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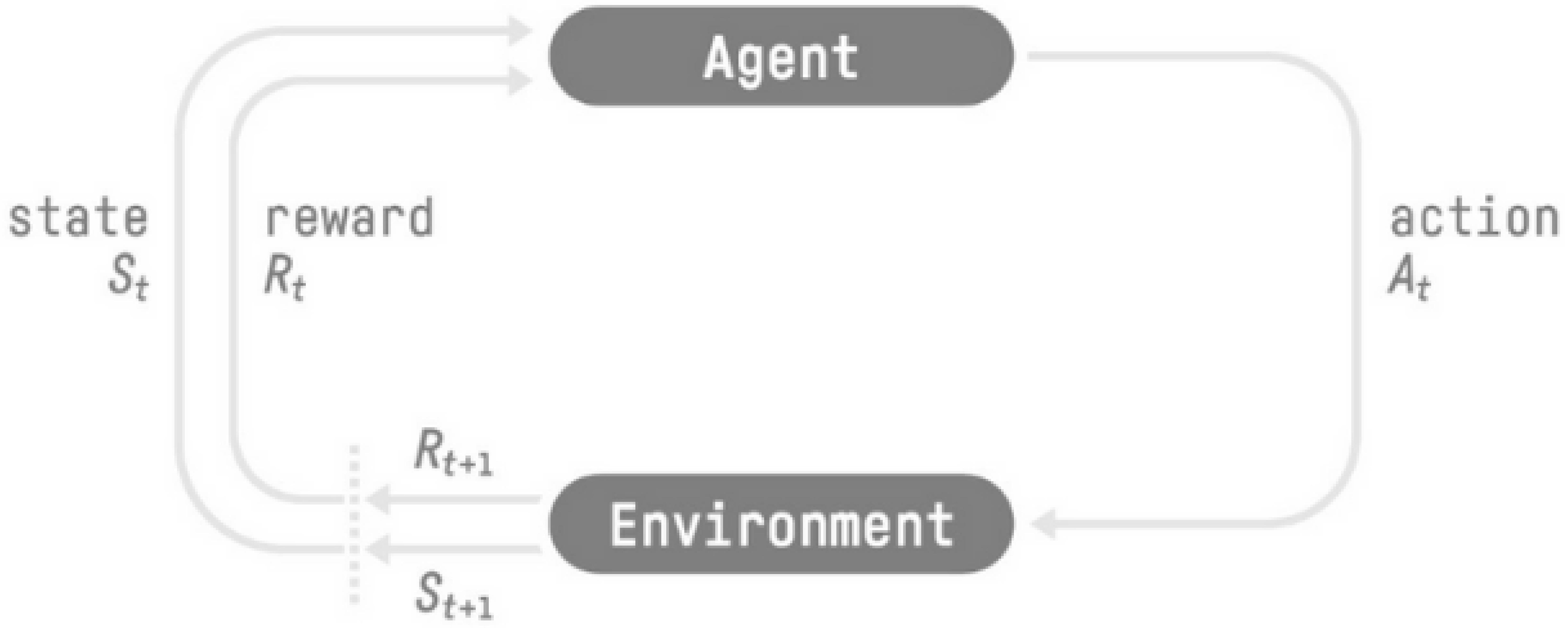
SOAI AI Camp

Solving RL: Value-Based Methods

Let’s do a recap about RL



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Example

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Goal

Maximizing the cumulative reward

$$R(\boxed{\tau}) = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \gamma^3 r_{t+4} + \dots$$

