Deep RL Project 3 - Collaboration and Competition

Overview

Environment Type: 2 player Tennis environment
Algorithm: Self-play using Deep Deterministic Policy Gradients (DDPG)

ALGORITHM SUMMARY
The DDPG algorithm aims to train an effective policy to solve the environment using an actor-critic architecture. The actor specifies an action policy conditioned on the observed environment state whilst the critic evaluates the action taken given the associated observation. This evaluation is a prediction of the expected cumulative future rewards resulting from a given state-action pair. Having a separate neural network for generating actions is particularly useful for continuous actions spaces, as opposed to Q learning which would require evaluating every state-action pair before sampling the appropriate action. There are a number of features that enable the algorithm to generalise well, outlined in the table below.

Feature	Purpose/Description
Action Space Noise	This adds noise to the actor network's outputs to encourage exploration during training.
Target Networks	These are copies of the agent's actor and critic networks that are updated at a slower rate than the originals via a 'soft update', with the new target model weights being a weighted average of old and new ones. This helps reduce the risk of overfitting the training data.
Experience Replay	A replay buffer is used to store past experiences in the form of 'experience tuples' (state, action, reward, next state, episode done). During the training step experience tuples are randomly sampled from the buffer to update the actor and critic.

The critic is updated using the mean squared error between the critic's evaluation of the current state-action pair and current reward **plus** the 'target' critic network's evaluation of the next state and its associated action (see the table above for a description of target networks). The intuition is that a perfect Q-value approximator would produce a loss of zero, since the current Q-value should be equal to the sum of the current reward and the Q-value of the next state-action pair.

Once the critic has been updated, a new set of actions is predicted for the current state. The new action pair is then evaluated by the updated critic, with the actor's training loss being the negative of the predicted Q-value (the 'better' the action, the lower the loss and visa-versa).

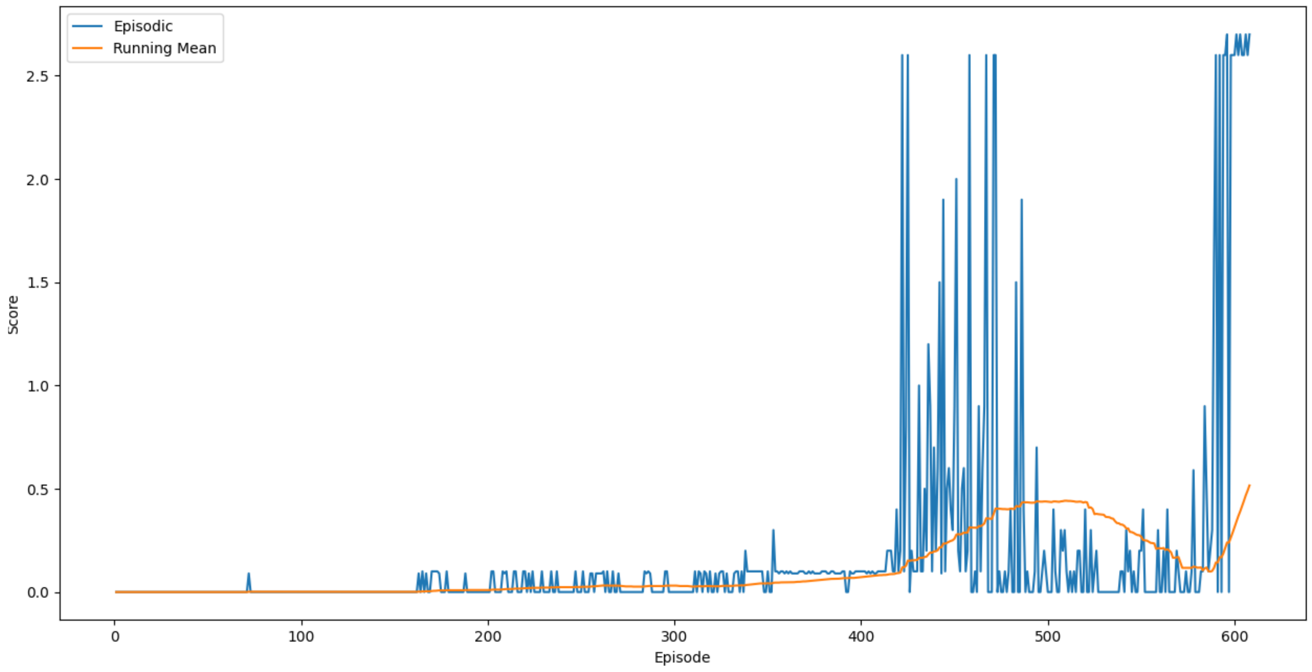
Episodes required to solve environment: 608

```
Running mean score: 0.516:  30%|███        | 607/2000 [10:27<23:59,  1.03s/it]

Environment solved in 608 episodes! Average Score: 0.52
```

