Monte Carlo vs Temporal Difference Learning

The last thing we need to discuss before diving into Q-Learning is the two learning strategies.

Remember that an RL agent **learns by interacting with its environment.** The idea is that **given the experience and the received reward, the agent will update its value function or policy.**

Monte Carlo and Temporal Difference Learning are two different **strategies on how to train our value function or our policy function.** Both of them **use experience to solve the RL problem.**

On one hand, Monte Carlo uses **an entire episode of experience before learning.** On the other hand, Temporal Difference uses **only a step ($S_t, A_t, R_{t+1}, S_{t+1}$) to learn.**

We'll explain both of them **using a value-based method example.**

Monte Carlo: learning at the end of the episode

Monte Carlo waits until the end of the episode, calculates G_t (return) and uses it as **a target for updating $V(S_t)$.**

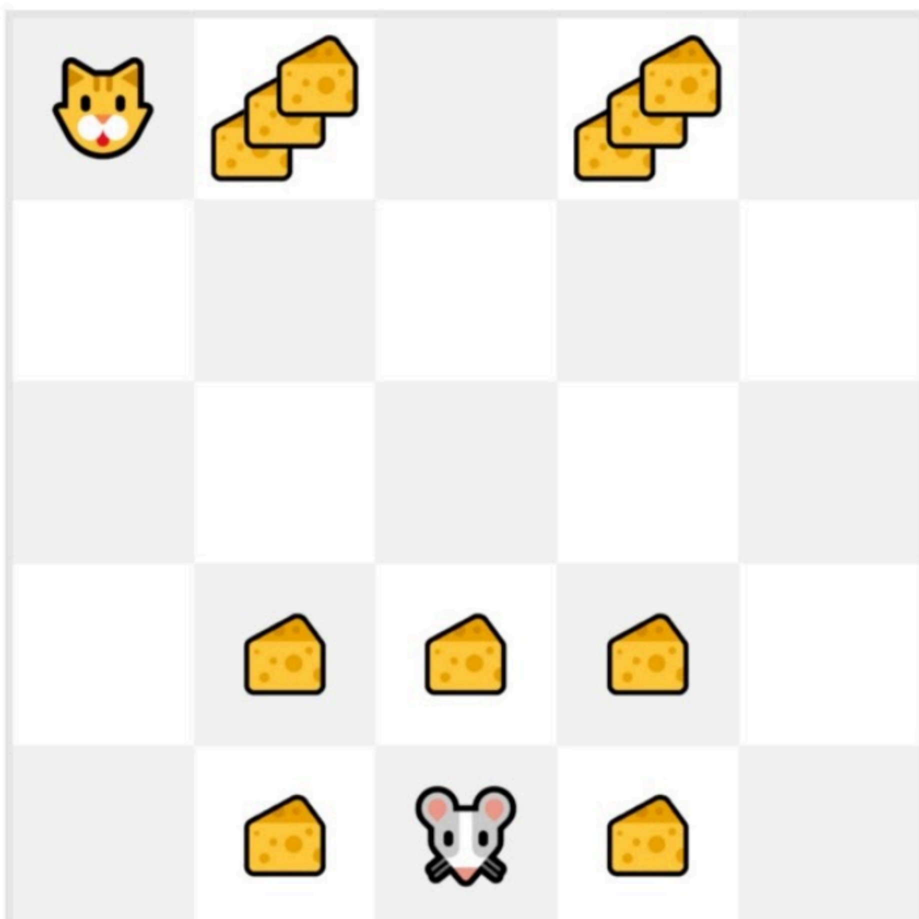
So it requires a **complete episode of interaction before updating our value function.**

Monte Carlo Approach:

***Monte Carlo:* waits until the end of the episode**, then calculates Gt (return) and uses it as a target for its value or policy.

$$\underbrace{V(S_t)}_{\text{New value of state t}} \leftarrow \underbrace{V(S_t)}_{\substack{\text{Former estimation}\\ \text{of value of state t}\\ \text{(= Expected return}\\ \text{starting at that state)}}} + \underbrace{\alpha}_{\substack{\text{Learning}\\ \text{Rate}}}[\underbrace{G_t}_{\substack{\text{Return at}\\ \text{timestep}\\ \text{t}}} - \underbrace{V(S_t)}_{\substack{\text{Former estimation}\\ \text{of value of state t}\\ \text{(= Expected return}\\ \text{starting at that}\\ \text{state)}}}]$$

If we take an example:

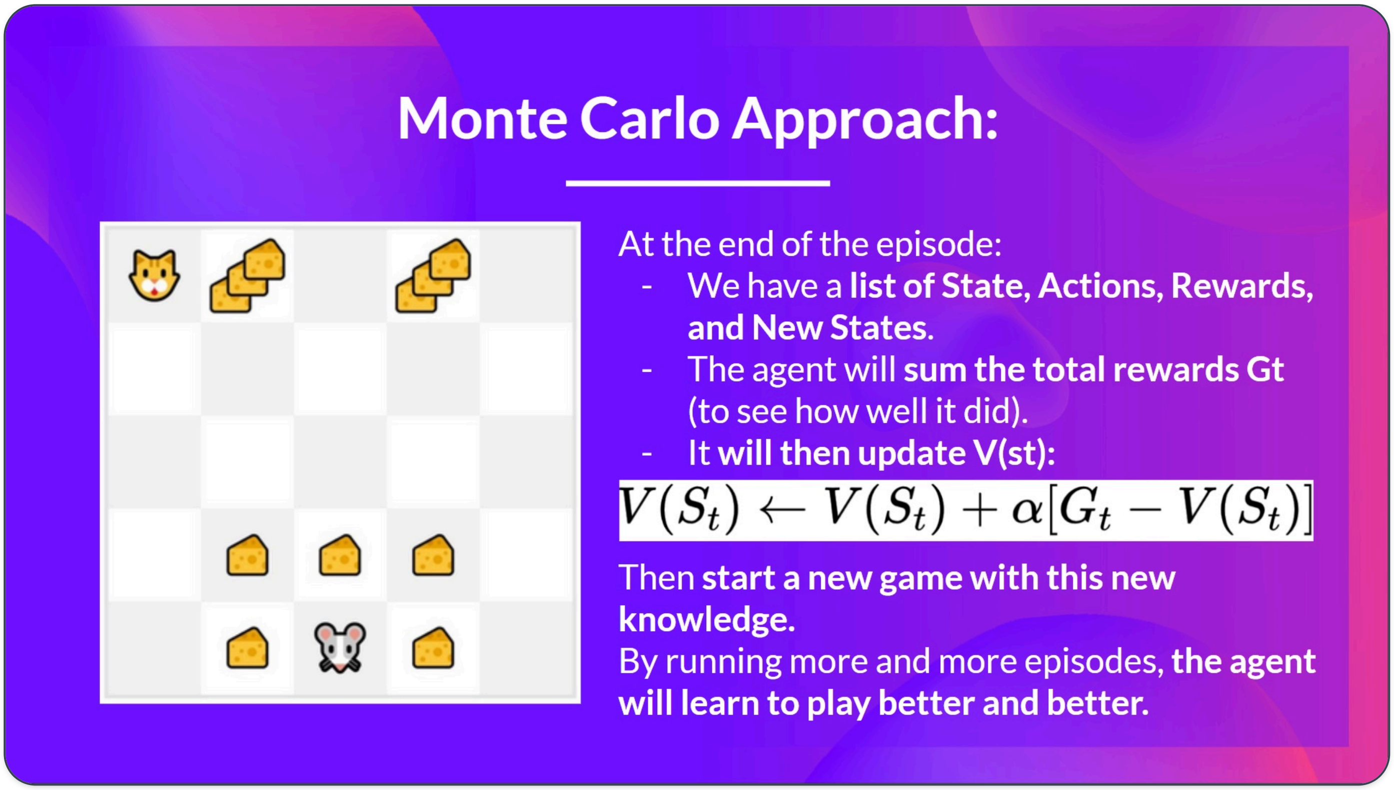


- We always start the episode **at the same starting point.**
- **The agent takes actions using the policy**. For instance, using an Epsilon Greedy Strategy, a policy that alternates between exploration (random actions) and exploitation.
- We get **the reward and the next state.**
- We terminate the episode if the cat eats the mouse or if the mouse moves > 10 steps.
- At the end of the episode, **we have a list of State, Actions, Rewards, and Next States tuples** For instance [[State tile 3 bottom, Go Left, +1, State tile 2 bottom], [State tile 2 bottom, Go Left, +0, State tile 1 bottom]…]
- **The agent will sum the total rewards** G_t (to see how well it did).
- It will then **update** $V(s_t)$ **based on the formula**

$$\underbrace{V(S_t)}_{\text{New value of state t}} \leftarrow \underbrace{V(S_t)}_{\substack{\text{Former estimation}\\ \text{of value of state t}\\ \text{(= Expected return}\\ \text{starting at that state)}}} + \underbrace{\alpha}_{\substack{\text{Learning}\\ \text{Rate}}}[\underbrace{G_t}_{\substack{\text{Return at}\\ \text{timestep}\\ \text{t}}} - \underbrace{V(S_t)}_{\substack{\text{Former estimation}\\ \text{of value of state t}\\ \text{(= Expected return}\\ \text{starting at that}\\ \text{state)}}}]$$

