# How to Train Your Robot

## An Introduction to Reinforcement Learning

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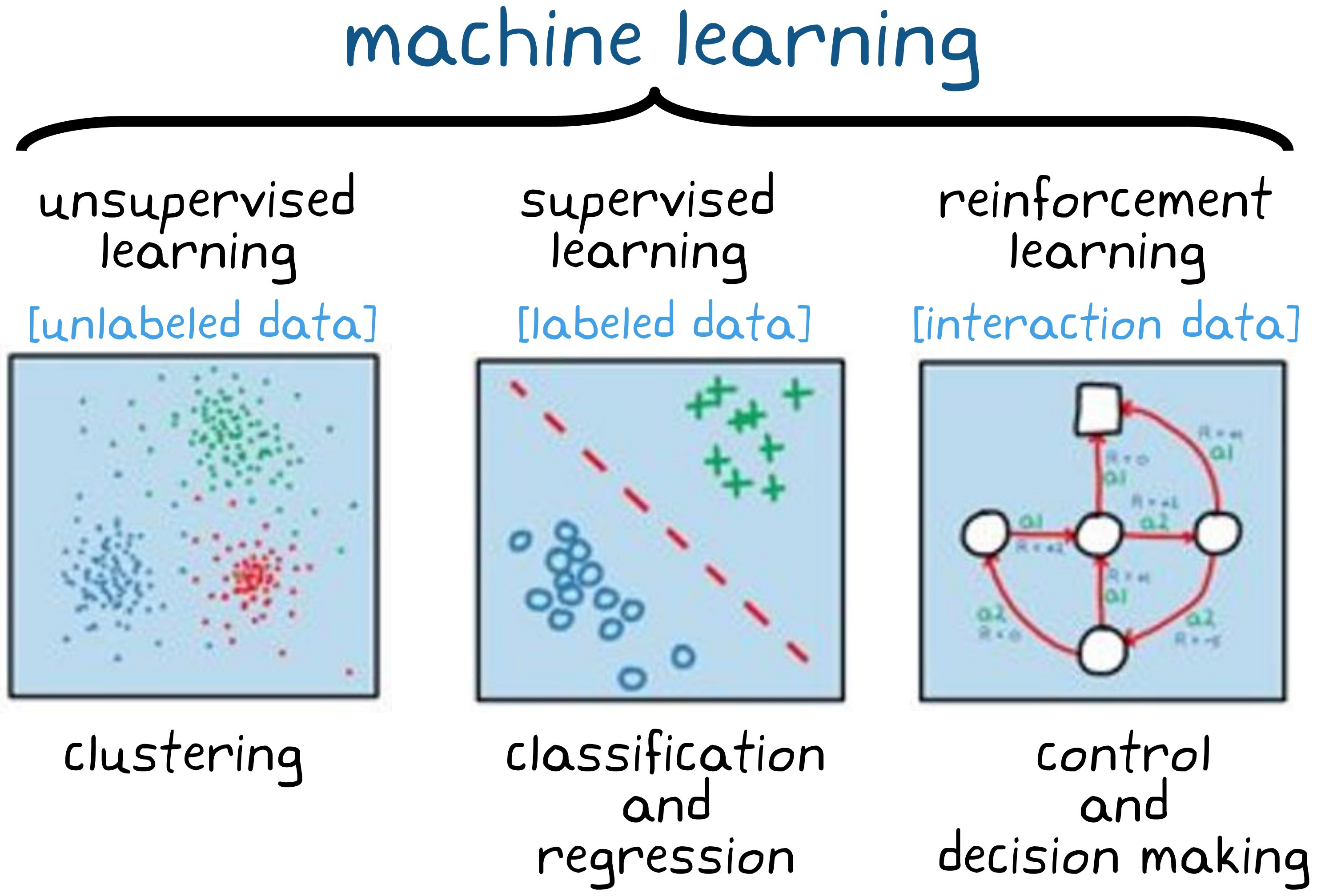
MathWorks

# Agenda

- How to Train a Robot to Walk (35 min)
  - What is reinforcement learning?
  - Overview of using a traditional controls approach
  - Applying the reinforcement learning workflow to train the robot

- Q&A (10 min)

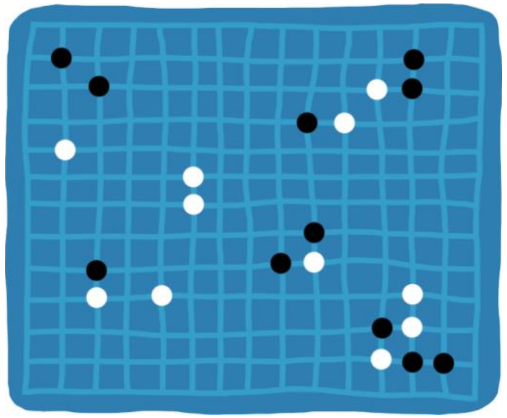
# Reinforcement Learning: A Subset of Machine Learning




## Reinforcement learning:

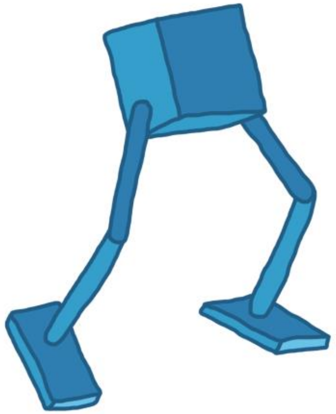
- Learning a **behavior** or accomplishing a **task** through trial & error
  [*interaction*]
- Complex problems typically need deep models
  [*Deep Reinforcement Learning*]

# Reinforcement Learning Applications



video games

autonomous vehicles

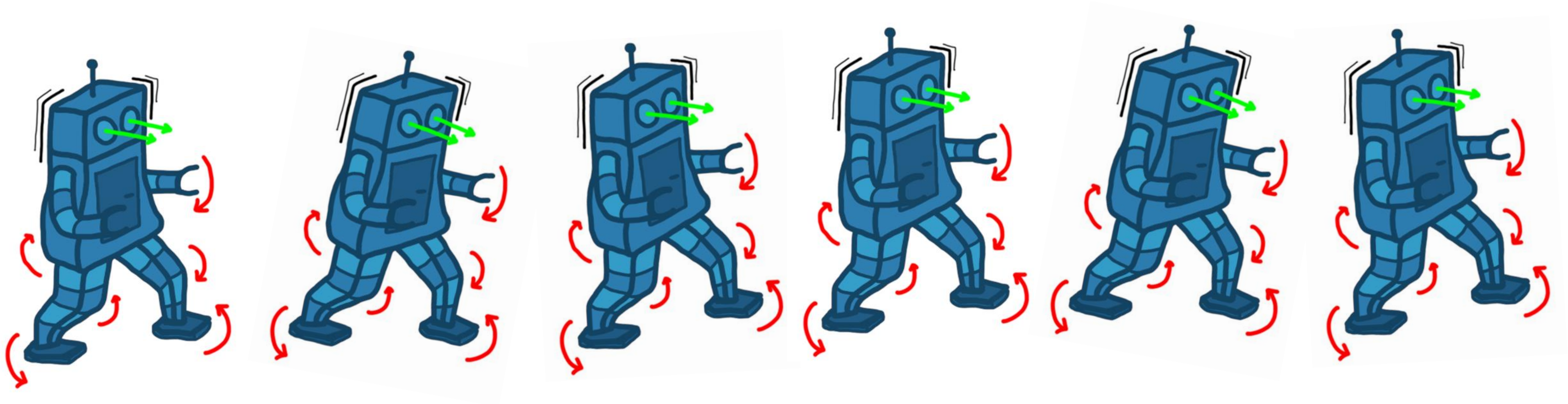


robotics

controls

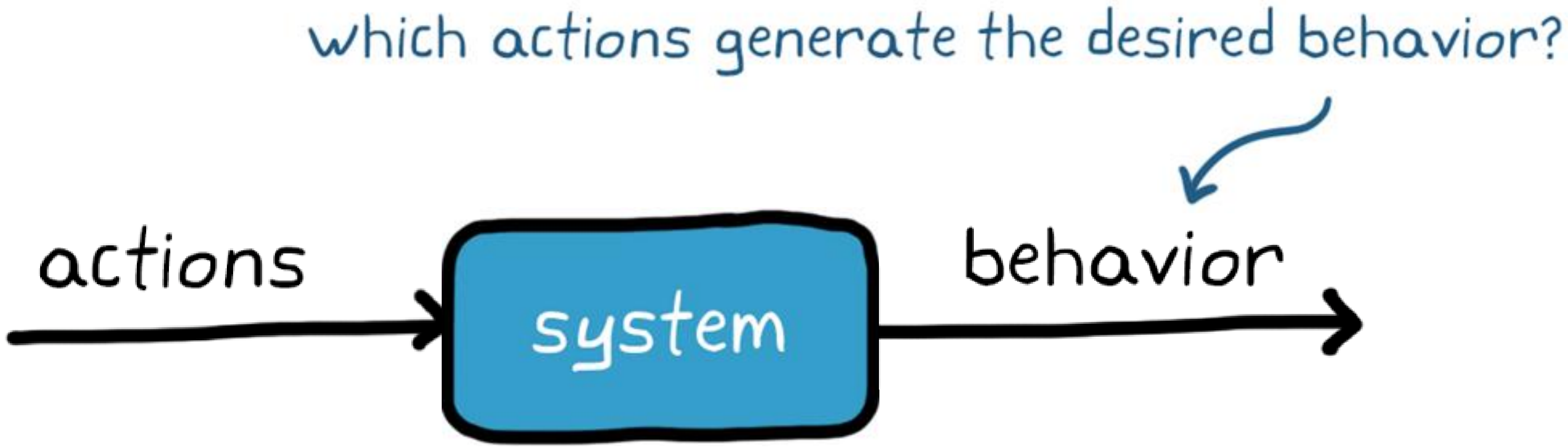
# How do We Train a Robot to Walk

Goal: Train a robot to walk a straight line

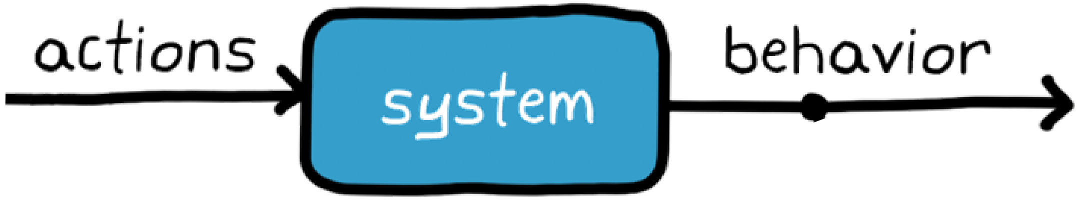


What sequence of motor commands do we need to make the robot walk?

