CSE 4/546: Reinforcement Learning

Self-driving cars

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DDQN Agent after 250 episodes of training

Car Racing - OpenAI Gym

Action Space	:	Discrete(Throttle, Left, Right, Brake, No movement)
Observation space	:	(96x96) RGB images
Each episode	:	1000 frames
Reward	:	1000 - 0.1*(x)

Q-learning

Loop for each step of episode:

Choose A from S using policy derived from Q (e.g., ε-greedy)

Take action A, observe R, S'

$$Q(S,A) \leftarrow Q(S,A) + \alpha\left[R + \gamma \max_a Q(S',a) - Q(S,A)\right]$$

$S \leftarrow S'$

until S is terminal

Target

Prediction

Immediate Reward

loss

Deep Q-Network(DQN)

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N

Initialize action-value function Q with random weights θ

Initialize target action-value function $\hat{Q}$ with weights $\theta^{-} = \theta$

For episode = 1, M **do**

  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$

  For $t = 1$,T **do**

    With probability ε select a random action a_t
    otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$

    Execute action a_t in emulator and observe reward r_t and image x_{t+1}

    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$

    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D

    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^{-}) & \text{otherwise} \end{cases}$

    Perform a gradient descent step on $\left(y_j - Q(\phi_j, a_j; \theta)\right)^2$ with respect to the network parameters θ

    Every C steps reset $\hat{Q} = Q$

  End For

End For

Double Deep Q-Network(DDQN)

Algorithm 1: Double DQN (Hasset et al. 2015

Initialize primary network Q_θ, target network $Q_{\theta'}$, replay buffer $\mathcal{D}$, $\tau < 1$, C
for *each iteration* **do**
  for *each step* **do**
    Observe state s_t and select $a_t \sim \pi(s_t)$
    Execute action a_t and observe next state s_{t+1} and reward r_t;
    Store transition (s_t, a_t, r_t, s_{t+1}) in replay buffer $\mathcal{D}$.
  end
  for *each update step* **do**
    Sample minibatch of transitions $(s_t, a_t, r_t, s_{t+1}) \sim \mathcal{D}$
    Compute target Q value:

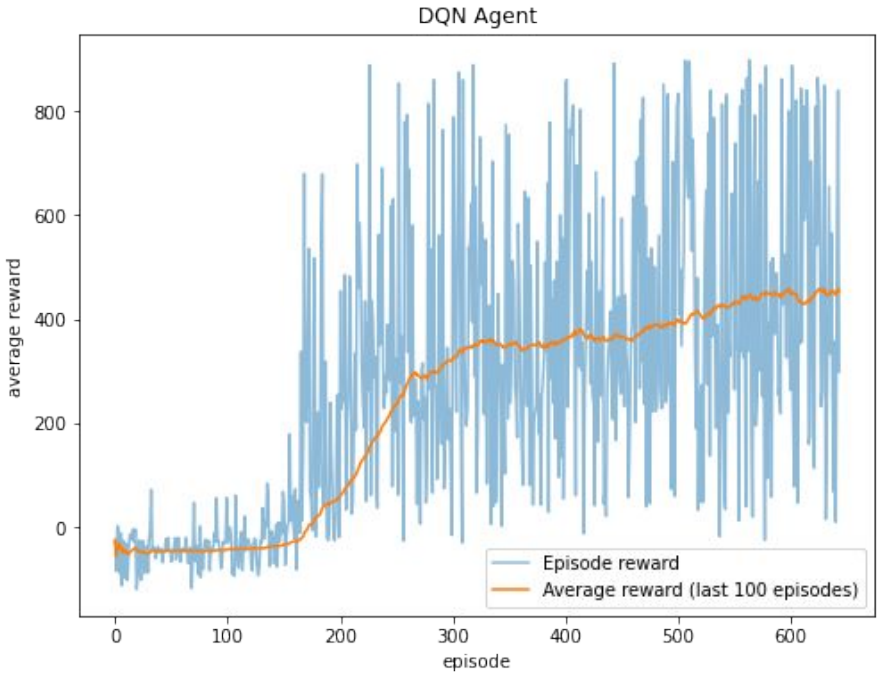
$$Q^*(s_t, a_t) = r_t + \gamma Q_{\theta'}(s_{t+1}, \arg\max_{a'} Q_\theta(s_{t+1}, a'))$$

