Introduction to Deep Reinforcement Learning

IA Frameworks

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Tools

ML Python Libraries

scikit learn

Keras

gensim

surprise

Gym

TensorFlow

NLTK

Python Environment

PC

jupyter

ANACONDA

Viz' Python Libraries

matplotlib
Version 3.1.1

seaborn

plotly

Framework & Tool

docker

Google Cloud Platform

git

Table of contents

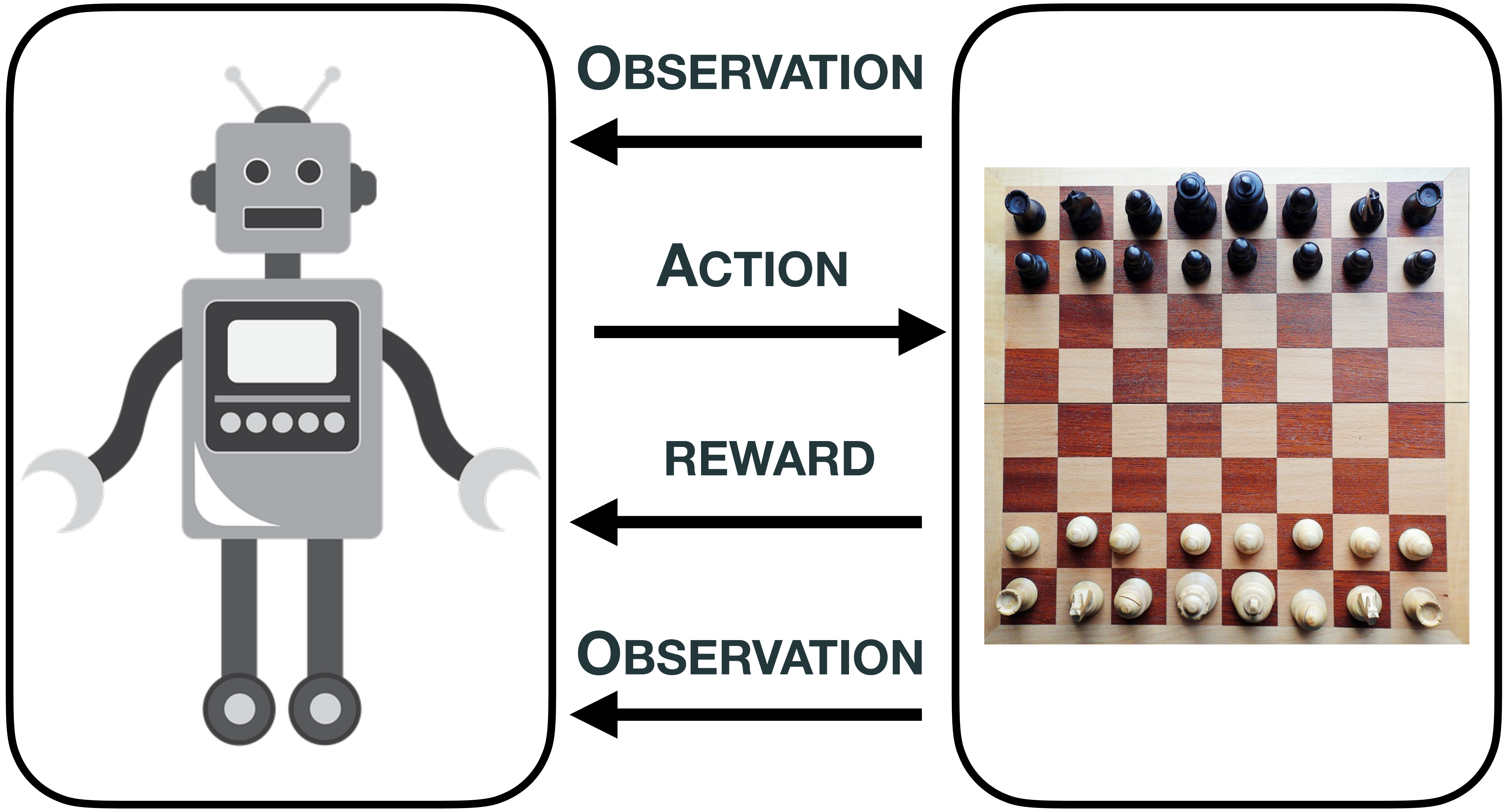
Introduction

Definitions

In reinforcement learning, an agent makes **OBSERVATIONS** of the **STATES** of an **ENVIRONMENT**.

It takes **ACTION** within the **ENVIRONMENT** and receives **REWARDS**.

Example: Chess Game



OBSERVATION: Locations of each pieces on the chessboard (32 x (id, x, y)).

ACTION: Move piece p from (x_a, y_a) to (x_b, y_b).

REWARD: Positive if a piece has been token.

Definitions

In reinforcement learning, an agent makes **OBSERVATIONS** of the **STATES** of an **ENVIRONMENT**.

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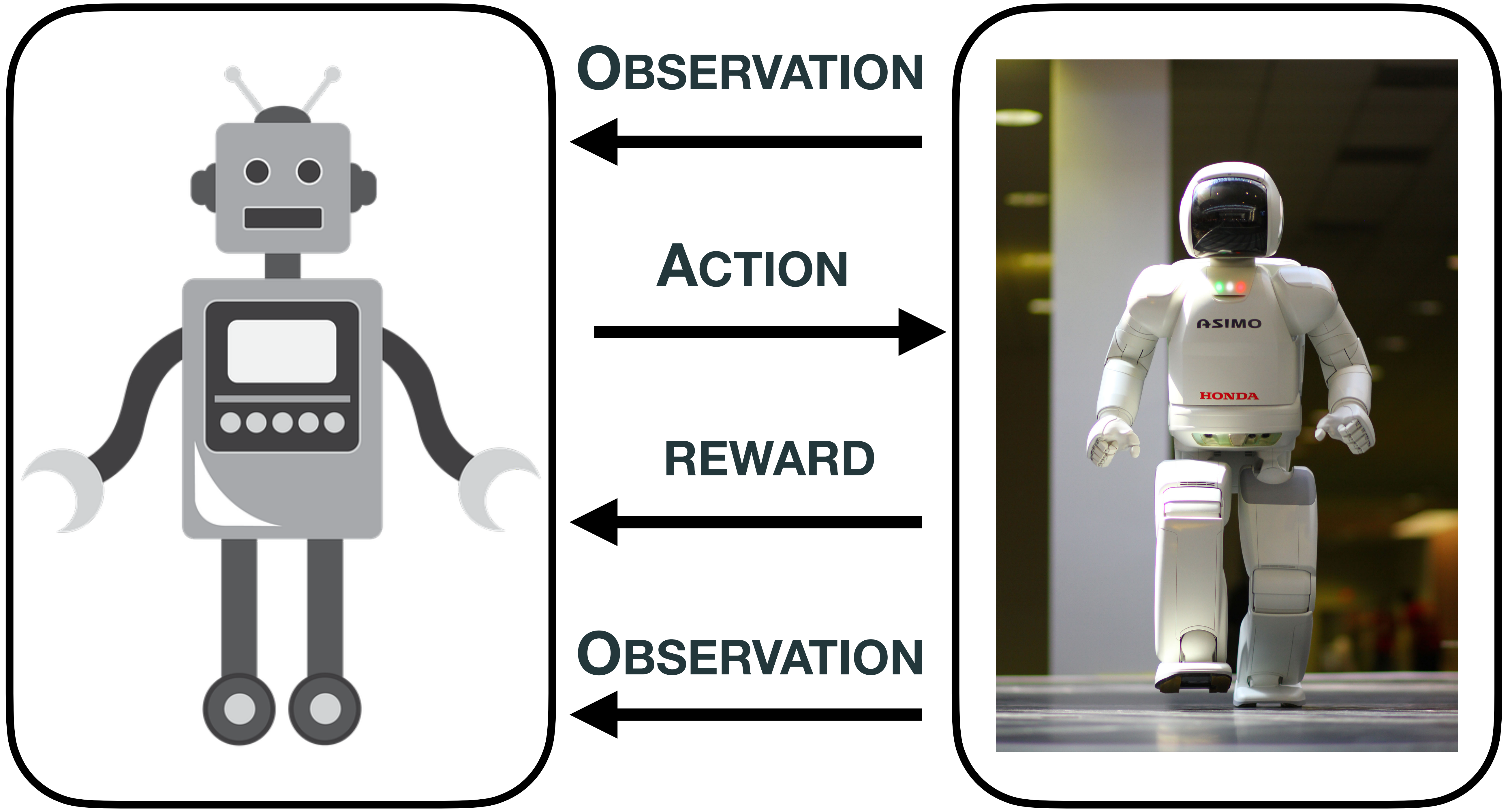
Example: Walking Robot



Observation: Measurement from various sensor (time series).

Action: Move members (3D).

Reward: Positive when it approach the destination. Negative otherwise.

Definitions

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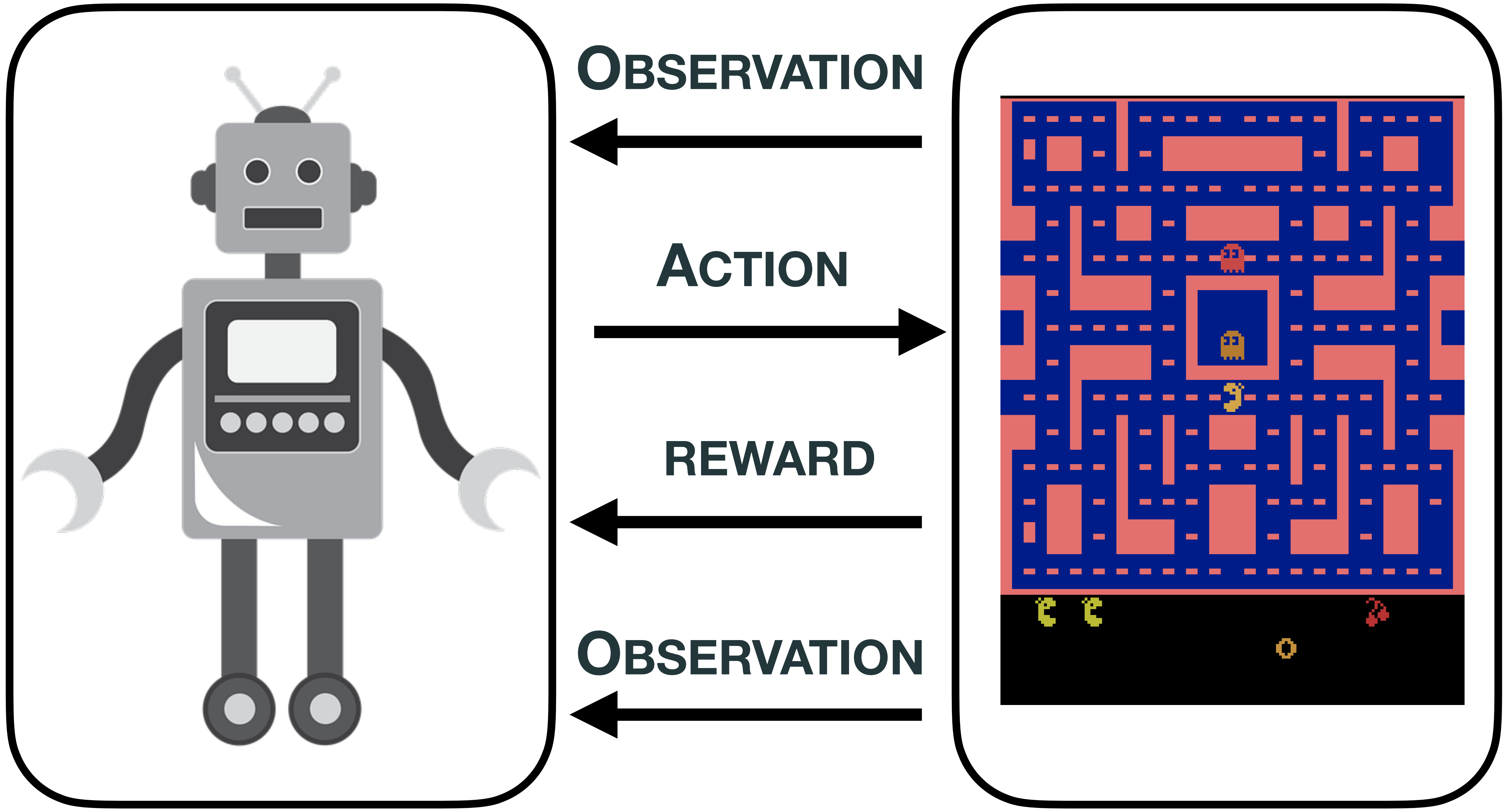
Example: Pac Man



OBSERVATION: The image itself.

