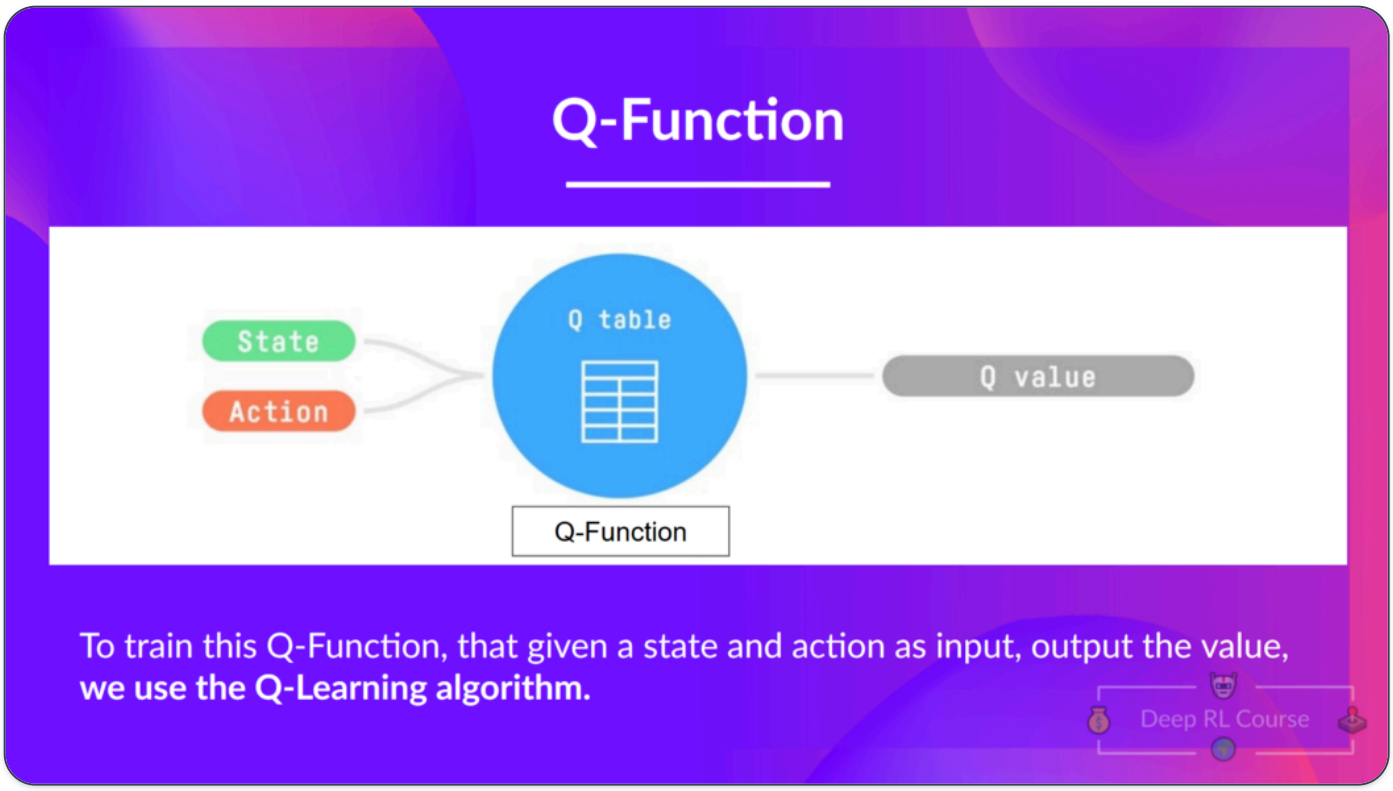
Introducing Q-Learning

What is Q-Learning?

Q-Learning is an **off-policy value-based method that uses a TD approach to train its action-value function:**

- *Off-policy*: we'll talk about that at the end of this unit.
- *Value-based method*: finds the optimal policy indirectly by training a value or action-value function that will tell us **the value of each state or each state-action pair.**
- *TD approach:* **updates its action-value function at each step instead of at the end of the episode.**

Q-Learning is the algorithm we use to train our Q-function, an **action-value function** that determines the value of being at a particular state and taking a specific action at that state.



Given a state and action, our Q Function outputs a state-action value (also called Q-value)

