Solving Lunar Lander using Deep Reinforcement Learning

AI course

Lemuel Puglisi, UniCT - 2023

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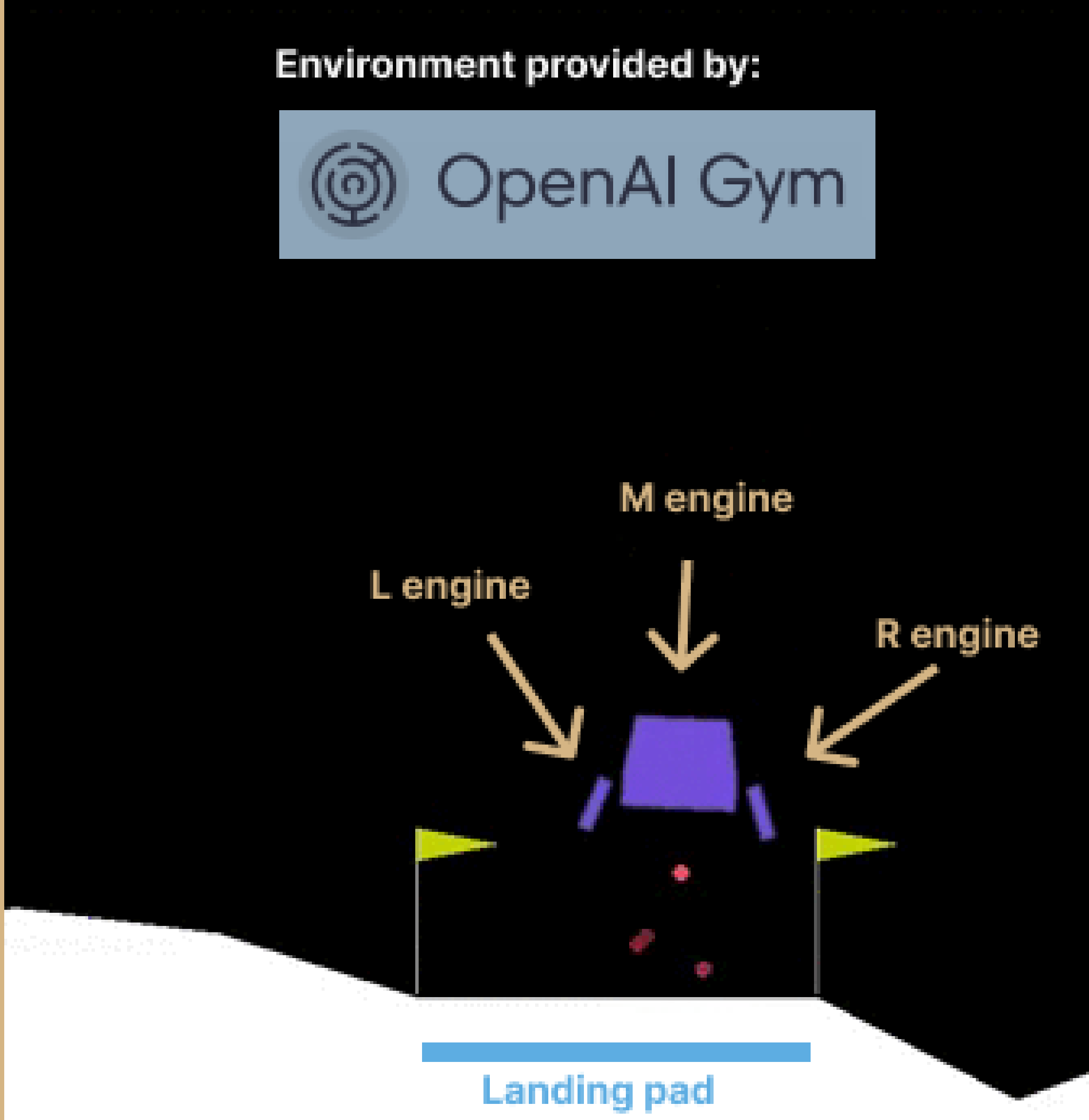
The problem

Design a **learning agent** that learns how to land the rocket inside the landing pad, by turning engines on and off.



