

# OOP Project

Group 18

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# PART 1

# MOUNTAIN CAR

# ENVIRONMENT SETUP

## Step 1: Create & Activate Virtual Environment

```
python -m venv .venv
```

```
source .venv/bin/activate
```

## Step 3: Install Additional Dependencies

```
pip install "gymnasium[classic_control]"
```

```
pip install matplotlib
```

## Step 2: Install Gymnasium (Editable Mode)

```
cd group_project/Gymnasium
```

```
pip install -e .
```

## Note (Windows Users)

```
.venv\Scripts\activate
```

# RUNNING PART 1

## Content

Train a reinforcement learning agent using Q-learning to solve the MountainCar-v0 environment.

## Purpose

Verify that the Gymnasium environment and required dependencies are correctly installed and functioning.

## Usage

`python mountain_car.py [option]`

<code>--train</code>	Train the agent
<code>--render</code>	Render the environment
<code>--episodes</code>	Number of episodes to run

# RUNNING PART 1

## Example

```
python mountain_car.py --train --episodes 5000
```

```
python mountain_car.py --render --episodes 10
```



# PART 2

# FROZEN LAKE

# FrozenLake-v1 (8x8)

## Problem Definition

- Map: 8x8 Grid World
- Goal: Navigate from Start (S) to Goal (G) safely.
- Hazards: Avoid falling into Holes (H).

## State & Action Space

- Discrete States: 0 to 63.
- Discrete Actions: 4 (Left, Down, Right, Up).

## Key Challenge

- Slippery Surface: Stochastic transitions – The agent has a chance to move in a perpendicular direction, ignoring the chosen action.
- Sparse Reward: The agent receives a reward of +1 only at the goal and 0 everywhere else. This makes initial learning extremely difficult.

# CORE ALGORITHM

## Algorithm Choice

- Tabular Q-Learning

## Key Hyperparameters

$\alpha$  (Learning Rate): How fast new information overrides old.

$\gamma$  (Discount Factor): Importance of future rewards (Set to 0.999).

$\epsilon$  (epsilon) :Balance between Exploration (random) and Exploitation (best action).

## Mechanism

- Maintains a Q-Table of size 64x4 to store the value of each action in each state.
- Agent learns by interacting with the environment (Trial-and-Error).