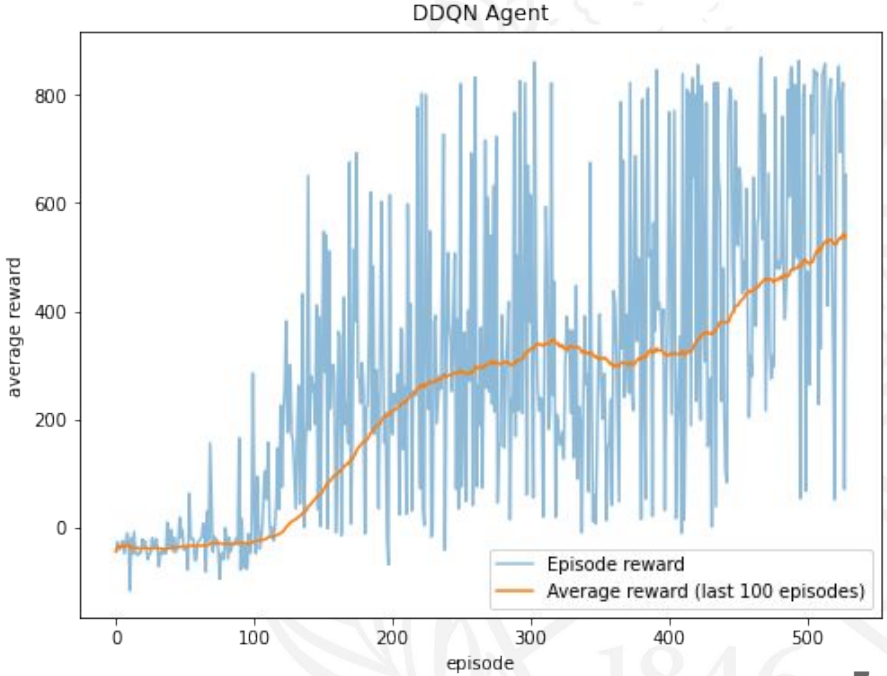
    Perform a gradient descent step on $(Q^*(s_t, a_t) - Q_\theta(s_t, a_t))^2$ with respect to the primary network parameters θ
    Every C steps update target network parameters:

$$\theta' \leftarrow \tau * \theta + (1 - \tau) * \theta'$$

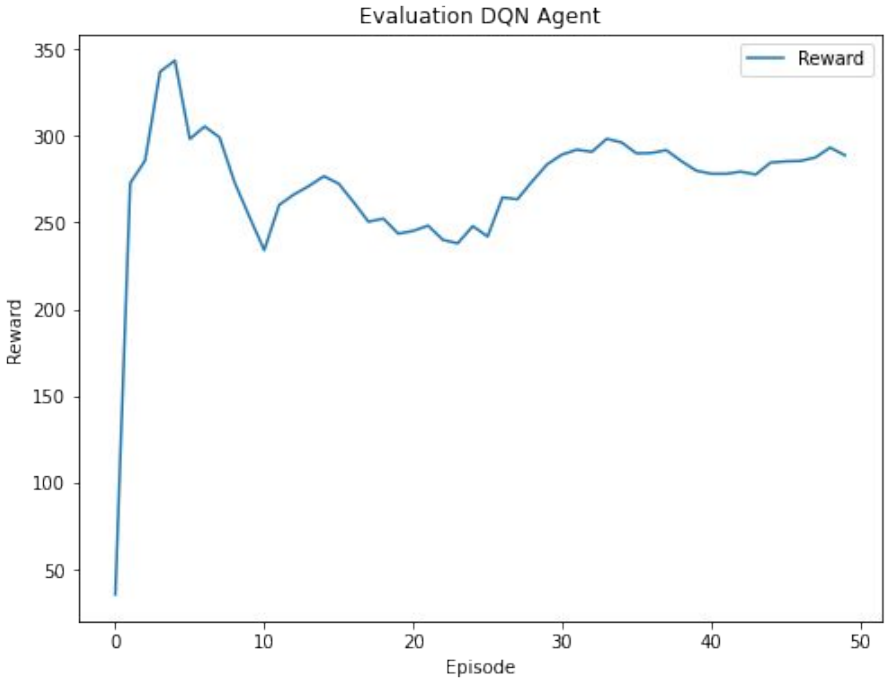
  end
end

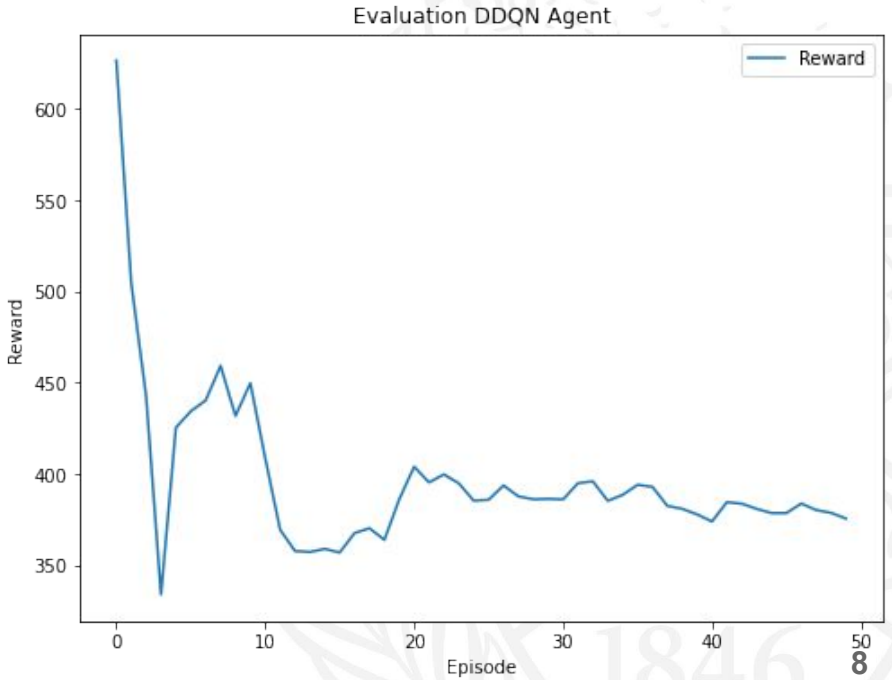
Training: DQN vs DDQN





Evaluation: DQN vs DDQN





3 Basic Approaches of RL

- Value Based
- Policy Based
- Model Based

  - Optimizing the policy Pi from the goal.
  - Best in Continuous Space and High Dimensional Space
  - It Follows Policy gradient trying to find the best parameters and smooth the update each step.
  - It does not need explore exploit strategies, as it uses stochastic policies.
  - Here we don’t need a value function that tells us the expected sum of rewards given a state and action. Here we try to find the policy function that will tell us the action directly as it maps actions to state.

Policy Optimization Method

- This method does not need any replay buffer to store the experience.
- We update the policy with one batch of experience and discard the batch.
- We need to define the policy gradient laws as this.

Loss Function:

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

Algorithm

$$A_\pi(s,a) = Q_\pi(s,a) - V_\pi(s), \text{ where } a_t \sim \pi(a_t|s_t), s_{t+1} \sim P(s_{t+1}|s_t, a_t), \text{ for } t \geq 0$$

Algorithm 5 PPO with Clipped Objective

Input: initial policy parameters θ_0, clipping threshold ϵ

for $k = 0, 1, 2, \ldots$ **do**

Collect set of partial trajectories $\mathcal{D}_k$ on policy $\pi_k = \pi(\theta_k)$

