Model-Based RL and

^

# Multi-Task and Goal-Conditioned Reinforcement Learning

CS 224R

# Course reminders

- Homework 3 due next Friday, May 16
- Project milestone due Friday, May 23

# The plan for today

1. Model-based reinforcement learning
   a. Using a learned model via synthetic data generation
   b. When to use model-based RL
2. Multi-task imitation and reinforcement learning
   a. Task conditioning
   b. Goal-reaching tasks
   c. Hindsight relabeling

} **Part of homework 4!**

# Recap: Planning with learned models

1. Can *plan* $\mathbf{a_1}$, …, $\mathbf{a_H}$ with gradient-based or sampling-based optimization
2. *Update the model* using data collected with planning
3. *Replan* periodically to help account for mistakes.

+ Simple

+ Easy to plug in different goals / rewards (possibly even at test time!)

- Compute intensive at test time

- Only practical for short-horizon problems (or very shaped reward functions)

Why only short horizons?

**(a)** too compute expensive to make long plans

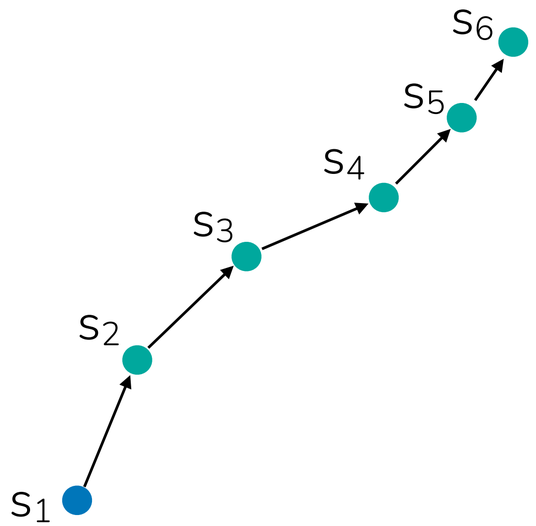
**(b)** model is not accurate for long horizons

Can we *train a policy* using a learned model?

# Model-based policy optimization

**Key idea**: augment data with model-simulated roll-outs.

Example real trajectory



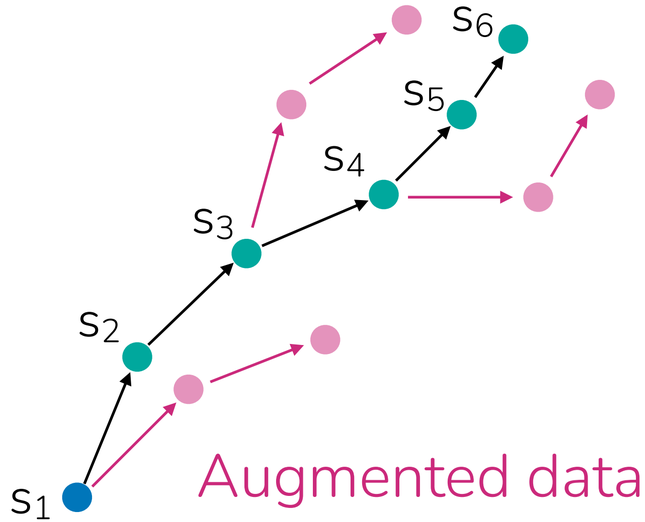

How to augment?

- generate full trajectories from initial states?
  - model may not be accurate for long horizons
- generate *partial trajectories* from initial states?
  - may not get good coverage of later states

# Model-based policy optimization

**Key idea**: augment data with model-simulated roll-outs.

Example real trajectory




How to augment?

- generate full trajectories from initial states?
  - model may not be accurate for long horizons
- generate *partial trajectories* from initial states?
  - may not get good coverage of later states
- generate *partial trajectories* from *all states* in the data 💡

# Model-based policy optimization

Key idea: augment data with model-simulated roll-outs.

**Full algorithm**

1. Collect data using current policy $\pi_\theta$, add to $D_{env}$
2. Update model $p_\psi(s' \mid s, a)$ using $D_{env}$
3. Collect short synthetic roll-outs using $\pi_\theta$ in model $p_\psi$ from states in $D_{env}$; add to $D_{model}$
4. Update policy $\pi_\theta$ (and critic $Q_\phi$) using $D_{env} \bigcup D_{model}$

Notes:
- compatible with variety of model-free RL methods (step 4)
- could additionally use $D_{env}$ in policy update

# When to use model-based RL?

**Big upsides and big downsides**

+ Immensely useful, far more data efficient if model is easy to learn
+ Model can be trained on data without reward labels (fully self-supervised)
+ Model is somewhat task-agnostic (can sometimes be transferred across rewards)
- Models don't optimize for task performance
- Sometimes harder to learn than a policy
- Another thing to train, more hyperparameters, more compute intensive

Whether to use a model depends on how hard it is to learn!