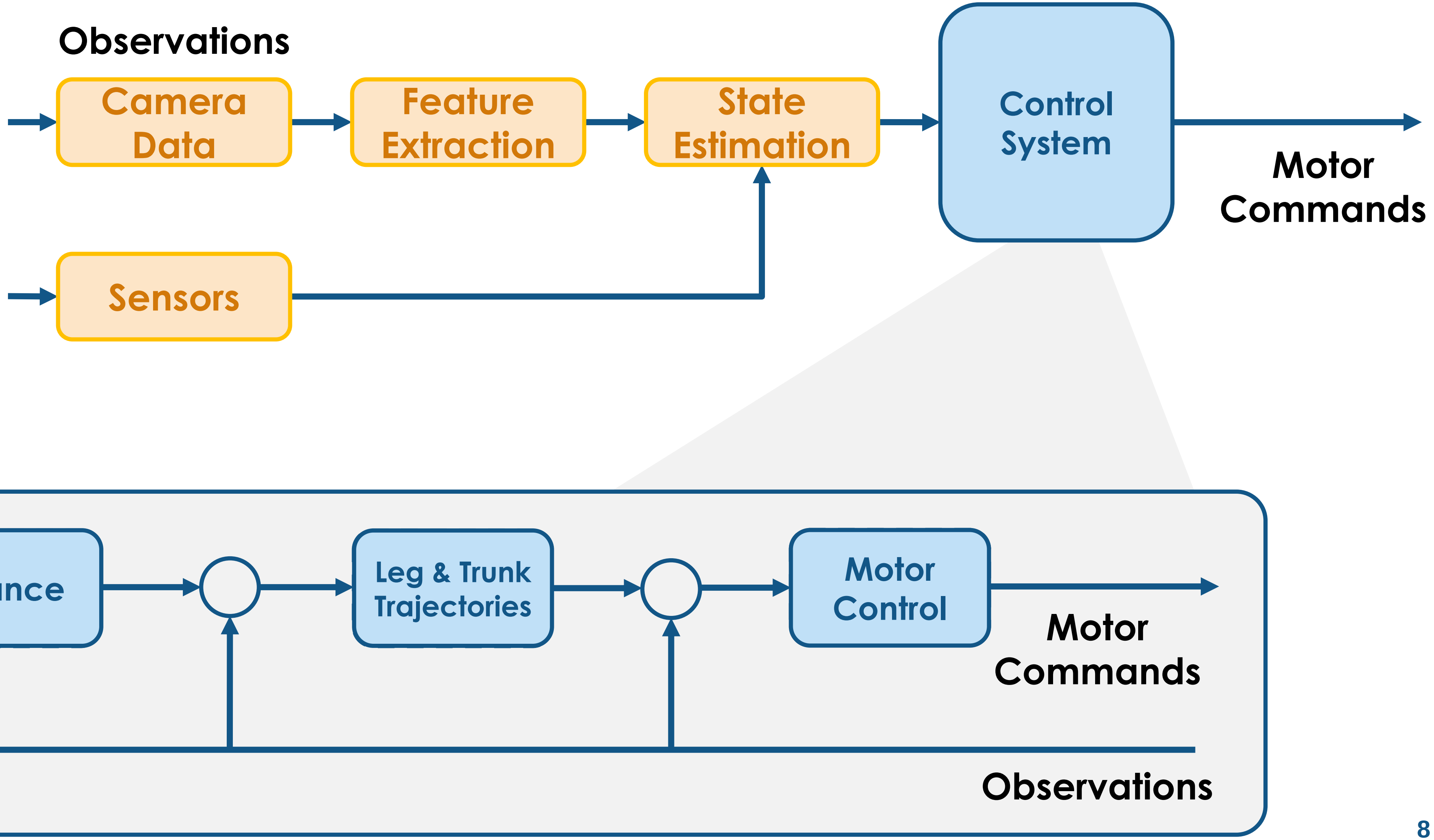
# The goal of control



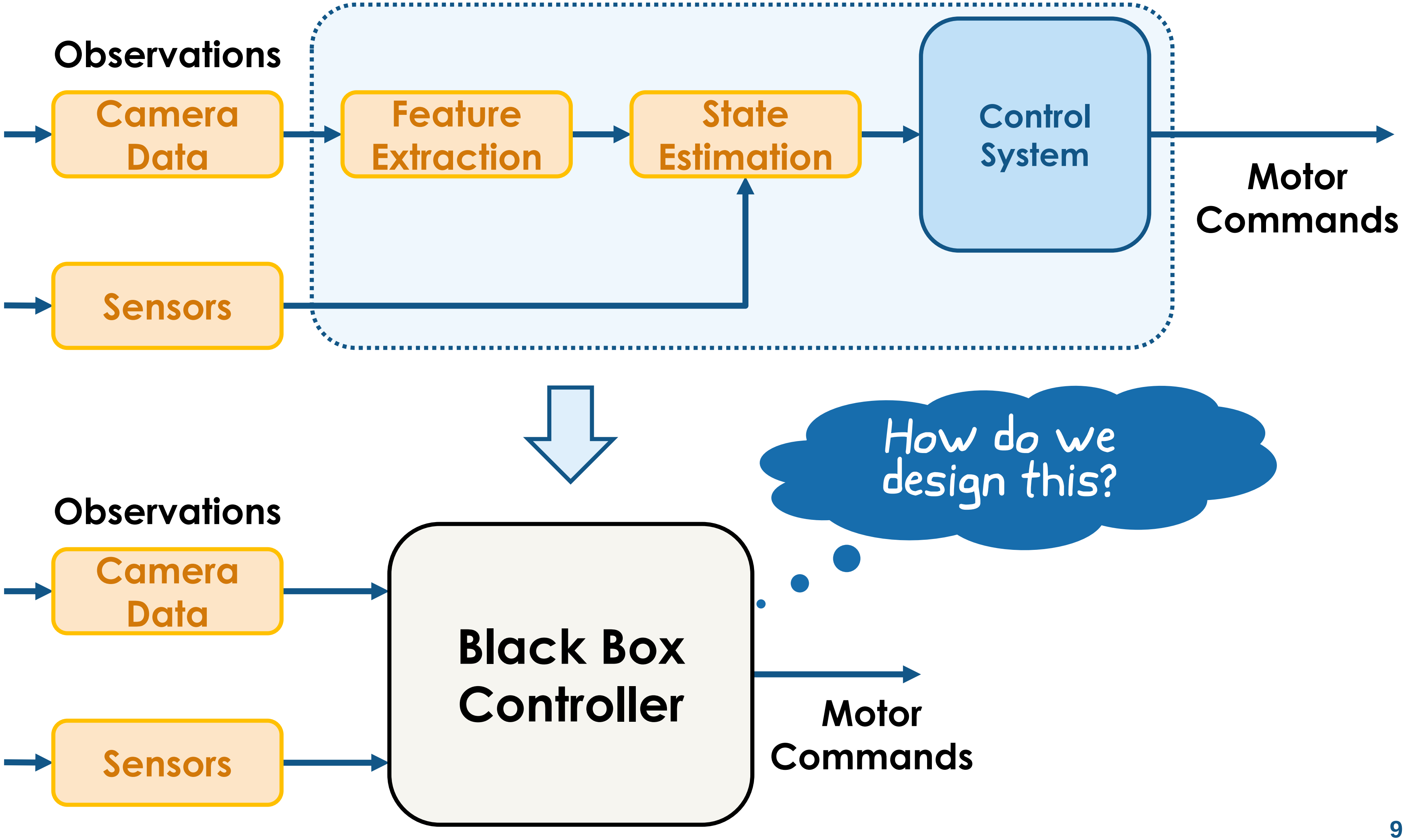
# The goal of control



# A walking robot – a traditional controls approach

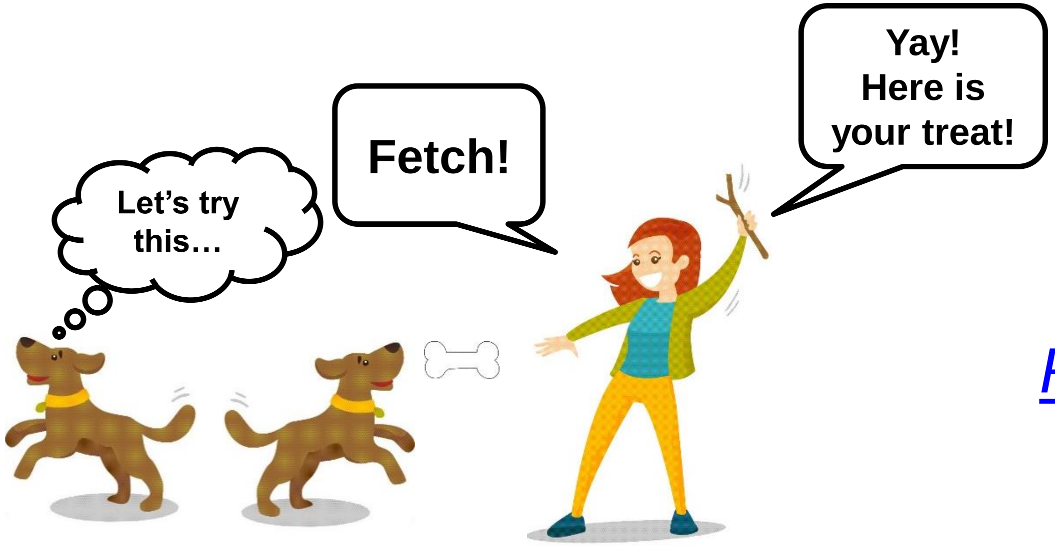


# A walking robot – an alternative approach



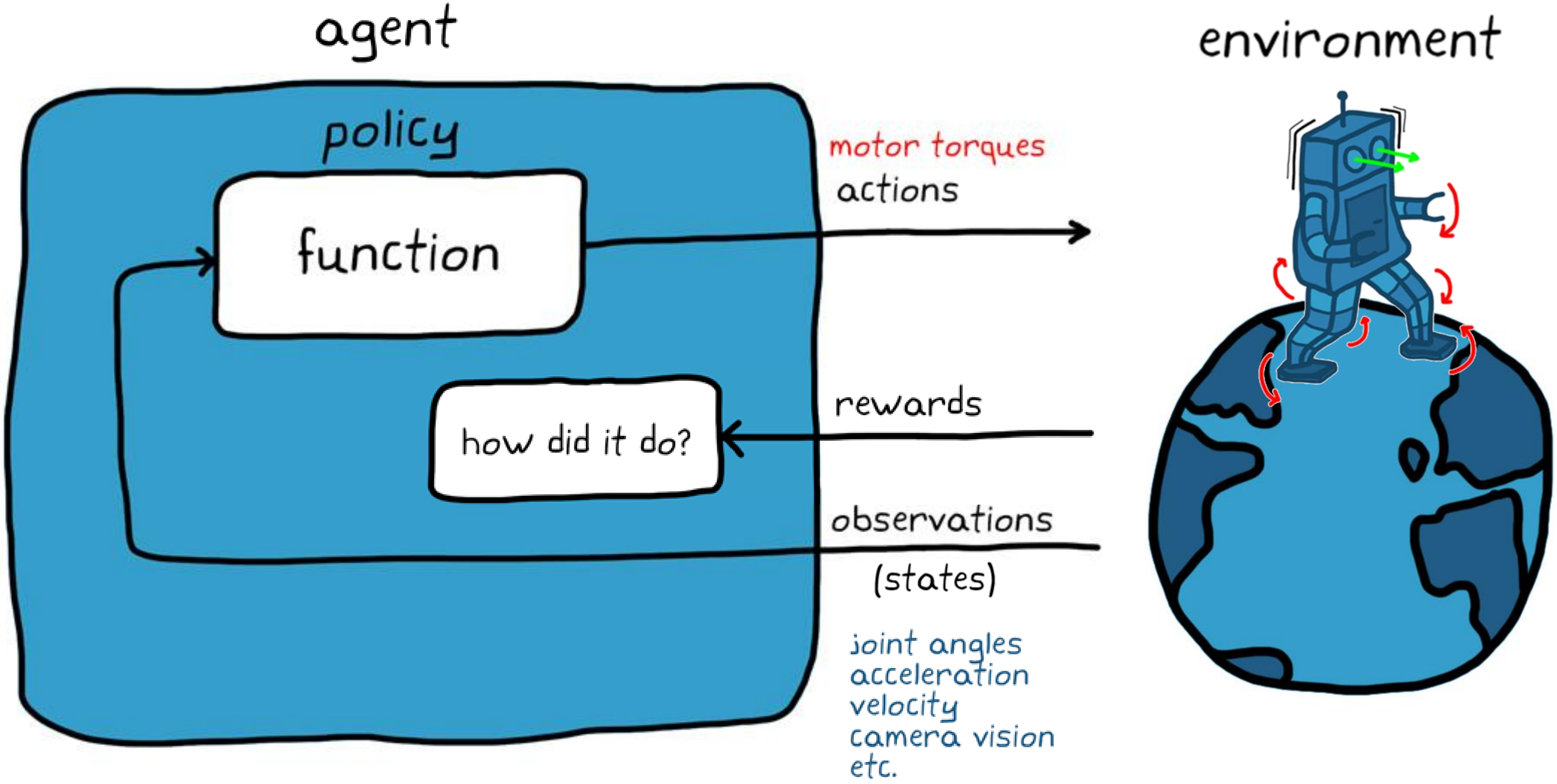
# What Is Reinforcement Learning?

> Reinforcement learning is learning what to do—how to map situations to actions—so as to maximize a numerical reward signal.
>
> The learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them.




Sutton and Barto,
*Reinforcement Learning: An Introduction*

# Some Reinforcement Learning Terminology



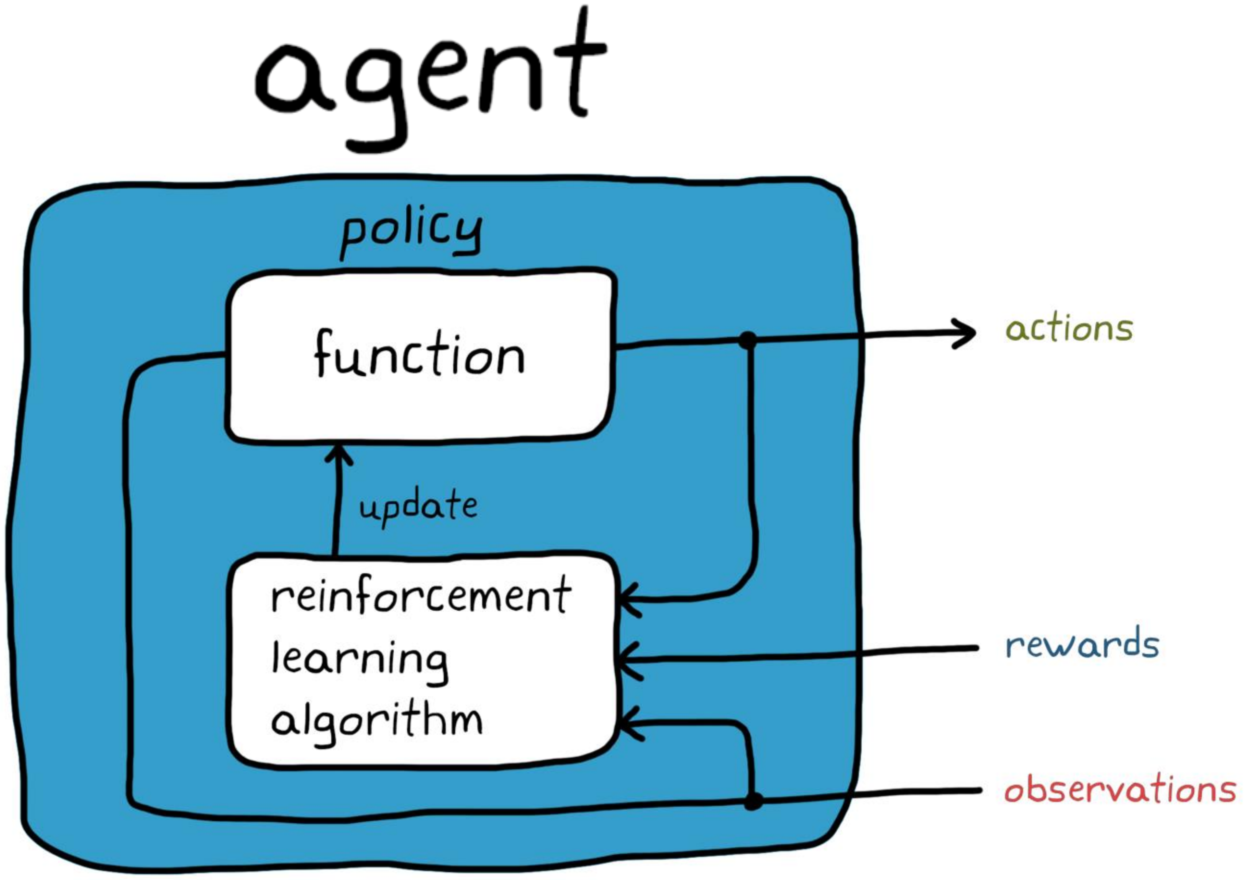
# Learning the Optimal Policy

**Policy**

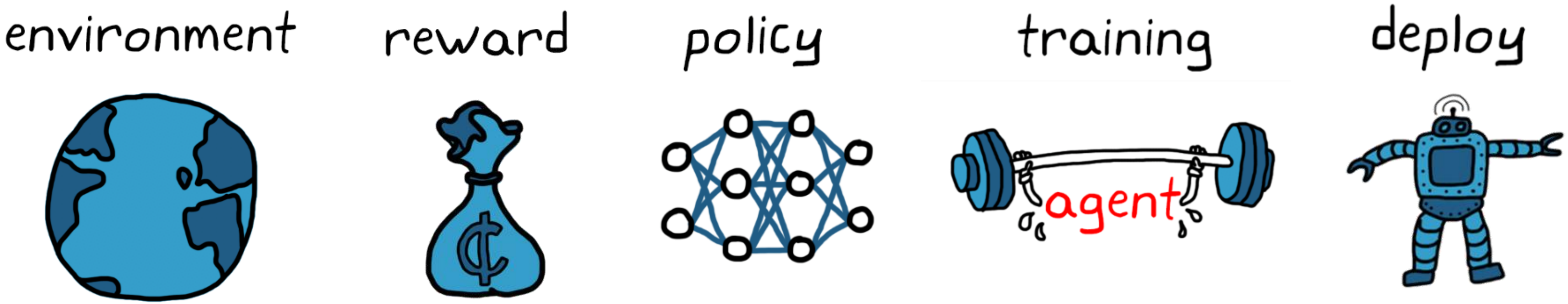
function that maps observations to actions

**Reinforcement Learning Algorithm**

optimization method used to find the optimal policy that maximizes accumulative long-term reward



