深度强化学习

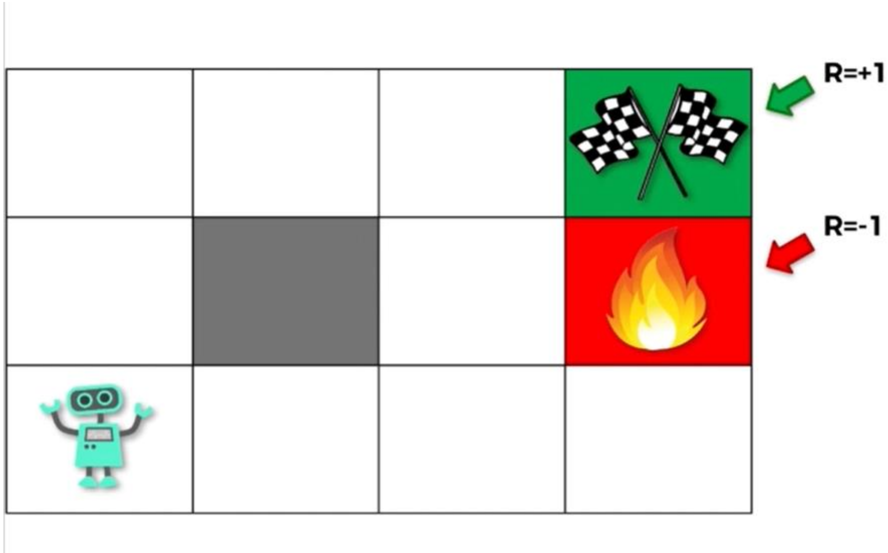
Deep Reinforcement Learning

1. Fundamentals of Reinforcement Learning

Process：Agent 在当前时刻t位于状态s_t，作出一个动作a_t，到达一个新的状态s_{t+1}，并获得奖赏$R_{(s_t,a_t)}$，如果游戏还没有结束，可执行下一个动作a'，以此类推。