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The environment

- Partially observable
- Deterministic
- Sequential
- Static
- Continuous
- Single-agent

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Action space

The action space is discrete:

- 0: do nothing
- 1: fire left orientation engine
- 2: fire main engine
- 3: fire right orientation engine

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Observation space

The state is an 8-dimensional vector: the coordinates of the lander in (x, y), its linear velocities in (x, y), its angle, its angular velocity, and two booleans that represent whether each leg is in contact with the ground or not.

Starting state

The lander starts at the top center of the viewport with a random initial force applied to its center of mass.

Rewards mechanism (1)

- decreased proportionally to the distance to the landing pad
- decreased proportionally to the speed of the lander
- decreases proportionally to the angle w.r.t. the ground
- increased by 10 points for each leg in contact with the ground
- decreased by 0.03 when side engines are actioned
- decreased by 0.3 when the main engine is actioned

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Reward mechanism (2)

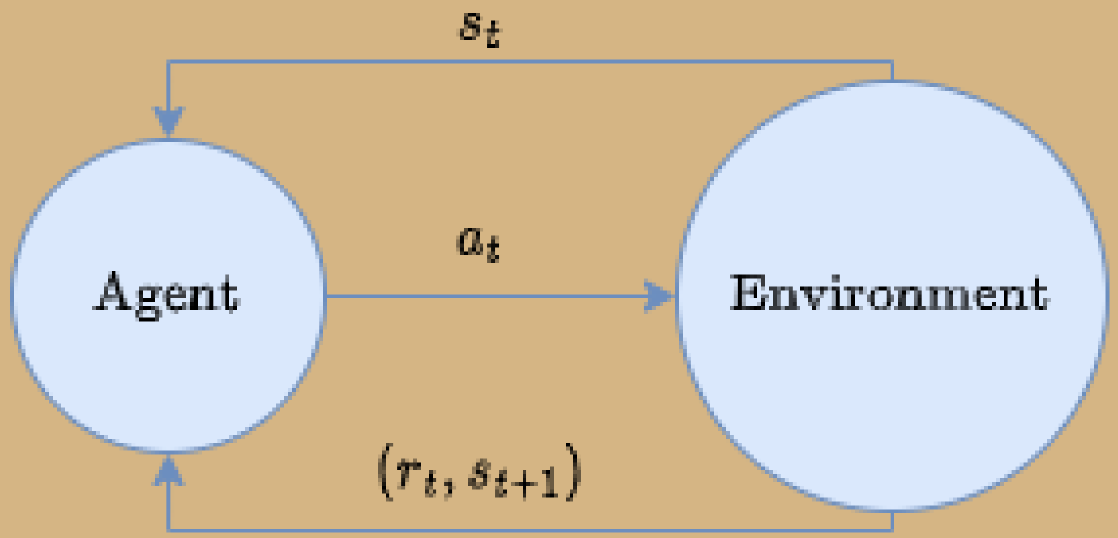
The episode ends if the lander crashes or gets outside of the viewport.
When an episode ends, the agent:

- receives an additional reward of +100 for landing safely
- receives an additional penalty (negative reward) of -100 for crashing the lander.

How does the agent learn?

Reinforcement learning

At time t, the agent interacts with the environment, which has a state s_t, by performing an action a_t. The agent receives a reward r_t based on the pair (s_t, a_t) and the environment changes to a new state s_{t+1}.



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Markov decision process

This process can be formalized as a Markov Decision Process (S, A, P, R, γ) where:

- S is the set of the environment states
- A is the set of possible actions
- R is the reward distribution
- P is the transition distribution

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Policy

The action a_t performed by the agent is determined by a function $\pi : S \rightarrow A$ called **policy**.

