Deep Reinforcement Learning

Introduction

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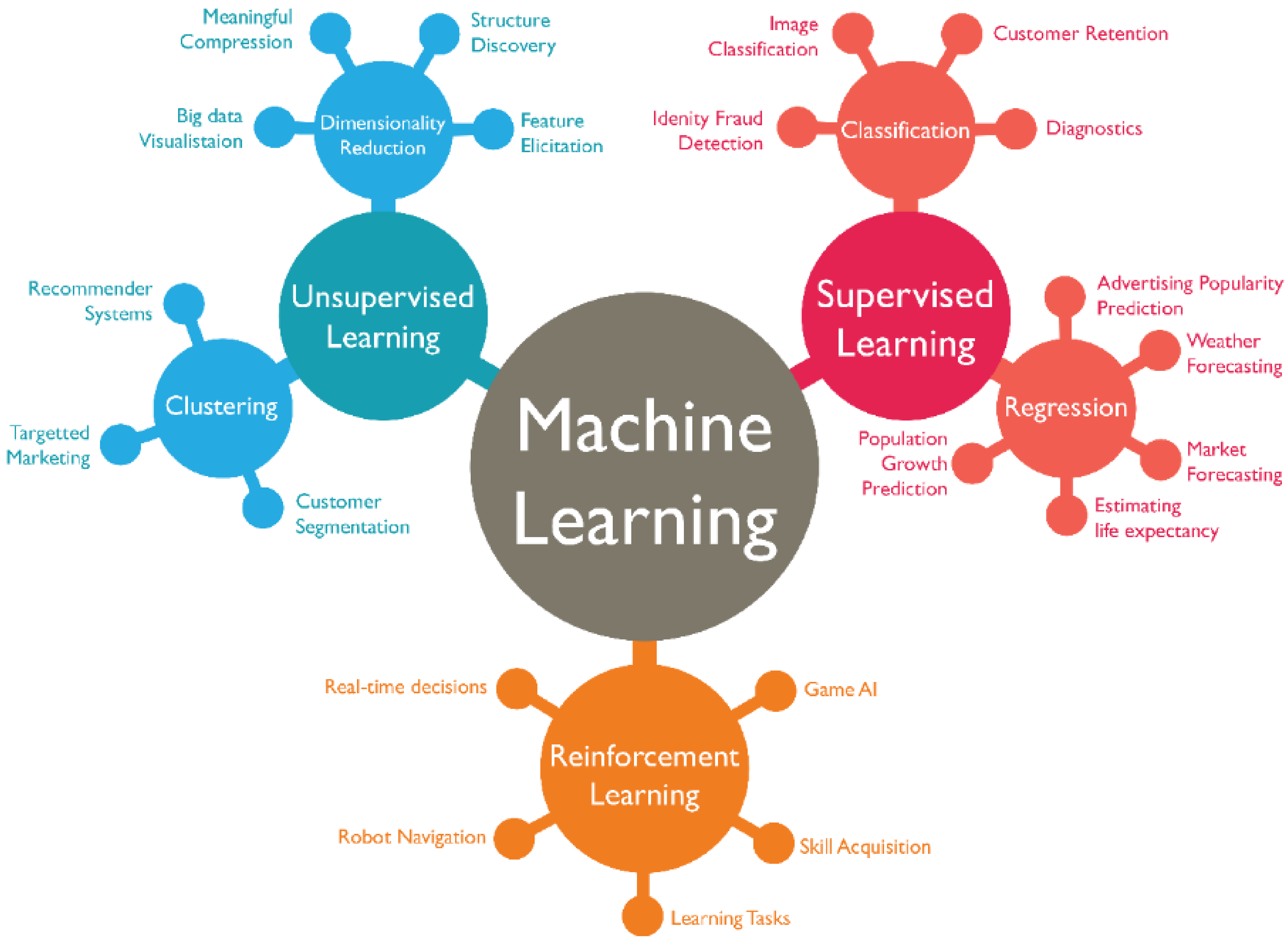
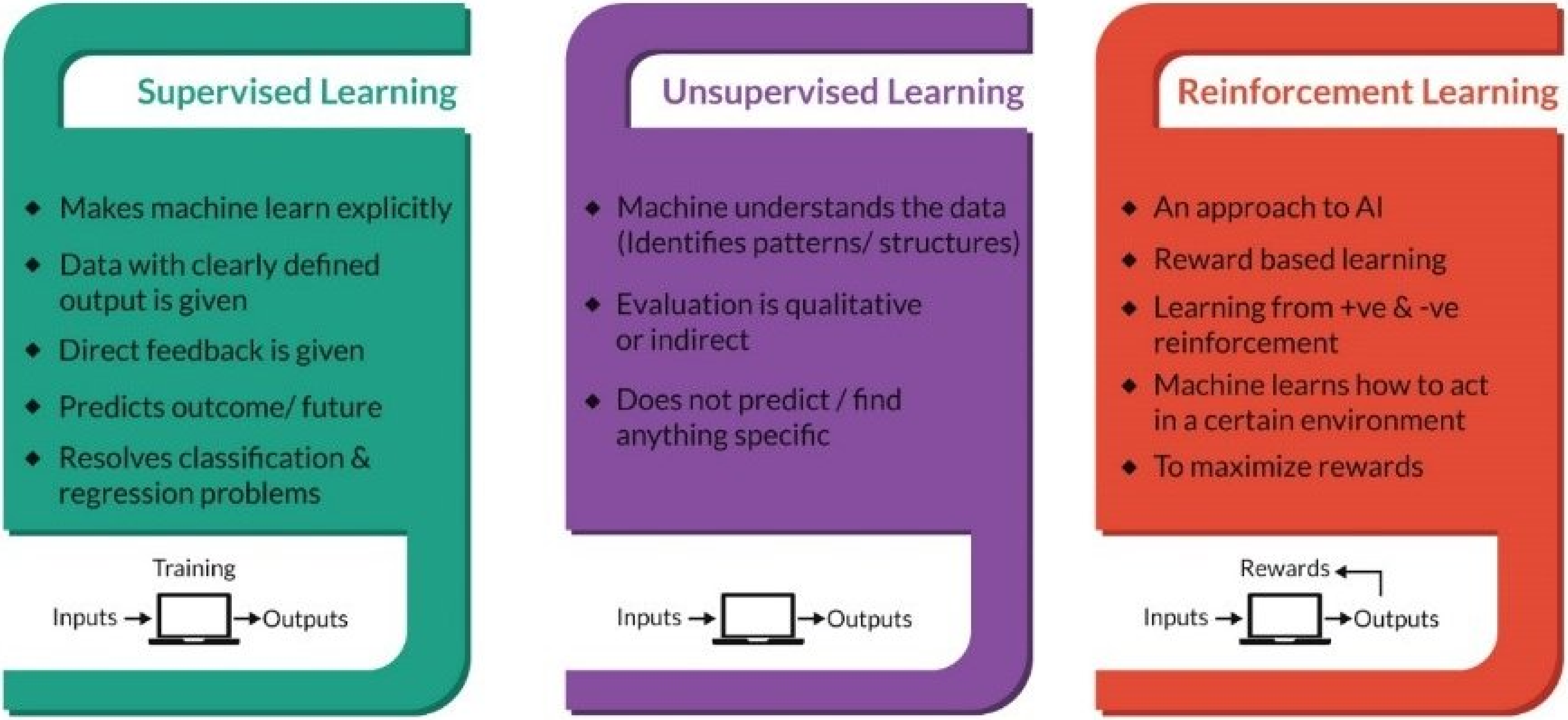
https://tu-chemnitz.de/informatik/KI/edu/deeprl



Machine Learning
Unsupervised Learning
Dimensionality Reduction
Meaningful Compression
Structure Discovery
Big data Visualistaion
Feature Elicitation
Clustering
Recommender Systems
Targetted Marketing
Customer Segmentation
Supervised Learning
Classification
Image Classification
Customer Retention
Idenity Fraud Detection
Diagnostics
Regression
Advertising Popularity Prediction
Weather Forecasting
Population Growth Prediction
Market Forecasting
Estimating life expectancy
Reinforcement Learning
Real-time decisions
Game AI
Robot Navigation
Skill Acquisition
Learning Tasks

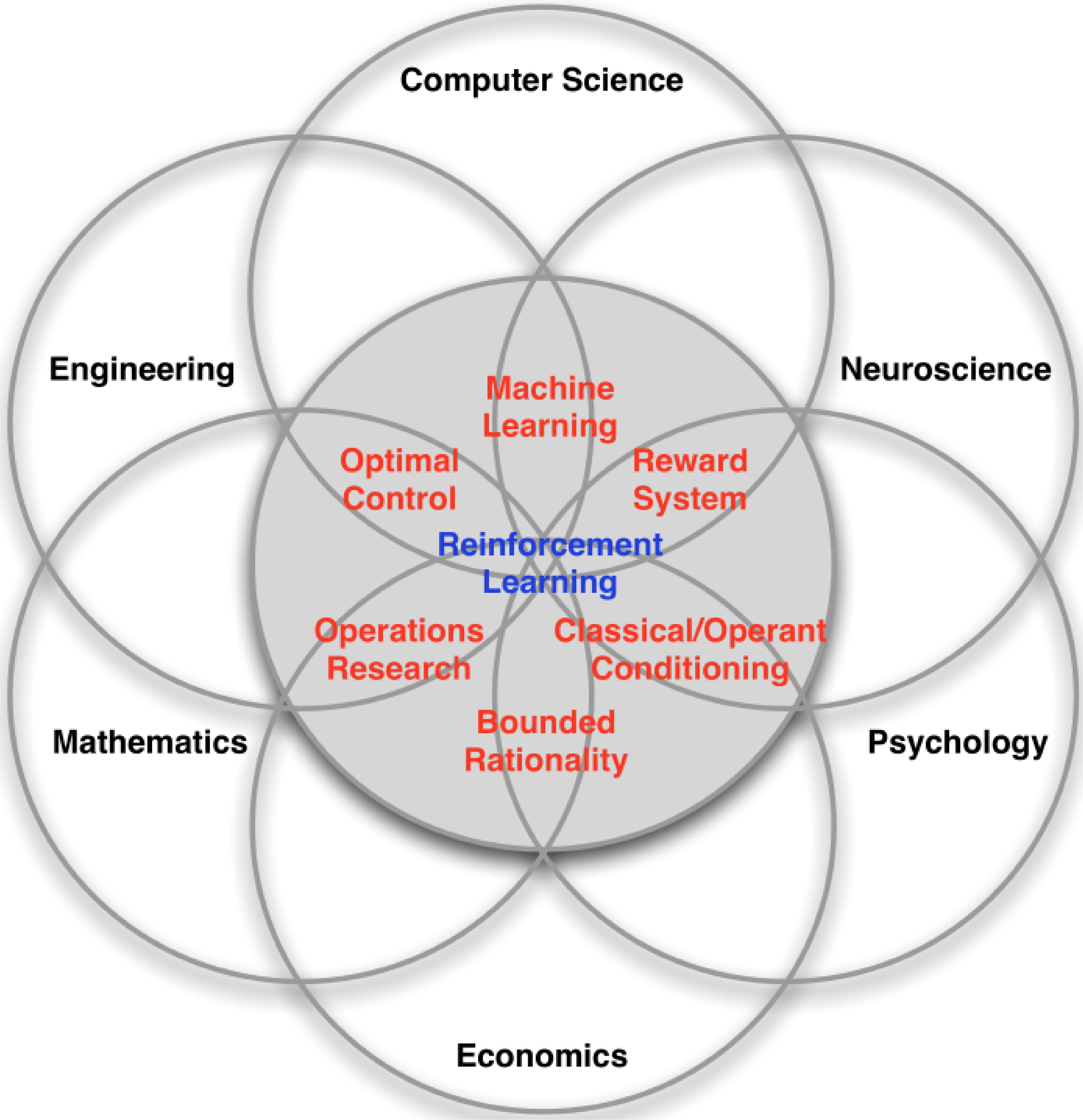
Different types of machine learning depending on the feedback

- **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.



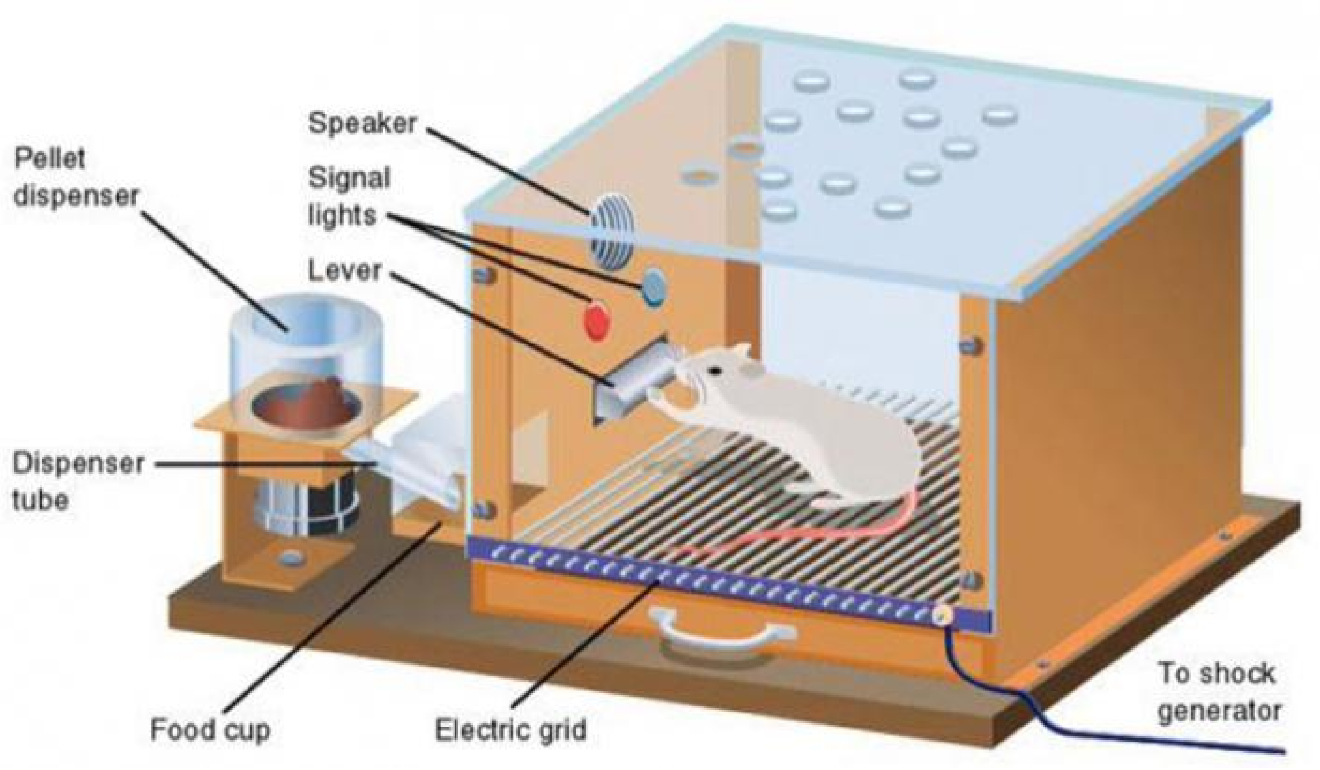
Source: https://www.analyticsvidhya.com/blog/2016/12/artificial-intelligence-demystified/