# Other kinds of models

So far: modeling $p(\mathbf{s}_{t+1} \mid \mathbf{s}_t, \mathbf{a}_t)$

Many alternatives

- inverse model $p(\mathbf{a}_t \mid \mathbf{s}_t, \mathbf{s}_{t+1})$
- multi-step inverse model $p(\mathbf{a}_t \mid \mathbf{s}_t, \mathbf{s}_{t+n})$ or $p(\mathbf{a}_{t:t+n} \mid \mathbf{s}_t, \mathbf{s}_{t+n})$
- future prediction without actions $p(\mathbf{s}_{t+1:t+n} \mid \mathbf{s}_t)$
- video interpolation $p(\mathbf{s}_{t+1:t+n} \mid \mathbf{s}_t, s_{t+n+1})$
- transition distribution $p(\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{t+1})$

These kinds of models can be useful too! Have various purposes.

# The plan for today

1. Model-based reinforcement learning
   a. Using a learned model via synthetic data generation
   b. When to use model-based RL
2. **Multi-task imitation and reinforcement learning**
   a. Task conditioning
   b. Goal-reaching tasks
   c. Hindsight relabeling

} **Part of homework 4!**

# What is multi-task RL?

Can we train generalist policies to do many “tasks”, not just one?

Examples:

**Generalist LLM assistant**: travel booking, grocery shopping, …

**Legged robot**: walk, run, dance, crouch, …

**Mobile manipulator**: hang up a towel, unload a dishwasher, wipe a spill, …

**Music recommender system**: personalization to many distinct users

**Game player**: play Flappy bird, Pokemon, Pinball, …

May have different reward functions, different dynamics, different action spaces, …!

Key idea will be to condition on the task.

# Why multi-task RL?

Can we train generalist policies to do many “tasks”, not just one?

Fundamentals of CS224r so far:

- Imitation
- On-policy, off-policy and offline RL
- Model-free and model-based RL
- Reward functions

Biggest challenge so far?

Data efficiency

Can we **amortize the data complexity** across many tasks & scenarios?

Plenty of learnings can be shared across tasks!

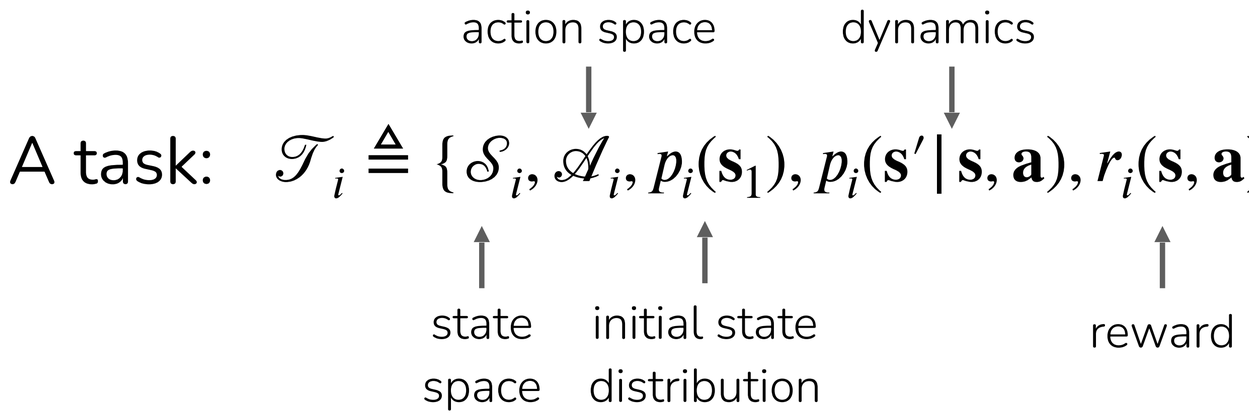
LLM assistant: grammar  Legged robots: balance  Personal recommenders: user similarities

**There’s also a deeper motivation.**

Generalist ML systems are often more reliable, performant than specialists.

# How do we formalize what different “tasks” are?

Different tasks can just be different MDPs!



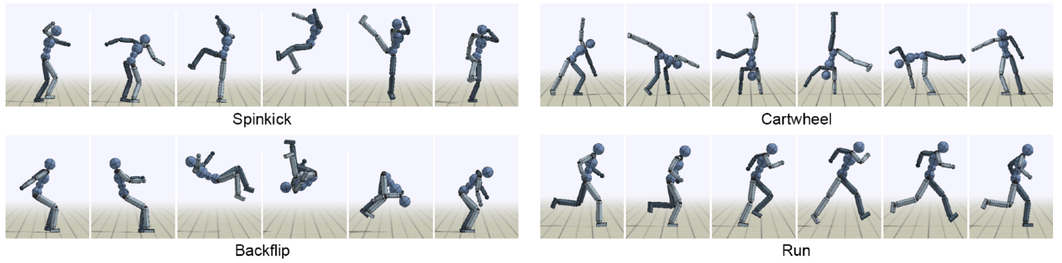

**Note**: This allows for much more variety than the semantic meaning of “task”!

# A Few Examples Task Distributions

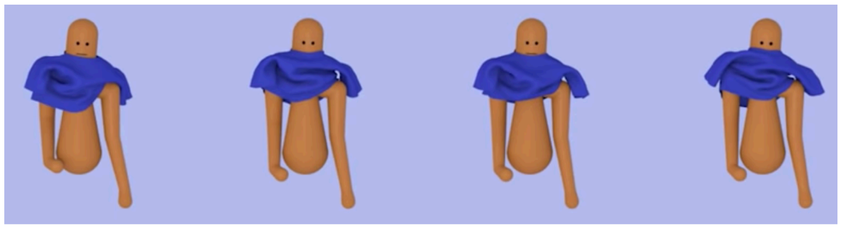
A task: $\mathcal{T}_i \triangleq \{\mathcal{S}_i, \mathcal{A}_i, p_i(\mathbf{s}_1), p_i(\mathbf{s}'|\mathbf{s},\mathbf{a}), r_i(\mathbf{s},\mathbf{a})\}$

