TAAP

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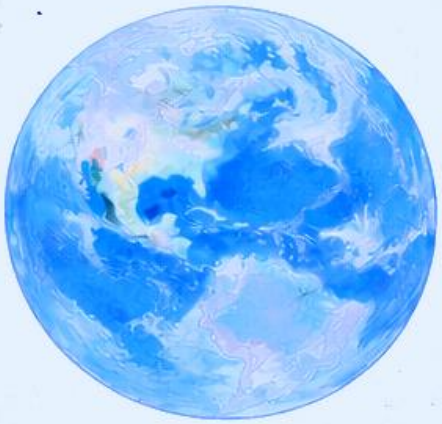

Advanced Topics in Deep Learning

MINI-PROJECT 02

DEEP REINFORCEMENT LEARNING
DQN AND PPO IN LUNARLANDER V3

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1. Introduction

Deep Reinforcement Learning (DRL) has become a central paradigm for solving complex sequential decision-making problems, particularly those involving continuous state spaces, stochastic dynamics, and delayed rewards. Among the wide range of DRL algorithms, Deep Q-Network (DQN) and Proximal Policy Optimization (PPO) represent two fundamentally different approaches: value-based learning and policy-based learning. Comparing these two algorithms provides valuable insight into how different learning mechanisms behave under the same environment conditions.

In this project, we investigate the performance of DQN and PPO in the LunarLander-v3 environment from Gymnasium. This environment simulates the control of a lunar lander that must descend and touch down smoothly within a designated landing zone. The agent receives an 8-dimensional continuous state vector and must choose among four discrete actions, making the task suitable for both value-based and policy-based methods. The environment includes dense rewards, penalties for fuel consumption, and strong negative rewards for crashes, creating a challenging control problem that requires stability, precision, and efficient exploration.

The goal of this work is to train, evaluate, and compare DQN and PPO under controlled experimental conditions. We analyse their learning curves, sample efficiency, stability across multiple random seeds, and qualitative behaviour through recorded simulations. Additionally, we examine theoretical aspects such as overestimation bias in DQN, the role of clipping and Generalized Advantage Estimation (GAE) in PPO, and the differences between epsilon-greedy and entropy-driven exploration.

By combining quantitative metrics with qualitative observations, this study aims to provide a comprehensive understanding of how DQN and PPO behave in the LunarLander-v3 environment, highlighting their strengths, limitations, and the impact of hyperparameter choices on the final performance.

2. Environment Analysis

2.1 State Space

The LunarLander-v3 environment provides an 8-dimensional continuous state vector describing the physical configuration of the lander at each timestep: 1. Horizontal position (x) relative to the landing zone 2. Vertical position (y) above the ground 3. Horizontal velocity (vx) 4. Vertical velocity (vy) 5. Lander angle (θ) 6. Angular velocity (ω) 7. Left leg contact indicator (0 or 1) 8. Right leg contact indicator (0 or 1)

These variables allow the agent to infer its location, orientation, stability, and motion, which are essential for controlling the descent.

2.2 Action Space

The action space is discrete with four possible actions:

- 0 - Do nothing

- 1 - Fire left thruster (pushes the lander to the right)
- 2 - Fire main thruster (reduces vertical speed)
- 3 - Fire right thruster (pushes the lander to the left)

These actions allow the agent to control both horizontal movement and vertical descent.

2.3 Reward Function

The reward function is dense and designed to encourage smooth and stable landings while penalizing unsafe or inefficient behaviour.

Positive rewards include: - Moving closer to the landing zone - Reducing horizontal and vertical velocity - Maintaining a stable angle - Each leg touching the ground (+10 each) - Successful landing (+100 to +140)

Penalties include: - High velocities - Large tilt angles - Excessive use of the main thruster (fuel cost) - Crashes (around -100)

A score of **200 or higher** typically indicates a successful landing.

2.4 Termination Rules

An episode terminates when one of the following occurs: 1. **Successful landing** within the designated zone 2. **Crash** due to excessive speed or unstable angle 3. **Leaving the screen boundaries** 4. **Reaching the maximum number of steps** allowed by the environment (1000 timesteps)

These termination conditions apply equally to both PPO and DQN agents.

```
Session prefix: dqn_ppo
Algorithms: ['dqn', 'ppo']
Seeds: [42, 123, 3407]
Wind enabled: False
Total timesteps per seed: 1,500,000
Evaluation episodes per seed: 20
Chart update frequency: every 10 episodes
Checkpoint frequency: every 100 episodes
Eval callback frequency: every 25,000 timesteps (20 episodes)
Solved threshold: 200
Device: cpu
```

3. Experimental Setup

This section describes the training and evaluation methodology used to compare DQN and PPO in the LunarLander-v3 environment. All experiments were conducted under controlled and reproducible conditions to ensure a fair comparison between the two algorithms.

3.1 Total Environment Steps

Both DQN and PPO were trained using a total of **1,500,000 environment steps per seed**. Since the project uses 3 seeds, this results in:

- 3 seeds x 1,500,000 steps = **4,500,000 training steps per algorithm**

Using the same number of interactions ensures that the comparison between DQN and PPO is based on equal sample budgets.

3.2 Hyperparameter Configurations

The hyperparameters for each algorithm were selected based on Stable-Baselines3 recommendations and refined through empirical testing. Tables 1 and 2 summarize the final configurations used for training.

Hyperparameter	Value
Policy	MlpPolicy
Learning rate	linear_schedule(6.3e-4)
Buffer size	750,000
Batch size	128
Gamma (discount factor)	0.99
Learning starts	50,000
Exploration strategy	ϵ-greedy
Exploration fraction	0.12
Final ϵ	0.1
Target update interval	250
Train frequency	4
Gradient steps	4
Network architecture	256 x 256 MLP

Table 1 - DQN Hyperparameters

Hyperparameter	Value
Policy	MlpPolicy
Learning rate	0.00025
n_steps	2048

Hyperparameter	Value
Batch size	64
n_epochs	10
Gamma (discount factor)	0.999
GAE λ	0.95
Clip range	0.2
Entropy coefficient	0.01
Network architecture	256 x 256 MLP

Table 2 - PPO Hyperparameters

These hyperparameters were kept constant across all seeds to isolate the effect of stochasticity in training.

3.3 Random Seeds

To evaluate robustness and training stability, both algorithms were trained using **3 different random seeds**: - Seed 1: **42** - Seed 2: **123** - Seed 3: **3407**

Each seed corresponds to a full independent training run of 1,500,000 steps.

3.4 Evaluation Protocol

Each trained model was evaluated over **20 deterministic episodes per seed**, for a total of 60 evaluation episodes per algorithm. Deterministic evaluation ensures that the policy is tested without exploration noise, providing a fair assessment of the learned behaviour.

3.5 Best-Model Selection

During training, an evaluation callback assessed the model every 25,000 environment steps using 20 deterministic episodes. The best model was selected based on a combined metric: **mean reward - standard deviation**. This metric favours models that are both high-performing and consistent, rather than models that achieve high mean reward with large variance.

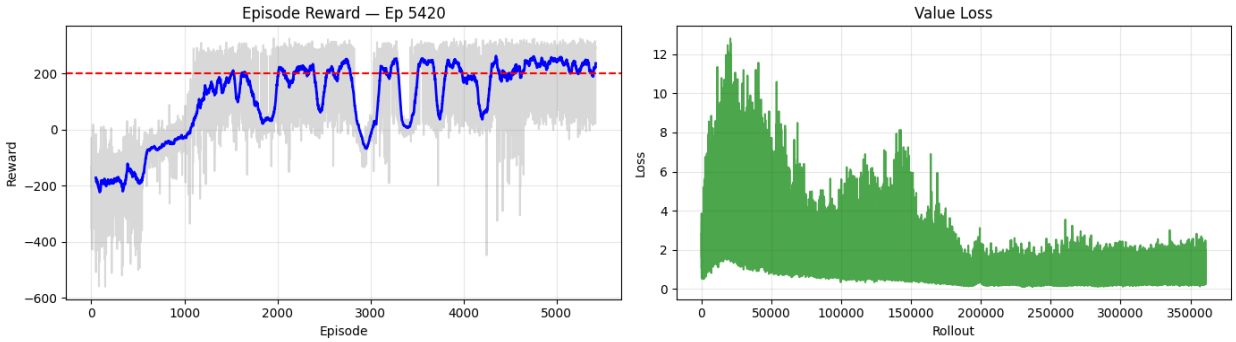
A two-tier selection gate ensures that once any model crosses a mean reward of 200, only solved models can replace the current best.

3.6 Reproducibility

All experiments used fixed random seeds for Python, NumPy, PyTorch, and the Gymnasium environment. Deterministic algorithms were enabled in PyTorch to minimize non-determinism from GPU operations.

```
Python: 3.12.3
PyTorch: 2.10.0+cu130
Device: cpu
```

```
CUDA: 13.0


Observation space: Box([ -2.5        -2.5        -10.        -10.         -6.28318
55 -10.
  -0.         -0.       ], [ 2.5        2.5       10.        10.         6.283185
5 10.
  1.         1.       ], (8,), float32)
Action space: Discrete(4)
Initial observation: [-0.00170641  1.4186276  -0.17285168  0.3425566   0.00198406
  0.03915349
  0.          0.        ]



============================================================
DQN | Seed 42
============================================================



Output()



'Episode 5420 | Last 50 Ep — Mean: 236.2 | Std: 95.5 | Min: 15.8 | Max: 315.9 | S
uccess: 82%'
```

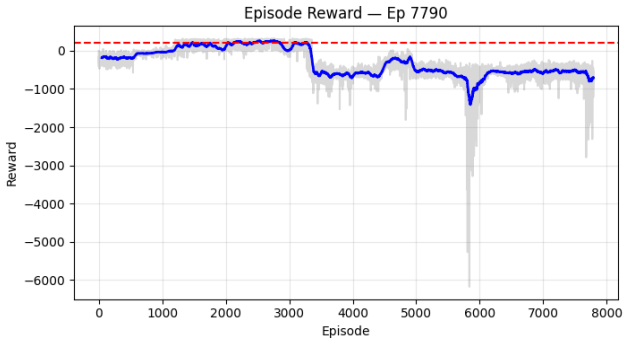


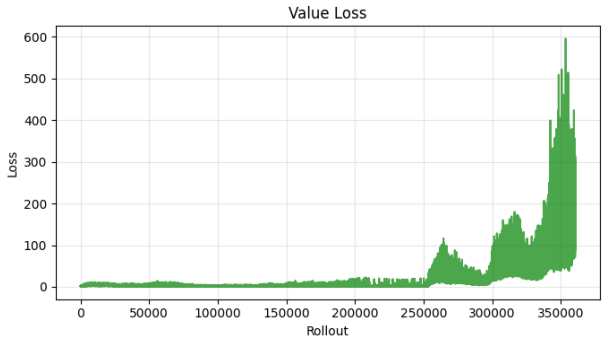

```
'[Checkpoint] Episode 5400 saved'



'Eval @ 1500000 steps | Reward: 276.50 +/- 16.66 [SOLVED] | Success: 100% | Score
 (mean-std): 259.85 | Best: 266.35'
```

```
Output()
```

```
'Episode 7790 | Last 50 Ep — Mean: -708.5 | Std: 349.2 | Min: -2311.8 | Max: -26
2.3 | Success: 0%'
```

```
Training time: 47.6 min (2856 s)
Final model:  /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_02_53
_32/dqn_ppo_dqn_42
Best model:   /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_02_53
_32/best_model
Checkpoints:  /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_02_53
_32/checkpoints
Best model stats: Reward: 283.74 +/- 17.39 | Success: 100% | Score (mean-std): 26
6.35 | @ 1,425,000 steps

============================================================
DQN | Seed 123
============================================================
```



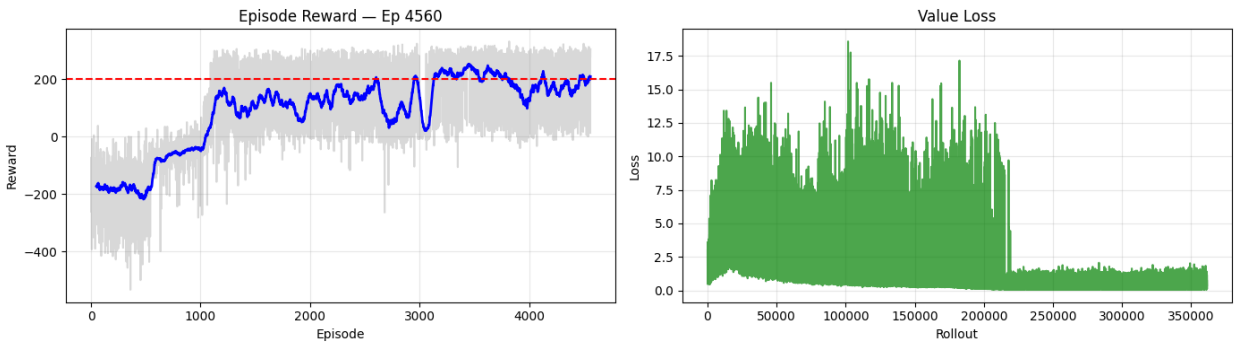



```
'[Checkpoint] Episode 7700 saved'
```

```
'Eval @ 1500000 steps | Reward: -926.29 +/- 368.67 | Success: 0% | Score (mean-st
d): -1294.96 | Best: 259.82'
Output()
```

