Deep Reinforcement Learning 1

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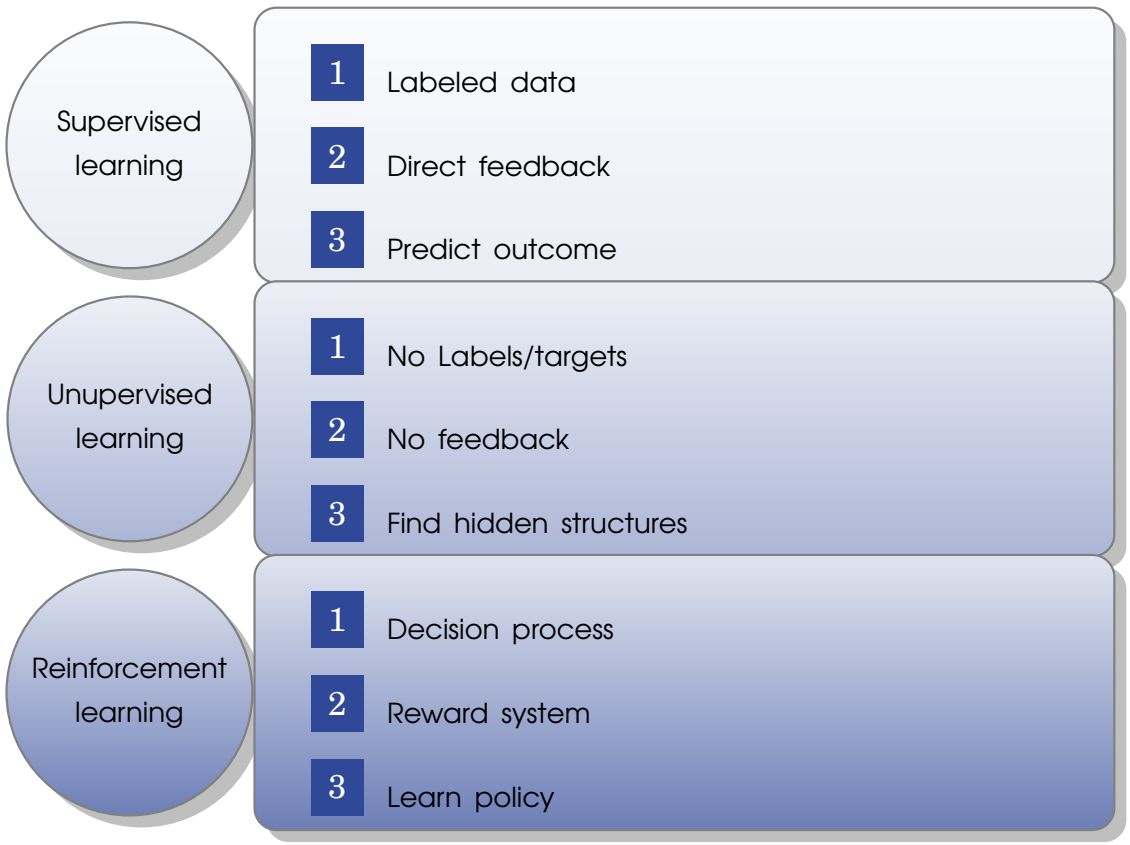
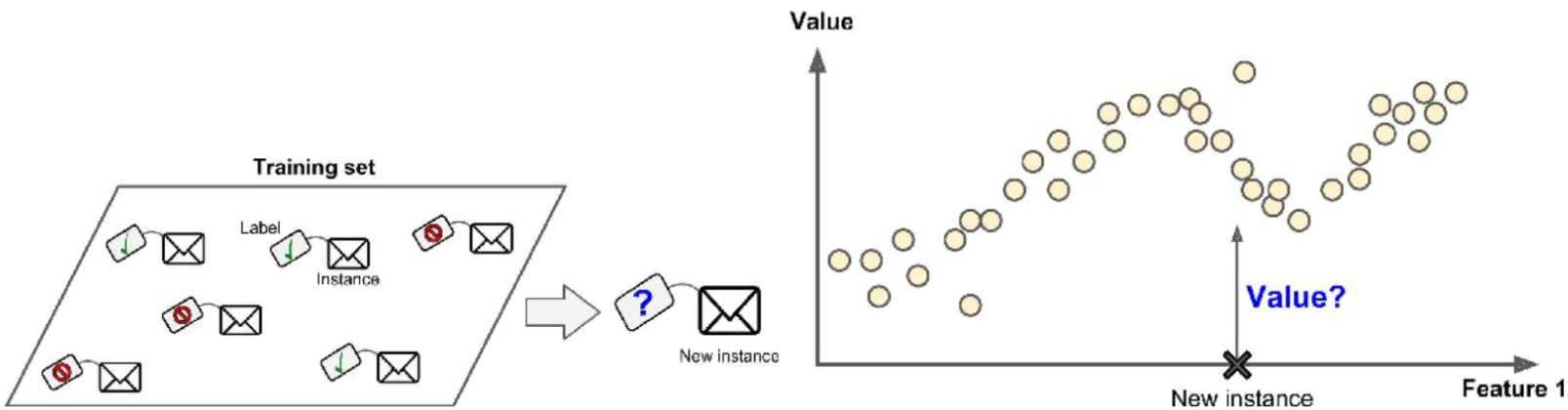
A POSSIBLE TAXONOMY OF MACHINE LEARNING ALGORITHMS



SUPERVISED LEARNING

Supervised learning

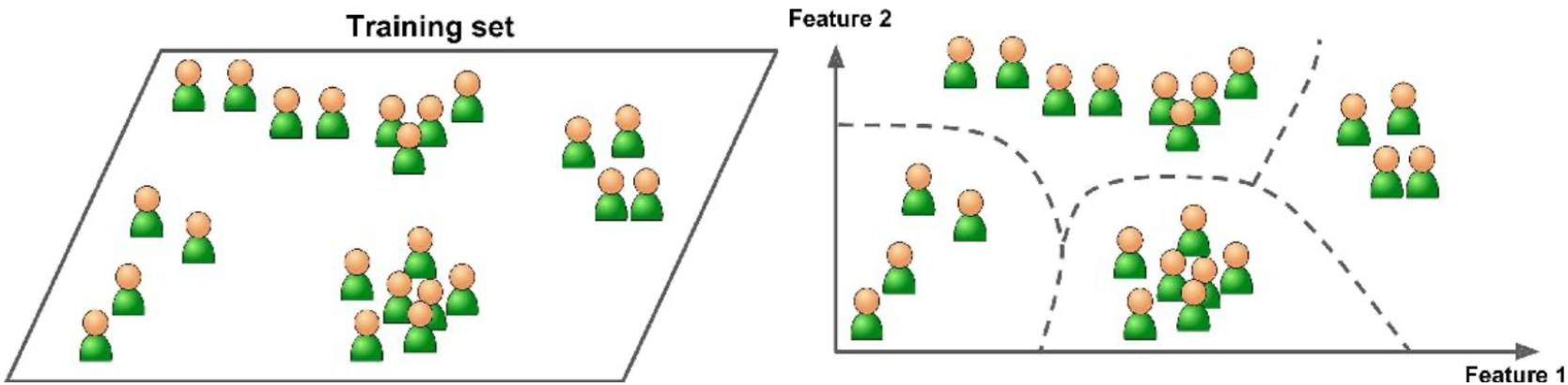
1. Labeled data
2. Direct feedback
3. Predict outcome