1.1 State Value Function，V 函数

通过比较 V 值，来选择接下来要进行的动作。

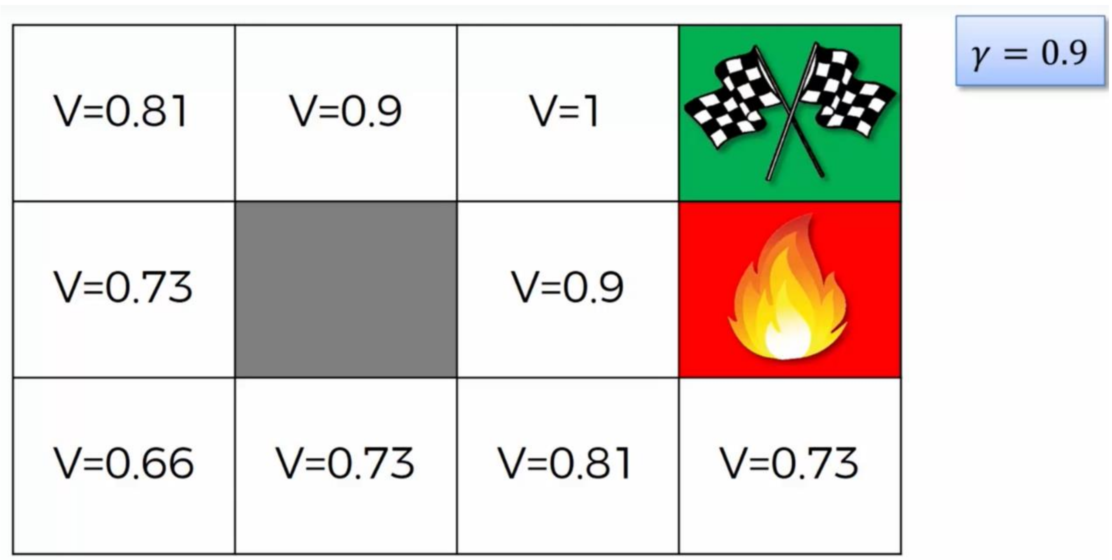


对于这个环境，我们如何指导 agent 到达终点

Bellman equation：

$$V(s) = \max_a (R(s,a) + \Upsilon V(s'))$$

Υ可认为是折扣因子 discount，属于(0,1)。



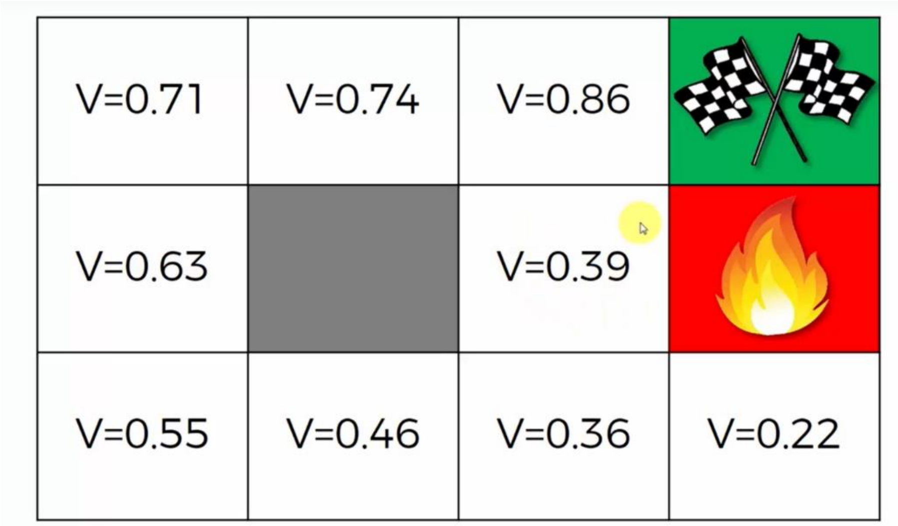
缺点：未能考虑掉入火坑的风险，未考虑随机性。

改进：引入 Markov Decision Process（MDP）的 Bellman equation

$$V(s) = \max_a(R(s,a) + \Upsilon \sum_{s'} P(s,a,s')\,V(s'))$$

下一个动作是s'的概率仅与s, a有关——马尔可夫性质。

比如，Agent 希望向上走，但是由于外界因素，实际有10%的概率往左或往右走。



0.9 变成了 0.39
若初始位置在 0.39，agent 宁可选择绕长路，以避免掉入火坑的危险。

Living penalty： 除了终点的 1 与-1，在每个位置增加R，$R < 0$，以督促 agent 走更短的路径。

1.2 State-Action Value Function，Q 函数

$$V(s) = \max_a(R(s,a) + \Upsilon \sum_{s'} P(s,a,s')\,V(s'))$$

$$Q(s,a) = R(s,a) + \Upsilon \sum_{s'} P(s,a,s')\,V(s')$$

可见

$$V(s) = \max_a Q(s,a)$$

V： 状态的质量 $R(s,a)$：即时奖励
Q：动作的质量 $\Upsilon\, V(s')$：未来值函数的加权结果
易得迭代方程：

$$Q(s,a) = R(s,a) + \Upsilon \sum_{s'} P(s,a,s') \max_{a'} Q(s',a')$$

一种更新 Q-value 的方法：
Temporal difference 时序差分

在实际中，很难一次性算得某个动作的 Q-value，比如有些 Q-value 的计算需要用到其他 Q-value。因此需要用新信息更新旧结果。

为简单起见，这里先不考虑马尔可夫性质。

$$Q(s,a) = R(s,a) + \Upsilon \max_{a'} Q(s',a')$$

旧结果：$Q(s,a)$

新结果：$R(s,a) + \Upsilon \max_{a'} Q(s',a')$

$$TD(a,s) = R(s,a) + \Upsilon \max_{a'} Q(s',a') - Q(s,a)$$

用新样本改进先验的思想

$$Q_t(s,a) = Q_{t-1}(s,a) + \alpha TD(a,s)$$

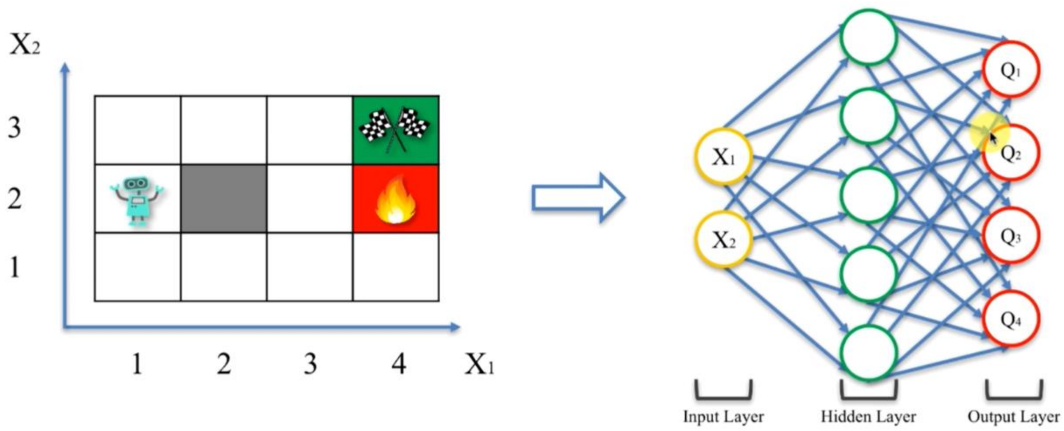
消去$TD(a,s)$

$$Q_t(s,a) = Q_{t-1}(s,a) + \alpha(R(s,a) + \Upsilon \max_{a'} Q(s',a') - Q_{t-1}(s,a))$$