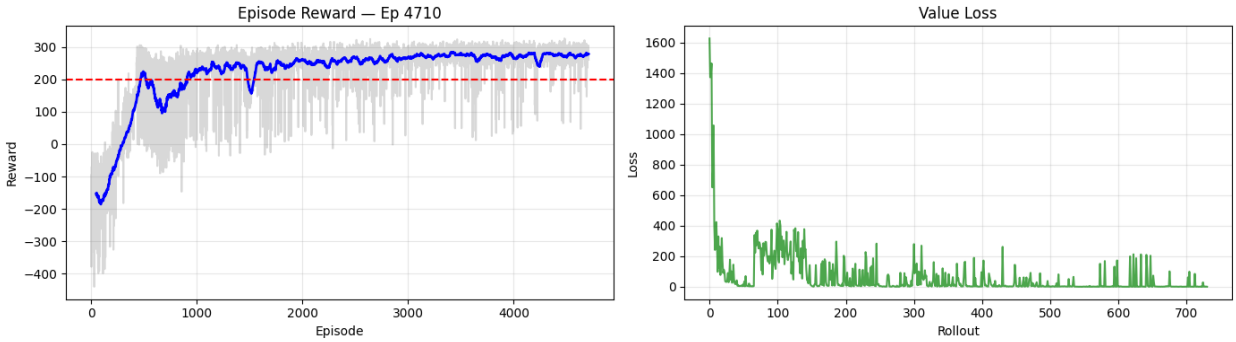
```
'Episode 4560 | Last 50 Ep — Mean: 209.7 | Std: 112.3 | Min: 0.6 | Max: 313.2 | S
uccess: 70%'
```

```
Training time: 47.0 min (2818 s)
Final model:  /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_03_41
_09/dqn_ppo_dqn_123
Best model:   /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_03_41
_09/best_model
Checkpoints:  /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_03_41
_09/checkpoints
Best model stats: Reward: 275.61 +/- 15.80 | Success: 100% | Score (mean-std): 25
9.82 | @ 875,000 steps

============================================================
DQN | Seed 3407
============================================================
```




```
'[Checkpoint] Episode 4500 saved'



'Eval @ 1500000 steps | Reward: 250.47 +/- 82.52 [SOLVED] | Success: 85% | Score
(mean-std): 167.95 | Best: 243.87'
Output()



Training time: 47.3 min (2839 s)
Final model:  /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_04_28
_07/dqn_ppo_dqn_3407
Best model:   /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_04_28
_07/best_model
Checkpoints:  /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_04_28
_07/checkpoints
Best model stats: Reward: 261.53 +/- 17.66 | Success: 100% | Score (mean-std): 24
```

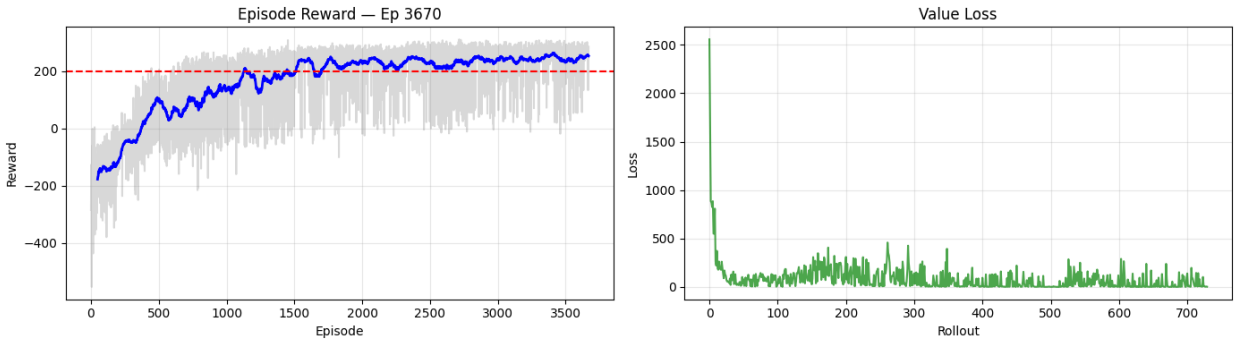
```
3.87 | @ 1,300,000 steps

DQN: All 3 seeds trained.

============================================================
PPO | Seed 42
============================================================



'Episode 4710 | Last 50 Ep — Mean: 278.3 | Std: 31.3 | Min: 146.7 | Max: 320.5 |
Success: 96%'
```




```
'[Checkpoint] Episode 4700 saved'



'Eval @ 1500000 steps | Reward: 289.50 +/- 21.48 [SOLVED] | Success: 100% | Score
 (mean-std): 268.02 | Best: 266.36 >> New best model!'
Output()



Training time: 20.2 min (1211 s)
Final model:  /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_15
_27/dqn_ppo_ppo_42
Best model:   /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_15
_27/best_model
Checkpoints:  /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_15
_27/checkpoints
Best model stats: Reward: 289.50 +/- 21.48 | Success: 100% | Score (mean-std): 26
8.02 | @ 1,500,000 steps

============================================================
```

```
PPO | Seed 123
============================================================
```

```
'Episode 3670 | Last 50 Ep — Mean: 252.4 | Std: 46.9 | Min: 56.7 | Max: 301.1 | S
uccess: 90%'
```

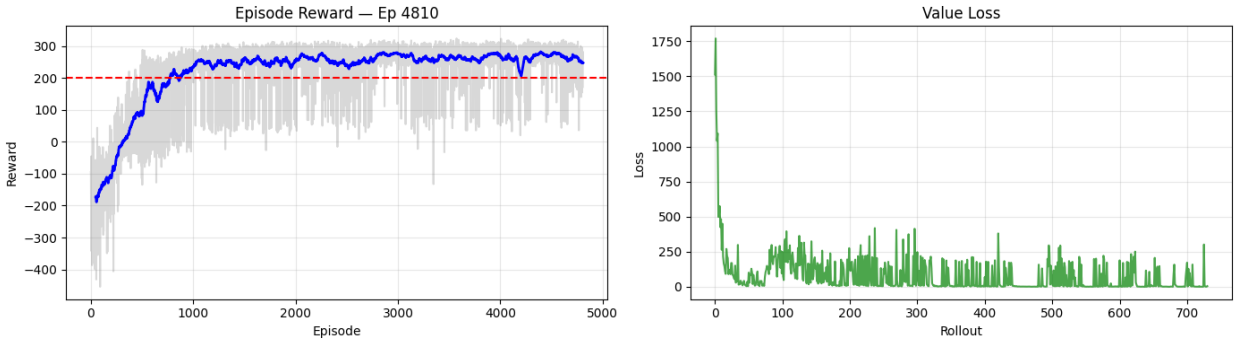



```
'[Checkpoint] Episode 3600 saved'
```

```
'Eval @ 1500000 steps | Reward: 257.63 +/- 35.30 [SOLVED] | Success: 95% | Score
(mean-std): 222.33 | Best: 249.47'
Output()
```

```
Training time: 23.0 min (1380 s)
Final model:  /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_35
_37/dqn_ppo_ppo_123
Best model:   /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_35
_37/best_model
Checkpoints:  /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_35
_37/checkpoints
Best model stats: Reward: 267.61 +/- 18.14 | Success: 100% | Score (mean-std): 24
9.47 | @ 1,300,000 steps

============================================================
PPO | Seed 3407
============================================================
```

```
'Episode 4810 | Last 50 Ep — Mean: 247.0 | Std: 54.3 | Min: 36.0 | Max: 299.4 | S
uccess: 86%'
```



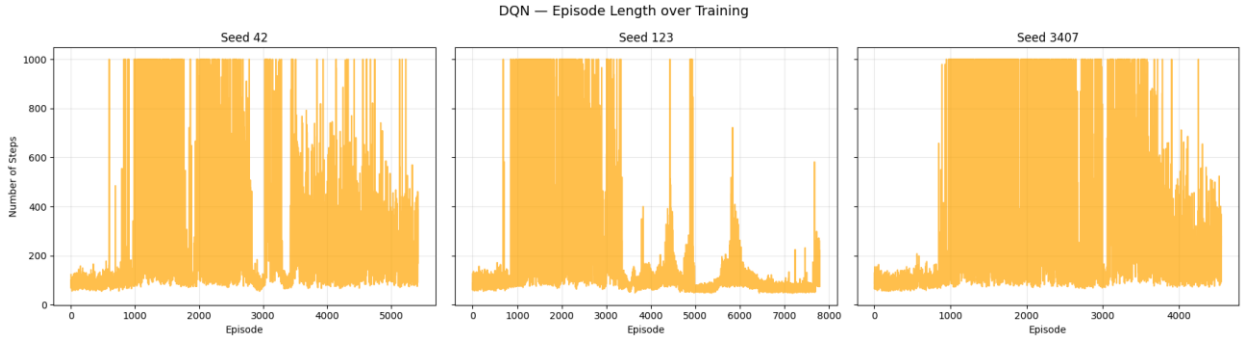

```
'[Checkpoint] Episode 4800 saved'
```

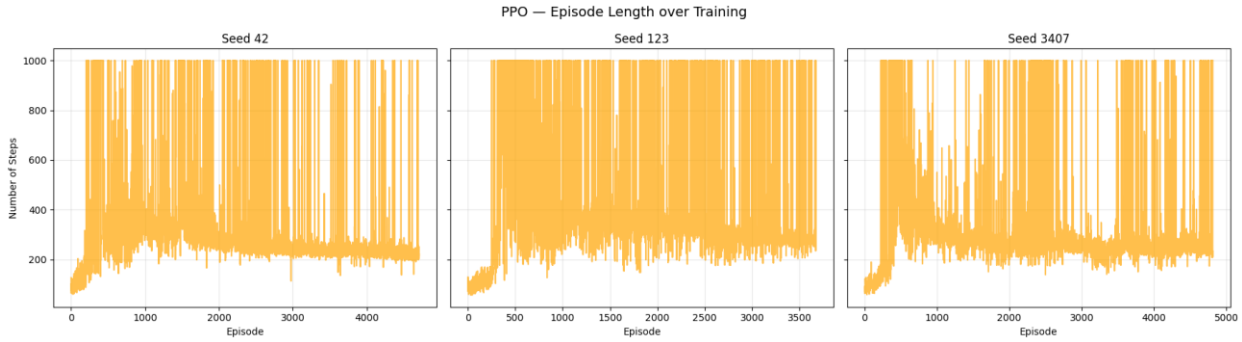
```
'Eval @ 1500000 steps | Reward: 265.17 +/- 52.61 [SOLVED] | Success: 95% | Score
(mean-std): 212.56 | Best: 263.95'
Training time: 20.8 min (1248 s)
Final model:  /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_58
_38/dqn_ppo_ppo_3407
Best model:   /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_58
_38/best_model
Checkpoints:  /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_58
_38/checkpoints
Best model stats: Reward: 280.95 +/- 17.01 | Success: 100% | Score (mean-std): 26
3.95 | @ 1,375,000 steps

PPO: All 3 seeds trained.

============================================================
BEST MODEL SUMMARY (all algorithms x seeds)
============================================================

Algorithm  Seed Mean Reward Std Reward Success Score (mean-std) @ Timestep
      DQN    42      283.74      17.39    100%           266.35  1,425,000
      DQN   123      275.61      15.80    100%           259.82    875,000
      DQN  3407      261.53      17.66    100%           243.87  1,300,000
      PPO    42      289.50      21.48    100%           268.02  1,500,000
      PPO   123      267.61      18.14    100%           249.47  1,300,000
      PPO  3407      280.95      17.01    100%           263.95  1,375,000

All training complete.
```

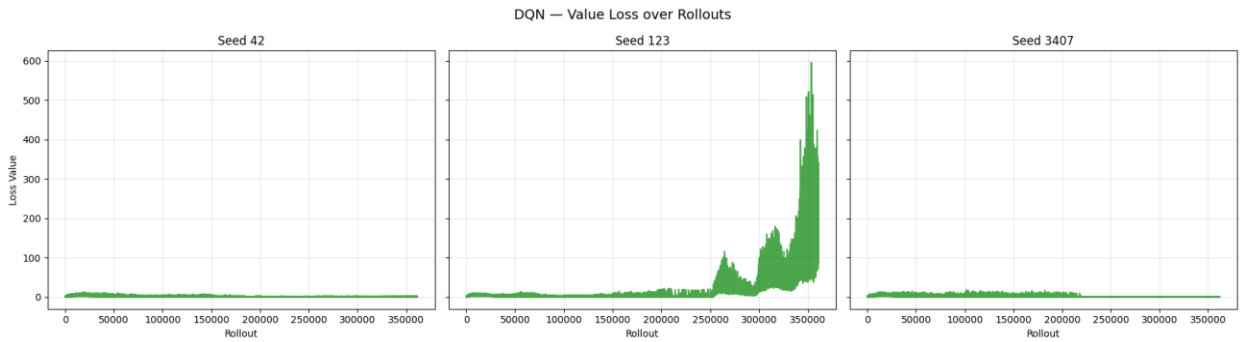
```
Saved DQN seed 42: 5424 episodes -> /home/logus/env/iscte/taap_p2/report/../model
s/dqn/2026-02-23_02_53_32/training_log.npz
Saved DQN seed 123: 7796 episodes -> /home/logus/env/iscte/taap_p2/report/../mode
ls/dqn/2026-02-23_03_41_09/training_log.npz
Saved DQN seed 3407: 4560 episodes -> /home/logus/env/iscte/taap_p2/report/../mod
els/dqn/2026-02-23_04_28_07/training_log.npz
Saved PPO seed 42: 4710 episodes -> /home/logus/env/iscte/taap_p2/report/../model
s/ppo/2026-02-23_05_15_27/training_log.npz
Saved PPO seed 123: 3675 episodes -> /home/logus/env/iscte/taap_p2/report/../mode
ls/ppo/2026-02-23_05_35_37/training_log.npz
Saved PPO seed 3407: 4813 episodes -> /home/logus/env/iscte/taap_p2/report/../mod
els/ppo/2026-02-23_05_58_38/training_log.npz


*** TRAINING TIME SUMMARY ***
Timesteps per seed: 1,500,000 | Device: cpu

Algorithm Seed Time (s) Time (min)
      DQN   42     2856       47.6
      DQN  123     2818       47.0
      DQN 3407     2839       47.3
      PPO   42     1211       20.2
      PPO  123     1380       23.0
      PPO 3407     1248       20.8
      DQN Mean     2838       47.3
      PPO Mean     1280       21.3


*** GRADIENT UPDATES SUMMARY ***
Algorithm Actual (from training) Analytical (computed) Total Env Steps Ratio (upd
ates/steps)
      DQN              1,449,996             1,450,000       1,500,000
      0.967
      PPO                  7,320               234,240       1,500,000
      0.005

DQN: train_freq=4, gradient_steps=4 -> 4 gradient updates per training call, call
ed every 4 env steps
PPO: n_steps=2048, n_epochs=10, batch_size=64 -> 320 updates per rollout
```

