Report - Navigation Project (P1)

Udacity - Deep Reinforcement Learning Nanodegree

For: **Narendra Devta Prasanna**

Date: 01/26/2019

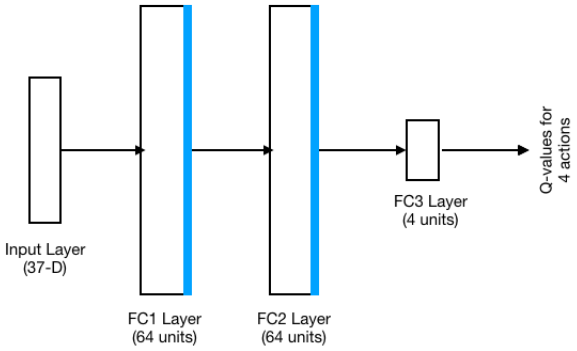
For this project, we have to train an agent using DQN to pick yellow bananas and avoid purple bananas in the 'Banana' Unity-ML environment. We train the agent using three DQN approaches that all use DNN for state-action value estimation.

The state observation is in the form of a 37-D state vector. The state action space consists of 4 discrete actions: walk forward, walk backward, turn left and turn right. More details are in the README.md file provided as part of the project description.

Implementation:

The first implementation uses the vanilla DQN approach [Minh 15] as outlined in the Nature-2015 paper. It utilizes an experience replay buffer and distinct DNN networks for Q-target and Q-local. The code for this implementation and the hyperparameters are directly re-used from the course assignment that was used for solving OpenAI's Lunar-lander environment.

The DNN architecture is also adapted directly from the same course project and consists of a 3-layer MLP (input layer + 2 hidden layer + output layer). Figure below depicts the MLP network used for Q-value estimation. FC1 and FC2 layers have ReLU activation whereas no activation is applied to the output of FC3 and it's output (4-D vector) is directly used to estimate the Q-value for the 4 possible actions.



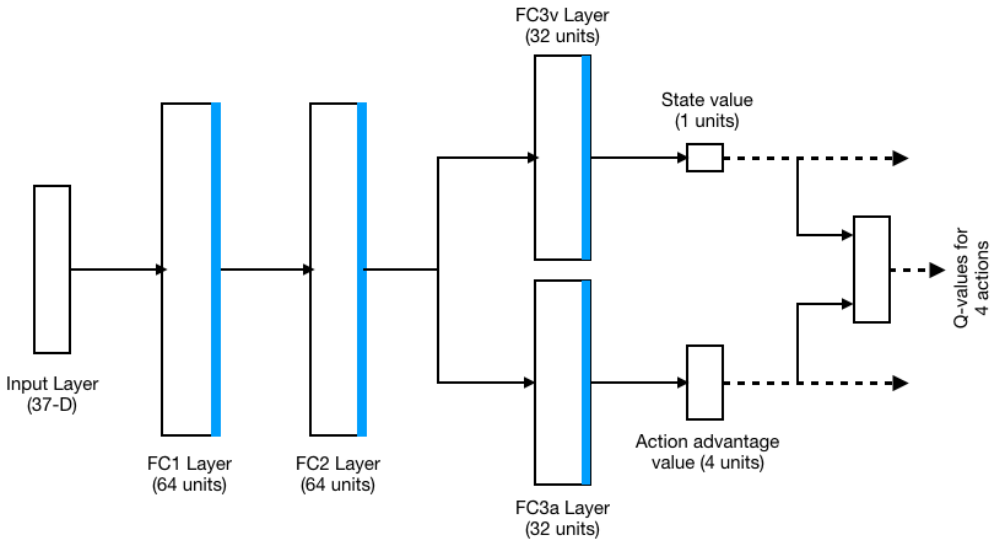
Python notebook	Navigation_dqn.ipynb
Model	model_dqn.py
Agent	dqn_agent.py
Trained network weights	model_dqn.pt

The second implementation is based on the Double DQN (DDQN) approach [Hasselt 15]. Function approximation techniques, especially those that utilize bootstrapping such as the TD(0) based approach used here, tend to suffer from overestimation of the state-action value function which can result in sub-optimal learning. To alleviate this, when the target Q-value is calculated, two different networks are used to first determine the optimal action and then to determine the action value. In this case, the action to be taken is determined from the local network and the Q-value of that action is derived from the target network. The DNN architecture is the same MLP as that used for DQN implementation above.

