无人系统设计

课　程：软件工程专业-专业实践类课程
学　分：3
总课时：48

课程参考教材：

《认识飞行（第二版）》/《Understanding Flight，2nd》
作者： David F. Anderson, Scott Eberhardt
译者：周尧明（2019年） / 韩莲（2011年）
北京联合出版公司2019.07 / 航空工业出版社2011.01

授课教师：王赓
课程助教：李旭辉、蒋李康、方俊杰、张源娣、范文婷、曹恺洋、杨逍

课程主要内容

（1）认识飞行
- 牛顿力学（作用力与反作用力）
- 刚体转动（转矩、陀螺、进动） /大学物理基础

（2）认识多种多样的无人飞行系统
- 飞行原理
- 动力技术（螺旋桨、喷气式）

（3）控制技术
- 飞行操纵原理（机翼、襟翼、旋翼、尾桨、自动倾斜器）
- 作动器（电动机、舵机（PWM调制））
- 传感器（电子指南针、加速度计、陀螺仪、GPS、高度计、高速相机、全景相机、……）
- 电子控制器（PID算法、飞行控制原理与算法）

（4）飞行性能（飞行性能指标体系、稳定性、可靠性、易操作性）

课程主要内容

（5）基于4旋翼、固定翼模型机的认知验证实验
（含早期自由组合发现学习过程）

（6）仿真技术
- 飞行器建模（动力学、运动学）/大学物理基础、高等数学
- 软件技术（Unity3D、MATLAB/Simulink）

（7）仿真技术实践（半实物）
- 无人AI战机模拟格斗对抗系统
- 软件技术（Unity3D、MATLAB/Simulink、图像处理技术、人工智能AI技术、计算加速技术 ……）

（8）发挥想象力和所学的自由拓展设计（理论设计/尽量据情实验验证）

（9）课程综合设计与答辩

本讲内容：关于强化学习方法

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References and Acknowledgement

- Some slides in this lecture are from Prof. Weinan Zhang's course for machine Learning.

Weinan Zhang

Shanghai Jiao Tong University

http://wnzhang.net

Review-Machine Learning

- **Supervised Learning**
  - To perform the desired output given the data and labels
  - e.g., to build a loss function to minimize
  - Deep Learning, aka. Deep Supervised Learning
- **Unsupervised Learning**
  - To analyze and make use of the underlying data patterns/structures
  - e.g., to build a log-likelihood function to maximize
- **Reinforcement Learning**

Review-Supervised Learning

- Given the training dataset of (data, label) pairs,

$$D = \{(x_i, y_i)\}_{i=1,2,\ldots,N}$$

- Let the machine learn a function from data to label

$$y_i \simeq f_\theta(x_i)$$

- Learning is referred to as updating the parameter θ
- Learning objective: make the prediction close to the ground truth

$$\min_\theta \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}(y_i, f_\theta(x_i))$$

Review-Unsupervised Learning

- Given the training dataset

$$D = \{x_i\}_{i=1,2,\ldots,N}$$

  - Let the machine learn the data underlying patterns
- Sometimes build latent variables

$$z \longrightarrow x$$

Review-Unsupervised Learning

- Estimate the probabilistic density function (p.d.f.)

$$p(x;\theta) = \sum_z p(x|z;\theta)p(z;\theta)$$

- Learning is also referred to as updating the parameter θ
- Maximize the log-likelihood of training data

$$\max_\theta \frac{1}{N}\sum_{i=1}^{N} \log p(x;\theta)$$

  - e.g. BERT

Two Kinds of Machine Learning

Prediction

- Predict the desired output given the data (supervised learning)
- Generate data instances (unsupervised learning)

Decision Making

- Take actions based on a particular state in a dynamic environment (reinforcement learning)
  - to transit to new states
  - to receive immediate reward
  - to maximize the accumulative reward over time
- Learning from interaction

Machine Learning Categories

- Supervised Learning
  - To perform the desired output given the data and labels

$$p(y|x)$$

- Unsupervised Learning
  - To analyze and make use of the underlying data patterns/structures

$$p(x)$$

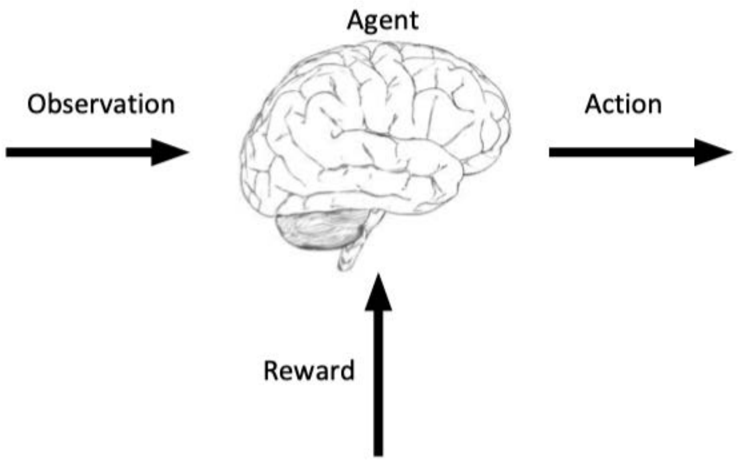
- Reinforcement Learning
  - To learn a policy of taking actions in a dynamic environment and acquire rewards

$$\pi(a|x)$$

Contents

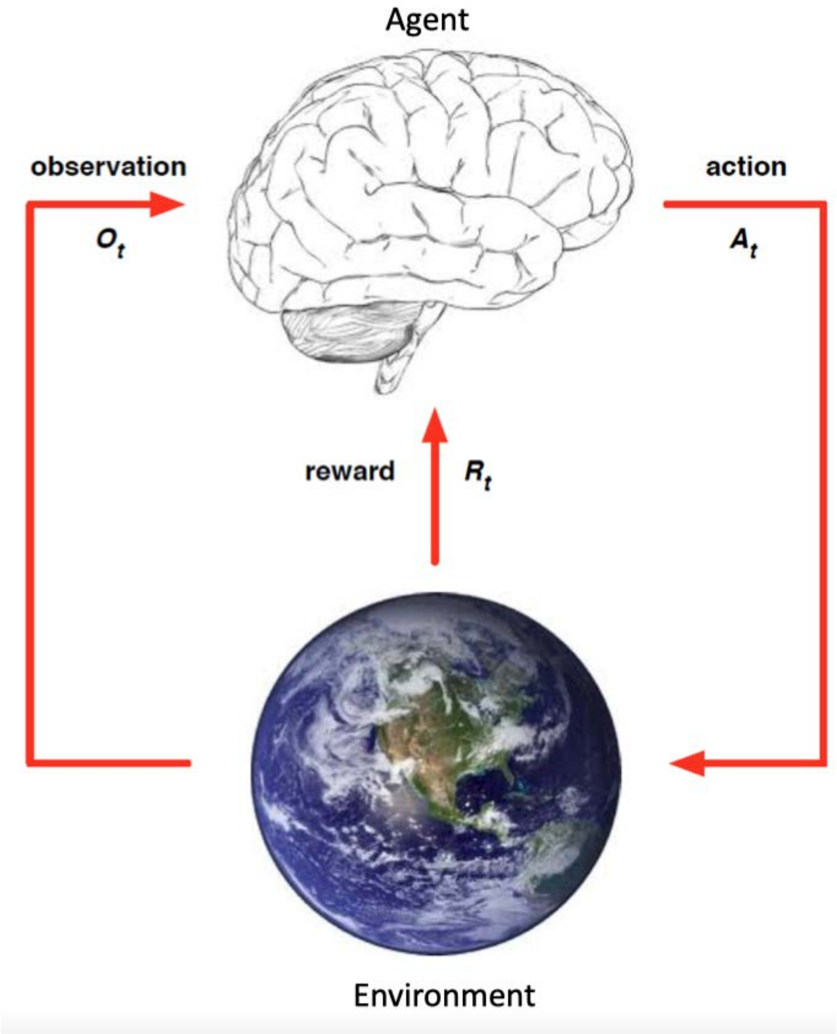
Reinforcement Learning Definition

- A computational approach by learning from interaction to achieve a goal



- Three aspects
  - Sensation: sense the state of the environment to some extent
  - Action: able to take actions that affect the state and achieve the goal
  - Goal: maximize the cumulative reward over time

Reinforcement Learning



- At each step t, the agent
  - Receives observation O_t
  - Receives scalar reward R_t
  - Executes action A_t

- The environment
  - Receives action A_t
  - Emits observation O_{t+1}
  - Emits scalar reward R_{t+1}

Elements of RL Systems

- History is the sequence of observations, action, rewards

$$H_t = O_1, R_1, A_1, O_2, R_2, A_2, \ldots, O_{t-1}, R_{t-1}, A_{t-1}, O_t, R_t$$

  - i.e. all observable variables up to time t
  - E.g., the sensorimotor stream of a robot or embodied agent
- What happens next depends on the history:
  - The agent selects actions
  - The environment selects observations/rewards
- State is the information used to determine what happens next (actions, observations, rewards) Formally, state is a function of the history:

$$S_t = f(H_t)$$

Elements of RL Systems

- Policy is the learning agent's way of behaving at a given time
  - It is a map from state to action
  - Deterministic policy

$$a = \pi(s)$$

  - Stochastic policy

$$\pi(a|s) = P(A_t = a | S_t = s)$$

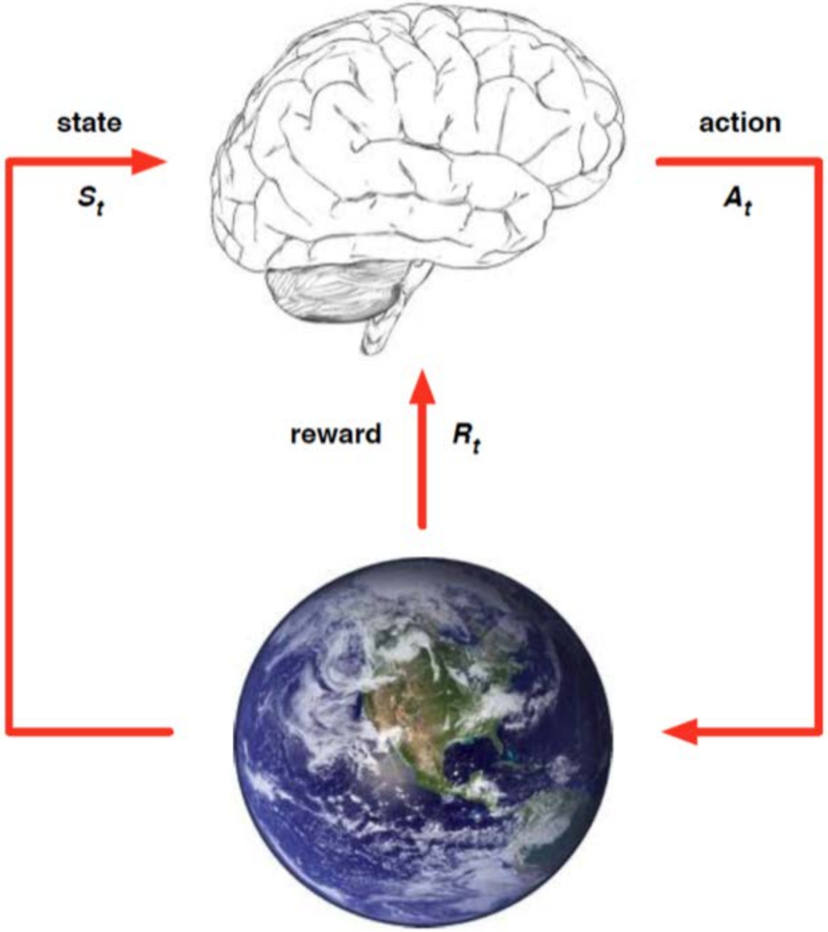
Elements of RL Systems

- A **Model** of the environment that mimics the behavior of the environment
  - Predict the next state

$$\mathcal{P}_{sa}(s') = \mathbb{P}[S_{t+1} = s' | S_t = s, A_t = a]$$

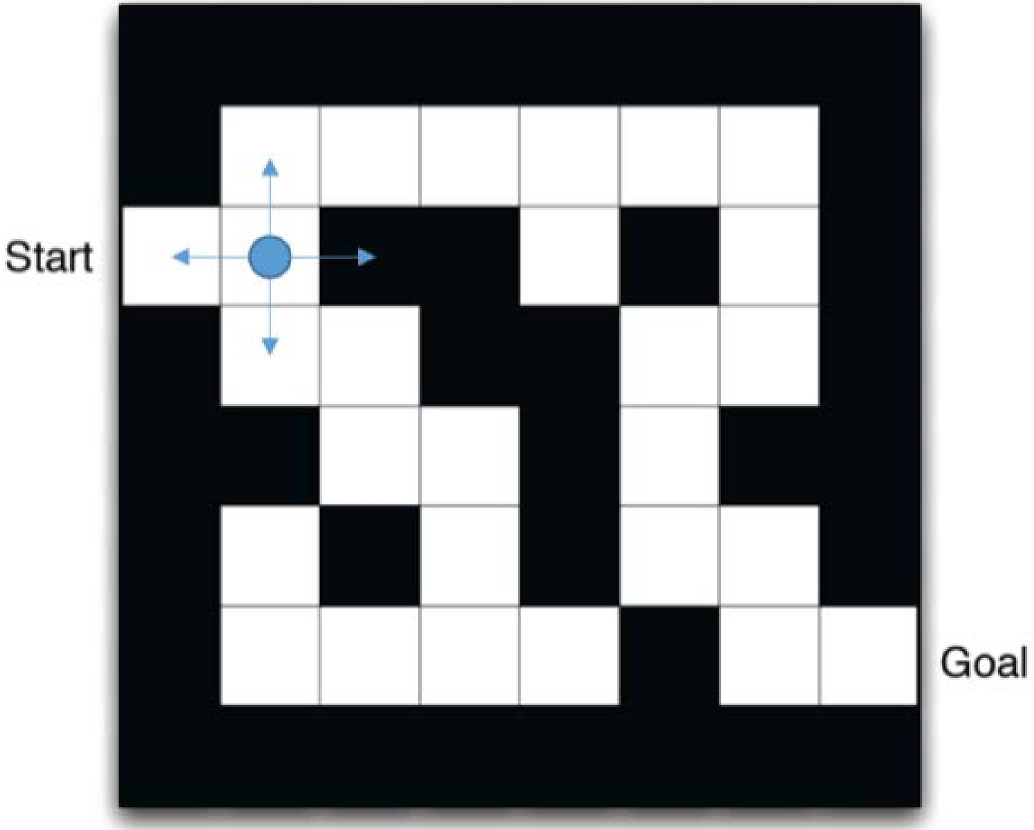
- Predicts the next (immediate) reward

$$\mathcal{R}_s(a) = \mathbb{E}[R_{t+1} | S_t = s, A_t = a]$$



Elements of RL Systems

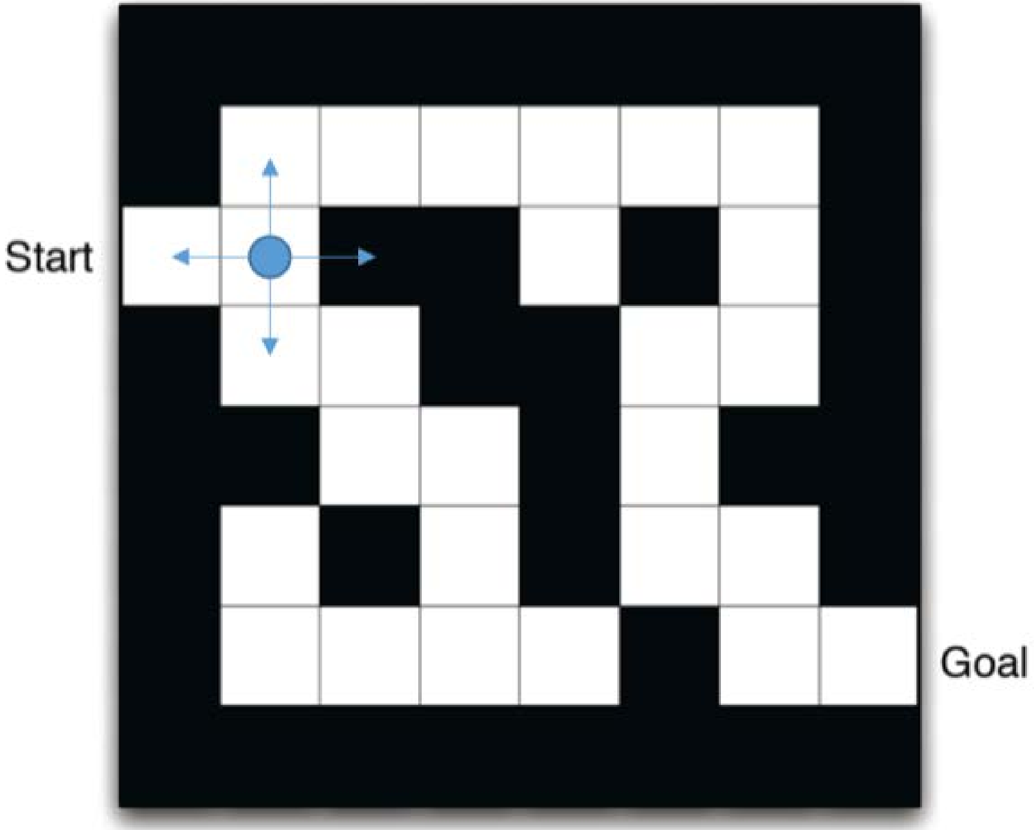
- Maze Example



- State: agent’s location
- Action: N,E,S,W

Elements of RL Systems

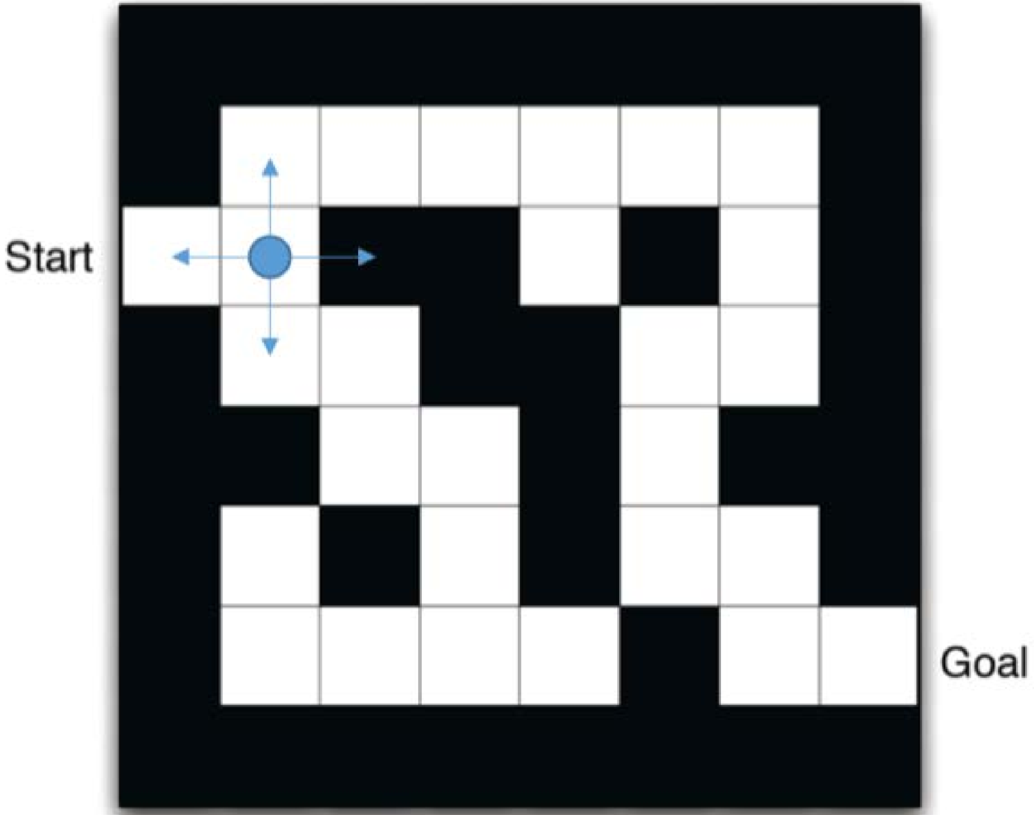
- Maze Example



- State: agent's location
- Action: N,E,S,W
- State transition: move to the next grid according to the action
  - No move if the action is to the wall

