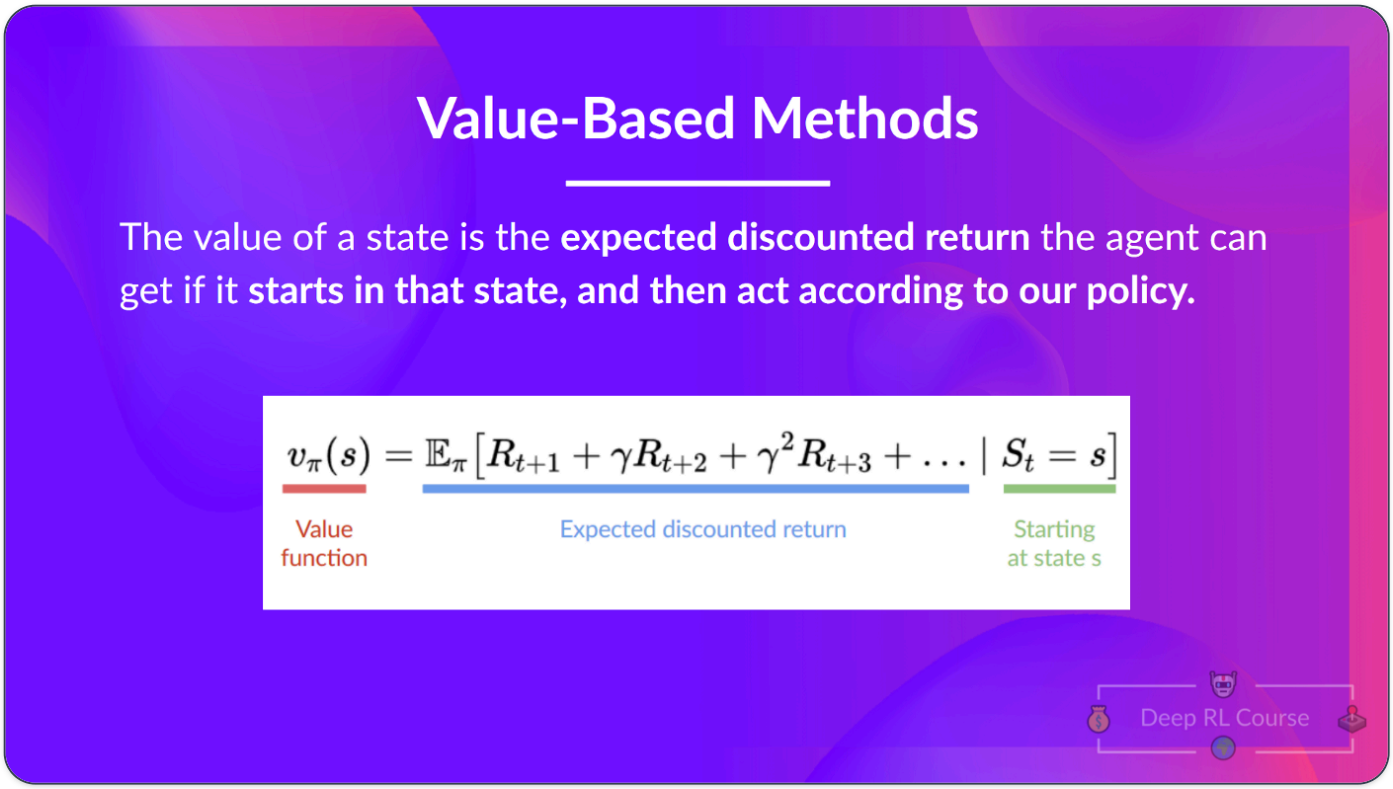
Two types of value-based methods

In value-based methods, **we learn a value function** that **maps a state to the expected value of being at that state.**