Personalized recommendations: $p_i(\mathbf{s}'|\mathbf{s},\mathbf{a}), r_i(\mathbf{s},\mathbf{a})$ vary across tasks

Character animation: across maneuvers $r_i(\mathbf{s},\mathbf{a})$ vary




across garments & initial states $p_i(\mathbf{s}_1), p_i(\mathbf{s}'|\mathbf{s},\mathbf{a})$ vary

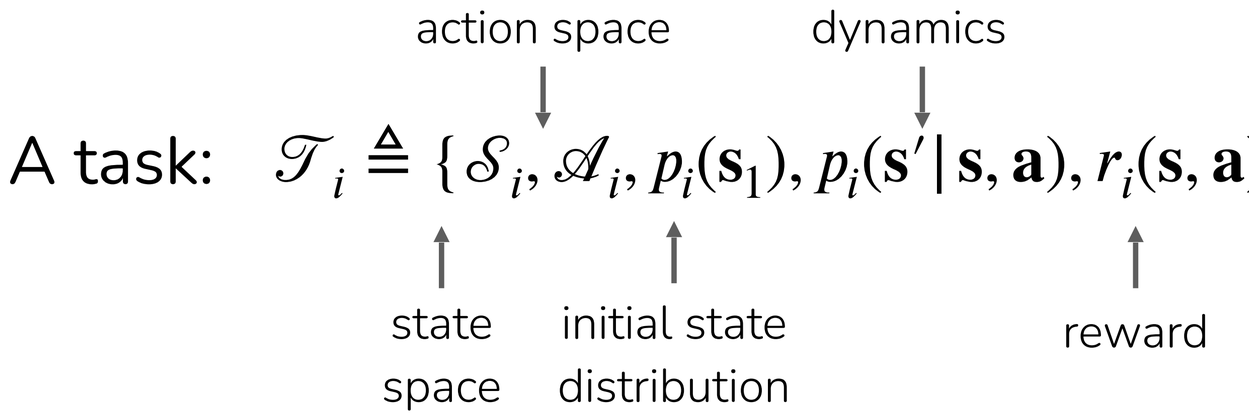


Multi-robot RL:

$\mathcal{S}_i, \mathcal{A}_i, p_i(\mathbf{s}_1), p_i(\mathbf{s}'|\mathbf{s},\mathbf{a})$ vary

# How do we formalize what different “tasks” are?

Different tasks can just be different MDPs!




**How can do we identify one task from another?**

Assign task index (e.g. task 0, task 1, …)