The **Q comes from "the Quality" (the value) of that action at that state.**

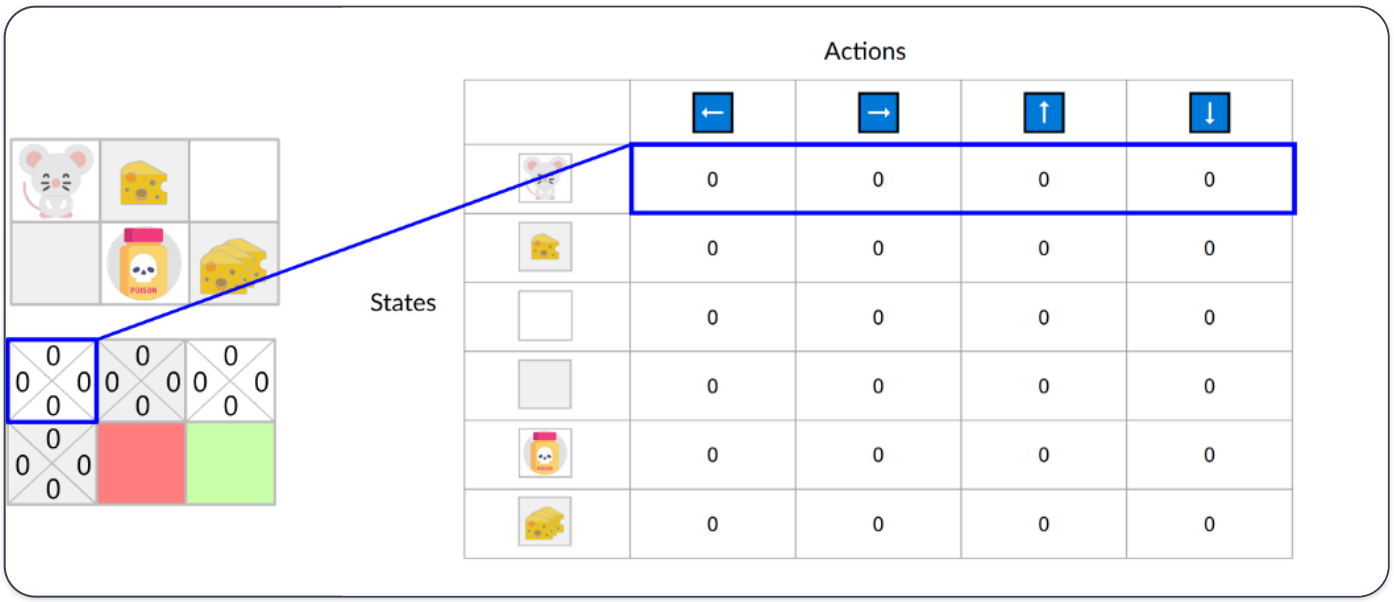
Let's recap the difference between value and reward:

- The *value of a state*, or a *state-action pair* is the expected cumulative reward our agent gets if it starts at this state (or state-action pair) and then acts accordingly to its policy.
- The *reward* is the **feedback I get from the environment** after performing an action at a state.

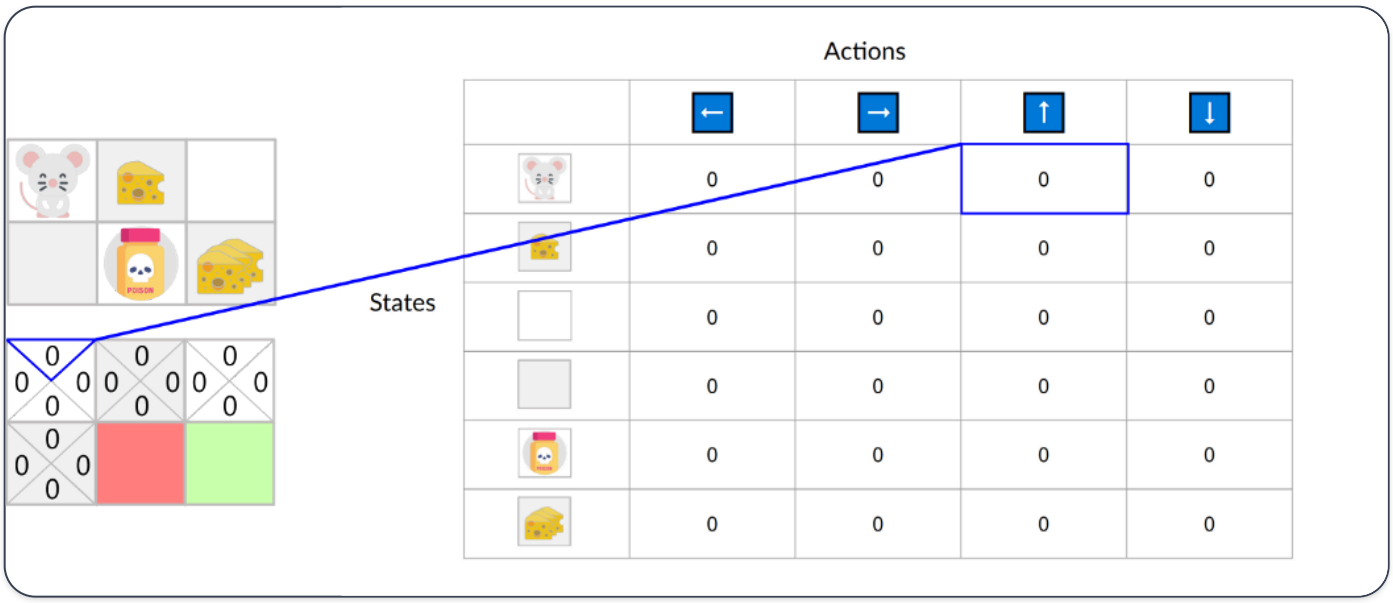
Internally, our Q-function is encoded by **a Q-table, a table where each cell corresponds to a state-action pair value.** Think of this Q-table as **the memory or cheat sheet of our Q-function.**

Let's go through an example of a maze.

