# Lecture 11
# Markovian Modeling II

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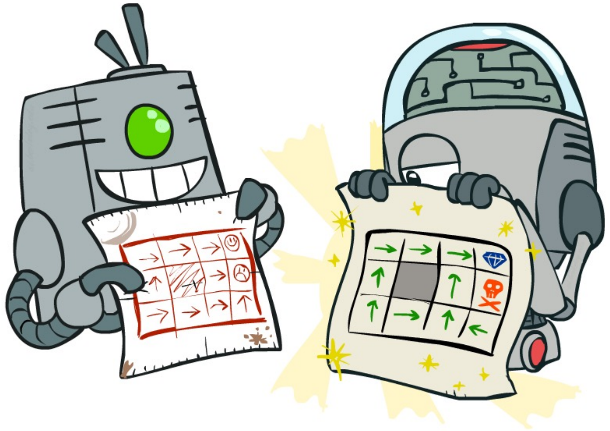
# Policy Iteration

# The Policy Iteration Algorithm

*If one action is clearly better than all others,*
*then the exact magnitude of the utilities on the states involved need not be precise*



- **Starts**
  - with some initial policy $\pi_0$
- **Repeat**
  - Policy evaluation
    - Given a policy $\pi_i$, calculate $U_i = U^{\pi_i}$, the utility of each state if $\pi_i$ were to be executed.
  - Policy improvement
    - Calculate a new MEU policy $\pi_{i+1}$, using one-step look-ahead based on $U_i$
- **Terminates**
  - when the policy improvement step yields no change in the utilities

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# The Policy Iteration Algorithm

*for calculating an optimal policy*

Start

Repeat

- Evaluation
- Improvement

Terminate

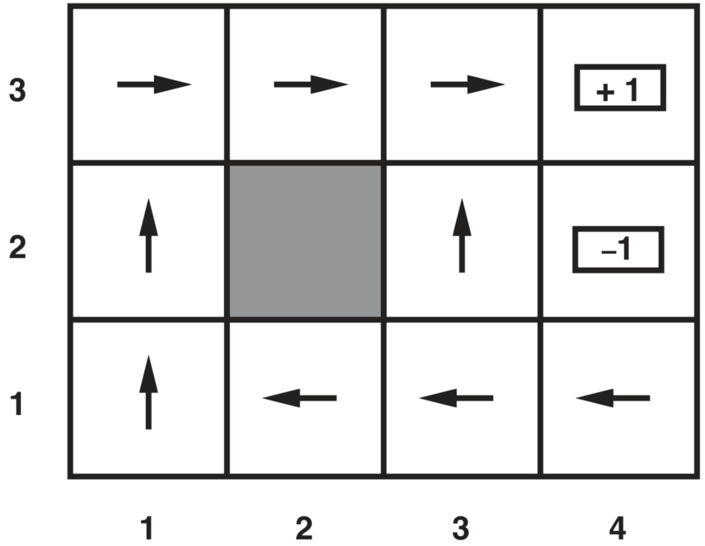
```
function POLICY-ITERATION($mdp$) returns a policy
    inputs: $mdp$, an MDP with states $S$, actions $A(s)$, transition model $P(s' \mid s, a)$
    local variables: $U$, a vector of utilities for states in $S$, initially zero
                     $\pi$, a policy vector indexed by state, initially random

    repeat
        $U \leftarrow$ POLICY-EVALUATION($\pi, U, mdp$)
        $unchanged? \leftarrow$ true
        for each state $s$ in $S$ do
            if $\max_{a \in A(s)} \sum_{s'} P(s' \mid s, a)\ U[s'] > \sum_{s'} P(s' \mid s, \pi[s])\ U[s']$ then do
                $\pi[s] \leftarrow \operatorname{argmax}_{a \in A(s)} \sum_{s'} P(s' \mid s, a)\ U[s']$
                $unchanged? \leftarrow$ false
    until $unchanged?$
    return $\pi$
```

# A Simplified Version of the Bellman Equation

*the action in each state is fixed by the policy*

- At the $i$th iteration, the policy $\pi_i$ specifies the action $\pi_i(s)$ in state $s$

$$U(s) = R(s) + \gamma \max_{a\in A(s)} \sum_{s'} P(s' \mid s, a)\, U(s') \longrightarrow U_i(s) = R(s) + \gamma \sum_{s'} P\big(s' \mid s, \pi_i(s)\big)\, U_i(s')$$



| | $n$ states | $n$ equations | $n$ unknowns |
|---|---|---|---|
| $\pi_i$ | $\pi_i(1,1) = Up$ | $U_i(1,1) = -0.04 + 0.8U_i(1,2)+0.1U_i(1,1)+0.1U_i(2,1)$ | |
| | $\pi_i(1,2) = Up$ | $U_i(1,2) = -0.04 + 0.8U_i(1,3)+0.2U_i(1,2)$ | |
| | $\pi_i(1,3) = Right$ | $U_i(1,3) = ?$ | |
| | $\pi_i(2,1) = Left$ | … | |
| | … | … | |

***Linear*** Simplified Bellman Equations

- Can be solved in time $O(n^3)$
- Efficient for small state spaces
- What about large state spaces?

# The Simplified Bellman Process

*it is not necessary to do exact policy evaluation*

- Perform some number of simplified value iteration steps to give a reasonably good approximation of the utilities

$$U_i(s) = R(s) + \gamma \sum_{s'} P\big(s' \mid s, \pi_i(s)\big)\, U_i(s') \xrightarrow{\text{Repeat } k \text{ times}} U_{i+1}(s) \leftarrow R(s) + \gamma \sum_{s'} P\big(s' \mid s, \pi_i(s)\big)\, U_i(s')$$

- Modified Policy Iteration
  - Much more efficient than standard policy iteration or value iteration
- Asynchronous Policy Iteration
  - It is not necessary to update the utility or policy for all states at once
  - On each iteration, we can pick *any subset* of states and apply *either* kind of updating (policy improvement or simplified value iteration) to that subset

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# Formalizing Manipulation Learning

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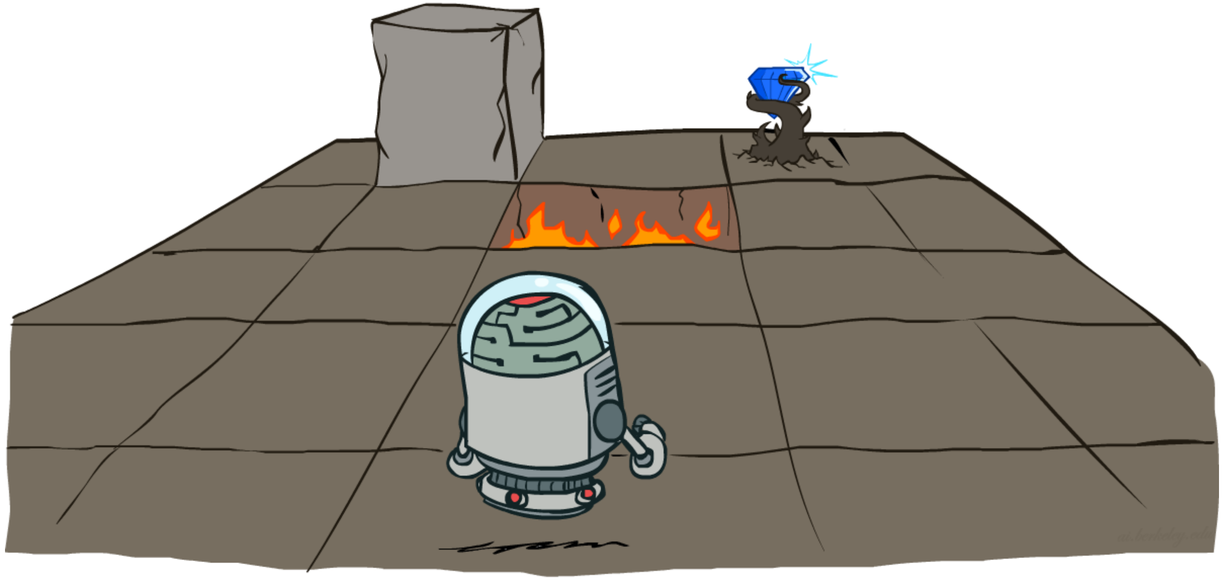
# Formalizing Robot Learning Problems

