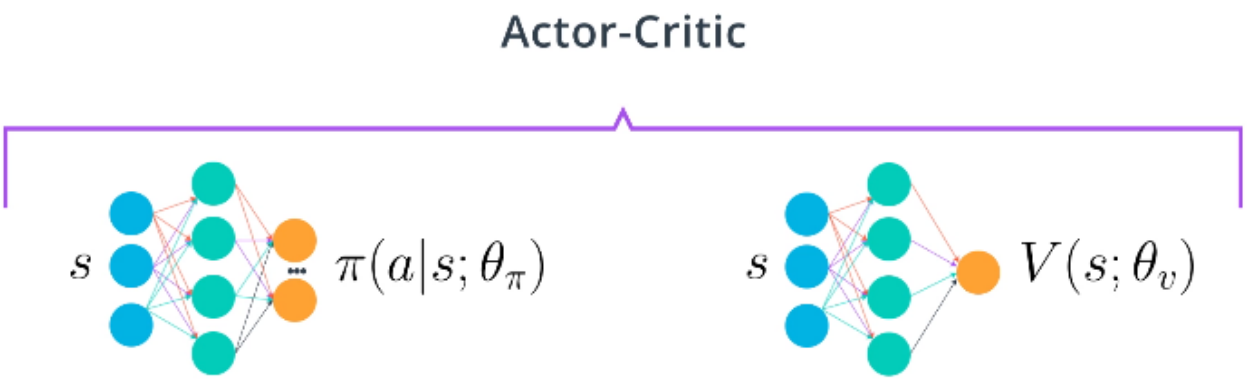
Udacity Deep Reinforcement Learning Nanodegree

Project 2: Continuous Control

Introduction

This report details the implementation of a reinforcement learning algorithm to solve the continuous control problem in Unity's Reacher environment. The solution presented here uses the Deep Deterministic Policy Gradient (DDPG) algorithm, which is a form of model-free actor-critic reinforcement learning that operates over continuous action spaces.



DDPG is a method that is similar to Deep Q Learning, and uses two neural networks to complete a task – the Actor to determine the best action from the policy deterministically,

$$a^* = argmax_a Q(s,a),$$

and the Critic to determine the action value function,

$$Q(s,\mu(s;\theta_\mu);\theta_Q).$$

The algorithm runs as follows (from Lillicrap et al. 2016):

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

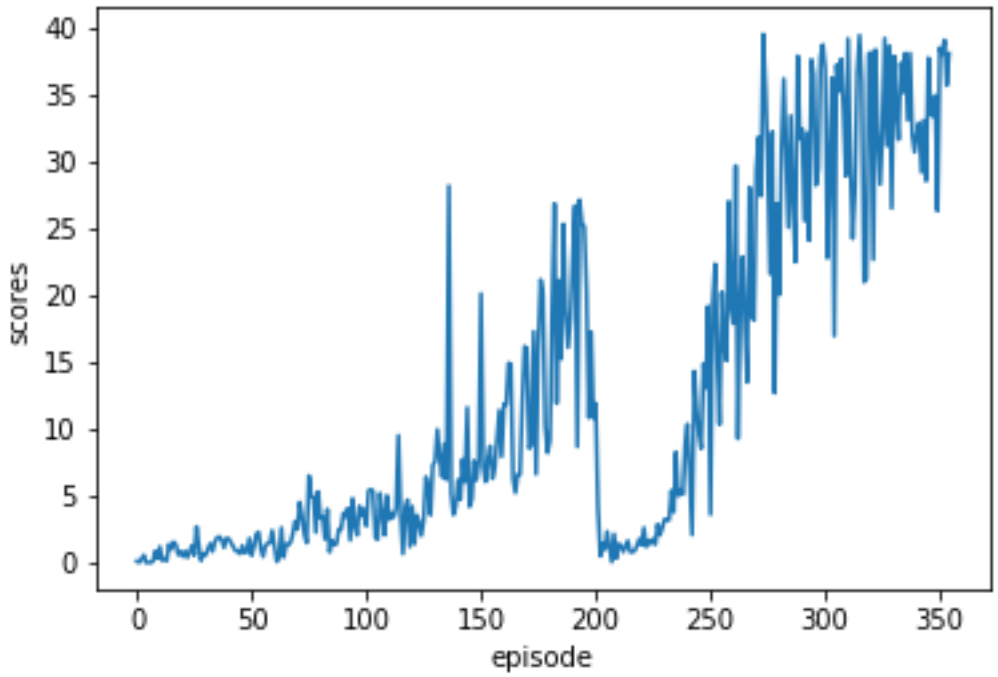
Implementation Details

As in the original Lillicrap implementation, we also use a replay buffer containing tuples of previous transitions, that we periodically revisit to improve sample efficiency. In addition, a soft update is used in order to slowly blend a target and the regular network weights. In this solution, both the actor and the critic are composed of four-layer neural networks, with a fully connected layer, followed by a batch normalization layer, followed by two additional fully-connected layers.

In order to encourage the agent to explore, we impose noise on the actions that are chosen by the actor, so that the actions that are actually taken have an additional term dictated by an Ornstein-Uhlenbeck process. This is a stationary Gauss-Markov process, and is a form of mean-reverting random walk. We also impose a decay factor on the process, to reduce the amount of exploration as time goes on and the agent's policy becomes more feasible. Since the action output can only take values between -1 and 1, the outputs of the actor are clipped to be between -1 and 1.

Results

The DDPG training solved the environment in 354 episodes (with the window of episodes 254-354 averaging more than +30 reward). The plot of the rewards is shown below. In an earlier run, the solution was actually found in approximately 270 episodes, but an error occurred while saving the network weights that forced a reversion to an earlier copy of the actor and critic networks (saved at episode 200). Unfortunately, not all the decayed parameters were returned to their state at episode 200, so the score dropped dramatically upon reloading. Still, as shown in episodes 200-300, starting with network weights that were previously trained somewhat did help the agent get a "warm start." This segment could be compared to episodes 0-100, which showed significantly less improvement in score, since it started from random network weights.



Future Work

Bootstrap initial training by imitating a pre-programmed controller. In the environment, the agent is essentially attempting to learn inverse kinematics from scratch. A variety of methods exist to solve an inverse kinematics problem like this from the robotics domain, so it may be advantageous for the agent to initially attempt to replicate a known controller, which may speed up the initially slow learning period. This might be done by biasing the agent's actions towards what a known controller would do, before gradually decreasing the bias – a form a guided exploration, rather than the purely stochastic Ornstein-Uhlenbeck process used here. This is similar to the way that AlphaGo and AlphaStar initially imitated professional Go and Starcraft players to get their policies up to a reasonable state before training on their own.

Use prioritized experience replay. In the current implementation, the replay buffer is sampled uniformly randomly. Given the number of experiences stored, it stands to reason that some of these experiences are more valuable for correcting mistakes than others. A prioritized replay buffer could, for example, weight the probability of selecting replays based on the magnitude of the error, allowing larger errors to be corrected more quickly. There is additional computational cost involved in calculating the errors associated with these replays, but this cost is offset by potentially allowing for less retraining of the networks.