Udacity Deep Reinforcement Learning Nanodegree

Project #1 Navigation

Report

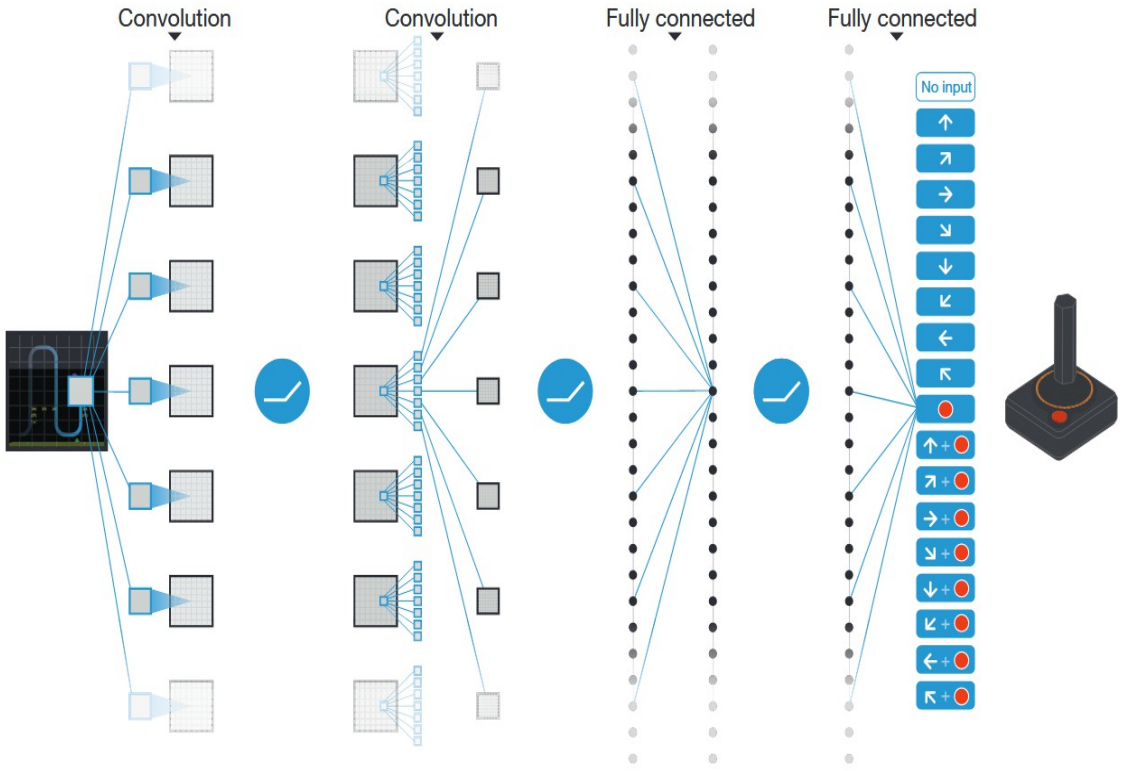
1. Learning Algorithm

The algorithm implemented is a *Deep Q-Network algorithm*, that is, an algorithm which approximates the state-value Q function with the use of a Neural Network.

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\left[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)\right]$$

Source: Sutton and Barto, Reinforcement Learning, 2nd Edition

Such algorithm usually takes as input several frames of the game and outputs the state values for each action, and the network is composed of Convolutional and Fully Connected layers, as shown below.



Source: https://storage.googleapis.com/deepmind-media/dqn/DQNNaturePaper.pdf

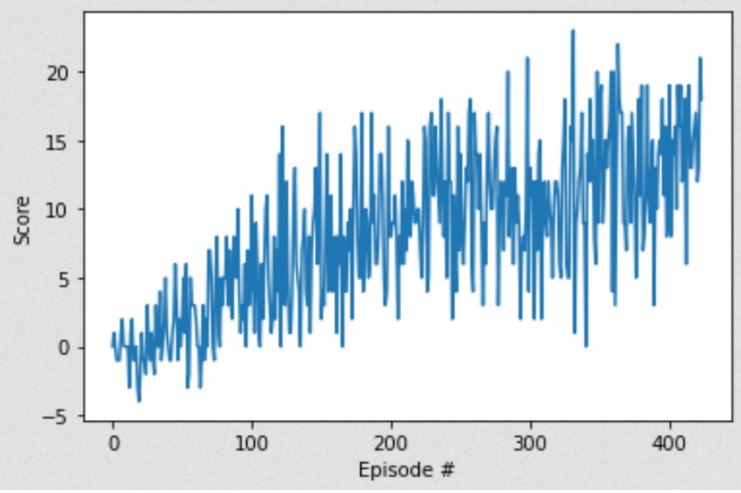
In this particular implementation, however, the input state is a vector containing information from the agent observing the environment and the network is composed of two Fully Connected layers (of size 128 and 64) without the Convolutional ones, as this was enough to solve the provided environment and in order to keep the implementation simple and straightforward.

The algorithm uses the Experience Replay optimization, for storing the episode steps in memory for off-policy learning, where samples are drawn from the replay memory at random. Additionally, the Q-Network is optimized towards a frozen target network that is updated using a soft-update strategy with the use of an hyperparameter. The latter makes training more stable by preventing short-term oscillations from a moving target. The former tackles autocorrelation that would occur from on-line learning, and having a replay memory makes the problem more like a supervised learning problem.

For solving the environment, the hyperparameters have been chosen as following:

- **GAMMA** (discount factor): 0.99
- **TAU** (for soft-update of target parameters): 1e-3
- **LR** (learning rate): 5e-4
- **BUFFER_SIZE** (replay buffer size): 1e5
- **BATCH_SIZE** (minibatch size): 64
- **EPS_DECAY_RATE** (decay rate for epsilon value): 0.95 (ranging from 1.0 to 0.01)

2. Plot of Rewards



Plot of rewards over episodes.

The agent was able to solve the environment (i.e. get *an average reward of +13 over 100 consecutive episodes*) in **324** episodes.

3. Ideas for Future Work

There are many possible improvements for the DNQ algorithm:

1. Double DQN: Deep Q-Learning tends to overestimate action values. Double Q-Learning has been shown to work well in practice to help with this.
2. Prioritized Experience Replay: Deep Q-Learning samples experience transitions *uniformly* from a replay memory. Prioritized experienced replay is based on the idea that the agent can learn more effectively from some transitions than from others, and the more important transitions should be sampled with higher probability.
3. Dueling DQN: Currently, in order to determine which states are (or are not) valuable, we have to estimate the corresponding action values *for each action*. However, by replacing the traditional Deep Q-Network (DQN) architecture with a dueling architecture, we can assess the value of each state, without having to learn the effect of each action.
4. Rainbow extensions.

Last, but not least, the use of pixels as input would be a nice to have feature, updating the Neural Network in order to accommodate some initial Convolutional Layers as needed.

4. Sources

- **https://paperswithcode.com/method/dqn**
- **http://incompleteideas.net/book/RLbook2020.pdf**
- **https://storage.googleapis.com/deepmind-media/dqn/DQNNaturePaper.pdf**
- **https://github.com/udacity/deep-reinforcement-learning/tree/master/p1_navigation**