Sample-efficient Reinforcement Learning with Implicitly Quantized Representations

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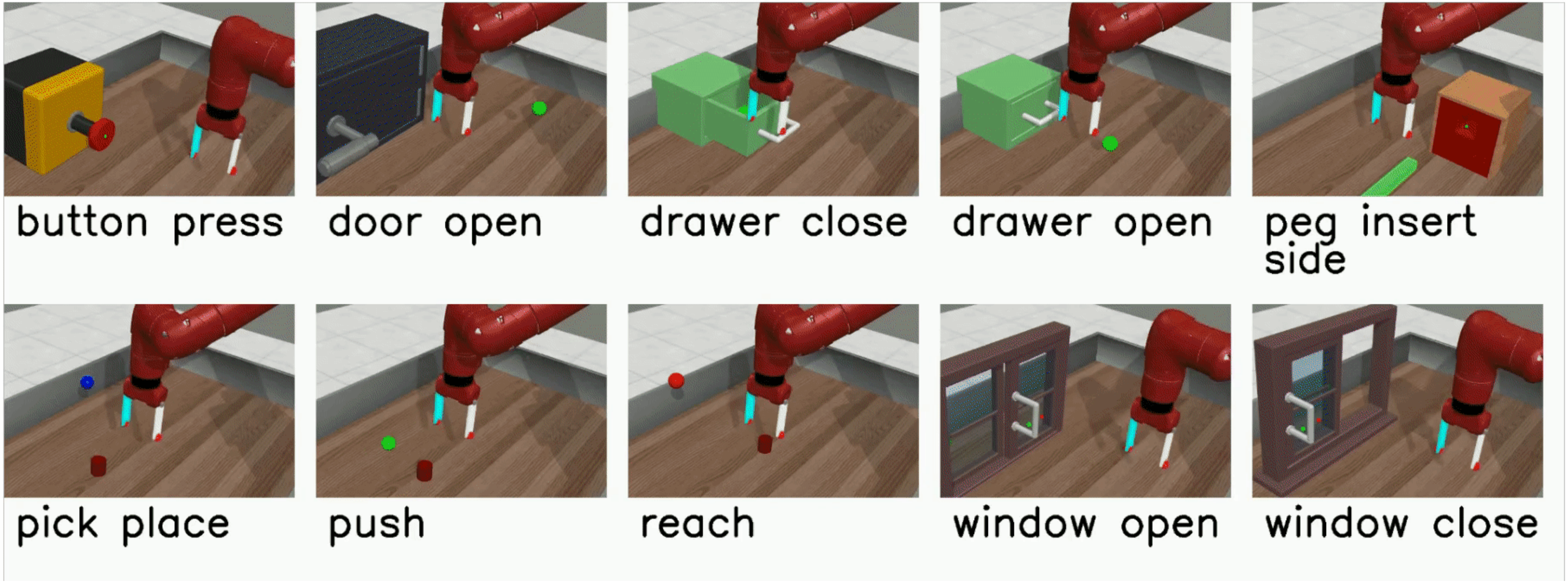
Motivation: Robotic Manipulation



Reinforcement Learning (RL)

Markov Decision Process (MDP)

States $s \in \mathcal{S}$

Actions $a \in \mathcal{A}$

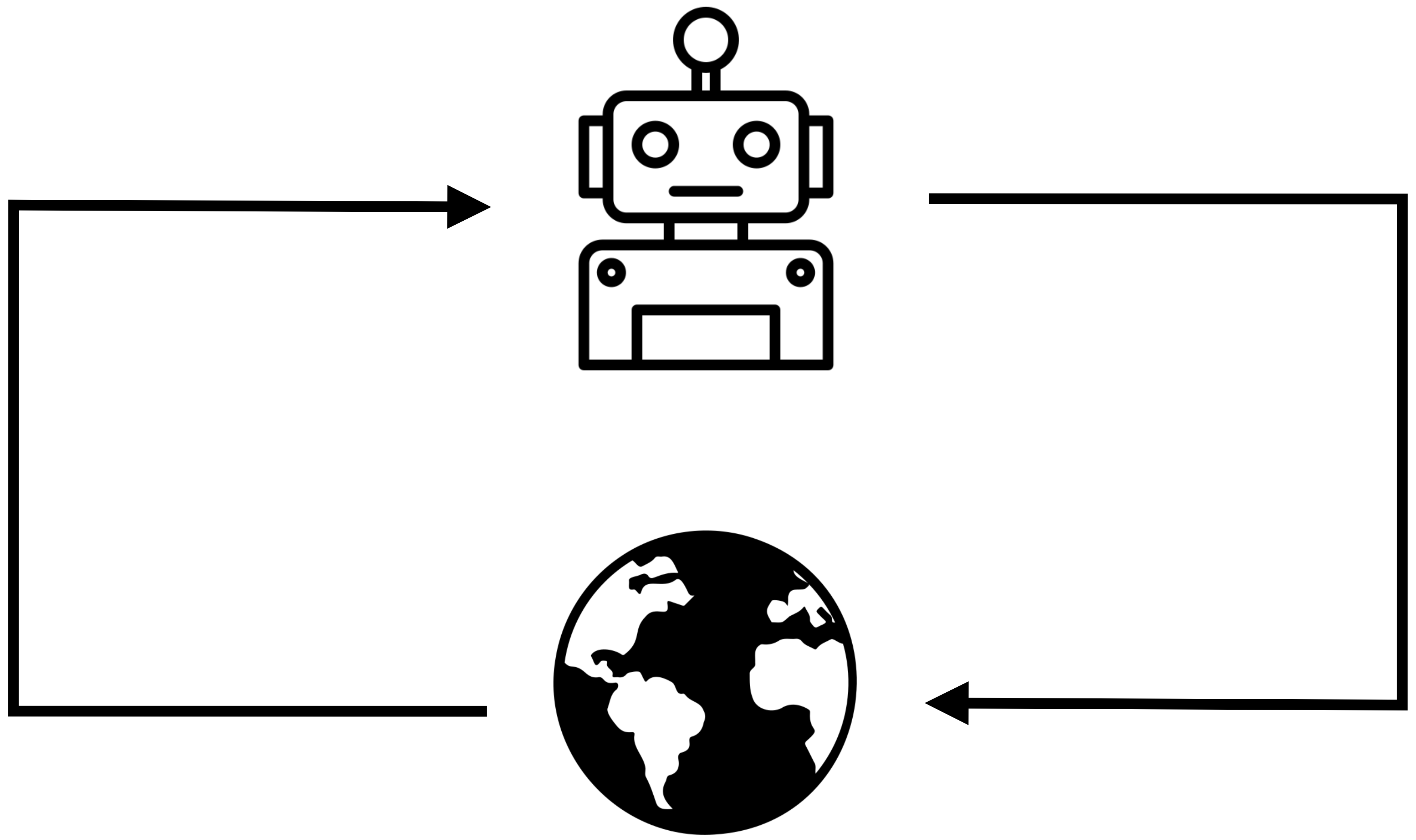
Policy $\pi : \mathcal{S} \to \mathcal{A}$

Transition function $P(s_{t+1} \mid s_t, a_t)$

Reward function $r_t = r(s_t, a_t)$

Discount factor $\gamma \in [0,1]$

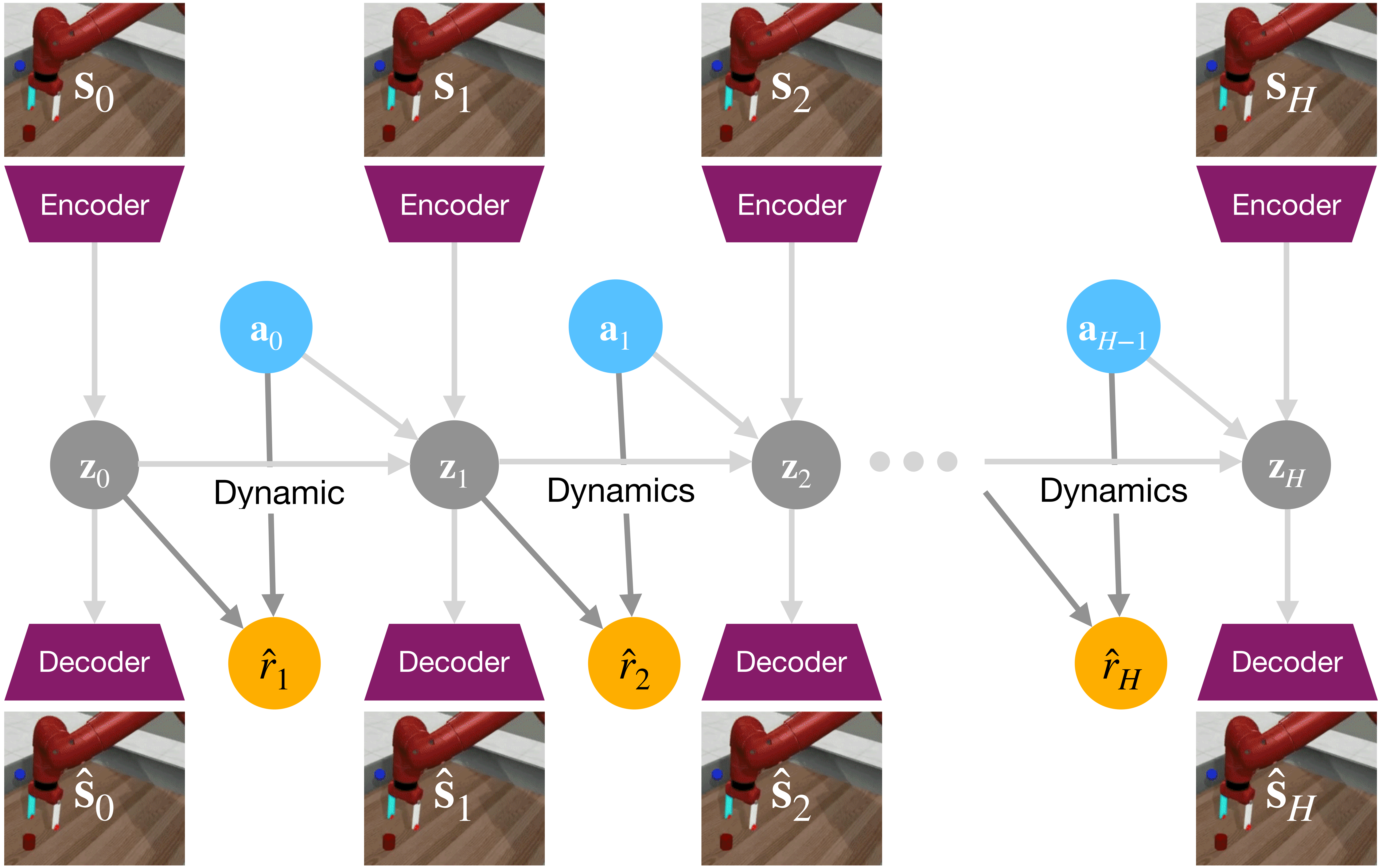
In model-based RL
these are the “model”



