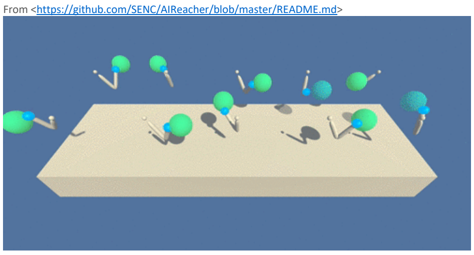
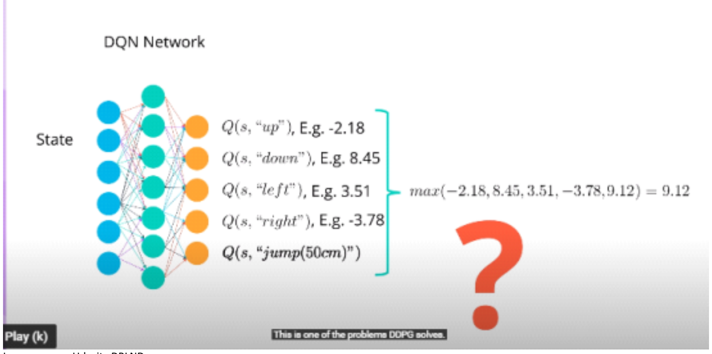
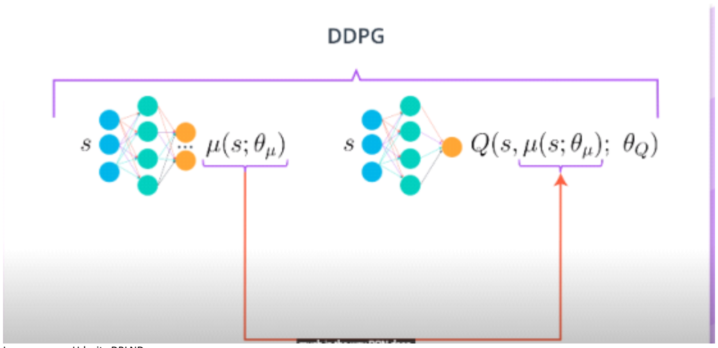
Report - Continuous Control -DDPG

Sunday, 19 July 2020 11:39 PM

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) proved 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 maximizes 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 • DDPG 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 Critic'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
		  $Q(s, \mu (s ; \theta_\mu);\theta_Q)$
		
		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:

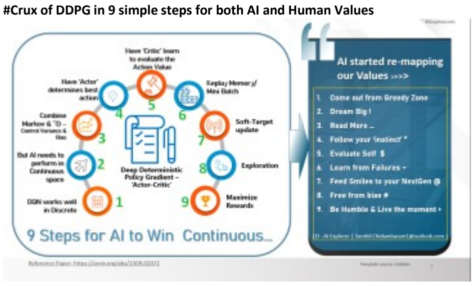
$$\nabla_{\theta^\mu} J \approx \frac{1}{N}\sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s|\theta^\mu)|_{s_i}$$

    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

#Crux of DDPG in 9 simple steps for both AI and Human Values



6. Hyper parameters - Value configurations

Udacity Workspace	Local Windows Env

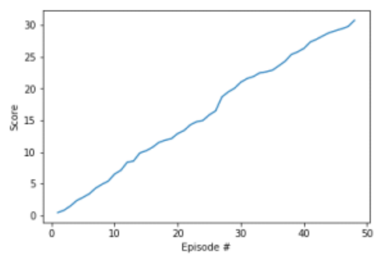
BUFFER_SIZE = 500000 # replay buffer size
BATCH_SIZE = 258 # minibatch size
GAMMA = 0.997 # discount factor
TAU = 0.0013 # for soft update of target parameters
LR_ACTOR = 0.00017 # learning rate of the actor
LR_CRITIC = 1e-3 # learning rate of the critic
WEIGHT_DECAY = 0 # L2 weight decay
theta=0.1 # Noise Sampling
sigma=0.2
Random seed = 1 #reacherAI = DDPGAgent(state_size,action_size,random_seed=1)
	# Iteration Ver 15 - Test run with 100 Episodes
	#BUFFER_SIZE = 500000 #int(1e4) # replay buffer size
	#BATCH_SIZE = 256 #128 # minibatch size
	#GAMMA = 0.997 # discount factor
	#TAU = 0.0013 # for soft update of target parameters
	#LR_ACTOR = 0.00013 # learning rate of the actor
	#LR_CRITIC = 0.0001 # learning rate of the critic
	#WEIGHT_DECAY = 0 # L2 weight decay
	
