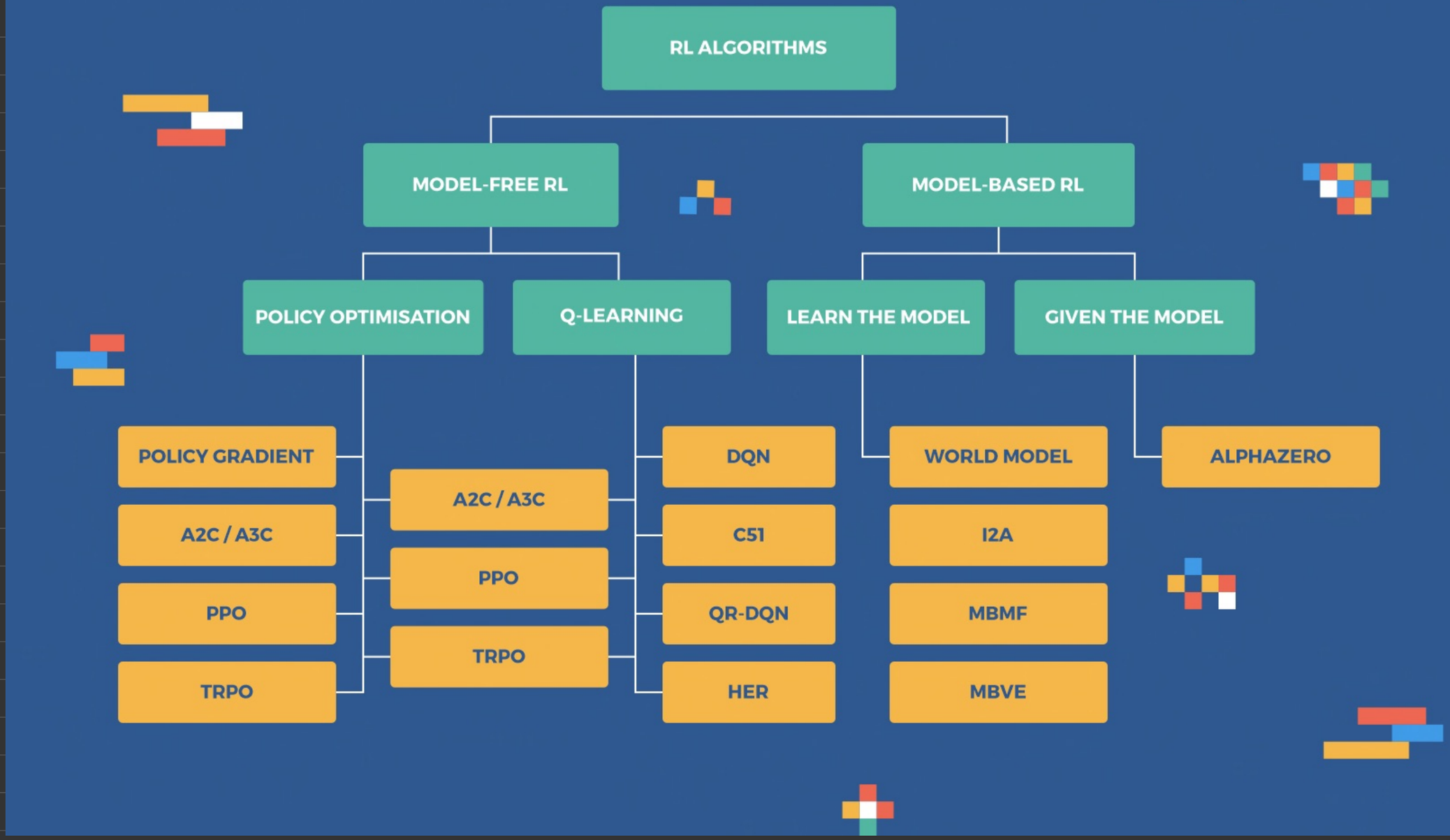
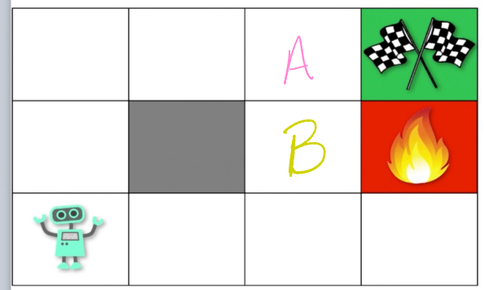
REINFORCEMENT LEARNING ALGORITHMS MAP



