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Deep Deterministic Policy Gradient (DDPG)

Deep Deterministic Policy Gradient (DDPG) is a model-free off-policy algorithm for learning continuous actions.

- It is a **reinforcement learning technique** that combines ideas from **DPG (Deterministic Policy Gradient)** and **DQN (Deep Q-Network)**.

DDPG = DPG + DQN

- From **DQN**, it uses:

Experience Replay and Slow-learning target networks

- From **DPG**, is incorporates:

Operating over continuous action spaces

DDPG being an Actor-Critic technique:

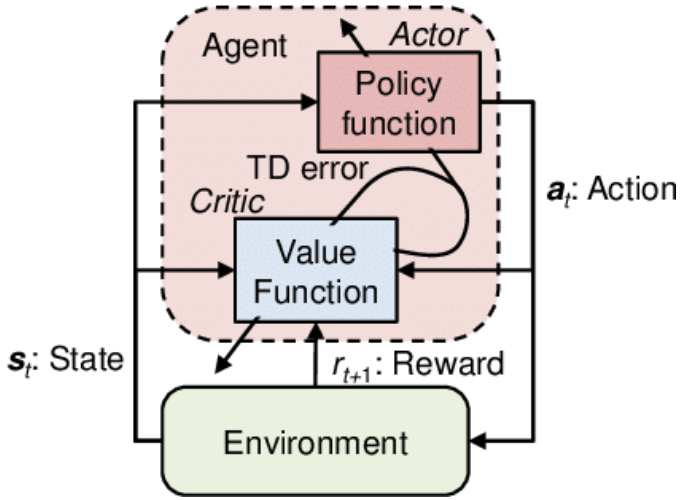
- DDPG being an **actor-critic technique** consists of two models:

  Actor: Actor is the **policy network** that takes the state as input and outputs the exact action (continuous), instead of a probability distribution over actions. The learning of the actor is based on **policy gradient approach**.

  Critic: The critic is a **Q-value network** that takes in state and action as input and outputs the Q-value. Critics **evaluate the action** produced by the actor by computing the Q-value function.

- The actor model decided **which action should be taken** and critic inform the actor **how good was the action** and how it should adjust.

- In DDPG, during the **update process of the actor**, **TD (Temporal Difference) error** from a critic is used. The critic network gets updated based on the **TD error** similar to Q-learning update rule.



DDPG being an “off”-policy method:

- Off-Policy learning algorithms **evaluate and improve a policy that is different from Policy that is used for action selection**.
  In short:

Target Policy != Behavior Policy

- DDPG is an off-policy algorithm because it uses **two separate policies** for the **exploration and updates**. It uses a **stochastic behaviour policy for the exploration** and **deterministic policy for the target update**.

- DQN works in a discrete action space (exploration) and DPG extends it to the continuous action space (target) while learning a deterministic policy.

DDPG Theories (Mathematically)

DPG Theory:

- Traditionally, **policy gradient algorithms** are being used with **stochastic policy function π(.|s)**. That means policy function π(.|s) is represented as a distribution over actions. For a given state, there will be **probability distribution** for each action in the action space. The grad objective function of the stochastic Policy gradient algorithm can be written as below:

$$\nabla_\theta J(\theta) = E[\nabla_\theta log_{\pi_\theta}(s,a) Q^w(s,a)]$$

- In **DPG**, instead of the stochastic policy, π, **deterministic policy μ(.|s)** is followed. For a given state, there will be **deterministic decision: a=μ(s)** instead of distribution over actions. We can rewrite the above equation with the deterministic policy as shown below:

$$\nabla_\theta J(\theta) = E[\nabla_\theta \mu_\theta(s) \nabla_a Q^\mu(s,a)]$$

DQN Theory:

- Learning is a value-based off-policy **temporal difference (TD)** reinforcement learning. **Off-policy** means an agent follows a behaviour policy for choosing the action to reach the next state **s_t+1** from state **s_t**. From **s_t+1**, it uses a **policy π** that is different from behaviour policy.

- In Q-learning, we take **absolute greedy action as policy π** from the next state s_t+1.

$$Q(s,a) = r(s,a) + \gamma \max_a Q(s',a)$$

- It is important to mention the **update rule** in Q-learning. New Q value is the sum of **old Q value and TD error**.

$$Q(s_t, a_t) \leftarrow old\ Q\ value + TD\ error$$

- **TD error** is computed by **subtracting the new Q value from the old Q value**.

$$Q(s_t, a_t) \leftarrow old\ Q\ value + (new\ Q\ value - old\ Q\ value)$$
$$new\ Q\ value = [r_t + \gamma max Q(s_{t+1}, a_t)]$$

- The below equation shows the elaborate view of the updating rule.

$$Q^{new}(s_t, a_t) \leftarrow \underbrace{Q(s_t, a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\Big(\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\text{estimate of optimal future value}}}^{\text{new value (temporal difference target)}} - \underbrace{Q(s_t, a_t)}_{\text{old value}}\Big)}^{\text{TD error}}$$

- Overall, the off-policy learning algorithm is as follows:

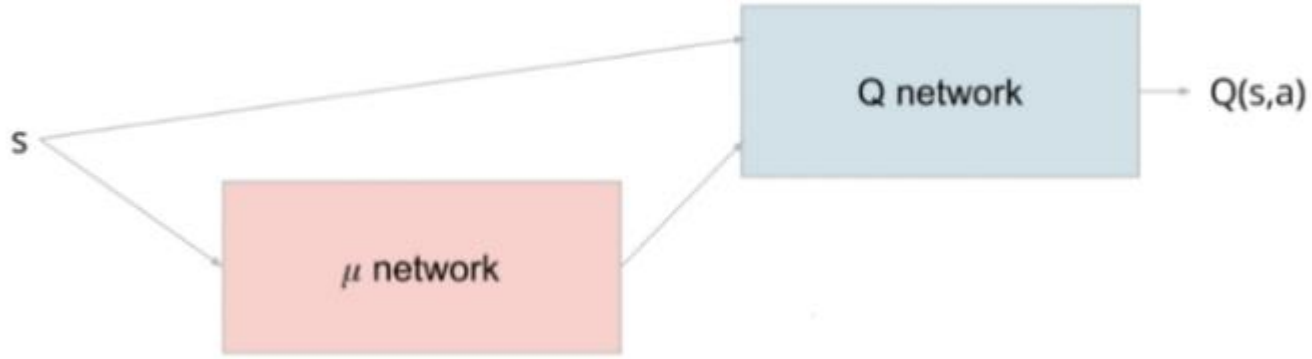
```
Initialize Q(s, a) arbitrarily
Repeat (for each episode):
   Initialize s
   Repeat (for each step of episode):
      Choose a from s using policy derived from Q
         (e.g., ε-greedy)
      Take action a, observe r, s'
      Q(s, a) <-- Q(s, a) + α [r + γ max_α Q(s', a') - Q(s, a)]
      s <-- s';
   until s is terminal
```

Network Models in DDPG

Actor-Critic Network (μ & Q):

- In DDPG, **Actor is the policy network (mu).** It is deterministic since it **directly outputs the action** (action can be continuous). In order to **promote exploration** some **Gaussian noise** is added to the action determined by the policy.

- To calculate the **Q-value** of a state, **the actor output is fed into the Q-network (Q)**.



- To **stabilize learning** we create **target networks** for both critic and actor. These target networks will have **"soft"-updates** based on main networks. This part is described next:

Target Networks:

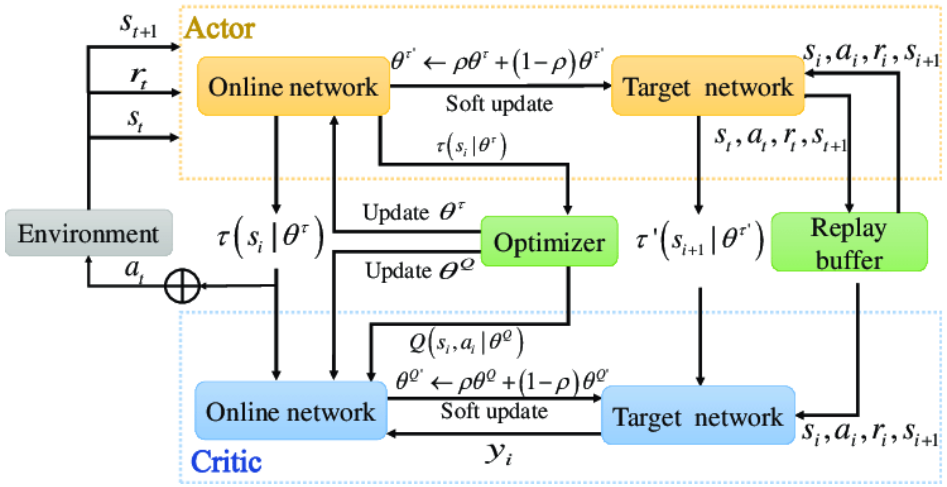
- To increase stability during training we include **target critic and actor networks** to calculate Q-value for next state in TD-error computations.

- The target networks are **delayed networks** compared to **main/current networks**. The **weights of targets** are **updated periodically** based on the main networks.

- In DQN the target gets the main network weights copied over periodically, this is known as a "**hard update"**. However, in DDPG we perform a **"soft update"** where only a fraction of main weights are transferred in the following manner:

$$\theta^{\mu}{}_{targ} \leftarrow \tau\theta^{\mu}{}_{targ} + (1-\tau)\theta^{\mu}$$
$$\theta^{Q}{}_{targ} \leftarrow \tau\theta^{Q}{}_{targ} + (1-\tau)\theta^{Q}$$

- **Tau** is a parameter that is typically chosen to be close to 1 (for example: 0.999).



Replay Buffer:

- As with other deep reinforcement learning techniques, DDPG relies on the use of Replay Buffer for stability. The replay buffer needs to maintain a balance of old and new experiences.

- **Definition:**
  The replay buffer contains a collection of experience tuples (S, A, R, S'). The tuples are gradually added to the buffer as we ar e interacting with the Environment. The simplest implementation is a buffer of fixed size, with new data added to the end of the buffer so that it pushes the oldest experience out of it.

- **Purpose:**
  A buffer of past experiences is used to stabilize training by decorrelating the training examples in each batch used to update t he neural network. This buffer records past states, the actions taken at those states, the reward received and the next state t hat was observed.

DDPG Algorithm

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 of DDPG

Content: https://colab.research.google.com/drive/1sGbtFRo8SerRtd-EP2-Hks7BDpqoCEOf?usp=sharing

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