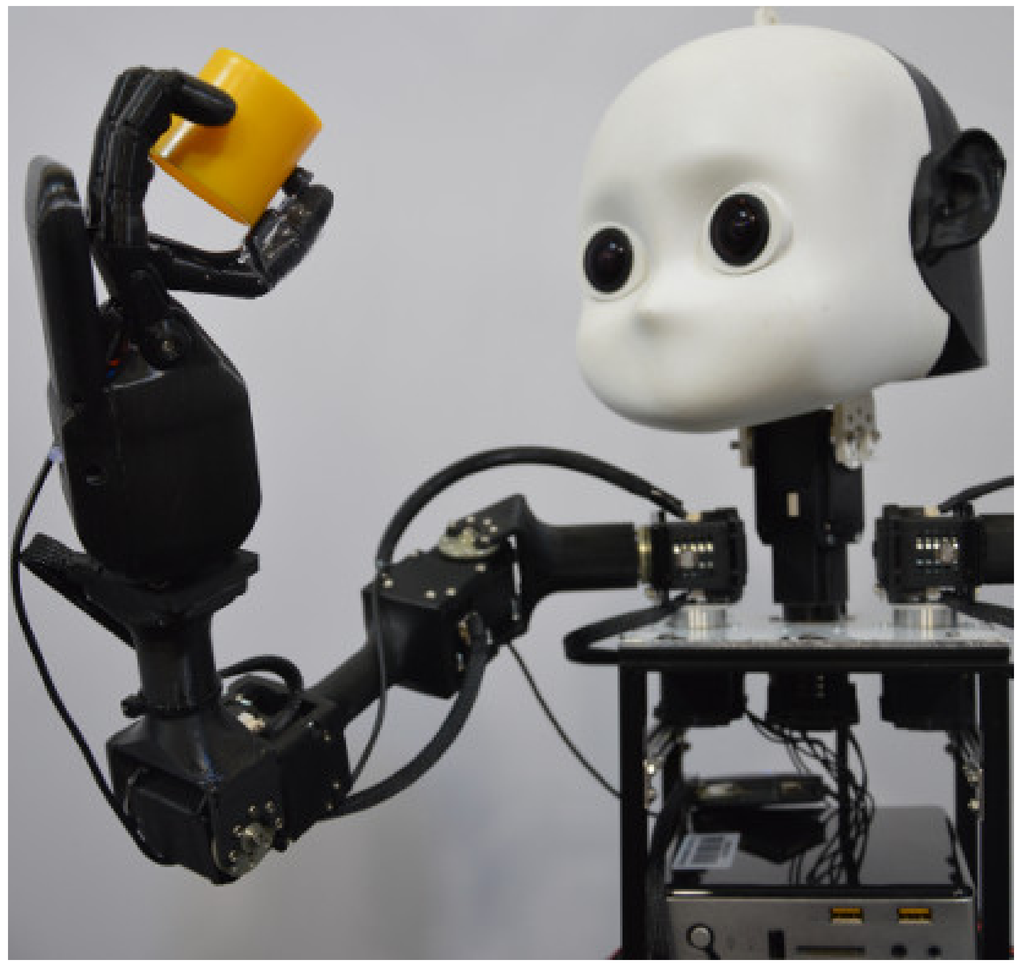
Many faces of RL



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

A brief history of reinforcement learning

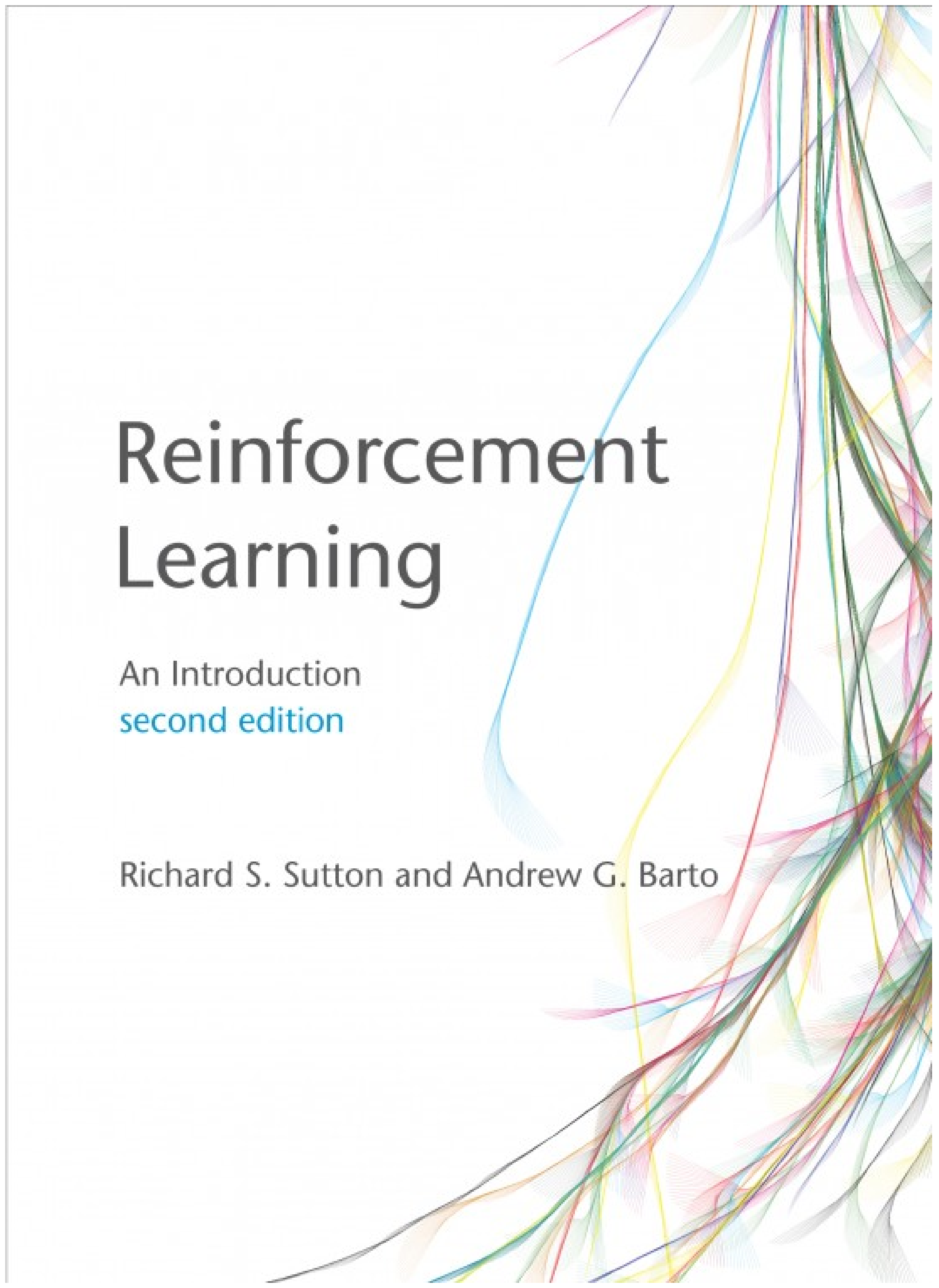




- **Early 20th century**: animal behavior, psychology, operant conditioning
  - Ivan Pavlov, Edward Thorndike, B.F. Skinner
- **1950s**: optimal control, Markov Decision Process, dynamic programming
  - Richard Bellman, Ronald Howard
- **1970s**: trial-and-error learning
  - Marvin Minsky, Harry Klopf, 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, Hassabis...)
  - OpenAI (Sutskever, Schulman...)
  - Berkeley (Sergey Levine)

See http://www.incompleteideas.net/book/ebook/node12.html

The RL bible



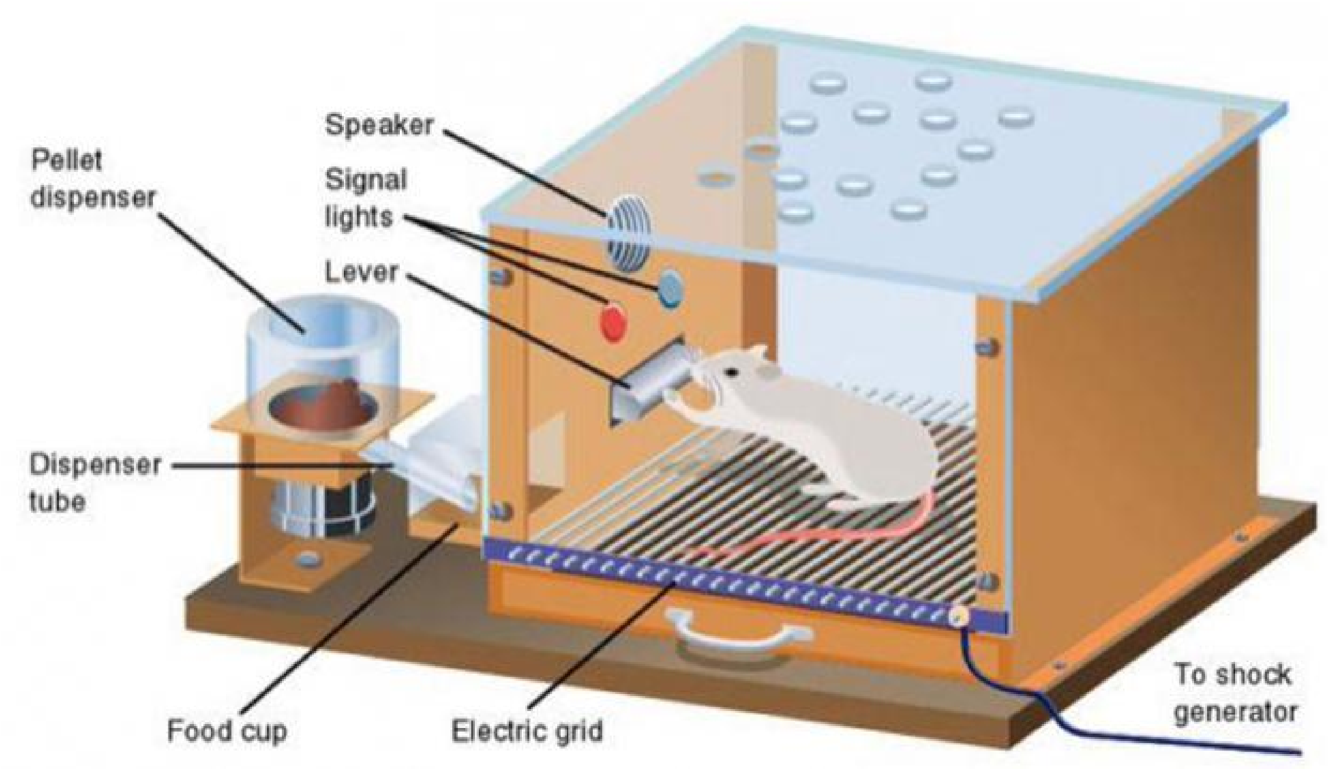
Sutton and Barto (1998). Reinforcement Learning: An Introduction. MIT Press.

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

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

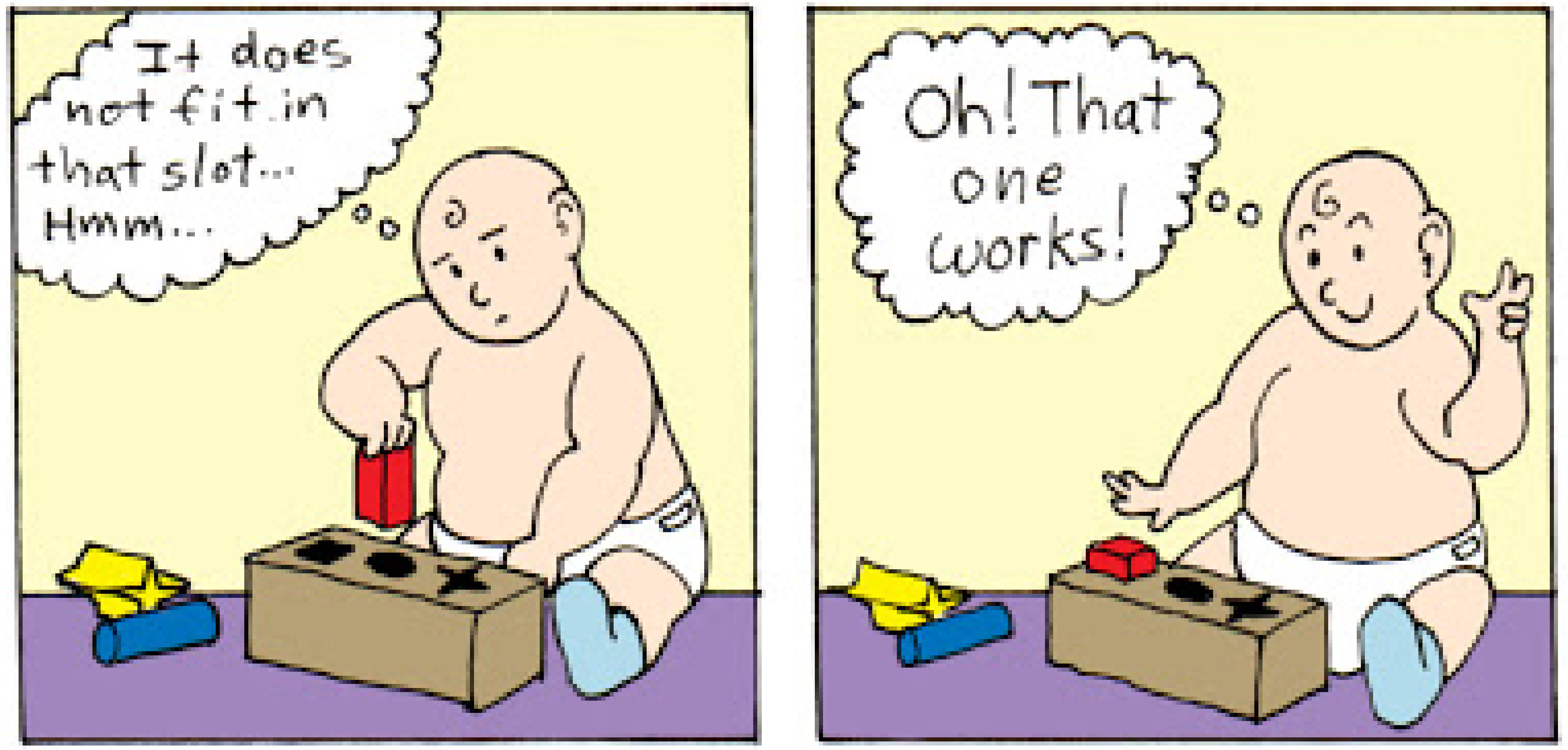
Operant conditioning

- 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



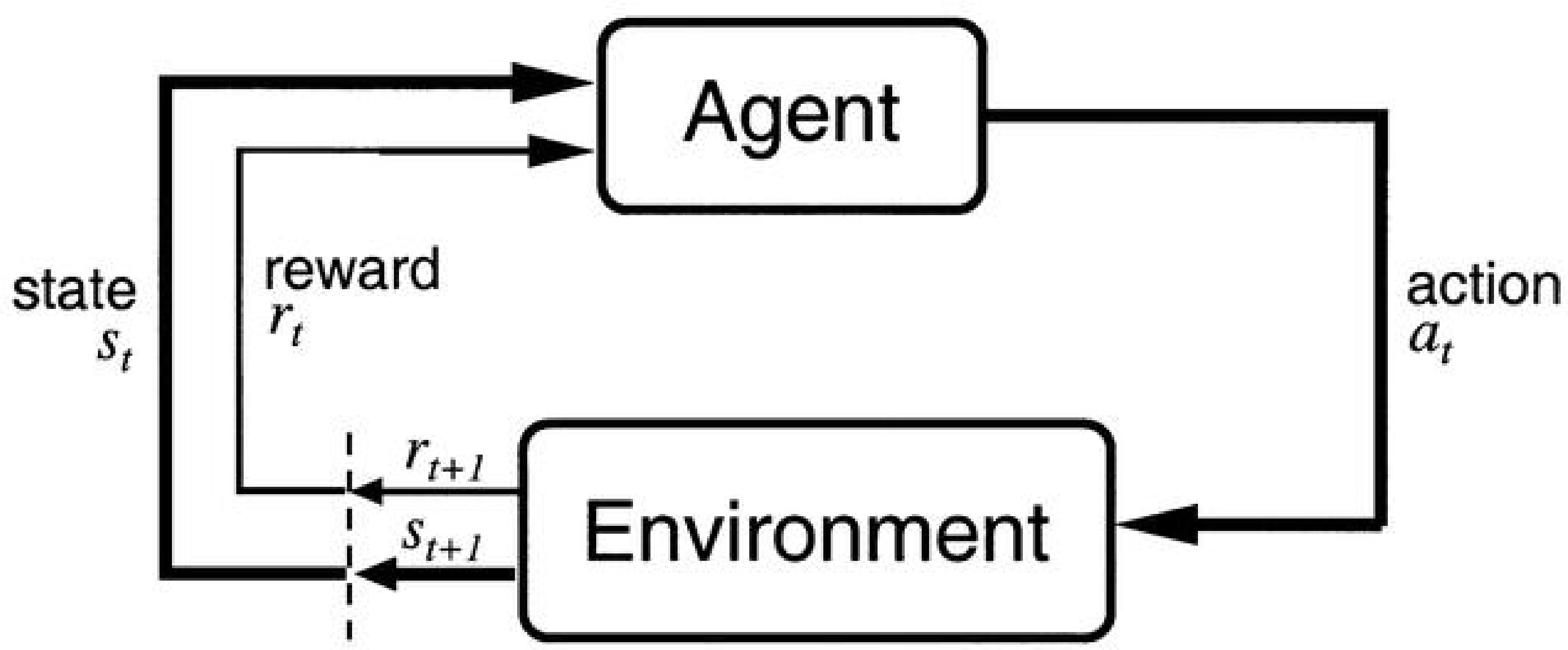
Source: https://sites.google.com/site/acrader4th2014/home/part-3-unity-and-diversity-of-life/trialanderrorlearning

- 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.

