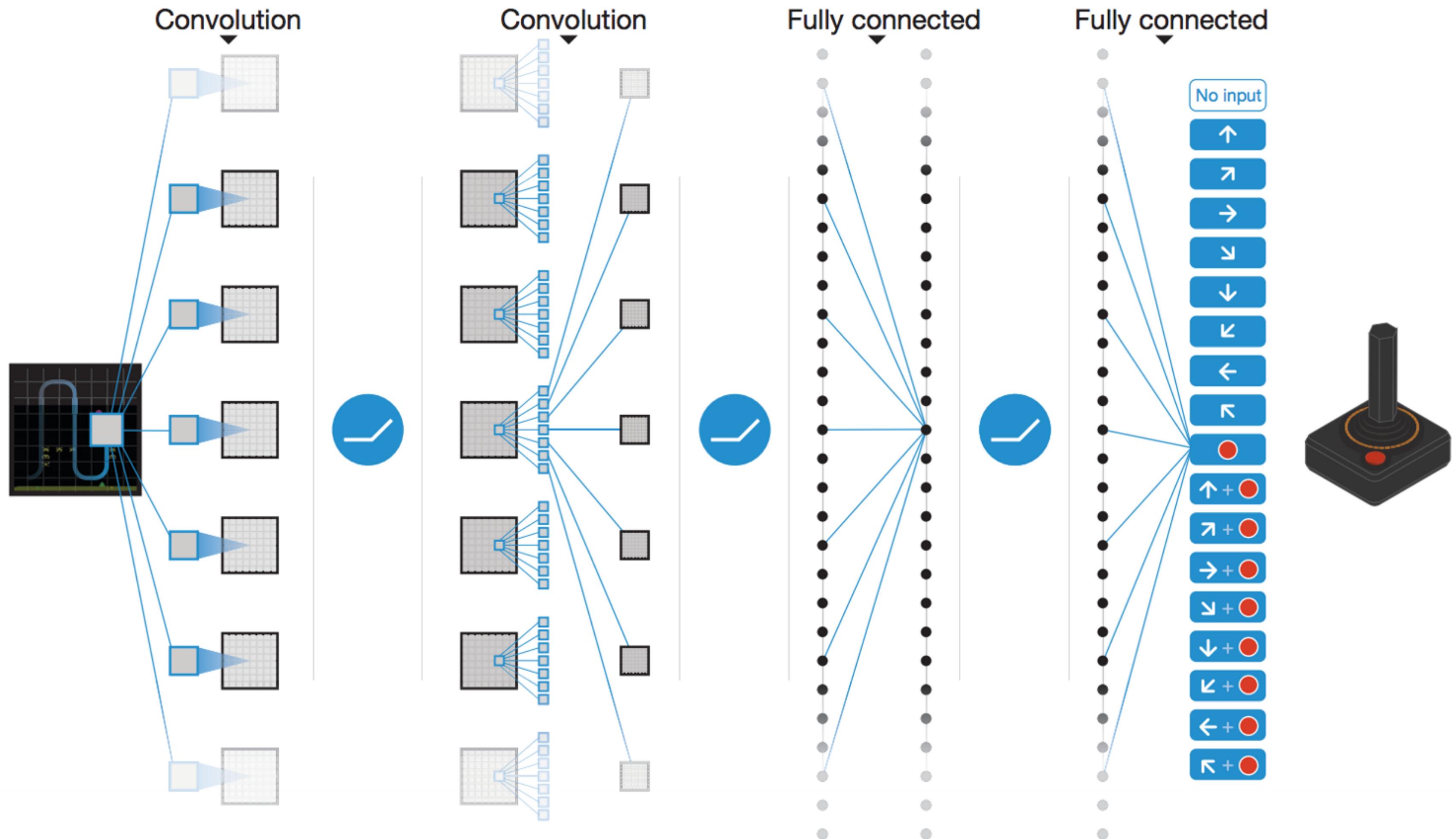
button presses.

- **Rewards:**

score increases.



Applications of RL : Atari games



Applications of RL : simulated cars

- **States:**

pixel frames.

- **Actions:**

direction, speed.