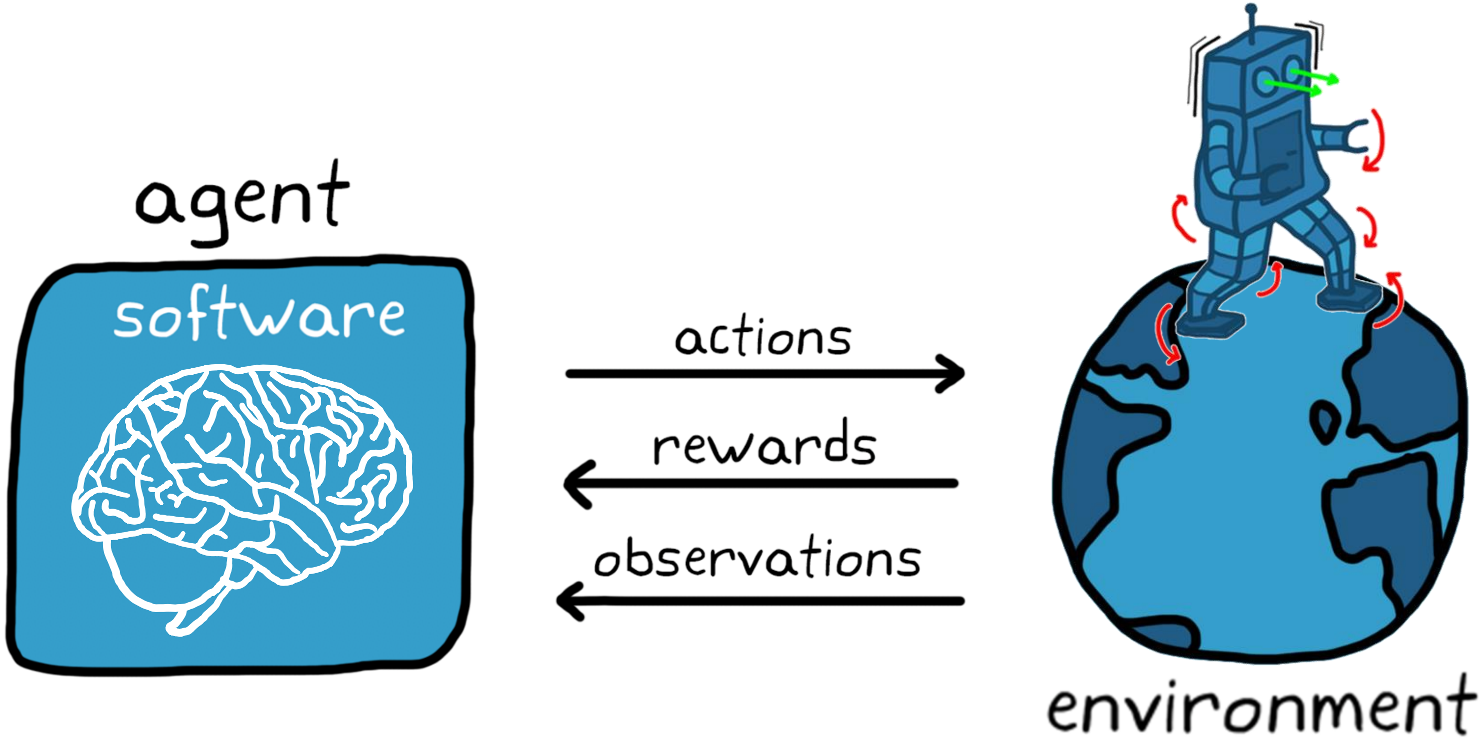
# Reinforcement Learning Workflow



# Reinforcement Learning Workflow

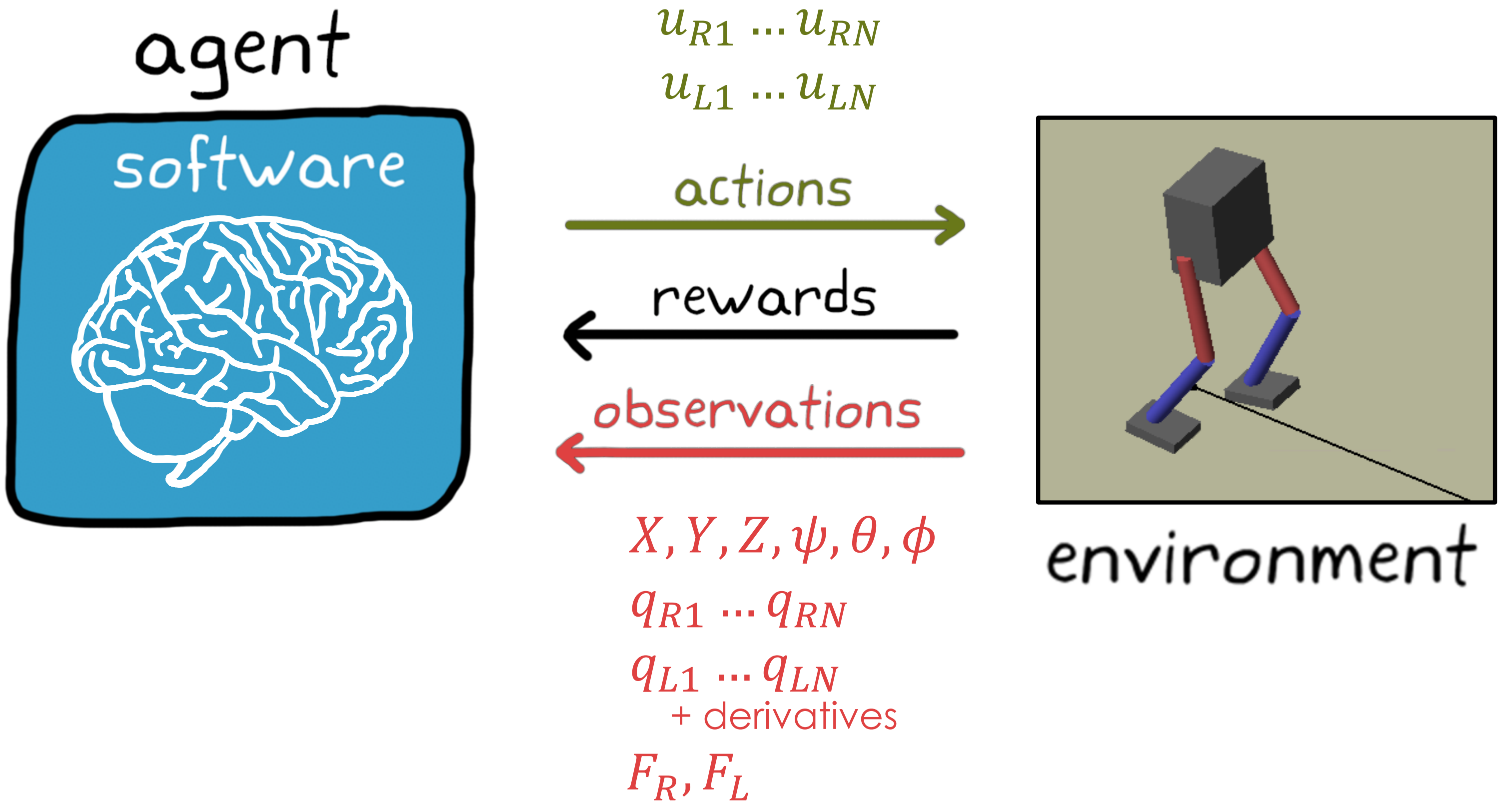
# Environment


- Everything outside of an agent




# Environment

- Everything outside of an agent



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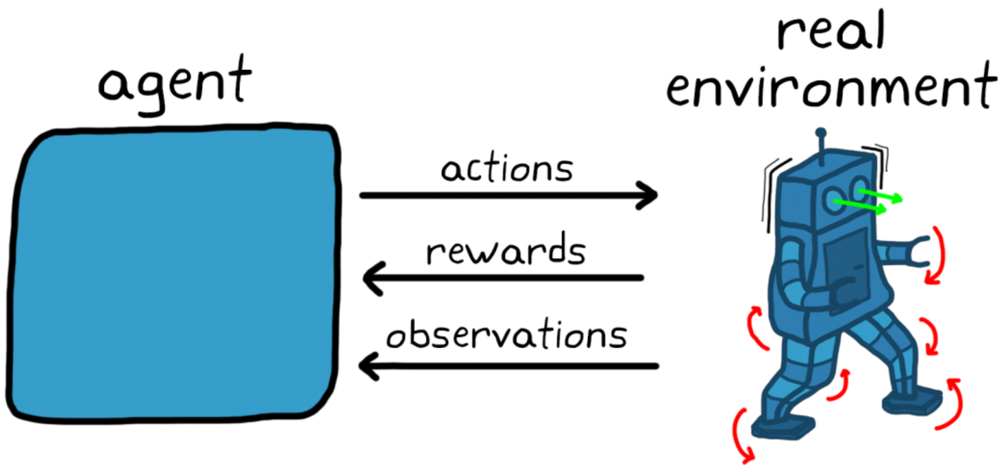
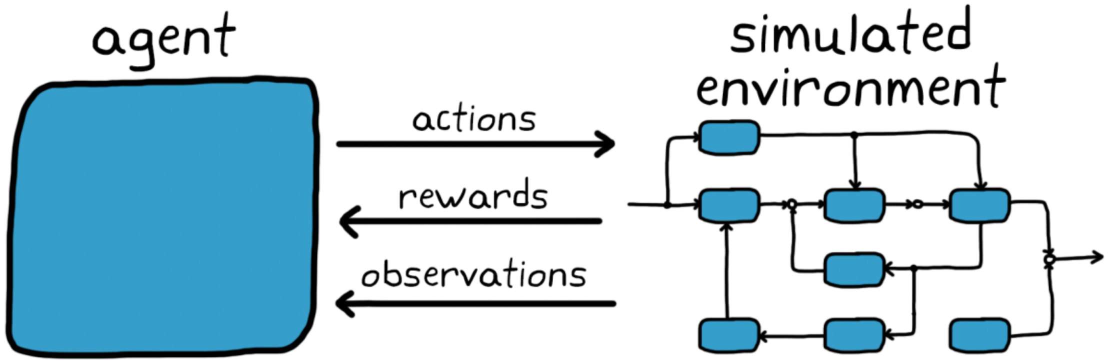
# Real vs Simulated Environments




