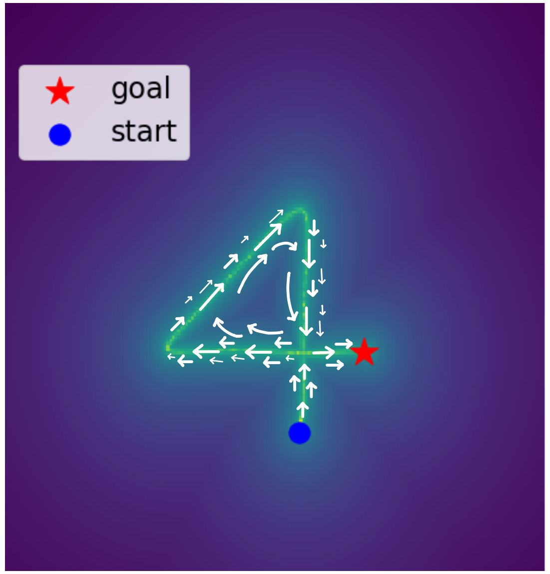
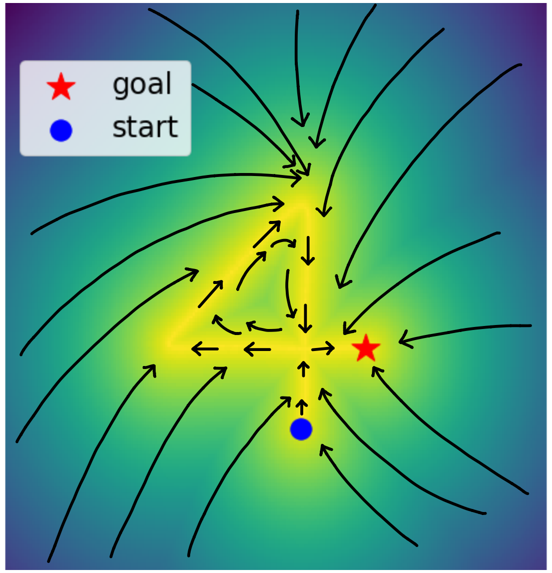
Neural Dynamic Policies for End-to-End Sensorimotor Learning



Vanilla Policy



NDP (Ours)

Shikhar Bahl, Mustafa Mukadam, Abhinav Gupta, Deepak Pathak


KINOVA

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✓ Needs to consider momentum and forces

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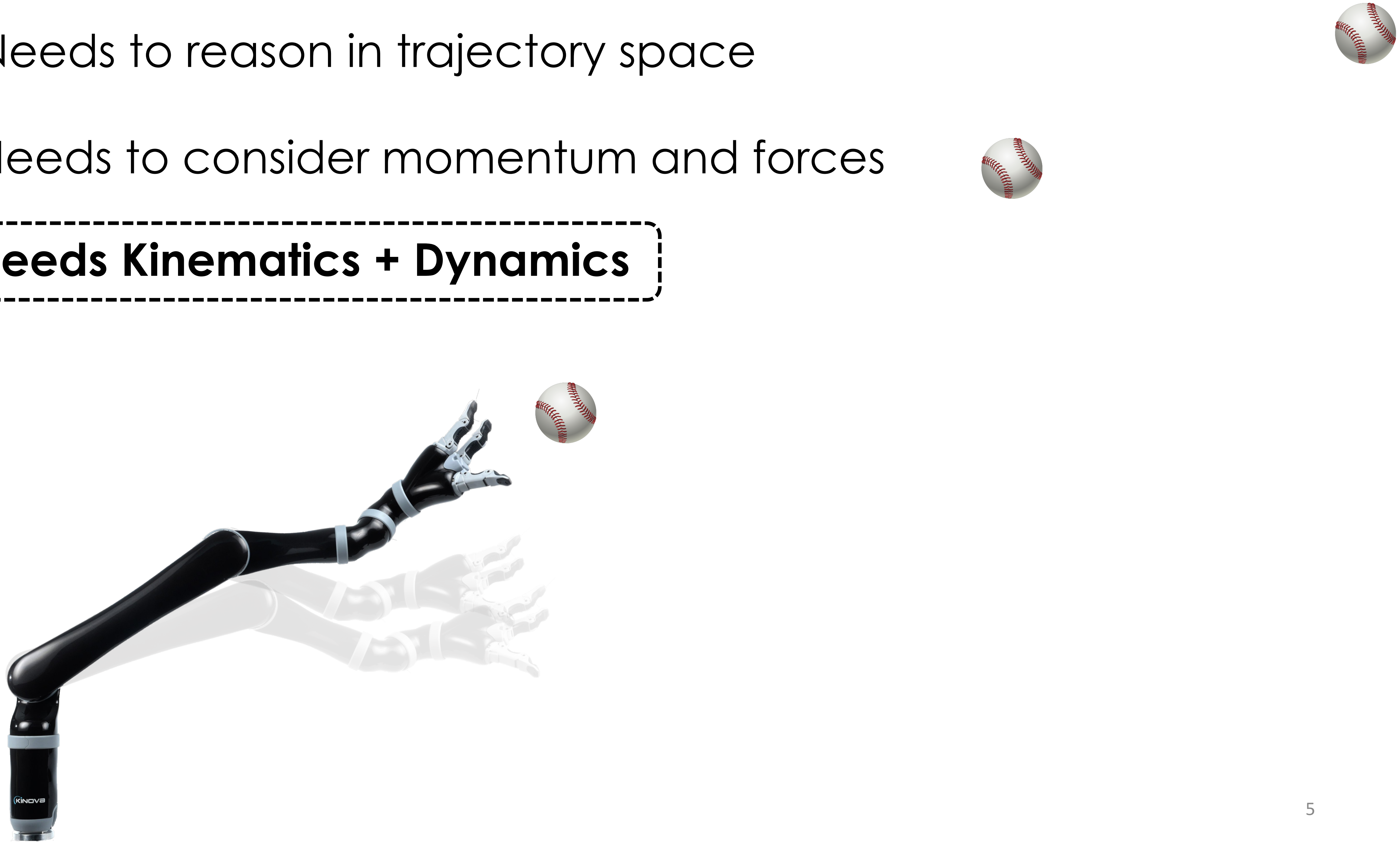
Needs Kinematics + Dynamics



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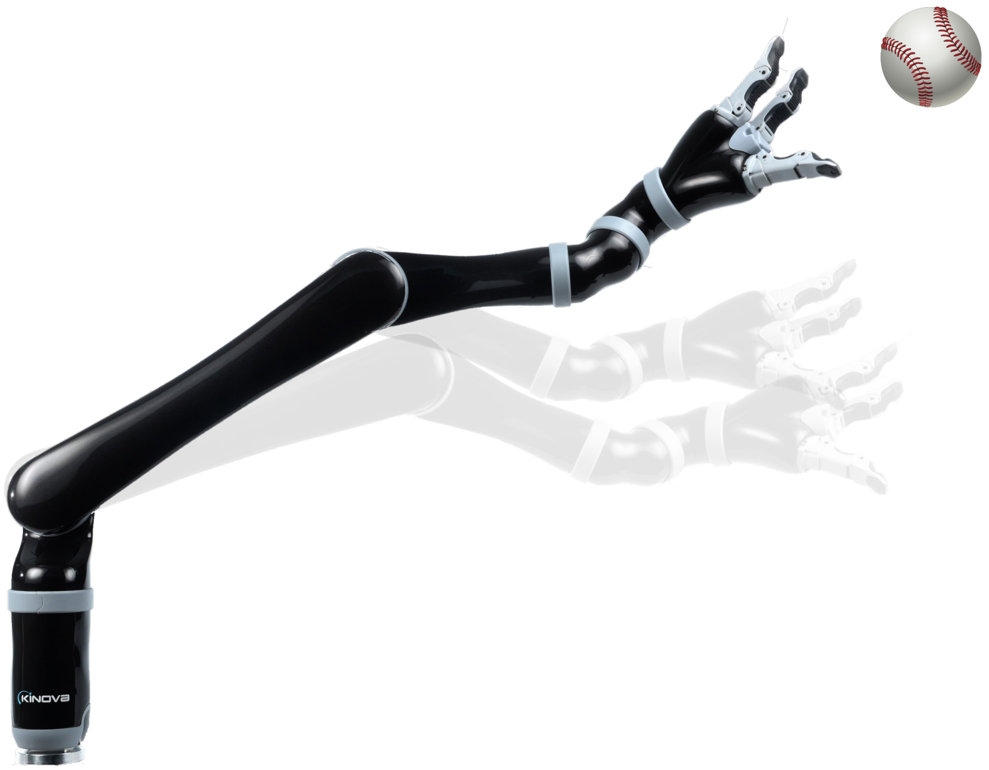

✗ Deep robot learning methods only reason at each timestep

✗ Only operate in raw action space (torque, joint angles, etc)

Can we build policies that reason directly in trajectory space?

Many natural phenomena are dynamical systems which are described by ***differential equations***, i.e. $\ddot{y} = m^{-1} f(y, \dot{y})$

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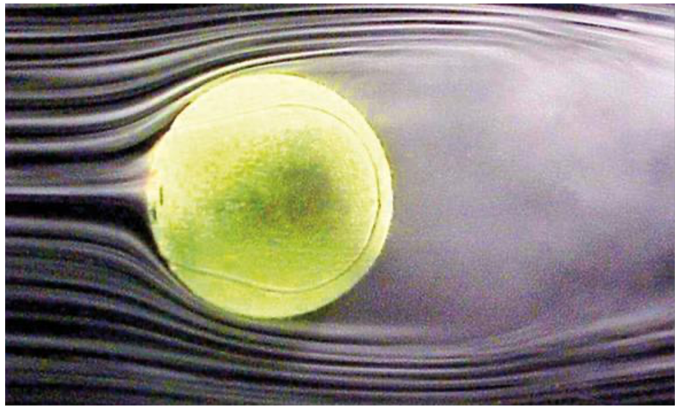

Fluids

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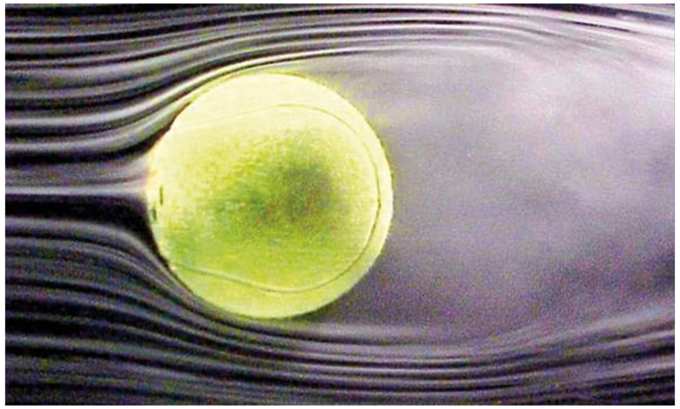

