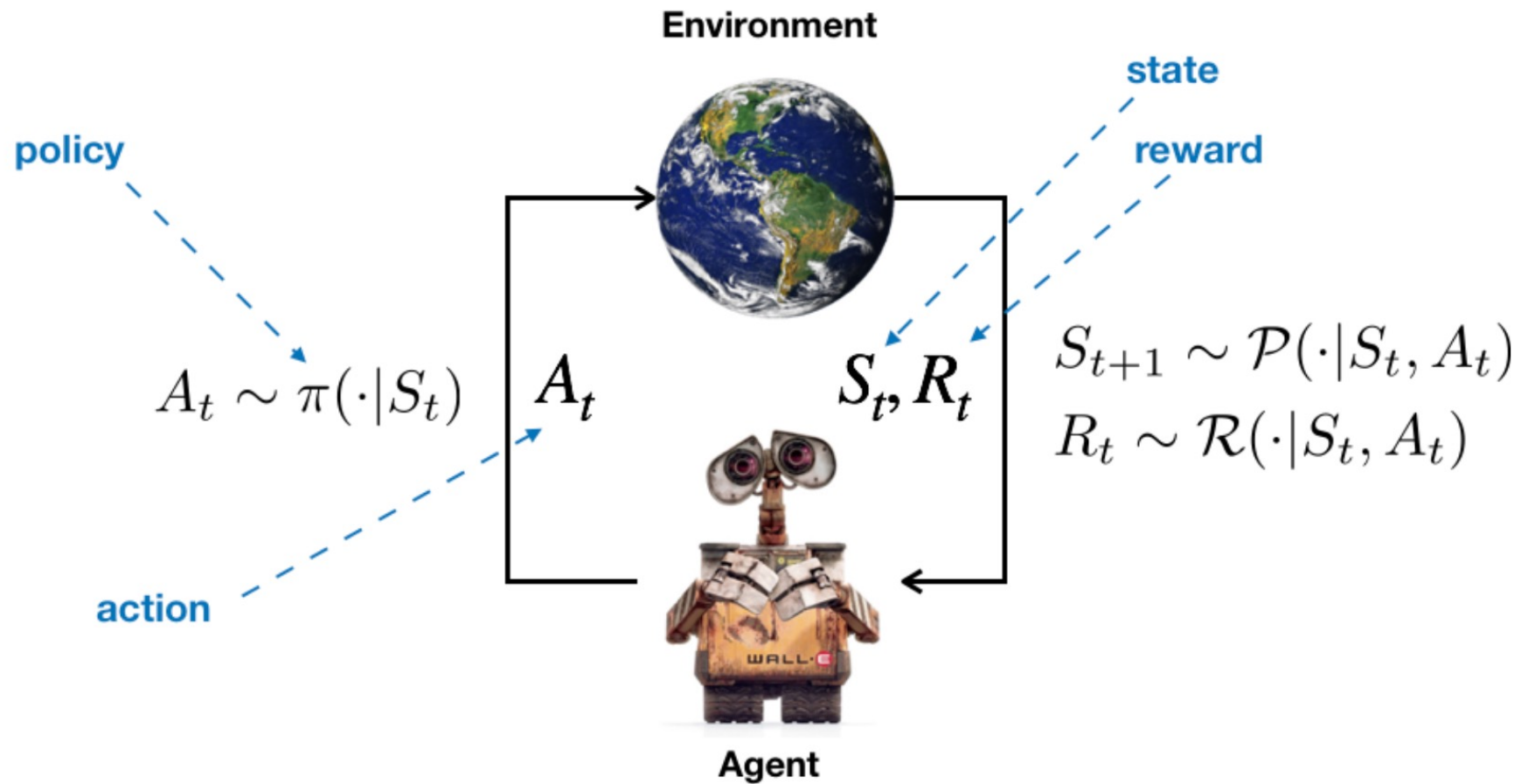


Introduction to Reinforcement Learning

What is Reinforcement Learning?



