Project 2 - Continuous Control -DDPG

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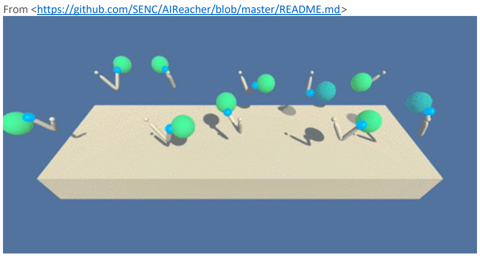
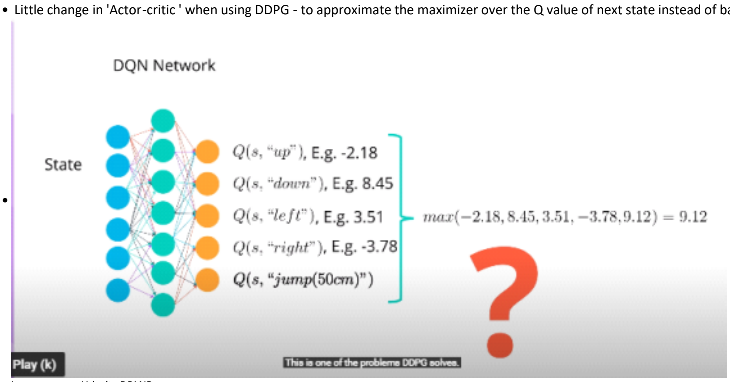
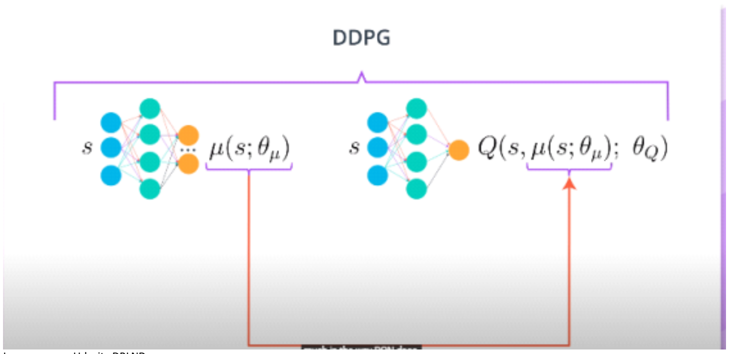
S.No	Topic	Details
1.	Project Goal	This Reacher project is as part of Udacity Nanodegree - AI Deep Reinforcement Learning Expert and aims to develop an AI Agent - "a double-jointed arm" - move to target location in Continuous space using Policy-based 'Actor-critic' Methods using Deep Neural Networks. From <https://github.com/SENC/AIReacher/blob/master/README.md> 
2.	Scope	• Develop an AI Agent using 'actor-critic' methods - which should learn the best policy to maximize its rewards by taking best actions in the given continuous environment • Goal The environment is considered solved, when the average (over 100 episodes) of those average scores is at least +30. • Decided to solve the First Version Option 1: The task is episodic and the Agent must get an average score of +30 over 100 consecutive episodes
3.	Purpose	• One of the primary goal of AI is to solve complex tasks in high dimensional , sensory inputs . Though Deep Q Network (DQN) pr oved to be high performance on many Atari video games but handles well in discrete and low-dimensional action spaces .DQN can't applied directly to continuous domain since the core part to find the action that maximi zes the action-value function. • This project aims to build a model-free, off-policy actor-critic [Deterministic Policy - action-value] algorithm using deep function approximators that can learn policies in continuous space • DQN Paper: https://arxiv.org/abs/1509.02971
4.	Solution Approach -Policy based Methods	• Policy Gradients - An alternative to the familiar DQN (Value based method) and aims to make it perform well in continuous state space. Off-policy algorithm - Essential to learn in mini-batches rather than Online • Develop 'Actor-Critic' agent uses Function approximation to learn a policy (action) and value function • Have 2 Neural Networks ○ One for an Actor - Takes stats information as an input and actions distribution as an output ▪ Take the action to move to next state and check the reward (Experience)and using TD estimate of the reward to predict the Cri tic's estimate for the next state ○ Next one for a Critic - Takes states as input and state value function of Policy as output. ▪ Learn to evaluate the state value function Vπ using TD estimate To calculate **the advantage function** and train the actor using this value. So ideally train the actor using the calculated advantages as a baseline. • Instead of having baseline using TD estimate , can use Bootstrapping to reduce the variance ○ Bootstrapping - generalization of a TD and Monte-Carlo estimates ▪ TD is one step bootstrapping and MC is infinite bootstrapping ▪ Mainly to reduce biasness and variances under controlled & fast convergence • Like DQN , have 'Replay Memory' - a digital memory to store past experiences and correlates set of actions -REINFORCE- to choose actions which mostly yields positive rewards • Randomly collect experiences from the Replay Memory in to Mini-batches so the experiences may not be in same correlation as Replay Memory to train the Network successfully • Buffer size can be large so allowing the algorithm to benefit from learning across a set of uncorrelated transitions • Little change in 'Actor-critic ' when using DDPG - to approximate the maximizer over the Q value of next state instead of baseline to train the value •  Image source: Udacity DRLND **#1** In Actor NN : used to **approximate the maximizer** - an optimal best policy (action) deterministically - so the Critic learns to evaluate the optimal policy - Action-Value function for the best action Approximate the Maximizer - to calculate the new target value for training the action value function Q(s, µ (s ; θµ);θ Q)  Image source: Udacity DRLND Regular/local network - UpToDate network since training is done here but target network used to predict the stabilize strain #2 Soft Target updates: Weight of the target network are updated by having them slowly track the learned networks to improve the stability of learning
5.	Algorithm	Deep deterministic Policy Gradient Published as a conference paper at ICLR 2016