ACTION: left/right/up/down/nothing.

REWARD: Game Point.

Definitions

When using reinforcement learning you need to define:

An **Agent**. The one who will take action within the environment.

An **Environment** where the action will be taken.

> The **State** of the environment defines it after each action.
>
> The **Observation** is what we will used from the state to decide the next action.

A list of possible **Actions** actions that will affect the environment and produce a new state.

A **Reward**. A numerical value which reveal how positive or negative the action is.

You can’t apply reinforcement learning if you’re not able to define these objects properly!

Objective

Maximise the long-term rewards.

Do not pull all the effort on capturing the queen if it means losing all you pieces.

How ? There are two mains approaches**:**

Value-Based. Look for the optimal **reward**.

- *Learn to estimate the expected rewards for each action in each state.*
- *Use this knowledge to choose the best action.*

Policy-Based. Look for the optimal **policy**.

- *Learn directly the best action to take for each observation.*

NB: Methods like Actor-Critic try to optimise both policy and rewards.

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Definitions

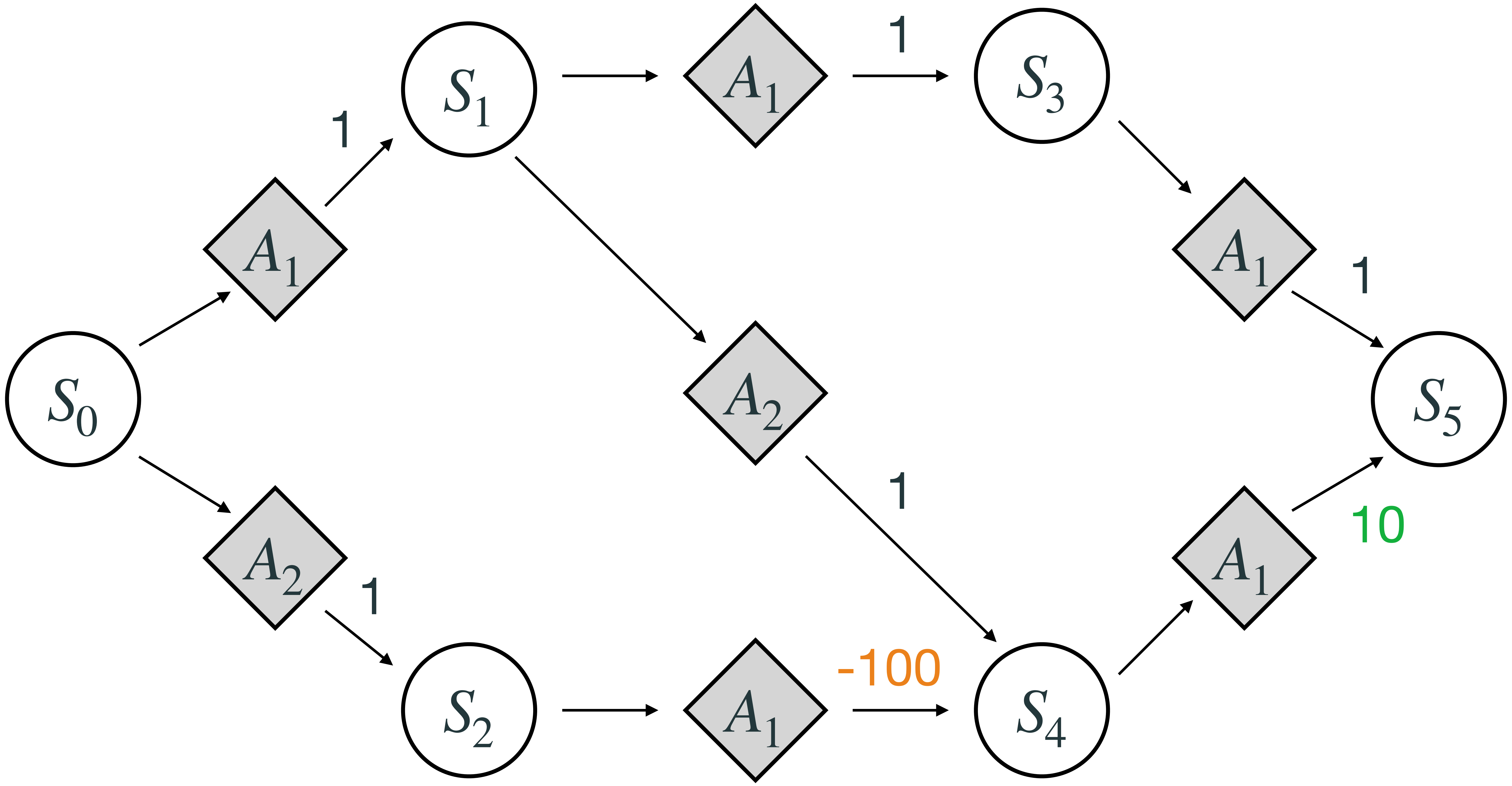
Markov Decision Process - Definition

A **M**arkov **D**ecision **P**rocess is composed of :

- A set of state $S = \{s_1, s_2, ..., s_n\}$.
- A set of action $A = \{a_1, a_2, ..., a_m\}$
- A reward function : $R = S \times A \times S \rightarrow \mathscr{R}$
- A transition function: $P_{ij}^{a} = P(s_j \,|\, s_i, a_k)$

Markov Decision Process - Example

- A set of state $S = \{1,2,3,4,5\}$.
- A set of action $A = \{1,2\}$
- A reward function : $R = \left[\{0,A,1\} = 1,\{0,B,2\} = 2,\ldots\right]$
- A transition function: $P_{ij}^{a} = 1, \forall\ (i, j, a),\ 0$ otherwhise



Policies

There are 3 policies for this **MDP**.

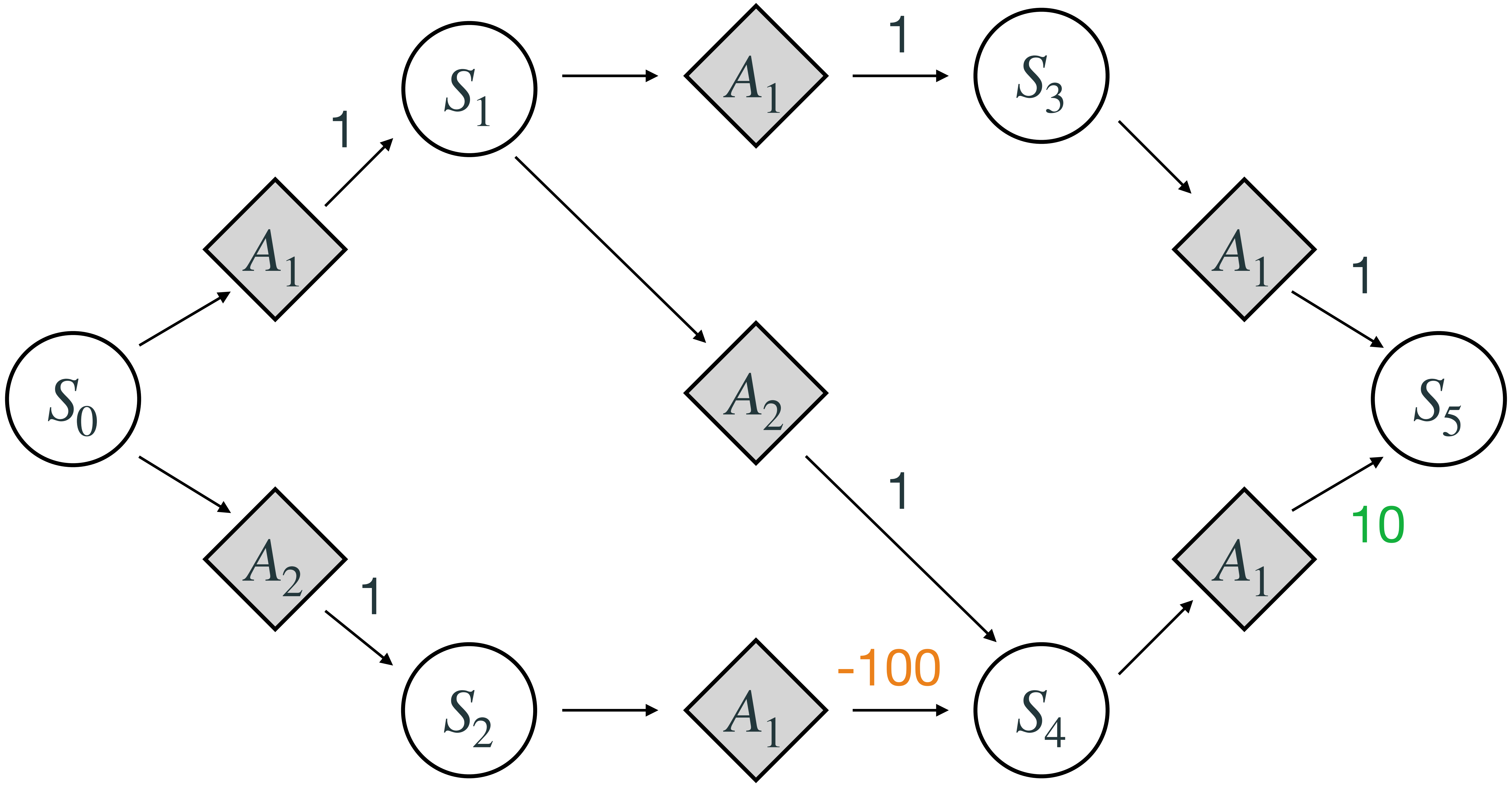
$\Pi_1 = \{0 \rightarrow 1 \rightarrow 3 \rightarrow 5\}$ $\quad R = 3$

$\Pi_2 = \{0 \rightarrow 1 \rightarrow 4 \rightarrow 5\}$ $\quad R = 12$

$\Pi_3 = \{0 \rightarrow 2 \rightarrow 4 \rightarrow 5\}$ $\quad R = -89$

Which one is the best?