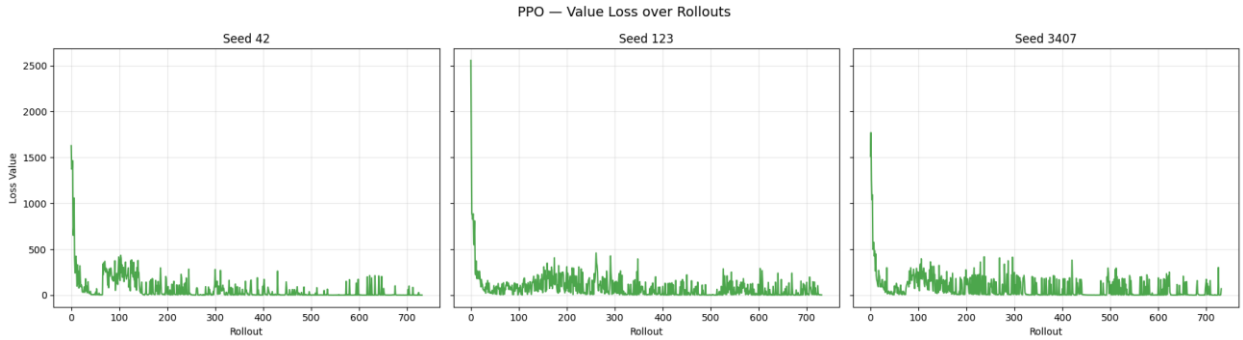

DQN — Episode Reward over Training
Seed 42
Seed 123
Seed 3407
Total Reward
Episode

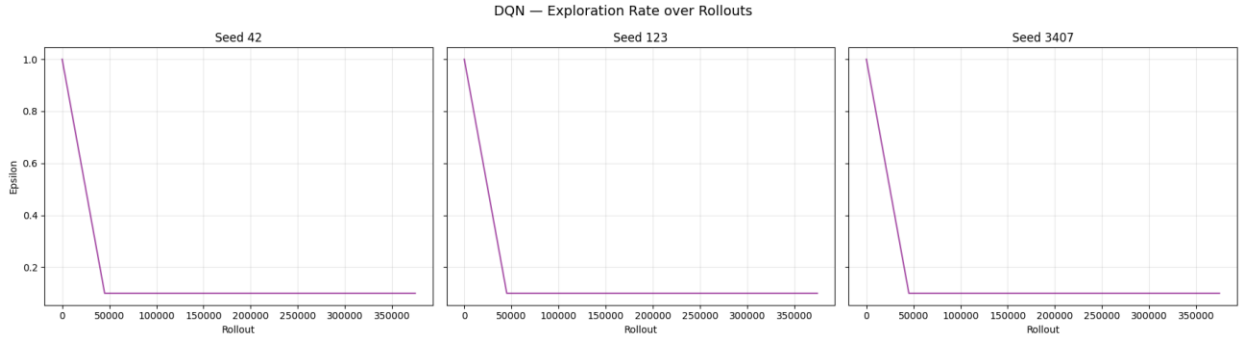

PPO — Episode Reward over Training
Seed 42
Seed 123
Seed 3407
Total Reward
Episode

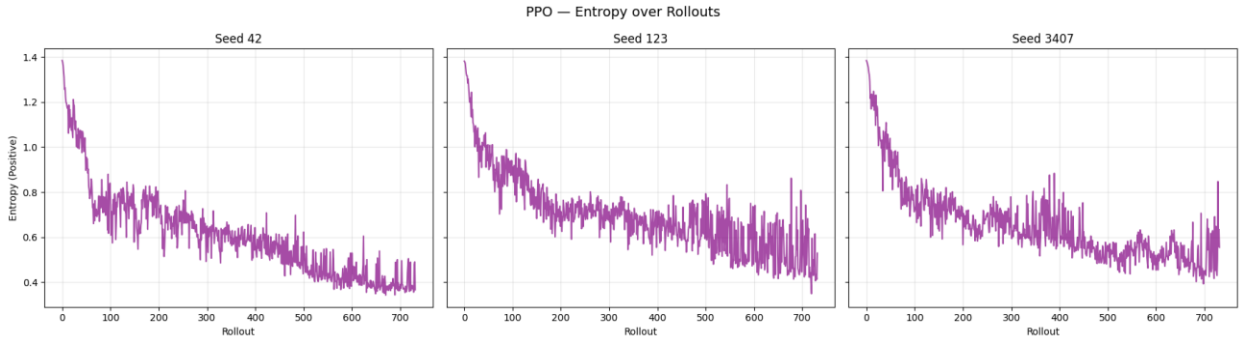

DQN — Episode Length over Training
Seed 42
Seed 123
Seed 3407
Number of Steps
Episode


PPO — Episode Length over Training
Seed 42
Seed 123
Seed 3407
Number of Steps
Episode

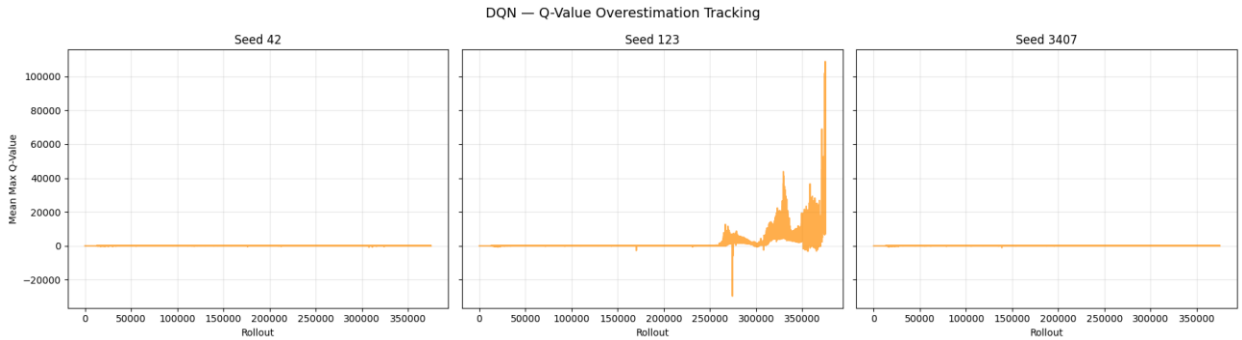

DQN — Value Loss over Rollouts
Seed 42
Seed 123
Seed 3407
Loss Value
Rollout


PPO — Value Loss over Rollouts
Seed 42
Seed 123
Seed 3407
Loss Value
Rollout

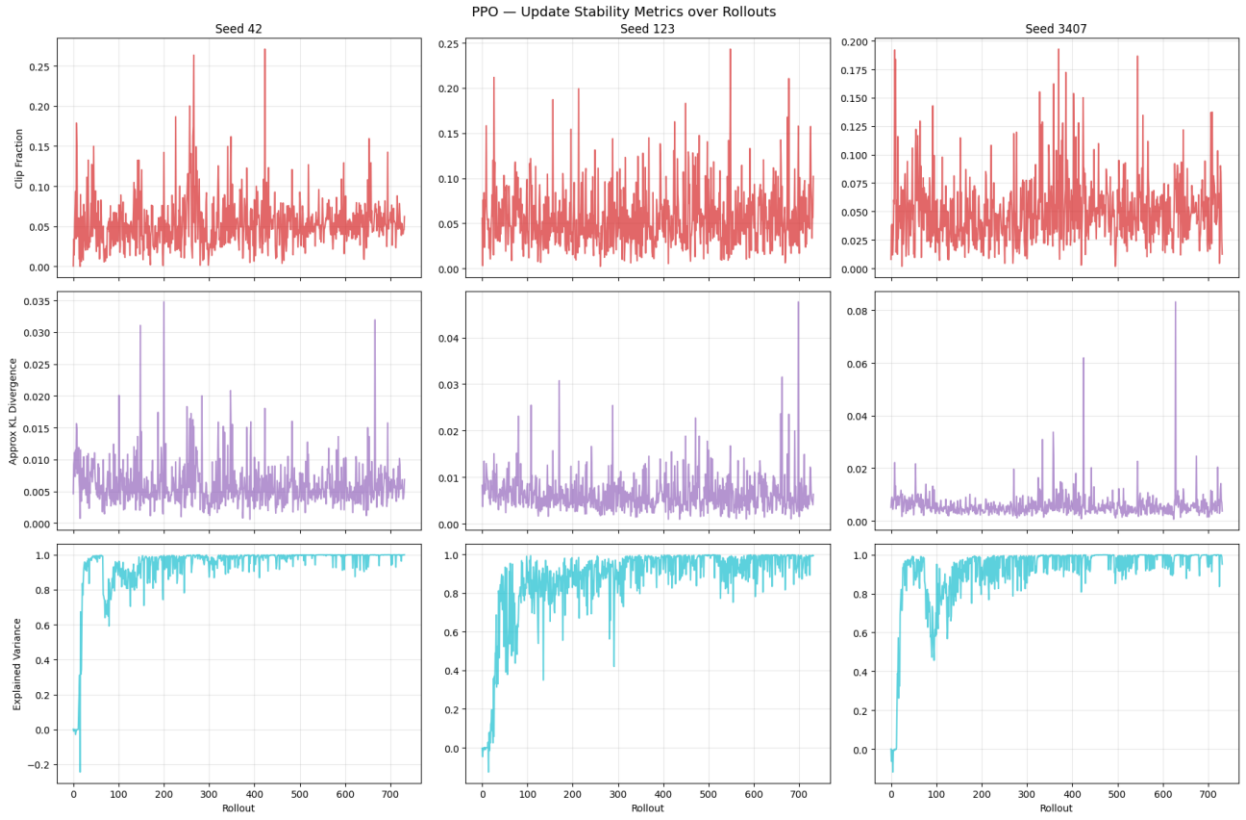

DQN — Exploration Rate over Rollouts
Seed 42
Seed 123
Seed 3407
Epsilon
Rollout


PPO — Entropy over Rollouts
Seed 42
Seed 123
Seed 3407
Entropy (Positive)
Rollout

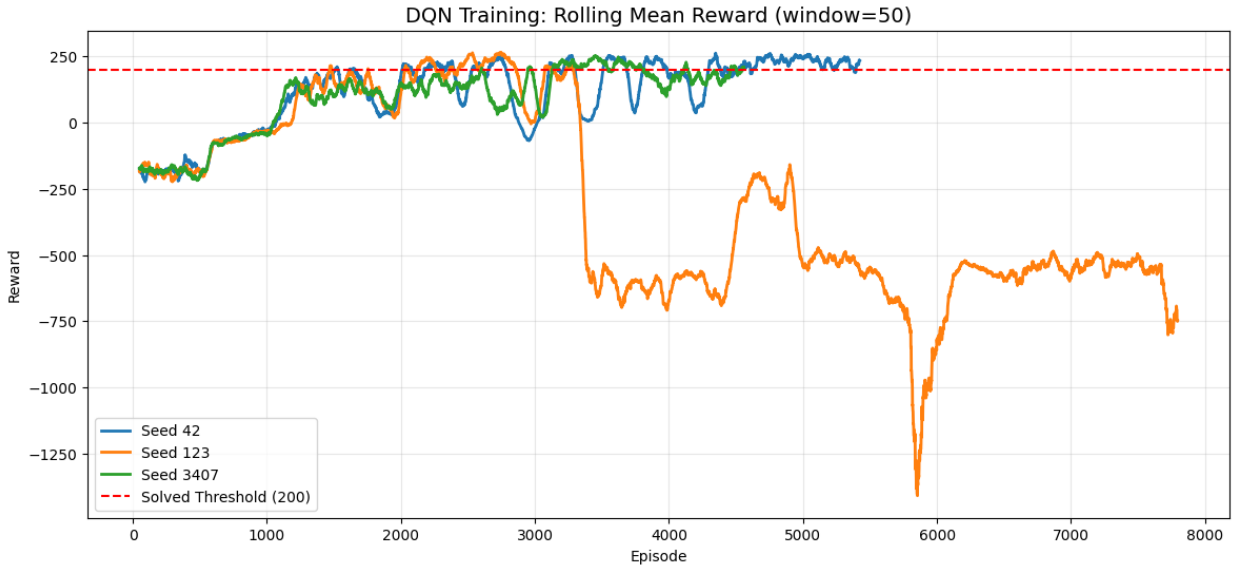

PPO — Policy Gradient Loss over Rollouts
Seed 42
Seed 123
Seed 3407
Policy Loss
Rollout

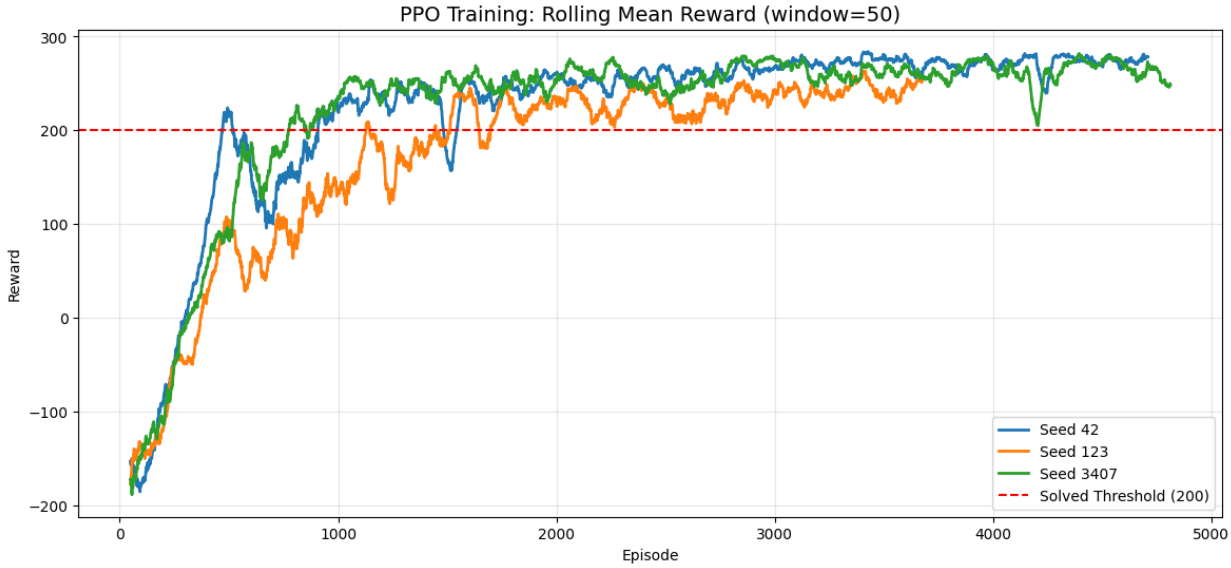

DQN — Q-Value Overestimation Tracking
Seed 42
Seed 123
Seed 3407
Mean Max Q-Value
Rollout