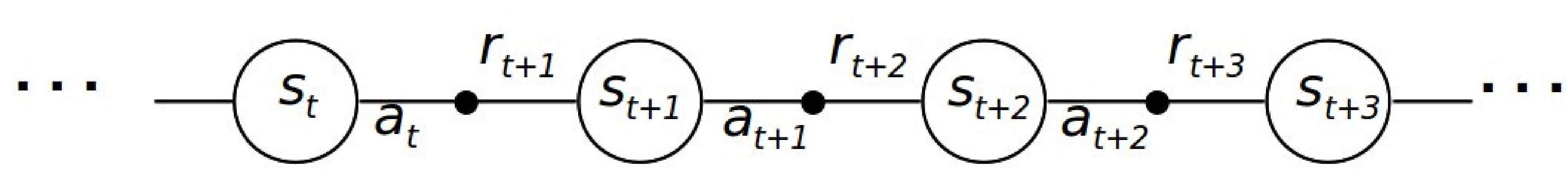
The agent-environment interface



Source: Sutton and Barto (1998).

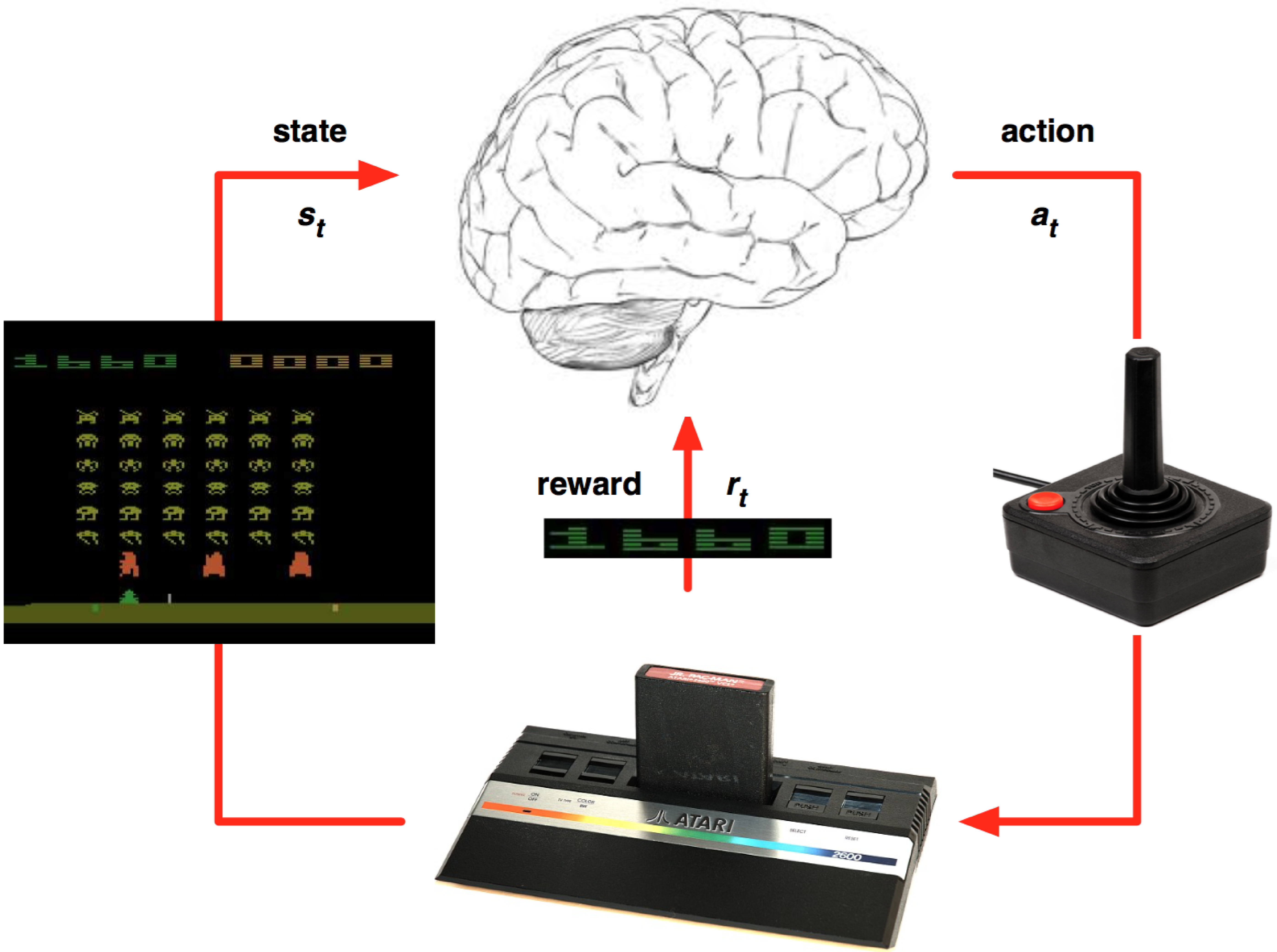
- The agent and the environment interact at discrete time steps: t=0, 1, ...
- The agent observes its state at time t: $s_t \in \mathcal{S}$
- It produces an action at time t, depending on the available actions in the current state: $a_t \in \mathcal{A}(s_t)$
- It receives a reward according to this action at time t+1: $r_{t+1} \in \Re$
- 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.



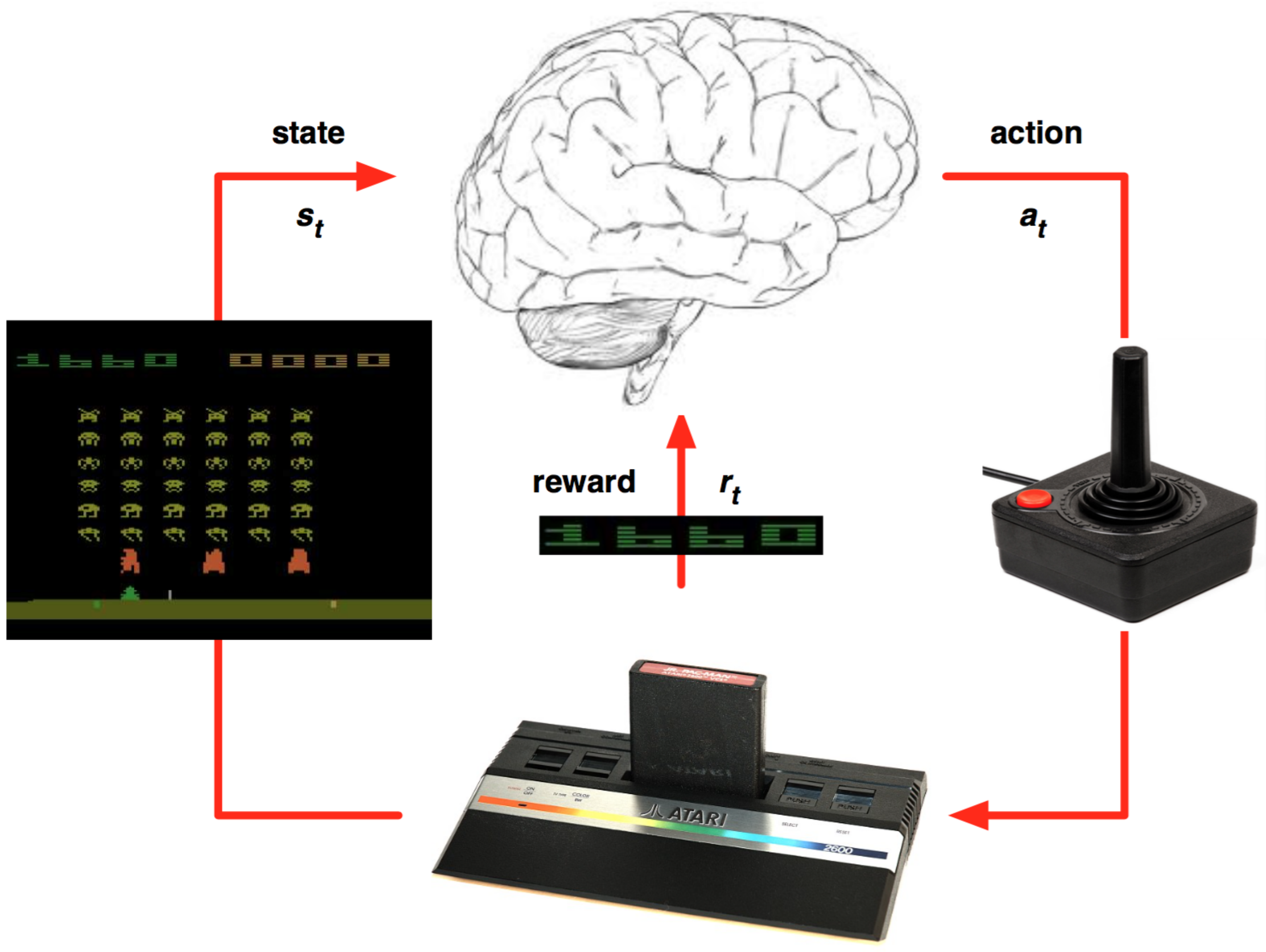
- Sequences $\tau = (s_0, a_0, r_1, s_1, a_1, \ldots, s_T)$ are called **episodes**, **trajectories**, **histories** or **rollouts**.

The agent-environment interface



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

Environment and agent states



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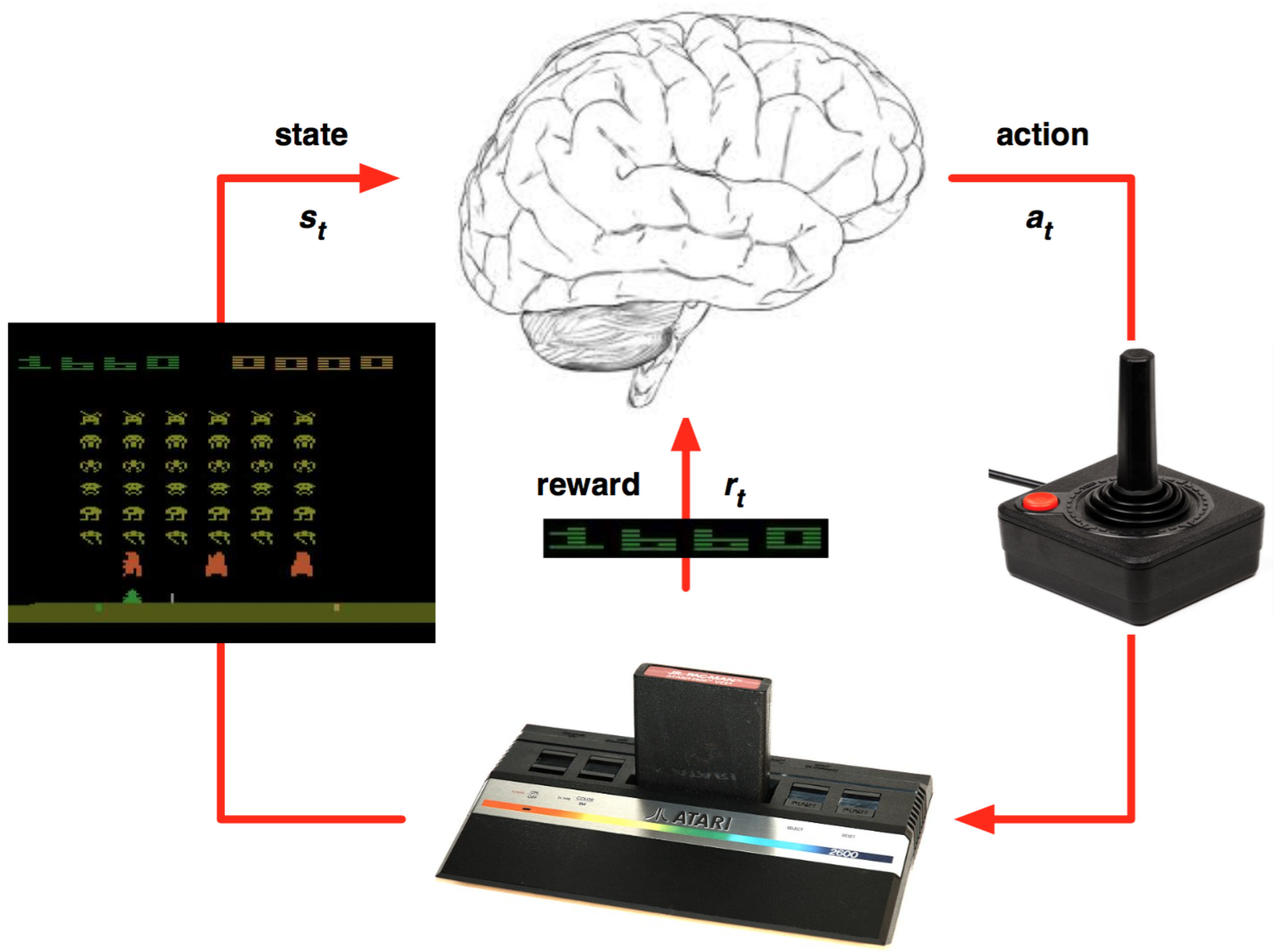
- The state s_t can relate to:
    - the **environment state**, i.e. all information external to the agent (position of objects, other agents, etc).
    - the **internal state**, information about the agent itself (needs, joint positions, etc).
- Generally, the state represents all the information necessary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

$$o_t = f(s_t)$$

- 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.



