

MATLAB EXPO

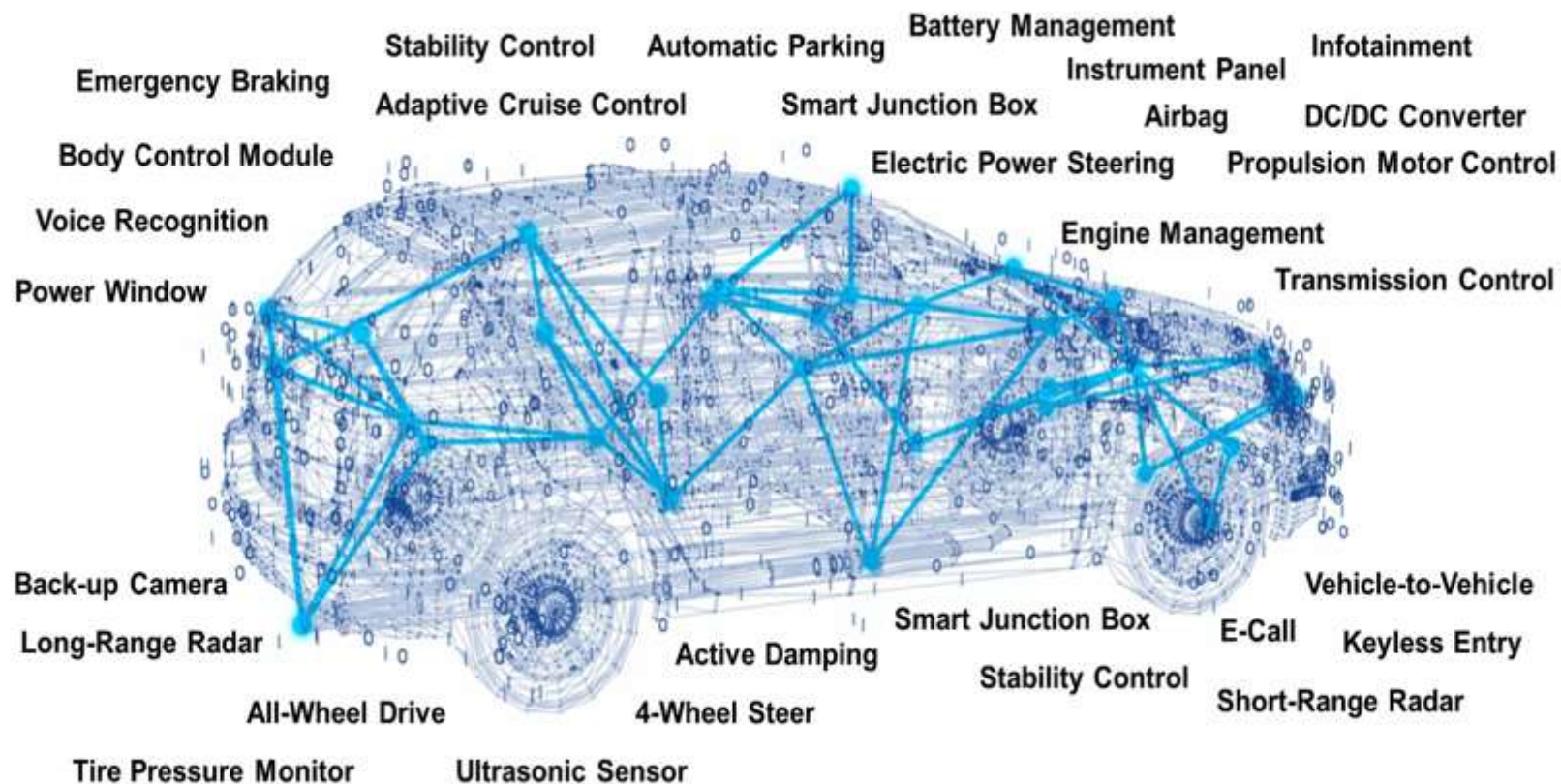
AI不同，择与为谋：MathWorks助你跨学科深度创新
袁航，MathWorks应用工程师



内容概要

- 机械、电子、自动化与人工智能的跨学科应用场景
- 在 MATLAB 中实现基于强化学习的自主系统设计

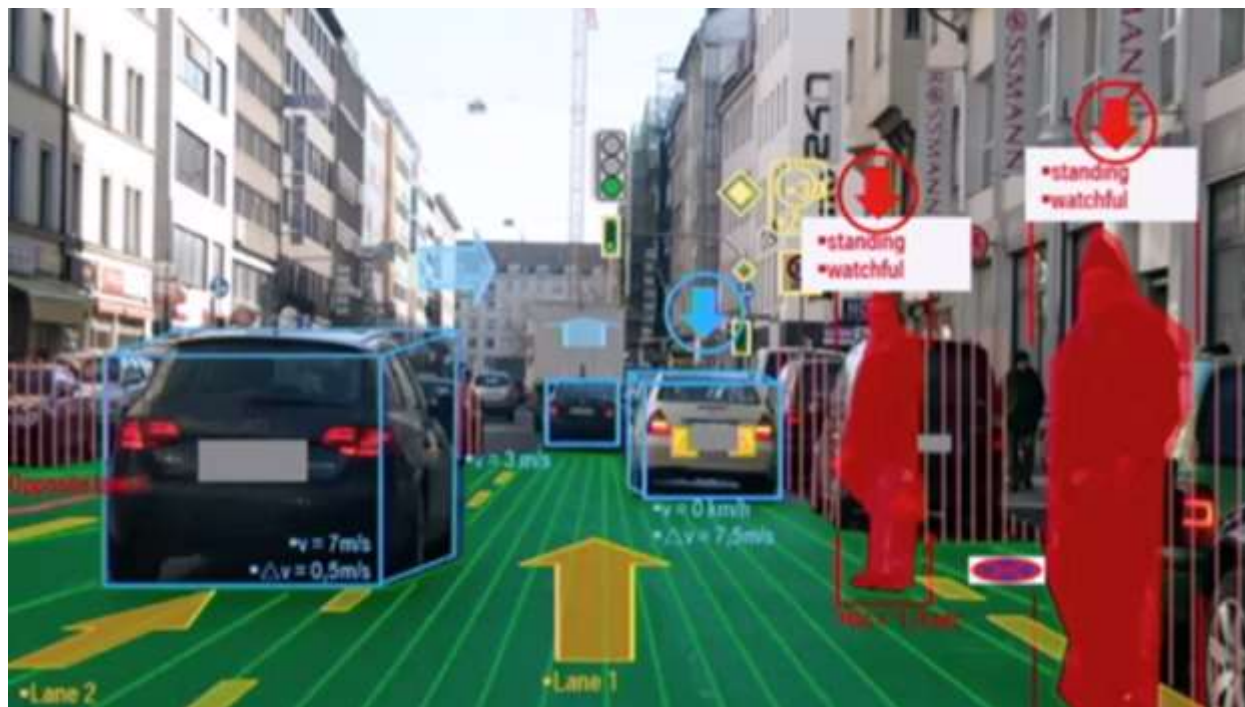
嵌入式软件的普及



数字变革

人工智能的渗透

数据驱动算法
机器学习和深度学习
自主系统





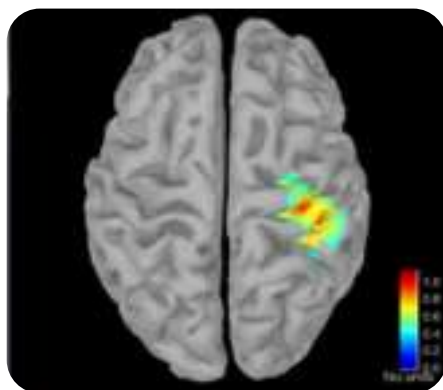
机器人



自动驾驶



机器学习



医药创新

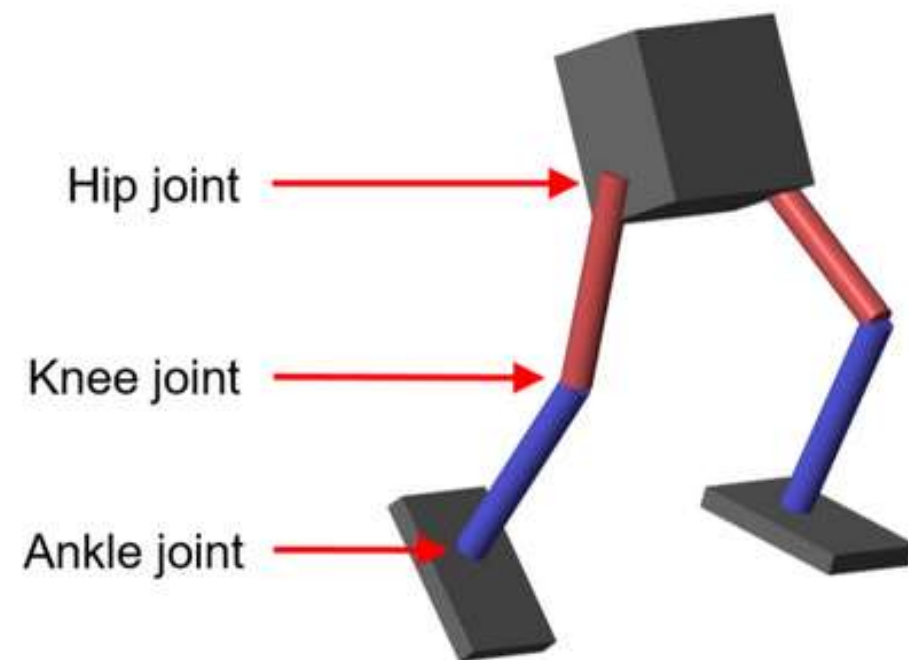
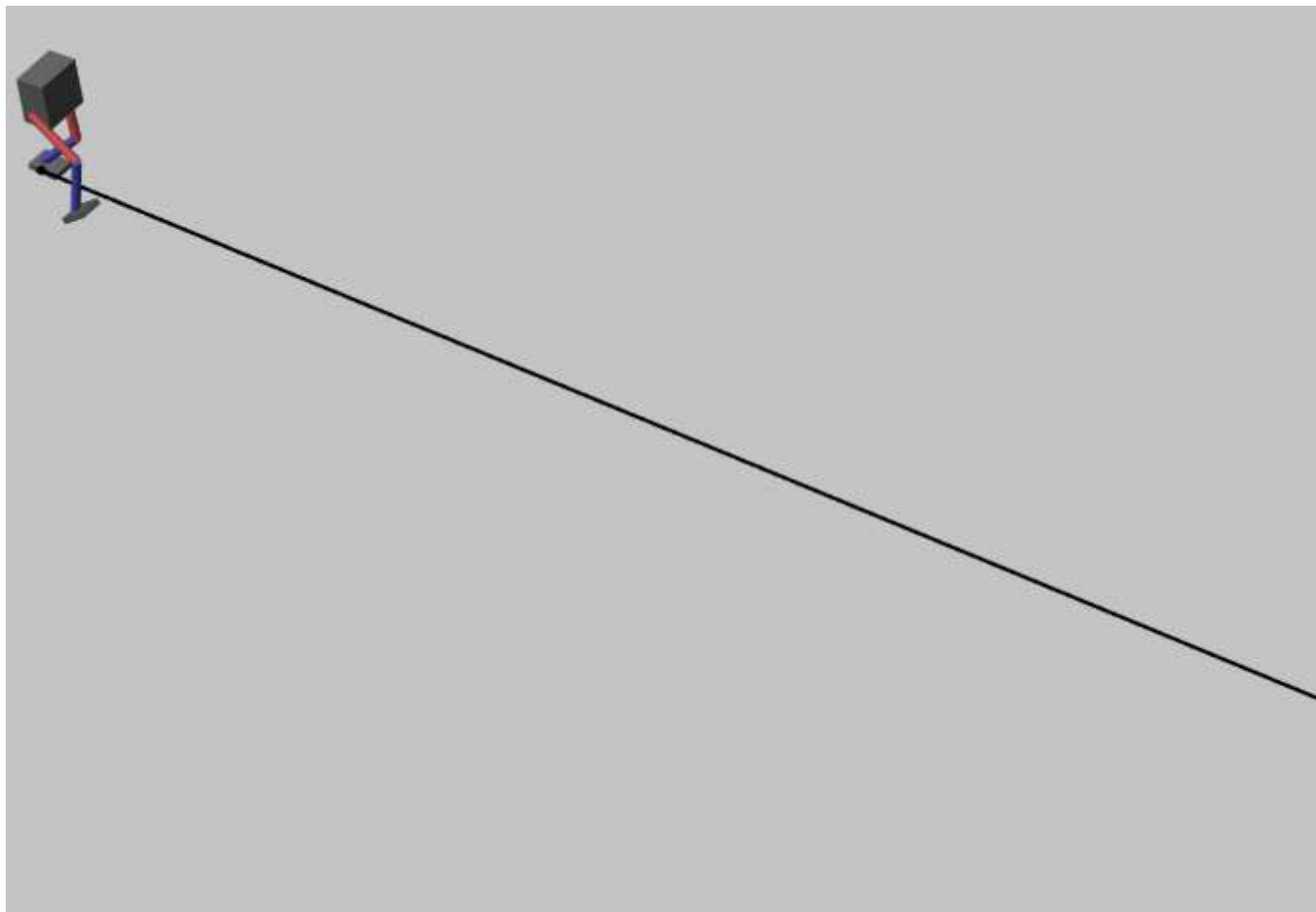