☺ Accuracy

☹ Risk



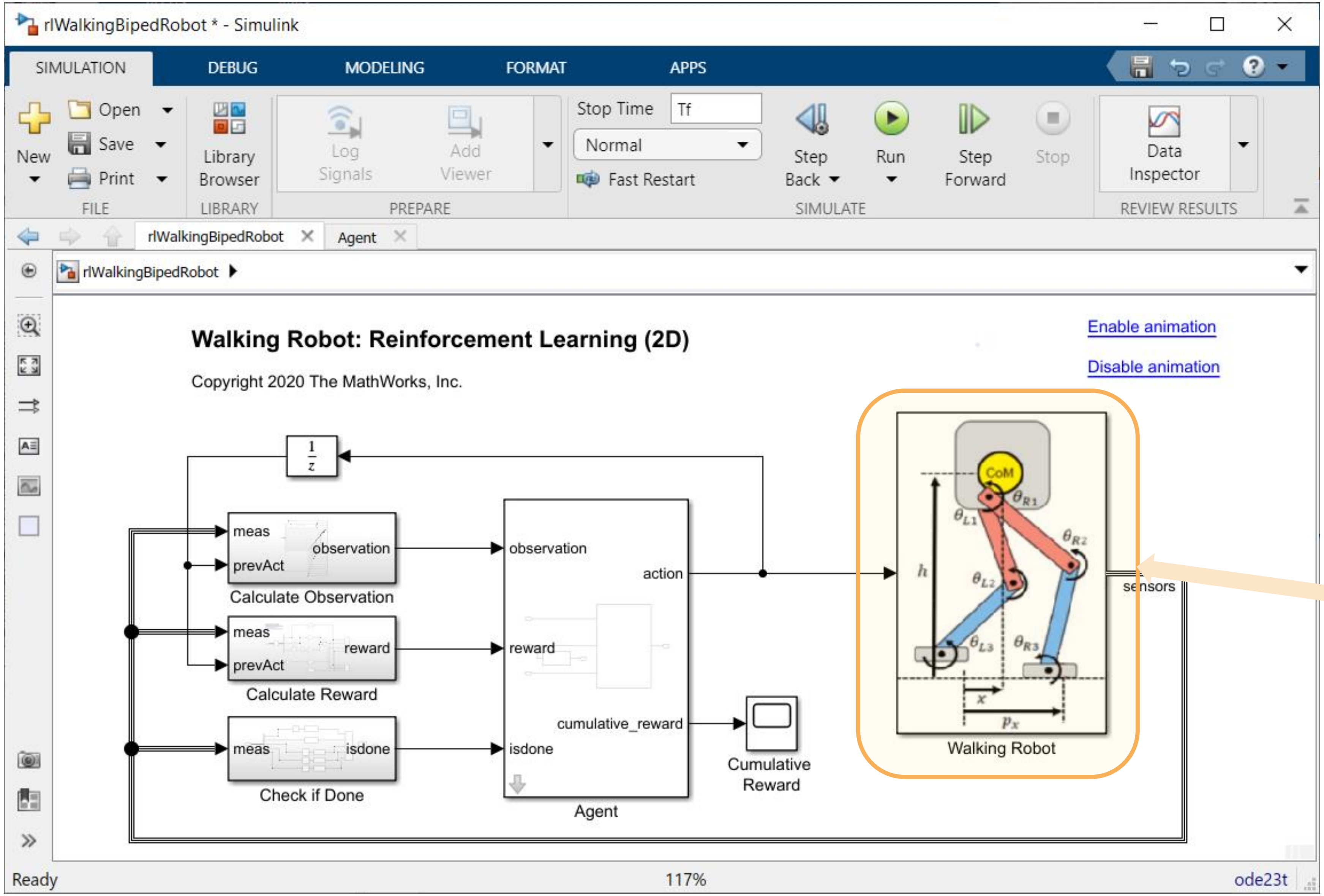

☺ Training speed

☺ Flexible simulated conditions

☺ Safety

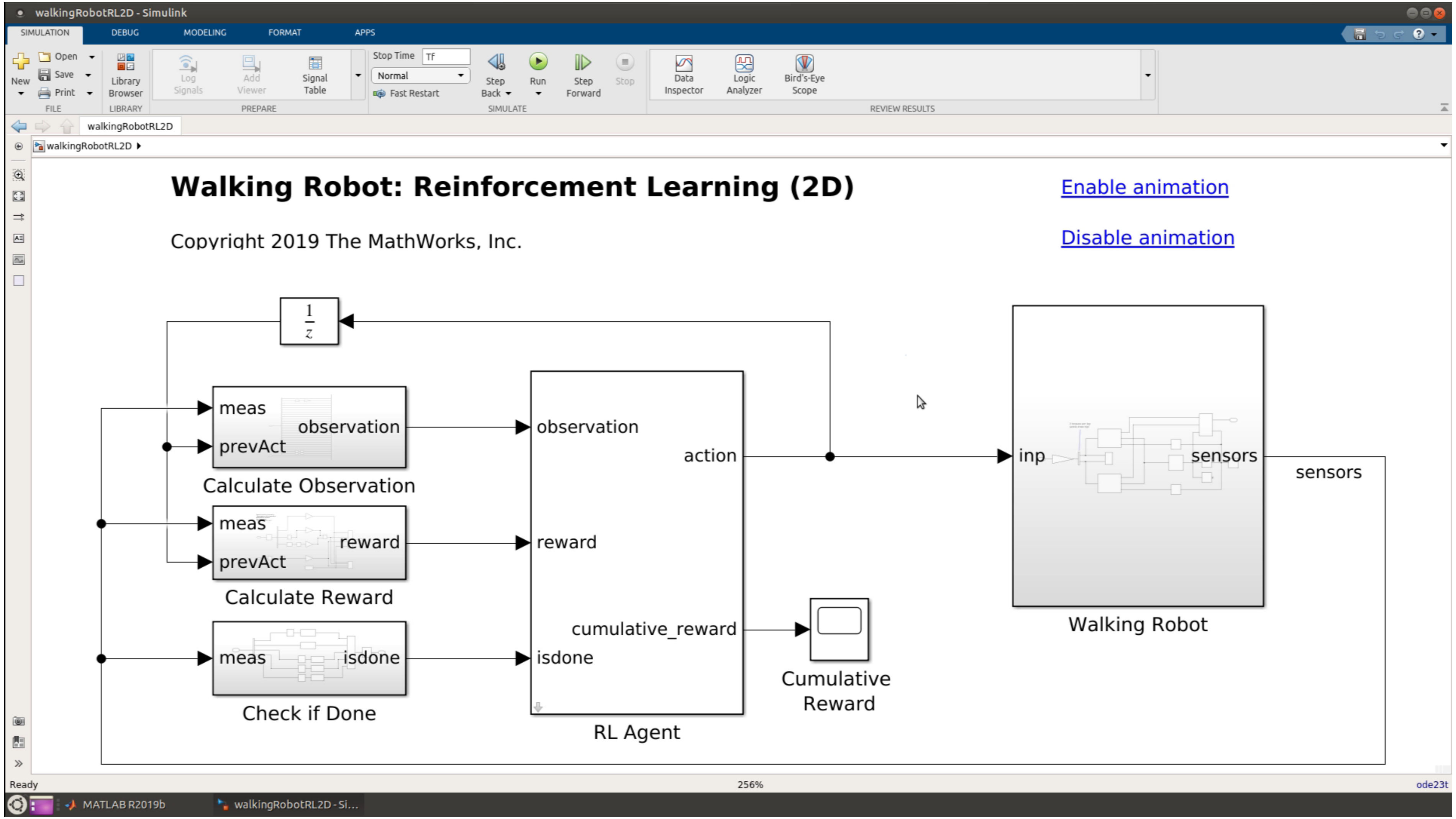
☹ Model inaccuracies

# Define Simulated Environment




Physical modeling of robot dynamics and contact forces using Simscape

# Environment - Simulink

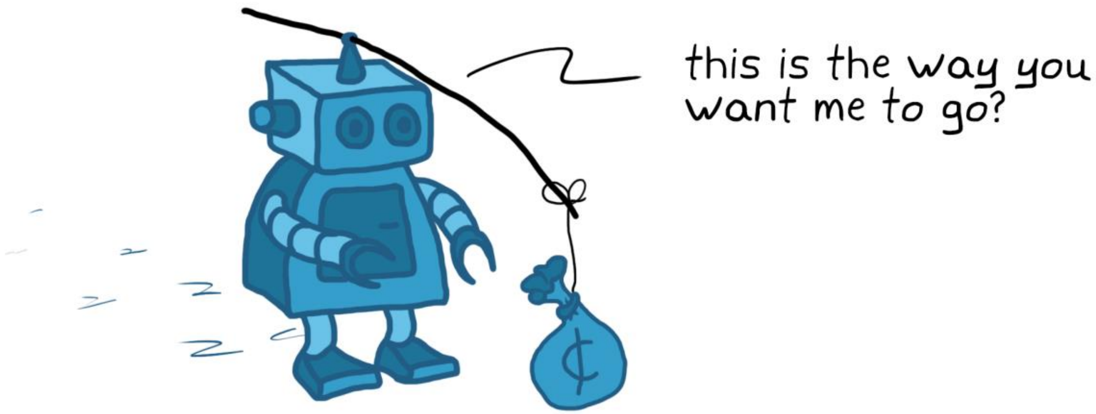
# Reinforcement Learning Workflow

# Reward


A function that outputs a **scalar number** that represents the immediate **"goodness"** of an agent being in a particular **state** and taking a particular **action**.


reward = function (state, action)


# Defining the Reward




$$r_t = v_x - 3y^2 - 50\hat{z}^2 + 25\frac{T_s}{T_f} - 0.02\sum_i {u^i_{t-1}}^2$$

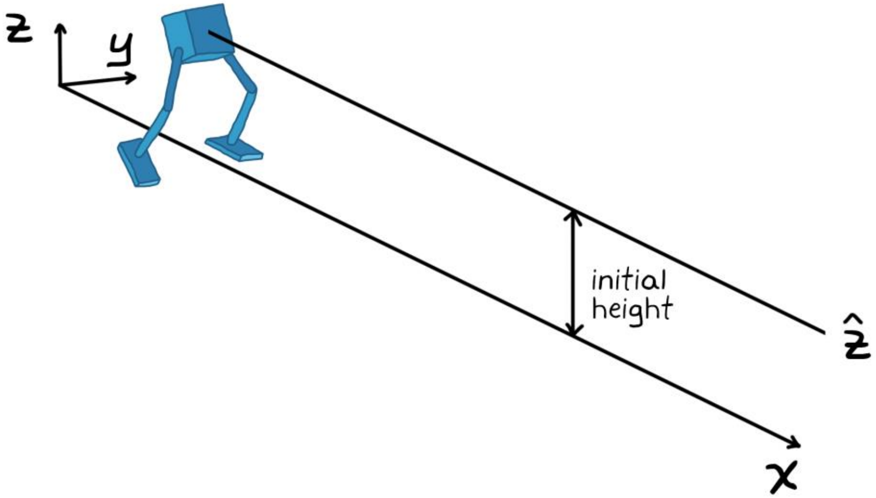
minimize actuator effort

walk as long as possible

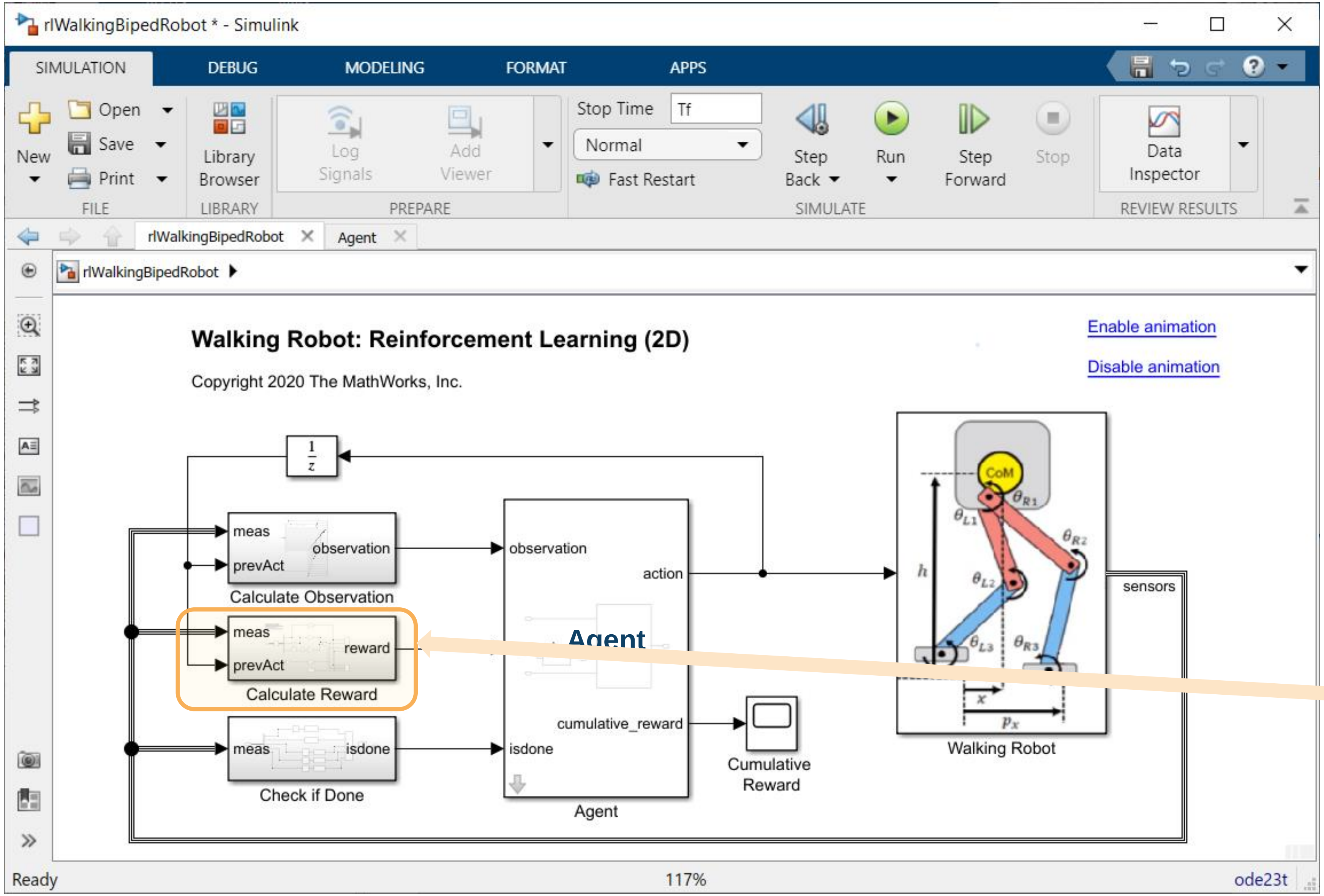
keep trunk at initial height

don't stray from path

forward velocity

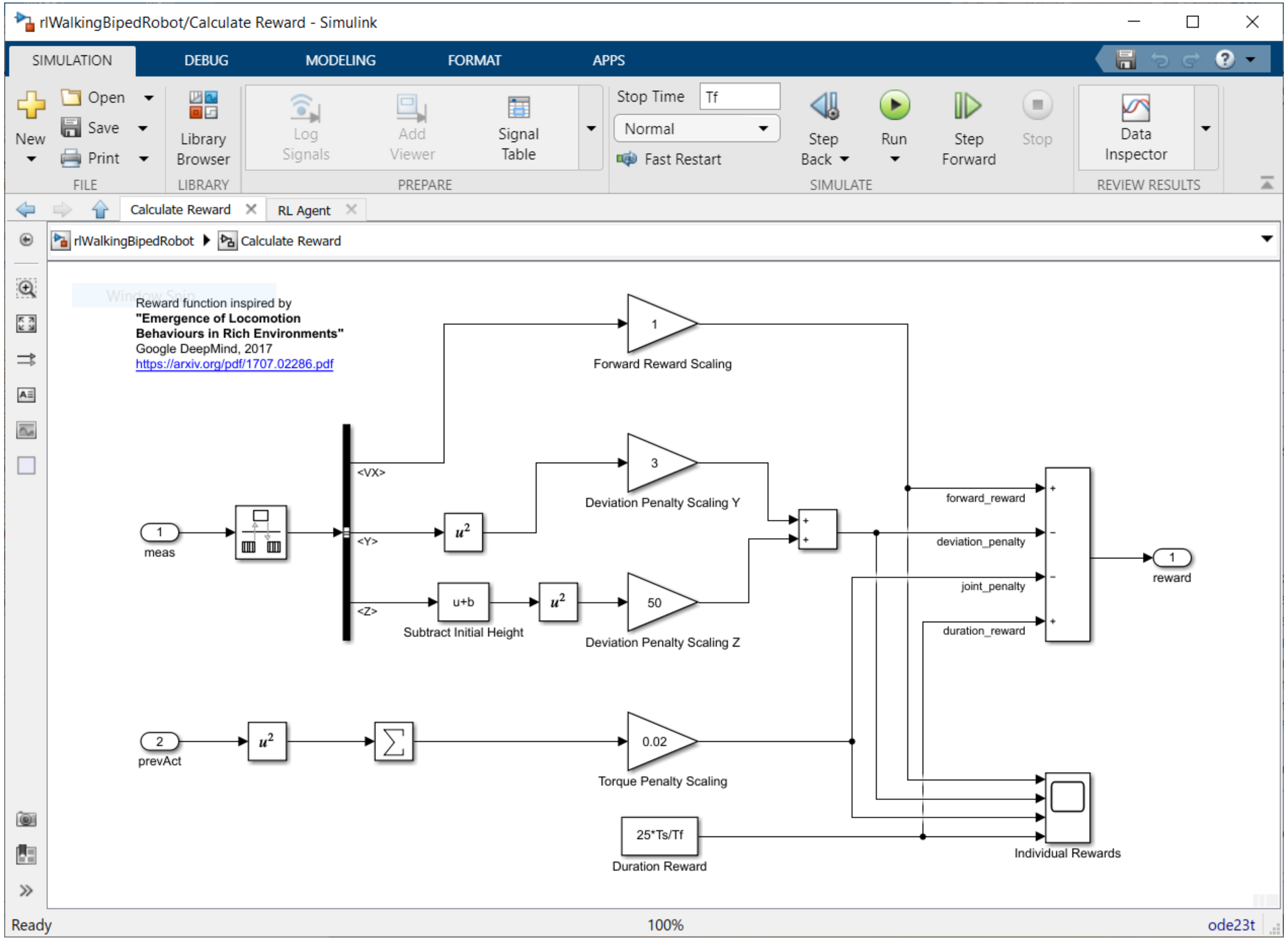


# Defining the Reward


Reward defines task to learn

# Defining the Reward


$$r_t = v_x - 3y^2 - 50\hat{z}^2 + 25\frac{T_s}{T_f} - 0.02\sum_i {u^i_{t-1}}^2$$

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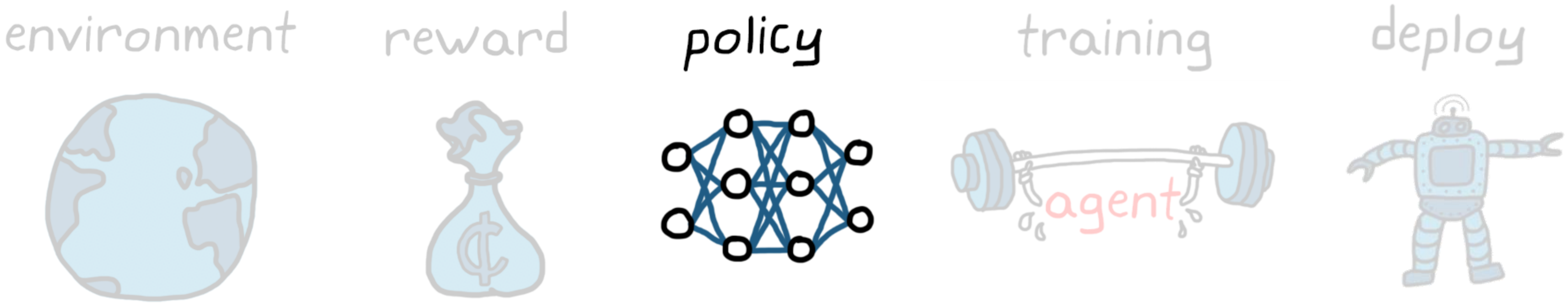
# Reinforcement Learning Workflow