$$0 < \alpha < 1$$

1.3 Deep Q-learning

Intuition：



把每个方格用坐标表示，即可引入神经网络

x_1, x_2： state

Simple Q-learning 与 Deep Q-learning 的对比

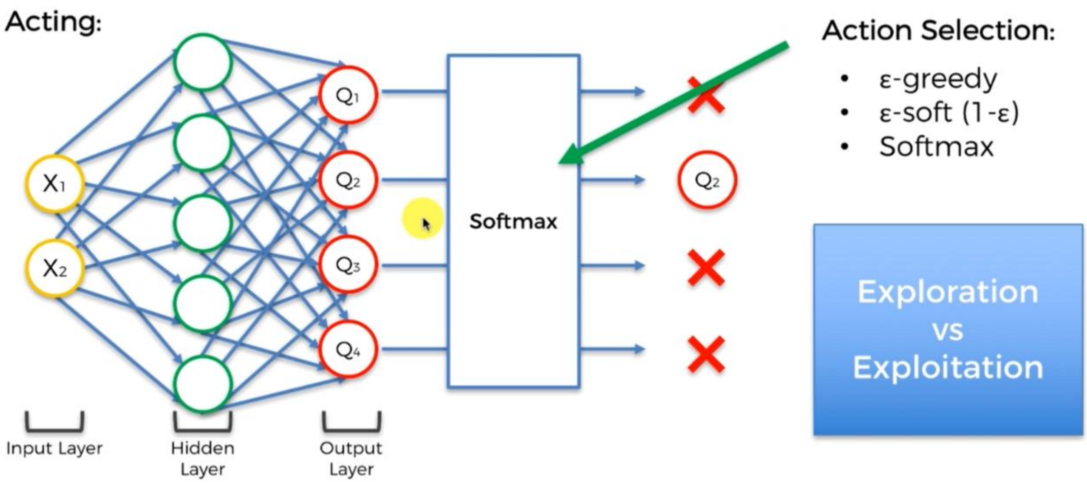
Simple Q-learning：

$$TD(a,s) = R(s,a) + \Upsilon \max_{a'} Q(s',a') - Q(s,a)$$

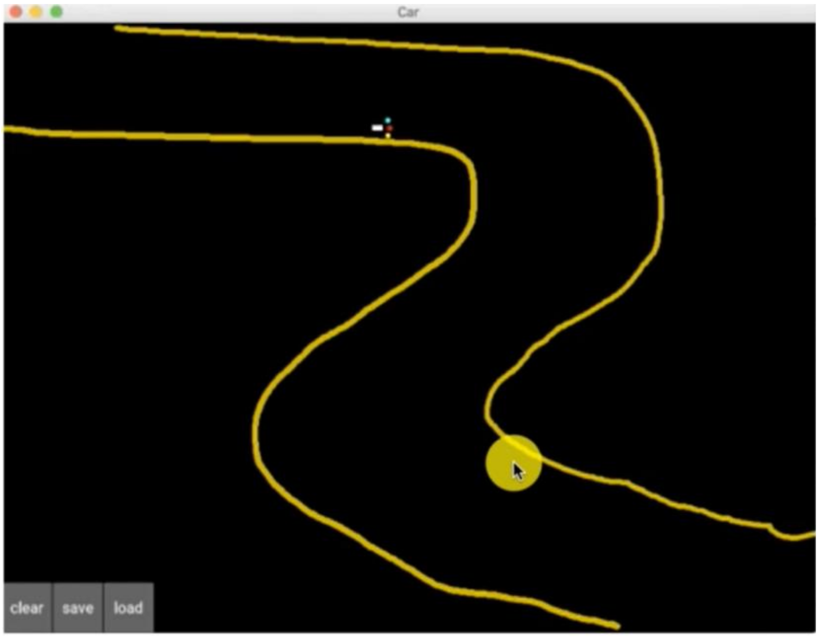
Deep Q-learning

$$L = \sum(Q\_Target - Q\_pred)^2$$

Action Selection Policies



Experience Replay



储存足够多的 experience，$\{(s_1, s_1', a_1, r_1), (s_2, s_2', a_2, r_2) \ldots\}$，再按照均匀分布抽样，训练。

Trick1：连续的状态通常是相关的，会给神经网络带来偏差 bias。
Trick2：Experience Replay 有利于让稀有经验多次被学习。

2. Q-learning

Initialization (First iteration):

For all couples of states s and actions a, the Q-values are initialized to 0.

Next iterations:

At each iteration t ≥ 1, we repeat the following steps:

1. We select a random state s_t from the possible states.
2. From that state, we play a random action a_t.
3. We reach the next state s_{t+1} and we get the reward $R(s_t, a_t)$.
4. We compute the Temporal Difference $TD_t(s_t, a_t)$:

$$TD_t(s_t, a_t) = R(s_t, a_t) + \gamma \max_a (Q(s_{t+1}, a)) - Q(s_t, a_t)$$

5. We update the Q-value by applying the Bellman equation:

$$Q_t(s_t, a_t) = Q_{t-1}(s_t, a_t) + \alpha TD_t(s_t, a_t)$$

