Introduction to (Deep) Reinforcement Learning

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How do we build intelligent systems/machines?

- Data $\underbrace{\rightarrow}_{\text{intelligence}}$ Information
- Information $\underbrace{\rightarrow}_{\text{intelligence}}$ Decision

강화학습: intelligent Decsion making framework

Intelligent systems must be able to adapt to uncertainty

Uncertainty:

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- Other cars

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Intelligent systems must be able to adapt to uncertainty

Uncertainty:

- Other cars
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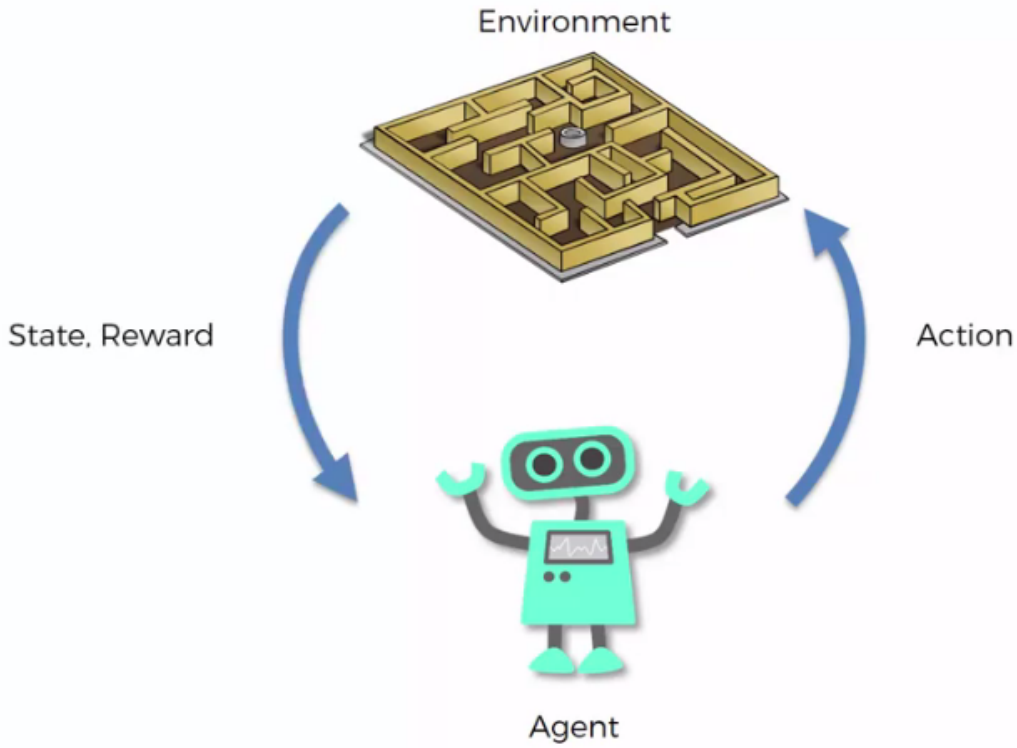
- Passenger

RL provides a formalism for behaviors

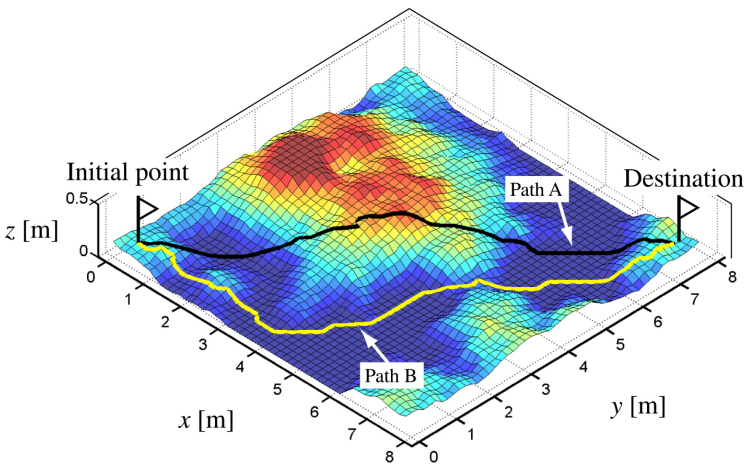


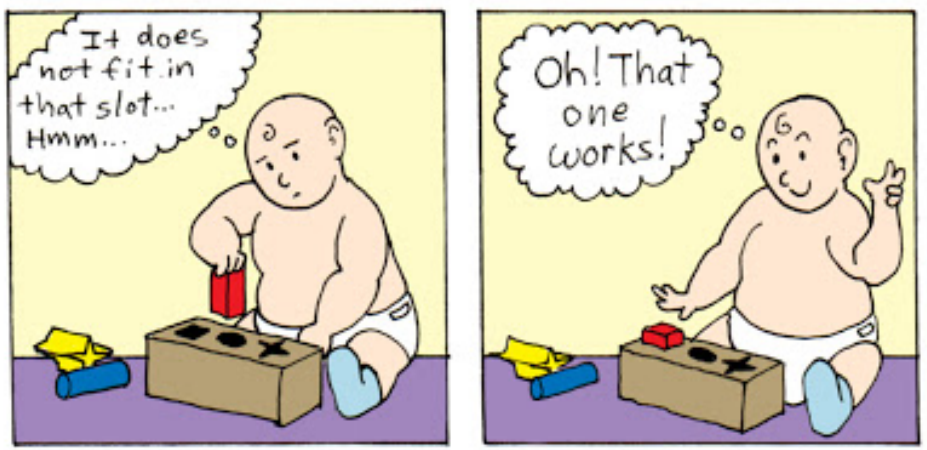
- "Problem of a goal-directed agent $\underbrace{\textit{interacting with}}_{\text{feedback \& decision}}$ an uncertain environment"
- Interaction $\Longrightarrow$ adaptation

Brief History: Roots of RL

Two threads:

1. Optimal Control
2. Psychology (trial-and-error learning)





Thread I: Optimal Control

"Problem of designing a controller to maximize the performance of a dynamical system's behavior over time"

- 1950's: Dynamic programming (Richard Bellman)
- Two limitations:
  1. Knowledge about models
  2. Scalability: "Curse of dimensionality"

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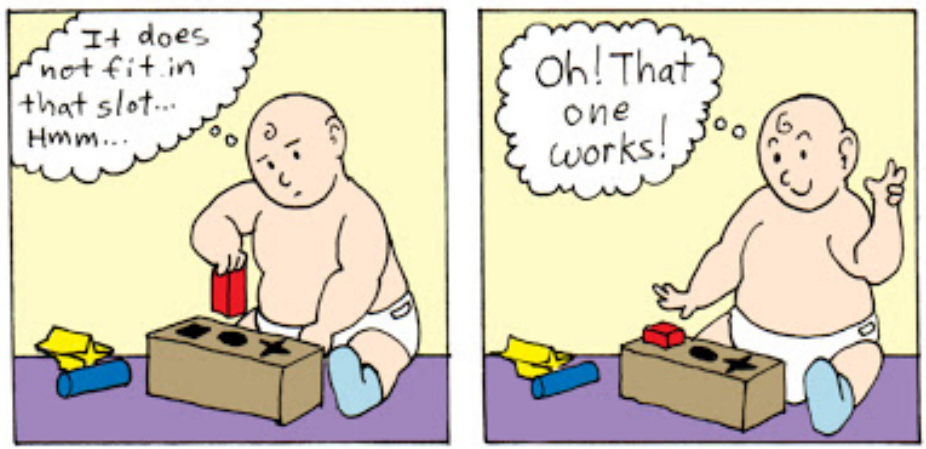
$\Longrightarrow$ RL aims to resolve these issues in (stochastic) optimal control

Thread II: Psychology (trial-and-error learning)

- Edward Thorndike (1911) "Law of Effect": Of several responses made to the same situation, those which are accompanied by satisfaction to the animal will be more firmly connected with the situation, so that, when it recurs, they will be more likely to recur; those which are accompanied by discomfort to the animal will have their connections with that situation weakened, so that, when it recurs, they will be less likely to occur.



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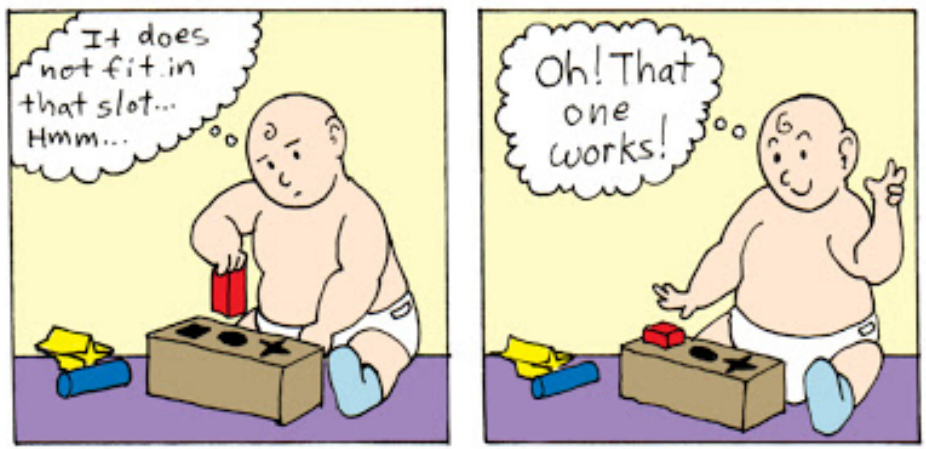

1. Selectional (search): trying alternatives and selecting among them by comparing their consequences
2. Associative (memory): the alternatives found by selection are associated with particular situations

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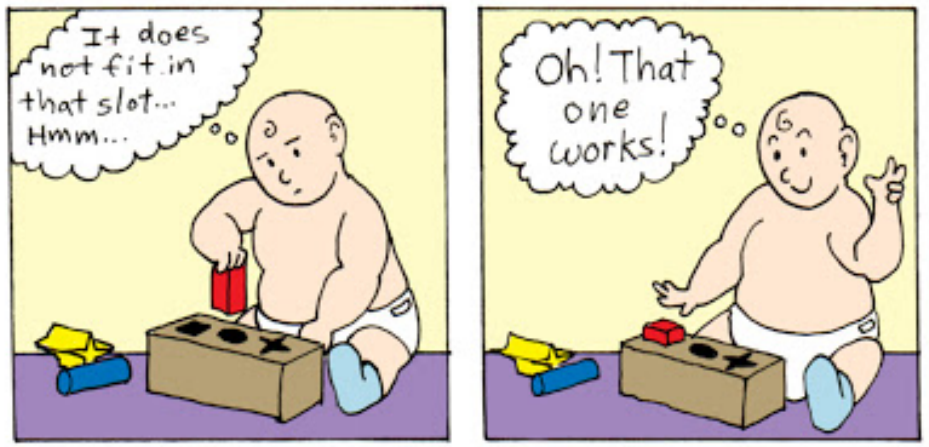