UNSUPERVISED LEARNING

Unupervised learning

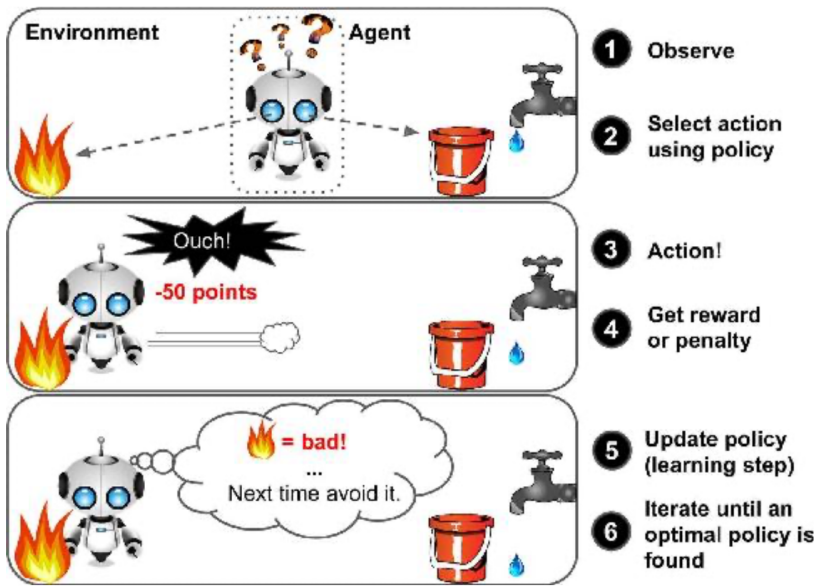
1. No Labels/targets
2. No feedback
3. Find hidden structures



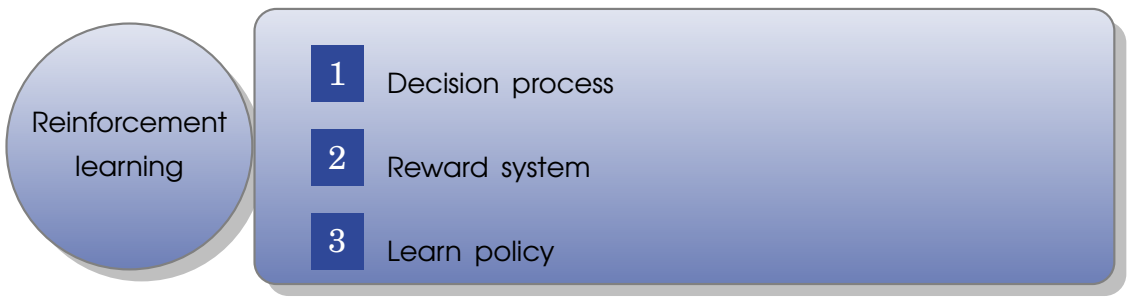
REINFORCEMENT LEARNING

Reinforcement learning

1. Decision process
2. Reward system
3. Learn policy



REINFORCEMENT LEARNING



Topic of the two next lectures

Agent: takes actions

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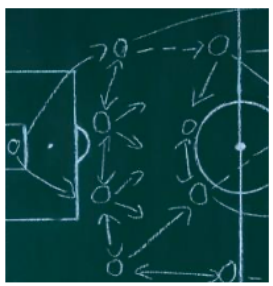
Environment: the "world"



Environment

Agent

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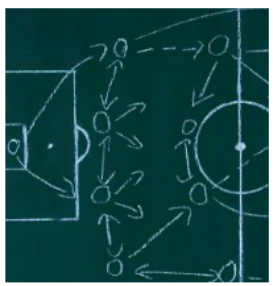
Action space



Environment

Agent

Action

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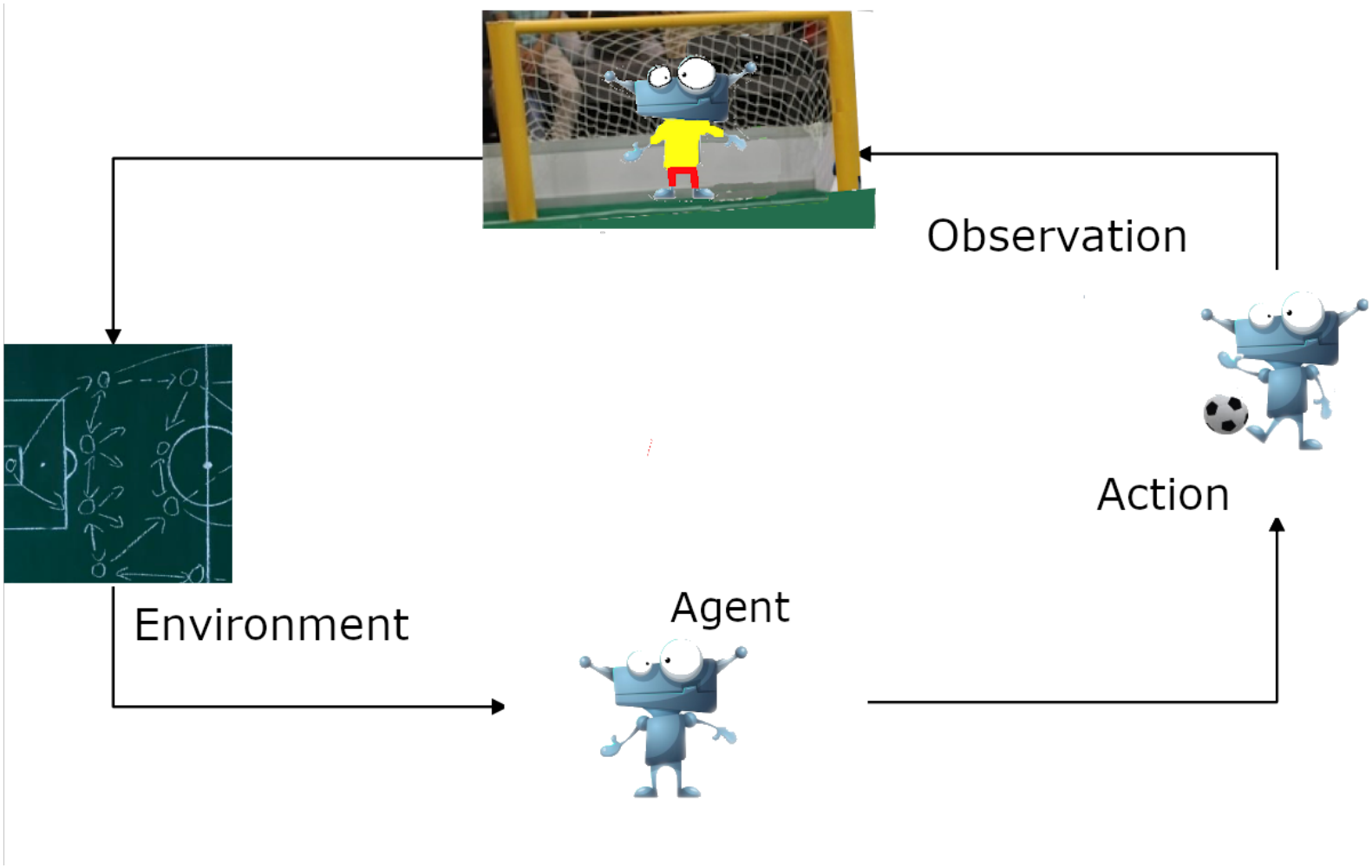
Changes in the environment