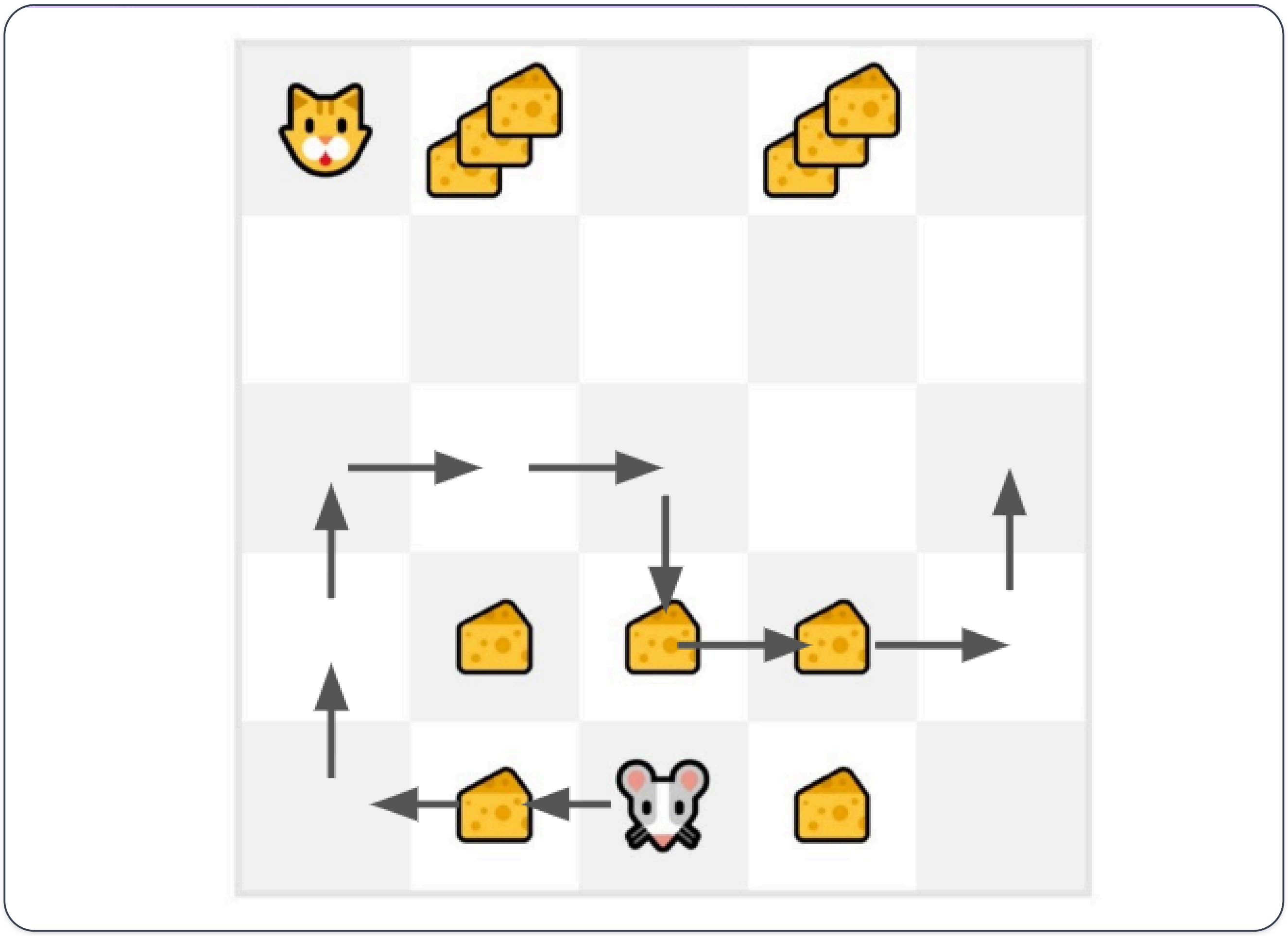
- Then **start a new game with this new knowledge**

By running more and more episodes, **the agent will learn to play better and better.**