*Typically formulated as individual Markov Decision Processes (or MDPs)*

- A 5-tuple formalization $(S, A, T, R, \gamma)$
  - A finite set of **states** $S \subseteq \mathbb{R}^n$
  - A finite set of **actions** $A \subseteq \mathbb{R}^m$
  - A **transition function** $T(s' | s, a)$
  - A **reward function** $R(s' | s, a)$
  - A **discount factor** $\gamma \in [0, 1]$



- Goal of Learning
  - To find a control policy $\pi_s^* = \mathrm{argmax}_\pi \sum_{t=0}^{\infty} \gamma^t R(s_t)$

To identify and exploit task structure to obtain faster learning and better generalization

- POMDPs (Partially Observable MDPs)
  - A more accurate characterization, but more difficult to solve

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# Structured Collection of MDPs as a Task Family

*Ideally attempt to learn a policy that generalizes across the entire task family*

- Task Family
  - A distribution, $P(M)$, over MDPs, each of which is a *task*.
- Action Space
  - Determined by the robot and remains the same across tasks
  - Each task may have its own state space and transition and reward functions
- Reward Function
  - Typically formulated as a robot-dependent background cost function
  - Shared across the entire family
  - Plus a terminal reward that is specific to that task

$$R_i = \boxed{G_i} - \boxed{C}$$

the reward function for the $i^{th}$ task

the general background cost function

# Structured Collection of MDPs as a Task Family

*Ideally attempt to learn a policy that generalizes across the entire task family*

- State Space
  - The state space of the $i^{th}$ task

$$S_i = \boxed{S_r} \times \boxed{S_{e_i}}$$

the state of the robot

the state of the $i^{th}$ environment

- raw pixels and sensor values
- a highly pre-processed collection of relevant task variables

- Factorize the environment as a collection of object states
  - Many task environments will consist of ***a collection of objects*** and the variables describing ***the aspects of those objects*** that are relevant to the task

$$S_{e_i} = \boxed{S_{\omega_i}} \times \Omega_1^i \times \ldots \times \boxed{\Omega_{k_i}^i}$$

the state of the general environment

the state of the $j^{th}$ relevant object in task $i$, and task $i$ contains $k_i$ objects

- Facilitates **object-centric** generalization
  - Can be **reused** in new environments containing the same objects

# Structure in Transition Function

*the robot will only be able to affect a subset of objects and state variables from any given state*

- Modularity in Transition Functions
  - Model the tasks as hybrid systems with piecewise continuous dynamics
- **Mode**: *Each of the continuous dynamical subsystems*
  - the state will often contain discrete variables to capture the current mode
- **Mode Switches**: *occur when the robot enters certain sets of states*
  - when the robot makes or breaks contact with an object.
- Limit the state variables that the robot may alter by restricting itself to certain modes

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# Structure in Action Space, or *Skills*

*Exploited using higher-level actions*

- Typically modeled using a hierarchical learning framework
  - Models each motor skill as an *option*: $o = (I_o, \beta_o, \pi_o)$
  - $I_o: S \rightarrow \{0, 1\}$ is the *initiation set*
    - an indicator function describing the states from which the option may be executed.
  - $\beta_o: S \rightarrow [0, 1]$ is the *termination condition*
    - describing the probability that an option ceases execution upon reaching state s.
  - $\pi_o$ is the *option policy*
    - mapping states in the option's initiation set to low-level motor actions and corresponding to the motor skill controller.
- Examples of the robot action space
  - Pre-equipped with a set of motor skills to reuse across the family of tasks
  - Discovers reusable skills as part of its learning task

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# A Dilemma between a Single Task and a Task Family

*Challenges when transfer learned functions across a task family*

- Learned policies for a single task may not share the same task space with others
  - Different tasks in a task family may require different functions of the task state

- Adding extra information to the task
  - for example, information about the color and shape of various objects in the task
  - Incompatible with the state space representation (no change)

- Extra information modelled as a *context vector* $\tau$
  - Added to each task MDP, and which the robot can use to inform its behavior.
  - Can be monolithic for each task, or factored into object contexts.

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# Modeling a Family of Manipulation Tasks

*a task family specified by a distribution of manipulation MDPs, $P(M)$*

- A 6-tuple $M_i = (S_i, A, R_i, T_i, \gamma, \tau_i)$ of $P(M)$
  - $S_i = S_r \times S_{e_i}$ is the **state space**
    - Where $S_r$ describes the robot state, and $S_{e_i}$ the environment state. Often the environment state is primarily factored into a collection of object states: $S_{e_i} = S_{\omega_i} \times \Omega_1^i \times \ldots \times \Omega_{k_i}^i$, for a task with $k_i$ objects;
  - $A$ is the **action space**
    - Common across tasks, which may include both low-level primitive actions and a collection of options $O$;
  - $R_i = G_i - C$ is the **reward function**
    - Comprising a background cost function $C$ (common to the family) and a task-specific goal function $G_i$ ;
  - $T_i$ is the **transition function**
    - May contain exploitable structure across the sequence of tasks, especially object-centric structure;
  - $\gamma$ is a **discount factor**
  - $\tau_i$ is task-specific **context information**
    - A vector of real numbers, possibly factored into object context: $\tau_i = \tau_1^i \times \ldots \times \tau_k^i$, for $k$ objects.