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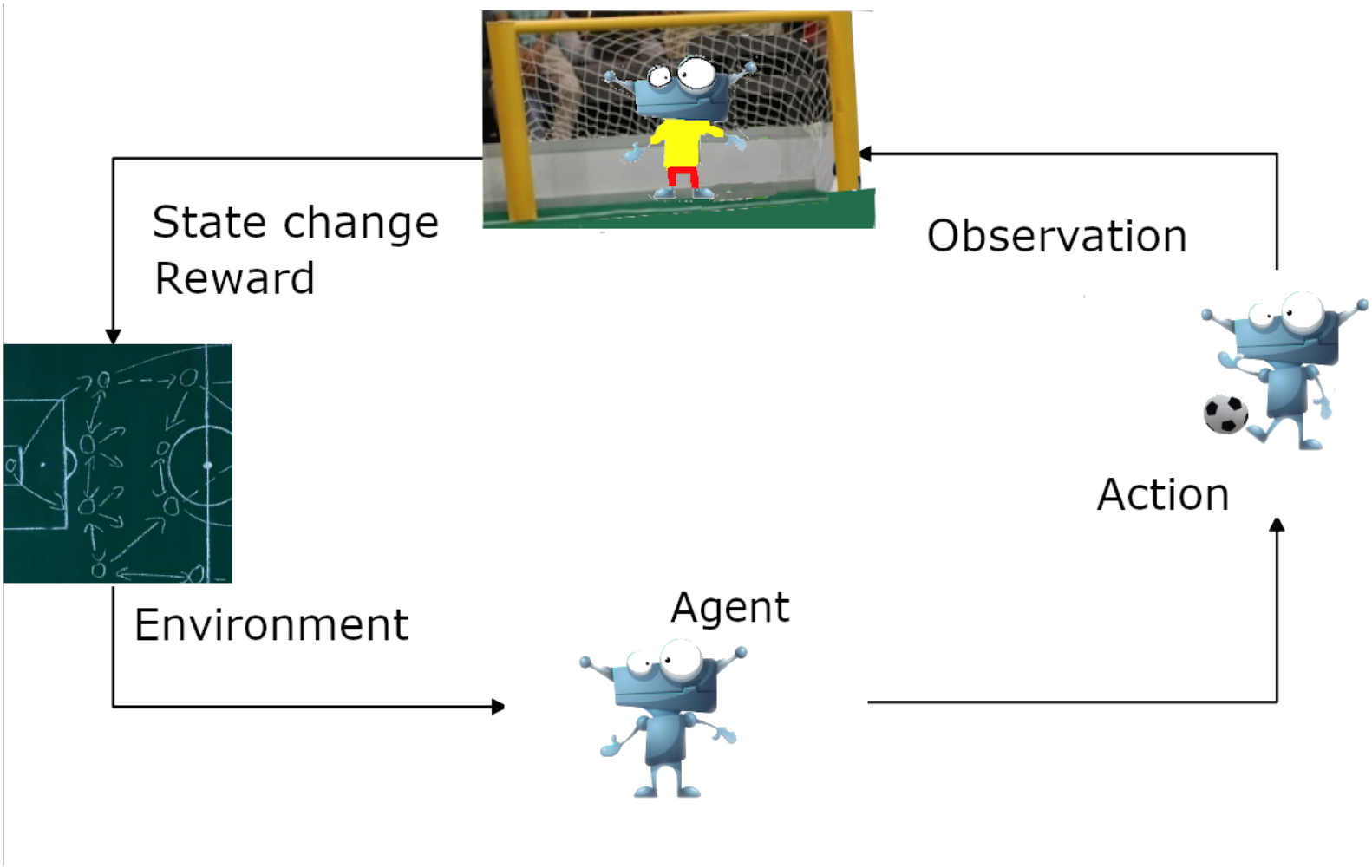
State and reward