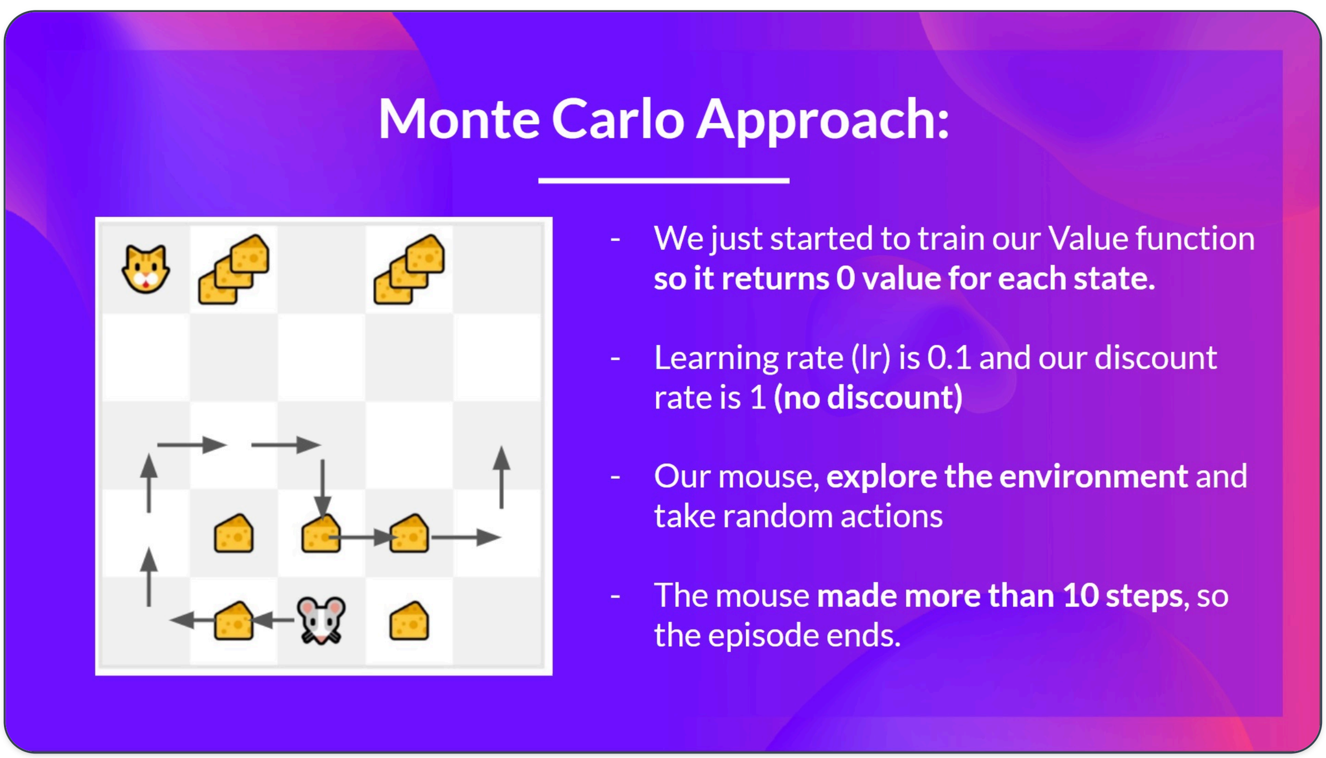


For instance, if we train a state-value function using Monte Carlo:

- We initialize our value function **so that it returns 0 value for each state**
- Our learning rate (lr) is 0.1 and our discount rate is 1 (= no discount)
- Our mouse **explores the environment and takes random actions**

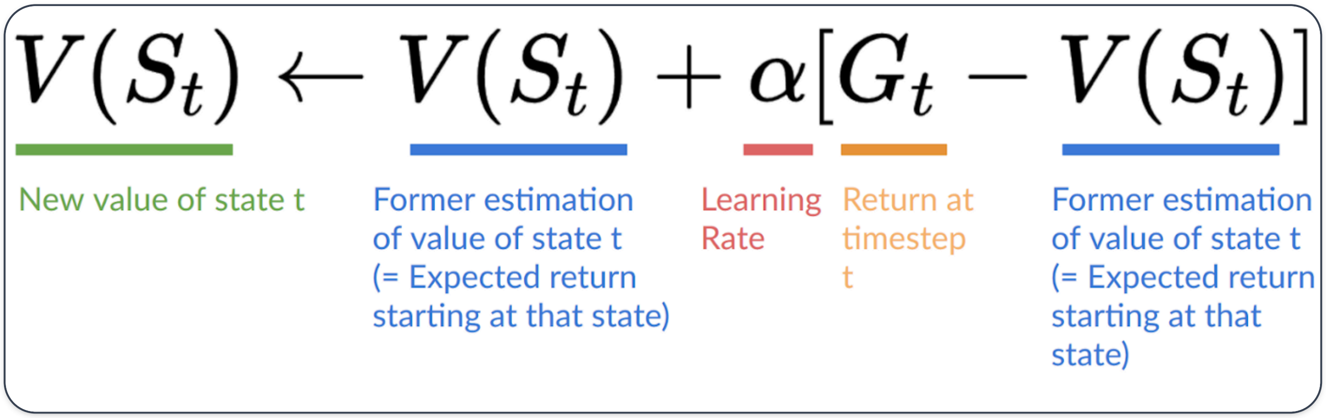


- The mouse made more than 10 steps, so the episode ends .