Goal:

$$\max_{\pi} \mathbb{E}_{\pi,P_\phi}\left[\left[\sum_{t=0}^{\infty} \gamma^t r_\xi(s_t, a_t) \mid s_0 = s, \pi\right]\right]$$

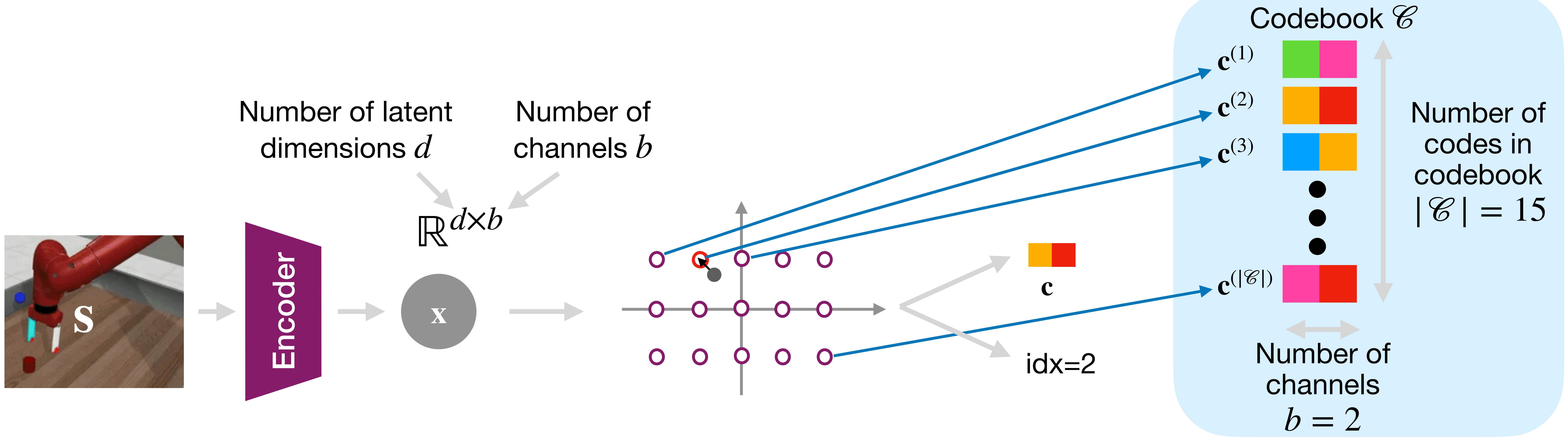
World Models



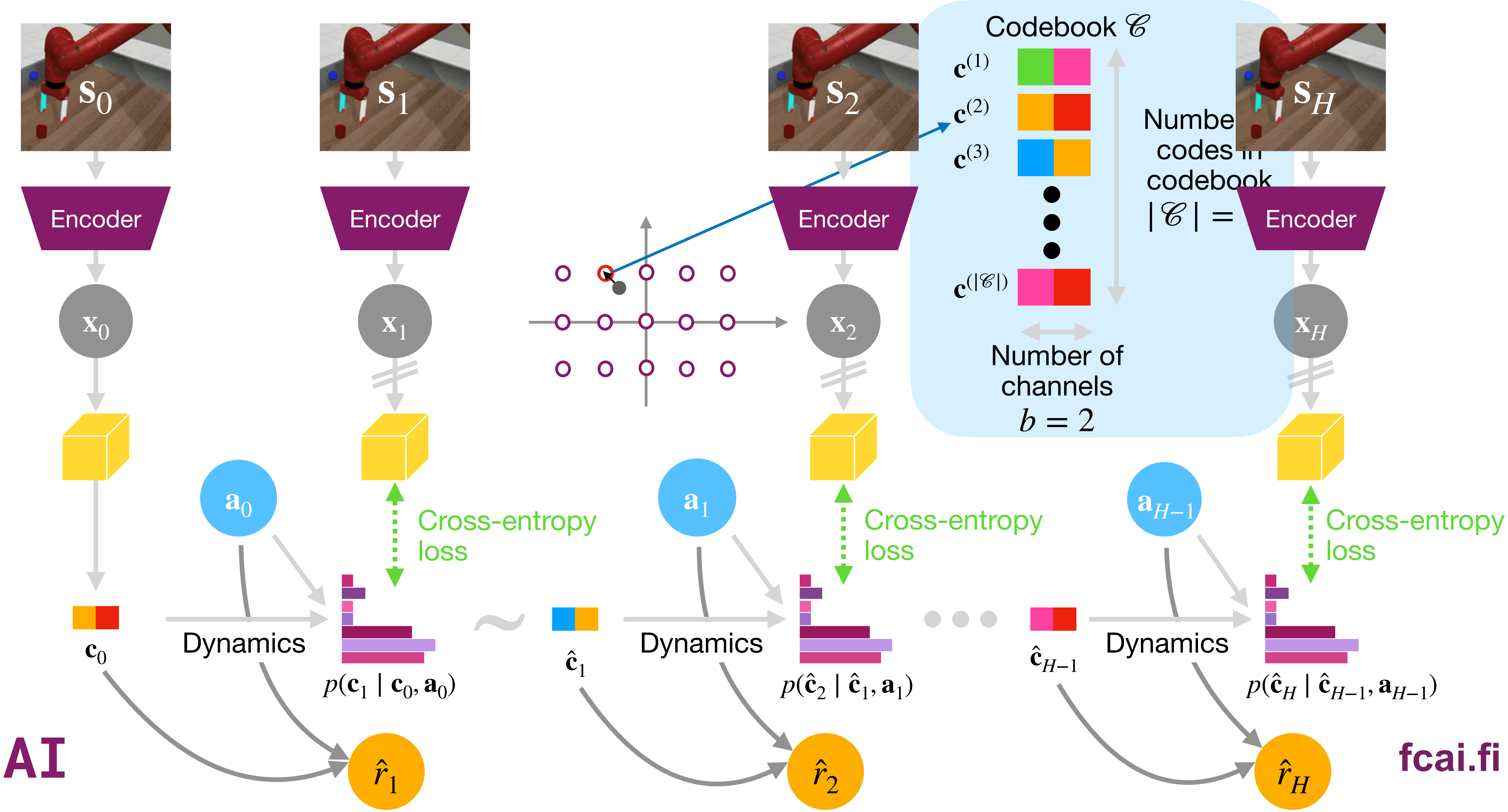
- Decoder vs self-supervised?
- Continuous vs discrete?

