

MATLAB EXPO

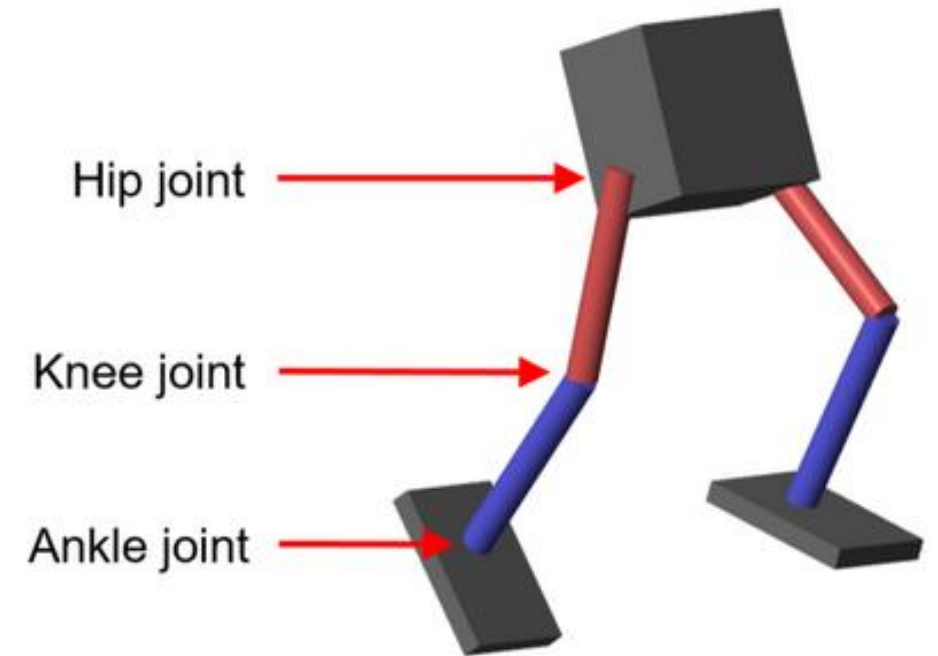
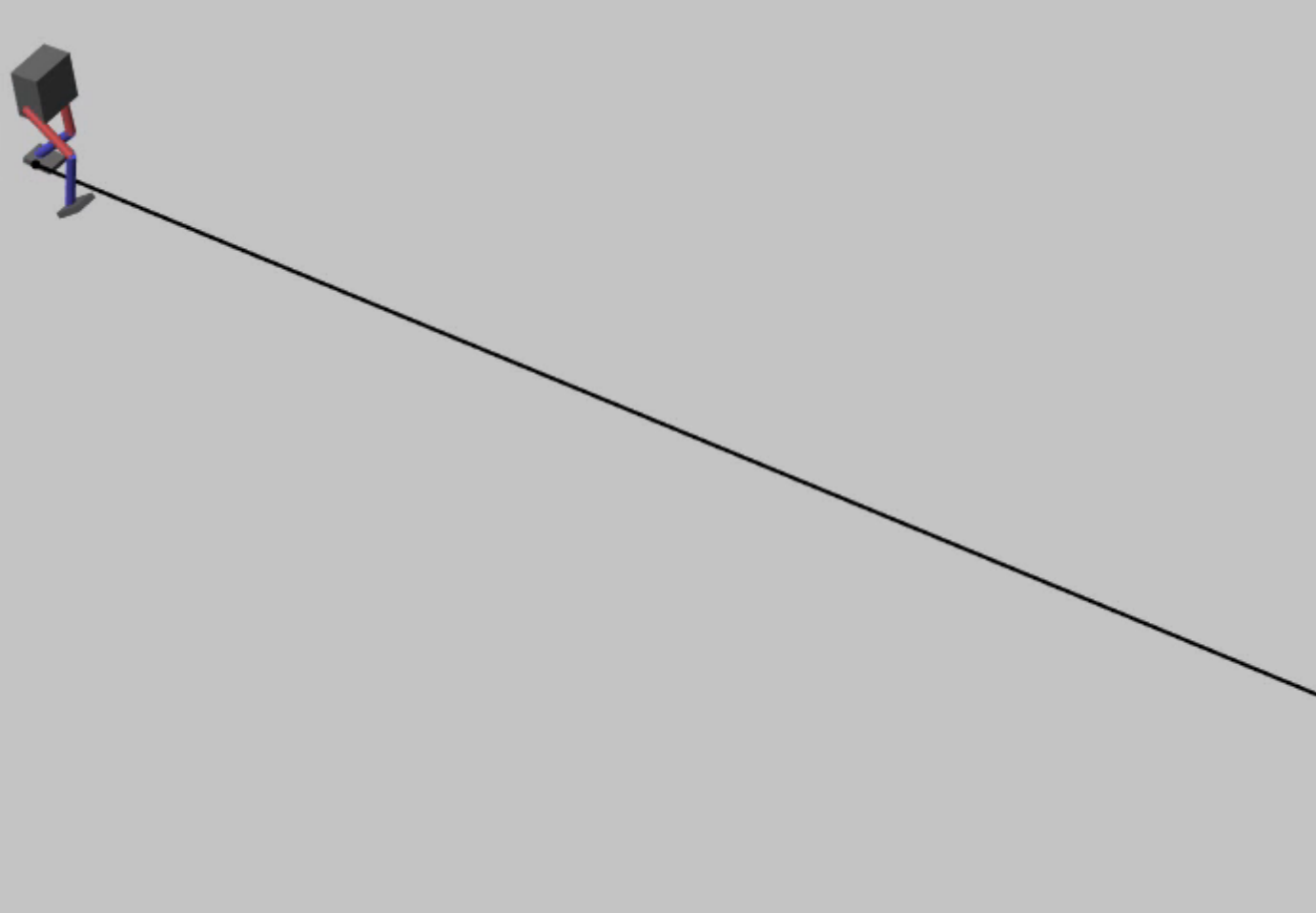
Reinforcement Learning Workflows for AI



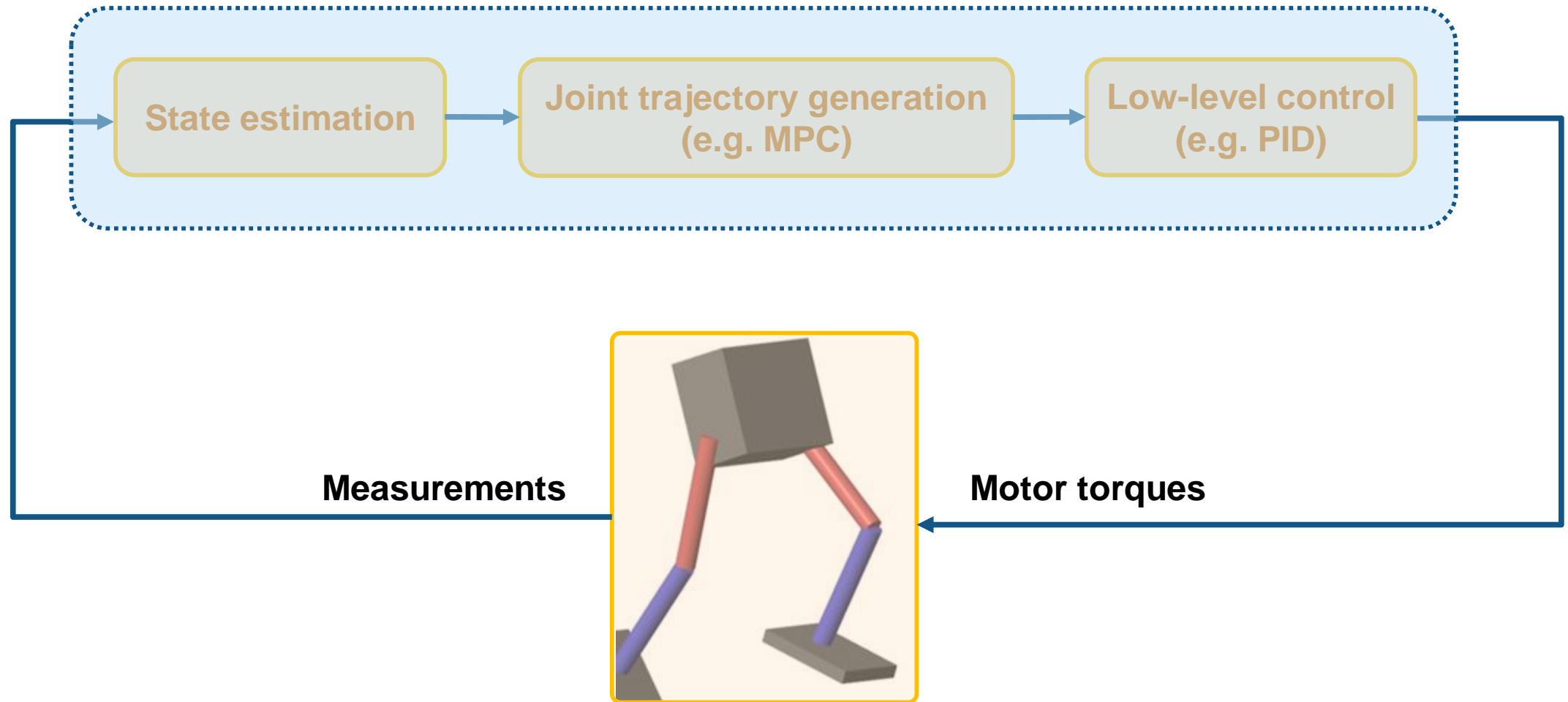
Key Takeaways

- What is reinforcement learning and why should I care about it?
- How do I set up and solve a reinforcement learning problem?
- What are some common challenges?

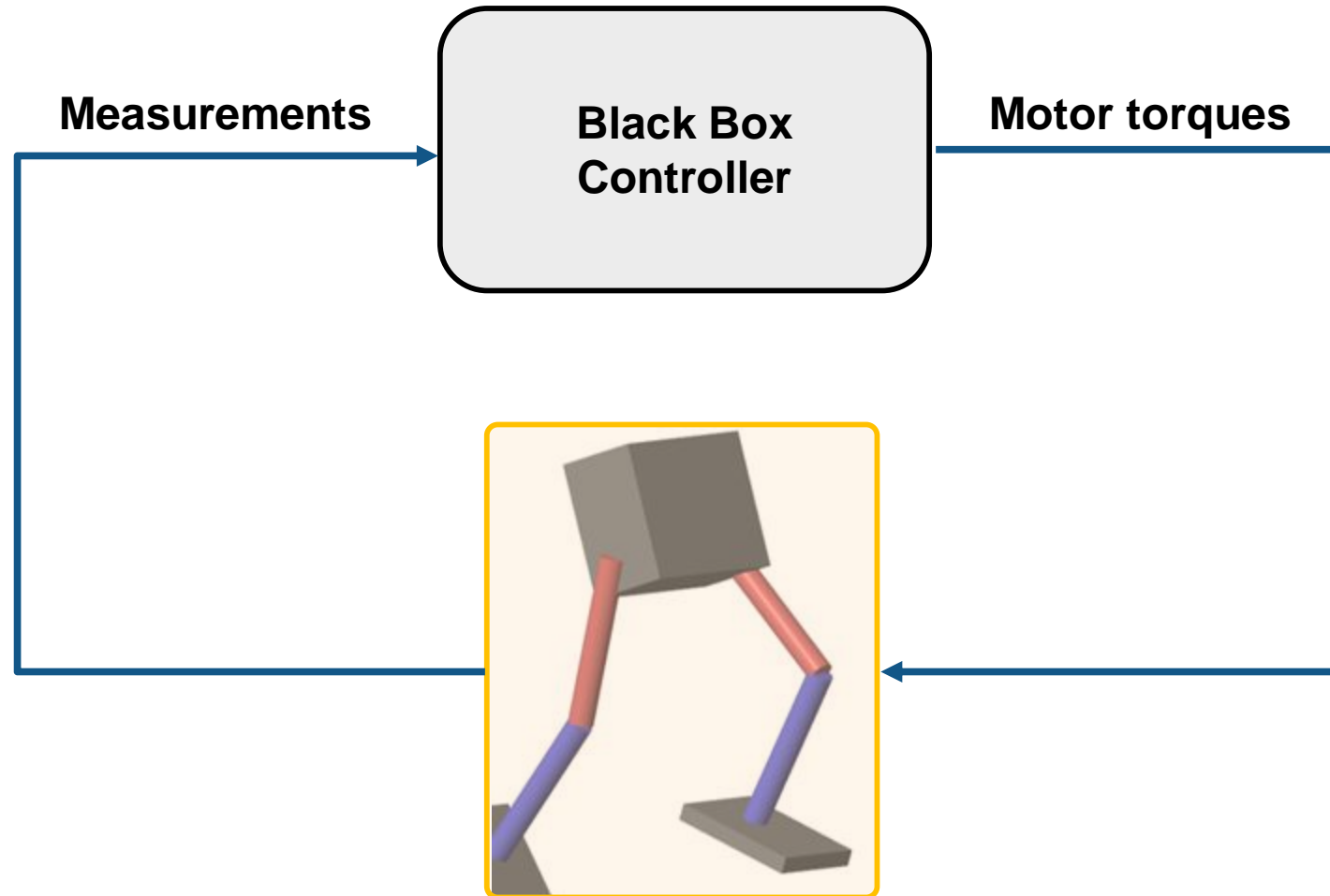
Why Should You Care About Reinforcement Learning?