Elements of RL Systems

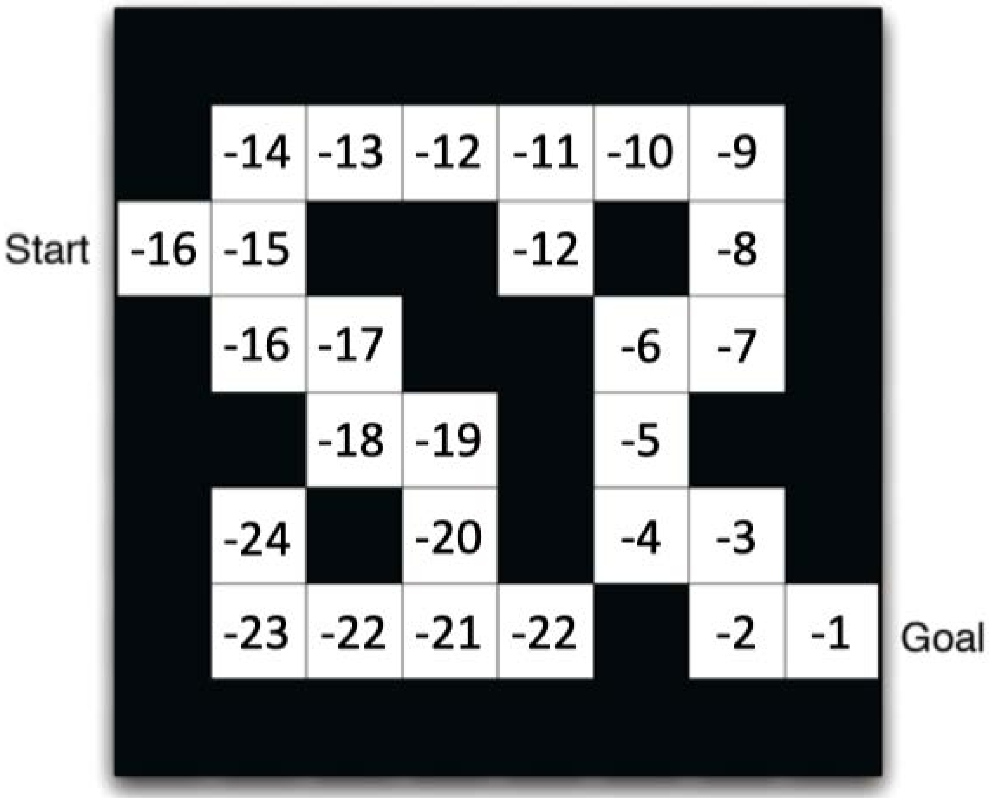
- Maze Example



- State: agent's location
- Action: N,E,S,W
- State transition: move to the next grid according to the action
  - No move if the action is to the wall
- Reward: -1 per time step

Elements of RL Systems

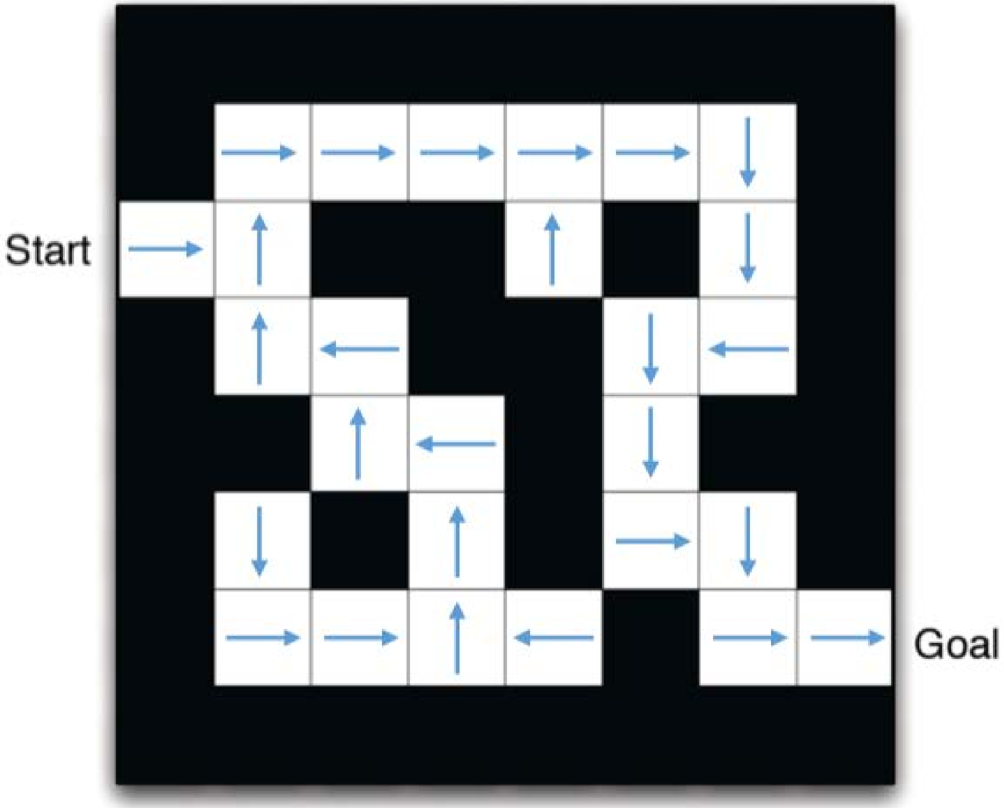
- Maze Example



- State: agent's location
- Action: N,E,S,W
- State transition: move to the next grid according to the action
  - No move if the action is to the wall
- Reward: -1 per time step
- Numbers represent value $v_\pi(s)$ of each state s.

Elements of RL Systems

- Maze Example



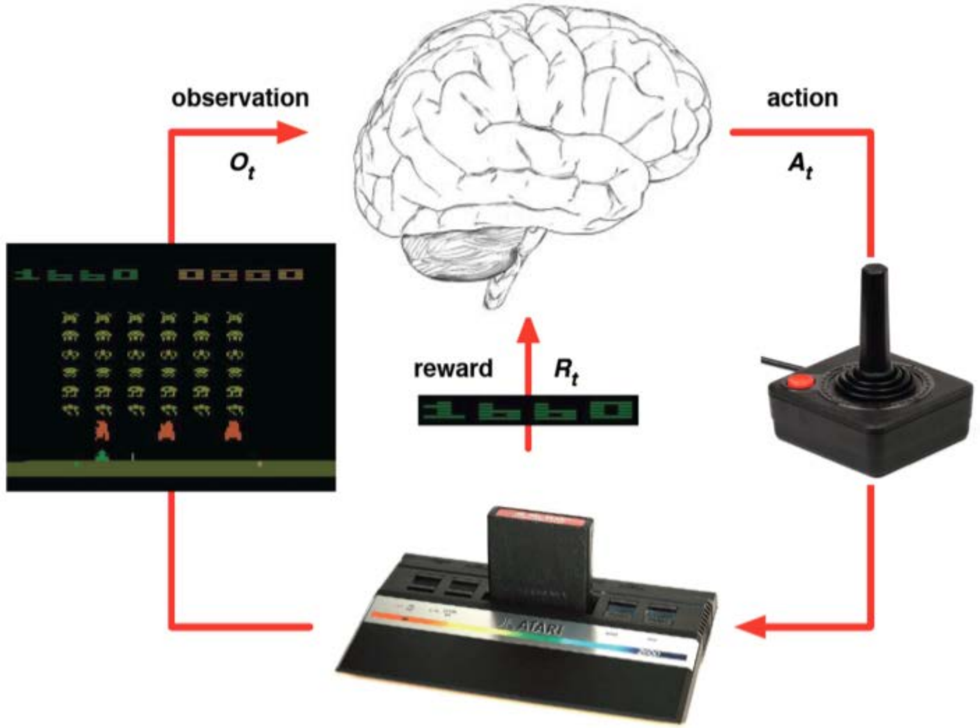
- State: agent's location
- Action: N,E,S,W
- State transition: move to the next grid according to the action
  - No move if the action is to the wall
- Reward: -1 per time step
- The given policy
  - Arrows represent policy $\pi(s)$ for each state s.

Categorizing RL Agents

- Model based RL
  - Policy and/or value function
  - Model of the environment
  - E.g., the maze game, game of Go
- Model-free RL
  - Policy and/or value function
  - No model of the environment
  - E.g., general playing Atari games

Atari Example

- Rules of the game are unknown
- Learn from interactive game-play
- Pick actions on joystick, see pixels and scores



Categorizing RL Agents

- Model based RL
  - Markov Decision Process
  - Planning by Dynamic Programming
- Model-free RL
  - Policy and/or value function
  - No model of the environment
  - E.g., general playing Atari games

Markov Decision Process

- Markov decision processes (MDPs) provide a mathematical framework for modeling decision making in situations where outcomes are partly random and partly under the control of a decision maker.

- MDPs formally describe an environment for RL
  - where the environment is FULLY observable
  - i.e. the current state completely characterizes the process (Markov property)

Markov Property

- "The future is independent of the past given the present"
- Definition
  - A state S_t is Markov if and only if

$$\mathbb{P}[S_{t+1}|S_t] = \mathbb{P}[S_{t+1}|S_1, \ldots, S_t]$$

- Properties
  - The state captures all relevant information from the history
  - Once the state is known, the history may be thrown away
  - i.e. the state is sufficient statistic of the future

Markov Decision Process

- A Markov decision process is a tuple $(S, A, \{P_{sa}\}, \gamma, R)$
- S is the set of states
  - E.g., location in a maze, or current screen in an Atari game
- A is the set of actions
  - E.g., move N, E, S, W, or the direction of the joystick and the buttons
- P_{sa} are the state transition probabilities
  - For each state $s \in S$ and action $a \in A$, P_{sa} a distribution over the next state in S
- $\gamma \in [0,1]$ is the discount factor for the future reward
- R is the reward function

Markov Decision Process

- The dynamics of an MDP proceeds as
  - Start in a state S_0
  - The agent chooses some action $a_0 \in A$
  - The agent gets the reward $R(s_0, a_0)$
  - MDP randomly transits to some successor state $s_1 \sim P_{s0a0}$
- This proceeds iteratively

$$s_0 \xrightarrow[R(s_0,a_0)]{a_0} s_1 \xrightarrow[R(s_1,a_1)]{a_1} s_2 \xrightarrow[R(s_2,a_2)]{a_2} s_3 \cdots$$

- The total payoff of the agent is

$$R(s_0, a_0) + \gamma R(s_1, a_1) + \gamma^2 R(s_2, a_2) + \cdots$$

Markov Decision Process

- For a large part of cases, reward is only assigned to the state
  - E.g., in maze game, the reward is on the location
  - In game of Go, the reward is only based on the final territory
- The reward function R(s)
- MDPs proceed

$$s_0 \xrightarrow[R(s_0)]{a_0} s_1 \xrightarrow[R(s_1)]{a_1} s_2 \xrightarrow[R(s_2)]{a_2} s_3 \cdots$$

- cumulative reward (total payoff)

$$R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + \cdots$$

Reward on State Only

- The goal is to choose actions over time to maximize the expected cumulative reward

$$\mathbb{E}[R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + \cdots]$$

- $\gamma \in [0,1]$ is the discount factor for the future reward, which makes the agent prefer immediate reward to future reward
  - In finance case, today's $1 is more valuable than $1 in tomorrow
- Given a particular policy $\pi(s)$
- Define the value function for π:

$$V^\pi(s) = \mathbb{E}[R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + \cdots | s_0 = s, \pi]$$

  - i.e. expected cumulative reward given the start state and taking actions according to π

Bellman Equation for Value Function

- Define the value function for π

$$V^\pi(s) = \mathbb{E}[R(s_0) + \underbrace{\gamma R(s_1) + \gamma^2 R(s_2) + \cdots}_{\gamma V^\pi(s_1)} | s_0 = s, \pi]$$

$$= R(s) + \gamma \sum_{s' \in S} P_{s\pi(s)}(s') V^\pi(s')$$

Bellman Equation

Immediate Reward

Time decay

State transition

Value of the next state

Optimal Value Function

- The optimal value function for each state s is best possible sum of discounted rewards that can be attained by any policy

$$V^*(s) = \max_{\pi} V^{\pi}(s)$$

- The Bellman's equation for optimal value function and the optimal policy

$$V^*(s) = R(s) + \max_{a \in A} \gamma \sum_{s' \in S} P_{sa}(s') V^*(s')$$

$$\pi^*(s) = \arg\max_{a \in A} \sum_{s' \in S} P_{sa}(s') V^*(s')$$

- For every state s and every policy π

$$V^*(s) = V^{\pi^*}(s) \geq V^{\pi}(s)$$

Value Iteration & Policy Iteration

- Note that the value function and policy are correlated

$$V^{\pi}(s) = R(s) + \gamma \sum_{s' \in S} P_{s\pi(s)}(s') V^{\pi}(s')$$

$$\pi(s) = \arg\max_{a \in A} \sum_{s' \in S} P_{sa}(s') V^{\pi}(s')$$

- It is feasible to perform iterative update towards the optimal value function and optimal policy
  - Value iteration
  - Policy iteration

Value Iteration

- For an MDP with finite state and action spaces

$$|S| < \infty, |A| < \infty$$

- Value iteration is performed as

1. For each state s, initialize V(s) = 0.
2. Repeat until convergence {

   For each state, update

$$V(s) = R(s) + \max_{a \in A} \gamma \sum_{s' \in S} P_{sa}(s')V(s')$$

   }

Synchronous vs. Asynchronous

- Synchronous value iteration stores two copies of value functions
  - For all s in S

$$V_{\text{new}}(s) \leftarrow \max_{a \in A}\left(R(s) + \gamma \sum_{s' \in S} P_{sa}(s') V_{\text{old}}(s')\right)$$

  - Update $V_{\text{old}}(s') \leftarrow V_{\text{new}}(s)$
- In-place asynchronous value iteration stores one copy of value function
  - For all s in S

$$V(s) \leftarrow \max_{a \in A}\left(R(s) + \gamma \sum_{s' \in S} P_{sa}(s') V(s')\right)$$

Value Iteration Example: Shortest Path

- Setting: Reward is -1 for every step

g			

Problem

0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0

V_1

0	-1	-1	-1
-1	-1	-1	-1
-1	-1	-1	-1
-1	-1	-1	-1

V_2

0	-1	-2	-2
-1	-2	-2	-2
-2	-2	-2	-2
-2	-2	-2	-2

V_3

0	-1	-2	-3
-1	-2	-3	-3
-2	-3	-3	-3
-3	-3	-3	-3

V_4

0	-1	-2	-3
-1	-2	-3	-4
-2	-3	-4	-4
-3	-4	-4	-4

V_5

0	-1	-2	-3
-1	-2	-3	-4
-2	-3	-4	-5
-3	-4	-5	-5

V_6

0	-1	-2	-3
-1	-2	-3	-4
-2	-3	-4	-5
-3	-4	-5	-6

V_7

Policy Iteration

- For an MDP with finite state and action spaces

$$|S| < \infty, |A| < \infty$$

- Policy iteration is performed as
  - Initialize π randomly
  - Repeat until convergence {
    - Let $V := V^{\pi}$
    - For each state, update

$$\pi(s) = \arg\max_{a \in A} \sum_{s' \in S} P_{sa}(s') V(s')$$

Policy Iteration

- For an MDP with finite state and action spaces

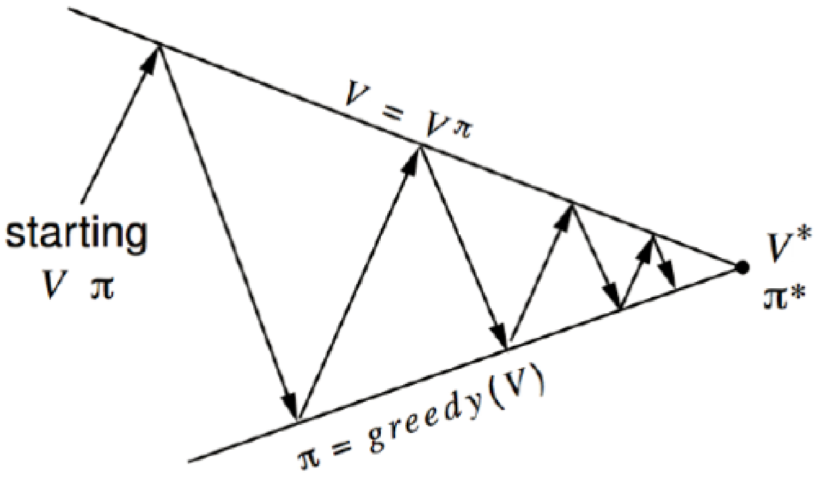
$$|S| < \infty, |A| < \infty$$

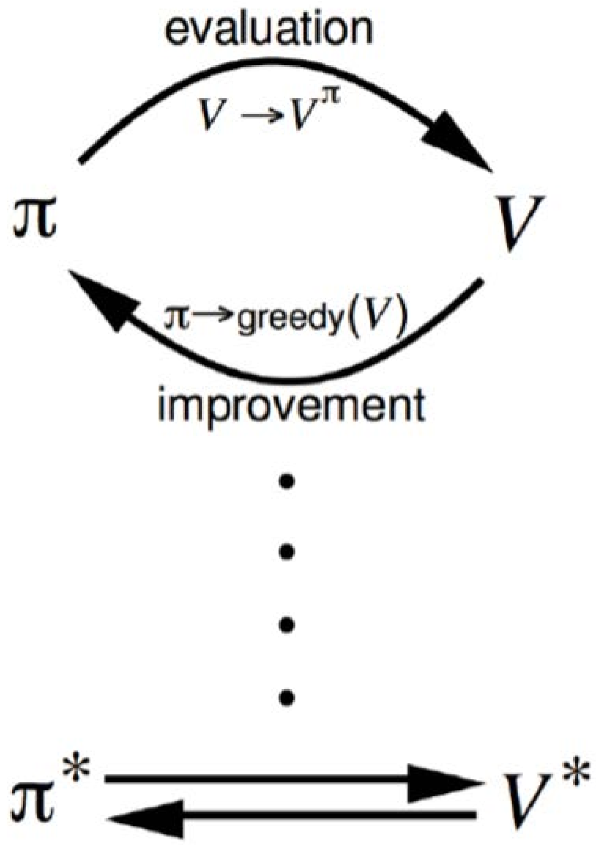
- Policy iteration is performed as
  - Initialize π randomly
  - Repeat until convergence {
    - Let $\boxed{V := V^{\pi}}$
    - For each state, update