DCWM: Discrete Codebook World Model

Discrete Codebook



DCWM: World Model Training



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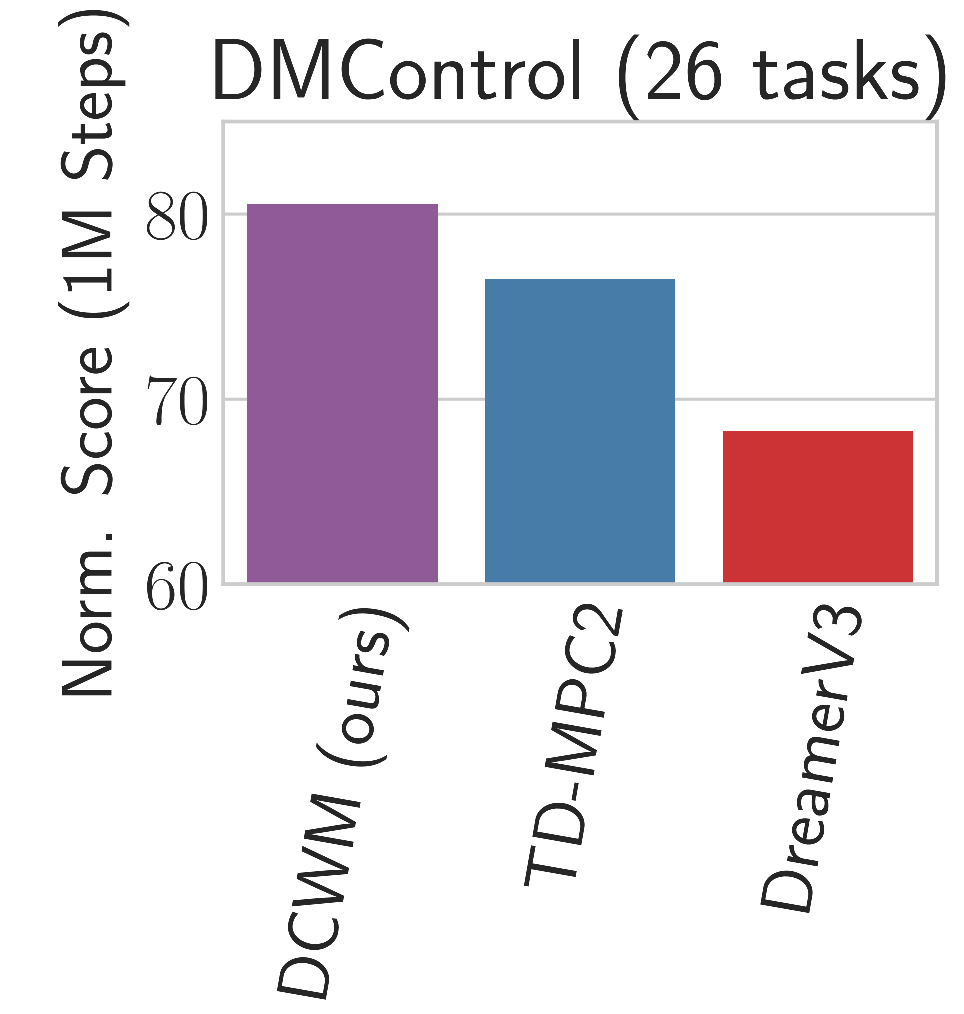
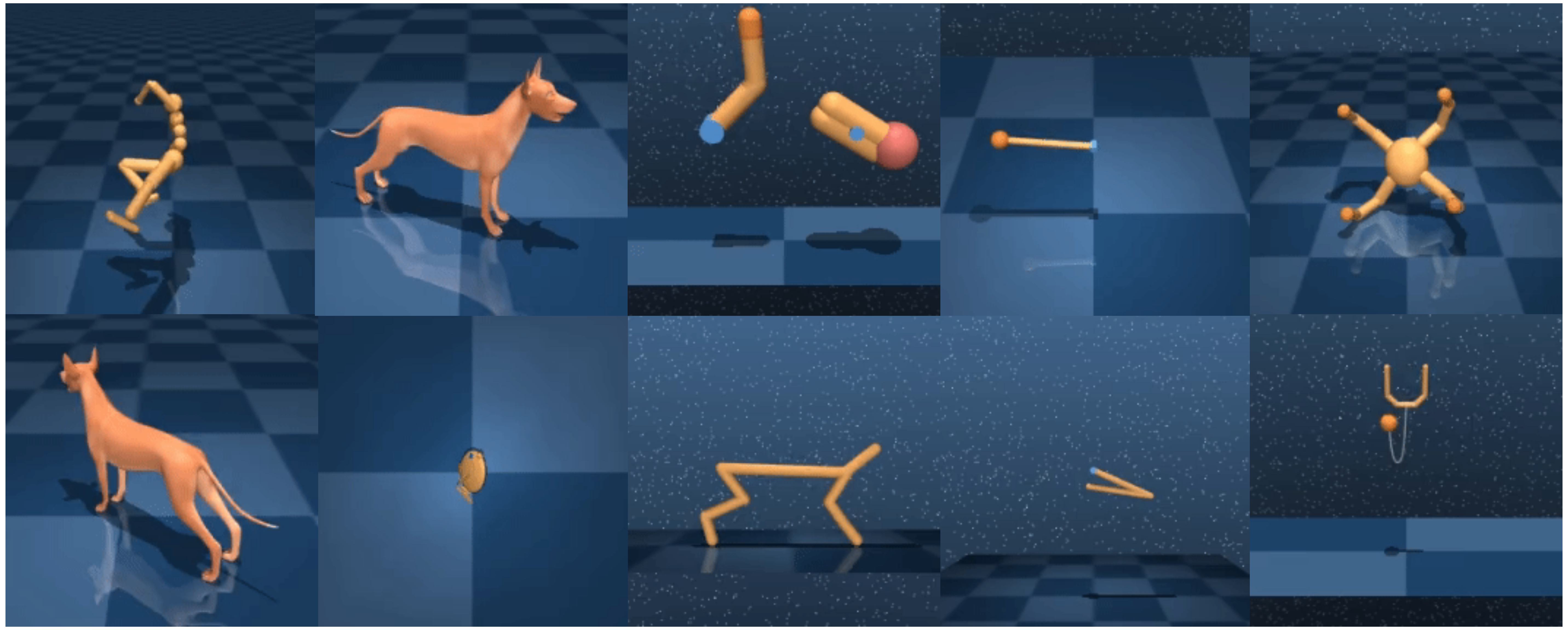
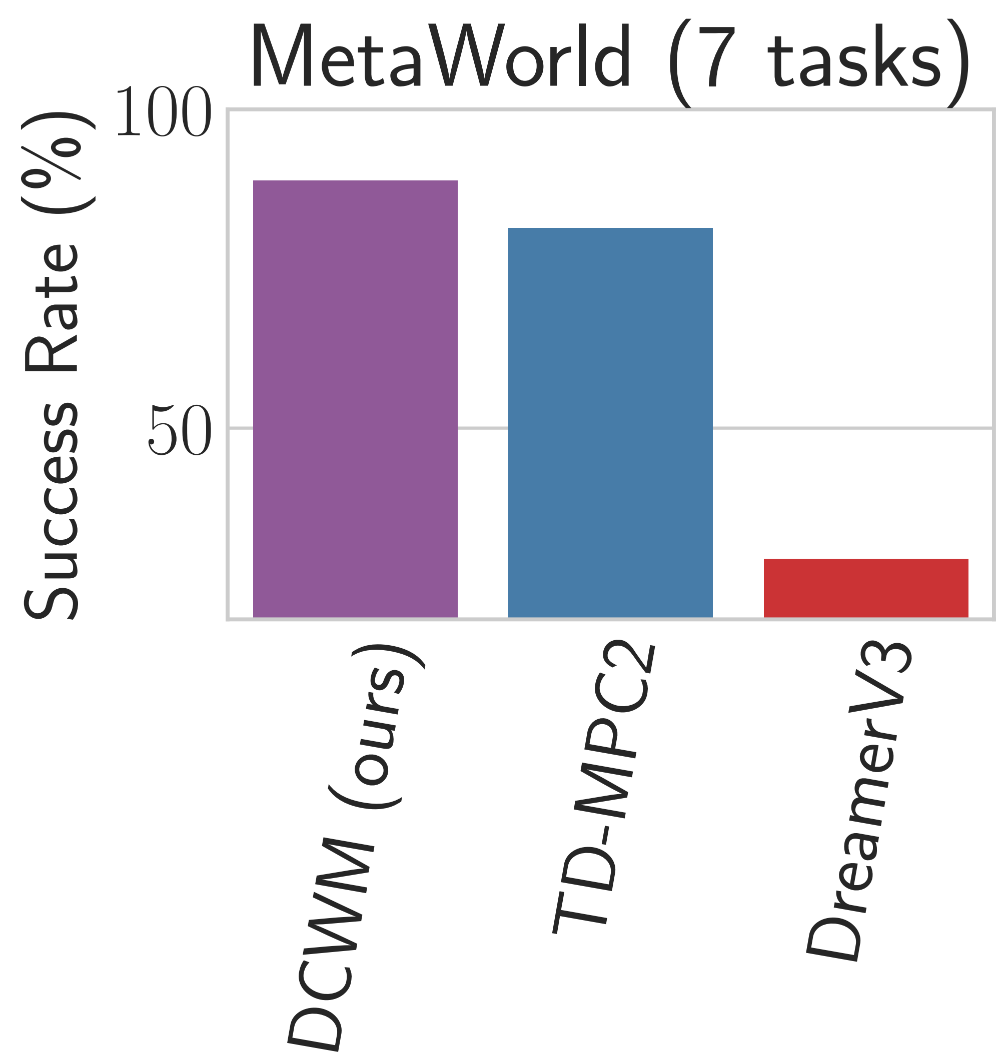
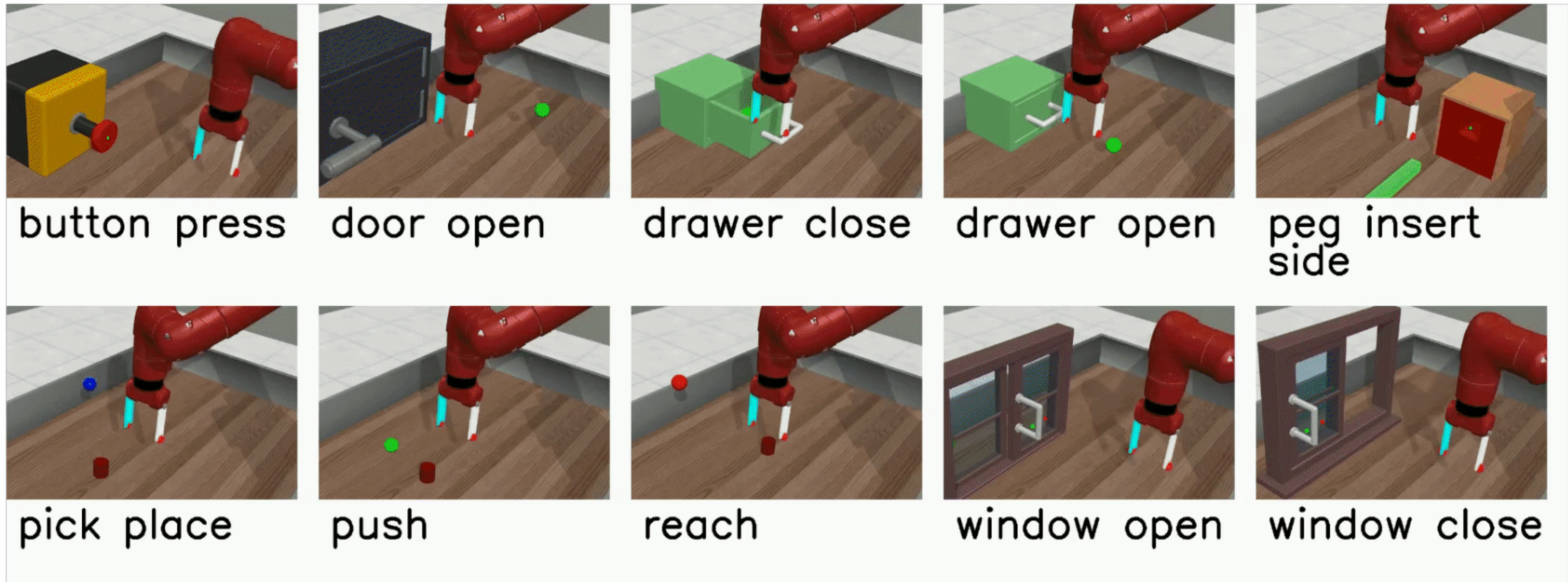
Results: Overview

Strong Performance in DMControl and MetaWorld Manipulation Tasks



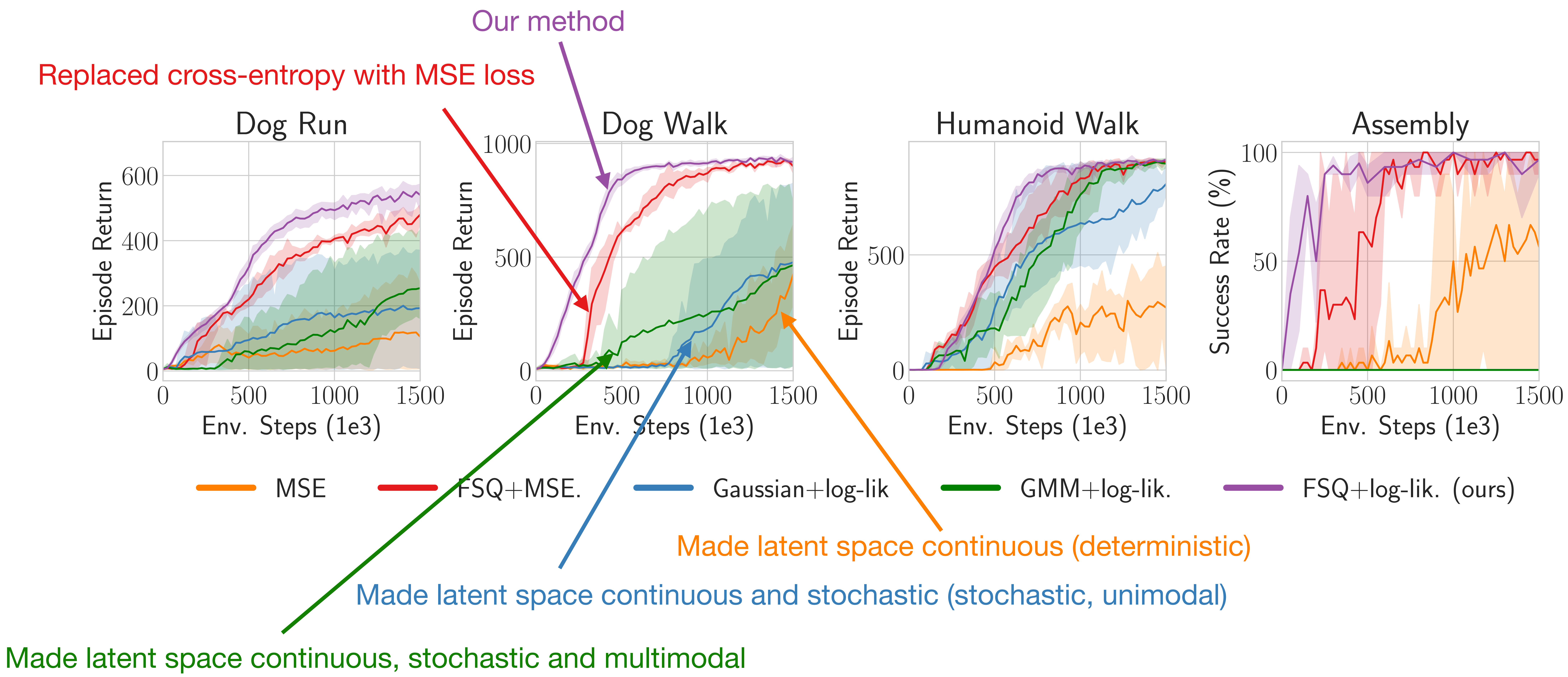






Why Does DCWM Work So Well?