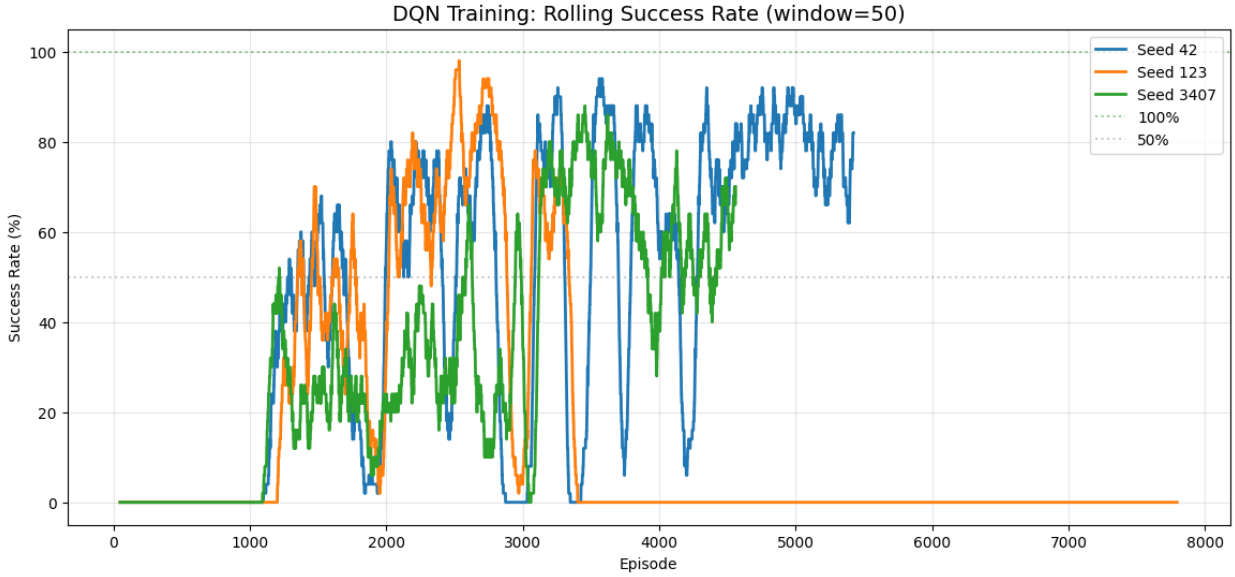
Note: Steadily rising Q-values that diverge from actual returns indicate overesti
mation.
A stable or slowly growing curve suggests the target network is controlling overe
stimation.

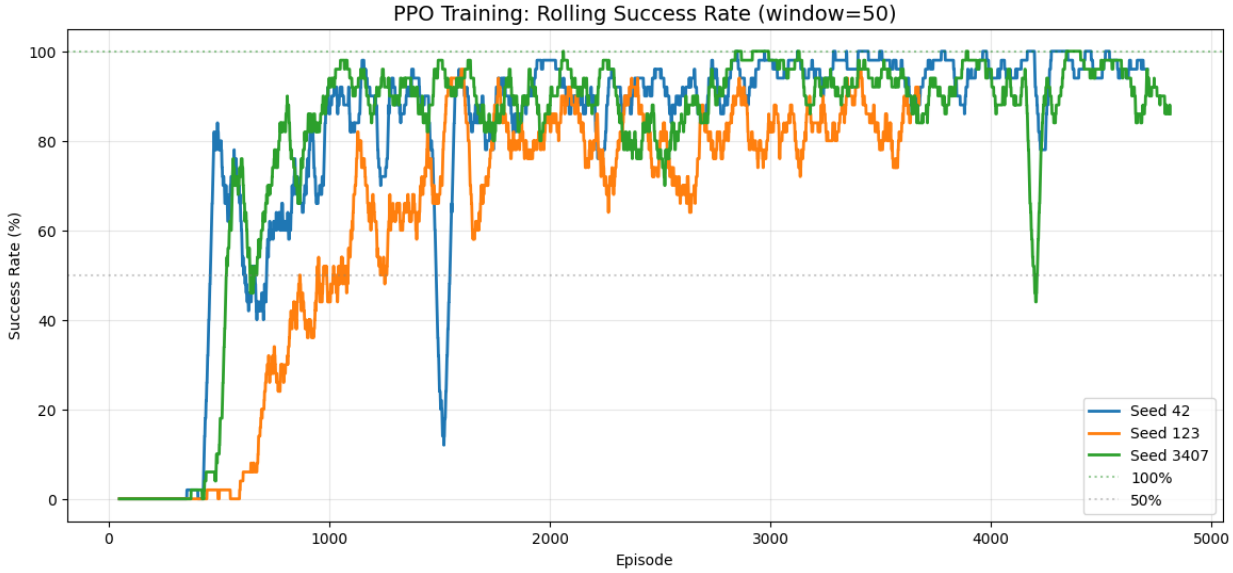


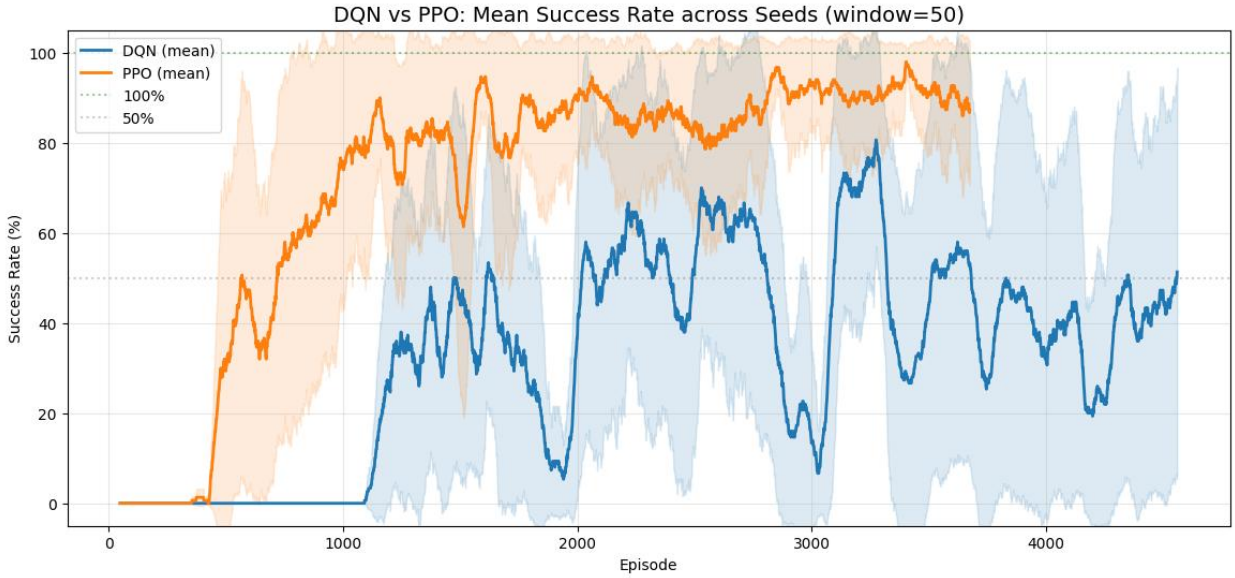
Clip Fraction: Fraction of policy updates clipped by PPO. High values suggest t
he policy is changing too fast.
Approx KL Divergence: KL divergence between old and new policy. Spikes indicate
large policy shifts.
Explained Variance: How well the value function predicts returns. 1.0 = perfec
t, 0 = no better than mean.

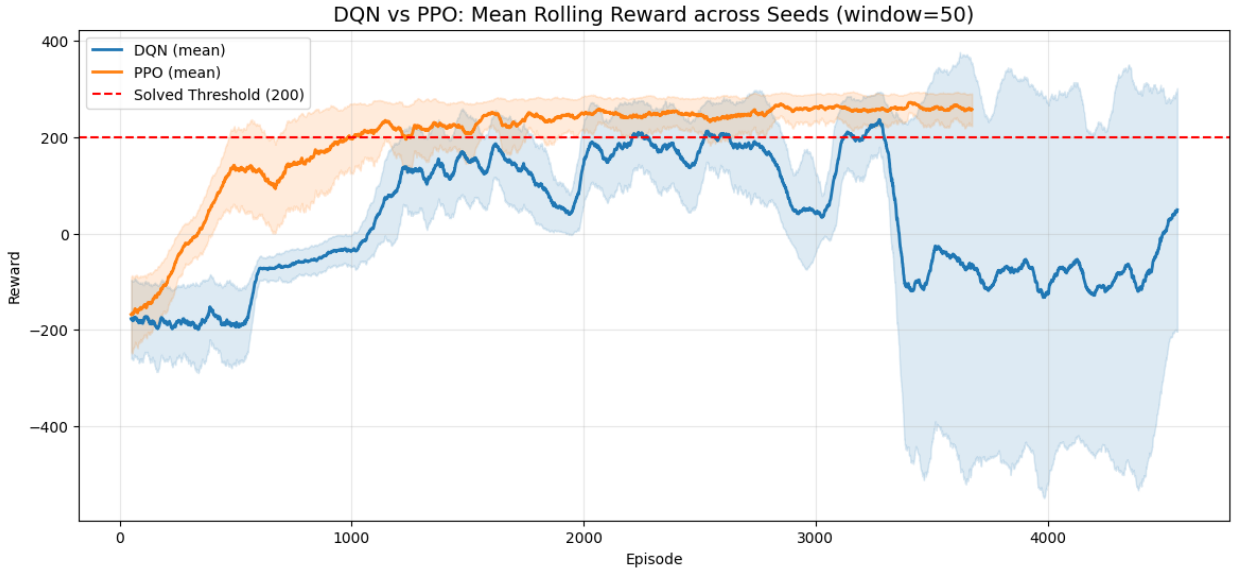

DQN Training: Rolling Mean Reward (window=50)
Reward
Episode
Seed 42
Seed 123
Seed 3407
Solved Threshold (200)


PPO Training: Rolling Mean Reward (window=50)
Reward
Episode
Seed 42
Seed 123
Seed 3407
Solved Threshold (200)


DQN Training: Rolling Success Rate (window=50)
Success Rate (%)
Episode
Seed 42
Seed 123
Seed 3407
100%
50%


PPO Training: Rolling Success Rate (window=50)
Success Rate (%)
Episode
Seed 42
Seed 123
Seed 3407
100%
50%


DQN vs PPO: Mean Success Rate across Seeds (window=50)
DQN (mean)
PPO (mean)
100%
50%
Success Rate (%)
Episode


DQN vs PPO: Mean Rolling Reward across Seeds (window=50)
DQN (mean)
PPO (mean)
Solved Threshold (200)
Reward
Episode

4. Evaluation

The following tables summarize the evaluation performance of each algorithm across all seeds. Each model was evaluated over 20 deterministic episodes. The overall row aggregates all episodes across seeds.