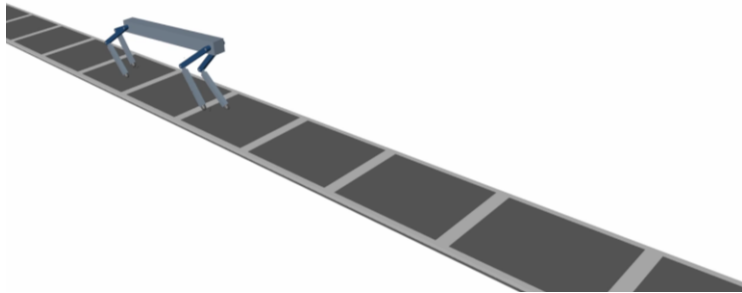
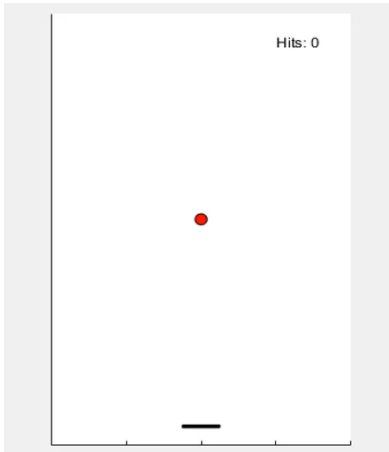
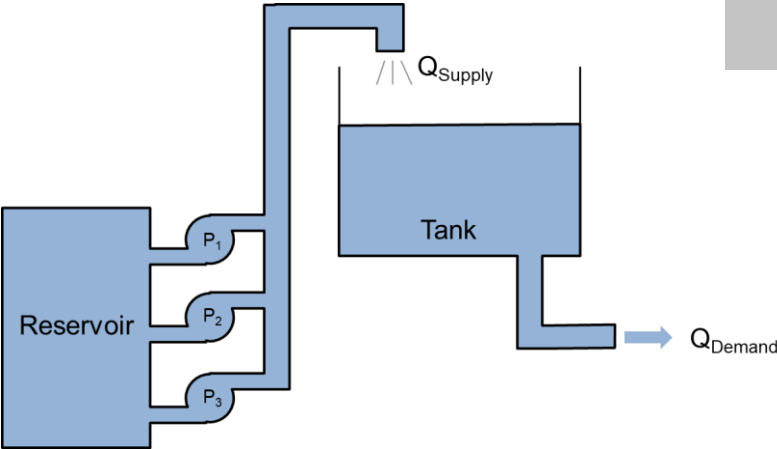
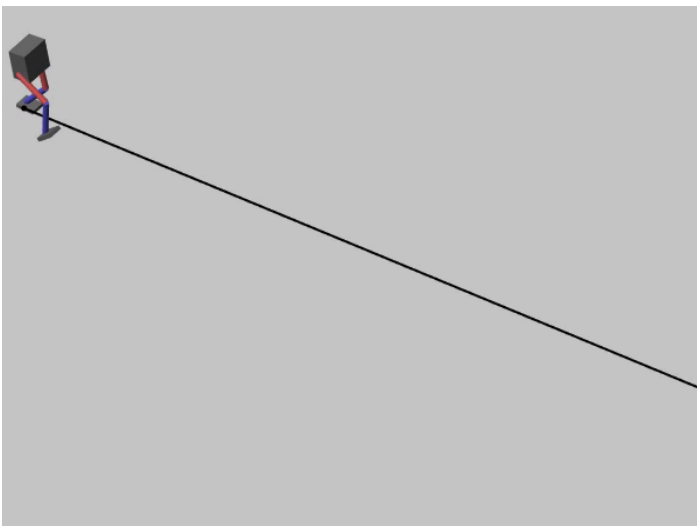
One Approach Could Be...



Any Alternatives?



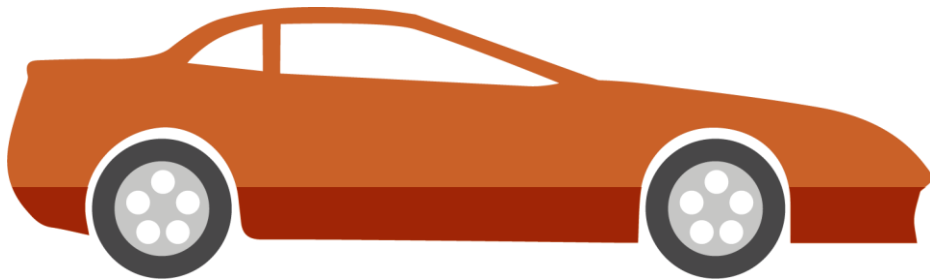
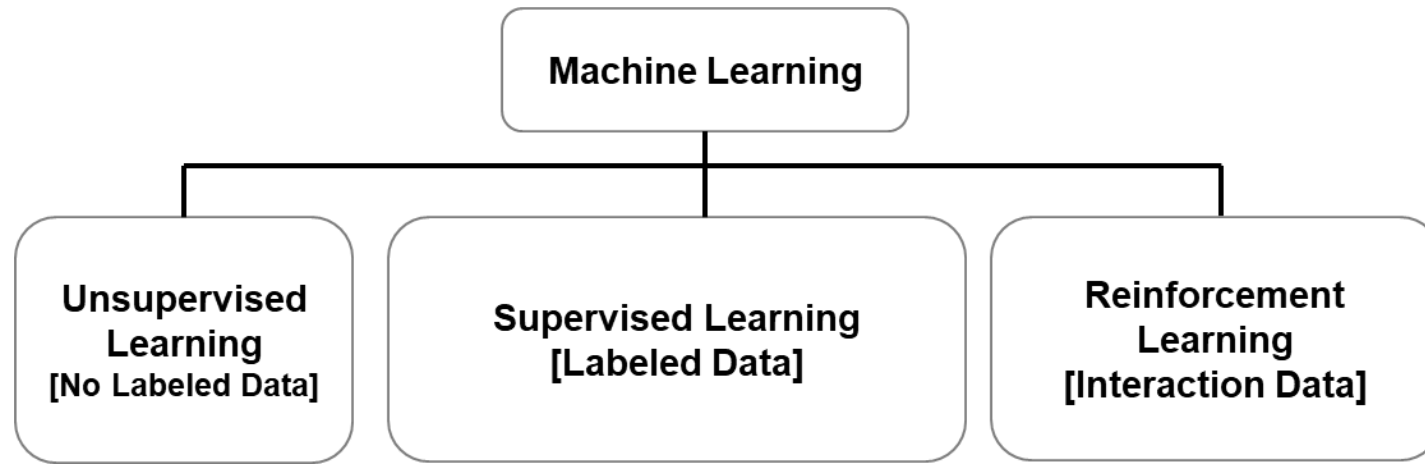
Applications of Reinforcement Learning



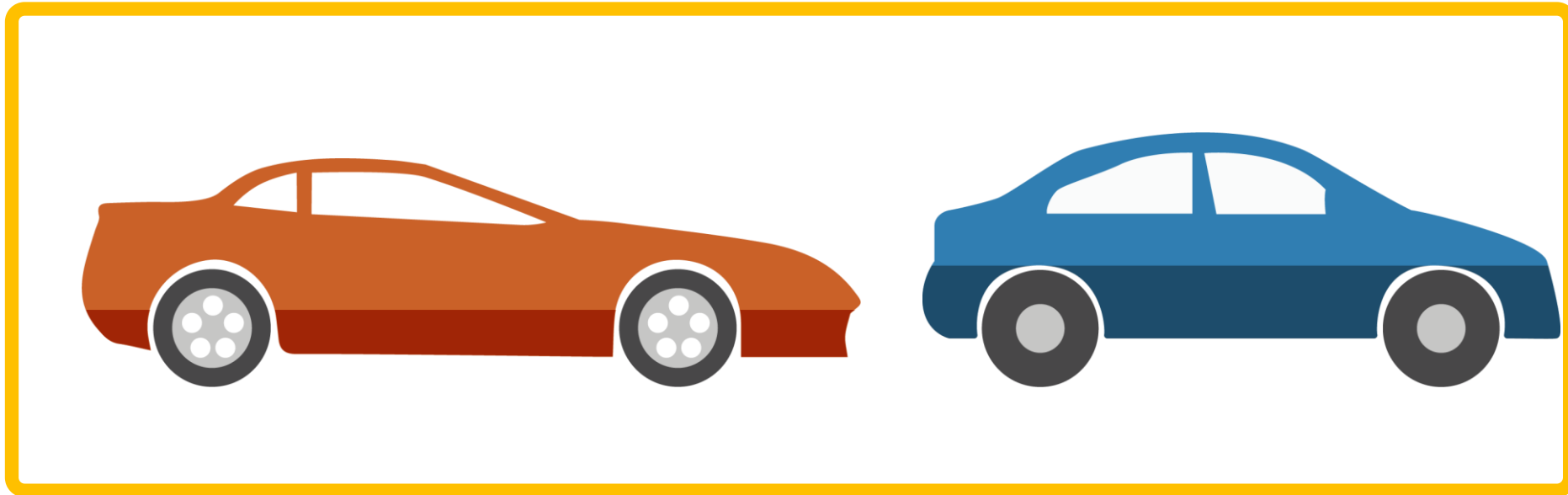
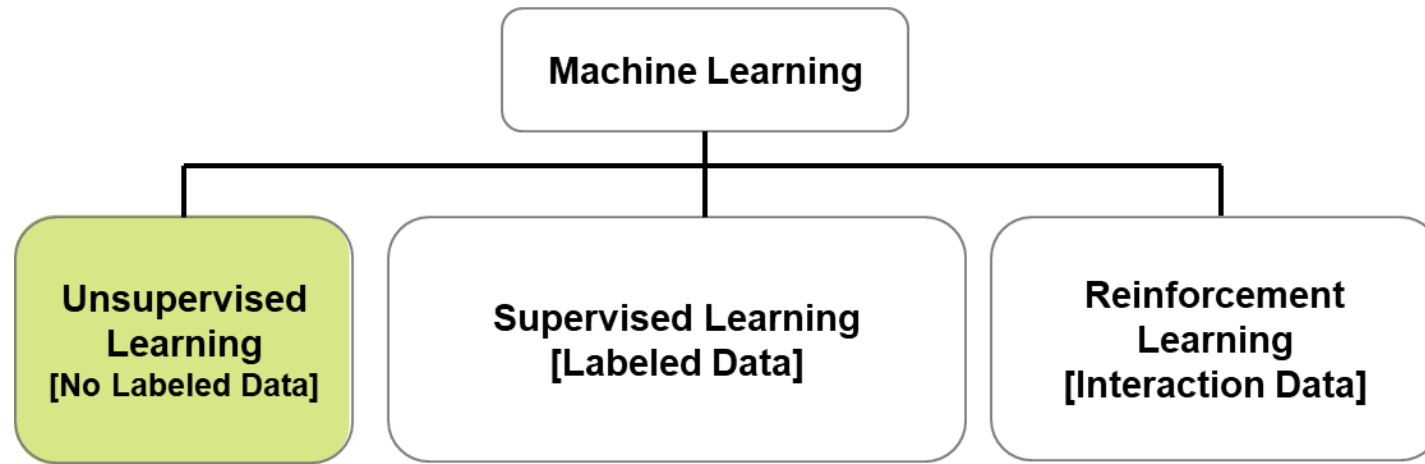
What is reinforcement learning?

Type of machine learning that trains an **'agent'** through trial & error interactions with an **environment**

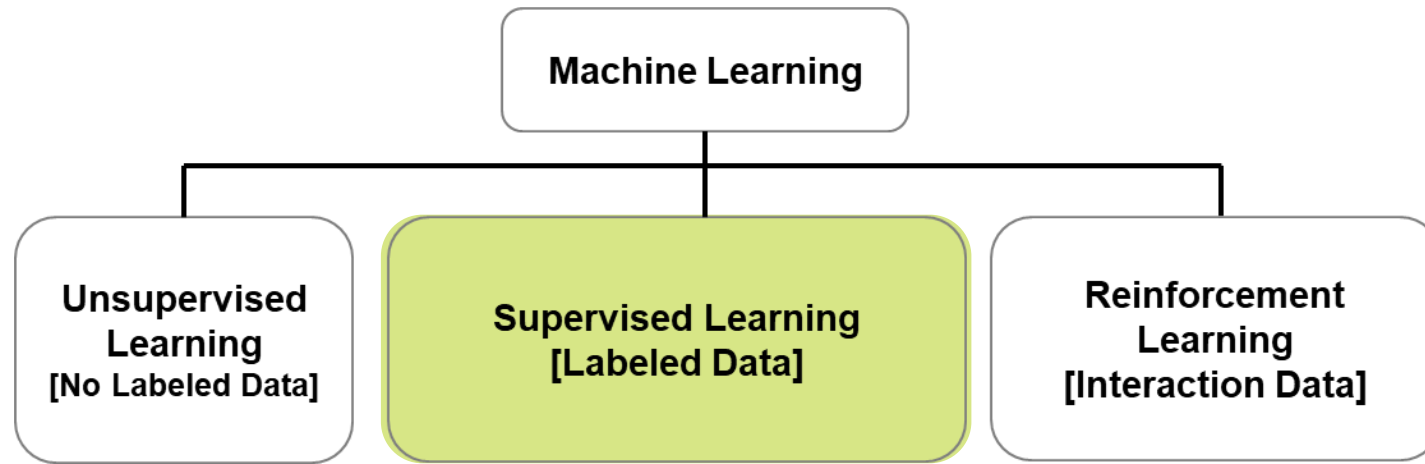
Reinforcement Learning vs Machine Learning vs Deep Learning