Combination of Discrete Representation and Cross Entropy Loss



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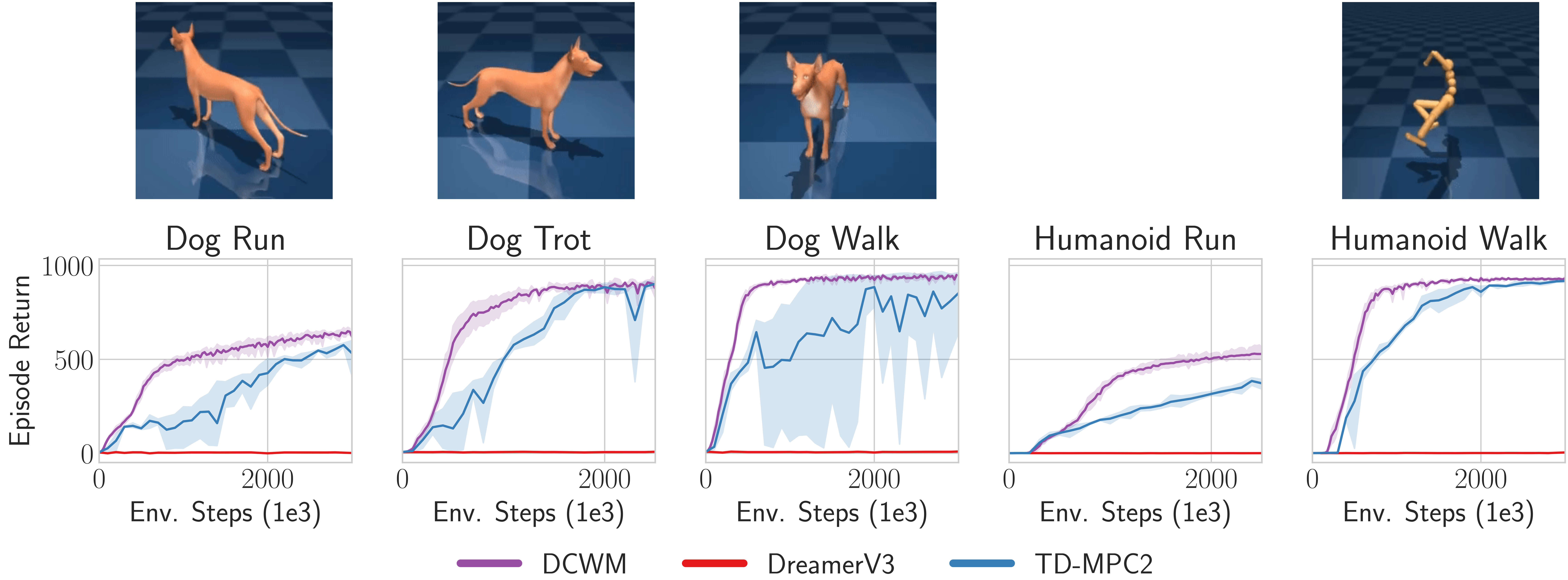
Main Takeaway:

Learning discrete codebook encodings with a self-supervised cross-entropy loss improves sample efficiency in continuous control tasks

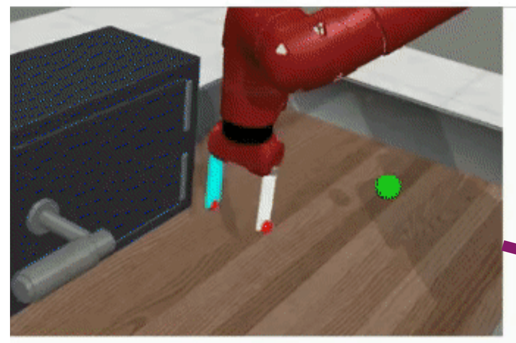
Results: DeepMind Control Suite

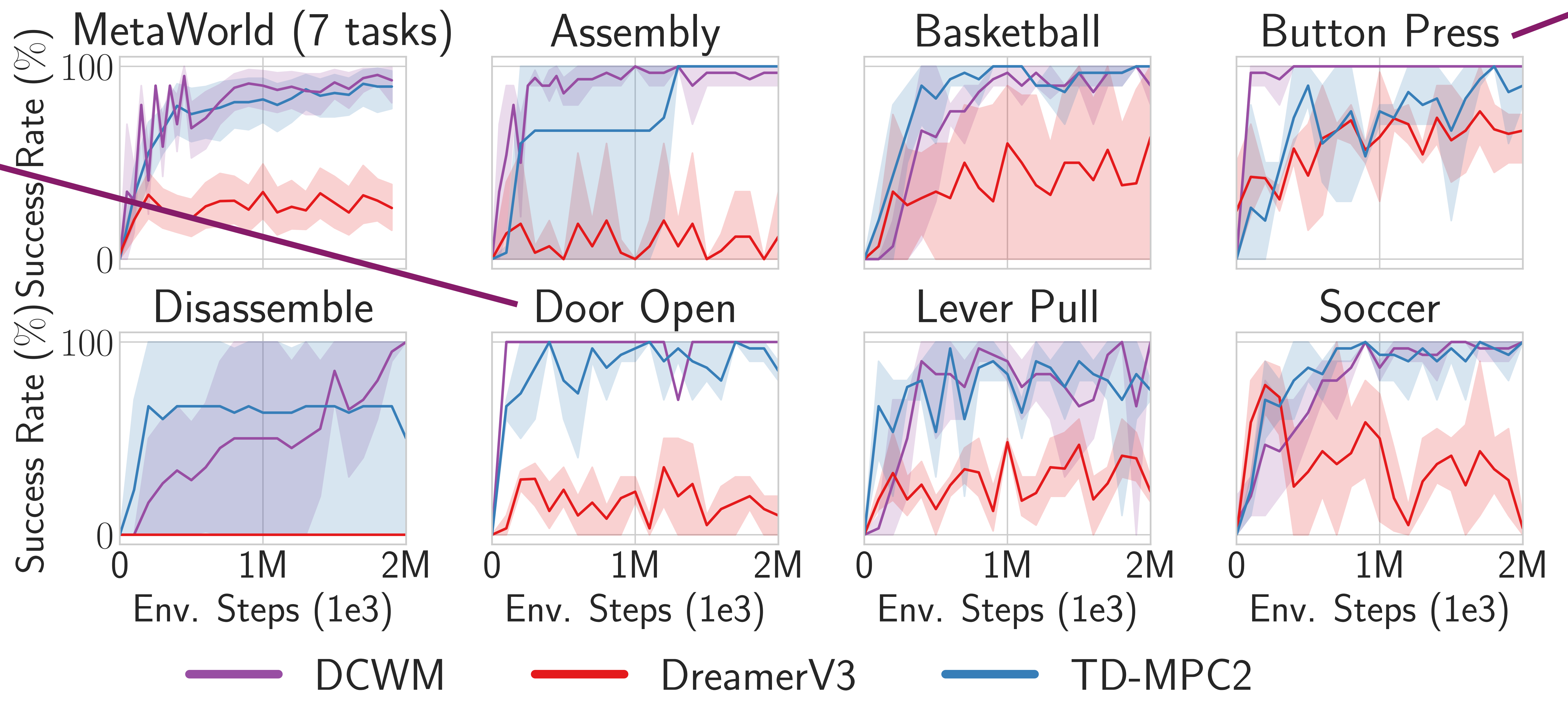
Strong Performance in Hard DMControl Tasks