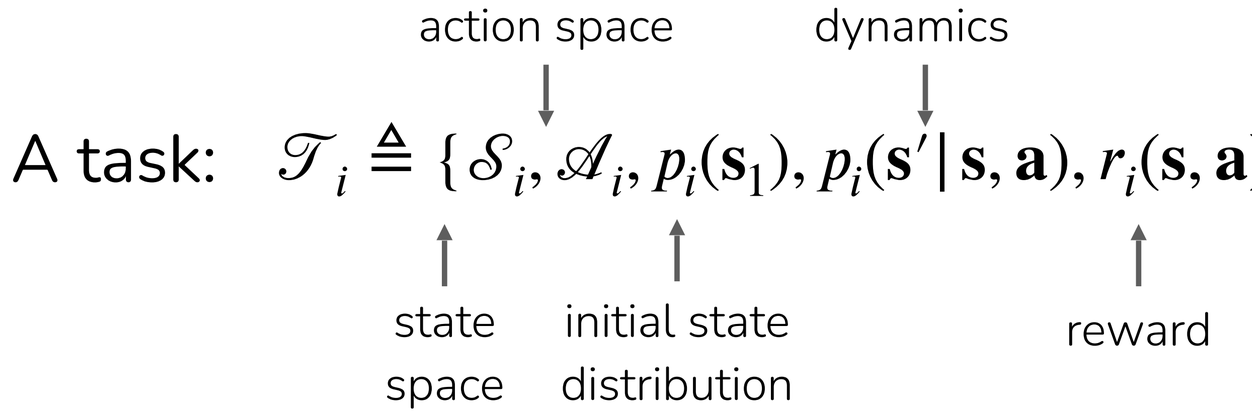
Language description

Video illustration of what to do

} These are task identifiers, $\mathbf{z}_i$

# How do we formalize what different “tasks” are?

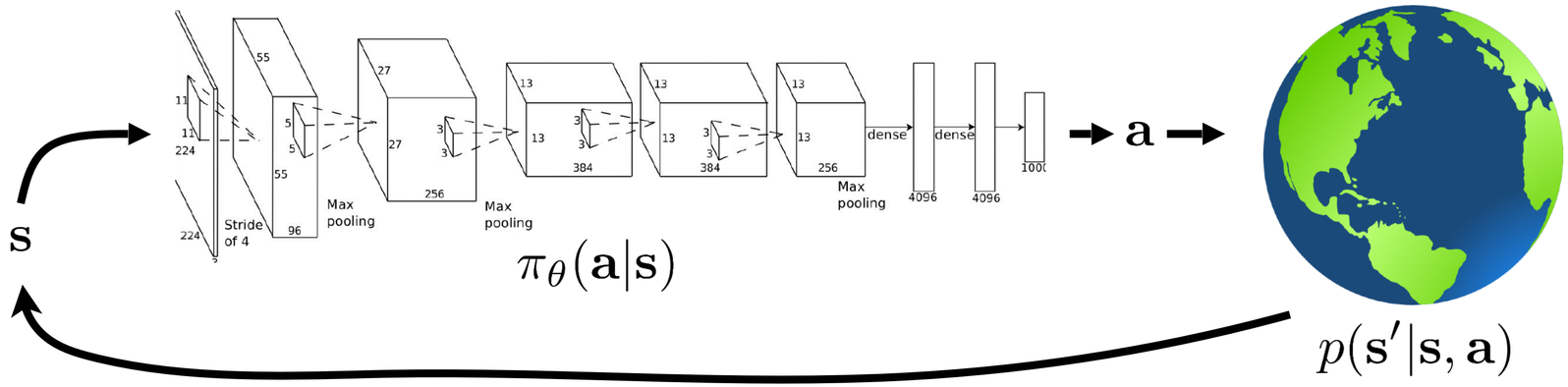
Different tasks can just be different MDPs!




**An alternative view:** A task identifier is part of the state: $\mathbf{s} = (\bar{\mathbf{s}}, \mathbf{z}_i)$

original state

# The goal of multi-task reinforcement learning




## Multi-task RL

The same as before, except:

a task identifier is part of the state: $\mathbf{s} = (\bar{\mathbf{s}}, \mathbf{z}_i)$

e.g. one-hot task ID

language description

desired goal state, $\mathbf{z}_i = \mathbf{s}_g$ ← "goal-conditioned RL"

If it's still a standard Markov decision process,

then, why not apply standard RL algorithms? You can! You can do better in some cases.

## What is the reward?

The same as before

Or, for goal-conditioned RL:

$r(\mathbf{s}) = r(\bar{\mathbf{s}}, \mathbf{s}_g) = -d(\bar{\mathbf{s}}, \mathbf{s}_g)$

Distance function $d$ examples:

- Euclidean $\ell_2$
- sparse 0/1

# Let’s start with multi-task imitation learning

Single task imitation learning

$$\min_\theta -E_{(\mathbf{s},\mathbf{a})\sim\mathcal{D}} \log \pi_\theta(\mathbf{a}|\mathbf{s})$$

$$\min_\theta \mathcal{L}(\theta, \mathcal{D}) \longrightarrow \min_\theta \sum_{i=1}^{T} \mathcal{L}(\theta, \mathcal{D}_i)$$

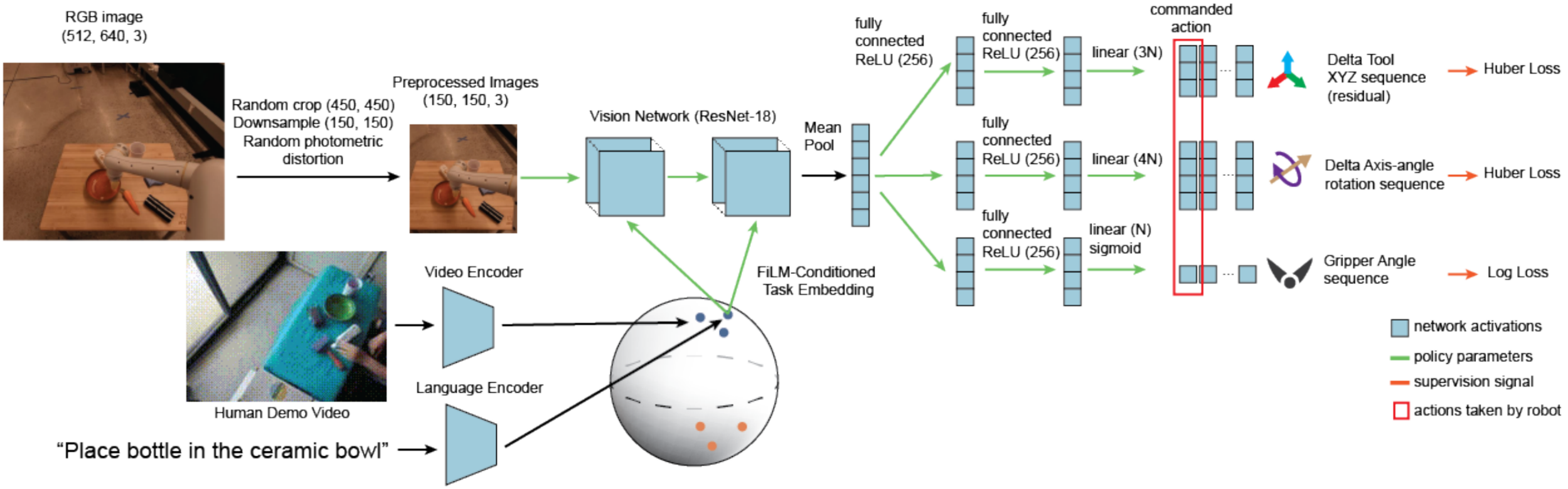
Multi-task imitation learning

One useful trick from multi-task supervised learning: **stratified sampling**

Construct each minibatch with data from each task.