物联网

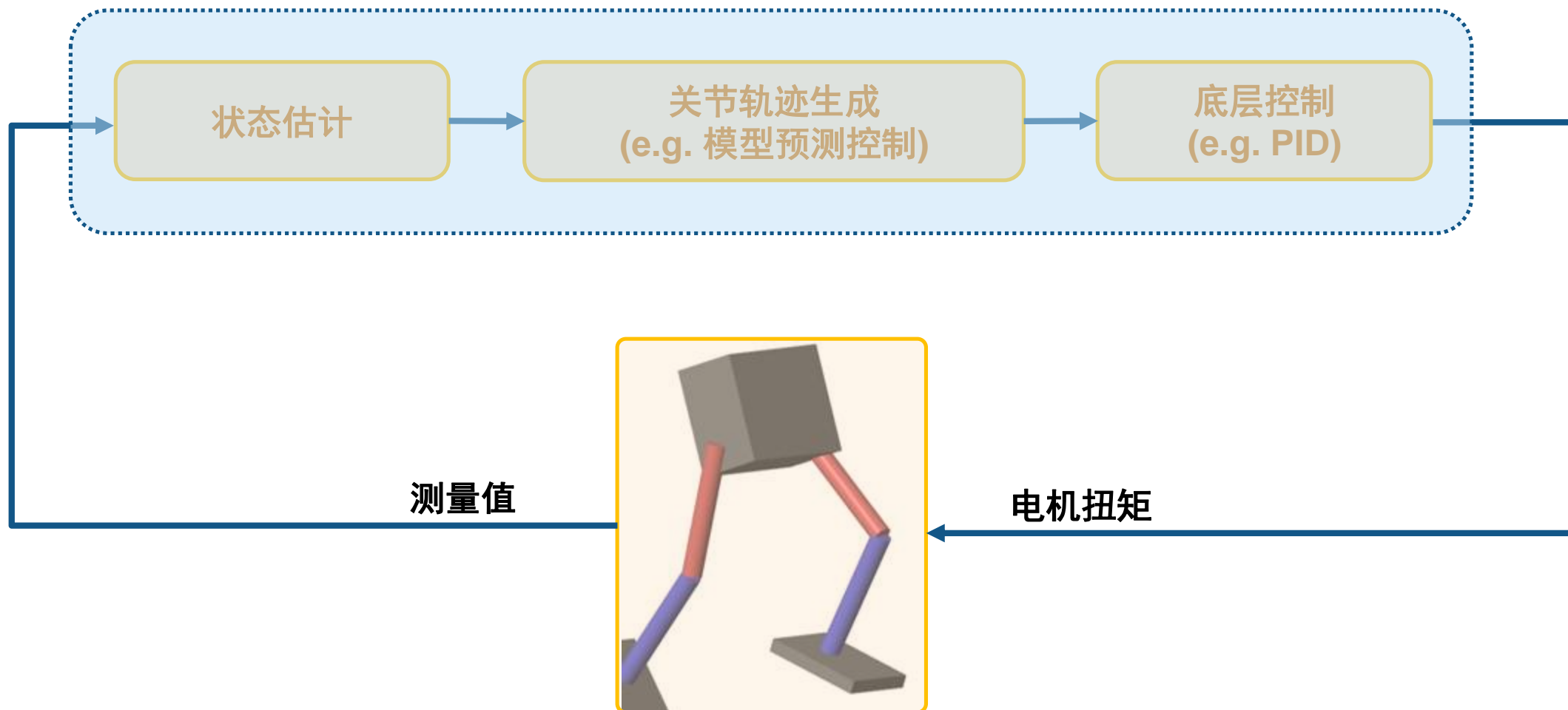
如何培养未来的科学家和工程师？

机械、电子、自动化与人工智能的跨学科应用场景

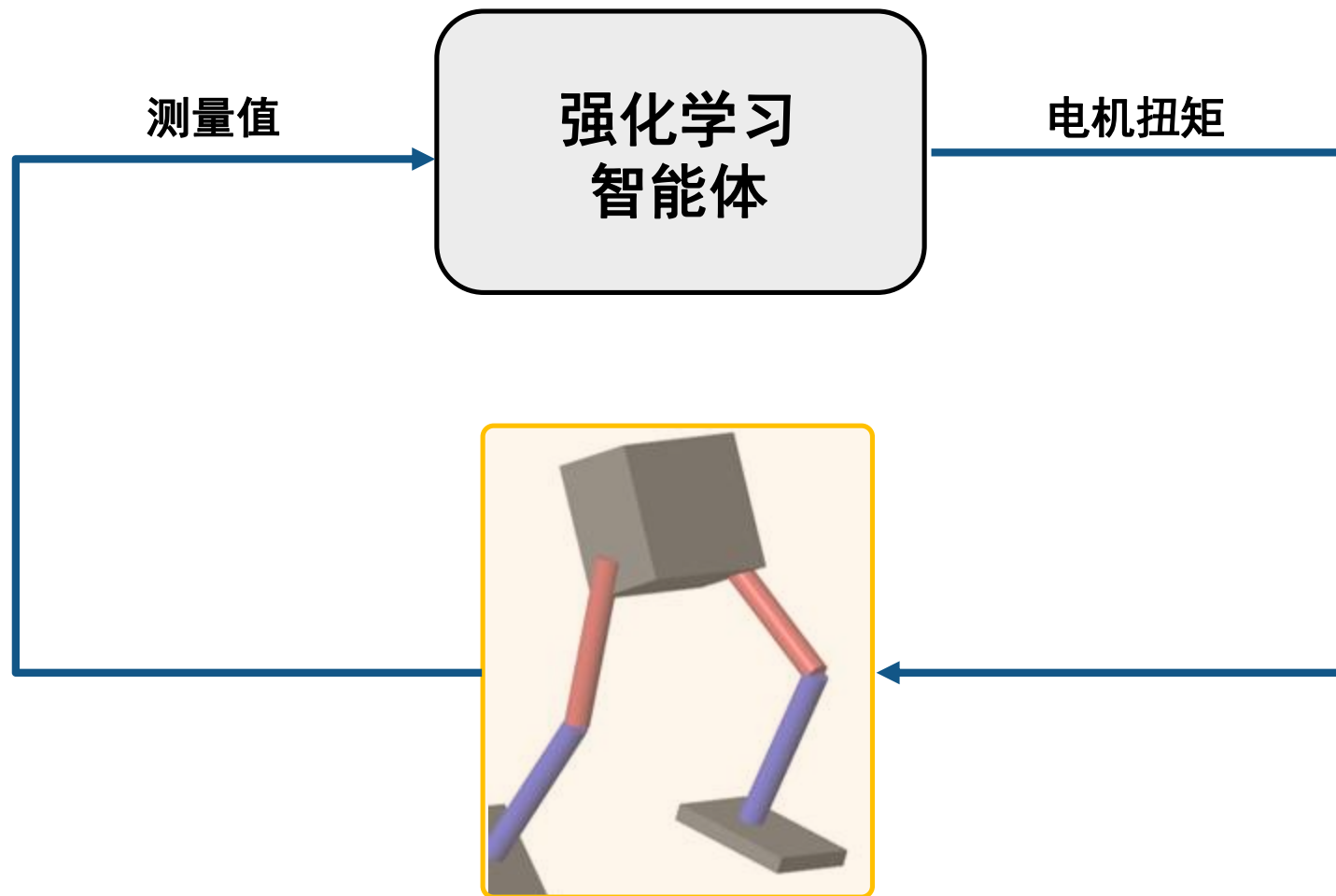
人工智能的跨学科应用场景 —— 双足机器人行走控制



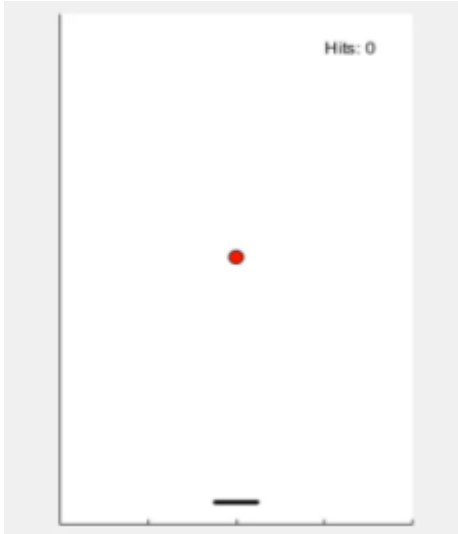
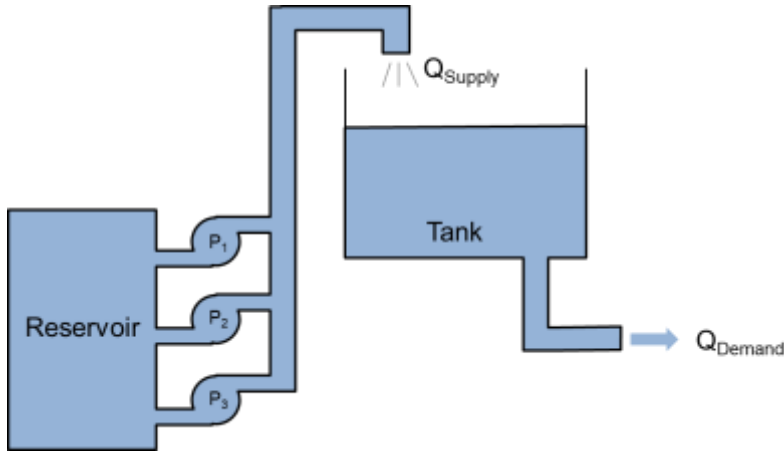
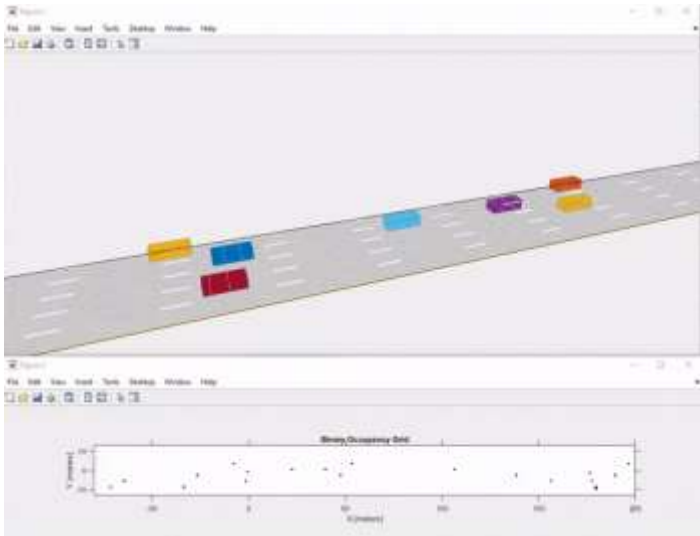
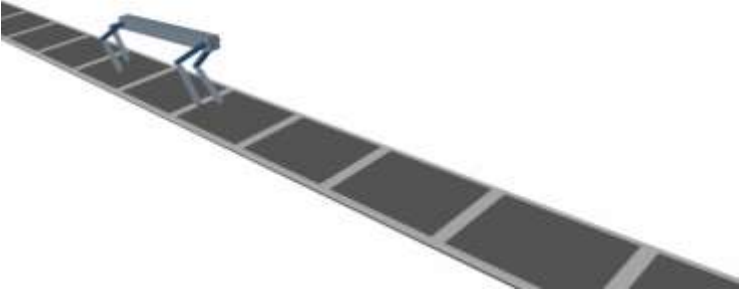
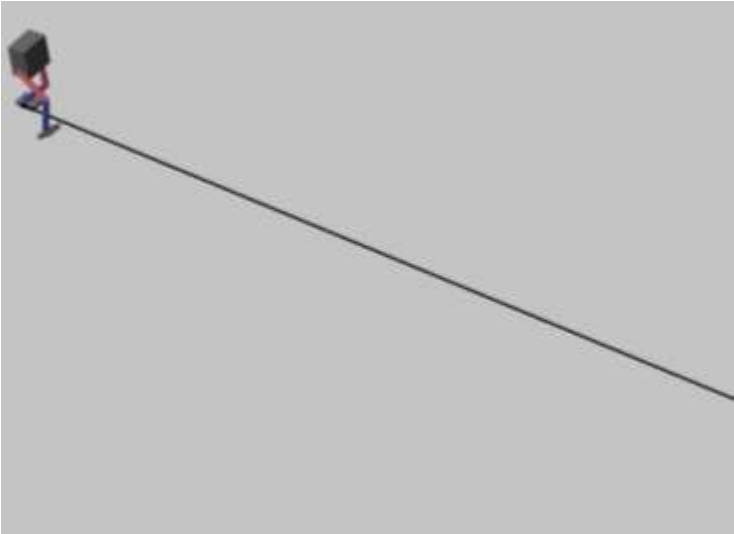
传统学科研究方向