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Return

We want to find an optimal policy π^*, i.e. a policy that optimizes the return R_{t_0}

$$R_t = \sum_{t'=t}^{T} \gamma^{(t'-t)} r_{t'}$$

Where $\gamma \in [0, 1]$ is called **discount rate** and is used to balance the trade-off between short-term and long-term rewards, and T is the total number of steps.

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Optimal Q-value function

Let $Q^* : S \times A \rightarrow \mathbb{R}$ be a function, called optimal Q-value function, that predicts the final return we will receive by choosing an action a_t given a state s_t and then proceeding with an optimal policy π^*. The Q^* function satisfies the **Bellman equation**, thus can be written as:

$$Q^*(s, a) = r + \gamma \max_{a'} Q^*(s', a')$$

Where s' is the next state given (s, a).

Optimal policy

Given the Q-value function Q^*, defining the optimal policy is trivial:

$$\pi^*(s) = \arg\max_a Q^*(s, a)$$

Deep Q-learning

Deep Q-learning tries to estimate the $Q^*(s, a)$ function using a parametrized function $Q(s, a; \theta)$ (i.e., a deep neural network). If we obtain $Q(s, a; \theta) \approx Q^*(s, a)$, then the agent policy will be set to:

$$\pi(s) = \arg\max_a Q(s, a; \theta)$$

The algorithm can be divided in two phases, **collecting experience** and **learning**, repeated until convergence.

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Collecting experience

Collect experience (s, a, r, s') in a memory, called **replay buffer** D, by playing the agent for m episodes in the simulator.

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ϵ-greedy policy

To perform better exploration, we adopt an ϵ-greedy policy:

$$\pi_\epsilon(s) = \begin{cases} \text{random action } a & \text{with probability } \epsilon \\ \arg\max_{a \in A} Q(s, a; \theta_i) & \text{with probability } 1 - \epsilon \end{cases}$$

The ϵ value can be scheduled during the epochs, starting from a high value and decreasing it to strengthen the agent's strategy.

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Learning phase (1)

Sample a batch $B \subset D$ of random experience $(s, a, r, s') \in B$ from the replay buffer D and computing the **temporal difference error** $\mathcal{L}$:

$$\mathcal{L}(s, a, r, s', \theta_t) = Q(s, a; \theta_t) - (r + \gamma \max_a Q(s', a; \theta_{t-1}))$$

By minimizing $\mathcal{L}$ we **force** the Bellman equation:

$$0 = Q(s, a, \theta_t) - (r + \gamma \max_a Q_(s', a; \theta_{t-1}))$$

$$Q(s, a, \theta_t) = (r + \gamma \max_a Q_(s', a; \theta_{t-1}))$$

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Deep Q-learning (3)

The parameters are optimized by minimizing the following loss function computed on the batch:

$$\mathcal{J}(\theta_t) = \frac{1}{|B|} \sum_{(s,a,r,s') \in B} \mathcal{L}(s, a, r, s', \theta_t)$$

E.g. by using common optimizers like SGD.

Avoiding catastrophic forgetting (1)

Did you notice that we use two different versions of Q to compute the loss?

$$\mathcal{L}(s, a, r, s', \theta_t) = Q(s, a; \theta_t) - (r + \gamma \max_a Q(s', a; \theta_{t-1}))$$

$Q(\cdot, \cdot; \theta)$ is called the Q-network, while $Q(\cdot, \cdot; \theta_{t-1})$ is called the target network, and it is updated every τ batches with the weights of the Q-network.

Avoiding catastrophic forgetting (2)

Using two networks mitigates the catastrophic forgetting phenomenon, i.e., forgetting skills learned in the past while learning new skills.