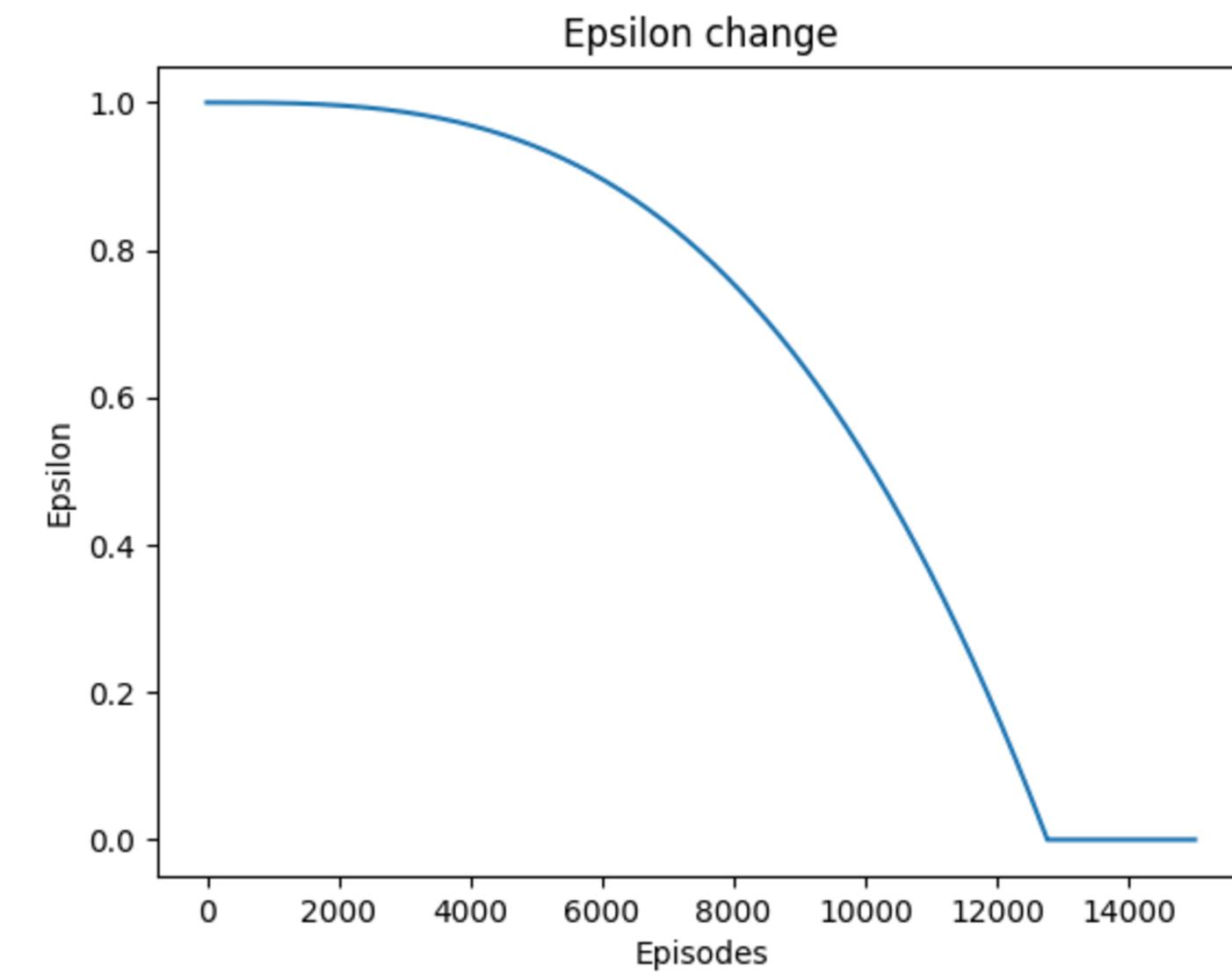
