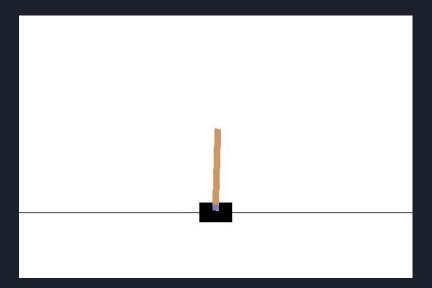


Group 9

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Introduction

• CartPole-v1¹



¹https://gym.openai.com/envs/CartPole-v1/

REINFORCE

- Monte-Carlo Policy Gradient
- On-policy
- Actor-only
- Estimates the policy directly

Implementation from Ching -Yao Chuang¹

¹https://github.com/chingyaoc/pytorch-REINFORCE

Advantage Actor Critic (A2C)¹

- On-Policy
- Actor Critic Method
 - Actor: selects action, updates the policy in the direction suggested by the Critic
 - Critic: critiques the action selected, providing feedback on how to adjust
- Concept of Advantage
- Implementation based on Dongmin Lee's code²

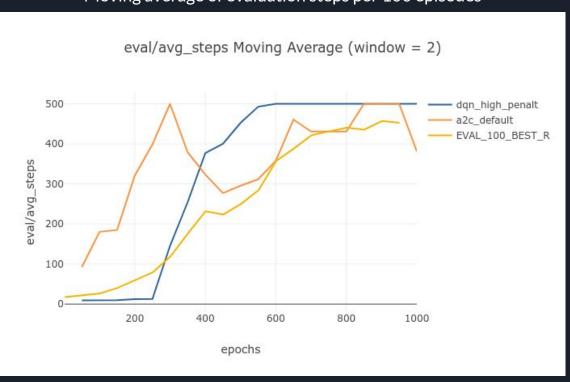
¹https://arxiv.org/abs/1602.01783

Deep Q Networks (DQN)¹

- Off-policy
- Use neural networks to approximate the Q function
- Replay Memory plus epsilon-greedy exploration to help training

Non-Linear Function Approximators

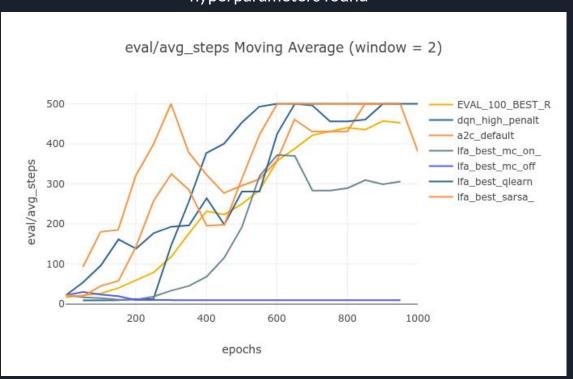
Moving average of evaluation steps per 100 episodes



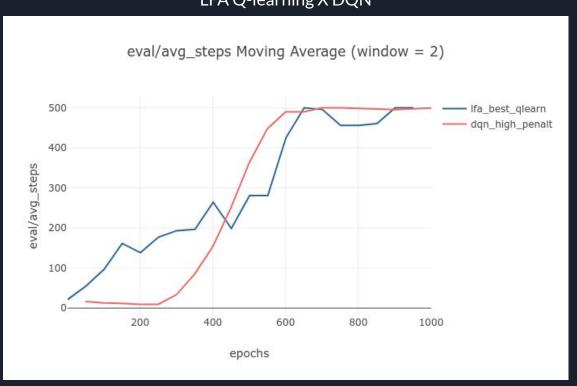
Training and evaluation duration of all methods



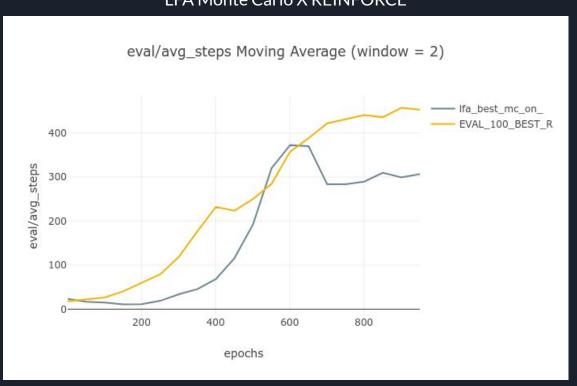
Moving average of steps over 100 episodes for all methods with best hyperparameters found



LFA Q-learning X DQN



LFA Monte Carlo X REINFORCE



Conclusion

- Three potential methods to solve CartPole problem
- DQN and Actor-Critic performed better
- REINFORCE is faster, but has high variance
- For simple problems, like Cartpole, LFA can perform better than deep RL

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