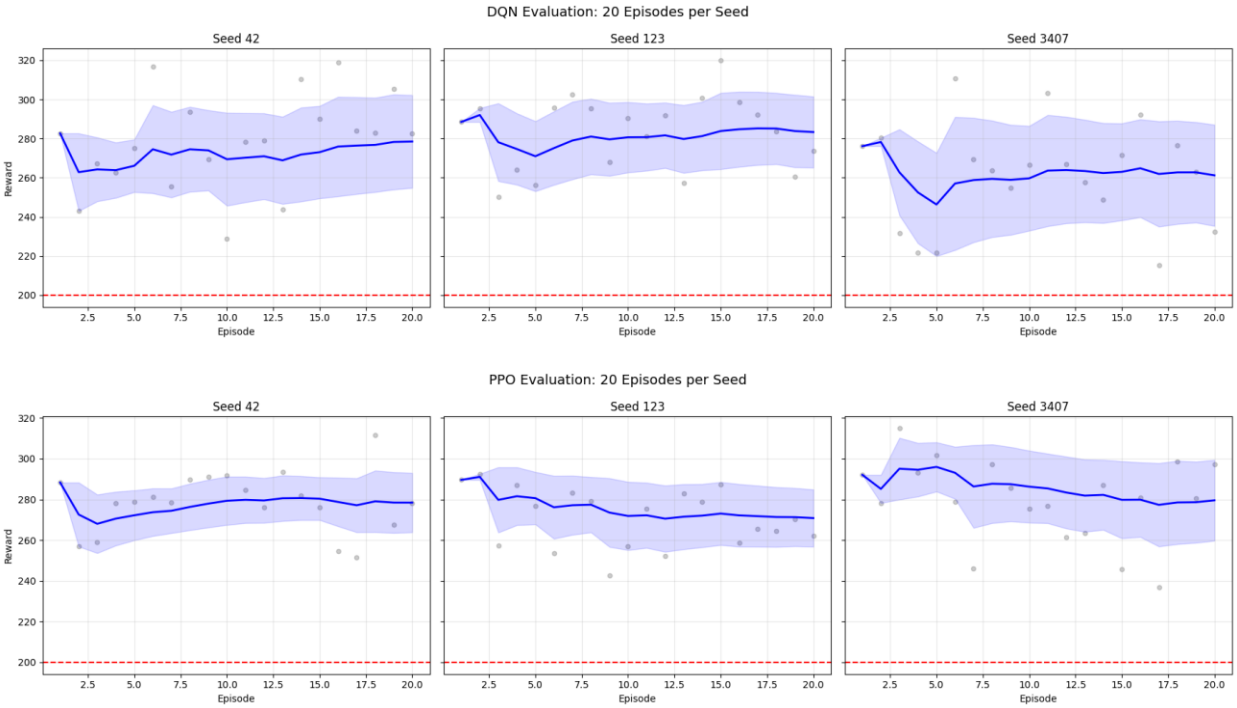
```
Session: dqn_ppo
Algorithms: ['dqn', 'ppo']
Seeds: [42, 123, 3407]

Discovered best models:
  DQN seed 42: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_02_5
3_32/best_model.zip
  DQN seed 123: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_03_
41_09/best_model.zip
  DQN seed 3407: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_04
_28_07/best_model.zip
  PPO seed 42: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_1
5_27/best_model.zip
  PPO seed 123: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_
35_37/best_model.zip
  PPO seed 3407: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05
_58_38/best_model.zip

Discovered eval logs:
  DQN seed 42: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_02_5
3_32/eval_log/evaluations.npz
  DQN seed 123: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_03_
41_09/eval_log/evaluations.npz
  DQN seed 3407: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_04
_28_07/eval_log/evaluations.npz
  PPO seed 42: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_1
5_27/eval_log/evaluations.npz
  PPO seed 123: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_
35_37/eval_log/evaluations.npz
  PPO seed 3407: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05
_58_38/eval_log/evaluations.npz

Discovered training logs:
  DQN seed 42: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_02_5
3_32/training_log.npz
  DQN seed 123: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_03_
41_09/training_log.npz
  DQN seed 3407: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_04
_28_07/training_log.npz
```

```
  PPO seed 42: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_1
5_27/training_log.npz
  PPO seed 123: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_
35_37/training_log.npz
  PPO seed 3407: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05
_58_38/training_log.npz


Loading and evaluating DQN seed 42 (best model)...
Loading and evaluating DQN seed 123 (best model)...
Loading and evaluating DQN seed 3407 (best model)...
DQN: evaluation complete.

Loading and evaluating PPO seed 42 (best model)...
Loading and evaluating PPO seed 123 (best model)...
Loading and evaluating PPO seed 3407 (best model)...
PPO: evaluation complete.

All evaluations complete.
```

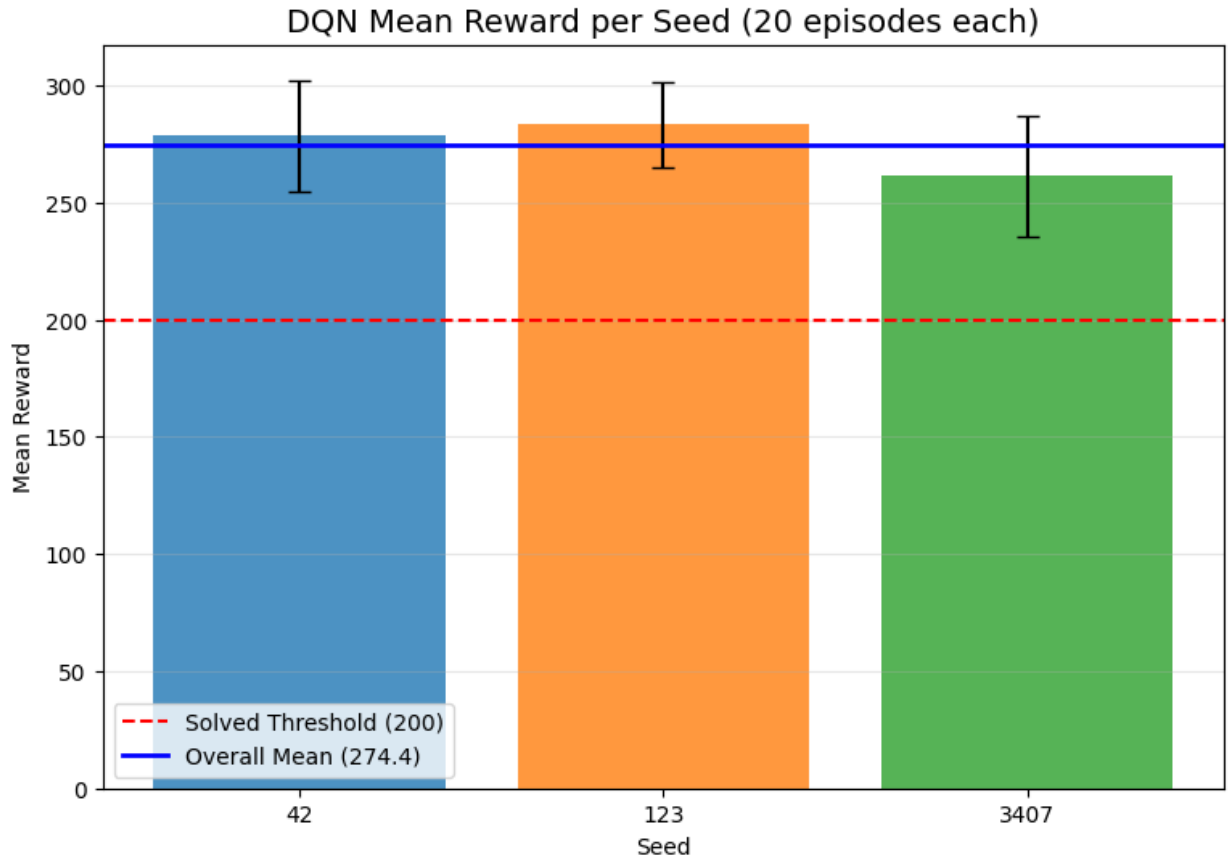
4.1 Per-Algorithm Results

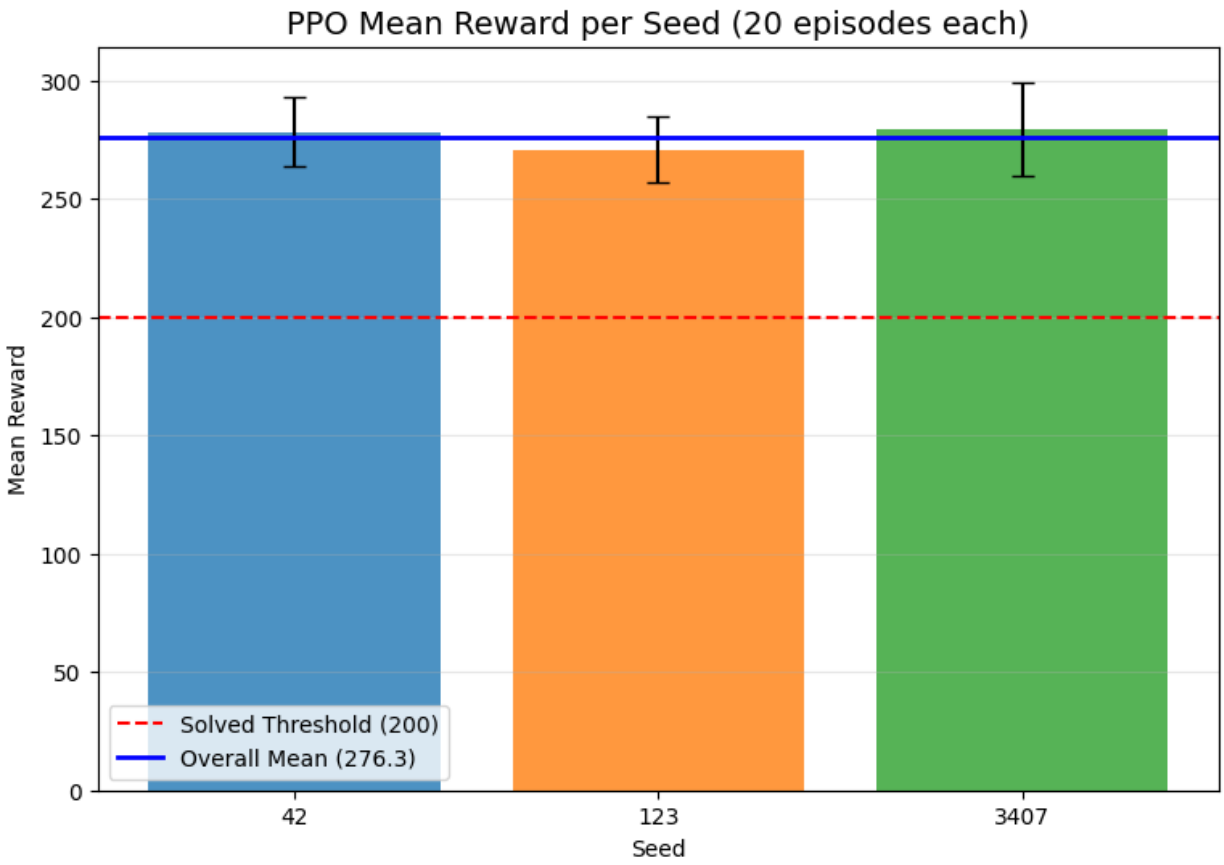
```
*** DQN MULTI-SEED EVALUATION SUMMARY ***
Episodes per seed: 20 | Total: 60
   Seed Mean Reward Std Dev Min Reward Max Reward Success Rate
     42      278.51   23.70     228.67     318.97       100.0%
    123      283.34   18.19     250.33     319.93       100.0%
   3407      261.22   25.88     215.37     310.74       100.0%
Overall      274.36   24.72     215.37     319.93       100.0%

*** PPO MULTI-SEED EVALUATION SUMMARY ***
Episodes per seed: 20 | Total: 60
   Seed Mean Reward Std Dev Min Reward Max Reward Success Rate
     42      278.43   14.56     251.45     311.70       100.0%
    123      270.83   14.06     242.53     292.55       100.0%
   3407      279.56   19.83     236.91     314.95       100.0%
Overall      276.27   16.81     236.91     314.95       100.0%
```

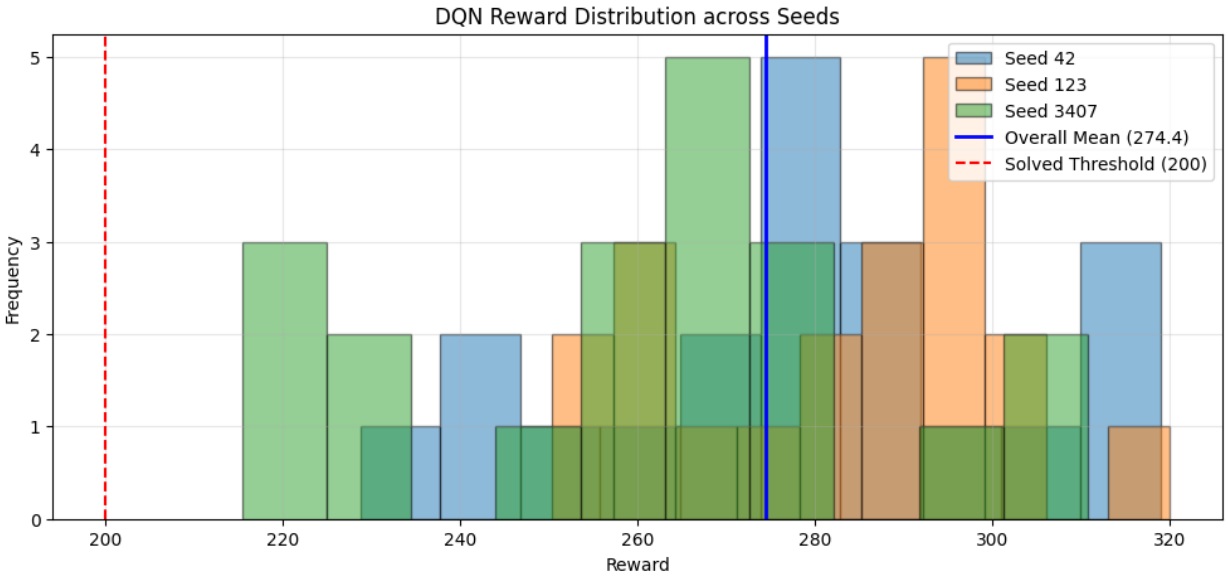
These convergence plots show the running mean reward across the 20 evaluation episodes for each seed. The shaded region represents one standard deviation. A flat, high running mean indicates consistent performance.

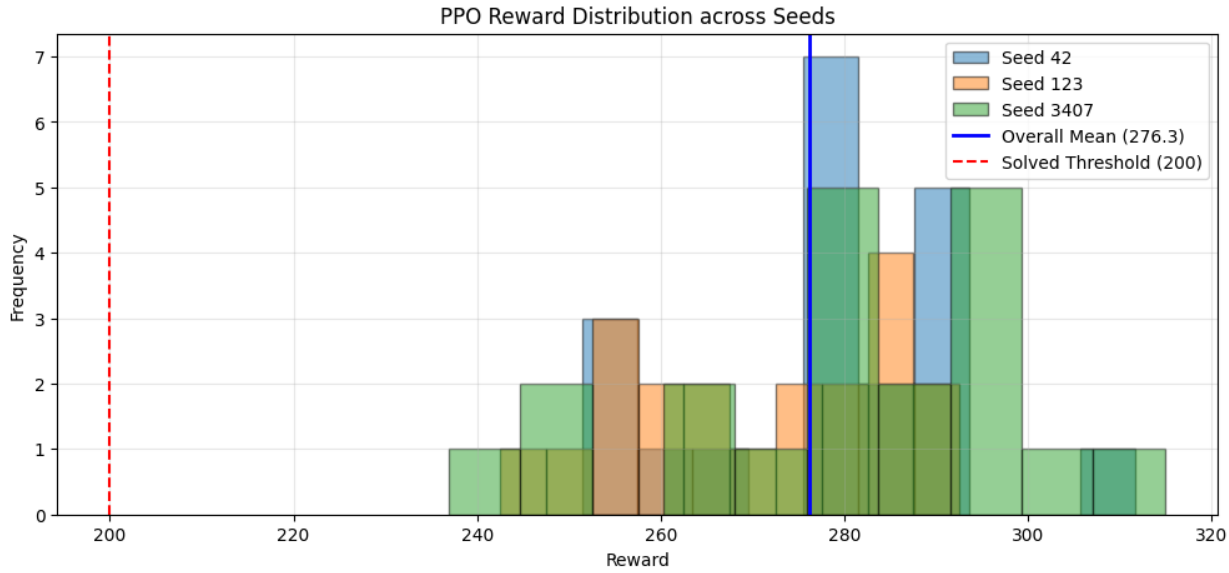


These convergence plots show the running mean reward across the 20 evaluation episodes for each seed. The shaded region represents one standard deviation. A flat, high running mean indicates consistent performance.