训练完后，agent 选择当前状态下获得最高 Q-value 的动作。

3. Deep Q-learning（DQN）

Initialization:

1. The memory of the Experience Replay is initialized to an empty list M.
2. We choose a maximum size of the memory.

At each time t, we repeat the following process, until the end of the epoch:

1. We predict the Q-values of the current state s_t.
2. We play the action that has the highest Q-value: $a_t = \underset{a}{\operatorname{argmax}}\{Q(s_t, a)\}$
3. We get the reward $R(s_t, a_t)$.
4. We reach the next state s_{t+1}.
5. We append the transition (s_t, a_t, r_t, s_{t+1}) in the memory M.
6. We take a random batch $B \subset M$ of transitions. For all the transitions $(s_{t_B}, a_{t_B}, r_{t_B}, s_{t_B+1})$ of the random batch B:

   We get the predictions: $Q(s_{t_B}, a_{t_B})$

   We get the targets: $R(s_{t_B}, a_{t_B}) + \gamma \max_a (Q(s_{t_B+1}, a))$

   We compute the loss between the predictions and the targets over the whole batch B:

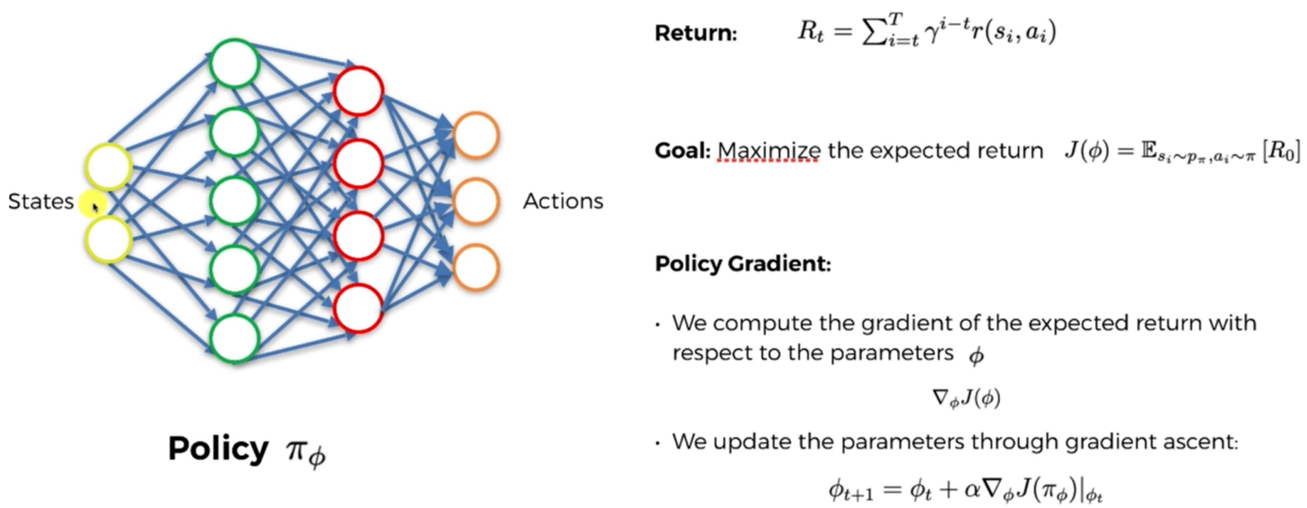
$$\text{Loss} = \frac{1}{2}\sum_B \left(R(s_{t_B}, a_{t_B}) + \gamma \max_a (Q(s_{t_B+1}, a)) - Q(s_{t_B}, a_{t_B})\right)^2 = \frac{1}{2}\sum_B TD_{t_B}(s_{t_B}, a_{t_B})^2$$