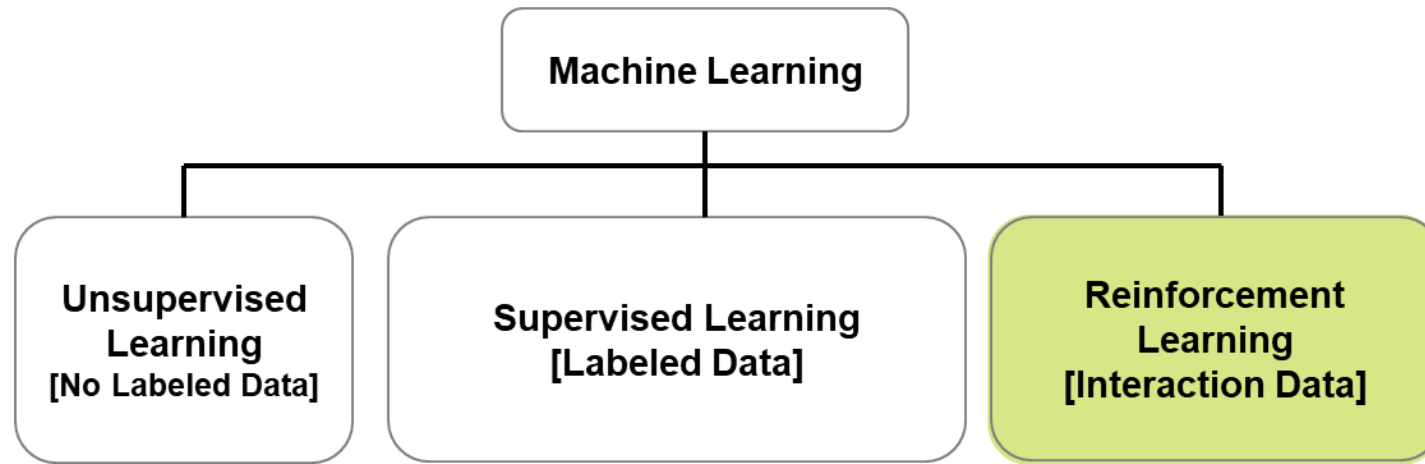
Reinforcement Learning vs Machine Learning vs Deep Learning



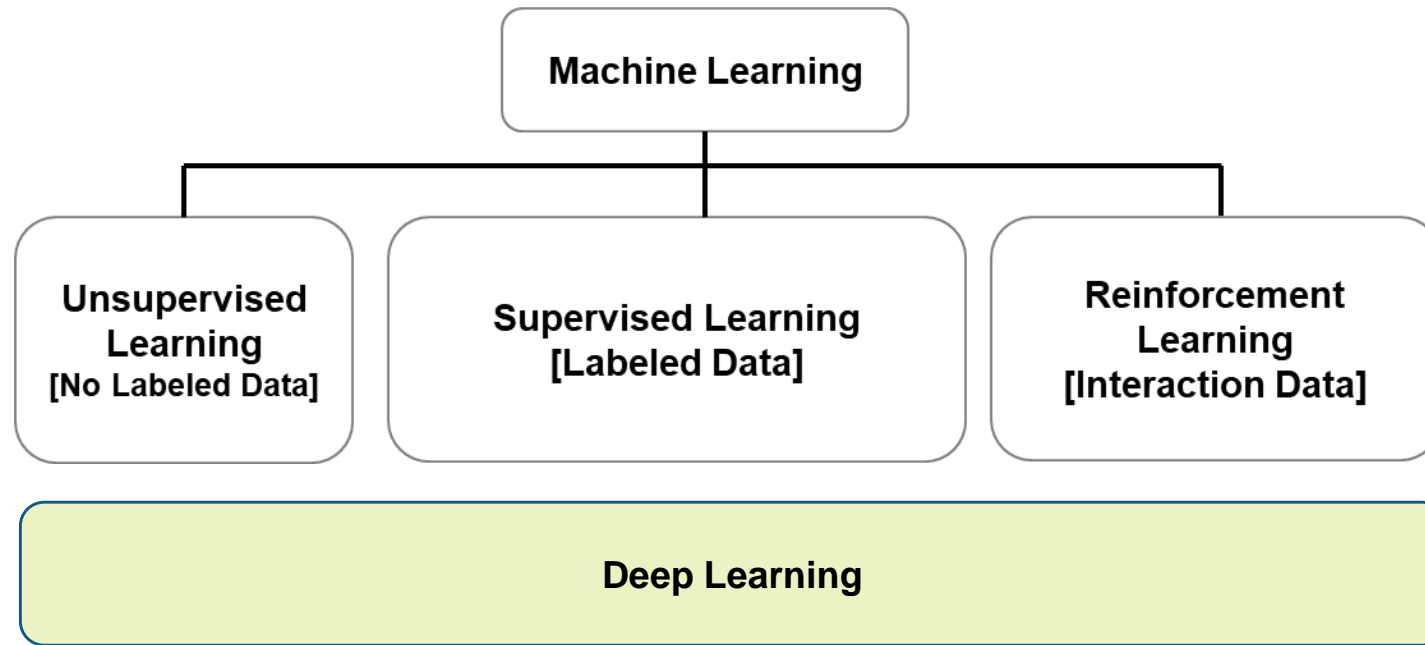
Reinforcement Learning vs Machine Learning vs Deep Learning



Reinforcement Learning vs Machine Learning vs Deep Learning



Reinforcement Learning vs Machine Learning vs Deep Learning

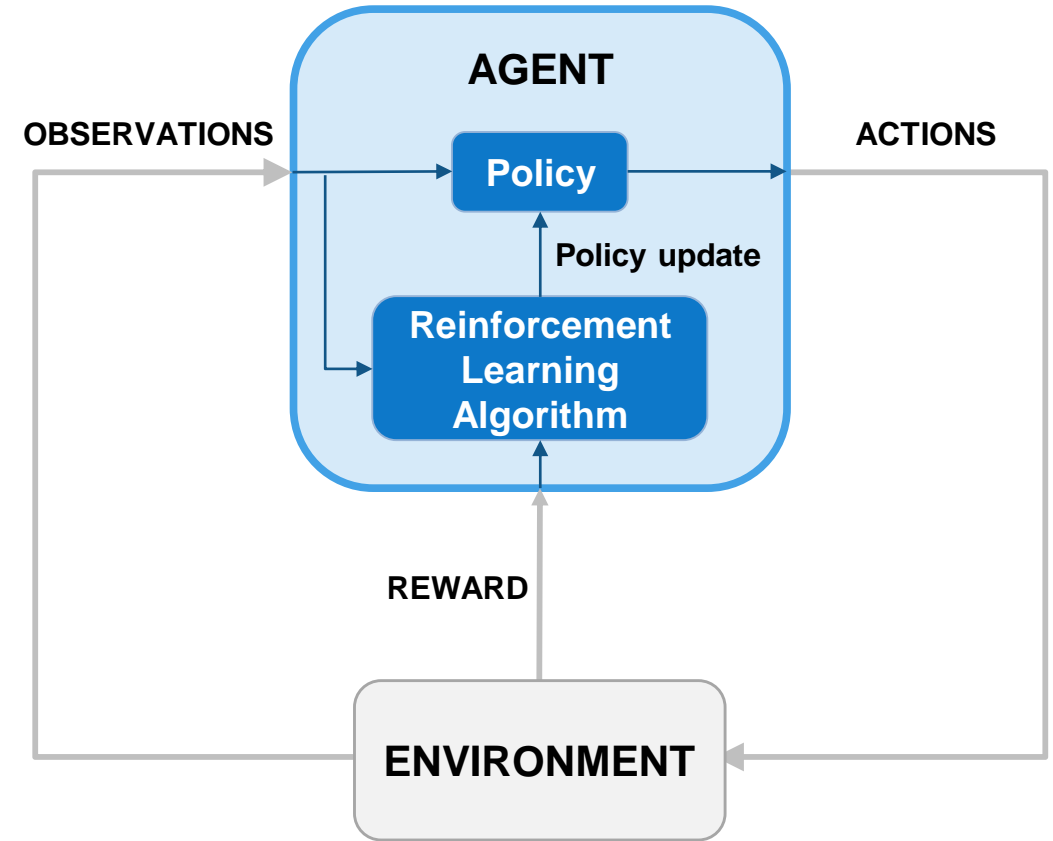
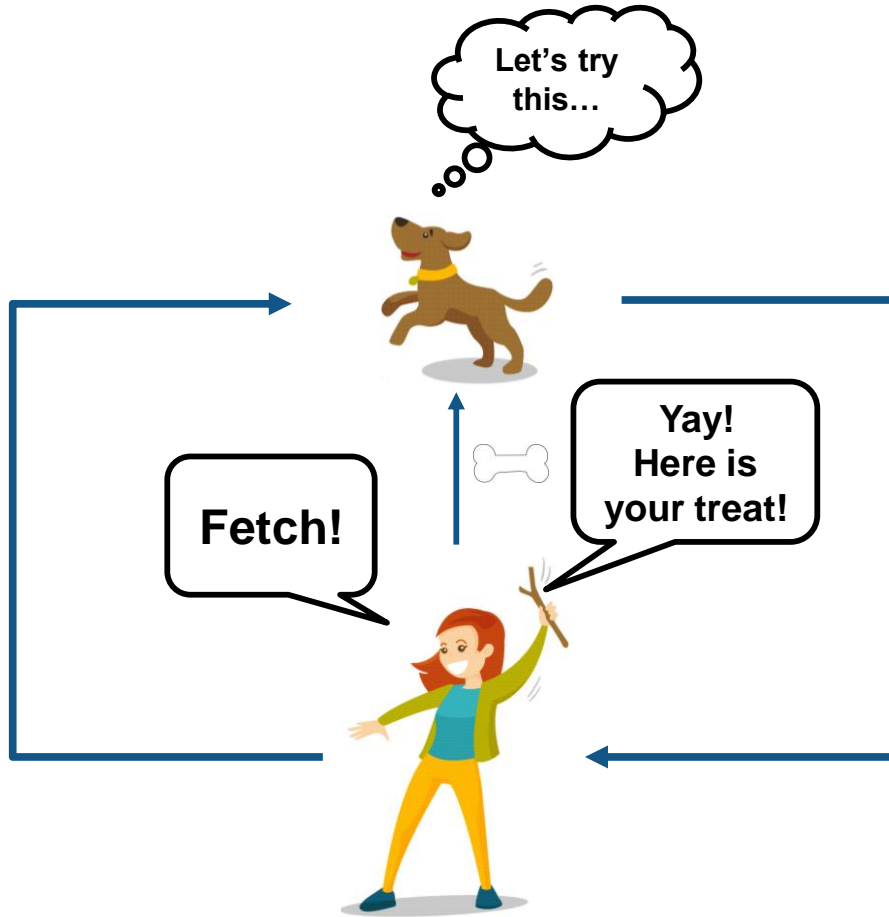


What about deep learning?

Complex reinforcement learning problems typically need deep neural networks
[Deep Reinforcement Learning]

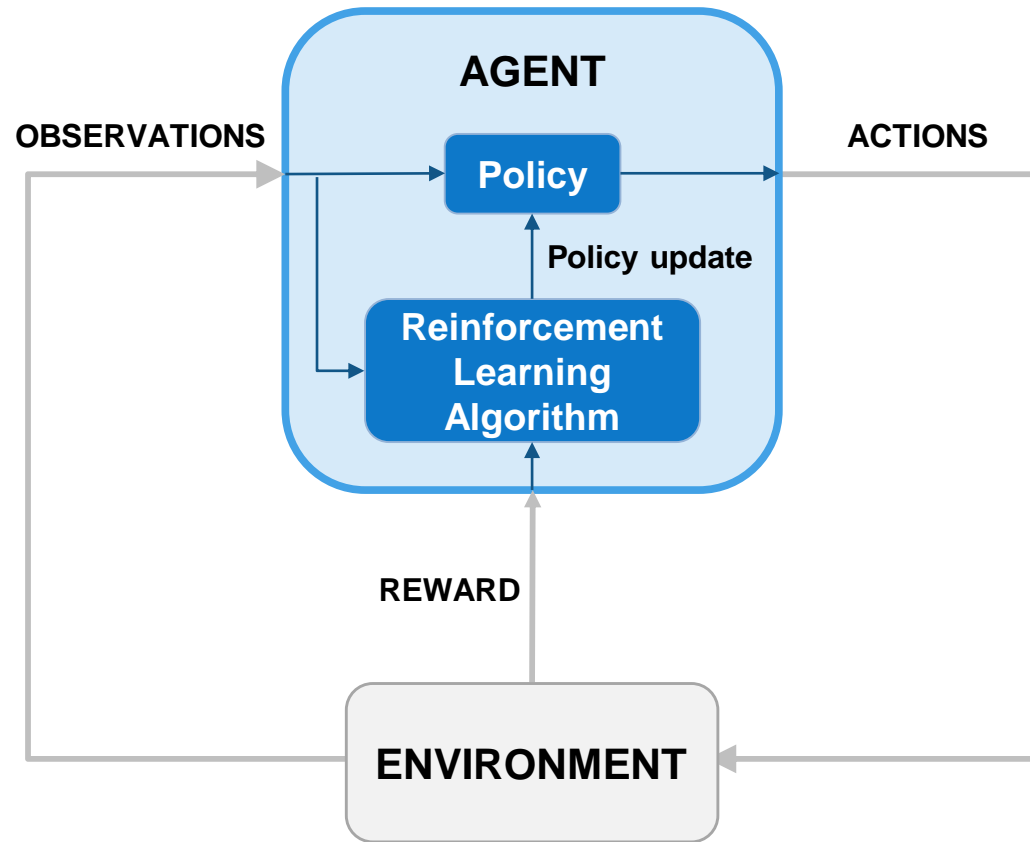
How does reinforcement learning training work?