-> lower variance gradients

# How to condition on the task in practice?



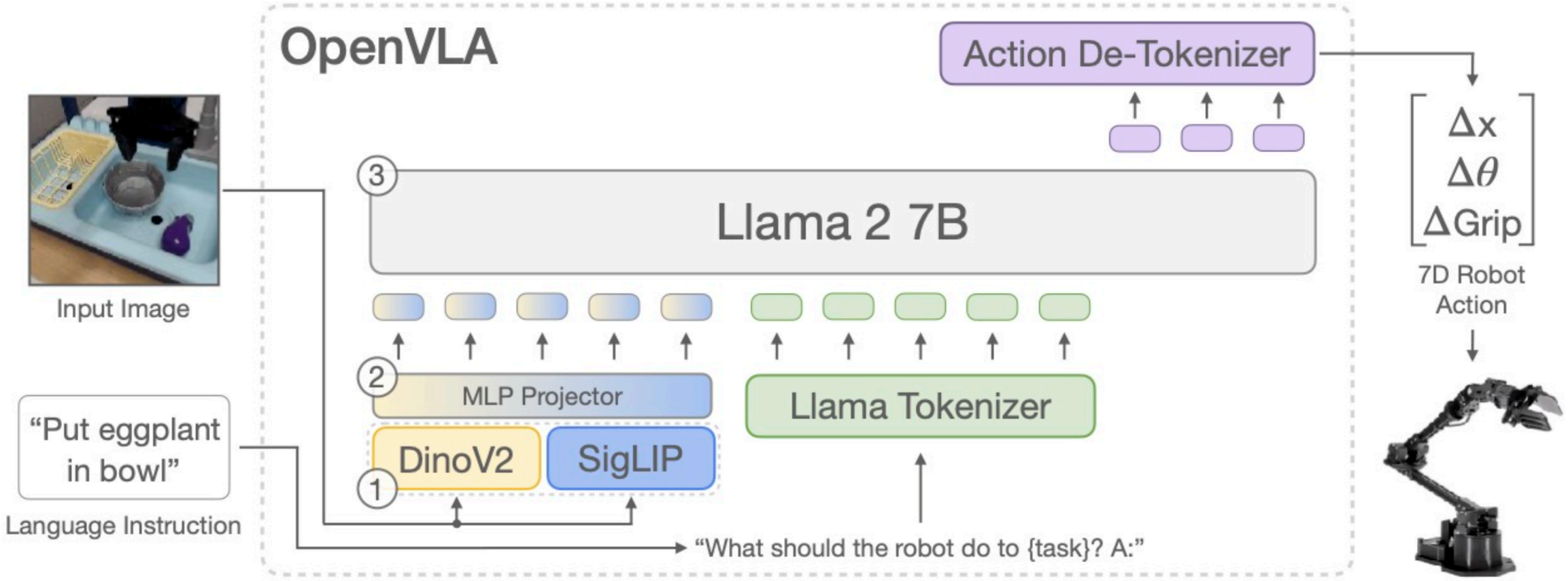

$$\min \sum_{\text{task } i} \sum_{\substack{(s,a)\sim\mathcal{D}_e^i \\ w_h\sim\mathcal{D}_h^i \bigcup \mathcal{D}_e^i}} \underbrace{-\log \pi(a|s, z^i)}_{\text{behavior cloning}} \text{, where } \underbrace{z_h^i \sim q(\cdot|w_h)}_{\text{video encoder}}, \underbrace{z_\ell^i \sim q(\cdot|w_\ell^i)}_{\text{language encoder}}$$



Jang et al. BC-Z: Zero-Shot Task Generalization with Robotic Imitation Learning CoRL 2021.