Return: cumulative reward

Gamma: discount rate

Trajectory (read Tau)
Sequence of states and actions

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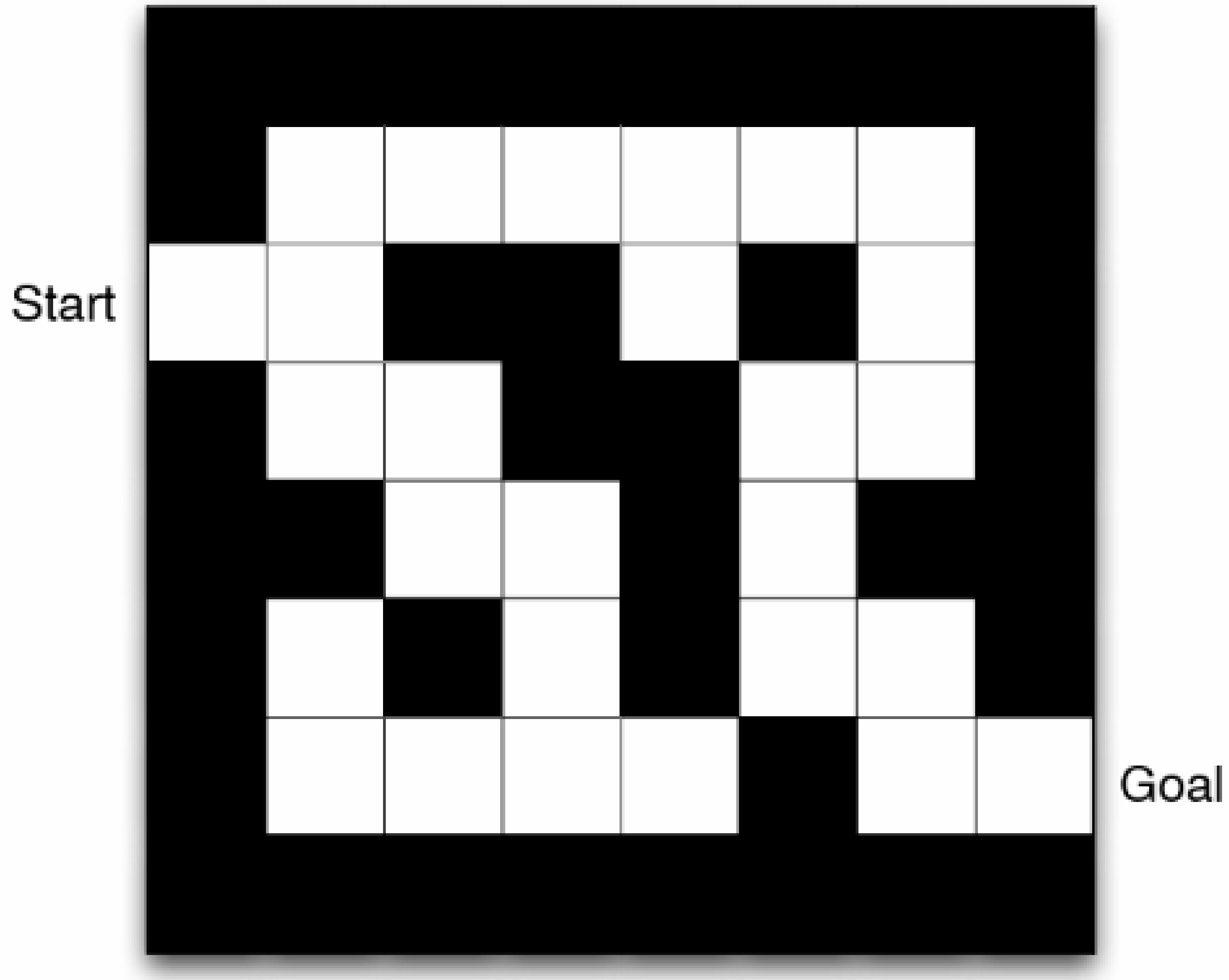
Solving Reinforcement Learning