Fundamentals: 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:

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

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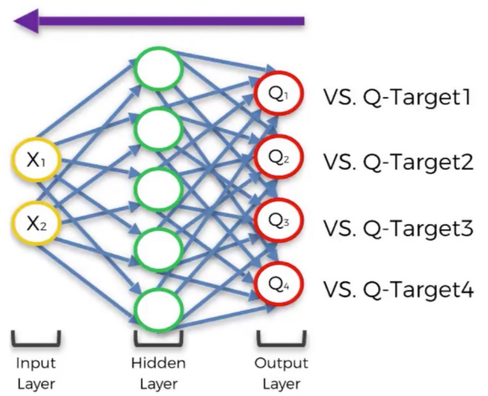
It will learn the Q values which is based on Q learning and it will

Fundamentals: Deep Q-Learning



$$L = \sum (Q\text{-}Target - Q)^2$$

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: $a_t = \underset{a}{\text{argmax}}\{Q(s_t, a)\}$
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.

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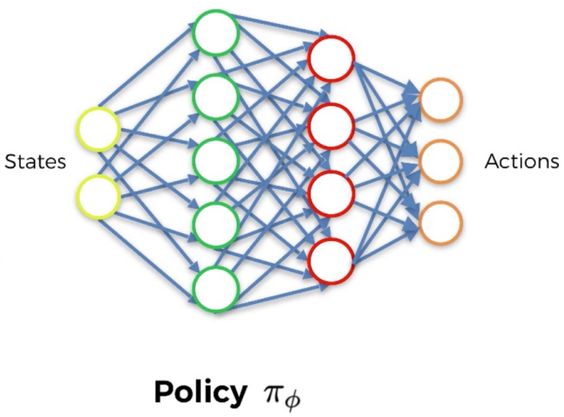
- TD3 will learn two values at same time
  - The Q-value
  - the parameters to Policy, so that make better choices

- The Q-value Represents the quality of being in a state S and take an action a.

- The Q-value of being in state A and take the action Right will be the highest of all others, because it move the agent to the goal.

- In contrast the Q-value of being in state B and took action Right will be the lowest, because the agent will loose the game.

Fundamentals: Policy Gradient



Policy π_ϕ

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

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

Policy Gradient:

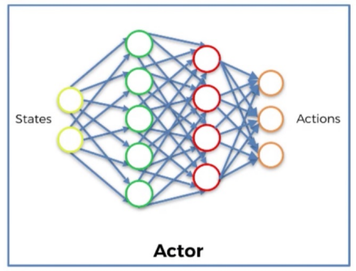
- We compute the gradient of the expected return with respect to the parameters ϕ

$$\nabla_\phi J(\phi)$$

- We update the parameters through gradient ascent:

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

Fundamentals: Actor-Critic



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:

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

- In the previous model we try to estimate the Q-value.
- Given the Q-value the Agent apply some policy to choose the best action.
- The policy may be pick the action that gives the higher reward $\arg\max_a [Q(s,a)]$
- Now this kind of algo try to learn the best policy, not the best Q-value.

- In this model we have two networks
  1. Actor "Policy" get the states and output the possible actions
  2. The critic that get States, Actions and produces the Q-value
- Actor try to find the best action.
- Critic try to find the best Q-values.

Fundamentals: Taxonomy of AI models

Model-Free vs. Model-Based

Value-Based vs. Policy Based

Off-Policy vs. On-Policy

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Model Free

- Do not try to learn how the env work.
- Just take the env output, do some process and choose the action.
- Q-learning, Actor-Critic and most of the Algo.

Model Based

- Try to understand the env and create a model to represent it
- The model is trying to capture the transition func and the reward func.

