## Report

## **Learning Algorithm**

I used Deep Q-Learning with fixed Q-targets and experience replay to train the agent.

The architecture for the Agent's network was chosen as follows (two hidden layers):

Layer	Туре	Size	Activation
0	Input	1x37	None
1	Fully Connected	37x128	ReLU
2	Fully Connected	128x64	ReLU
3	Output	64x4	None

In order to facilitate exploration an expontentially decaying epsilon was used. Beginning at 1.0, going down until 0.01.

Hyperparameters used in DQN algorithm:

• Max no. of episodes: 1000

• Starting epsilion: 1.0 • Ending epsilion: 0.01

• Epsilion decay rate: 0.995

• Memory size: 10.000

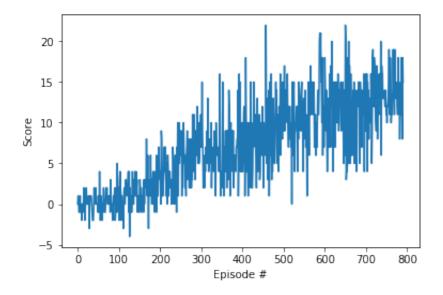
• Sample size: 50

• No. of steps until target network gets updated: 10

• Discount factor for future rewards: 0.9

## Plot of rewards

Giving the outlined hyperparameters I was able to achieve the target average reward of 13 in 756 episodes.



```
Episode 100 Average Score 0.05
Episode 200 Average Score 1.31
Episode 300 Average Score 4.58
Episode 400 Average Score 5.15
Episode 500 Average Score 6.13
Episode 600 Average Score 8.82
Episode 700 Average Score 10.18
Episode 800 Average Score 11.65
```

Environment solved in 756 episodes!

Average Score: 13.06

## **Ideas for Future Work**

In general, there are different directions that could be explored to improve on the results, e.g. to improve the speed of learning:

- 1. Extensive hyperparameter optimization (Network architecture, etc.)
- 2. Improved versions of DQN
  - Double DQN
  - Prioritized Experience Replay
  - Dueling DQN
  - Rainbow
- 3. Trying different state representations (including learning from pixels)