Deep Reinforcement Learning – Collaboration Competition

Overview

The goal of this project is to achieve an average reward of at least +0.5 over 100 episodes in the environment. This is calculated by taking the maximum score from the two agents which is added up without discounting at the end of the episode

The environment consists of two agents that control racquets to bounce a ball over a net.

A reward of +0.1 is given to an agent if it hits the ball over the net. If an agent lets a ball hit the ground or hits the ball out of bounds, it receives a reward of -0.01. The goal of each agent is to keep the ball in play.

The state space consists of 8 variables corresponding to the position and velocity of the ball and racquet. Each agent receives its own, local observation.

The action space is two continuous actions, corresponding to movement toward (or away from) the net, and jumping.

Implementation

The project was solved using Deep Reinforcement Learning, more specifically using Multi-Agent Deep Deterministic Policy Gradient or MADDPG. The code was based upon the ddpg-bipedal and ddpg-pendulum example from the Udacity Deep Reinforcement Learning GitHub repo. This was modified and updated to work with the Unity-ML environment and extended with new model architecture. Some of the code was separated out to modules, for example ReplayBuffer class in memory.py.

The Jupyter notebook results.ipynb contains the implementation for training the agent in the environment.

Agent.py contains a DDPG agent which interacts with the environment to optimize the reward.

Memory.py contains the Replay Buffer which is used by the Agent to record and sample a (state, action, reward, next_state) tuples for training the model.

Model.py contains the Actor and Critic Neural Network Class which takes in the input state and outputs the desired Q-values

Noise.py contains the OUNoise Class which contains the Ornstein-Uhlenback process which adds noise to actions.

Learning algorithm

The Deep Deterministic Policy Gradient algorithm (https://arxiv.org/abs/1509.02971) was chosen to solve the environment. It is an Actor-Critic method but could be called an approximate DQN. This is because it is different to normal Actor Critic algorithms in that the Critic is used to approximate the maximizer over the Q-Values of the next state and not a learnt baseline. It uses a Replay Buffer and is Off-Policy and Model-Free. At its core, DDPG is a policy gradient algorithm that uses a stochastic behavior policy for good exploration but estimates a deterministic target policy, which is much easier to learn

Replay Buffer

One of the break throughs with the DQN architecture was the introduction of Experience Replay. This has been ported to the Actor-Critic method for the DDPG algorithm and works in the same way. It stores experiences in a Replay Buffer so that learning is separated and can take place on both the current experience and past experiences. This allows us to use Supervised Deep Learning techniques. This is done by randomly sampling the stored tuples in the Replay Buffer for training the model. The agent imports this class from memory.py as ReplayBuffer

Noise

OUNoise Class is used to add noise to actions to promote exploration. It uses the Ornstein-Uhlenback process to achieve this.

Model Architecture

Two Neural Network models are used in the DDPG algorithm. An Actor and a Critic network both with a Local and Target network each.