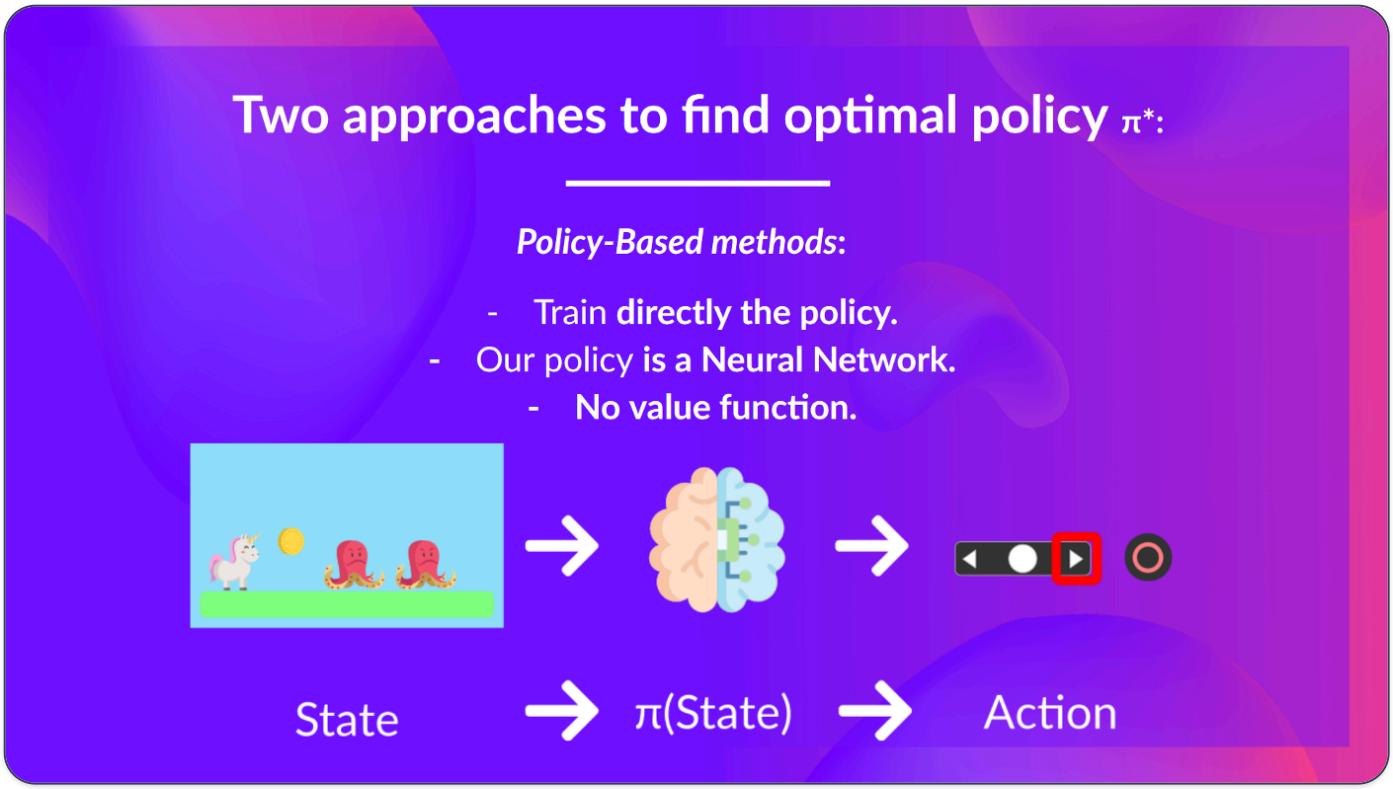
The value of a state is the **expected discounted return** the agent can get if it **starts at that state and then acts according to our policy.**

> But what does it mean to act according to our policy? After all, we don't have a policy in value-based methods since we train a value function and not a policy.

Remember that the goal of an **RL agent is to have an optimal policy π***.

To find the optimal policy, we learned about two different methods:

- *Policy-based methods:* **Directly train the policy** to select what action to take given a state (or a probability distribution over actions at that state). In this case, we **don't have a value function.**