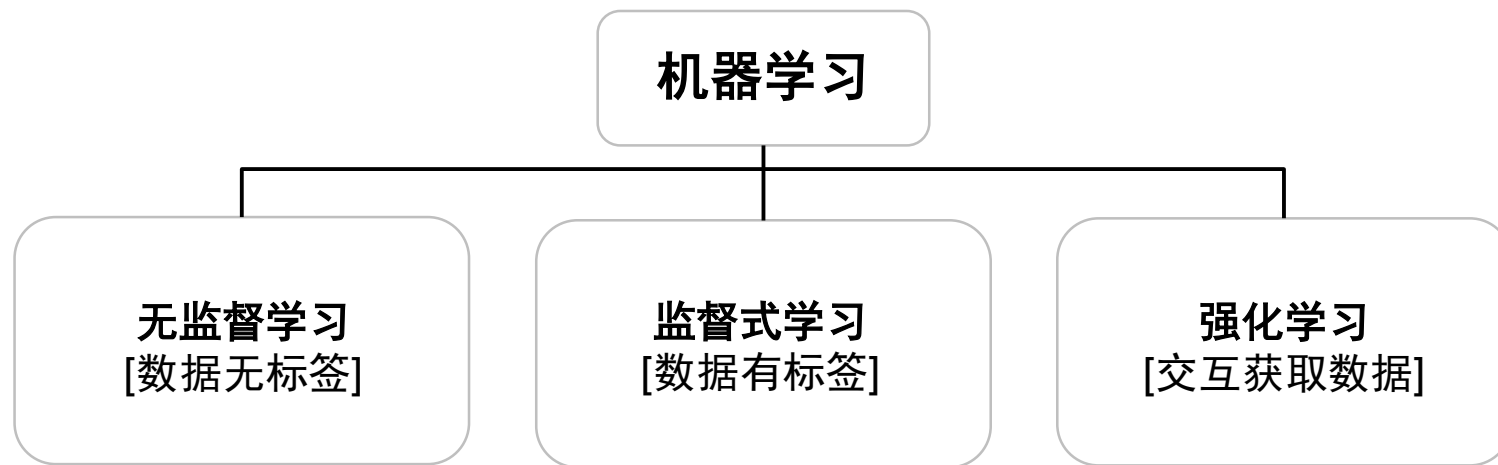
基于强化学习的双足机器人行走控制



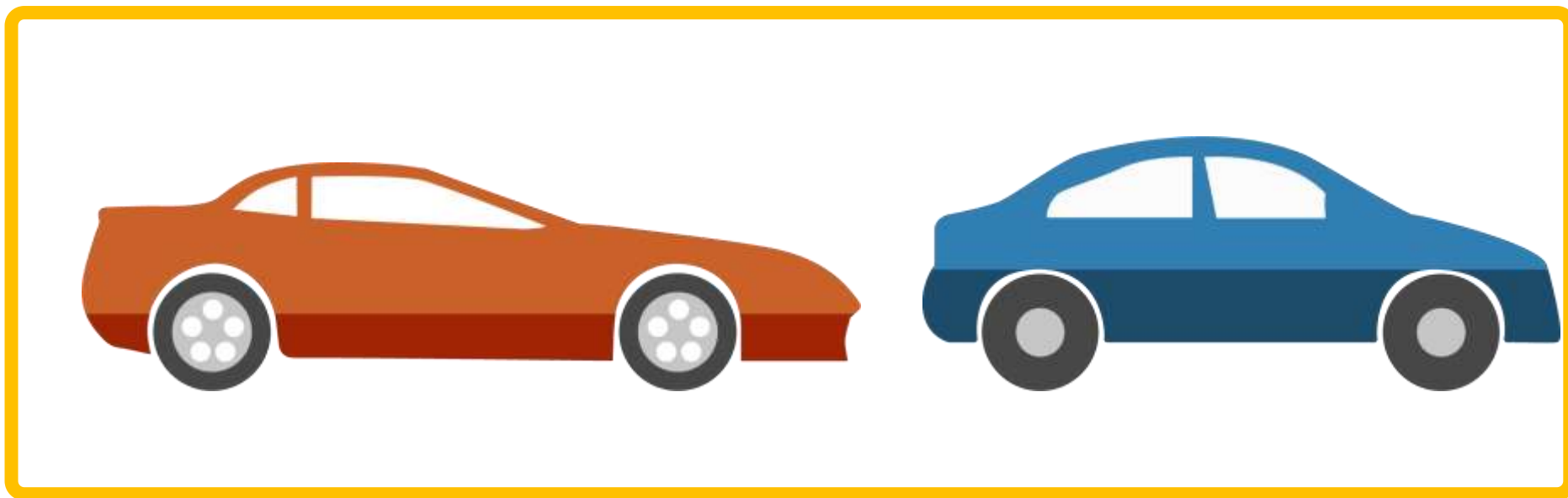
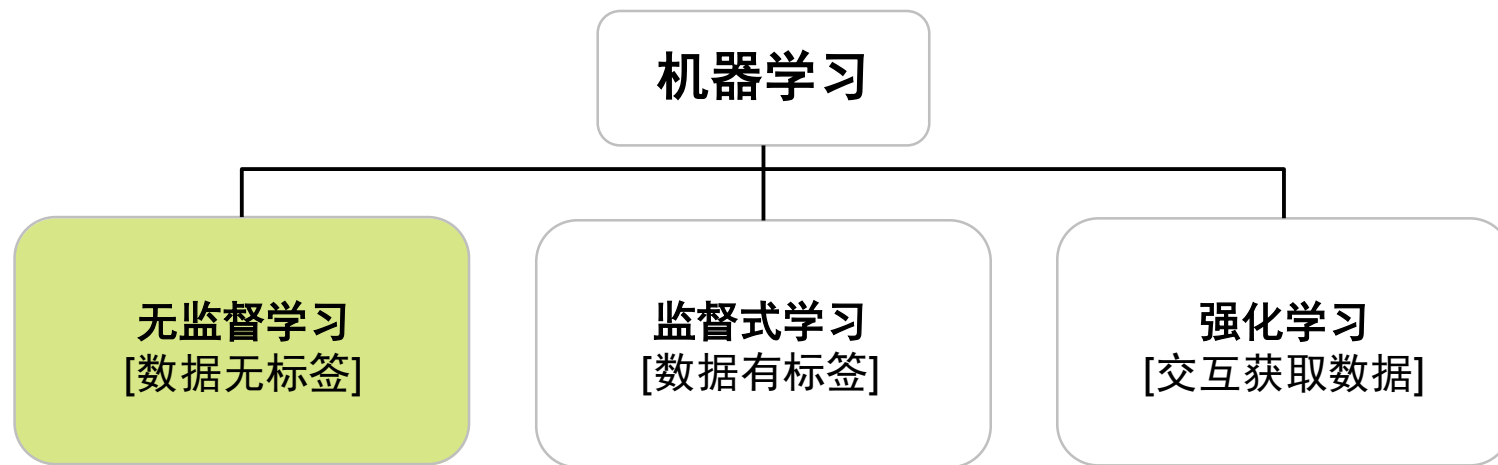
强化学习应用领域