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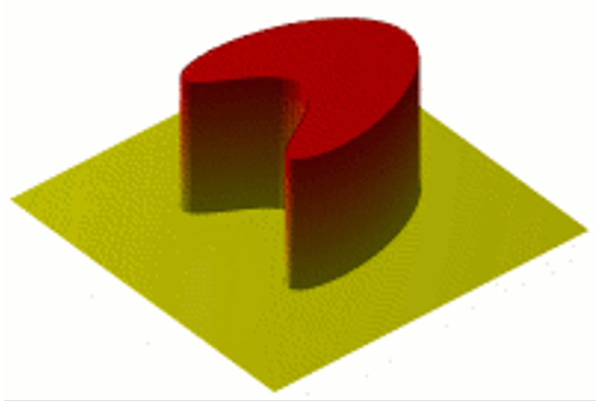

Heat

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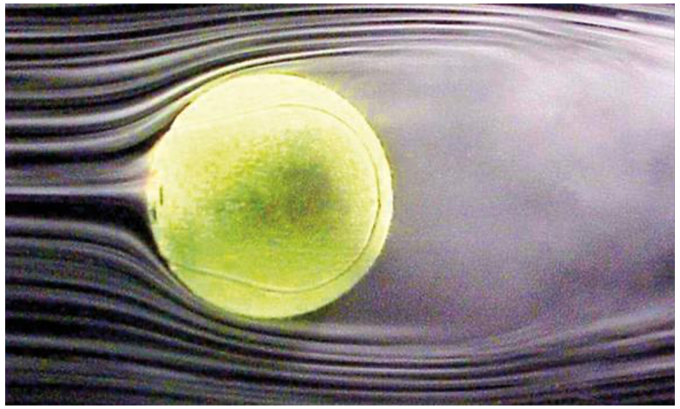

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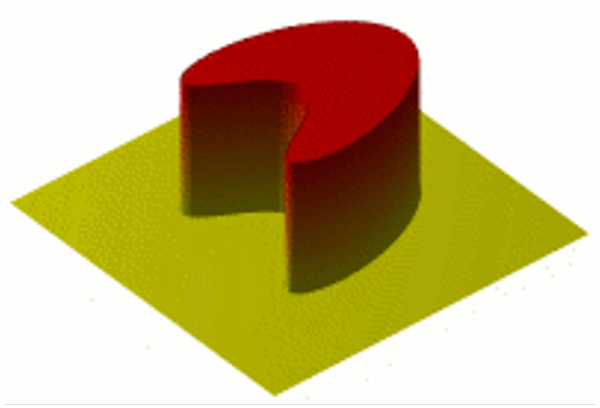

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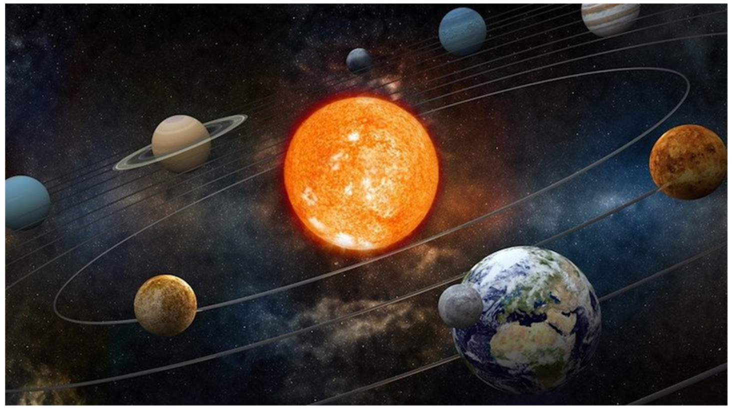

Gravity

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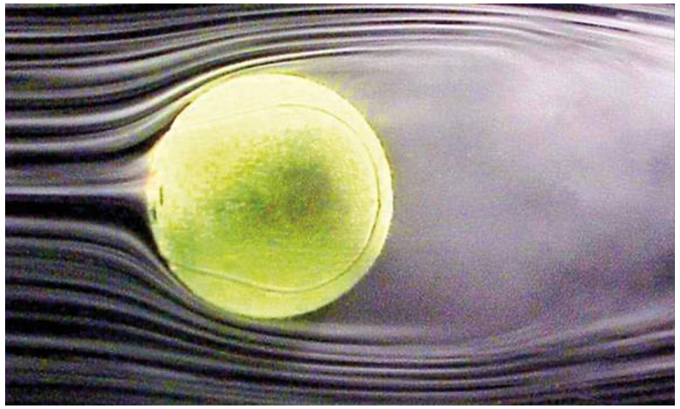

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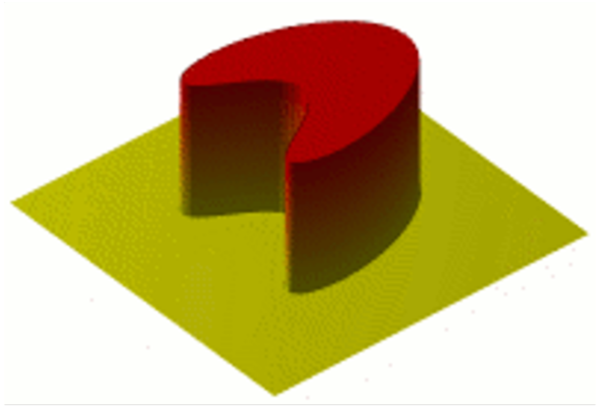

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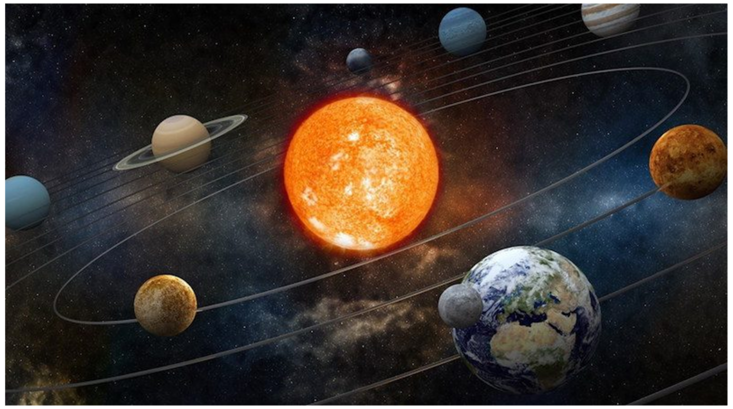

Gravity

Can we use the same formulation be used to describe the motion of a robot?

Popular in classical robotics: ***Dynamic Movement Primitives (DMPs)*** [Schaal, 2002]

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Second order dynamical system

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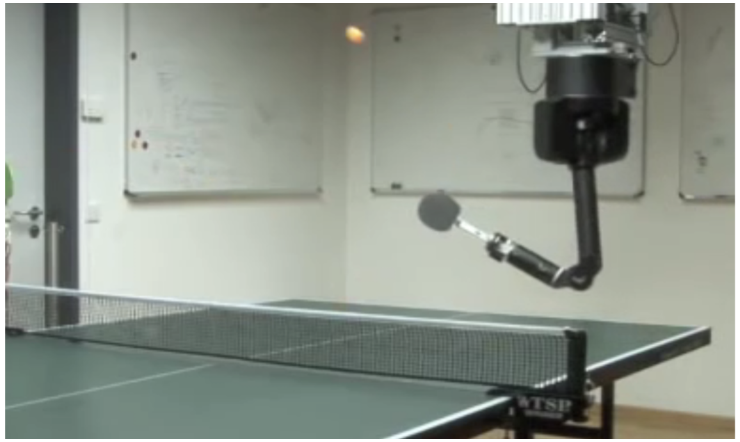
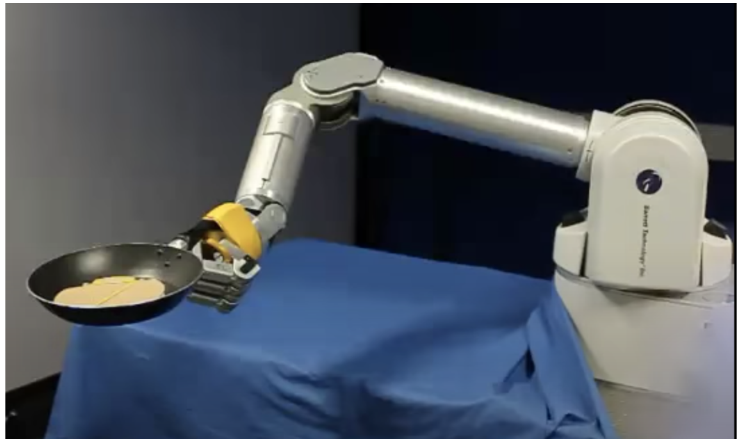
Table Tennis



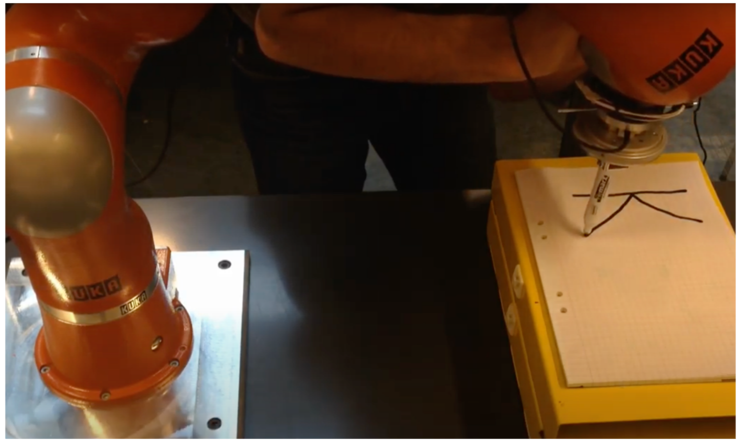
[Muelling et. al, 2013]

Pancake Flipping



[Kormushev et. al, 2010]

Letter Writing



[Steinmetz, 2014]

DMP-based Methods

Handle dynamic tasks well

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DMP-based Methods	Deep RL
Handle dynamic tasks well	Can handle high-dimensional input (i.e. images)
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Do not scale to high dimensional inputs	Difficulty with dynamic tasks

How can we bridge the gap between these two paradigms?