# Learning to Open Doors

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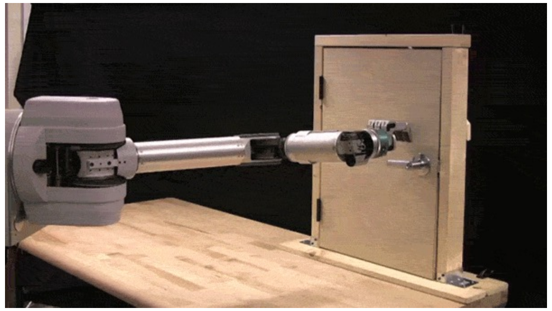
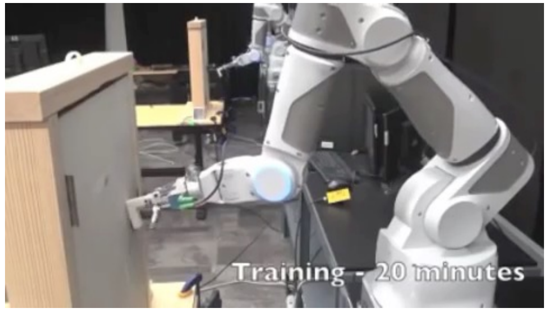
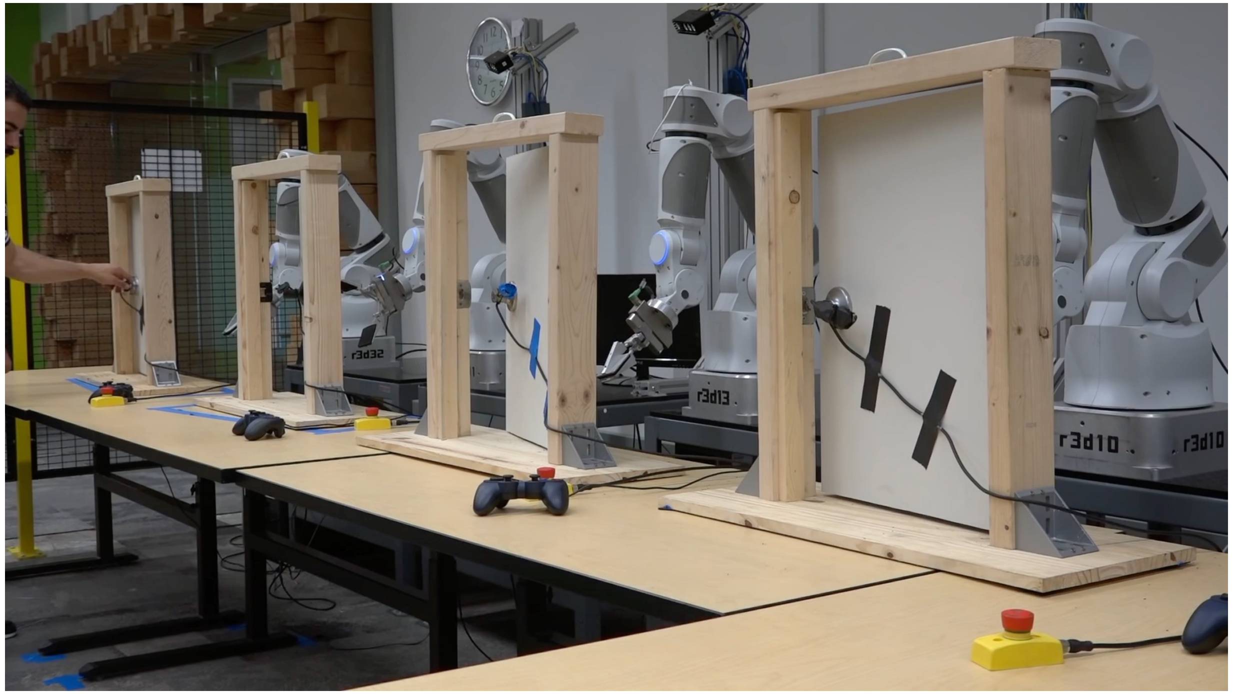
# Example: Learning to Open Doors

*Many doors …*







**A successful door opening policy**

- Robust to many different
  - doors
  - lighting conditions
  - environment settings
- Quick, reliable, and safe

**Subtask decomposition**

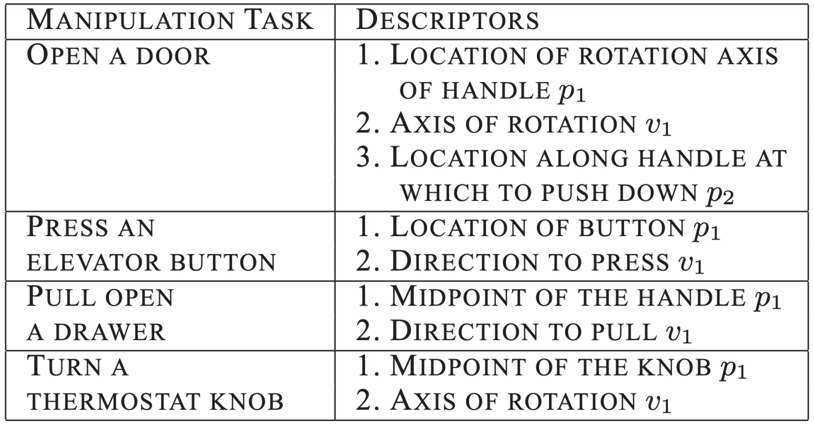
- Turning the handle
- Pulling open the door

Sources: Google Brain, UC Berkley, Boston Dynamics

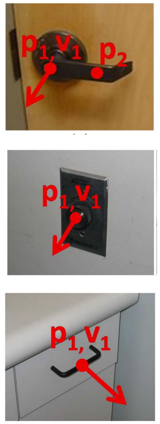
# Approaches to Learn Openning Doors

## *Door Keypoint Detection, Model Based, and Reinforcement Learning based*

- Door Keypoint Detection
  - locating the doorknob location, and axes of rotation,
  - then using motion planning to open the door



| Manipulation Task | Descriptors |
|---|---|
| Open a door | 1. Location of rotation axis of handle $p_1$<br>2. Axis of rotation $v_1$<br>3. Location along handle at which to push down $p_2$ |
| Press an elevator button | 1. Location of button $p_1$<br>2. Direction to press $v_1$ |
| Pull open a drawer | 1. Midpoint of the handle $p_1$<br>2. Direction to pull $v_1$ |
| Turn a thermostat knob | 1. Midpoint of the knob $p_1$<br>2. Axis of rotation $v_1$ |

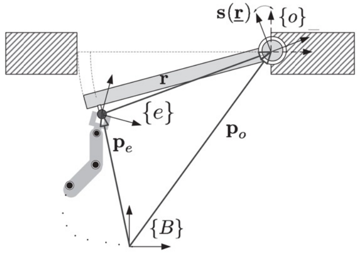


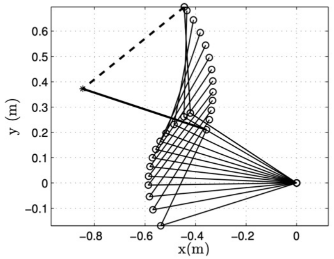
sci-hub.si/10.1109/IROS.2010.5649847

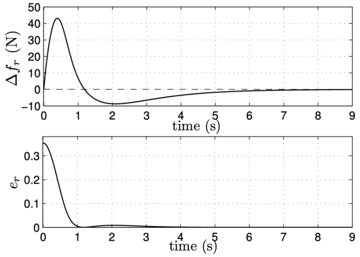
sci-hub.si/10.1109/iros.2012.6385835

sci-hub.si/10.1109/icar.2017.8023522

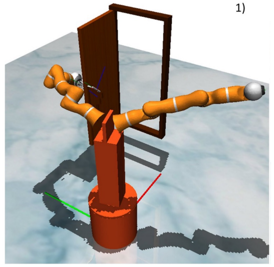
- Model Based
  - Creating a model of the door
  - Learning the kinematics of doors