- **Rewards:**

linear velocity (+),
crashes (-)



Applications of RL : Parkour

- **States:**

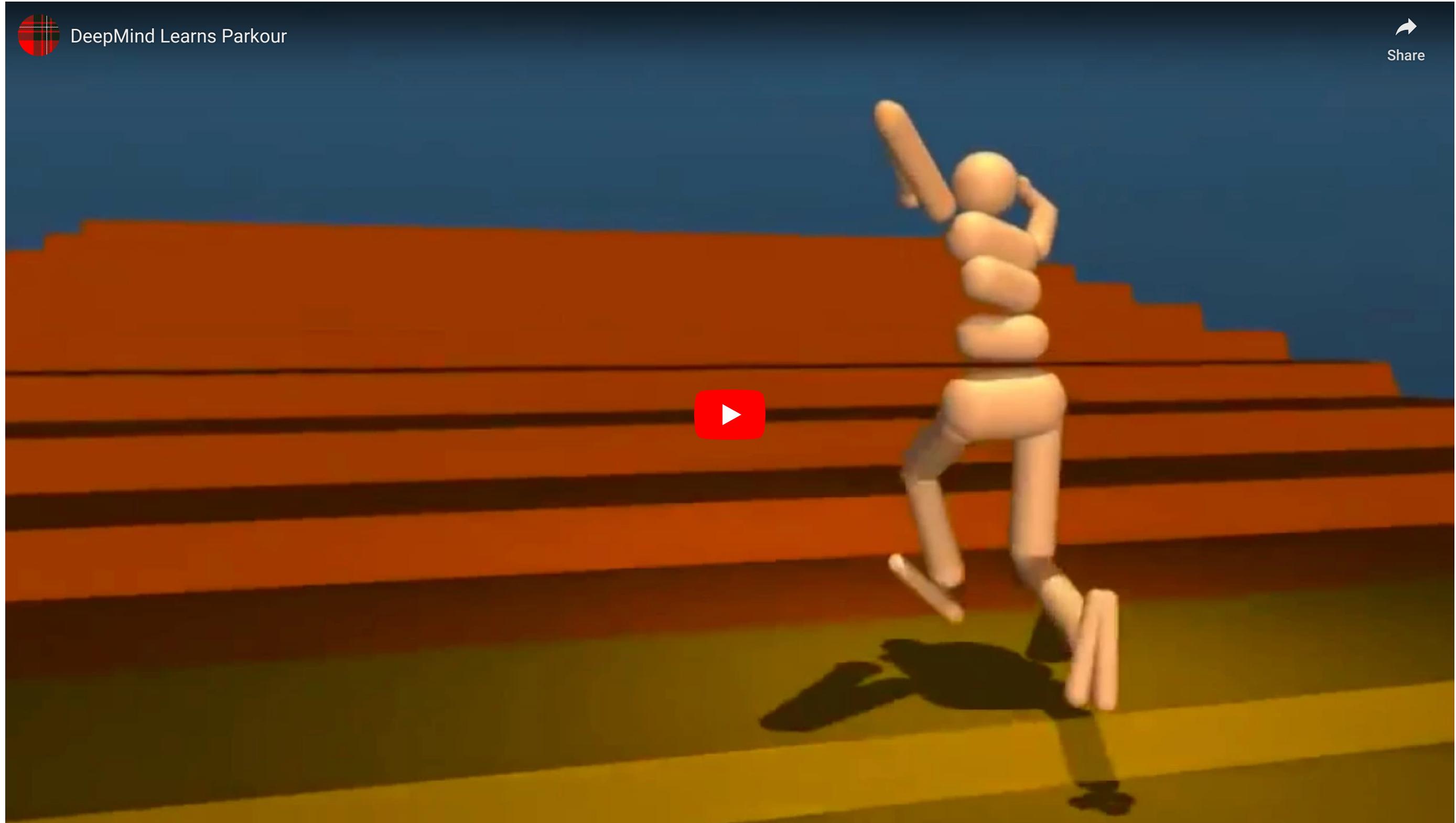
joint positions.

- **Actions:**

joint displacements.