$$\pi(s) = \arg\max_{a \in A} \sum_{s' \in S} P_{sa}(s')V(s')$$

- The step of value function update could be time-consuming

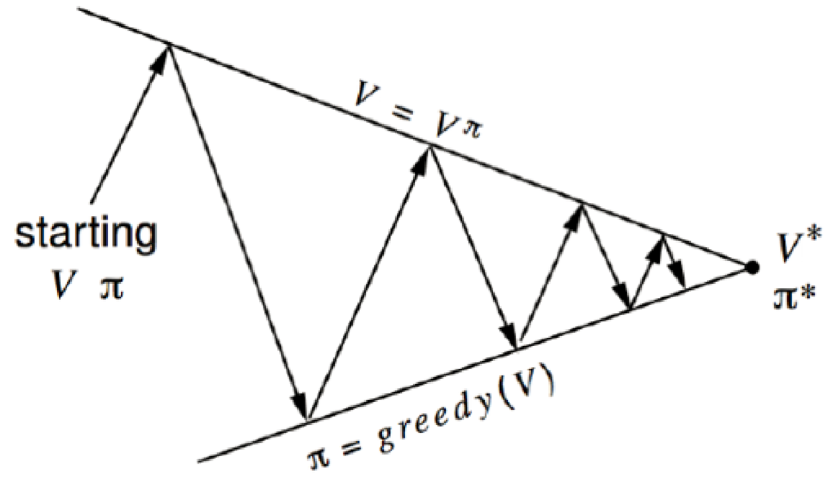
Policy Iteration

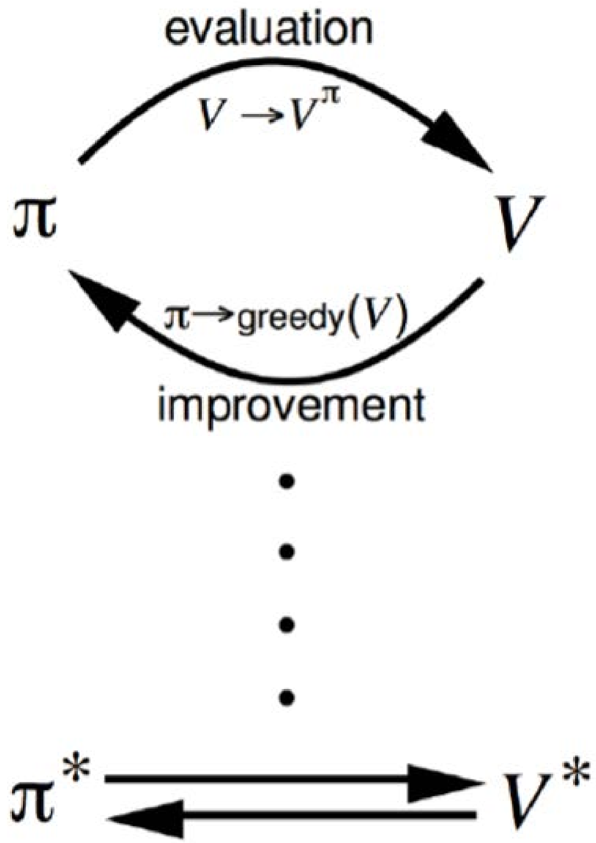




- Policy Iteration
  - Estimate V^π
  - Iterative policy evaluation

Policy Iteration





- Policy Improvement
  - Generate $\pi' \geq \pi$
  - Greedy Policy Improvement

Value Iteration vs. Policy Iteration

Value iteration

1. For each state *s*, initialize *V*(*s*) = 0.
2. Repeat until convergence {

   For each state, update

$$V(s) = R(s) + \max_{a \in A} \gamma \sum_{s' \in S} P_{sa}(s') V(s')$$

}

Policy iteration

1. Initialize π randomly
2. Repeat until convergence {
   a) Let $V := V^{\pi}$
   b) For each state, update

$$\pi(s) = \arg\max_{a \in A} \sum_{s' \in S} P_{sa}(s') V(s')$$

}

Value Iteration vs. Policy Iteration

- Remarks:
  - Value iteration is a greedy update strategy
  - In policy iteration, the value function update by bellman equation is costly
  - For small-space MDPs, policy iteration is often very fast and converges quickly
  - For large-space MDPs, value iteration is more practical (efficient)
  - Value iteration is like SGD and policy iteration is like BGD

Reinforcement Learning Materials

- Our slides on RL is mainly based on the materials from these masters.

Prof. Richard Sutton

- University of Alberta, Canada
- http://incompleteideas.net/sutton/index.html
- Reinforcement Learning: An Introduction (2nd edition)
- http://www.incompleteideas.net/book/the-book-2nd.html

Dr. David Silver

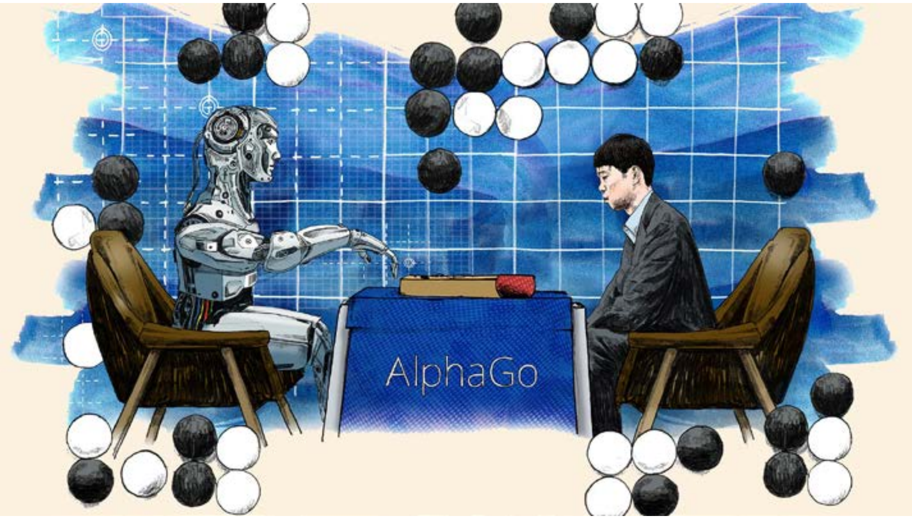
- Google DeepMind and UCL, UK
- http://www0.cs.ucl.ac.uk/staff/d.silver/web/Home.html
- UCL Reinforcement Learning Course
- http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html

Prof. Andrew Ng

- Stanford University, US
- http://www.andrewng.org/
- Machine Learning (CS229) Lecture Notes 12: RL
- http://cs229.stanford.edu/materials.html

Matlab 中的强化学习

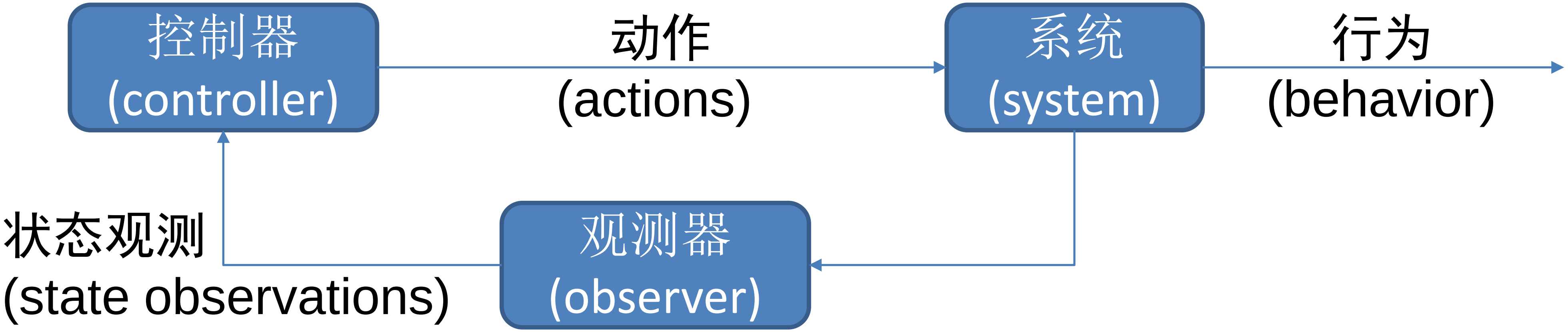
- 回顾强化学习基础知识，了解强化学习的基本工作流程
- 学习如何在 Matlab 中进行强化学习
- demo 讲解




什么是强化学习？

强化学习旨在学习如何做，即如何根据情况采取动作，从而实现数值奖励信号最大化。学习者不会接到动作指令，而是必须自行尝试去发现回报最高的动作方案。

—— Sutton and Barto，*Reinforcement Learning: An Introduction*

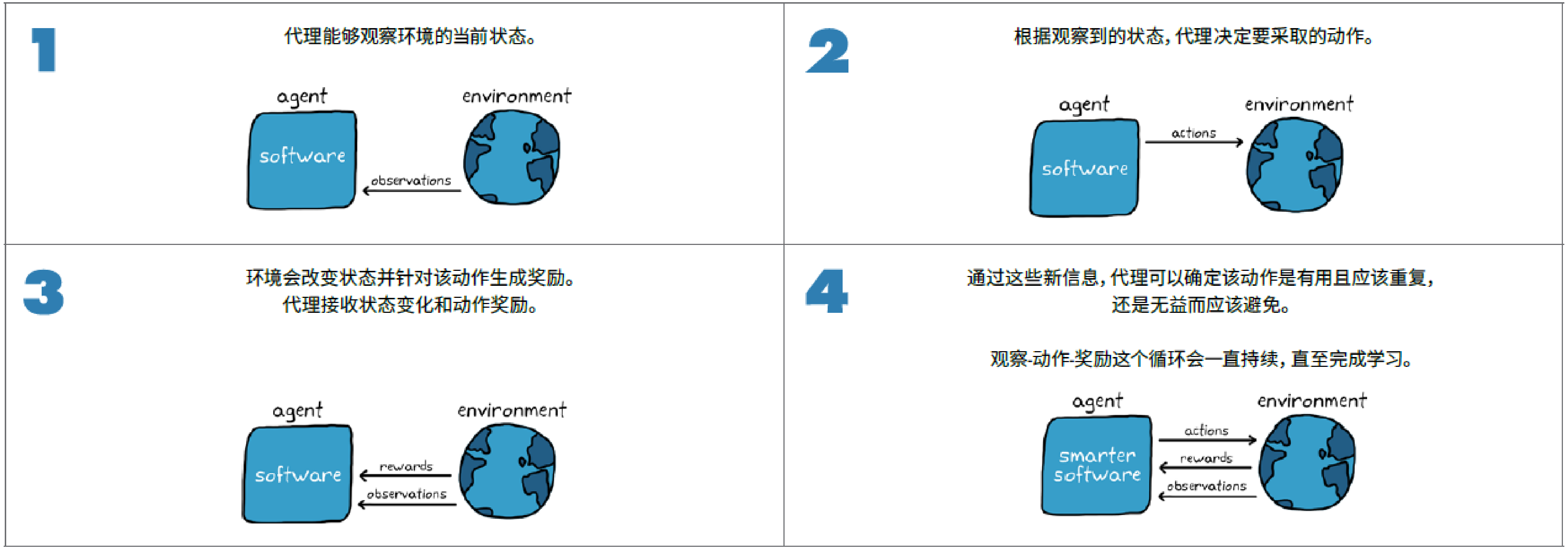


强化学习的优点

- 如果一个问题可以描述成或转化成序列决策问题，可以对状态、动作、奖赏进行定义，那么强化学习很可能可以帮助解决这个问题。
- 强化学习有可能帮助自动化、最优化手动设计的策略。
- 强化学习考虑序列问题，具有长远眼光，考虑长期回报，这种长远眼光对很多问题找到最优解非常关键。

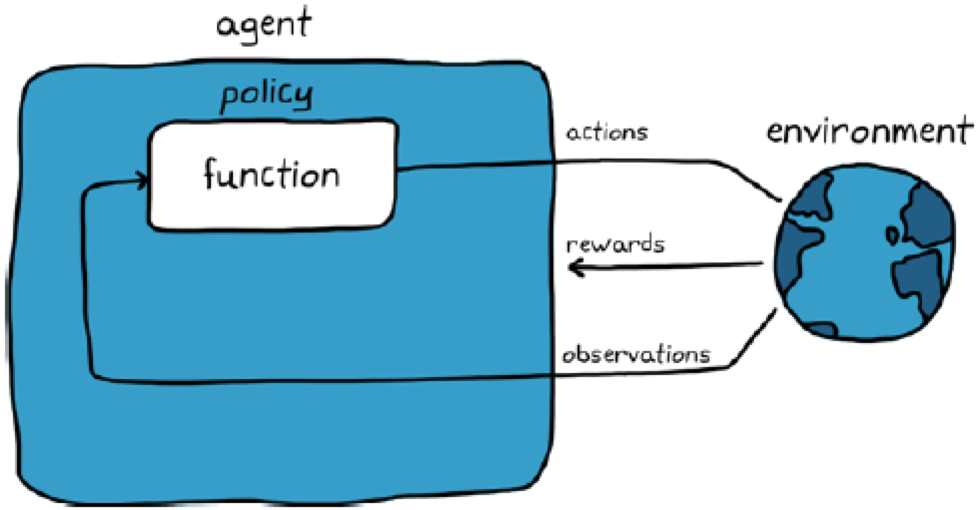
强化学习概述

- 强化学习采用动态环境数据，其目标是确定生成最优结果的最佳动作序列。
- 强化学习通过一个软件（代理）来探索环境、与环境交互并从环境中学习。



强化学习概述

- 代理中有一个函数可接收状态观测量（输入），并将其映射到动作集（输出）。此函数称为策略（policy），策略根据一组给定的观测量决定要采取的动作。
- 环境将生成奖励（rewards），向代理反映采取该动作指令的效果。
- 代理使用强化学习算法学习最佳环境交互策略，根据已采取的动作、环境状态观测量以及获得的奖励值来改变策略。



强化学习工作流程概述

1 您需要一个环境，供您的代理开展学习。您需要选择环境里应该有什么，是仿真还是物理设置。

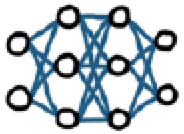
environment

2 您需要考虑最终想要代理做什么工作，并设计奖励函数，激励代理实现目标。

reward

3 您需要选择一种表示策略的方法。思考您想如何构造参数和逻辑，由此构成代理的决策部分。

policy

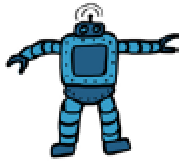


4 您需要选择一种算法来训练代理，争取找到最优的策略参数。

training

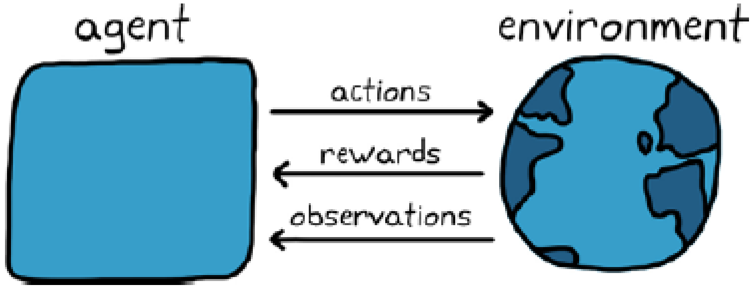
5 最后，您需要在实地部署该策略并验证结果，从而利用该策略。

deploy

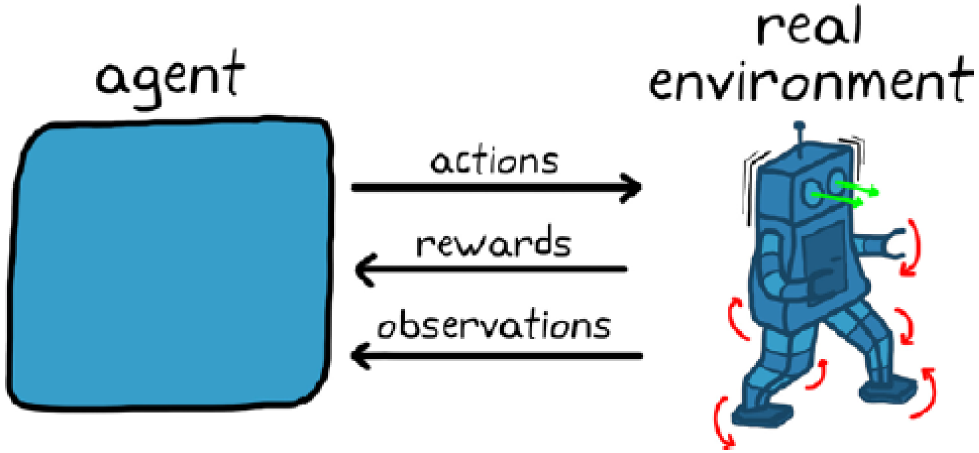


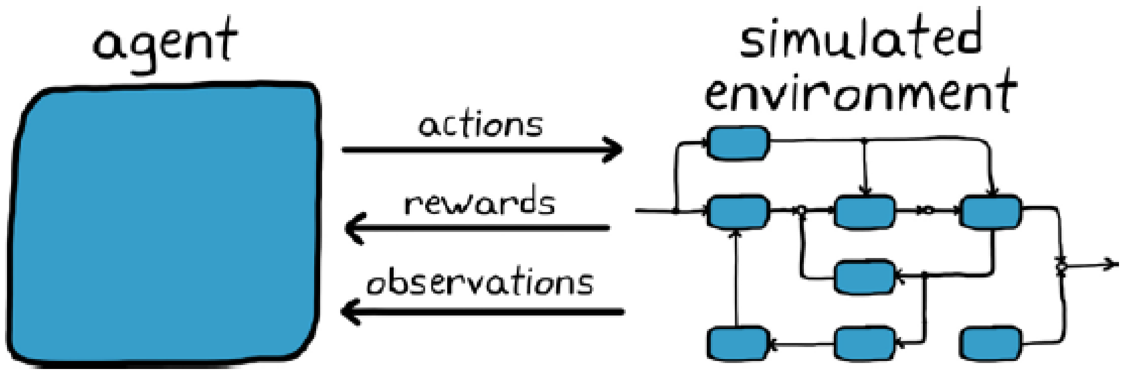
环境

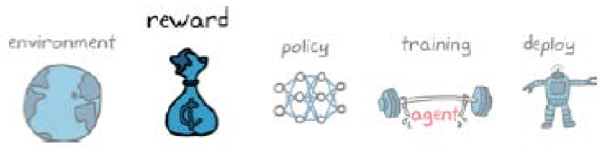
■ 环境是指存在于代理之外的一切元素。它既是代理动作产生作用的地方，又能生成奖励和观测量。