Let's get our hands dirty

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Implementing the agent

The following pseudo-code gives an idea of how the agent is implemented:

```
class LearningAgent:

  def __init__(self, q_network):
    self.q_network = q_network

  def policy(self, observations):
    best_action = argmax(self.q_network(observations))
    return best_action
```

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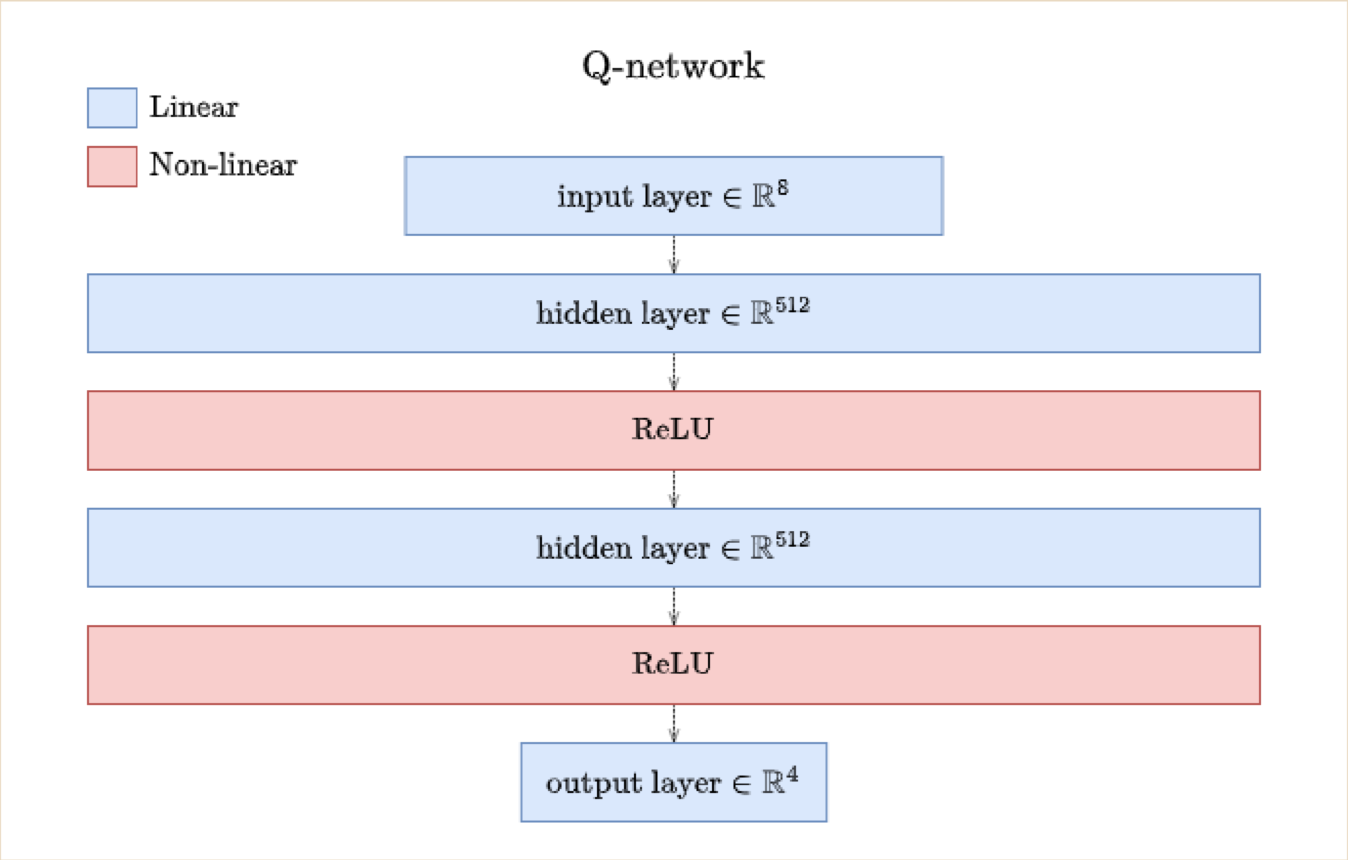
Q-network architecture



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ϵ-scheduling

The ϵ value of the ϵ-greedy policy is scheduler w.r.t. the current epoch t using the following function:

$$\epsilon(t) = \max\left(0.1, 1 - \frac{2t}{E}\right)$$

Where E is the total number of epochs.