Analogies with pet training



Reinforcement Learning Concepts

Training a self-driving car

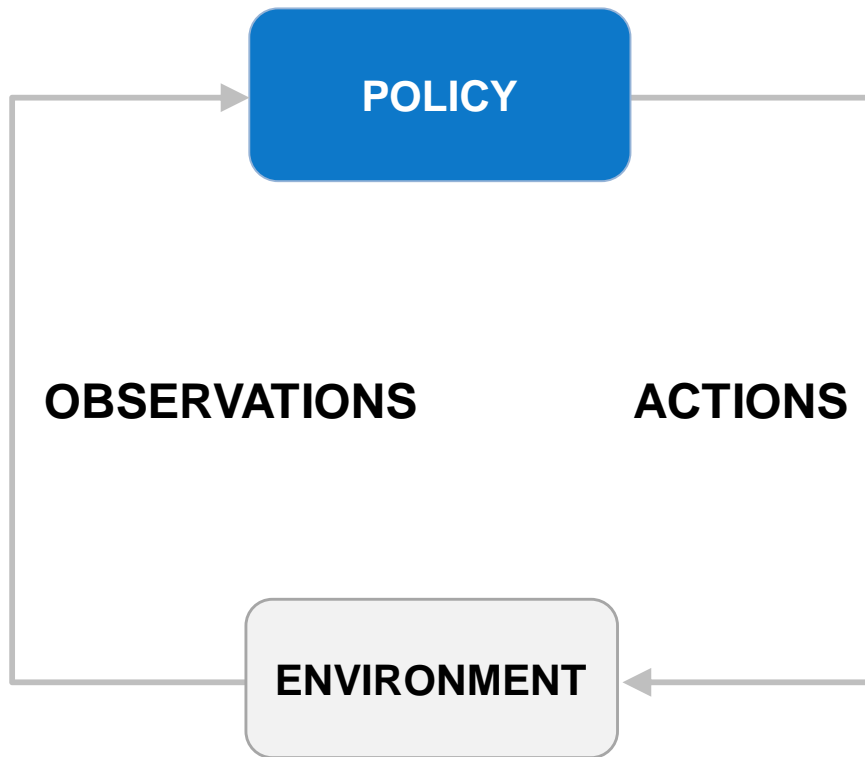


- Vehicle's computer...
(**agent**)
- is reading sensor measurements from LIDAR, cameras,...
(**observations**)
- that represent road conditions, vehicle position,...
(**environment**)
- and generates steering, braking, throttle commands,...
(**action**)
- based on an internal state-to-action mapping...
(**policy**)
- that tries to optimize, e.g., lap time & fuel efficiency...
(**reward**).
- The policy is updated through repeated trial-and-error by a **reinforcement learning algorithm**

Reinforcement Learning Concepts

Training a self-driving car

After training, only trained policy is needed

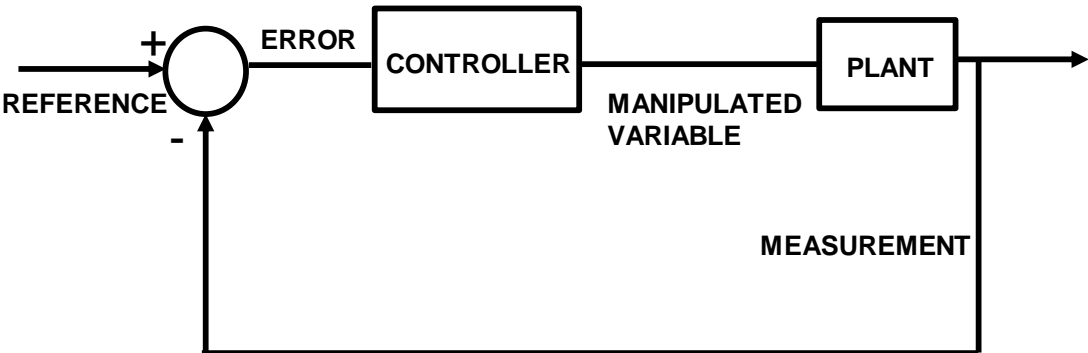


- Vehicle's computer uses the final state-to-action mapping... (**policy**)
- to generate steering, braking, throttle commands,... (**action**)
- based on sensor readings from LIDAR, cameras,... (**observations**)
- that represent road conditions, vehicle position,... (**environment**).

By definition, this trained policy is optimizing lap time & fuel efficiency

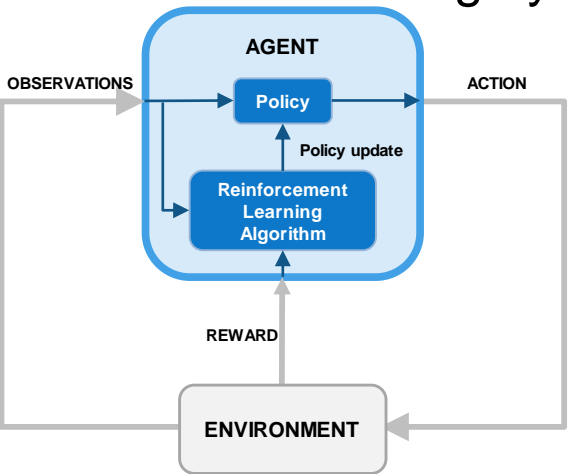
Reinforcement Learning vs Controls

Control system



- Adaptation mechanism
- Error/Cost function
- Manipulated variable
- Measurement
- Plant
- Controller

Reinforcement learning system



- RL Algorithm
- Reward
- Action
- Observation
- Environment
- Policy

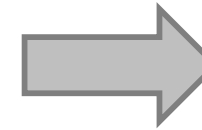
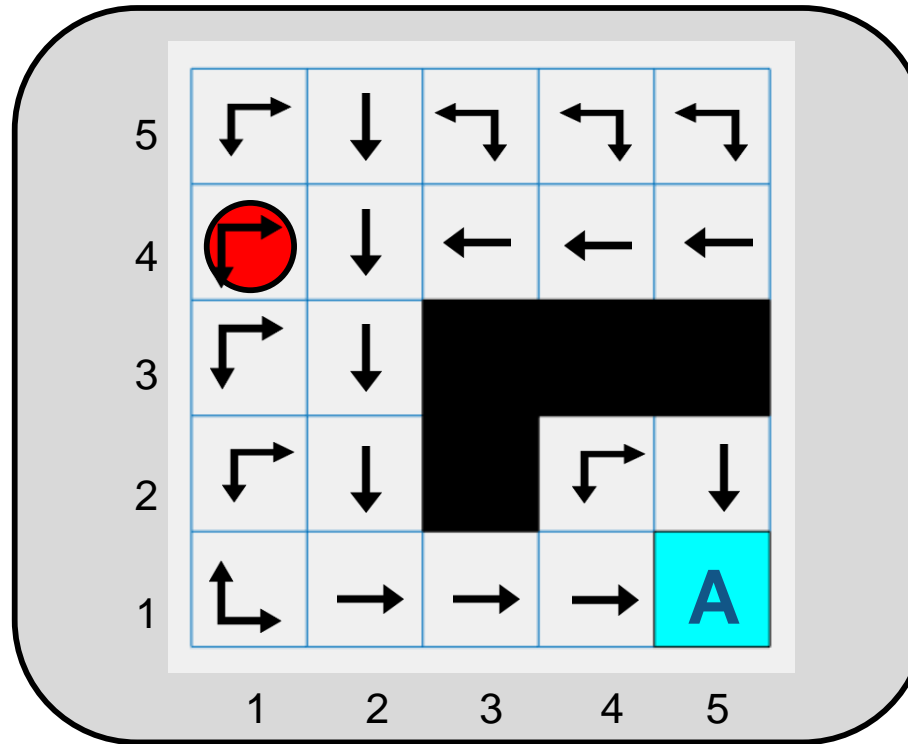
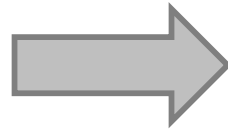
Reinforcement learning has parallels to **control system design**

Policy Representation and Deep Learning

Representation options

- Look-up table
- Polynomials

Observations



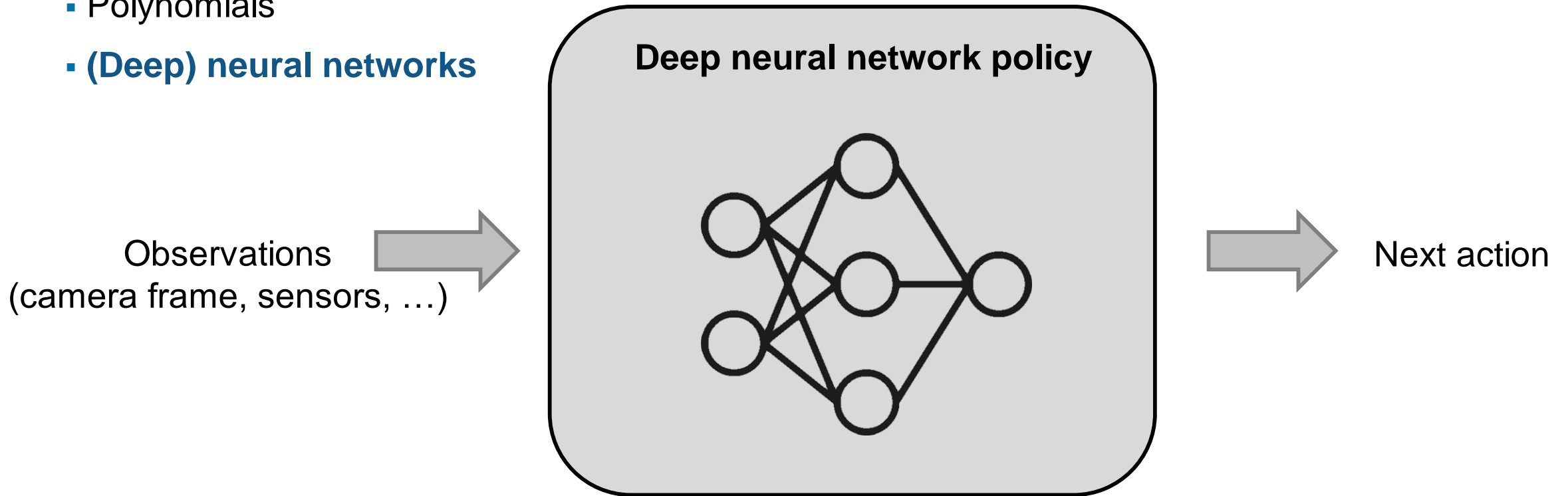
Next action

Look-up tables **do not scale** well

Policy Representation and Deep Learning

Representation options

- Look-up table
- Polynomials
- **(Deep) neural networks**



Neural networks allow representation of **complex policies**

How do I set up and solve a reinforcement learning problem?

Reinforcement Learning Workflow

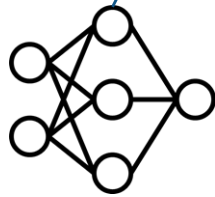
- Simulation models or real hardware
- Virtual models are safer and cheaper



Environment



Reward



Policy
representation



Agent



Training



Deployment

- Deep network? Table? Polynomial?

