# Twin-Delayed Deep Deterministic Policy Gradient (TD3)

> Fujimoto, S., Van Hoof, H., & Meger, D. (2018). Addressing Function Approximation Error in **Actor-**Critic Methods. 35th International Conference on Machine Learning, ICML 2018, 4, 2587–2601.

### 1. Motivation

- In DDPG, we use a Critic network (q-value) to evaluate and train the Actor network (policy), hence the actor's performance strongly depends on how well Critic network estimates the action-value `q`.
- Due to boostrap learning mechanism, i.e learning by temporal-difference, the `Critic` is subject to estimation error, namely the overestimation bias and high variance build-up.
- In Double Q-Learning, we know that using an extra Q-network can help reduce this bias. This is the key idea of TD3: We use an extra network Critic, named twin-network, to perform another estimation of `q-value`. By having two Critic networks compete to each other, we can eliviate the over-confident estimation error.

### 2. Twin-Delayed DDPG (TD3)

- Compare two DDPG, the main change is that TD3 uses two Critic networks, namely $Q_1(s, a|\theta_1)$ and $Q_2(s, a|\theta_2)$, which are identical (twin) but with different iniatialized weights $\theta_1$ and $\theta_2$.
  - Let $Q_{T1}(s', a'|\theta_{T1})$ and $Q_{T2}(s', a'|\theta_{T2})$ be their corresponding target, respectively.
  - Also, let $A(s|\phi)$ be the Actor network, and $A_T(s'|\phi_T)$ be the Actor-target network.
- We update the `q_target` as follows:
  - From the Replayed-Buffer, we sample a mini-batch $(s, a, r, s')$.
  - We predict the next action for the next state $s'$ using the Actor-target network, disturbed by a small Gaussian noise:

$$a' = A_T(s'|\phi_T) + N(0, \sigma)$$

  - We compute two action-values using the twin-Critic Target networks:

$$q_1 = Q_{T1}(s', a'|\theta_{T1}), q_2 = Q_{T2}(s', a'|\theta_{T2})$$

  - We compute the `q_target` by

$$q_{target} = r + \gamma \min(q_1, q_2)$$

- Then, we update the Critic Networks by:
  - Evaluate the current action-values using the twin-Critic networks:

$$q_1 = Q_1(s', a'|\theta_1), q_2 = Q_2(s', a'|\theta_2)$$

  - Compute the loss to update the Critic-Networks using MSE loss:

$$Loss = \frac{1}{2}[(q_1 - q_{target})^2 + (q_2 - q_{target})^2]$$

- The Actor network $A(s|\phi)$ is trained as done in DDPG, using either one of the Critic, e.g. $Q_1$:
    - We predict the action for the curernt state $s$ using the Actor network:

$$a = A(s|\phi)$$

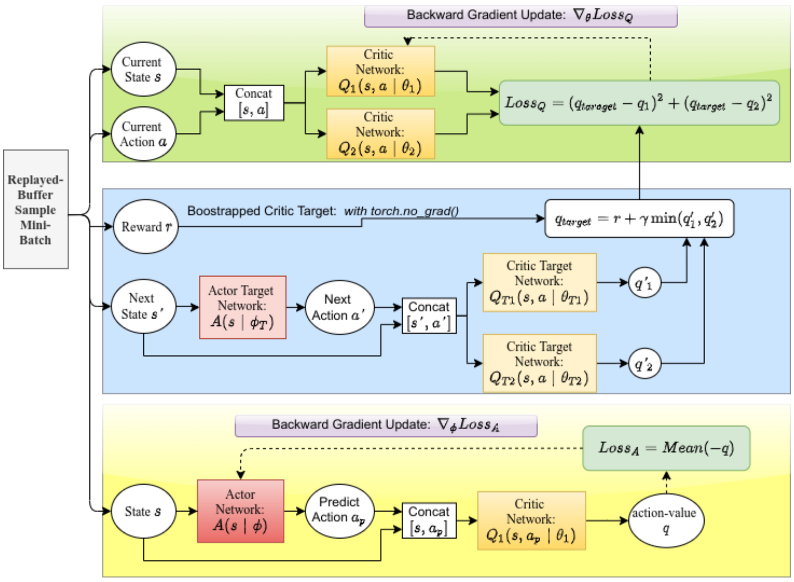
    - Loss for Actor network:

$$Loss = Mean(-Q_1(s, a|\theta_1))$$

## 3. What makes TD3 works?

- As mentioned above, using the Twin-Critic Network helps reducing the over-confident estimation for `q_target` value.
- An important trick is that, we `delay` updating the Actor and the target networks. For every two iterations, we update them **once**.

## 4. TD3 Pseudo Code




**Algorithm 1** TD3

Initialize critic networks $Q_{\theta_1}, Q_{\theta_2}$, and actor network $\pi_\phi$ with random parameters $\theta_1, \theta_2, \phi$
Initialize target networks $\theta'_1 \leftarrow \theta_1, \theta'_2 \leftarrow \theta_2, \phi' \leftarrow \phi$
Initialize replay buffer $\mathcal{B}$
**for** $t = 1$ **to** $T$ **do**
  Select action with exploration noise $a \sim \pi_\phi(s) + \epsilon$, $\epsilon \sim \mathcal{N}(0, \sigma)$ and observe reward $r$ and new state $s'$
  Store transition tuple $(s, a, r, s')$ in $\mathcal{B}$

  Sample mini-batch of $N$ transitions $(s, a, r, s')$ from $\mathcal{B}$
  $\tilde{a} \leftarrow \pi_{\phi'}(s') + \epsilon, \quad \epsilon \sim \text{clip}(\mathcal{N}(0, \tilde{\sigma}), -c, c)$
  $y \leftarrow r + \gamma \min_{i=1,2} Q_{\theta'_i}(s', \tilde{a})$
  Update critics $\theta_i \leftarrow \text{argmin}_{\theta_i} N^{-1} \sum (y - Q_{\theta_i}(s, a))^2$
  **if** $t$ mod $d$ **then**
    Update $\phi$ by the deterministic policy gradient:
    $\nabla_\phi J(\phi) = N^{-1} \sum \nabla_a Q_{\theta_1}(s, a)|_{a=\pi_\phi(s)} \nabla_\phi \pi_\phi(s)$
    Update target networks:
    $\theta'_i \leftarrow \tau \theta_i + (1 - \tau)\theta'_i$
    $\phi' \leftarrow \tau \phi + (1 - \tau)\phi'$
  **end if**
**end for**

**To train DDPG agent for Mountain Car Continous problem, do**:

```
python tools/train.py configs/TD3/td3_mountaincar_continuous.py
```

Result after training 260 episodes: