Project Report: Deep Reinforcement Learning Nanodegree - Project 2: Continuous Control

Learning Algorithm

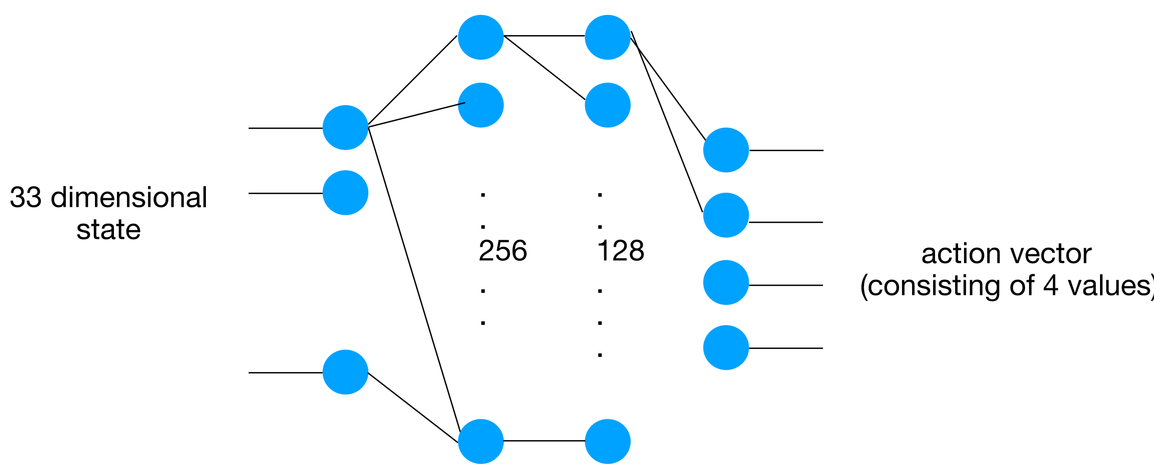
In the project we train a Deep Reinforcement Learning agent based on the Deep Deterministic Policy Gradient (DDPG) approach. The task in hand requires a model that can generate continuous action values.

The DDPG model consists of 2 parts: an Actor and a Critic

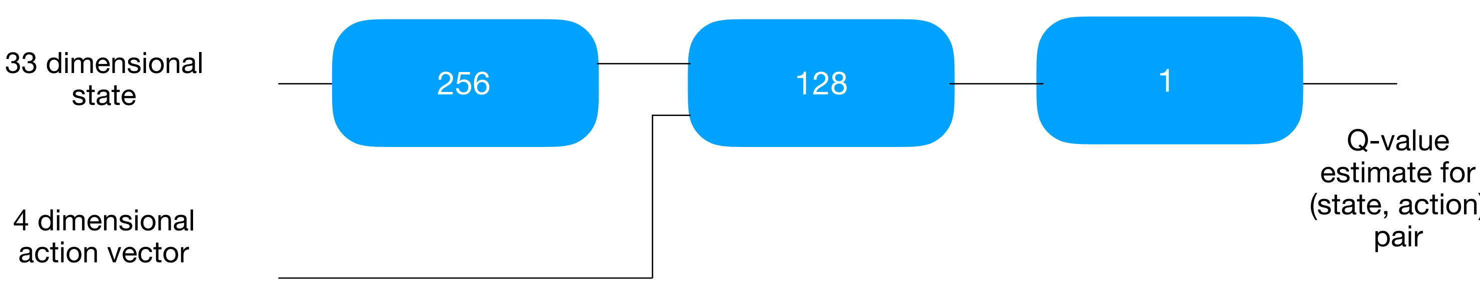
- Actor: The actor takes the current state as input and generates a deterministic action corresponding to this state.
- Critic: The critic takes in both the current state and the action chosen by the actor. The critic's job is to estimate the Q-value corresponding to this (state, action) pair.

To improve the stability of converence, we use a separate local / target network for both the actor and critic. The target networks parameters are updated using a soft-update with τ = 1e-3.

Actor network



Critic network

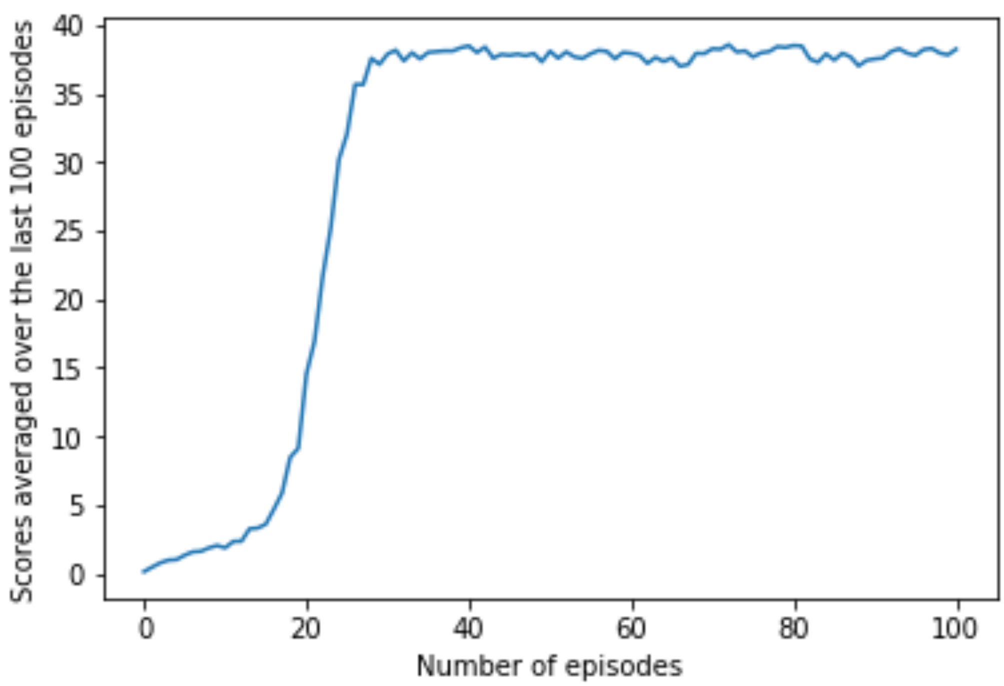


Experience Replay

An experience is defined as a tuple of (state, action, reward, next_state, done). As we progress through training, these tuples are stored in a deque of buffer size 1e5. Batches of size 128 are drawn from this deque, and used to train the DDPG model.

Rewards

The below plot shows the rewards obtained by the agent as training progressed. On the x-axis is the number of episodes. The y axis shows scores averaged over the last 100 episodes. Although the scores started off low, between episodes 20-30, there was a substantial increase in scores, and hence the environment was solved in 101 episodes.



Ideas for Future Work
Convergence with DDPG can be somewhat unstable. Duan et al (Benchmarking Deep Reinforcement Learning for Continuous Control, https://arxiv.org/pdf/1604.06778.pdf), observed that approaches such as TNPG (Truncated Natural Policy Gradient), TRPO (Trust Region Policy Optimization) performed much better. This can be an avenue for further exploration.