Compute their total reward !



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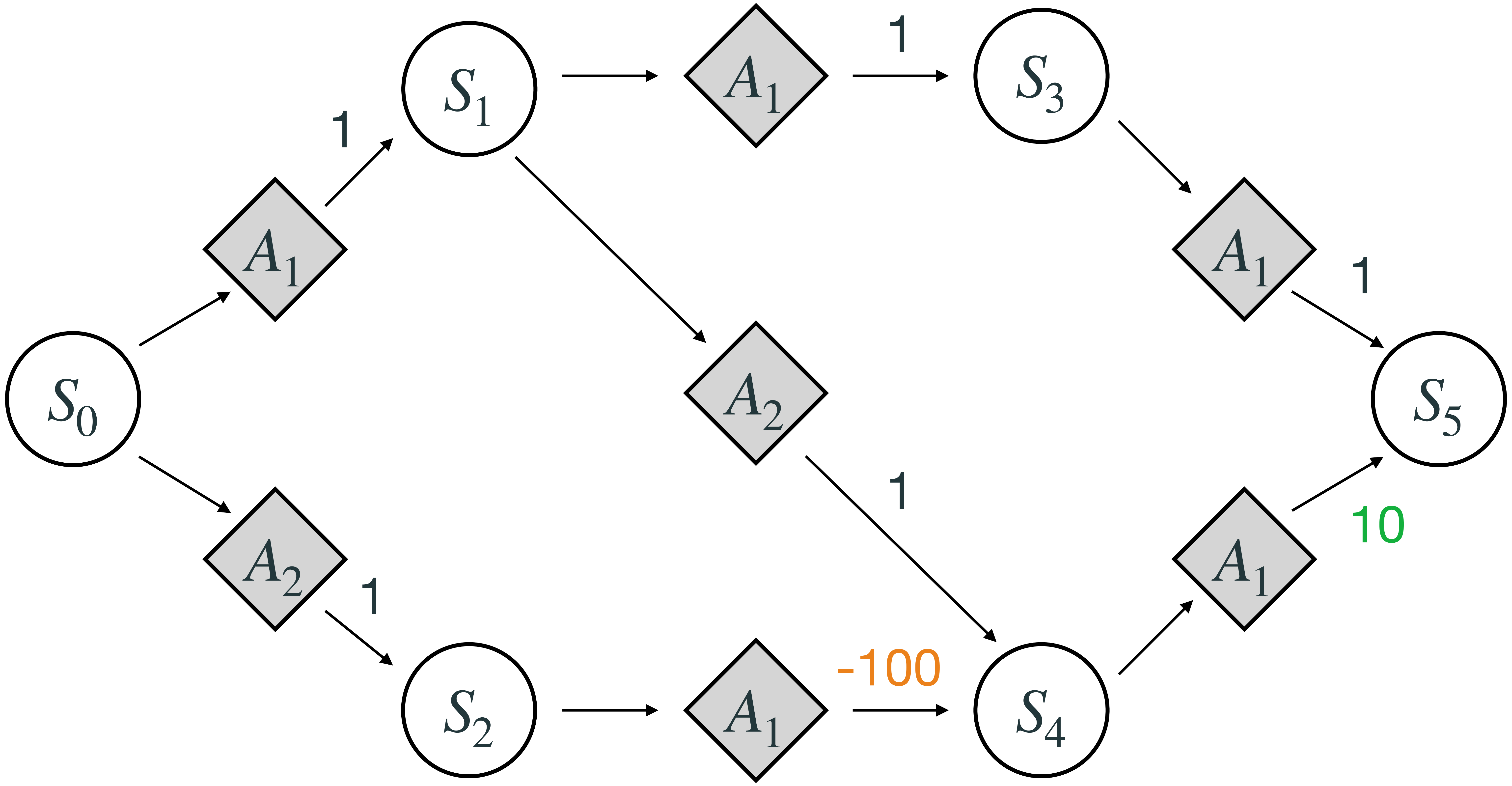
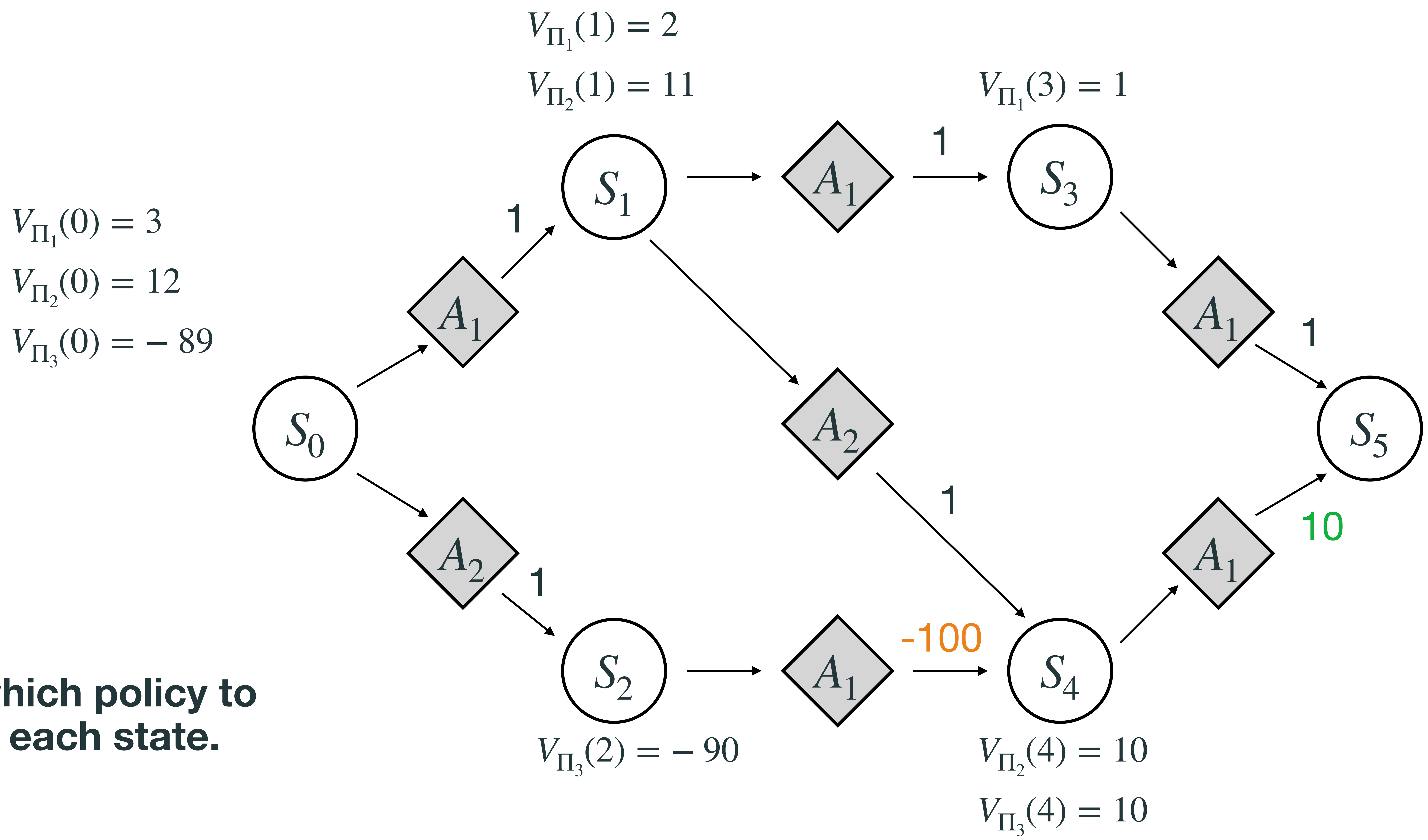


SATE VALUE

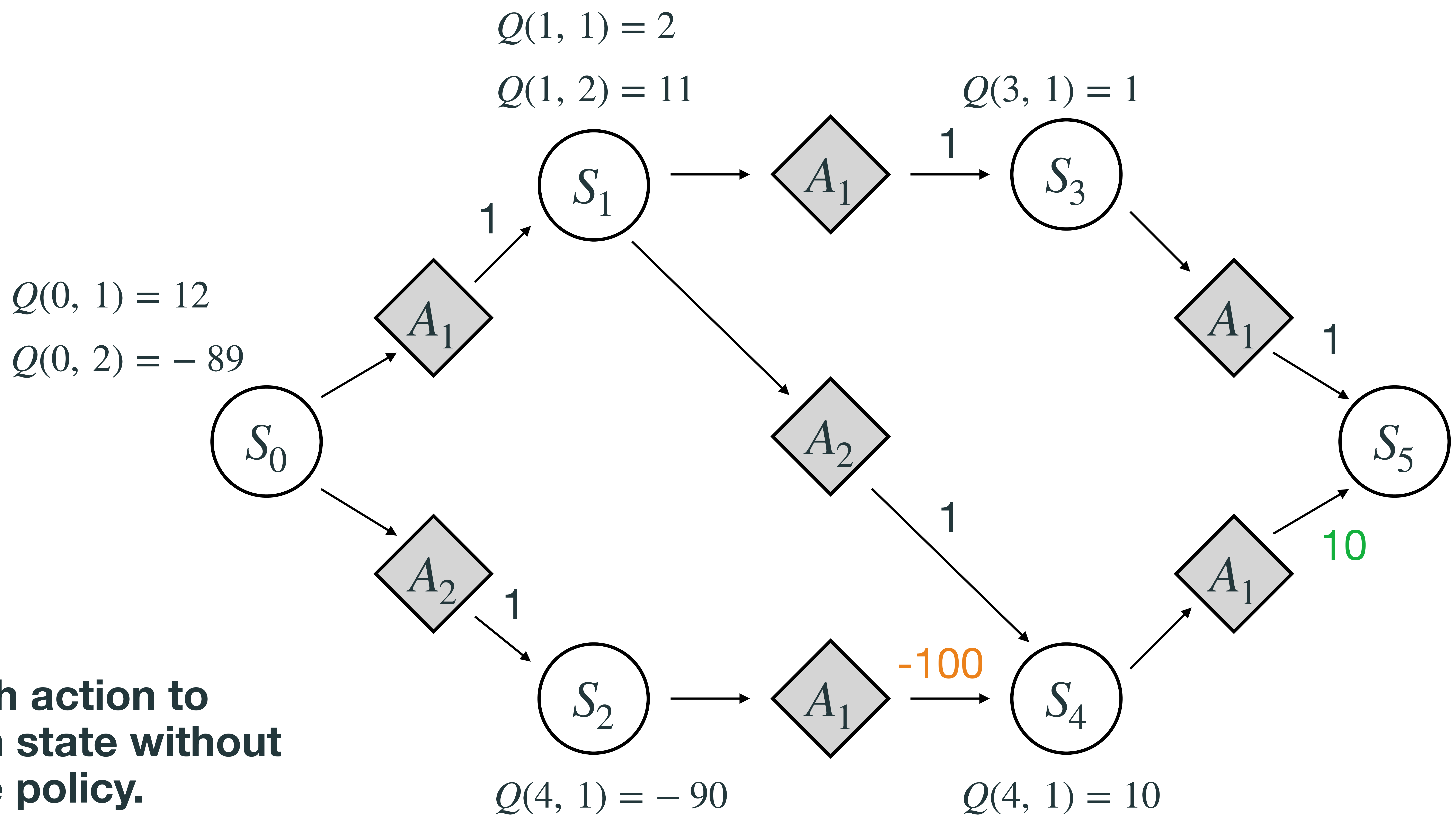
A state value $V_\Pi(s)$ describes how good is it to run policy Π from state s.