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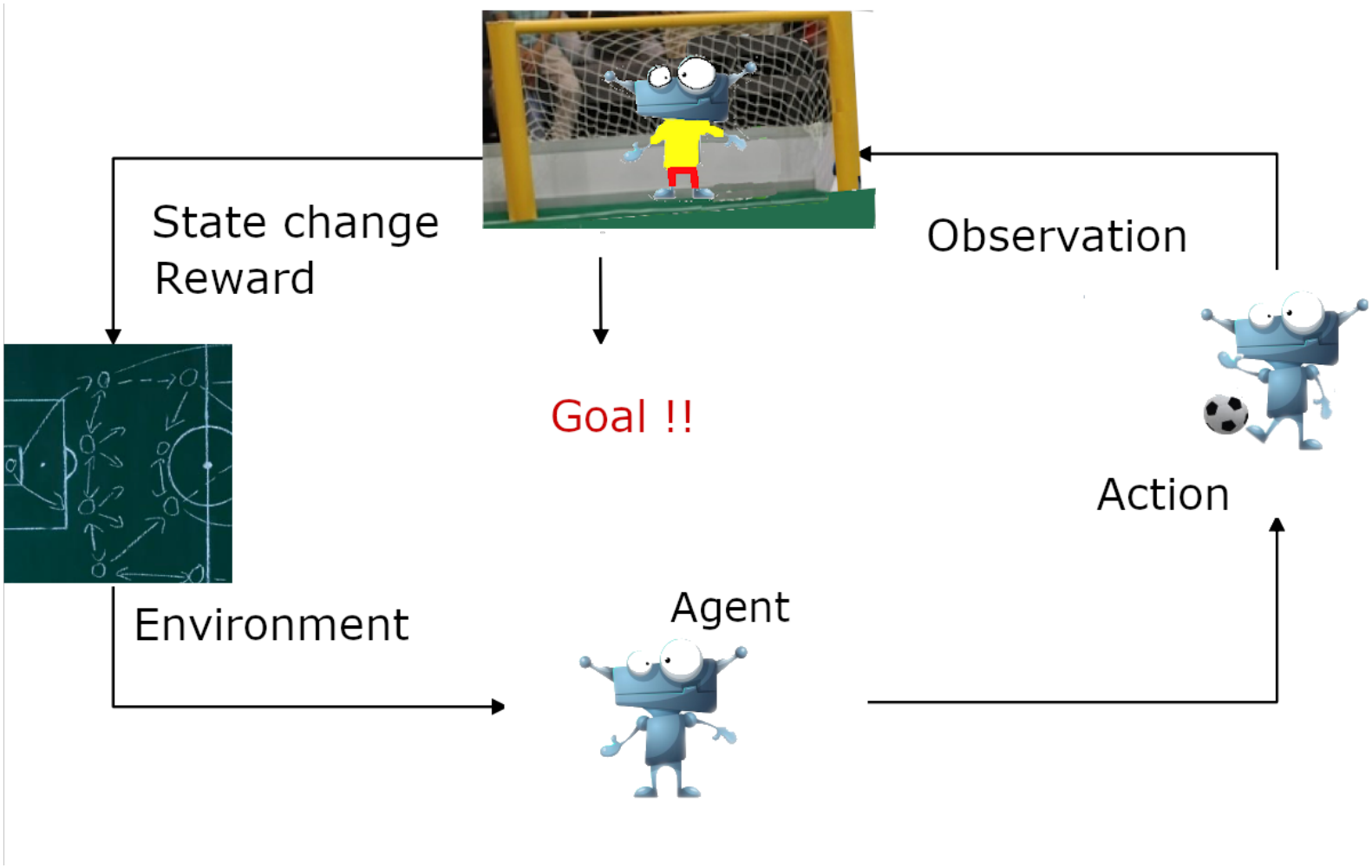
Objective function



Notations

Space, Action, Reward

For each timestep t:

- $a_t \in A$: action
- $s_t \in S$: state
- $r_t : S \times A \times S \to \mathbb{R}^+$: reward obtained when arriving at s_{t+1} from s_t, taking action a_t

$\forall t$, the agent receives a state representation s_t , selects an action a_t , and receives a reward r_t after which it will find itself in a new state s_{t+1}.

Trajectory: $\tau = (s_0, a_0, r_0, \cdots s_{T-1}, a_{T-1}, r_{T-1}, s_T)$

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Hypothesis

Markovian environment:

- $P(s_{t+1}|s_t, a_t \cdots s_0, a_0) = P(s_{t+1}|s_t, a_t)$
- $P(r_t|s_t, a_t \cdots s_0, a_0) = P(r_t|s_t, a_t)$

Notations

Objective

Total reward: $R_t = \sum_{i=t}^{+\infty} r_i$

Total discounted reward: $R_t = \sum_{i=t}^{+\infty} \gamma^i r_i$

$0 < \gamma < 1$: discount factor, controls the trade-off between immediate and long-term rewards.

Notations

Objective

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Total discounted reward: $R_t = \sum_{i=t}^{+\infty} \gamma^i r_i$

$0 < \gamma < 1$: discount factor, controls the trade-off between immediate and long-term rewards.

Objective: maximise the long-term rewards.

$$R_t = \sum_{i=t}^{+\infty} \gamma^i r_i$$

Value function

$$R_t = \sum_{i=t}^{+\infty} \gamma^i r_i$$

- Estimate how good/bad it is for an agent to be in a particular state
- Goodness of state s_t defined in terms of future rewards that can be expected by from s_t.

Value function

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Policy function $\pi : S \rightarrow A$

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Policy function $\pi : S \rightarrow A$

- state-value function $V^{\pi}(s) = \mathbb{E}\left(R_t | s_t = s, \pi\right)$
- state-action function $Q^{\pi}(s_t, a_t) = \mathbb{E}(R_t | s_t, a_t, \pi)$

Value function

- The environment is unknown.
- $V^\pi, Q^\pi \sim$ knowledge representation of an agent, accumulating knowledge through its interactions with the environment, stored by updating its value function.
- If a value function is accurate an agent will know everything he needs to know for interacting with an environment.

Q FUNCTION

Q function

$$Q(s_t, a_t) = \mathbb{E}(R_t | s_t, a_t)$$

Captures the expected reward of a agent being in state s_t at time t, and taking the action a_t.

Question: how to decide actions to take, given a Q function ?

Policy

Policy

- Policy function $\pi : S \rightarrow A$
- Infer the best action to take when being in state $s \in S$

$$\pi^*(s) = arg\max_{a \in A} Q(s, a)$$

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Value Learning

Find $Q(s, a)$

$$a = arg\max_{a' \in A} Q(s, a')$$

Policy

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Value Learning

Find $Q(s, a)$

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Policy Learning

Find $\pi(s)$

Sample $a \sim \pi(s)$

Q-LEARNING

In classical reinforcement learning, problem related to Markov Decision Processes (ouf of scope).

Q-learning algorithm

1. build a memory table to store Q-values for all possible combinations of $s \in S$ and $a \in A$
2. as the algorithm evolves, the table is updated...
3. ... until convergence...
4. ... using some tricks (ϵ-greedy policy)

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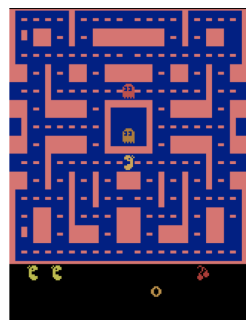
Q-learning does not scale to large problems

If A and/or S are large.

Pacman:

- 240 pellets can be present/absent/eaten
- $2^{240} \approx 10^{72}$ configurations
- + ghost and Pacman positions....