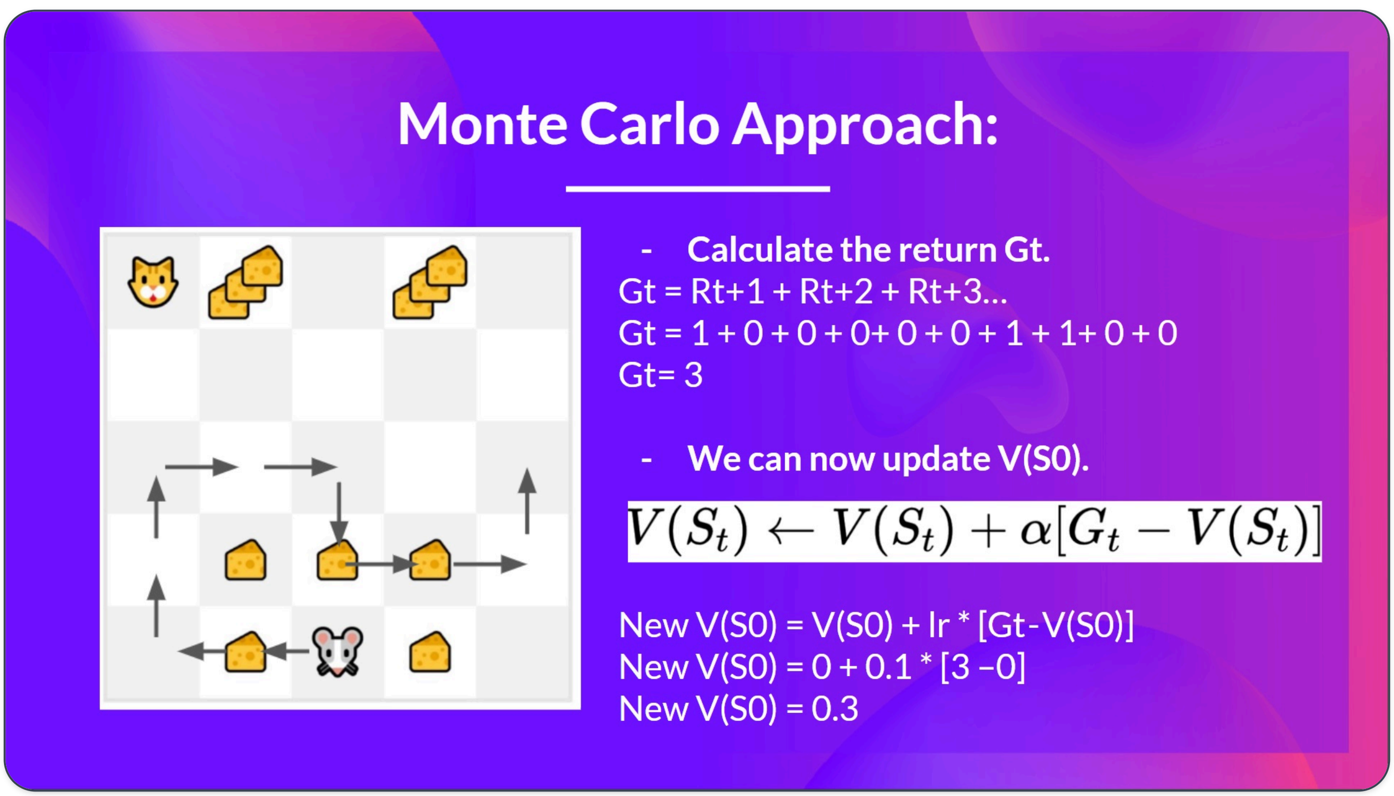


- We have a list of state, action, rewards, next_state, **we need to calculate the return** $Gt = 0$ $G_t = R_{t+1} + R_{t+2} + R_{t+3} \ldots$ (for simplicity, we don't discount the rewards) $G_0 = R_1 + R_2 + R_3 \ldots G_0 = 1 + 0 + 0 + 0 + 0 + 0 + 1 + 1 + 0 + 0 \, G_0 = 3$

- We can now compute the **new** $V(S_0)$:



$V(S_0) = V(S_0) + lr * [G_0 — V(S_0)] \, V(S_0) = 0 + 0.1 * [3 – 0] \, V(S_0) = 0.3$



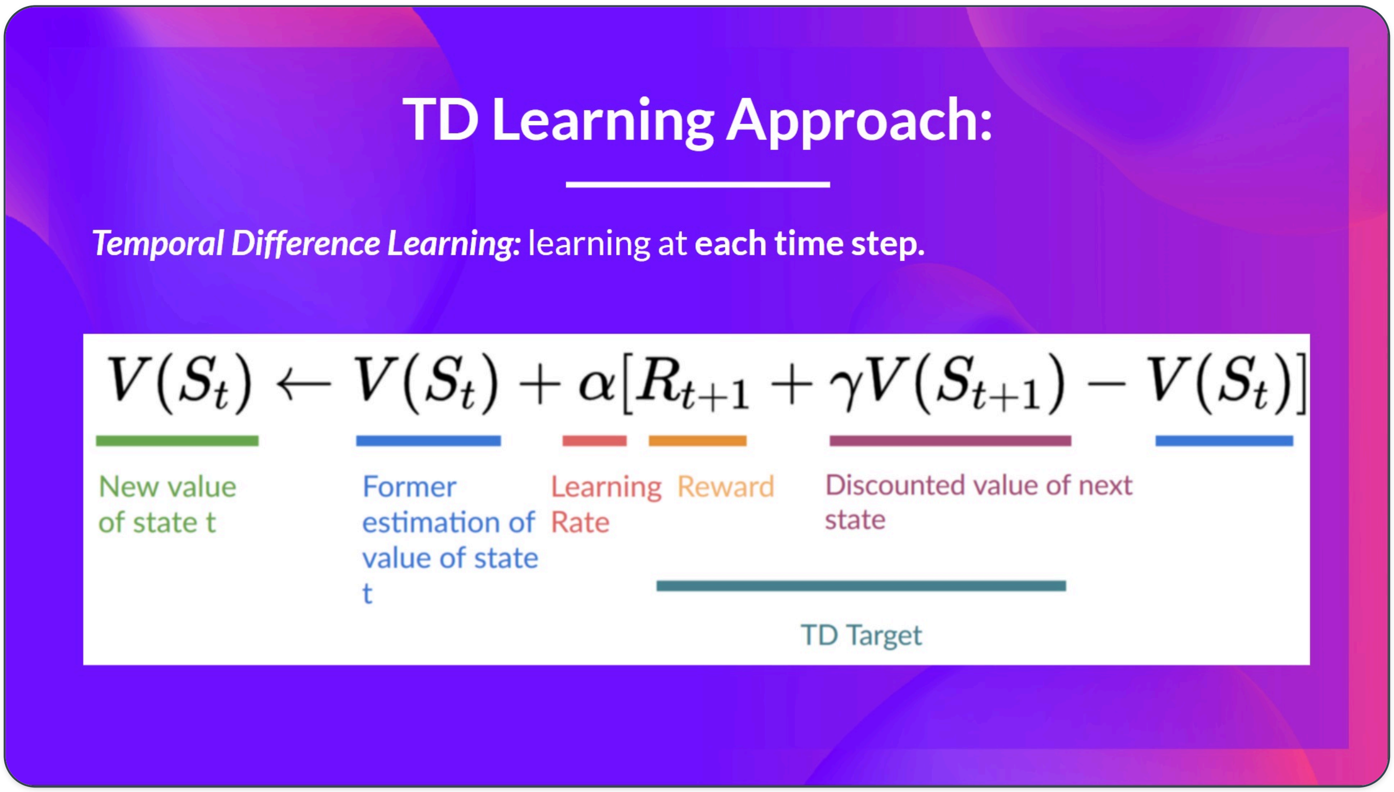
Temporal Difference Learning: learning at each step

Temporal Difference, on the other hand, waits for only one interaction (one step) S_{t+1} to form a TD target and update $V(S_t)$ using R_{t+1} and $\gamma * V(S_{t+1})$.

The idea with **TD is to update the** $V(S_t)$ **at each step.**

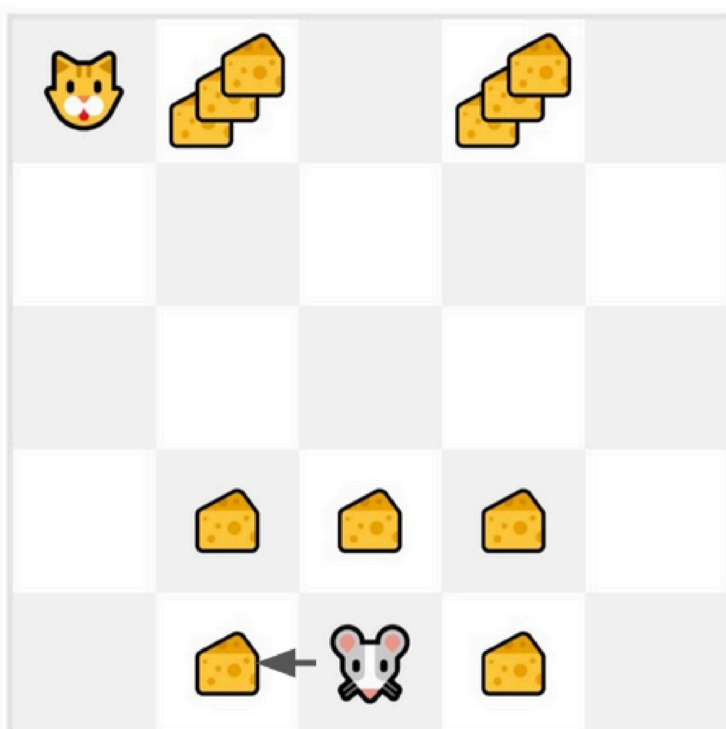
But because we didn't experience an entire episode, we don't have G_t (expected return). Instead, **we estimate** G_t **by adding** R_{t+1} **and the discounted value of the next state.**

This is called bootstrapping. It's called this **because TD bases its update in part on an existing estimate** $V(S_{t+1})$ **and not a complete sample** G_t.