DMP-based Methods

Handle dynamic task well

Are sensitive to parameter tuning and require dense supervision

Do not scale to high dimensional inputs

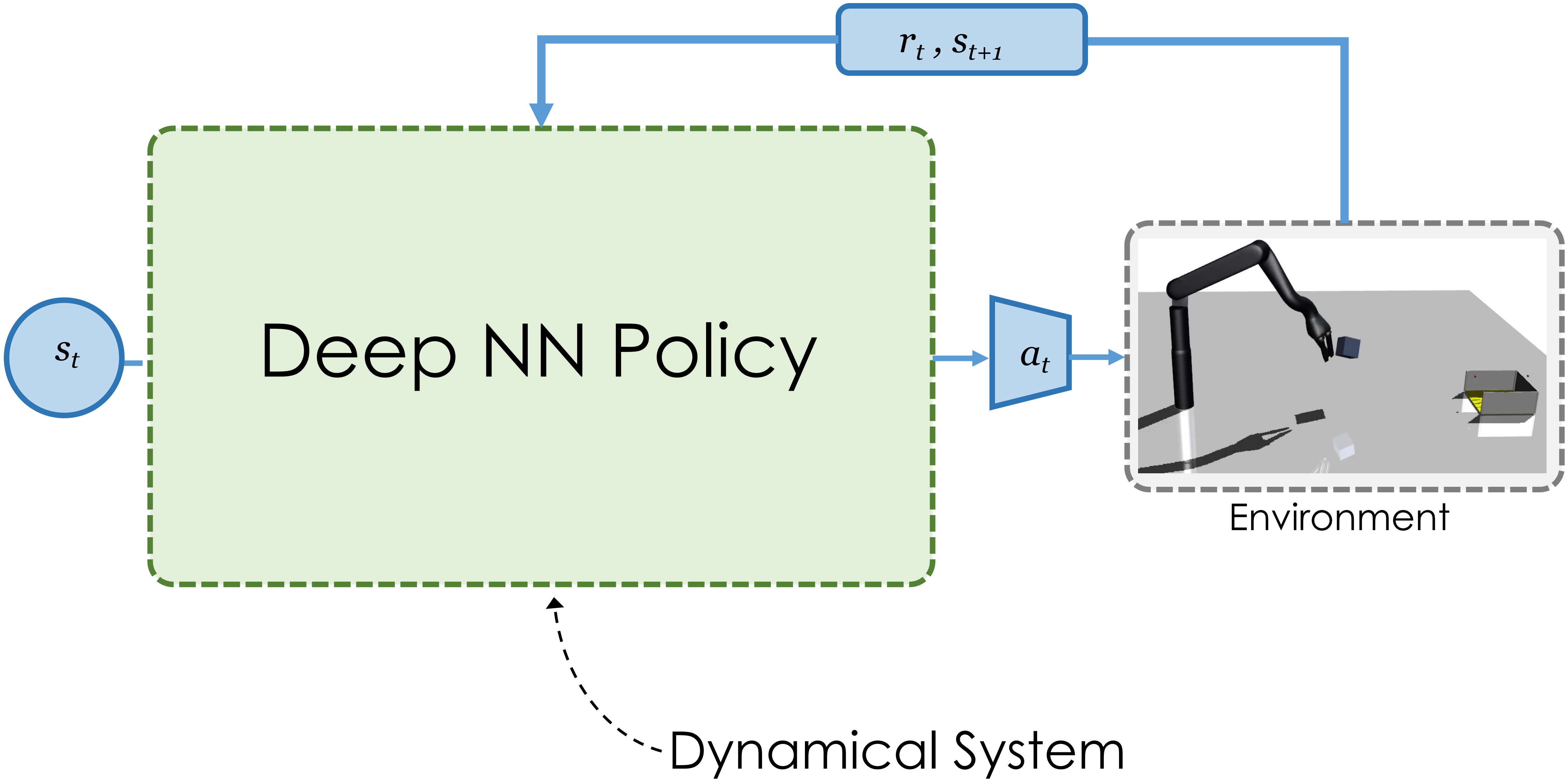
Deep RL

Can handle high-dimensional input (i.e. images)

supervision (i.e. rewards)