Applications of Reinforcement Learning

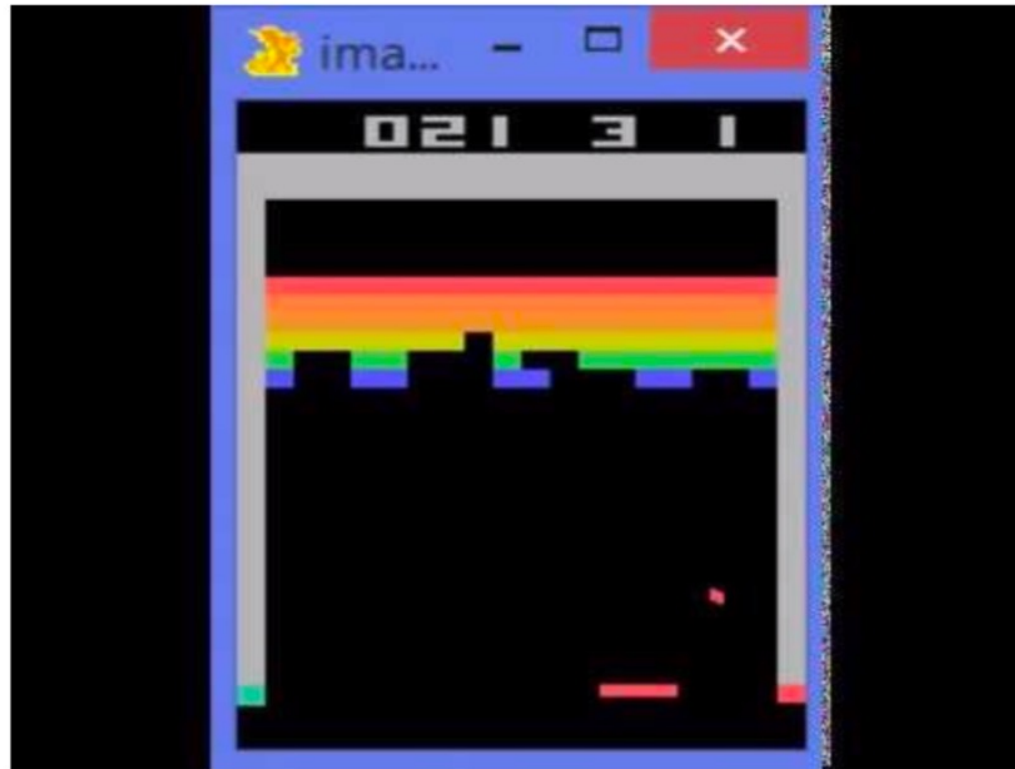