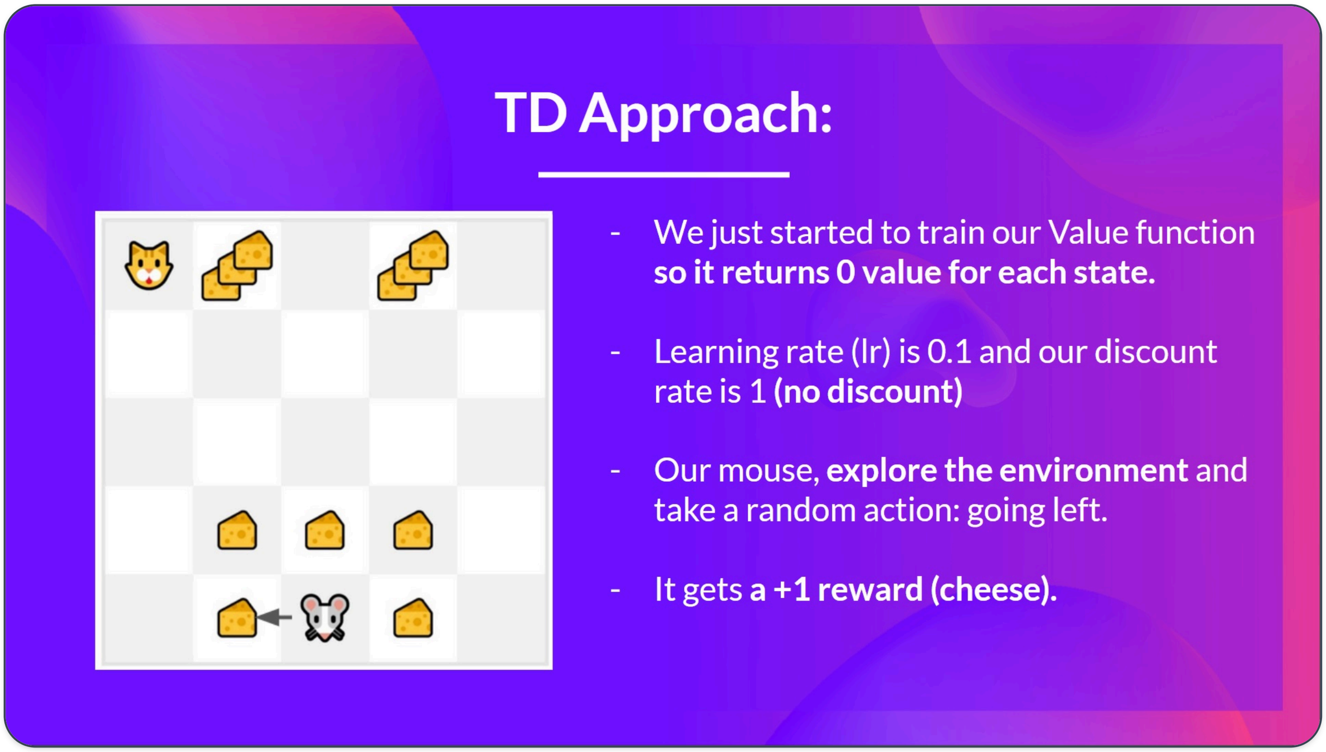
This method is called TD(0) or **one-step TD (update the value function after any individual step).**

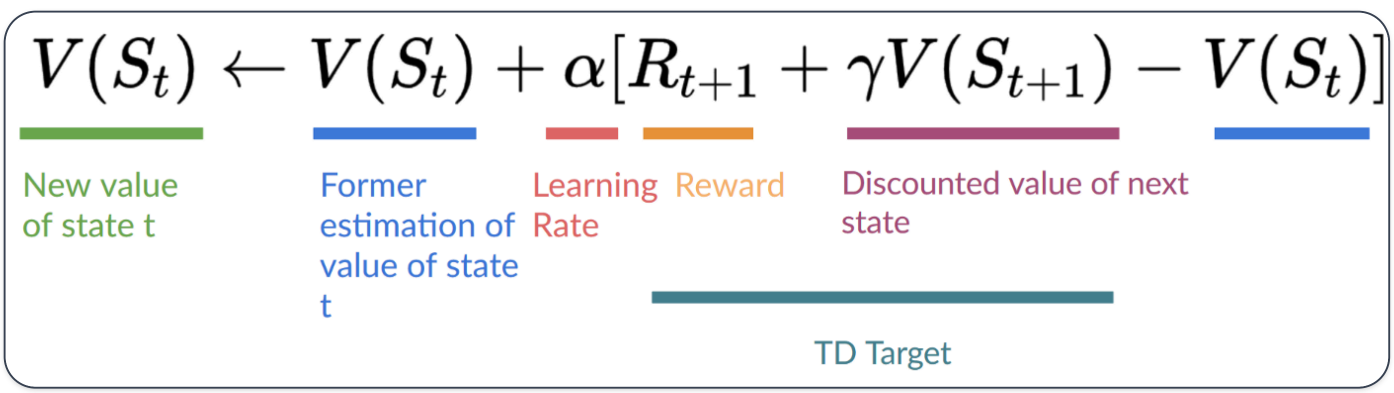
If we take the same example,



- We initialize our value function so that it returns 0 value for each state.