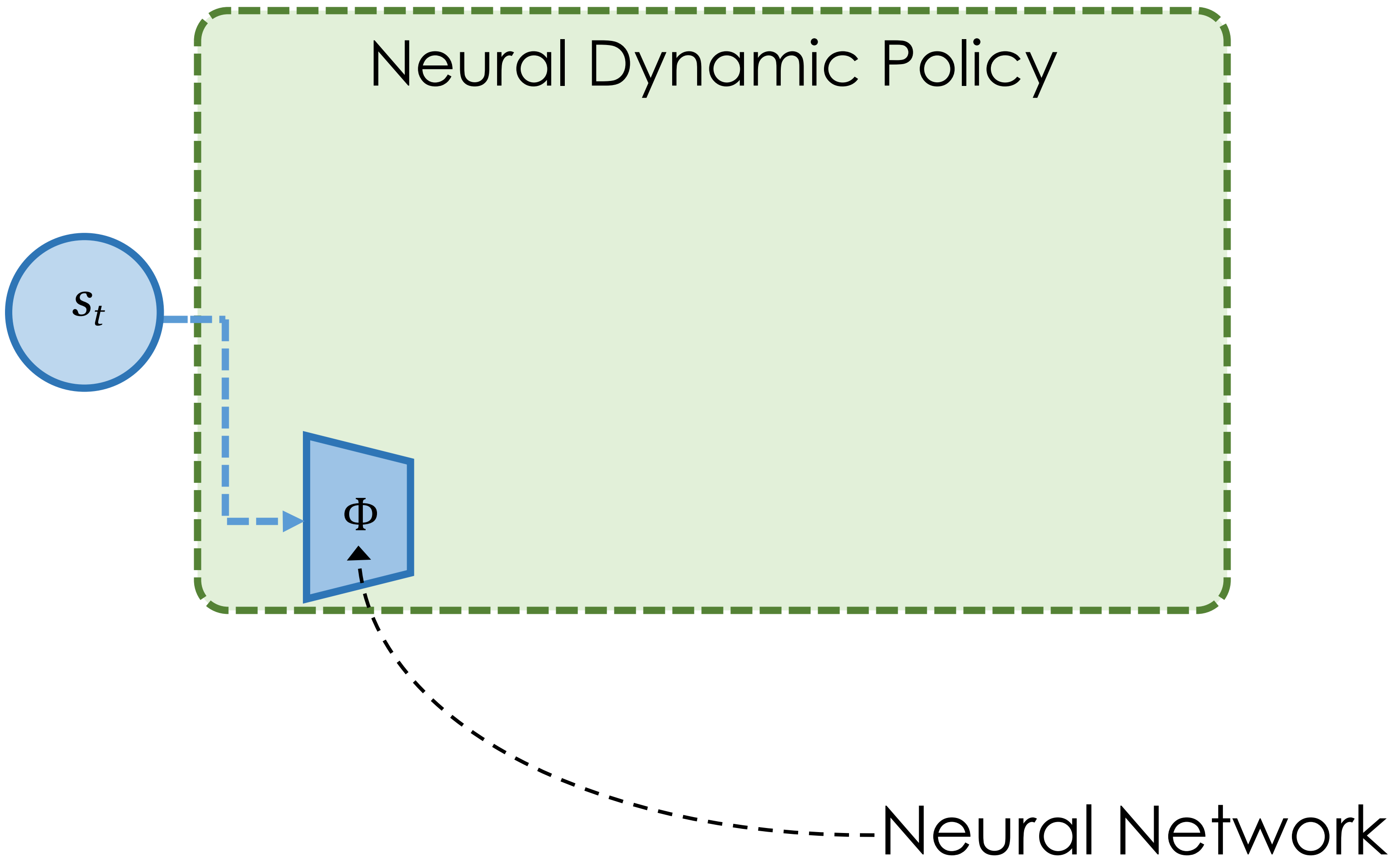
Reason at each timestep

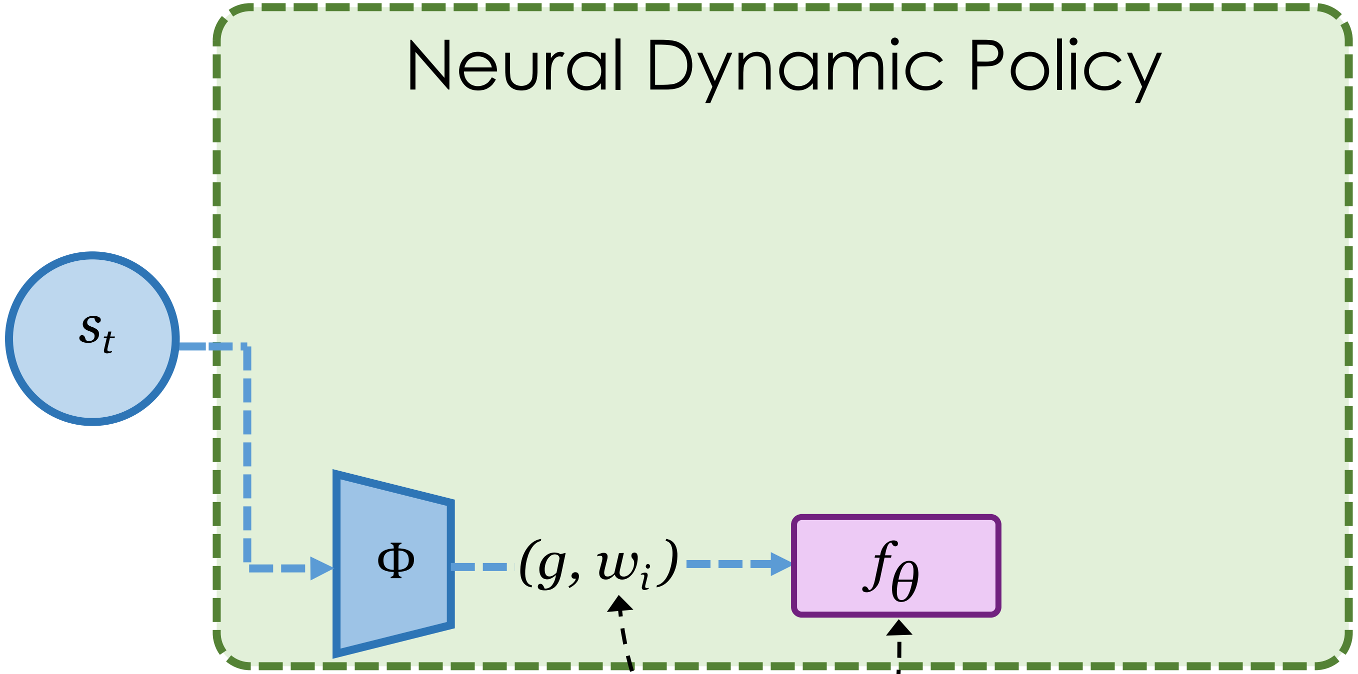
Difficulty with dynamic tasks



r_t , s_{t+1}
s_t
Deep NN Policy
a_t
Environment
Dynamical System

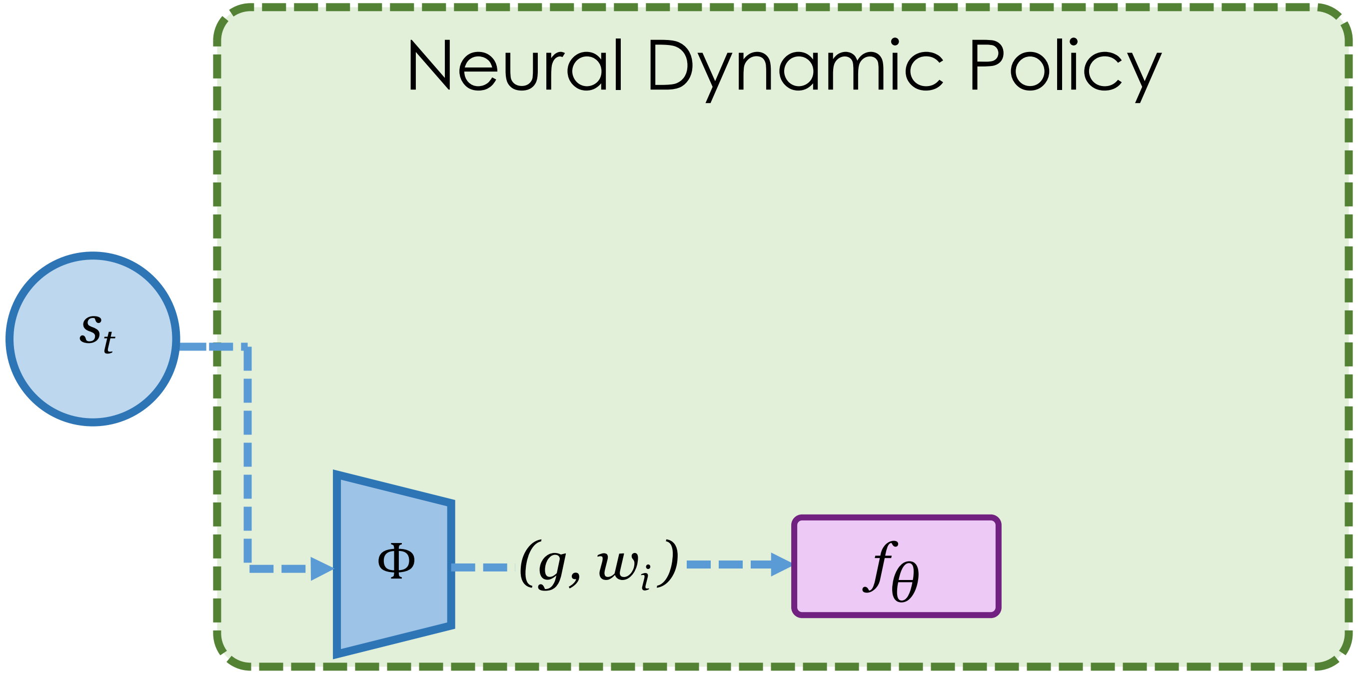
Neural Dynamic Policy


Neural Dynamic Policy
s_t
Φ
Neural Network



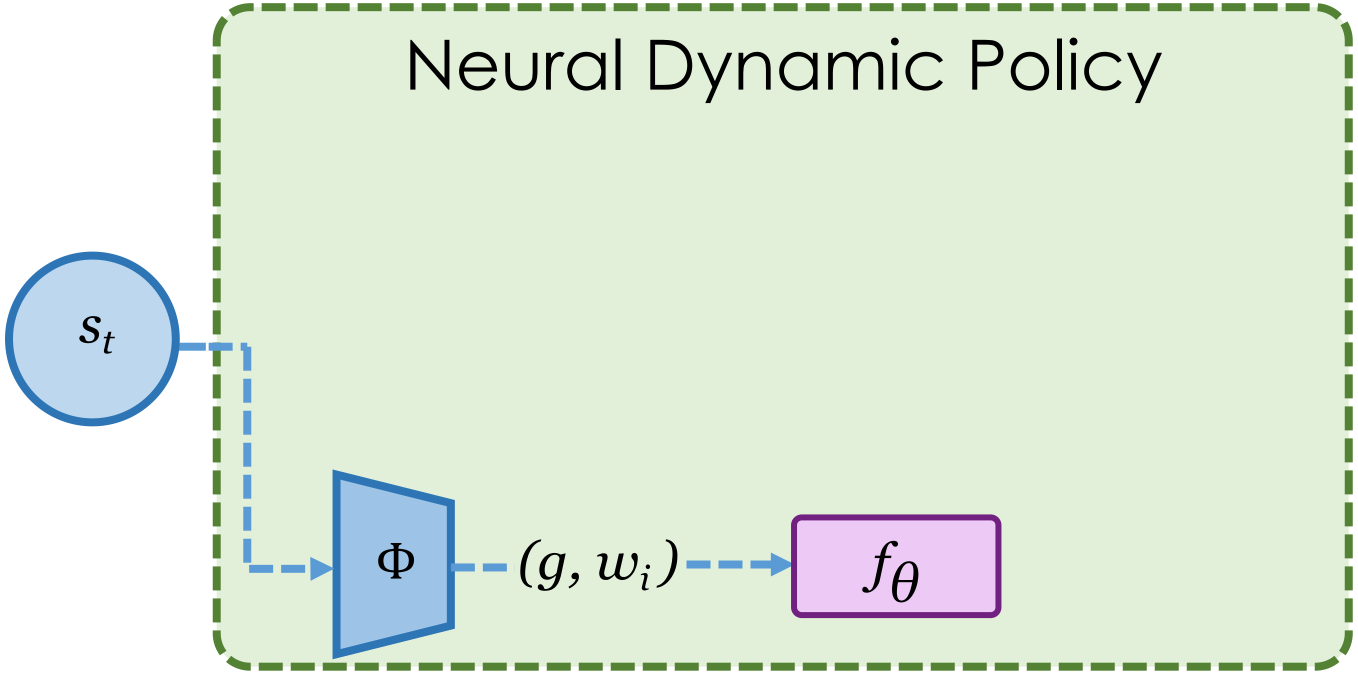
$$\mathbf{a} = -\alpha(\mathbf{y} - \boxed{g}) - \beta\dot{\mathbf{y}} + \boxed{f}$$

DMP Parameters



$$\mathbf{a} = -\alpha(\boxed{\mathbf{y}} - g) - \beta\dot{\mathbf{y}} + f$$

Robot position



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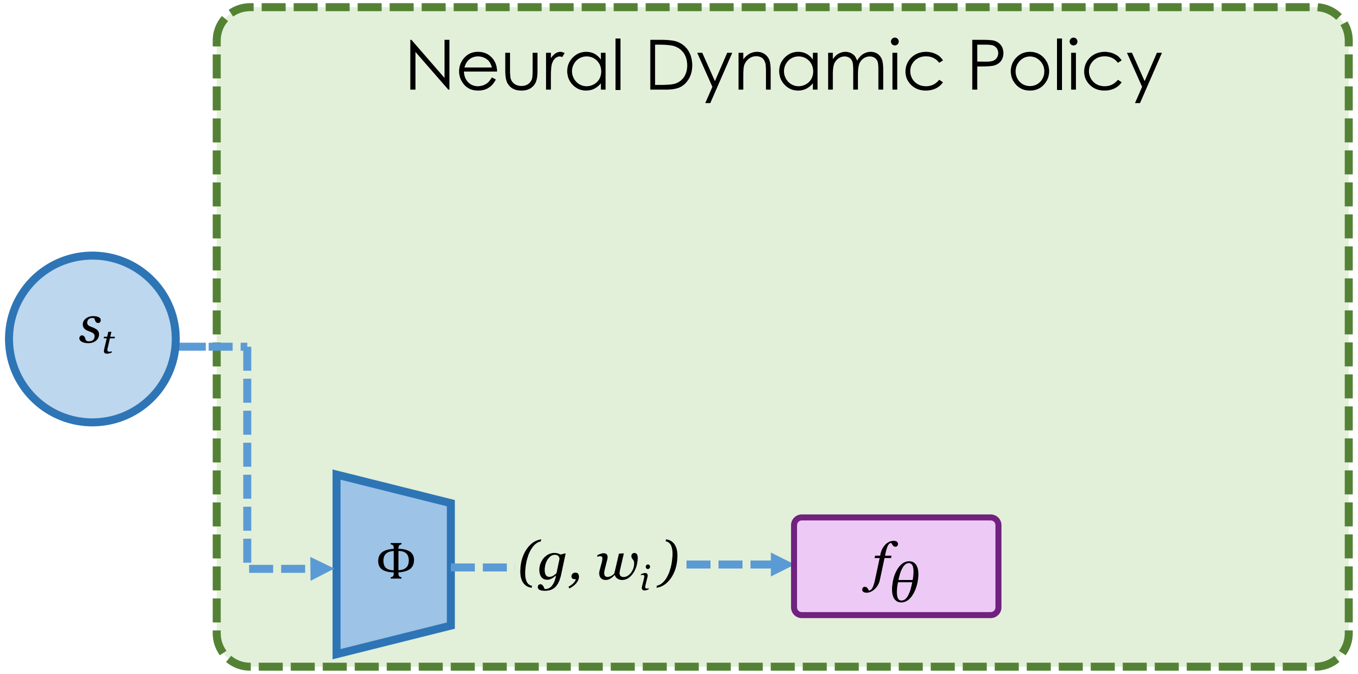
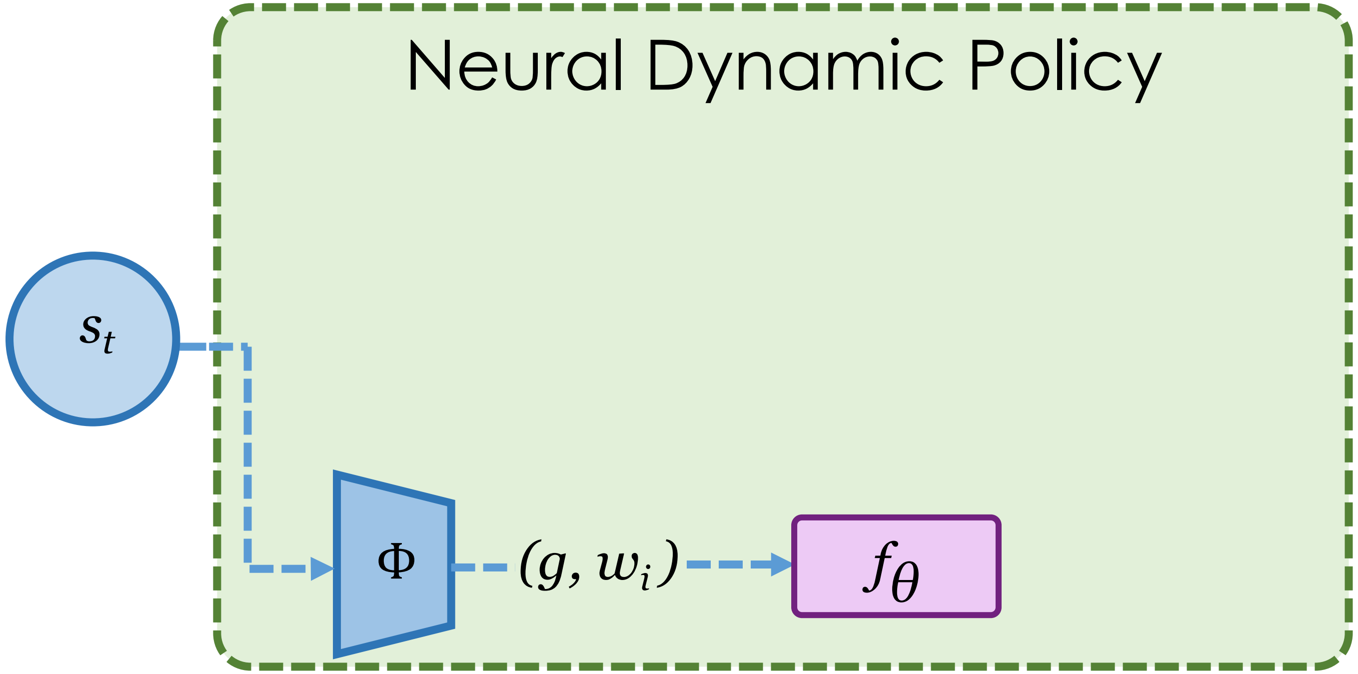
Goal position