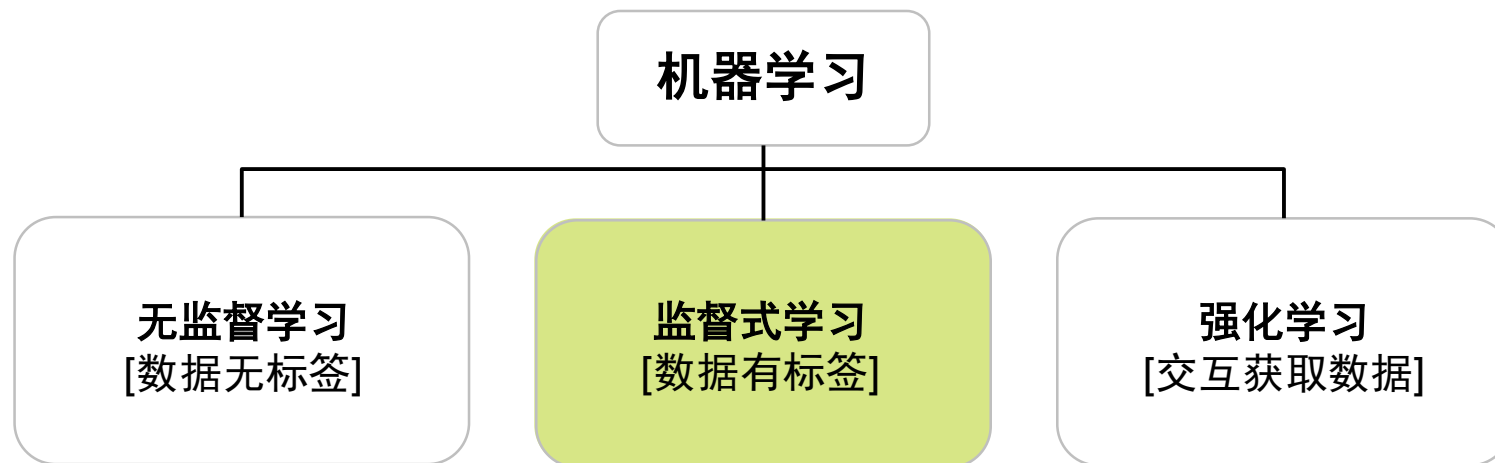
强化学习、机器学习、深度学习



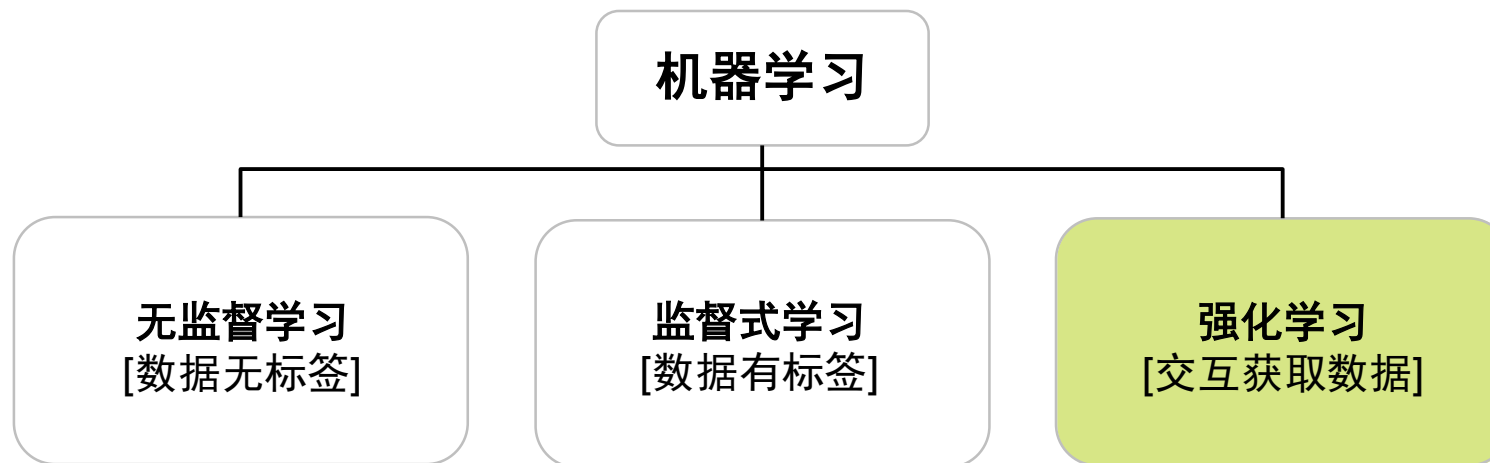
强化学习、机器学习、深度学习



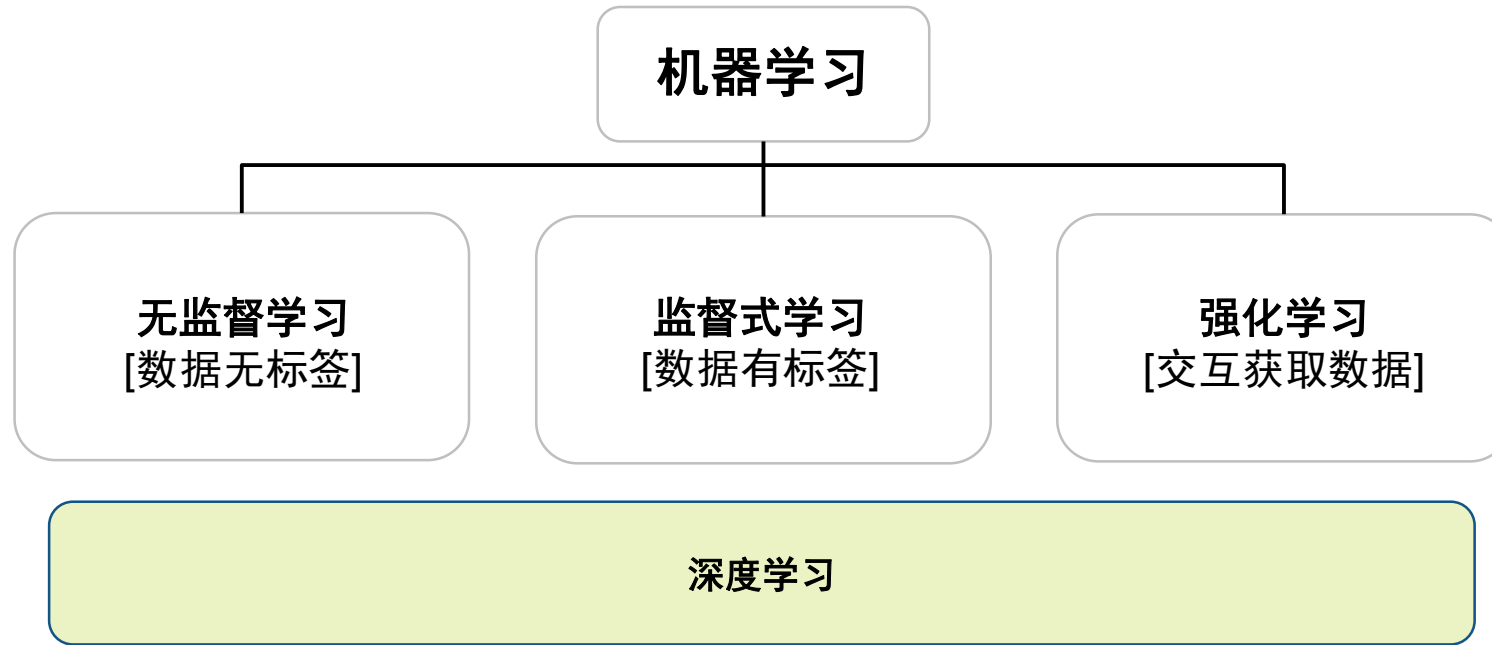
强化学习、机器学习、深度学习



强化学习、机器学习、深度学习



强化学习、机器学习、深度学习

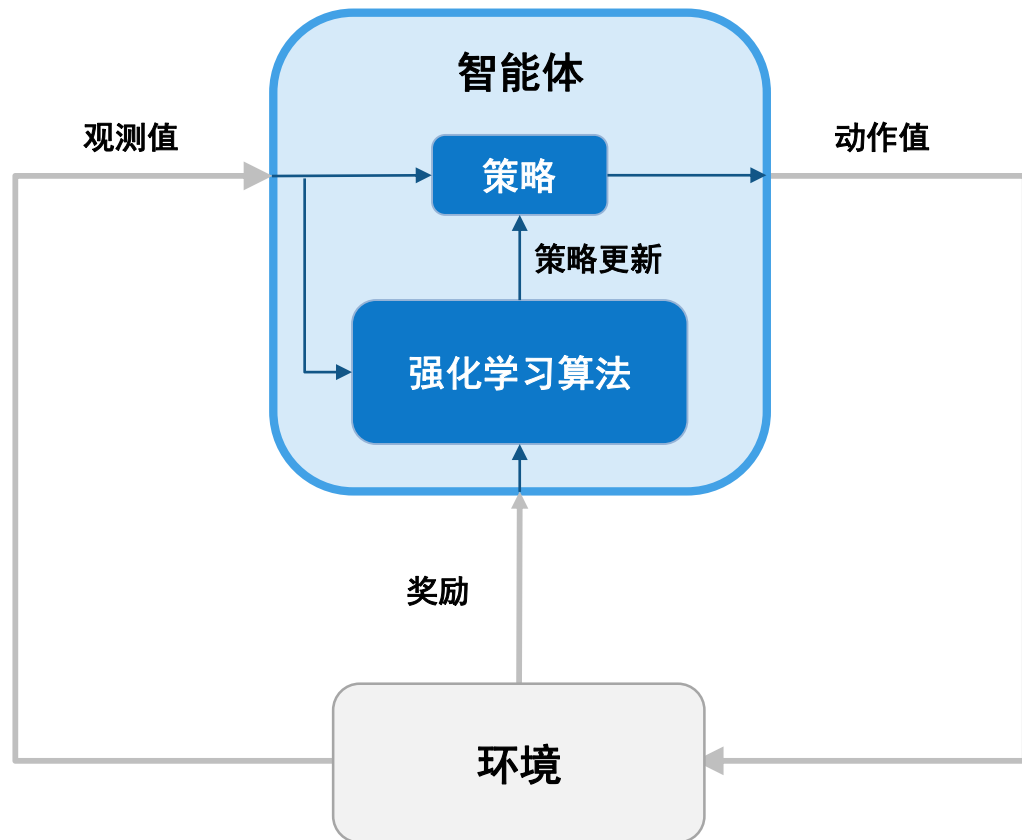


深度学习扮演着什么角色？

复杂的强化学习问题通常需要借助深度神经网络
[深度强化学习]

强化学习基本概念

自动驾驶场景



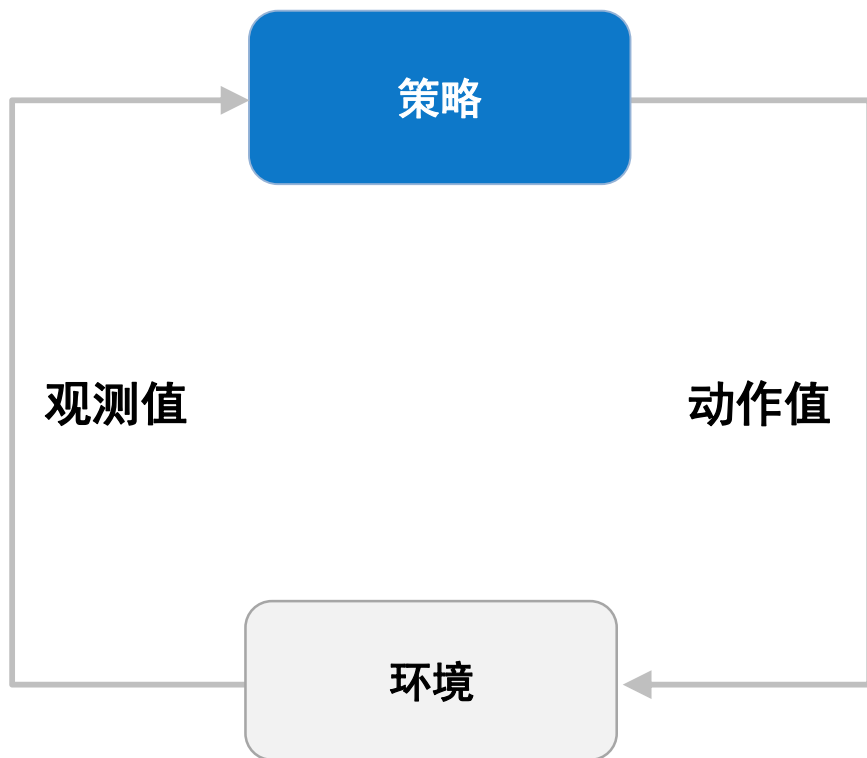
- 车载计算机...
(智能体)
- 从激光雷达、摄像头等读取传感器数据...
(观测值)
- 以表征道路状况、汽车位置等...
(环境)
- 并生成转向、刹车和油门指令...
(动作值)
- 根据内置的状态-动作映射关系...
(策略)
- 试图优化设计目标，例如单圈时间、燃油经济性...
(奖励)

- 通过不断试错，强化学习算法将更新策略

强化学习基本概念

自动驾驶场景

训练完成后, 只需要根据策略
进行控制

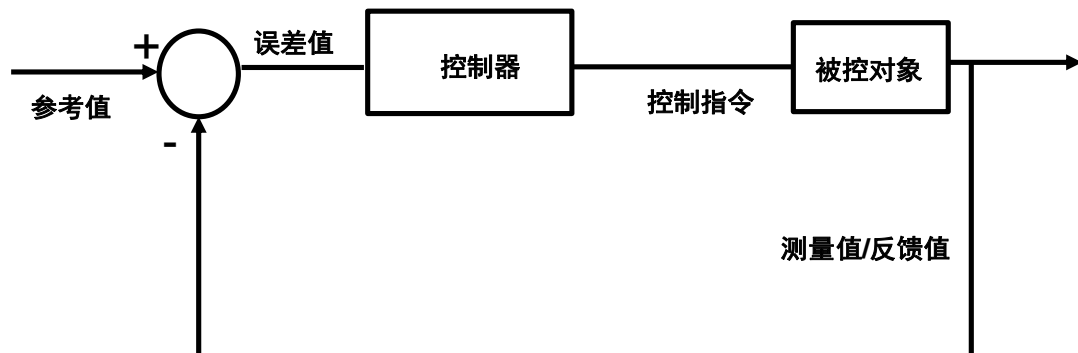


- 车载计算机使用最后更新好的状态-动作映射...
(策略)
- 生成转向、刹车和油门指令...
(动作)
- 根据激光雷达、摄像头等传感器数据...
(观测值)
- 用于表征道路状况、车辆位置...
(环境)

根据任务定义, 训练好的策略
将优化单圈时间和燃油经济性

强化学习 vs 控制论

控制系统



调整机制

误差/损失函数

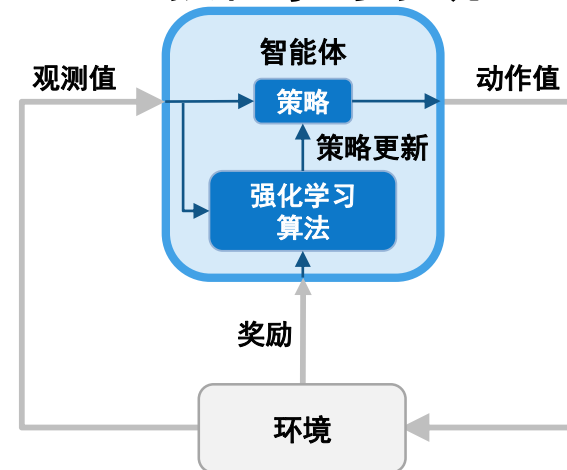
控制指令

测量值/反馈值

被控对象

控制器

强化学习系统



强化学习算法

奖励

动作值

观测值

环境

策略

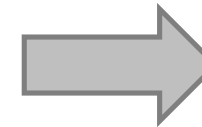
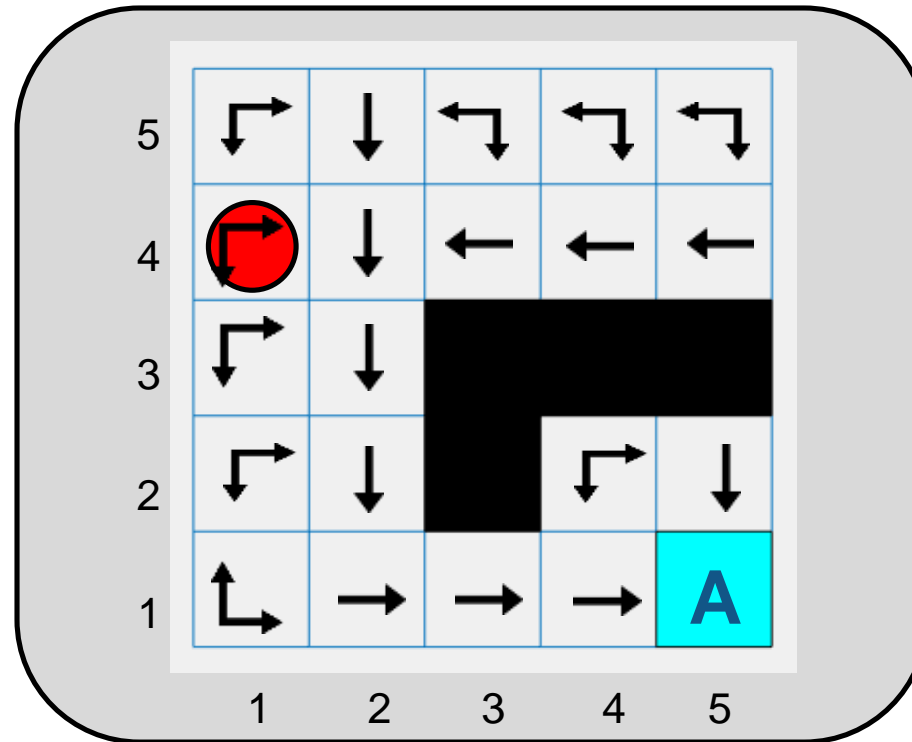
强化学习和控制系统设计的横向类比

策略表达和深度学习

表达形式

- 查找表
- 多项式

观测值



下一个动作值

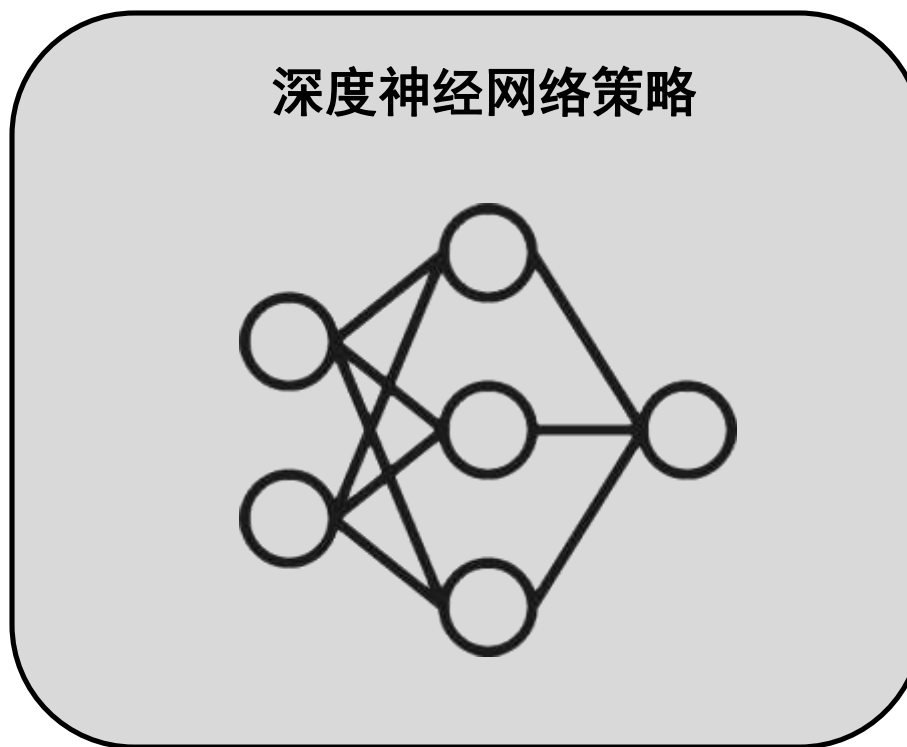
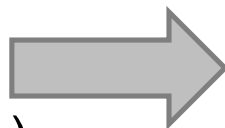
查找表 无法很好地扩展到高维空间

策略表达和深度学习

表达形式

- 查找表
- 多项式
- (深度) 神经网络

观测值
(摄像头, 传感器 ...)