- Klopf (1972) linked the idea with trial-and-error learning and related it to the massive empirical database of animal learning psychology
- Sutton and Barto (70's-80's): temporal-difference learning

Bringing the two together: RL

"Trial-and-error learning approach to optimal control"

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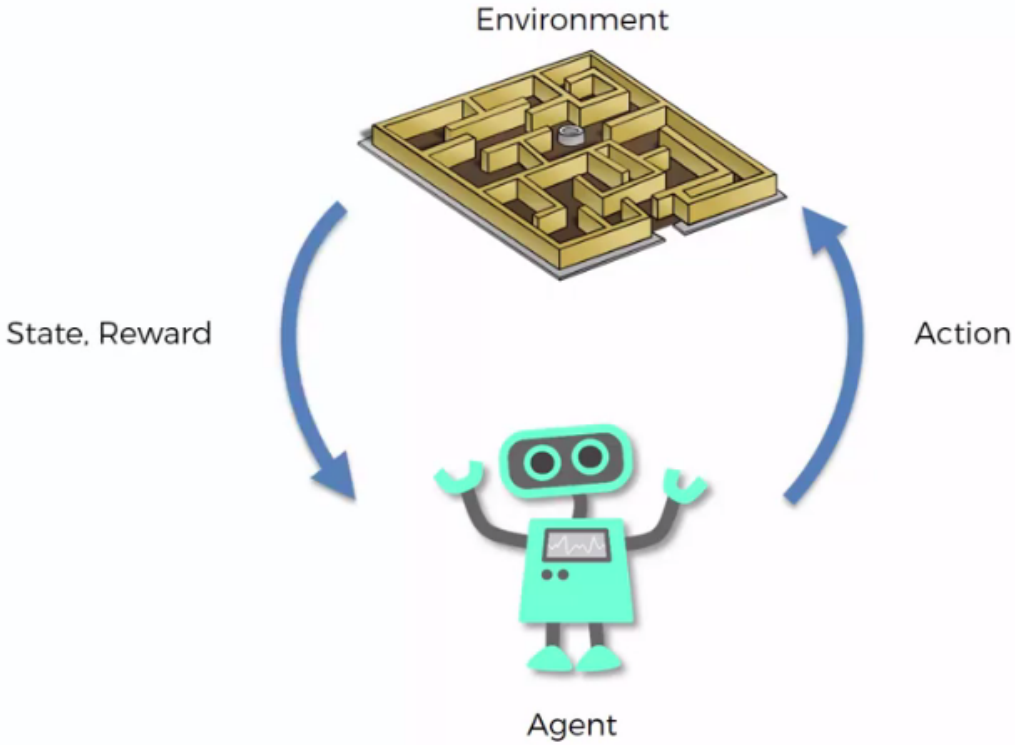
- Actor-critic: Witten, Barto, Sutton, Degris, White, etc.
- Applications ($\sim$2010)
  - Game: Tetris, Chess
  - Robotics

Application I: Games

Application II: Robotics

Distinct Features of RL



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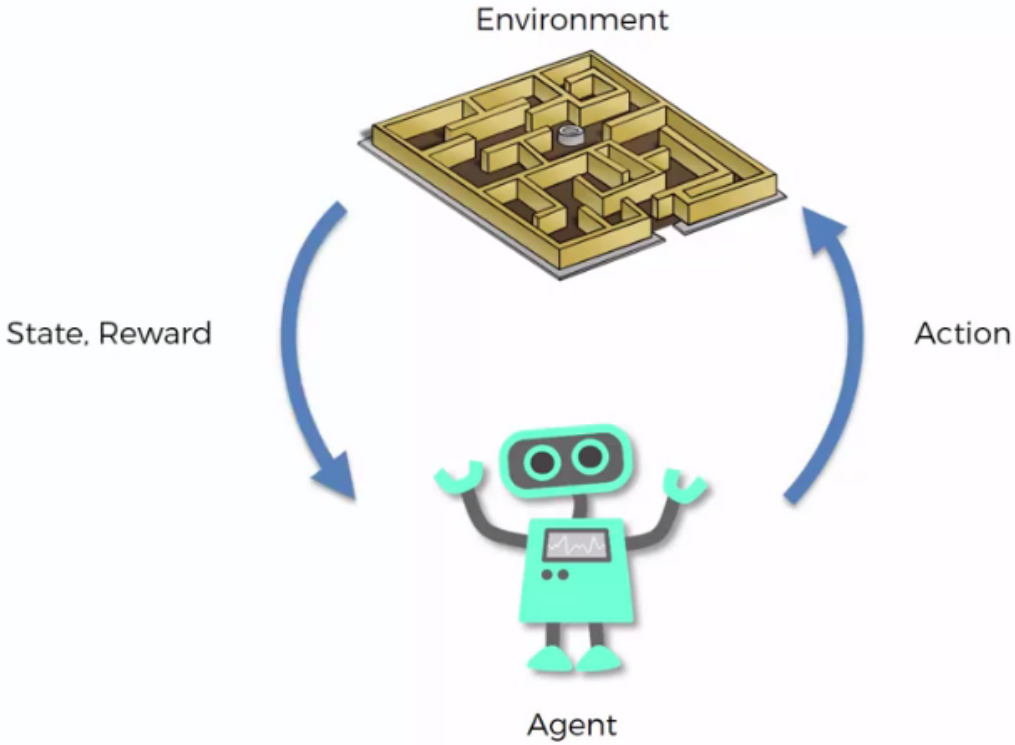

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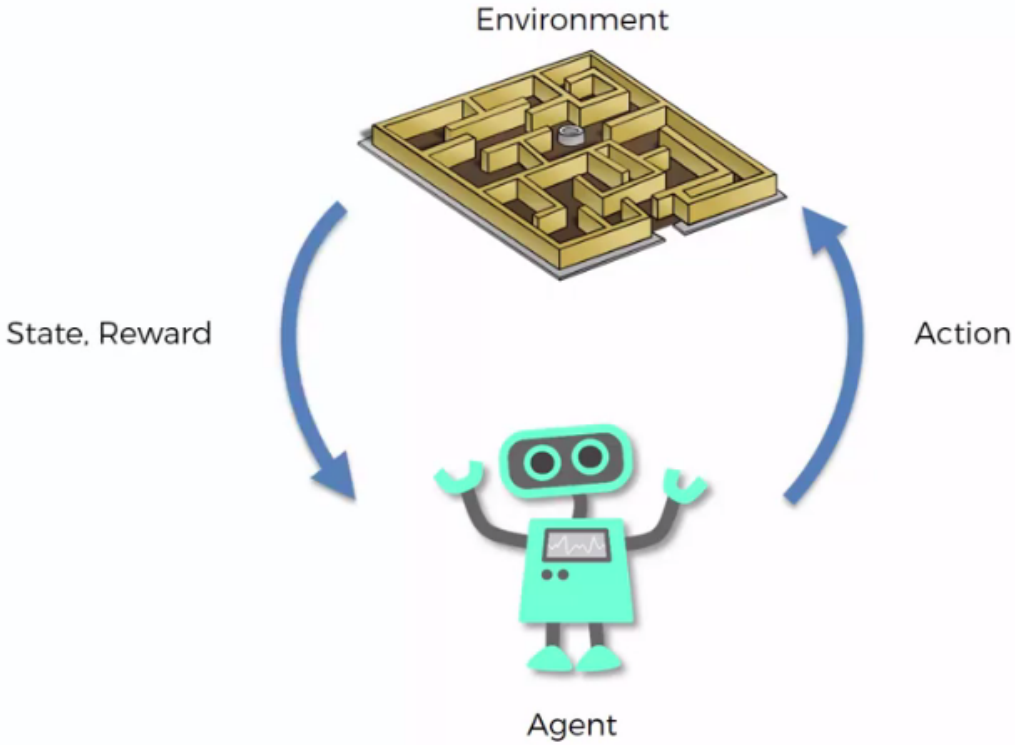

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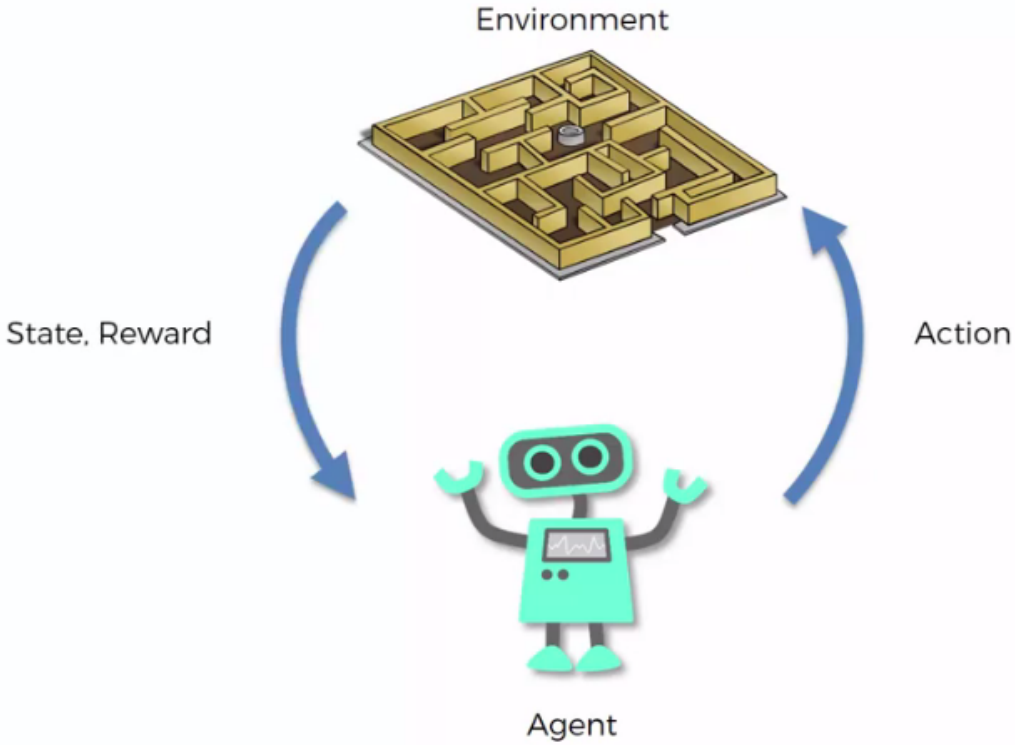