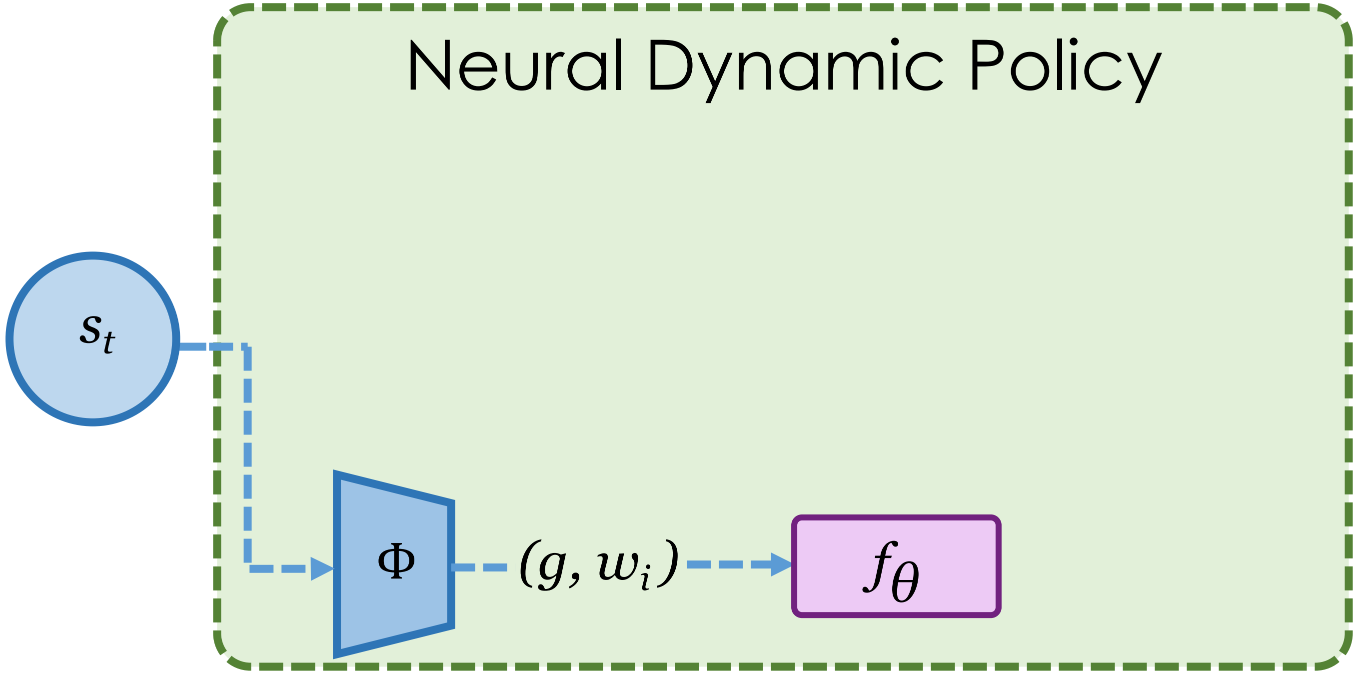
$$\boxed{\mathbf{a} = -\alpha(\mathbf{y} - g) - \beta\dot{\mathbf{y}} + f}$$

2nd Order Differential Equation in y

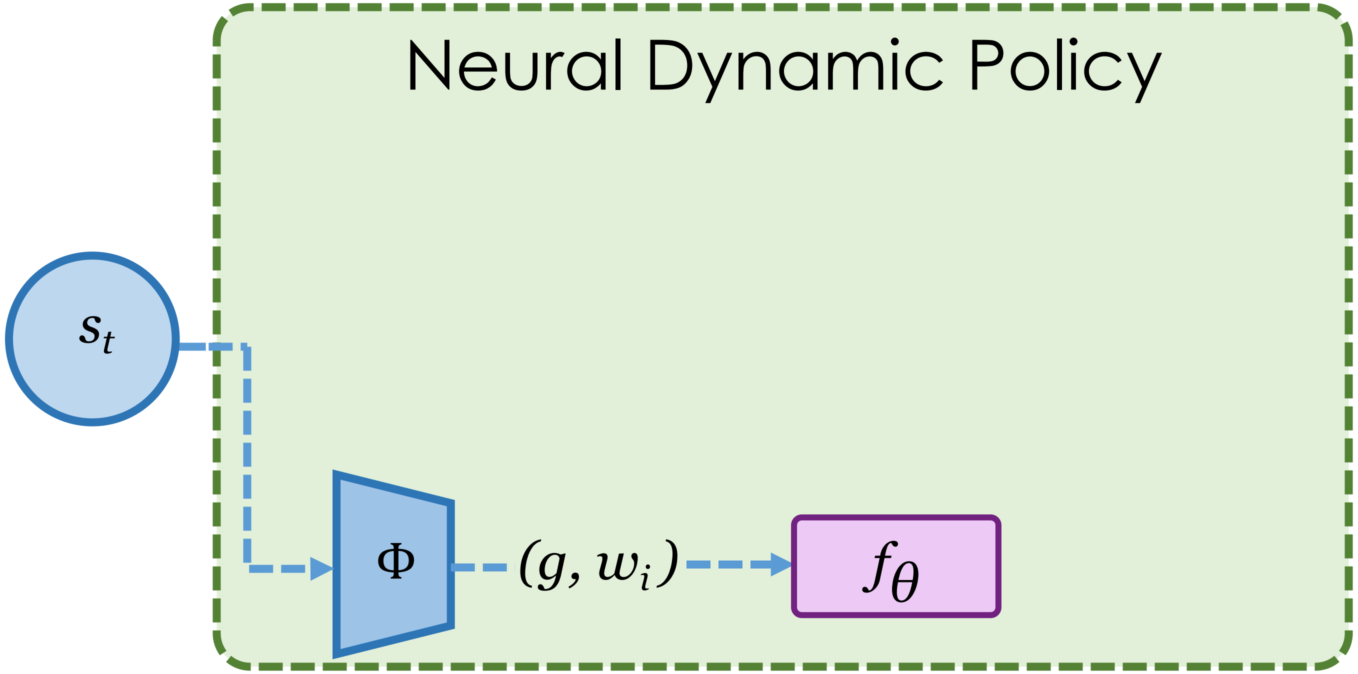


$$\mathbf{a} = -\alpha(\mathbf{y} - g) - \beta\dot{\mathbf{y}} + \boxed{f}$$

Forcing function



$$f(x) = \frac{\sum_{i=1}^{N} \Psi_i(x) w_i}{\sum_{i=1}^{N} \Psi_i(x)} x(g - y_0)$$



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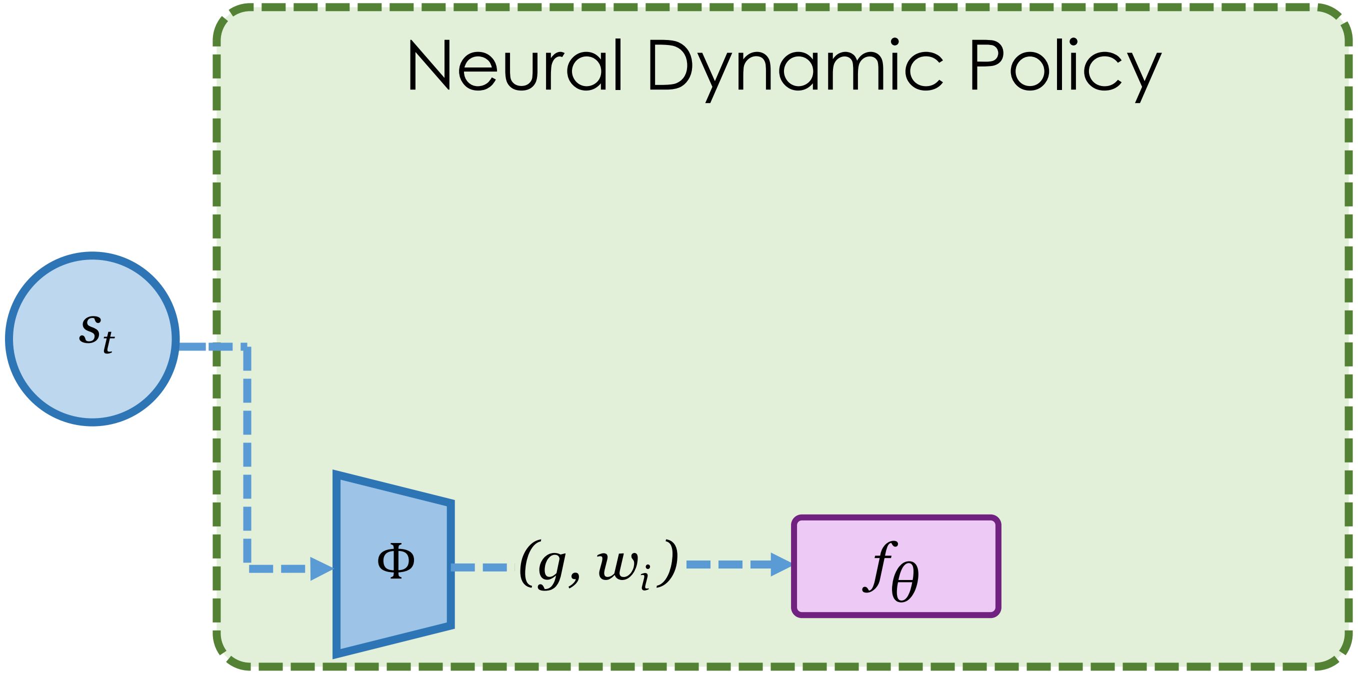
Radial Basis Function