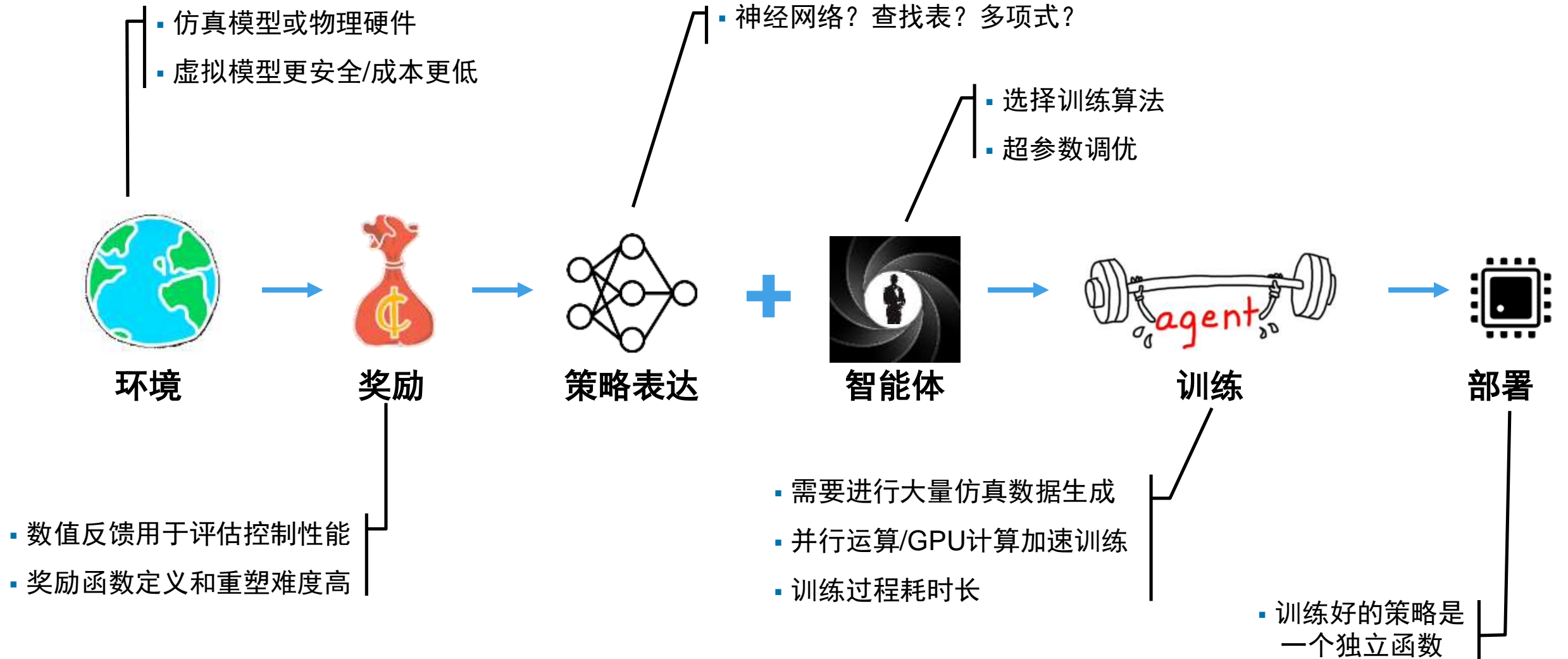
下一个动作值

神经网络支持**复杂策略**的表达

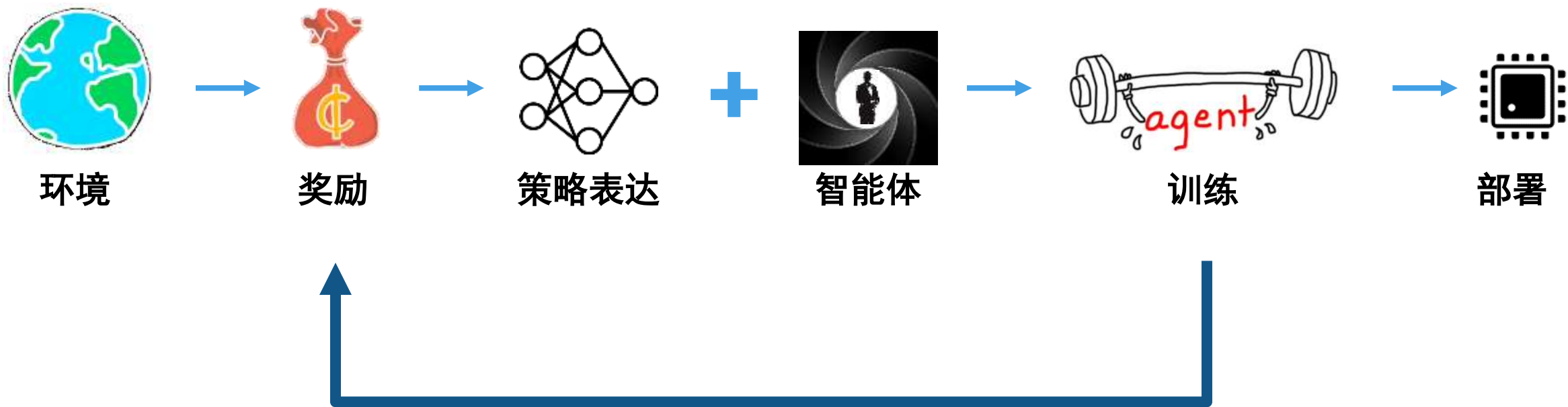
如何在MATLAB中实现 基于强化学习的自主系统设计 workflow

示例：机器人、自动驾驶

强化学习 workflow



强化学习 workflow



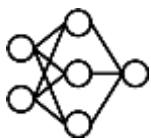
示例：双足机器人



环境



奖励



策略



智能体

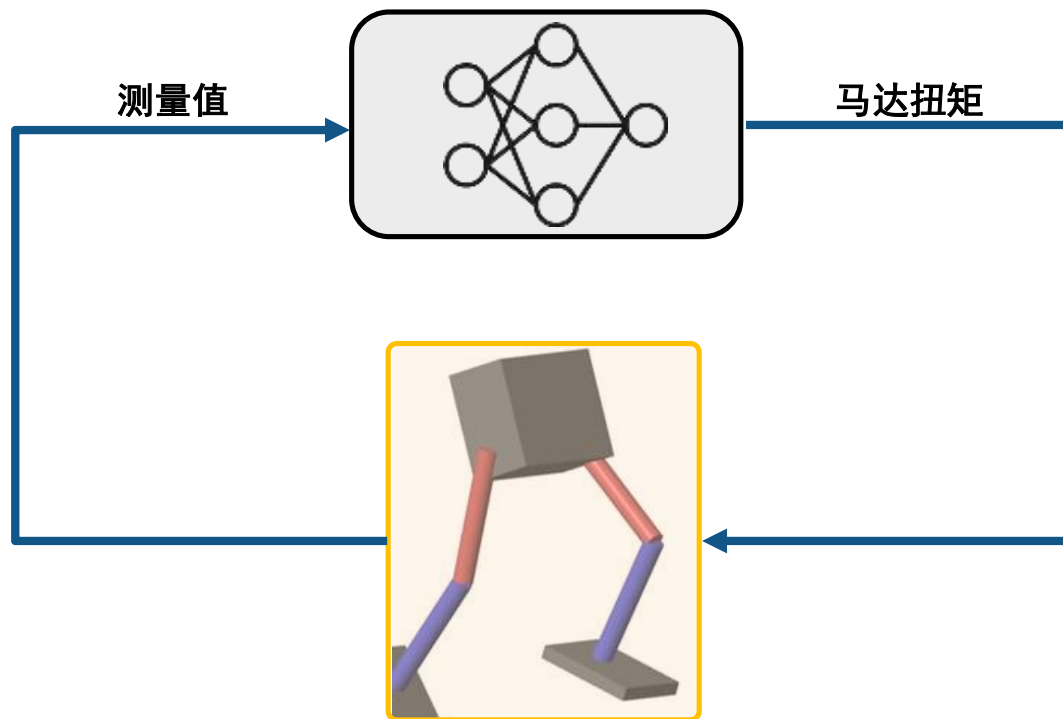


训练



部署

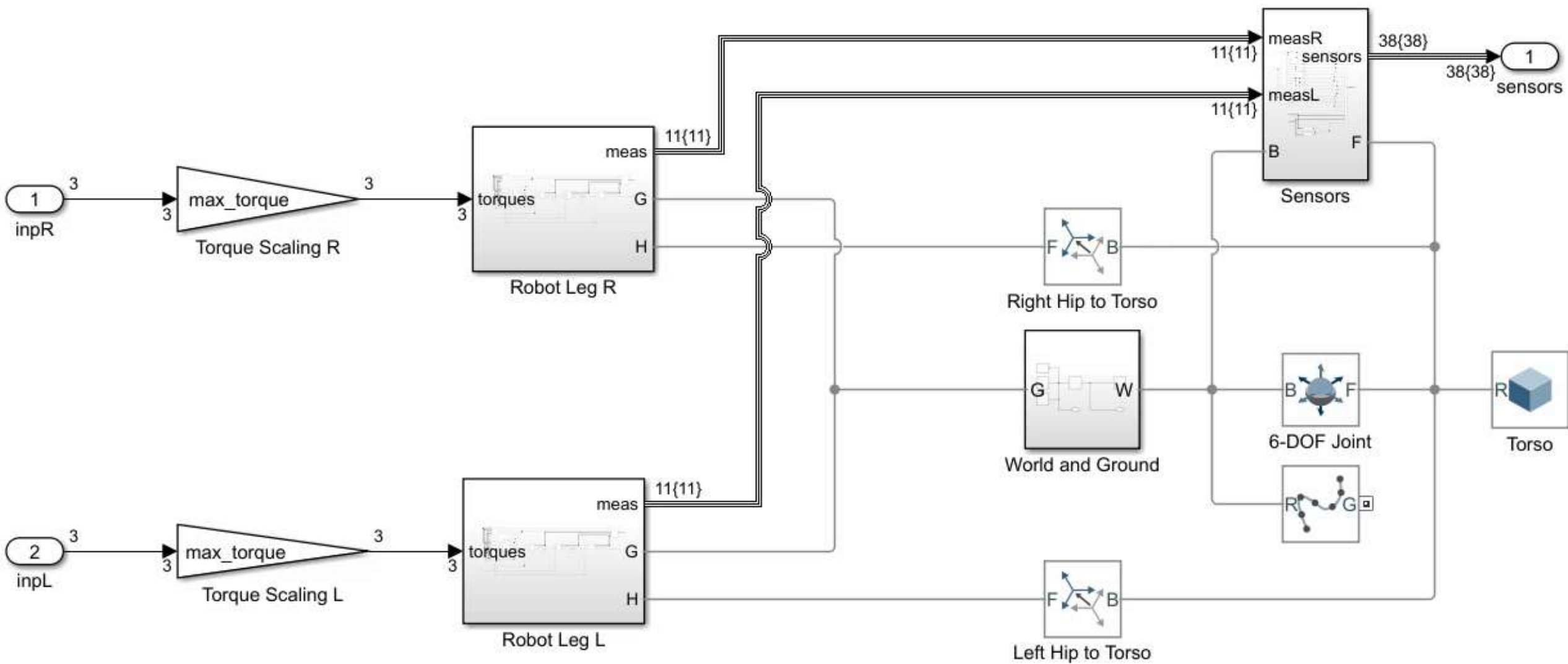
控制目标：沿直线行走



创建环境



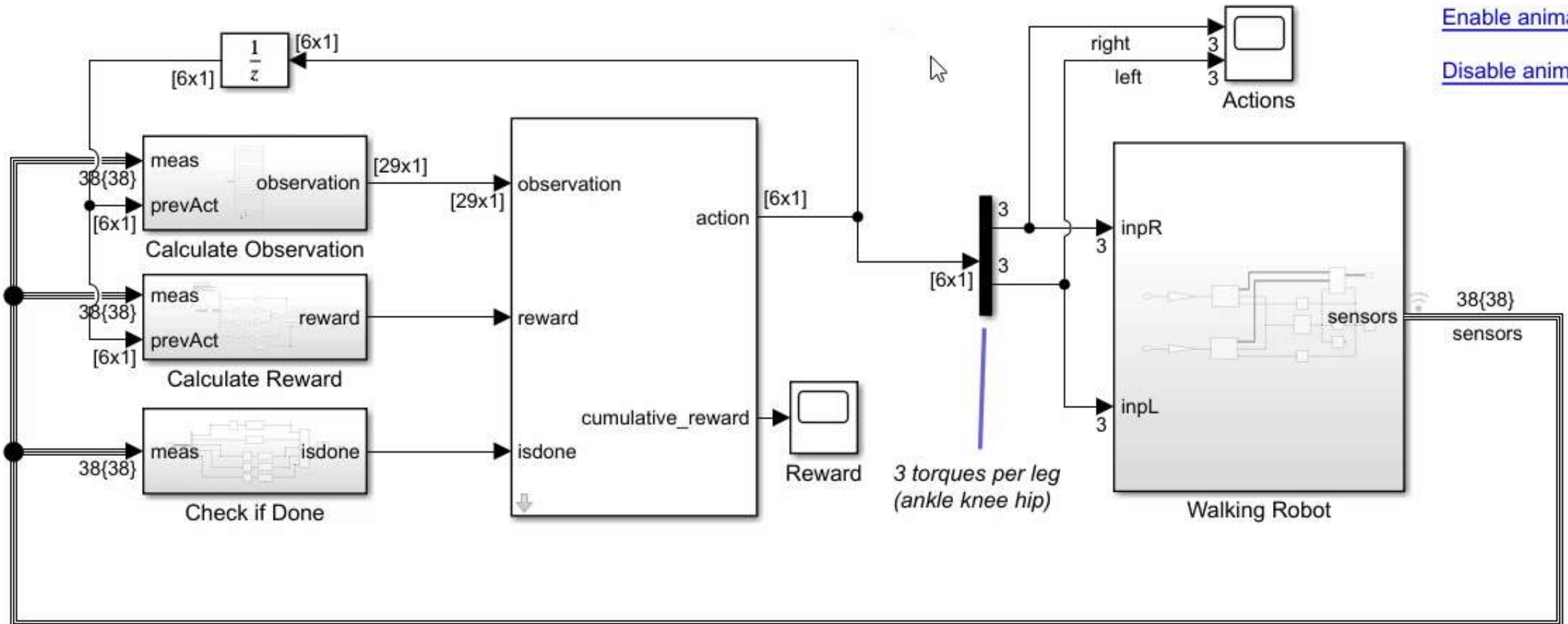
rWalkingBipedRobot_Template ▶ Walking Robot ▶





Walking Robot: Reinforcement Learning (2D)

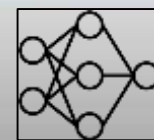
Copyright 2019 The MathWorks, Inc.