Define which policy to follow at each state.

Action-State value

An action-state value $Q(s, a)$ describes the value of taking and action a from state s.



Define which action to take at each state without knowing the policy.

general Definition

State value of a policy π:

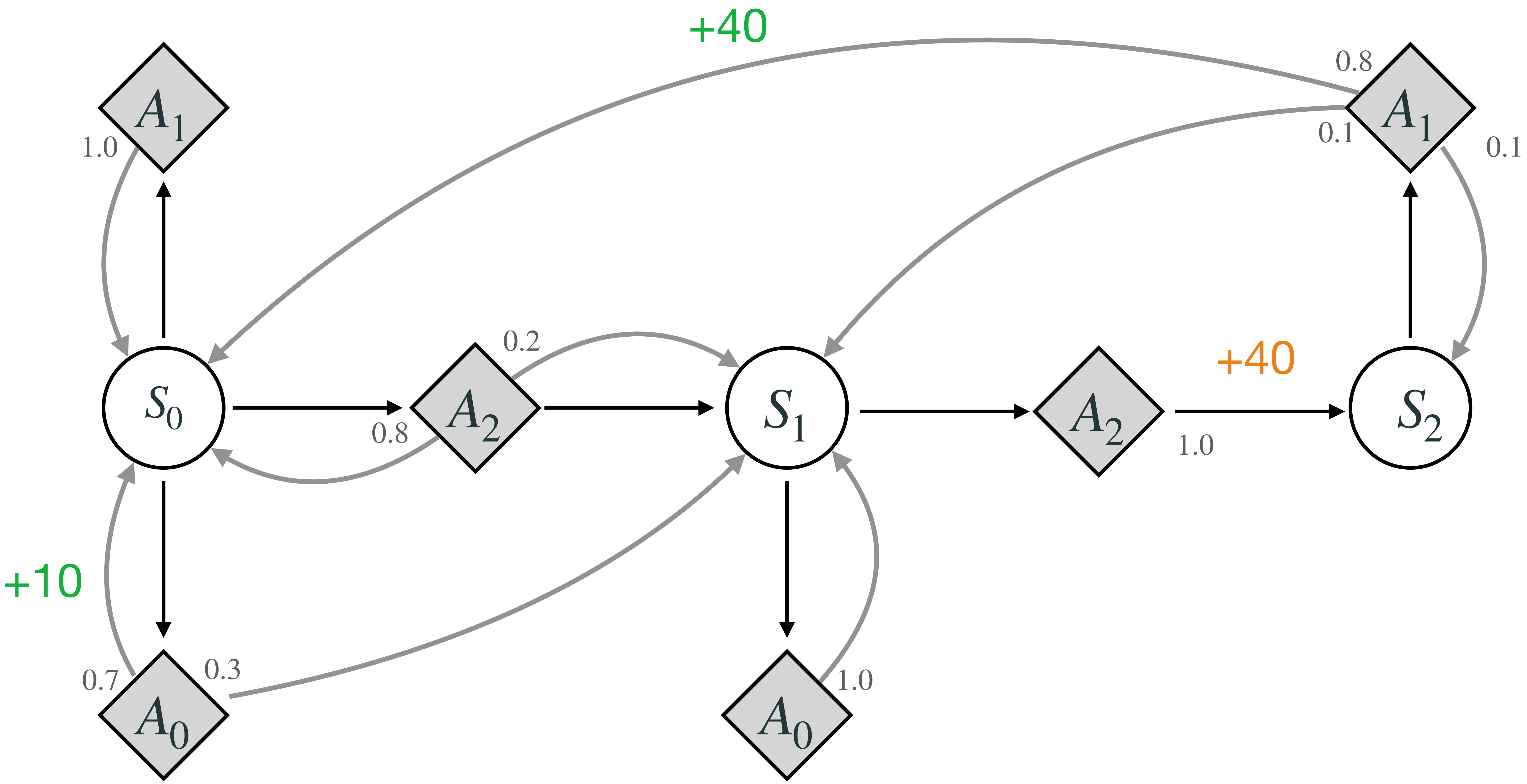
$$V^{\pi}(s) = \mathbb{E}\left(\lim_{H \to \infty} \sum_{t=0}^{H} \gamma^t r_t \,\middle|\, s_0 = s, \pi \right)$$

Action-state value function of a policy

$$Q^{\pi}(s, a) = \mathbb{E}\left(\lim_{H \to \infty} \sum_{t=0}^{H} \gamma^t r_t \,\middle|\, s_0 = s, a_0 = a, \pi \right)$$

Action-State value - Probabilistic Action

What if your action can lead you to different state ?



From state $= S_0$

$P^{A_0}_{S_0,S_0} = 0.7 \quad P^{A_0}_{S_0,S_1} = 0.3$

$P^{A_1}_{S_0,S_0} = 1$

$P^{A_2}_{S_0,S_0} = 0.8 \quad P^{A_2}_{S_0,S_1} = 0.2$

From state $= S_1$

$P^{A_0}_{S_1,S_1} = 1$

$P^{A_2}_{S_0,S_2} = 1$

From state $= S_2$

$P^{A_1}_{S_2,S_0} = 0.8 \quad P^{A_1}_{S_2,S_1} = 0.1 \quad P^{A_1}_{S_2,S_2} = 0.1$

SOLUTION: The Bellman Equation

Bellman Optimality Equation

For all s :

$$V^{\star}(s) = max_a \sum_{s'} P^a_{s,s'} \big[R(s,a,s') + \gamma \cdot V^{\star}(s') \big]$$

- $V^{\star}$ is the optimal state value at state s.
- $P^a_{s,s'}$ is the transition probability from state s to state s' given that the agent choice action a.
- $R(s,a,s')$ is the reward that the agent gets when it goes from state s to state s' given that the agent choose action a.
- γ is the discount rate (t*he importance we give to future rewards).*

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How to estimate this optimal sates? The **Value Iteration algorithm.**

Iteration algorithm

Iteration Algorithm

Value Iteration algorithm.

- Initialise: $V_0(s) = 0, \forall s$.
- Iterate, $\forall s$:

$$V_{k+1}(s) \leftarrow max_a \sum_{s'} P^a_{s,s'} \left[R(s,a,s') + \gamma \cdot V_k(s') \right]$$

- $V_k(s)$ is the estimated value of state s at the k^{th} iteration of the algorithm.
- Algorithm is guaranteed to converge to the optimal state value (given enough time)

We can now evaluate the optimal policy…

… but we don't know which action to take at each state !

Iteration Algorithm

Q-Value Iteration algorithm.

- Initialise: $Q_0(s,a) = 0,\ \forall(s,a)$.
- Iterate, $\forall(s,a)$:

$$Q_{k+1}(s,a) \leftarrow \sum_{s'} P^{a}_{s,s'}\left[R(s,a,s') + \gamma \cdot max_{a'}\ Q_k(s',a')\right]$$

Once you have the optimal ***Q-value***, $Q*$, the ***optimal policy***,$\Pi*(s)$, is defined as:

$$\Pi*(s) = argmax_a\ Q*(s,a)$$

Real application

Problem: The **Q-value iteration algorithm** required to know the complete MDP:

- complete list of possible states $s \in S$ and actions $a \in A$,
- all transition probabilities $T(s, a, s')$
- all possible reward $R(s, a, s')$

In real case, the agent has only partial knowledge of the MDP:

- complete list of possible states $s \in S$ and actions $a \in A$,
- $T(s, a, s')$ and $R(s, a, s')$ are unknown

Proposition: Estimate those values

- $R(s, a, s')$ requires to see each transition at least once.
- $T(s, a, s')$ requires to experience it multiple times.

Q-Learning

Temporal Difference Learning

TD-Learning iteration algorithm

$$V_{k+1}(s) \leftarrow (1-\alpha)V_k(s) + \alpha V^*_{k+1}(s)$$

- Initialise: $V_0(s) = 0, \ \forall s$.
- At iteration k, we have an estimation of the optimal state value $V_k(s)$, then $\forall s$:
  - Choose a reachable state s' *(we'll come back to that later)*.
  - Compute an estimation of the next state value $V^*_{k+1}(s) = R(s, a, s') + \gamma \cdot V_k(s')$
  - Update V_{k+1} as a combination of the previous estimation $V_k(s)$ and the estimation $V^*_{k+1}(s)$

  Where the learning rate $\alpha \in [0,1]$

Temporal Difference Learning VS Value Iteration Algorithm

TD-Learning iteration algorithm.

$$V_{k+1}(s) \leftarrow (1-\alpha)V_k(s) + \alpha\left[R(s,a,s') + \gamma \cdot V_k(s')\right]$$

$$V_{k+1}(s) \leftarrow (1-\alpha)V_k(s) + \alpha V^*_{k+1}(s)$$

Value Iteration algorithm.

$$V_{k+1}(s) \leftarrow max_a \sum_{s'} P^a_{s,s'}\left[R(s,a,s') + \gamma \cdot V_k(s')\right]$$

$$V_{k+1}(s) \leftarrow max_a \sum_{s'} P^a_{s,s'} V^*_{k+1}(s)$$

- The **discount rate** γ represent how much you can trust the features reward.
- The **learning rate** α represent how much you can trust the next state value estimation.

The Q-value iteration algorithm can be adapted the same way.

Q-Learning

Q-Learning iteration algorithm

$$Q_{k+1}(s,a) \leftarrow (1-\alpha)Q_k(s,a) + \alpha\left[R(s,a,s') + \gamma \cdot \max_{a'} Q_k(s',a')\right]$$

- We build a memory table to store **Q-value** for all possible combinations of s and a.
- As we keep playing we update this table.
- And it will converge…
- …with some tricks!

Off Policy

Off-Policy algorithm

The **TD-Learning** and **Q-learning** iteration algorithm used with random policy exploration.

Π_l : The policy you are learning *(by updating either the Q-value or the state value).*

Π_e : The policy you are executing *(to choose the action you're taking).*

- Π_e is random when using off-policy algorithm
- You are learning how to act by observing someone doing random action.
- Q-learning will learn only if the exploration policy explores the MDP enough.
- It may take and extremely long time to do so..

Can't we do better?