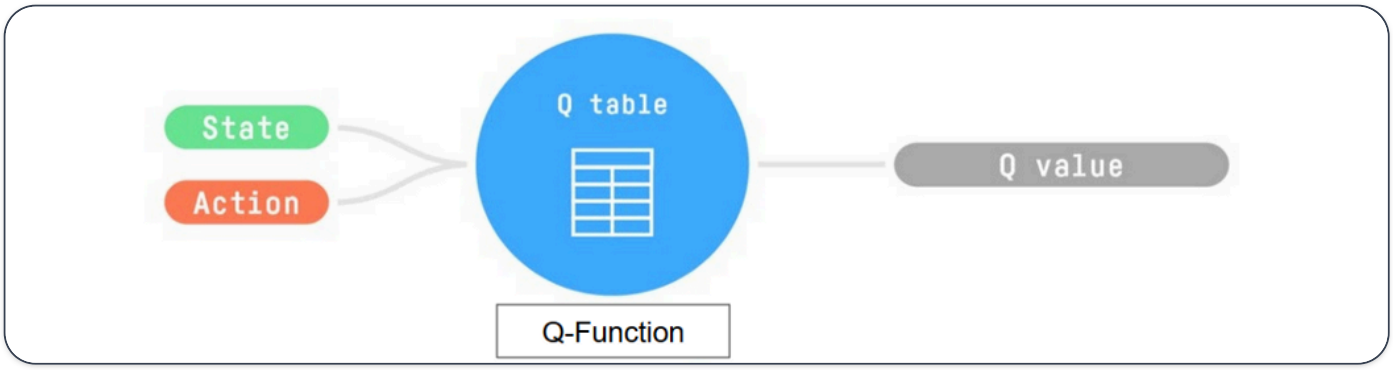
The Q-table is initialized. That's why all values are = 0. This table **contains, for each state and action, the corresponding state-action values.** For this simple example, the state is only defined by the position of the mouse. Therefore, we have 2*3 rows in our Q-table, one row for each possible position of the mouse. In more complex scenarios, the state could contain more information than the position of the actor.



Here we see that the **state-action value of the initial state and going up is 0:**



So: the Q-function uses a Q-table **that has the value of each state-action pair.** Given a state and action, **our Q-function will search inside its Q-table to output the value.**



If we recap, *Q-Learning* **is the RL algorithm that:**

- Trains a *Q-function* (an **action-value function**), which internally is a **Q-table that contains all the state-action pair values.**
- Given a state and action, our Q-function **will search its Q-table for the corresponding value.**
- When the training is done, **we have an optimal Q-function, which means we have optimal Q-table.**
- And if we **have an optimal Q-function**, we **have an optimal policy** since we **know the best action to take at each state.**

The link between Value and Policy:

$$\pi^*(s) = \arg\max_a Q^*(s, a)$$

Finding **an optimal value function** leads to having **an optimal policy.**

In the beginning, **our Q-table is useless since it gives arbitrary values for each state-action pair** (most of the time, we initialize the Q-table to 0). As the agent **explores the environment and we update the Q-table, it will give us a better and better approximation** to the optimal policy.

Q-Learning

	←	→	↑	↓
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0

Training

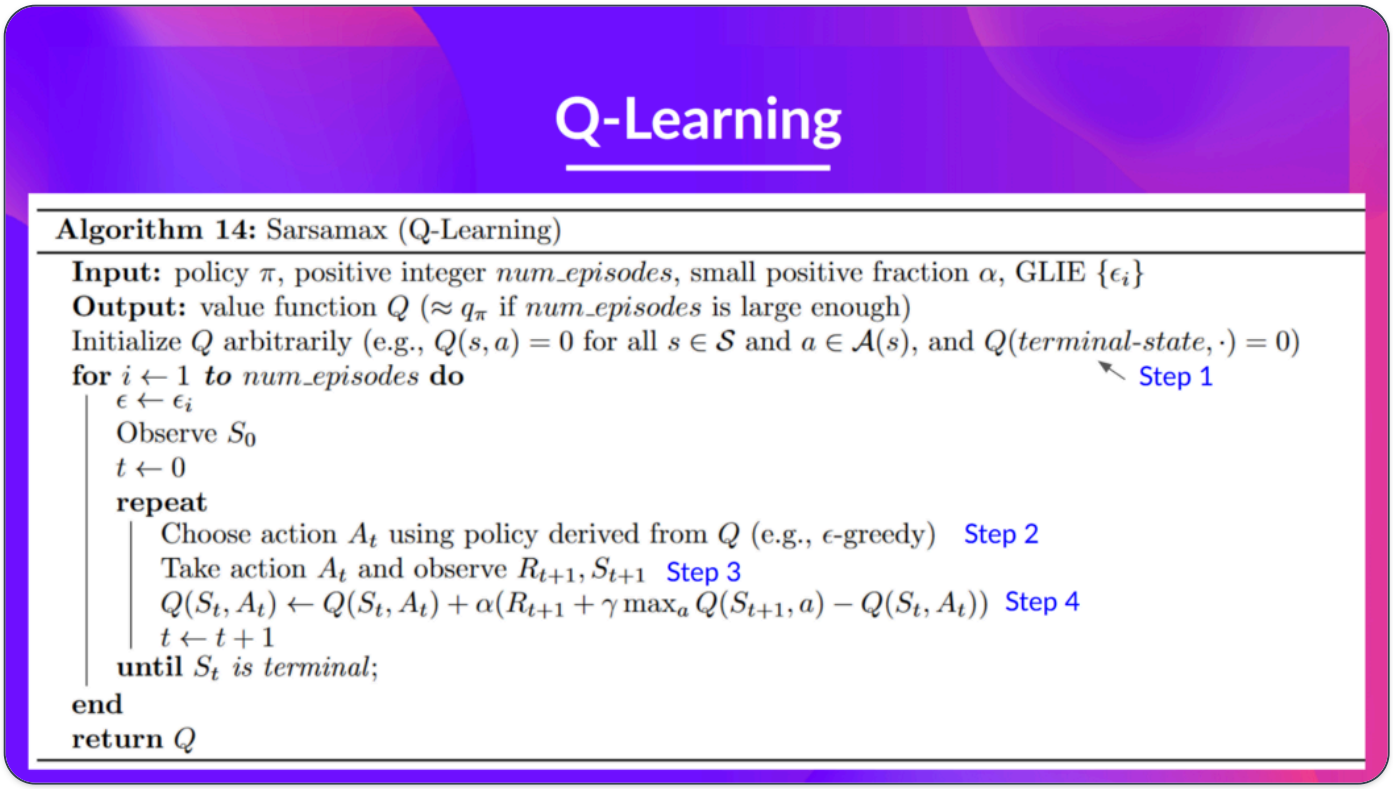
	←	→	↑	↓
	0	10.8	0	0
	0	9.9	0	-10
	0	0	0	10
	0	-10	0	0
	0	0	0	0
	0	0	0	0