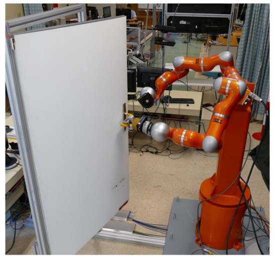


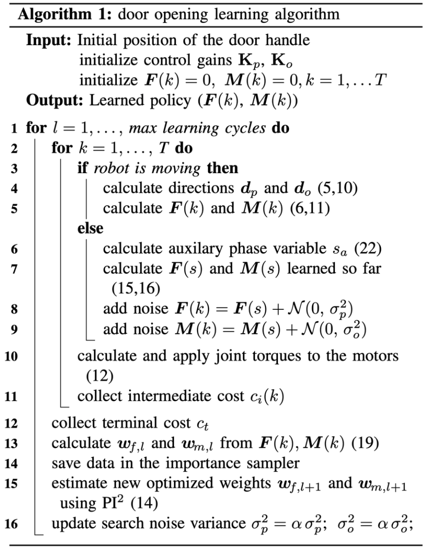




- Reinforcement Learning based
  - A growing interest of research







```
Algorithm 1: door opening learning algorithm
  Input: Initial position of the door handle
         initialize control gains $\mathbf{K}_p$, $\mathbf{K}_o$
         initialize $\boldsymbol{F}(k) = 0,\ \boldsymbol{M}(k) = 0, k = 1, \dots T$
  Output: Learned policy $(\boldsymbol{F}(k),\ \boldsymbol{M}(k))$
  for $l = 1, \dots,$ max learning cycles do
      for $k = 1, \dots, T$ do
          if robot is moving then
              calculate directions $\boldsymbol{d}_p$ and $\boldsymbol{d}_o$ (5,10)
              calculate $\boldsymbol{F}(k)$ and $\boldsymbol{M}(k)$ (6,11)
          else
              calculate auxilary phase variable $s_a$ (22)
              calculate $\boldsymbol{F}(s)$ and $\boldsymbol{M}(s)$ learned so far (15,16)
              add noise $\boldsymbol{F}(k) = \boldsymbol{F}(s) + \mathcal{N}(0, \sigma_p^2)$
              add noise $\boldsymbol{M}(k) = \boldsymbol{M}(s) + \mathcal{N}(0, \sigma_o^2)$
          calculate and apply joint torques to the motors (12)
          collect intermediate cost $c_i(k)$
      collect terminal cost $c_t$
      calculate $\boldsymbol{w}_{f,l}$ and $\boldsymbol{w}_{m,l}$ from $\boldsymbol{F}(k), \boldsymbol{M}(k)$ (19)
      save data in the importance sampler
      estimate new optimized weights $\boldsymbol{w}_{f,l+1}$ and $\boldsymbol{w}_{m,l+1}$ using PI$^2$ (14)
      update search noise variance $\sigma_p^2 = \alpha\,\sigma_p^2;\ \sigma_o^2 = \alpha\,\sigma_o^2;$
```

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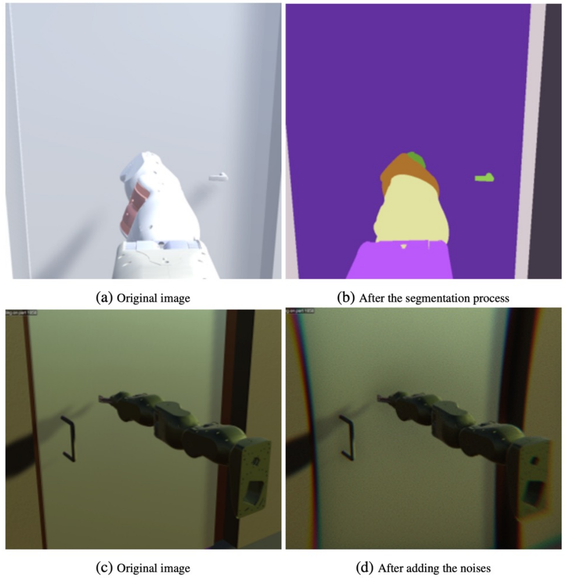
# Domain Randomization in Reinforcement Learning

*Bridge the reality gap between simulation and the real world*

- **Drawbacks in Reinforement Learning**
  - sample inefficiency, the curse of dimensionality, and
  - the **reality gap** between simulators and the real world
- **Assumption**
  - Hard to model the real world perfectly, but easy to create many different simulations that approximate the real world.
- **Proposal**
  - It is possible to ensemble a variety of simulator environments with different visual or physical properties to generalize to a domain that overlaps the real world

Examples of the post processing that can be apply by Unity



(a) Original image

(b) After the segmentation process

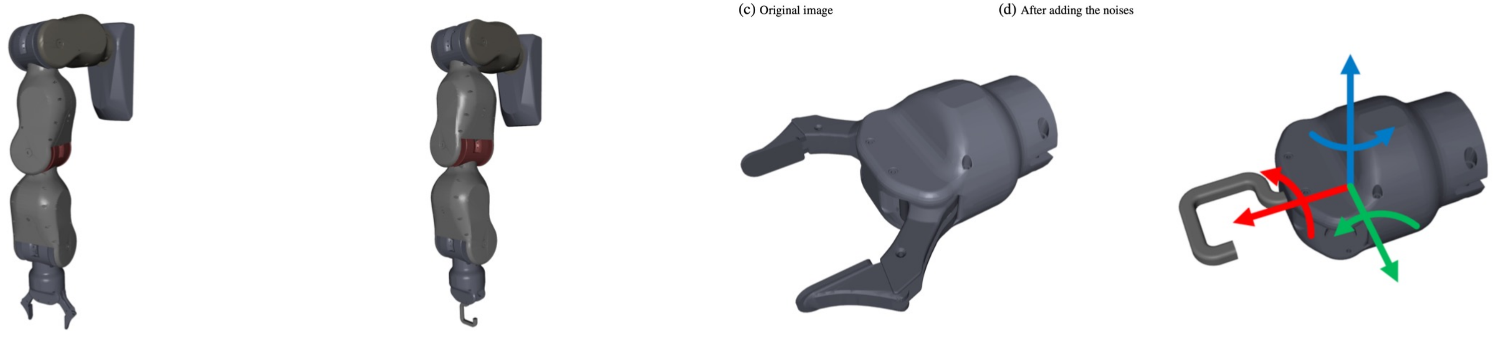
(c) Original image

(d) After adding the noises

Top row shows the function to make semantic segmentation labels.

Bottom row shows the image when the Gaussian noise, camera distortion, and chromatic aberration are added.

