Project 1: Navigation

Project Details

For this project, I trained an agent to navigate (and collect bananas!) in a large, square world.

- A reward of +1 is provided for collecting a yellow banana, and a reward of -1 is provided for collecting a blue banana.
- The goal is to collect as many yellow bananas as possible while avoiding blue bananas, within 300 fixed timesteps.
- The state space has 37 continous dimensions and contains the agent's velocity, along with ray-based perception of objects around agent's forward direction.
- The action space is 1-dimensional, whose value has 4 discrete (0-indexed) options: move forward, move backward, turn left, turn right
- The task is considered solved when the agent gets an average score of +13 over 100 consecutive episodes (during training).

Getting Started

1. Download the environment from one of the links below. You need only select the environment that matches your operating system:
    - Linux: click here
    - Mac OSX: click here
    - Windows (32-bit): click here
    - Windows (64-bit): click here

   (*For Windows users*) Check out this link if you need help with determining if your computer is running a 32-bit version or 64-bit version of the Windows operating system.
   (*For AWS*) If you'd like to train the agent on AWS (and have not enabled a virtual screen), then please use this link to obtain the environment.
2. Place the file in the DRLND GitHub repository, in the `p1_navigation/` folder, and unzip (or decompress) the file.
3. Follow these instructions to install conda Python 3.6 env and create `drlnd` venv.
4. Navigate terminal to (unzipped) project directory, activate `drlnd` conda venv, and run `pip install -r requirements.txt` to install Python dependencies.

Instructions

Run all cells in `Navigation.ipynb` sequentially to both train and evaluate my DQN agent.

Report

The DQN implementation is heavily derived from DRLND's solution codebase from the previous lesson on DQN.

Learning Algorithm

I used the plain DQN implementation, with the following simple modifications:

- The Q Network model class now takes a list of `hidden_layers` rather than 2 layers of hard-coded 64 neurons each.
- All hyperparameters are exposed as constructor arguments for the DQN agent class.
- Instead of a geometric decaying exploration parameter epsilon, I used a linear decay procedure instead.

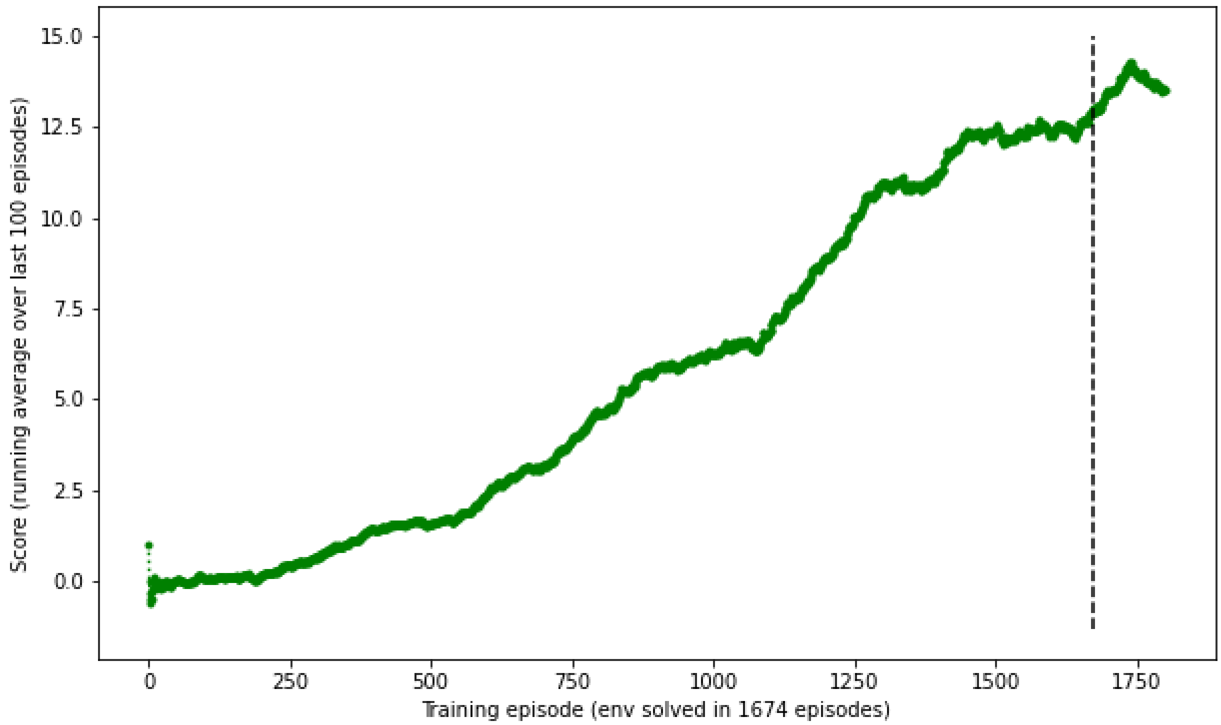
The chosen hyperparameters for the algorithm and training regime are as follows:

- number of episodes (`num_episodes`): 1800
- reproducible random seed (`seed`): 0
- discount factor for environment (`gamma`): 0.99
- number of neurons in each hidden layer (`hidden_layers`): (128, 64)
- learning rate (`lr`): 1e-3
- target network soft exponential update gain (`tau`): 1e-3
- training batch size (`batch_size`): 128
- do one step of backprop learning after every N env steps (`update_every`): 4
- replay memory buffer size (`buffer_size`): 300,000
- Initial epsilon exploration factor (`epsilon_decay_init`): 1.0
- Final epsilon exploration factor (`epsilon_decay_final`): 0.05
- Number of episodes for linear epsilon decay (`epsilon_decay_num_episodes`): 1500

In particular, the architecture of the Q network takes the state as input, has 2 fully-connected layers (MLP) with rectified linear unit (ReLU) activation, and a final linear layer that predicts the Q value for each of the 4 possible action values.

Plot of rewards

As shown below, my agent solved the environment in 1674 episodes (a.k.a. reached an average reward over 100 past episodes of at least +13).



Future Work Ideas

- Integrate training loop into Ray Tune and perform efficient automated hyperparameter tuning (e.g. using Bayesian Optimization, or Population-Based Bandits).
- Implement RAINBOW (a.k.a. tuned version of Double DQN, Dueling DQN, N-step TD targets, PER - Prioritized Experience Replay, C51 - Distributional DQN, NoisyNets - Noisy DQN).
- Further improve upon Distributional DQN formulation with QR-DQN - Quantile Regression DQN / IQN - Implicit Quantile Network / FPF - Fully Parametrized Quantile Function.