   We backpropagate this loss error back into the neural network, and through stochastic gradient descent we update the weights according to how much they contributed to the loss error.

缺点：$\Upsilon \underset{a}{max} Q(s_{tB+1}, a)$使得 DQN 难以处理连续的动作。

4. Actor-Critic（AC）演员-评论家模型

4.1 Policy Gradient



容易证明，通过梯度上升，神经网络将输出能够获得更大总回报的 action。

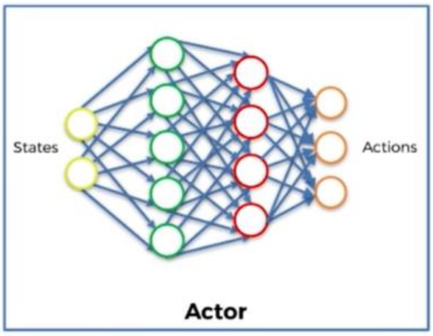
$$J(\pi_\emptyset) = \int \pi_\emptyset(\tau) R(\tau) d\tau$$

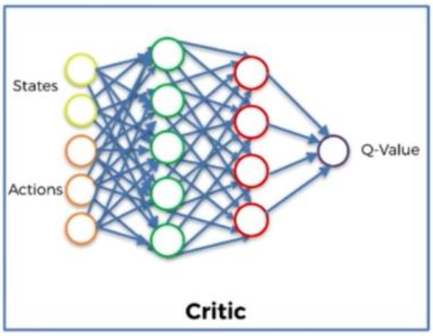
$$\frac{dJ(\pi_\emptyset)}{d\emptyset} = E_{\tau \sim \pi_\emptyset}(\tau) \left[\frac{\partial log\pi_\emptyset(\tau)}{\partial\emptyset} R(\tau) \right]$$

其中τ是一个完整的轨迹，即$s_1, a_1, r_1, s_2, a_2, r_2, \dots, s_T$。$R(\tau)$是一次轨迹$\tau$的累计奖励。

可见当$R(\tau) > 0$时，$\frac{dJ(\pi_\emptyset)}{d\emptyset}$与$\frac{\partial log\pi_\emptyset(\tau)}{\partial\emptyset}$同向，$J$变大则$log\pi_\emptyset(\tau)$变大，即鼓励产生更多这样的$\tau$，即证。

4.2 Actor-Critic（AC）





Return: $R_t = \sum_{i=t}^{T} \gamma^{i-t} r(s_i, a_i)$

Goal: Maximize the expected return $J(\phi) = \mathbb{E}_{s_i \sim p_\pi, a_i \sim \pi} [R_0]$

Deterministic Policy Gradient:

- In actor-critic methods, the policy, known as the actor, can be updated through the deterministic policy gradient algorithm:

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

- We update the policy parameters through gradient ascent:

$$\phi_{t+1} = \phi_t + \alpha \nabla_\phi J(\pi_\phi)|_{\phi_t}$$

5. Twin Delayed DDPG（TD3）

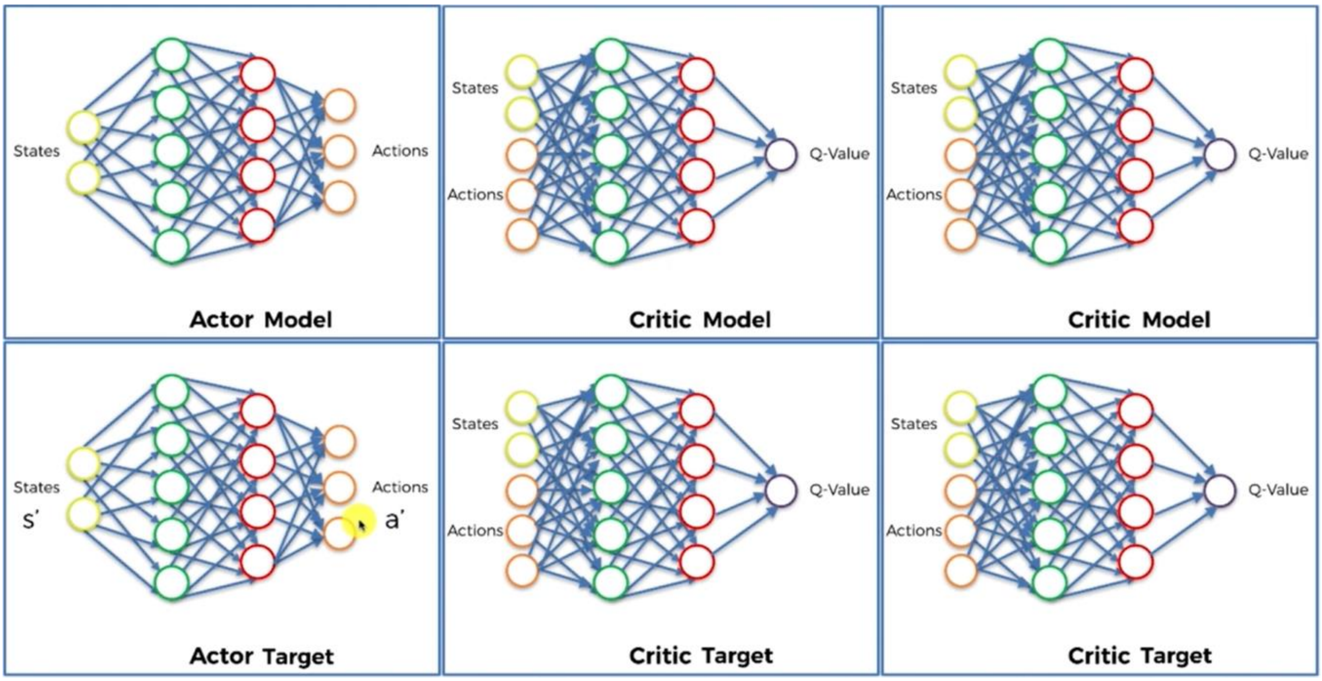
解决了连续动作空间的问题

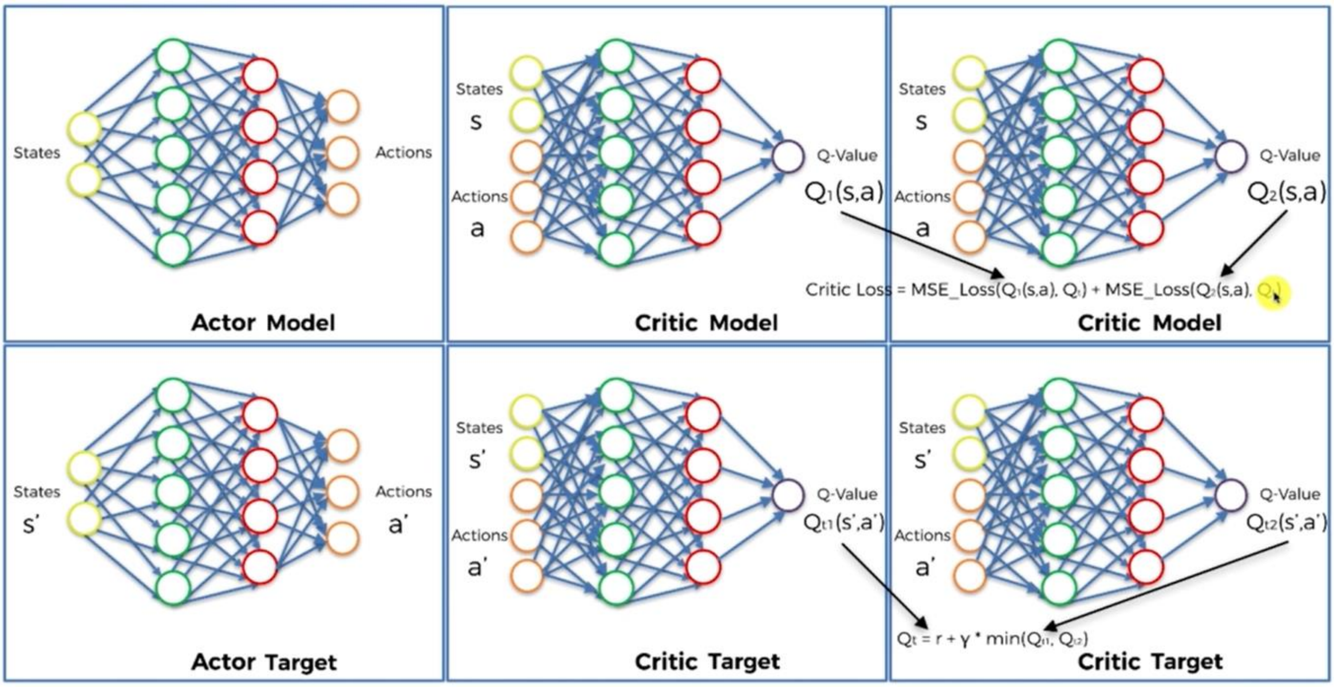
Initialization:

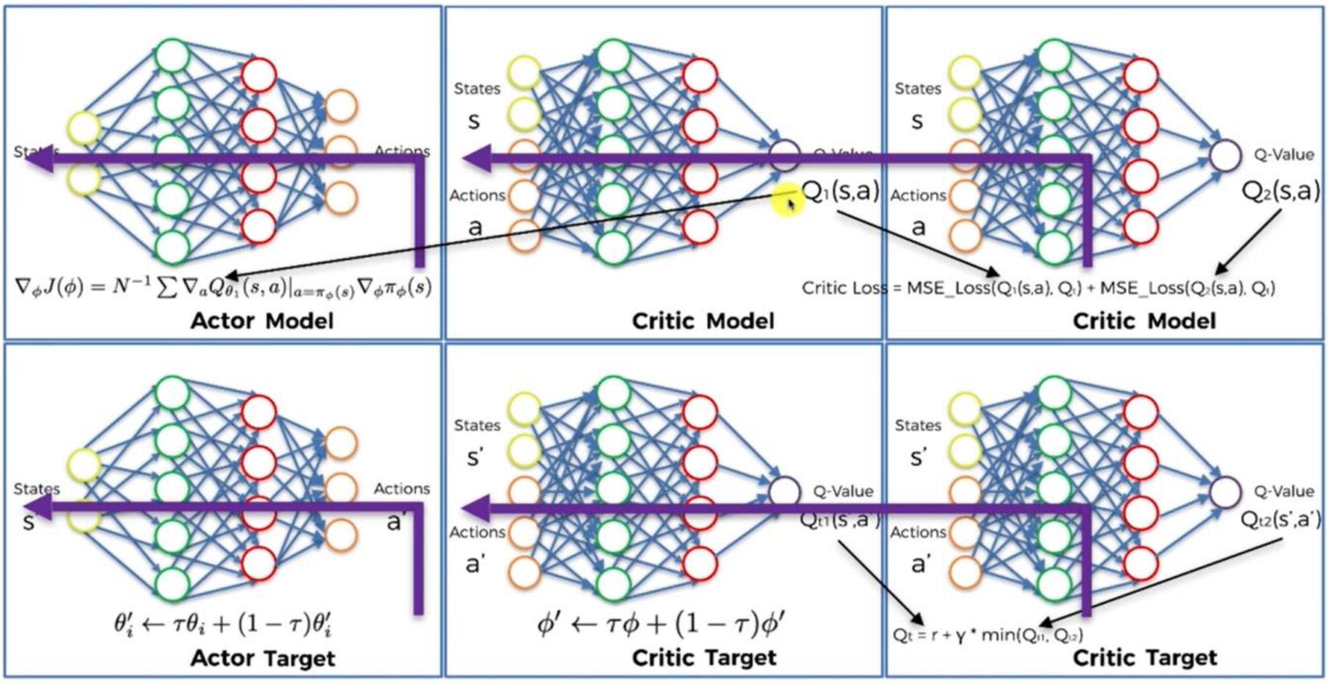
Step 1: We initialize the Experience Replay memory, with a size of 20000. We will populate it with each new transition.
Step 2: We build one neural network for the Actor model and one neural network for the Actor target.
Step 3: We build two neural networks for the two Critic models and two neural networks for the two Critic targets.

