Deep Reinforcement Learning Nanodegree Project 2 - Continuous Control

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In this report, I have trained an agent that has continuous action spaces with Deep Deterministic Policy Gradient(DDPG) algorithms. The Reacher of Unity Environment, which is a double jointed arm that moves to target location, is used. I tested with 20 agents to collect experiences in parallel. The agent receives a reward of +0.1 for each step and the project goal was to archieve average scores +30 over 100 consecutive episodes over all agents. (Option 2)

Unity Reacher Agent Environment:

1. Number or agents: 20
2. Size of action for each agent: 4
    A. Value between [-1.1]
3. Size of states for each agent: 33

I tested with multple hidden layers (400,300), (256,128), (128,64), (64,32). I searched other papers and got these hidden layer sets.

Deep Deterministic Policy Gradient (DDPG) Algorithm

I trained the actor and the critic network with DDPG algorighm. Actor networks creates policy network that takes state values as input parameter and returns the actions. Critics calculates Q values taking current states and actions that predicted from actor policy as inputs. Target networks simply replica of Actor, Critics were used to reduce the variance of the networks. I used Reply buffer to save experiences from all agents.

Critic loss - Mean Squared Error of y - Q(s, a) where y is the expected return as seen by the Target network, and Q(s, a) is action value predicted by the Critic network. y is a moving target that the critic model tries to achieve; we make this target stable by updating the Target model slowly.

Actor loss - This is computed using the mean of the value given by the Critic network for the actions taken by the Actor network. We seek to maximize this quantity.

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

Methods

I found many documents without Batch Normalization, the training results were the worst. So I used Batch Normalization for the Actor and the Critic. I tested with below hidden layers

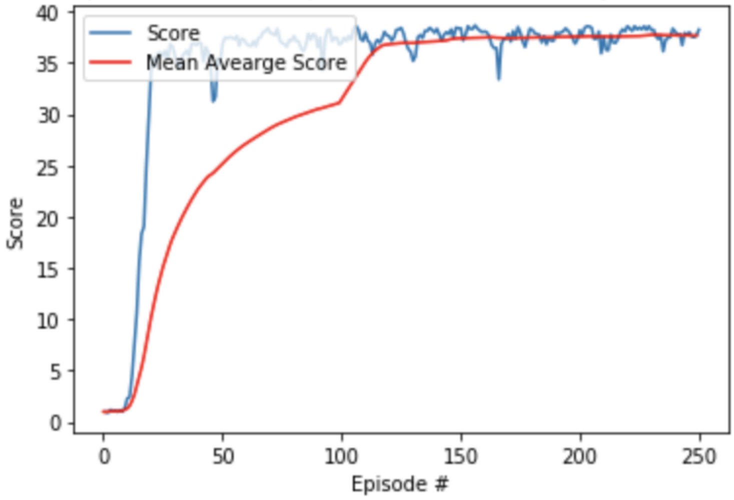
1. Hidden Layers: 400, 300
2. Hidden Layers: 256, 128
3. Hidden Layers: 128, 64
4. Hidden Layers: 64, 32

Results

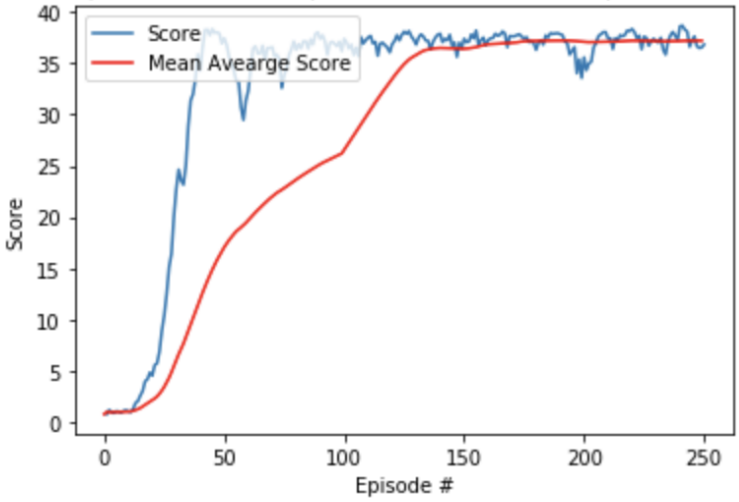
The result of agent trainings for DDPG algorithms are shown below. The agents solved the environment in 80 ~ 140 episodes. 80 episodes is enough for finding the goal, +30 scores in 400x300 Hidden Layers. And the Hidden Layers 400x300 was the best performance