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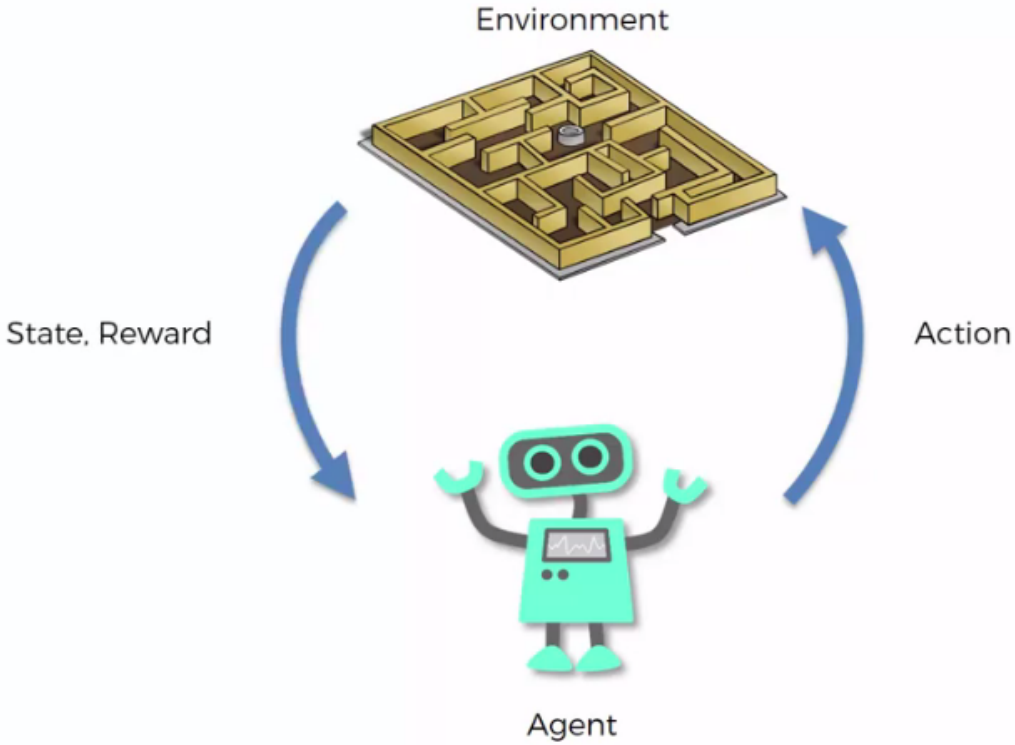

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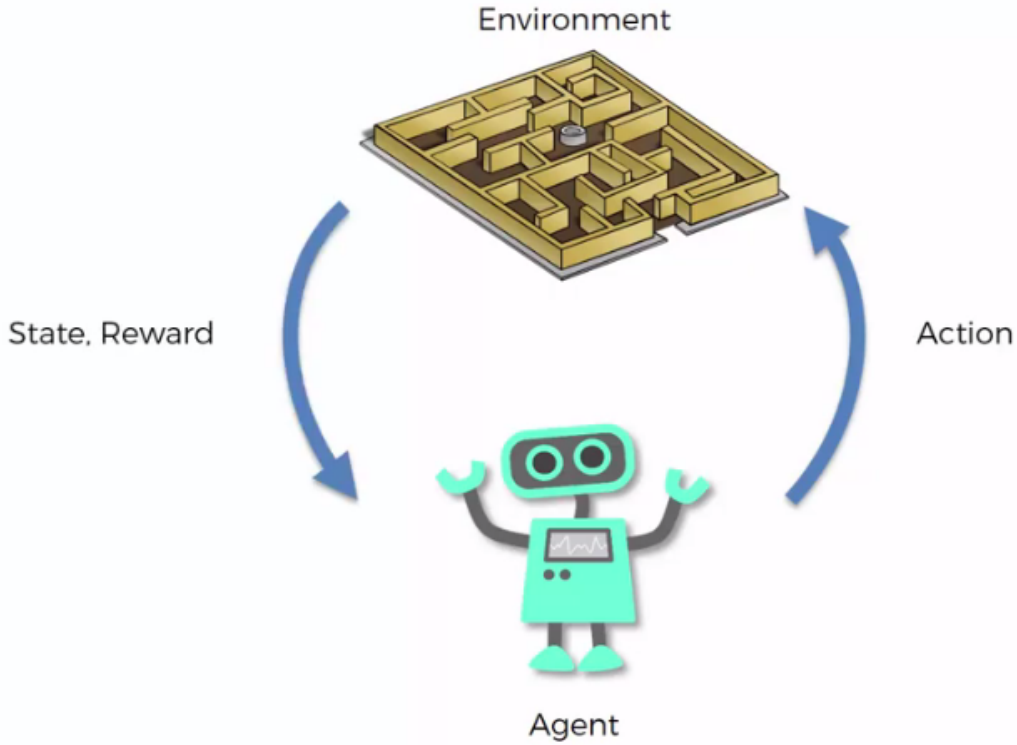
2. Feedback is delayed, not instantaneous
3. Time really matters (sequential, non i.i.d data)
4. Agent's actions affect the subsequent data it receives
5. Tradeoff between exploration and exploitation

탐색결과에 대한 이득

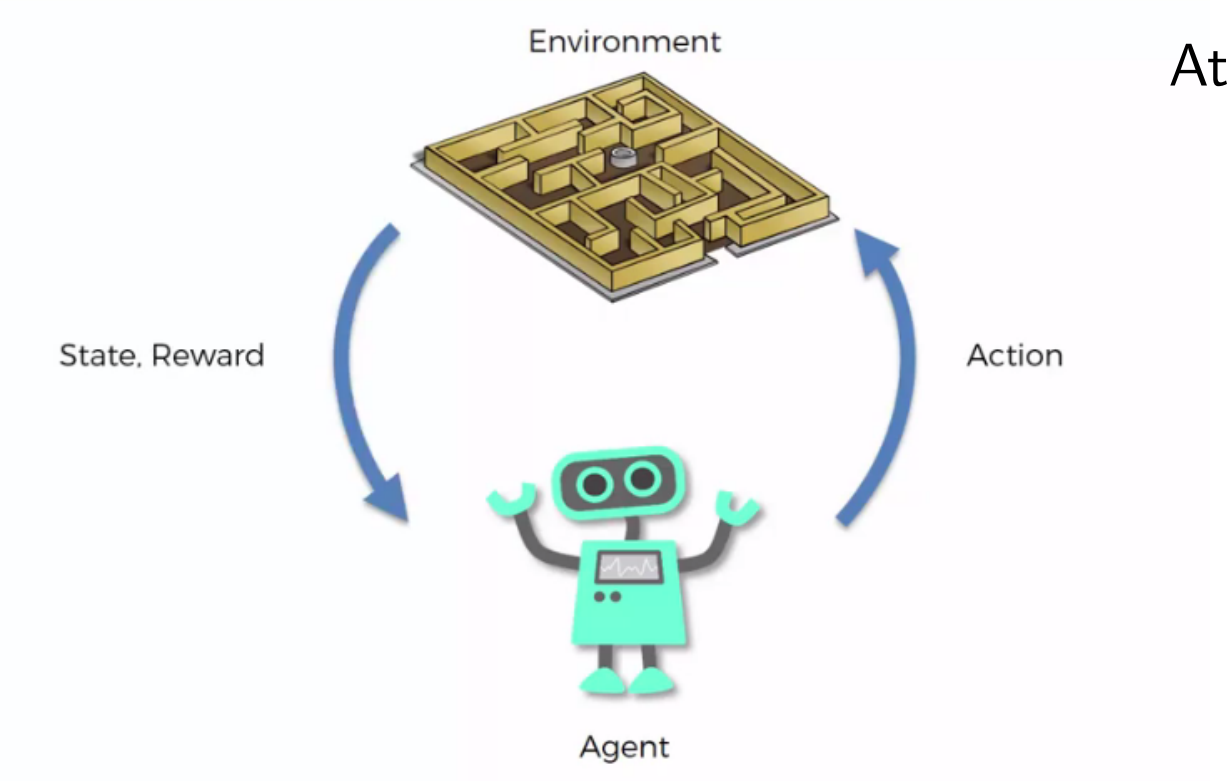
눈앞의 이득

Components of the RL Problem



- State of the environment/system
- Action determined by the agent: affects the state
- Reward: evaluates the benefit of state and action

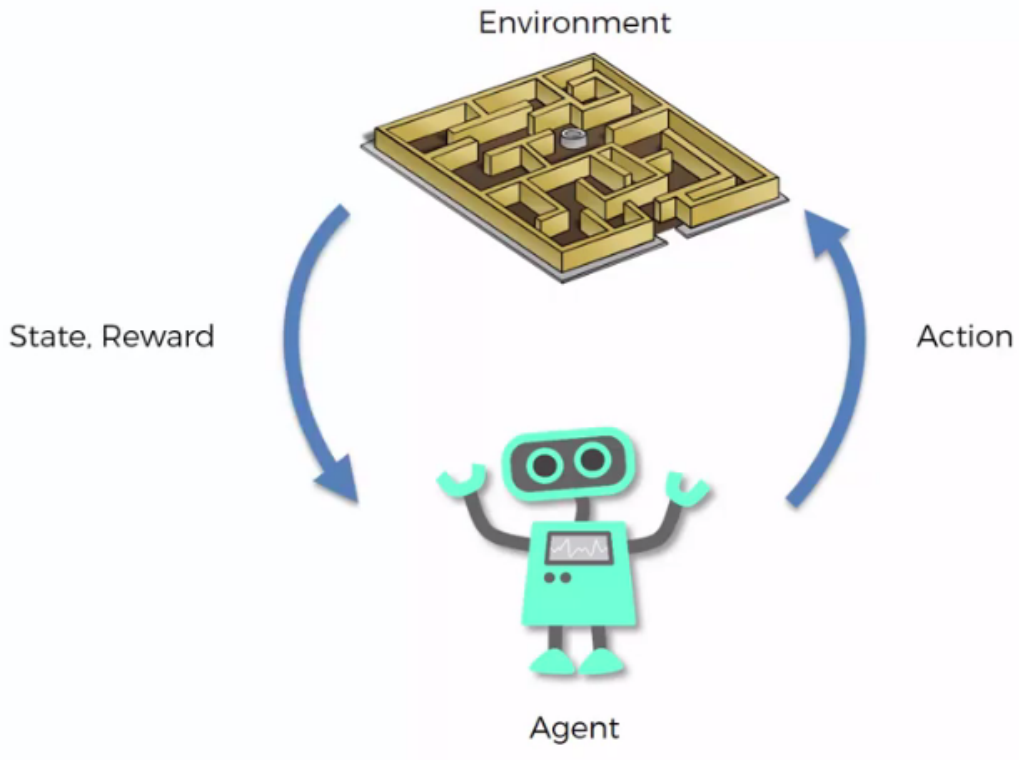
Agent and Environment



At each time step t:

- Agent

Agent and Environment



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  1. observes state s_t

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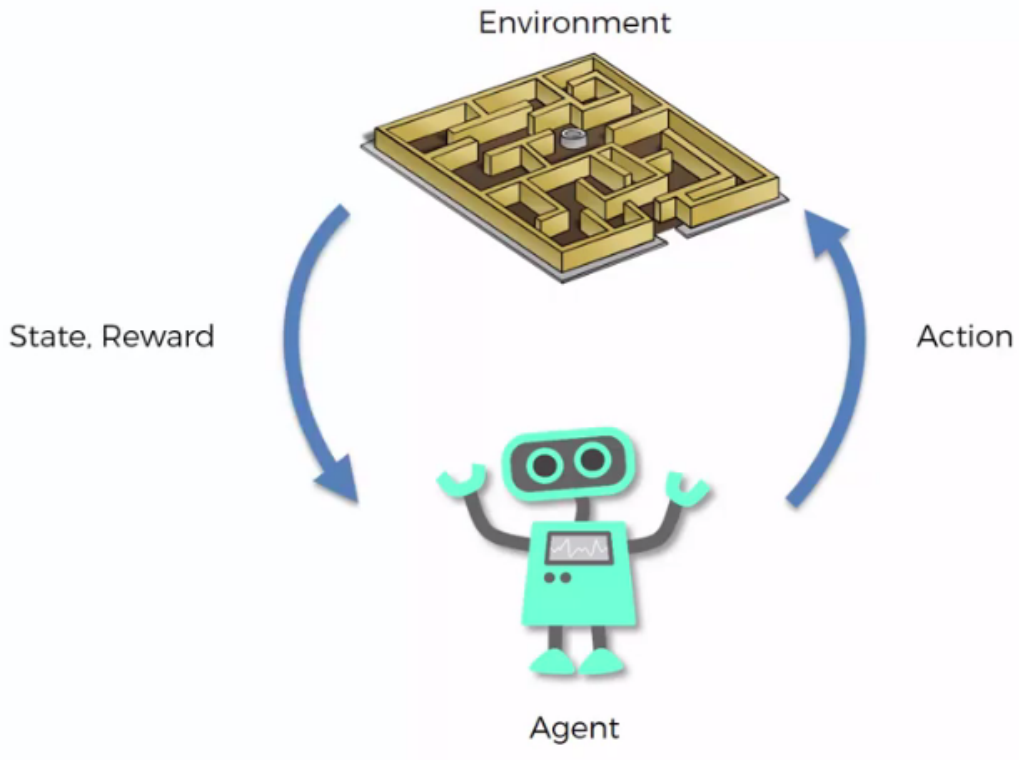

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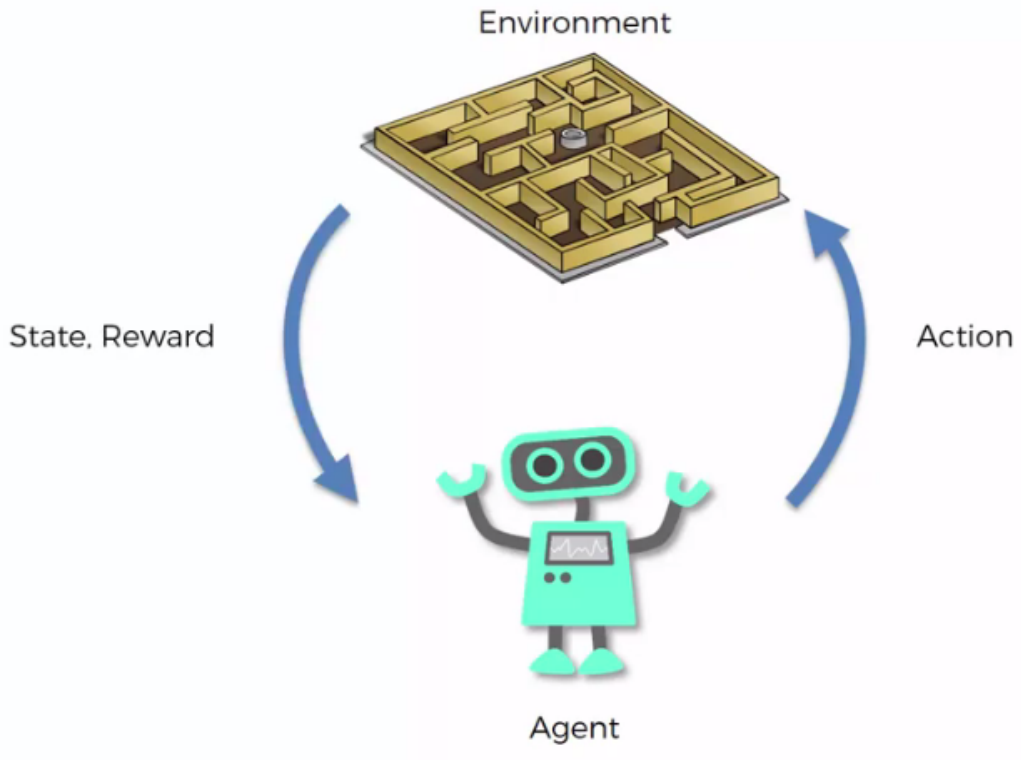

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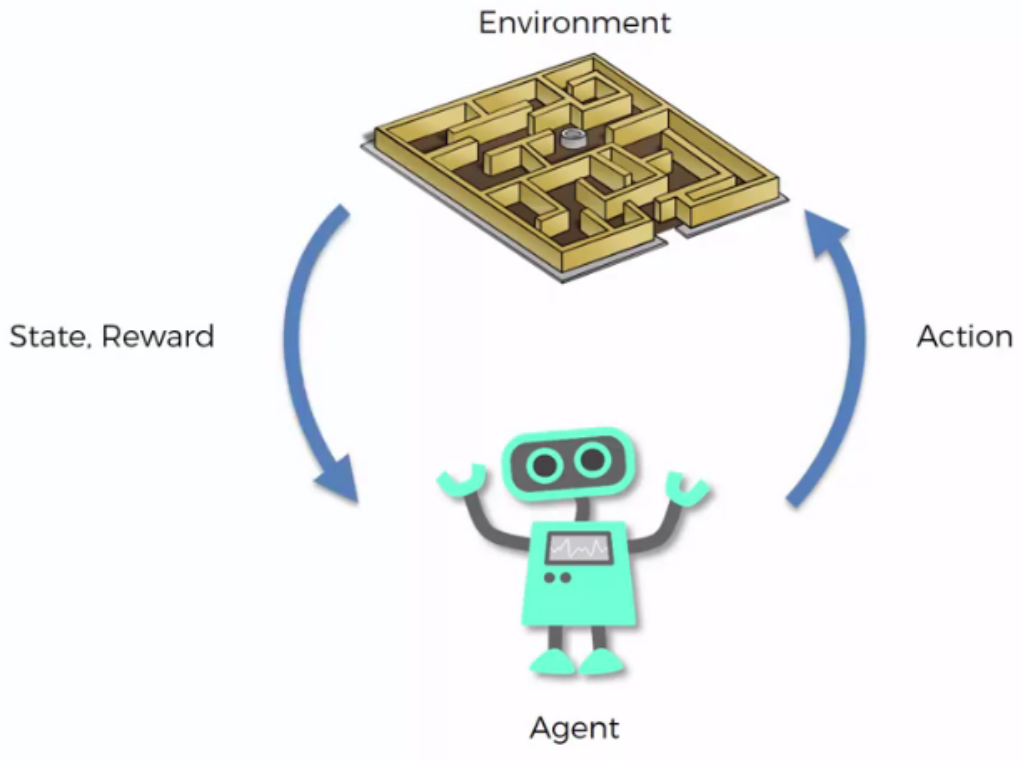

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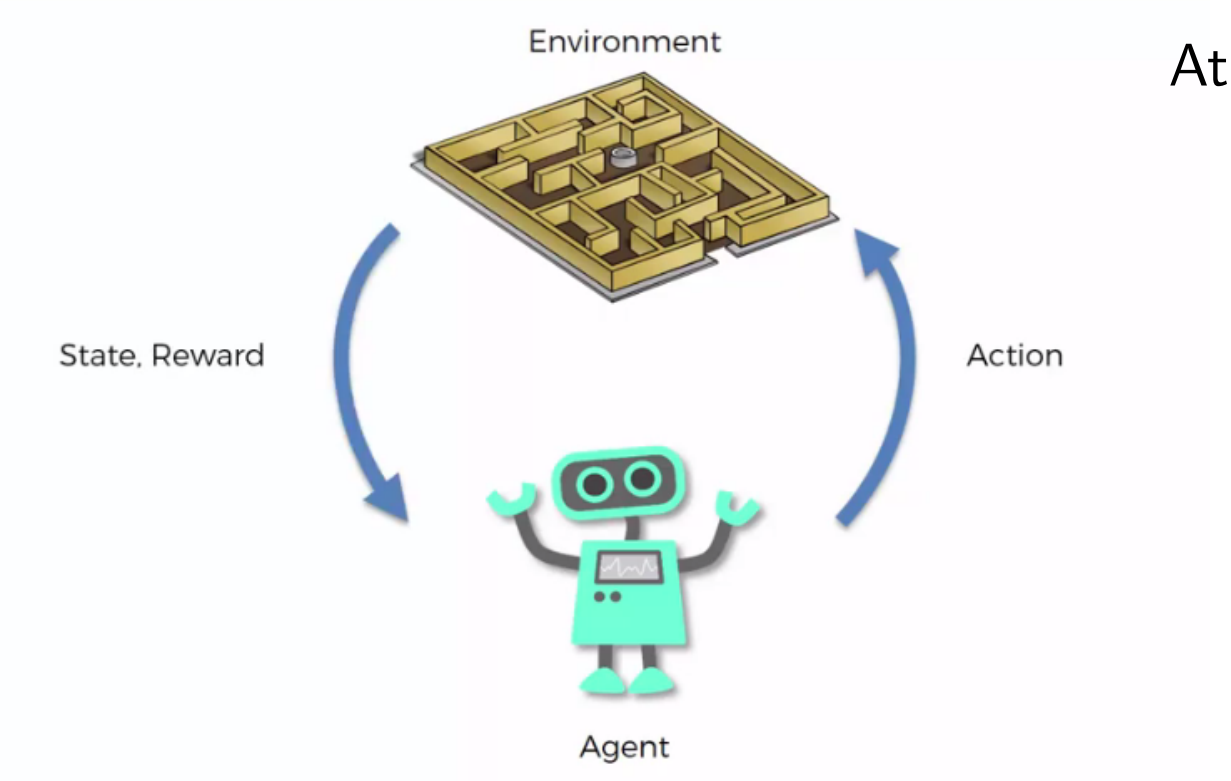

