Continuous Reinforcement Learning Problem Report

In this exercise, I used a Deterministic Deep Policy Gradient (DDPG) Agent to control a unity environment brain, that in turns controls an arm agent that must touch and object at all time. In this report, I documented the characteristics of the environment, the method used to solve the environment control problem, the result of the training process, and what can be done to improve it.

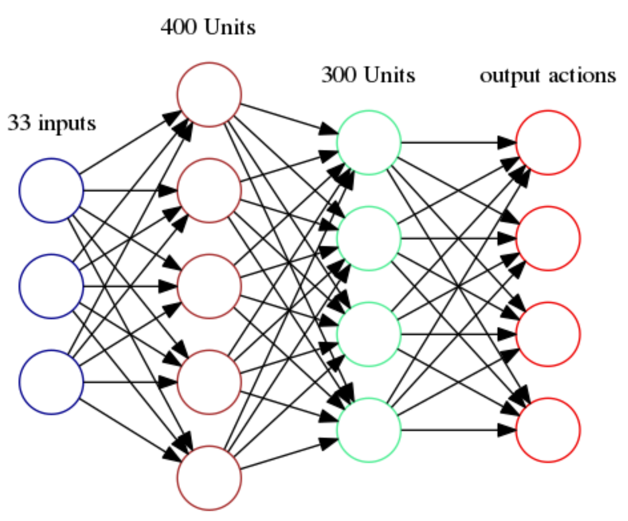
The Environment

In this environment, a double-jointed arm can move to target locations. A reward of +0.1 is provided for each step that the agent's hand is in the goal location. Thus, the goal of your agent is to maintain its position at the target location for as many time steps as possible.

The observation space consists of 33 variables corresponding to position, rotation, velocity, and angular velocities of the arm. Each action is a vector with four numbers, corresponding to torque applicable to two joints. Every entry in the action vector should be a number between -1 and 1.

The Agent

The agent is a version of a DDPG (https://arxiv.org/pdf/1509.02971) that uses two deep neural network the actor represents the agent policy, the critic calculates the q_value of the actions taken by the actor.



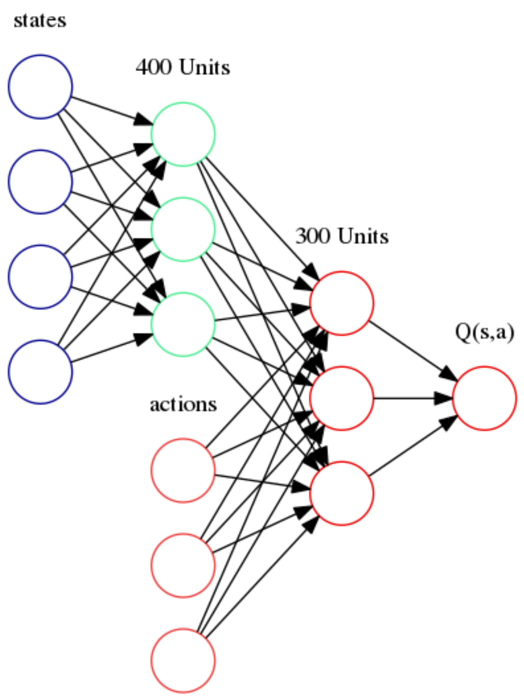


Illustration 1: Actor Network (left), Critic Network (Rigth)

The main idea behind the DDPG agents is the use on the Actor to determine directly the actions and their magnitude, that the agent has to apply in any given state. The role of the critic is used the action taken by the actor on a particular state and calculate the value of that action on that state.

The Optimization

The Critic is optimized by taken the action produced by the actor, the state in which it took the action, then use the result next state and the actor again we collect (using the same actor network) the action that applies to the next state. The resulting tuple: state, action, next_state and next_action, is used with the Bellman equation (https://en.wikipedia.org/wiki/Bellman_equation) to calculate an estimate value of the q_value of the next state. We use the difference of the q_value calculated using the Bellman equation and the q_value produced by the critic as the loss or error signal of the critic, in turn we used that loss to optimized the critic.

The Actor optimization process is based on the David Silver "Deterministic Policy Gradient" paper (http://proceedings.mlr.press/v32/silver14.pdf). The paper explains that the error signal of the Actor or agent policy function is in proportion of the sum of the negative of the gradient of the Critic q_values .

In my model I take all the q_values of a particular buffer sample I add them up and get its negative, this value will work as the q_values proportion and the error signal of the actor model; I backward propagate this figure in the actor model to calculate its gradient, and then optimized the agent parameters with it. It is not clear to me yet why the negative sum of the q_values makes a good proportion figure. I plan to further investigate this and once I have the answer I will modify this report.