hidden layers	mean_score	first_episode_achieved
400, 300	37.7503	85
256, 128	37.2035	111
128, 64	35.4912	126
64, 32	32.6857	140

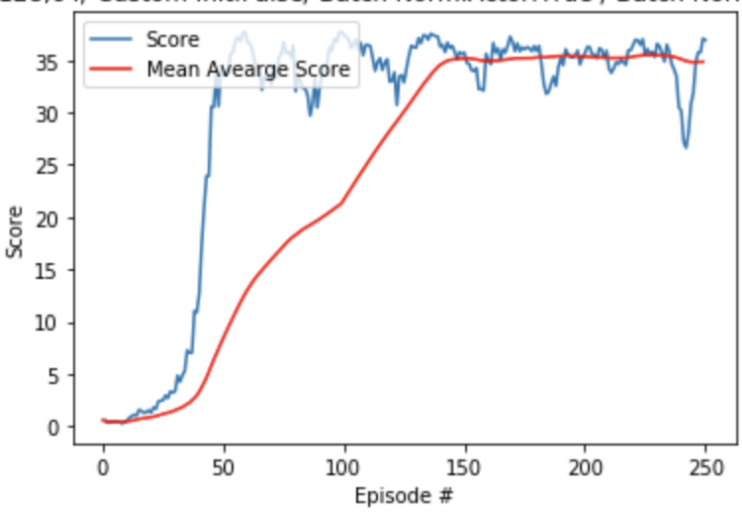
Layers:400,300/ Custom Init:False/ Batch Norm.Actor:True / Batch Norm.Critic:True

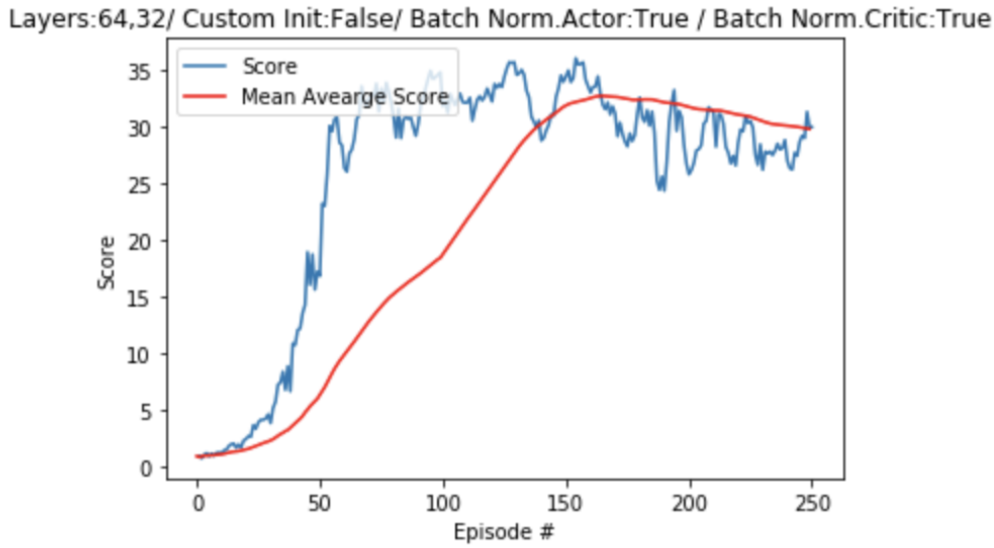


Layers:256,128/ Custom Init:False/ Batch Norm.Actor:True / Batch Norm.Critic:True



Layers:128,64/ Custom Init:False/ Batch Norm.Actor:True / Batch Norm.Critic:True





References

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