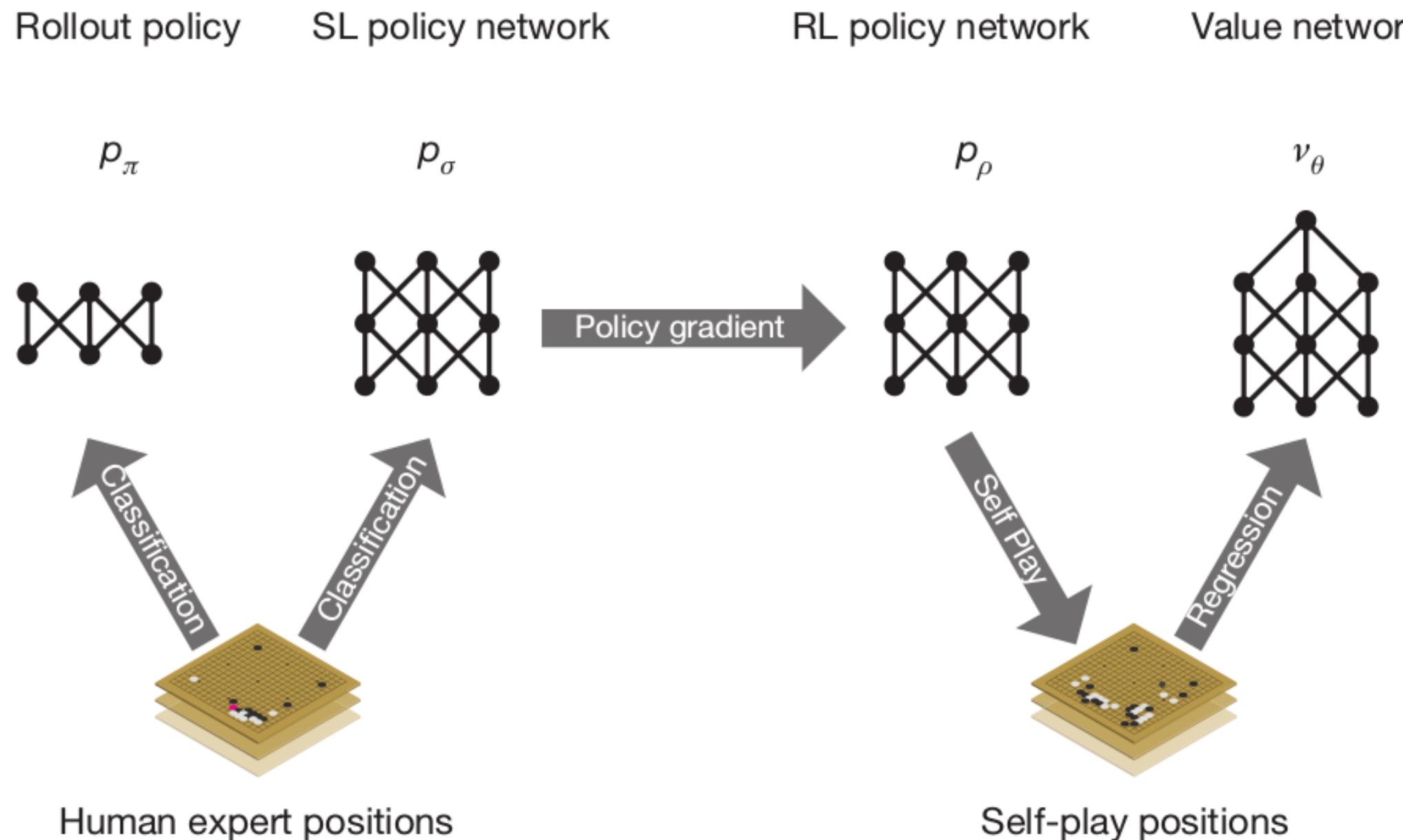
- **Rewards:**

linear velocity (+),
crashes (-)