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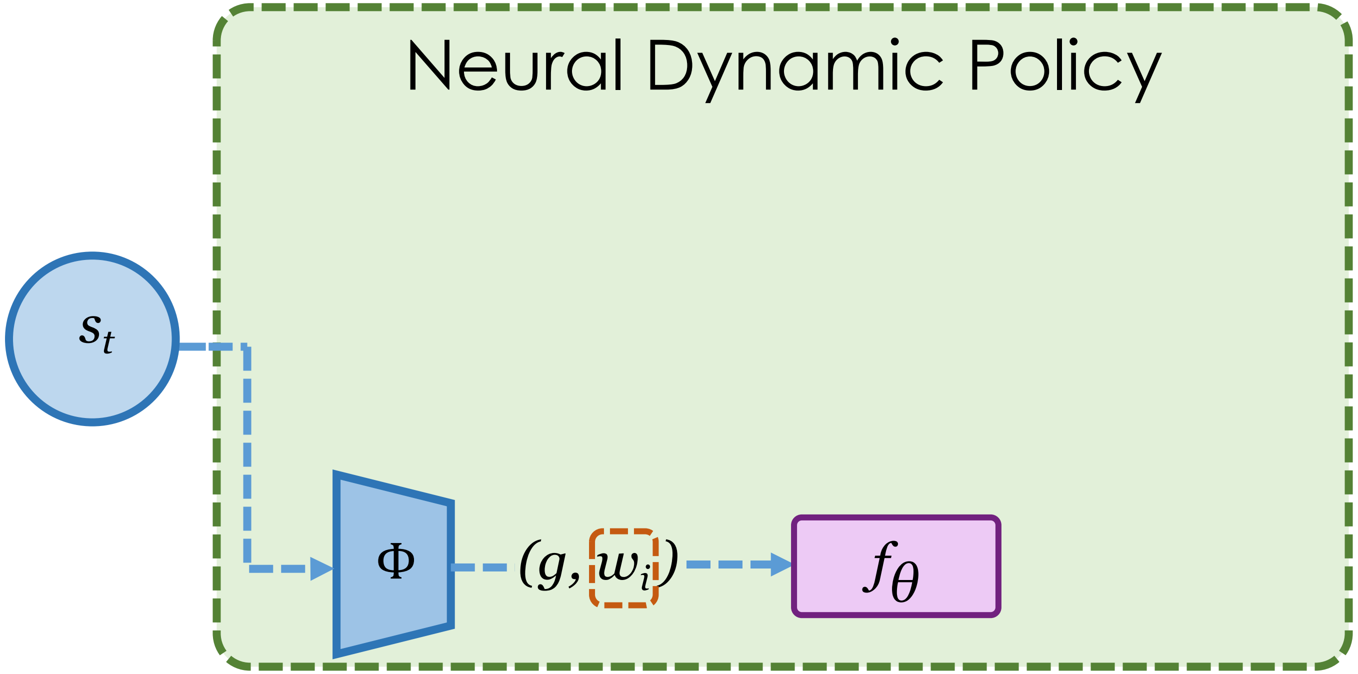

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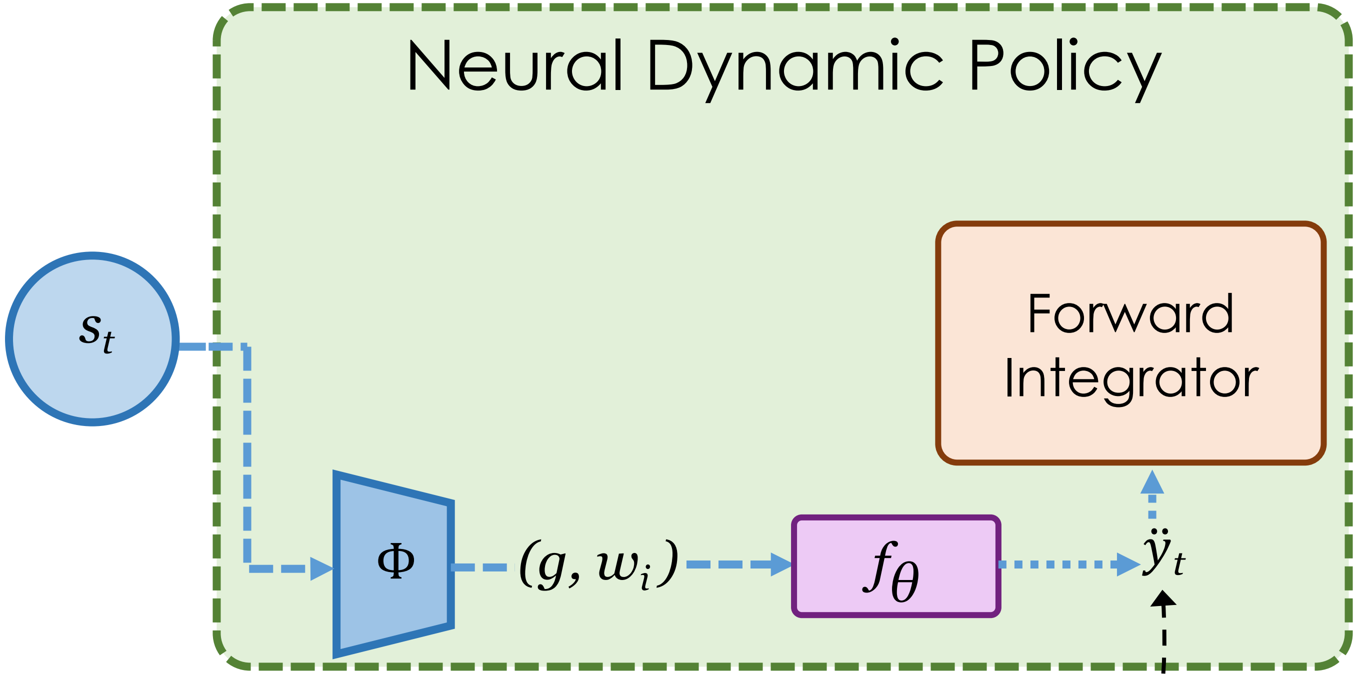
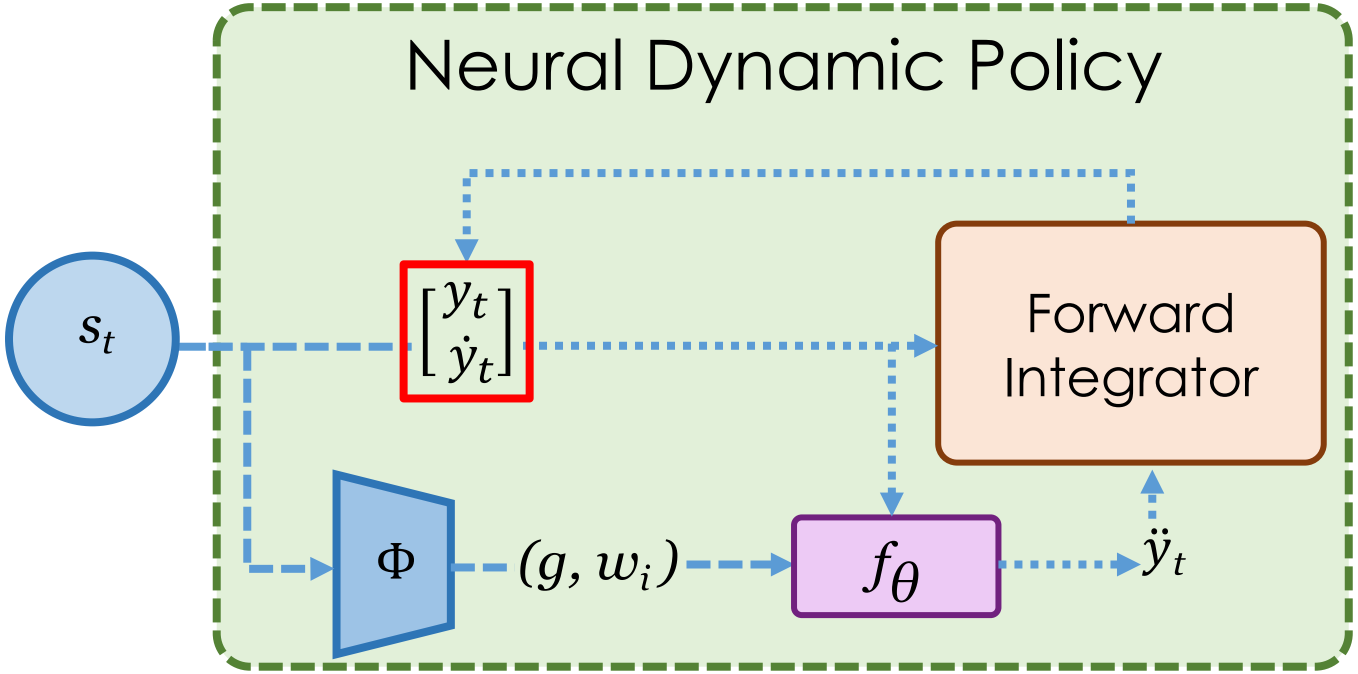
Weight of RBF