Estimate advantages $\hat{A}_t^{\pi_k}$ using any advantage estimation algorithm

Compute policy update

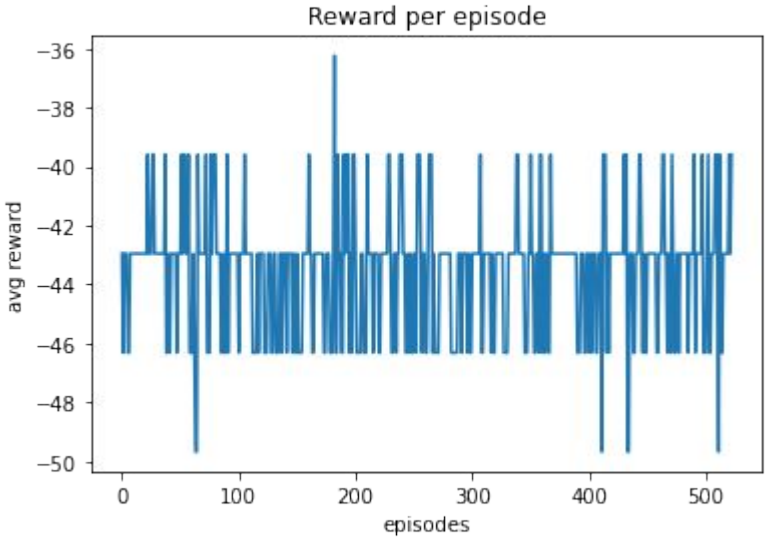
$$\theta_{k+1} = \arg\max_\theta \mathcal{L}_{\theta_k}^{CLIP}(\theta)$$

by taking K steps of minibatch SGD (via Adam), where

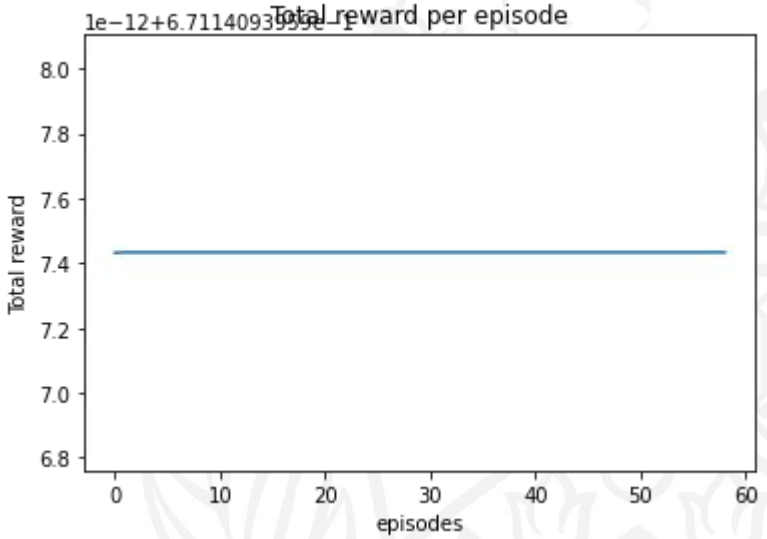
$$\mathcal{L}_{\theta_k}^{CLIP}(\theta) = \mathop{\mathrm{E}}_{\tau \sim \pi_k}\left[\sum_{t=0}^{T}\left[\min(r_t(\theta)\hat{A}_t^{\pi_k}, \text{clip}\left(r_t(\theta), 1-\epsilon, 1+\epsilon\right)\hat{A}_t^{\pi_k})\right]\right]$$

end for

Training the agent for 500 Episodes



Evaluating the agent for 60 Episodes



Contribution

- DQN and DDQN - Arjun Ramesh Kaushik (kaushik3)
- PPO - Ritesh Manchikanti (vmanchik)

References

- https://arxiv.org/abs/1509.06461
- https://www.gymlibrary.dev/
- https://www.youtube.com/watch?v=vQ_ifavFBkI
- https://arxiv.org/pdf/1707.06347.pdf
- Lecture Slides

THANK YOU