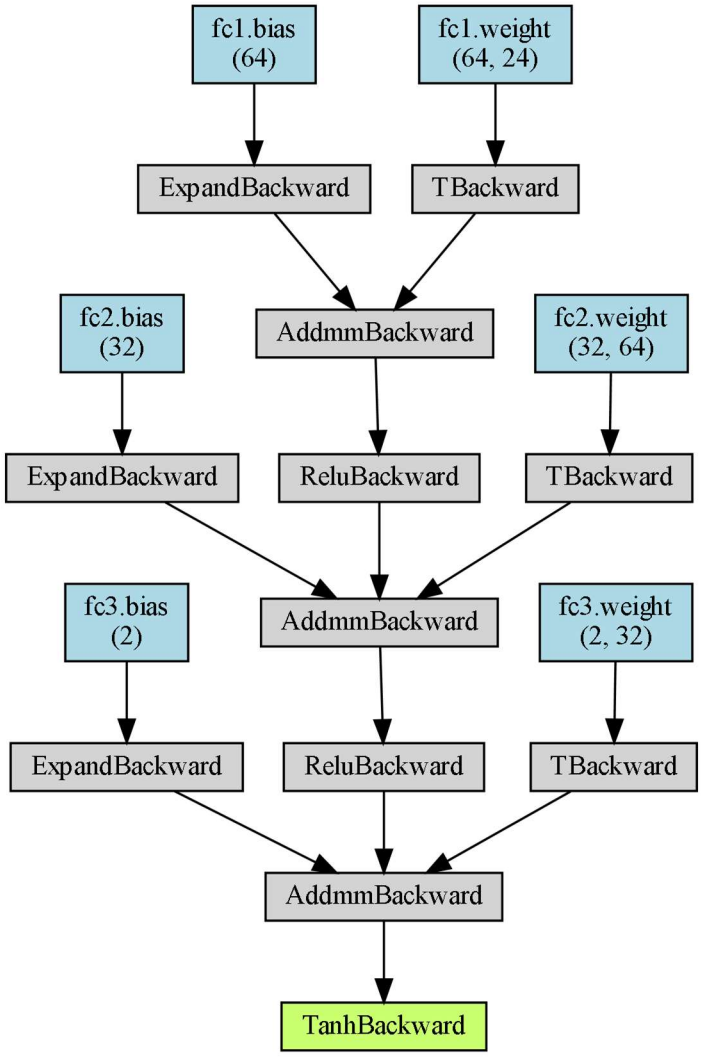
Actor Network

The Actor or Policy network maps states to actions

- The model has 3 fully connected layers

- The first layer takes in the state passes it through 64 nodes with Relu activation
- The second layer take the output from the first layer and passes through 32 nodes with Relu activation
- The third layer takes the output from the previous layer and outputs a single real value representing an action chosen from a continuous action space
- Adam optimizer is used.

The following diagram displays the Actor Network architecture



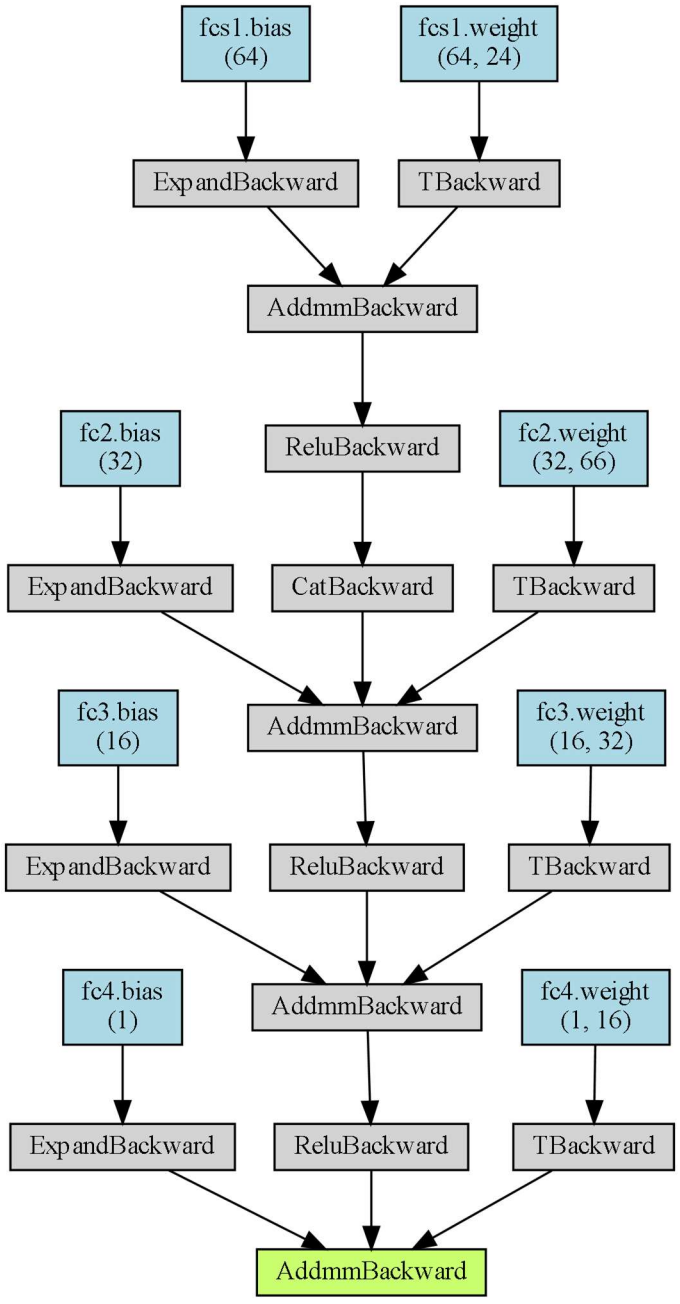
Critic Network

The Critic or Value network maps (state, action) pairs -> Q-values.

- The model has 4 fully connected layers
- The first layer takes the state and passes through 64 nodes with Relu activation

- Then we take the output from the first layer and concatenate it with the action size
- We then forward this to a second layer which passes it through 32 nodes with Relu activation
- The third layer takes the output from the previous layer and passes it through 16 nodes with Relu activation
- The Critic's output is estimated Q-value of the current state and of the action given by the actor
- Adam optimizer is used.