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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

1. Initialize Critic Neural Network Q(s, a | θQ) and Actor Neural Network with random initialized weights 'θ'
2. Initialize target network Q' and μ' with weights from step #1

6. Hyper parameters

BUFFER_SIZE = 500000 # replay buffer size
BATCH_SIZE = 300 # minibatch size
GAMMA = 0.997 # discount factor
TAU = 0.0013 # for soft update of target parameters
LR_ACTOR = 0.0002 # learning rate of the actor
LR_CRITIC = 1e-3 # learning rate of the critic
WEIGHT_DECAY = 0 # L2 weight decay

theta=0.17 # Noise Sampling
sigma=0.24
Random seed = 9 #reacherAI = AiAgent(state_size,action_size,random_seed=9)

7. Rewards

Workspace SEND F

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Run Code

```
Episode 62      Average Score: 0.2200
```

In [13]:

```
#Ver 7.3 19Jul
#Change params to default
#BUFFER_SIZE = 500000    #int(1e4)  # replay buffer size
#BATCH_SIZE = 300        #128        # minibatch size
#GAMMA = 0.997            # discount factor
#TAU = 0.0013              # for soft update of target parameters
#LR_ACTOR = 0.0002         # learning rate of the actor
#LR_CRITIC = 1e-3         # learning rate of the critic
#WEIGHT_DECAY = 0

scores = Ddpg()

fig = plt.figure()
ax = fig.add_subplot(111)
plt.plot(np.arange(1, len(scores)+1), scores)
plt.ylabel('Score')
plt.xlabel('Episode #')
plt.show()
```

```
Episode 100     Average Window Score: 1.7100
Episode 200     Average Window Score: 7.0200
Episode 300     Average Window Score: 11.8900
Episode 400     Average Window Score: 13.7100
Episode 500     Average Window Score: 16.9300
Episode 600     Average Window Score: 20.4300
Episode 700     Average Window Score: 22.0900
Episode 800     Average Window Score: 27.2800
Episode 868     Average Score: 30.1100
Environment solved in 768 episodes!     Average Score: 30.1100
```

8. Source code

1. Nn_model.py -Convolutional Neural Network model with 3 layer architecture

```
#Test to create the instance of AiAgent
reacherAI = AiAgent(state_size,action_size,random_seed=9)
print(reacherAI.actor_local)
print(reacherAI.critic_local)
```

```
Actor(
  (fc1): Linear(in_features=33, out_features=24, bias=True)
  (fc2): Linear(in_features=24, out_features=48, bias=True)
  (fc3): Linear(in_features=48, out_features=4, bias=True)
)
Critic(
  (fcs1): Linear(in_features=33, out_features=24, bias=True)
  (fc2): Linear(in_features=28, out_features=48, bias=True)
  (fc3): Linear(in_features=48, out_features=1, bias=True)
)
```

2. Agent : Agent with properties for local and Target networks , soft update , step, act, reset , learn and class and functions For Noise and Replay Memory
3. Continuous Control.ipynb - Python Notebook covers all the Code and Results
4. Checkpoint_actor30.pth - saved model weights for Actor
5. Checkpoint_critic30.pth - saved model weights for Critic

9. Ideas for future work

1. Work on Option 2 and try parallel learning
2. Solve a more difficult continuous control environment
   where the goal is to teach a creature with four legs to walk forward without falling.

Ref https://github.com/Unity-Technologies/ml-agents/blob/master/docs/Learning-Environment-Examples.md#crawler

THANKS TO UDACITY TEAM!!