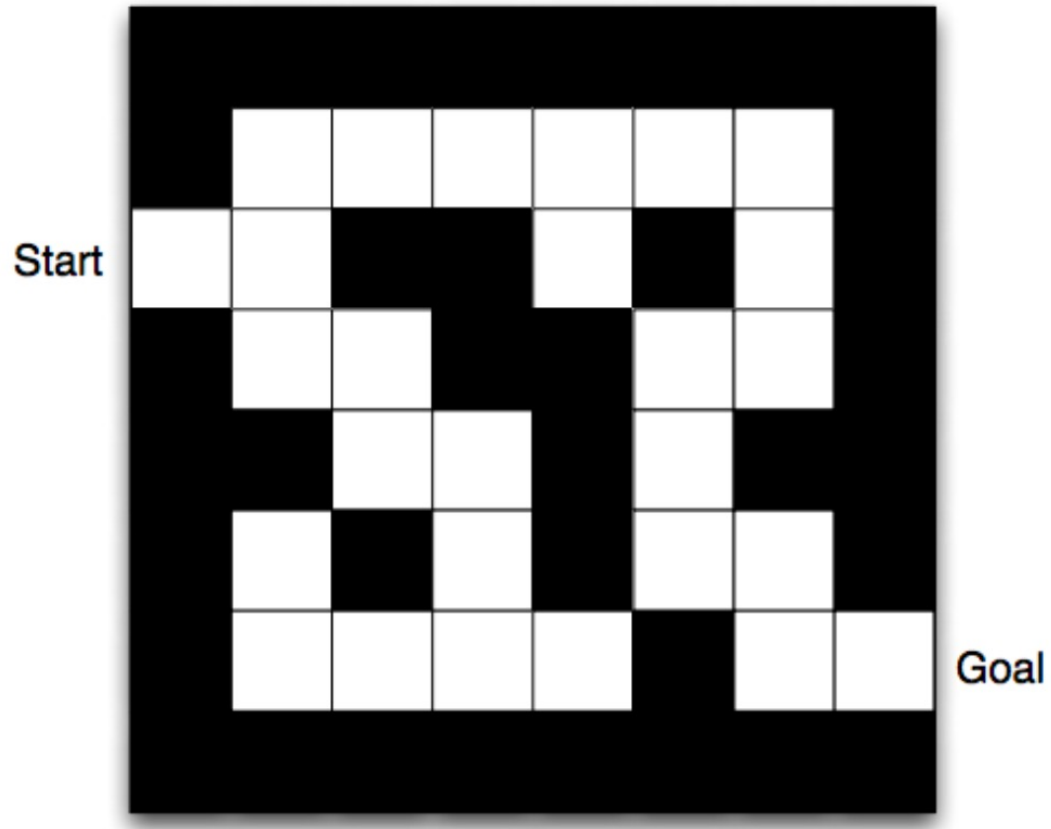
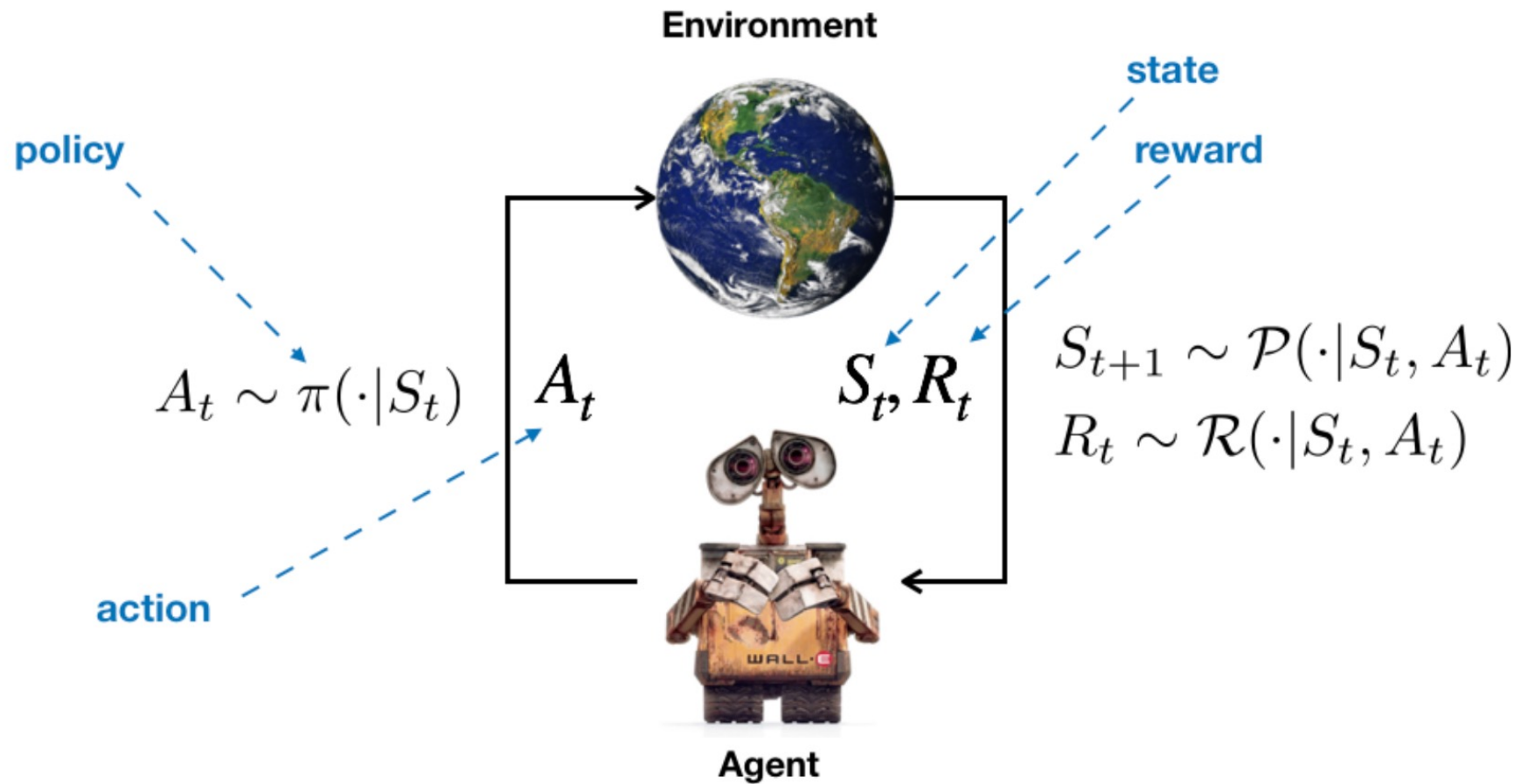