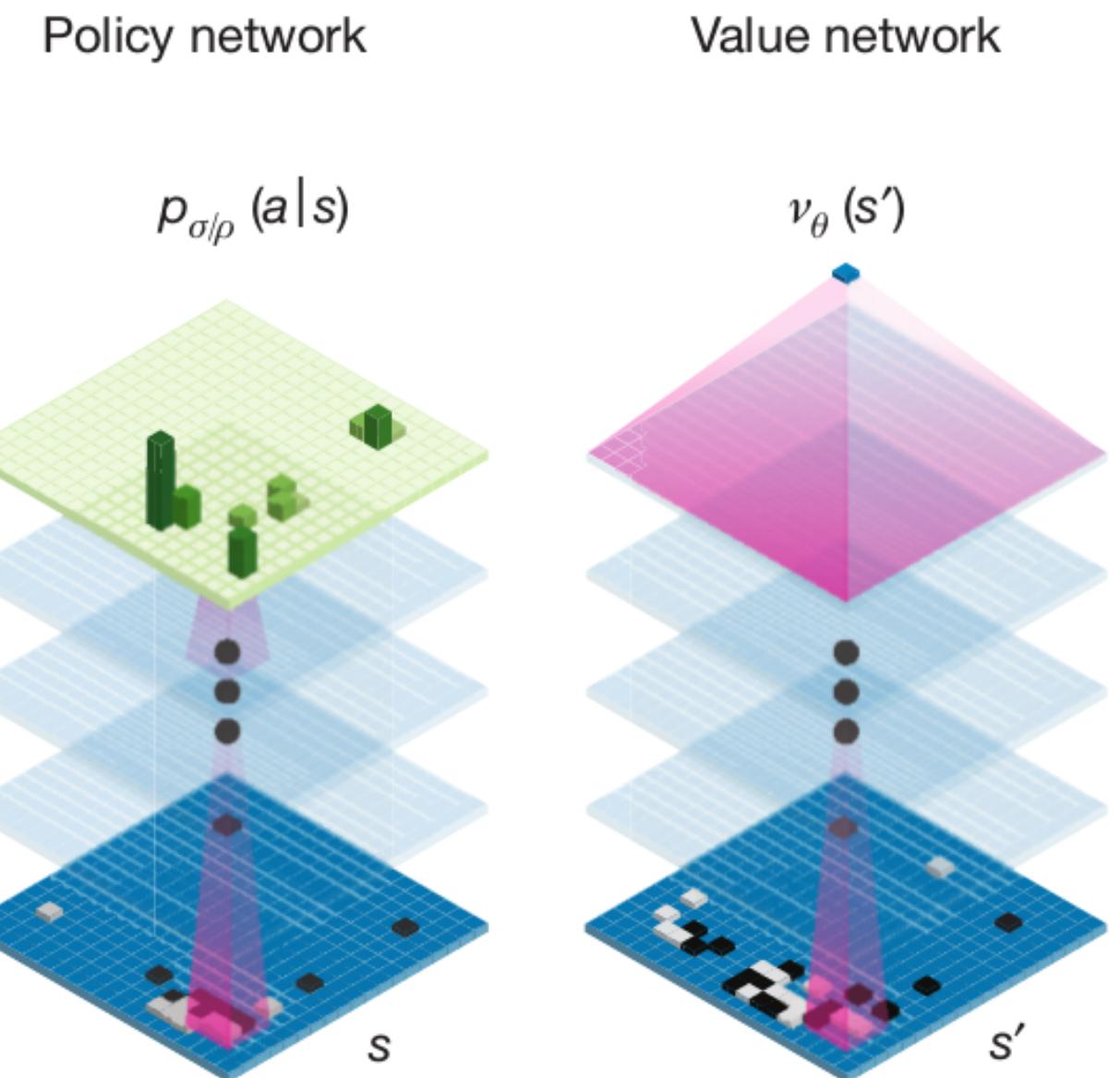


Applications of RL : AlphaGo

a



b

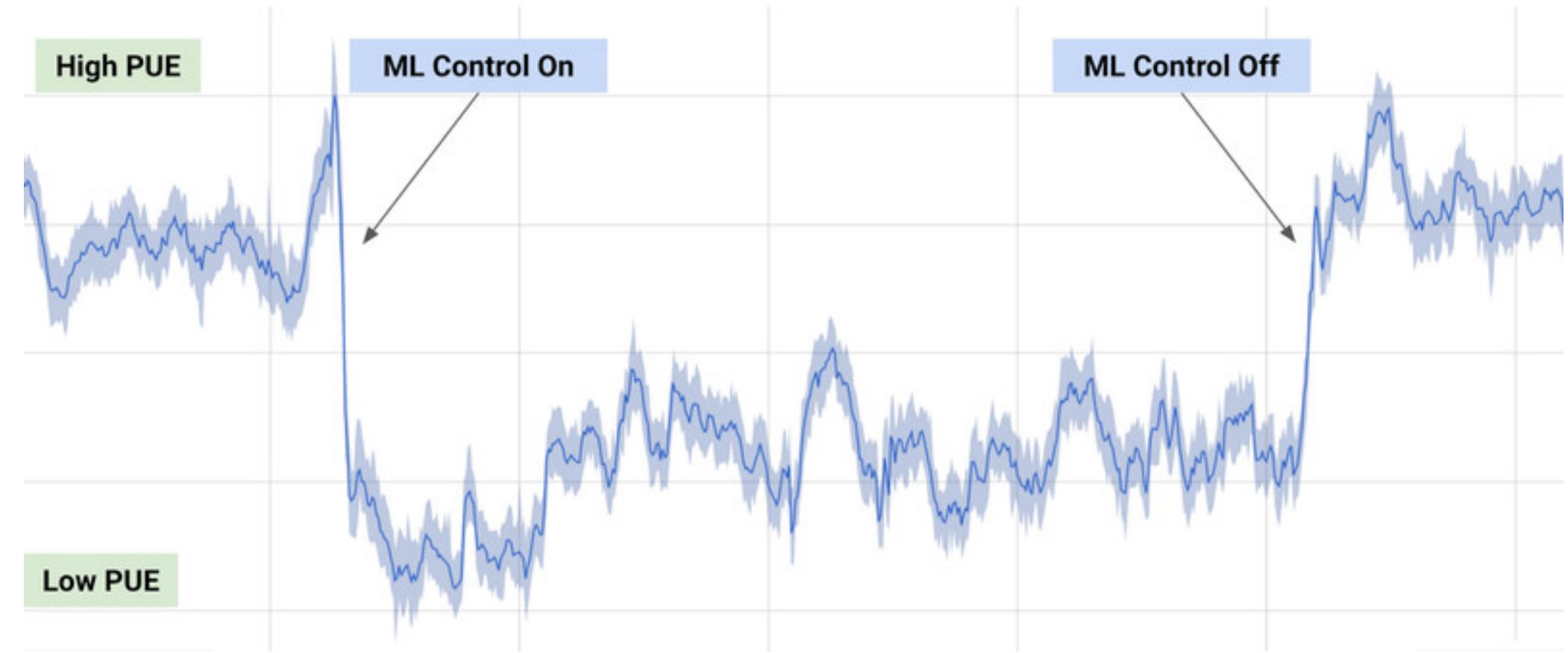


- AlphaGo was able to beat Lee Sedol in 2016, 19 times World champion.
- It relies on human knowledge to **bootstrap** a RL agent (supervised learning).
- The RL agent discovers new strategies by using self-play: during the games against Lee Sedol, it was able to use **novel** moves which were never played before and surprised its opponent.
- Training took several weeks on 1202 CPUs and 176 GPUs.

Applications of RL : AlphaGo



Applications of RL: process control



Source: <https://deepmind.com/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-40/>

- 40% reduction of energy consumption when using deep RL to control the cooling of Google's datacenters.
- **States:** sensors (temperature, pump speeds).
- **Actions:** 120 output variables (fans, windows).
- **Rewards:** decrease in energy consumption

Applications of RL : real robotics

- **States:**

pixel frames.

- **Actions:**

joint movements.

- **Rewards:**

successful
grasping.



