Project Collaboration and Competition

Environment Background

The environment used for this project is a modified version of the UnityML Agents Tennis environment. The environment involves two agents playing tennis opposite each other. Each agent can move their racket forward or backward and up or down in a continuous manner. The goal of the agents is to keep the ball from going out for as long as possible.

Each agent receives a reward of +0.1 if they hit the ball over the net. Each agent receives a reward of -0.01 if it hits the ball out of bounds or misses hitting the ball back. The state space is the position and velocity of the ball and the racket and has a size of 24. The agent's action space has a size of 2. Each agent receives its own local observation, indicating that each agent can be trained somewhat independently of the other. The environment is considered solved when the agents' average a score of +0.5 over 100 episodes.

Since there are two agents, the reward calculation is different than a simple sum. Each agent's rewards are determined per episode without discounting and the maximum of the two scores is considered the score for that episode.

DDPG Algorithm

Theory

The DDPG algorithm stands for the Deep Deterministic Policy Gradient Algorithm. It was first presented in a paper that applied Deep Q-learning to a continuous action space. In the original paper, the authors used DDPG to solve different physics tasks. The algorithm as presented in the original paper is an actor-critic model free algorithm and is recreated as it was presented in the original paper in the figure below.

Figure 1: DDPG Algorithm

Algorithm 1 DDPG algorithm

Randomly initialize critic network $Q(s, a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights θ^Q and θ^μ.
Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^Q$, $\theta^{\mu'} \leftarrow \theta^\mu$
Initialize replay buffer R
for episode = 1, M **do**
  Initialize a random process $\mathcal{N}$ for action exploration
  Receive initial observation state s_1
  for t = 1, T **do**
    Select action $a_t = \mu(s_t|\theta^\mu) + \mathcal{N}_t$ according to the current policy and exploration noise
    Execute action a_t and observe reward r_t and observe new state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in R
    Sample a random minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from R
    Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
    Update critic by minimizing the loss: $L = \frac{1}{N}\sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$
    Update the actor policy using the sampled policy gradient:

$$\nabla_{\theta^\mu} J \approx \frac{1}{N} \sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s|\theta^\mu)|_{s_i}$$

    Update the target networks:

$$\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$$
$$\theta^{\mu'} \leftarrow \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

  end for
end for

Implementation

The DDPG Algorithm solution presented in this project involves defining an Actor, a Critic, a DDPG agent, a noise process, a replay buffer, and the algorithm used to train the agent. Each component's implementation is described below.

Actor: The Actor is a neural network that consists of three layers. The first layer has inputs of the environment's state size and outputs of size 480. The second layer has inputs of size 480 and outputs of size 240. The third layer has inputs of size 240 and outputs of the agents action size. The Actor has three methods: __init__, reset_parameters, and forward.

- The __init__ method creates the neural network with the architecture described above.
- The reset_parameters method resets the weight values for the neural network using the hidden_init function, which takes a layer as input and returns a range of values to fill that layers weights with.
- The forward method takes the state as an input. It propagates the input state through the network with Rectified Linear Units(ReLU) functions between each layer. The hyperbolic tangent function is applied to the output of layer 3. The output of the tangent function is returned from the method.

Critic: The Critic is a neural network that consists of three layers. The first layer has inputs of the environment's state size and outputs of size 480. The second layer has inputs equal to the sum of the agent's action size and 480. This layer has and output of size 240. The third layer has inputs of size 240 and output of size 1. The Critic has three methods: __init__, reset_parameters, and forward.

- The __init__ method creates the Critic neural network with the architecture described above.
- The reset_parameters method resets the weight values for the neural network using the hidden_init() function.
- The forward method takes a state and action as an input. The state is propagated through the first layer. The output of the firs t layer and the action input are concatenated using torch.cat into the input of the second layer. The output of the third layer is then returned from the method.

DDPG Agent: The DDPG Agent is created by the DDPGAgent class. The class is defined with the following methods: init, step, act, reset, learn, and soft update.

- The __init__ method takes the action_size, state_size, and random_seed as parameters. It creates the agent's actor and critic networks, the noise process used for exploration, and the memory buffer. Each agent has two actor networks, a local and a target, and two critic networks, a local and a target. In this solution, the ActorLocal and ActorTarget networks are predefined to allow for two agents to share the same actor networks. A predefined shared memory buffer is also input as a parameter to allow both agents to share a memory buffer. To allow for updating network weights at intervals, it creates a timestep counter, t_step.
- The step method takes an experience tuple(state, action, reward, next_state, done) components as individual parameters. The memory buffer is updated with that tuple. If

the timestep count is a multiple of the UPDATE_EVERY hyperparameter, the agent samples a batch from the buffer and learns from that batch.

- The act method takes the state of the environment and a boolean addNoise value. The agent uses the state to decide on and return an action to take in the environment. If the addNoise boolean is True, then noise is added to the decided action value to encourage exploration of the environment.
- The reset method is used to reset the noise process.
- The learn method takes an experience batch and a gamma hyperparameter as parameters. The agent uses the experience batch to update the Critic and Actor networks.
- Soft update takes a local network, a target network, and tau as parameters. The method updates the target network.

The Agent has the following hyperparameters

- BUFFER_SIZE : the size of the memory buffer
- BATCH_SIZE: the size each batch sampled from the memory buffer
- GAMMA: the gamma value for reward discounting
- TAU: the interpolation factor used to update the target network
- LR_ACTOR: the learning rate for the actor local and target network
- LR_CRITIC: the learning rate for the critic local and target network
- WEIGHT_DECAY: the L2 weight decay used by the critic network
- UPDATE_EVERY: the number of timesteps after which to update the actor and critic networks.