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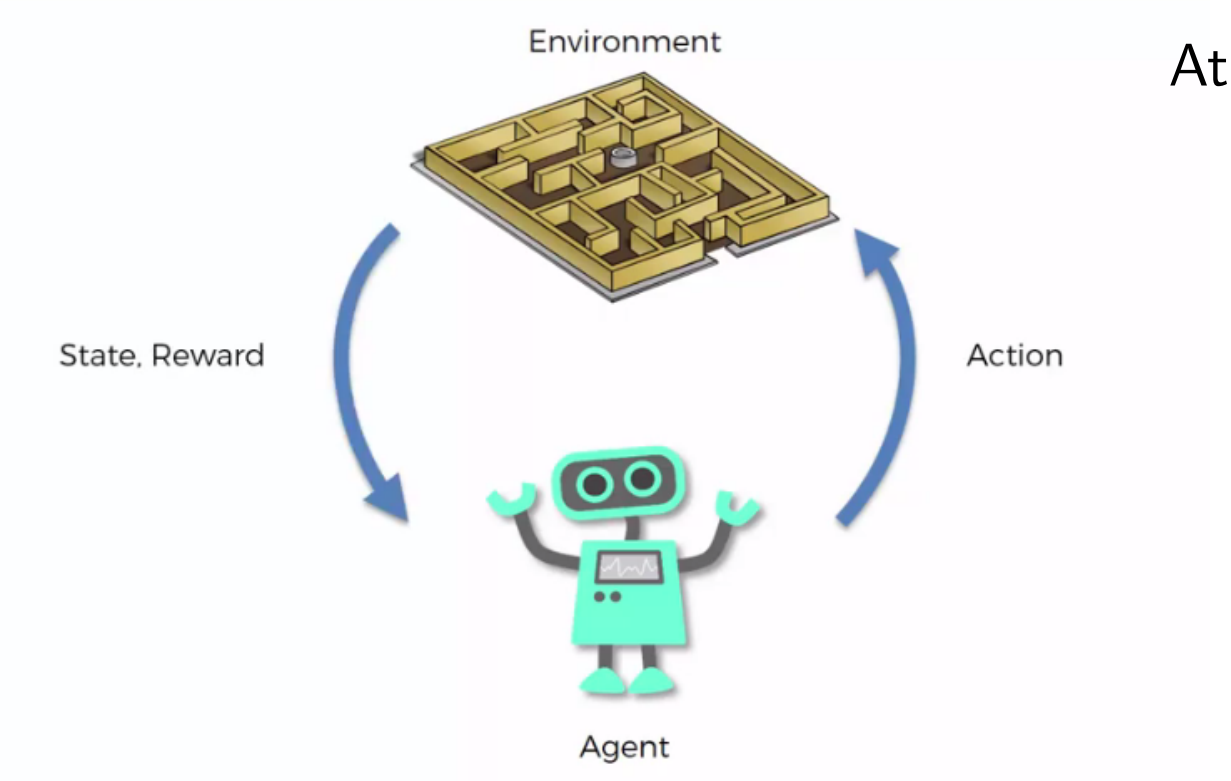

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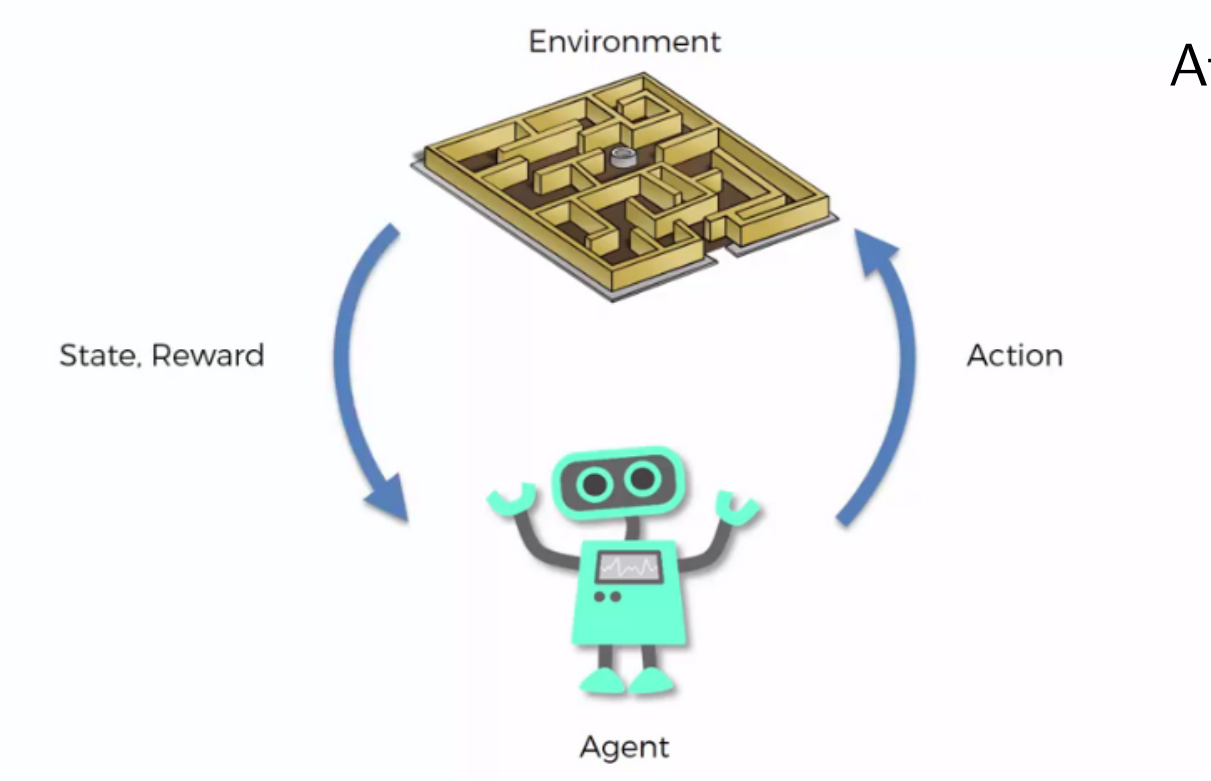

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  3. updates state to s_{t+1}

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Assumptions

All goals can be described by the maximization of expected cumulative rewards.

Examples of Rewards

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   - $+$ reward for following desired trajectory
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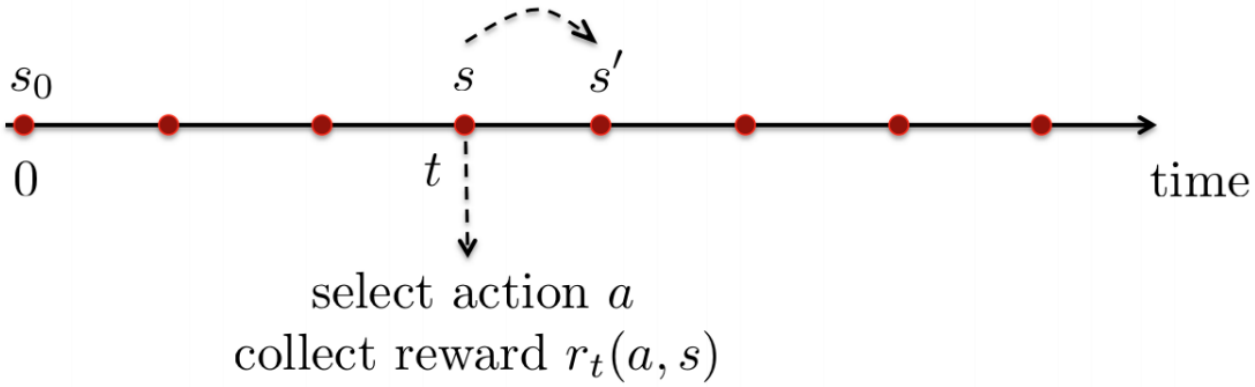
4. (Computer) Games
   - $+$ reward for increasing score
   - $-$ reward for decreasing score

Sequential Decision Making



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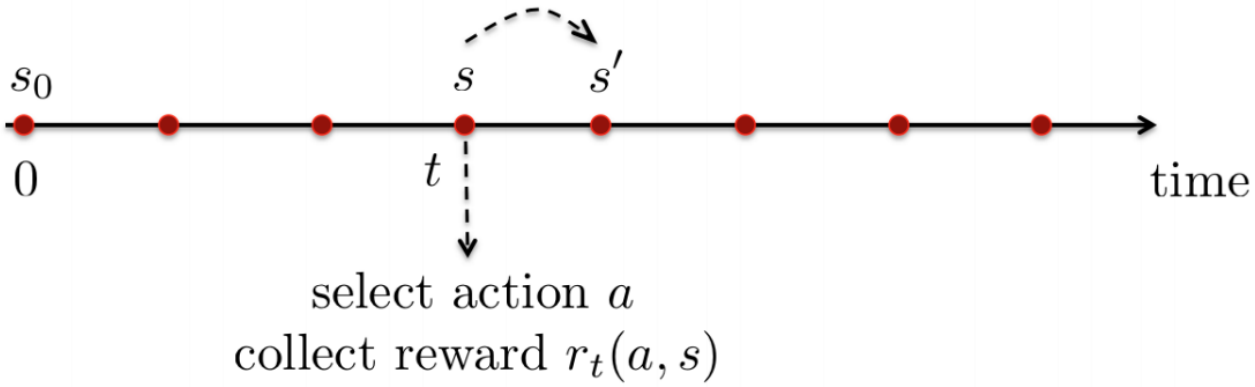