Note: The running mean score is calculated by averaging the max score between the two agents over the last 100 episodes.

Training Score Plot



DDPG Hyperparameters

Hyperparameter	Description	Value
BUFFER_SIZE	Determines the maximum size of the replay buffer to store past experiences	1e5
BATCH_SIZE	Specifies the mini-batch sized used for learning updates	256
GAMMA	The discount rate on historical rewards	0.99
TAU	The soft update parameter, controlling the degree to which the	1e-1

	actor and critic target networks are updated during a learning step	
LR_ACTOR	The learning rate for the actor model optimiser	2e-4
LR_CRITIC	The learning rate for the critic model optimiser	2e-4
WEIGHT_DECAY	L2 regularisation on model weight parameters to reduce overfitting	0

Neural Network Architectures

Actor

```
self.fc1 = nn.Linear(state_size, fc1_units)
self.fc2 = nn.Linear(fc1_units, fc2_units)
self.fc3 = nn.Linear(fc2_units, action_size)
```

- State_size = 24
- Action_size =2
- Fc1_units = 256
- Fc2_units = 128
- Activations = ReLU (fc1), ReLU (fc2), Tanh

Critic

```
self.fcs1 = nn.Linear(state_size*n_agents, fcs1_units)
self.fc2 = nn.Linear(fcs1_units+action_size*n_agents, fc2_units)
self.fc3 = nn.Linear(fc2_units, output_dim)
```

- n_agents = 1
- state_size = 24
- fc1_units = 256
- fc2_units = 128 + 2
- Activations = ReLU (fcs1), ReLU (fc2), None

Note: The n_agents parameter allows the critic to be repurposed for Multi-Agent DDPG, which is yet to be implemented

Further Work/Improvements

MULTI-AGENT DDPG

The MADDP implementation from Udacity's Competition and Collaboration lab showed the efficacy of decentralised execution and centralised learning. Modifying that implementation for the Tennis environment should be viable, particularly since notebooks/training scripts from other students have demonstrated some success.

PARAMETER SPACE NOISE

My DDPG implementation applies noise to the actions output by the agent’s actor network. An alternative would be to use parameter space noise, which has been demonstrated to accelerate learning in experiments conducted by OpenAI. The intuition seems to be that adding noise to the parameters rather than the network output encourages exploration without distorting the relationship between performing an action in a given state and the subsequent observations and rewards.
Source: https://openai.com/blog/better-exploration-with-parameter-noise/

EXPERIMENTING WITH NOISE DISTRIBUTIONS

The current implementation uses a Ornstein-Uhlenbeck process to generate noise in the action space. Alternatives such as the Gaussian and Beta distributions may be viable alternatives, with the magnitude of the noise input being decayed over time to shift the algorithm’s focus from exploration to exploitation.

DISTRIBUTIONAL VALUE ESTIMATION

The Critic could be redesigned to output a value distribution as opposed to a scalar value. The predicted Q-value would be determined by taking a random sample from said distribution. This would allow the model to be more expressive in its predictions, which may prove useful when encountering state-action pairs with similar (but not identical) representations. A good example of this being implemented for the Tennis environment can be found in the repo linked below.
Source:
https://github.com/Remtasya/Distributional-Multi-Agent-Actor-Critic-Reinforcement-Learning-MADDPG-Tennis-Environment