Applications of RL : learning dexterity

- **States:**

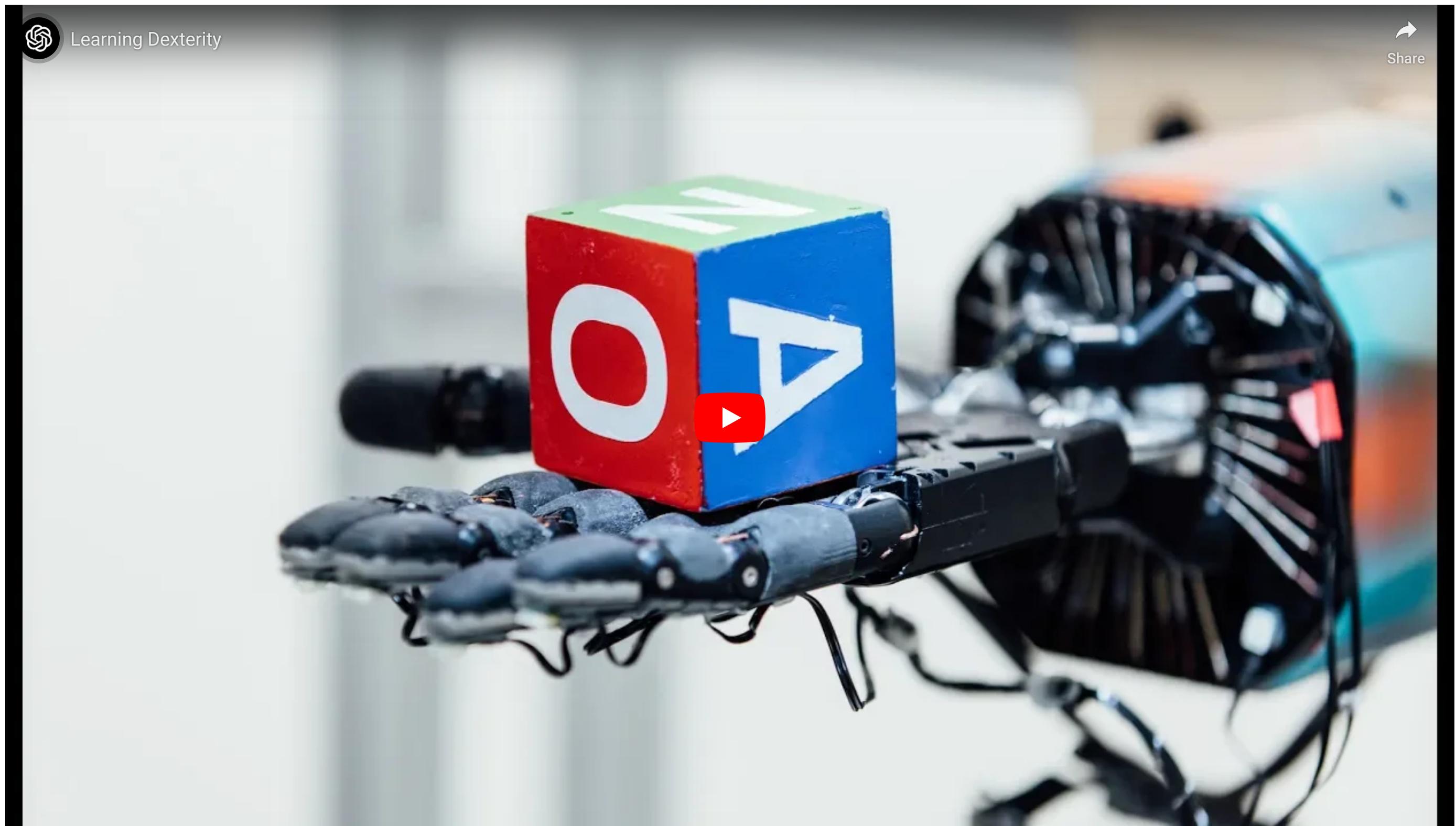
pixel frames, joint position.

- **Actions:**

joint movements.

- **Rewards:**

shape obtained.



Applications of RL : real cars

- **States:**

pixel frames.