We see here that with the training, our Q-table is better since, thanks to it, we can know the value of each state-action pair.

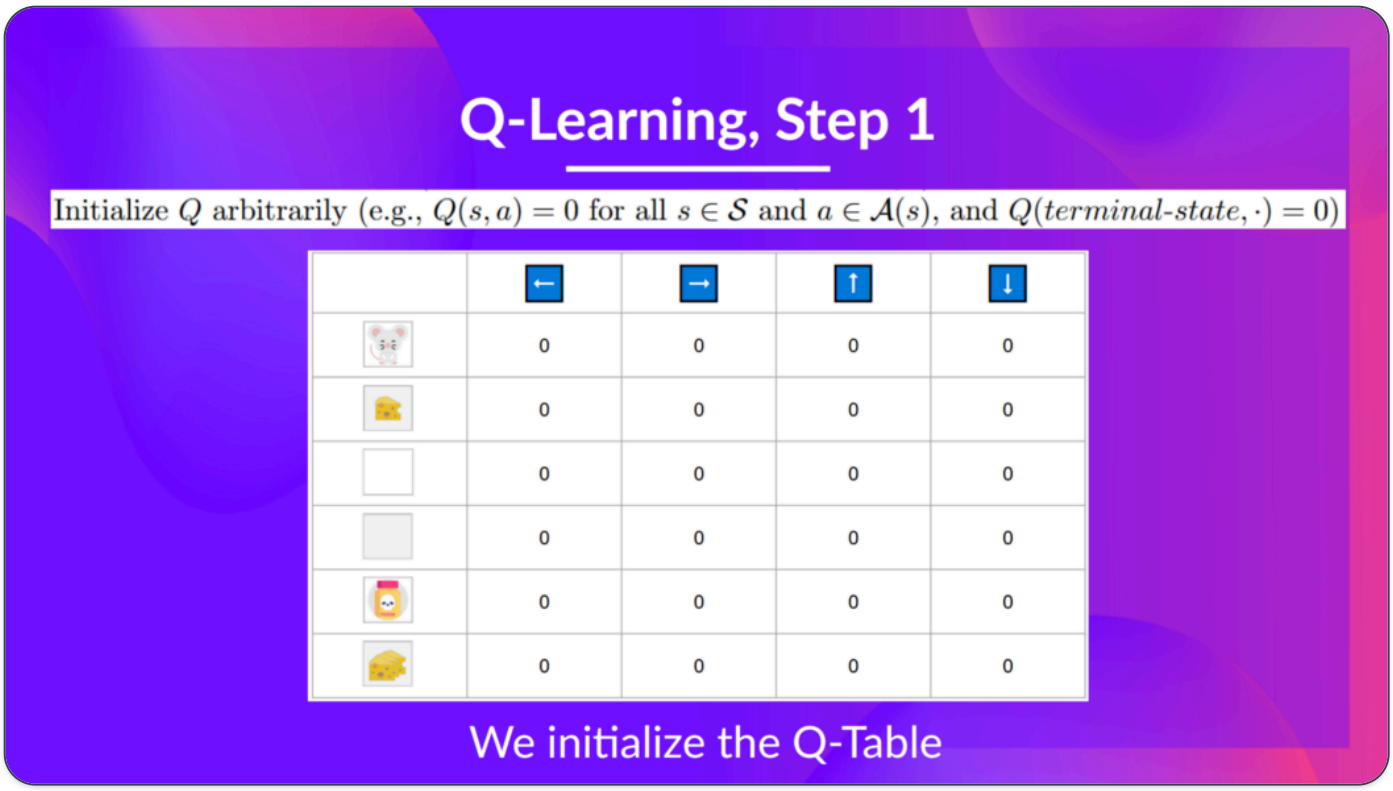
Now that we understand what Q-Learning, Q-functions, and Q-tables are, **let's dive deeper into the Q-Learning algorithm.**

The Q-Learning algorithm

This is the Q-Learning pseudocode; let's study each part and **see how it works with a simple example before implementing it.** Don't be intimidated by it, it's simpler than it looks! We'll go over each step.