Training settings

- Optimizer: Adam
- Learning rate: 0.001
- Replay memory size: 5×10^5
- Sync-rate τ: every 10 batches
- Batch size: 512

Winning the game

The game is considered to be won when the agent achieves a return of around 200. Our agent **surpassed this threshold** after approximately 35 epochs.

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Ablation study

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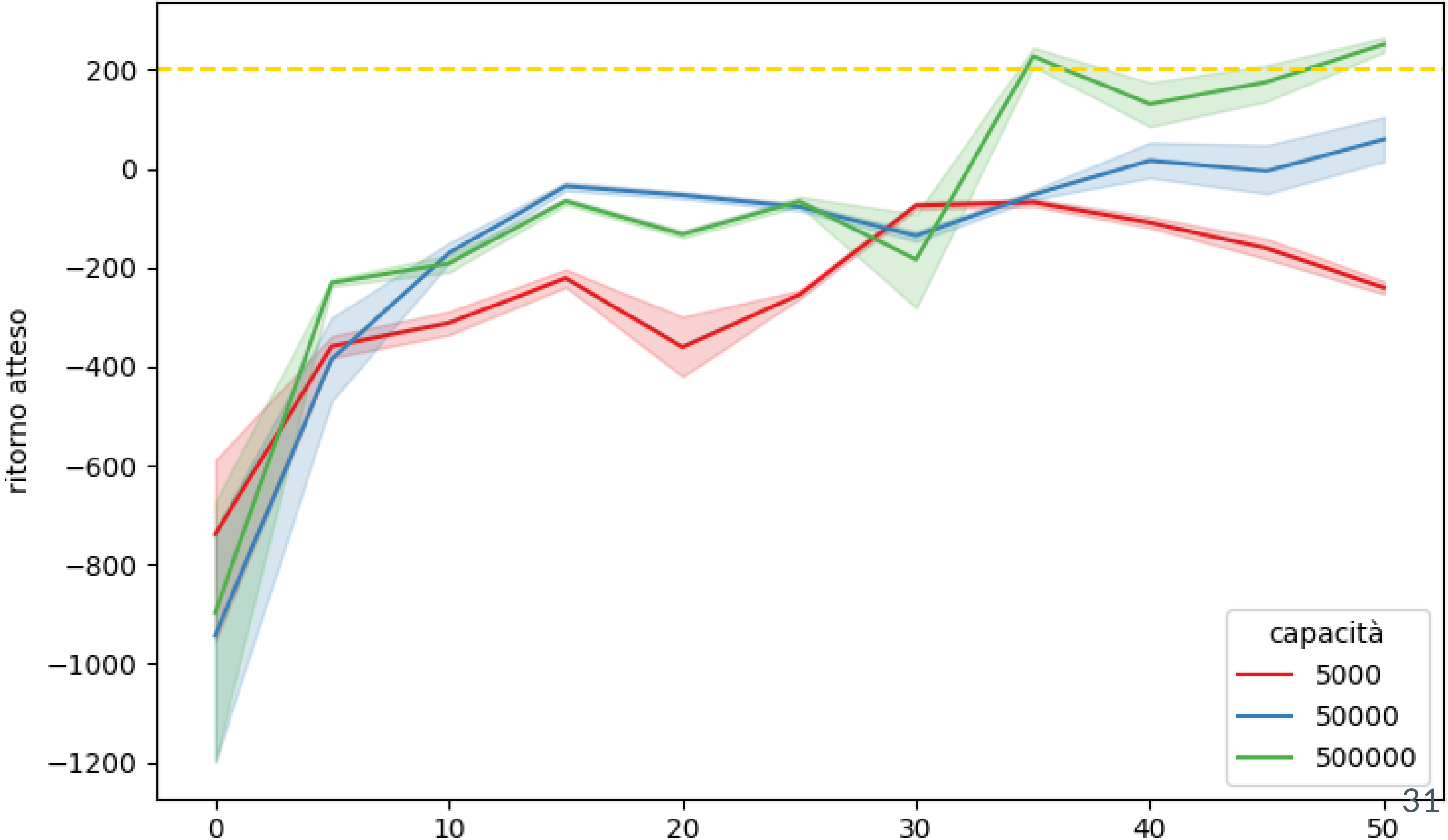
Ablation study: Capacity