OpenAI Gym



(a) 8DoF BLUE with grippers

(b) 7DoF BLUE with hook

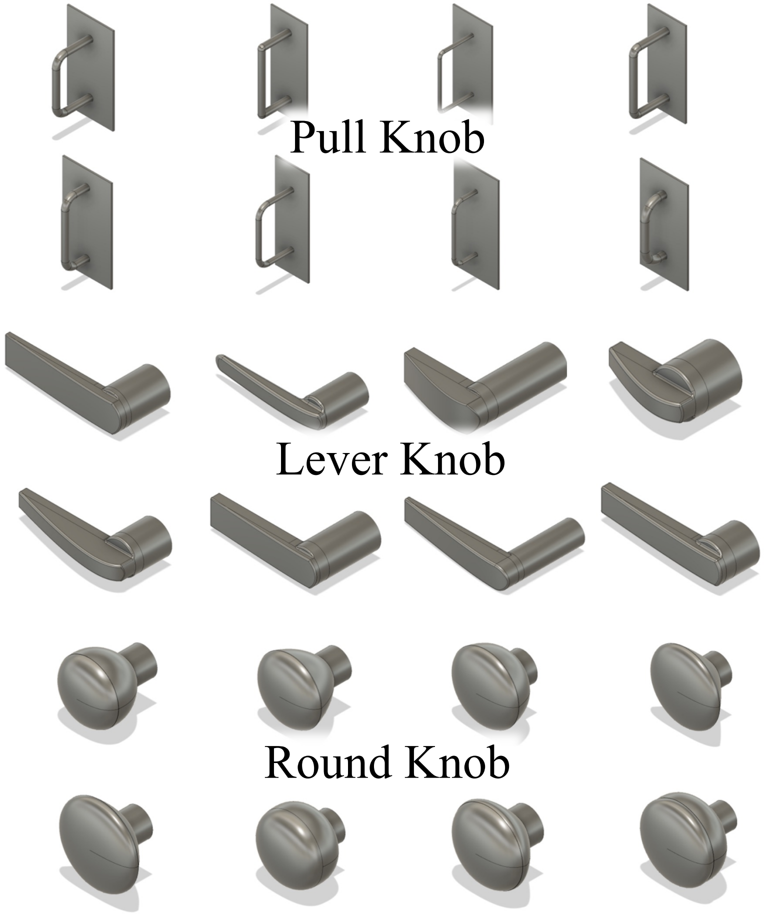
(c) 7DoF Floating gripper

(d) 6DoF Floating hook

# List of Randomized Parameters in the Door World

## *Door*

| **Randomization Parameters** | | **Scalling Factor Range** | **Unit** |
|---|---|---|---|
| | **Door Physical parameters** | | |
| Wall Property | wall location | y-axis: Uniform[-200, 200] | mm |
| Door Frame Joint Property | door frame damper | Uniform[0.1, 0.2] | - |
| | door frame spring | Uniform[0.1,0.2] | - |
| | door frame frictionloss | Uniform[0, 1] | - |
| Door Property | door height | Uniform[2000, 2500] | mm |
| | door width | Uniform[800, 1200] | mm |
| | door thickness | Uniform[20, 30] | mm |
| | knob height | Uniform[950, 1050] | mm |
| | knob horizontal location ratio | Uniform[0.10, 0.20] | - |
| | door mass | Uniform[22.4, 76.5] | kg (Based on MDF density) |
| | hinge position | left hinge/right hinge | - |
| | opening direction | push/pull | - |
| Knob Door Joint Property | knob door damper | Uniform[0.1, 0.2] | - |
| | knob door spring | Uniform[0.1, 0.15] | - |
| | knob door frictionloss | Uniform[0, 1] | - |
| | knob rot range | Uniform[75, 80] | degree |
| Knob Property | knob mass | Uniform[4, 7] | fg |
| | knob surface friction | Uniform[0.50, 1.00] | - |



STL models

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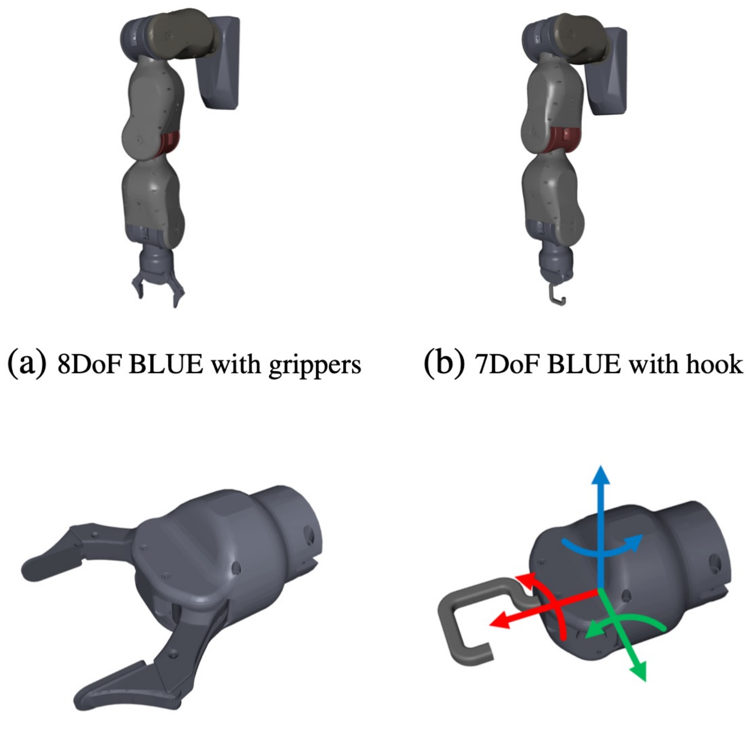
# List of Randomized Parameters in the Door World

## *Robot*

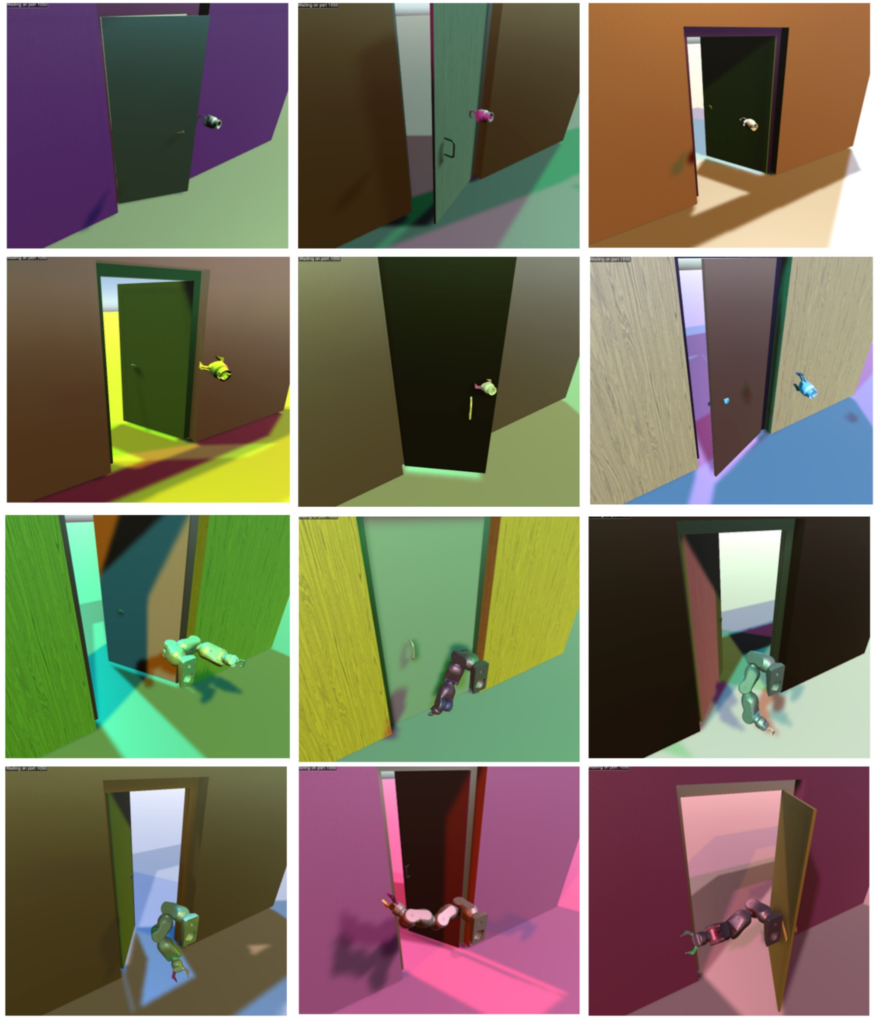
| Randomization Parameters | | Scalling Factor Range | Unit |
|---|---|---|---|
| **Robot Physical Parameters** | | | |
| Robot Property | arm joint damping | Uniform[0.1, 0.3] | - |