If, after learning the Agent can make predictions about what the next state/Reward is before it do the action than it's a MODEL-BASED, otherwise if it can't predict what next state/Reward would, it's a MODEL FREE

Value Based

- Agent calculates the Q-value and choose the action that results in the highest Reward.
- the agent doesn't learn the action, it learn the value, and the policy will be choose the highest action value. $\text{Argmax}_a[Q(s,a)]$

Policy Based

- Instead of predict the Q-value to later choose the action, It predict the action directly from observed state.

Off-Policy

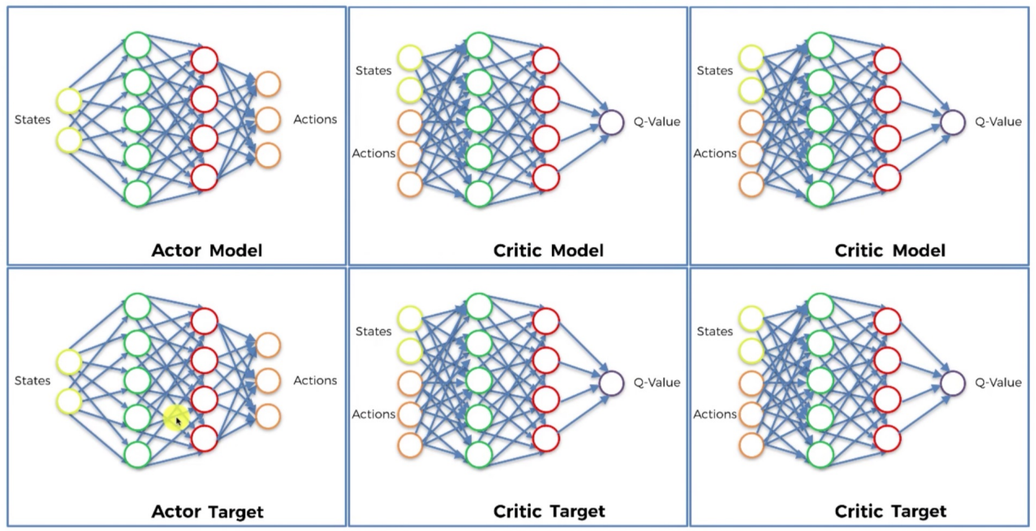
- use a experience Replay Memory to store past transitions so that it can sample and learn from the history

On-Policy

- Do not store past transitions. Learn just from new observations.

	Deep Q-Learning	Policy Gradient	Actor-Critic	World Models
Model-Free vs. Model-Based	Model-Free	Model-Free	Model-Free	Model-Based
Value-Based vs. Policy-Based	Value-Based	Policy-Based	Both	Policy-Based
Off-Policy vs. On-Policy	Off-Policy	On-Policy	Off-Policy	On-Policy

Twin-Delayed DDPG (TD3)



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- This algo produces continuous outputs, instead of discret output actions as Q_learning
- Remember the $\max_a [Q(s,a)]$ on Q_learning. This only works in discrete number of actions a