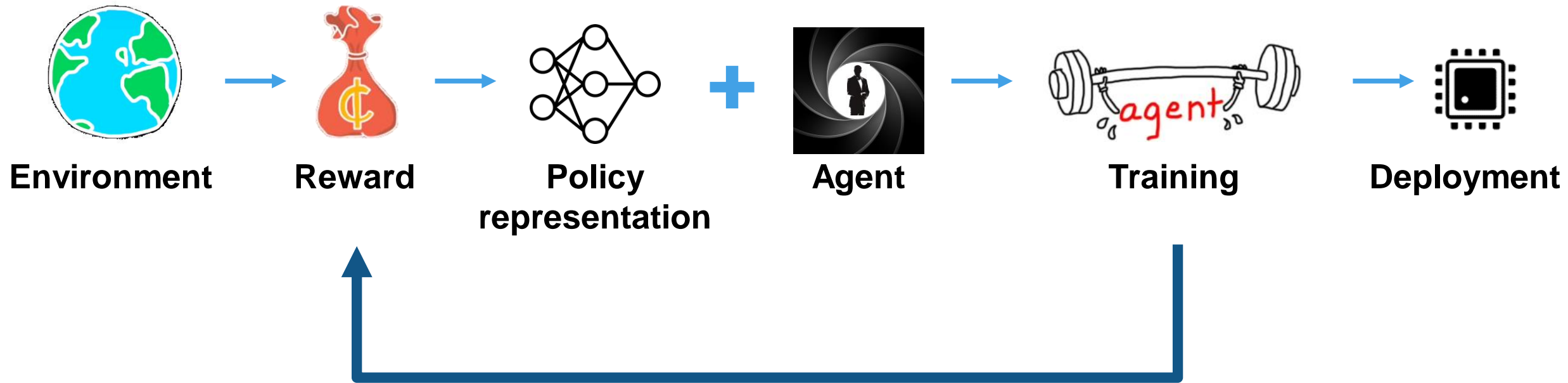
- Select training algorithm
- Tune hyperparameters

- Trained policy is a standalone function

- Numerical value that evaluates goodness of policy
- Reward shaping can be challenging

- Large number of simulations needed
- Parallel & GPU computing can speed up training
- Training could still take hours or days

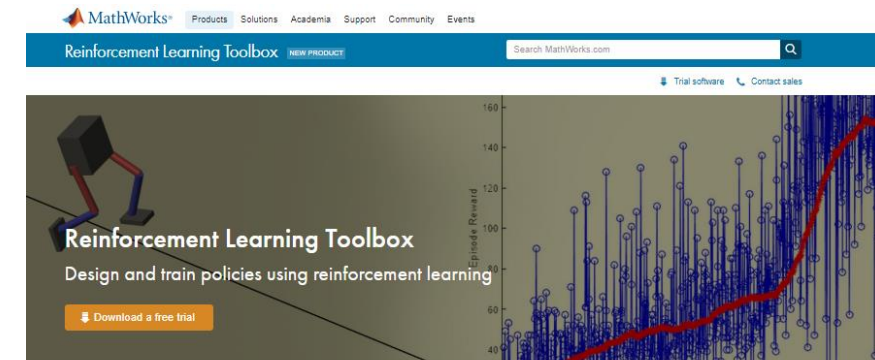
Reinforcement Learning Workflow



Reinforcement Learning Toolbox

Introduced in R2019a

- Built-in and custom reinforcement learning algorithms
- Environment modeling in MATLAB and Simulink
 - Existing scripts and models can be reused
- Deep Learning Toolbox support for representing policies
- Training acceleration with Parallel Computing Toolbox and MATLAB Parallel Server
- Deployment of trained policies with GPU Coder and MATLAB Coder
- Reference examples for getting started

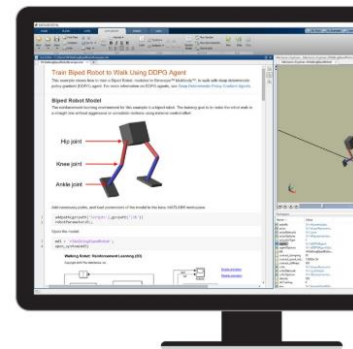


Reinforcement Learning Toolbox™ provides functions and blocks for training policies using reinforcement learning algorithms including DQN, A2C, and DDPG. You can use these policies to implement controllers and decision-making algorithms for complex systems such as robots and autonomous systems. You can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

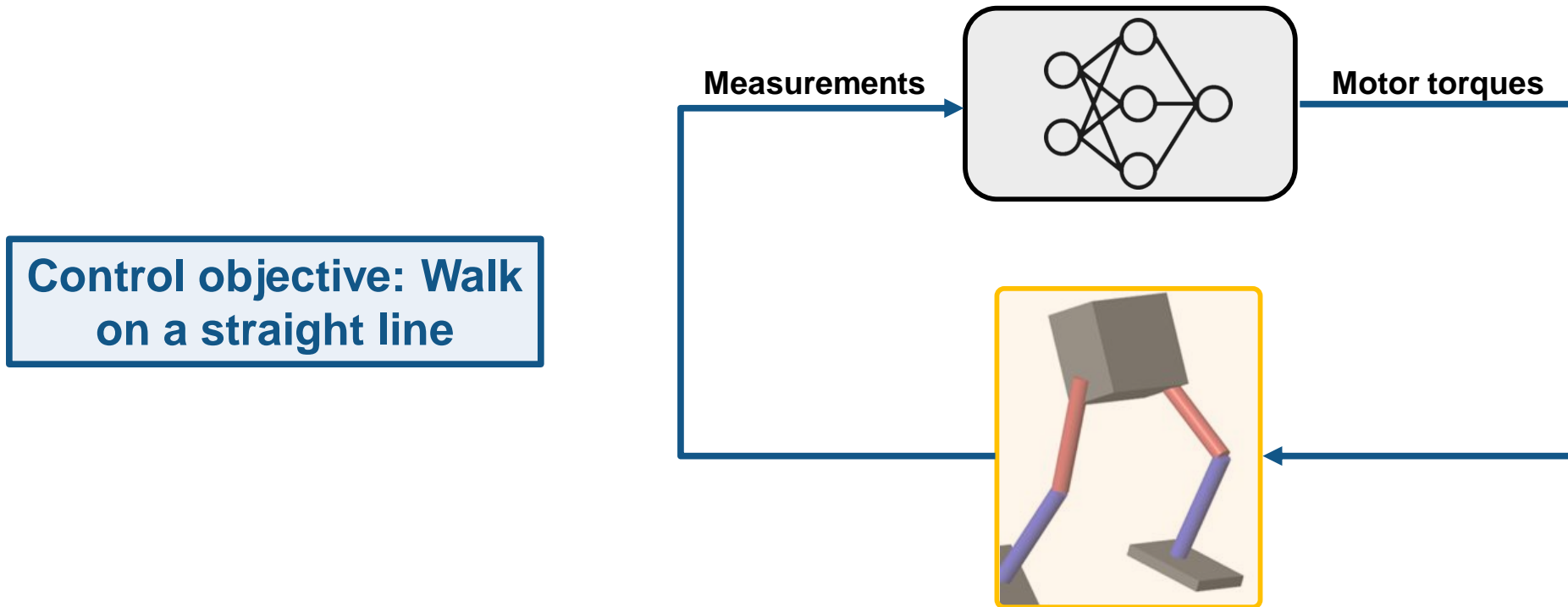
The toolbox lets you train policies by enabling them to interact with environments represented by MATLAB® or Simulink® models. You can evaluate algorithms, experiment with hyperparameter settings, and monitor training progress. To improve training performance, you can run simulations in parallel on the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

Through the ONNX™ 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 automated driving applications.



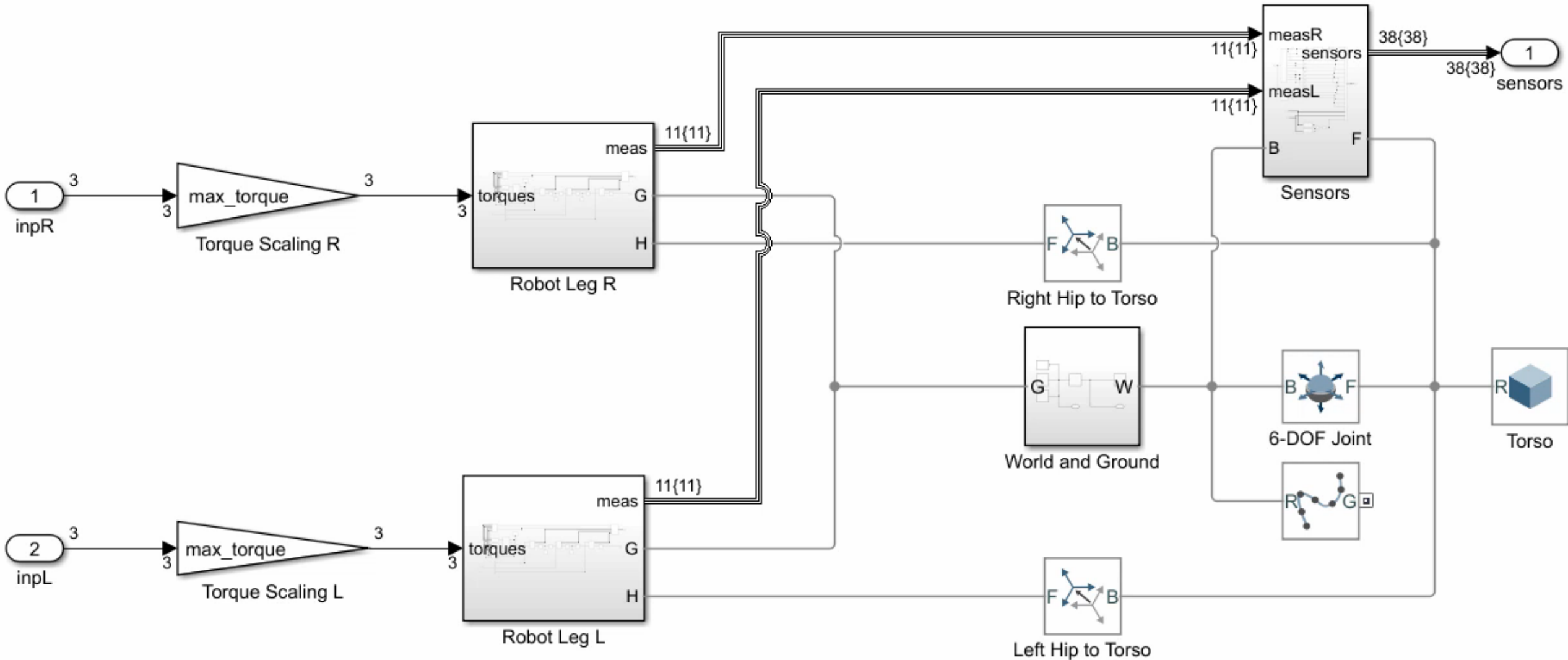
Example: Walking Robot



Creating the Environment



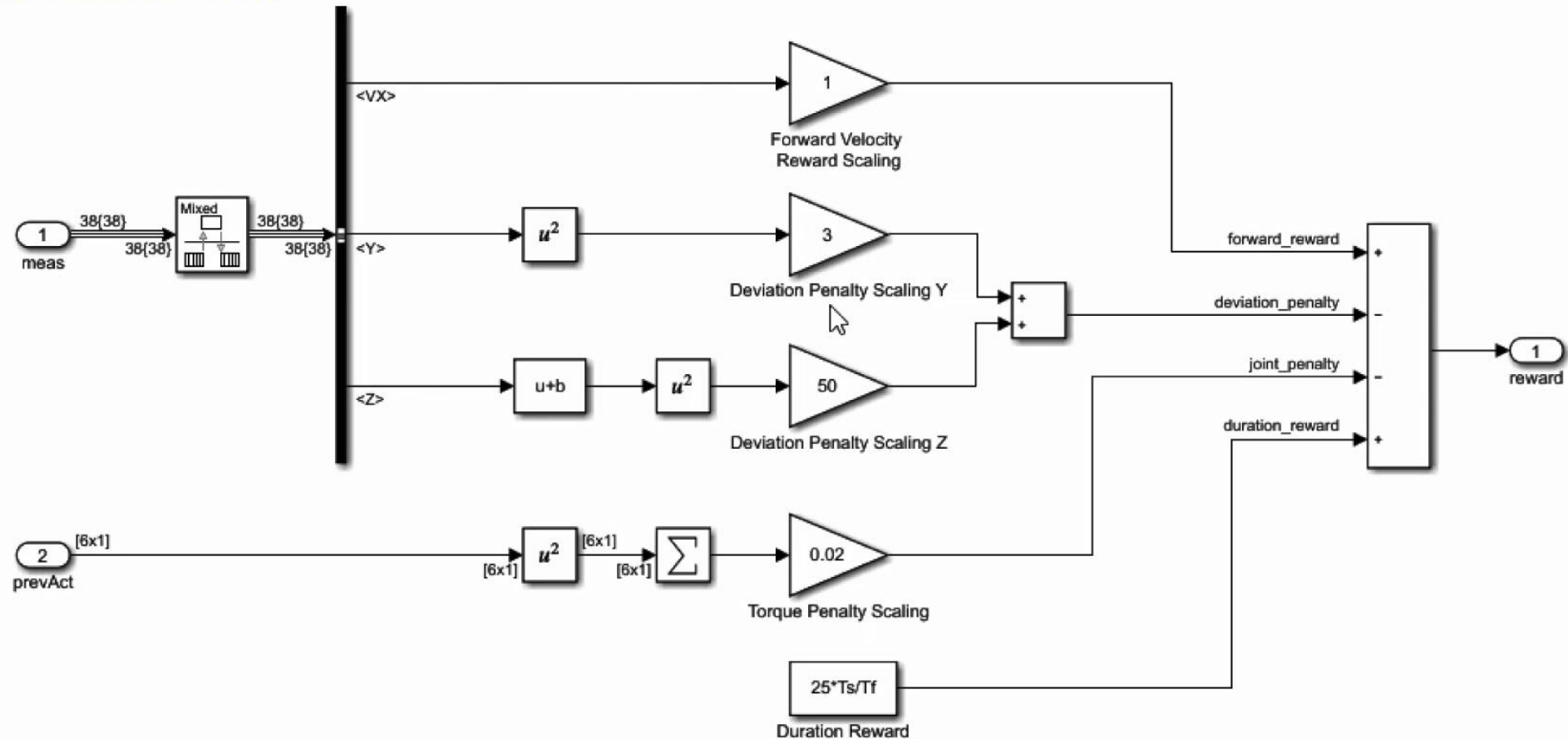
rlWalkingBipedRobot_Template ▶ Walking Robot ▶



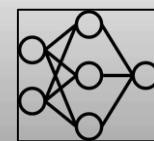
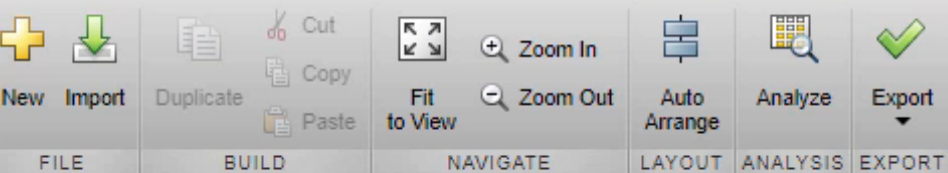
Reward Shaping



Reward function inspired by
**"Emergence of Locomotion
Behaviours in Rich Environments"**
Google DeepMind, 2017
<https://arxiv.org/pdf/1707.02286.pdf>



DESIGNER



LAYER LIBRARY

Filter layers...