(a) 8DoF BLUE with grippers (b) 7DoF BLUE with hook

(c) 7DoF Floating gripper (d) 6DoF Floating hook

https://www.berkeleyopenarms.org/

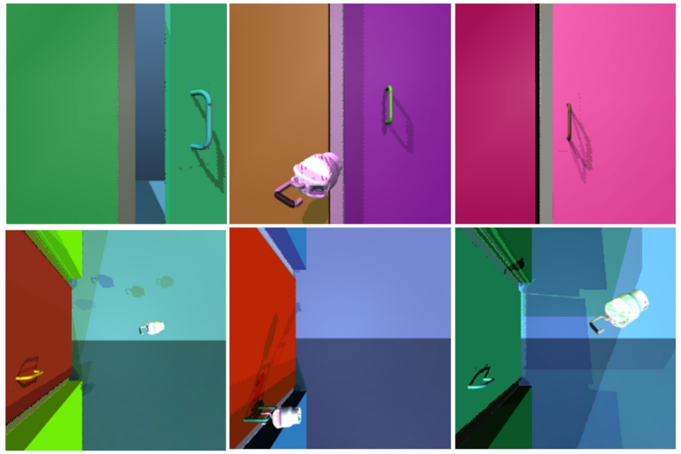


# List of Randomized Parameters in the Door World

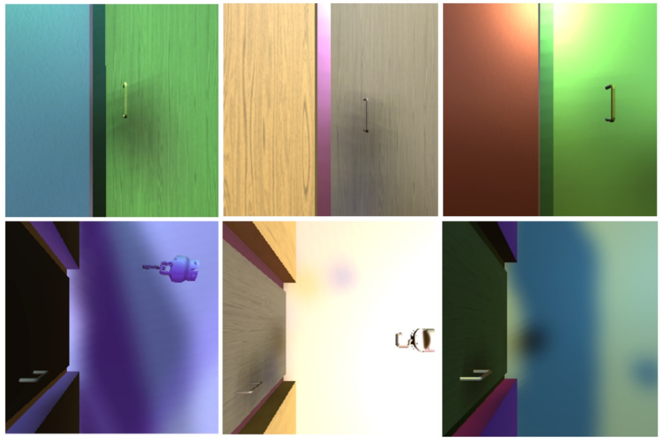
## *Vision*

| Randomization Parameters | | Scalling Factor Range | Unit |
|---|---|---|---|
| | **Vision Parameters** | | |
| Lighting | light number | Uniform[2-6] | - |
| | light diffuse | Uniform[0.0, 1.0] | RGBA |
| | light position | x:Uniform[0.0, 5]<br>y:Uniform[-5, 5]<br>z:Uniform[3, 7] | m |
| | light direction | x:Uniform[-0.5, 0.5]<br>y:Uniform[-0.5, 5.0]<br>z:Uniform[-0.5, -0.25] | rad |
| Wall Material | wall shininess | Uniform[0.01, 0.50] | - |
| | wall specular | Uniform[0.01, 0.50] | - |
| | wall rgb1 | Uniform[0.0, 1.0] | RGBA |
| Frame Material | frame shininess | Uniform[0.01, 0.70] | - |
| | frame specular | Uniform[0.01, 0.80] | - |
| | frame rgb1 | Uniform[0.0, 1.0] | RGBA |
| Door Material | door shininess | Uniform[0.01, 0.30] | - |
| | door specular | Uniform[0.01, 0.80] | - |
| | door rgb1 | Uniform[0.0, 1.0] | RGBA |
| | door rgb2 | Uniform[0.0, 1.0] | RGBA |
| Doorknob Material | knob shininess | Uniform[0.50, 1.00] | - |
| | knob specular | Uniform[0.80, 1.00] | - |
| | knob rgb1 | Uniform[0.0, 1.0] | RGBA |
| Robot Material | robot shininess | Uniform[0.01, 0.70] | - |
| | robot specular | Uniform[0.01, 0.80] | - |
| | robot rgb | Uniform[0.0, 1.0] | RGBA |

MuJoCo API



(a) MuJoCo rendered images



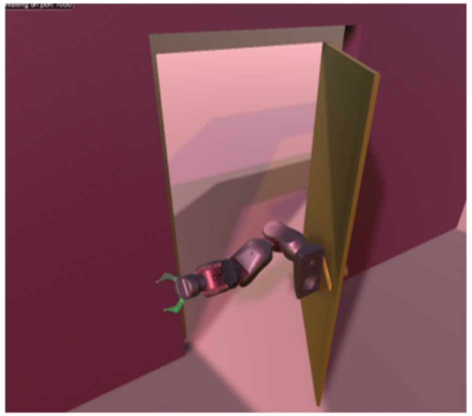
Unity can render realistic shadows and detailed textures.

(b) Unity rendered images

# The ***Shaped*** Reward Function for DoorGym

*Use simple and readily available observations from the environment*

- Elements of an observation
  - The position and the velocity of each robot joint
  - The position of the door-knob
    - *Can be obtained directly from the simulator, or using a 256x256 RGB image and vision network*
  - The position of the end-effector in world coordinates



- Policy actions
  - Force for linear actuators and torque for rotational actuators, which can be configured to use position control
  - The size of the action space corresponds to the # DoF of each robot

Subscript indicate the value at time *t*

To minimize (-)

To maximize (+)

**The Reward Function to incentivize the agent to open the door**

$$r_t = \boxed{-a_0\boxed{d_t} - a_1\boxed{log(d_t + \alpha)} - a_2\boxed{o_t} - a_3\sqrt{\boxed{u_t^2}}} + \boxed{a_4\boxed{\phi_t} + a_5\boxed{\psi_t}}$$

The distance between the fingertip of the end-effector and the center coordinate of the doorknob

To give a precision when the agent get close to a target ($\alpha = 0.005$)

The difference between the current fingertip orientation of the robot and the ideal orientation to hook/grip the doorknob

The control input to the system

The angle of the door

The angle of the door-knob

***Quiz***:
The robot tries to open the door ***before or after*** it hooks or rotates the door knob ?

$a_{0,1,2,3} = 1$

$a_4 = 30$

$a_5 = 50$

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# The *Unshaped* Reward Function for DoorGym

## *Other forms of evaluation*

- We define a successful attempt as the robot opening the door at least 0.2 radians within 10 seconds.
  - For attempt $i$, $\mathbb{1}_i = \begin{cases} 1 & \text{if } \phi > 0.2 \text{ rad and t} < 10 \\ 0 & \text{otherwise} \end{cases}$
  - Two unshaped reward function (*measured over 100 attempts*)

The average success rate of opening a door

$$r_{\text{AT}} = \frac{1}{n}\sum_{i=1}^{n} t_i$$

The average time to open the door

$$r_{\text{ASR}} = \frac{1}{100}\sum_{i=1}^{100} \mathbb{1}_i$$

$t_i$: the time to completion for successful attempts
$n$: the number of successful attempts

### The Reward Function to incentivize the agent to open the door

To minimize (-)

To maximize (+)

$$r_t = -a_0\boxed{d_t} - a_1\boxed{log(d_t+\alpha)} - a_2\boxed{o_t} - a_3\sqrt{\boxed{u_t^2}} + a_4\boxed{\phi_t} + a_5\boxed{\psi_t}$$

Subscript indicate the value at time *t*

The distance between the fingertip of the end-effector and the center coordinate of the doorknob

To give a precision when the agent get close to a target ($\alpha = 0.005$)