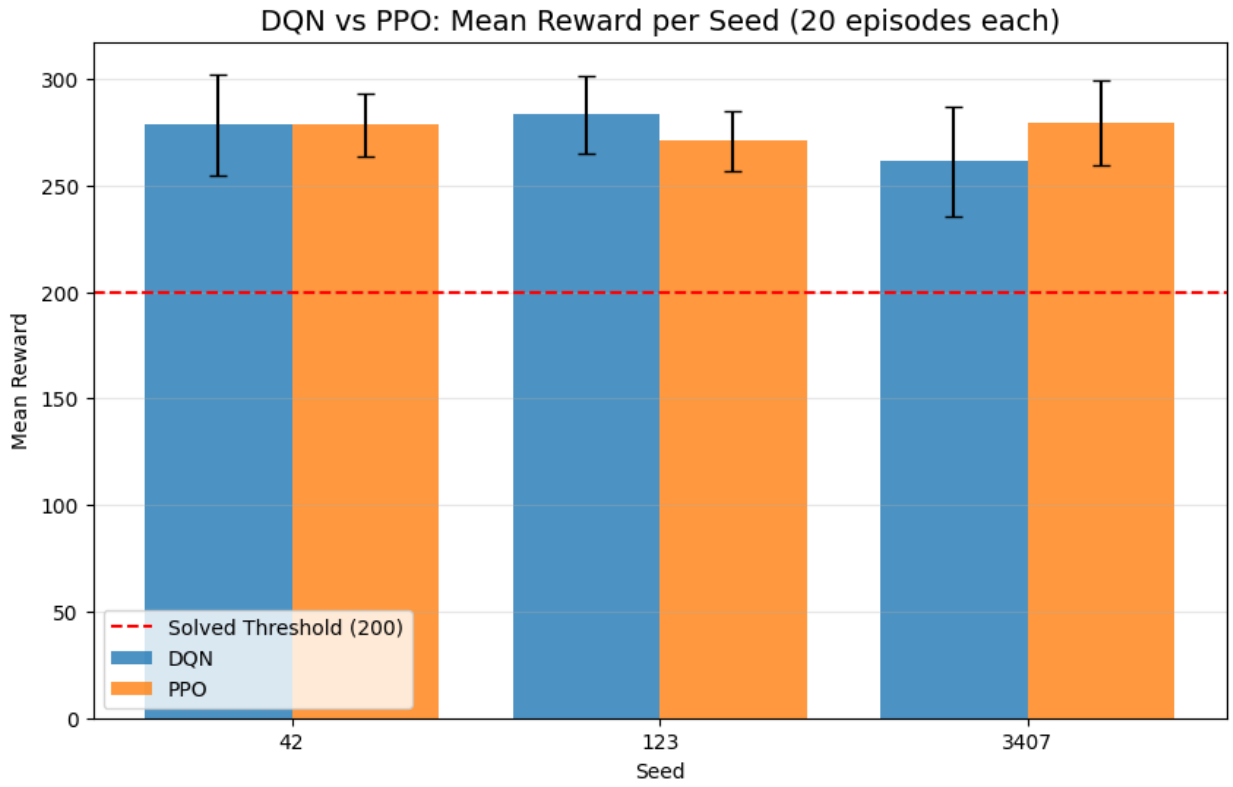

PPO Mean Reward per Seed (20 episodes each)
Mean Reward
300
250
200
150
100
50
0
Solved Threshold (200)
Overall Mean (276.3)
42
123
3407
Seed

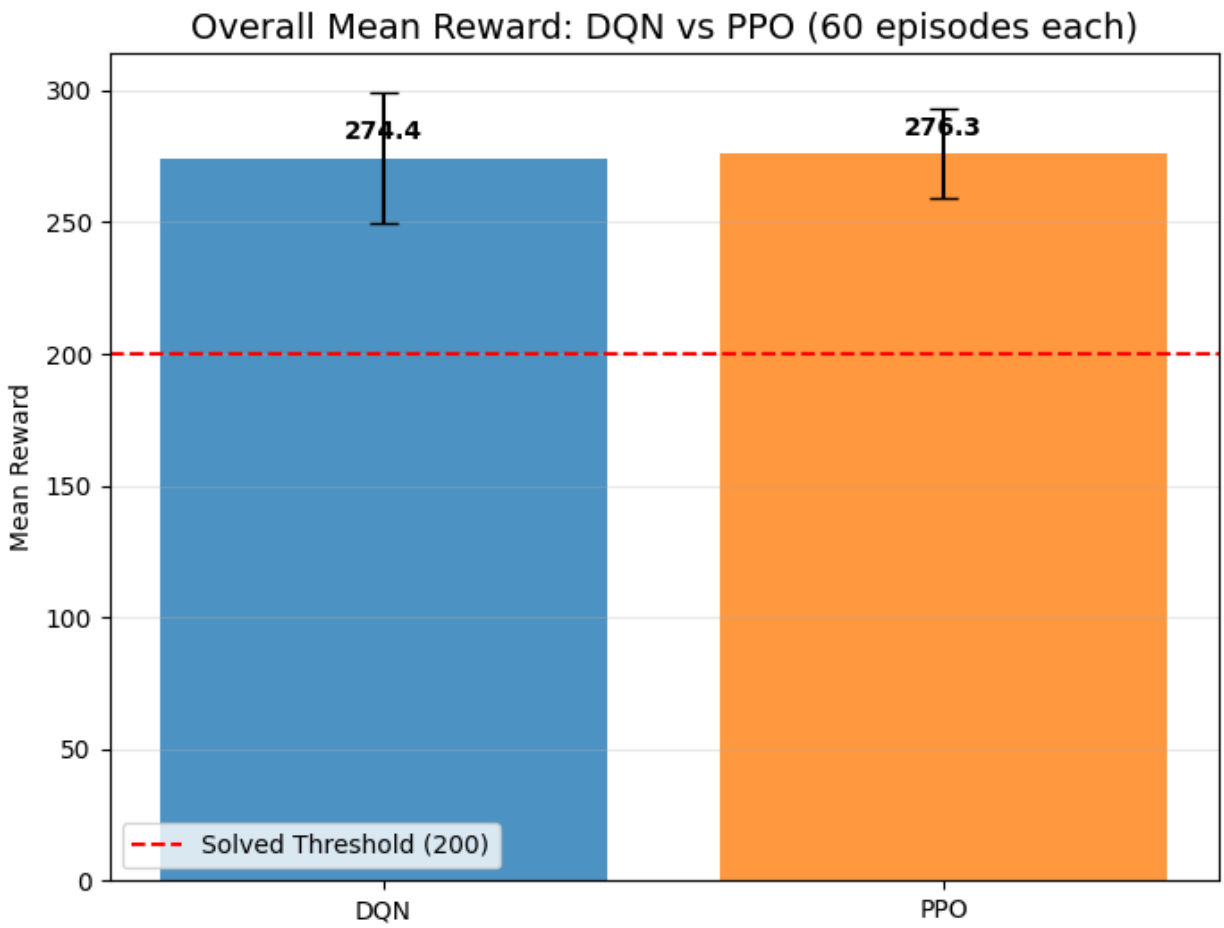

DQN Reward Distribution across Seeds
Seed 42
Seed 123
Seed 3407
Overall Mean (274.4)
Solved Threshold (200)
Frequency
5
4
3
2
1
0
200
220
240
260
280
300
320
Reward

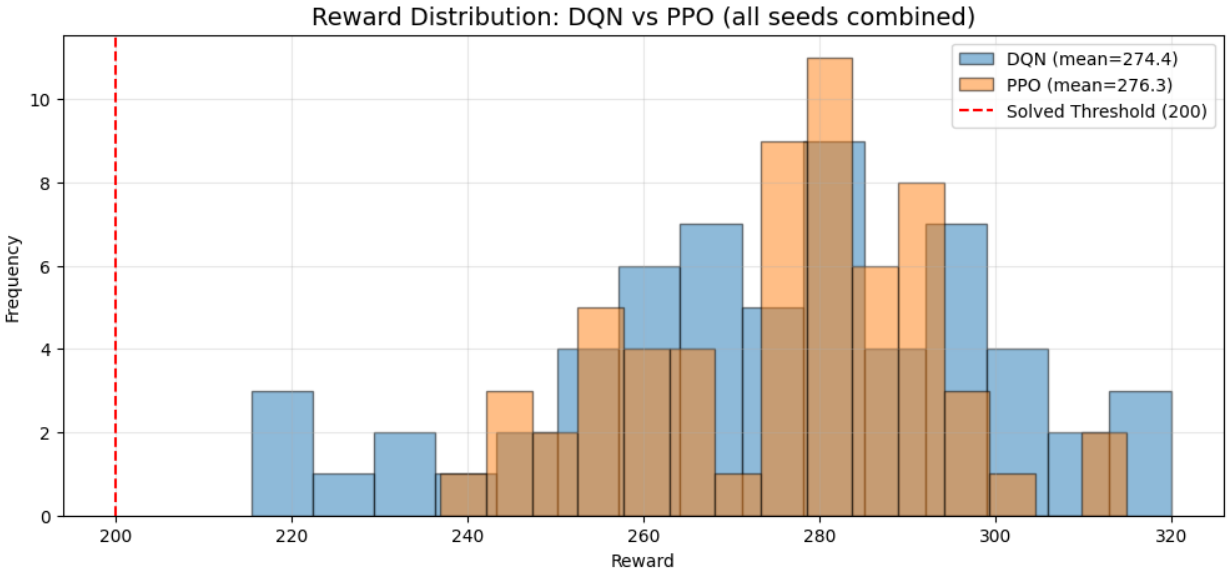


4.2 Cross-Algorithm Comparison

```
*** CROSS-ALGORITHM EVALUATION SUMMARY ***
Seeds: [42, 123, 3407] | Episodes per seed: 20
Total episodes per algorithm: 60

Algorithm Mean Reward Std Dev Min Reward Max Reward Success Rate
      DQN      274.36   24.72     215.37     319.93       100.0%
      PPO      276.27   16.81     236.91     314.95       100.0%
```

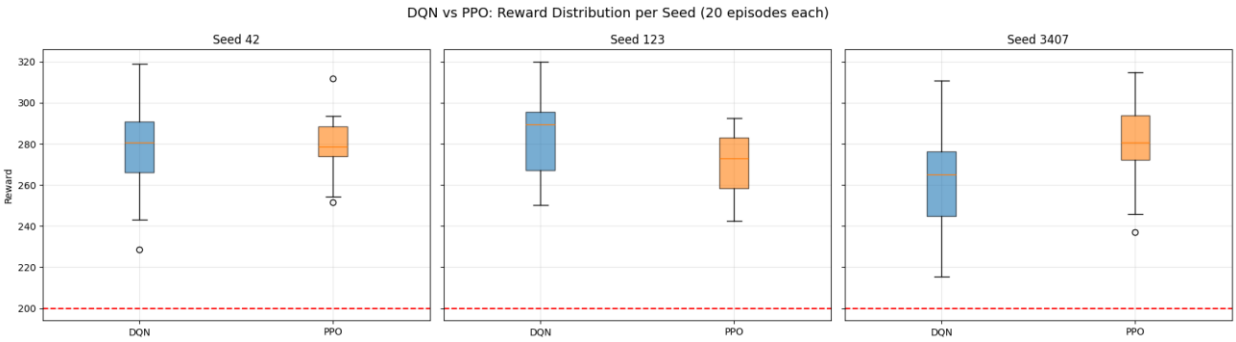







```
/tmp/ipykernel_6515/3208474440.py:9: MatplotlibDeprecationWarning: The 'labels' p
arameter of boxplot() has been renamed 'tick_labels' since Matplotlib 3.9; suppor
t for the old name will be dropped in 3.11.
  bp = ax.boxplot(data, labels=[a.upper() for a in algo_names], patch_artist=Tru
e)
/tmp/ipykernel_6515/3208474440.py:9: MatplotlibDeprecationWarning: The 'labels' p
arameter of boxplot() has been renamed 'tick_labels' since Matplotlib 3.9; suppor
```

```
t for the old name will be dropped in 3.11.
  bp = ax.boxplot(data, labels=[a.upper() for a in algo_names], patch_artist=Tru
e)
/tmp/ipykernel_6515/3208474440.py:9: MatplotlibDeprecationWarning: The 'labels' p
arameter of boxplot() has been renamed 'tick_labels' since Matplotlib 3.9; suppor
t for the old name will be dropped in 3.11.
  bp = ax.boxplot(data, labels=[a.upper() for a in algo_names], patch_artist=Tru
e)
```