Figure: DeepMind Nature, 2015



- Rewards: -1 per time-step
- Actions: N, E, S, W
- States: Agent's location

What is Reinforcement Learning?



Markov Assumption

State s_t is Markov if and only if:

$$p(s_{t+1}|s_t, a_t) = p(s_{t+1}|h_t, a_t)$$

Future is independent of past given present

Overall Objective

$$G_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \gamma^3 r_{t+3} + \dots$$

Value Functions

$$V^{\pi}(s) \triangleq \mathbb{E}_{\pi} \left[\sum_{t \geq 0} \gamma^t R_t \mid S_0 = s \right]$$

$$Q^{\pi}(s, a) \triangleq \mathbb{E}_{\pi} \left[\sum_{t \geq 0} \gamma^t R_t \mid S_0 = s, A_0 = a \right]$$

Value & Policy Iteration

Value Iteration, for estimating $\pi \approx \pi_*$

Algorithm parameter: a small threshold $\theta > 0$ determining accuracy of estimation
Initialize $V(s)$, for all $s \in \mathcal{S}^+$, arbitrarily except that $V(\text{terminal}) = 0$

Loop:

```
|  $\Delta \leftarrow 0$   
| Loop for each  $s \in \mathcal{S}$ :  
|    $v \leftarrow V(s)$   
|    $V(s) \leftarrow \max_a \sum_{s',r} p(s', r | s, a) [r + \gamma V(s')]$   
|    $\Delta \leftarrow \max(\Delta, |v - V(s)|)$   
until  $\Delta < \theta$ 
```

Output a deterministic policy, $\pi \approx \pi_*$, such that
 $\pi(s) = \operatorname{argmax}_a \sum_{s',r} p(s', r | s, a) [r + \gamma V(s')]$

Policy Iteration (using iterative policy evaluation) for estimating $\pi \approx \pi_*$

1. Initialization

$V(s) \in \mathbb{R}$ and $\pi(s) \in \mathcal{A}(s)$ arbitrarily for all $s \in \mathcal{S}$; $V(\text{terminal}) \doteq 0$

2. Policy Evaluation

Loop:

$\Delta \leftarrow 0$

Loop for each $s \in \mathcal{S}$:

$v \leftarrow V(s)$

$V(s) \leftarrow \sum_{s',r} p(s', r | s, \pi(s)) [r + \gamma V(s')]$

$\Delta \leftarrow \max(\Delta, |v - V(s)|)$

until $\Delta < \theta$ (a small positive number determining the accuracy of estimation)

3. Policy Improvement

policy-stable \leftarrow true

For each $s \in \mathcal{S}$:

old-action $\leftarrow \pi(s)$

$\pi(s) \leftarrow \operatorname{argmax}_a \sum_{s',r} p(s', r | s, a) [r + \gamma V(s')]$

If *old-action* $\neq \pi(s)$, then *policy-stable* \leftarrow false

If *policy-stable*, then stop and return $V \approx v_*$ and $\pi \approx \pi_*$; else go to 2

Value Iteration

Value Iteration, for estimating $\pi \approx \pi_*$

Algorithm parameter: a small threshold $\theta > 0$ determining accuracy of estimation
Initialize $V(s)$, for all $s \in \mathcal{S}^+$, arbitrarily except that $V(\text{terminal}) = 0$

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Output a deterministic policy, $\pi \approx \pi_*$, such that
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Policy Iteration

Policy Iteration (using iterative policy evaluation) for estimating $\pi \approx \pi_*$

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If *policy-stable*, then stop and return $V \approx v_*$ and $\pi \approx \pi_*$; else go to 2