■ 环境可以是真实环境或仿真环境。

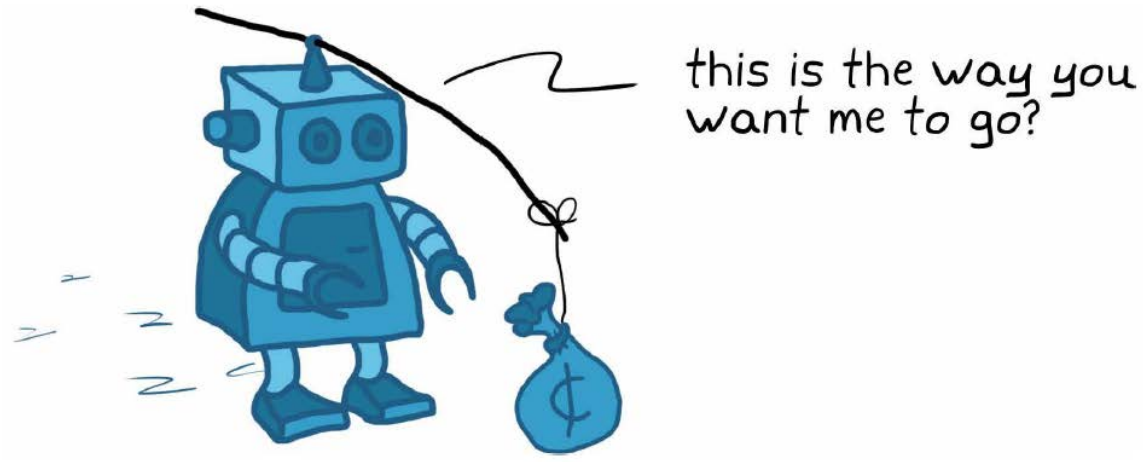






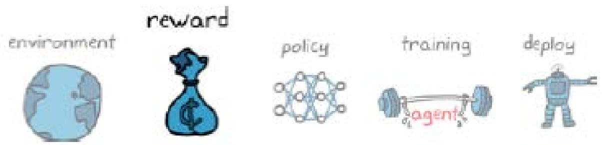
奖励

- 奖励让学习算法“明白”什么情况下策略变得更好，最终趋向目标结果。



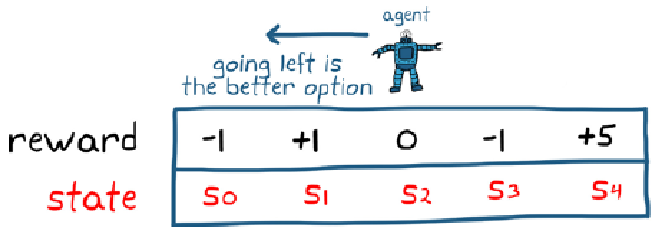
- 奖励是一个函数，会生成一个标量，代表处于某个特定状态并采取特定动作的代理的“优度”。在强化学习中对于创建奖励函数没有任何限制。可以采用稀疏奖励，或在每个时间步长后奖励，或者仅在较长一段时间后一个片段完全结束时给予奖励。奖励可以使用非线性函数计算，也可以通过几千个参数来计算。这完全取决于采取什么方式才能有效地训练代理。

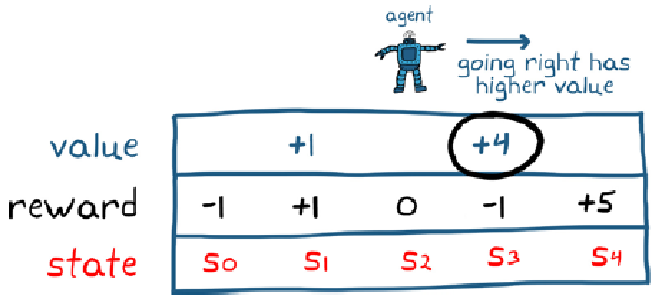
reward = function (state, action)



价值

- 评估一个状态或动作的价值，而不是奖励，可以帮助代理选择将会在一段时间内收取最多奖励（而不是短期利益）的动作。奖励是处于某一状态或采取特定动作的即时收益，价值是代理预期从某一状态和往后将会获得的总回报。



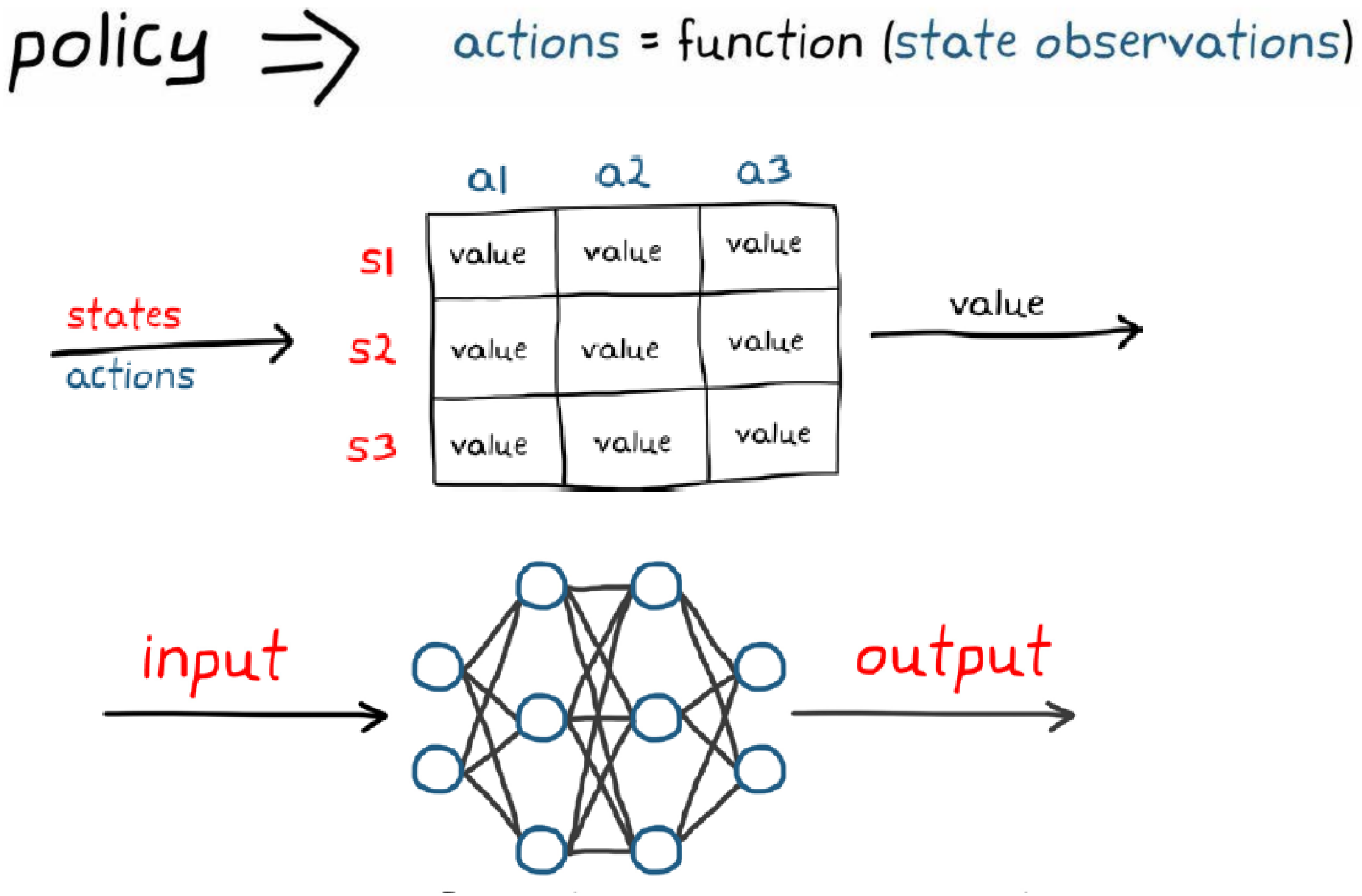


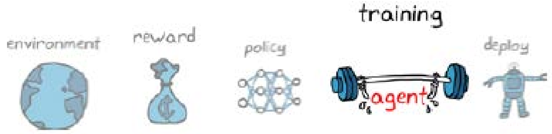
- 对更远的将来所能获取的奖励的预测不大可靠，在强化学习中，通过对奖励打折，越远的未来折扣越大，可以设置折扣系数 gamma，介于 0 到 1 之间。

$$\text{total discounted reward} = r_1 + \gamma r_2 + \gamma^2 r_3 + \gamma^3 r_4 + \ldots = \sum_{i=1}^{T} \gamma^{i-1} r_i$$

策略

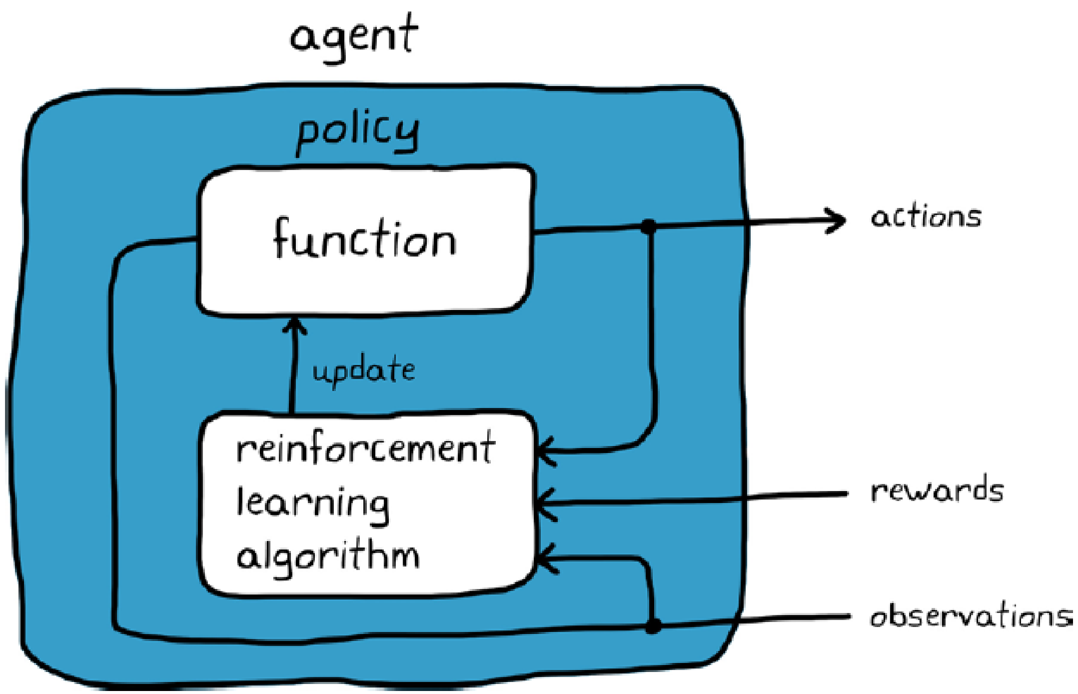
■ 策略是将观测量映射到动作的函数，需要通过学习算法进行优化。

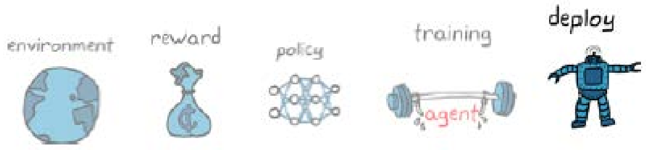




训练

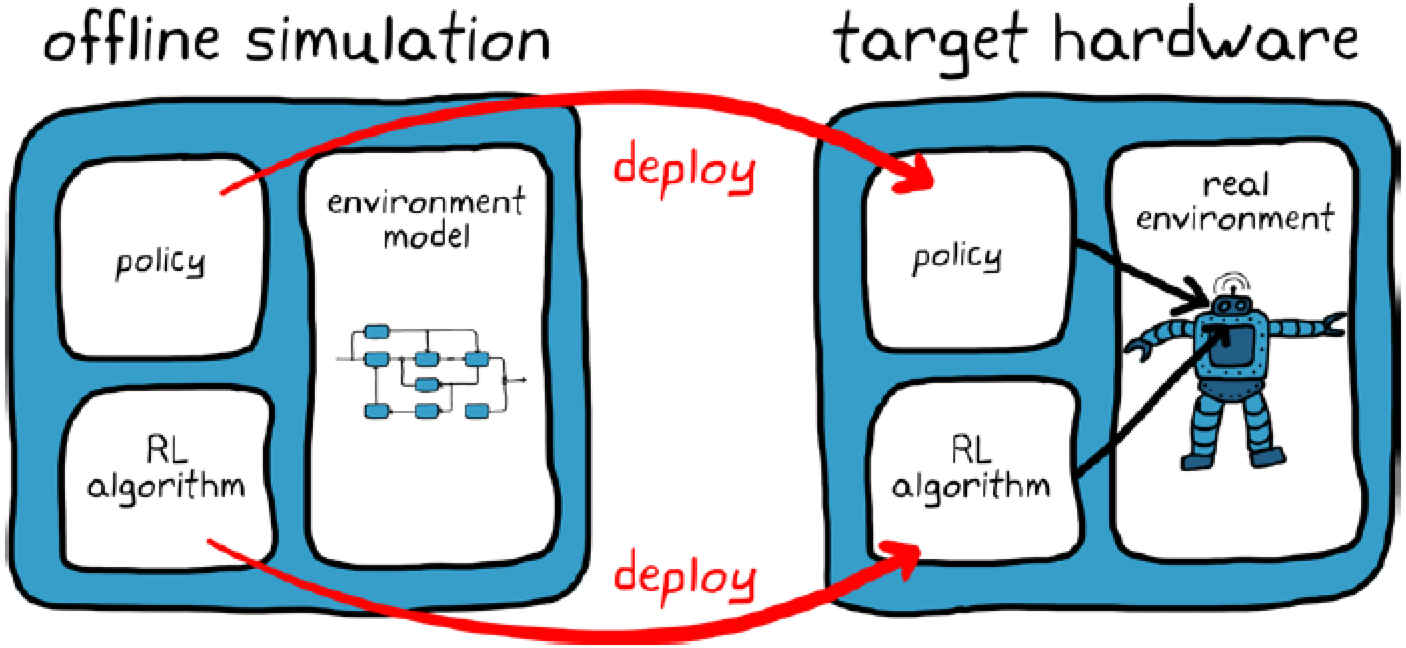
- 学习算法通过代理与环境不断交互的结果构建最优策略。





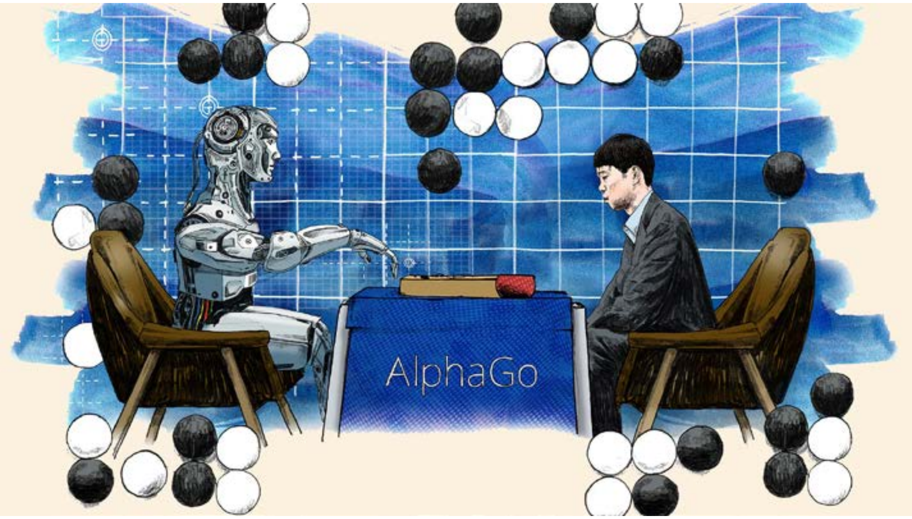
部署

- 如果在仿真环境中进行学习，最后需要将训练好的策略部署到目标硬件上，如果部署后仍然可能需要使用真实物理硬件继续开展学习，还需要将学习算法也部署到目标硬件上。



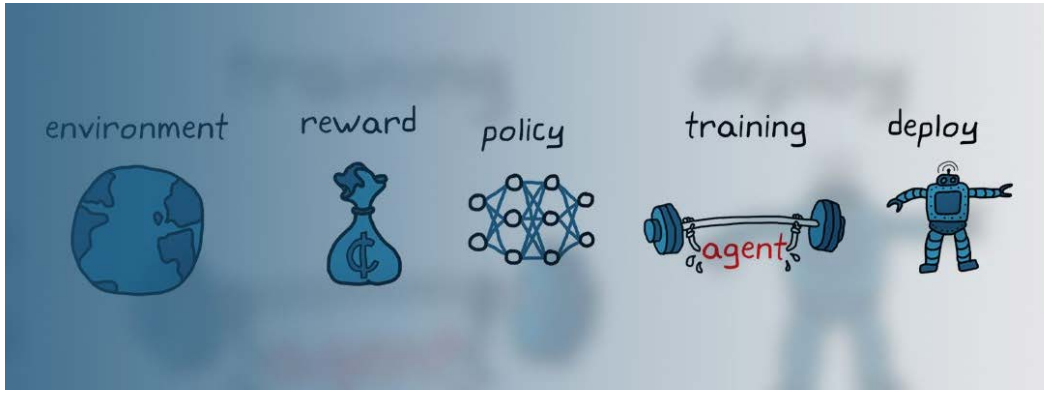
Matlab 中的强化学习

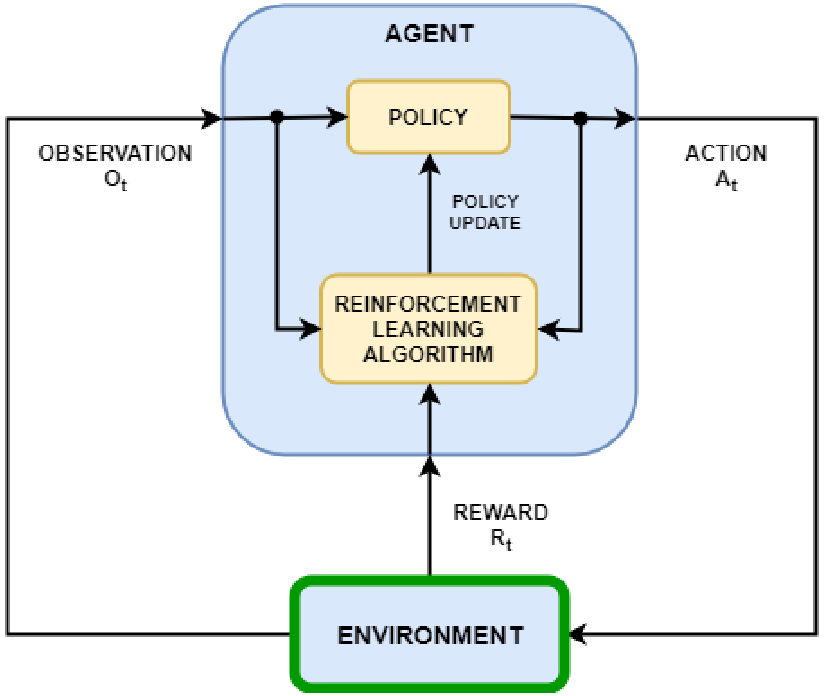
- 回顾强化学习基础知识，了解强化学习的基本工作流程
- 学习如何在 Matlab 中进行强化学习
- demo 讲解