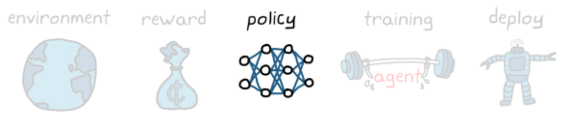


# The Agent



agent
software
actions
rewards
observations
environment

# Learning the Optimal Policy

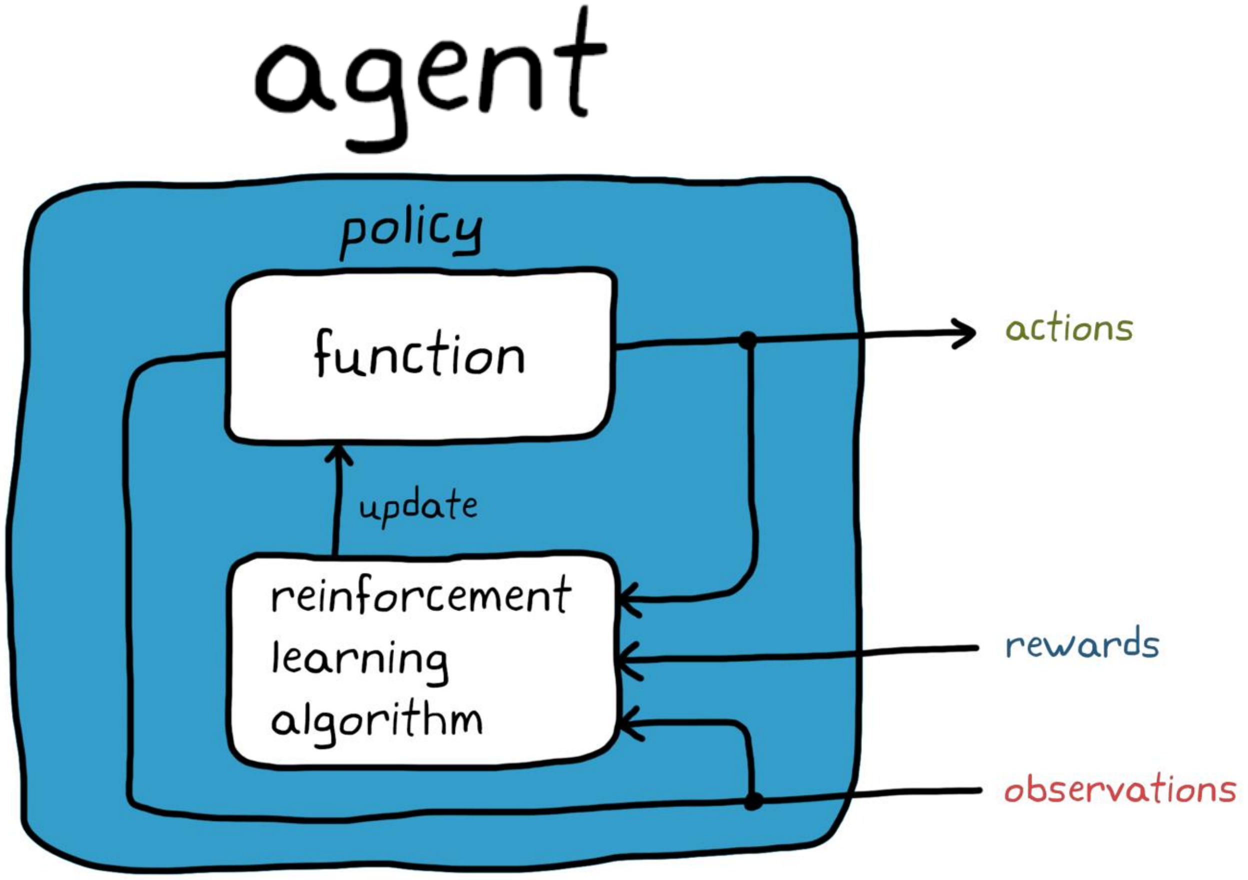



**Policy**

function that maps observations to actions

**Reinforcement Learning Algorithm**

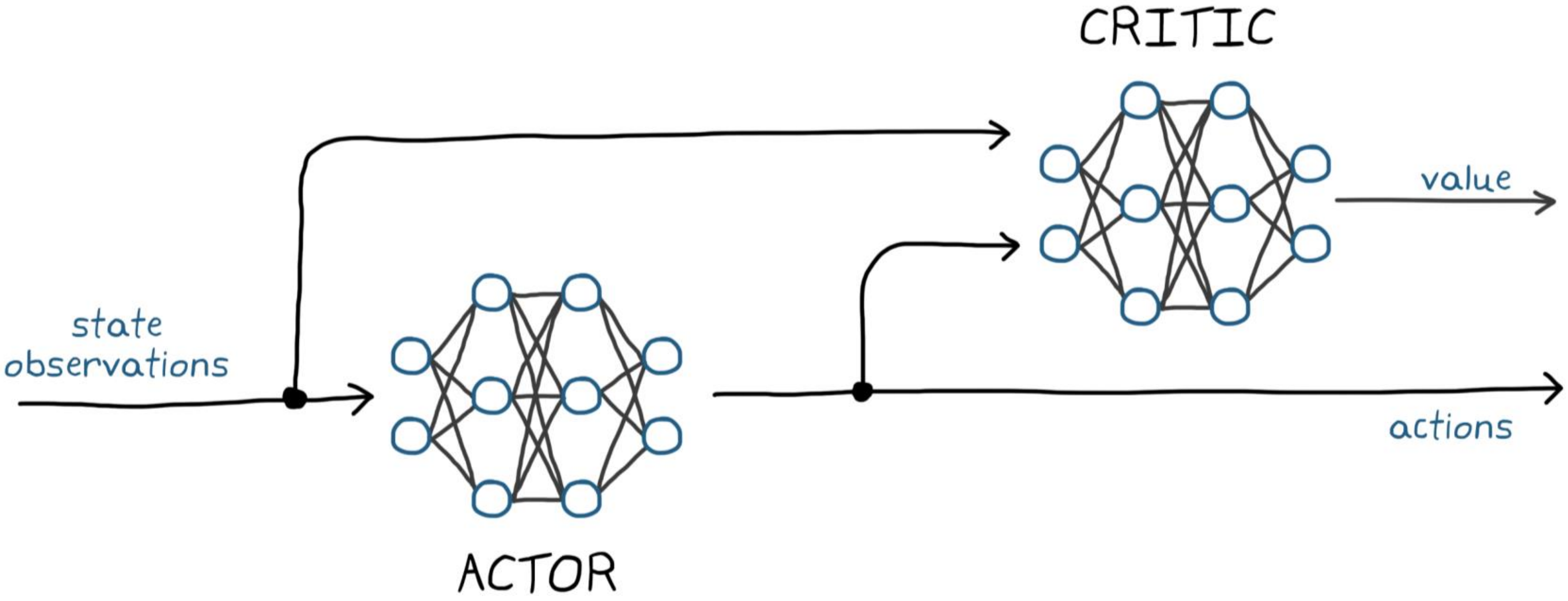
optimization method used to find the optimal policy



# Actor-Critic Methods

environment reward policy training deploy

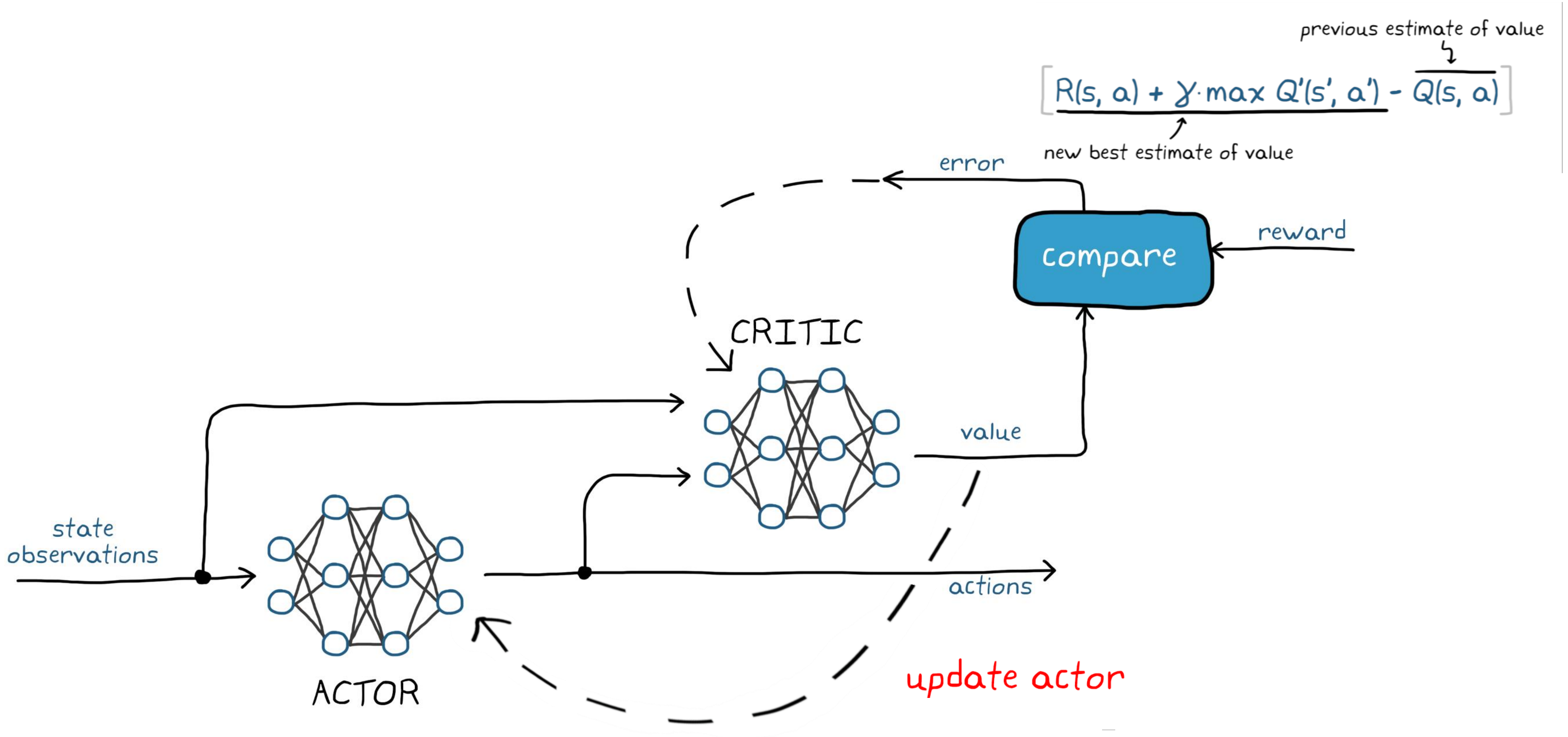
- **Two** neural networks (typically) are **simultaneously tuned** during training:
  - The actor tries to learn the best action at each state
  - The critic tries to
    - estimate the value of each state/state & action the actor takes
    - critique/guide the actor’s choices



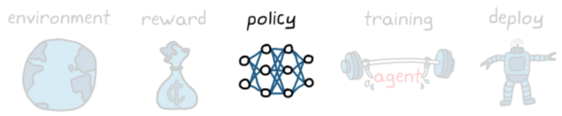

**value** the **total reward** an agent expects to receive **from a state and onwards into the future**

# Actor-Critic Training Cycle

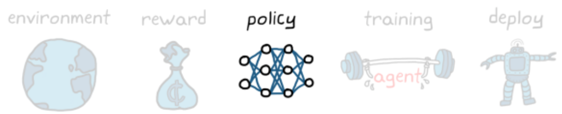




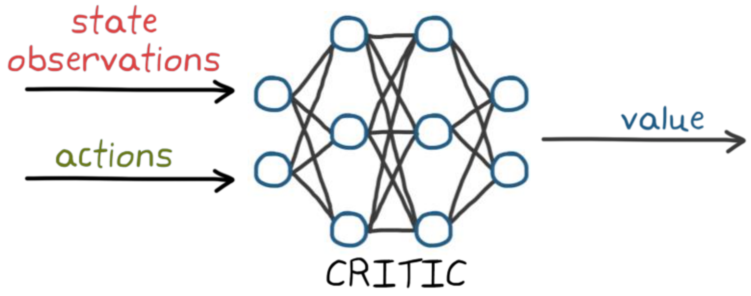
# Creating the Agent

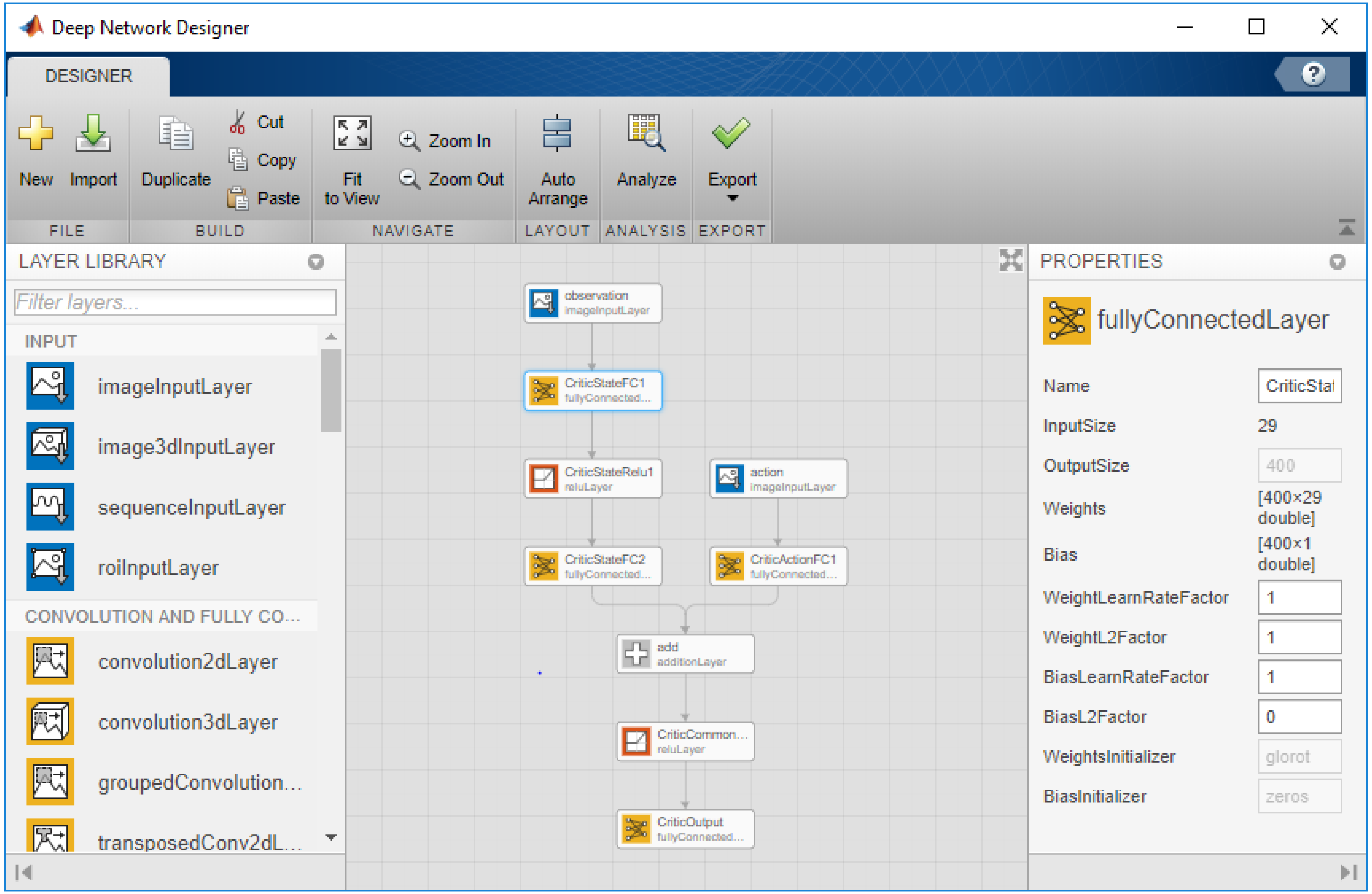



- Constructing a DDPG (Deep Deterministic Policy Gradient) Agent
  - Create the critic network
  - Create the policy network
  - Create the agent with actor and critic network and set hyperparameters