Approximating Q functions

Aim: build an approximation of the Q-function

- Approximate Q-learning: train $Q_{\boldsymbol{W}}$ that will generalize the memory table of the Q-learning algorithm

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- Approximate Q-learning: train $Q_{\boldsymbol{W}}$ that will generalize the memory table of the Q-learning algorithm
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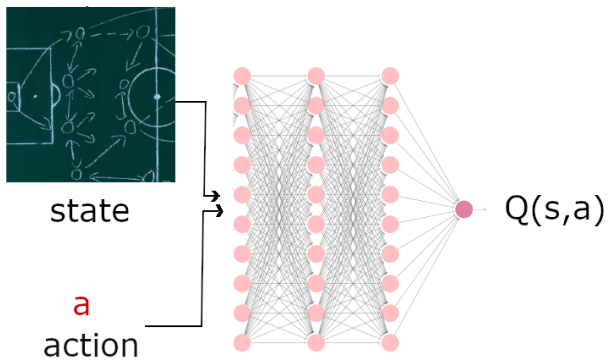
V^{π} can be approximated in the same way

Using Deep Networks to model Q functions

Deep Q-Networks (DQN)



$$S \times A \rightarrow Q(s, a)$$

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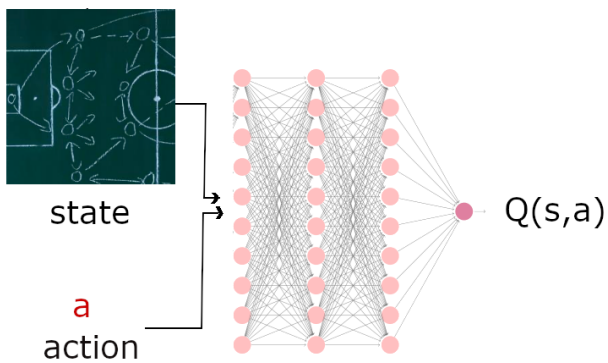

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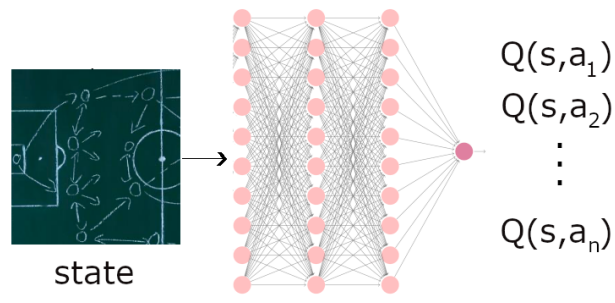

$$S \rightarrow Q(s,a)$$

Training

Strategy

- take all the best actions

$\Rightarrow$ Maximize expected reward

$\Rightarrow$ Train the agent

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Let put it in equation

Training

Strategy

- take all the best actions

$\Rightarrow$ Maximize expected reward

$\Rightarrow$ Train the agent

$$\underbrace{(r + \gamma \max_{a'} Q(s, a'))}_{\text{target}}$$

Training

Strategy

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$$\underbrace{(r + \gamma \max_{a'} Q(s, a'))}_{\text{target}} \underbrace{Q(s, a)}_{\text{predicted}}$$

Training

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$$\underbrace{(r + \gamma \max_{a'} Q(s, a'))}_{\text{target}} \quad \underbrace{- Q(s, a)}_{\text{predicted}}$$

Training

Strategy

- take all the best actions

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$$\mathcal{L} = \mathbb{E}[||\underbrace{(r + \gamma \max_{a'} Q(s, a'))}_{\text{target}} - \underbrace{Q(s, a)}_{\text{predicted}} ||^2] \quad Q\text{-loss}$$

Training

Strategy

- take all the best actions

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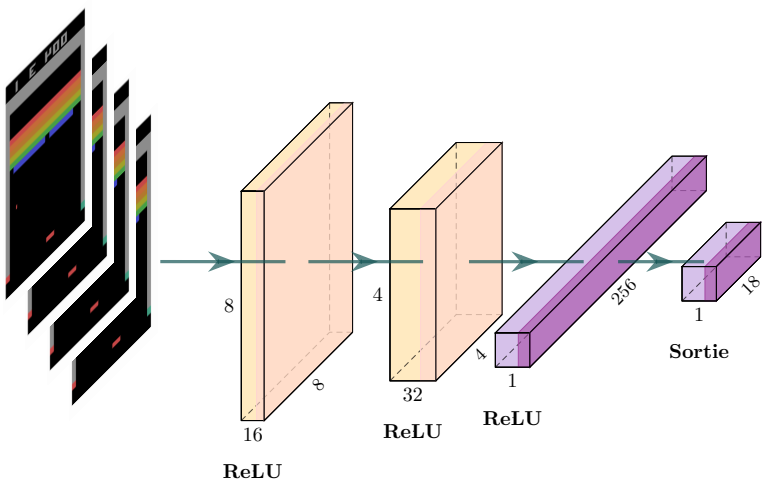
And so

1. Use a (deep) neural network to learn Q function and use it to infer the optimal policy $a_t = \pi^*(s_t)$.
2. Send action back to the environment: $s_t \xrightarrow{a_t} s_{t+1}$

Example - DQN



Deep Q-Network (DQN) on 49 ATARI games (Mnih et al., 2015).

- Input $4 \times 84 \times 84$ images
- Conv(16)-ReLU
- Conv(32)-ReLU
- FCC(256)
- Output: FCC(18): joystick positions

Example - DQN

Add-ons

- Experience replay: previous agent experiences (s_t, a_t, s_{t+1}, r_t) are stored in a replay memory and randomly drawned during training

$\Rightarrow$ suppress the correlation between training data

- Use of a target network $Q_{\boldsymbol{W}^-}$, keeping its own parameters and frequently updating them

$\Rightarrow$ reduce the correlations between Q -values and the target $r + \gamma \max_{a'} Q(s, a')$

$$\mathcal{L} = \mathbb{E}\left[\|(r + \gamma \max_{a'} Q_{\boldsymbol{W}_t^-}(s, a')) - Q_{\boldsymbol{W}_t}(s, a)\|^2 \right]$$

Example - DQN

Episode = a complete run of game; S: target network update step; T: length of a game : x_t input at time t ;

ϕ: preprocessing function

begin

Input : Image of the game; score, T, S

Output : Q value

Initialize Experience replay memory D

Initialize Q with random weights $\boldsymbol{W}$

Initialize target $\hat{Q}$ with weights $\boldsymbol{W}^- = \boldsymbol{W}$

foreach *episode* **do**

Initialize a sequence $s_1 = \{x_1\}, \phi_1 = \phi(s_1)$

for t=1 *to* T **do**

Select an action $a_t = \begin{cases} \text{randomly} & \text{with probability } \epsilon \\ Arg\max_a Q(\phi(s_t), a, \boldsymbol{\theta}) & \text{otherwise} \end{cases}$

Execute a_t and observe r_t and x_{t+1}

$s_{t+1} = s_t, a_t, x_{t+1}$

$\phi_{t+1} = \phi(s_{t+1})$

$D \leftarrow D \cup (\phi_t, a_t, r_t, \phi_{t+1})$;