INPUT

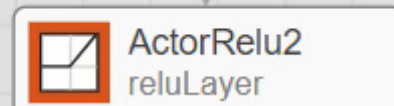
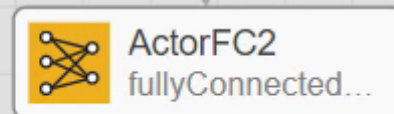
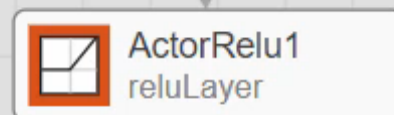
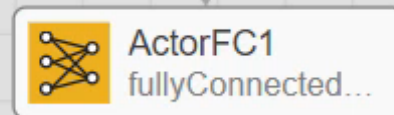
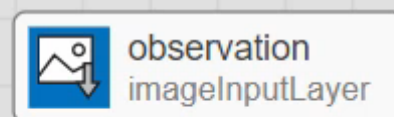
- imageInputLayer
- image3dInputLayer
- sequenceInputLayer
- roiInputLayer

CONVOLUTION AND FULLY CONNECTED

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

SEQUENCE

- lstmLayer
- biLstmLayer



PROPERTIES

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

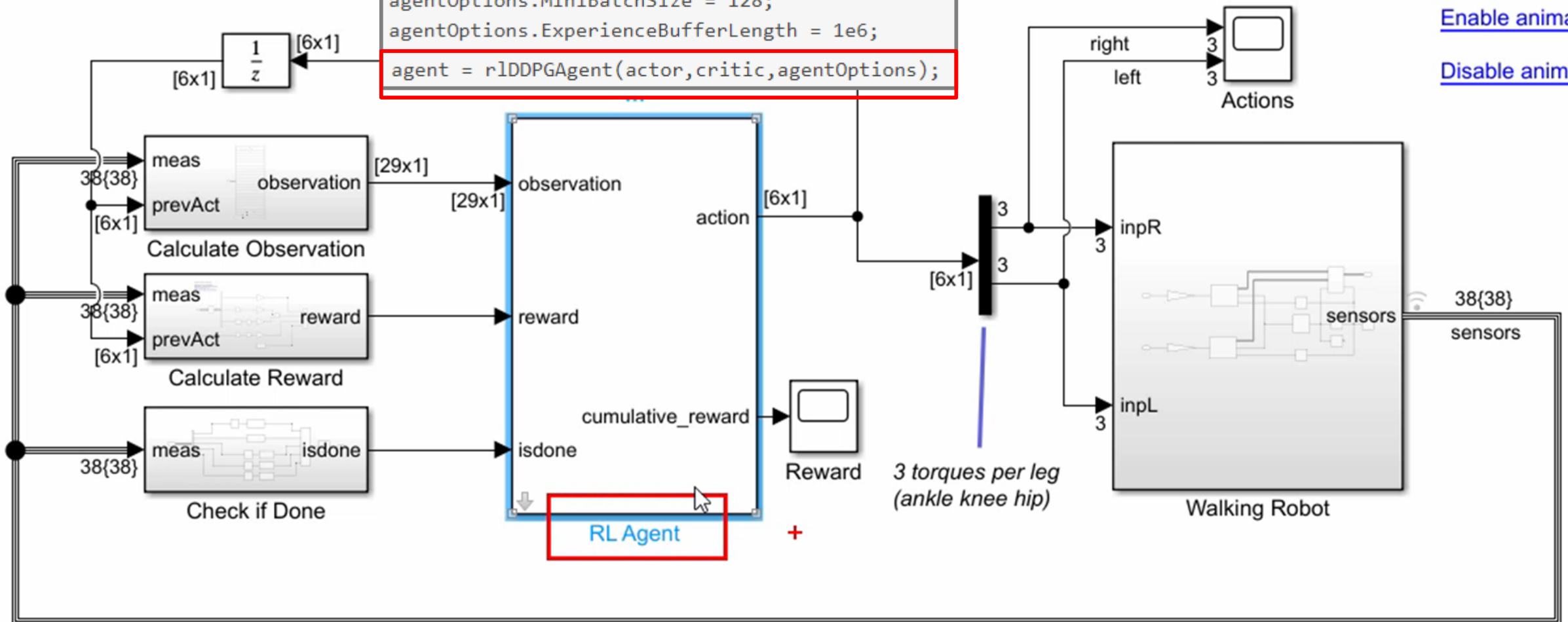
Creating the Agent



Walking Robot: Reinforcement Learning

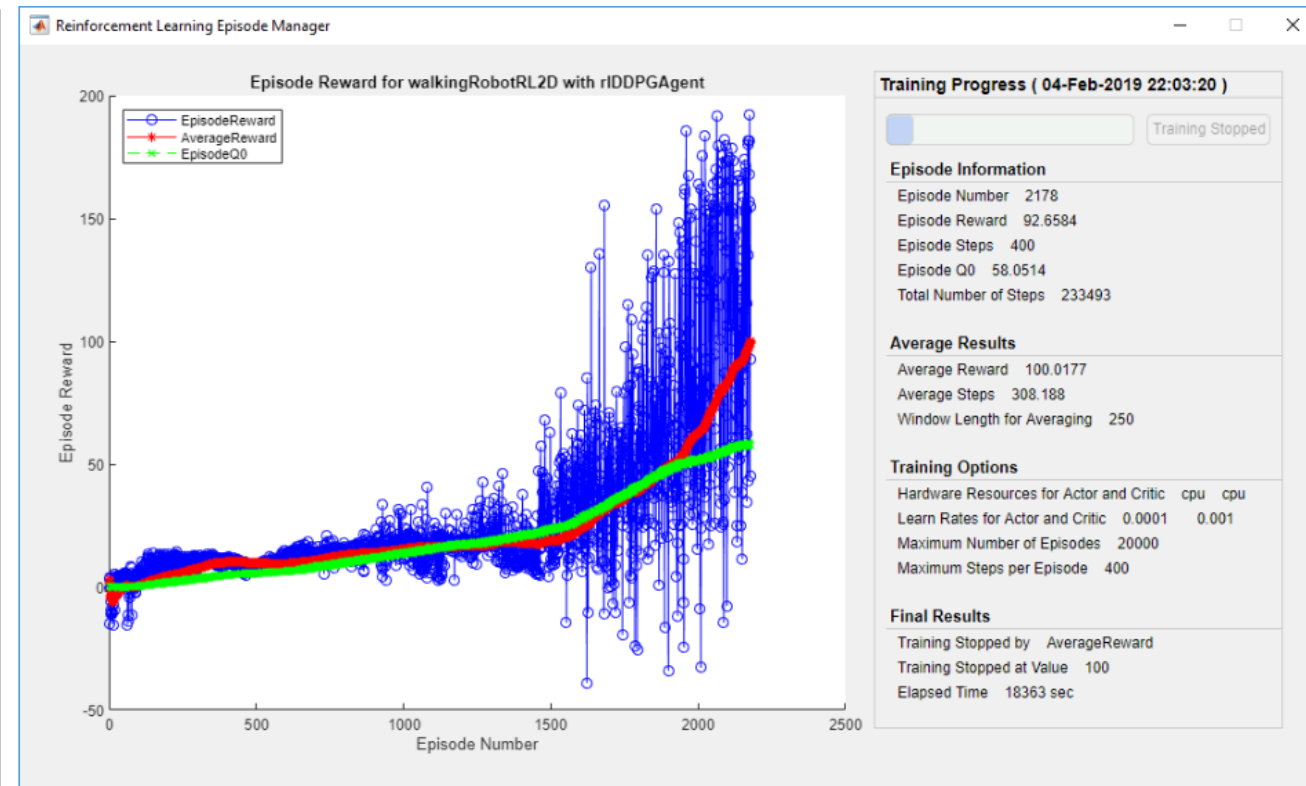
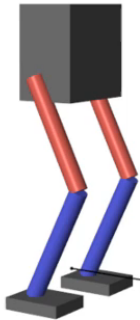
Copyright 2019 The MathWorks

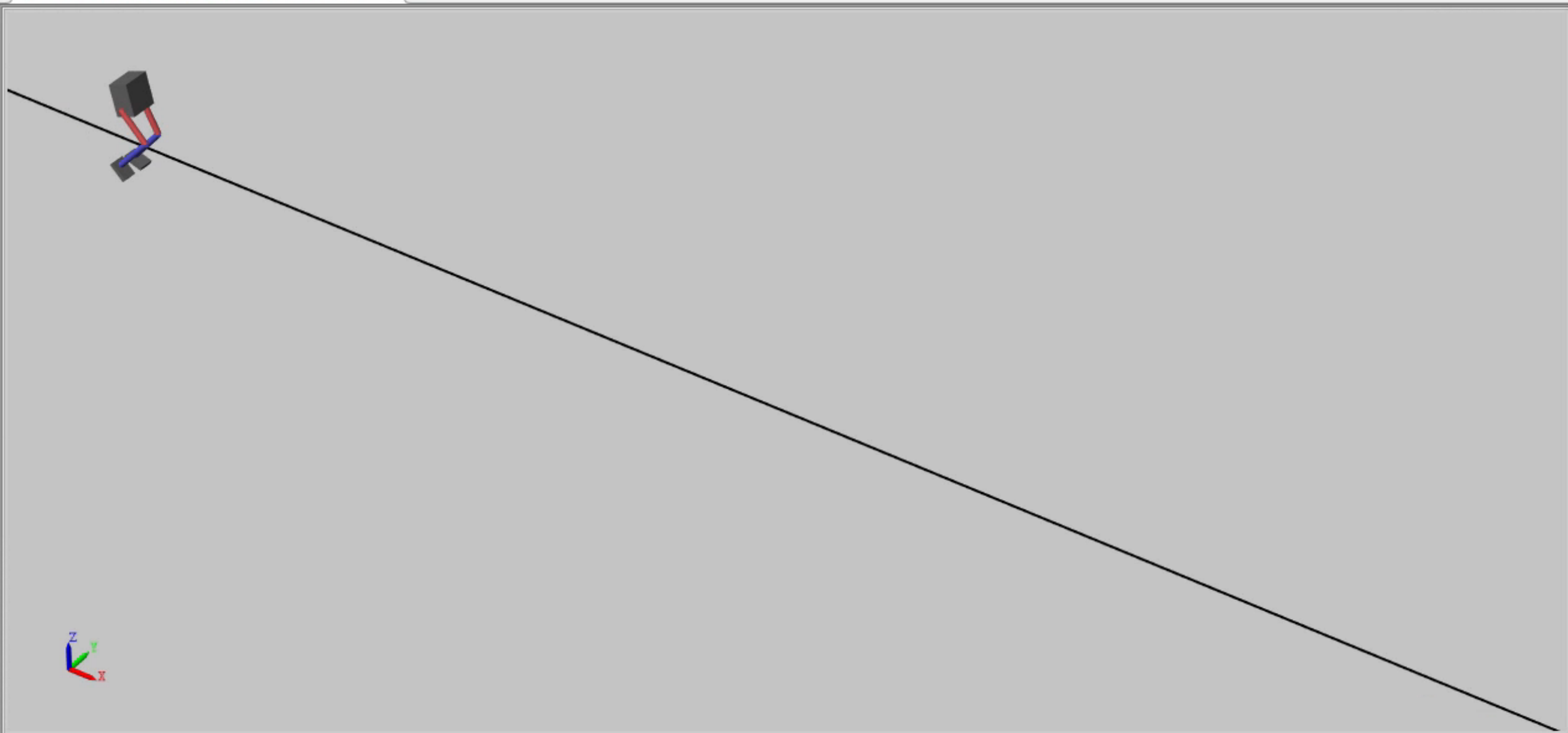
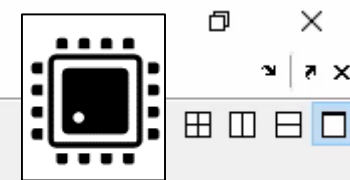
```
agentOptions = rlDDPGAgentOptions;  
agentOptions.SampleTime = Ts;  
agentOptions.DiscountFactor = 0.99;  
agentOptions.MinibatchSize = 128;  
agentOptions.ExperienceBufferLength = 1e6;  
agent = rlDDPGAgent(actor,critic,agentOptions);
```



