
MLDS 490 Lab 5

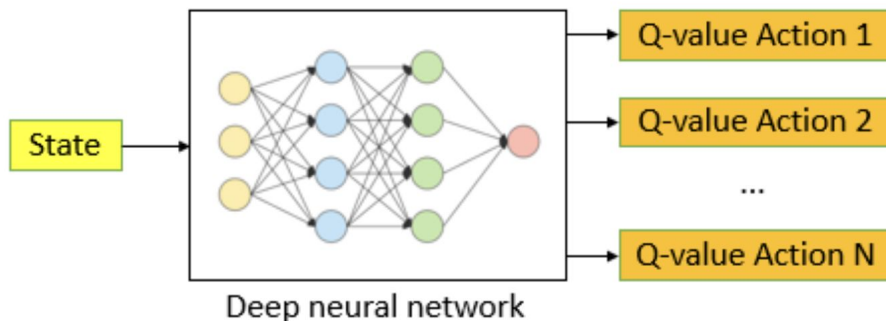
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Deep Q-Network

Recall the definition of **Q-factor** (or Q-function, action value function)

$$Q(s, a) = r(s, a) + \gamma \max_{a'} \mathbb{E}_{s' \sim p(s'|s, a)} Q(s', a')$$

Deep Q-Network algorithm models the Q-function using a deep neural network, which outputs a vector of Q-values (one number for each action).



Epsilon-Greedy Policy

No policy *network* is used for DQN. We follow a policy using the Q-function:
At each time step t , take an action

$$a_t = \begin{cases} \text{randomly selected action } a & \text{with probability } \epsilon \\ \operatorname{argmax}_a Q(s_t, a) & \text{with probability } 1 - \epsilon \end{cases}$$

How to select $\max Q(s, a)$ with a Q-Network?

with probability $1 - \epsilon$:

1. Do a forward pass of the Q-Network with input s_t : $Q_\theta(s_t)$
2. From the output vector $v_t = [Q(s_t, a_1), \dots, Q(s_t, a_N)]$ select the action with the **maximum Q-value**

Deep Q-Network

Algorithm 1 Deep Q-Network

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1: Initialize Q-network weights  $\theta$ 
2: Initialize the replay buffer  $\mathcal{B}$  with capacity  $D$ .
3: Initialize target network  $\hat{Q}_{\theta'}$  weights  $\theta' = \theta$ 
4: for episode=1, ...,  $M$  do
5:   for  $t = 1, \dots, T$  do
6:     Based on the current state  $s_t$ , choose action  $a_t$  according to  $\epsilon$ -Greedy policy.
7:     Take action  $a_t$ , collect a tuple  $(s_t, a_t, r_t, s_{t+1})$  and add to the replay buffer  $\mathcal{B}$ .
8:     Randomly sample a mini-batch of tuples  $\mathcal{S} = \{(s_i, a_i, r_i, s_{i+1})\}$  from the replay buffer  $\mathcal{B}$ .
9:     for each tuple  $(s_i, a_i, r_i, s_{i+1})$  in the batch  $\mathcal{S}$  do
10:      Compute  $y_i$ :
11:      if episode terminates after step  $i$  then
12:         $y_i = r_i$ 
13:      else
14:         $y_i = r_i + \gamma \max_{a'} \hat{Q}_{\theta'}(s_{i+1}, a')$  using the target network with weights  $\theta'$ 
15:      end if
16:    end for
17:    Update  $\theta$  by taking an optimization step on the loss  $L(\theta) = \sum_i (Q_\theta(s_i, a_i) - y_i)^2$ 
18:    Update  $\theta'$  after every  $N$  optimization steps.
19:  end for
20: end for
```

Key components

- Q-network
- Replay buffer: deque (`from collections import deque`)
- Target network

About deliverables:

1. Q plot: for each episode, compute the **average** of **max Q values** in this episode, and plot it against the number of episodes.
2. Reward plot: plot the sum of rewards (without discounting) in an episode, overlay with the moving average.