主要流程

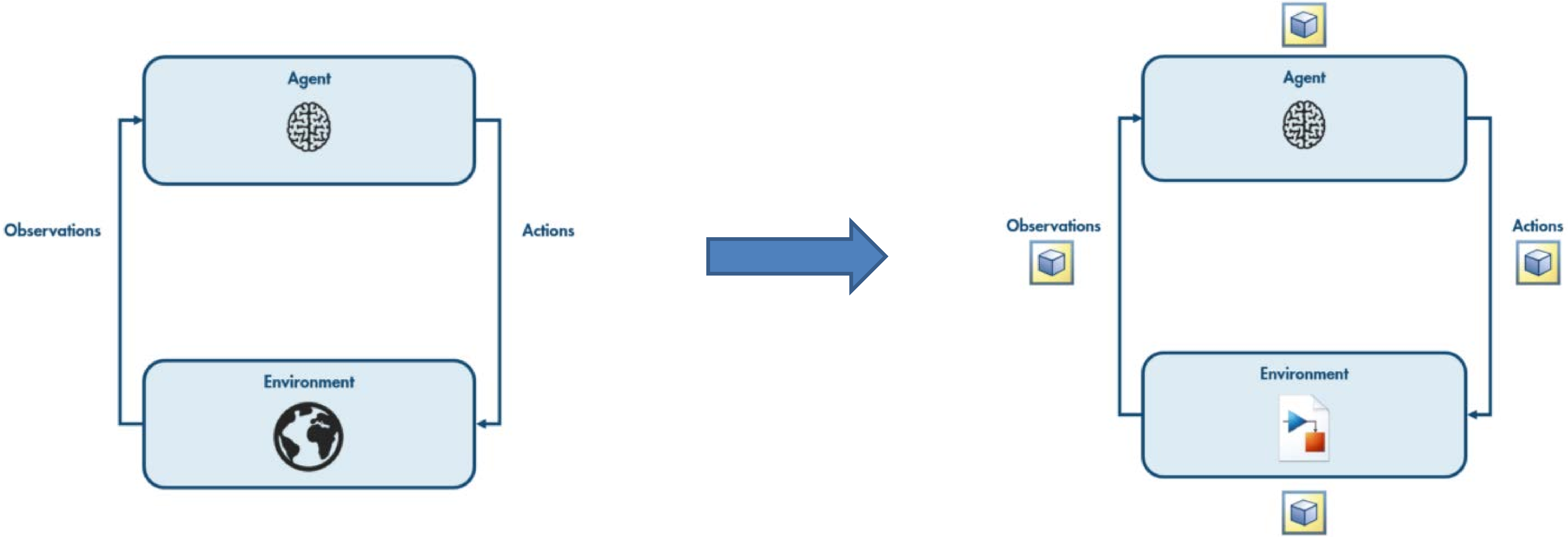
- 定义环境，包括需要模拟的环境，Observation 和 Action 接口，Reward 计算函数等
- 定义 Agent，包括需要采取的策略结构，学习算法等
- 使用定义好的环境和 Agent 进行训练





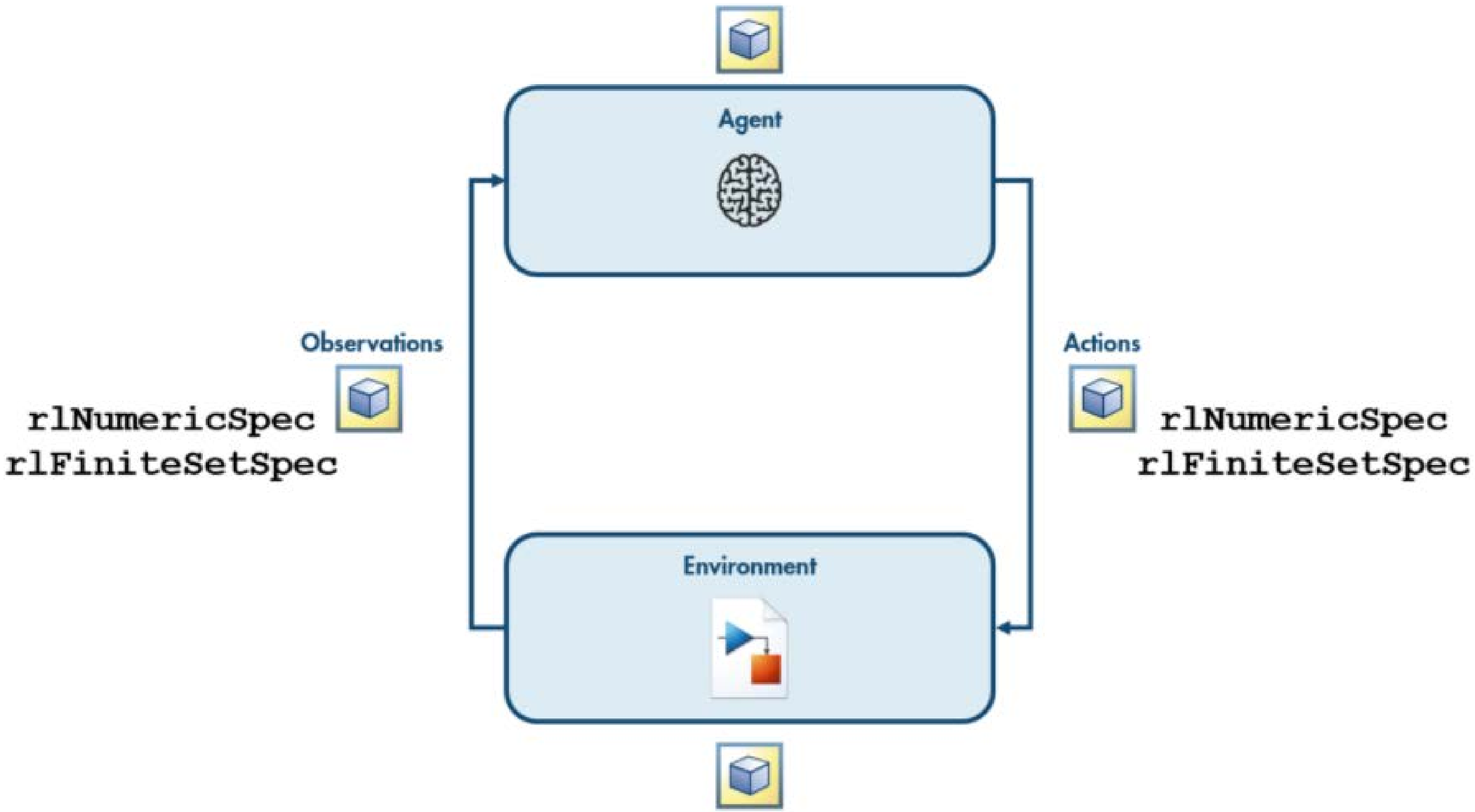
定义环境

- Agent 通过观测值做出行动，并与环境交互，环境对行为的反应通常可以使用 Simulink 来模拟。
- 在 Matlab 中，Agent、Environment、Observations、Actions 都被表示为变量。