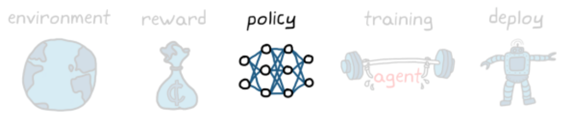


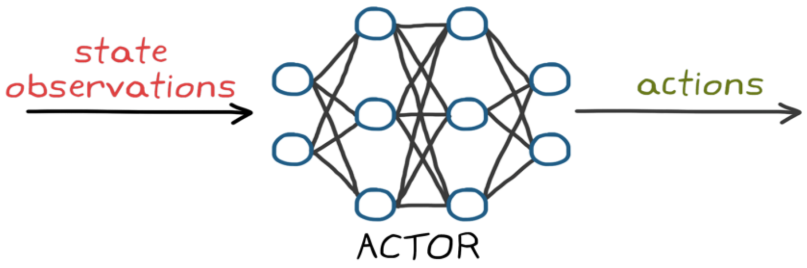

# Create Critic Network

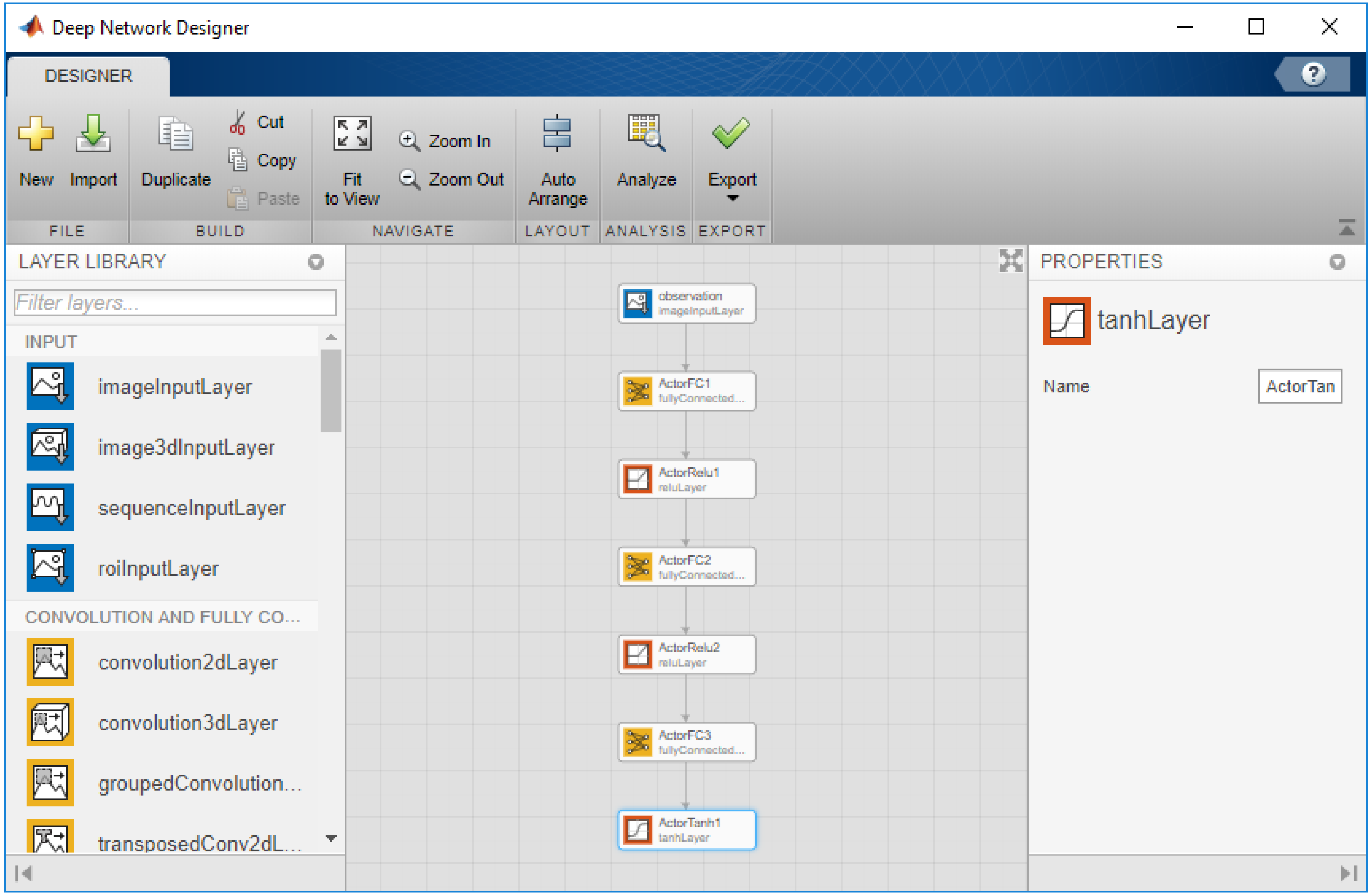


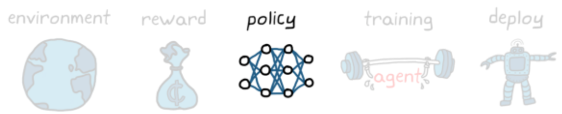
# Create Actor Network



# Create DDPG Agent




Specify options for the critic and actor representations using `rlRepresentationOptions`.

```
criticOptions = rlRepresentationOptions('Optimizer','adam','LearnRate',1e-3, ...
                                        'GradientThreshold',1,'L2RegularizationFactor',1e-5);
actorOptions = rlRepresentationOptions('Optimizer','adam','LearnRate',1e-4, ...
                                       'GradientThreshold',1,'L2RegularizationFactor',1e-5);
```

Create the critic and actor representations using the specified deep neural networks and options. You must also specify the action and observation information for each representation, which you already obtained from the environment interface. For more information, see `rlRepresentation`.

```
critic = rlRepresentation(criticNetwork,obsInfo,actInfo,'Observation',{'observation'},'Action',{'action'},criticOptions);
actor  = rlRepresentation(actorNetwork,obsInfo,actInfo,'Observation',{'observation'},'Action',{'ActorTanh1'},actorOptions);
```

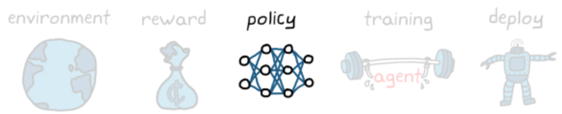
To create the DDPG agent, first specify the DDPG agent options using `rlDDPGAgentOptions`.

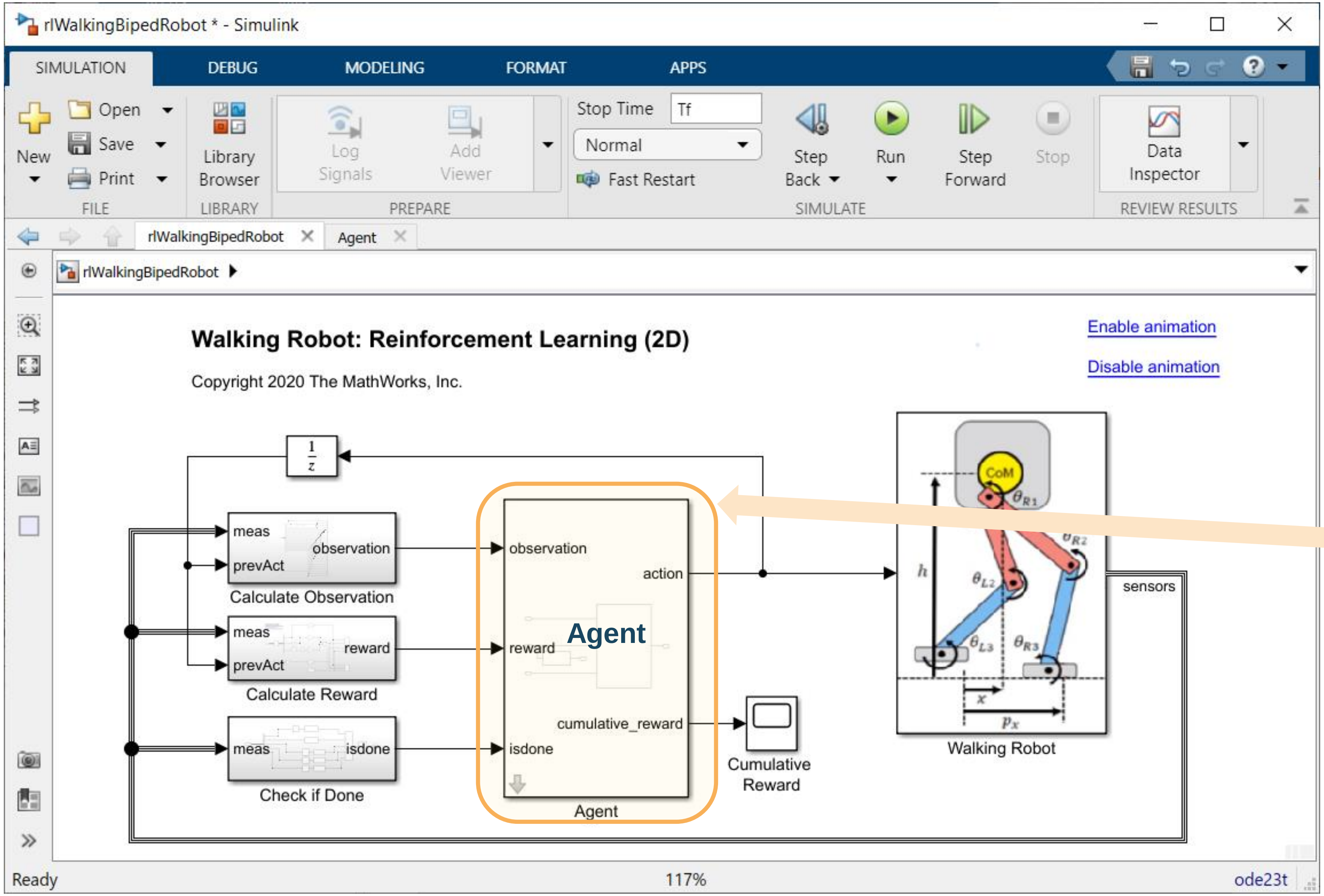
```
agentOptions = rlDDPGAgentOptions;
agentOptions.SampleTime = Ts;
agentOptions.DiscountFactor = 0.99;
agentOptions.MiniBatchSize = 128;
agentOptions.ExperienceBufferLength = 1e6;
agentOptions.TargetSmoothFactor = 1e-3;
agentOptions.NoiseOptions.MeanAttractionConstant = 1;
agentOptions.NoiseOptions.Variance = 0.1;
```

Then, create the DDPG agent using the specified actor representation, critic representation, and agent options. For more information, see `rlDDPGAgent`.

```
agent = rlDDPGAgent(actor,critic,agentOptions);
```

# Defining the Agent

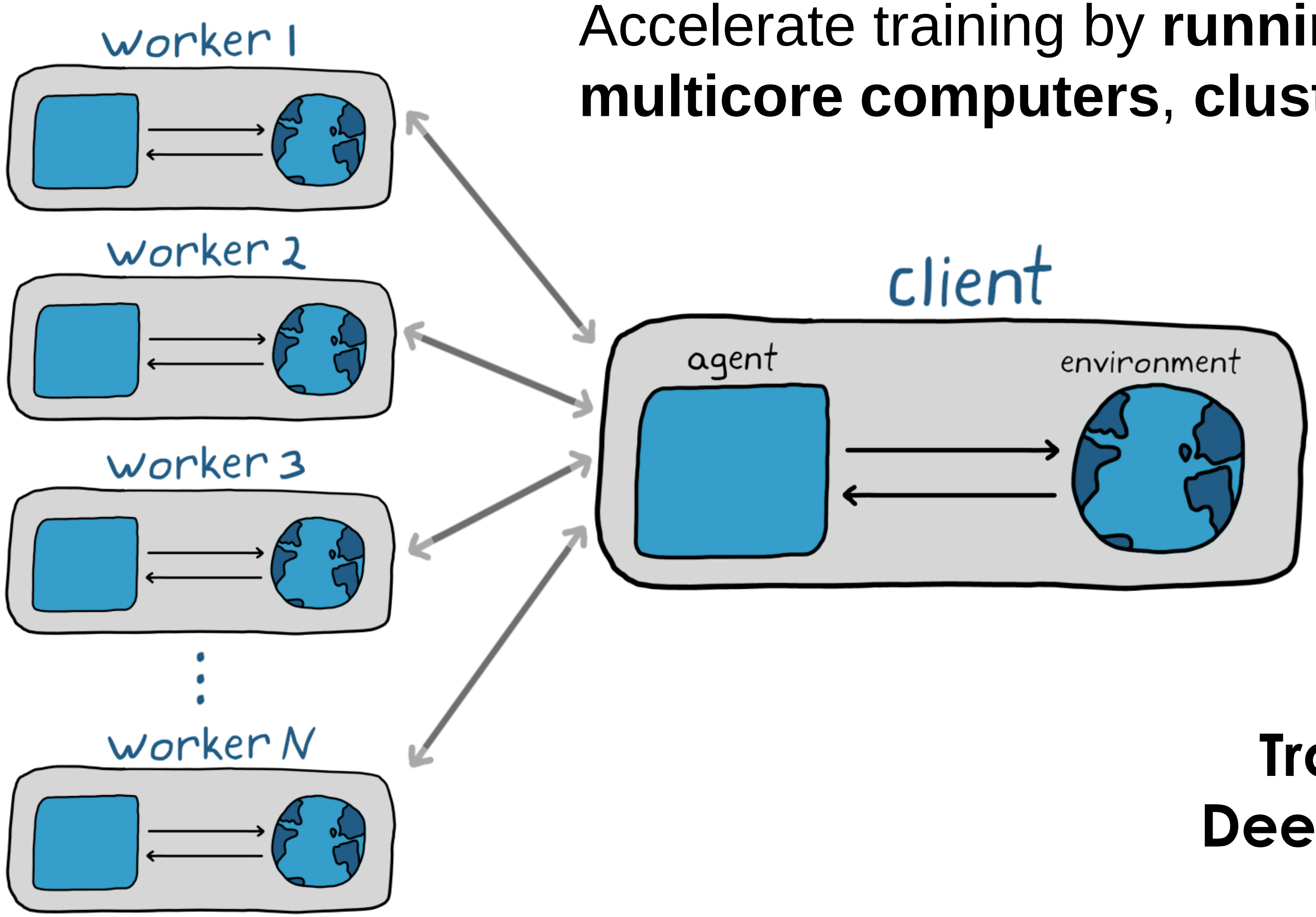


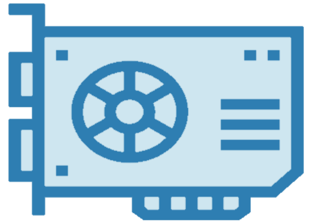

Define the agent

# Reinforcement Learning Workflow

# Training Our Deep Reinforcement Learning Agent


Accelerate training by **running simulations in parallel** on **multicore computers**, **clusters** or the **cloud**



**Train with the GPU** when using **Deep Neural Networks** for Actor or Critic representations

# Training the Agent


```
maxEpisodes = 20000;
maxSteps = Tf/Ts;
trainOpts = rlTrainingOptions(...
    'MaxEpisodes',maxEpisodes,...
    'MaxStepsPerEpisode',maxSteps,...
    'ScoreAveragingWindowLength',250,...
    'Verbose',false,...
    'Plots','training-progress',...
    'StopTrainingCriteria','AverageReward',...
    'StopTrainingValue',100,...
    'SaveAgentCriteria','EpisodeReward',...
    'SaveAgentValue',150);
```