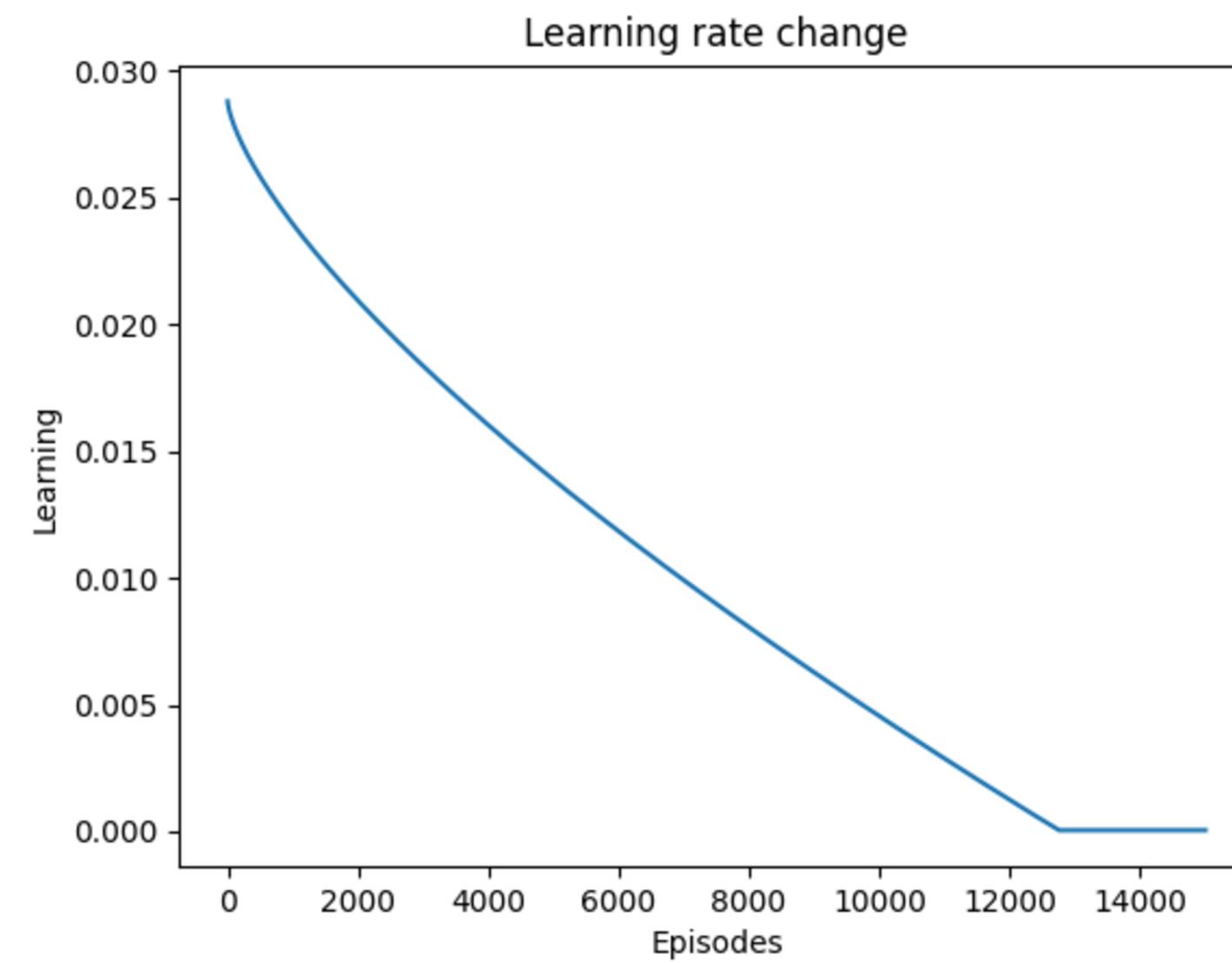
## The Update Rule