Problem

Maze World



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Problem

Maze World

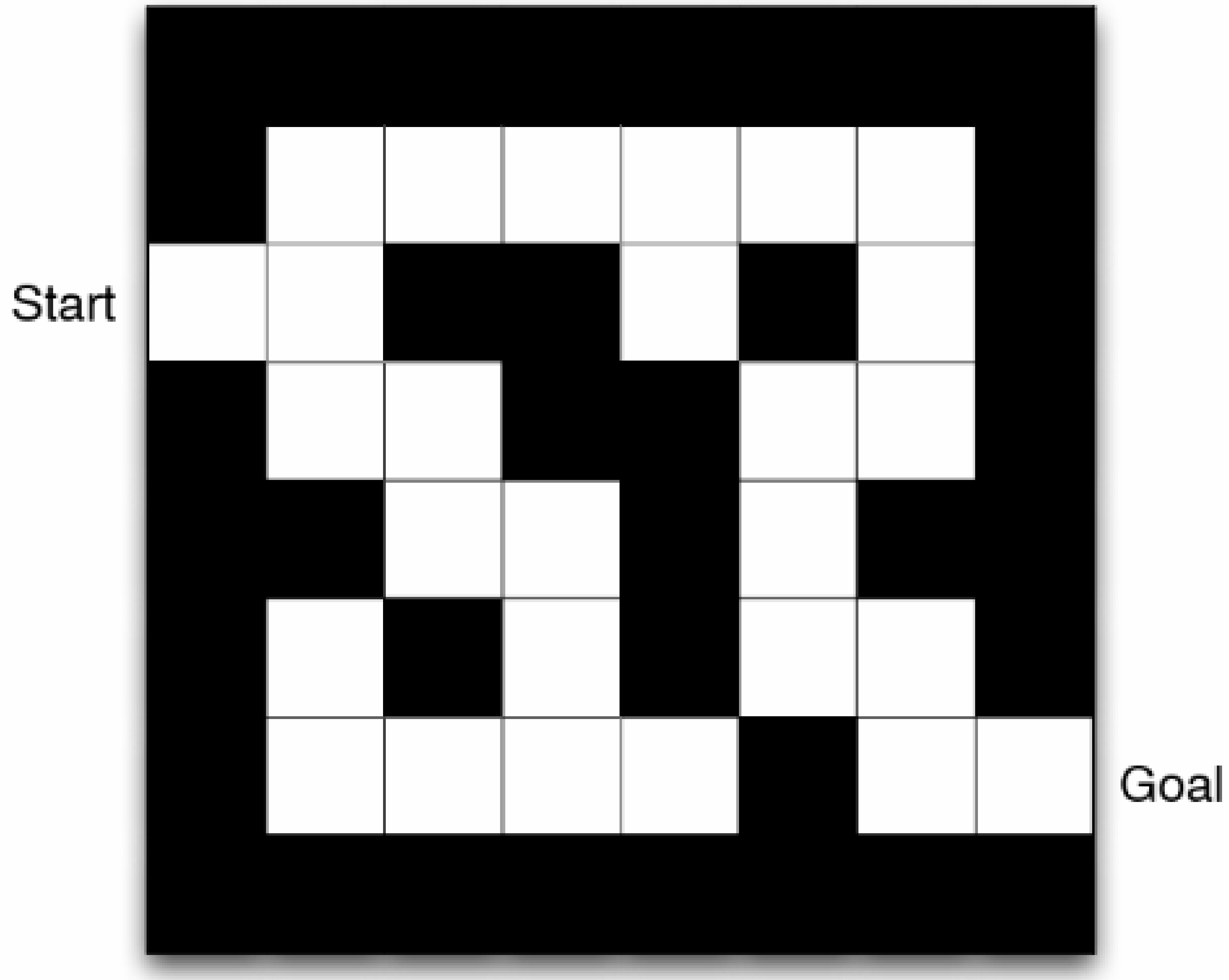
Actions

Up

Down

Left

Right



Rewards

-1 per step

-2 hitting wall

States

S: initial state

G: terminal state

Value functions

State Value Function

$$\underbrace{v_\pi(s)}_{\text{Value function}} = \underbrace{\mathbb{E}_\pi\left[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \ldots\right.}_{\text{Expected discounted return}} \mid \underbrace{\left.S_t = s\right]}_{\text{Starting at state s}}$$

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Value functions

State-Action Value Function

$$Q^{\pi}(s,a) = \mathbb{E}_{\pi}\Big[\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \Big| s_t = s, a_t = a\Big]$$

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Value functions

Relation

$$v_*(s) = \max_{a(s)} q_{\pi*}(s, a)$$

How to adjust our estimations

Policy

Greedy Policy

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

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Estimation Adjustment

$$\underbrace{Q(S_t, A_t)}_{\text{New Q-value estimation}} \leftarrow \underbrace{Q(S_t, A_t)}_{\text{Former Q-value estimation}} + \underbrace{\alpha}_{\text{Learning Rate}}[\underbrace{\underbrace{\underbrace{R_{t+1}}_{\text{Immediate Reward}} + \underbrace{\gamma max_a Q(S_{t+1}, a)}_{\text{Discounted Estimate optimal Q-value of next state}}}_{\text{TD Target}} - \underbrace{Q(S_t, A_t)}_{\text{Former Q-value estimation}}}_{\text{TD Error}}]$$

Math & Theory is cool. But
Let's build up intuition!

