Q Learning and Deep Q Network

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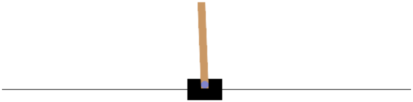
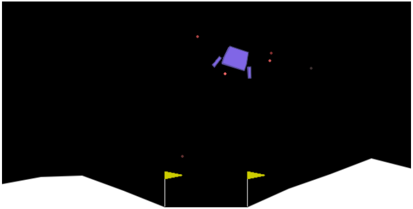
Games

CartPole



Lunar Lander



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- Q Learning
  - Model-free reinforcement learning algorithm
  - Uses a table to store Q values for each state-action pair
  - Effective in simple environments
  - Struggles in more complexe environments since it is impractical to store and update Q values for all the state-action pairs
- Deep Q Network (DQN)
  - Uses neural networks to learn policies to map states to Q values
  - Neural networks can handle large state spaces and continuous action spaces

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Q Learning

- Impractical to store all Q values for a continuous observation space
- Discretization needed
- Hyperparameters used for Q Learning
  - Discount factor $\gamma = 0.99$
  - Start epsilon of 1
  - End epsilon of 0.001
  - Epsilon decay of 5^{-4}
  - 10 bins
  - learning rate of 0.25 and 0.005 for CartPole and Lunar Lander, respectively

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Q Learning Algorithm

Algorithm Q Learning(episodes, α, ϵ, γ)

Initialize $Q(s, a)$ for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$ arbitrarily
Set $Q(\mathit{terminal}, \cdot) = 0$ for all terminal states
for each episode in episodes **do**
    Initialize s
    $\mathit{done} \leftarrow$ False
    while not *done* **do**
        Choose $a \in \mathcal{A}$ from s using policy derived from Q
        Take action a and observe reward r and next state s'
        $Q(s, a) \leftarrow Q(s, a) + \alpha \left[r + \gamma \max_a Q(s', a) - Q(s, a)\right]$
        $s \leftarrow s'$
    end while
end for

DQN Algorithm Setup

- Implementation of `ReplayMemory`, which acts as a replay buffer
- Implementation of deep neural network
  - Two hidden layers, each with 128 units
  - ReLU activation function
  - Adam's optimizer
  - Huber loss

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DQN Algorithm

Algorithm DQN(episodes, $\alpha, \epsilon, \gamma, C$)

Initialize replay buffer $\mathcal{D}$ with maximum capacity 100000
Initialize policy network Q with random weights θ
Initialize target network $\tilde{Q}$ with random weights $\tilde{\theta}$
for each episode in episodes **do**
    Initialize s
    Set $t \leftarrow 0$
    $done \leftarrow$ False
    while not $done$ **do**
        Choose $a \in \mathcal{A}$ from s using policy network Q
        Take action a and observe reward r, next state s' and $done$
        Store transition $(s, a, r, s', done)$
        Sample a minibatch of random transitions $(s, a, r, s', done)$ from $\mathcal{D}$
        Set $\hat{y} = \begin{cases} r & \text{if } s \text{ is a terminal state} \\ r + \gamma \max_a \tilde{Q}(s', a; \tilde{\theta}) & \text{otherwise} \end{cases}$
        Perform gradient descent on $(\hat{y} - Q(s, a; \theta))^2$ w.r.t. the policy network parameters θ
        if $t \bmod C = 0$ **then**
            $\tilde{Q} \leftarrow Q$
        end if
    end while
end for

- Discount factor $\gamma = 0.99$
- Learning rate 0.003
- Start epsilon of 1
- End epsilon of 0.01
- Epsilon decay of 5^{-4}
- $\tau = 0.005$
- Default batch size of 64

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        end if
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end for

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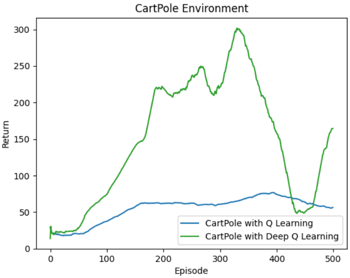
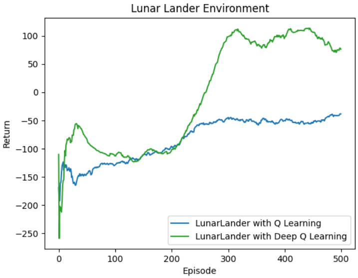
Plots



(a) CartPole



(b) Lunar Lander

Figure: 500 training episodes for Q Learning and DQN. Returns are averaged over the last 100 episodes.

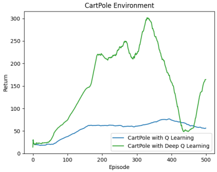
CartPole

DQN

- Learns much quicker than Q Learning
- Reached an average return of 300 at around 300 episodes
- Unstable learning process: significant drop at episode 350
- Agent is possibly trying to escape a local minimum

Q Learning

- Learns much slower compared to DQN
- Not great returns, even after 500 training episodes
- Agent might be stuck in a local minima



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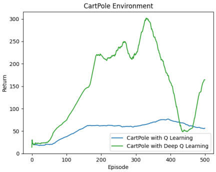

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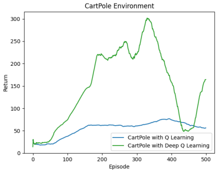

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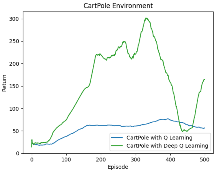

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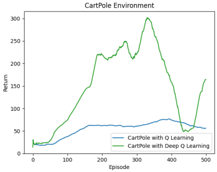

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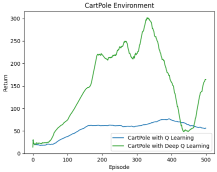

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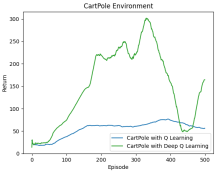

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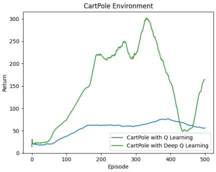

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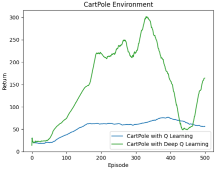

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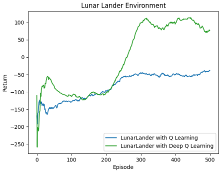
  Instead, the average return slowly increases



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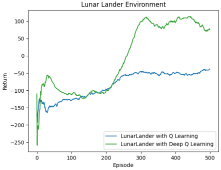

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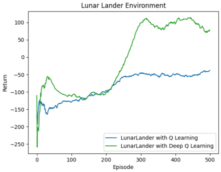

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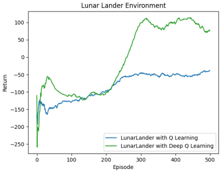

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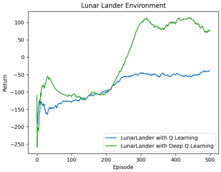

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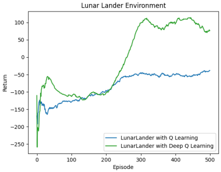

Conclusion

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- Learns much faster in both games, but the agent exhibited some instability during the learning process

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- Learns much slower, but more steadily

The choice of algorithm depends on the specific application and trade-offs between speed and stability.

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Future Work

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- Combines Q Learning with policy gradients to learn a deterministic policy directly
- This has shown to be effective in continuous action spaces and could address some of the instability issues observed in DQN.

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