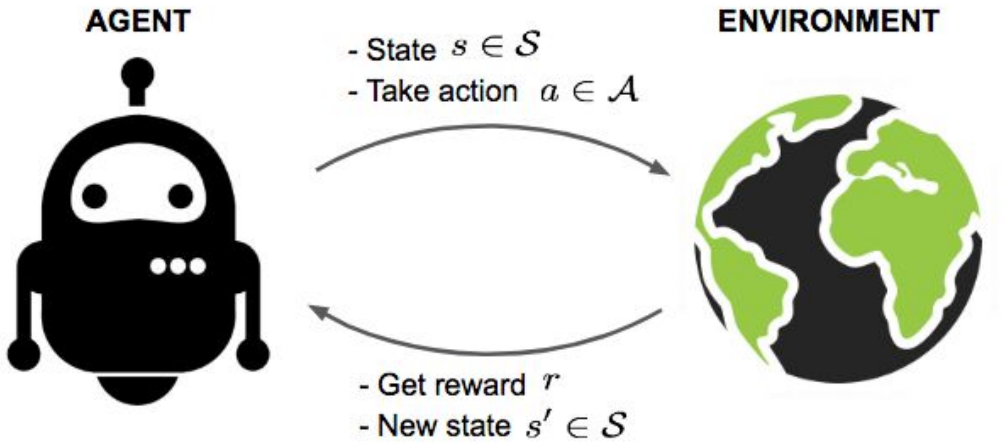
Ensemble Learning

Teaching Agents to Walk

Problem Statement



Problem Statement - Contd.

➔ Discounted returns represent the sum of all rewards '$\mathbf{r_t}$' *ever* obtained by the agent discounted by $\gamma^t \in (0,1)$

$$R_t = \sum_{t=0}^{\infty} \gamma^t r_t$$

➔ Goal of RL is to learn the optimal policy '$\boldsymbol{\pi_\theta}$' which maximizes the expected return:

$$\pi_\theta^* = \max_{\pi_\theta} \mathbb{E}_{\pi_\theta}[R_t]$$

Background

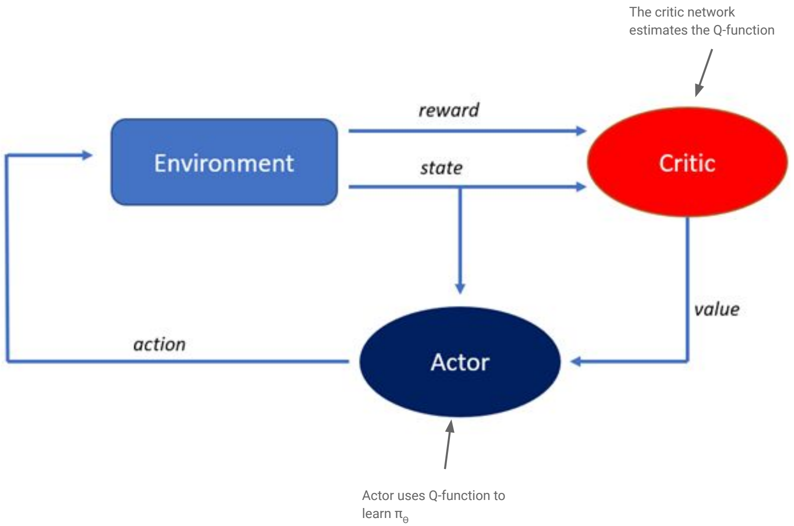
- ➔ Our proposed algorithm builds upon TD3
- ➔ We will go over the necessary information:
  - ◆ Deep Deterministic Policy Gradients (DDPG)
  - ◆ Twin Delayed DDPG (TD3)

Deep Deterministic Policy Gradients (DDPG)

➔ Based on the actor-critic framework:
- ***<u>Actor Network</u>***: Learns the deterministic policy (π_θ)
- ***<u>Critic Network</u>***: Approximates the Q-function

➔ DDPG is a model-free, off-policy algorithm.

➔ Makes use of two target networks:
- Target Actor Network
- Target Critic Network



DDPG: Q-Function Estimation

- The target is approximated using Temporal Difference in conjunction with the secondary target networks:

Target Network

$$y = r(s, a) + \gamma Q_{\phi'}(s', a')$$

Target

Present rewards

a’ sampled from target actor

- Using the target, we minimize the following error:

$$L(\phi') = \mathbb{E}_{s,a,s',a'}\left[(Q_{\phi}(s, a) - y)^2\right]$$

DDPG: Policy Eval & Replay Buffer

- Policy Evaluation:

➔ Since the Q-function is differentiable, we can just perform gradient ascent to find the optimal policy:

$$\nabla_\theta J(\theta) = \mathbb{E}_{s \sim p_\pi} \left[\nabla_a Q_\pi(s, a)|_{a=\pi_\theta(s)} \nabla_\theta \pi_\theta(s) \right]$$