4.3 Statistical Significance

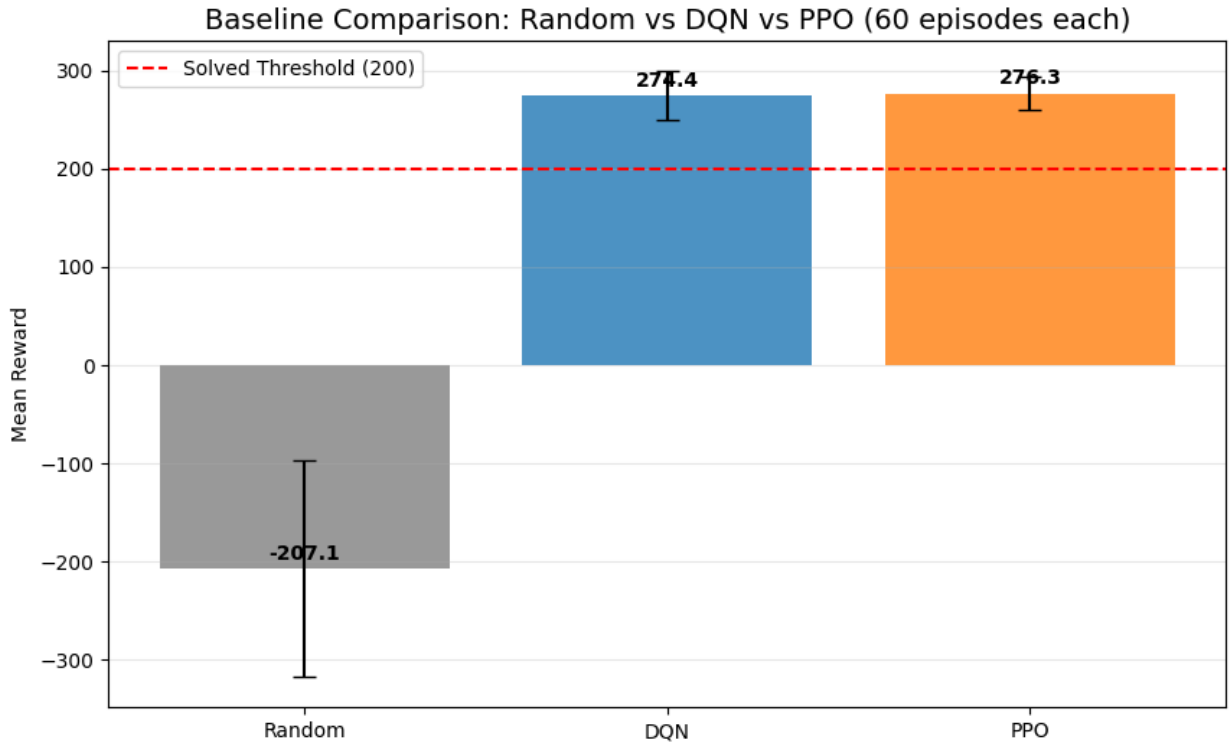
Two statistical tests assess whether the observed performance difference between DQN and PPO is significant. The Mann-Whitney U test compares reward distributions (non-parametric, no normality assumption). The Chi-squared test compares success rates as a proportion.

```
*** STATISTICAL SIGNIFICANCE TESTS ***
Sample size per algorithm: 60 episodes (20 episodes x 3 seeds)

              Metric DQN Value PPO Value                                Test Stat
istic p-value Significant (p<0.05)
         Mean Reward    274.36    276.27                    Mann-Whitney U    1
771.0  0.8811                   No
Success Rate (>=200)    100.0%    100.0% Chi-squared (skipped: zero row/col)
 0.00  1.0000                   No
```

4.4 Baseline Comparison

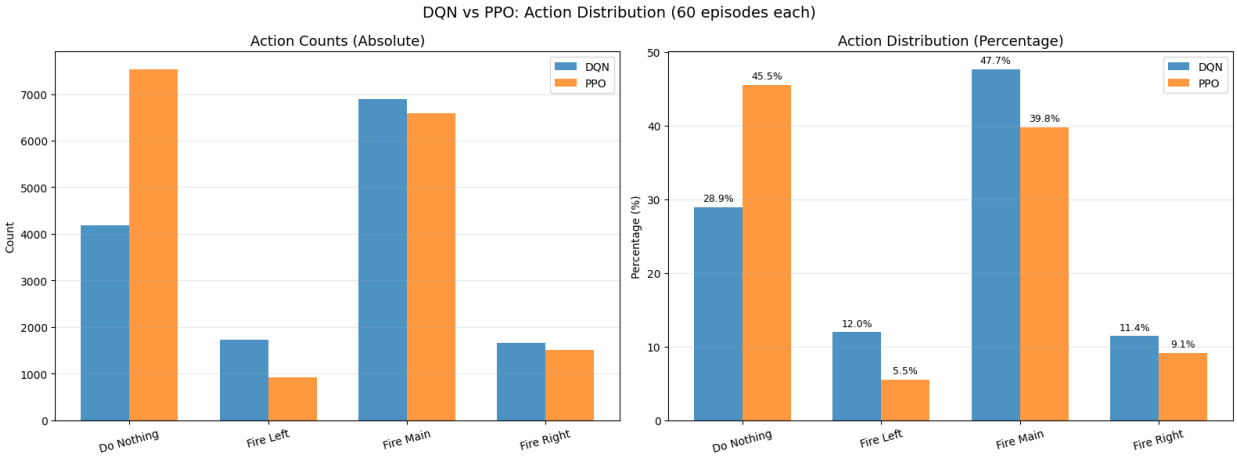
```
Running random agent with seed 42...
Running random agent with seed 123...
Running random agent with seed 3407...
Random baseline evaluation complete.


*** BASELINE COMPARISON ***
```

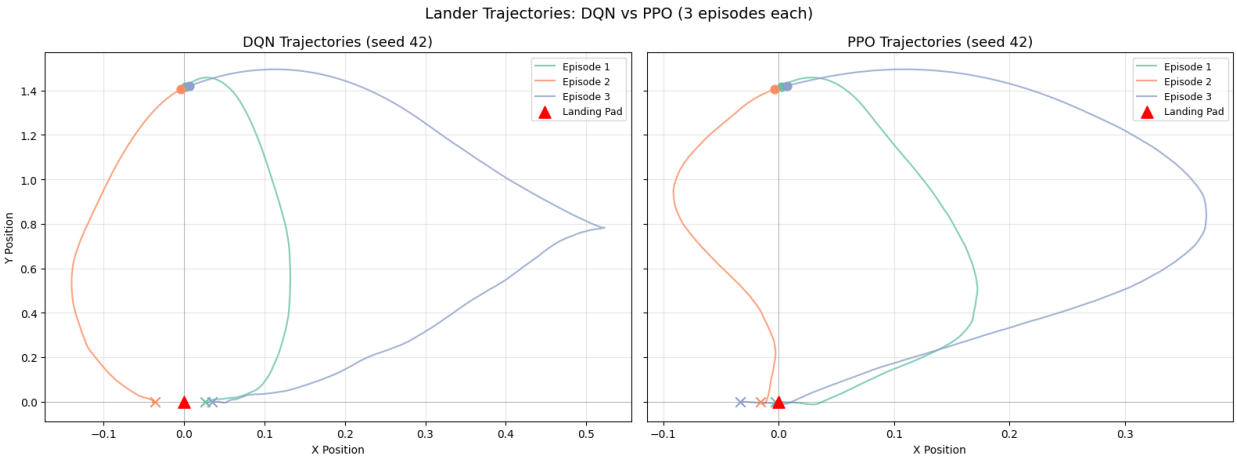
```
  Agent Mean Reward Std Dev     Min     Max Success Rate
Random     -207.06  110.45 -416.10   15.45         0.0%
   DQN      274.36   24.72  215.37  319.93       100.0%
   PPO      276.27   16.81  236.91  314.95       100.0%
```

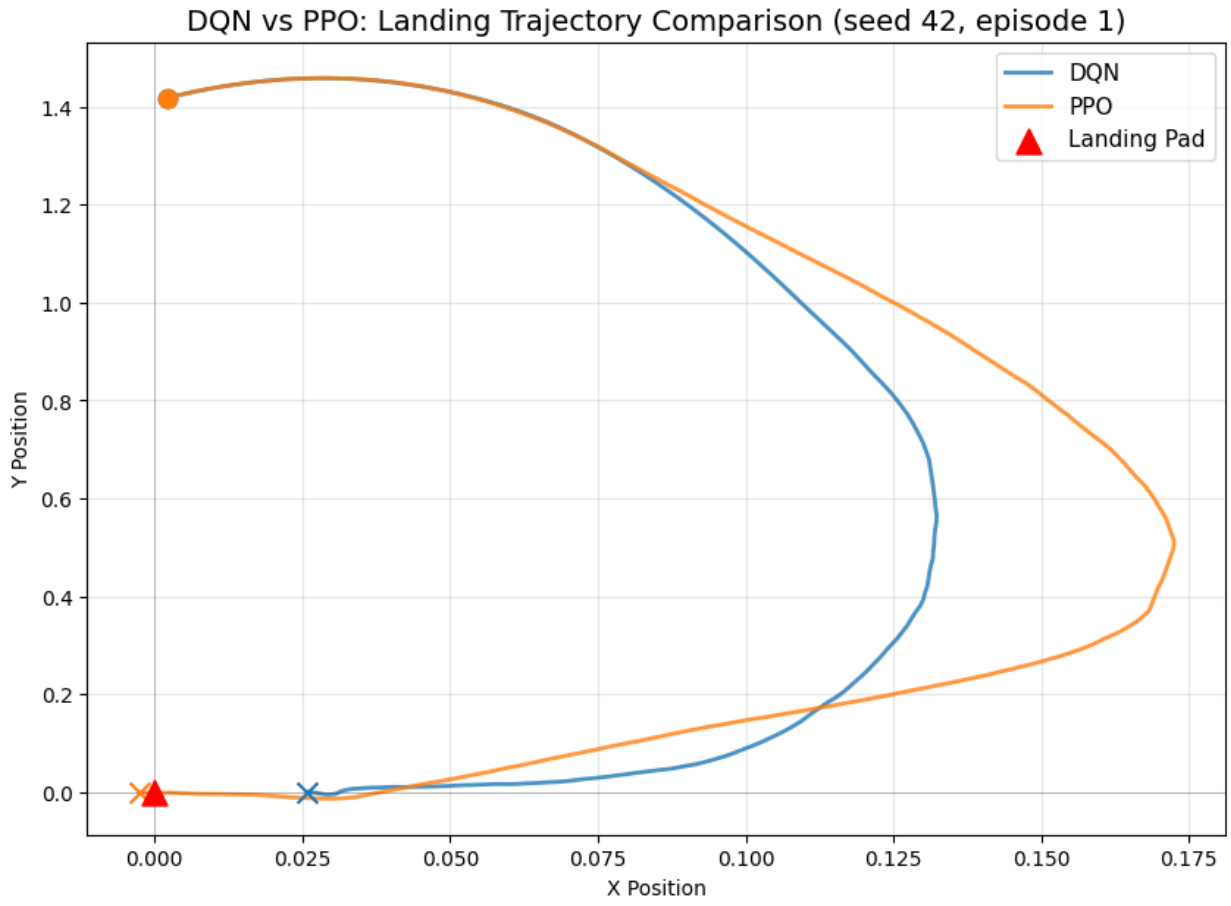


4.5 Agent Behavior Analysis

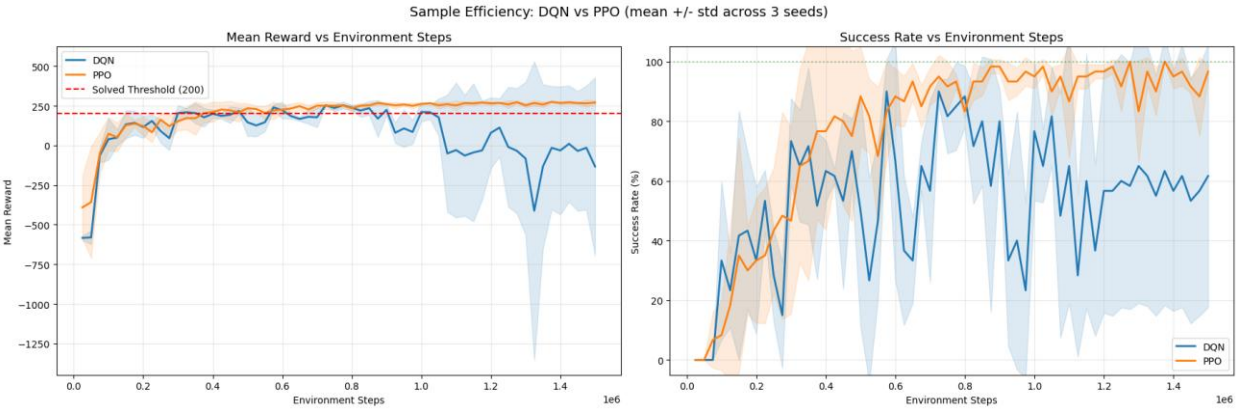
```
DQN: 14,451 total actions collected across 60 episodes
PPO: 16,544 total actions collected across 60 episodes

Behavior data collection complete.
```







4.6 Sample Efficiency Analysis



```
*** SAMPLE EFFICIENCY: FIRST SOLVED TIMESTEP ***
Solved = mean evaluation reward >= 200
Evaluated every 25,000 timesteps with 20 episodes

Algorithm Seed First Solved at Step
      DQN   42              300,000
      DQN  123              300,000
      DQN 3407              150,000
      DQN Mean              250,000
      PPO   42              150,000
      PPO  123              525,000
      PPO 3407              325,000
      PPO Mean              333,333
```

4.7 Training Milestone Timeline

This chart overlays the training reward curves with vertical milestone markers showing when each algorithm reached key performance thresholds. The background curves show the rolling mean reward (window=100 episodes) plotted against cumulative environment steps, reconstructed from the per-episode training logs. Three milestones are marked per algorithm:

- Best model (solid line): the checkpoint selected by the combined metric (mean - std) during training
- First solved (dashed line): first point where the rolling 100-episode mean reward >= 200
- First all-pass (dotted line): first point where all 100 consecutive episodes scored >= 200

Discovered training logs: DQN seed 42: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_02_53_32/training_log.npz DQN seed 123: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_03_41_09/training_log.npz DQN seed 3407: /home/logus/env/iscte/taap_p2/report/../models/dqn/2026-02-23_04_28_07/training_log.npz PPO seed 42: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_15_27/training_log.npz PPO seed 123: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_35_37/training_log.npz PPO seed 3407: /home/logus/env/iscte/taap_p2/report/../models/ppo/2026-02-23_05_58_38/training_log.npz