The control input to the system

The angle of the door

The angle of the door-knob

$a_{0,1,2,3} = 1$
$a_4 = 30$
$a_5 = 50$

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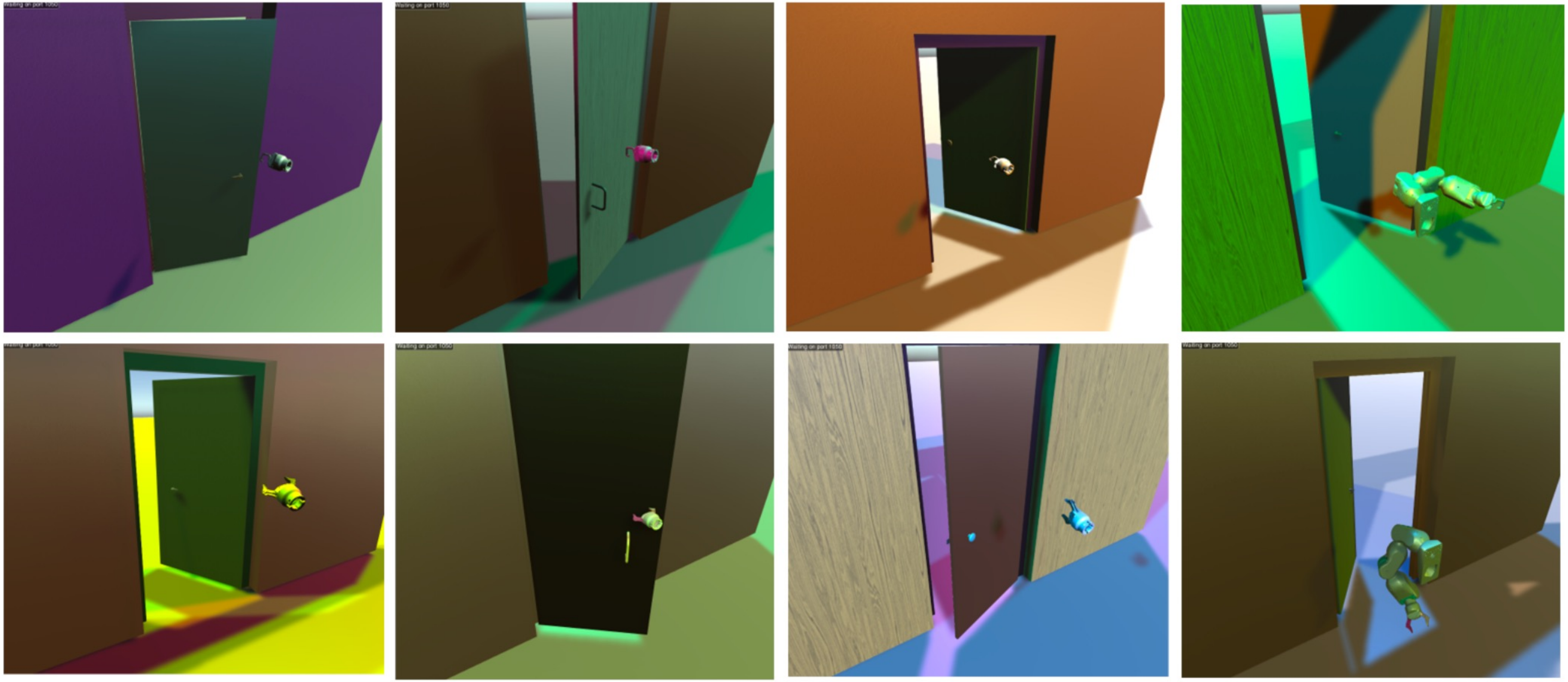
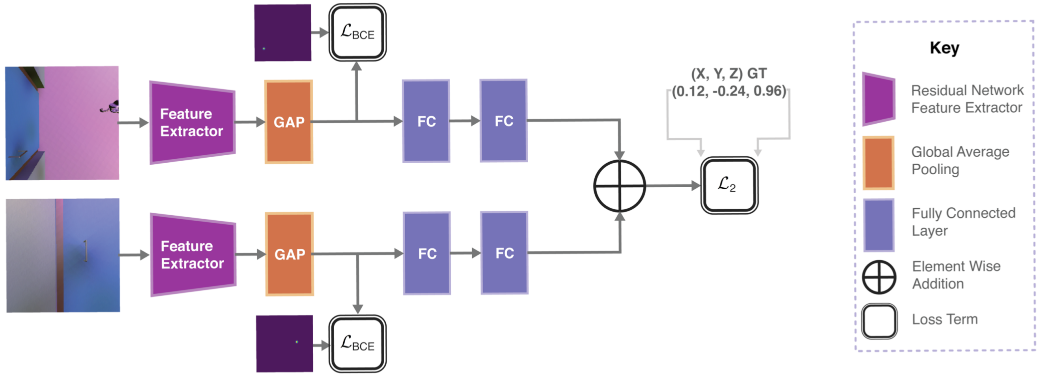
# Environment Summary

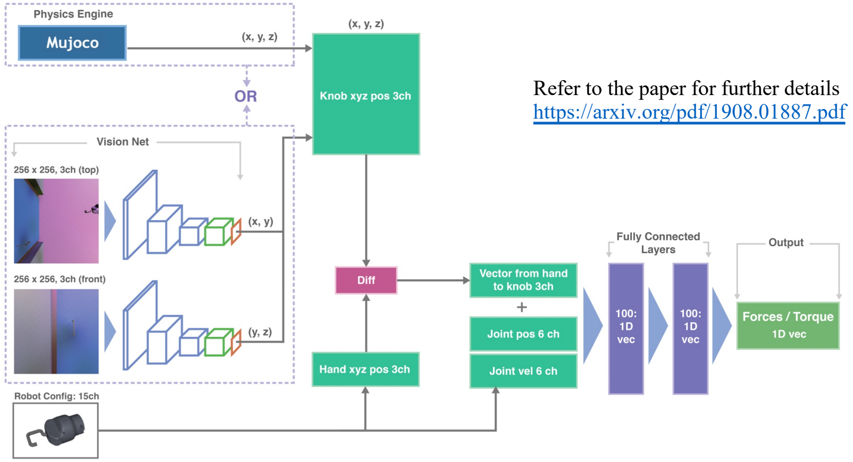
*36 possible environment combinations with 3 grippers, 6 robots, and 2 directions (push/pull)*



# The Door Opening Agent

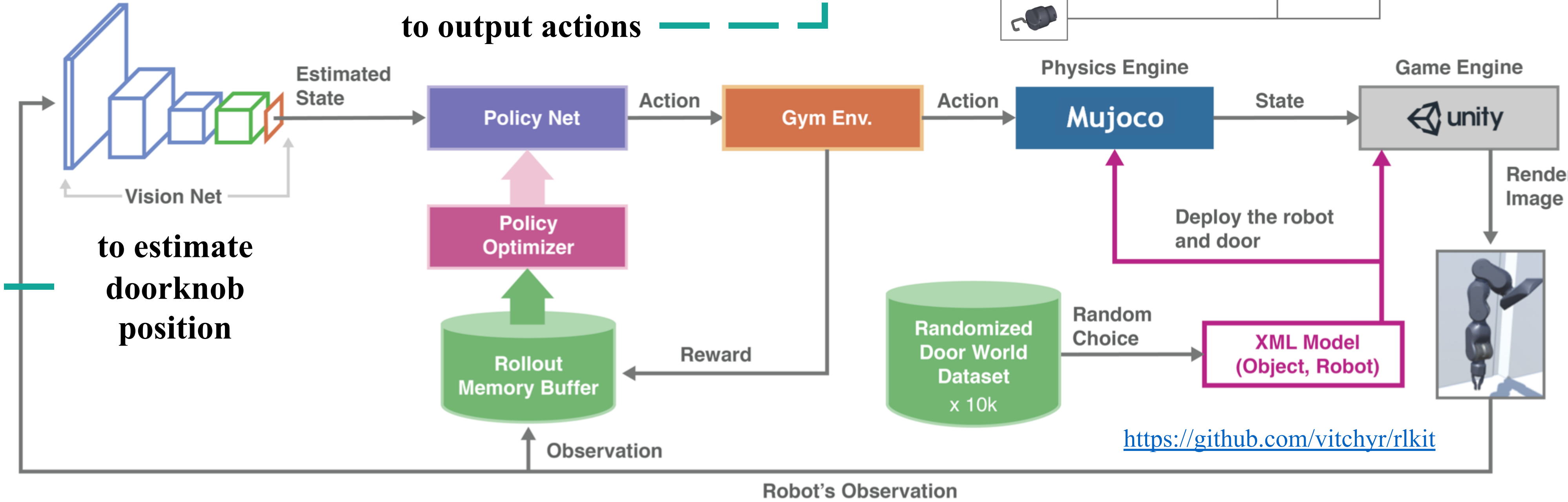
*An on-policy (**P**roximal **P**olicy **O**ptimization) and off-policy (**S**oft **A**ctor **C**ritic) update algorithm*