`/* Experience replay */`

Sample a batch $(\phi_j, a_j, r_j, \phi_{j+1})$ from D ;

$y_j = \begin{cases} r_j & \text{if episode finishes in } j+1 \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a', \boldsymbol{\theta}^-) & \text{otherwise} \end{cases}$

Gradient descent step w.r.t. $\boldsymbol{\theta}$ on $(y_j - Q(\phi_j, a_j, \boldsymbol{\theta}))^2$

`/* Update target network */`

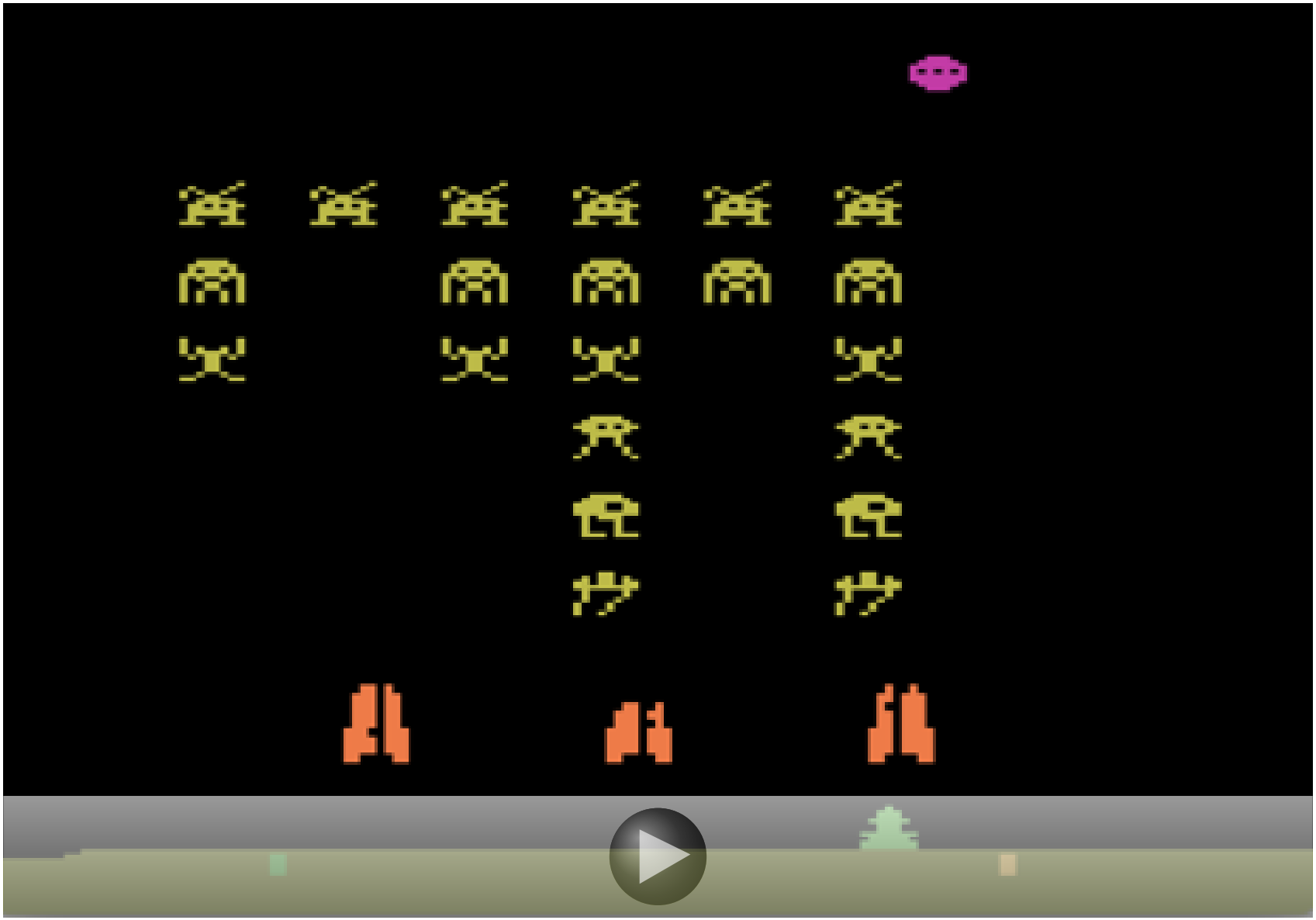
Each S step do $\boldsymbol{\theta}^- = \boldsymbol{\theta}$