DESIGNER

New Import Duplicate Copy Paste Cut Copy Paste Fit to View Zoom In Zoom Out Auto Arrange Analyze Export

FILE BUILD NAVIGATE LAYOUT ANALYSIS EXPORT



LAYER LIBRARY

Filter layers...

INPUT

- imageInputLayer
- image3dInputLayer
- sequenceInputLayer
- roiInputLayer

CONVOLUTION AND FULLY CONNECTED

- convolution2dLayer
- convolution3dLayer
- groupedConvolution2dLayer
- transposedConv2dLayer
- transposedConv3dLayer
- fullyConnectedLayer

SEQUENCE

- lstmLayer
- hilstmLayer



PROPERTIES

| | |
|-----------------------|-------|
| Number of layers | 7 |
| Number of connections | 6 |
| Input type | Image |
| Output type | None |

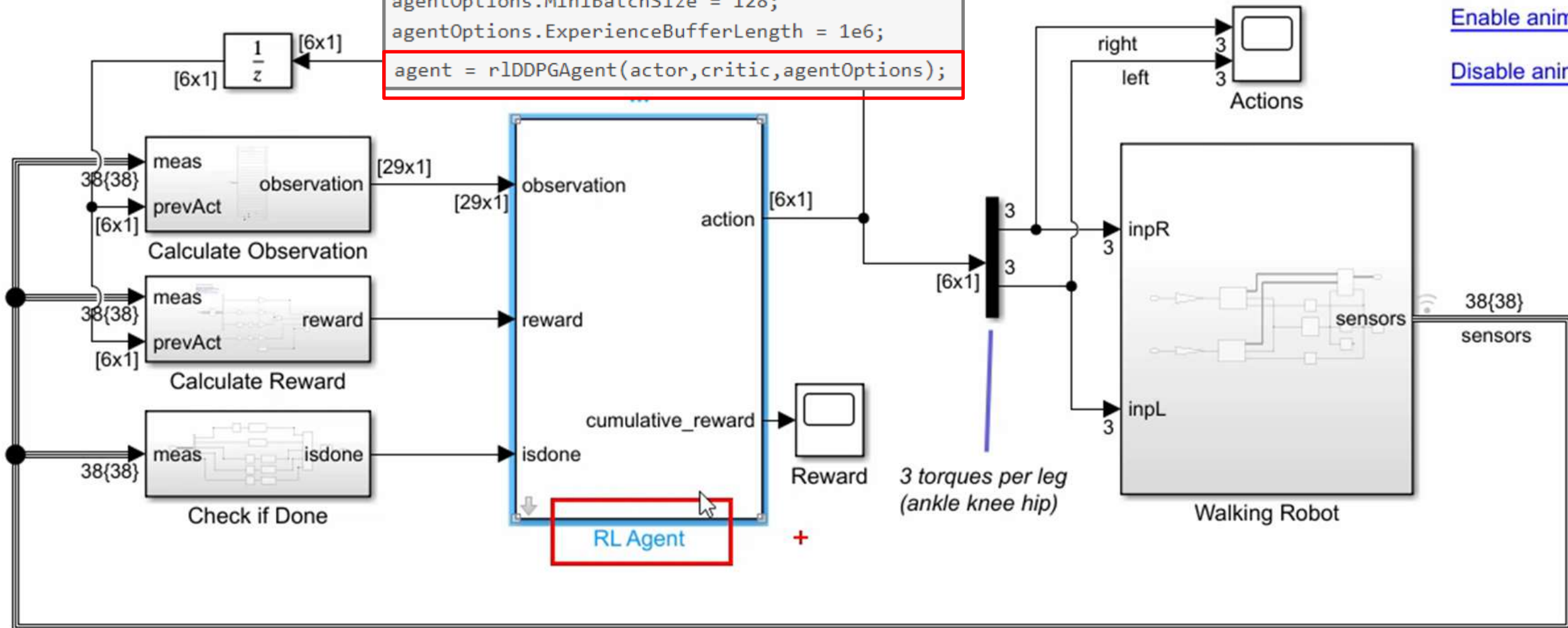
创建智能体



Walking Robot: Reinforcement Learning

Copyright 2019 The MathWorks

```
agentOptions = rlDDPGAgentOptions;  
agentOptions.SampleTime = Ts;  
agentOptions.DiscountFactor = 0.99;  
agentOptions.MinibatchSize = 128;  
agentOptions.ExperienceBufferLength = 1e6;  
agent = rlDDPGAgent(actor, critic, agentOptions);
```

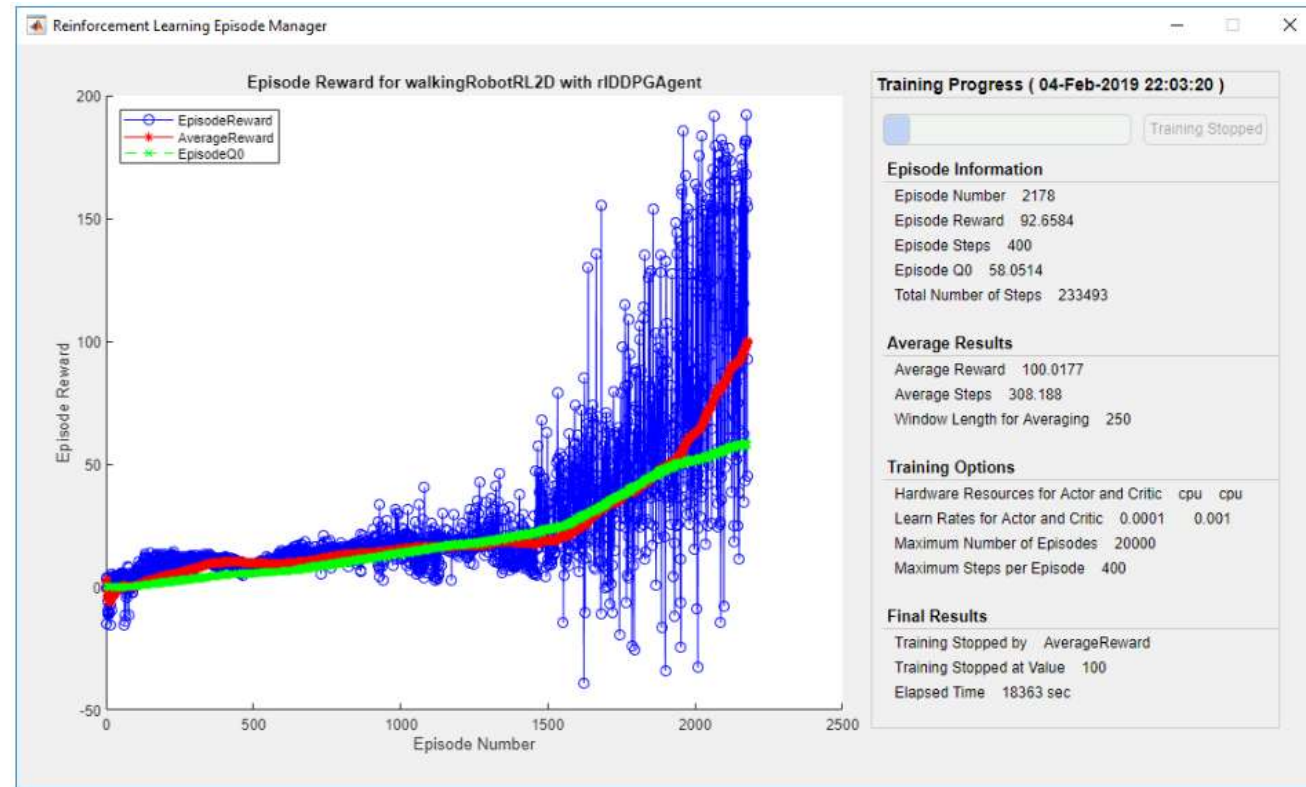


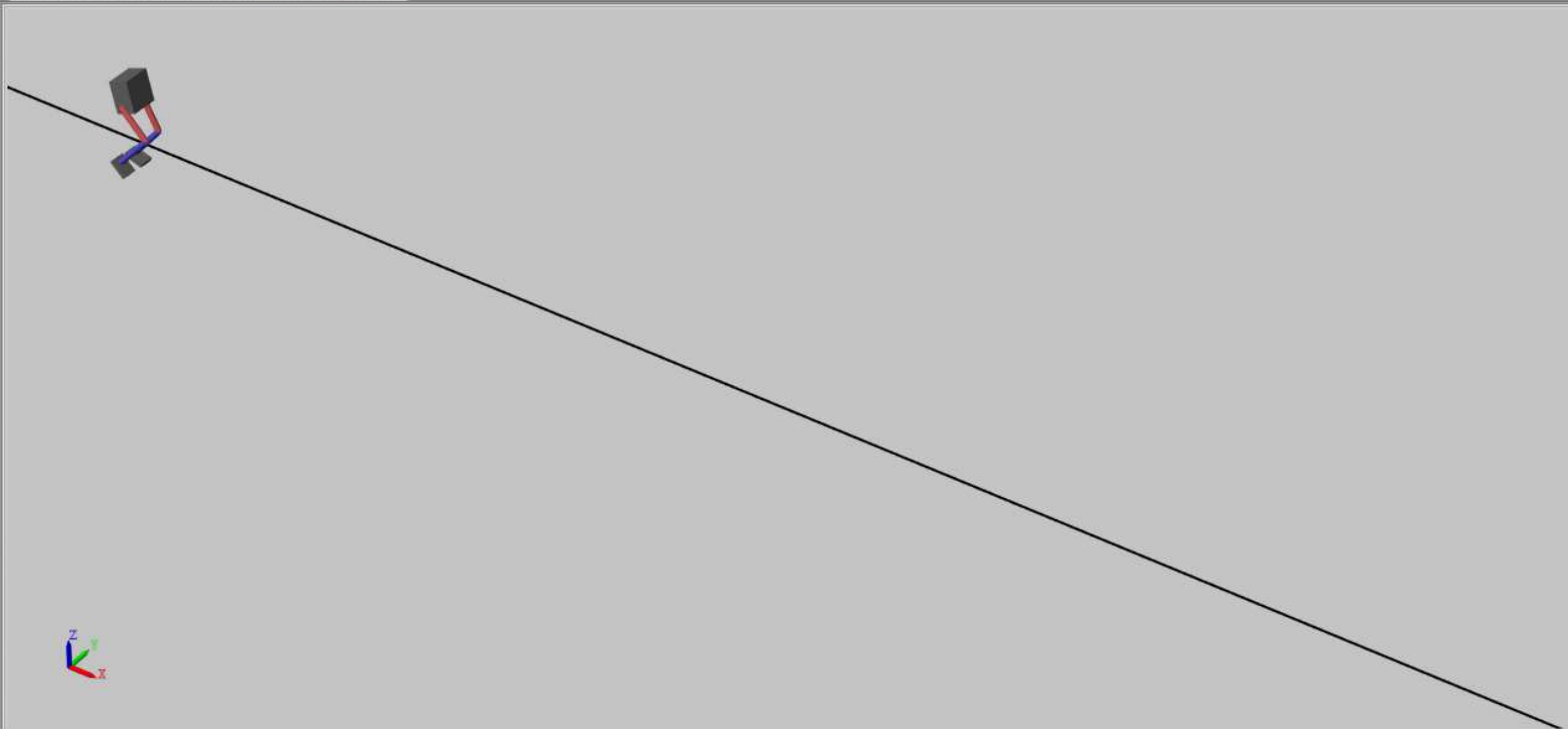
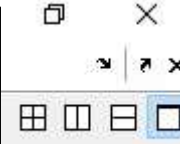
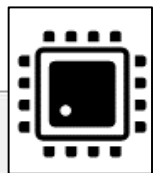
[Enable animation](#)

[Disable animation](#)