Python notebook	**Navigation_ddqn.ipynb**
Model	model_ddqn.py
Agent	ddqn_agent.py
Trained network weights	model_ddqn.pt

The third and final implementation is based on the dueling network architecture [Wang 16] and also combined with the DDQN approach. The dueling network architecture explicitly separates the representation of the state value and the action advantage (state-dependent) value while sharing a common feature learning network. The separation between state value and action advantage representation leads to more frequent updates to the value function and thus faster learning and also more robust learning resulting in a more optimal policy.

The DNN architecture for dueling network is shown below. It has a common feature trunk consisting of two hidden layers (FC1 and FC2). The output of the feature estimator feeds two parallel branches consisting of one hidden layer (FC3v and FC3a respectively) and an output layer each for state value estimate and action-advantage value estimate. The state-value and action advantage values are used to calculate the state-action values as part of the network itself.



Python notebook	Navigation.ipynb / Navigation_dueling_ddqn.ipynb
Model	model.py / model_dueling_ddqn.py
Agent	dueling_ddqn_agent.py
Trained network weights	model.pt / model_dueling_ddqn.pt

Hyperparameters:

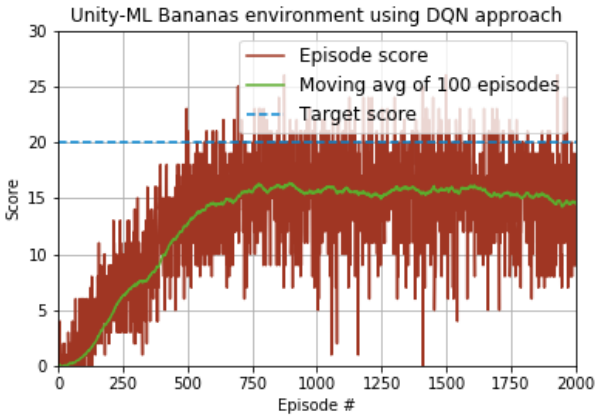
The following hyperparameters are used for training all the 3 agents.

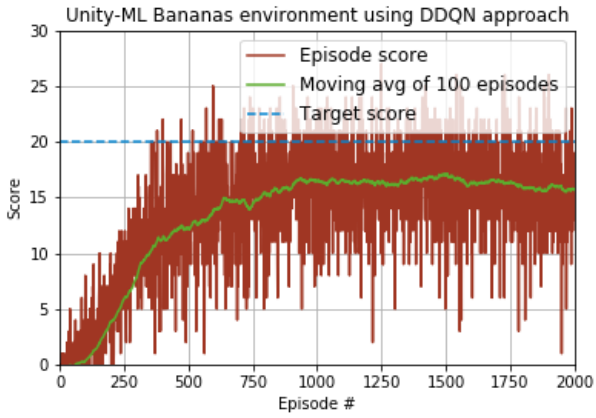
Hyperparameter	Description	Value
BUFFER_SIZE	Size of experience replay buffer	1E+05
BATCH_SIZE	Number of experiences used for single pass of training	64
GAMMA	Discount factor	0.99
TAU	Update factor to update target network parameters from local network parameters	1E-03
LR	Learning rate for updating local network	5E-04
UPDATE_EVERY	Number of experiences frequency for learning/ updating local network	4

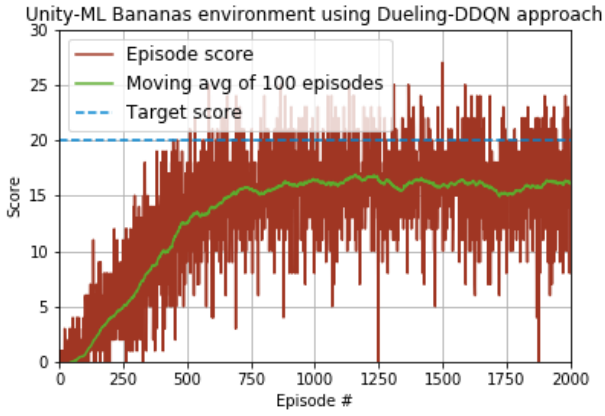
Training and Results:

First, each of the three implementations is let to run for 2000 episodes and the maximum agent score is observed as well as the learning. The score observed is the moving average over the past 100 episodes. From these trial runs it is observed that both DQN and DDQN implementations achieve a maximum score (moving average of 100 episodes) of between 16 and 17. However, the score oscillates more in the case of DQN than for DDQN implementation. For the case of Dueling+DDQN implementation, the max score observed is between 17 and 18 which is higher than what is achievable for either DQN or DDQN approaches.