end

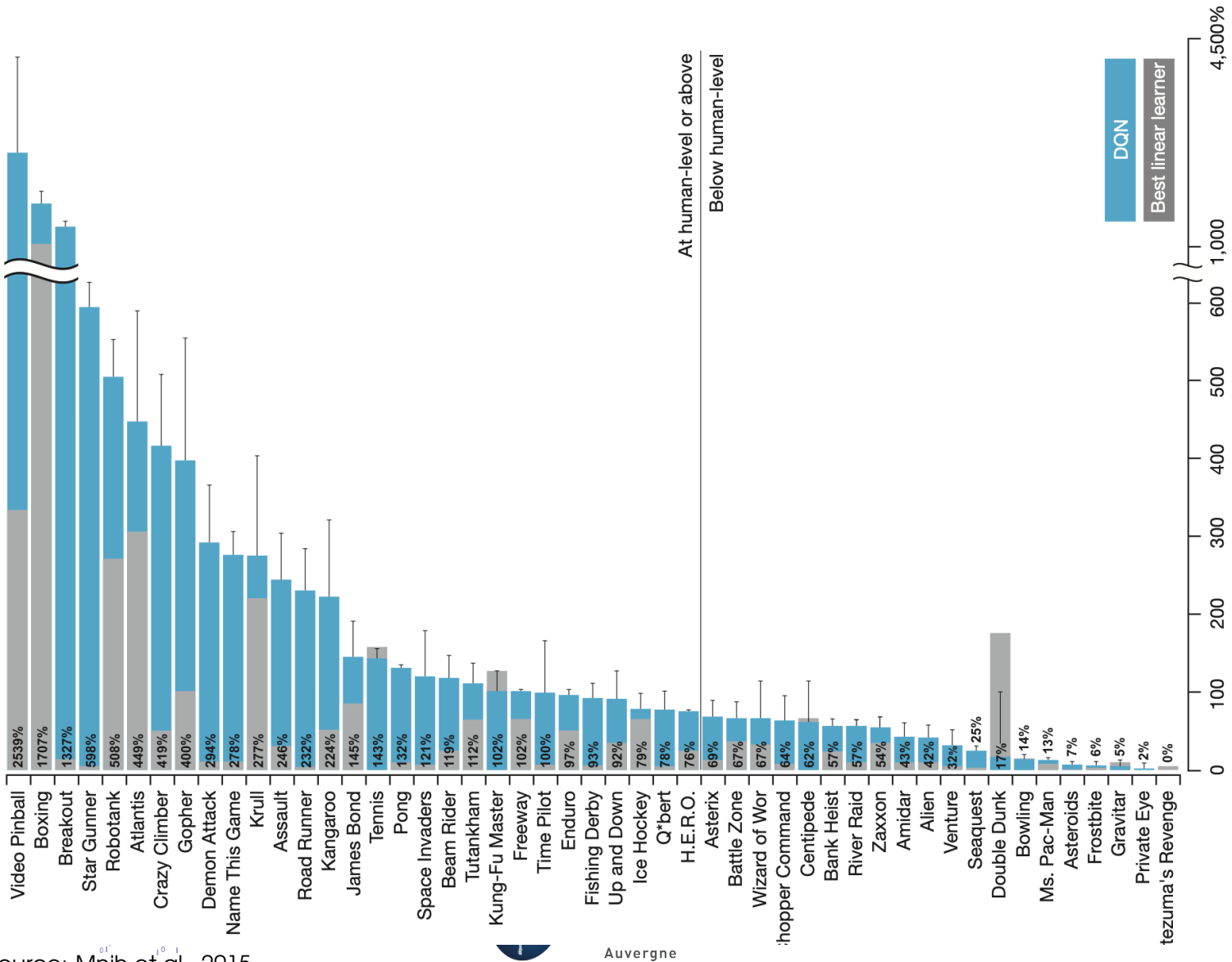
end

end

Example - DQN



Example - DQN

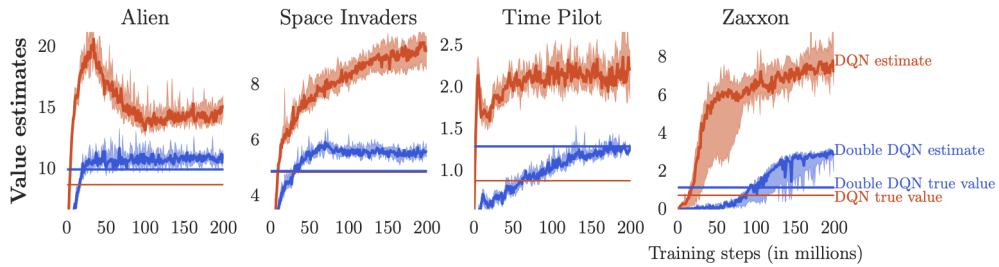


source: Mnih et al., 2015

Improvments

Improvments

- Double DQN (2016)



- Q Learning has been shown to overestimate its targets, because it uses a single estimator for estimating the Q values and choosing the maximum over actions.
- Solution: to overcome this, Double Q Learning uses a double estimator technique:
  - The target network is used for estimation
  - The online network for choosing the greedy action

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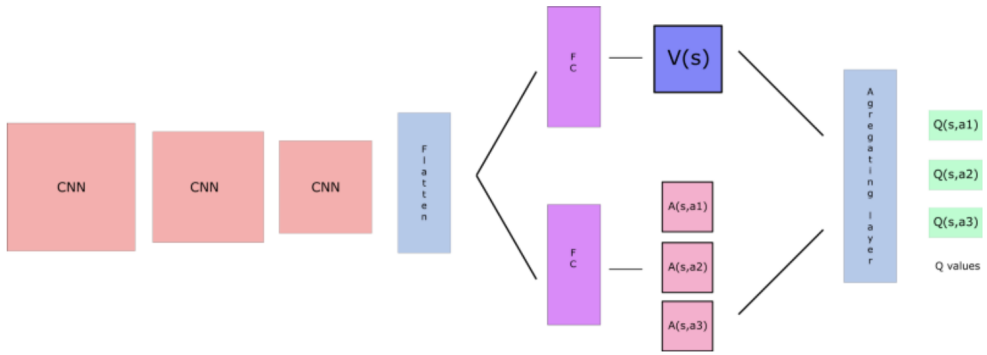
Improvments

Improvments

- Double DQN (2016)
- Dueling DQN (2016)



Dueling architecture:

- Decompose the Q value into a state-dependent part and a state-action dependent part
- This allows to share the state-dependent estimations (good for actions that are less chosen), focuses in estimating the state-action dependent part (good for relative ranking of the actions).

Pros and cons

Flexibility

- Q determines π^* in a deterministic way

$\Rightarrow$ cannot manage stochastic policies

Complexity

- OK if $|A|$ small, and A discrete
- KO if A is continuous

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See next lecture

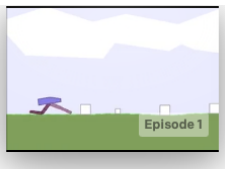
Policy gradient methods

Gym

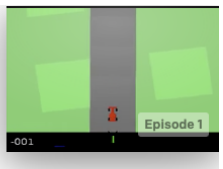
Gym: toolkit for developing and comparing reinforcement learning algorithms

Environments

BipedalWalker-v2
Train a bipedal robot to walk.



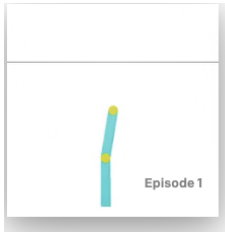
BipedalWalkerHardcore-v2
Train a bipedal robot to walk over rough terrain.



CarRacing-v0
Race a car around a track.

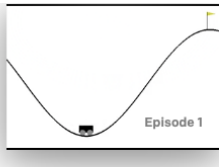
LunarLander-v2
Navigate a lander to its landing pad.

LunarLanderContinuous-v2
Navigate a lander to its landing pad.

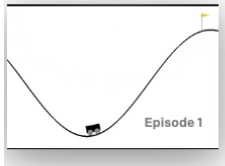


Acrobot-v1
Swing up a two-link robot.

CartPole-v1
Balance a pole on a cart.



MountainCar-v0
Drive up a big hill.



MountainCarContinuous-v0
Drive up a big hill with continuous control.

Pendulum-v0
Swing up a pendulum.

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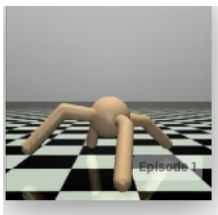
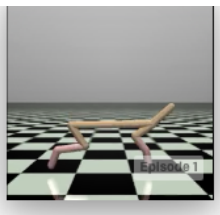
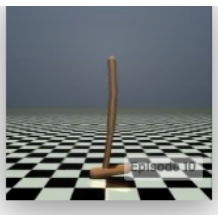
Environments



Ant-v2
Make a 3D four-legged robot walk.



HalfCheetah-v2
Make a 2D cheetah robot run.



