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Reinforcement Learning

Q-LEARNING ALGORITHM

Autonomous Cars

State space:

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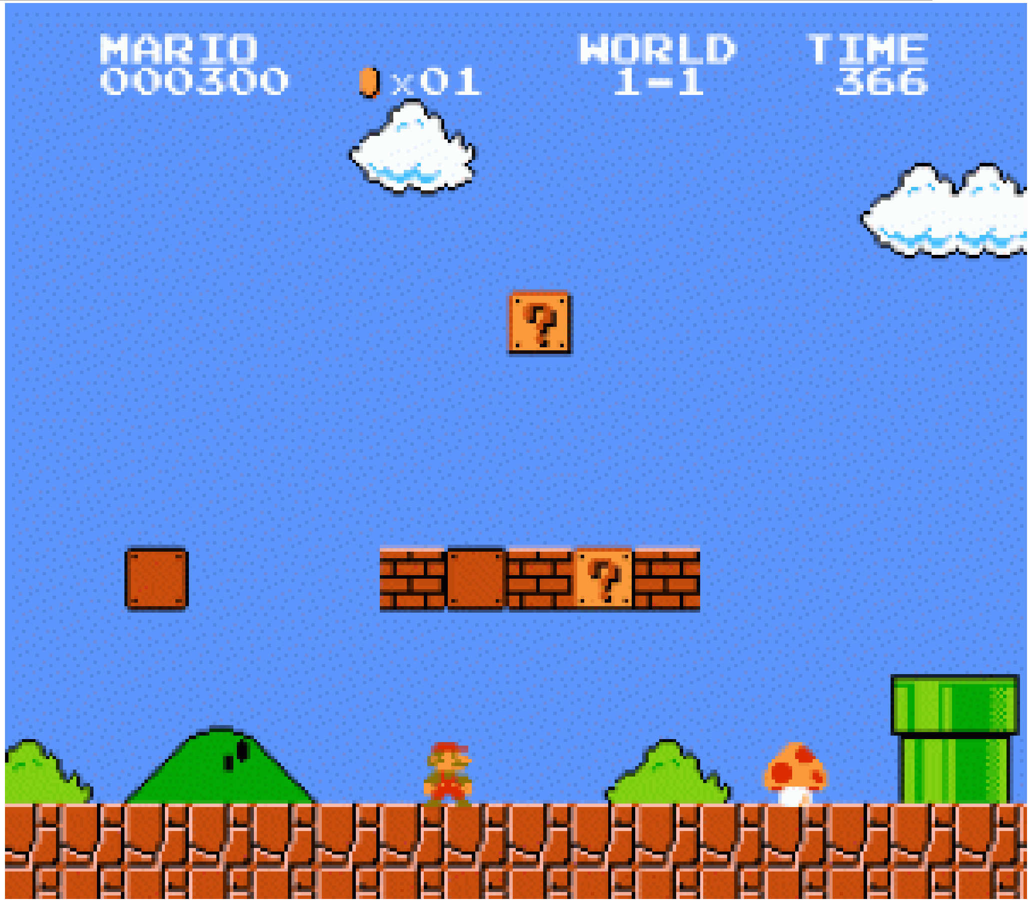
Autonomous Cars

- Simpler environment
- Fewer variables on the state space
- Controlled by Open AI Gym.



Markov Decision Process

- Mathematical framework for modeling decision making.
- Describes the best action for each state in the MDP, known as the optimal policy.
- Is a 4-tuple (S, A, P_a, R_a).

$$\pi(s) := \operatorname{argmax}_a \left\{ \sum_{s'} P(s' \mid s, a) \left(R(s' \mid s, a) + \gamma V(s') \right) \right\}$$

$$V(s) := \sum_{s'} P_{\pi(s)}(s, s') \left(R_{\pi(s)}(s, s') + \gamma V(s') \right)$$

MDP has the following workflow:

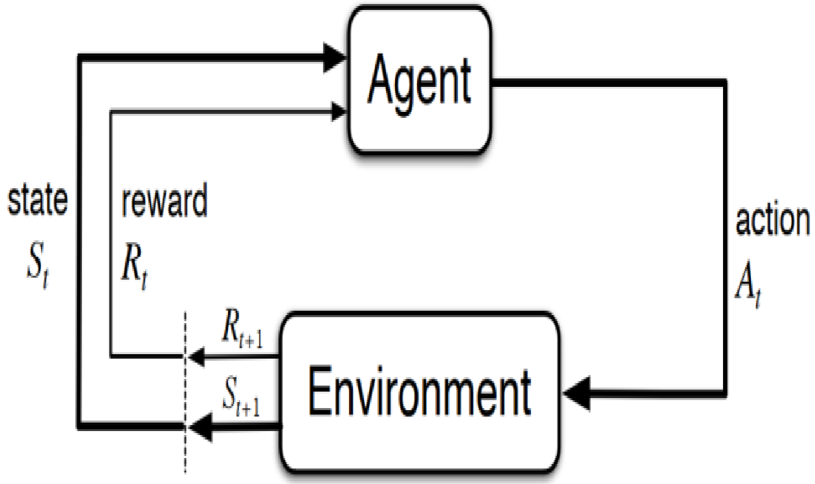


Abbildung 1: Markov Decision Processes Workflow. Retrieved from :http://deeplizard.com/learn/video/my207WNoeyA

Q learning Algorithm

Algorithm 1: Q-learning: Learn function $Q : \mathcal{X} \times \mathcal{A} \to \mathbb{R}$

Require:
  Sates $\mathcal{X} = \{1, \ldots, n_x\}$
  Actions $\mathcal{A} = \{1, \ldots, n_a\}$, $\quad A : \mathcal{X} \Rightarrow \mathcal{A}$
  Reward function $R : \mathcal{X} \times \mathcal{A} \to \mathbb{R}$
  Black-box (probabilistic) transition function $T : \mathcal{X} \times \mathcal{A} \to \mathcal{X}$
  Learning rate $\alpha \in [0, 1]$, typically $\alpha = 0.1$
  Discounting factor $\gamma \in [0, 1]$
  procedure QLEARNING($\mathcal{X}$, A, R, T, α, γ)
    Initialize $Q : \mathcal{X} \times \mathcal{A} \to \mathbb{R}$ arbitrarily
    while Q is not converged **do**
      Start in state $s \in \mathcal{X}$
      while s is not terminal **do**
        $a \leftarrow \pi(s)$
        $r \leftarrow R(s, a)$ ▷ Receive the reward
        $s' \leftarrow T(s, a)$ ▷ Receive the new state
        $Q(s', a) \leftarrow (1 - \alpha) \cdot Q(s, a) + \alpha \cdot (r + \gamma \cdot \max_{a'} Q(s', a'))$
        $s \leftarrow s'$
    $Q* \leftarrow Q$
    $\pi* = max_{a \epsilon A} Q * (s, a)$
    return $\pi*$, $Q*$

Determines best policy to achieve goal state.

Key items:

- States, actions
- Q table
- Policy Function
- Reward Function
- Transition Function

Desktop Test

The Bellman Equation:

$$Q(s_t, a_t) \leftarrow (1-\alpha) \cdot \underbrace{Q(s_t, a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\left(\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\text{estimate of optimal future value}} \right)}^{\text{learned value}}$$

Desktop Test

For this test, assume that every action is enumerated from 0 to 5 and leads to the state of the same number, i.e. action 5 leads to state 5. Then let the Q table be initialized to 0:

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Let R be a matrix with the following values, arbitrarily picked for this example:

$$R = \begin{bmatrix} -1 & -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 & -1 & 100 \\ -1 & -1 & -1 & 100 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 100 \\ -1 & 0 & -1 & -1 & 0 & 100 \end{bmatrix}$$

Desktop Test

Q(1,5)

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Q(5,2)

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -0.1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Q(2,3)

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10 \\ 0 & 0 & 0 & 10 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -0.1 & 0 & 0 & 0 & 0 \end{bmatrix}$$