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Q-Learning Algorithm

Algorithm 14: Sarsamax (Q-Learning)

Input: policy π, positive integer *num_episodes*, small positive fraction α, GLIE $\{\epsilon_i\}$
Output: value function Q ($\approx q_\pi$ if *num_episodes* is large enough)
Initialize Q arbitrarily (e.g., $Q(s,a) = 0$ for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$, and $Q(terminal\text{-}state, \cdot) = 0$) Step 1
for $i \leftarrow 1$ *to num_episodes* **do**
  $\epsilon \leftarrow \epsilon_i$
  Observe S_0
  $t \leftarrow 0$
  repeat
    Choose action A_t using policy derived from Q (e.g., ϵ-greedy) Step 2
    Take action A_t and observe R_{t+1}, S_{t+1} Step 3
    $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t))$ Step 4
    $t \leftarrow t + 1$
  until S_t *is terminal*;
end
return Q

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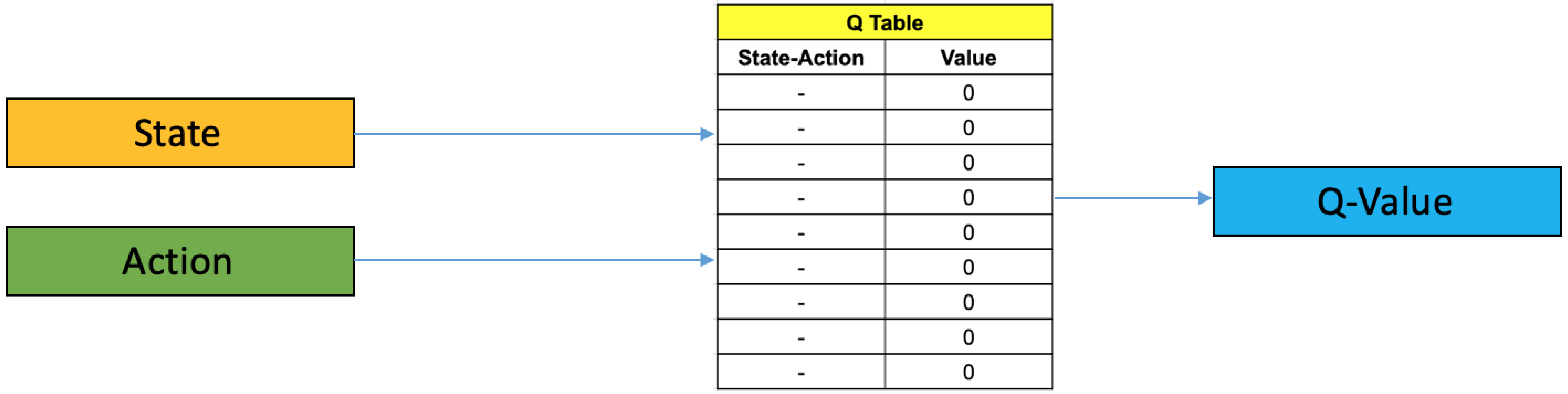
Q-Learning is so cool!
BUT

Q-Learning Limitations

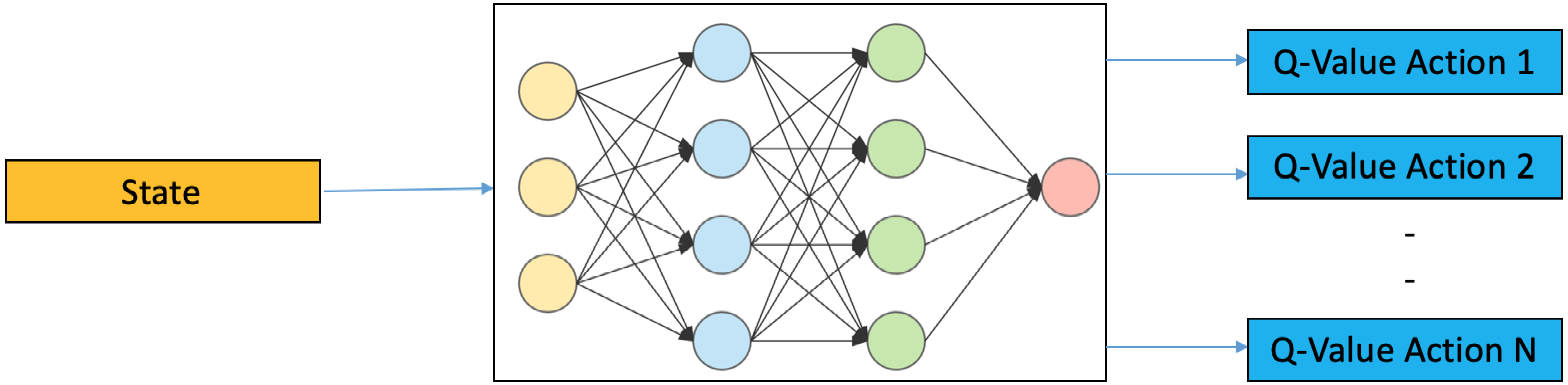
- Handling high dimensional state/action spaces
- Function approximation generalization capabilities
- Familiarity and usability only in discrete action spaces