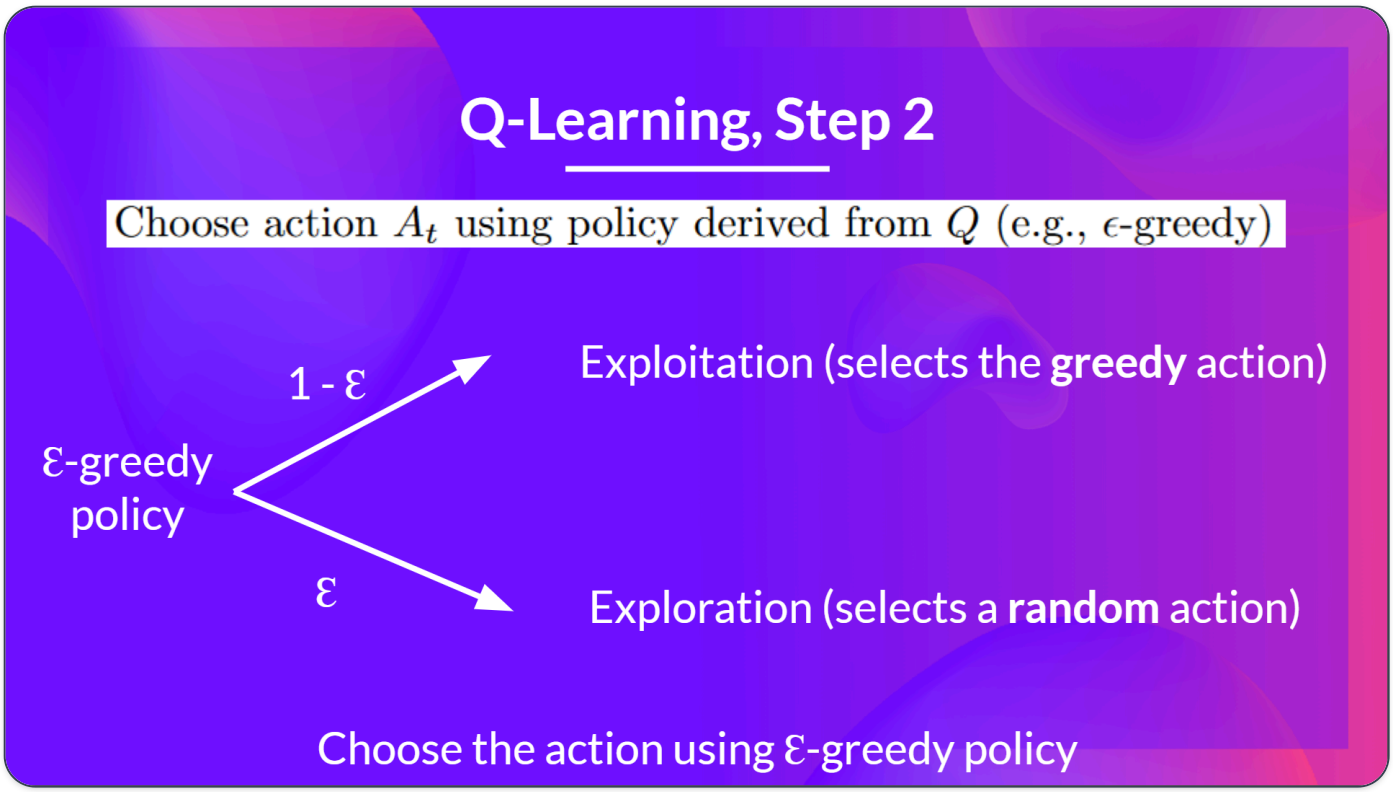


Step 1: We initialize the Q-table



We need to initialize the Q-table for each state-action pair. **Most of the time, we initialize with values of 0.**