	#Noise mu=0., theta=0.17, sigma=0.24
	#Random seed = 1

7. Result & Rewards plot

Udacity Workspace

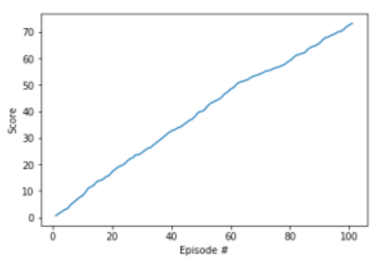
Environment solved in 48 episodes!Average Score: 30.7300
0:09:26.237652

```
Environment solved in 48 episodes!	Average Score: 30.7300
0:09:26.237652
```



```
2020-07-24 07:38:29.767245
Episode 100	Average Score: 0.7266	AcScore 72.6600

Environment solved in 101 episodes!	Average Score: 73.1800
0:02:57.254219
```

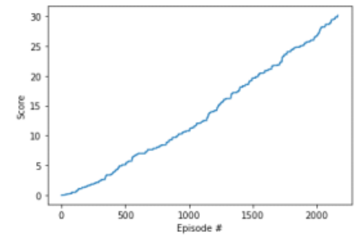


2020-07-24 08:25:05.268124
Episode 10 Average Score: 0.6520 AcScore 6.5200
Episode 20 Average Score: 0.6450 AcScore 12.9000
Episode 30 Average Score: 0.6997 AcScore 20.9900
Episode 40 Average Score: 0.6577 AcScore 26.3100
Environment solved in 48 episodes! Average Score: 30.7300
0:09:26.237652

Local Windows Setup

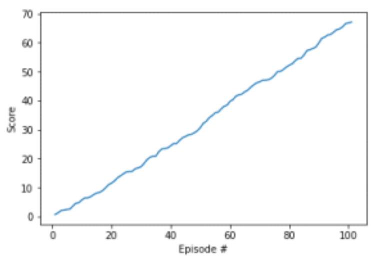
Environment solved in 40 episodes!
Average Score: 30.0700
0:02:11.374991

```
Environment solved in 2165 episodes!	Average Score: 30.1300
1:49:15.377123
```



```
Episode 100	Average Score: 0.6680	AcScore 66.8000

Environment solved in 101 episodes!	Average Score: 67.1200
0:06:24.060748
```



Episode 10 Average Score: 0.8800 AcScore 8.8000
Episode 20 Average Score: 0.7545 AcScore 15.0900
Episode 30 Average Score: 0.7630 AcScore 22.8900
Episode 40 Average Score: 0.7517 AcScore 30.0700

8. Source code Details

1. **Nn_model.py** -Convolutional Neural Network model with 3 layer architecture
   Having constructor to initialize seed and Input , Output and Hidden layers
   Feedforward function to Neuron activation using Relu function to make output 0 or >0 [y = max(0, x)] and method to reset the weights

```
#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. **DDPG : Agent.py** : Agent to have properties and functions covering
   - local and Target networks ,
   - soft update ,
   - Noise for exploration
   - Replay Memory for Experience Replay
   - step, act, reset , learn functions

S.No	Activity	Core
1.	Initialize local and target network for both Actor and Critic	Deep CNN - 3 Layers
2.	Initialize replay memory based on Buffer size, Mini Batch and seed	Recall Experience
3.	Call "Learn " Function when actor.step : Core Algo - Update Policy and Value params based on experiences	**Get Next_Action and Qvalue to Q_targets = r + γ * critic_target(next_state, actor_target(next_state))** where: actor_target(state) -> action critic_target(state, action) -> Q-value From the Memory , take random set of experiences and predict target based on current states and reward
4.	• Get the Next_action from action_target and caluclate Q_target Value for given (s,a) • Compute Q target from current reward • Compute the Critic Loss by Qexpected - Qtarget • Optimizer	Basically , update the weights of Actor and Critic Network targeting minimize the loss with Current vs Expected Result
5.	Smooth copy of local to target network	Stable Learning

3. **Continuous Control.ipynb** - Python Notebook covers all the Code and detailed executed report
   1. Libraries , Environment and Agent initialization , DDPG , Rewards summary and plot
4. Checkpoint_actor30.pth - saved model weights for Actor
5. Checkpoint_critic30.pth - saved model weights for Critic

#Learnings: Sampling from standard Normal distribution is so important and improved training process and correction on actions clip btw -1 to 1

9. Ideas for future work

1. Work on Option 2 and try parallel learning PPO
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

10. In Simple

A BIG THANKS TO UDACITY TEAM!!