Exploration policy : $\epsilon - greedy$ policy

At each step you will choose either:

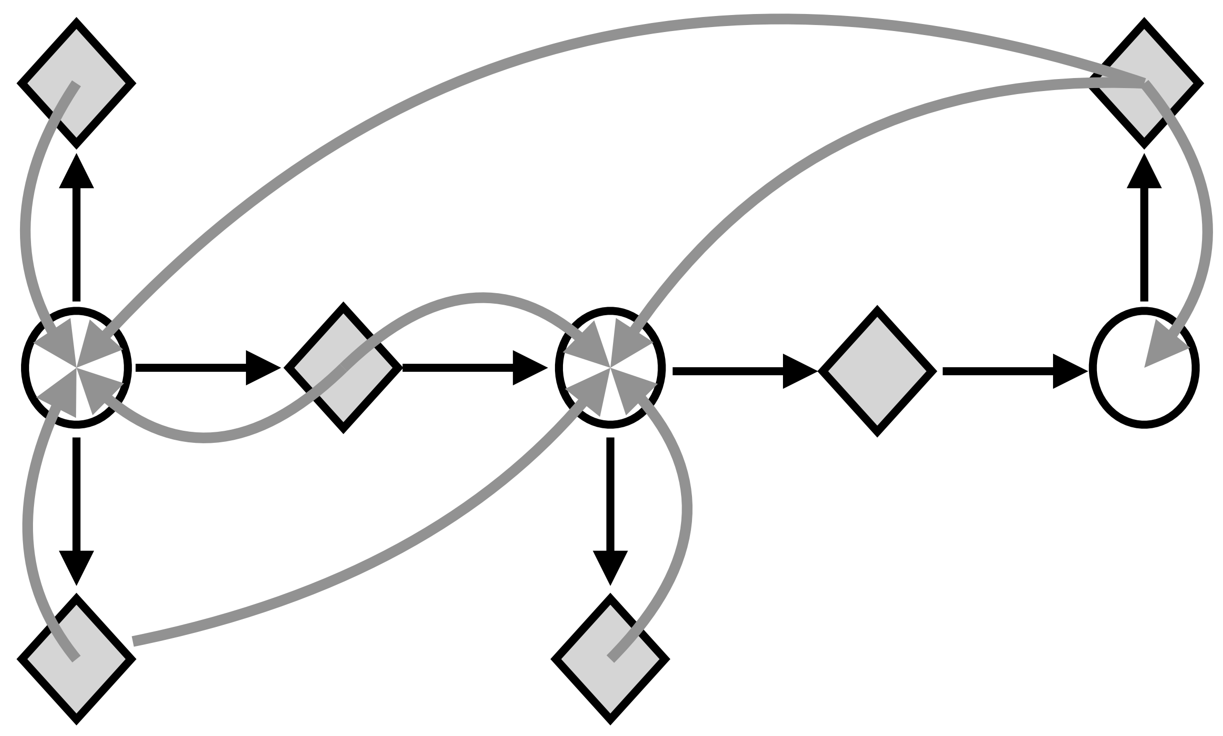
- The exploration policy (random one) Π_e with a probability ϵ
- The learned policy Π_l with a probability $(1 - \epsilon)$

You start with $\epsilon = 1$: purely random exploration of the environment.

You decrease the value of epsilon over iteration to explore less and exploit more the interesting pars of the environment

TP

- *Q_learning.ipynb :* Implement **Q-VALUE ITERATION ALGORITHM** and ***Q-LEARNING ITERATION ALGORITHM*** on the toy MDP of this presentation



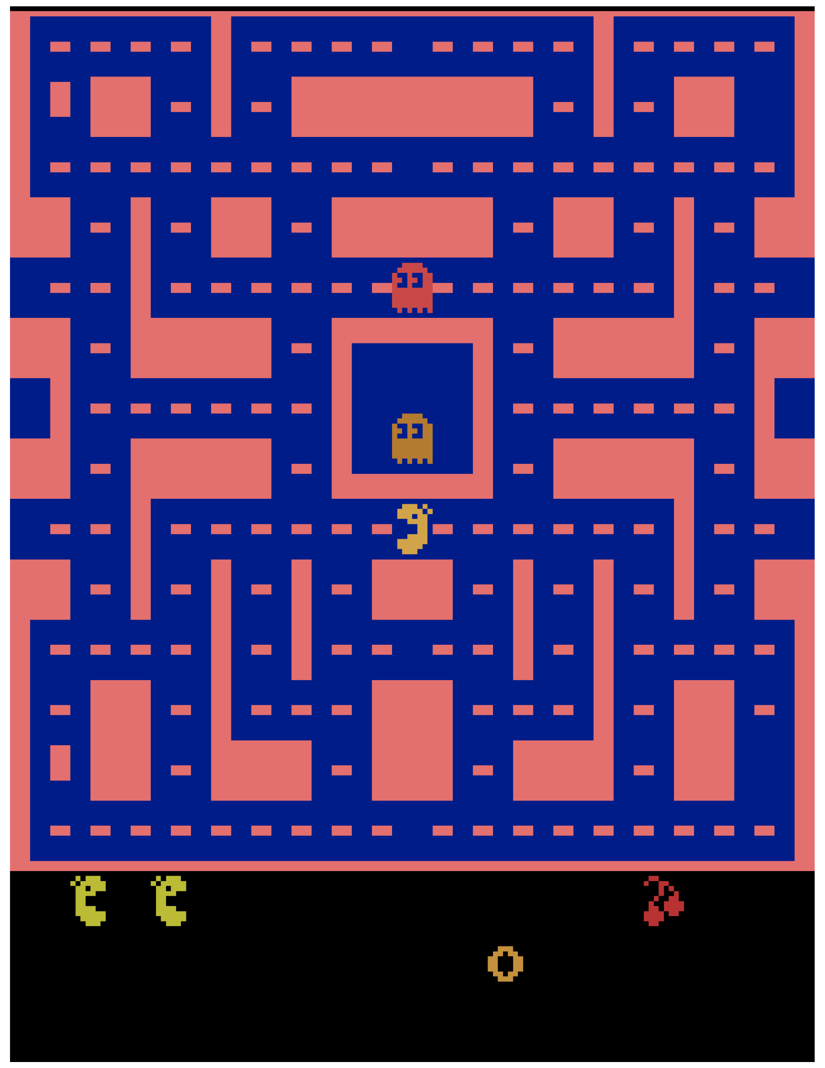
Deep Q-Learning (DQN)

Approximate Q-Learning

Problem: Q-learning still does not scale to large MDPs

- $T(s, a, s')$ and $R(s, a, s')$ are not computed for every (s, a) couple.
- But $Q(s, a)$ are!

Example: Pacman



- 240 pellets that can be eaten or here or not.
- It represent $2^{240} \approx 10^{72}$ configuration. *Number of atoms in the universe.*
- And we need to consider ghost and Pacman position...

We can' compute nor store Q-value for every (s, a) couple.

Approximate and Deep Q-learning

Objective: Use a function to evaluate the Q-value

Q-Learning

Store and update all Q-values in a big table

Pick value from it.

Approximate Q-Learning

We train a function Q_θ that will generalise the approximation of the Q-values table

Use this function to estimate value

Compute hand-crafted features (localisation of paceman, distance to the ghost, localisation of remaining pellets…)

Deep Q-Learning

Use a CNN network as a Q_θ function and use image as features.

DeepMind makes it work (very well) on various Atari Game in 2014.

Approximate and Deep Q-learning

Q-Value Iteration algorithm.

$$Q_{k+1}(s,a) \leftarrow \sum_{s'} P^a_{s,s'}\left[R(s,a,s') + \gamma \cdot max_{a'}\, Q_k(s',a')\right]$$

Q-Learning

$$\begin{aligned} target &= R(s,a,s') + \gamma \cdot \max_{a'} Q_k(s',a') \\ Q_{k+1}(s,a) &\leftarrow (1-\alpha)Q_k(s,a) + \alpha\left[target\right] \end{aligned}$$

Approximate/Deep Q-Learning

$$target = R(s,a,s') + \gamma \cdot \max_{a'} Q_k(s',a')$$

At step k, generate $batch\_size\ \ targets$ and train model on this batch

$$\theta_{k+1} \leftarrow \theta_k - \alpha \nabla_\theta \mathbb{E}_{s\sim' P(s'|s,a)}[(Q_\theta(s,a) - target(s'))^2]_{\theta=\theta_k}$$

- θ_k are the weights of the (Deep) Q function computed at step k (batch)
- α is the learning rate and can be interpreted the same way.

Pseudo Code

- Create Q network.
- Iterate while $max\_number\_episode$ or $goal\_reward$ is not achieved:
  - Play one episode - Explore randomly or Exploit with Q according to $random\_probability$.
  - If we train more than $min\_pre\_trained\_episode$
    - Create target using Q.
    - Train the Q network.
    - Start decreasing $random\_probability$.

DEFINITIONS

EPISODE: One complete run of a game.

Pacman: all the move until the pacman died.

STEP: One move of the game.

Pacman: one action taken in the environment (up, down, left, right)

EXPERIENCE: All the information that resume one step: .

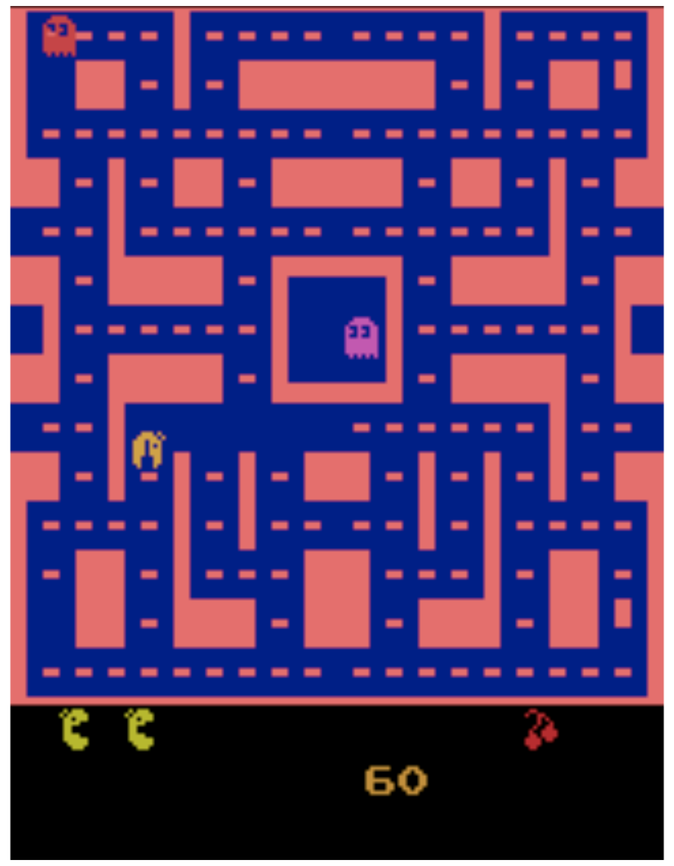
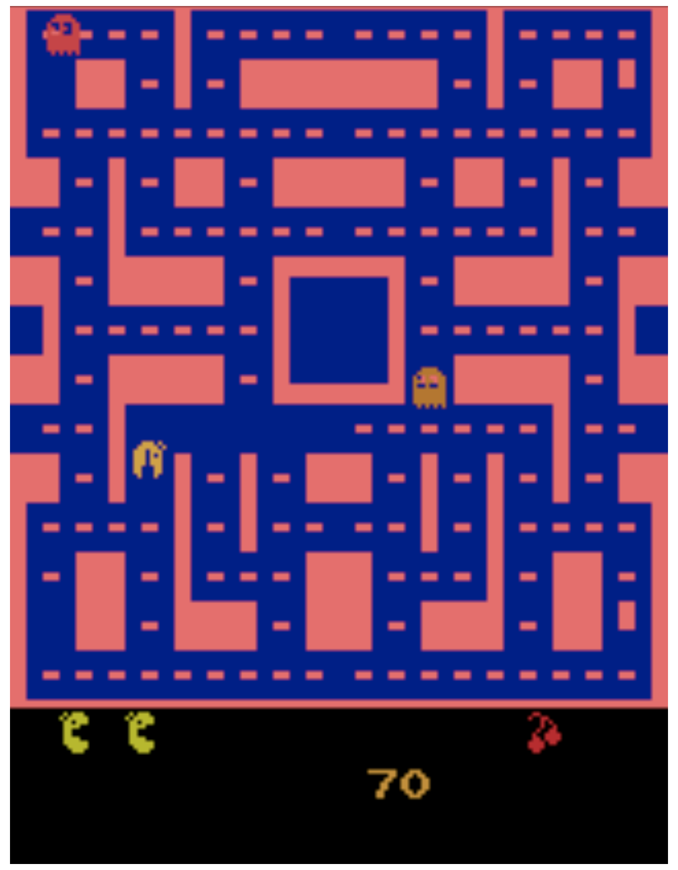
s: from state