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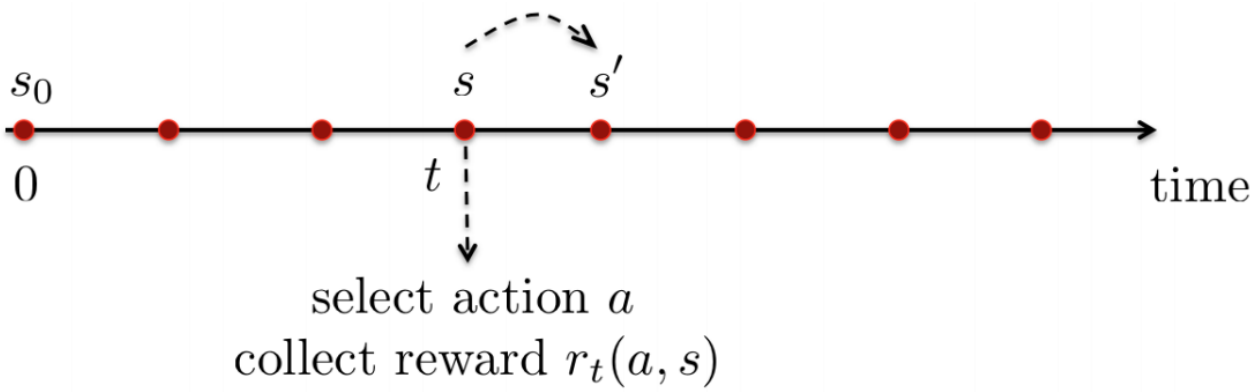

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- It may be better to sacrifice immediate reward to gain more long-term reward. *Q) How?*

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- Action: $a_t \in A$

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$\Longrightarrow$ **Policy is what we want to optimize!**

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- $\gamma \in (0, 1]$: discount factor

The MDP problem

To find an **optimal policy** that *maximizes the expected cumulative reward*:

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- Difficult to solve *Q) Why?*

policy 라는 "함수"를 최적화 하는 문제라서

gamma: discounting for 미래
if gamma ==1:
과거, 현재, 미래 가중치 동일

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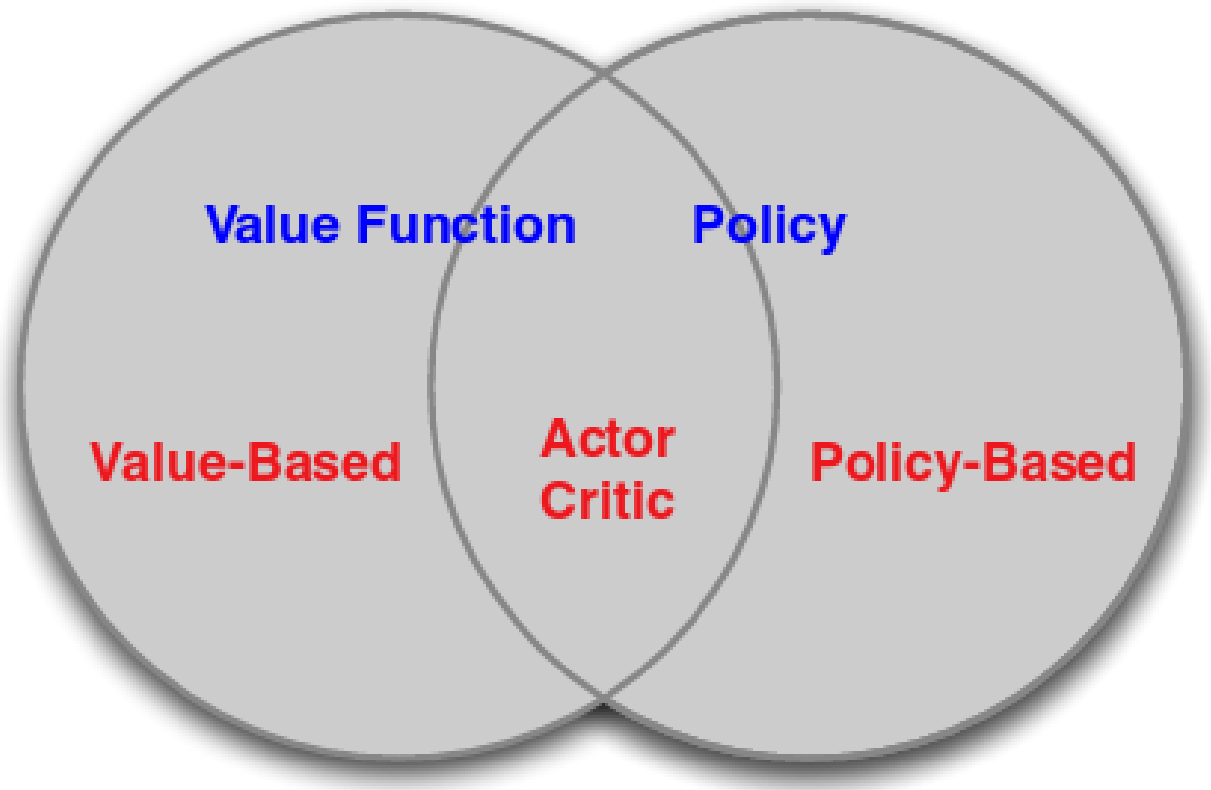
Categorizing RL algorithms



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- Static environments
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Q) But, what about this?

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- Complex sensory inputs
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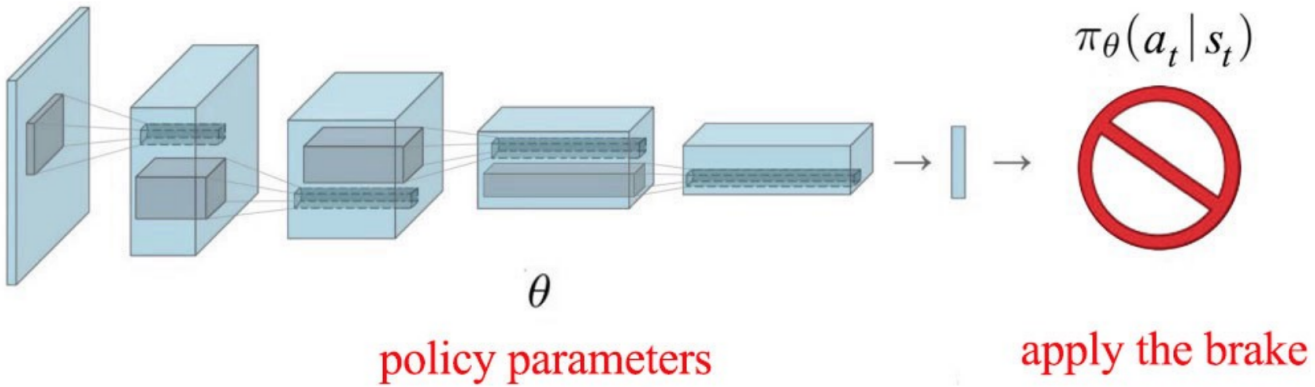

[S. Levine, CS285]

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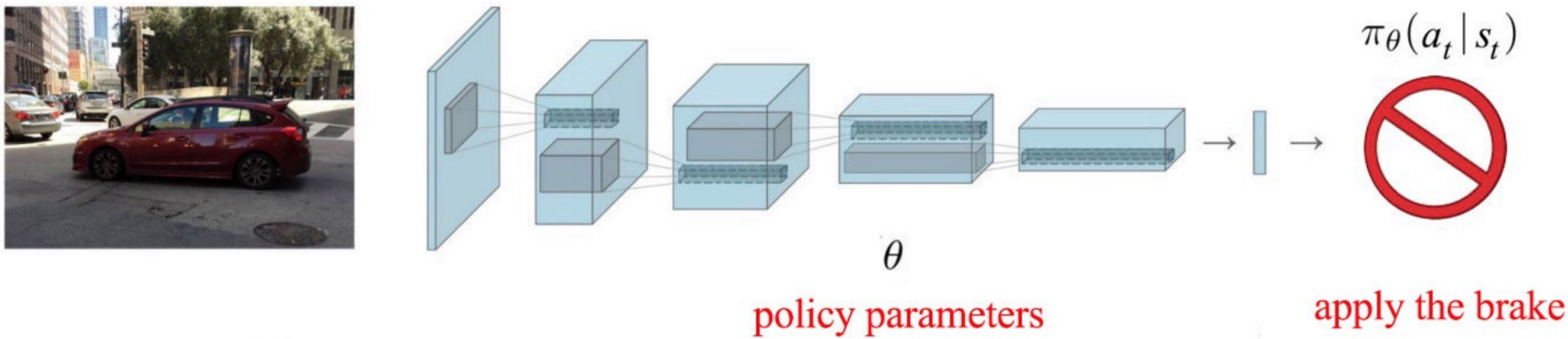

[S. Levine, CS285]

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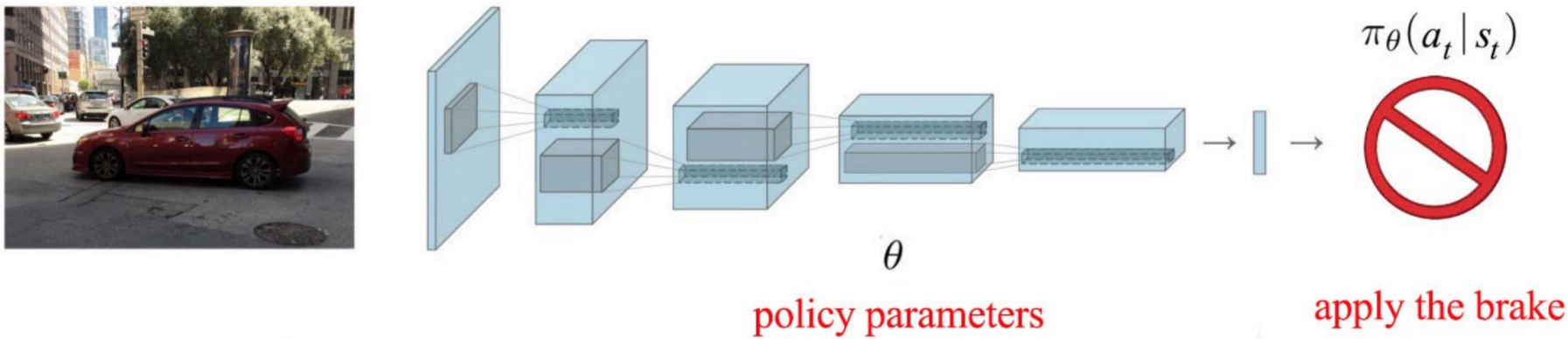