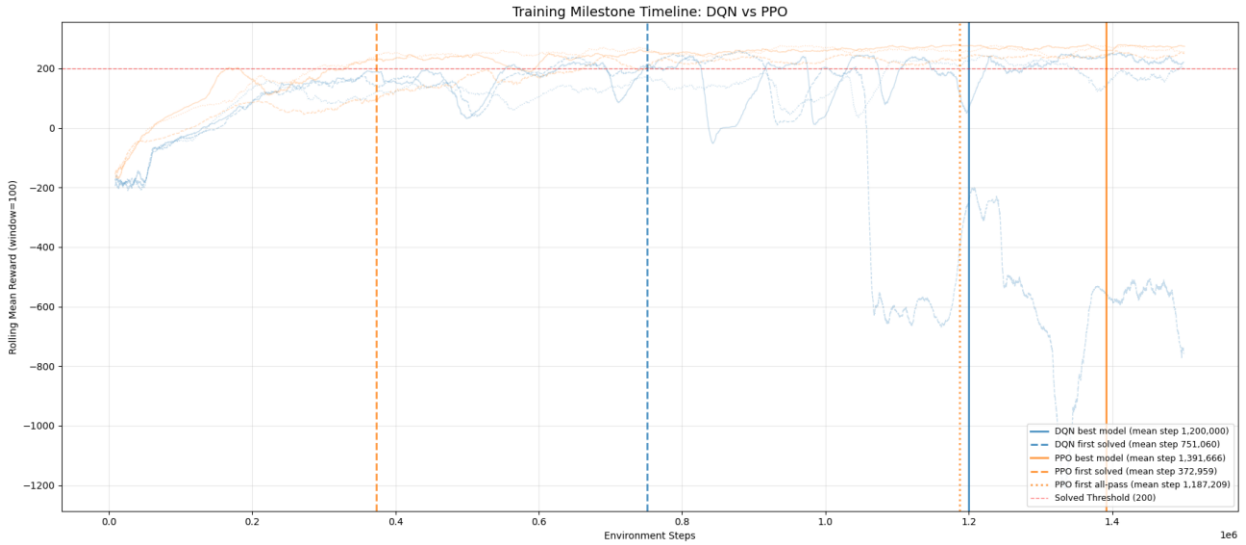


Figure 14 - Training milestone timeline showing rolling mean reward curves (per-seed, light lines) with vertical markers for best model selection, first solved (rolling 100-episode mean >= 200), and first all-pass (all 100 consecutive episodes >= 200) milestones.

```
*** TRAINING MILESTONES PER SEED ***
Rolling window: 100 episodes
Solved threshold: mean reward >= 200
All-pass threshold: every episode in window >= 200

Algorithm  Seed First Solved (rolling mean >= 200) First All-Pass (all 100 >= 20
0)
      DQN    42                            553,533                     Not reache
d
      DQN   123                            614,569                     Not reache
d
      DQN  3407                          1,085,079                     Not reache
d
      PPO    42                            166,110                       1,407,53
2
      PPO   123                            662,791                     Not reache
d
      PPO  3407                            289,977                         966,88
6
```

4.8 Final vs Best Model Comparison

```
Evaluating DQN seed 42 (final model)...
Evaluating DQN seed 123 (final model)...
Evaluating DQN seed 3407 (final model)...
Evaluating PPO seed 42 (final model)...
Evaluating PPO seed 123 (final model)...
```

```
Evaluating PPO seed 3407 (final model)...

Final model evaluation complete.


*** BEST MODEL vs FINAL MODEL ***
Episodes per evaluation: 20

Algorithm  Seed Best Mean Best Success Final Mean Final Success Delta Mean
      DQN    42    278.51         100%     266.82           95%     +11.69
      DQN   123    283.34         100%    -935.49            0%   +1218.83
      DQN  3407    261.22         100%     286.92          100%     -25.70
      PPO    42    278.43         100%     276.39           95%      +2.04
      PPO   123    270.83         100%     247.72           85%     +23.11
      PPO  3407    279.56         100%     267.67           95%     +11.88

Positive Delta Mean = best model selection improved over end-of-training snapsho
t.
```

4.9 Hyperparameter Exploration Summary

```
*** DQN Final Hyperparameters ***
             Parameter                                                  Value
                policy                                              MlpPolicy
         learning_rate <function linear_schedule.<locals>.func at 0x75da6d15cc20>
       learning_starts                                                 50000
           buffer_size                                                750000
            batch_size                                                   128
                 gamma                                                  0.99
  exploration_fraction                                                  0.12
 exploration_final_eps                                                   0.1
target_update_interval                                                   250
            train_freq                                                     4
        gradient_steps                                                     4
         policy_kwargs                          {'net_arch': [256, 256]}
                device                                                   cpu
       total_timesteps                                             1,500,000
                device                                                   cpu
                policy                                              MlpPolicy

*** PPO Final Hyperparameters ***
      Parameter     Value
  learning_rate   0.00025
        n_steps      2048
```

```
     batch_size        64
       n_epochs        10
          gamma     0.999
     gae_lambda      0.95
       ent_coef      0.01
     clip_range       0.2
total_timesteps 1,500,000
         device       cpu
         policy MlpPolicy



*** DQN HYPERPARAMETER EXPLORATION ***

       Config
                      Key Changes Success Rate  Mean Reward
                                  Notes
 A (baseline)                         lr=6.3e-4, buffer=100k, eps_final=0.01, expl
ore=0.5, soft updates (tau=0.005)        84.0%       245.47                  Slow
 exploration decay, soft target updates
B (Zoo-style)                         lr=linear(6.3e-4), buffer=1M, eps_final=0.1,
 explore=0.12, hard updates (250)        96.0%       263.02   Short exploration,
high final epsilon, hard target updates
    C (final) lr=linear(6.3e-4), buffer=750k, eps_final=0.1, explore=0.12, hard u
pdates (250), learning_starts=50k TBD (lab011) TBD (lab011) Added learning_starts
 buffer fill, gradient_steps=4 explicit

*** PPO HYPERPARAMETER EXPLORATION ***

   Config                                                                  Key Chan
ges Success Rate Mean Reward                                 Notes
A (final) lr=2.5e-4, gamma=0.999, n_steps=2048, batch=64, n_epochs=10, ent_coef=
0.01        98.0%      269.21 Standard config, single environment

Note: Update Config C results and add any additional configs tested during lab011
 runs.
```

4.10 Visualizations

```
Generating GIF for DQN seed 42 (best model)...
  Saved: /home/logus/env/iscte/taap_p2/report/outputs_dqn/dqn_seed42.gif
```

```
<IPython.core.display.Image object>


Generating GIF for DQN seed 123 (best model)...
  Saved: /home/logus/env/iscte/taap_p2/report/outputs_dqn/dqn_seed123.gif



<IPython.core.display.Image object>


Generating GIF for DQN seed 3407 (best model)...
  Saved: /home/logus/env/iscte/taap_p2/report/outputs_dqn/dqn_seed3407.gif



<IPython.core.display.Image object>


Generating GIF for PPO seed 42 (best model)...
  Saved: /home/logus/env/iscte/taap_p2/report/outputs_ppo/ppo_seed42.gif



<IPython.core.display.Image object>


Generating GIF for PPO seed 123 (best model)...
  Saved: /home/logus/env/iscte/taap_p2/report/outputs_ppo/ppo_seed123.gif



<IPython.core.display.Image object>


Generating GIF for PPO seed 3407 (best model)...
  Saved: /home/logus/env/iscte/taap_p2/report/outputs_ppo/ppo_seed3407.gif



<IPython.core.display.Image object>
```

5. Experimental Setup

```
Environment: LunarLander-v3
Observation space: Box([ -2.5        -2.5       -10.        -10.         -6.28318
55 -10.
  -0.         -0.       ], [ 2.5        2.5       10.        10.         6.283185
5 10.
  1.         1.       ], (8,), float32)
Action space: Discrete(4)
Wind enabled: False

Sample observation: [ 0.00229702  1.4181306   0.2326471   0.3204666  -0.00265488
-0.05269805
  0.          0.        ]
Observation labels: [x, y, vx, vy, angle, angular_vel, left_leg, right_leg]


Python: 3.12.3
PyTorch: 2.10.0+cu130
Stable-Baselines3: 2.7.1
Gymnasium: 1.2.3
NumPy: 2.4.2
Device: cpu
CUDA: 13.0
```

6. Conceptual Discussion

This section presents a theoretical discussion of the core conceptual differences between value-based and policy-based reinforcement learning methods, the sources of instability in deep RL, and the exploration mechanisms used in DQN and PPO.

6.1 Value-Based vs Policy-Based Learning

Reinforcement Learning algorithms can be categorised according to what is parameterised and optimised.

Value-Based Learning

Value-based methods approximate a value function, typically the action-value function:

$$Q^{\pi}(s,a) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^{t} r_t \mid s_0 = s, a_0 = a\right]$$

The optimal policy is derived implicitly:

$$\pi(s) = \underset{a}{\operatorname{argmax}} Q(s,a)$$

Deep Q-Networks (DQN) approximate $Q(s,a;\theta)$ and update parameters using the Bellman optimality equation:

$$Q(s,a) = r + \gamma \underset{a'}{\max} Q(s',a')$$

This introduces **bootstrapping**, since the target depends on the model's own predictions.

Key characteristics:

- Off-policy learning
- Bootstrapping
- Policy extracted via maximisation

However, the use of the max operator combined with function approximation introduces instability.

Policy-Based Learning

Policy-based methods parameterise the policy directly:

$$\pi_{\theta}(a|s)$$

and optimise the expected return:

$$J(\theta) = \mathbb{E}_{\pi_{\theta}}[R]$$

Using the policy gradient theorem:

$$\nabla_{\theta} J(\theta) = \mathbb{E}_{\pi_{\theta}}[\nabla_{\theta} \log \pi_{\theta}(a|s) A^{\pi}(s,a)]$$

These methods:

- Learn the policy directly
- Avoid explicit maximisation over value estimates
- Naturally handle continuous action spaces

Because they do not rely on a max operator over Q-values, they tend to be structurally more stable in deep settings.

6.2 Overestimation and Instability in Value-Based Algorithms

Overestimation Bias

Overestimation arises from the maximisation step $\max_a Q(s,a)$. If Q-value estimates contain zero-mean noise:

$$\mathbb{E}[\max(X_i)] \geq \max(\mathbb{E}[X_i])$$

Thus, even unbiased estimators lead to positively biased maximum estimates.

In DQN, the same network selects the action (argmax) and evaluates the action. This coupling amplifies overestimation bias.

Structural Instability: The Deadly Triad

Deep value-based RL combines:

1. Function approximation
2. Bootstrapping
3. Off-policy learning

This combination is known as the **deadly triad**, which may cause divergence or unstable oscillations.

PPO avoids these structural issues because:

- It does not use a max over Q-values
- It performs on-policy updates
- Value estimates are auxiliary rather than directly driving action selection

6.3 PPO Clipping and Generalised Advantage Estimation (GAE)

PPO Clipped Objective

PPO constrains policy updates through the clipped surrogate objective:

$$L^{CLIP}(\theta) = \mathbb{E}[\min(r_t(\theta)A_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)A_t)]$$

where:

$$r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}$$

This objective:

- Approximates a trust-region method
- Prevents excessively large updates
- Improves training stability

Generalised Advantage Estimation (GAE)

The advantage function is defined as:

$$A^\pi(s,a) = Q^\pi(s,a) - V^\pi(s)$$

GAE computes:

$$A_t^{GAE(\lambda)} = \sum_{l=0}^{\infty} (\gamma\lambda)^l \delta_{t+l}$$

where the temporal-difference residual is:

$$\delta_t = r_t + \gamma V(s_{t+1}) - V(s_t)$$

The parameter $\lambda \in [0,1]$ controls the bias-variance trade-off:

- $\lambda = 0$: lower variance, higher bias
- $\lambda = 1$: lower bias, higher variance

GAE reduces variance in policy gradient updates while maintaining acceptable bias, improving sample efficiency and stability.

6.4 Epsilon-Greedy vs Entropy-Driven Exploration

Epsilon-Greedy Exploration (DQN)

The behaviour policy is defined as:

$$\pi(a|s) = \begin{cases} \text{random action} & \text{with probability } \epsilon \\ \underset{a}{\text{argmax}} Q(s,a) & \text{otherwise} \end{cases}$$

Limitations:

- Uniform and uninformed exploration
- Independent of uncertainty
- Becomes fully greedy as $\epsilon \to 0$

Exploration is externally imposed rather than integrated into optimisation.

Entropy-Regularised Exploration (PPO)

PPO includes an entropy bonus in the objective:

$$L = L^{CLIP} + \beta \mathbb{E}[H(\pi_\theta(\cdot\,|s))]$$

where entropy is defined as:

$$H(\pi) = -\sum_a \pi\,(a|s)\log\pi(a|s)$$

This mechanism:

- Encourages stochastic policies early in training
- Gradually reduces randomness
- Couples exploration with optimisation

Unlike epsilon-greedy, exploration is intrinsic to the learning objective.

6.5 Conceptual Summary

In summary, value-based methods optimise an approximation of the value function and derive the policy implicitly through action maximisation. This structural reliance on the max operator and bootstrapping introduces overestimation bias and makes deep value-based methods particularly sensitive to instability when combined with function approximation and off-policy learning. In contrast, policy-based methods directly parameterise and optimise the policy, avoiding explicit maximisation over value estimates and thereby reducing structural sources of instability. PPO further improves stability through its clipped surrogate objective, which constrains policy updates, and through Generalised Advantage Estimation, which manages the bias-variance trade-off in gradient estimates. Regarding exploration, epsilon-greedy strategies impose external and uninformed randomness that vanishes as epsilon decays, whereas entropy-regularised exploration integrates stochasticity directly into the optimisation objective, allowing exploration to adapt naturally as learning progresses. Overall, these theoretical differences explain why PPO typically exhibits smoother and more stable learning dynamics compared to DQN in complex environments.