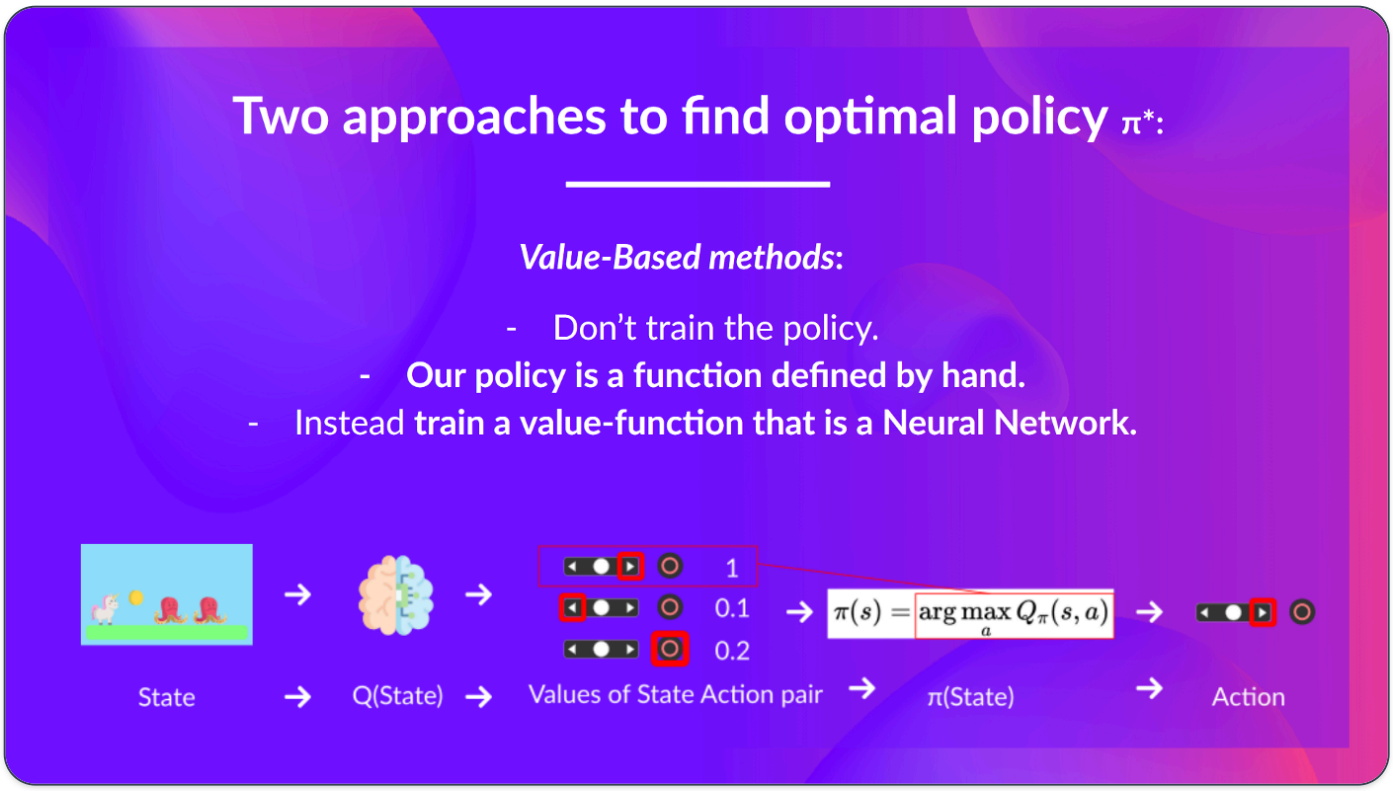


The policy takes a state as input and outputs what action to take at that state (deterministic policy: a policy that output one action given a state, contrary to stochastic policy that output a probability distribution over actions).

And consequently, **we don't define by hand the behavior of our policy; it's the training that will define it.**

- *Value-based methods:* **Indirectly, by training a value function** that outputs the value of a state or a state-action pair. Given this value function, our policy **will take an action.**

Since the policy is not trained/learned, **we need to specify its behavior.** For instance, if we want a policy that, given the value function, will take actions that always lead to the biggest reward, **we'll create a Greedy Policy.**