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

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

$$\pi : \mathcal{S} \times \mathcal{A} \rightarrow P(\mathcal{S})$$
$$(s, a) \rightarrow \pi(s, a) = P(a_t = a | s_t = s)$$

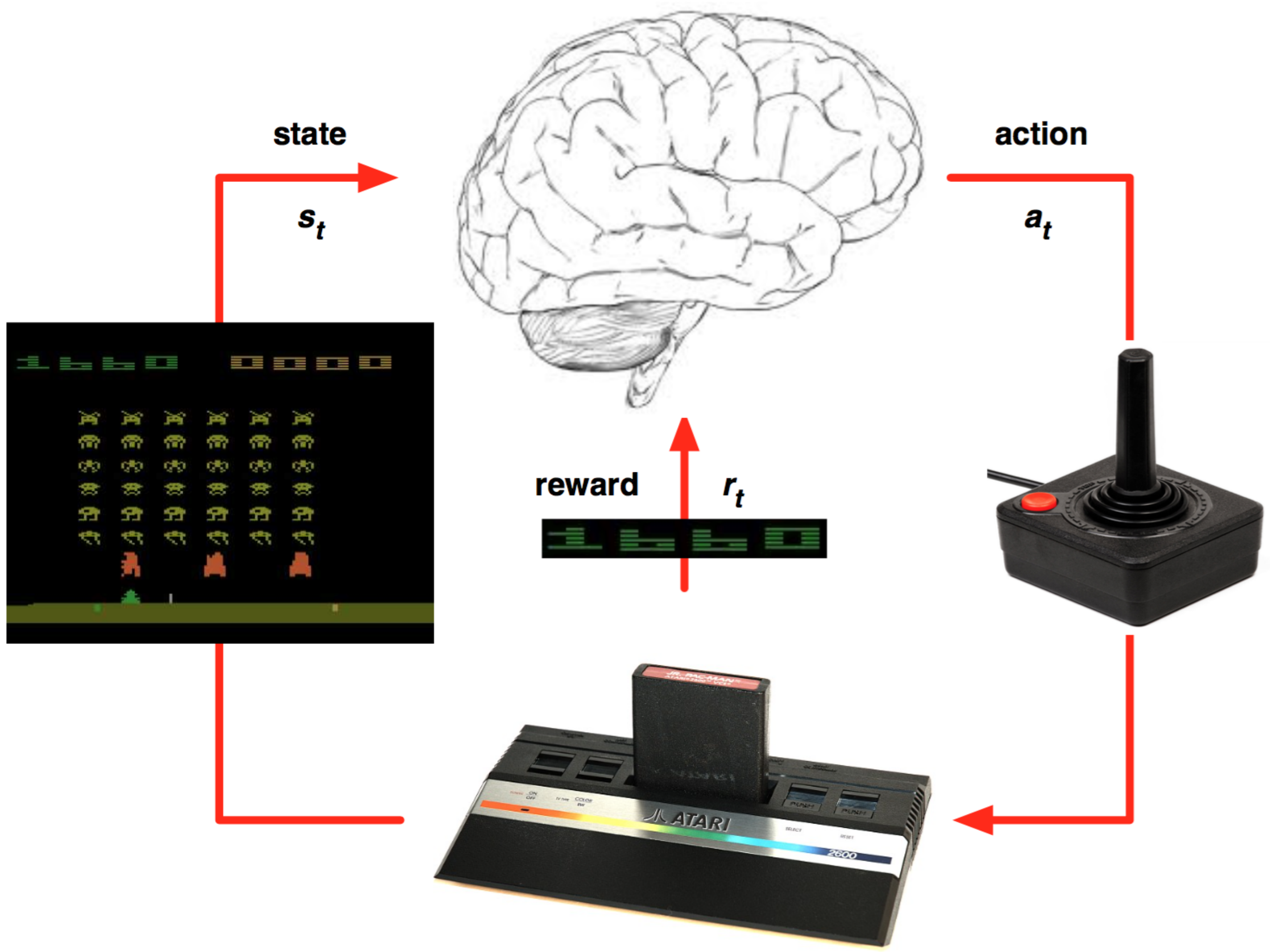
- $\pi(s, a)$ is the probability of selecting the action a in s. We have of course:

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

- 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



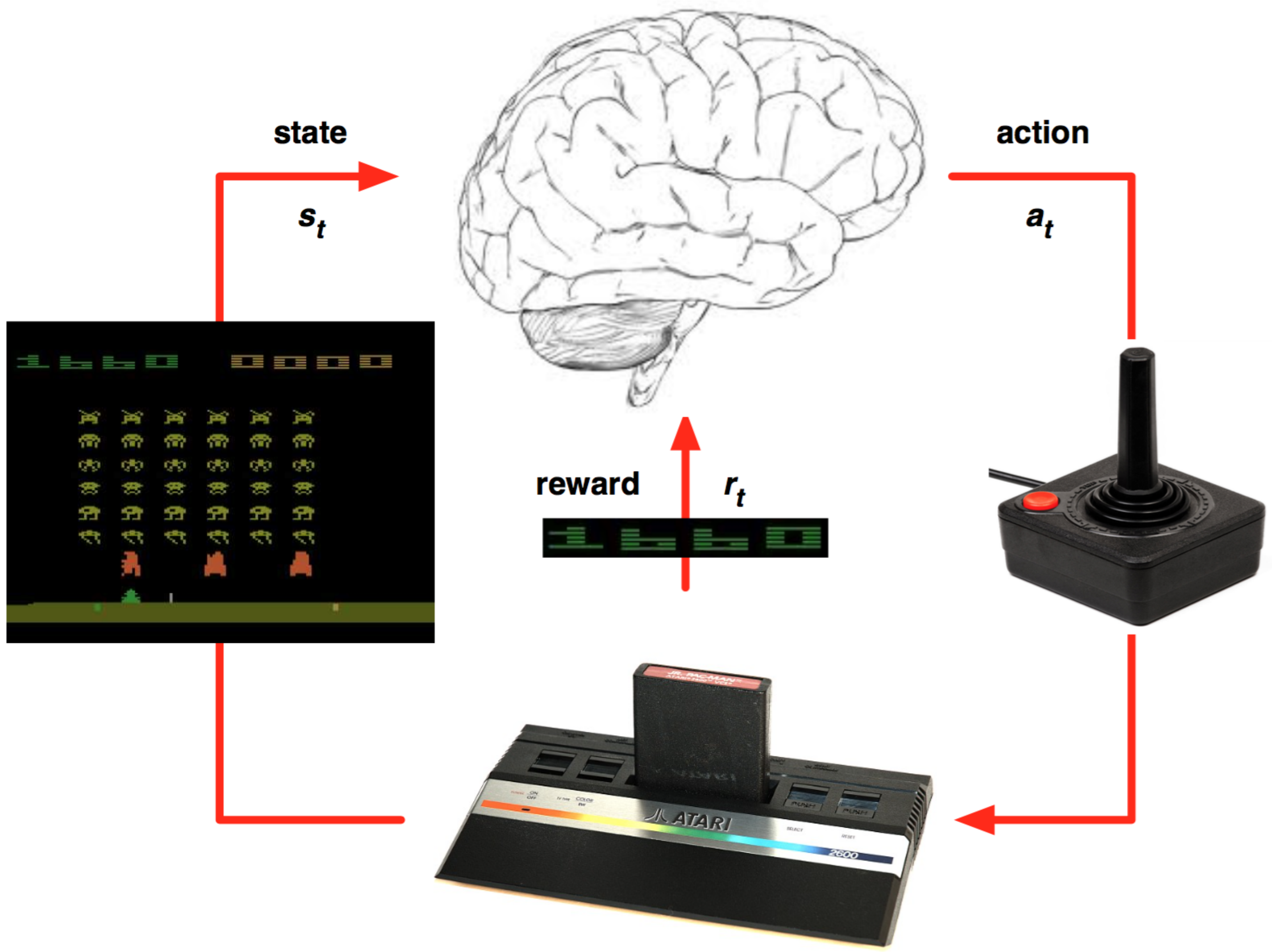
Source: David Silver.
http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html

- 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).

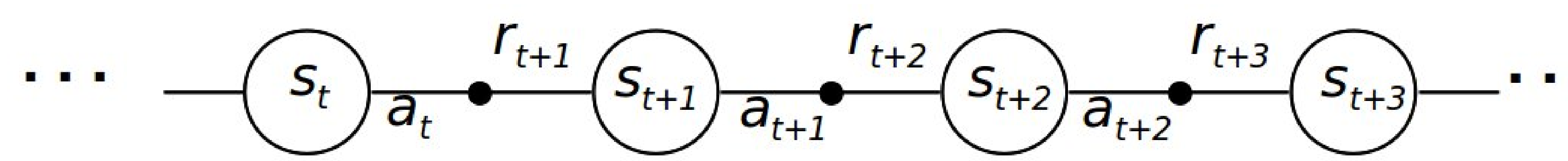
Returns



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

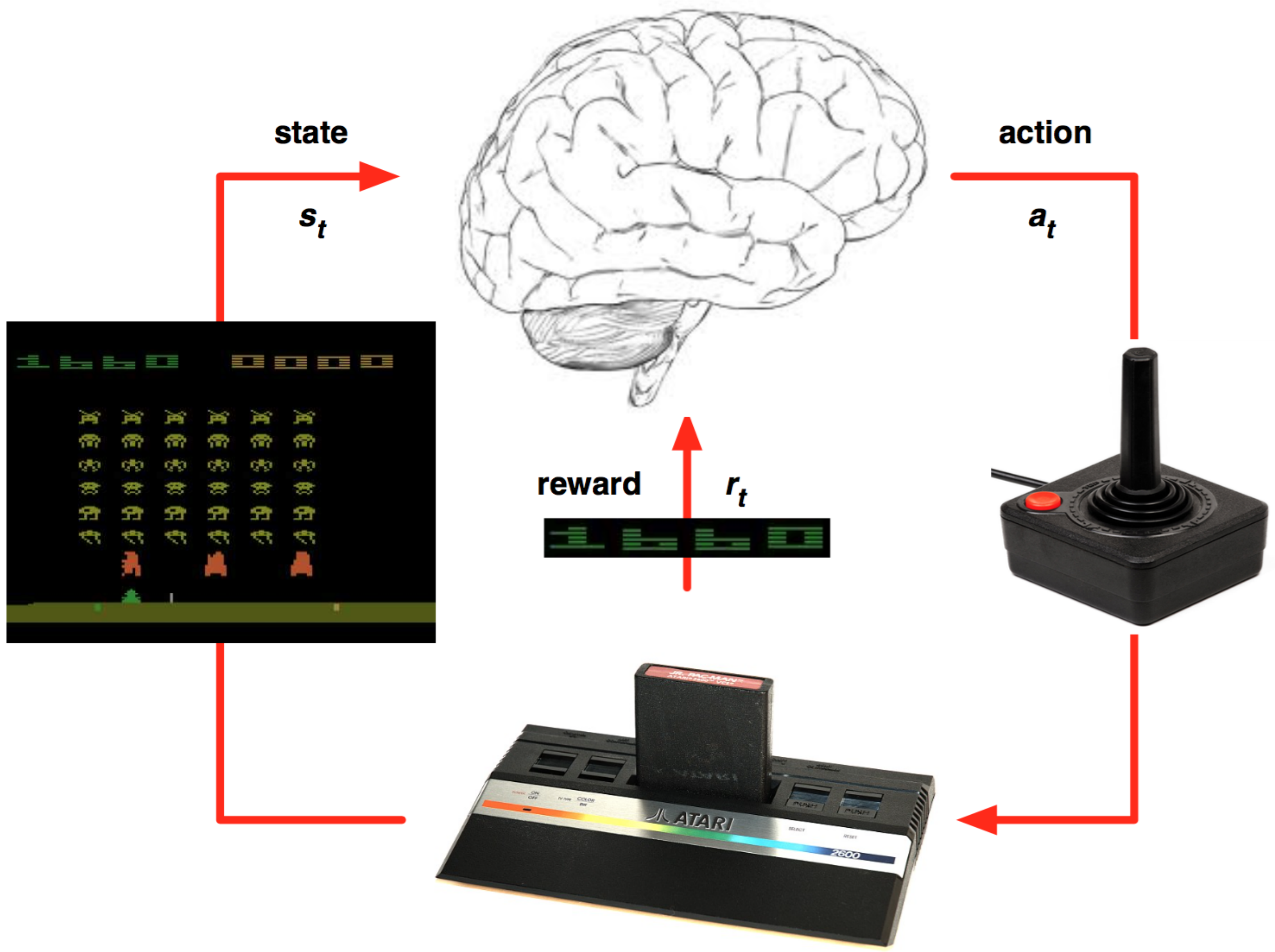
- The goal of the agent is to find a policy that **maximizes** the sum of future rewards at each timestep.
- The discounted sum of future rewards is called the **return**:

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



- 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



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

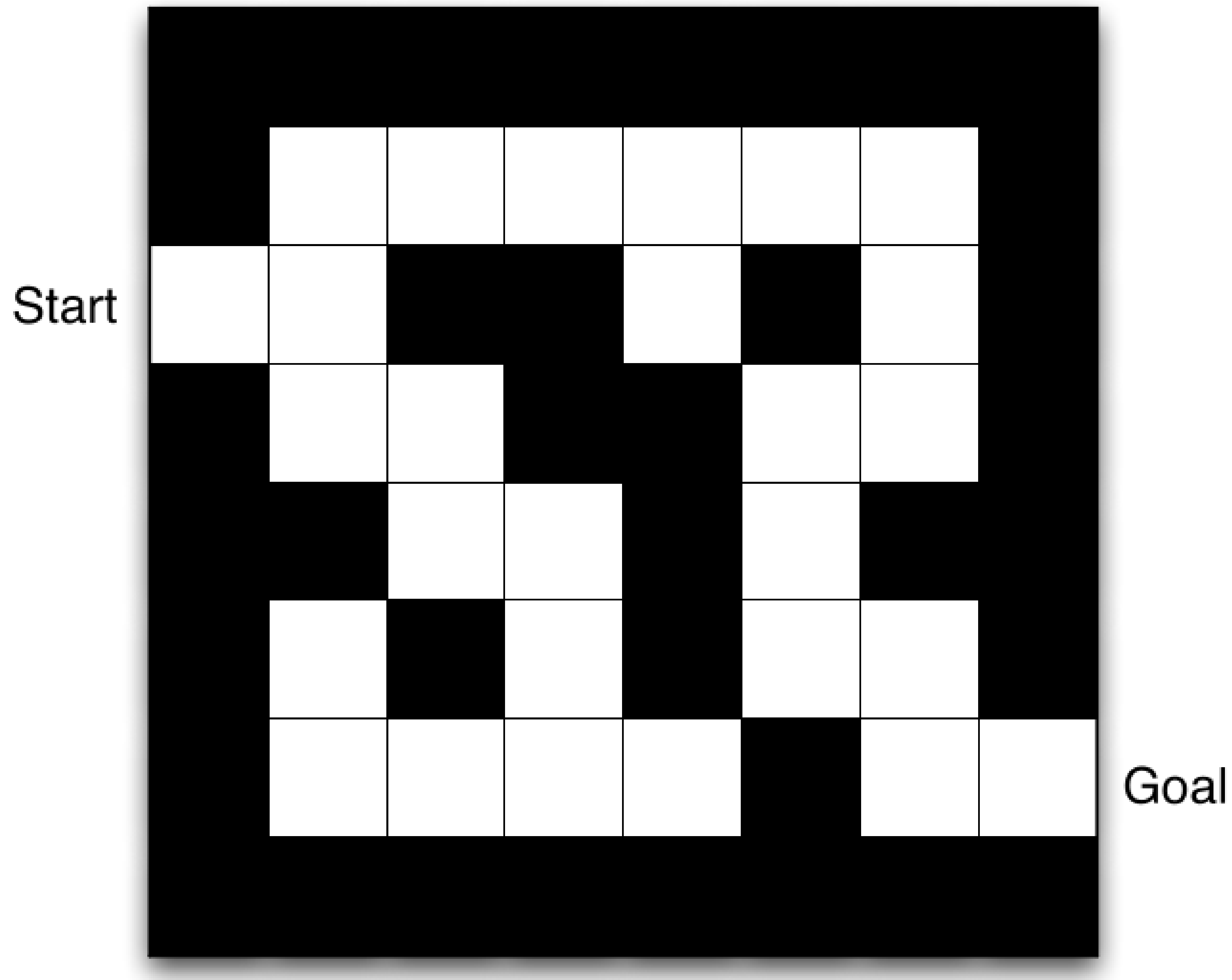
- The **expected return** in a state s is called its **value**:

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

- 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**.

- 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).