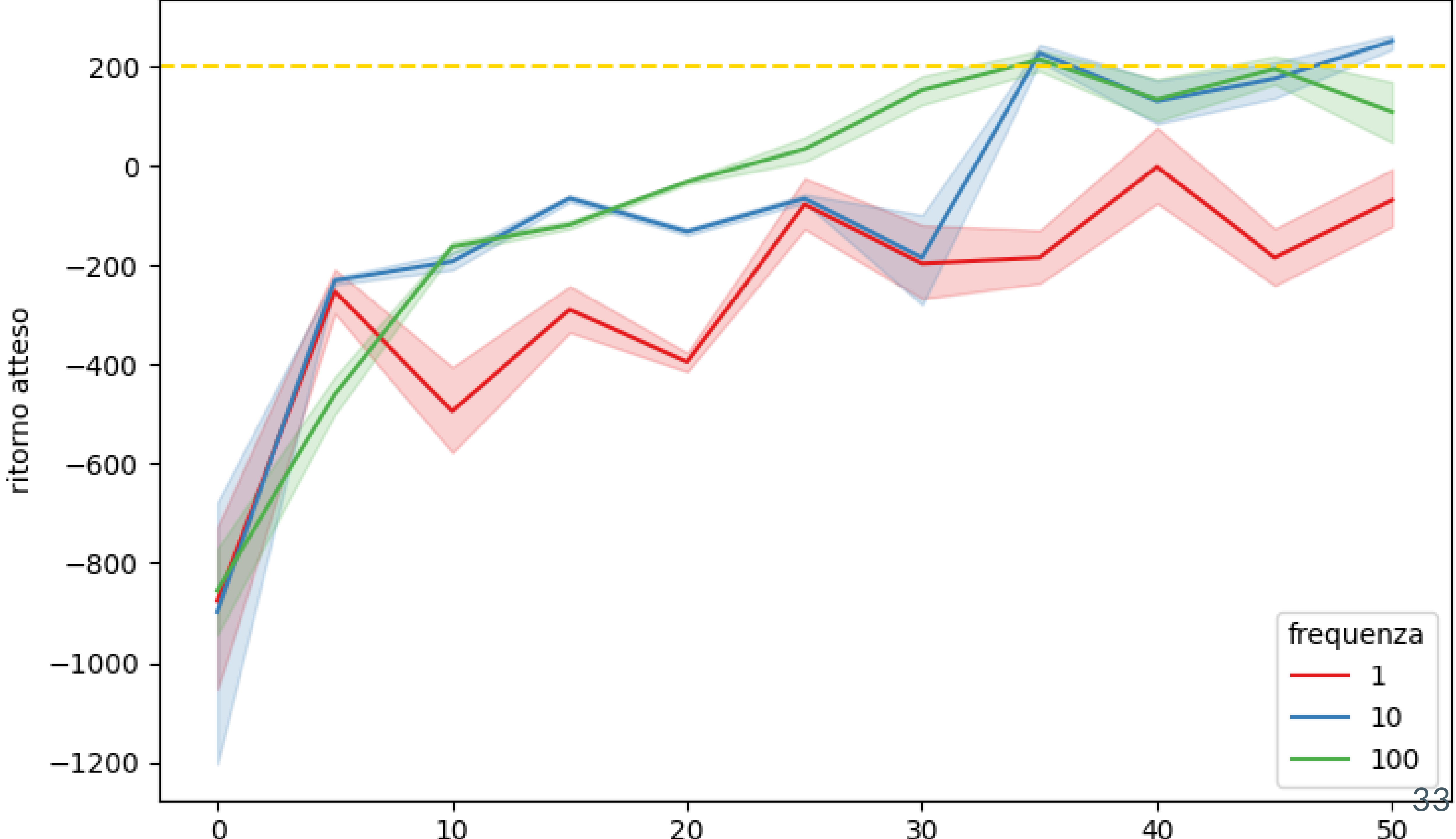
The following figure shows the performance of the trained agent using a replay memory capacity of 5×10^5, 5×10^4, and 5×10^3. We note that (1) performance increases proportionally with capacity; (2) if the capacity is not sufficient (red line), the agent's performance may degrade over time instead of improving (catastrophic forgetting).