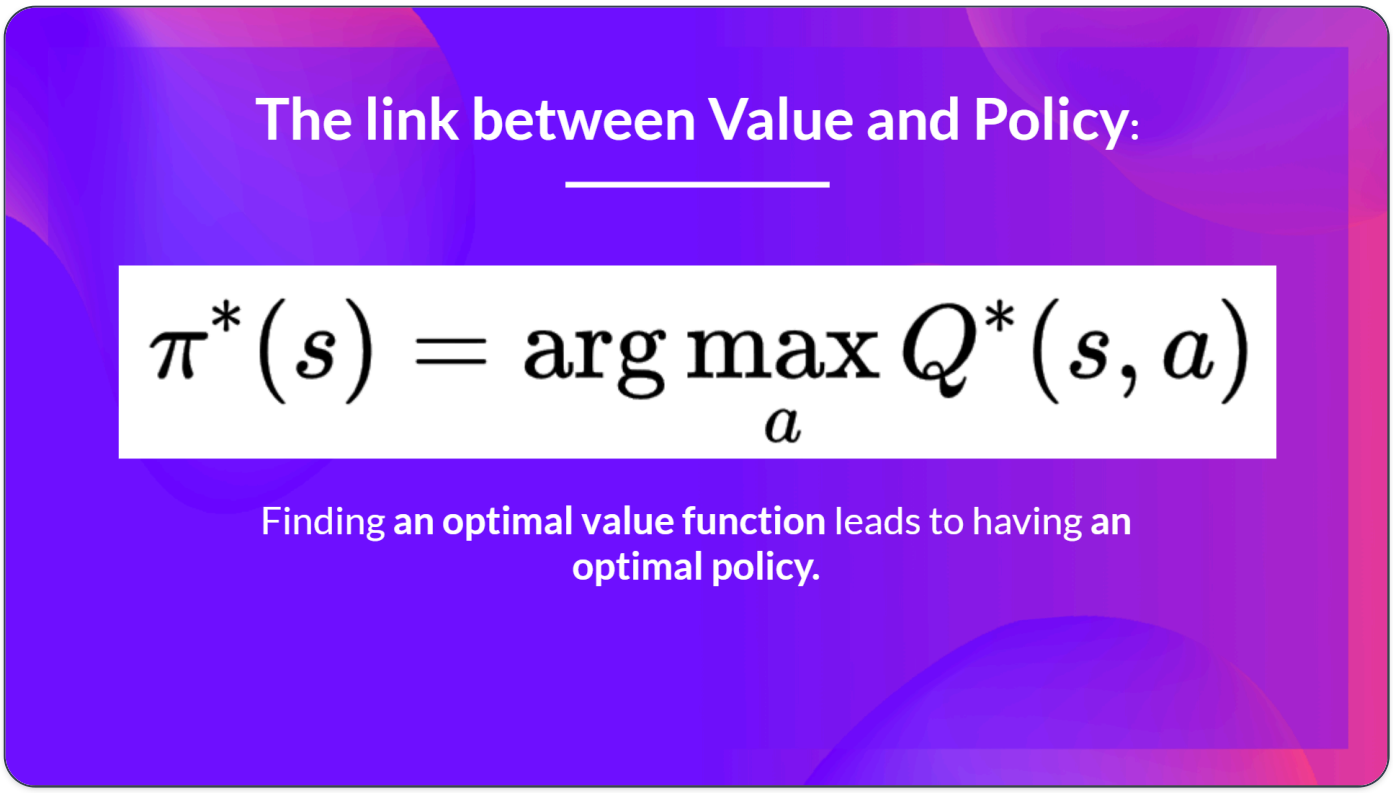


Given a state, our action-value function (that we train) outputs the value of each action at that state. Then, our pre-defined Greedy Policy selects the action that will yield the highest value given a state or a state action pair.

Consequently, whatever method you use to solve your problem, **you will have a policy**. In the case of value-based methods, you don't train the policy: your policy **is just a simple pre-specified function** (for instance, the Greedy Policy) that uses the values given by the value-function to select its actions.

So the difference is:

- In policy-based training, **the optimal policy (denoted π*) is found by training the policy directly.**
- In value-based training, **finding an optimal value function (denoted Q* or V*, we'll study the difference below) leads to having an optimal policy.**