Hopper-v2
Make a 2D robot hop.

Humanoid-v2
Make a 3D two-legged robot walk.

HumanoidStandup-v2
Make a 3D two-legged robot standup.

InvertedDoublePendulum-v2
Balance a pole on a pole on a cart.

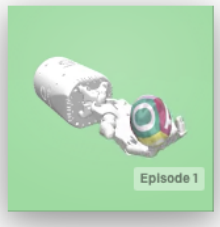
FetchPickAndPlace-v1
Lift a block into the air.

FetchPush-v1
Push a block to a goal position.

FetchReach-v1
Move Fetch to a goal position.

FetchSlide-v1
Slide a puck to a goal position.

HandManipulateBlock-v0
Orient a block using a robot hand.



HandManipulateEgg-v0
Orient an egg using a robot hand.

HandManipulatePen-v0
Orient a pen using a robot hand.

HandReach-v0
Reach a pose using a robot hand.

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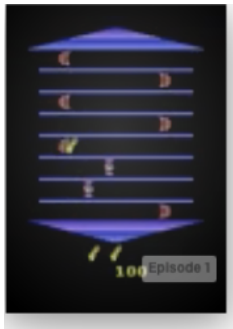
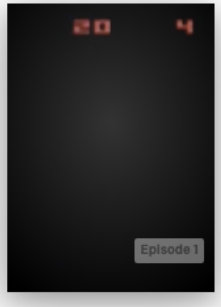
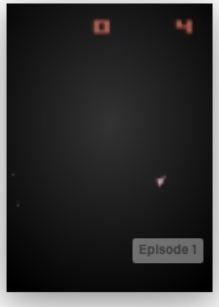
Environments



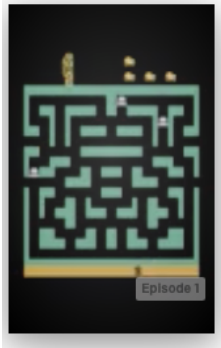
Asterix-v0
Maximize score in the game Asterix, with screen images as input



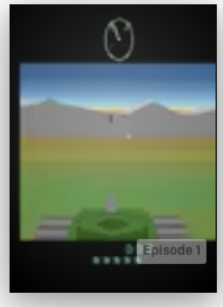
Asteroids-ram-v0
Maximize score in the game Asteroids, with RAM as input



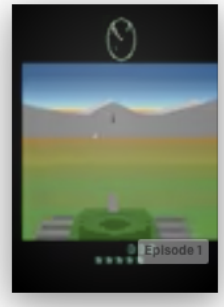
Asteroids-v0
Maximize score in the game Asteroids, with screen images as input



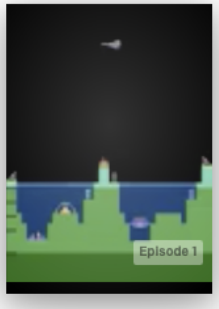
BankHeist-v0
Maximize score in the game BankHeist, with screen images as input



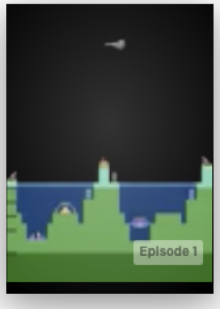
BattleZone-ram-v0
Maximize score in the game BattleZone, with RAM as input



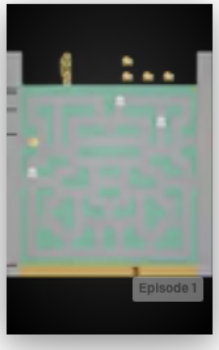
BattleZone-v0
Maximize score in the game BattleZone, with screen images as input



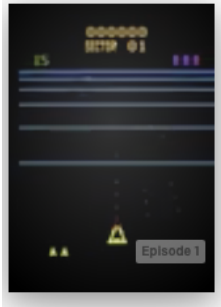
Atlantis-ram-v0
Maximize score in the game Atlantis, with RAM as input



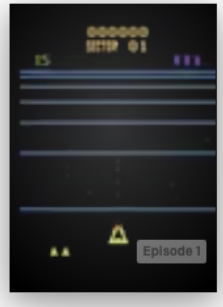
Atlantis-v0
Maximize score in the game Atlantis, with screen images as input



BankHeist-ram-v0
Maximize score in the game BankHeist, with RAM as input



BeamRider-ram-v0
Maximize score in the game BeamRider, with RAM as input



BeamRider-v0
Maximize score in the game BeamRider, with screen images as input

Berzerk-ram-v0
Maximize score in the game Berzerk, with RAM as input

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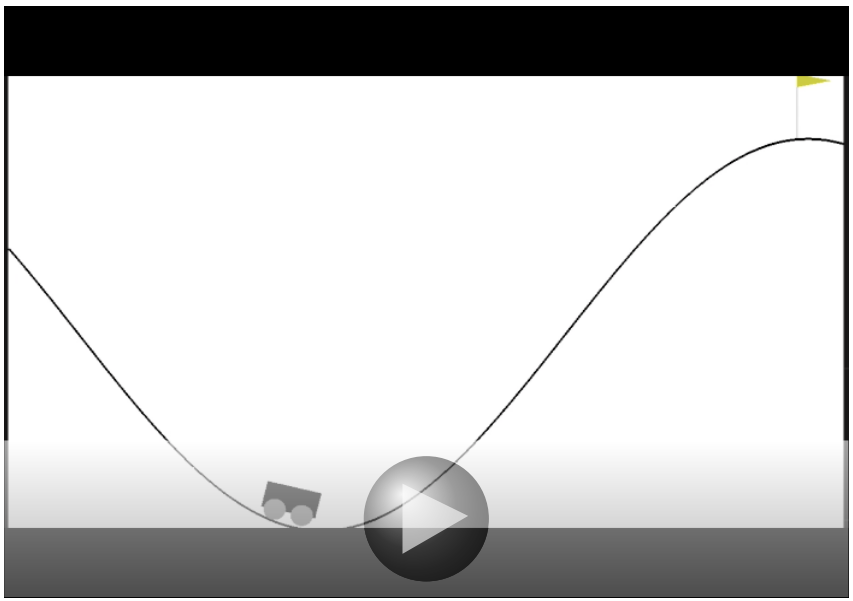
Code



```python
import gym
# Game to play
env = gym.make("MountainCar-v0")

# initial observation of the environment
observation = env.reset()

# A
print(env.action_space)

# S
print(env.observation_space)

for t in range(1000):

  env.render()

  # The agent chooses an action a(t)
  action = env.action_space.sample()

  # return s(t+1), r(t+1), time to reset, debugging info
  observation, reward, done, info = env.step(action)

  if done:
    # episode terminated
    observation = env.reset()
env.close()
```