$$\boxed{\mathbf{a} = -\alpha(\mathbf{y} - g) - \beta\dot{\mathbf{y}} + f}$$



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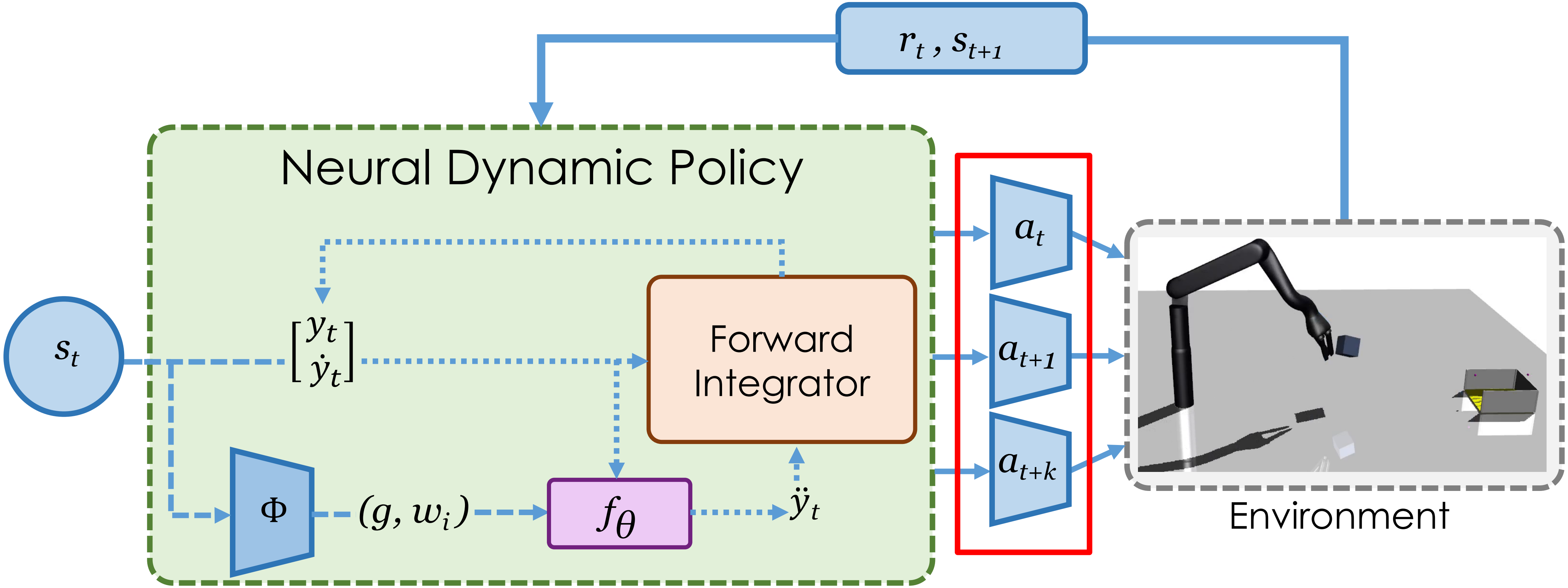

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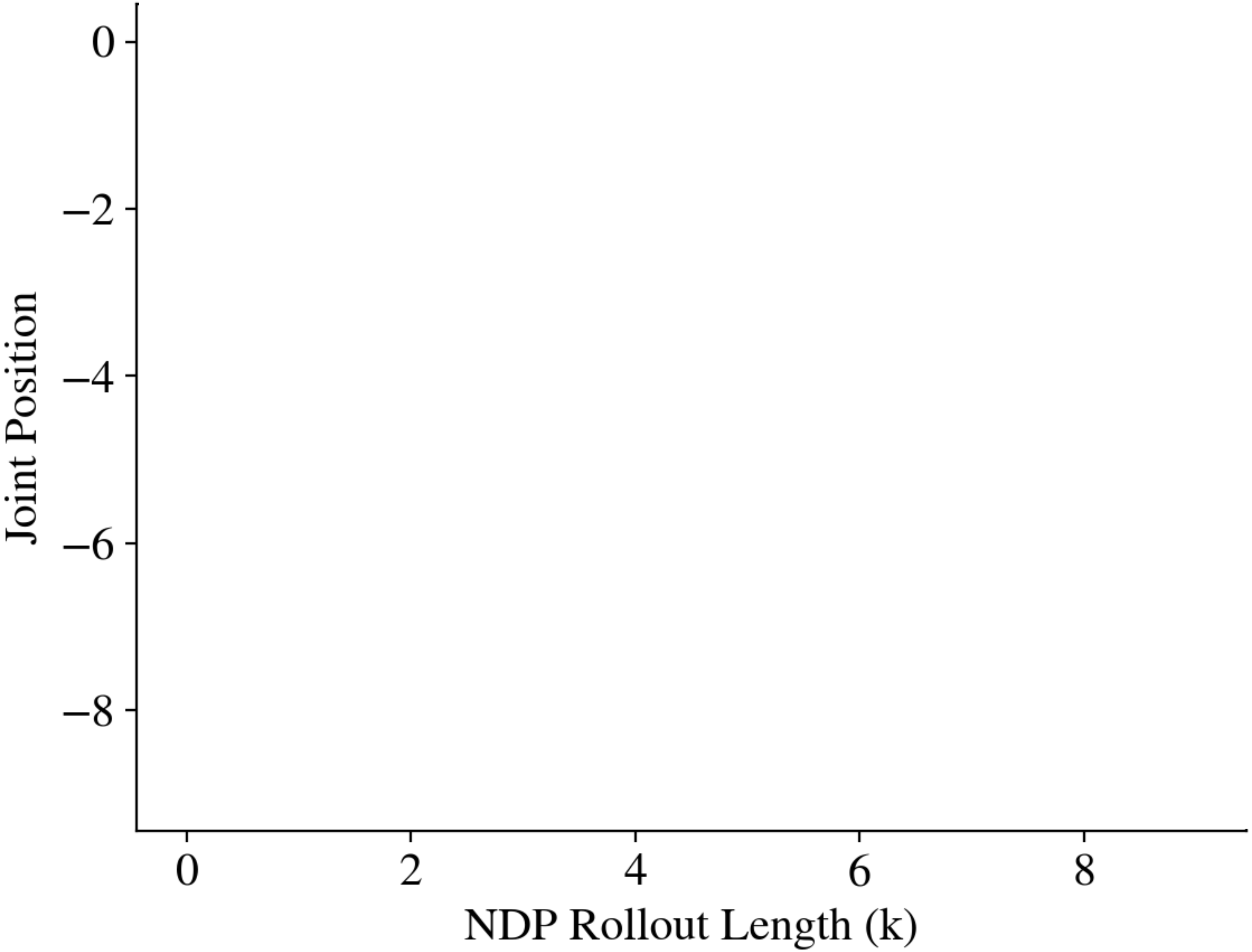
NDPs Intuition



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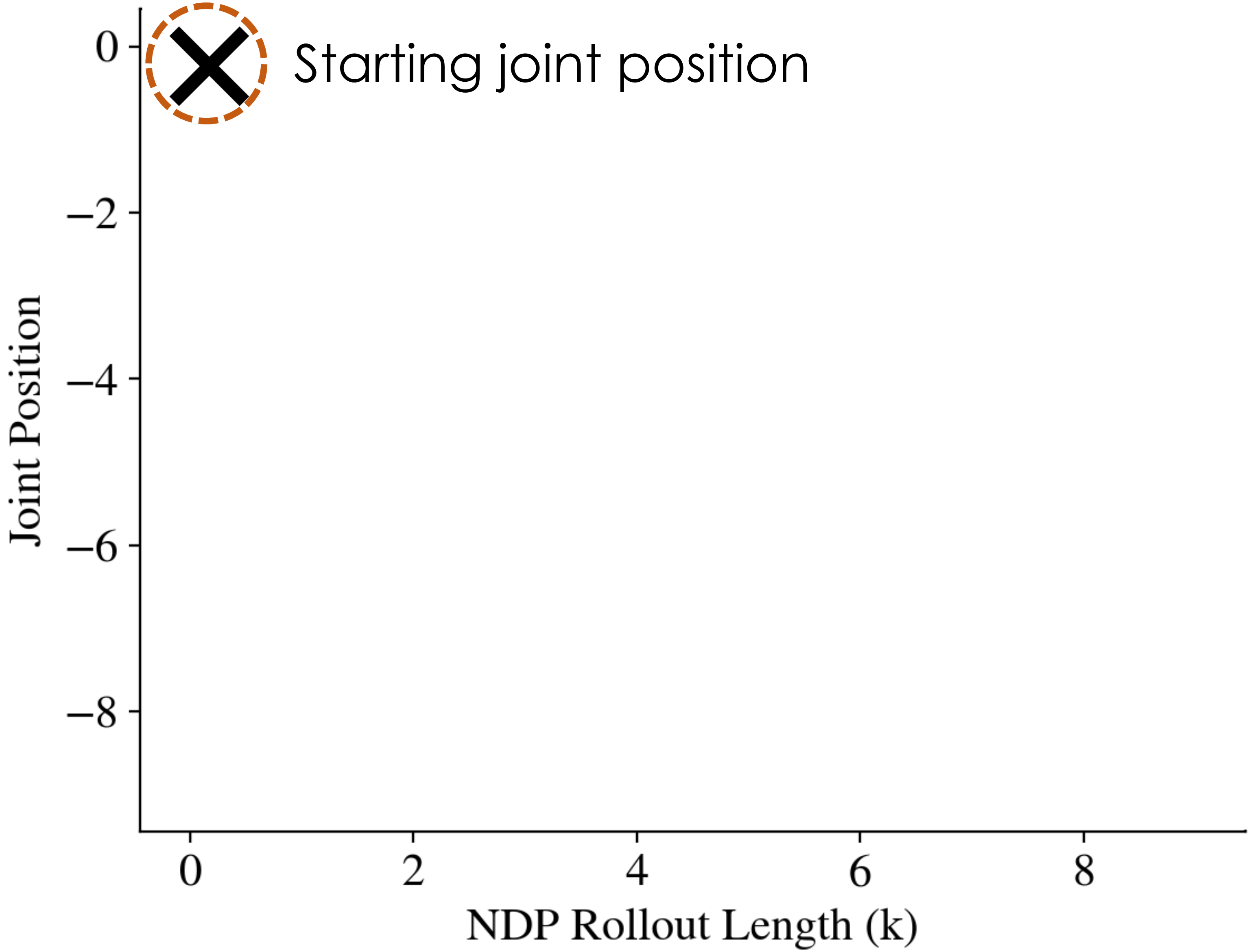