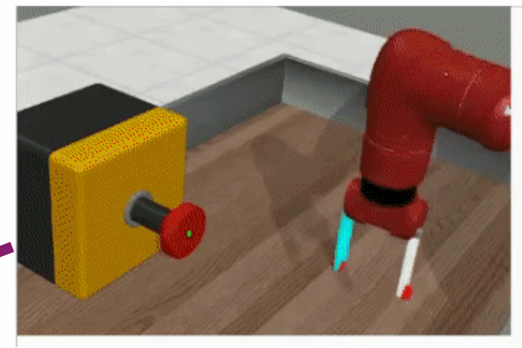


Results: MetaWorld

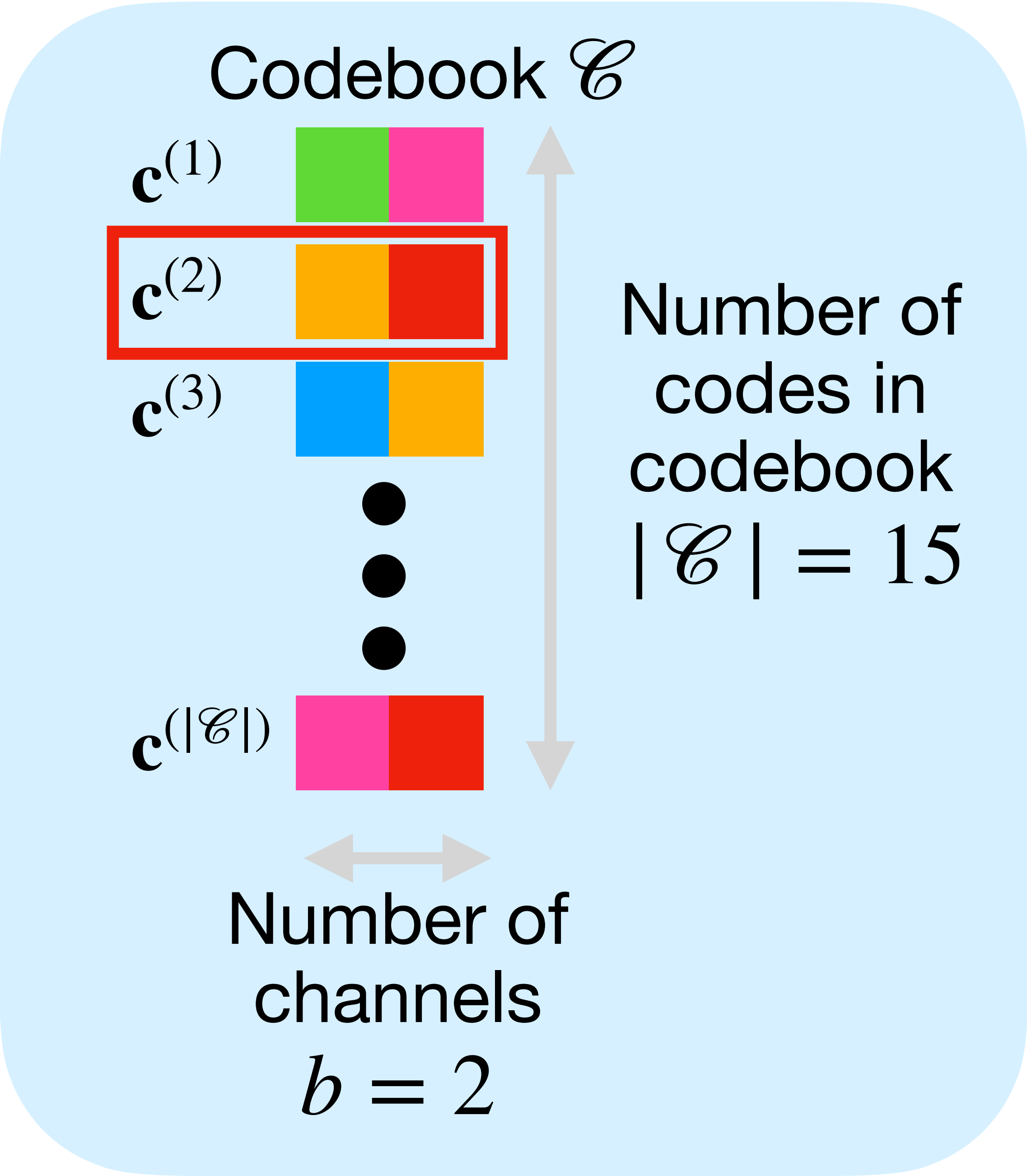
Competitive Performance in Robotic Manipulation







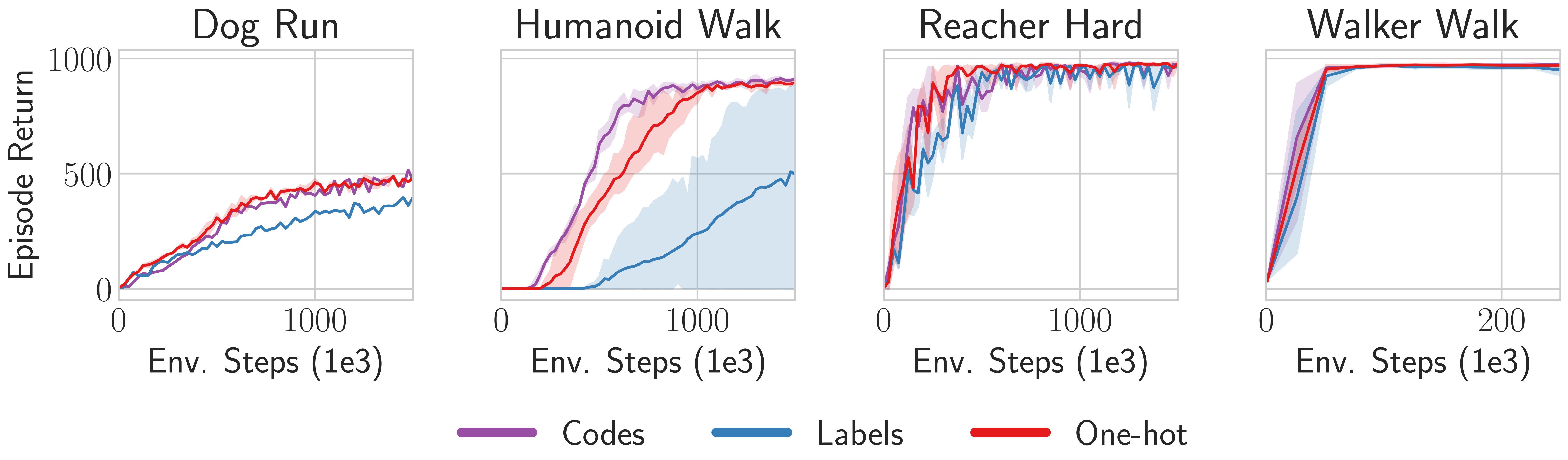
Comparison of Different Discrete Encodings



$$\mathbf{e}_{\text{code}} = \mathbf{c}^{(2)} = \{-0.5, 1\}$$

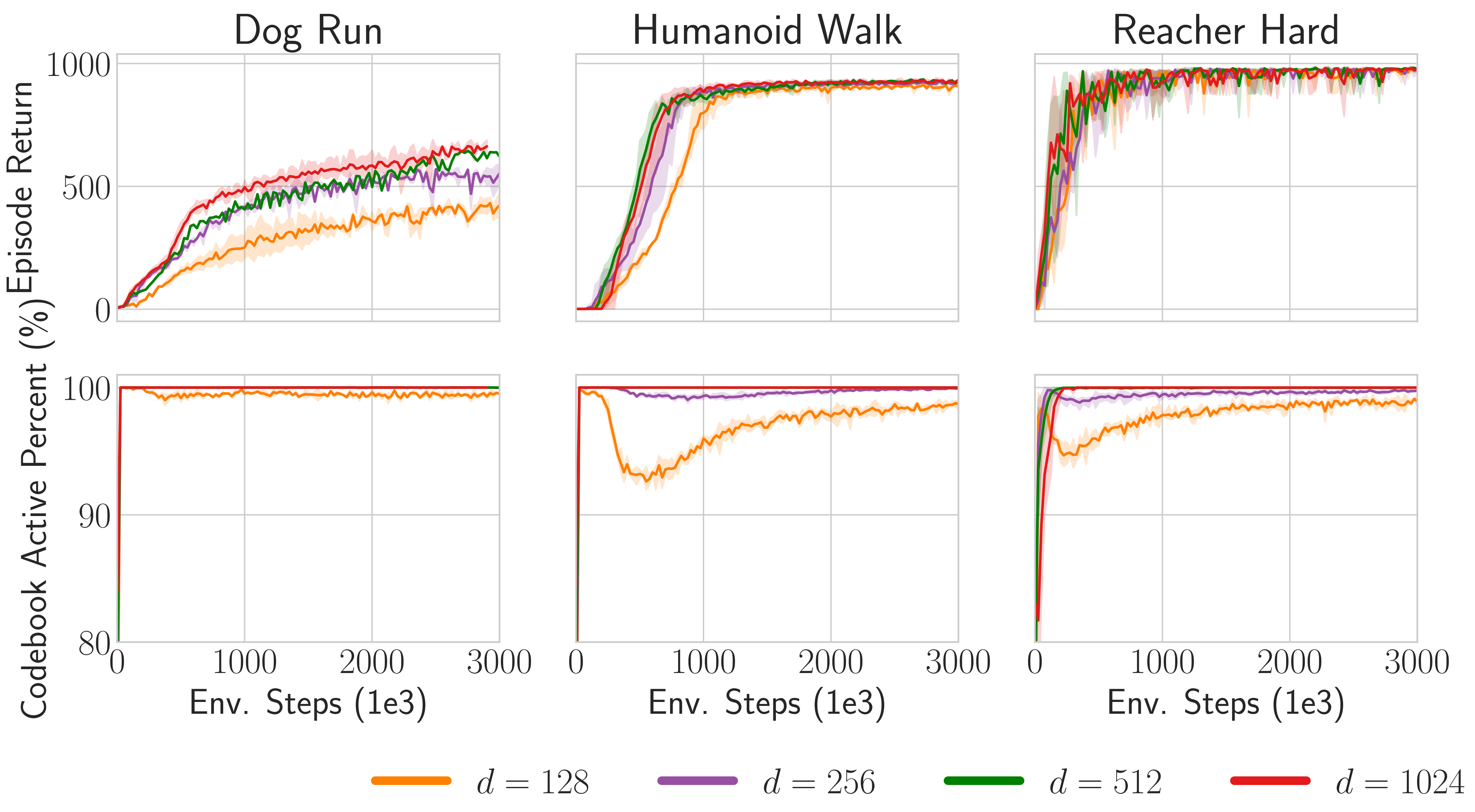
$$\mathbf{e}_{\text{label}} = 2$$

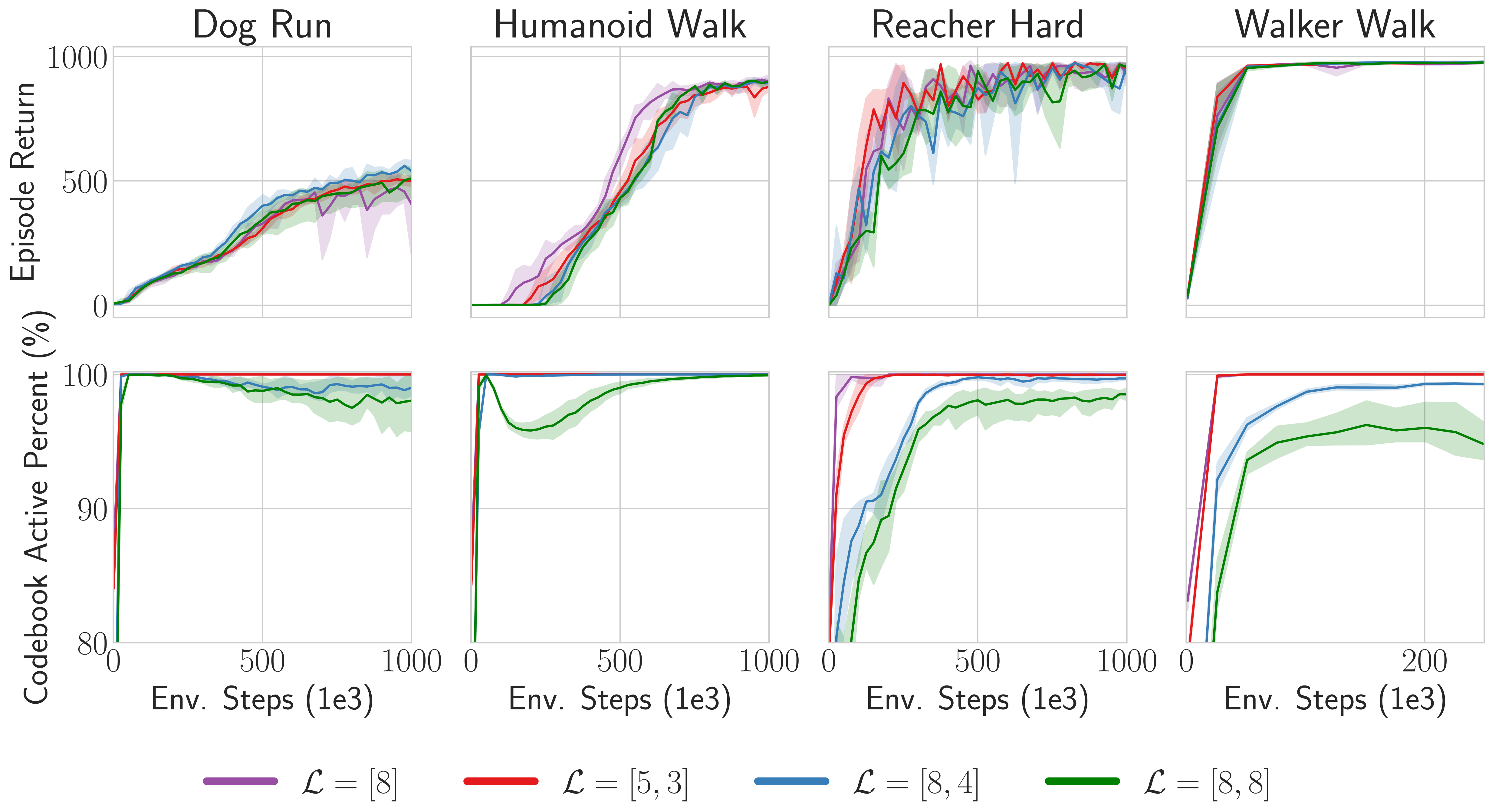
$$\mathbf{e}_{\text{one-hot}} = \{0,1,0,0,0,0,0,0,0,0,0,0,0,0,0\}$$