$$Q(s, a) \leftarrow Q(s, a) + \alpha[R + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

# OUR OPTIMIZATION STRATEGY

- PBRS: Accelerate convergence
- Small random Q table initialization ( $0 \sim 0.001$ ): Prevents rigid initial movements; ensures diversity.
- 85% exploration / 15% convergence:
  - phase 1 (0% ~ 85 %):
    - epsilon is decayed slowly at the beginning to encourage sufficient exploration, and more aggressively in later stages to stabilize exploitation.
  - phase 2 (85% ~ 100%):
    - $\text{eps} = 0$ ,  $\text{learning\_rate} = \text{min\_lr}$
    - Freezes the policy to fine-tune the best path found
- Optuna hyperparameter tuning
  - Search space:
    - learning rate:  $0.02 \sim 0.04$
    - $\text{min\_lr}$ :  $0.00001 \sim 0.00005$
    - $\text{min\_eps}$ :  $0.001 \sim 0.003$

# OUR OPTIMIZATION STRATEGY



# RUNNING PRAT 2

## Purpose

Achieve consistent success rate > 0.70

## Usage

```
python frozen_lake.py [--train|--tune|--eval] [--render]
```

--train

Train the agent

--tune

Tune hyperparameters

--eval

Evaluate the trained agent

--render

Render the environment

## Example

```
python frozen_lake.py --train
```

```
python frozen_lake.py --eval
```

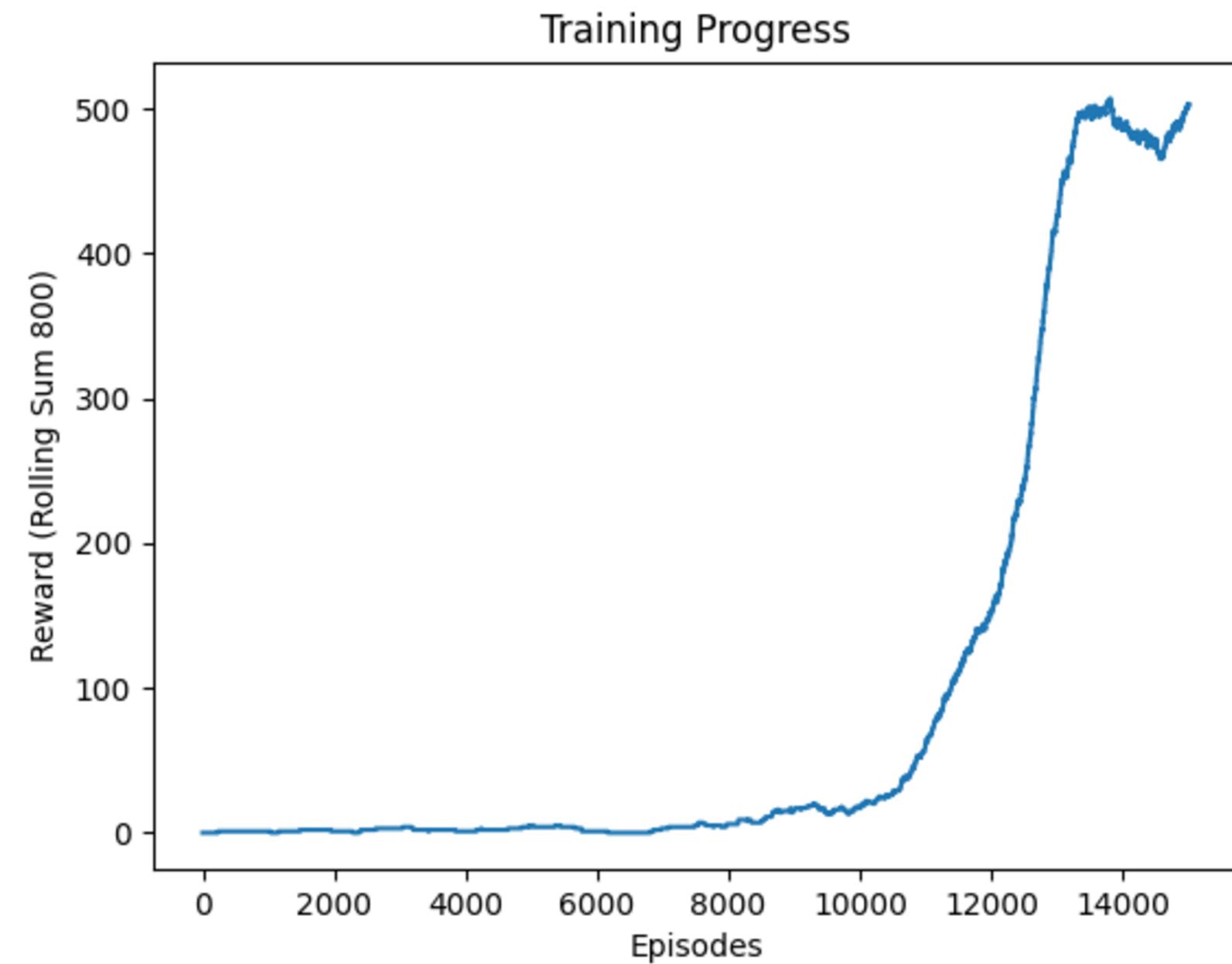
# RESULT

## Training phase

- Episodes: 15000
- learning\_rate\_a: 2.8789e-02
- min\_lr: 4.9905e-05
- min\_eps: 2.0718e-03

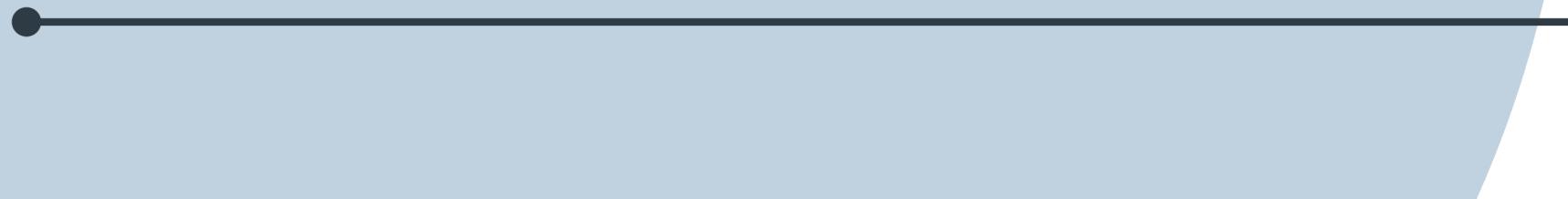
## Evaluating phase

- Episodes: 800
- Final success rate: 60% ~ 65%



# PART 3

## PENDULUM



# Pendulum-v1 & Discretization Strategy

## The Challenge: Continuous vs. Discrete

- Goal: Swing up the pendulum and keep it upright (counter-gravity).
- Problem: The environment is Continuous (Angle, Velocity, Torque),  
but Q-Learning requires Discrete states and actions.