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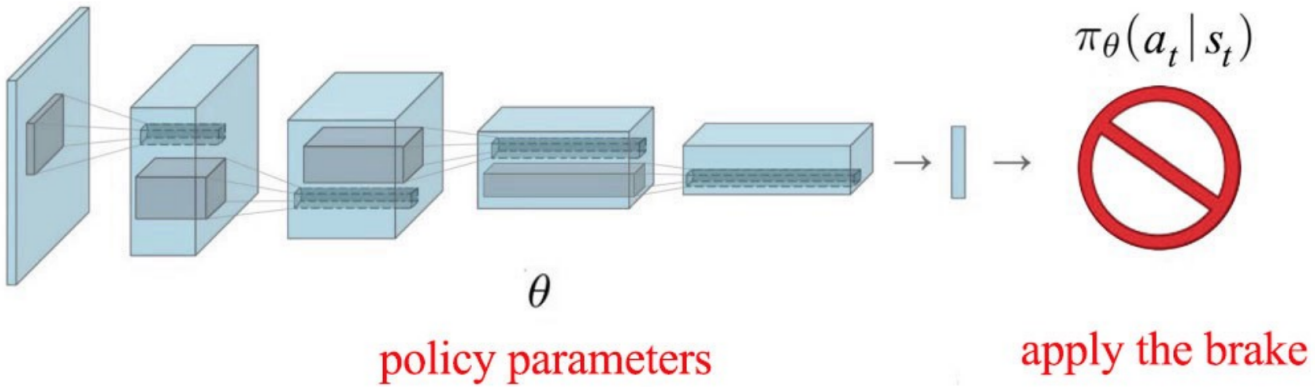

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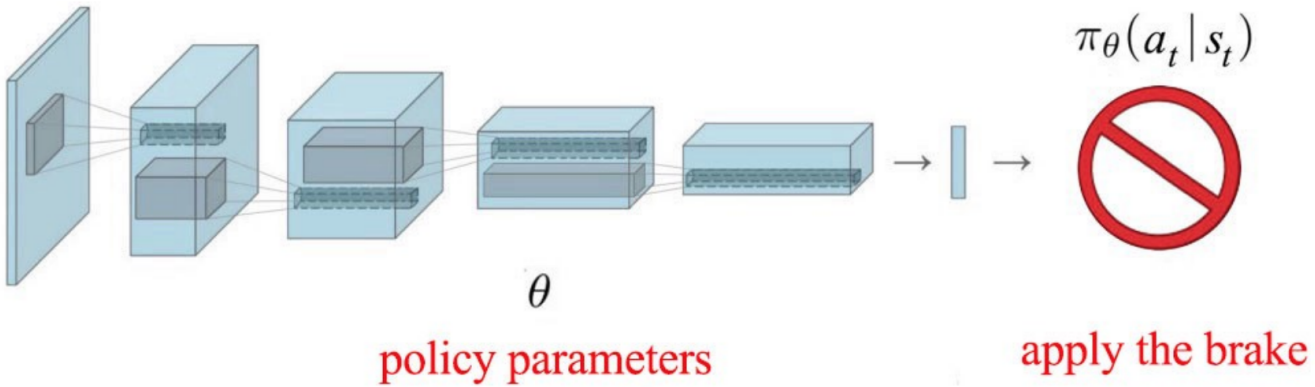

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- Powerful computing technology and algorithms for training

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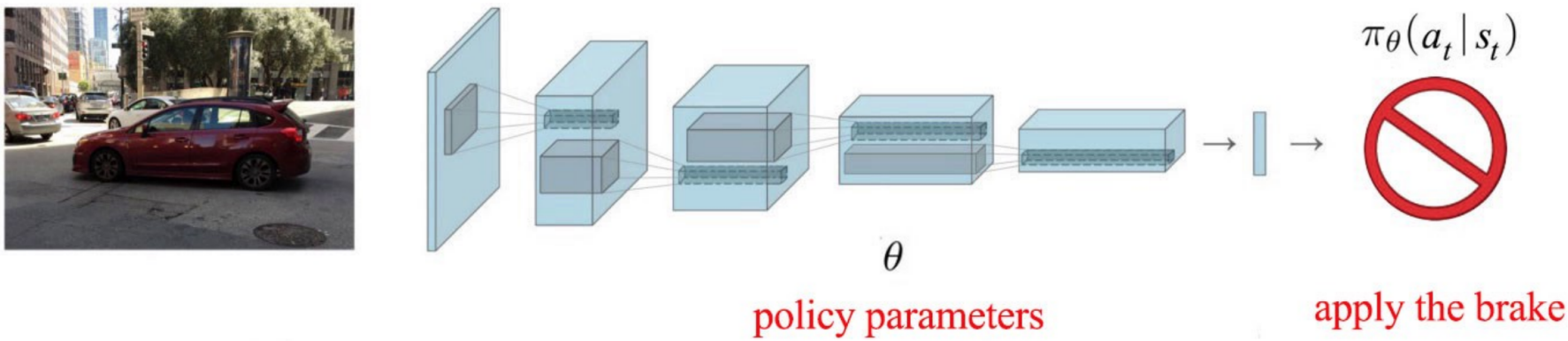

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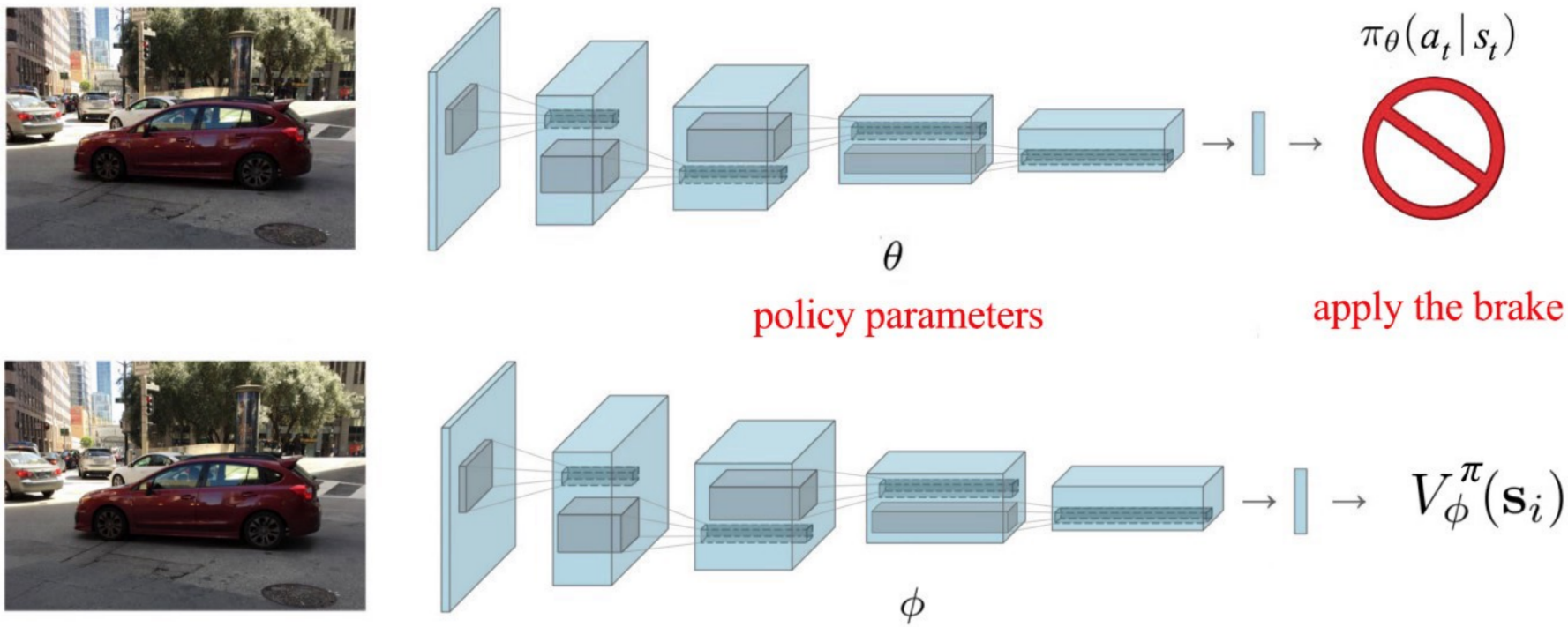

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End-to-end learning

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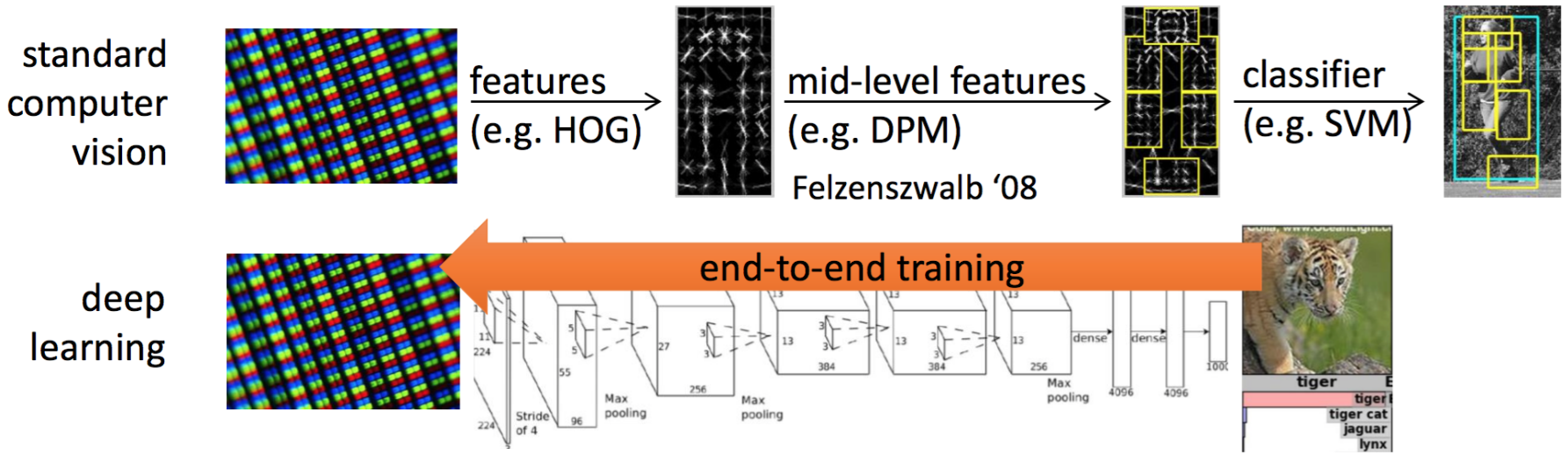