- Experience Replay Buffer:

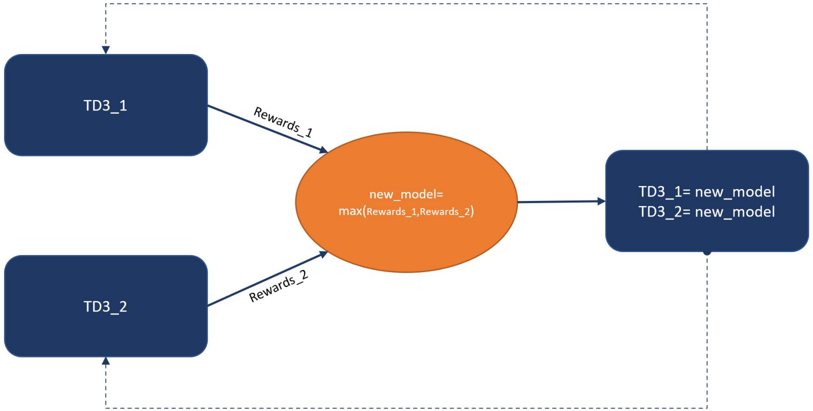
➔ DDPG uses an experience replay buffer to store previous experiences (states, action, reward).
➔ Prevents bias since batches of samples are drawn from it at random.

Twin Delayed DDPG (TD3)

- Successor to DDPG
- Addresses the overestimation of Q-values faced by DDPG
- Mitigates the problem by three tasks:
  - ***Target Policy Smoothing****:* Adds noise to the target actions, **a’**
  - ***Clipped Q-Learning***: Learns two Q-function
  - ***Delayed Policy Updates***: Policy and target policy are updated after every other step

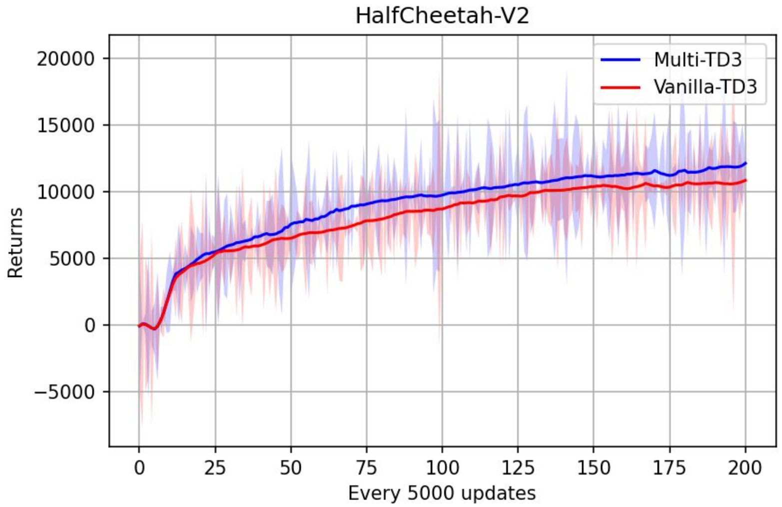
Multi-TD3

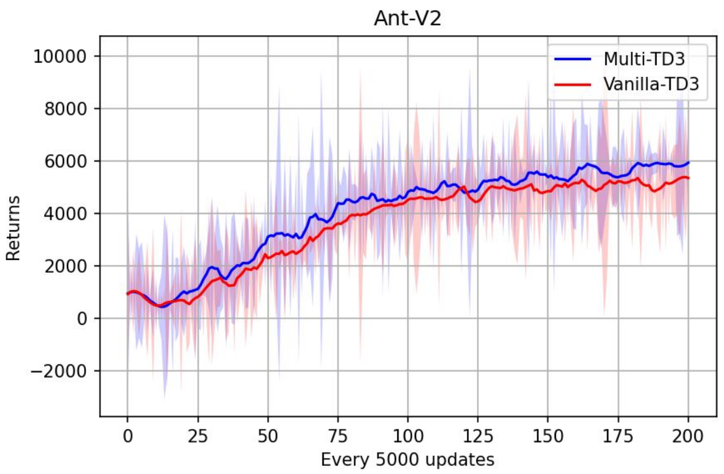
- ➔ Based on the TD3 algorithm
- ➔ Works on the principle of “Ensemble Learning”
- ➔ Performs the following tasks:
  - Two separate instances of TD3 networks are trained
  - Both networks push and sample from the same replay buffer
  - Model with highest rewards serves as the model to be trained in a new episode by the two networks
- ➔ Advantage:
  - Decreases the likelihood of selecting a relatively poor model
  - More experiences are sampled per episode