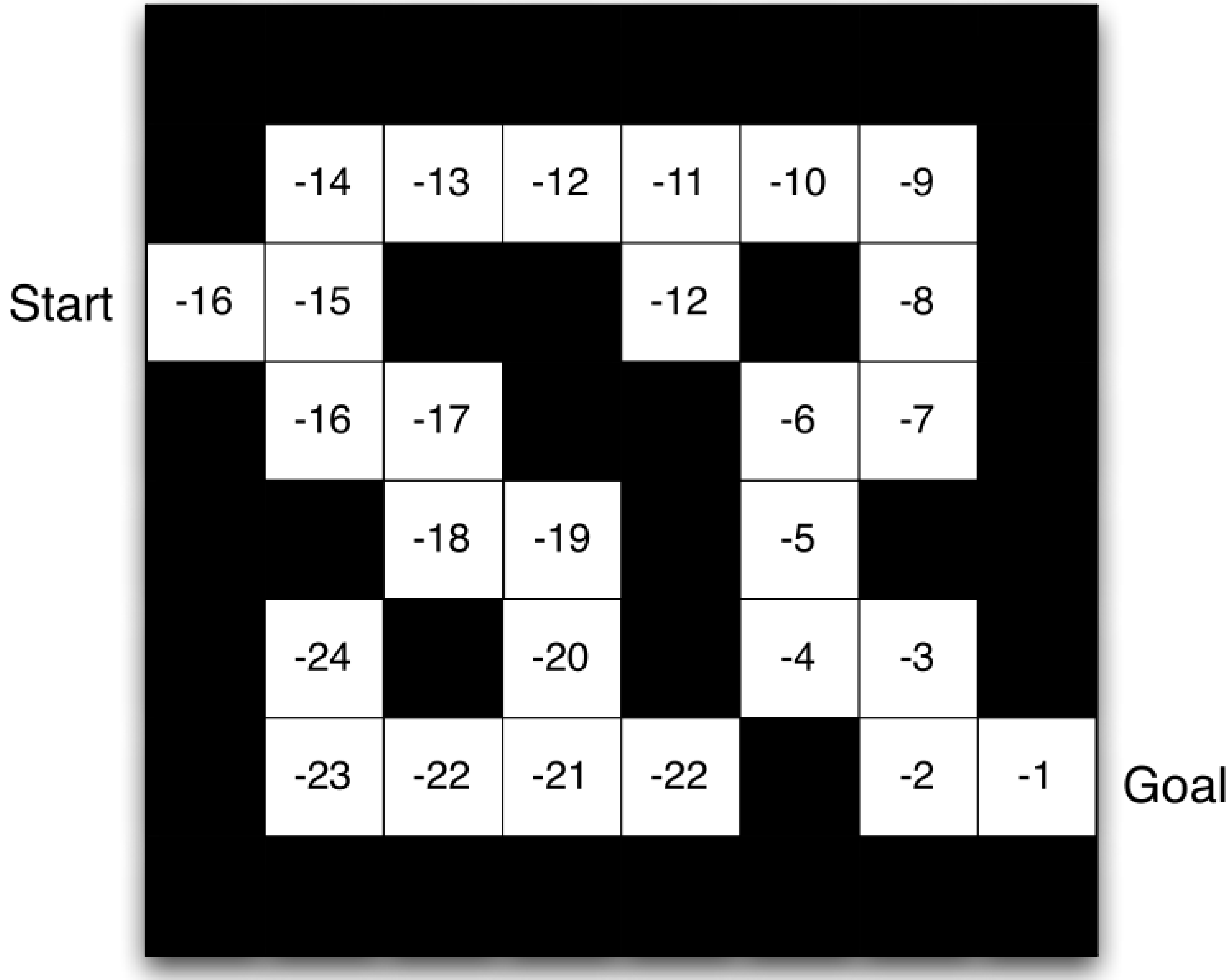
Simple maze



Goal: finding the exit as soon as possible.

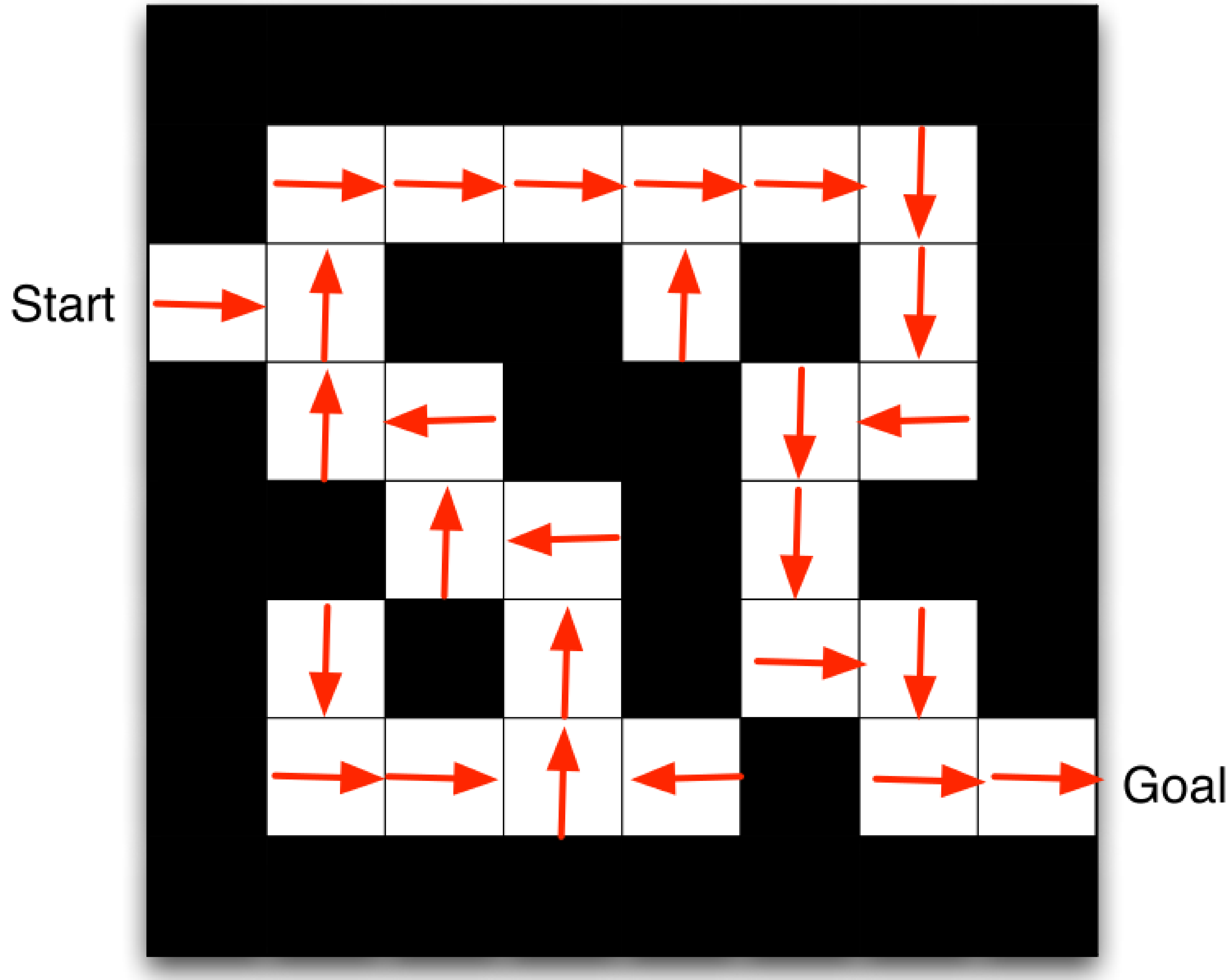
- **States**: position in the maze (1, 2, 3…).
- **Actions**: up, down, left, right.
- **Rewards**: -1 for each step until the exit.

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.

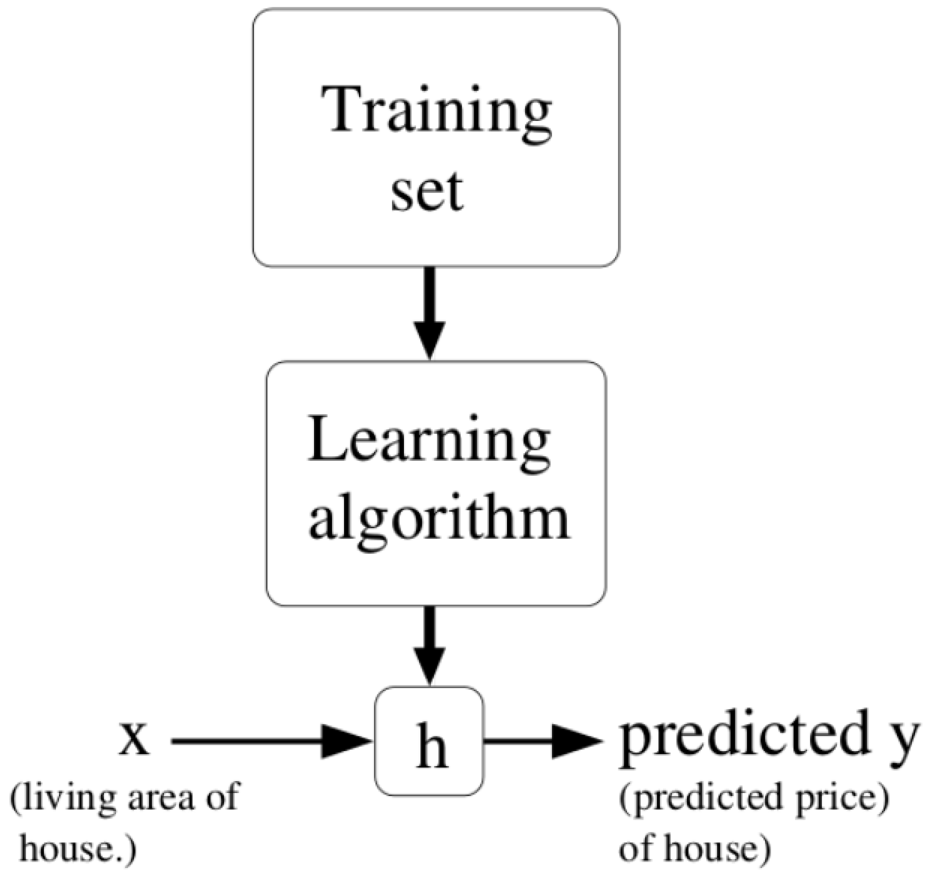
Note: the story is actually much more complicated...

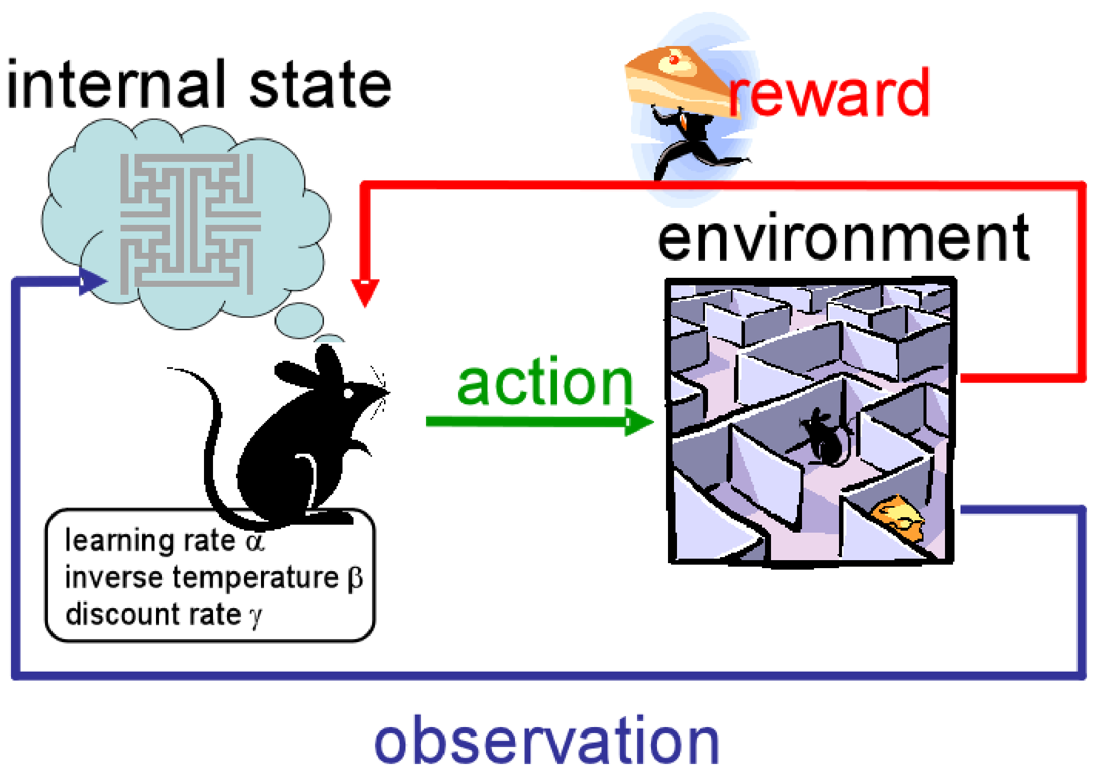
Supervised learning

- Correct input/output samples are provided by a **superviser** (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.

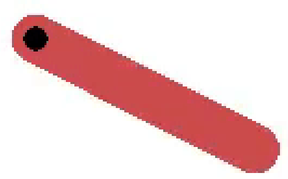


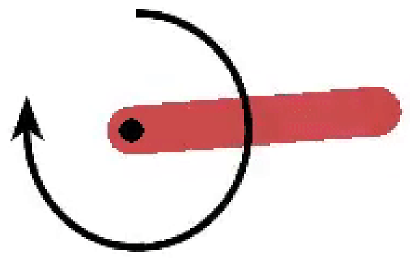


Applications of RL : Optimal control

Pendulum

Goal: maintaining the pendulum vertical.





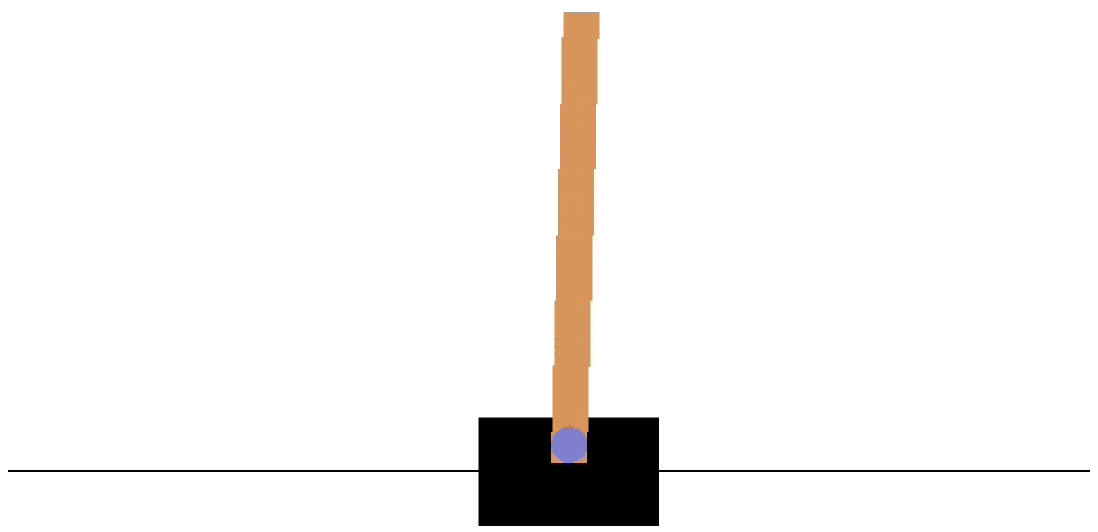
- **States**: angle and velocity of the pendulum.
- **Actions**: left and right torques.
- **Rewards**: cosine distance to the vertical.