ritorno atteso
200
0
−200
−400
−600
−800
−1000
−1200
0
10
20
30
40
50
capacità
5000
50000
500000

Ablation study: Sync-rate τ

The training is repeated using different target network update frequencies. Generally, we observe that with a higher frequency, such as 1 update per batch (red line), there is a slower progression. By decreasing the update frequency, for example, 1 every 10 or 100 batches (blue or green line), we notice a faster progression and greater stability.



ritorno atteso
200
0
−200
−400
−600
−800
−1000
−1200
0
10
20
30
40
50
frequenza
1
10
100

Conclusions

The proposed algorithm can solve the Lunar Lander problem by learning an optimal strategy in a limited number of iterations. However, it also presents some limitations, such as difficulty in defining the reward function and managing the algorithm's hyperparameters, which play a fundamental role. Currently, Deep Reinforcement Learning is becoming more widely used due to its flexibility in addressing a variety of problems.

Open-Source Implementation

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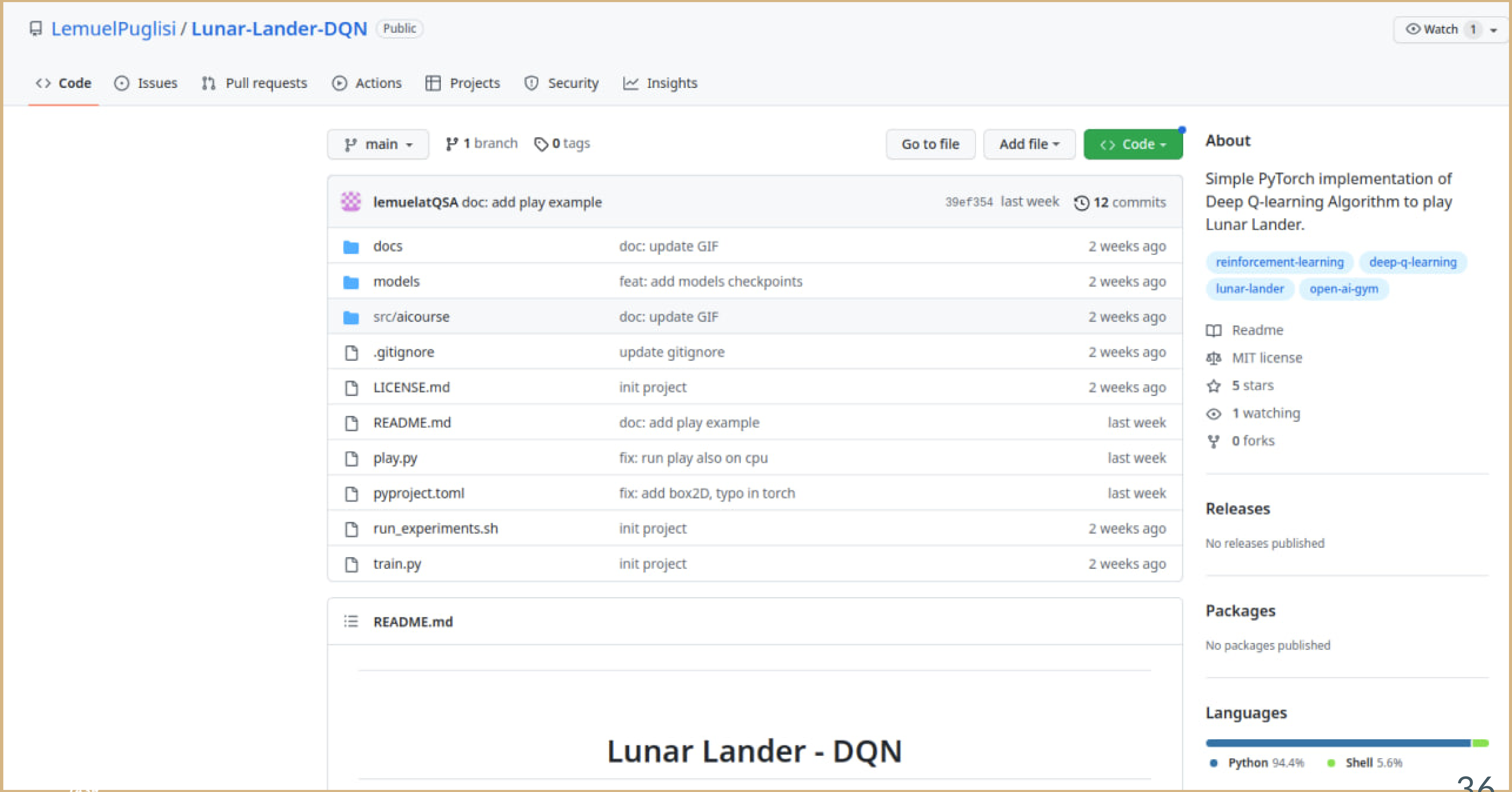