## Our Approach

- Transform Pendulum-v1 into a discretized, modular, and extensible  
RL system using Object-Oriented Programming (OOP).

# **pendulum\_agent.py**

- This module wraps Gymnasium's "Pendulum-v1" environment and provides state/action space discretization, making the continuous control problem suitable for tabular Q-Learning algorithms.

# **pendulum\_env.py**

- Creates a Gymnasium-compatible environment wrapper that provides a standard Gym interface for the discretized Pendulum problem. This allows the environment to be used with any Gym-compatible RL framework.

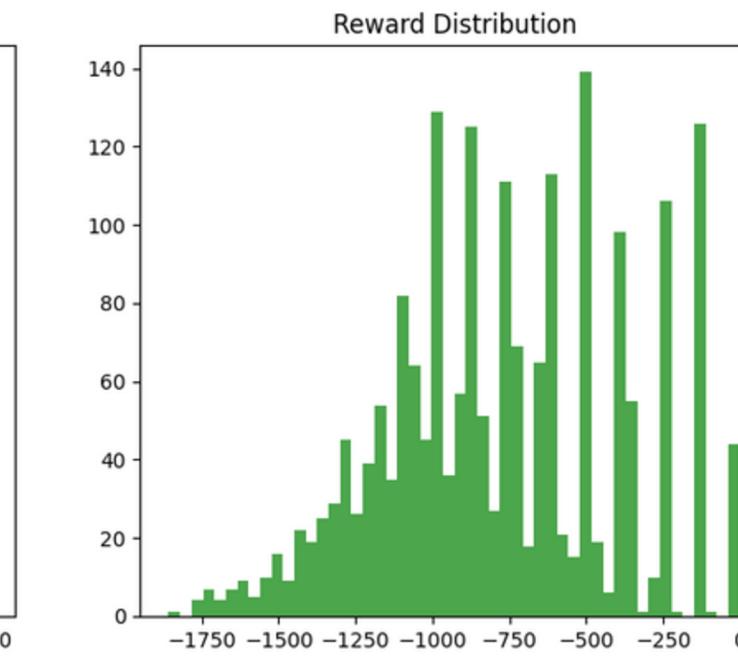
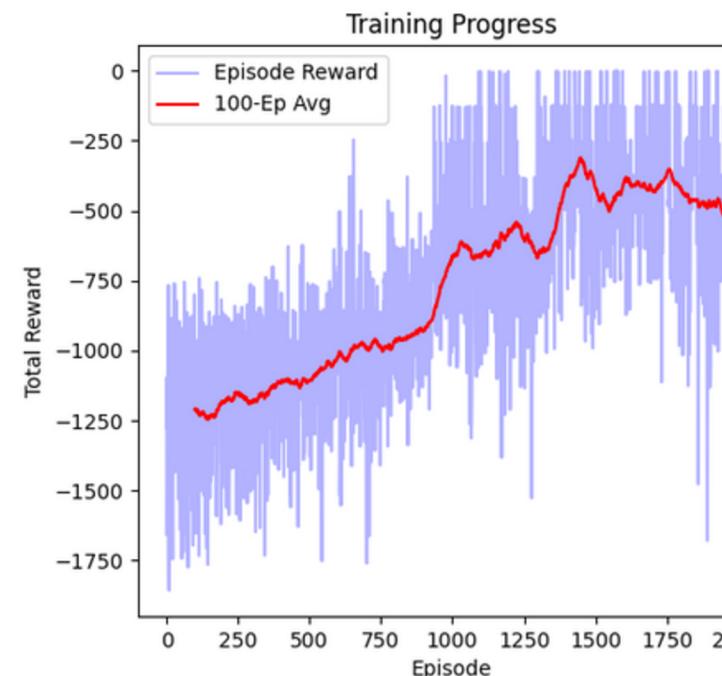
# train\_pendulum.py

- Implements the complete Q-Learning training pipeline, including agent logic, exploration strategies, and experiment orchestration. This module demonstrates advanced OOP design patterns.



## OOP Concepts

- Encapsulation
- Inheritance
- Polymorphism
- Abstraction
- Composition





# Thank You