a: action chosen

s': to state

r: reward obtained

d: is game over

Pacman	*From state*	*Action*	*To state*	*Reward*
		DOWN		10

Experiences for training dataset

$$\begin{array}{cccc} \textit{from state} & \textit{action} & \textit{to state} & \textit{reward} \end{array}$$

$$\begin{bmatrix} s_{0,0} & a_{0,0} & s'_{0,0} & r_{0,0} \\ s_{0,1} & a_{0,1} & s'_{0,1} & r_{0,1} \\ \dots & \dots & \dots & \dots \\ s_{0,ns_0} & a_{0,ns_0} & s'_{0,ns_0} & r_{0,ns_0} \\ s_{1,0} & a_{1,0} & s'_{0,1,0} & r_{1,0} \\ \dots & \dots & \dots & \dots \\ s_{ne,0} & a_{ne,0} & s'_{ne,0} & r_{ne,0} \\ \dots & \dots & \dots & \dots \\ s_{ne,ns_{ne}} & a_{ne,ns_{ne}} & s'_{ne,ns_{ne}} & r_{ne,ns_{ne}} \end{bmatrix}$$

- $\{s, a, s', r\}_{i,j}$, *from state, action, to state* and *reward* of episode i at step j.
- ne number of episodes in the training dataset.
- ns_i number of steps in episode i.
- Number of experience in the training dataset : $\sum_{i=0}^{ne} ns_i$

Problem: The input of the supervised learning problem are not $i.i.d.$

Experience Replay

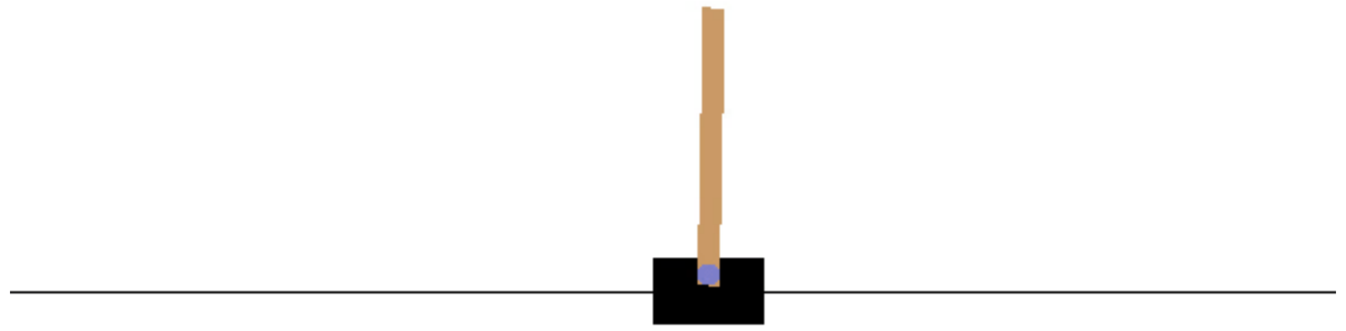
Solution: The Experience Replay

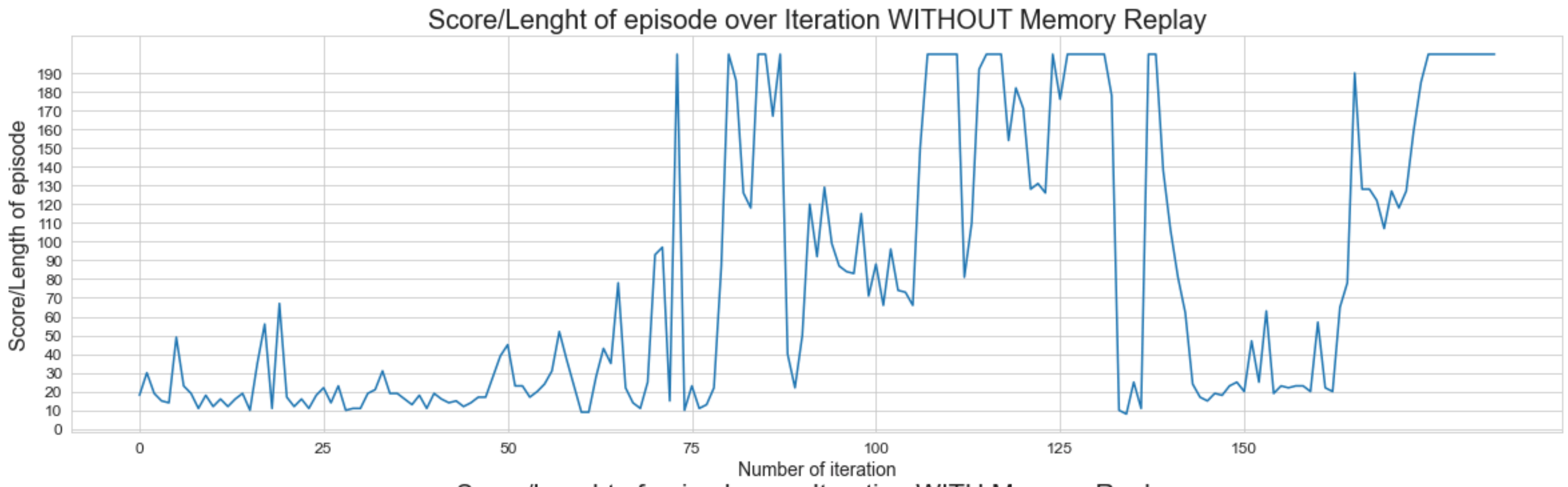
$$
\begin{array}{cccc}
\textit{from state} & \textit{action} & \textit{to state} & \textit{reward} \\
\end{array}
$$

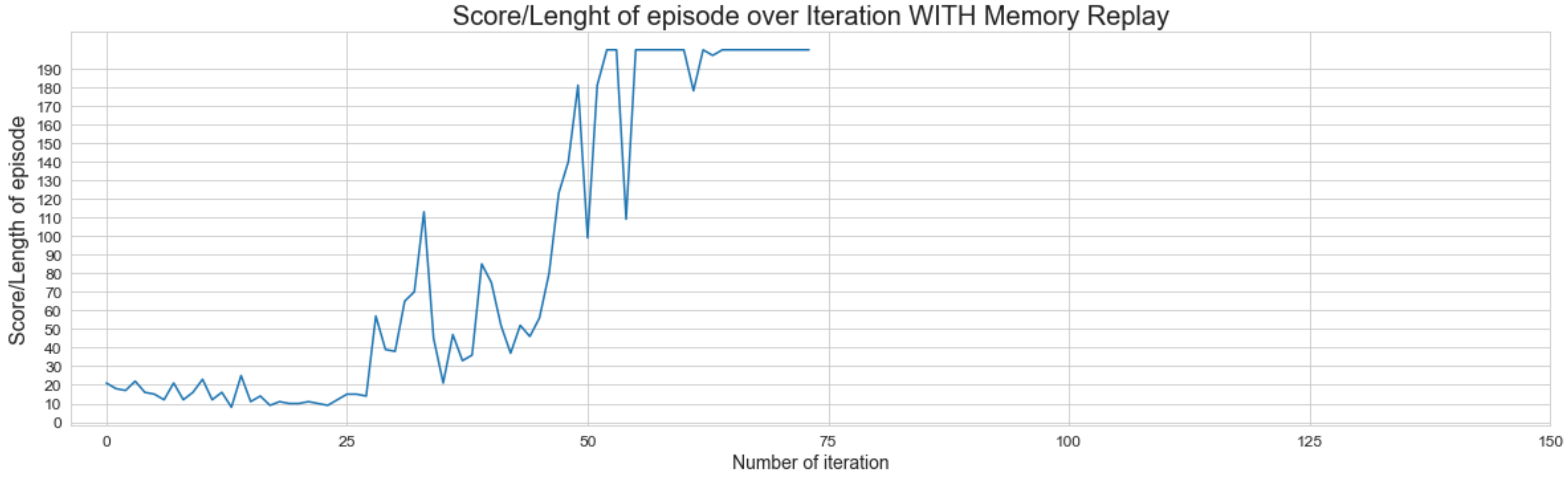
$$
\begin{bmatrix}
s_{10,3} & a_{10,3} & s'_{10,3} & r_{10,3} \\
s_{8,37} & a_{8,37} & s'_{8,37} & r_{8,37} \\
\dots & \dots & \dots & \dots \\
s_{3,17} & a_{3,17} & s'_{3,17} & r_{3,17} \\
s_{5,38} & a_{5,38} & s'_{5,38} & r_{5,38} \\
\dots & \dots & \dots & \dots \\
s_{8,6} & a_{8,6} & s'_{8,6} & r_{8,6} \\
\dots & \dots & \dots & \dots \\
s_{3,10} & a_{3,10} & s'_{3,10} & r_{3,10}
\end{bmatrix}
$$

- $\{s, a, s', r\}_{i,j}$, *from state, action, to state* and *reward* of episode i at step j.
- Fix the number of experiences in the training dataset ($batch\_size$).
- Play ne episodes such that $\sum_{i=0}^{ne} ns_i > batch\_size$.
- Sample $batch\_size$ experiences from the ne episodes generated.