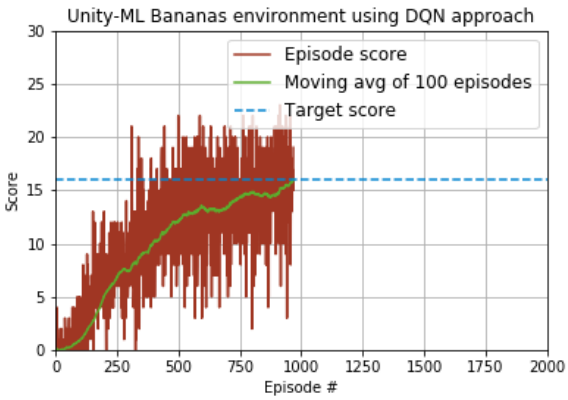
The learning curves from these first set of runs is shown in below graphs.

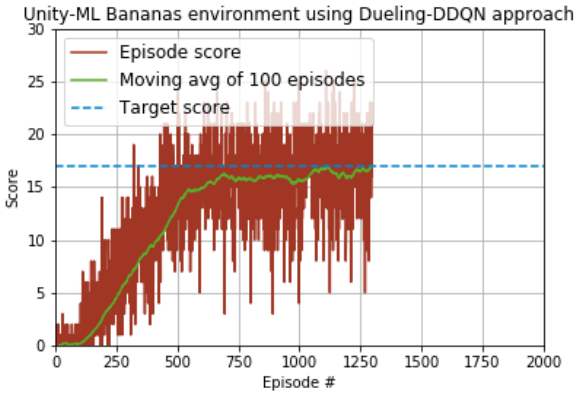


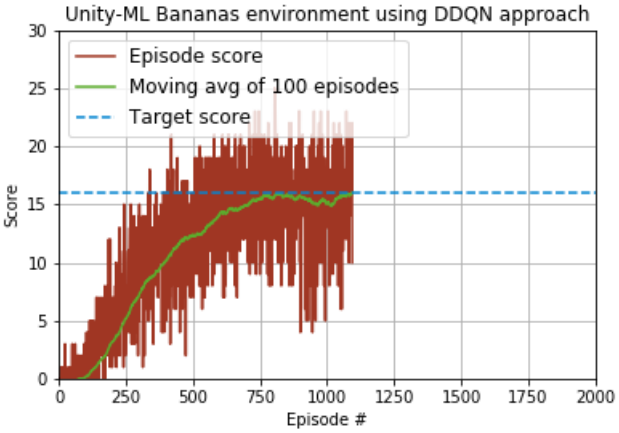




Then the agent is trained for a second time till it reaches the target score. The target score for DQN and DDQN is set to 16 and it is set to 17 for Dueling+DDQN implementation. The results are summarized in the table below. Training is done on a Mac-OS (High Sierra) machine with Nvidia GTX 780M GPU and Pytorch version 1.1. GPU is enabled for the training, and the plots show the learning curves for the three implementations.







Model	Run time (seconds)	Num. Episodes	Agent Score (moving avg of 100 episodes)
DQN	952	969	16
DDQN	1085	1095	16
Dueling+DDQN	1524	1299	17

Extensions:

In addition to the three implementations presented here, another technique that can be applied to this environment is the prioritized experience replay [Schaul 16] that has been shown to speed-up agent training when using DQN approaches.

Additionally, instead of reading the state space vector as currently provided by the environment, we can train the agent using the raw pixels (from the view point of the agent) to infer the current state of the environment and learn end-to-end from pixel observations to action determination without additional inputs from the environment.

References:

[Minh 15]: Human-level control through deep reinforcement learning, Vol 518, Nature, Feb 2015
[Hasselt 15]: Deep Reinforcement Learning with Double Q-learning, Dec 2015, Arxiv
[Wang 16]: Dueling Network Architectures for Deep Reinforcement Learning, Apr 2016, Arxiv
[Schaul 16]: Prioritized Experience Replay, Feb 2016, Arxiv