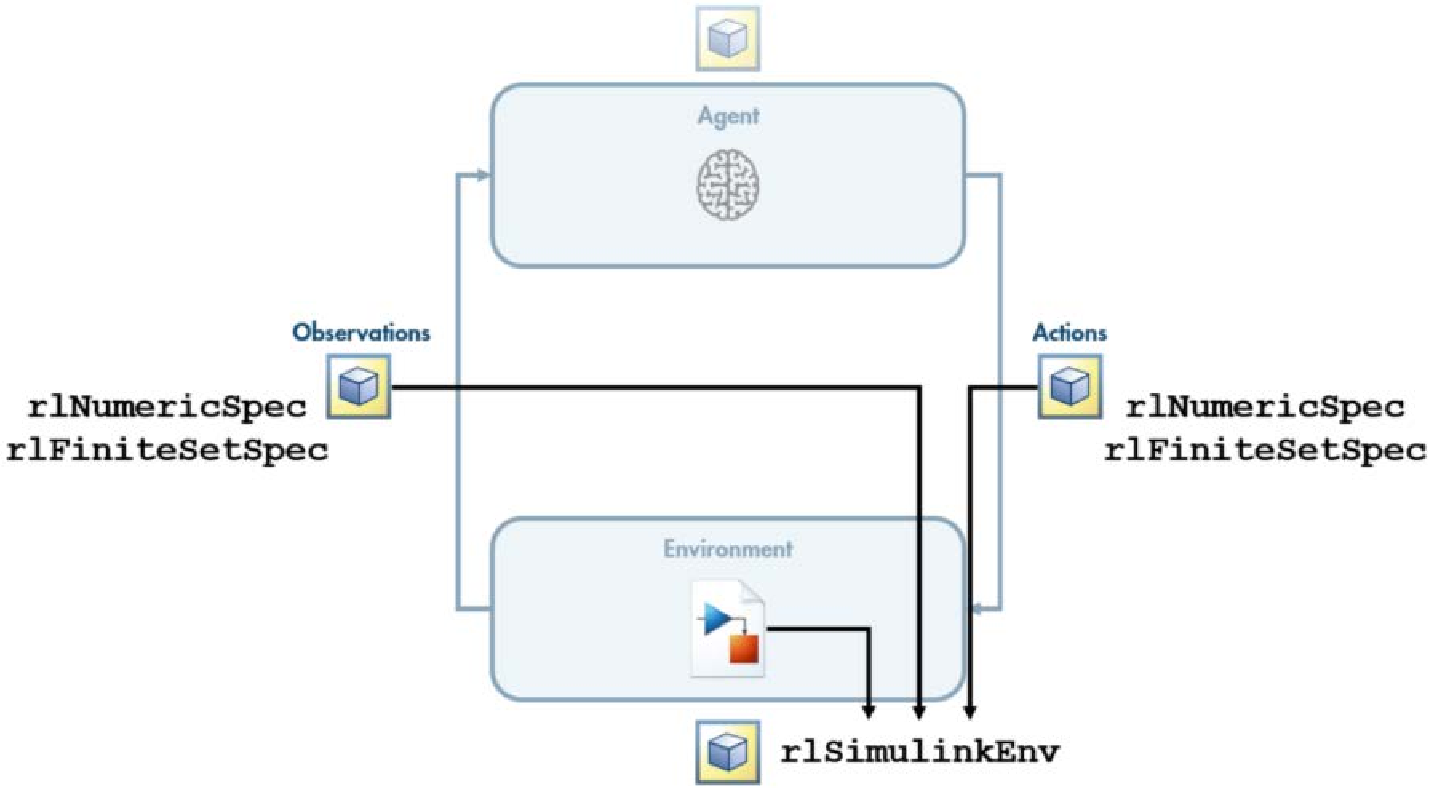
定义环境

- 使用 *rlNumericSpec* 或者 *rlFiniteSetSpec* 声明 Observations 和 Actions 变量



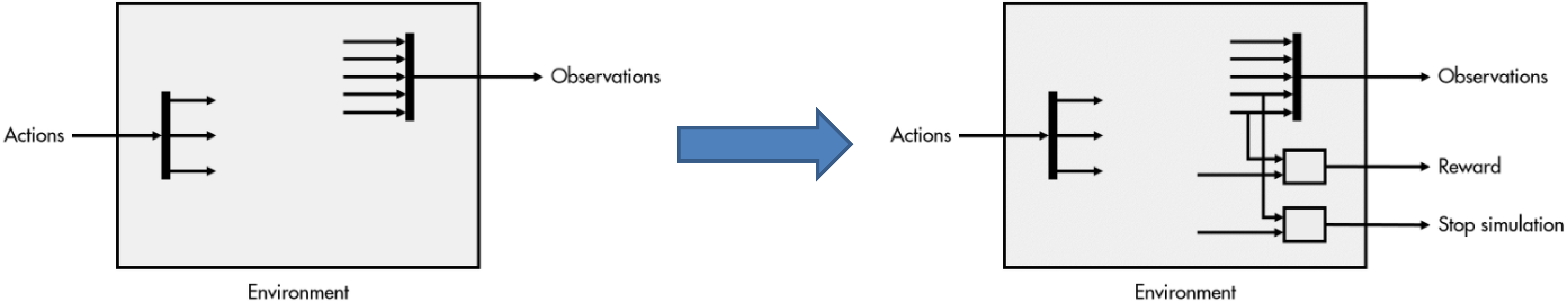
定义环境

■ 使用 *rlSimulinkEnv* 定义一个基于 Simulink 模型的环境变量



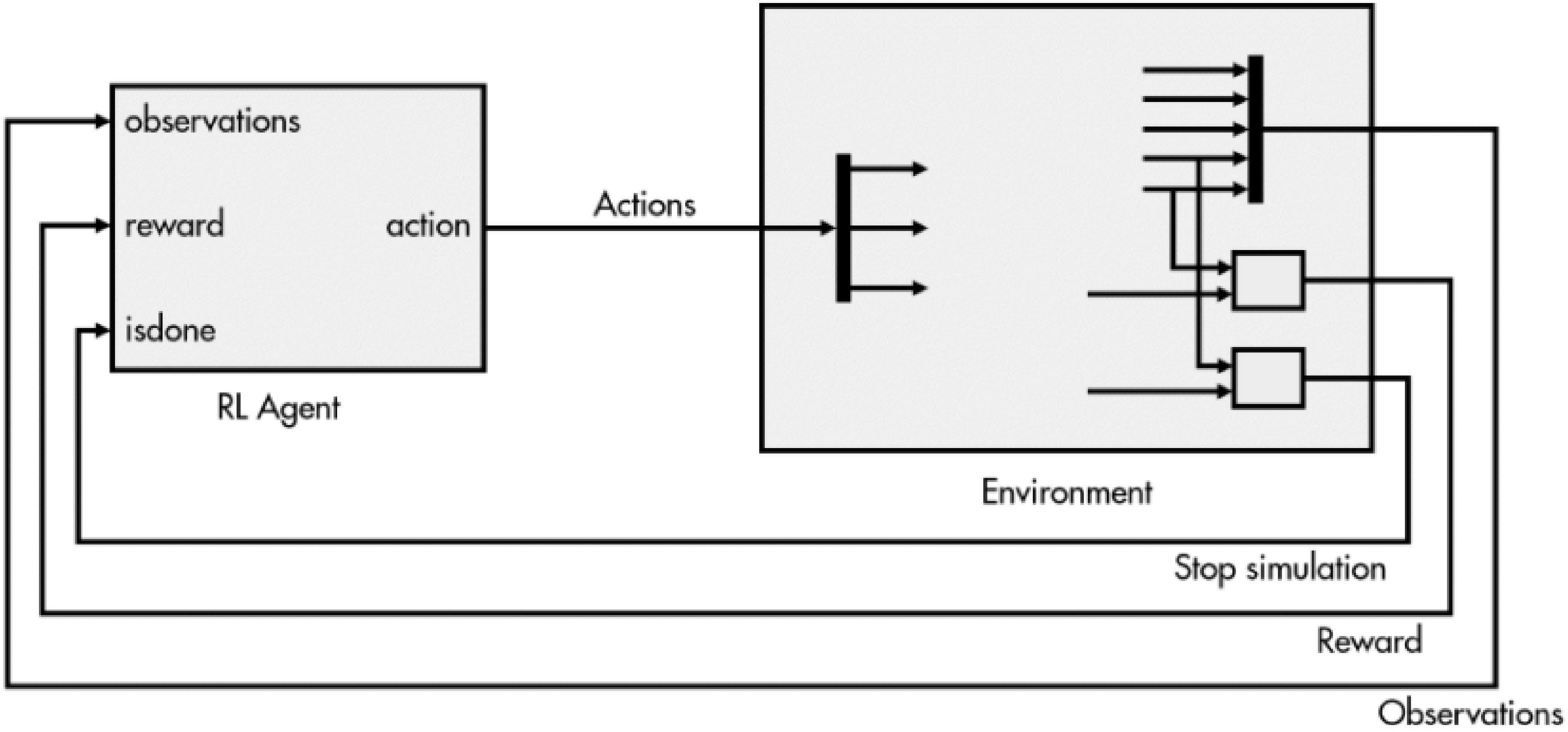
定义环境

- 环境还需要根据 Observations 或者其他信息为 Agent 提供 Reward，同时判定一次模拟过程是否结束



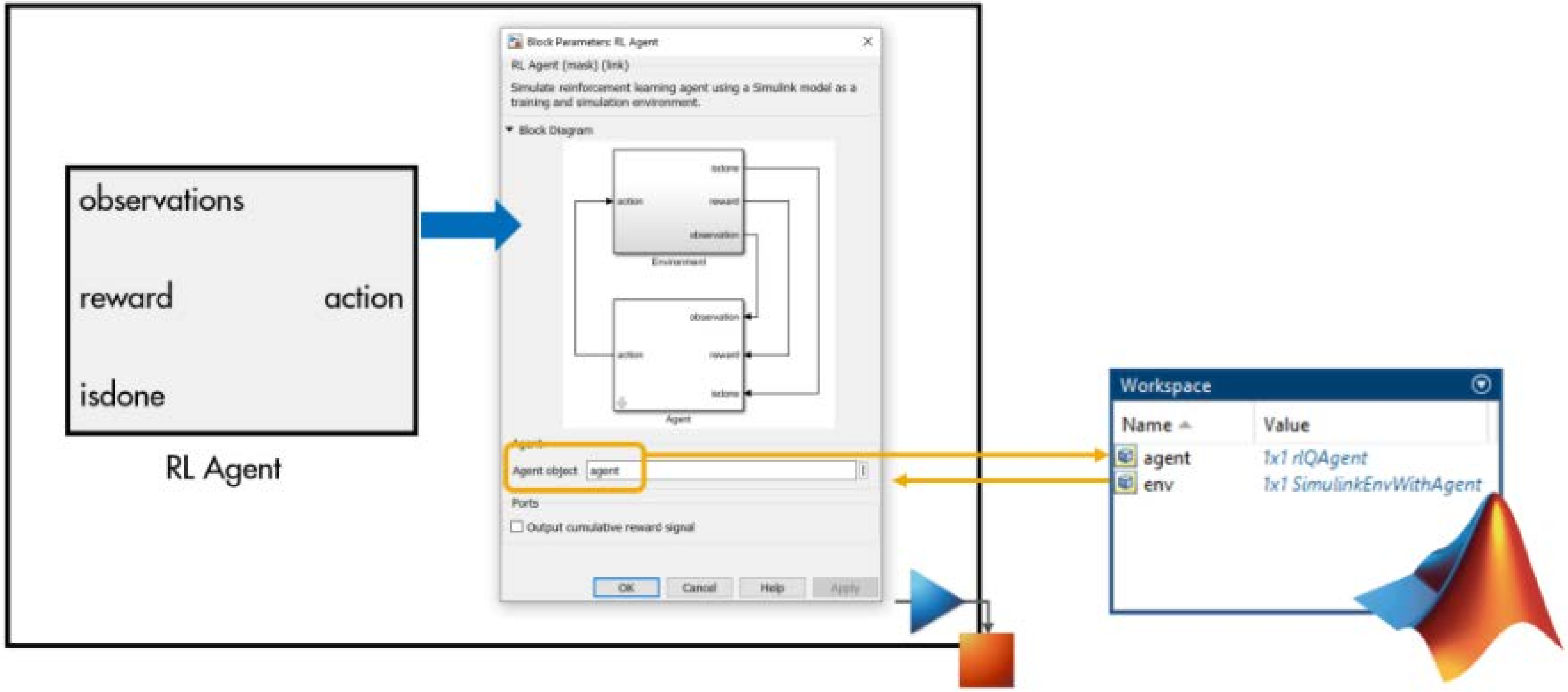
定义环境

■ 在 Simulink 中添加一个 *RL Agent* 模块，并且连接相应输入输出



定义环境

- *RL Agent* 模块需要指明参数 *Agent Object*， 即 Agent 变量名，在训练之前或模拟之前该变量需存在于 Matlab 工作区



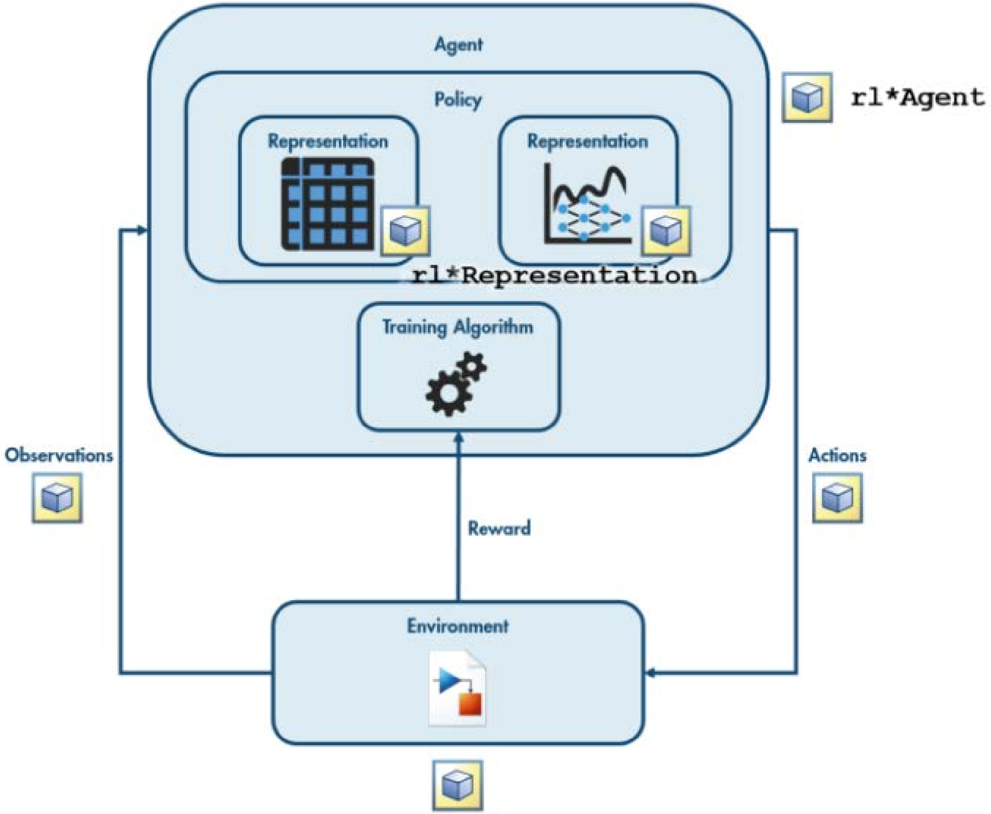
定义 Agent

■ 使用 *rl*Agent* 定义不同学习算法的 Agent，不同类型的 Agent 可能接受不同类型的 Actions

Agent	Type	Action Space
Q-Learning Agents (Q)	Value-Based	Discrete
Deep Q-Network Agents(DQN)	Value-Based	Discrete
SARSA Agents	Value-Based	Discrete
Policy Gradient Agents (PG)	Policy-Based	Discrete or continuous
Actor-Critic Agents (AC)	Actor-Critic	Discrete or continuous
Proximal Policy Optimization Agents (PPO)	Actor-Critic	Discrete or continuous
Deep Deterministic Policy Gradient Agents (DDPG)	Actor-Critic	Continuous
Twin-Delayed Deep Deterministic Policy Gradient Agents (TD3)	Actor-Critic	Continuous
Soft Actor-Critic Agents (SAC)	Actor-Critic	Continuous

定义 Agent

- 使用 *rl*Representation* 定义 Agent 使用的不同策略形式，如 *rlValueRepresentation*, *rlQValueRepresentation*, *rlDeterministicActorRepresentation*, *rlStochasticActorRepresentation*



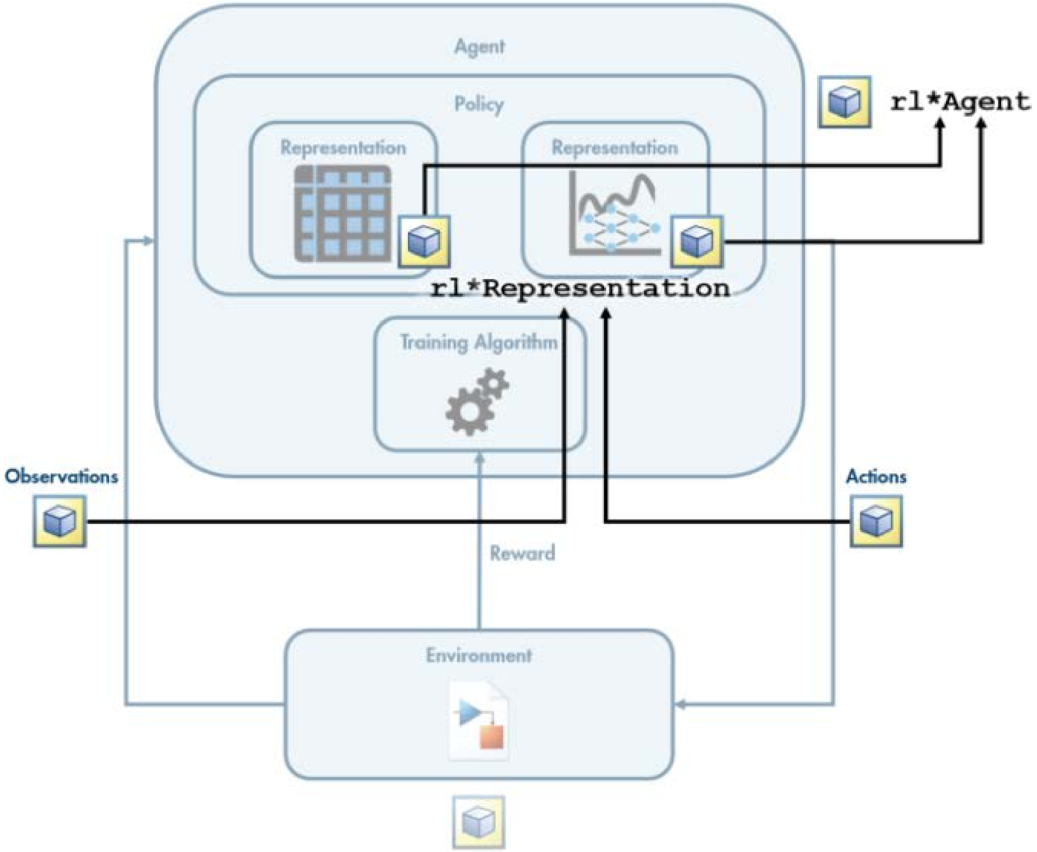
定义 Agent

- 使用 *rl*Representation* 定义 Agent 使用的不同策略形式，不同类型的 Agent 可能需要使用不同的策略形式

Representation	Q, DQN, SARSA	PG	AC, PPO	SAC	DDPG, TD3
Value function critic *V(S)*, which you create using `rlValueRepresentation`		X (if baseline is used)	X		
Q-value function critic *Q(S,A)*, which you create using `rlQValueRepresentation`	X			X	X
Deterministic policy actor *π(S)*, which you create using `rlDeterministicActorRepresentation`					X
Stochastic policy actor *π(S)*, which you create using `rlStochasticActorRepresentation`		X	X	X	

定义 Agent

- 使用定义好的 Observations、Actions 变量定义 Policy， 然后使用 Policy 变量定义 Agent

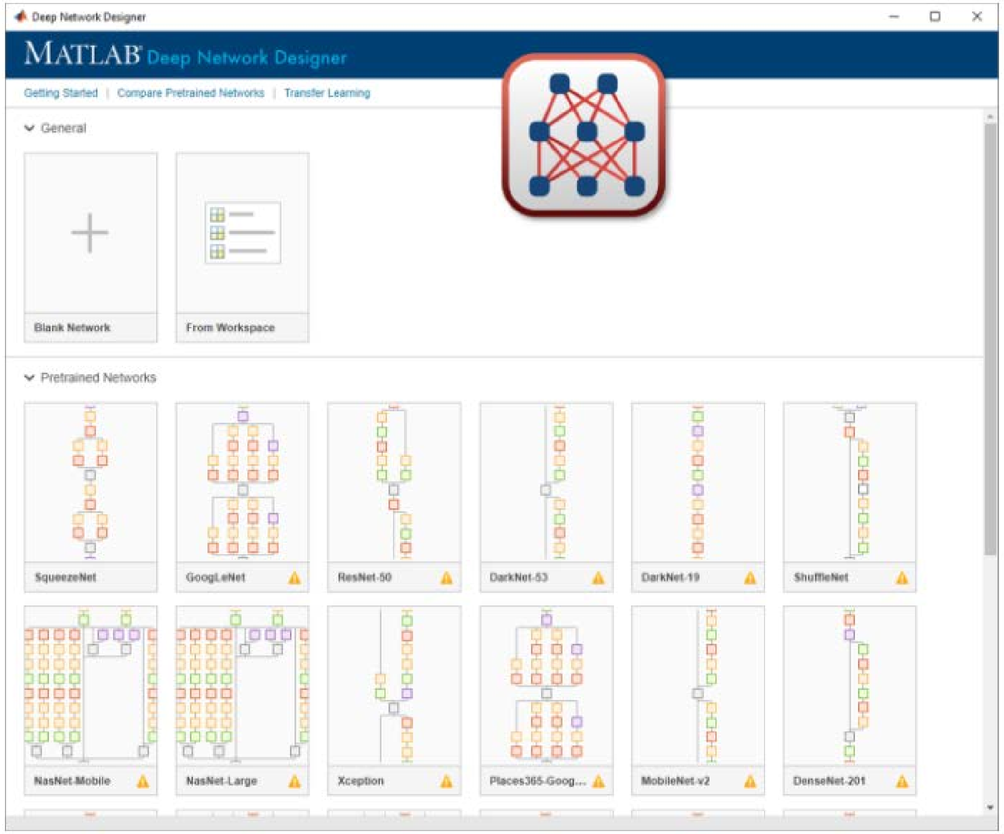


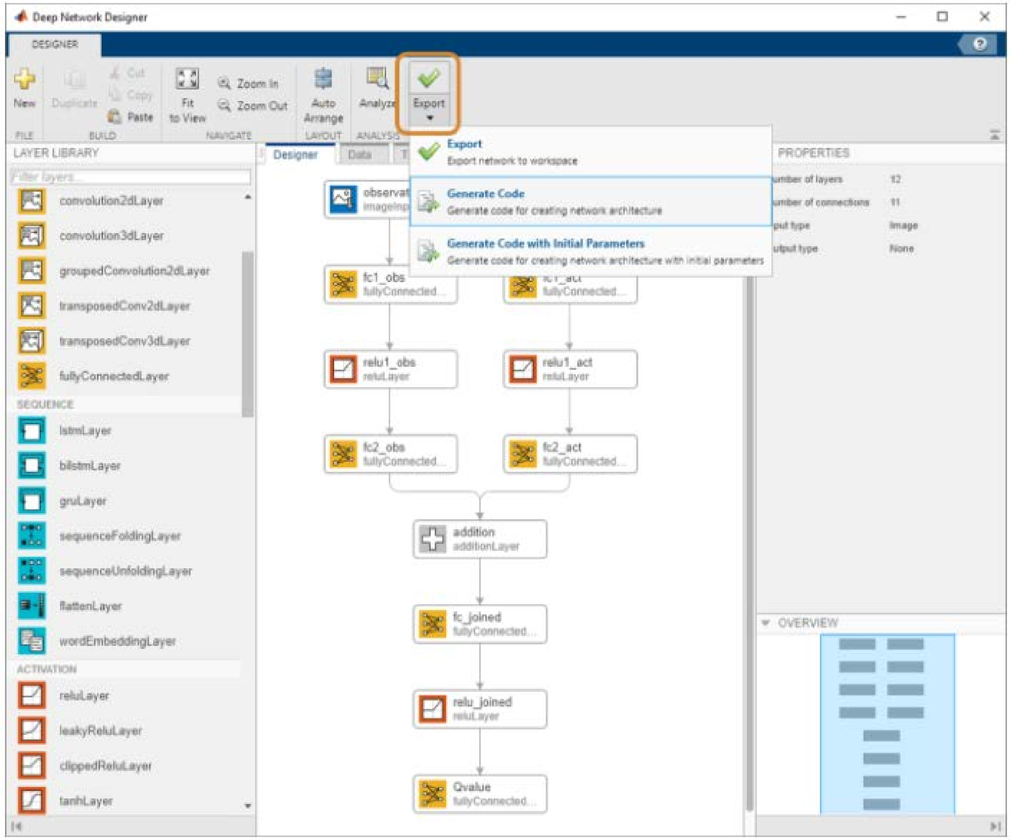
使用 Matlab 进行强化学习

Agent	Actions	Type	Representation(s)
Q-Learning rlQAgent	Discrete	Critic	rlQValueRepresentation
SARSA rlSARSAAgent	Discrete	Critic	rlQValueRepresentation
Deep Q-Network (DQN) rlDQNAgent	Discrete	Critic	rlQValueRepresentation
Policy Gradient rlPGAgent	Discrete or continuous	Actor or Actor-Critic	rlStochasticActorRepresentation (actor) rlValueRepresentation (critic)
Actor-Critic rlACAgent	Discrete or continuous	Actor-Critic	rlStochasticActorRepresentation (actor) rlValueRepresentation (critic)
Deep Deterministic Policy Gradient (DDPG) rlDDPGAgent	Continuous	Actor-Critic	rlDeterministicActorRepresentation (actor) rlQValueRepresentation (critic)
Proximal Policy Optimization (PPO) rlPPOAgent	Discrete or continuous	Actor-Critic	rlStochasticActorRepresentation (actor) rlValueRepresentation (critic)
Twin-Delayed Deep Deterministic Policy Gradient (TD3) rlTD3Agent	Continuous	Actor-Critic	rlDeterministicActorRepresentation (actor) rlQValueRepresentation (critic)
Soft Actor-Critic (SAC) rlSACAgent	Continuous	Actor-Critic	rlStochasticActorRepresentation (actor) rlQValueRepresentation (critic)