Training Process - We run a full episode with first 10,000 actions played randomly, and then with actions played by the Actor model. Then we repeat the following steps:

Step 4: We sample a batch of transitions (s, s', a, r) from the memory. Then for each element of the batch:
Step 5: From the next state s', the Actor target plays the next action a'.
Step 6: We add Gaussian noise to this next action a' and we clamp it in a range of values supported by the environment.
Step 7: The two Critic targets take each the couple (s', a') as input and return two Q-values $Q_{t1}(s',a')$ and $Q_{t2}(s',a')$ as outputs.
Step 8: We keep the minimum of these two Q-values: $\min(Q_{t1}, Q_{t2})$. It represents the approximated value of the next state.
Step 9: We get the final target of the two Critic models, which is: $Q_t = r + \gamma * \min(Q_{t1}, Q_{t2})$, where γ is the discount factor.
Step 10: The two Critic models take each the couple (s, a) as input and return two Q-values $Q_1(s,a)$ and $Q_2(s,a)$ as outputs.
Step 11: We compute the loss coming from the two Critic models: Critic Loss = $\text{MSE\_Loss}(Q_1(s,a), Q_t) + \text{MSE\_Loss}(Q_2(s,a), Q_t)$
Step 12: We backpropagate this Critic loss and update the parameters of the two Critic models with a SGD optimizer.
Step 13: Once every two iterations, we update our Actor model by performing gradient ascent on the output of the first Critic model: $\nabla_\phi J(\phi) = N^{-1} \sum \nabla_a Q_{\theta_1}(s,a)|_{a=\pi_\phi(s)} \nabla_\phi \pi_\phi(s)$, where ϕ and θ_1 are resp. the weights of the Actor and the Critic.
Step 14: Still once every two iterations, we update the weights of the Actor target by polyak averaging: $\theta'_i \leftarrow \tau\theta_i + (1-\tau)\theta'_i$
Step 15: Still once every two iterations, we update the weights of the Critic target by polyak averaging: $\phi' \leftarrow \tau\phi + (1-\tau)\phi'$


States
Actions
Actor Model
States
Actions
Q-Value
Critic Model
States
Actions
Q-Value
Critic Model
States
s'
Actions
a'
Actor Target
States
Actions
Q-Value
Critic Target
States
Actions
Q-Value
Critic Target


States
Actions
Actor Model
States
s
Actions
a
Q-Value
Q1(s,a)
Critic Model
States
s
Actions
a
Q-Value
Q2(s,a)
Critic Loss = MSE_Loss(Q1(s,a), Qt) + MSE_Loss(Q2(s,a), Qt)
Critic Model
States
s'
Actions
a'
Actor Target
States
s'
Actions
a'
Q-Value
Qt1(s',a')
Critic Target
States
s'
Actions
a'
Q-Value
Qt2(s',a')
Qt = r + γ * min(Qt1, Qt2)
Critic Target



States
Actions
$\nabla_\phi J(\phi) = N^{-1} \sum \nabla_a Q_{\theta_1}(s,a)|_{a=\pi_\phi(s)} \nabla_\phi \pi_\phi(s)$
Actor Model
States
s
Actions
a
Q-Value
Q1(s,a)
Critic Model
States
s
Actions
a
Q-Value
Q2(s,a)
Critic Loss = MSE_Loss(Q1(s,a), Qt) + MSE_Loss(Q2(s,a), Qt)
Critic Model
States
s
Actions
a'
$\theta'_i \leftarrow \tau\theta_i + (1-\tau)\theta'_i$
Actor Target
States
s'
Actions
a'
Q-Value
Qt1(s',a')
$\phi' \leftarrow \tau\phi + (1-\tau)\phi'$
Critic Target
States
s'
Actions
a'
Q-Value
Qt2(s',a')
Qt = r + γ * min(Qt1, Qt2)
Critic Target