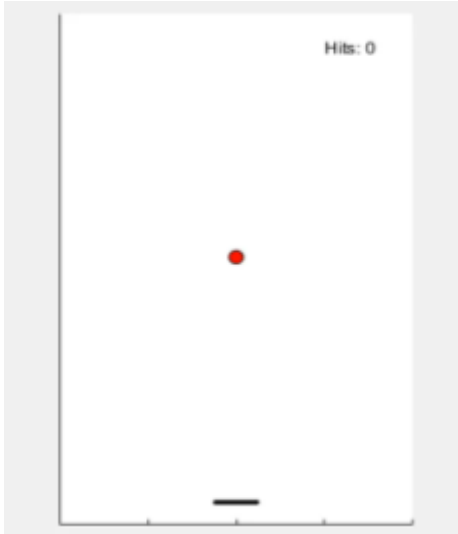
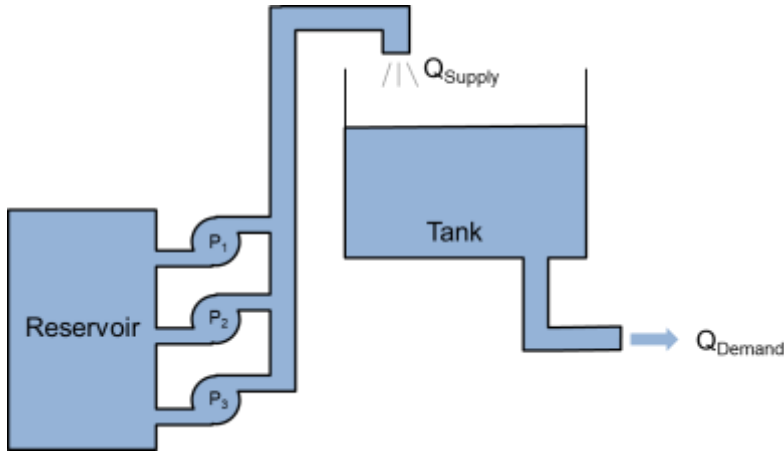
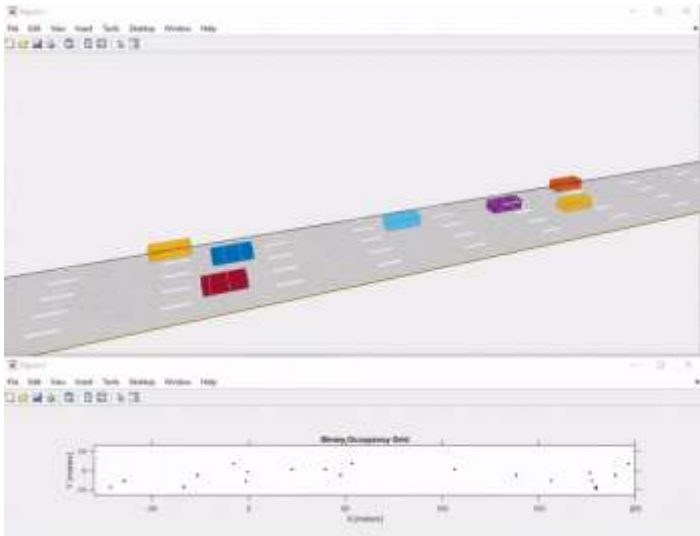
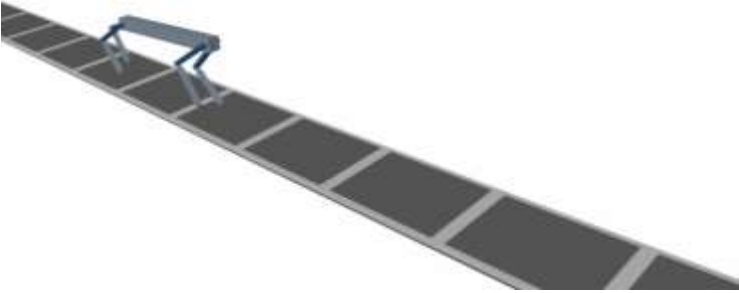
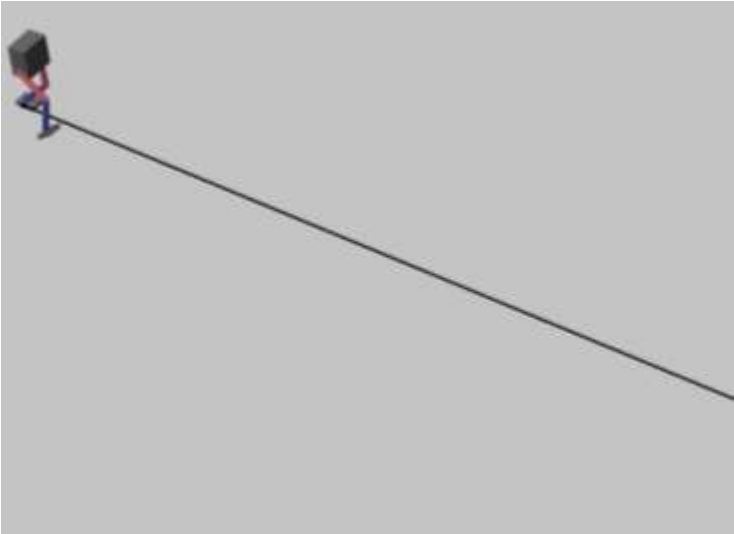
训练智能体

```
trainOpts.UseParallel = true;  
trainOpts.ParallelizationOptions.Mode = 'async';
```

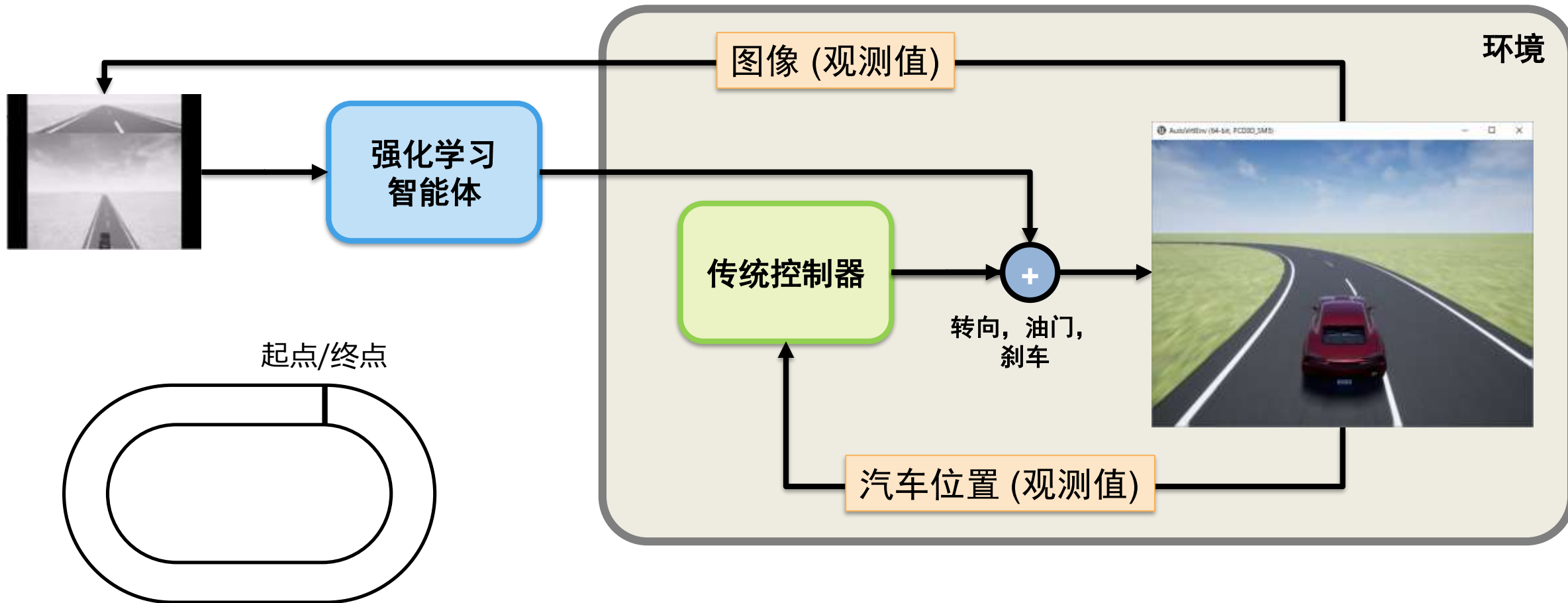




强化学习应用领域

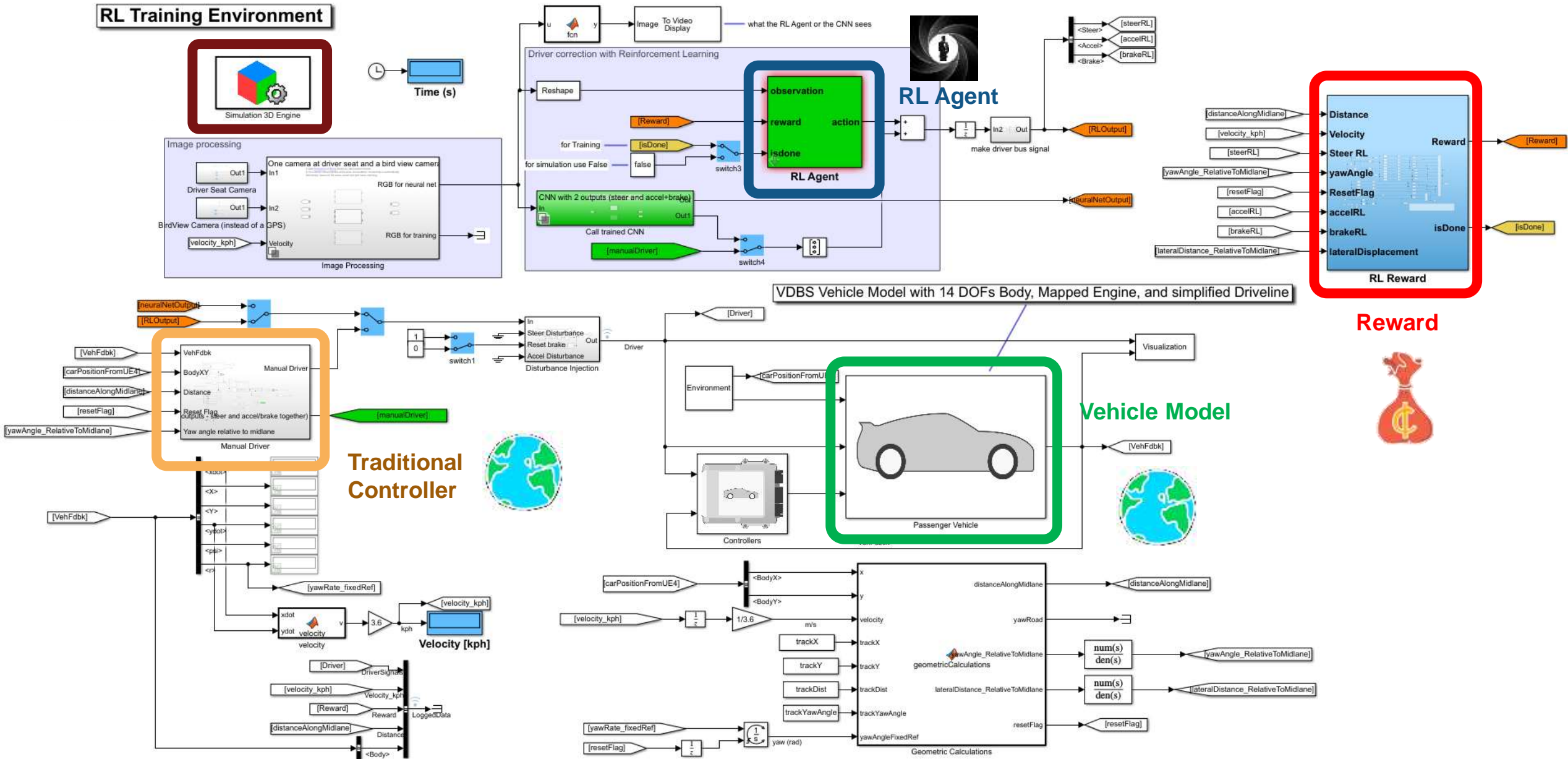


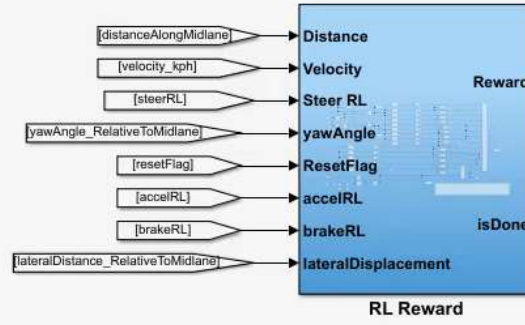
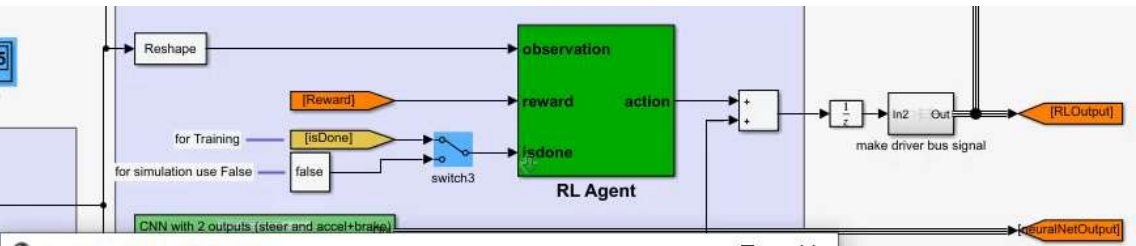
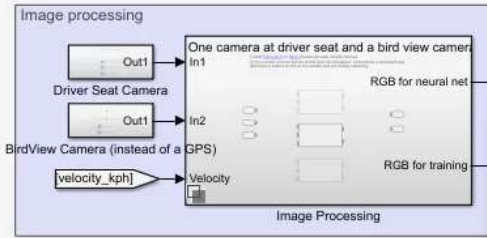
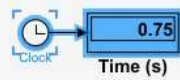
自动驾驶示例