OUNoise: The OUNoise is an Ornstein-Uhlenbeck noise process. This noise is used to encourage exploring early in the learning stages for the agent. The class is defined with the following methods: init, reset, and sample.

- The init method initializes the noise process by using parameters of size and random seed along with values for theta, mu, and sigma. Theta, mu, and sigma are components of the noise process and can be manipulated to alter the magnitude of the resulting noise.
- The reset method resets the noise process
- The sample method calculates and returns a new noise value that is later added to the action in the DDPG act method.

Replay Buffer: The ReplayBuffer class defines a memory buffer that stores experience tuples. The buffer is defined with the following methods: __init__, add, sample, and __len__.

- The __init__ method takes parameters of action_size, buffer_size, batch_size, and random seed value. The method initializes a ReplayBuffer of size, BUFFER_SIZE, with a namedtuple with field names of state, action, reward, next_states, and dones for the experience tuples. The random seed value is used to define a random seed.
- The add method takes in a state, action, reward, next_state, and done as input parameters. It adds this tuple as an experience tuple to the memory buffer
- The sample method extracts a set of experience tuples with a size of batch_size. The method separates them by states, actions, rewards, next_states, and dones and returns each set differently.

- The __len__ method returns the length of the memory buffer.

DDPG Algorithm: The algorithm is defined in the function ddpg(). The function takes input parameters of n_episodes, max_t, and print_every.

- n_episodes is the number of episodes
- max_t is the maximum number of timesteps per episode
- print_every is the number at which to print the average scores. This is used to observe and track the progress of the agent as it learns.

The function proceeds to iterate through the episode numbers as the agents act and receive a reward value after each timestep. The maximum of the scores for each agent is added to a list, scores_deque, that tracks the score over 100 episodes. In the function, an addNoiseValue is defined as True and passed as a parameter to the agent's act method, resulting in additional noise as the agent explores the environment.

If the episode number is a multiple of 100, the individual agent scores and the average of the scores_deque list is printed to monitor the agent's learning progress. If the average of scores_deque is above +0.1, the addNoiseValue is set to False. This allows for exploration until a potentially successful policy is learned and, once such a policy is discovered as indicated by a score greater than or equal to +0.1, further optimizing of that policy to eventually solve the environment. If the average score is equal to or exceeds +0.5, the network weights for the actor and critic networks are saved using PyTorch's inbuilt save function.

Hyperparameter values in a successful solution

The two agents share an actor local and an actor target network. The two agents also share a memory buffer. This allows for better learning in a multiagent environment. After testing and experimenting with different hyperparameter values, the following values produced a successful solution.

DDPG Agent and Replay Buffer Hyperparameters

BUFFER_SIZE = 1e6
BATCH_SIZE = 512
GAMMA = 1.0
TAU = 1e-3
LR_ACTOR = 1e-3
LR_CRITIC = 1e-3
WEIGHT_DECAY = 0
UPDATE_EVERY = 5
random_seed = 2

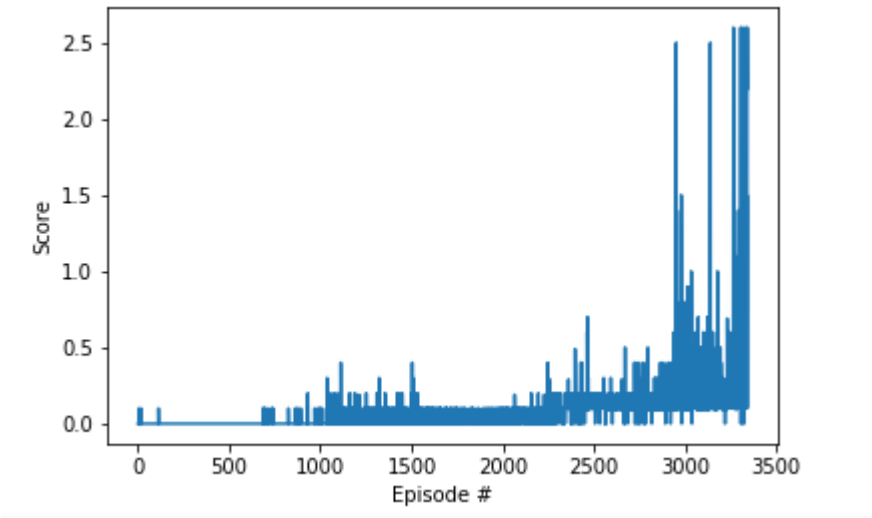
DDPG Function Parameters

n_episodes = 3500
max_t = 1000

The environment was solved in 3341 episodes with an average score of 0.5056. This means that for the 100 episode range from 3241 to 3341, the agents averaged a score of greater than or

equal to +0.5. A plot of the scores per episode is depicted below in Figure 2. As mentioned above, the scores for each episode is the maximum of the two agent scores per episode.

Figure 2



Future Directions

One possible future improvement is to implement the MADDPG algorithm that is designed for use with multiple agents. The paper identified in the References section outlines the MADDPG algorithm. The solution presented above involves only a shared actor network and a shared memory buffer. By using a better algorithm that takes advantage of the multiagent interaction, the environment could be solved in fewer episodes.

References

DDPG Paper: https://arxiv.org/pdf/1509.02971.pdf

MADDPG Paper: https://arxiv.org/pdf/1706.02275.pdf