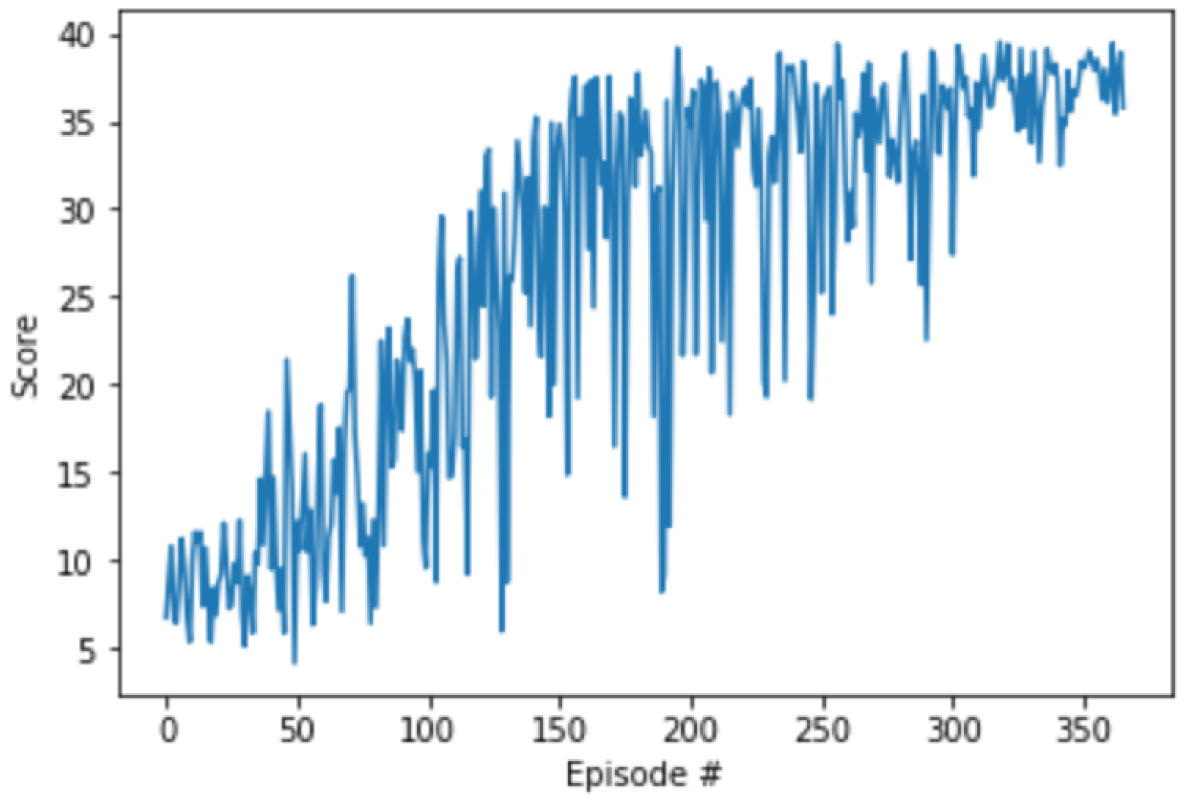
The parameters.

The replay buffer size was 1000000; the learning batch consisted of 128 samples. I used a discount factor of 0.99, to perform a soft update of the target weights (see the fix q-targets weight documentation in the dqn URL) I used a TAU factor of 0,001, my learning rate was of 0.0001 for the actor and 0.001 for the critic, and I performed weighs update every time step, once I had at least 128 samples in the replay buffer.

The network was created using Pytorch.

The result of the training

After ~200 episodes the model solved the problem, with a score of 30+ and kept improving (see chart below)



Improvements

Even if the agent was training to an acceptable level, the following improvement could be made to optimize the agent behavior and make it converge to the option q* value in less training episodes.

Double Deep Q-Network

The problem with the dqn agent is that it tends to overestimate the q values, this is because it uses the q value if the actions that maximize the q estimate function to determine the real q value, this produces a tendency toward given values to actions higher than the real ones. The solution to this problem is the use of two sets of Q-target networks weighs, one is used to select the action and the other set of weighs is used to select the value of that action.

Prioritize Experience Replay

The main idea behind this improvement is that during the selection of the experiences to be used in the learning process, we select these using a random process, with this we run the risk of selecting the same set of samples or even worst not selecting valuable experiences. The improvement consists of using a parameter to weigh the importance of the experience base on its value. The value we can use to prioritize the selection of important experiences can be the error term obtained when we are performing the weigh optimization, using this value we can calculate the probability of the sample selection, the higher the experience error term the highest its probability is of been selected.