# How to condition on the task in practice?

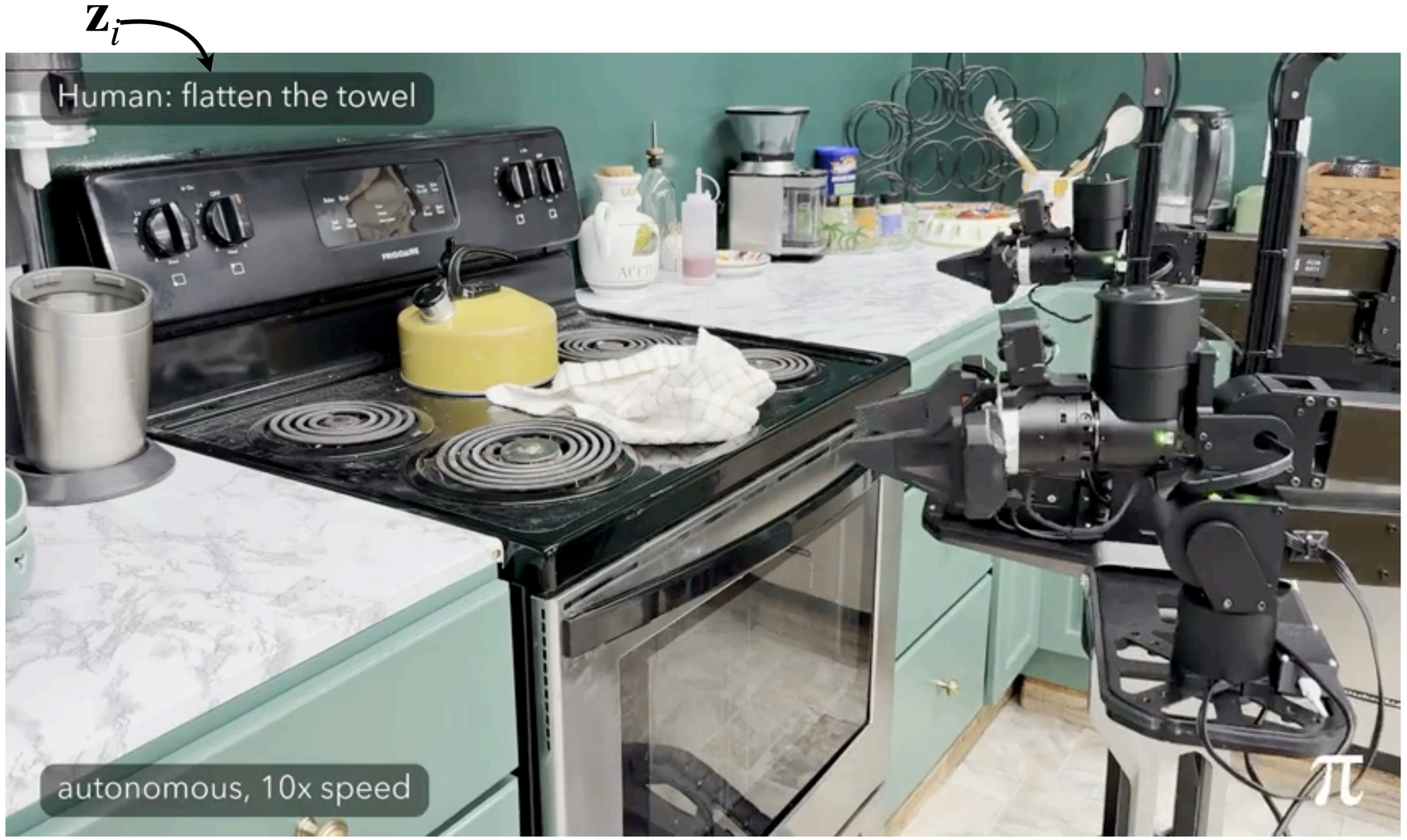
Modern policy architectures




Task identifier $\mathbf{z}_i$ passed as prompt into a (fine-tuned) LLM

Kim et al. OpenVLA: An Open-Source Vision-Language-Action Model. CoRL 2024.