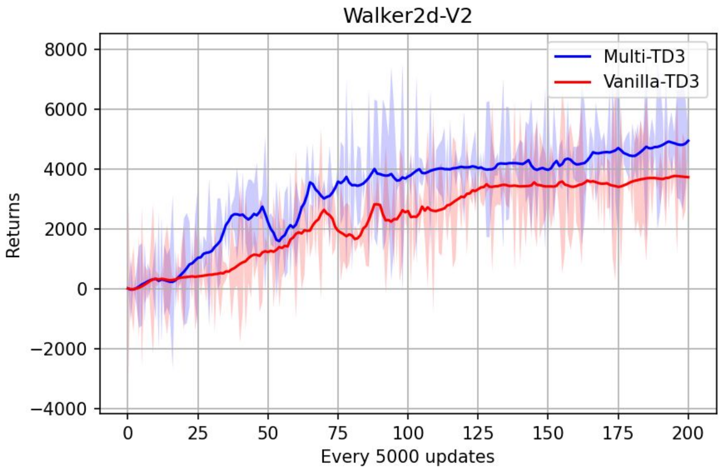


Multi-TD3: Ensemble Learning

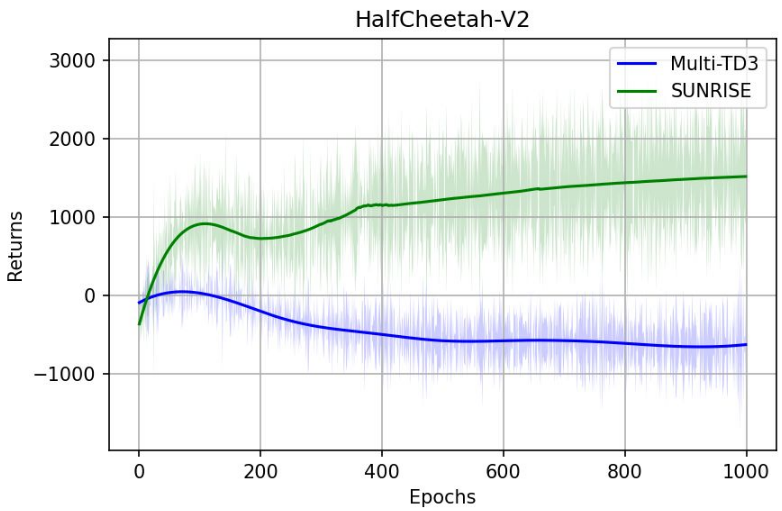
Results: Multi-TD3 vs TD3

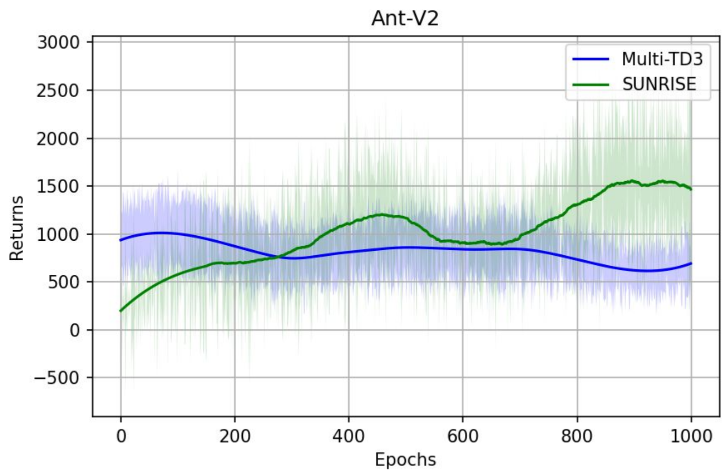


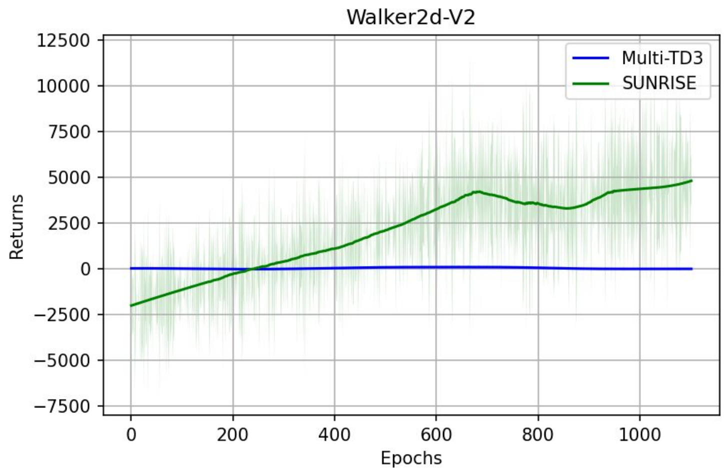




Results: Multi-TD3 vs SUNRISE







Discussion

Limitations

➔ SUNRISE required longer training times but performed much better on a shorter timescale

➔ Could not attempt training on Humanoid-V2 with limited time

Applications

➔ Multi-TD3 typically gives a slightly improved result over TD3

Thank you!

The End