Step 2: Choose an action using the epsilon-greedy strategy

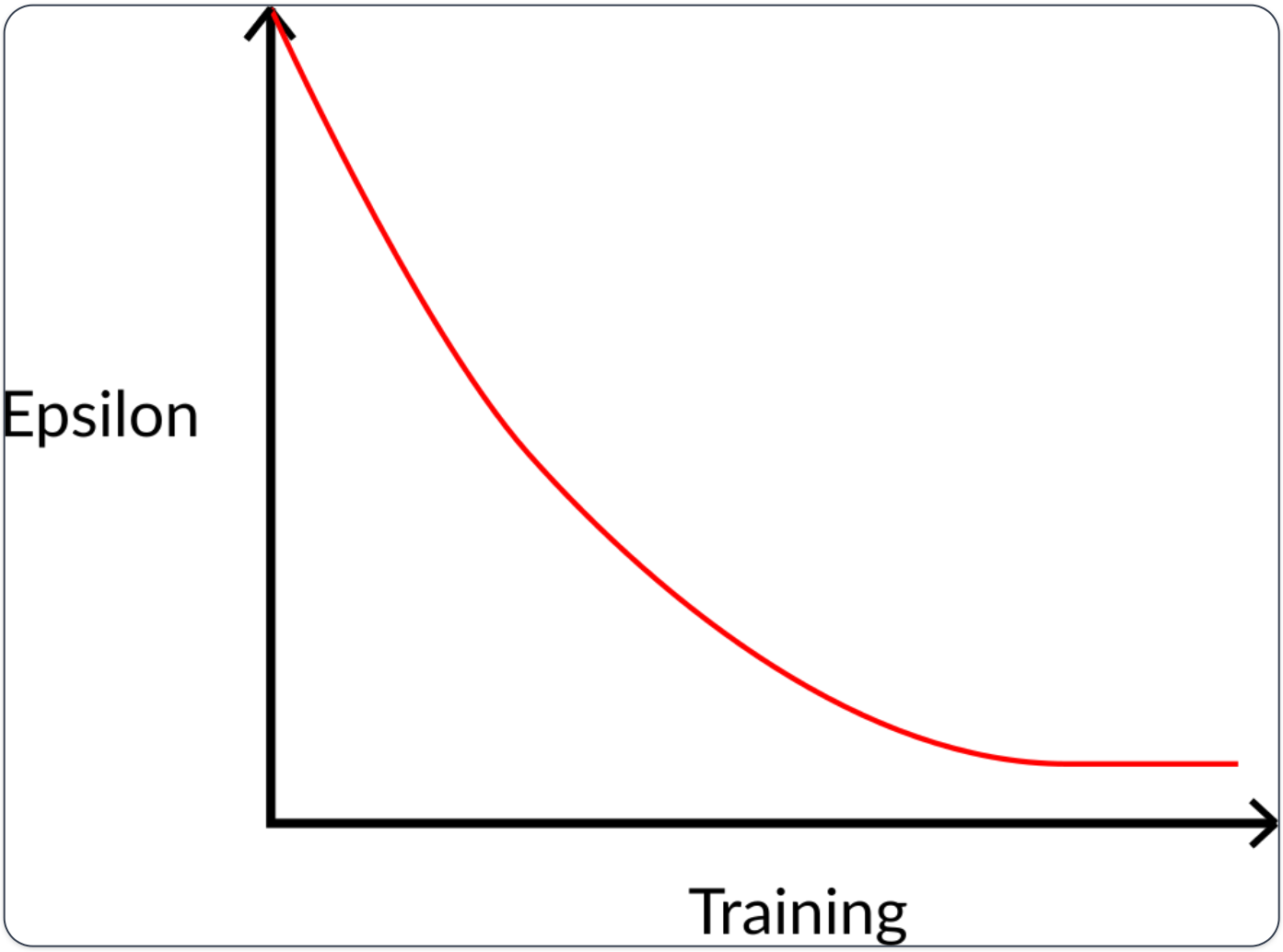


The epsilon-greedy strategy is a policy that handles the exploration/exploitation trade-off.

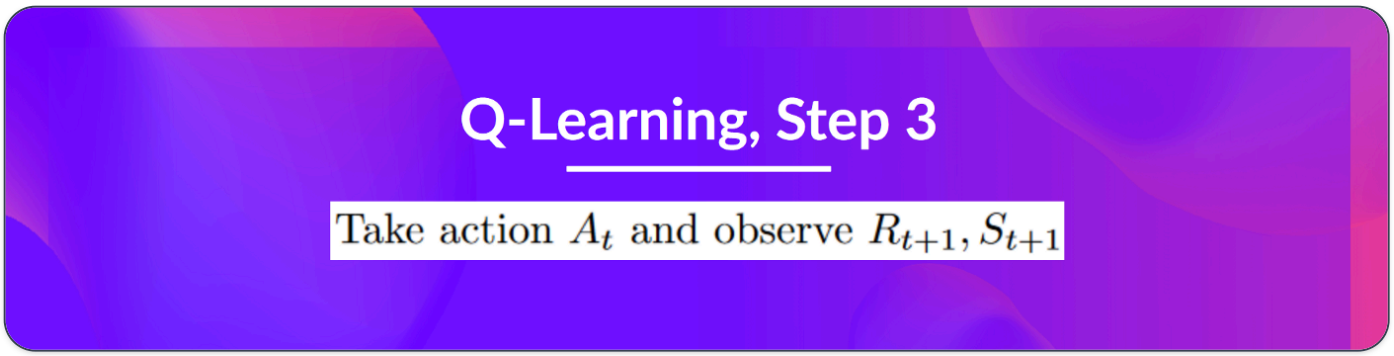
The idea is that, with an initial value of ε = 1.0:

- *With probability 1 — ε* : we do **exploitation** (aka our agent selects the action with the highest state-action pair value).
- With probability ε: **we do exploration** (trying random action).

At the beginning of the training, **the probability of doing exploration will be huge since ε is very high, so most of the time, we'll explore.** But as the training goes on, and consequently our **Q-table gets better and better in its estimations, we progressively reduce the epsilon value** since we will need less and less exploration and more exploitation.