Results: Latent Space Size

DCWM is Fairly Robust to its Latent Space Size





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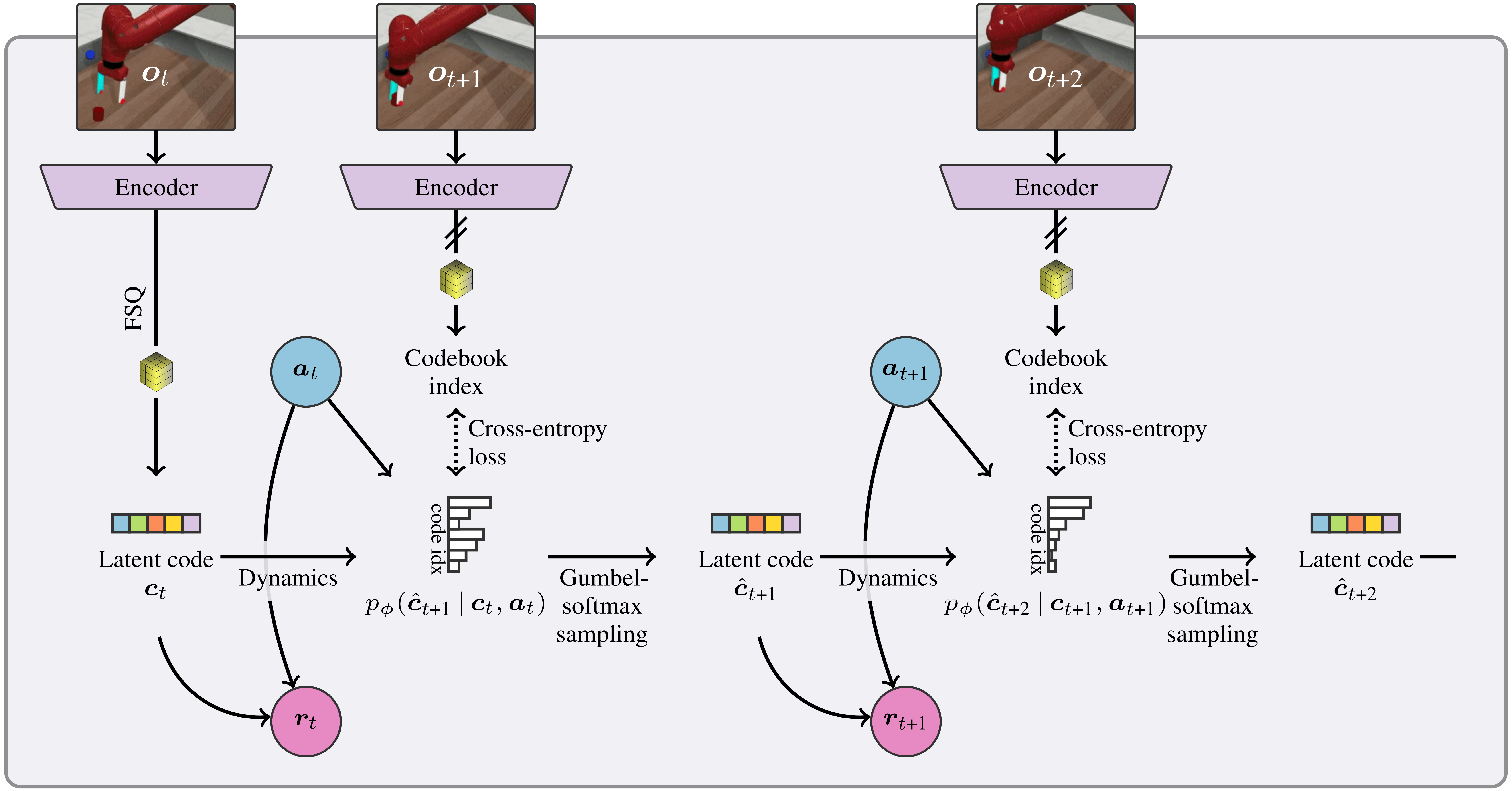
DCWM: Discrete Codebook World Model



DCWM: Components

Encoder $\mathbf{x}_t = e_\theta(\mathbf{s}_t) \in \mathbb{R}^{d\times b}$

Latent quantization $\mathbf{c}_t = f(\mathbf{x}_t) \in \mathscr{C}$

Dynamics $\hat{\mathbf{c}}_{t+1} \sim \text{Categorical}(p_1, \ldots, p_{|\mathscr{C}|})$ with $p_i = P_\phi(\mathbf{c}_{t+1} = \mathbf{c}^{(i)} \mid \mathbf{c}_t, \mathbf{a}_t)$

Reward $\hat{r}_{t+1} = R_\xi(\mathbf{c}_t, \mathbf{a}_t)$

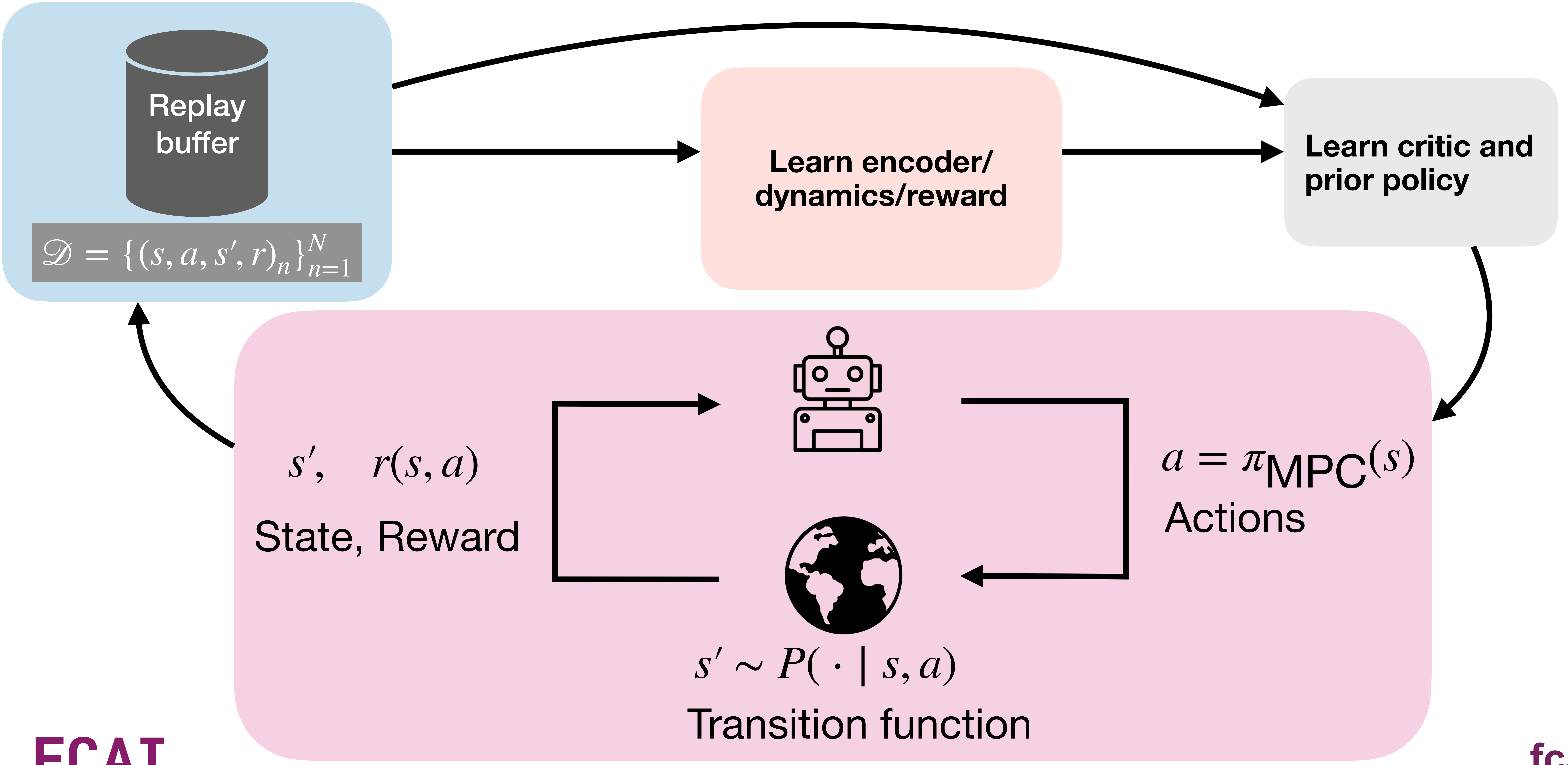
World model loss

$$\mathscr{L}(\theta, \phi, \xi; \mathscr{D}) = \mathbb{E}_{(\mathbf{o},\mathbf{a},\mathbf{o}',r)_{0:H}\sim\mathscr{D}} \left[\sum_{h=0}^{H-1} \gamma^h \left(\text{CE}(p_\phi(\hat{\mathbf{c}}_{h+1} \mid \hat{\mathbf{c}}_h, \mathbf{a}_h), \mathbf{c}_{h+1}) + \| R_\xi(\mathbf{c}_h, \mathbf{a}_h) - r_h \|_2^2 \right) \right]$$