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Watch 1
Code
Issues
Pull requests
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Security
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main
1 branch
0 tags
Go to file
Add file
Code
lemuelatQSA doc: add play example
39ef354 last week
12 commits
docs
doc: update GIF
2 weeks ago
models
feat: add models checkpoints
2 weeks ago
src/aicourse
doc: update GIF
2 weeks ago
.gitignore
update gitignore
2 weeks ago
LICENSE.md
init project
2 weeks ago
README.md
doc: add play example
last week
play.py
fix: run play also on cpu
last week
pyproject.toml
fix: add box2D, typo in torch
last week
run_experiments.sh
init project
2 weeks ago
train.py
init project
2 weeks ago
README.md
Lunar Lander - DQN
About
Simple PyTorch implementation of Deep Q-learning Algorithm to play Lunar Lander.
reinforcement-learning
deep-q-learning
lunar-lander
open-ai-gym
Readme
MIT license
5 stars
1 watching
0 forks
Releases
No releases published
Packages
No packages published
Languages
Python 94.4%
Shell 5.6%

Training the agent

```
(your_env) <Lunar-Lander-DQN> python train.py --help

usage: train.py [-h] [--dest DEST] [--epochs EPOCHS] [--episodes EPISODES] [--batch-size BATCH_SIZE] [--capacity CAPACITY]
                [--sync-rate SYNC_RATE]

optional arguments:
  -h, --help            show this help message and exit
  --dest DEST           destination folder
  --epochs EPOCHS       number of epochs
  --episodes EPISODES   number of episodes to play in an epoch
  --batch-size BATCH_SIZE   batch size on trainin phase
  --capacity CAPACITY   capacity of the replay memory
  --sync-rate SYNC_RATE     sync rate of the target network
```

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Agent in action

```
(your_env) <Lunar-Lander-DQN> python play.py --help

usage: play.py [-h] [--model-ckpt MODEL_CKPT] [--episodes EPISODES]

optional arguments:
  -h, --help            show this help message and exit
  --model-ckpt MODEL_CKPT
  --episodes EPISODES
```

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Thank you!