- **Actions:**

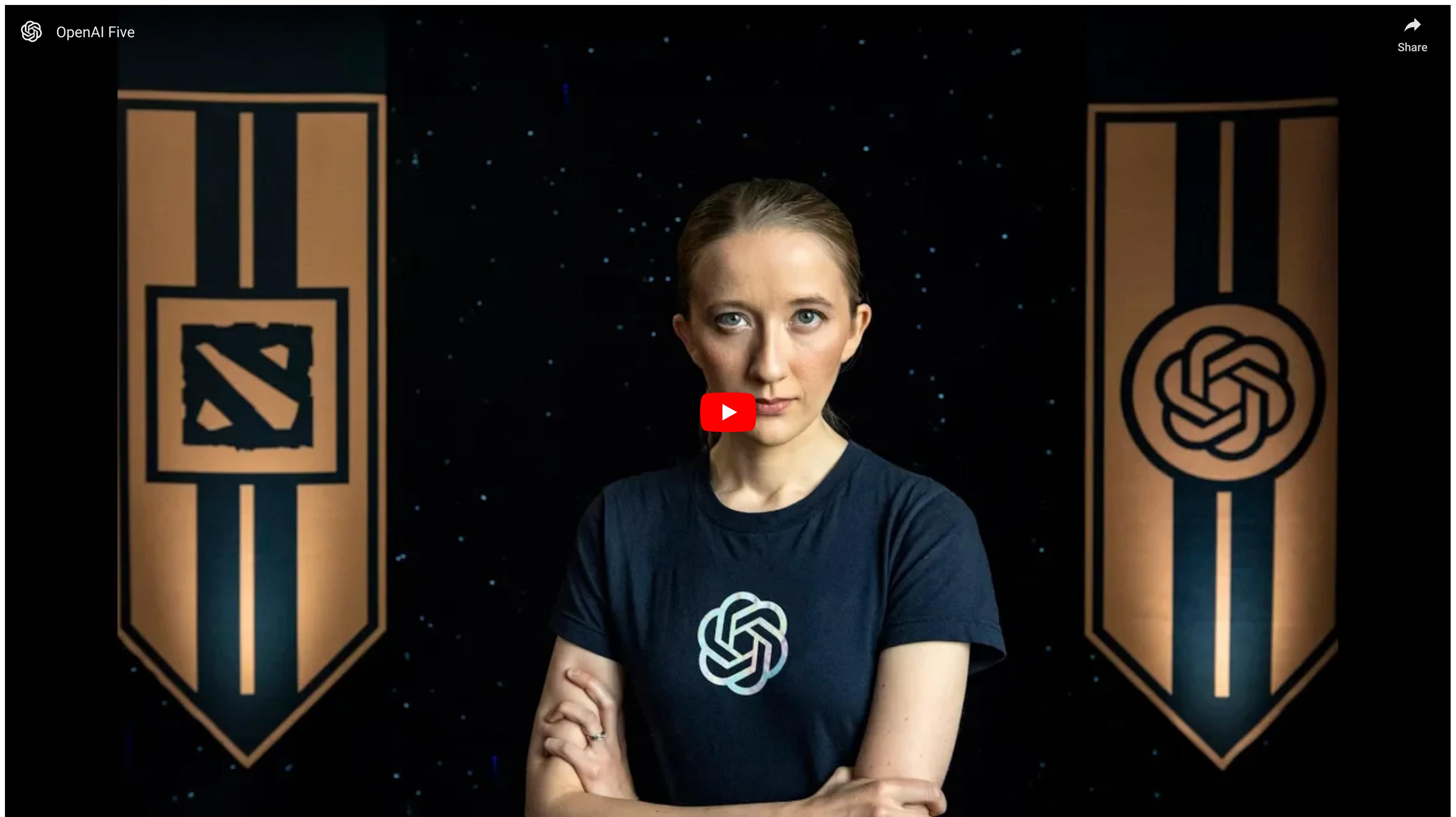
direction, speed.

- **Rewards:**

time before humans take control.