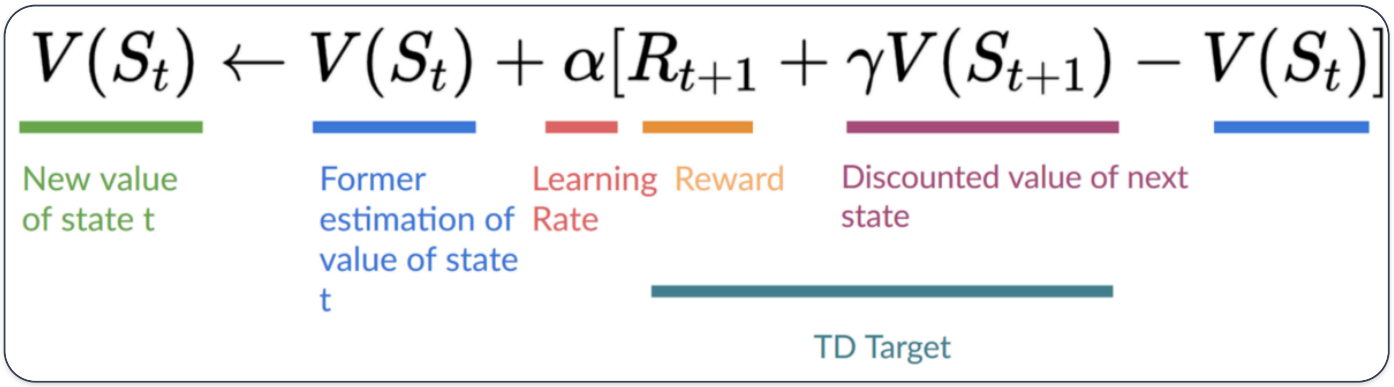
Step 3: Perform action At, get reward Rt+1 and next state St+1



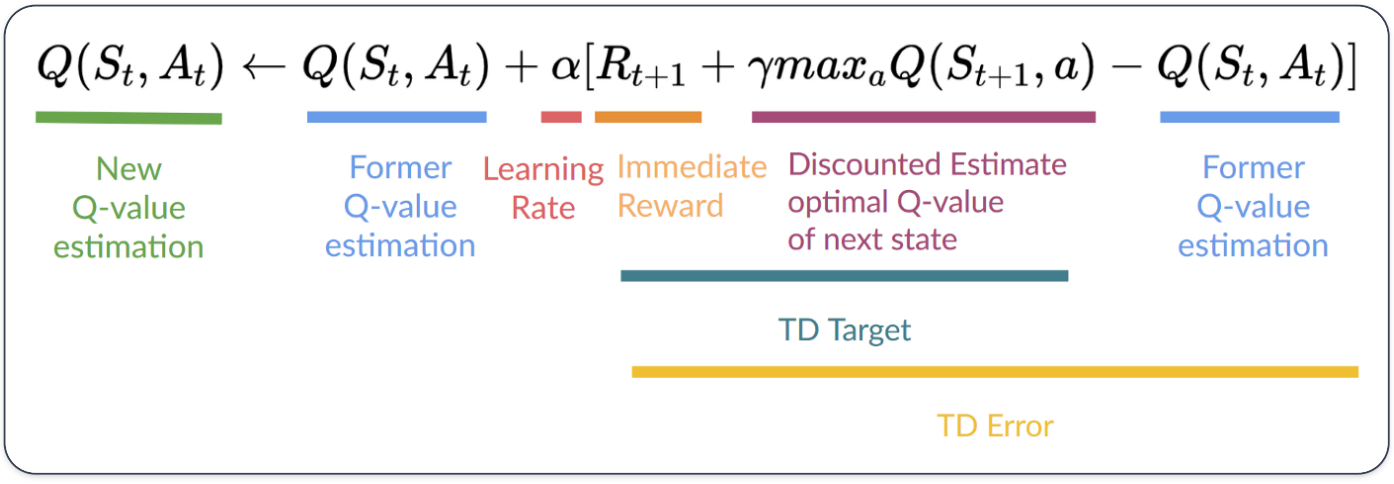
Step 4: Update Q(St, At)

Remember that in TD Learning, we update our policy or value function (depending on the RL method we choose) **after one step of the interaction.**

To produce our TD target, **we used the immediate reward** R_{t+1} **plus the discounted value of the next state**, computed by finding the action that maximizes the current Q-function at the next state. (We call that bootstrap).



Therefore, our $Q(S_t, A_t)$ **update formula goes like this:**



This means that to update our$Q(S_t, A_t)$:

- We need$S_t, A_t, R_{t+1}, S_{t+1}$.
- To update our Q-value at a given state-action pair, we use the TD target.

How do we form the TD target?

1. We obtain the rewardR_{t+1} after taking the actionA_t.
2. To get the **best state-action pair value** for the next state, we use a greedy policy to select the next best action. Note that this is not an epsilon-greedy policy, this will always take the action with the highest state-action value.

Then when the update of this Q-value is done, we start in a new state and select our action **using a epsilon-greedy policy again.**

This is why we say that Q Learning is an off-policy algorithm.