QL vs DQL



Q Table	
State-Action	Value
-	0
-	0
-	0
-	0
-	0
-	0
-	0
-	0
-	0

Q Learning



Deep Q Learning

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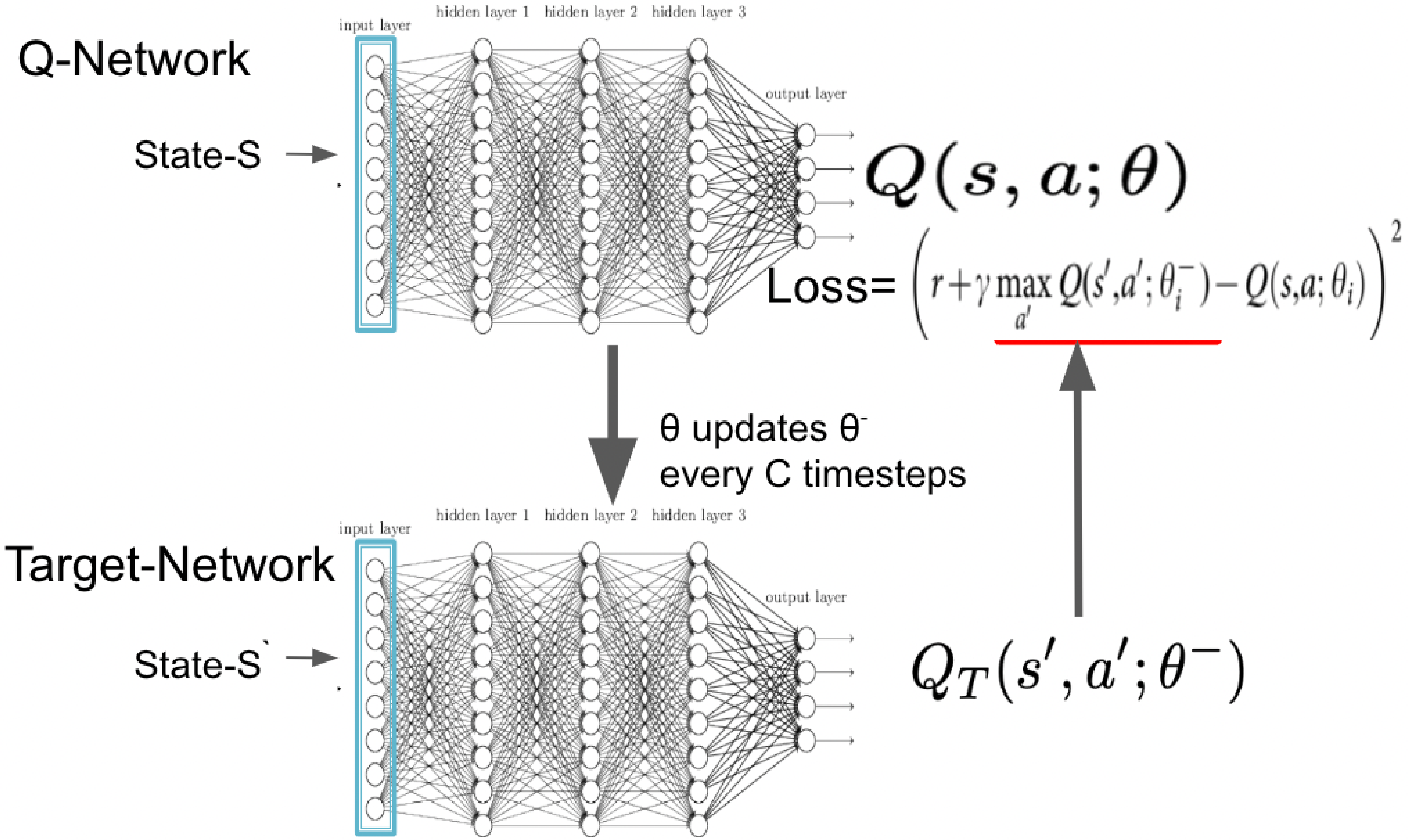
DQN Networks



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Deep Q Network Algorithm

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
    Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
    for $t = 1, T$ **do**
        With probability ϵ select a random action a_t
        otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
        Execute action a_t in emulator and observe reward r_t and image x_{t+1}
        Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
        Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
        Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
        Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
        Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation $\boxed{3}$
    end for
end for

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