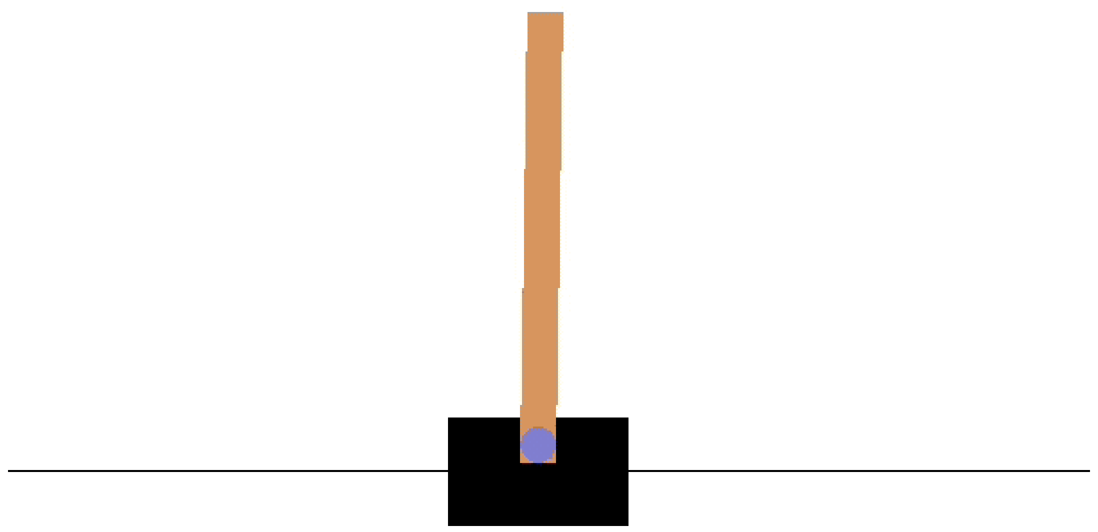
Source: https://keras.io/examples/rl/ddpg_pendulum/

Applications of RL : Optimal control

Cartpole

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

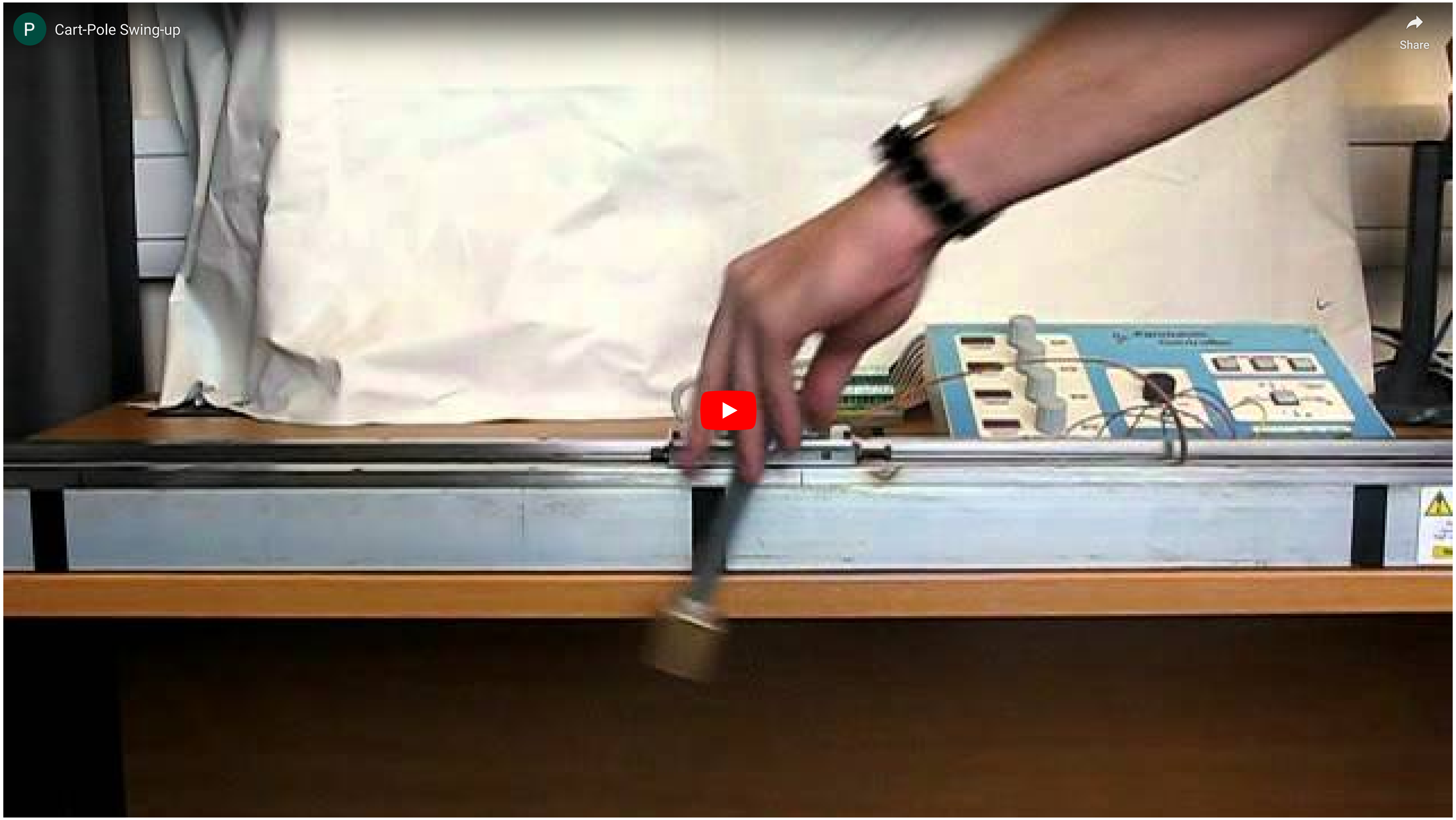




- **States**: position and speed of the cart, angle and velocity of the pole.
- **Actions**: left and right movements.
- **Rewards**: +1 for each step until failure.

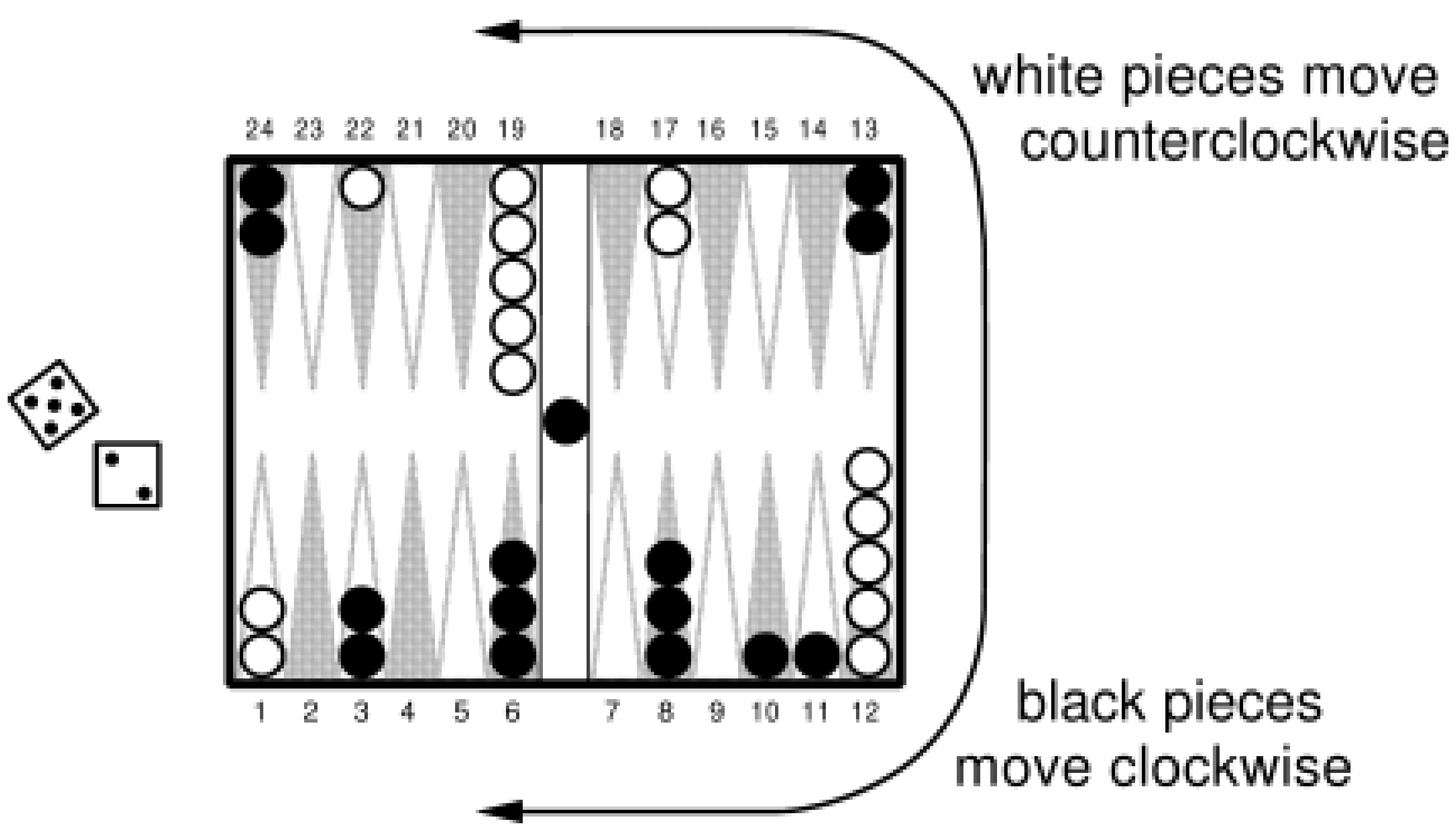
Source: https://towardsdatascience.com/cartpole-introduction-to-reinforcement-learning-ed0eb5b58288

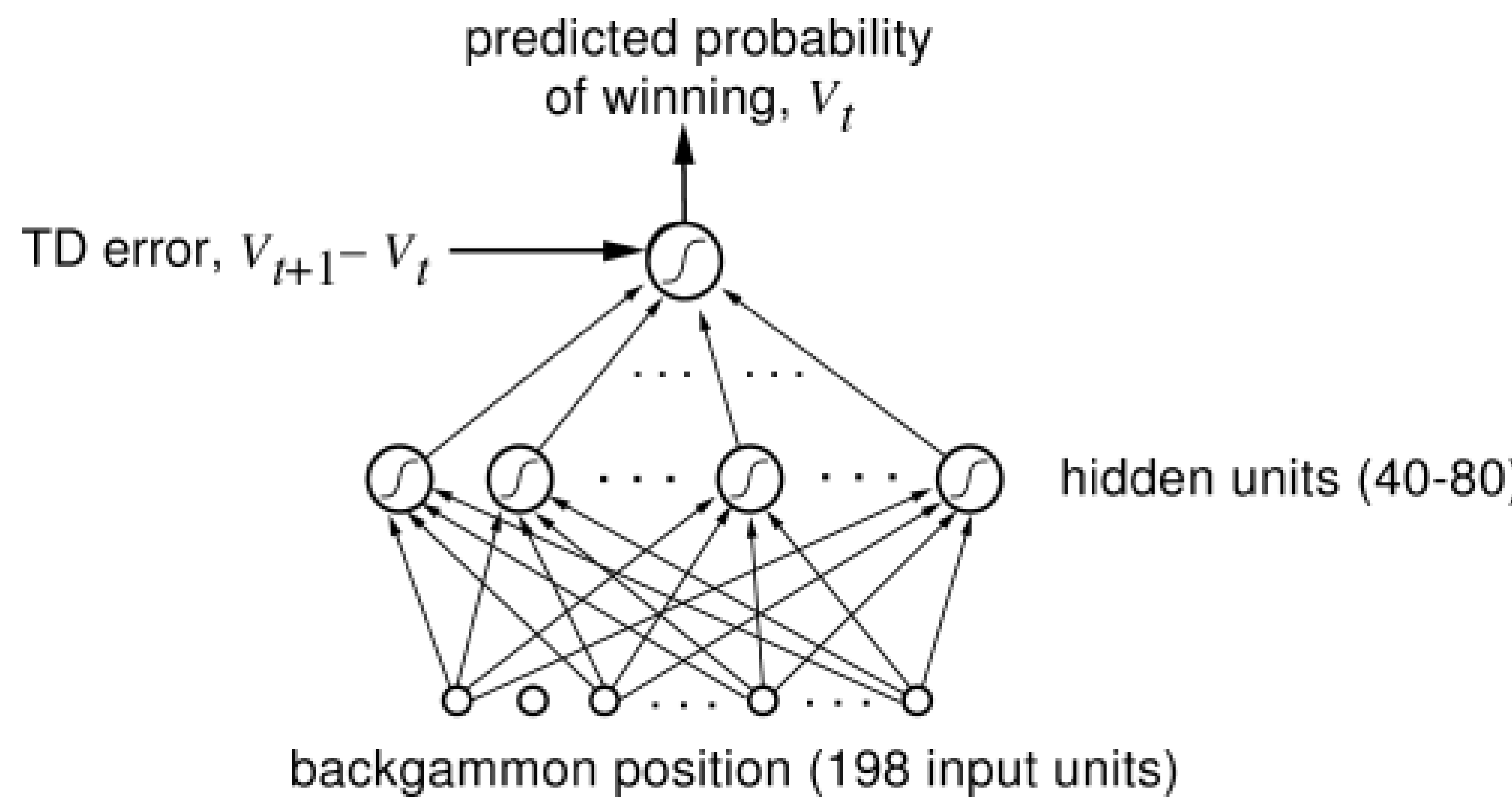
Applications of RL : Optimal control



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

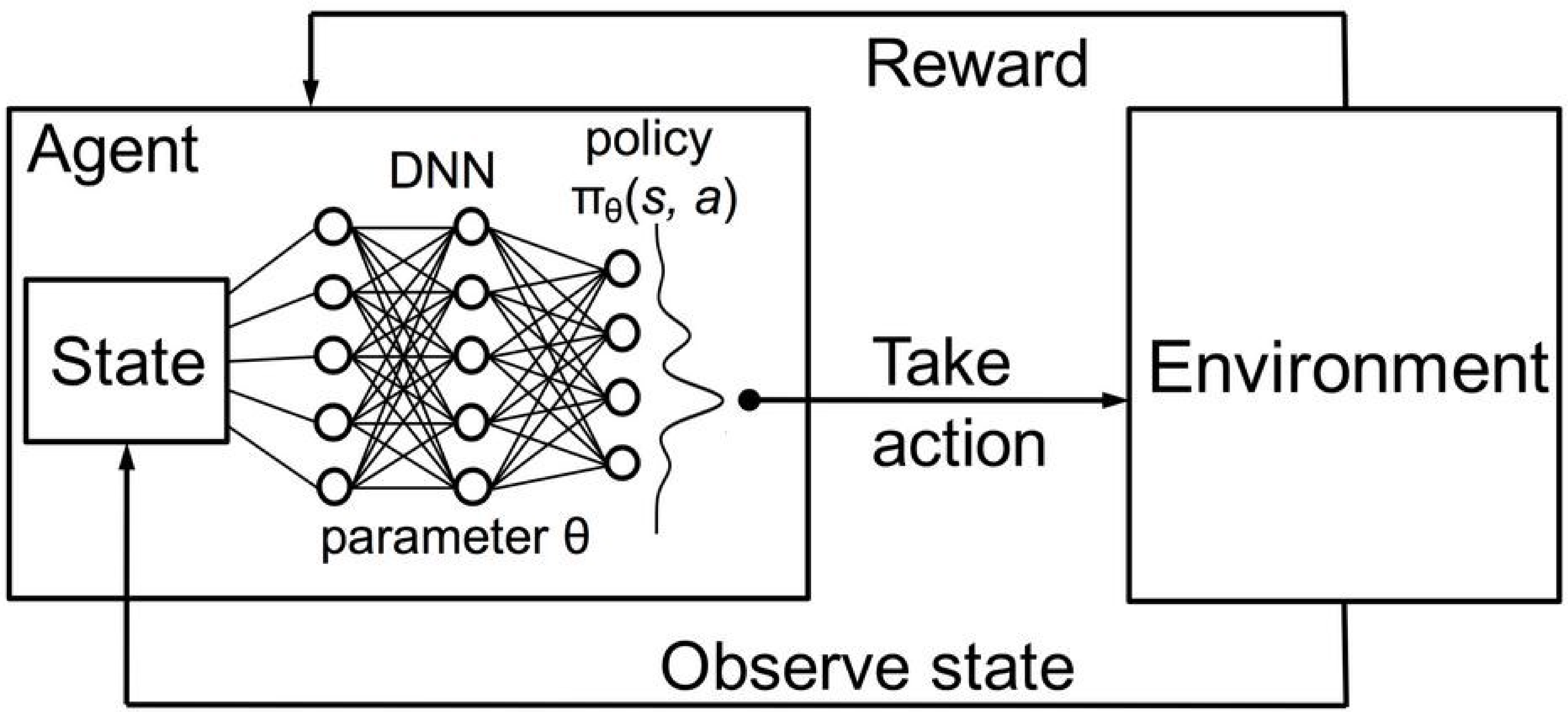
TD-Gammon (Tesauro, 1992) was one of the first AI to beat human experts at a complex game, Backgammon.





