P2 Continuous Control: Robotic Arm Environment with Deep Deterministic Policy Gradient (DDPG)

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Introduction *(From Udacity Course Website)*

The goal of this task is to train an agent with a double-jointed arm to move to target locations and maintain its lock on the target for as long as possible. The Unity environment allows for executing this task for 1 or 20 agents. This submission only considers the 1 agent scenario.

The state space consists of 33 states including the agent's position, rotation, velocity and angular velocities of its arm. The action space consists of a vector incorporating the torque associated with moving the two joints of an agent's arm and thus, has a dimension of four bounded by [-1,1].

In this episodic task, the agent is considered successful if an average score of +30 over 100 consecutive episodes is achieved and maintained.

Learning Algorithm

This task is approached by blending lessons learned from traditional value and policy-based reinforcement learning methods with Artificial Neural Networks, leading to a Deep Reinforcement Learning regime. Similar to the DQN network employed in P1: Navigation, the DDPG algorithm also employs an off-policy training with random samples drawn from a replay buffer to improve the stability of training. DDPG differs from DQN by employing the local and target networks for an actor and critic network each. The actor network is responsible for deterministic predictions on actions to take from a particular state, and the critic network evaluates the quality of these actions by computing the action-values (Q-values). Some noise is also incorporated via the Ornstein-Uhlenbeck process to aid with training. Detailed information on this strategy is presented by Lillicrap et al. [1] and Yoon [2].

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

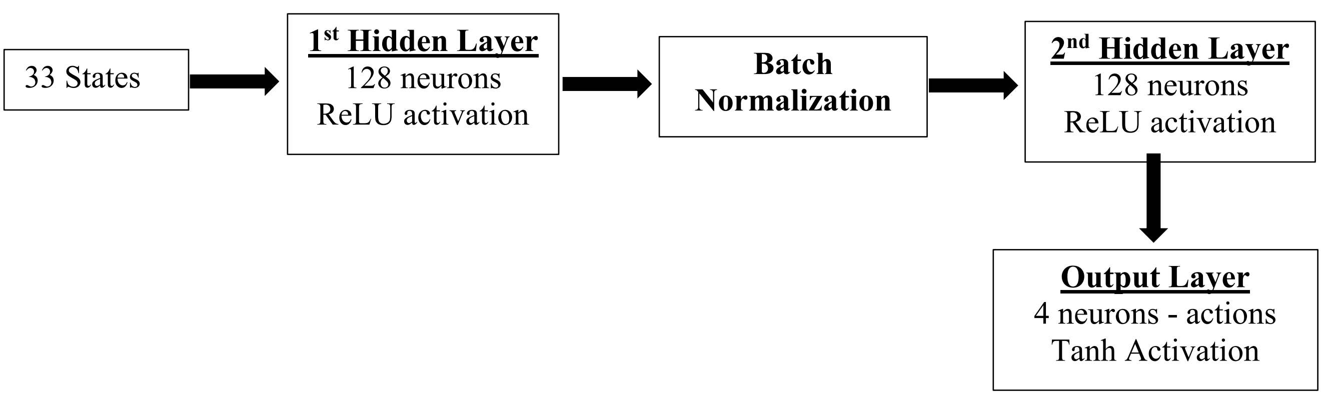
Figure 1: DDPG Algorithm (Credit: https://towardsdatascience.com/deep-deterministic-policy-gradients-explained-2d94655a9b7b)

Implementation

The implementation of the algorithm consists of design choices associated with the layer type, neurons and algorithms in the neural networks, and the hyperparameters for tuning these networks and for the training process.

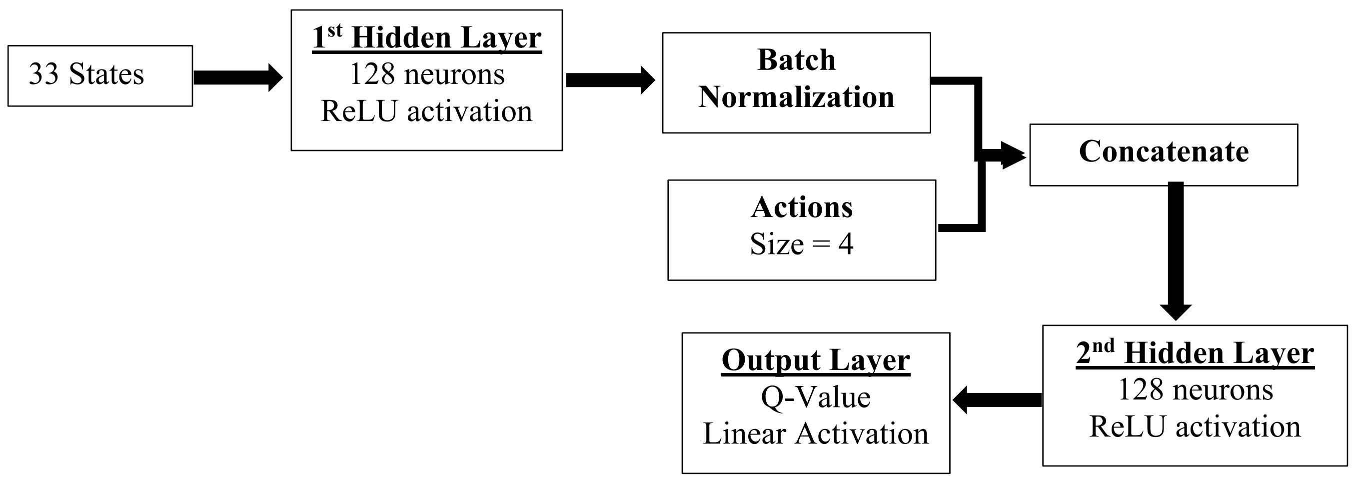
Neural Network Architecture – Actor Network

The actor neural network takes in the states as inputs and outputs the action to be taken from the state via a deterministic policy. This network consists of fully connected layers with the following neuron count and activation functions. Note that batch normalization is employed to address the numerical challenges arising from the variables in this training process being on different scales (e.g., positions, velocities, torques).