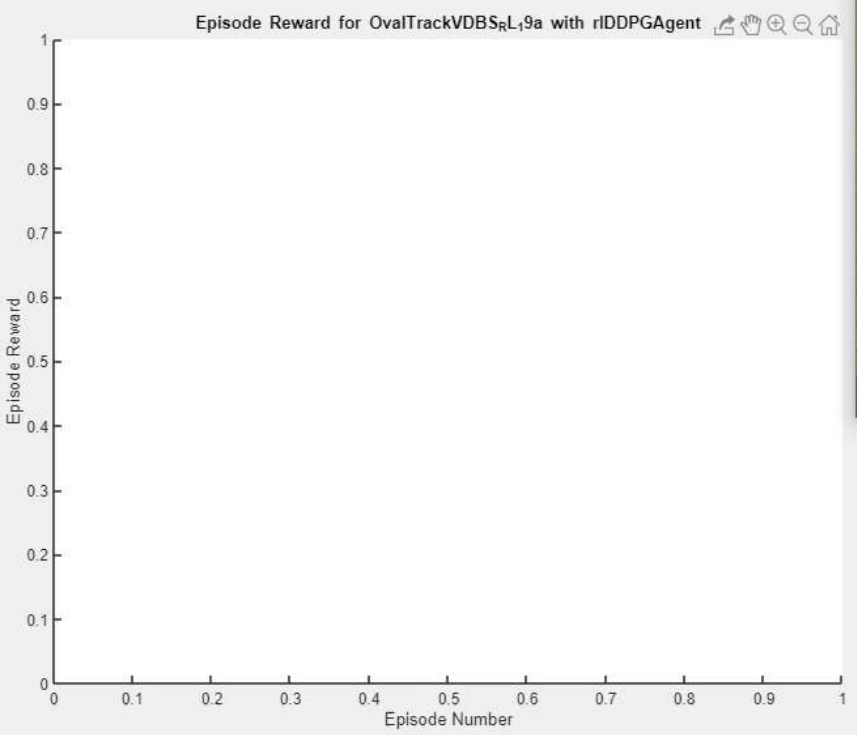
目标：通过强化学习
增强传统控制器以优化单圈时间

RL Training Environment

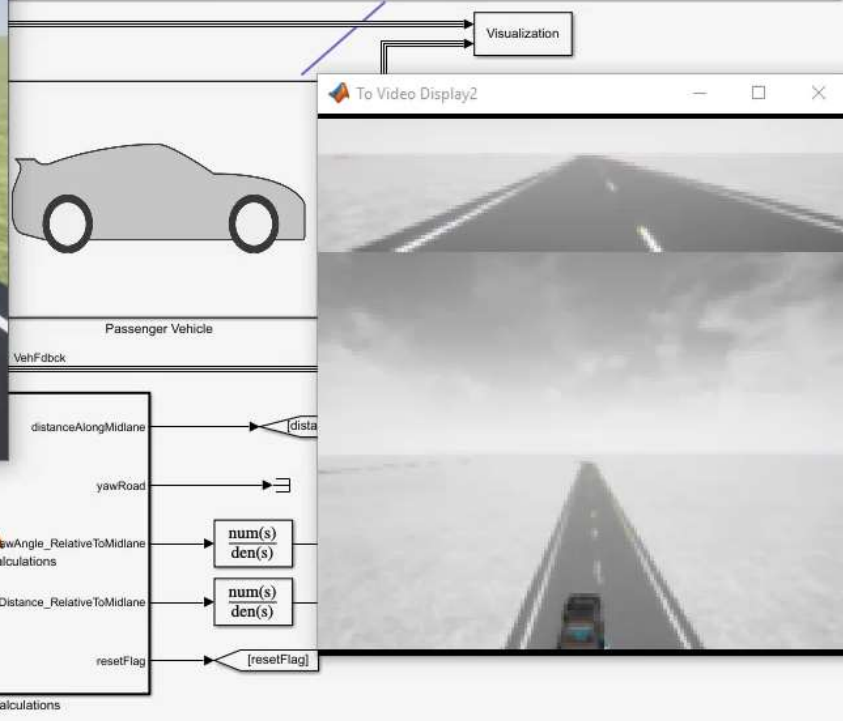




Reinforcement Learning Episode Manager



BS Vehicle Model with 14 DOFs Body, Mapped Engine, and simplified Driveline



Training Options

Hardware Resources for Actor and Critic: cpu cpu

Learn Rates for Actor and Critic: 0.001 0.0001

Maximum Number of Episodes: 5000

Maximum Steps per Episode: 167

Final Results

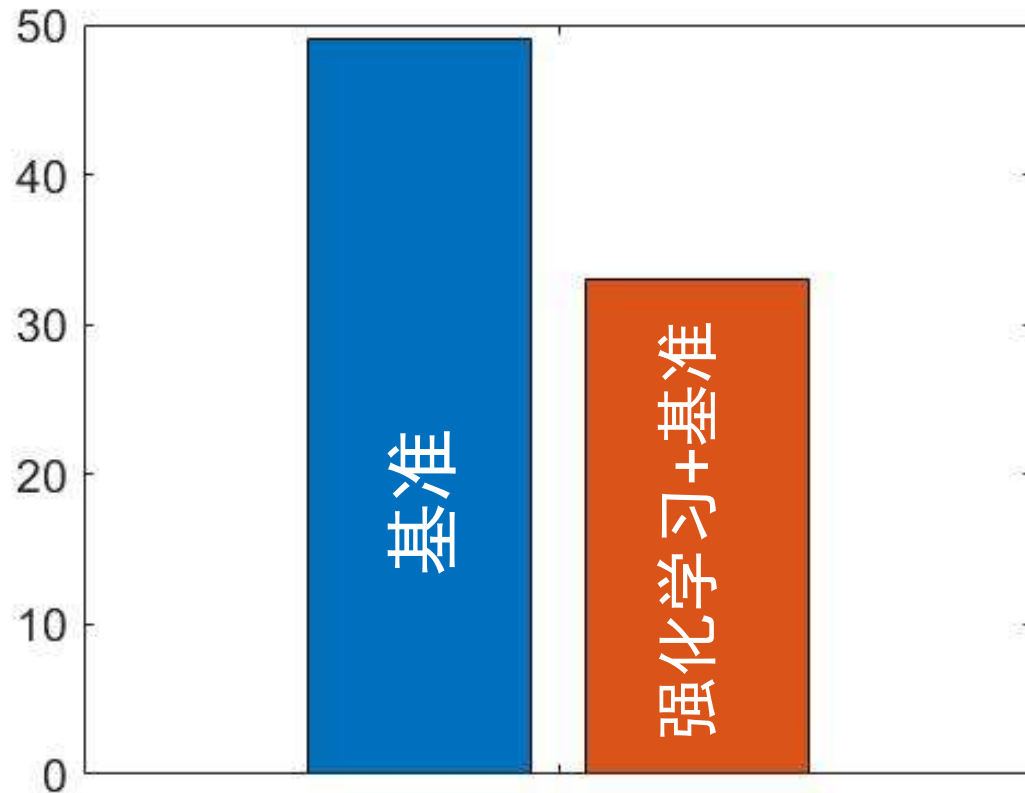
Training Stopped by: ...

Training Stopped at Value: ...

Elapsed Time: ...

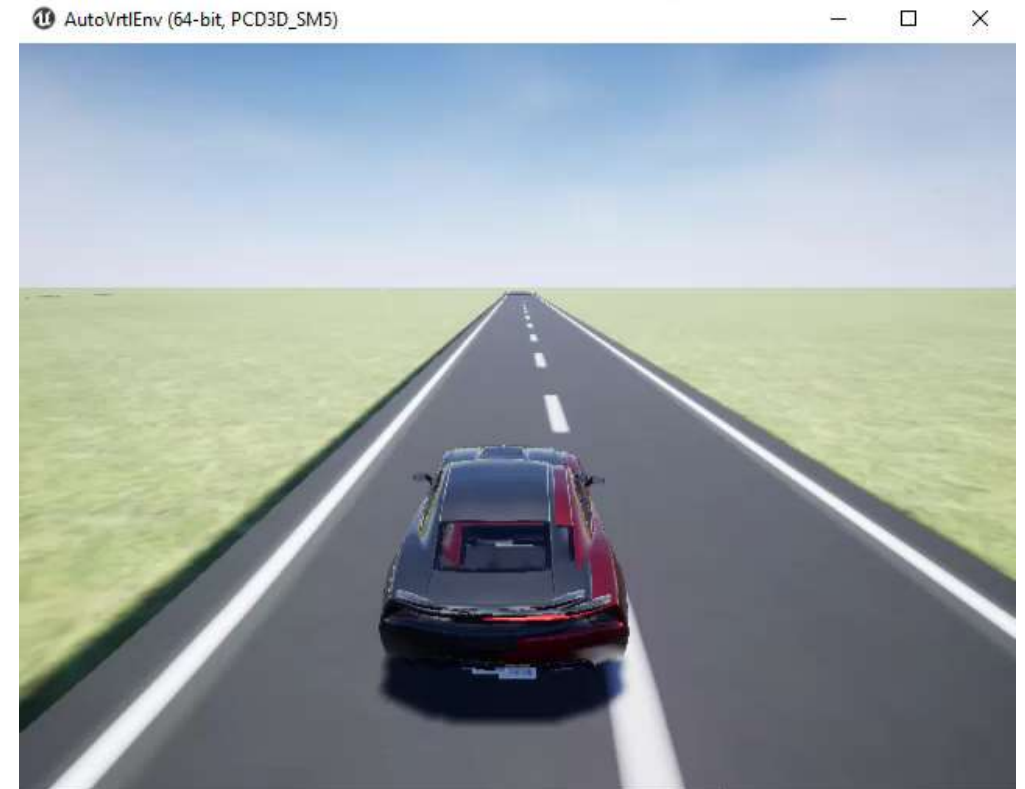
结果比较

单圈时间 (s)



30% 性能提高

传统控制器 + 强化学习



强化学习的优势与技术挑战

优势

- 训练前无需数据
- 为难以解决的问题提供了AI方向新的可能性
- 可处理不确定和非线性环境问题
- 可开发复杂的端到端解决方案

挑战

- 训练好的策略难以验证
(无法保障性能)
- 需要大量试错数据
(样本效率低)
 - 使用真实物理硬件进行训练成本高且具有危险性
- 大量设计参数
 - 奖励信号
 - 网络架构
 - 训练超参数

仿真是强化学习的关键

MATLAB和Simulink如何帮助您加快强化学习 workflow?

挑战

- 训练好的策略难以验证
(无法保障性能)
- 需要大量试错数据
(样本效率低)
 - 使用真实物理硬件进行训练成本高且具有危险性
- 大量设计参数
 - 奖励信号
 - 网络架构
 - 训练超参数

MATLAB® & SIMULINK®

- 复用现有的代码和模型创建环境
- 通过仿真验证策略
 - 仿真极端场景
- 并行运行仿真加速训练
- 参考强化学习工具箱示例
 - 通过仿真迭代调试

更多参考示例

- 控制器设计
- 机器人行走控制
- 车道保持辅助驾驶
- 自适应巡航控制
- 模仿学习

The collage features six project thumbnails, each with a title and a brief description:

- Train DDPG Agent to Control Flying Robot**: Shows a 2D plot with a yellow robot in the center.
- Train Biped Robot to Walk Using DDPG Agent**: Shows a 3D model of a biped robot with labels for Hip joint, Knee joint, and Ankle joint.
- Train DDPG Agent for Adaptive Cruise Control**: Shows a block diagram of a control system.
- Train DQN Agent for Lane Keeping Assist**: Shows a block diagram of a control system.
- Train DDPG Agent for Path Following Control**: Shows a plot with a red path and a black line.
- learning agent control**: Shows a plot with a red path and a black line.

了解更多

- 控制、自动驾驶、机器人等领域的参考示例
- 为工程师和领域专家撰写的专业文档
- 强化学习系列技术讲座视频
- MathWorks官网下载强化学习系列电子书

Train DDPG Agent to Control Flying Robot

Train Biped Robot to Walk Using DDPG Agent

Train DDPG Agent for Adaptive Cruise Control

Train a reinforcement learning agent to control a flying robot model.

Train a reinforcement learning agent to control a biped walking robot model.

MathWorks

Documentation

Reinforcement Learning Toolbox

Design and train policies using reinforcement learning.

Reinforcement Learning Toolbox™ provides functions and blocks for training policies using reinforcement learning algorithms including DQN, A2C, and DDPG. You can use these policies to implement controllers and decision-making algorithms for complex systems such as robots and autonomous systems. You can implement the policies using deep neural networks, polynomials, or look-up tables.

The toolbox lets you train policies by enabling them to interact with environments represented by MATLAB® or Simulink® models. You can evaluate algorithms, experiment with hyperparameter settings, and monitor training progress. To improve training performance, you can run simulations in parallel on the cloud, computer clusters, and GPUs (with Parallel Computing Toolbox™ and MATLAB Parallel Server™).

Through the OMV™ model format, existing policies can be imported from deep learning frameworks such as TensorFlow™ Keras and PyTorch (with Deep Learning Toolbox™). You can generate optimized C, C++, and CUDA code to deploy trained policies on microcontrollers and GPUs.

The toolbox includes reference examples for using reinforcement learning to design controllers for robotics and autonomous driving applications.

Getting Started
Learn the basics of Reinforcement Learning Toolbox

MATLAB Environments
Model reinforcement learning environments dynamics using MATLAB

Simulink Environments
Model reinforcement learning environment dynamics using Simulink models

Policies and Value Functions
Define policy and value function representations, such as deep neural networks and Q tables

Agents
Create and configure reinforcement learning agents using common algorithms, such as DQN

Training and Validation
Train and simulate reinforcement learning agents

Policy Deployment
Code generation and deployment of trained policies

Agent

Environment

actuator commands

Action

+50

Reward

Observation (state)

Joint angles
Camera vision