The following diagram displays the Critic Network architecture



Agent

The agent class in agent.py contains the DDPG algorithm. The algorithm interreacts with the environment to maximize reward. It has four networks, an Actor and Critic with both a Local and Target network which is imported from model.py. Replay memory is imported from memory.py and OUNoise is import from noise.py. It consists of five methods and hyperparameters. The methods are described below.

Step: Saves experiences in Replay memory. And uses random sample from Replay buffer to learn

Act: Returns actions for the given state as per current policy

Learn: Updates the policy and value parameter using given batch of experience tuples.

Q_target = r+y * Critic_target(next_state, Actor_target(next_state)where actor target(state) -> action and Critic_target(state, action) -> Q-values

The Critic network gets the predicted next state action and Q values from the target models. Then it computes the Q targets for the current state, computes the Critic loss and then minimizes that loss

The Actor computes the loss from the Critic and then minimizes the loss

Finally, it performs a soft update on the target networks

Reset: Resets the internal state (= noise) to mean (mu)

Soft_update: Performs a soft update of model parameters based on the TAU hyperparameter. The local model is updated based on TAU while the target model is updated based on 1.0 – TAU.

MADDPG

The MADDPG function in results.ipynb brings all these components together to train the network. It is basically a runner for the DDPG algorithm in the Agent class. The agents interact with the environment by viewing the state and performing an action based on the policy from the DDPG. The rewards and next state are then sent back to the agent. The agent records a tuple (s,a,r,s') into replay memory. It then samples these to updates the Actor and Critic networks to optimize rewards. This process is done until the desired average score is achieved over all agents which is 0.5+, it then discontinues training and finishes the loop. The main difference compared to the standard DDPG is that is takes the state, action, reward and next state from each agent interacting with the environments with variations of shared to separate Actor-Critic, Model, ReplayBuffer and state or reward.

Hyperparameters

The following hyperparameters were used for training the agent.

BUFFER_SIZE = 1000000 (replay buffer size)

BATCH_SIZE = 1024 (minibatch size)

GAMMA = 0.99 (discount factor)

TAU = 0.001 (soft update of target parameters)

LR_ACTOR = 0.0001 (Actor learning rate)

LR_CRITIC = 0.001(Critic learning rate)

WEIGHT_DECAY = 0.0 (L2 weight decay)

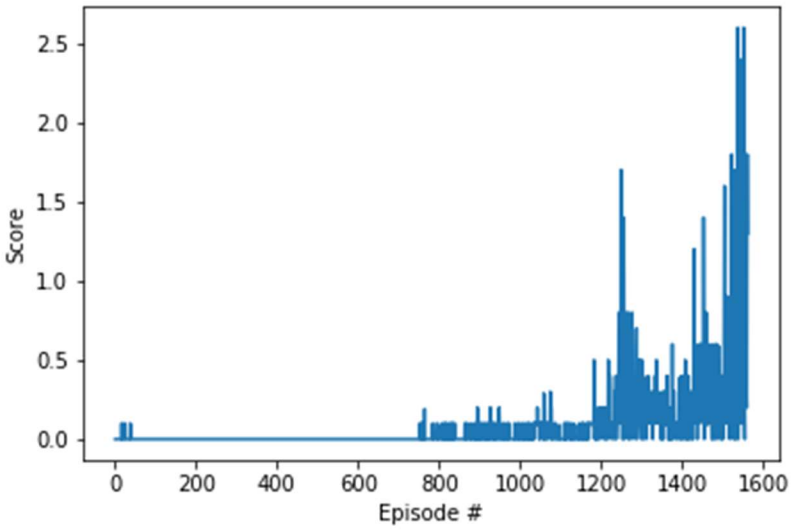
Results

Three different versions of the MADDPG were trained and compared. They all used the same hyperparameters and model but varied in their use of shared or separate networks and sampling

Here are the results for the three implementations

MADDPG with shared Actor-Critic, ReplayMemory and Mode

```
Episode:1562, Low Score:1.29, High Score:1.30, Score:1.30, Best Score:2.60
, Average Score:0.50, Best Avg Score:0.50
```