- **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**:

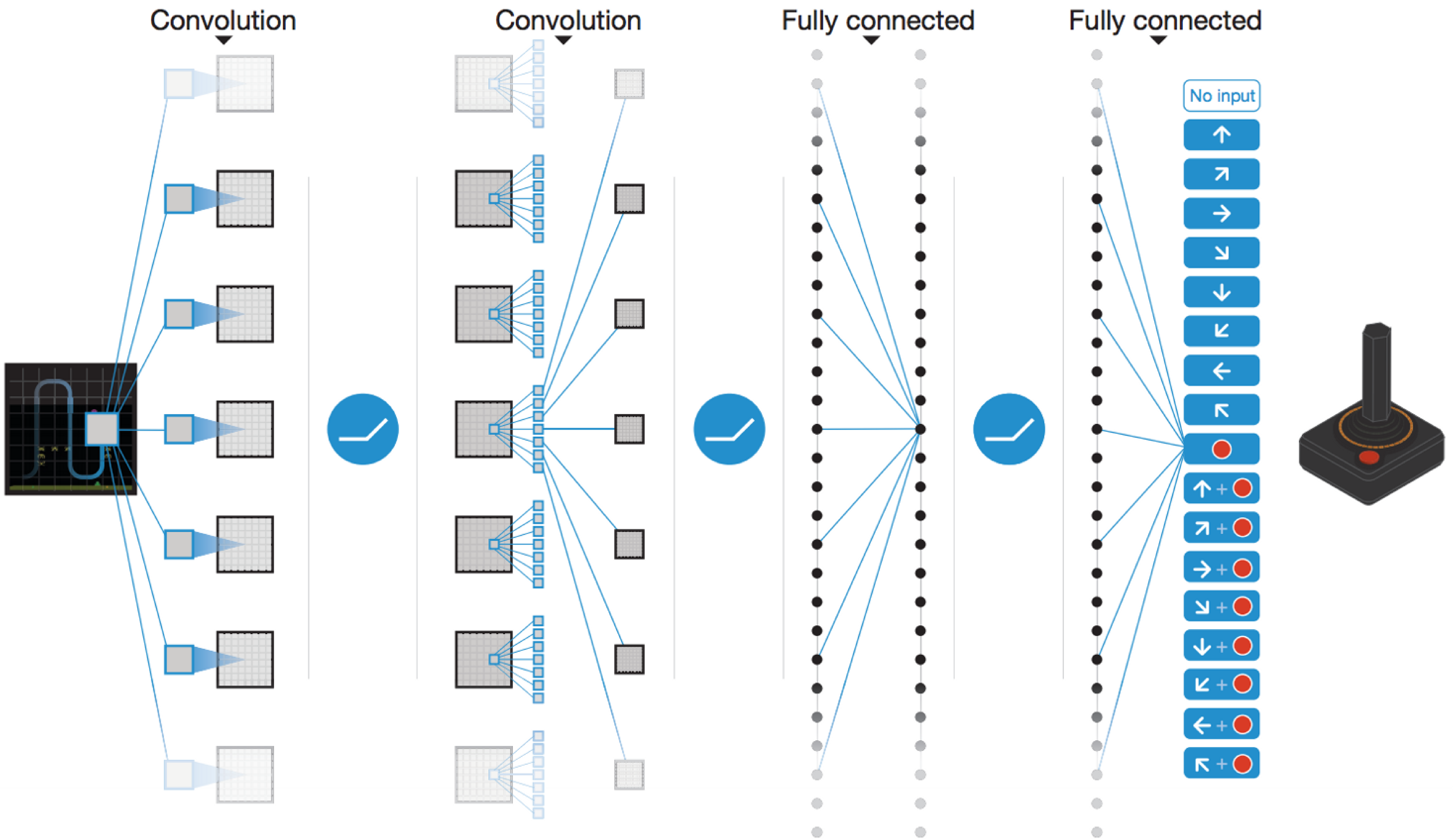
button presses.

- **Rewards**:

score increases.

Mnih et al. (2013). Playing Atari with Deep Reinforcement Learning. NIPS. http://arxiv.org/abs/1312.5602

Applications of RL : Atari games



Mnih et al. (2013). Playing Atari with Deep Reinforcement Learning. NIPS. http://arxiv.org/abs/1312.5602

Applications of RL : simulated cars

- **States**:

pixel frames.

- **Actions**:

direction, speed.

- **Rewards**:

linear velocity (+), crashes (-)

Applications of RL : Parkour

- **States**:

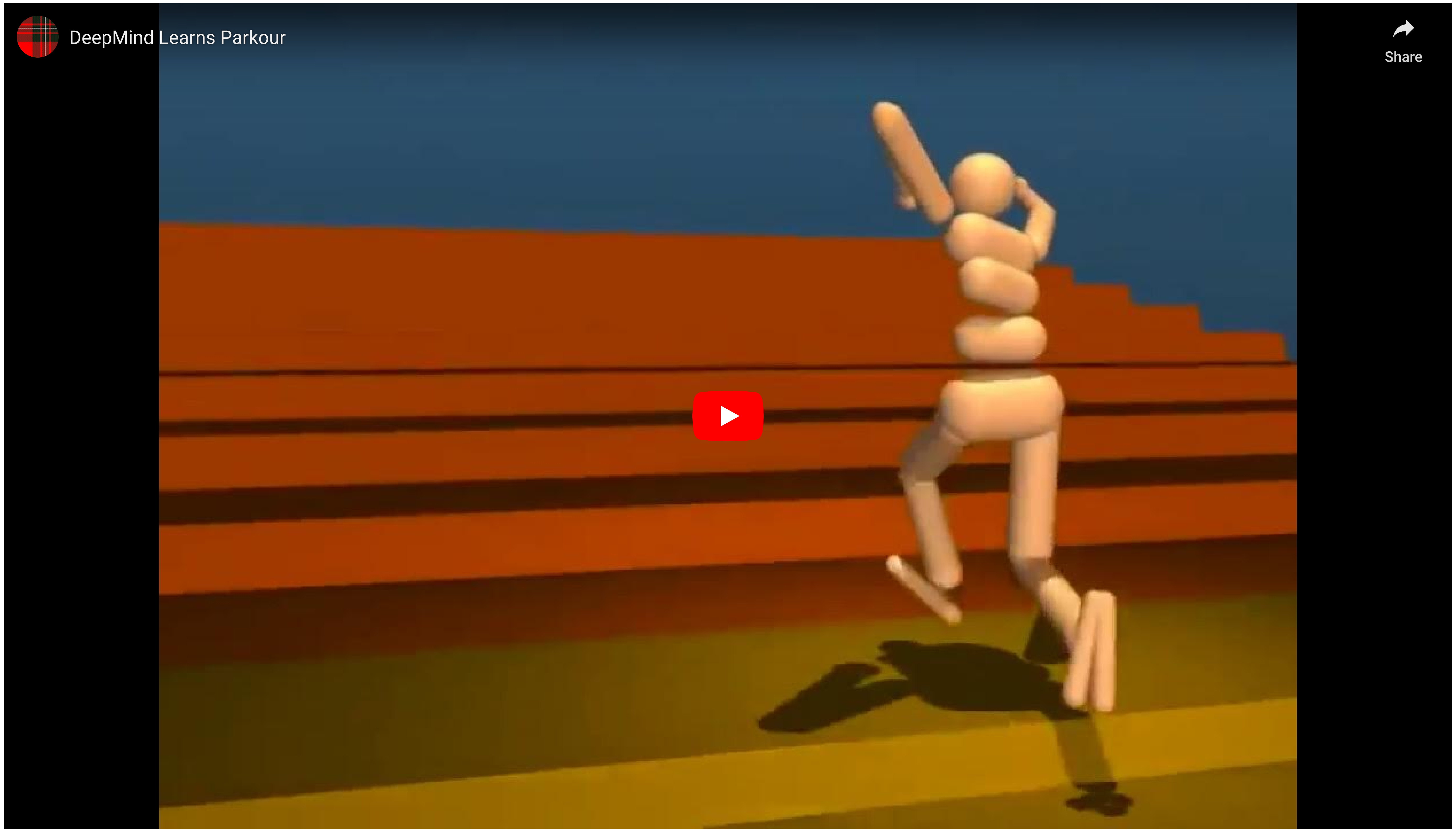
joint positions.

- **Actions**:

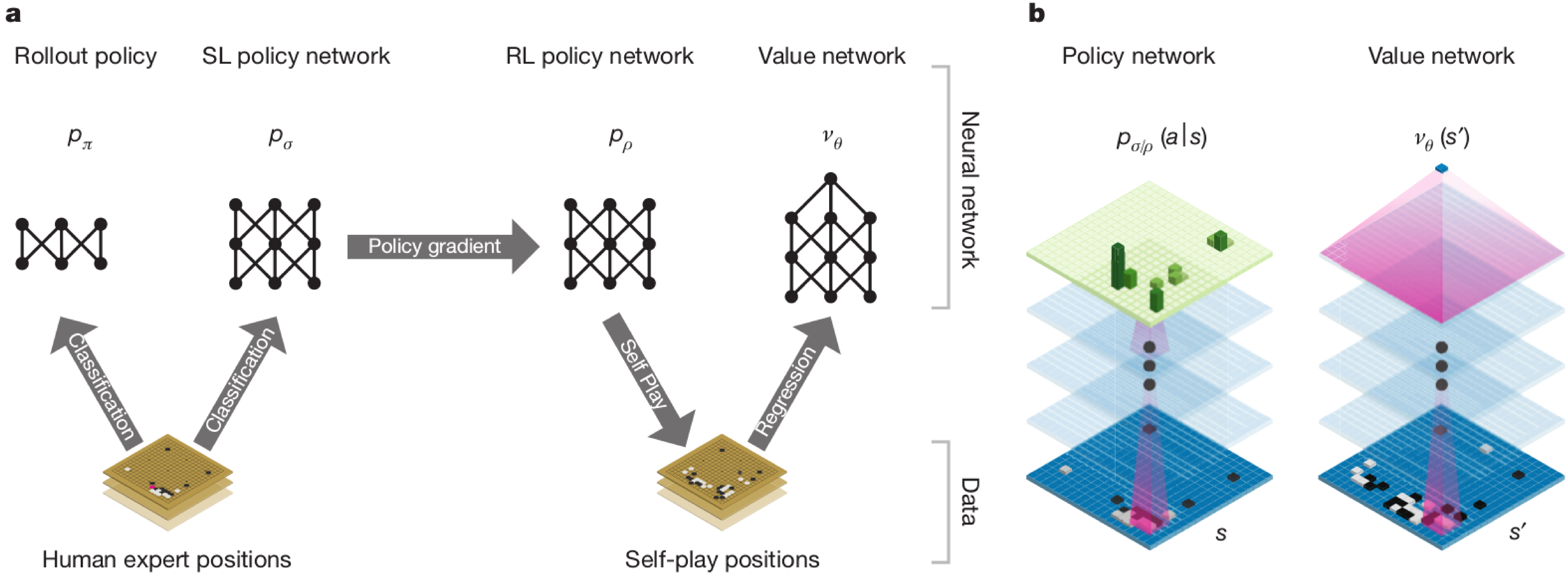
joint displacements.

- **Rewards**:

linear velocity (+), crashes (-)



Applications of RL : AlphaGo

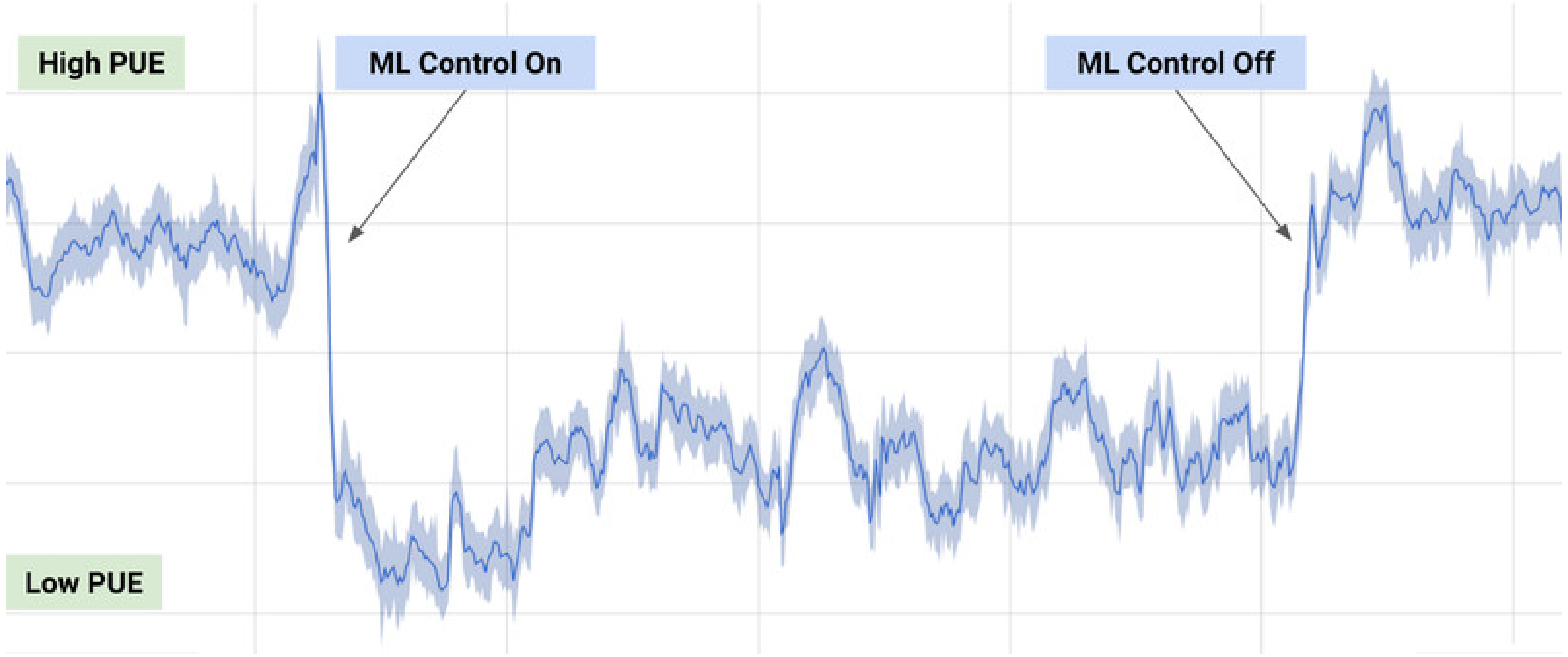


- AlphaGo was able to beat Lee Sedol in 2016, 19 times World champion.
- It relies on human knowledge to **bootstrap** a RL agent (supervised learning).
- The RL agent discovers new strategies by using self-play: during the games against Lee Sedol, it was able to use **novel** moves which were never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

