Udacity Deep Reinforcement Learning Nanodegree Program

Continuous Control

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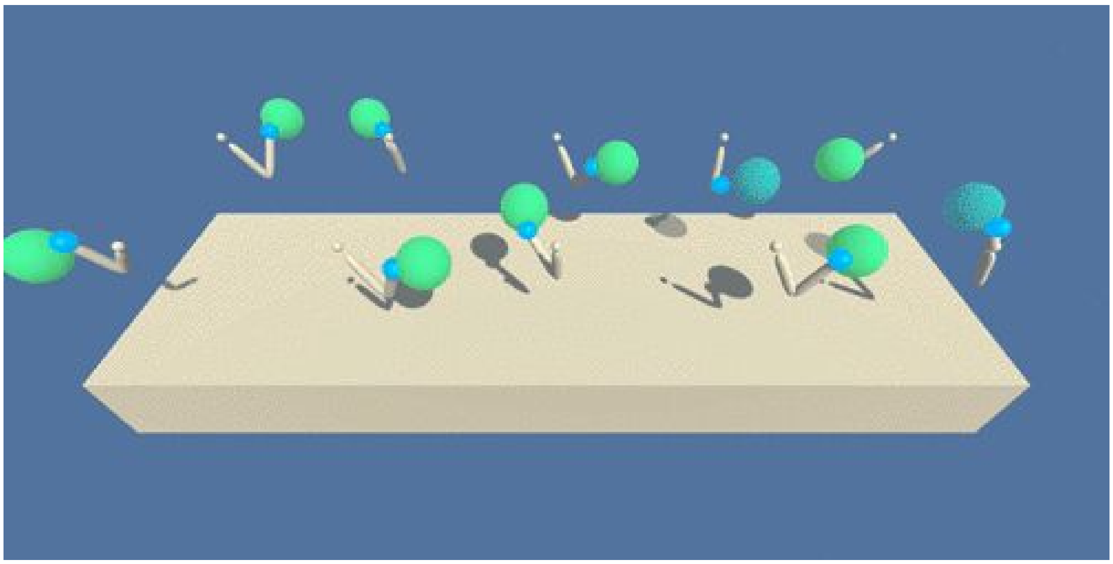


Introduction

This project is intended to provide an opportunity for students to gain more experience using Unity's ML-Agents machine learning toolset and apply their knowledge of Asynchronous Advantage Actor-Critic (A3C), Deep Deterministic Policy Gradient (DDPG), or Proximal Policy Optimization (PPO) algorithms to train a Deep Reinforcement Learning (DRL) agent to perform a task. The task is to train a double-jointed arm to track a target location as it orbits the arm's anchor point. The defined task environment includes 33 variables which include position, rotation, velocity, and angular velocities of the arm. The action performed by the agent is a four element vector corresponding to the torque at each of the two joints. Each element in the vector is a number that ranges from -1 to +1. A reward of +0.1 is given to the agent for every step the agent's hand is touching the target area. There are two versions of the environment which include a single agent or 20 agent distributed training scenario. The task is considered solved when the agent yields an average score of +30 over 100 consecutive episodes.

Learning Algorithm Used - DDPG

DDPG is a type of actor-critic method which can be seen as an approximate Deep Q-Network (DQN). The critic in DDPG is used to predict the maximum Q-value for the next state similar to the DQN algorithms estimate function. The main advantage that DDPG has over DQN is that it can be used in a continuous state and action space.

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

Figure 1: DDPG Algorithm[1]

Improvements Added:

A mean neural network was placed between the first and second hidden layers of the neural network.