MADDPG with separate Actor-Critic, ReplayMemory and Model

```
Episode:2163, Low Score:2.19, High Score:2.30, Score:2.30, Best Score:2.60
, Average Score:0.51, Best Avg Score:0.51
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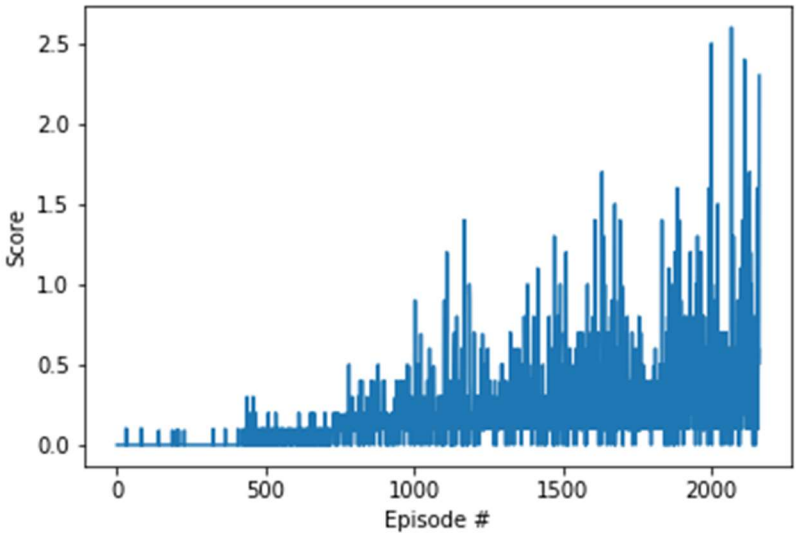

MADDPG with Separate Actor-Critic, Individual State, ReplayMemory and Model

```
Episode:2896, Low Score:1.89, High Score:1.90, Score:1.90, Best Score:2.60
, Average Score:0.50, Best Avg Score:0.50
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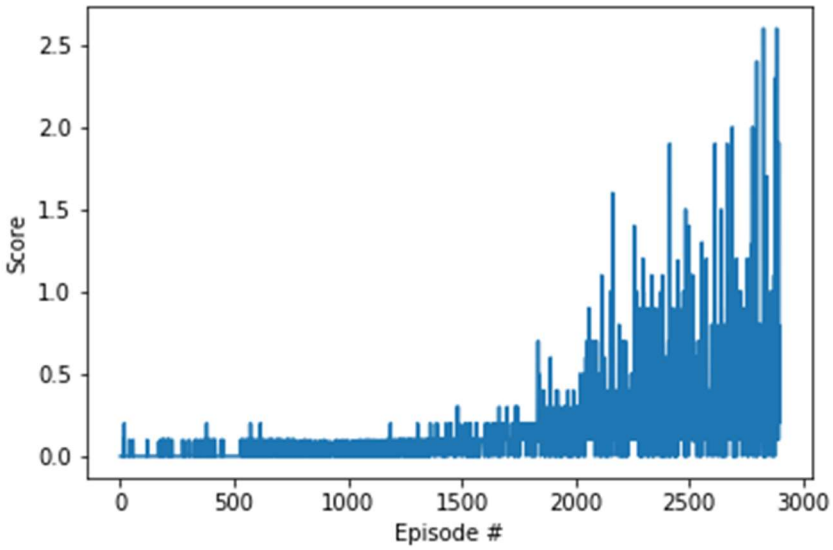

The results of all three were great but you can clearly see that the first MADDPG with shared Actor-Critic, model and replay trained faster. It was more inconsistent with its learning but once it worked it out it rapidly achieve high scores. The second MADDPG with separate agents with separate Actor-Critic, Model and ReplayBuffer was a little slower but had a consistent learning curve. The third MADDPG with separate Actor-Critic Model and ReplayBuffer that only sampled from it own state learnt slower presumably dues to half the samples. It achieved rapid and consistent learning once it understood the basics

Improvements

While the results achieved were great, there is always room for improvement. To try and achieve faster training or improve final scores I would implementing the following.

- Implement Prioritized Experience Replay
- Modifying the Hyperparameters. Changing the Hyperparameter could potentially speed up training or increase the final score
- Implement a different algorithm like PPO https://arxiv.org/pdf/1707.06347.pdf or D4PG https://openreview.net/pdf?id=SyZipzbCb
- Modifying the model architecture by changing the number of layers or neurons
- Change the update frequency of the networks in the step function

Conclusion

The project gave me a good insight to Multi-Agent reinforcement learning and the difficulties choosing the best architecture.

The environment solved is collaborative. The scores are based on the maximum of both agents rather than competing for scores like real tennis in which one agents win would be the other agent's loss. The MADDPG with a shared Actor-Critic, model and memory seemed to be the winner. I believe this is because all information is used by the networks for a common goal.

In a competitive environment I would use separate Agent class and Actor-Critic with shared ReplayBuffer and model.

I will continue to play with setup by modifying the states representation and rewards to see if alternate configurations may improve learning.

Next, I will implement the PPO algorithm to this environment and compare.