- Our learning rate (lr) is 0.1, and our discount rate is 1 (no discount).
- Our mouse begins to explore the environment and takes a random action: **going to the left**
- It gets a reward $R_{t+1} = 1$ since **it eats a piece of cheese**





We can now update $V(S_0)$:

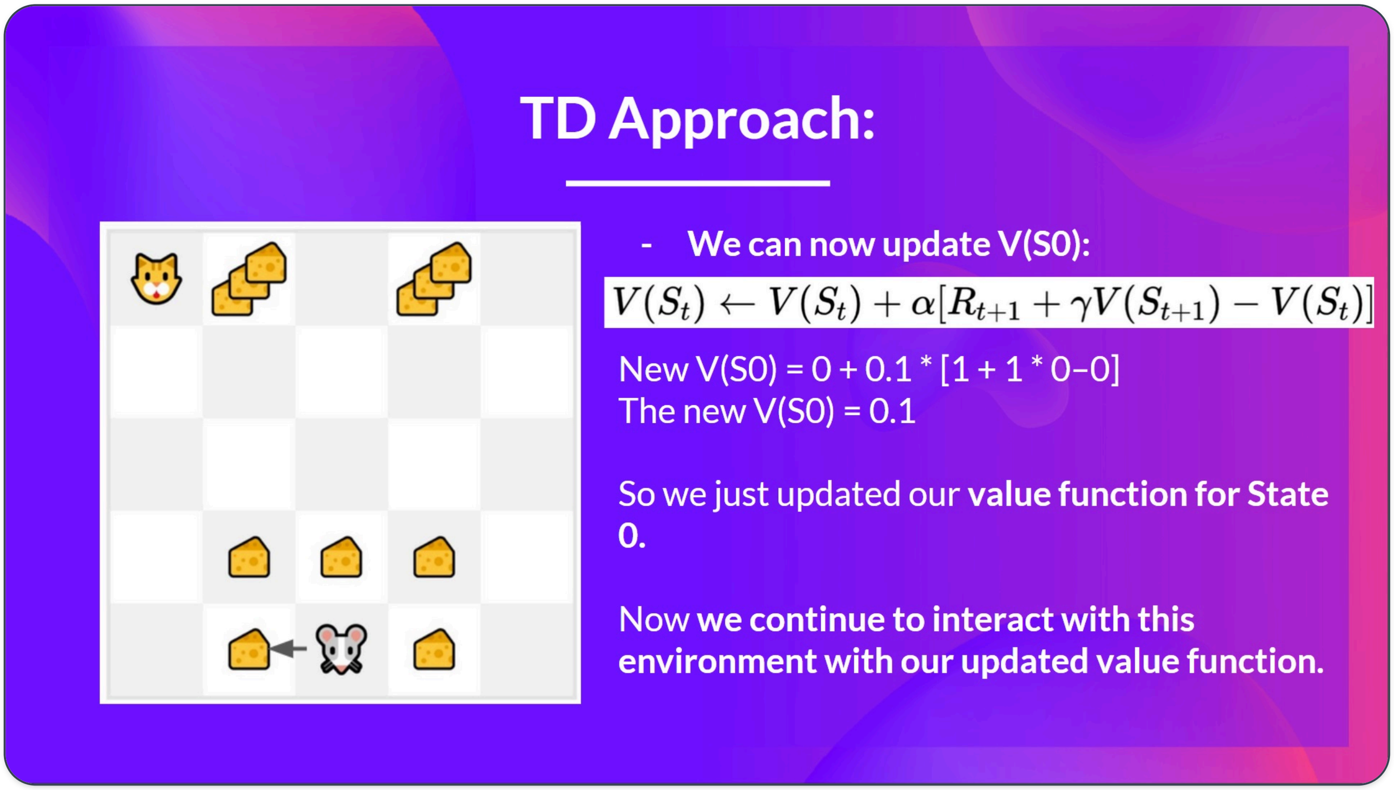
New $V(S_0) = V(S_0) + lr * [R_1 + \gamma * V(S_1) - V(S_0)]$

New$V(S_0) = 0 + 0.1 * [1 + 1 * 0 – 0]$

New$V(S_0) = 0.1$

So we just updated our value function for State 0.

Now we **continue to interact with this environment with our updated value function.**



To summarize:

- With *Monte Carlo*, we update the value function from a complete episode, and so we **use the actual accurate discounted return of this episode.**

- With *TD Learning*, we update the value function from a step, and we replace G_t, which we don't know, with **an estimated return called the TD target.**

Monte Carlo: $V(S_t) \leftarrow V(S_t) + \alpha[G_t - V(S_t)]$

TD Learning: $V(S_t) \leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)]$