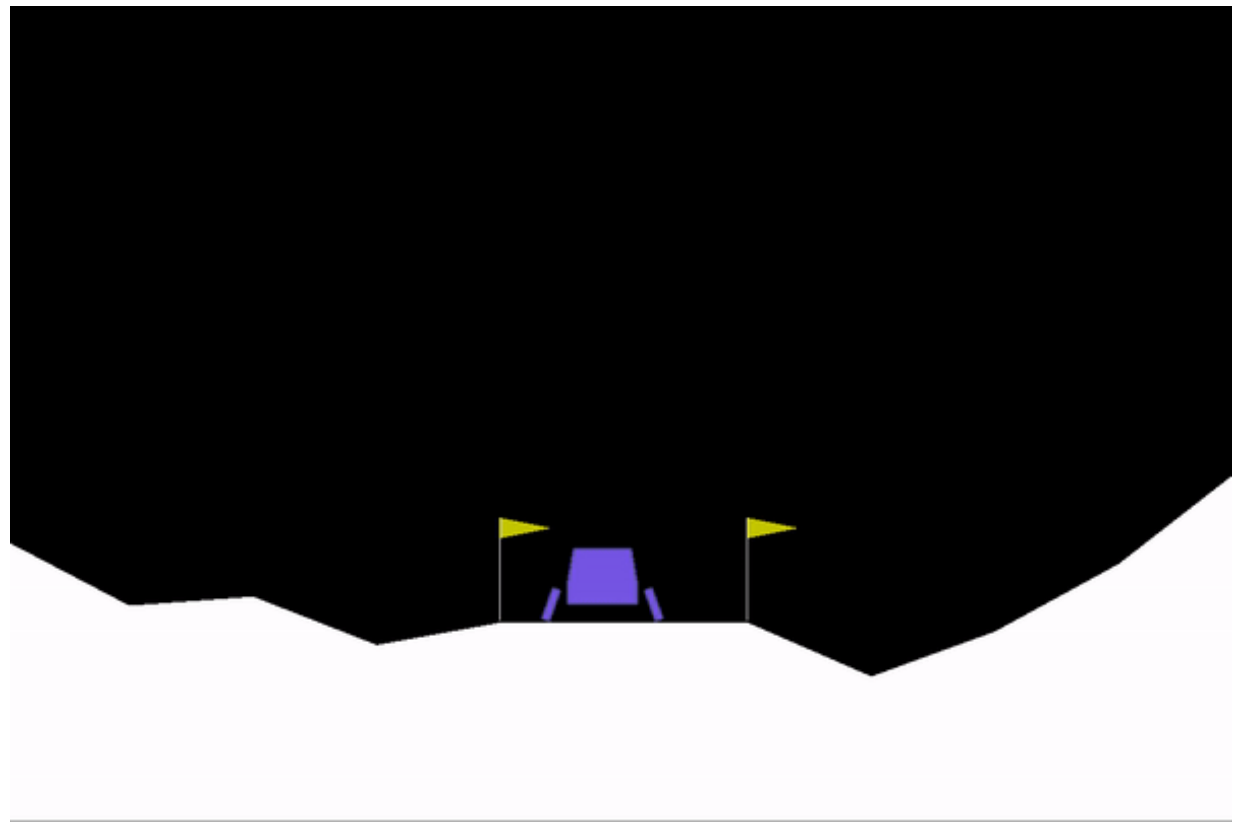
Experience replay - Cart Pole

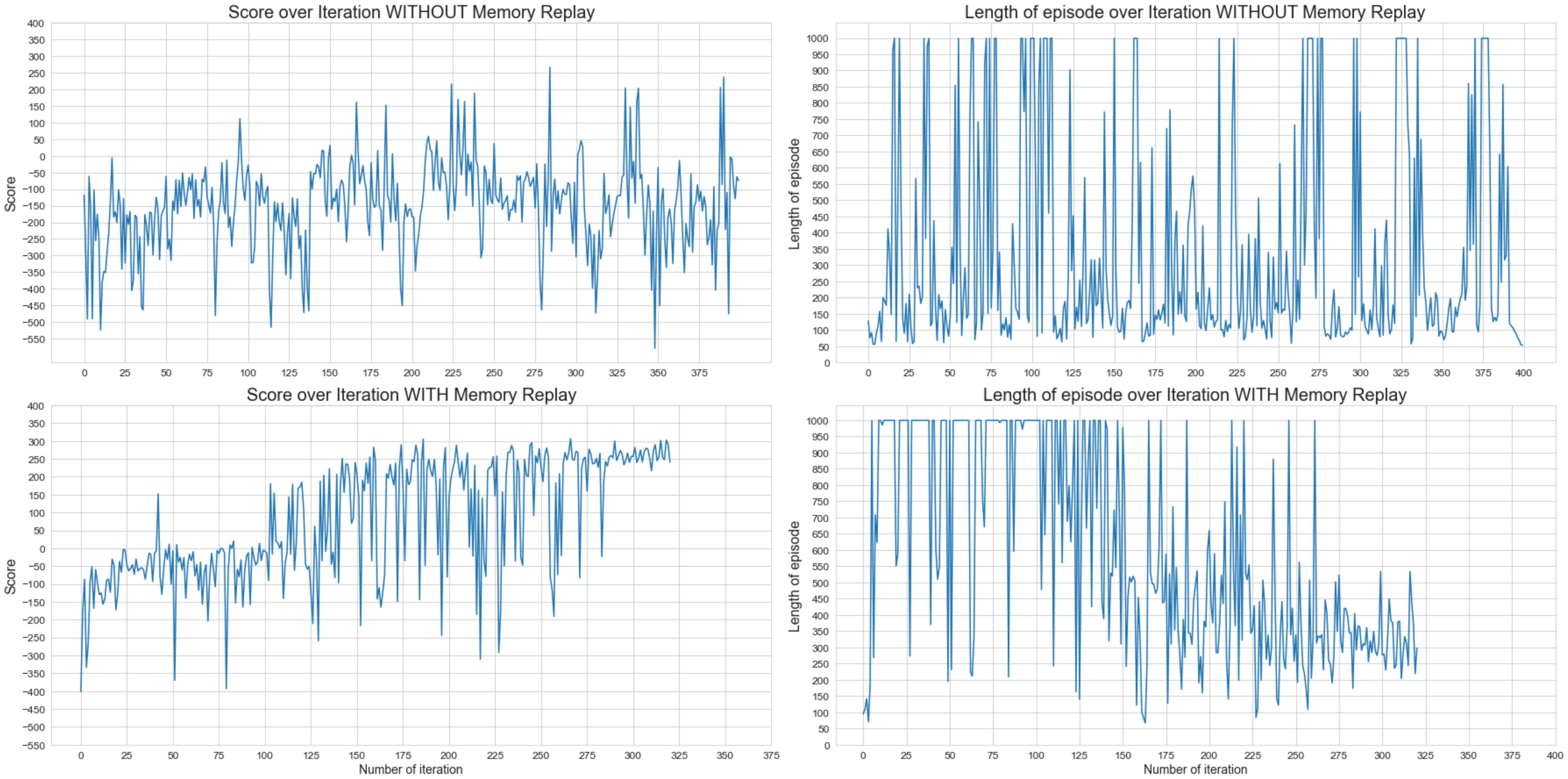






Experience replay - Lunar Landing





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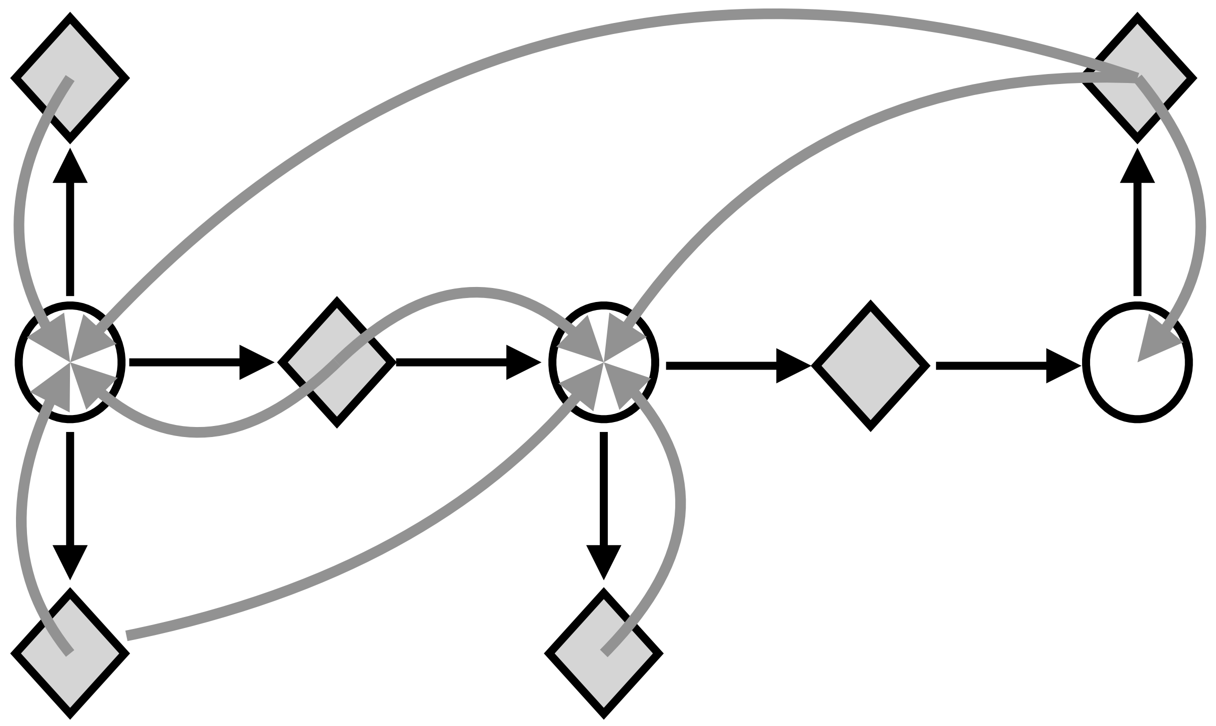
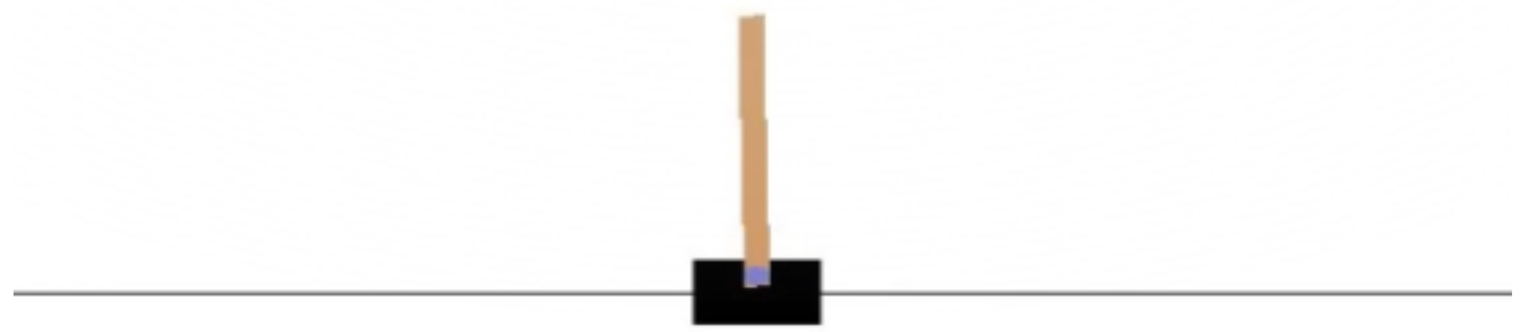


- *Deep_Q_learning_CartPole.ipynb :* Implement **Deep Q Learning** with and without Replay memory buffer on CartPole.



Target Network

Problem: The targets are unstable and depend of Q itself.

$$targets = [R(s, a, s') + \gamma \max_{a'} Q(s', a')]$$

$$\theta_{k+1} \leftarrow \theta_k - \alpha \nabla_\theta \mathbb{E}_{s \sim' P(s'|s,a)}[(Q_\theta(s, a) - target(s'))^2]_{\theta=\theta_k}$$

At each train iteration:

The Q values shift to get closer to the target which shift the same way.

It is chasing a **non-stationary target**

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$$targets = [R(s,a,s') + \gamma \max_{a'} Q_{target}(s',a')]$$
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The Q values shift to get closer to the target which shift the same way.

It is chasing a **non-stationary target**

Solution: Use a Q_{target} network to generate the target (different from the Q_{main} network) .

Q_{target} network is used to generate the target: $target = [R(s,a,s') + \gamma \max_{a'} Q_{target}(s',a')]$

Q_{main} network is the network train and used to generate experiences.