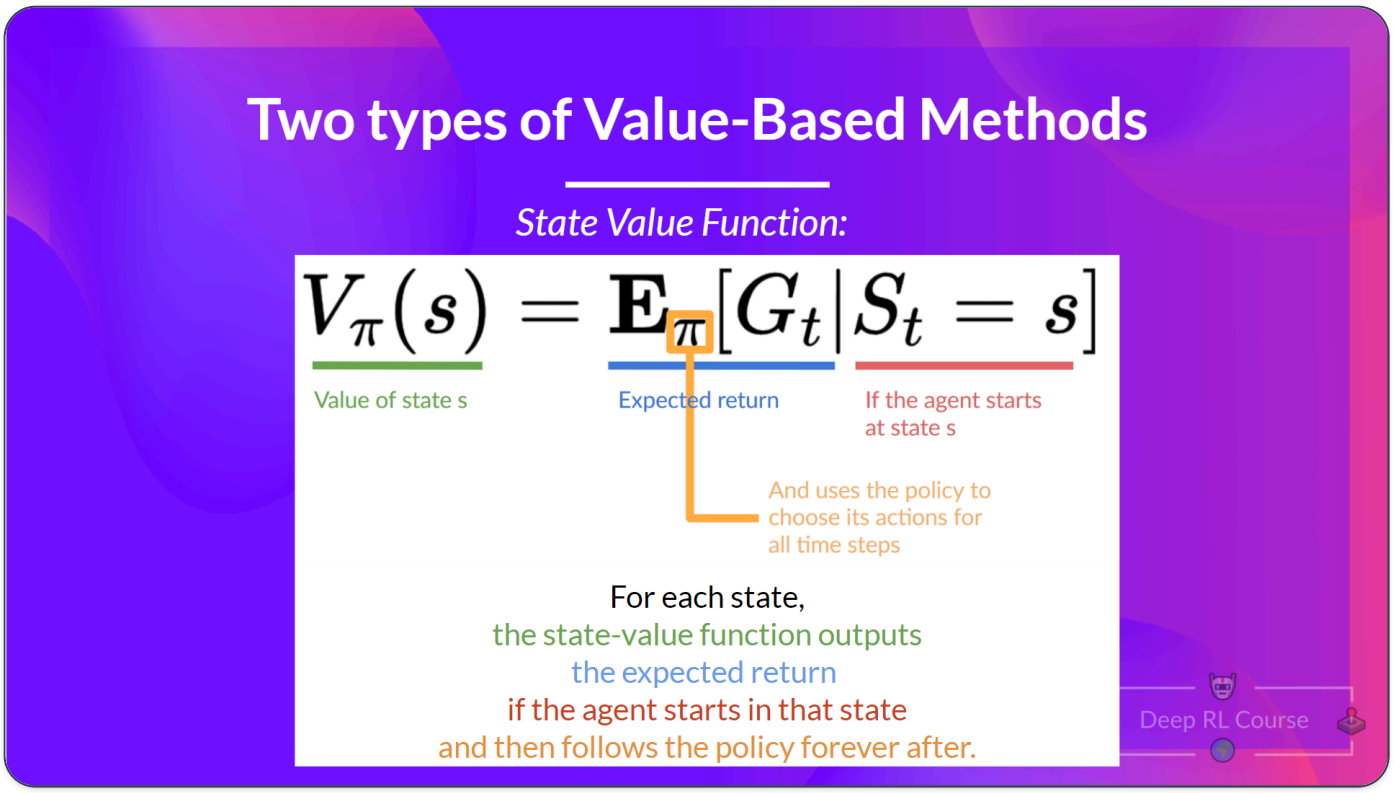


In fact, most of the time, in value-based methods, you'll use **an Epsilon-Greedy Policy** that handles the exploration/exploitation trade-off; we'll talk about this when we talk about Q-Learning in the second part of this unit.

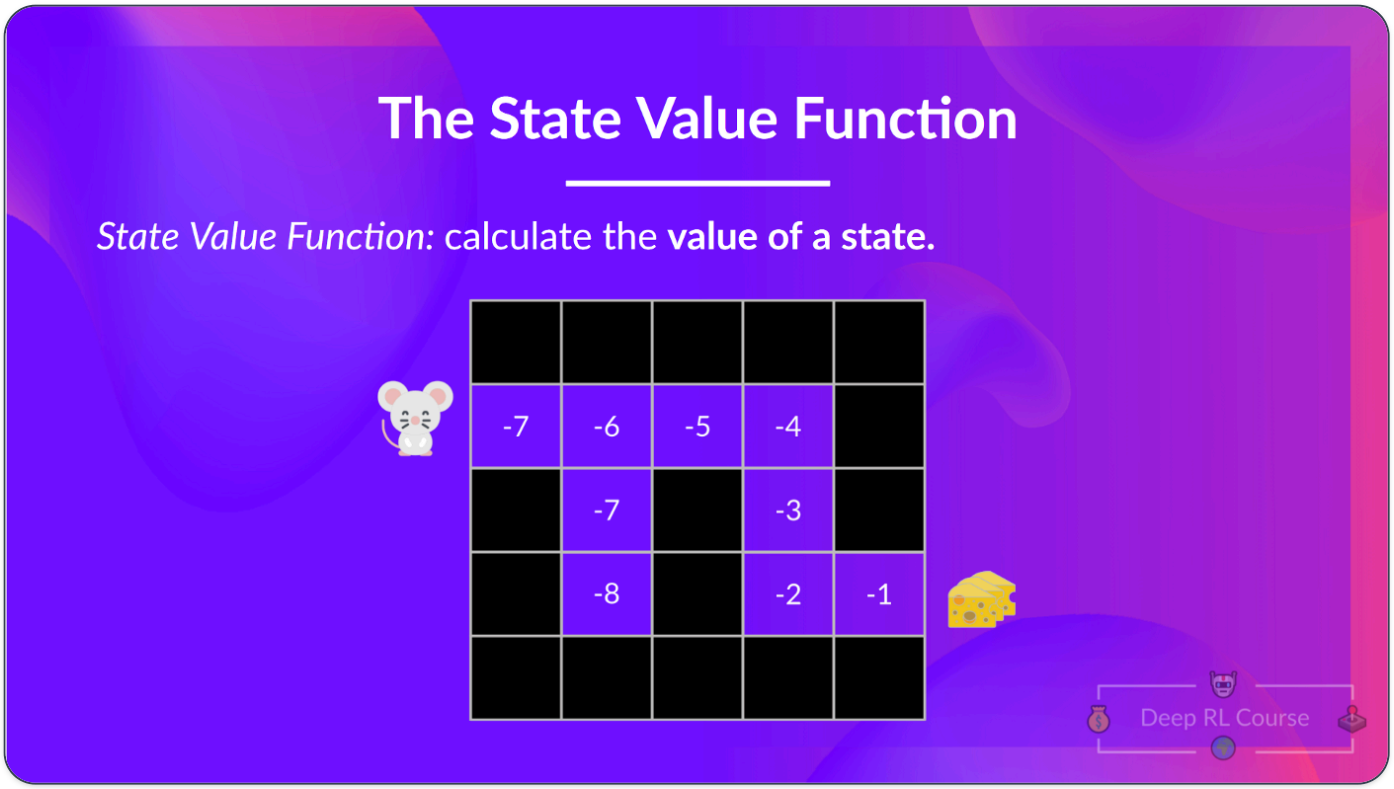
As we mentioned above, we have two types of value-based functions:

The state-value function

We write the state value function under a policy π like this:



For each state, the state-value function outputs the expected return if the agent **starts at that state** and then follows the policy forever afterward (for all future timesteps, if you prefer).

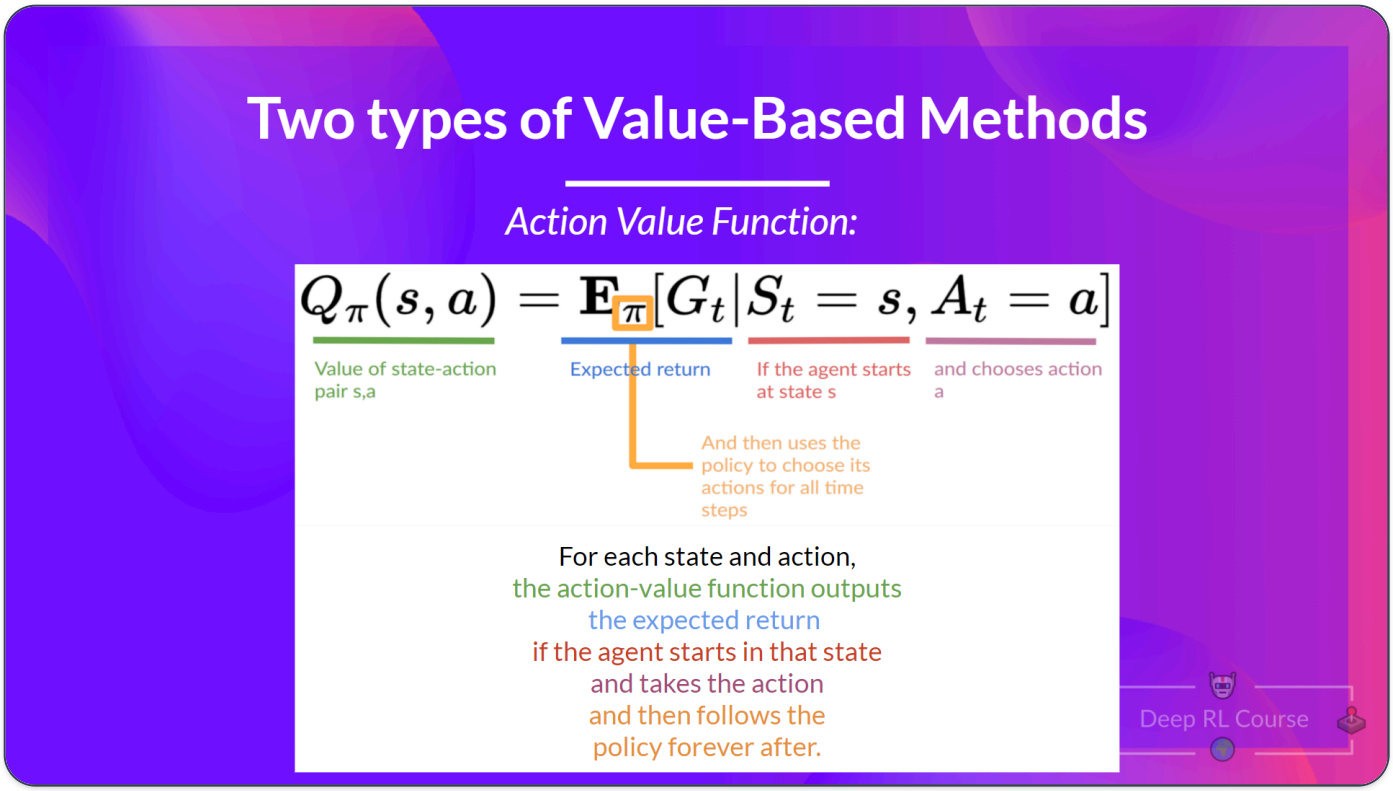


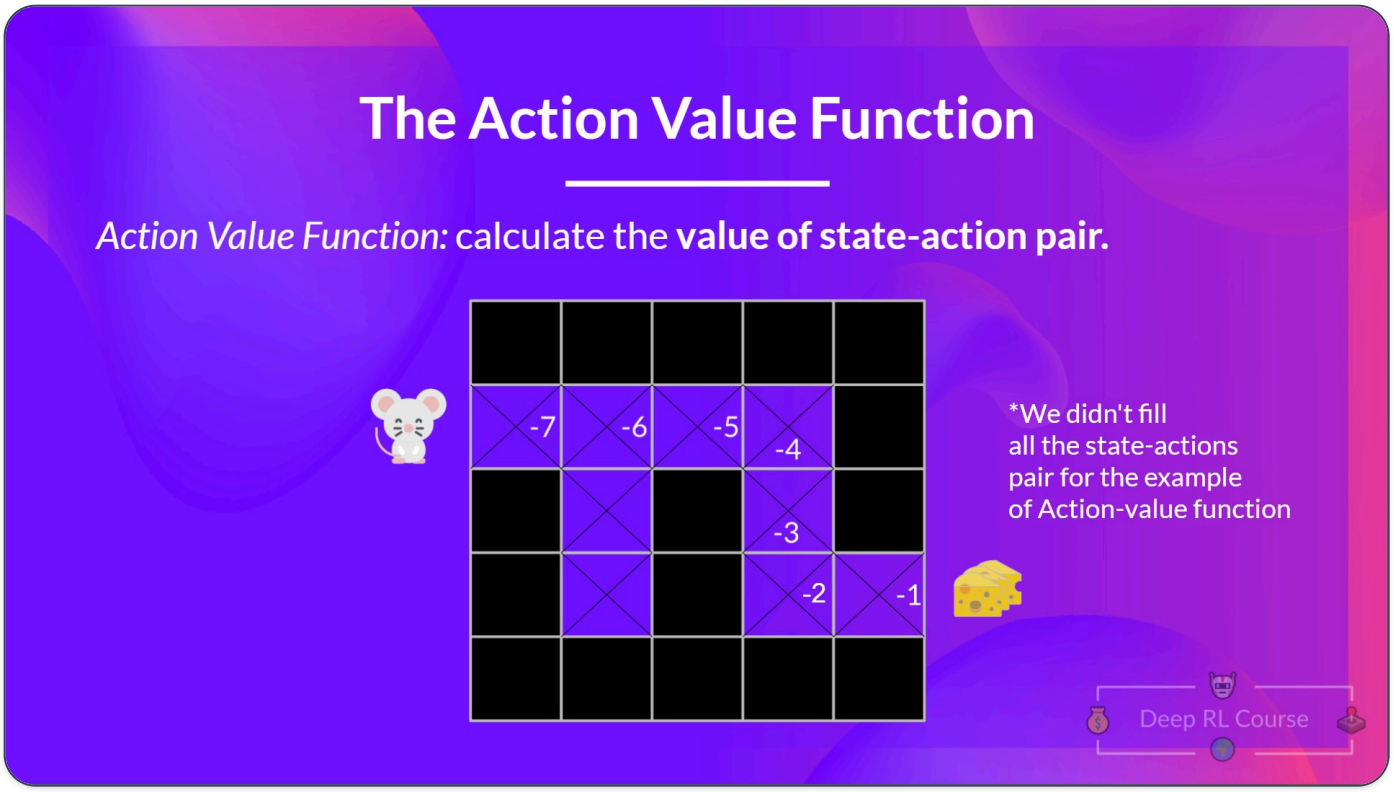
If we take the state with value -7: it's the expected return starting at that state and taking actions according to our policy (greedy policy), so right, right, right, down, down, right, right.

