Report

For the navigation project, we used a DQN model to determine the best action at each step.

Model architecture:

This model had a basic architecture of 2 fully connected neural networks with 64 nodes in each layer. The activation function used after each hidden layer is a RELU. The used architecture is the vanilla DQN model.

Hyperparameters:

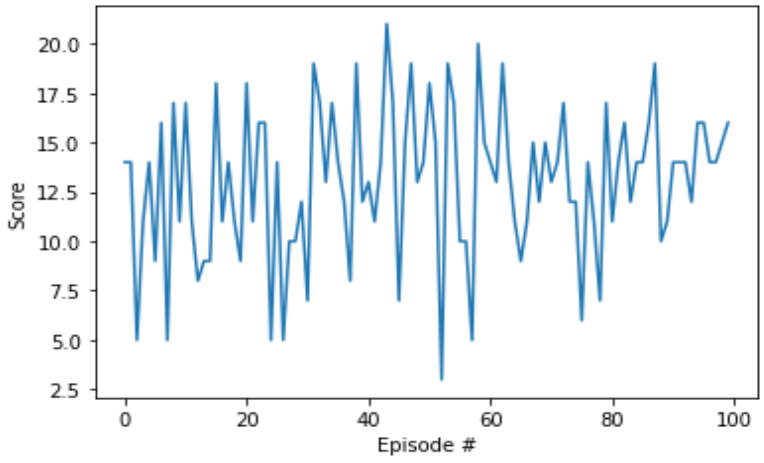
We initialized our variables to:

```
BUFFER_SIZE = 10000     # replay buffer size
BATCH_SIZE = 64         # minibatch size
GAMMA = 0.99            # discount factor
TAU = 1e-3              # for soft update of target parameters
LR = 5e-4               # learning rate
UPDATE_EVERY = 4
eps_start = 1.0         # starting value of epsilon, for epsilon-
greedy action selection
eps_end=0.01            # minimum value of epsilon
eps_decay=0.995         # multiplicative factor (per episode) for decreasing e
psilon
```

The maximum average score to reach before exiting the learning loop and save the checkpoint was initialized to 13.

Training the model with those variables had this output:

```
Episode 100     Average Score: 1.06
Episode 200     Average Score: 4.71
Episode 300     Average Score: 8.42
Episode 400     Average Score: 10.32
Episode 497     Average Score: 13.02
Environment solved in 397 episodes!     Average Score: 13.02
```



Next steps

The agent with a vanilla DQN was able to reach the 13 rewards but we got to aim higher. Trying a more complex model architecture could improve significantly the performance.

Here are the next step for this project:

- Add multiple models in different python files:
    - Rainbow: Combining Improvements in Deep Reinforcement Learning
    - Double DQN
    - Dueling DQN
    - Prioritized experience replay
- Make running a model configurable (choose the model to run from the config file)
- Make a scoring function based on the number of steps to reach a certain score and the best score a model can achieve to choose the best model.