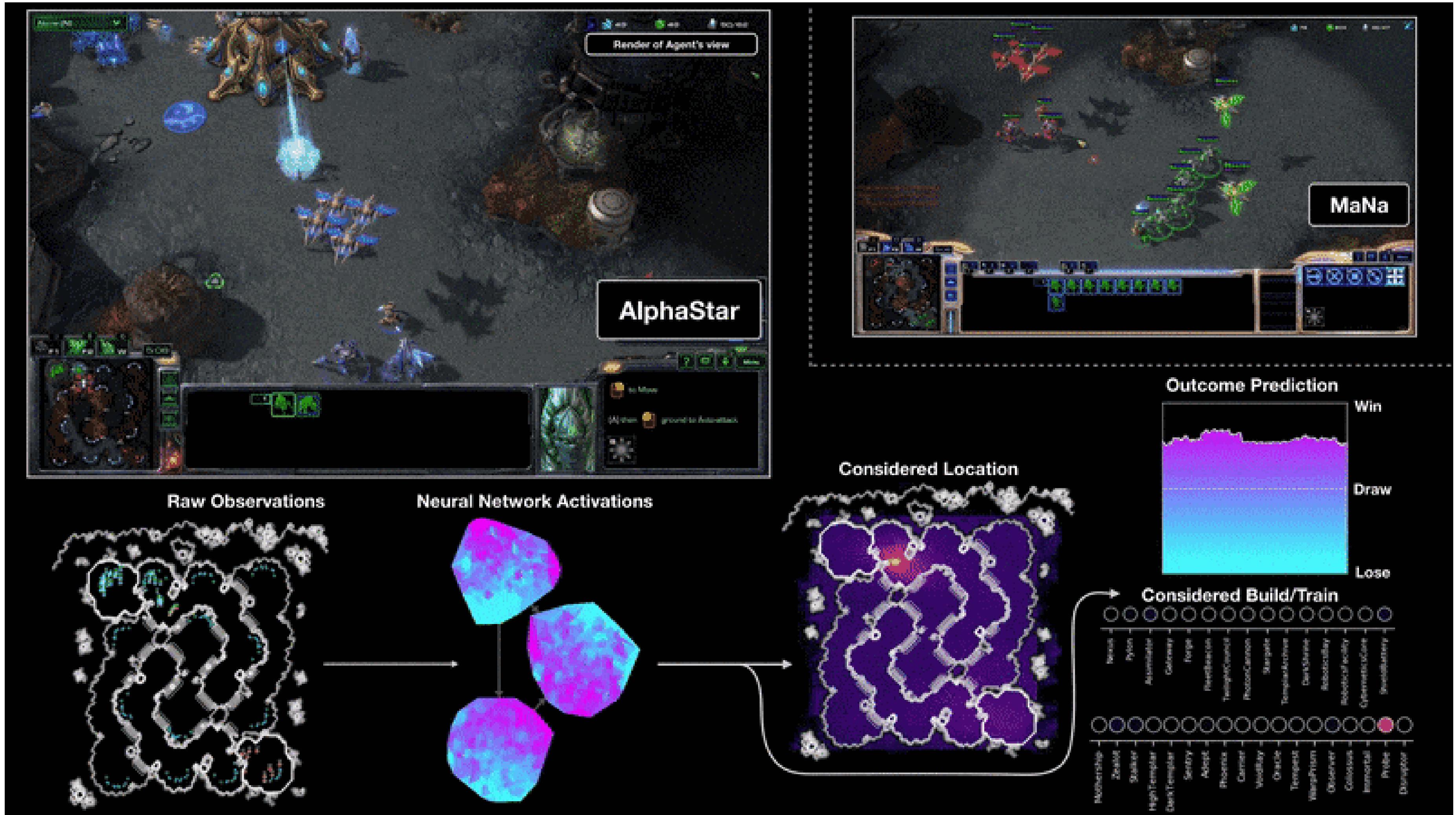


Applications of RL : Dota2 (OpenAI)



- 128,000 CPU cores and 256 Nvidia P100 GPUs on Google Cloud for 10 months (\$25,000 per day)...

Applications of RL : Starcraft II (AlphaStar)



Source: <https://deepmind.com/blog/article/alphastar-mastering-real-time-strategy-game-starcraft-ii>

Take home messages

- Deep RL is gaining a lot of importance in AI research.
 - Lots of applications in control: video games, robotics, industrial applications...
 - It may be AI's best shot at producing intelligent behavior, as it does not rely on annotated data.
- A lot of problems have to be solved before becoming as mainstream as deep learning.
 - Sample complexity is often prohibitive.
 - Energy consumption and computing power simply crazy (AlphaGo: 1 MW, Dota2: 800 petaflop/s-days)
 - The correct reward function is hard to design, ethical aspects. (*inverse RL*)
 - Hard to incorporate expert knowledge. (*model-based RL*)
 - Learns single tasks, does not generalize (*hierarchical RL, meta-learning*)

Plan of the course

1. Introduction

- 1. Applications
- 2. Crash course in statistics

2. Basic RL

- 1. Bandits
- 2. Markov Decision Process
- 3. Dynamic programming
- 4. Monte-Carlo control
- 5. Temporal difference,
Eligibility traces
- 6. Function approximation
- 7. Deep learning

3. Model-free RL

- 1. Deep Q-networks
- 2. Beyond DQN
- 3. Policy gradient,
REINFORCE
- 4. Advantage Actor-critic
(A3C)
- 5. Deterministic policy
gradient (DDPG)
- 6. Natural gradients (TRPO,
PPO)
- 7. Maximum Entropy RL
(SAC)

4. Model-based RL

- 1. Principle, Dyna-Q, MPC
 - 2. Learned World models
 - 3. AlphaGo
 - 4. Successor representations
- ## 5. Outlook
- 1. Hierarchical RL
 - 2. Inverse RL
 - 3. Meta RL

References

- Sutton and Barto (1998, 2017). Reinforcement Learning: An Introduction. MIT Press.

<http://incompleteideas.net/sutton/book/the-book.html>

- Szepesvari (2010). Algorithms for Reinforcement Learning. Morgan and Claypool.

<http://www.ualberta.ca/~szepesva/papers/RLAlgsInMDPs.pdf>

- CS294 course of Sergey Levine at Berkeley.

<http://rll.berkeley.edu/deeprlcourse/>

- Reinforcement Learning course by David Silver at UCL.

<http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html>