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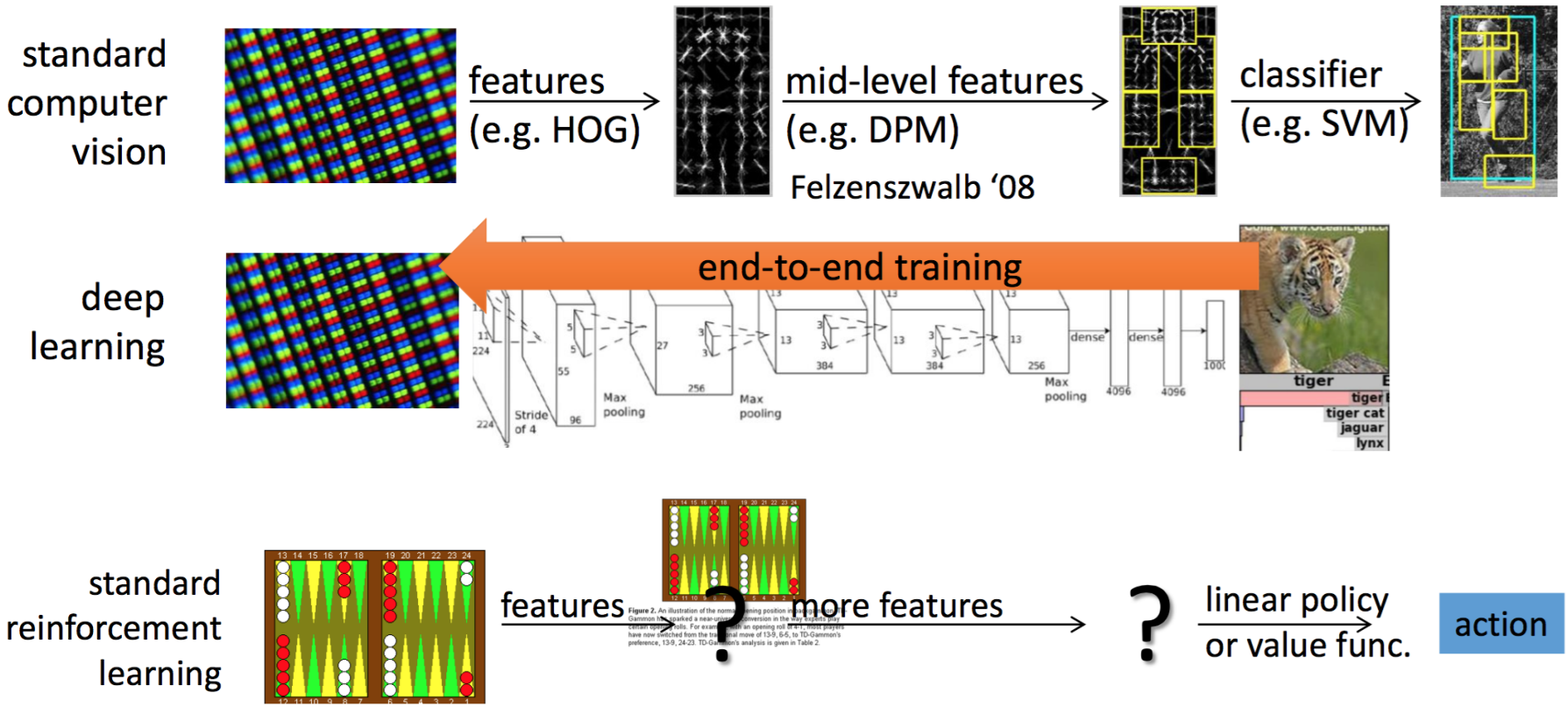

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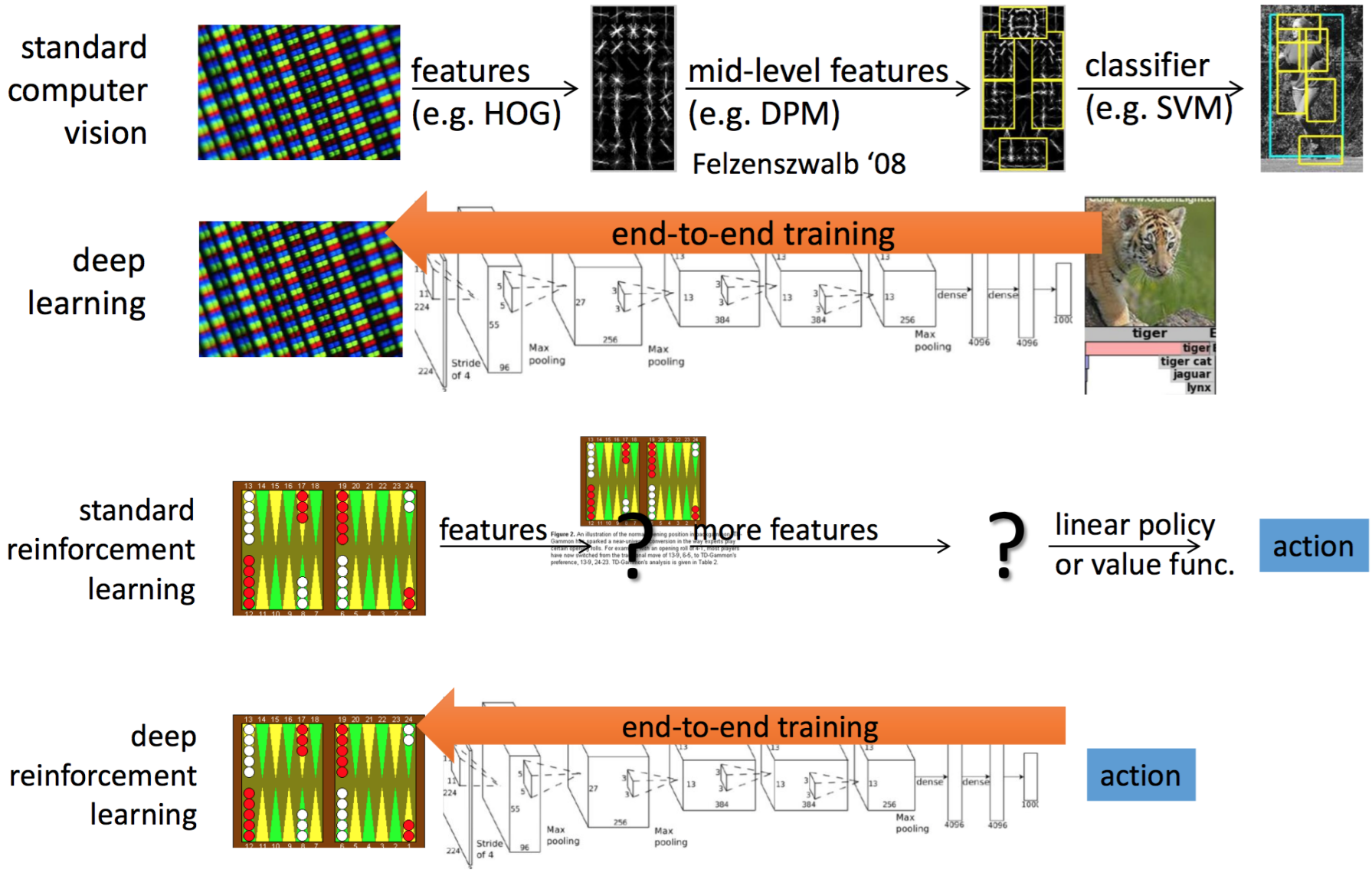

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- **High-performance simulators**

Some deep RL applications

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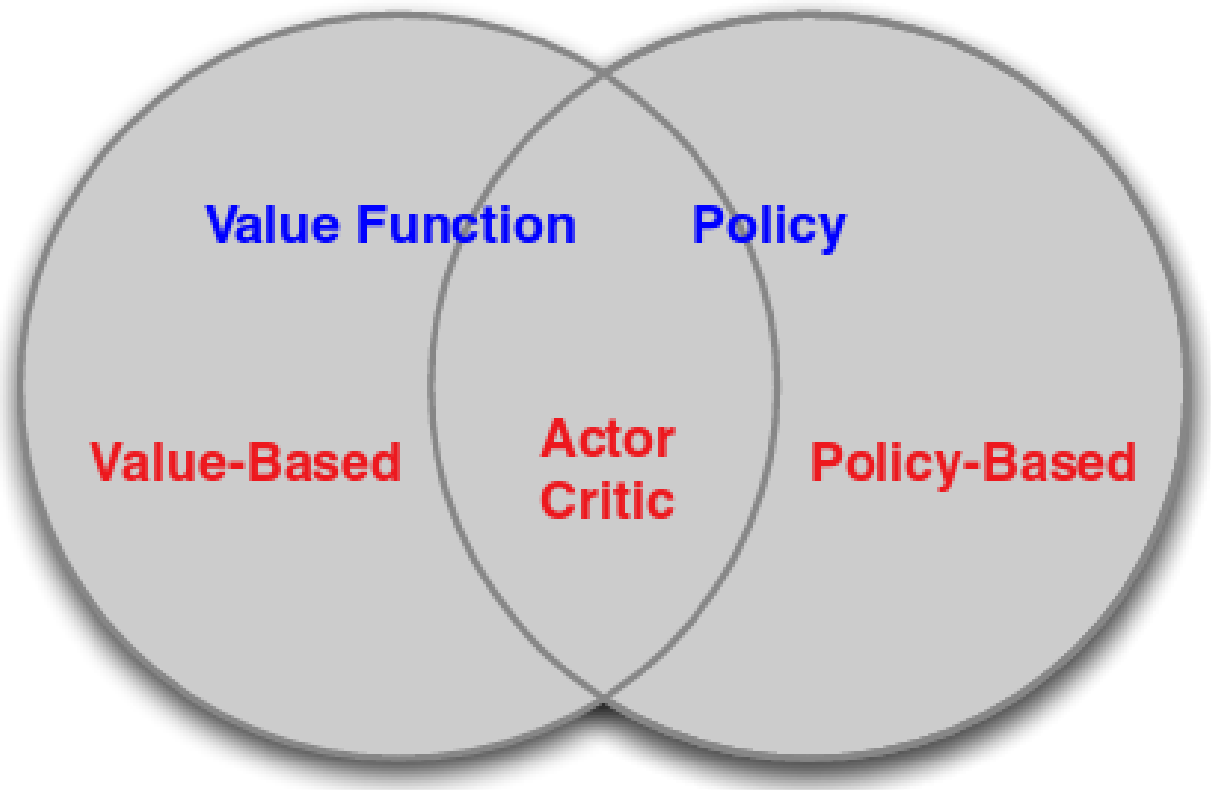
- **Simulator**

Roadmap


Value Function
Policy
Value-Based
Actor
Critic
Policy-Based