David Silver et al. (2016). Mastering the game of Go with deep neural networks and tree search. Nature, 529(7587):484–489, arXiv:1712.01815

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:**

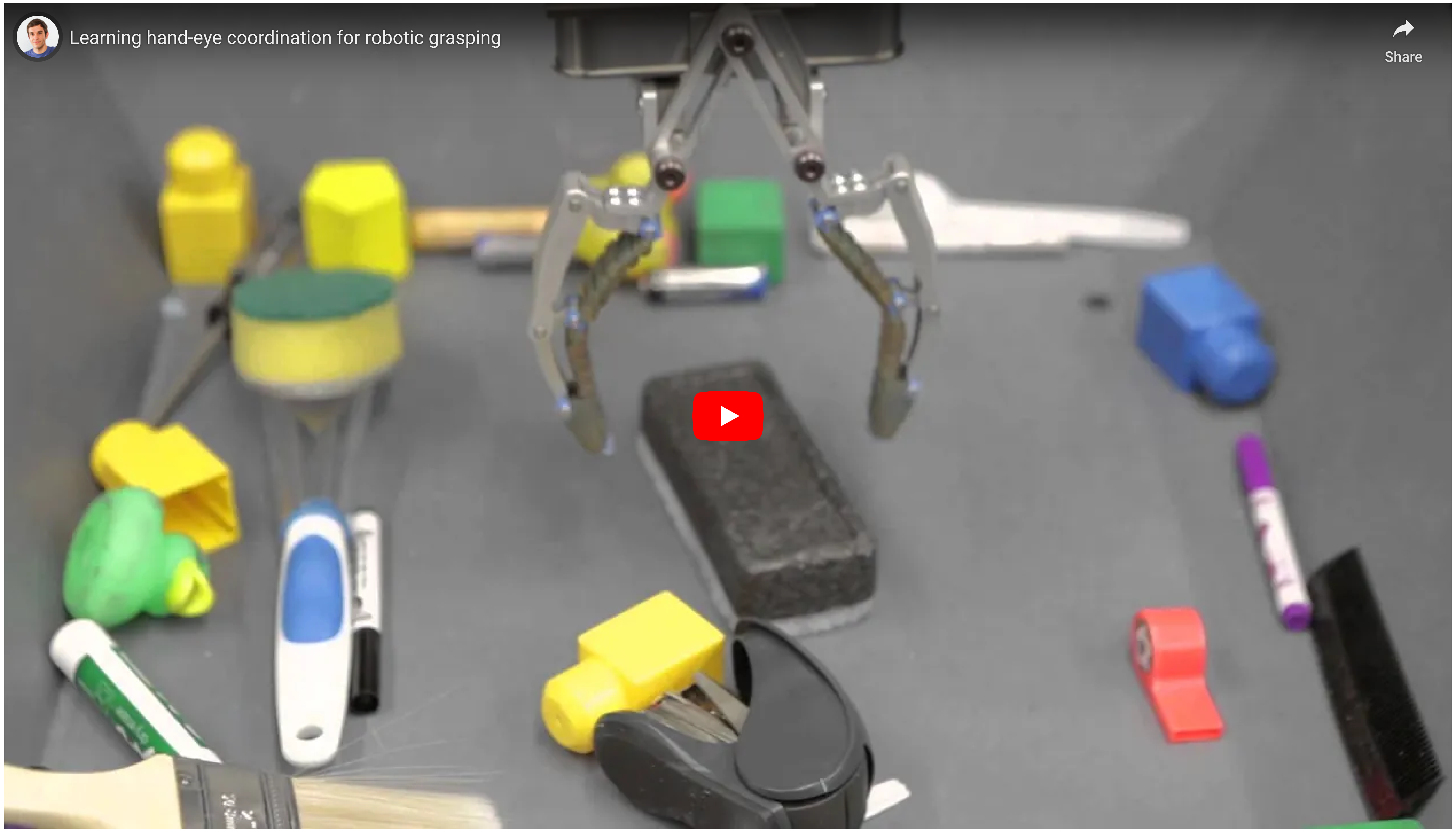
pixel frames.

- **Actions:**

joint movements.

- **Rewards:**

successful grasping.



Applications of RL : learning dexterity

- **States:**

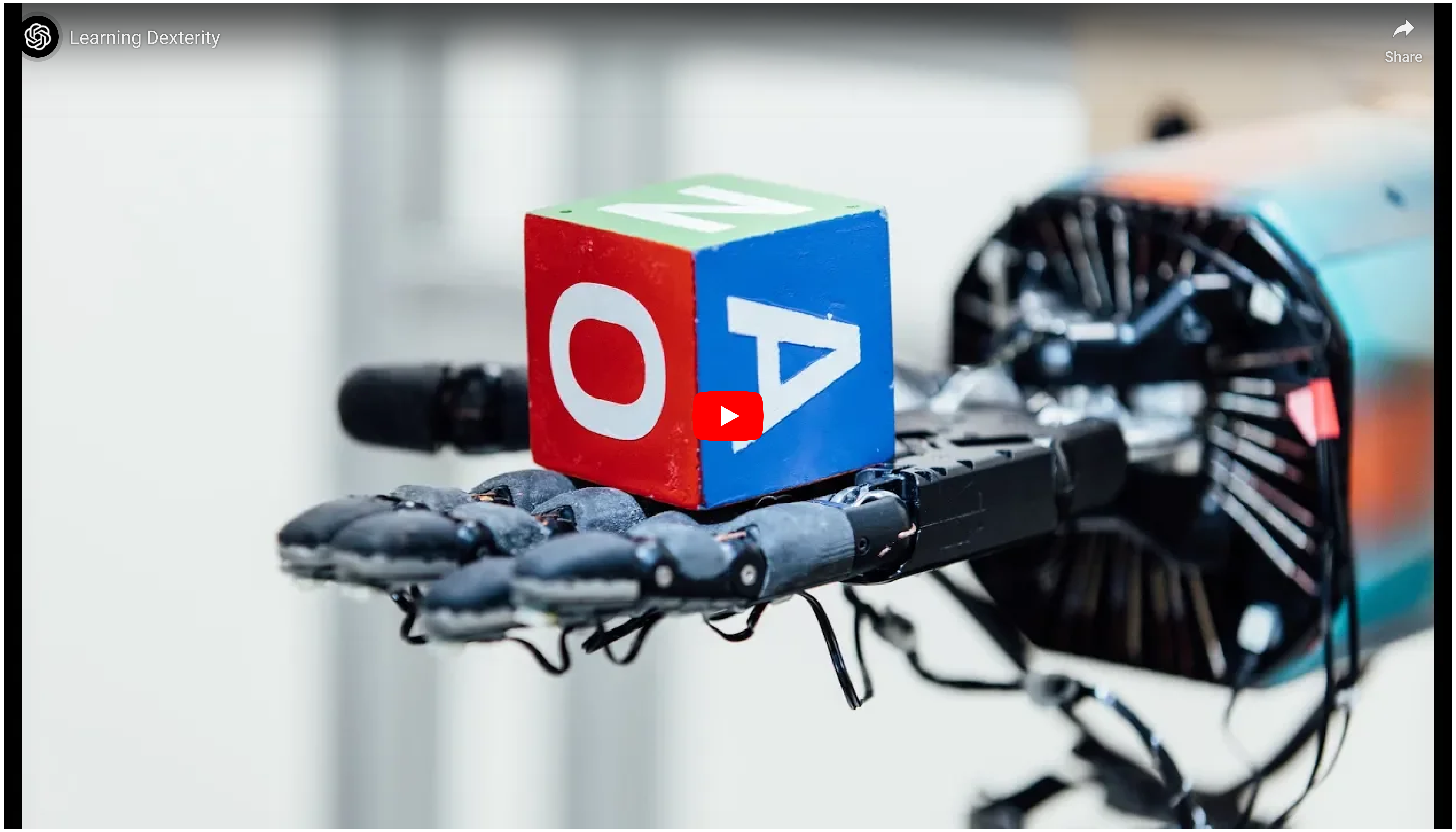
pixel frames, joint position.

- **Actions:**

joint movements.

- **Rewards:**

shape obtained.



Applications of RL : real cars

- **States:**

pixel frames.

- **Actions:**

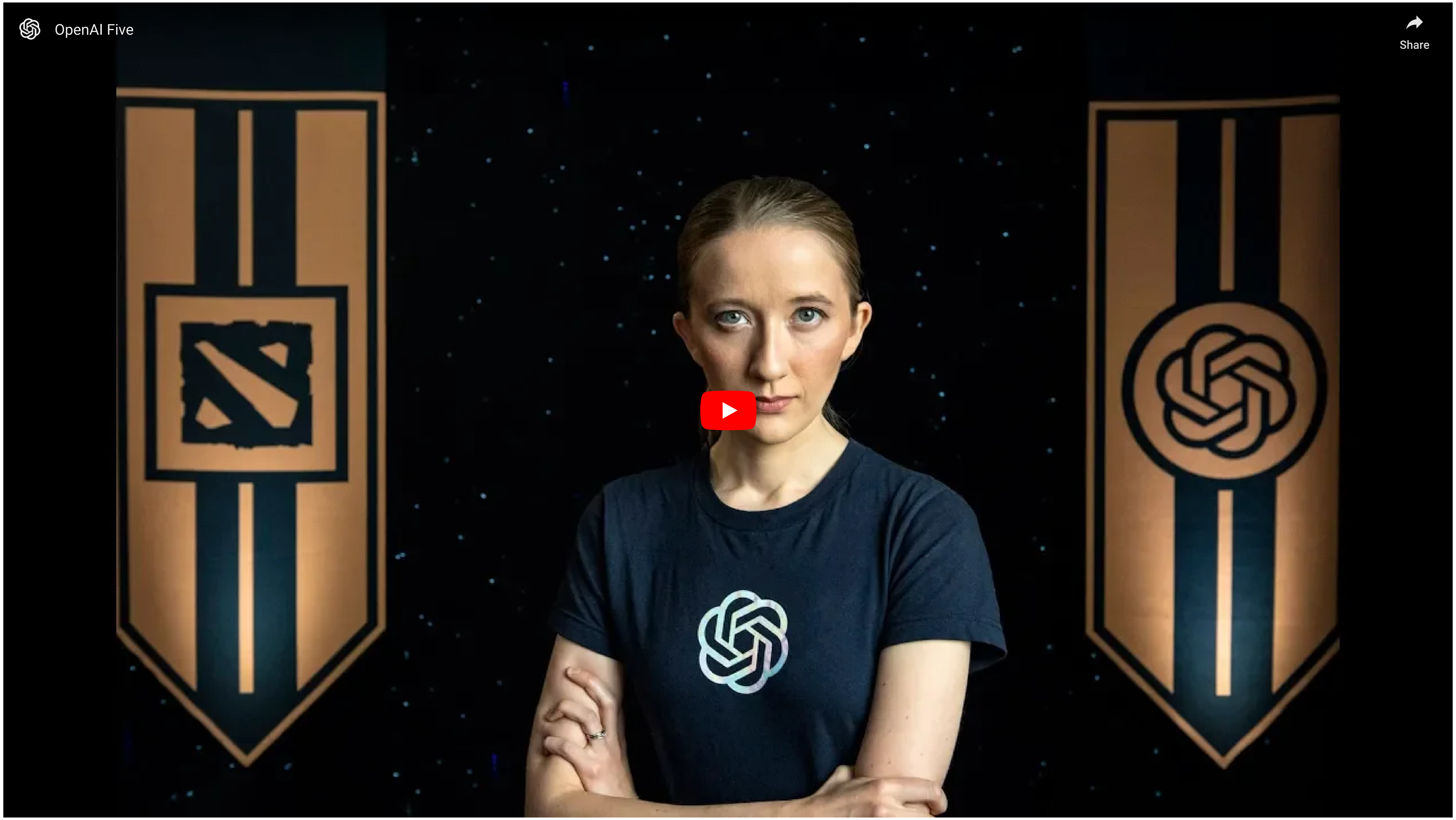
direction, speed.

- **Rewards:**

time before humans take control.

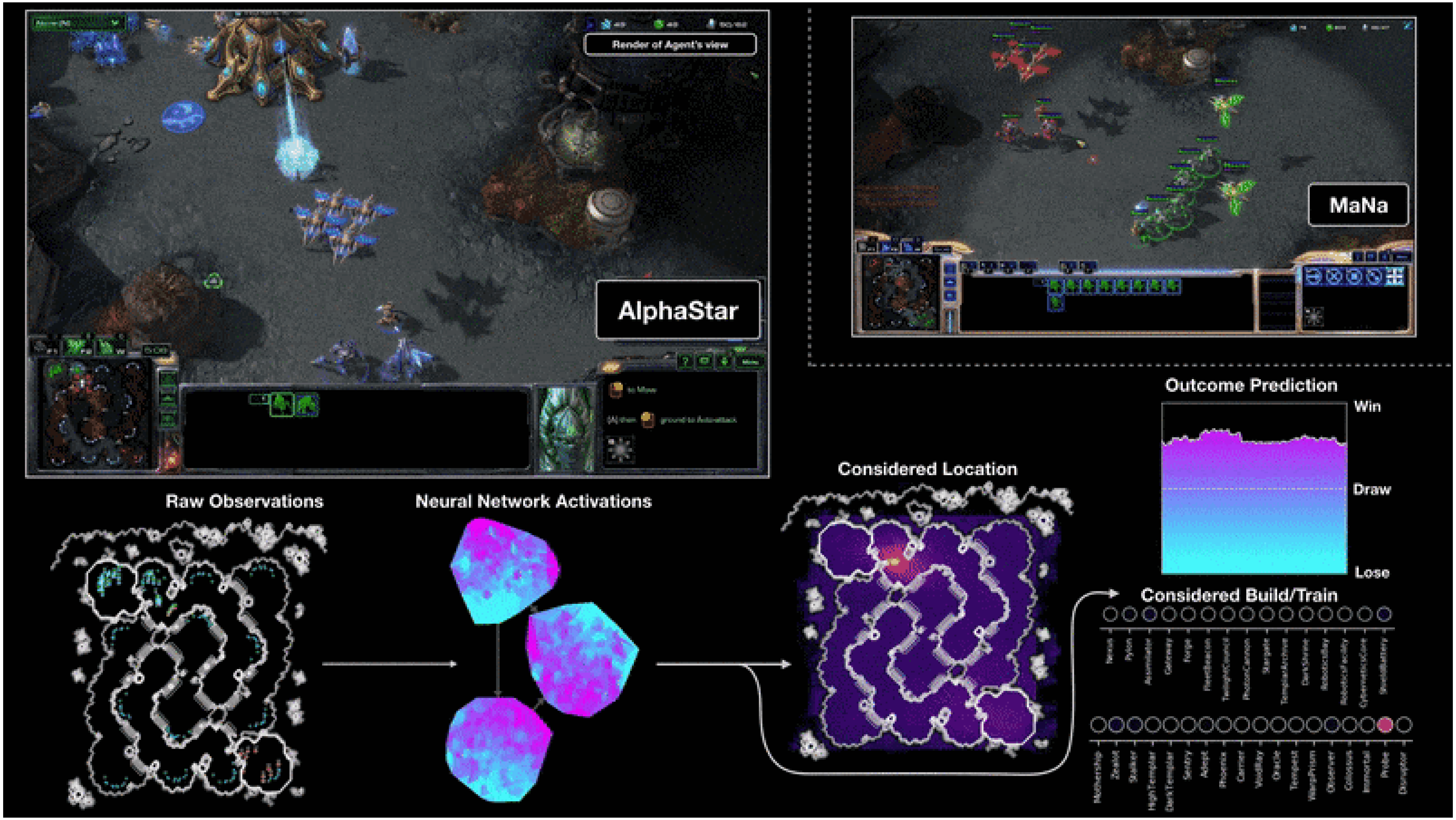
https://wayve.ai/blog/learning-to-drive-in-a-day-with-reinforcement-learning

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