[1] **"Continuous control with deep reinforcement learning." https://arxiv.org/abs/1509.02971. Accessed 24 Jul. 2019.**

Hyperparameters Used

BUFFER_SIZE = int(1e6) # replay buffer size

BATCH_SIZE = 1024   # minibatch size

GAMMA = 0.99   # discount factor

TAU = 1e-3   # for soft update of target parameters

LR_ACTOR = 2e-4   # learning rate of the actor

LR_CRITIC = 3e-4   # learning rate of the critic

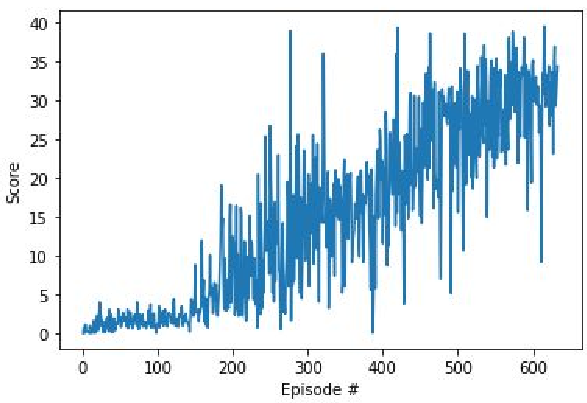
WEIGHT_DECAY = 0   # L2 weight decay

Model Architectures Used

The model architecture used for this project is an Actor-Critic network. The critic estimates the value function and the actor updates the policy in the direction recommended by the critic. Both the actor and critic have three linear hidden layers and one batch normalized layer between the first and second hidden linear layer. Both the actor and critic use a ReLU activation function to ensure the gradients remain large enough through the hidden layers. The batch normalization layer ensures the activation scaling is normalized to avoid covariance shift.

Results - Plot of Rewards

```
Environment Solved! It took 633 episodes!
Average Score: 30.01
```




```
Episode 100     Average Score: 1.32
Episode 200     Average Score: 4.05
Episode 300     Average Score: 10.72
Episode 400     Average Score: 15.92
Episode 500     Average Score: 23.09
Episode 600     Average Score: 28.62
Episode 633     Average Score: 30.01
Environment Solved! It took 633 episodes!
Average Score: 30.01
```

The figure above shows the agents average score throughout the training process which included 633 episodes. The table to the right of the plot shows the average score over 100 hundred episodes for every 100 episodes throughout the training session. Based on these results, it appears the environment was solved in 633 episodes.

Ideas for Future Work

Trust Region Policy Optimization (TRPO)

TRPO is similar to natural policy gradient methods and is effective for optimizing large nonlinear policies such as neural networks.[2]

Algorithm 1 Policy iteration algorithm guaranteeing non-decreasing expected return η

Initialize π_0.
for $i = 0, 1, 2, \dots$ until convergence **do**
  Compute all advantage values $A_{\pi_i}(s, a)$.
  Solve the constrained optimization problem

$$\pi_{i+1} = \arg\max_{\pi} \left[L_{\pi_i}(\pi) - C D_{\mathrm{KL}}^{\max}(\pi_i, \pi) \right]$$

  where $C = 4\epsilon\gamma/(1-\gamma)^2$
  and $L_{\pi_i}(\pi) = \eta(\pi_i) + \sum_s \rho_{\pi_i}(s) \sum_a \pi(a|s) A_{\pi_i}(s, a)$

end for

Figure 2: TRPO Algorithm[3]

Truncated Natural Policy Gradient (TNPG)

By computing an ascent direction that approximately ensures a small change in the policy distribution TNPG improves upon the REINFORCE algorithm.[4]

Distributed Distributional Deterministic Policy Gradients (D4PG)

D4DG adapts distributional reinforcement learning to the continuous control setting and combines it with distributed off-policy learning combined with improvement including N-step returns and prioritized experience replay.[5]

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[2] "Trust Region Policy Optimization." https://arxiv.org/abs/1502.05477. Accessed 24 Jul. 2019.
[3] "Trust Region Policy Optimization." https://arxiv.org/abs/1502.05477. Accessed 24 Jul. 2019.
[4] "Benchmarking Deep Reinforcement Learning for Continuous Control." 22 Apr. 2016, https://arxiv.org/abs/1604.06778. Accessed 24 Jul. 2019.
[5] "distributed distributional deterministic policy gradients - OpenReview." https://openreview.net/pdf?id=SyZipzbCb. Accessed 24 Jul. 2019.

Works Cited

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