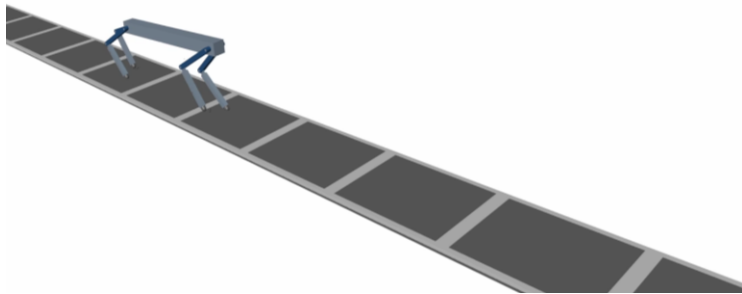
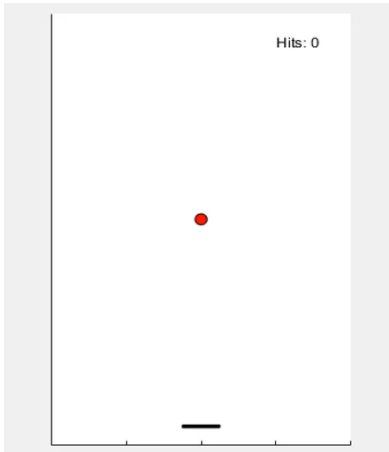
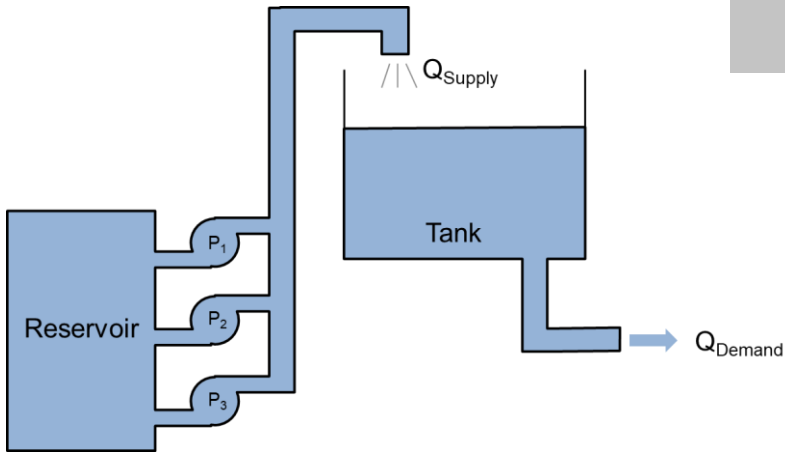
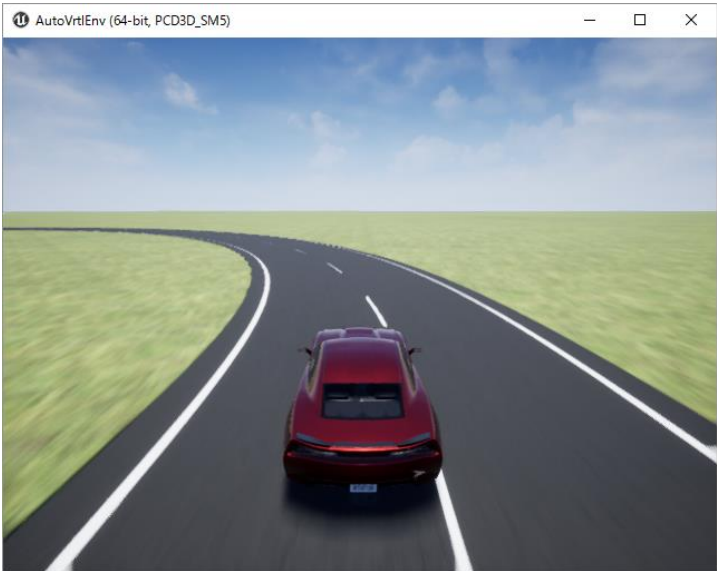
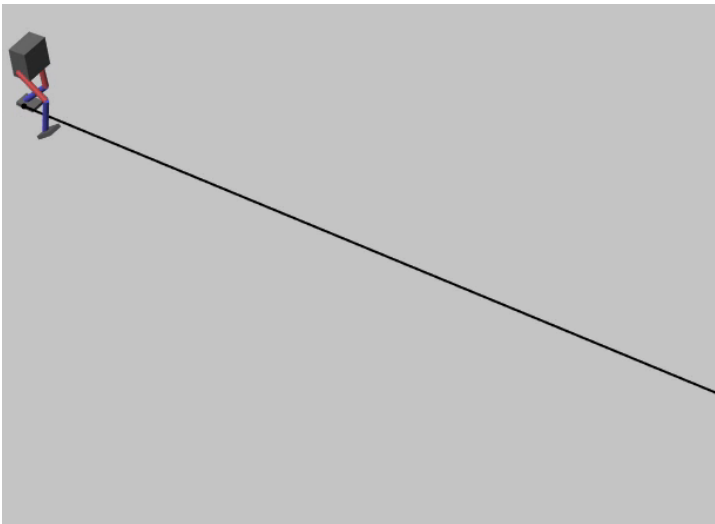
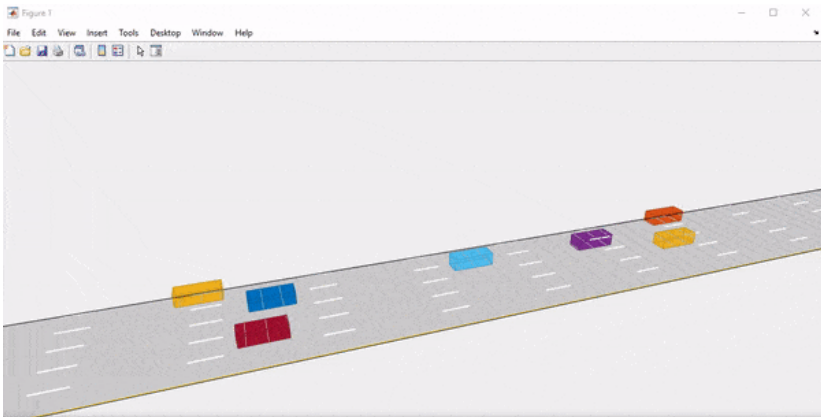
Training the Agent

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

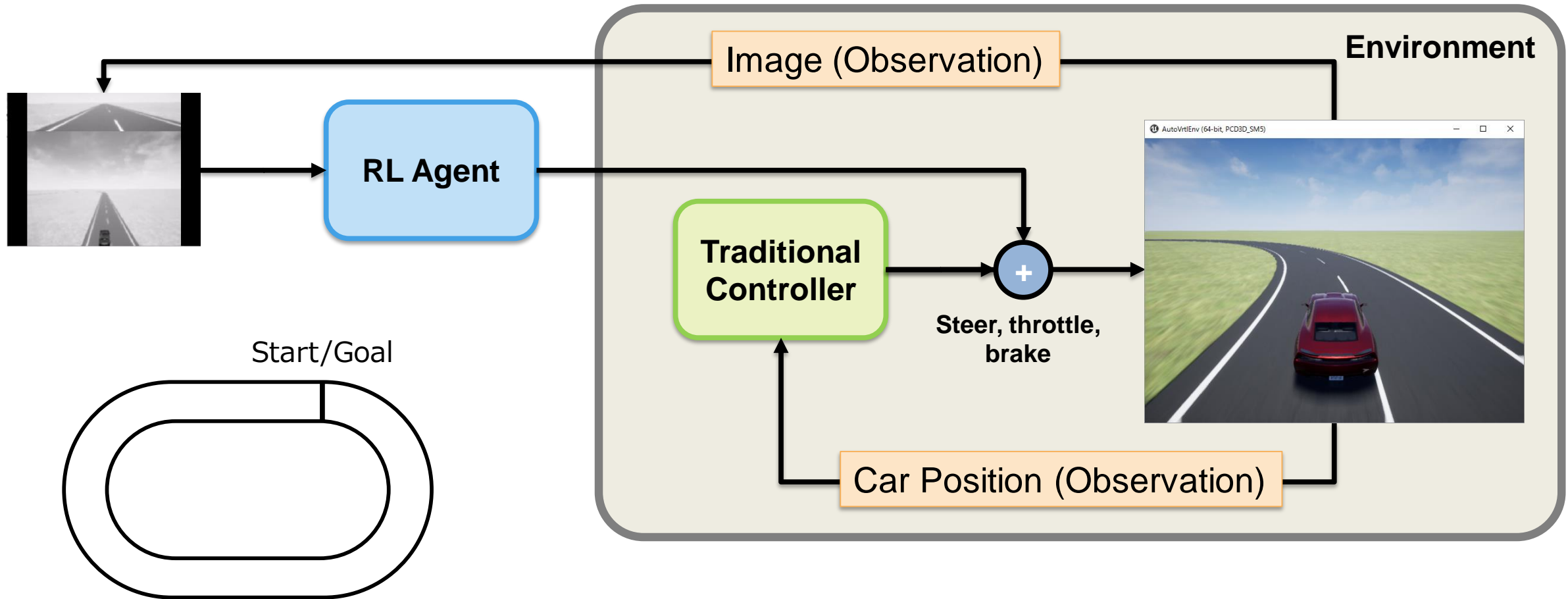




Applications of Reinforcement Learning

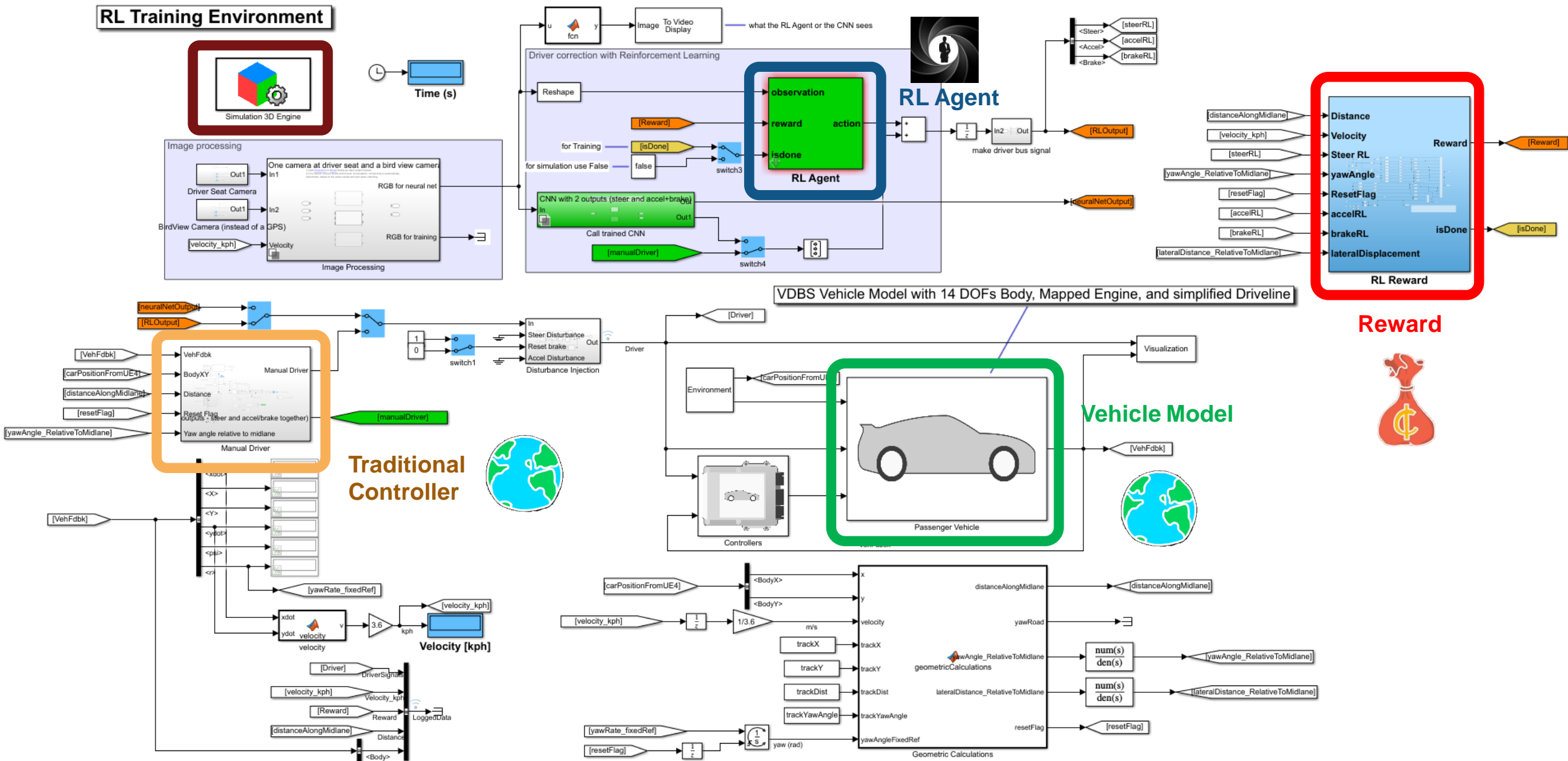


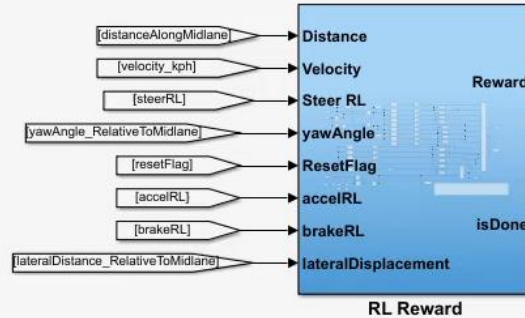
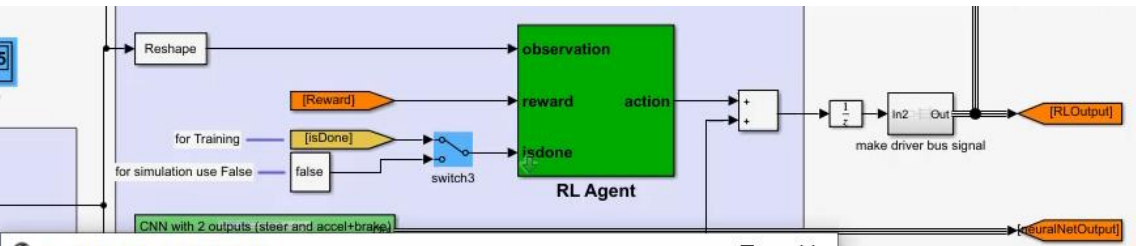
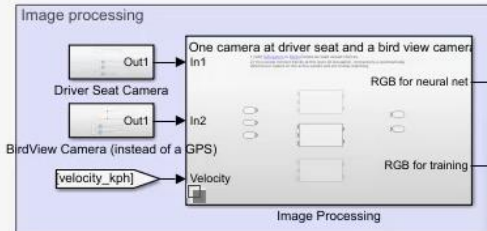
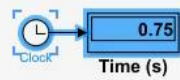
Autonomous Driving Example