The action-value function

In the action-value function, for each state and action pair, the action-value function **outputs the expected return** if the agent starts in that state, takes that action, and then follows the policy forever after.

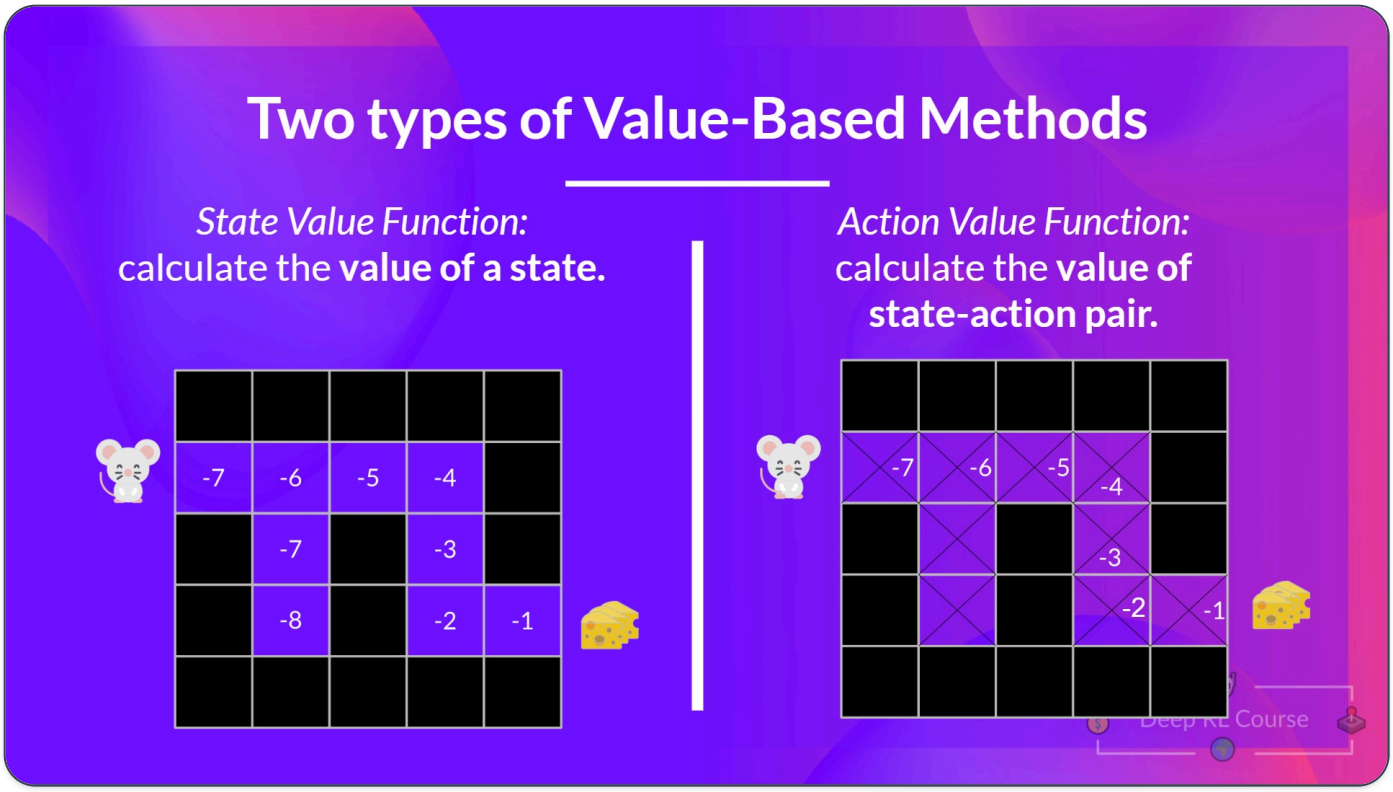
The value of taking action a in state s under a policy π is:





We see that the difference is:

- For the state-value function, we calculate **the value of a state** S_t
- For the action-value function, we calculate **the value of the state-action pair** (S_t, A_t) **hence the value of taking that action at that state.**



Note: We didn't fill all the state-action pairs for the example of Action-value function

In either case, whichever value function we choose (state-value or action-value function), **the returned value is the expected return.**

However, the problem is that **to calculate EACH value of a state or a state-action pair, we need to sum all the rewards an agent can get if it starts at that state.**

This can be a computationally expensive process, and that's **where the Bellman equation comes in to help us.**

← What is RL? A short recap

The Bellman Equation, simplify our value estimation →