定义 Agent

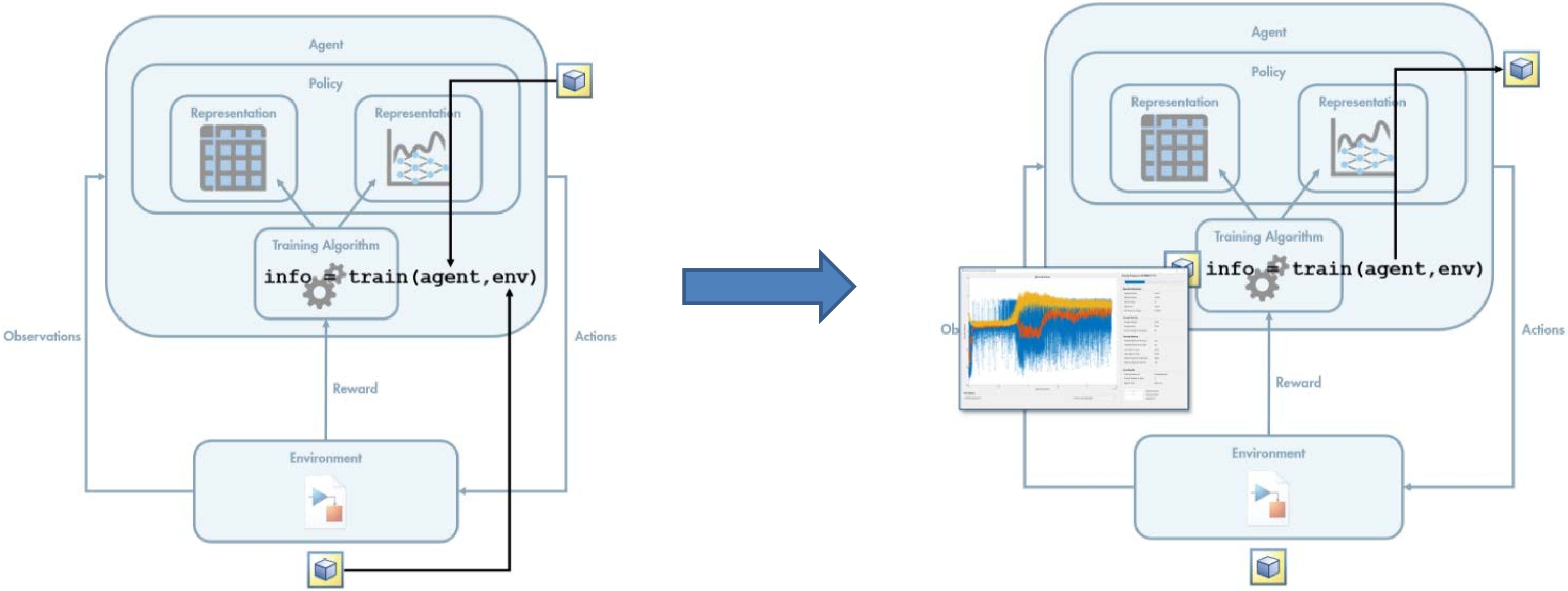
- Deep Network Designer





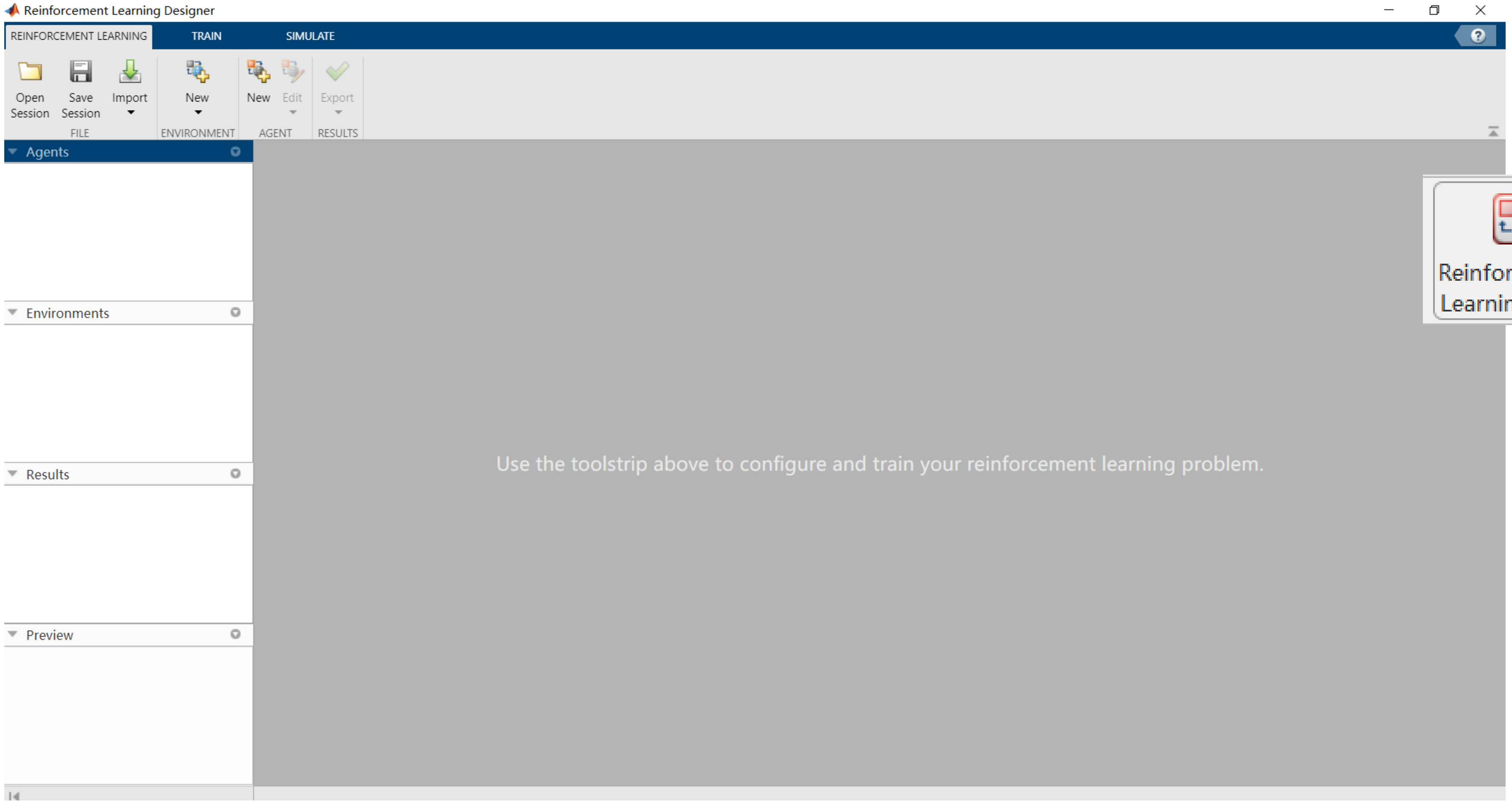
训练

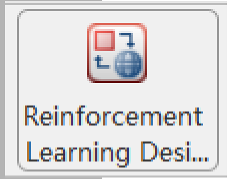
- 定义好环境和 Agent 之后，传入 *train* 进行训练，Agent 在训练过程中直接会被改变，输出为训练过程中产生的信息。训练结束以后可以使用 sim 进行模拟验证。



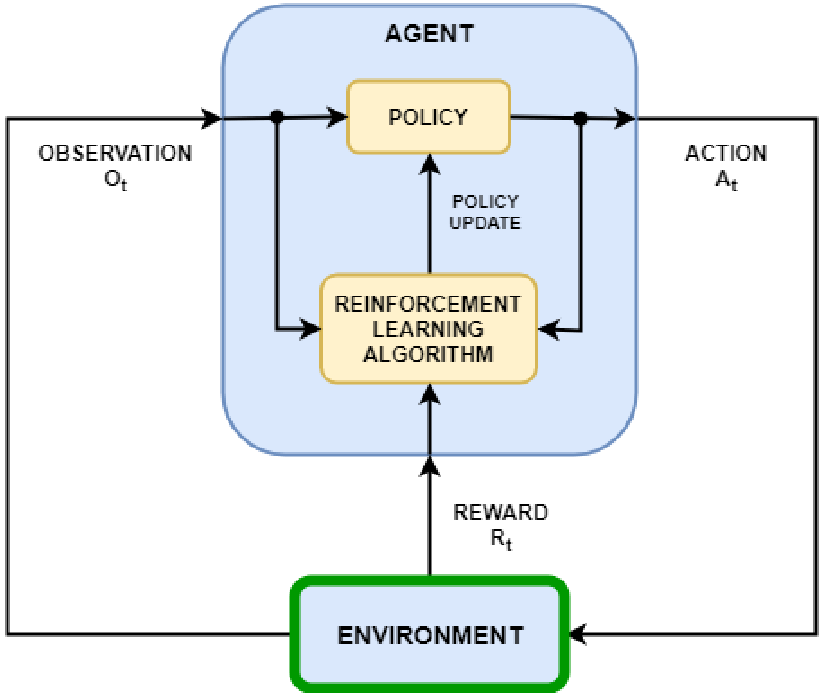
训练

■ Reinforcement Learning Designer



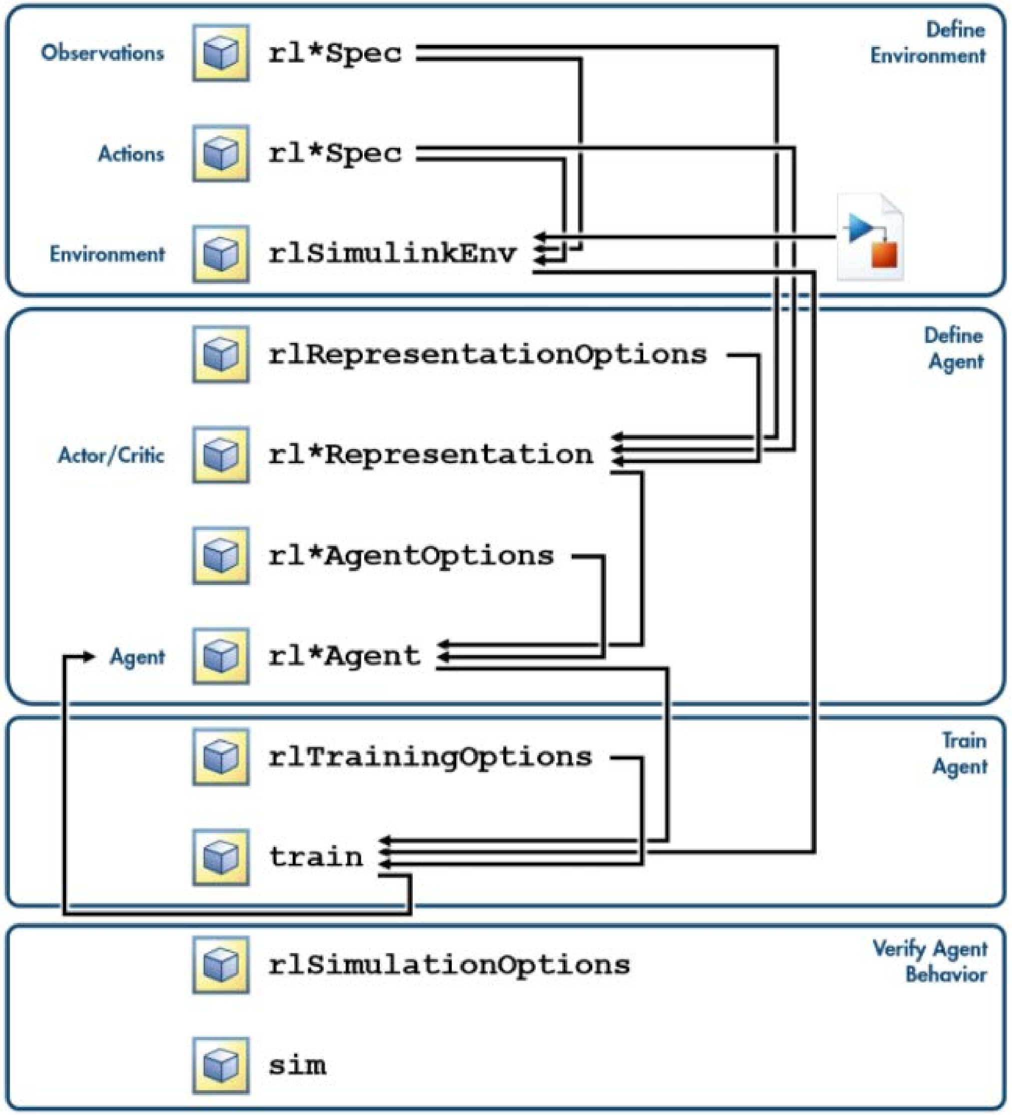


总结


AGENT
POLICY
OBSERVATION
O_t
ACTION
A_t
POLICY
UPDATE
REINFORCEMENT
LEARNING
ALGORITHM
REWARD
R_t
ENVIRONMENT


Define Environment
Set Agent Options
Define Agent
Train Agent
Evaluate Agent

总结


Observations
rl*Spec
Actions
rl*Spec
Environment
rlSimulinkEnv
Define Environment
rlRepresentationOptions
Actor/Critic
rl*Representation
rl*AgentOptions
Agent
rl*Agent
Define Agent
rlTrainingOptions
train
Train Agent
rlSimulationOptions
sim
Verify Agent Behavior

总结

	Functions	Options
Interface	rlFiniteSetSpec rlNumericSpec	
Environment	rlSimulinkEnv	
Representations (Actors & Critics)	rlQValueRepresentation rlValueRepresentation rlDeterministicActorRepresentation rlStochasticActorRepresentation	rlRepresentationOptions
Agents	rlQAgent rlSARSAAgent rlDQNAgent rlPGAgent rlACAgent rlPPOAgent rlDDPGAgent rlTD3Agent rlSACAgent	rlQAgentOptions rlSARSAAgentOptions rlDQNAgentOptions rlPGAgentOptions rlACAgentOptions rlPPOAgentOptions rlDDPGAgentOptions rlTD3AgentOptions rlSACAgentOptions
Training	train	rlTrainingOptions
Simulation	sim	rlSimulationOptions

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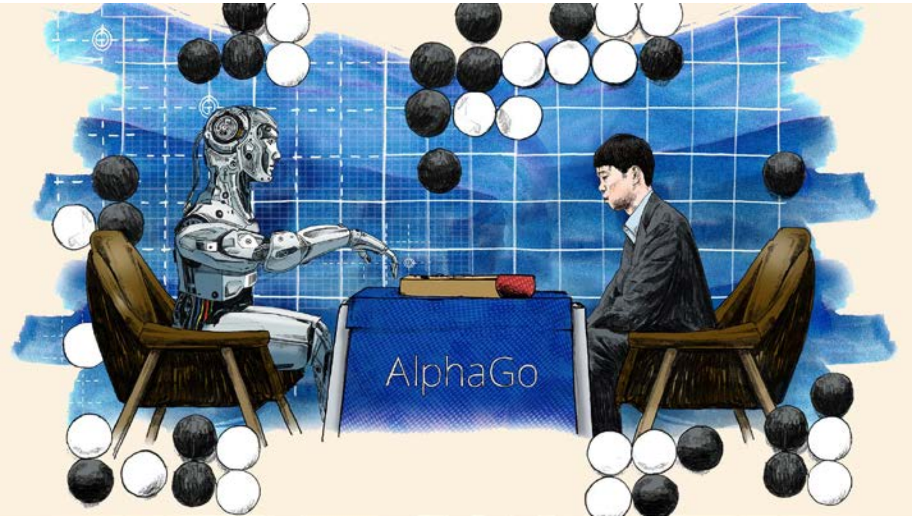
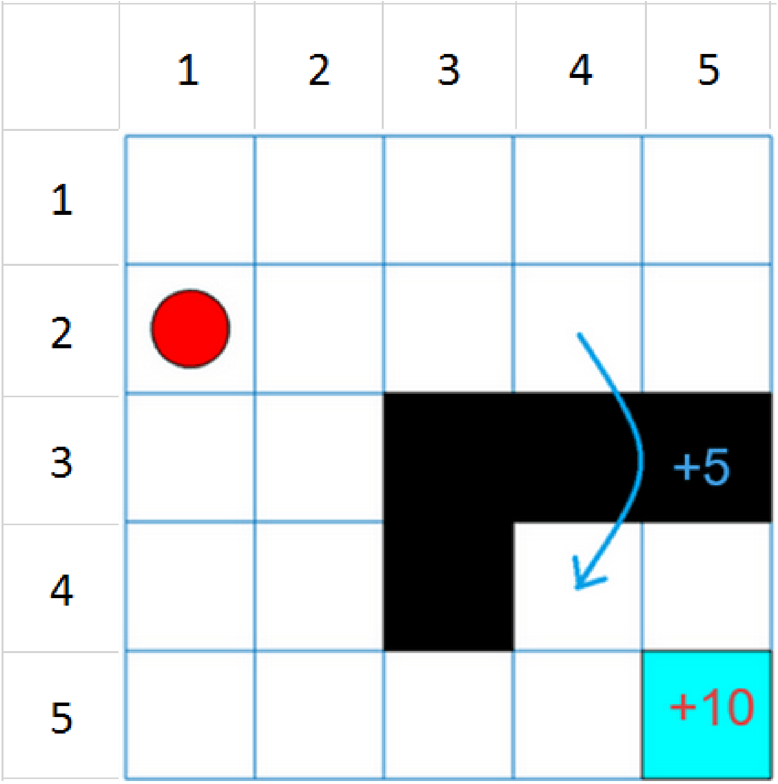


基础网格系统（Basic Grid World）

■ Agent 的目标是尽可能获得最大的分数

1. The grid world is 5-by-5 and bounded by borders, with four possible actions (North = 1, South = 2, East = 3, West = 4).
2. The agent begins from cell [2,1] (second row, first column).
3. The agent receives a reward +10 if it reaches the terminal state at cell [5,5] (blue).
4. The environment contains a special jump from cell [2,4] to cell [4,4] with a reward of +5.
5. The agent is blocked by obstacles (black cells).
6. All other actions result in –1 reward.

```
env = rlPredefinedEnv("BasicGridWorld");
```



基础网格系统（Actions & Observations）

■ Agent 可以产生往东、南、西、北四个方向走的动作

(North = 1, South = 2, East = 3, West = 4)

```
actionInfo =
  rlFiniteSetSpec - 属性:

       Elements: [4×1 double]
           Name: "MDP Actions"
    Description: [0×0 string]
      Dimension: [1 1]
       DataType: "double"
```

■ Agent 可以观测到方块位于 25 个网格中的哪一个网格

```
obsInfo =
  rlFiniteSetSpec - 属性:

       Elements: [25×1 double]
           Name: "MDP Observations"
    Description: [0×0 string]
      Dimension: [1 1]
       DataType: "double"
```

基础网格系统（Reward）

- Reward 由事先规定好的规则给出

3. The agent receives a reward +10 if it reaches the terminal state at cell [5,5] (blue).
4. The environment contains a special jump from cell [2,4] to cell [4,4] with a reward of +5.
5. The agent is blocked by obstacles (black cells).
6. All other actions result in −1 reward.