# Example of multi-task imitation learning



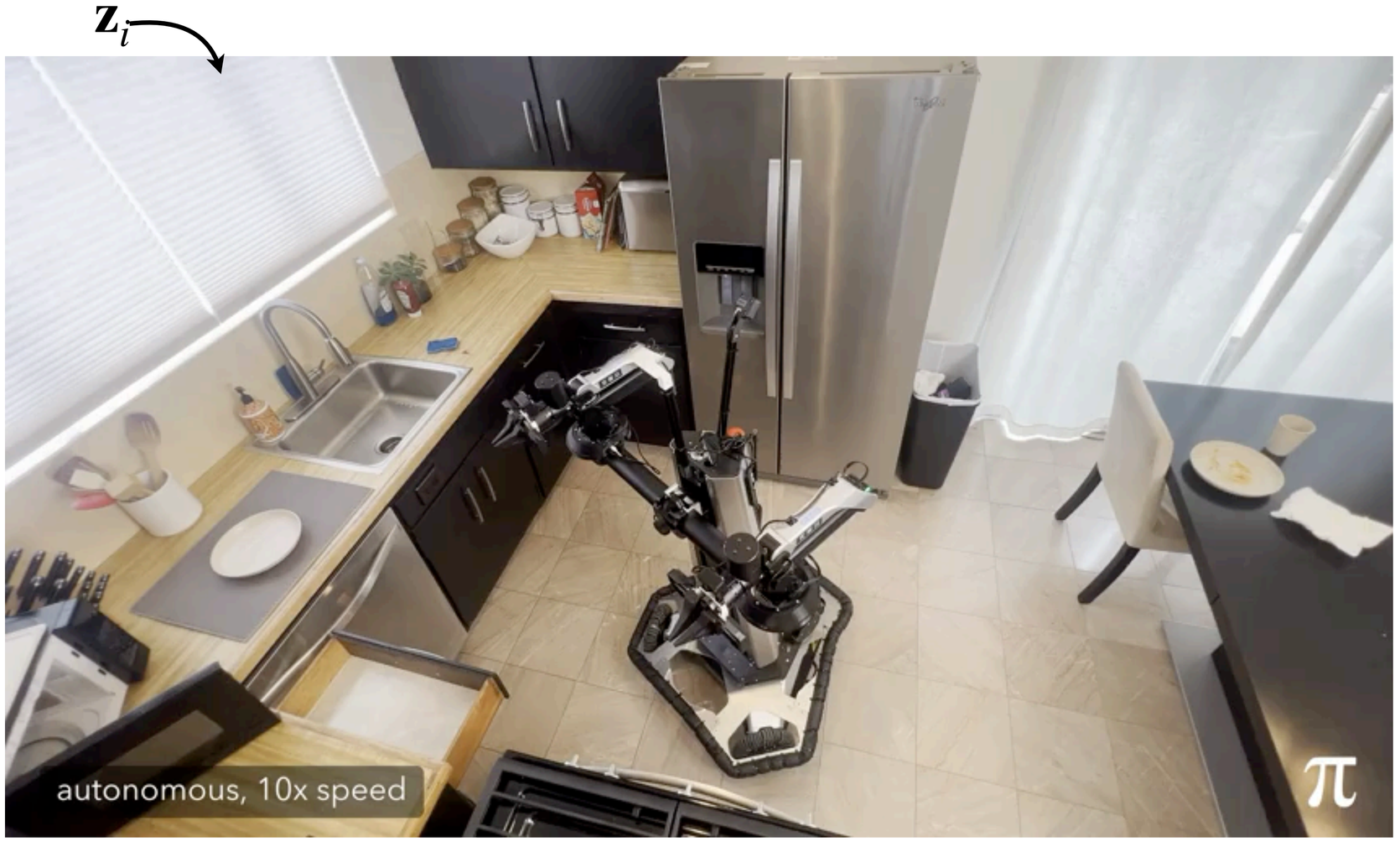

Two tasks:

$\mathbf{z}_1$ = ”flatten the towel”

$\mathbf{z}_2$ = ”hang the towel”

Pi Team et al. $\pi_{0.5}$: A Vision-Language-Action Model with Open-World Generalization arXiv 2025.

# Example of multi-task imitation learning




Many tasks:

$\mathbf{z}_1$ = ”put the plate in the drawer”
$\mathbf{z}_2$ = ”close the microwave”
$\mathbf{z}_3$ = ”drive base backward”
$\mathbf{z}_4$ = ”rotate base left”
$\mathbf{z}_5$ = ”throw the napkin away”
$\mathbf{z}_6$ = ”put the cup in the sink”
$\mathbf{z}_7$ = ”lift torso up”
$\mathbf{z}_8$ = ”clean the spill”

...

What about high-level, long-horizon tasks like “clean the kitchen”? -> Lecture on hierarchy

# Multi-Task RL Algorithms

**The basics**

Policy: $\pi_\theta(\mathbf{a} \mid \bar{\mathbf{s}}) \;\; \text{—>} \;\; \pi_\theta(\mathbf{a} \mid \bar{\mathbf{s}}, \mathbf{z}_i)$

Q-function: $Q_\phi(\bar{\mathbf{s}}, \mathbf{a}) \;\; \text{—>} \;\; Q_\phi(\bar{\mathbf{s}}, \mathbf{a}, \mathbf{z}_i)$

Consider per-task replay buffer for stratified sampling.

Can we share data *across tasks*?

If we collect policy data when conditioning on $\mathbf{z}_1$, can we reuse that data to learn something for task 2?

Would require relabeling the data with $\mathbf{z}_2$!

# An example

Task 1: passing

Task 2: shooting goals

What if you accidentally perform a good pass when trying to shoot a goal?

Store experience as normal. *and* Relabel experience with task 2 ID & reward and store.

“hindsight relabeling” "hindsight experience replay” (HER)

# Multi-task RL with relabeling

1. Collect data $\mathcal{D}_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}, \mathbf{z}_i, r_{1:T})\}$ using some policy
2. Store data in replay buffer $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_k$
3. Perform hindsight relabeling:
   a. Relabel experience in $\mathcal{D}_k$ for task $\mathcal{T}_j$:
      $\mathcal{D}'_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}, \mathbf{z}_j, r'_{1:T}\}$ where $r'_t = r_j(\mathbf{s}_t)$
   b. Store relabeled data in replay buffer $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}'_k$
4. Update policy using replay buffer $\mathcal{D}$

$k$++

<— Which task $\mathcal{T}_j$ to choose?

- randomly
- task(s) in which the trajectory gets high reward

When can we apply relabeling?