Neural Network Architecture – Critic Network

The critic neural network consists of fully connected layers with the following neuron count and activation functions. Note that batch normalization is employed to address the numerical challenges arising from the variables in this training process being on different scales (e.g., positions, velocities, torques). The gradient norm associated with this network is also clipped to aid with stability during training.



Hyperparameters

The training outcomes are very sensitive to the hyperparameters – thus, appropriate tuning is key to the agent being successful in its task. The following are the parameters used for the training process:

Parameter	**Value**
Number of episodes	1000
Number of steps within an episode	1000
Random Seed	1

The following are the hyperparameters used to tune the reinforcement learning process:

Hyperparameter	**Value**
Replay Buffer Size	1e6
Batch Size	128
Discount Factor (γ)	0.99
Soft Update Parameter (τ)	1e-3
Learning Rate - Actor	2e-4
Learning Rate - Critic	2e-4
Weight Decay	0
OuNoise - Asymptotic Mean – μ [3]	0
OuNoise - Strength of Reaction to Perturbation – θ [3]	0.15
OuNoise - Variation of the Noise – σ [3]	0.1

The Adam algorithm is employed for the gradient updates associated with the neural network computations.

Files

Continuous_Control.ipynb – Main file consisting of the environment set-up and also the training parameters for user modification.
ddpg_agent.py – File consisting of the definitions for the 'agent', 'OuNoise' and 'replay buffer' classes, and also the reinforcement learning hyperparameters for user modification.
model.py – File consisting of the neural network architectures and choices

Plot of Rewards

Using the parameters and hyperparameter choices listed earlier, the environment is solved (average reward of 30 over 100 consecutive episodes) in 518 episodes, as displayed in Fig. 2.

```
Episode 509     Average Score: 29.61
Episode 510     Average Score: 29.57
Episode 511     Average Score: 29.66
Episode 512     Average Score: 29.72
Episode 513     Average Score: 29.68
Episode 514     Average Score: 29.58
Episode 515     Average Score: 29.79
Episode 516     Average Score: 29.91
Episode 517     Average Score: 29.97
Episode 518     Average Score: 30.10

Environment solved in 518 episodes!     Average Score: 30.10
```

```
In [6]: fig = plt.figure()
        ax = fig.add_subplot(111)
        plt.plot(np.arange(len(scores)), scores, label='Scores')
        plt.ylabel('Score')
        plt.xlabel('Episode #')
        plt.show()
```

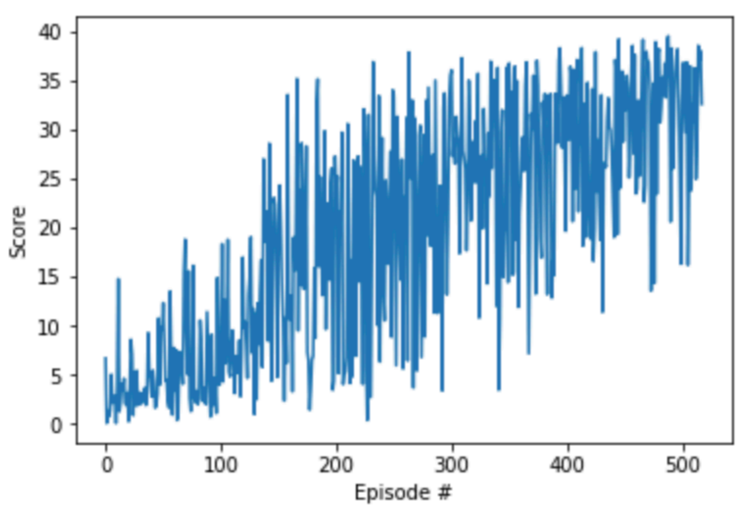


Figure 2: Plot of scores over episodes

Ideas for Future Work

- Further tuning of the hyperparameters would be attempted to investigate the potential impact on the results
- The impact of other reinforcement learning algorithms such as Trust Region Policy Optimization (TRPO), Truncated Natural Policy Gradient (TNPG), and Proximal Policy Optimization (PPO) could also be investigated.
- Modification of the neural network architecture choices could also be investigated.
- The impact of updating the DDPG network weights only periodically would be assessed

References

1. T. Lillicrap et al., *Continuous Control with Deep Reinforcement Learning*, ICLR, 2016, arXiv:1509.02971v6
2. Yoon, *Deep Deterministic Policy Gradients Explained*, https://towardsdatascience.com/deep-deterministic-policy-gradients-explained-2d94655a9b7b
3. http://web.math.ku.dk/~susanne/StatDiff/Overheads1b