基础网格系统（Agent）

- 场景较简单，状态、动作数量不多，采用 QTable 的策略形式即可

```
%% define agent
qTable = rlTable(getObservationInfo(env),getActionInfo(env));
qRepresentation = rlQValueRepresentation(qTable,getObservationInfo(env),getAc
tionInfo(env));
qRepresentation.Options.LearnRate = 1;
agentOpts = rlQAgentOptions;
agentOpts.EpsilonGreedyExploration.Epsilon = .04;
qAgent = rlQAgent(qRepresentation,agentOpts);
```

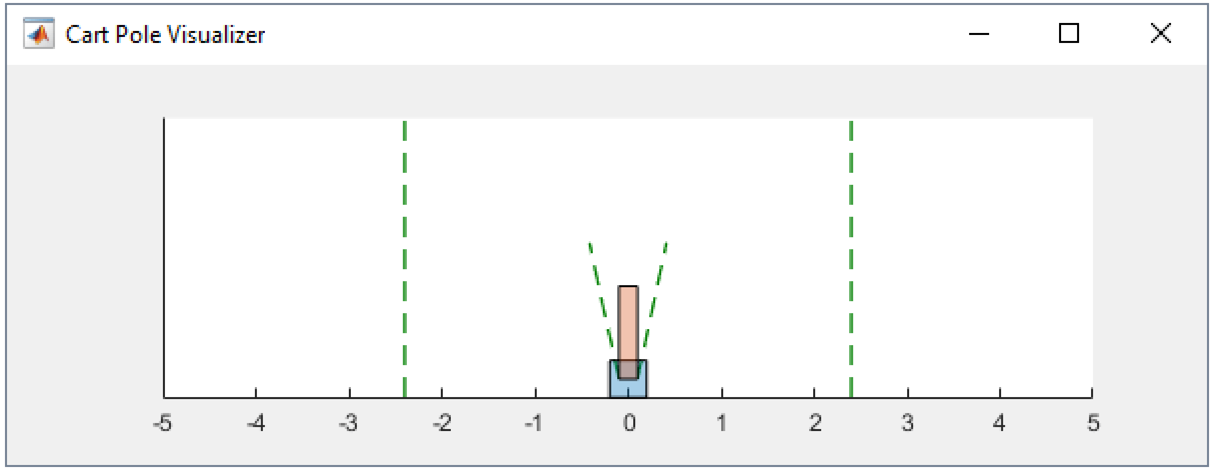
基础网格系统（训练）

```
%% train agent
trainOpts = rlTrainingOptions;
trainOpts.MaxStepsPerEpisode = 50;
trainOpts.MaxEpisodes= 200;
trainOpts.StopTrainingCriteria = "AverageReward";
trainOpts.StopTrainingValue = 11;
trainOpts.ScoreAveragingWindowLength = 30;
trainingStats = train(qAgent,env,trainOpts);
```

车杆系统（Cart-Pole）

- Agent 的目标是通过在移动的小车上施加水平方向上的力来保持杆的平衡
- 平衡条件 1： 杆的角度保持在给定范围内
- 平衡条件2： 小车的位置保持在给定范围内

```
env = rlPredefinedEnv("CartPole-Discrete");
```



车杆系统（环境）

Environment Properties

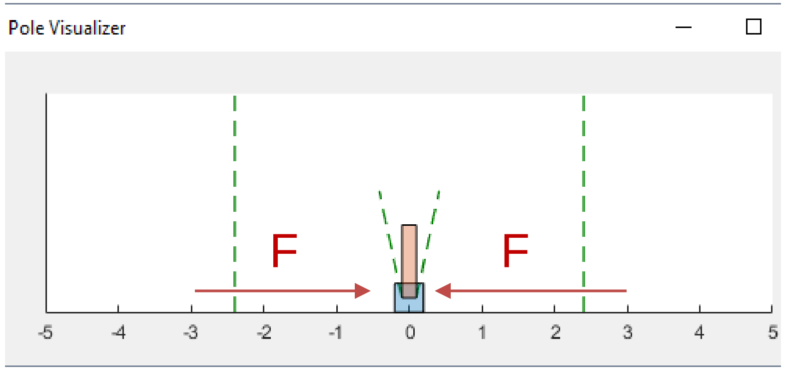
Property	Description	Default
`Gravity`	Acceleration due to gravity in meters per second	`9.8`
`MassCart`	Mass of the cart in kilograms	`1`
`MassPole`	Mass of the pole in kilograms	`0.1`
`Length`	Half the length of the pole in meters	`0.5`
`MaxForce`	Maximum horizontal force magnitude in newtons	`10`
`Ts`	Sample time in seconds	`0.02`
`ThetaThresholdRadians`	Pole angle threshold in radians	`0.2094`
`XThreshold`	Cart position threshold in meters	`2.4`
`RewardForNotFalling`	Reward for each time step the pole is balanced	`1`
`PenaltyForFalling`	Reward penalty for failing to balance the pole	Discrete — `-5` Continuous — `-50`
`State`	Environment state, specified as a column vector with the following state variables: • Cart position • Derivative of cart position • Pole angle • Derivative of pole angle	`[0 0 0 0]'`

车杆系统（Actions）

■ Agent 通过施加一个水平方向上的力与环境进行交互

```
actInfo =
  rlFiniteSetSpec - 属性:

      Elements: [-10 10]
          Name: "CartPole Action"
   Description: [0×0 string]
     Dimension: [1 1]
      DataType: "double"
```

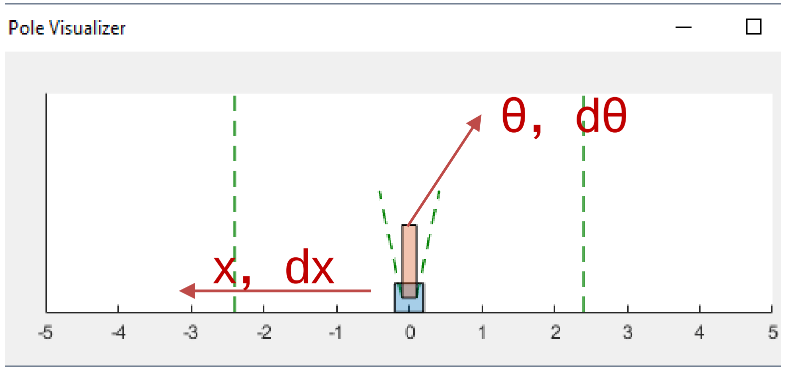


车杆系统（Observations）

- Agent 能够获取环境的所有状态值

```
obsInfo =
  rlNumericSpec - 属性:

    LowerLimit: -Inf
    UpperLimit: Inf
          Name: "CartPole States"
   Description: "x, dx, theta, dtheta"
     Dimension: [4 1]
      DataType: "double"
```



车杆系统（Reward）

- Reward 信号由两个部分组成：
- Positive reward：在一个步长下，杆的偏移没有超过边界
- Negative penalty：在一个步长下，杆或者车的偏移超过边界

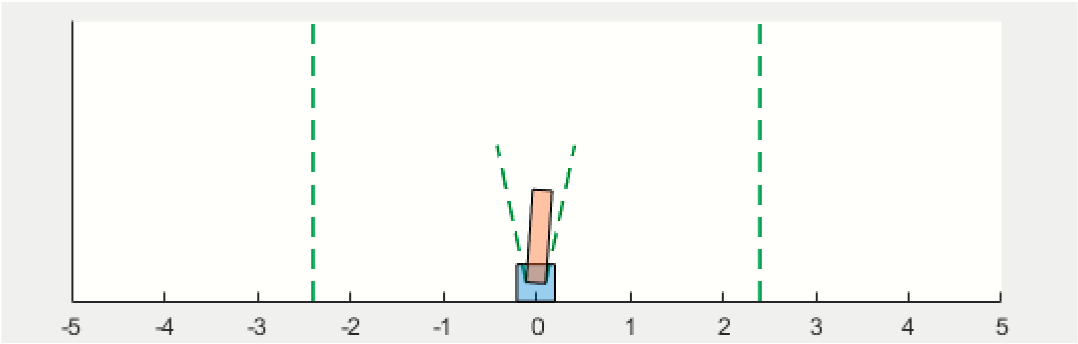
`RewardForNotFalling`	Reward for each time step the pole is balanced	`1`
`PenaltyForFalling`	Reward penalty for failing to balance the pole	Discrete — `-5` Continuous — `-50`

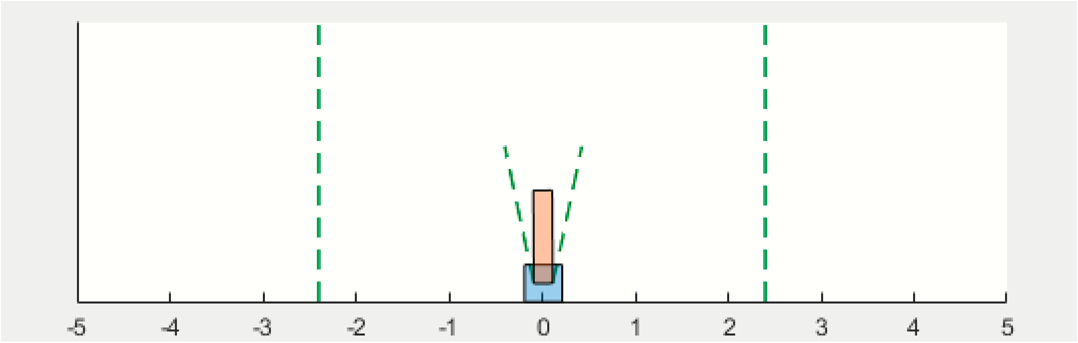
车杆系统（Agent）

```
%% critic
criticNetwork = [
    featureInputLayer(4,'Normalization','none','Name','state')
    fullyConnectedLayer(1,'Name','CriticFC')];
criticOpts = rlRepresentationOptions('LearnRate',8e-3,'GradientThreshold',1);
critic = rlValueRepresentation(criticNetwork,obsInfo,'Observation',{'state'},criticOpts);
%% actor
actorNetwork = [
    featureInputLayer(4,'Normalization','none','Name','state')
    fullyConnectedLayer(2,'Name','fc')
    softmaxLayer('Name','actionProb')];
actorOpts = rlRepresentationOptions('LearnRate',8e-3,'GradientThreshold',1);
actor = rlStochasticActorRepresentation(actorNetwork,obsInfo,actInfo,...
    'Observation',{'state'},actorOpts);
%% agent
agentOpts = rlACAgentOptions(...
    'NumStepsToLookAhead',32, ...
    'DiscountFactor',0.99);
agent = rlACAgent(actor,critic,agentOpts);
```

车杆系统（训练）

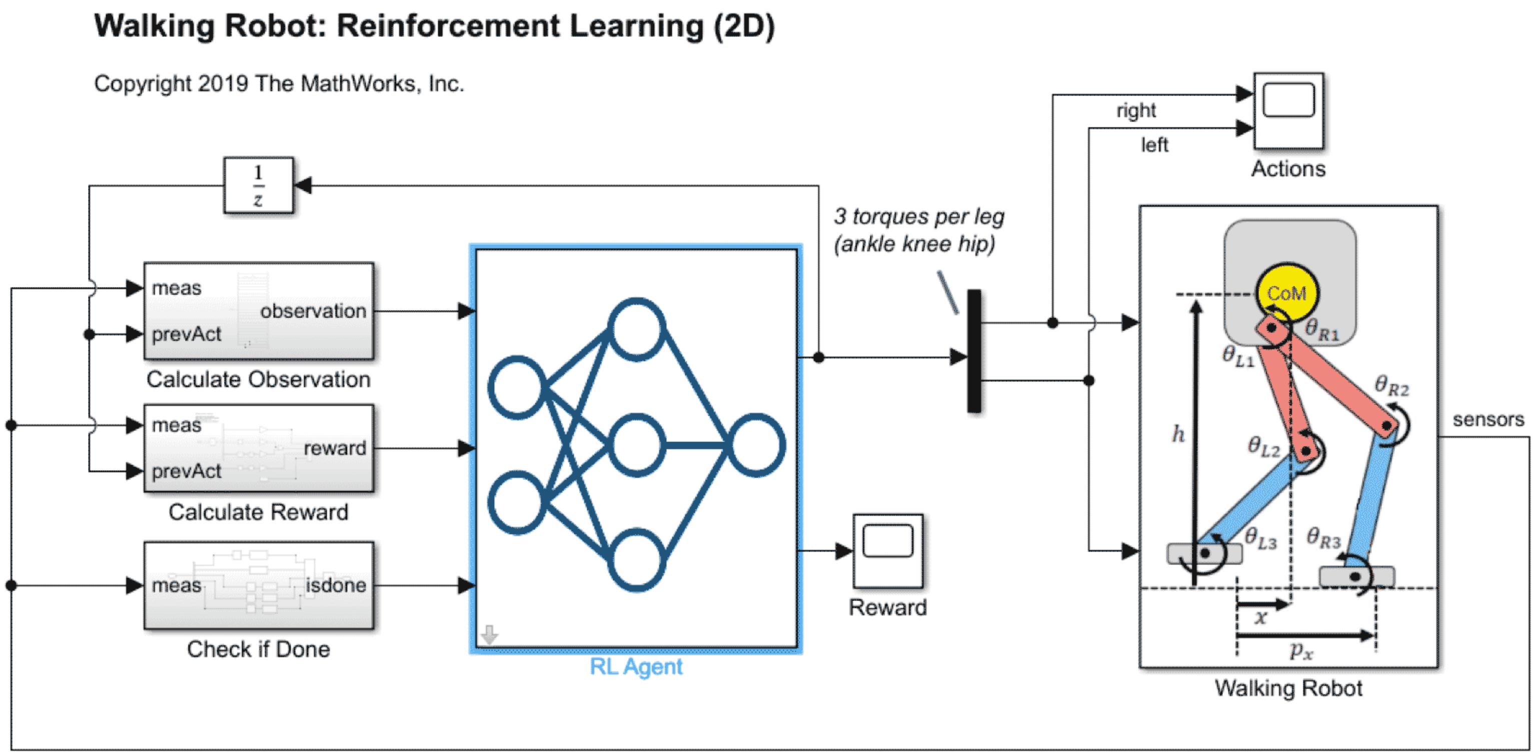
```
%% Train the agent
trainOpts = rlTrainingOptions(...
    'MaxEpisodes',1000,...
    'MaxStepsPerEpisode',500,...
    'Verbose',false,...
    'Plots','training-progress',...
    'StopTrainingCriteria','AverageReward',...
    'StopTrainingValue',480,...
    'ScoreAveragingWindowLength',10);
plot(env)
trainingStats = train(agent,env,trainOpts);
```



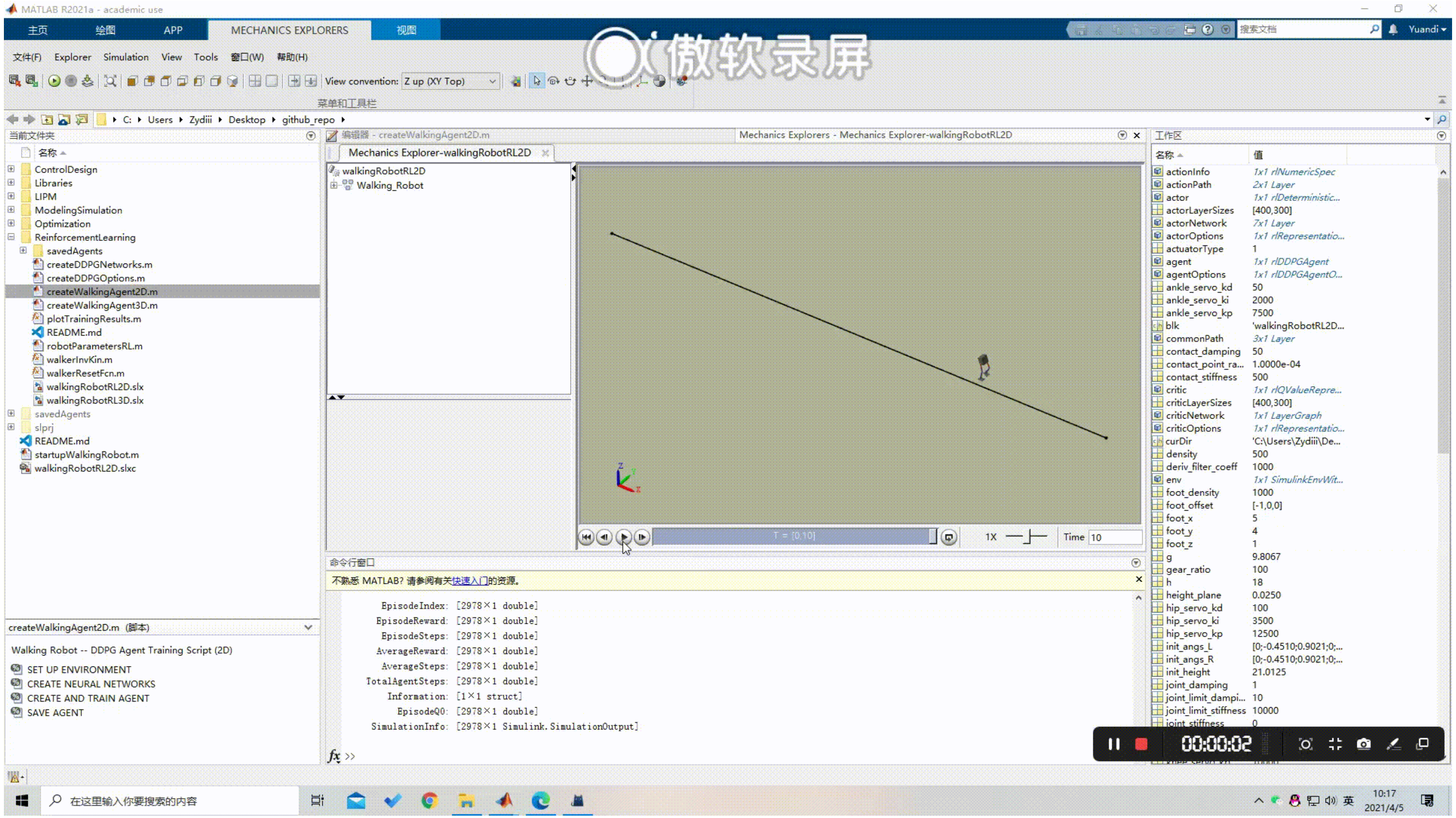


拓展——行走机器人（Walking Robot）

■ Agent 的目标是机器人能够保持身体平衡，在行走过程中不摔倒，同时移动速度尽可能快



拓展——行走机器人（Walking Robot）



学习资料

- Deep Reinforcement Learning for Walking Robots
  https://www.mathworks.com/videos/deep-reinforcement-learning-for-walking-robots--1551449152203.html
- Reinforcement Learning Onramp
  https://www.mathworks.com/learn/tutorials/reinforcement-learning-onramp.html
- Reinforcement Learning Toolbox
  https://www.mathworks.com/products/reinforcement-learning.html
- Reinforcement Learning: A Brief Guide
  https://ww2.mathworks.cn/company/newsletters/articles/reinforcement-learning-a-brief-guide.html?s_tid=srchtitle
- Reinforcement Learning Toolbox Help
  https://ww2.mathworks.cn/help/reinforcement-learning/

Question & Answer

任何疑问和建议，请不要犹豫！

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