- The Actor predicts the Policy
- the Critic predicts the Q-values

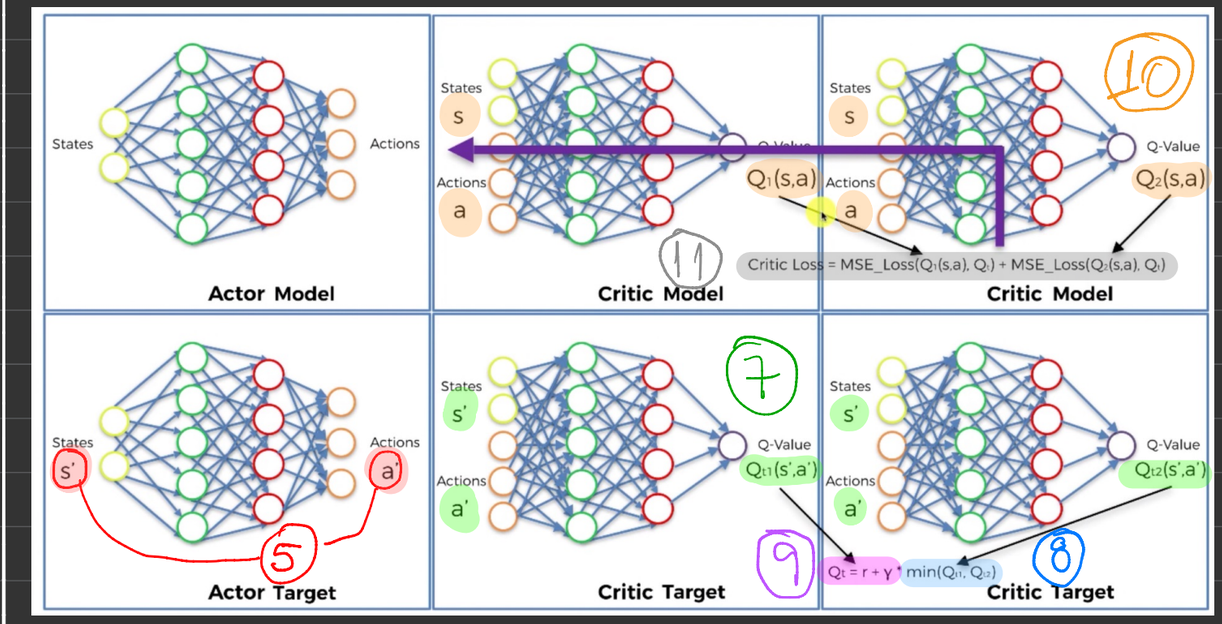
Initialization:
Step 1: We initialize the Experience Replay memory, with a size of 20000. We will populate it with each new transition.
Step 2: We build one neural network for the Actor model and one neural network for the Actor target.
Step 3: We build two neural networks for the two Critic models and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

Q-Learning Step

Twin-Delayed DDPG (TD3)

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 = MSE_Loss($Q_1(s,a)$, Q_t) + 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.



8)
- Taking the $\min(Q_{t1}, Q_{t2})$ is the same as the $\max_a [Q(s',a)]$ of Q_learning

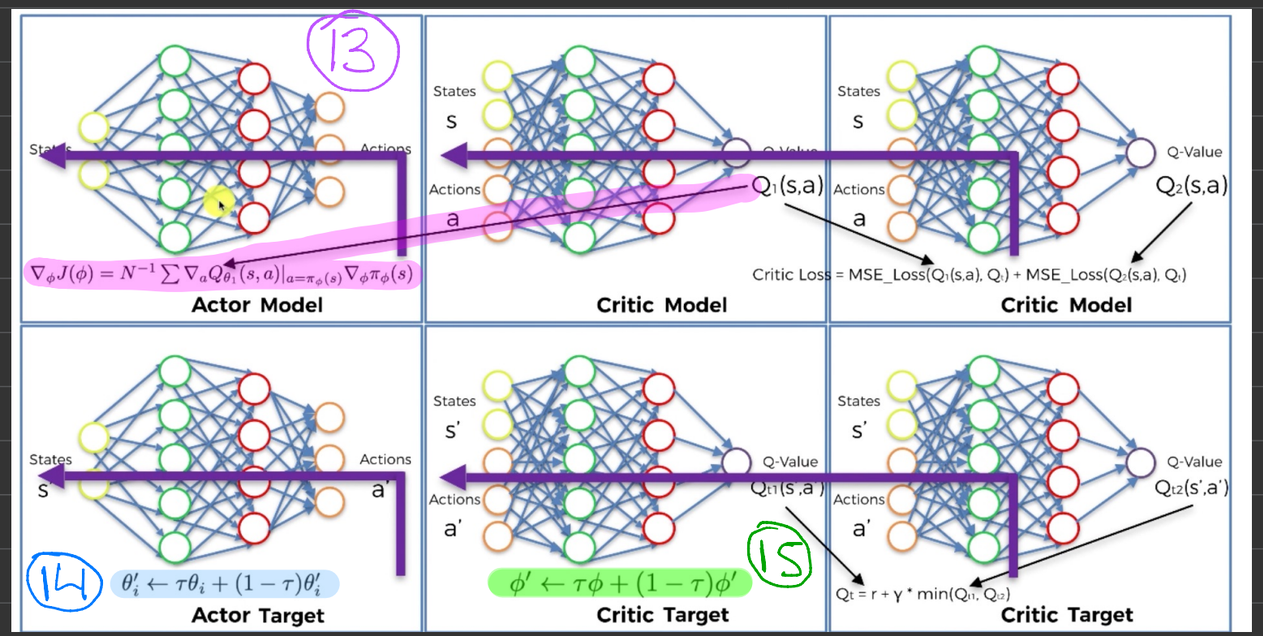
$$\tilde{a} \leftarrow \pi_{\phi'}(s') + \epsilon, \quad \epsilon \sim \text{clip}(\mathcal{N}(0, \tilde{\sigma}), -c, c)$$