DCWM: Components

Encoder	$\mathbf{x}_t = e_\theta(\mathbf{s}_t)$
Latent quantization	$\mathbf{c}_t = f(\mathbf{x}_t) \in \mathscr{C}$
Dynamics	$\hat{\mathbf{c}}_{t+1} \sim \mathrm{Categorical}(p_1, \ldots, p_{\lvert\mathscr{C}\rvert})$ with $p_i = P_\phi(\mathbf{c}_{t+1} = \mathbf{c}^{(i)} \mid \mathbf{c}_t, \mathbf{a}_t)$
Reward	$\hat{r}_{t+1} = R_\xi(\mathbf{c}_t, \mathbf{a}_t)$
Critic	$q_t = Q_\psi(\mathbf{c}_t, \mathbf{a}_t)$
Prior Policy	$\mathbf{a}_t \sim \pi_\eta(\mathbf{a}_t \mid \mathbf{c}_t)$

Model-based Reinforcement Learning



DCWM

Algorithm

i. For i in number of episodes

    i. Collect trajectory $\tau_i = \{\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{t+1}, r_t\}_{t=0}^{T}$

    ii. Add trajectory to replay buffer $\mathscr{D} \leftarrow \mathscr{D} \cup \tau_i$

    iii. Perform T updates to world model

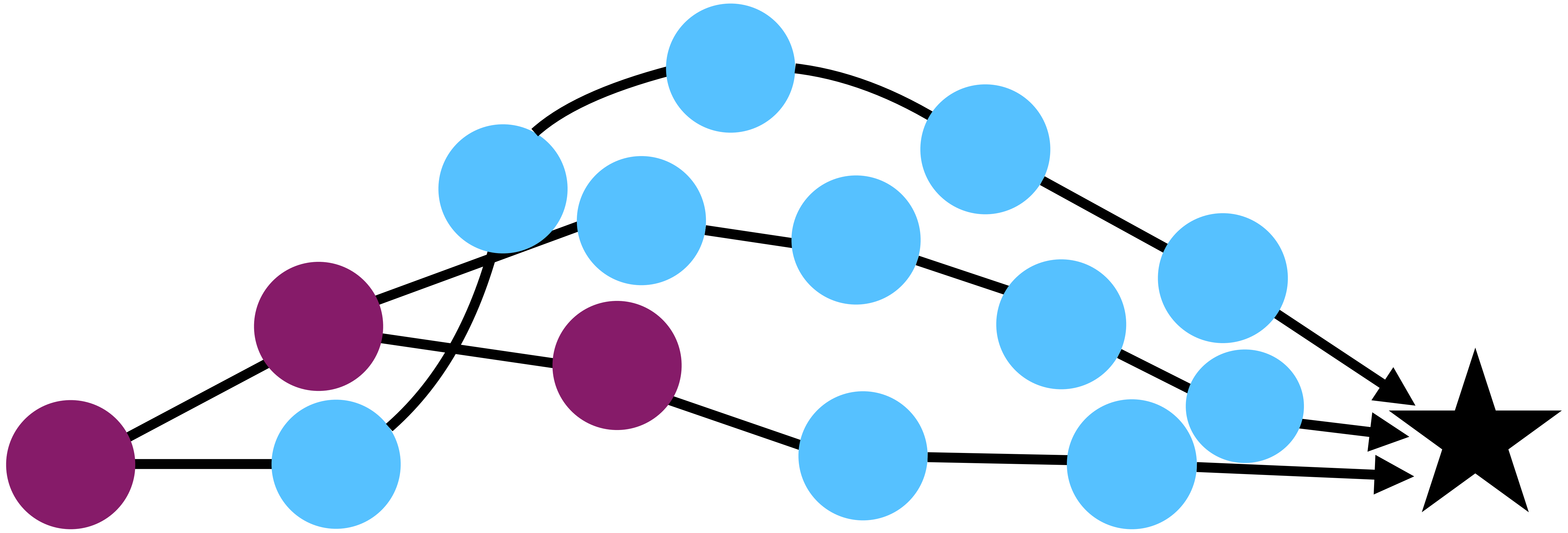
        i. Sample batch from replay buffer $\mathscr{D}$

        ii. Update encoder, dynamics and reward

        iii. Update actor and critic

Decision-time Planning

Model Predictive Control (MPC)



Diverged from planned trajectory…

And so on…

Discard $a_1, \ldots, a_H$

So let's replan.

For each environment step

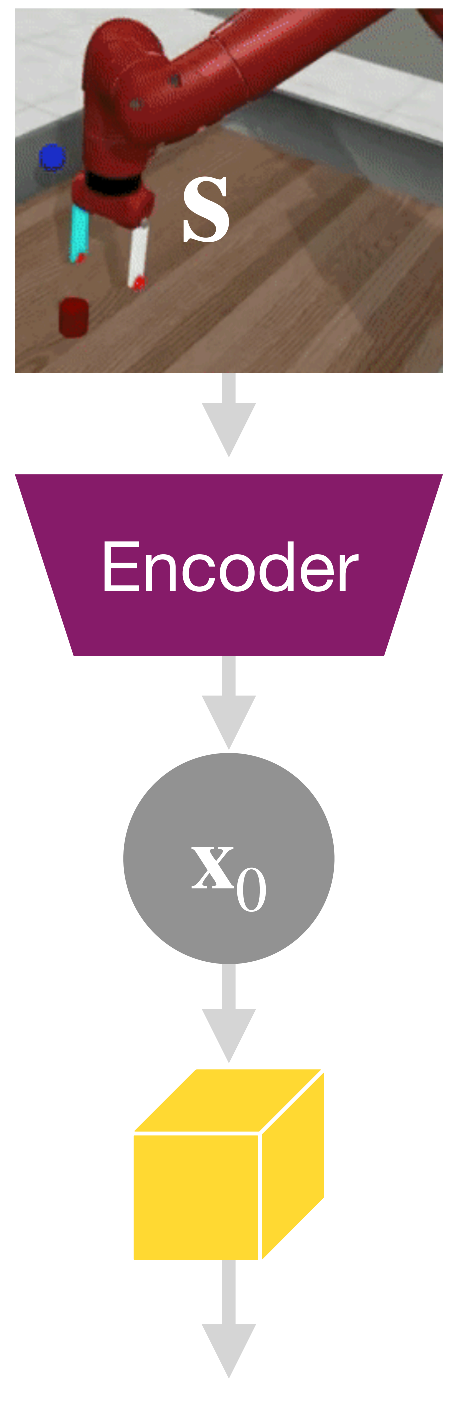
Observe state s

Model Predictive Path Integral Control (MPPI)

Plan $\boxed{a_{0:H}}$ to maximise return $\sum_{t=0}^{H-1} \gamma^t r(s_t, a_t) + \gamma^H Q_\theta(s_H, a_H)$

Execute a_0 and discard $a_1, \ldots, a_H$

DCWM: Decision-time Planning

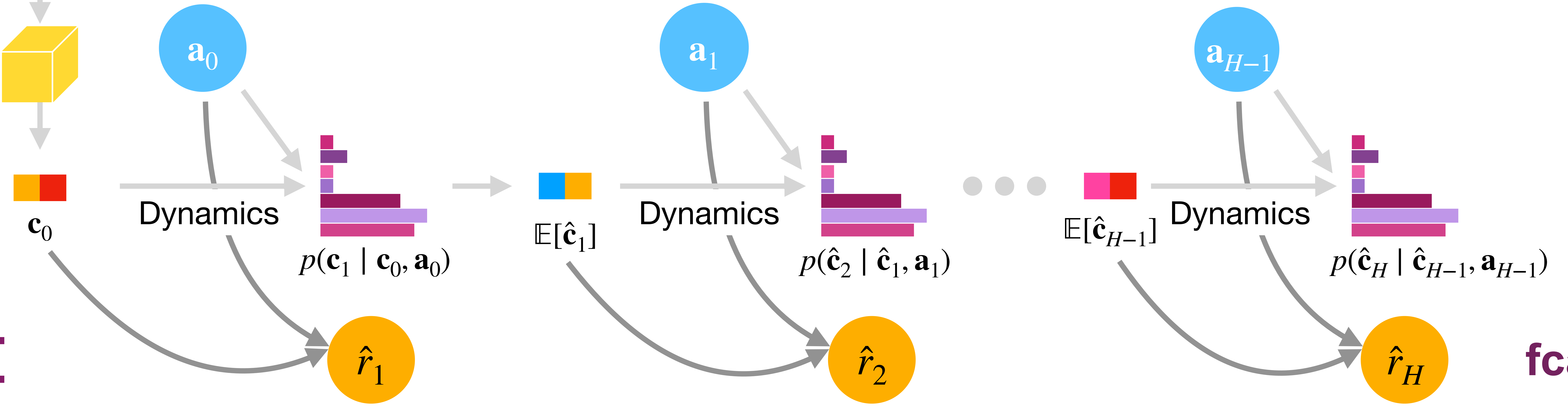


Bootstrap with action-value

Reward func.

$$J(\mathbf{a}_{0:H}, \mathbf{s}) = \boxed{\gamma^H Q_\psi(\hat{\mathbf{c}}_H, \mathbf{a}_H)} + \boxed{\sum_{h=0}^{H-1} \gamma^h R_\xi(\hat{\mathbf{c}}_h, \mathbf{a}_h)}$$