Q_{target}'s weights is updated with Q_{main}'s weights from time to time

Remarks

Model Dimension

The train model Q actually take only as an input and generate all $Q(s, a)$ value:

Pacman example: $Q : s \rightarrow [Q(s, a_1), Q(s, a_2), Q(s, a_3), Q(s, a_4)]$

Hence during training, the target dataset is generate with fixed valued for not tested a and *target* for tested a.

Pacman example:

experience: $[s, a_2, s', R(s, a_2, s')]$

input: s

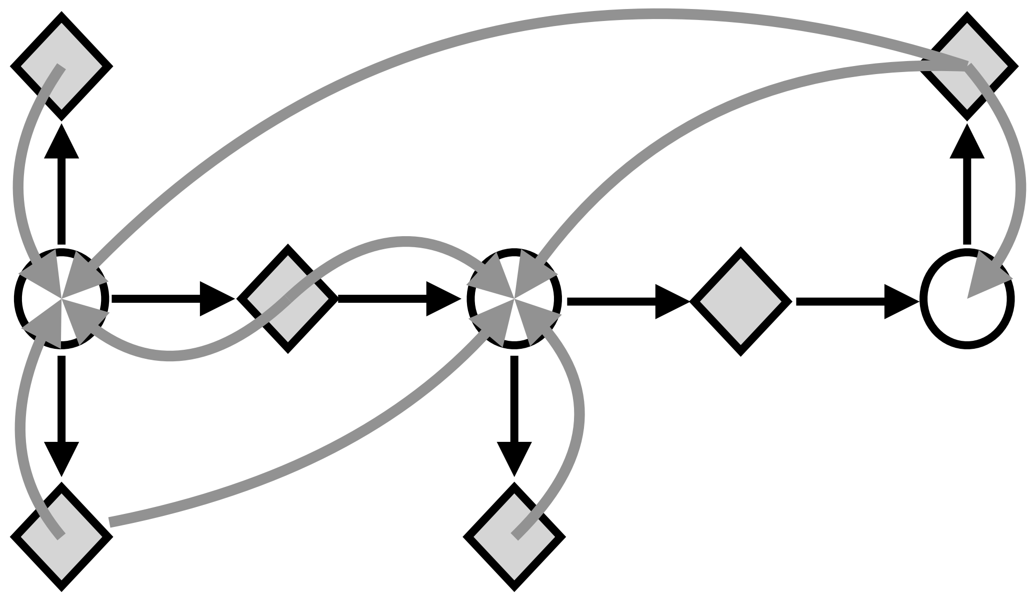
target: $$\begin{bmatrix} Q_{main}(s, a_1) \\ R(s, a_2, s') + \gamma \cdot max_{a'} Q_{target}(s', a') \\ Q_{main}(s, a_3) \\ Q_{main}(s, a_4) \end{bmatrix}$$

Deep-Q Network Mnih et al.[2015] - Pseudo code

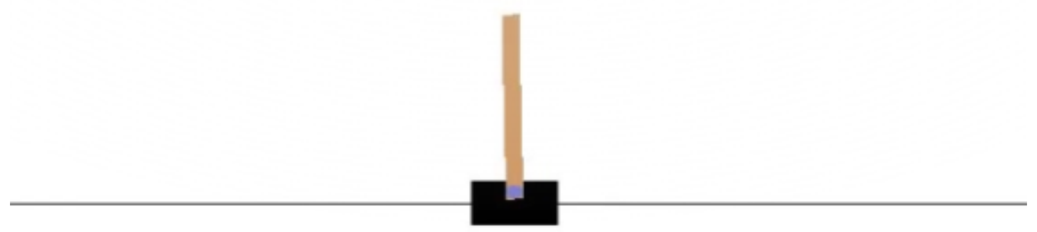
- Create Q_{main} and Q_{target} networks and initiate the replay memory M.
- Iterate while $max\_number\_episode$ or $goal\_reward$ is not achieved:
  - Play one episode - Explore randomly or Exploit with Q_{main} according to $random\_probability$.
  - Add the episode *(train data)* to M.
  - If we train more than $min\_pre\_trained\_episode$
    - Start decreasing $random\_probability$.
    - Every $train\_frequency$:
      - Sample $batch\_size$ experience from M.
      - Create target using Q_{target}
      - Train the Q_{main} network
      - Update Q_{target} weights with Q_{main} weights

TP

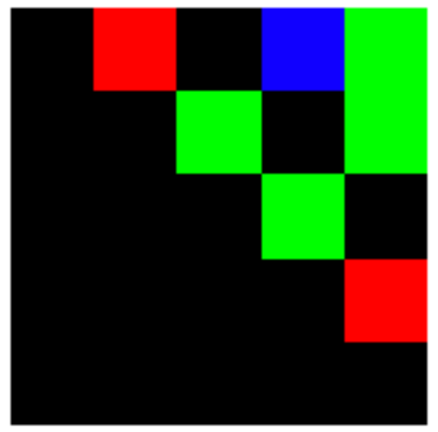
- *Q_learning.ipynb :* Implement **Q-VALUE ITERATION ALGORITHM** and ***Q-LEARNING ITERATION ALGORITHM*** on the toy MDP of this presentation.



- *Deep_Q_learning_CartPole.ipynb :* Implement **Deep Q Learning** with and without **Replay memory buffer** on CartPole.



- *Deep_Q_learning_Gridworld.ipynb :* Implement **Deep Q Learning** with **separated target network** on Gridworld.



D3QN

Deep-Q Network Improvement

Various improvement of the DQN algorithm lead to greater performance and stability.

- Dueling DQN. Wang et al. [2016]
- Doube DQN. Van Hasselt et al [2016].
- Prioritised Experience Replay. Shaul et al. [2015]

Deep-Q Network Improvement

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Dueling - Wang et al. [2016]

Main intuition

- Q-value represent how good it is to take an action a at a state s.
- It can be decomposed into two notions : $Q(s,a) = V(s) + A(s,a)$
  - The value function $V(s)$: *how good it is to be in this state?*
  - The advantage function $A(s,a)$: *how good it is to take this action in this state?*

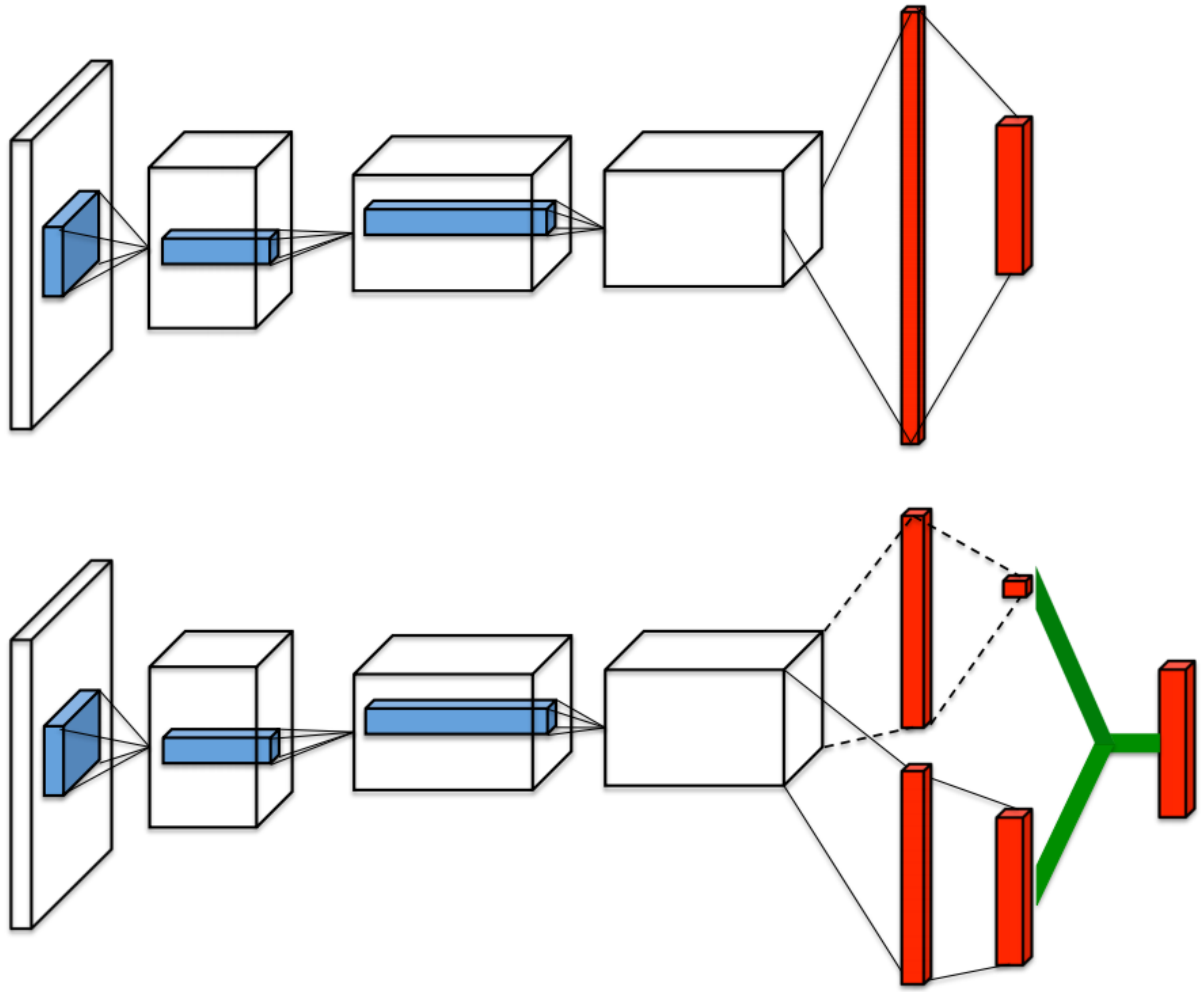
  —> It leads to poor performance.

- Let's force the Q value for the maximising action to equal V.

$$Q(s,a) = V(s) + \left(A(s,a) - max_{a' \in |\mathscr{A}|} A(s,a')\right)$$

- Which is approximate in practice by:

$$Q(s,a) = V(s) + \left(A(s,a) - \frac{1}{|\mathscr{A}|}\sum_{a'} A(s,a')\right)$$



Double DQN

Main intuition:

DQN overestimates the Q-values of the potential action to take

Separated Target Network

$$target = R(s, a, s') + \gamma \max_{a'} Q_{target}(s', a')$$

Double DQN

Use Q_{main} to chose the action

$$target = R(s, a, s') + \gamma Q_{target}\left(s', argmax_{a'}(Q_{main}(s', a')\right)$$

Blog & Code

https://medium.com/@awjuliani/simple-reinforcement-learning-with-tensorflow-part-4-deep-q-networks-and-beyond-8438a3e2b8df

https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-0-q-learning-with-tables-and-neural-networks-d195264329d0

https://towardsdatascience.com/reinforcement-learning-tutorial-part-3-basic-deep-q-learning-186164c3bf4

https://sergioskar.github.io/Reinforcement_learning/

http://www2.econ.iastate.edu/tesfatsi/RLUsersGuide.ICAC2005.pdf

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Van Hasselt, H., Guez, A., & Silver, D. (2015). Deep reinforcement learning with double q-learning. *arXiv preprint arXiv:1509.06461*.

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