- reward function form is known, evaluatable
- dynamics consistent across goals/tasks
- using an off-policy algorithm*

Kaelbling. Learning to Achieve Goals. IJCAI '93
Andrychowicz et al. Hindsight Experience Replay. NeurIPS '17

# Goal-conditioned RL with hindsight relabeling

1. Collect data $\mathcal{D}_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}, \mathbf{s}_g, r_{1:T})\}$ using some policy
2. Store data in replay buffer $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_k$
3. Perform hindsight relabeling:
   a. Relabel experience in $\mathcal{D}_k$ using last state as goal: $\mathcal{D}'_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}, \mathbf{s}_T, r'_{1:T}\}$ where $r'_t = -d(\mathbf{s}_t, \mathbf{s}_T)$
   b. Store relabeled data in replay buffer $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}'_k$
4. Update policy using replay buffer $\mathcal{D}$

$k$++

<— Other relabeling strategies?

use any state from the trajectory

Result: exploration challenges alleviated

You will implement hindsight relabeling in homework 4!

Kaelbling. Learning to Achieve Goals. IJCAI '93
Andrychowicz et al. Hindsight Experience Replay. NeurIPS '17

# Hindsight relabeling for goal-conditioned RL

Example: goal-conditioned RL, simulated robot manipulation

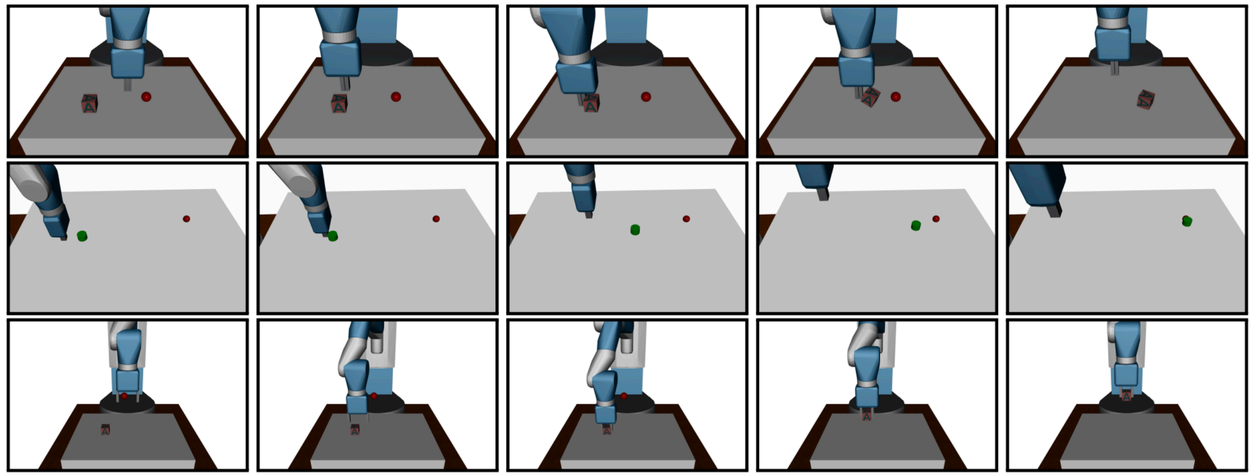
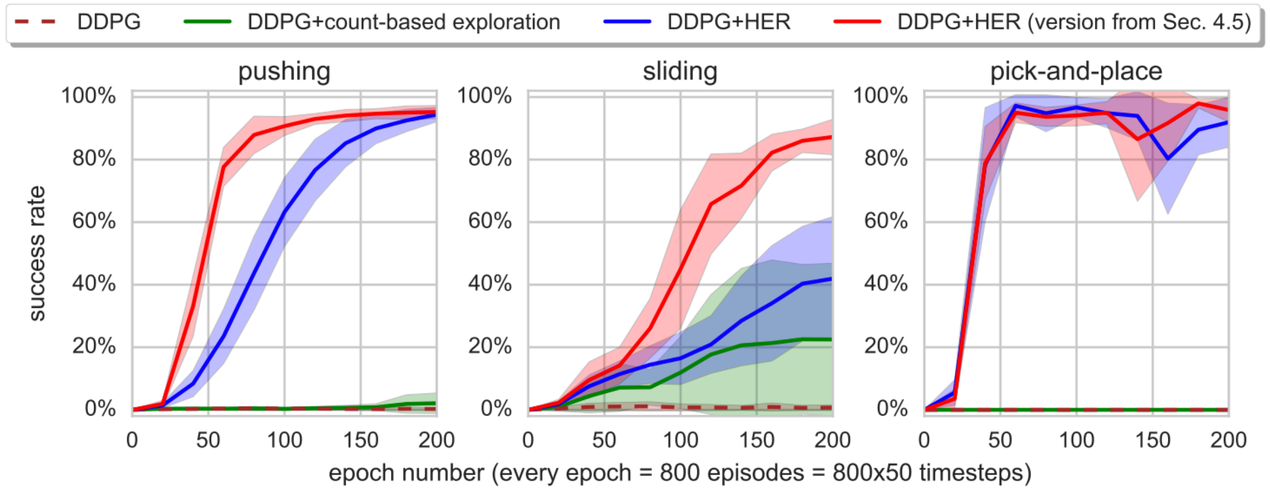


Figure 2: Different tasks: *pushing* (top row), *sliding* (middle row) and *pick-and-place* (bottom row). The red ball denotes the goal position.

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# Next Time

Can we quickly adapt to new tasks?

(e.g. in-context learning for RL)