Off-policy vs On-policy

The difference is subtle:

- *Off-policy*: using **a different policy for acting (inference) and updating (training).**

For instance, with Q-Learning, the epsilon-greedy policy (acting policy), is different from the greedy policy that is **used to select the best next-state action value to update our Q-value (updating policy).**

$$\text{Choose action } A_t \text{ using policy derived from } Q \text{ (e.g., } \epsilon\text{-greedy)}$$

Acting Policy

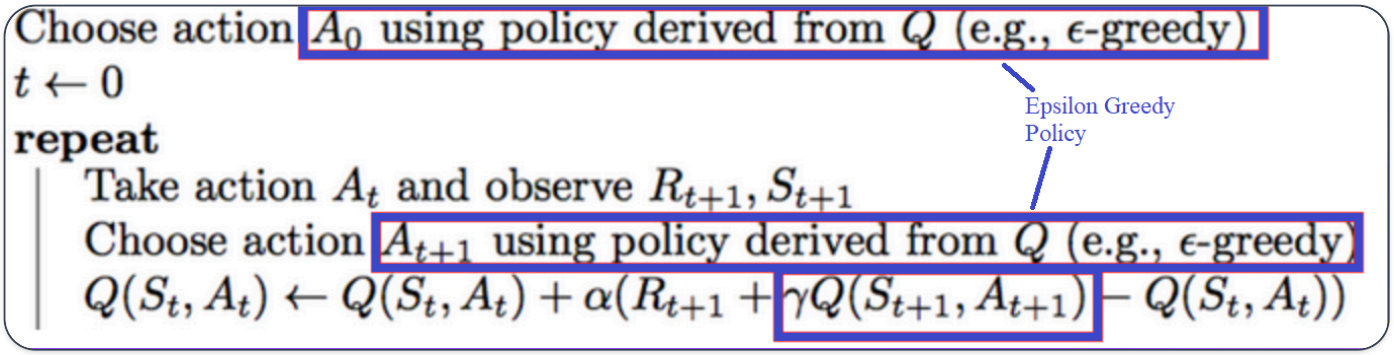
Is different from the policy we use during the training part:

$$\gamma \max_a Q(S_{t+1}, a)$$

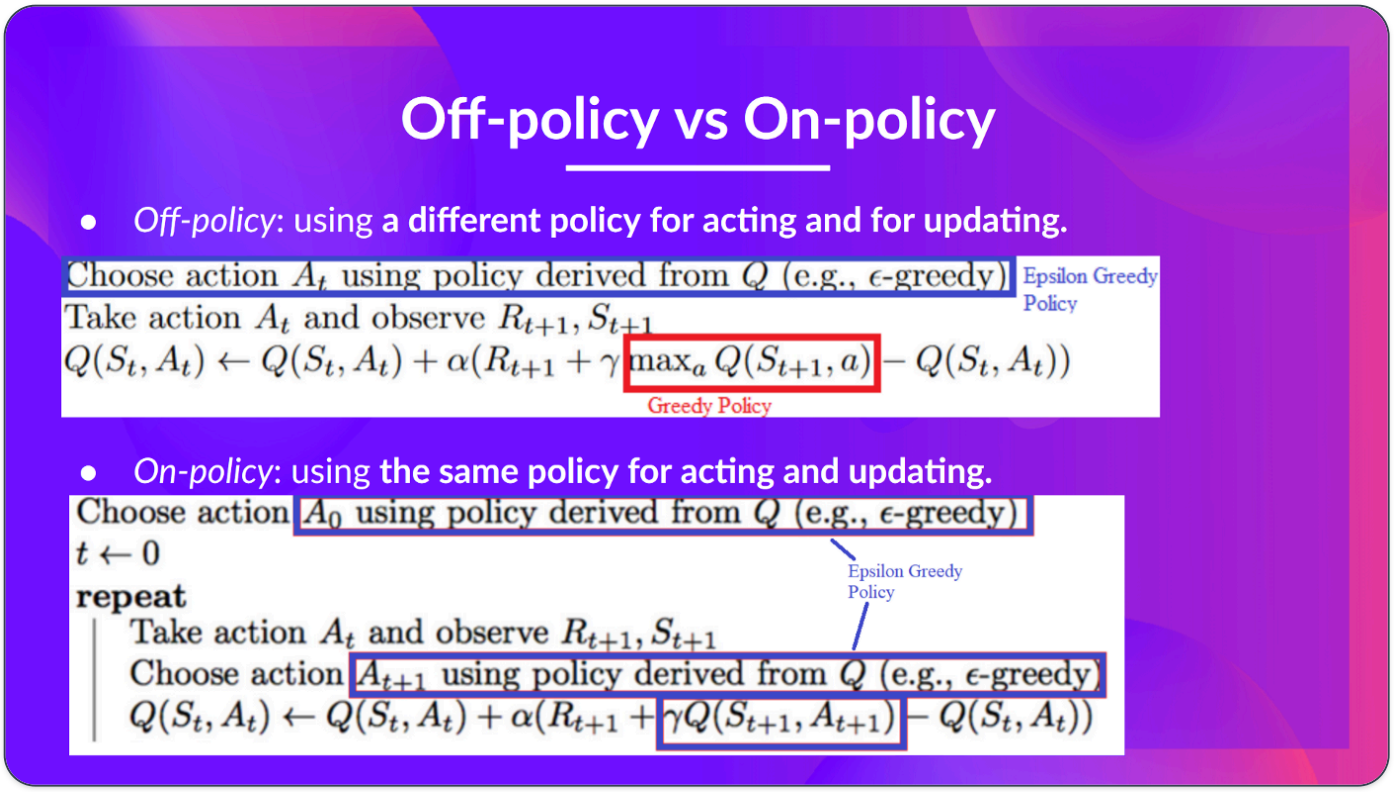
Updating policy

- *On-policy:* using the **same policy for acting and updating.**

For instance, with Sarsa, another value-based algorithm, **the epsilon-greedy policy selects the next state-action pair, not a greedy policy.**



Sarsa



← Mid-way Quiz

A Q-Learning example →