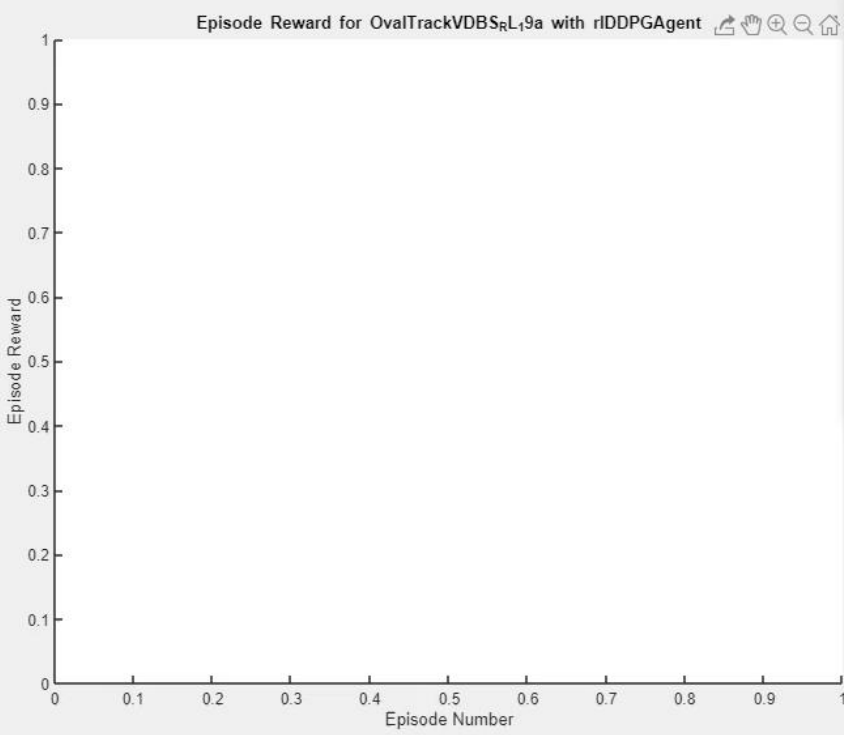
Objective: Augment traditional controller with reinforcement learning to improve lap time

RL Training Environment





Reinforcement Learning Episode Manager



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

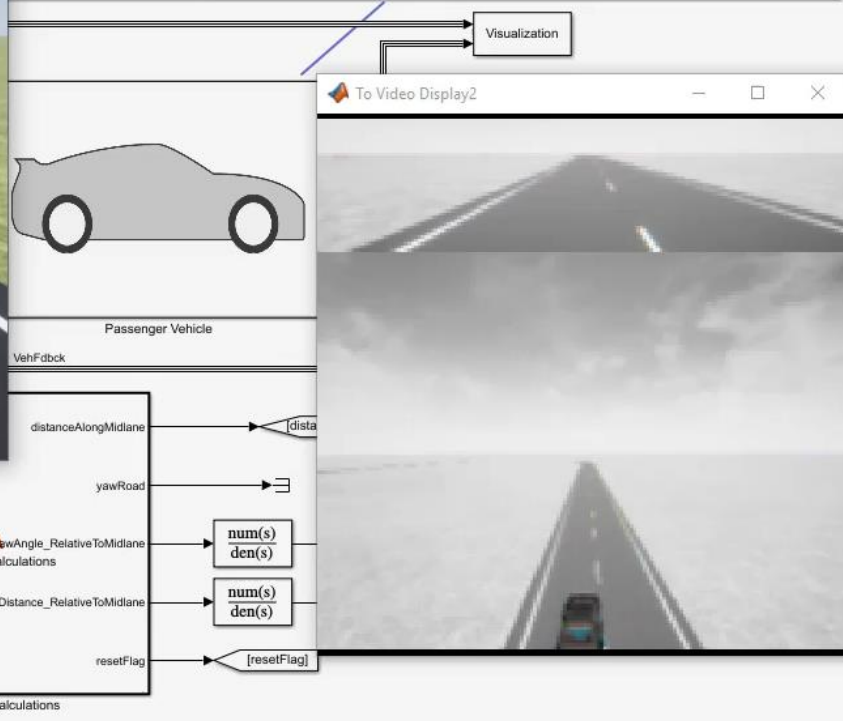
Final Results

Training Stopped by ...

Training Stopped at Value ...

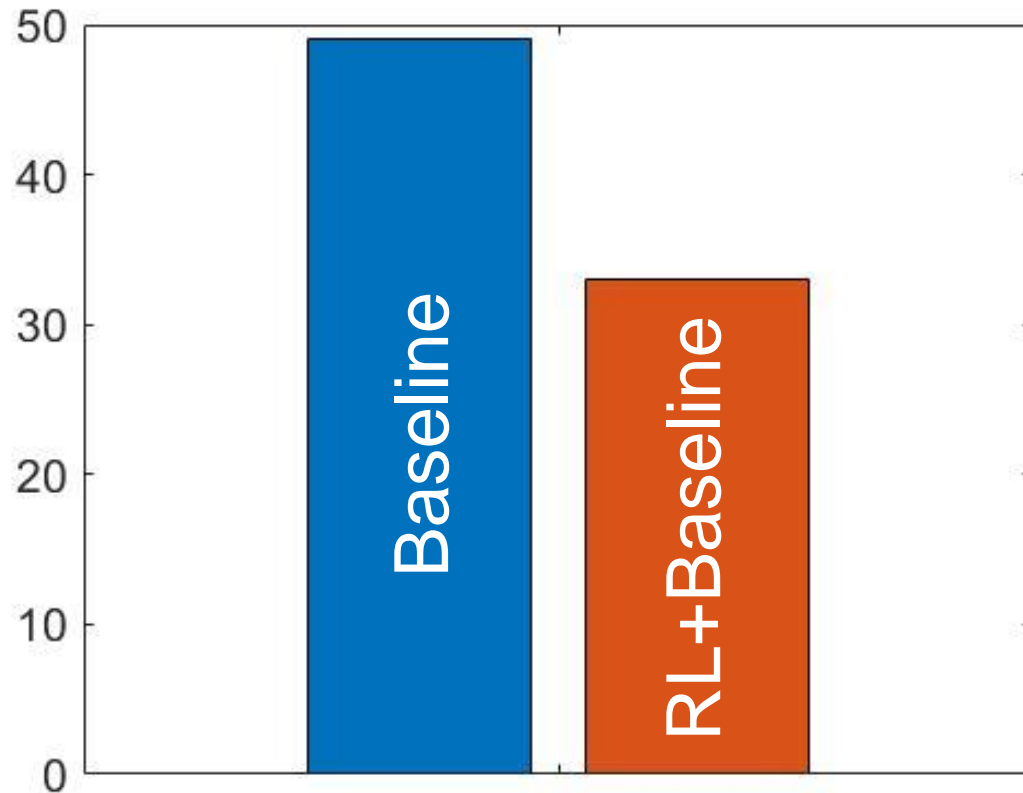
Elapsed Time ...

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



Results

Lap time (s)



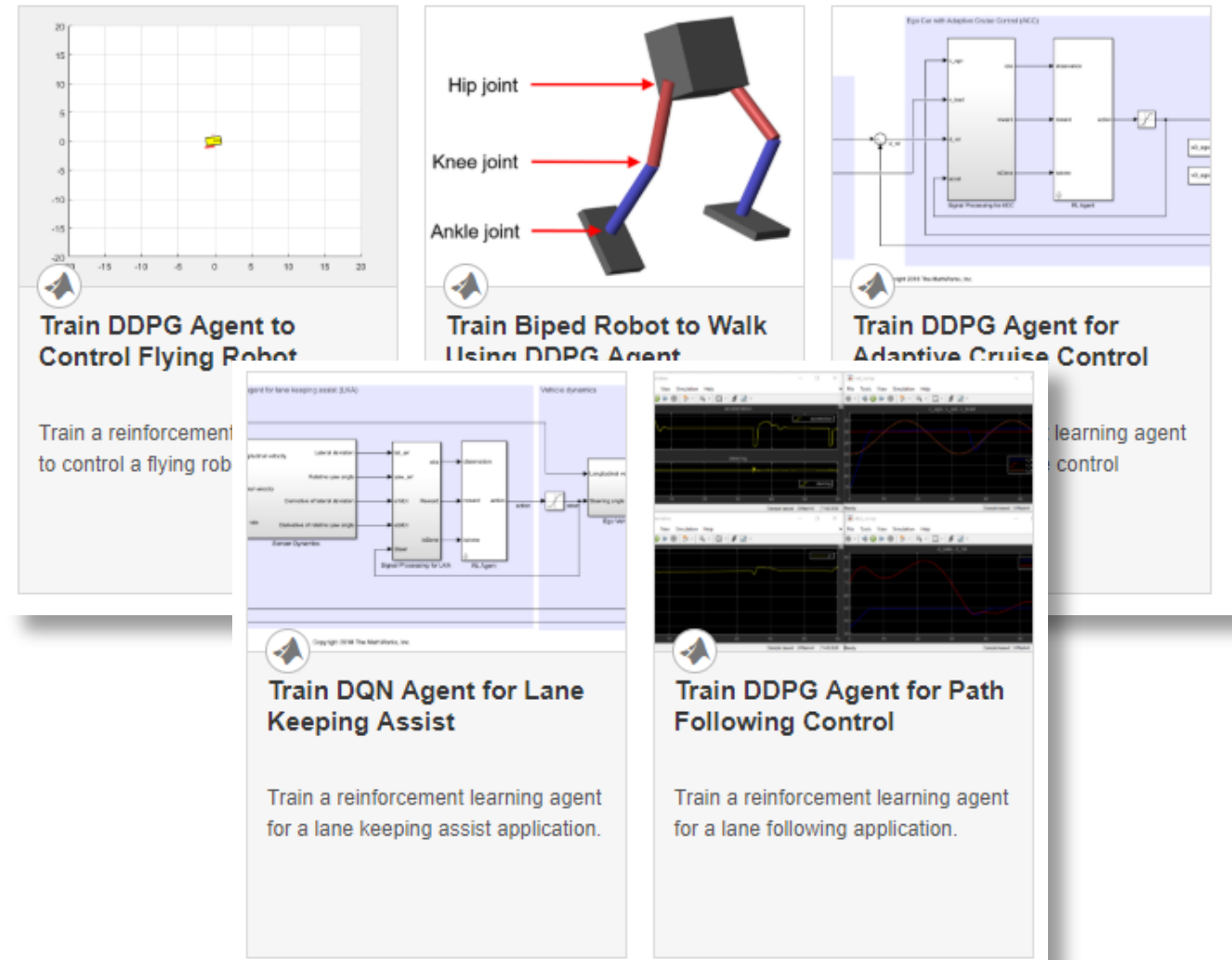
30% performance improvement

Traditional controller +
reinforcement learning



Reference Applications in Documentation

- Controller Design
- Robotic Locomotion
- Lane Keep Assist
- Adaptive Cruise Control
- Imitation Learning



Pros & Cons of Reinforcement Learning

Pros

- **No data** required before training
- **New possibilities** with AI for hard-to-solve problems
- Complex **end-to-end** solutions can be developed
- **Uncertain, nonlinear** environments can be used

Cons

- Trained policies are **hard to verify** (no performance guarantees)
- Many trials/data points required (**sample inefficient**)
 - Training with real hardware can be expensive and dangerous
- Large number of **design parameters**
 - Reward signal
 - Network architectures
 - Training Hyperparameters

Simulations are key in Reinforcement Learning

How Can MATLAB and Simulink Help?

Challenges

- Trained policies are **hard to verify** (no performance guarantees)
- Many trials/data points required (**sample inefficient**)
 - Training with real hardware can be expensive and dangerous
- Large number of **design parameters**
 - Reward signal
 - Network architectures
 - Training Hyperparameters

MATLAB® & SIMULINK®

- **Reuse** existing code and models for environments
- Use simulations for **policy verification**
 - Simulate extreme scenarios
- Run simulation trials **in parallel** to accelerate training
- Consult Reinforcement Learning Toolbox **examples**
 - Iterative tuning with simulations

Key Takeaways

- What is reinforcement learning and why should I care about it?
- How do I set up and solve a reinforcement learning problem?
- What are some common challenges?

Learn More

- Reference examples for controls, robotics, and autonomous system applications
- Documentation written for engineers and domain experts
- Tech Talk video series on Reinforcement Learning concepts
- Reinforcement Learning ebooks available at mathworks.com