Refer to the paper for further details
https://arxiv.org/pdf/1908.01887.pdf

**to output actions**



**to estimate doorknob position**

https://github.com/vitchyr/rlkit

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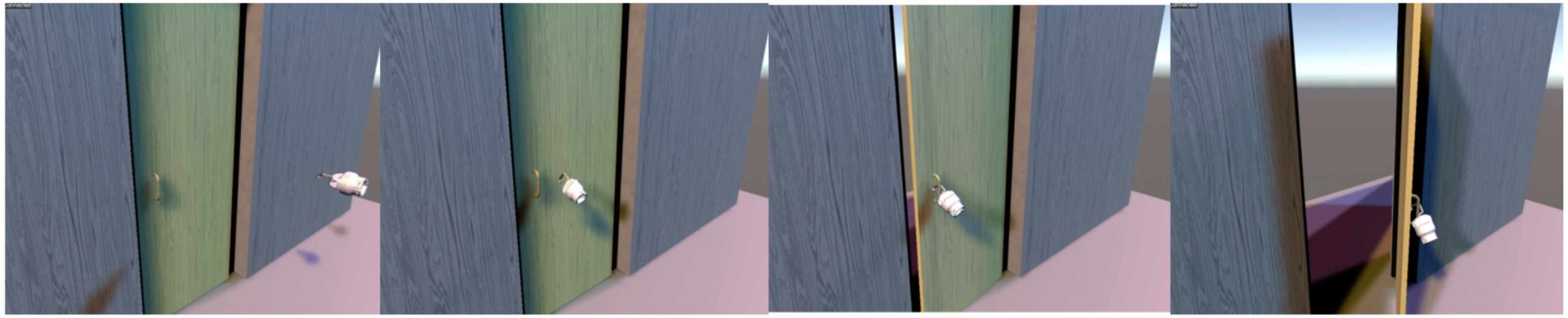
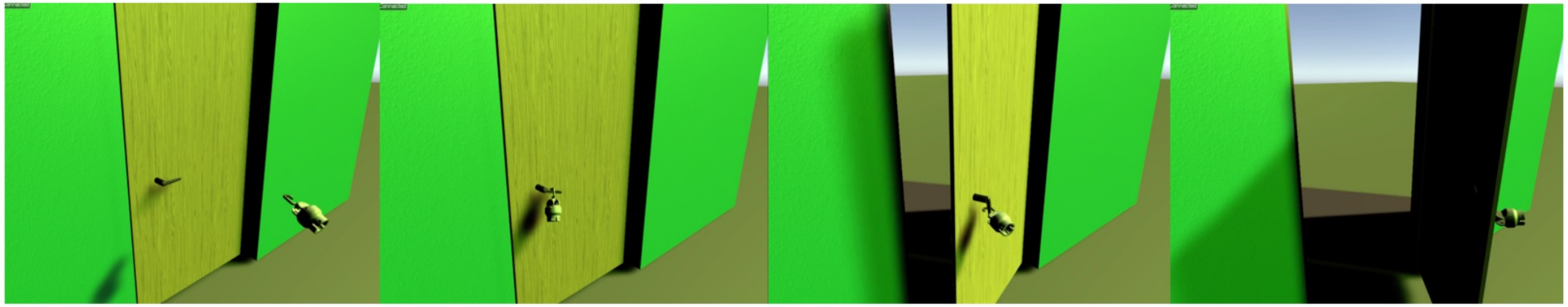
# Experiments

*The agent has 10.2sec to try open the door for each of the 100 test door-worlds*



Task 1 has a **pull knob** environment with ***floating hook***



Task 2 has a **lever knob** with ***floating hook***

Task 3 has a **pull knob** with the ***BLUE-with-gripper platform***

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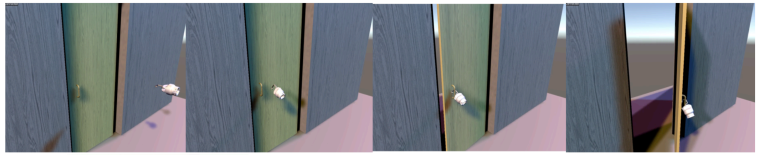
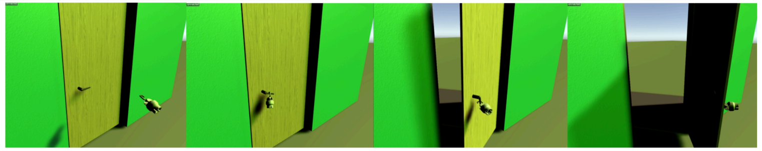
# Results

*Average Success Ratio and Average Time to Open measured in seconds*

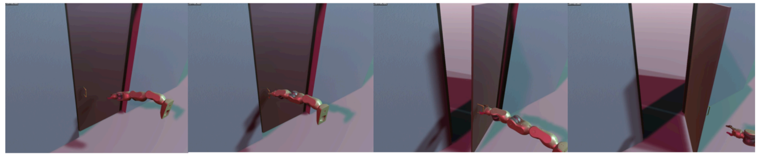
| | | Task 1 | | Task 2 | | Task 3 | |
|---|---|---|---|---|---|---|---|
| | | $r_{\text{ASR}}$ | $r_{\text{AT}}$ | $r_{\text{ASR}}$ | $r_{\text{AT}}$ | $r_{\text{ASR}}$ | $r_{\text{AT}}$ |
| PPO | Ground Truth Position | 0.73 | 3.73 | 0.68 | 4.12 | 0.71 | 5.13 |
| | Ground Truth Position + N(0, $\sigma$) | 0.70 | 4.28 | 0.54 | 4.11 | 0.65 | 4.73 |
| | Vision Network Estimated Position | 0.23 | 5.00 | 0.29 | 3.83 | 0.57 | 5.12 |
| SAC | Ground Truth Position | 0.23 | 4.29 | 0 | N/A | 0.33 | 5.02 |
| | Ground Truth Position + N(0, $\sigma$) | - | - | - | - | - | - |
| | Vision Network Estimated Position | 0 | N/A | 0 | N/A | 0.05 | 5.06 |



Task 1 has a **pull knob** environment with ***floating hook***



Task 2 has a **lever knob** with ***floating hook***



Task 3 has a **pull knob** with the ***BLUE-with-gripper platform***

- PPO (~70%) has a much higher successrate than SAC
- SAC shows better exploration and faster convergence, but PPO shows better exploitation in trade-off of its training speed
- Success rates of both algorithm decrease
  - When adding gaussian noise to the door knob position
  - When the door knob position information comes from the vision network
- Position estimation in the 3D space of the door knob is **extremely important** for the door opening task.

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# Thank you~

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