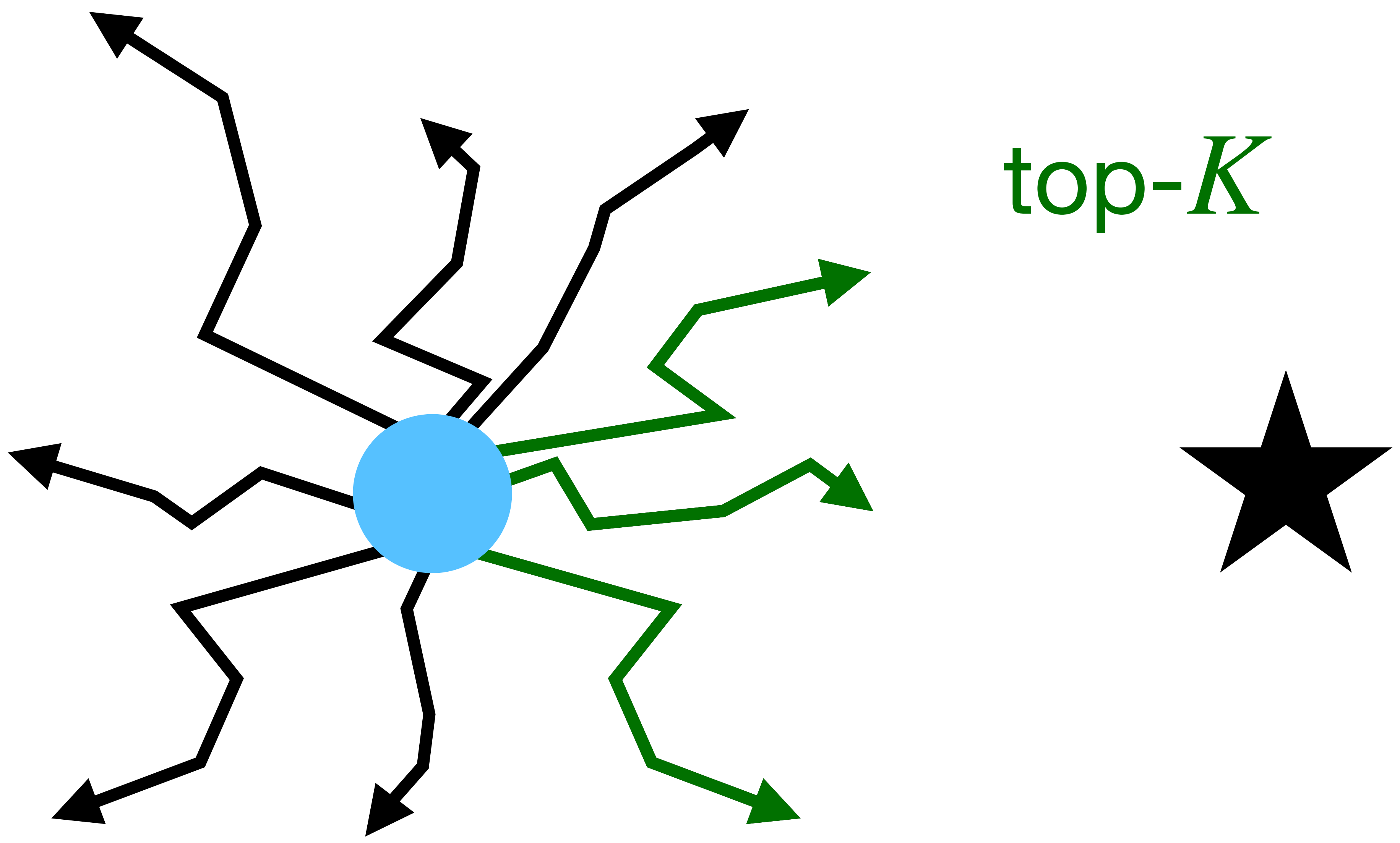
$$\mathbb{E}[\hat{\mathbf{c}}_{h+1}] = \sum_{i=0}^{|\mathscr{C}|} \underbrace{\Pr(\hat{\mathbf{c}}_{h+1} = \mathbf{c}^{(i)} \mid \hat{\mathbf{c}}_h, \mathbf{a}_h)}_{\text{prob. of code } i} \underbrace{\mathbf{c}^{(i)}}_{\text{code}}$$



DCWM: Decision-time Planning

Model Predictive Path Integral Control (MPPI)

Iteration 1



Initialise action sampling distribution $\{a_t \sim \mathcal{N}(\mu_t, \sigma_t^2)\}_{t=0}^{H}$

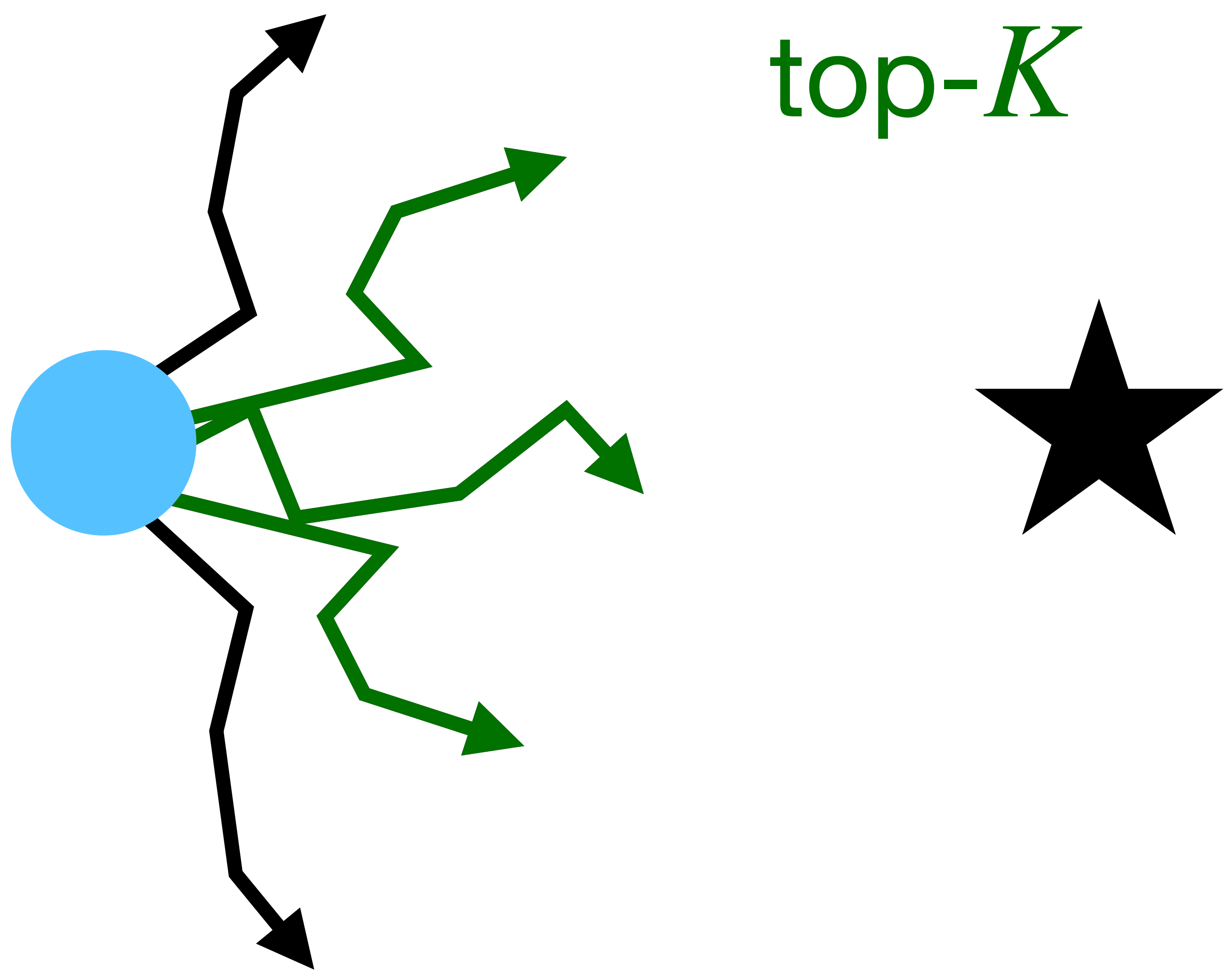
For each iteration

- **Sample** N action sequences $\{a_{0:H}^i\}_{i=1}^{N}$
- **Evaluate** objective $J(\mathbf{a}_{0:H}^i, \mathbf{s})$ for each sample
- **Select** top K performing samples
- **Update** action distribution parameters $\{\mu_t, \sigma_t^2\}_{t=0}^{H}$

DCWM: Decision-time Planning

Model Predictive Path Integral Control (MPPI)

Iteration 2



Initialise action sampling distribution $\{a_t \sim \mathcal{N}(\mu_t, \sigma_t^2)\}_{t=0}^{H}$

For each iteration

Sample N action sequences $\{a_{0:H}^i\}_{i=1}^{N}$

Evaluate objective $J(\mathbf{a}_{0:H}^i, \mathbf{s})$ for each sample

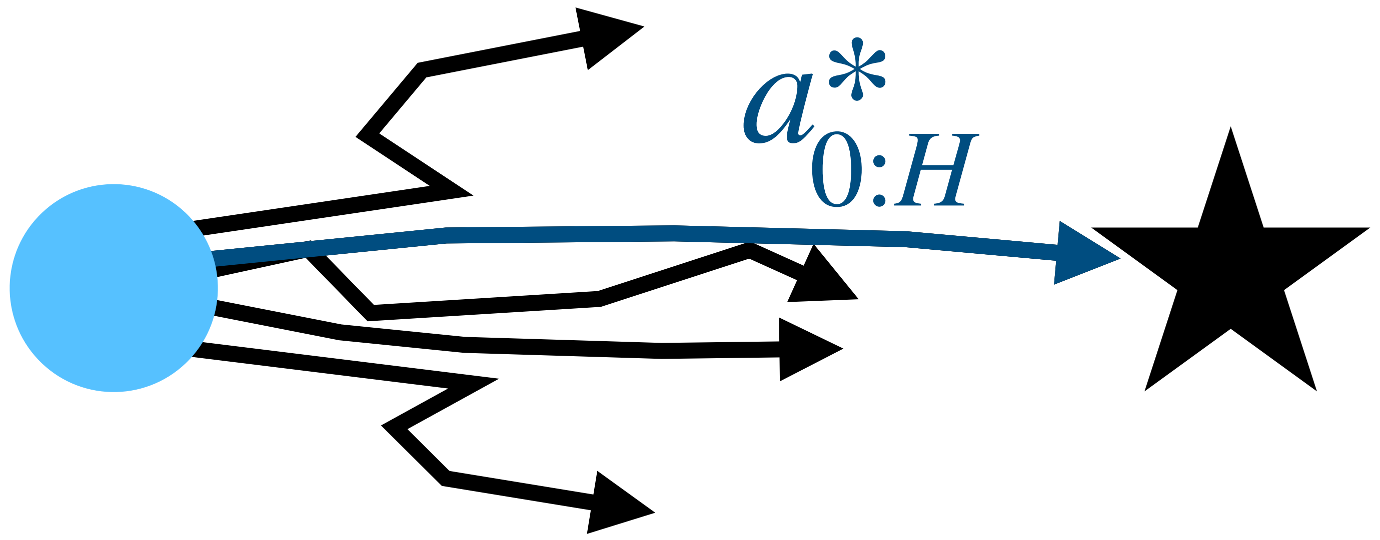
Select top K performing samples

Update action distribution parameters $\{\mu_t, \sigma_t^2\}_{t=0}^{H}$

DCWM: Decision-time Planning

Model Predictive Path Integral Control (MPPI)

Iteration 3



Initialise action sampling distribution $\{a_t \sim \mathcal{N}(\mu_t, \sigma_t^2)\}_{t=0}^H$

For each iteration

- **Sample** N action sequences $\{a^i_{0:H}\}_{i=1}^N$
- **Evaluate** objective $J(\mathbf{a}^i_{0:H}, \mathbf{s})$ for each sample
- **Select** top K performing samples
- **Update** action distribution parameters $\{\mu_t, \sigma_t^2\}_{t=0}^H$