Solving Lunar Lander using Deep Reinforcement Learning

Project proposal for AI course

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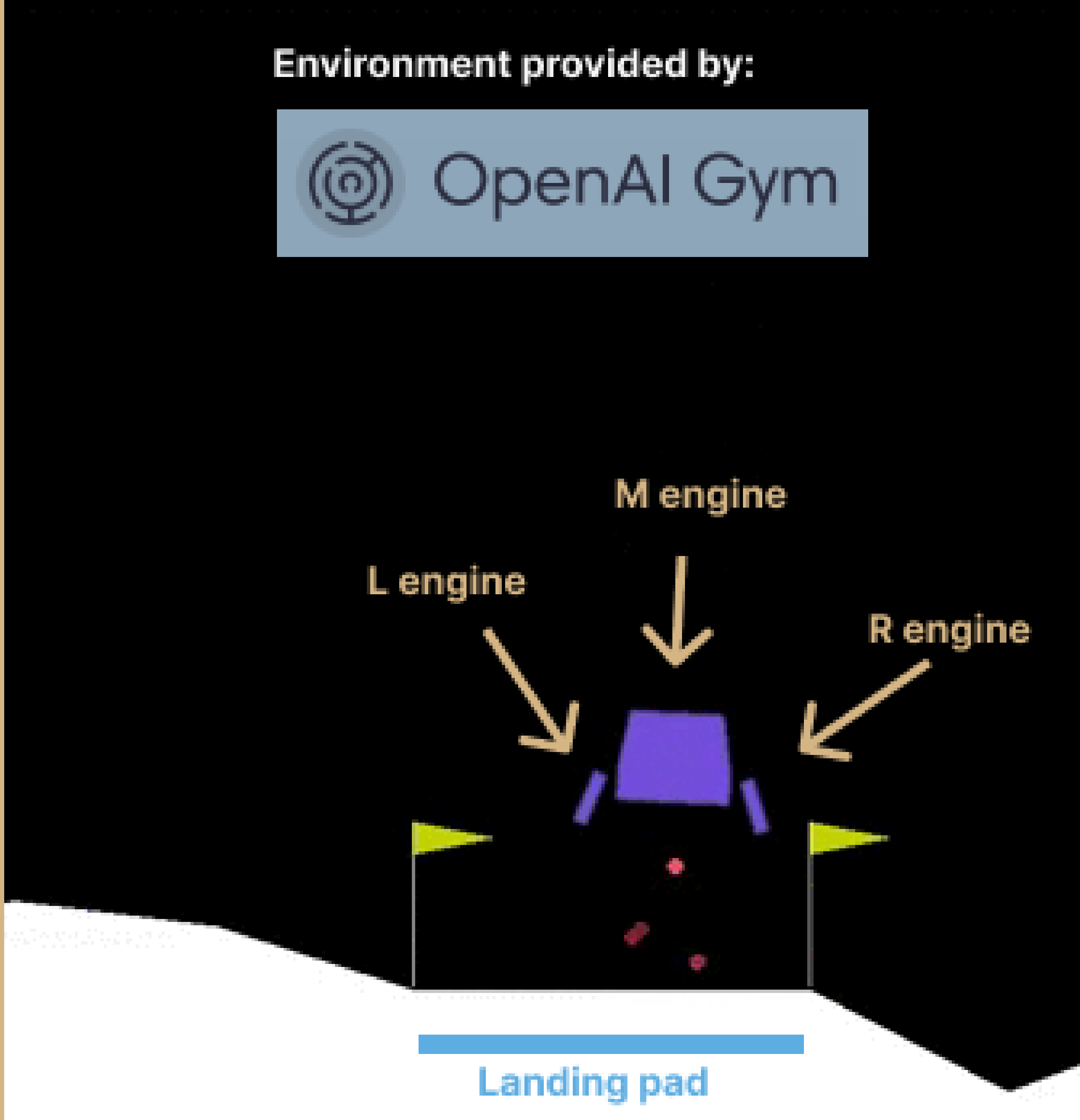
The problem

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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Action space

The action space is discrete:

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

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.

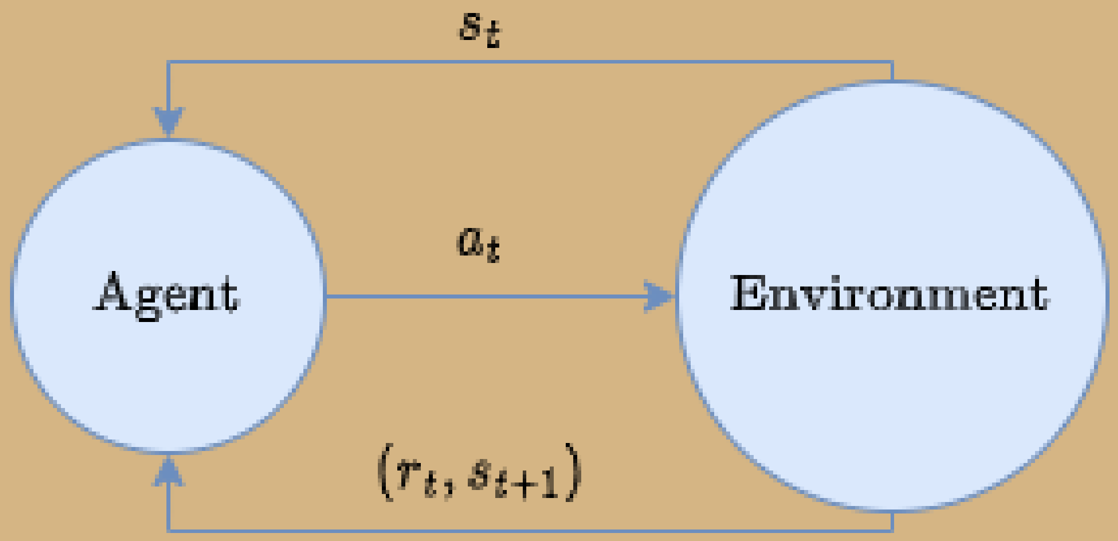
Starting state

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

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**.

Return

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

$$R_{t_0} = \sum_{t=t_0}^{\infty} \gamma^{t-t_0} \cdot r_t$$

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

What are the rewards for our agent?

Lunar lander rewards (1)

For each step, the reward is:

- decreased proportionally to the distance to the landing pad
- decreased proportionally to the speed of the lander
- 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

Lunar lander rewards (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.

Q-value function

Let $Q^* : S \times A \to \mathbb{R}$ 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:

$$Q^*(s,a) = r + \gamma Q^*(s', \pi^*(s'))$$

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

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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 (1)

Deep Q-learning is about optimizing a deep neural network Q_θ that fits the real Q^*. The network parameters $\theta^{(0)}$ are initialized randomly and then optimized till convergency. One iteration consists of: (i) collecting experience (s, a, r, s') in a memory, called **replay buffer**, by playing the agent for m episodes in the simulator.

Deep Q-learning (2)

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

$$\mathcal{L}(\delta) = Q_\theta(s, a) - (r + \gamma \max_a Q_\theta(s', a))$$

By minimizing $\mathcal{L}(\delta)$ we force the Bellman equation:

$$0 = Q_\theta(s, a) - (r + \gamma \max_a Q_\theta(s', a))$$
$$Q_\theta(s, a) = r + \gamma \max_a Q_\theta(s', a)$$

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Deep Q-learning (3)

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

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

E.g. by using common optimizers like SGD.

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Q.1 Can we get a working agent?

Q.2 How many iterations are required for convergence?

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Q.3 What is the correlation between network depth and agent accuracy?

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Thank you!