$$\tilde{a} \leftarrow \text{clip}(\tilde{a})$$

- Also taking the min() helps to AVOID over estimate the target Q_values.

Policy learning Step

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: $\phi' \leftarrow \tau\phi + (1-\tau)\phi'$



- Polyak uses a small number τ 0.8. This means we update the target network with a very small portion of Model weights, instead of Replace the entire target weights by the Target.

- Gradient Ascent to maximize the value

- In Step 13 we do:

```
a = Actor(state)
critic_out = Critic_1(state, a)
critic_out = - critic_out.mean()
critic_out.backward()
Actor_opt.step()
```

→ Reduce to a single value

→ Perform Grad. Asc. to update the actor weights so that it produces an Action that Results in a higher $Q_{1a}(s,a)$

```python
def train(self, iterations, batch_size=100, gamma=0.99, tau=0.005,
          policy_noise=0.2, noise_clip=0.5, policy_freq=2):
    if self.replay_buffer.mem_cntr < batch_size:
        return

    for i in range(iterations):
        # 4. Sample from memory
        batch_state, batch_action, batch_reward, batch_state_, batch_done = self.replay_buffer.sample(batch_size)
        state = torch.tensor(batch_state, dtype=torch.float, device=device)
        action = torch.tensor(batch_action, dtype=torch.float, device=device)
        reward = torch.tensor(batch_reward, dtype=torch.float, device=device).view(-1, 1)
        state_ = torch.tensor(batch_state_, dtype=torch.float, device=device)
        done = torch.tensor(batch_done, dtype=torch.bool, device=device).view(-1, 1)

        # 5. Actor target play state_
        action_ = self.actor_target(state_)

        # 6. Add gaussian noise the same shape as action (bs, n_actions)
        noise = torch.Tensor(batch_action).data.normal_(0, policy_noise).clamp(-noise_clip, noise_clip).to(device)
        action_ = (action_ + noise).clamp(-self.max_action, self.max_action)

        # 7. Critic target play with state_, action_
        q1_target, q2_target = self.critic_target(state_, action_)

        # 8. Min of q1_target and q2_target
        min_q = torch.min(q1_target, q2_target)  # remove from backpropagation

        # 9. Calculate bellman equation
        q_target = reward + (gamma * min_q).detach()
        q_target[done] = 0.0

        # 10. Critic play with state, action
        q1, q2 = self.critic(state, action)

        # 11. calculate critic loss of each Critic and the q_target
        critic_loss_1 = torch.nn.functional.mse_loss(q1, q_target)
        critic_loss_2 = torch.nn.functional.mse_loss(q2, q_target)
        critic_loss = critic_loss_1 + critic_loss_2

        # 12. backpropagation
        self.critic_optimizer.zero_grad()
        critic_loss.backward()
        self.critic_optimizer.step()

        # 13. Delayed update of Actor model by perform gradient ascent trying to
        if i % policy_freq == 0:
            actor_loss = - self.critic.q1(state, self.actor(state)).mean()
            self.actor_optimizer.zero_grad()
            actor_loss.backward()
            self.actor_optimizer.step()

            # 14. Update actor_target using Polyak Average
            for param, target_param in zip(self.actor.parameters(), self.actor_target.parameters()):
                target_param.data.copy_(tau * param.data + (1 - tau) * target_param.data)

            # 15. Update critic_target using Polyak Average
            for param, target_param in zip(self.critic.parameters(), self.critic_target.parameters()):
                target_param.data.copy_(tau * param.data + (1 - tau) * target_param.data)
```