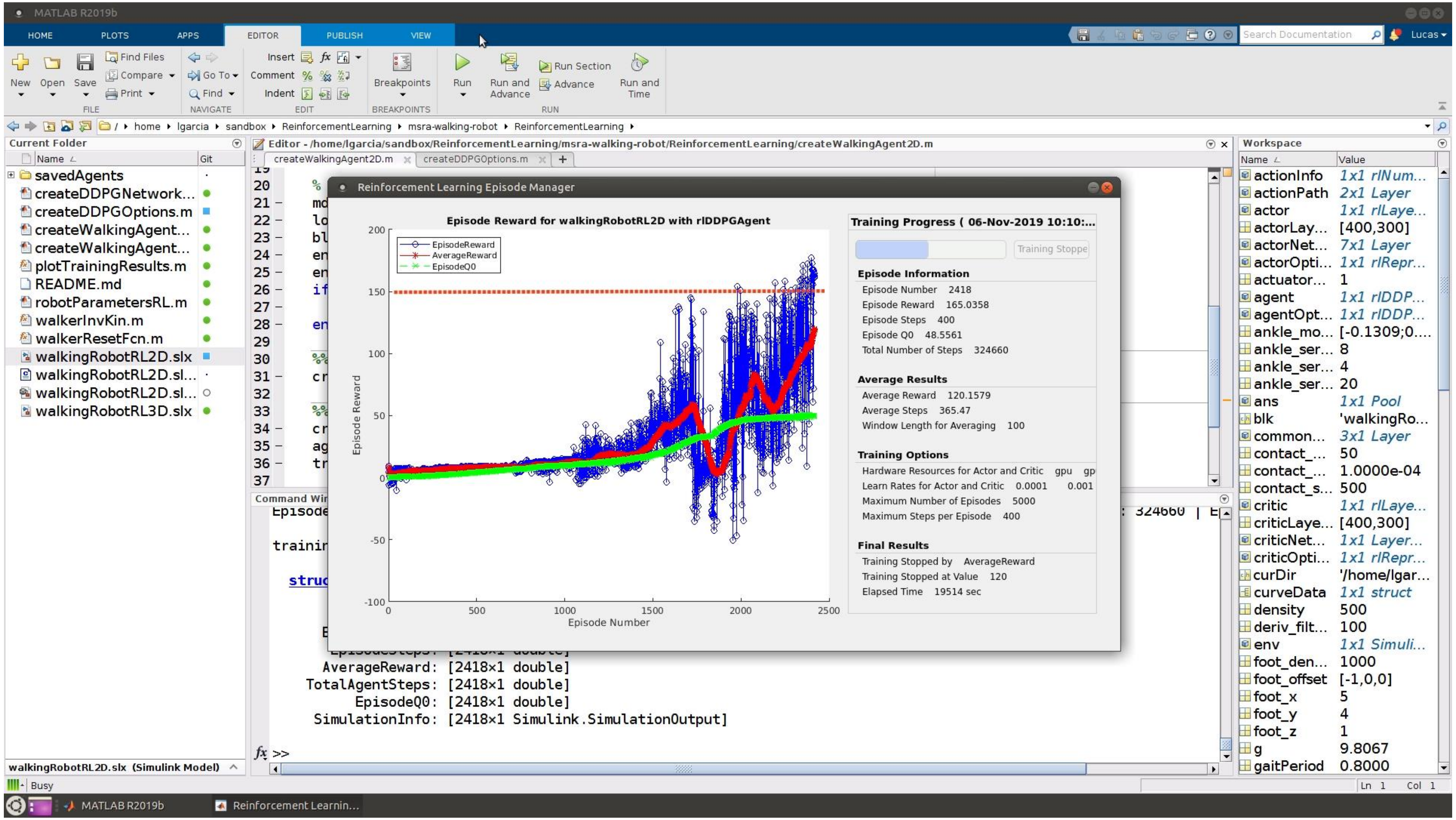
To train the agent in parallel, specify the following training options.

- Set the `UseParallel` option to `true`.
- Train the agent in parallel asynchronously.
- After every 32 steps, each worker sends experiences to the host.
- DDPG agents require workers to send `'Experiences'` to the host.

```
trainOpts.UseParallel = true;
trainOpts.ParallelizationOptions.Mode = 'async';
trainOpts.ParallelizationOptions.StepsUntilDataIsSent = 32;
trainOpts.ParallelizationOptions.DataToSendFromWorkers = 'Experiences';
```

```
trainingStats = train(agent,env,trainOpts);
```

# Training Our Deep Reinforcement Learning Agent

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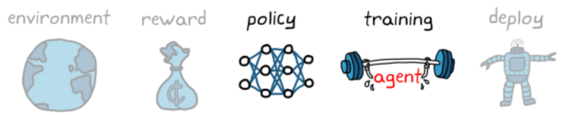
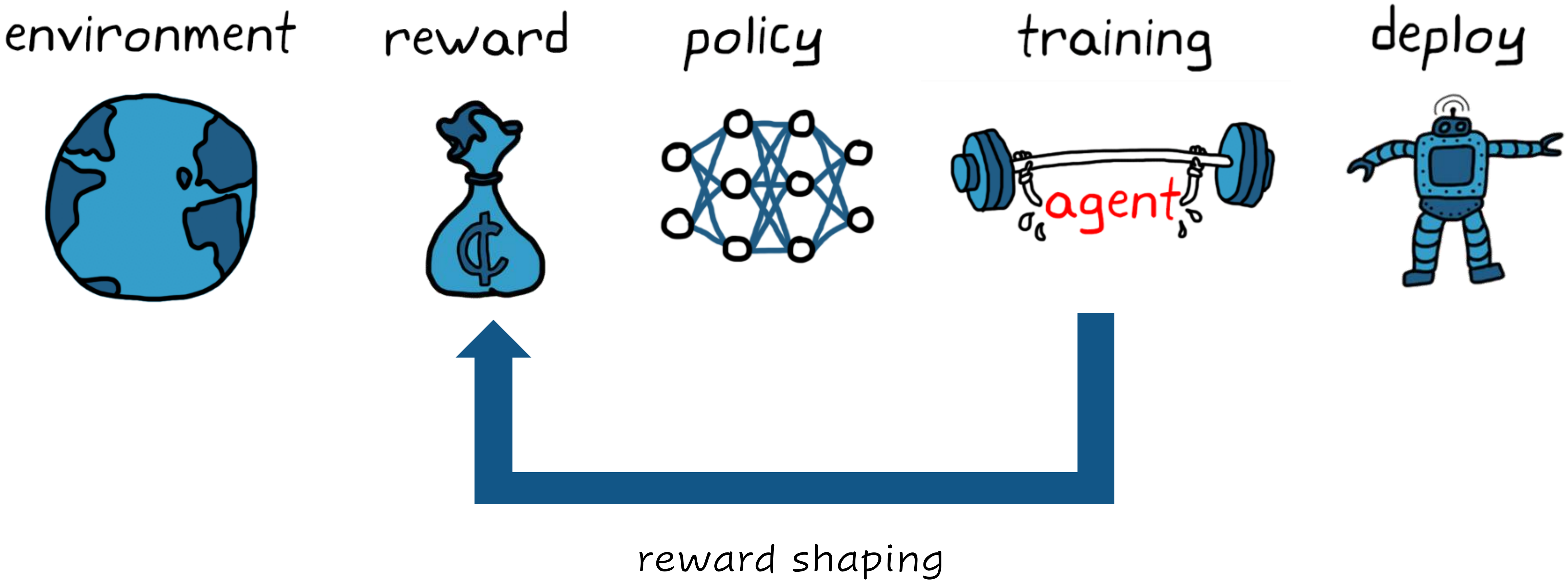
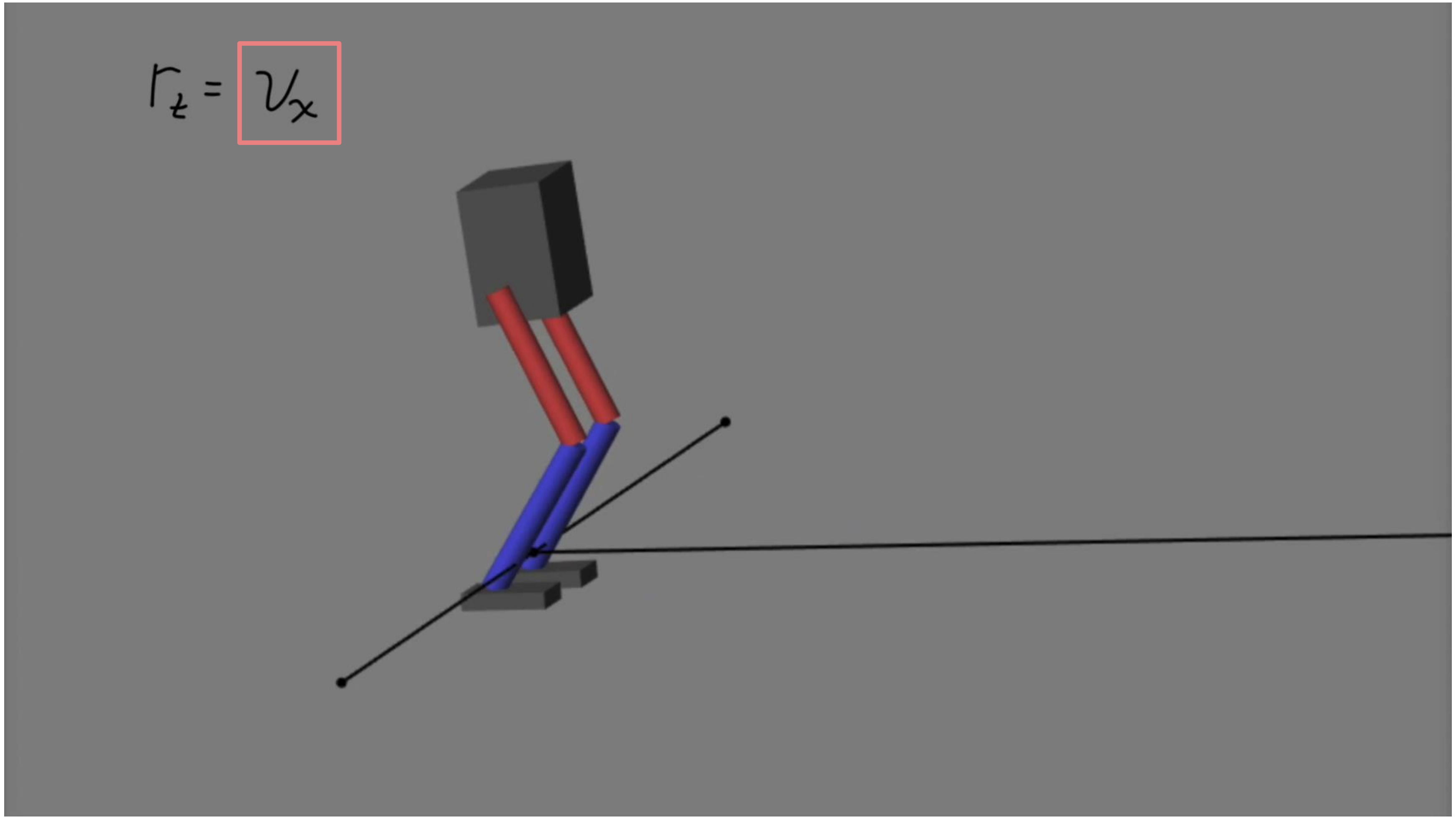
# Reinforcement Learning Workflow



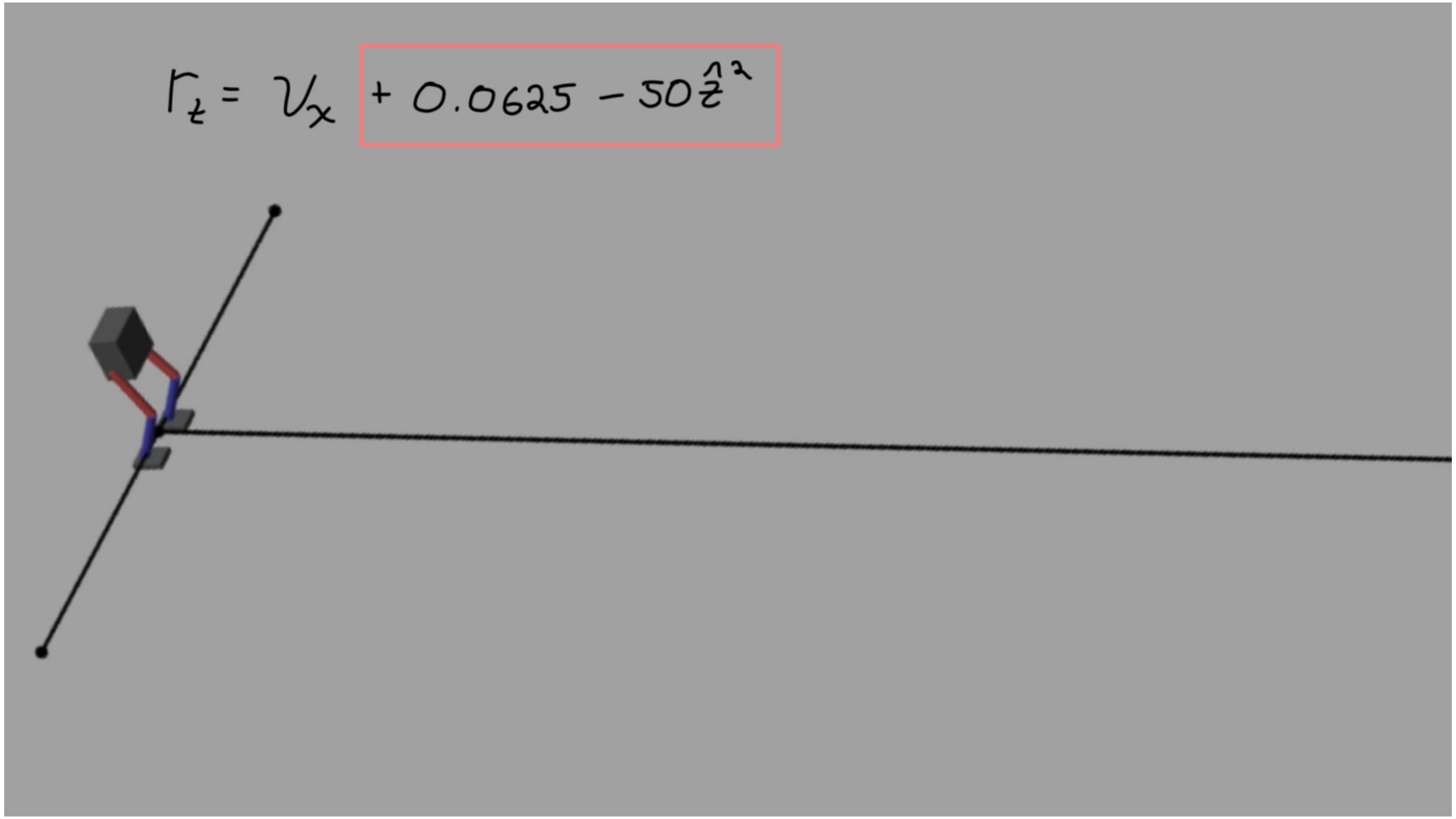



# Reward Function Design Matters



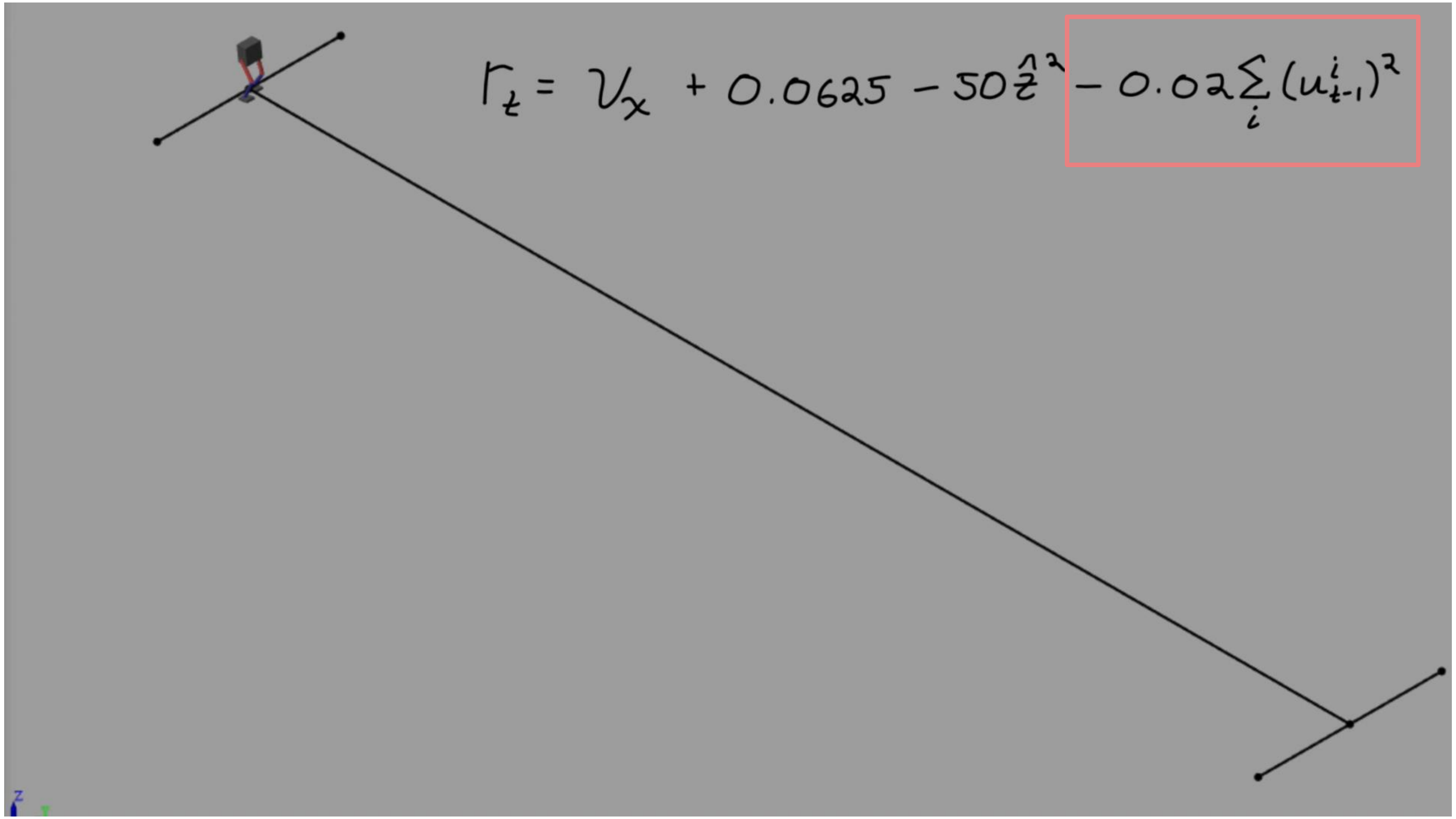

**I want my robot to walk forward. Let's set the reward to be the robot's forward velocity.**

# Reward Shaping to Improve Learning



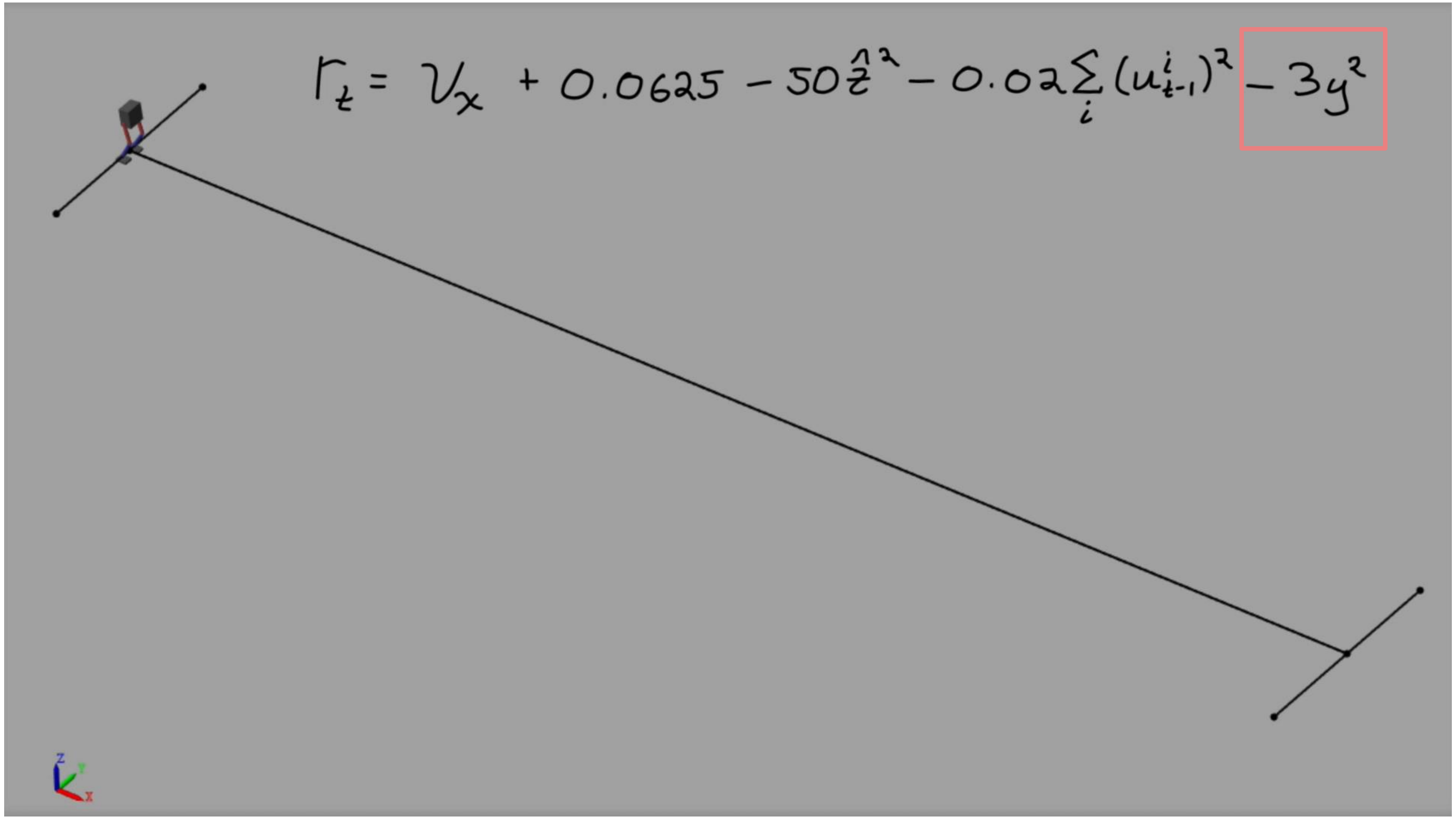

**Let’s add a reward term for each time step it remains upright and a penalty for not maintaining a torso height**


# Reward Shaping to Improve Learning




**Let’s add a penalty for the energy used for actuation**

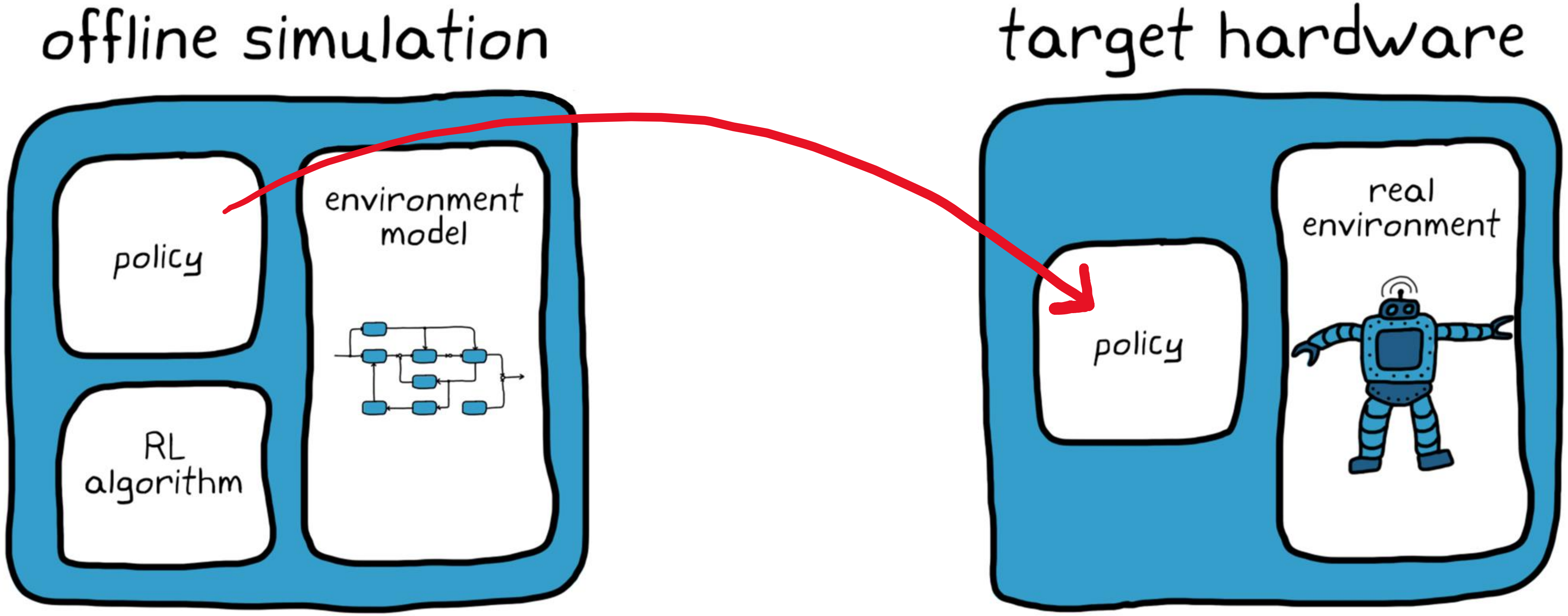
# Reward Shaping to Improve Learning


**Let’s add a penalty for deviating from the line**

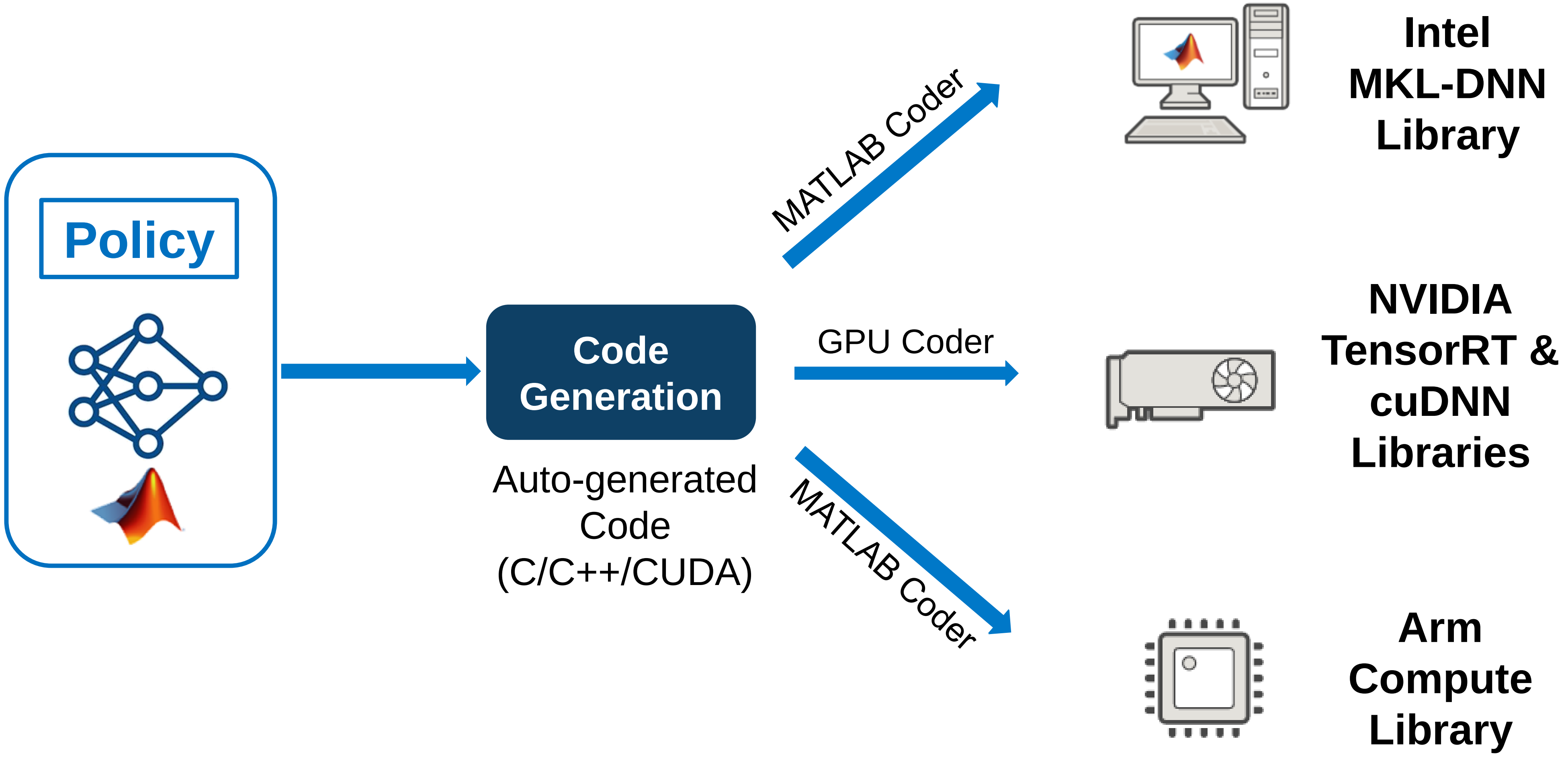
# Reinforcement Learning Workflow

# Deploy policy to the target hardware


**Automatically generate C/C++** or **CUDA** code
to run the **policy** on an **embedded system**


# Policy Deployment to Hardware Platforms

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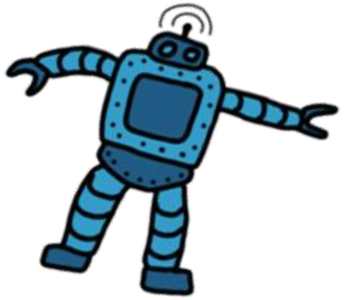
# Key takeaways

- **Reinforcement Learning** can solve complicated control and decision problems
- **Reward Shaping** can improve learning outcomes
- **MATLAB and Simulink** provide a **complete workflow for Deep Reinforcement Learning**



# Thank you!

# Q&A