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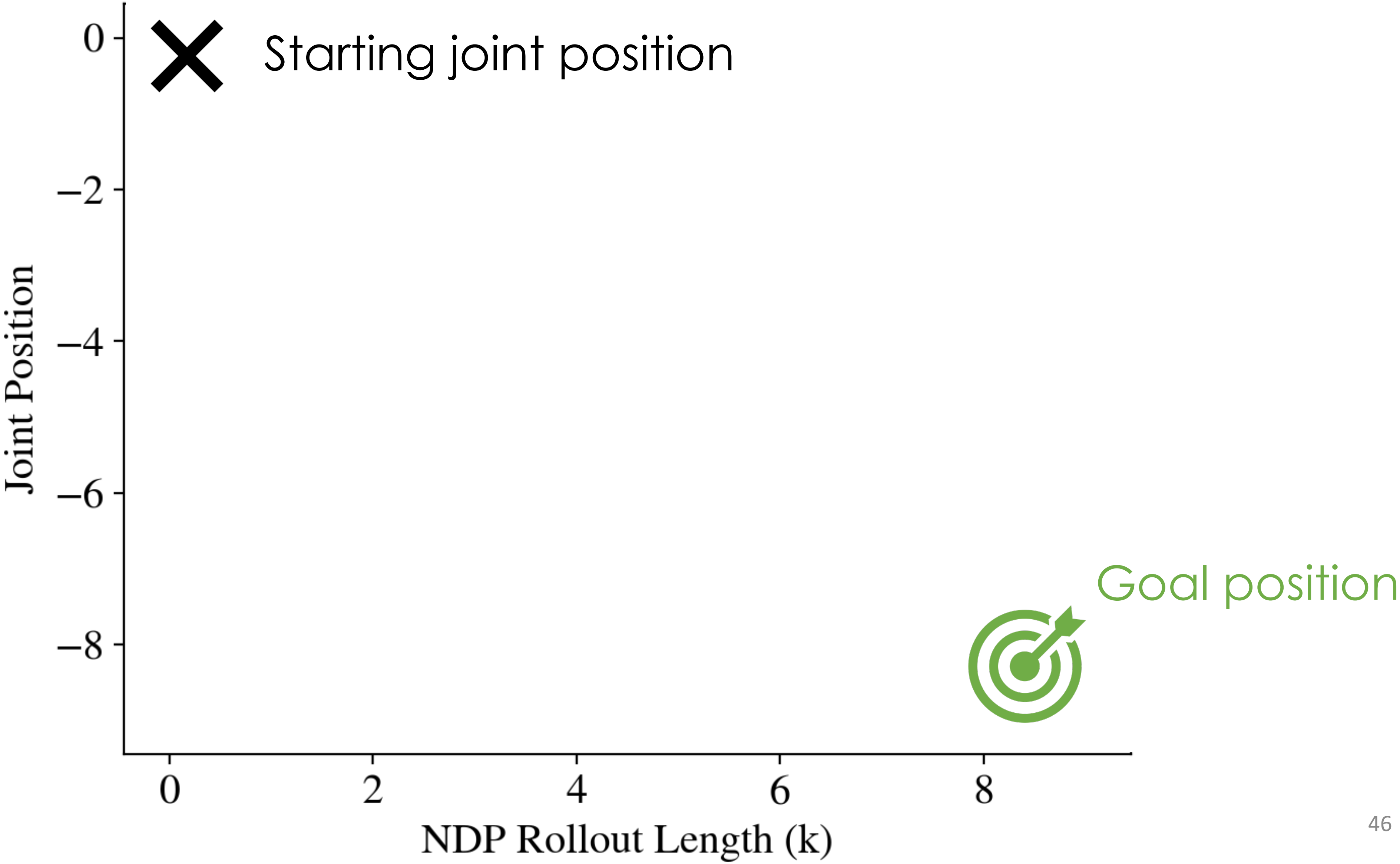

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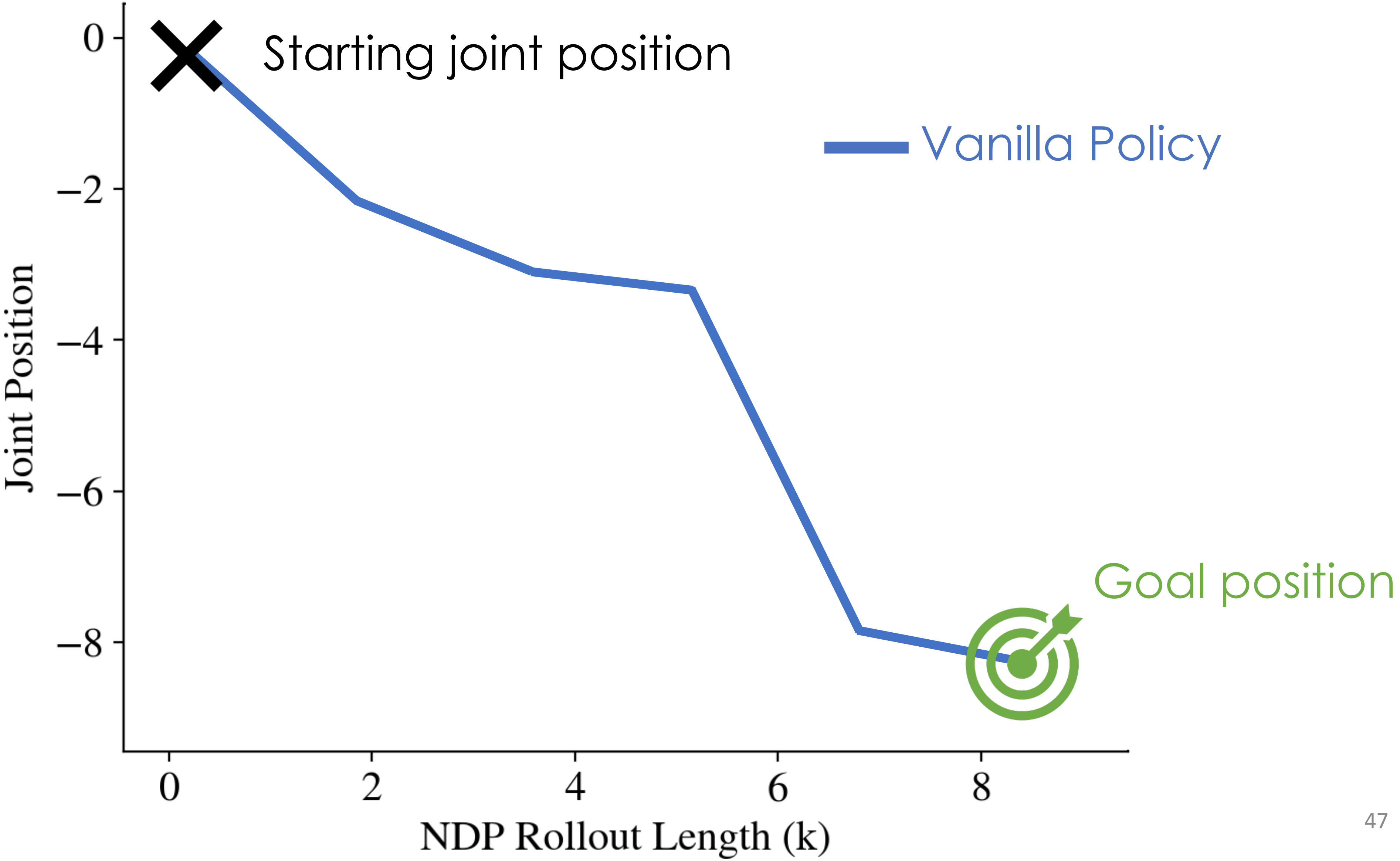

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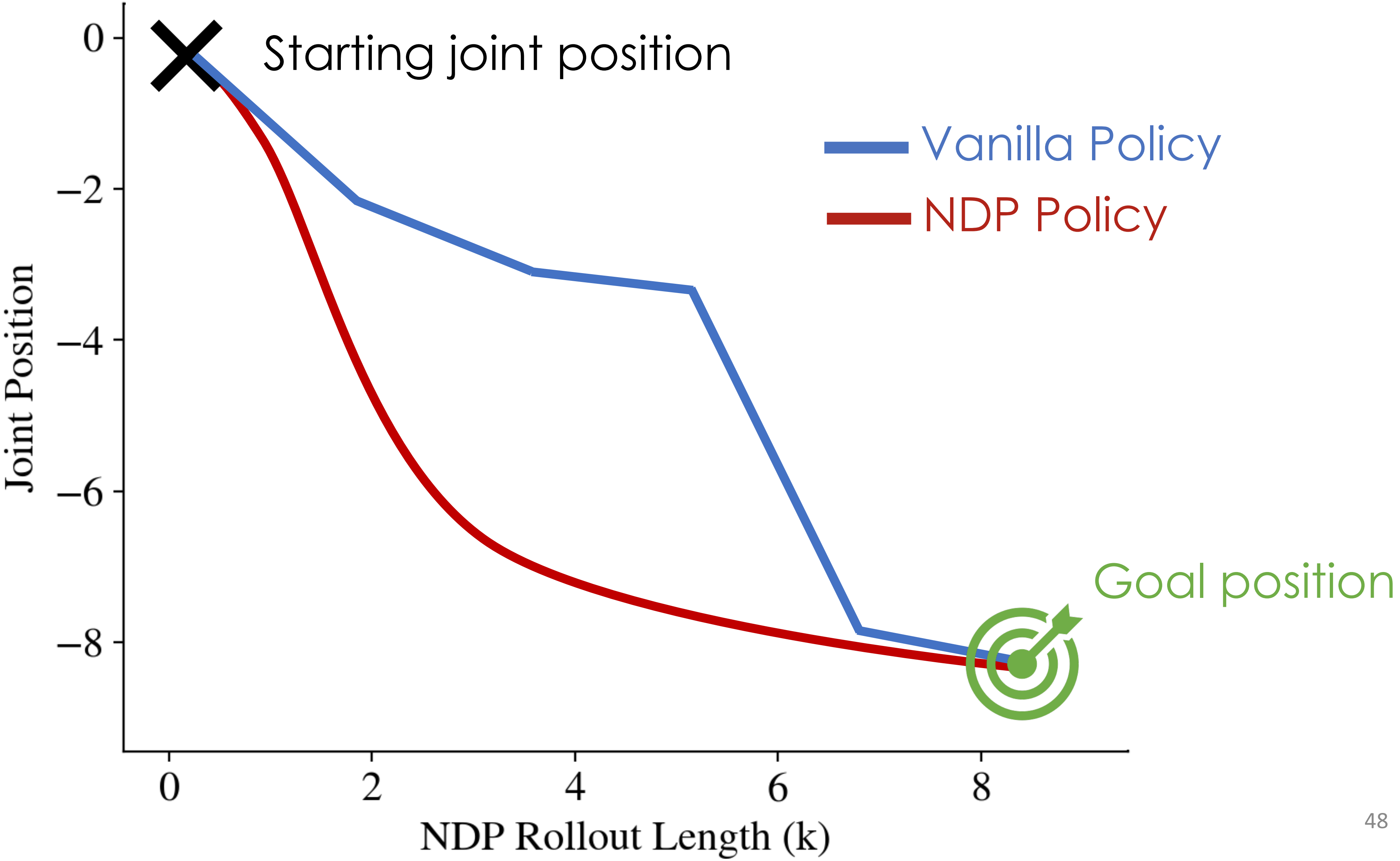


NDPs Intuition

NDPs show a much smoother convergence to the goal

RL Algorithm

Algorithm 1 Training NDPs for RL

Require: Policy π, k NDP rollout length, g low-level inverse controller

for $1, 2, \ldots$ episodes **do**

  for $t = 0, k, \ldots,$ until end of episode **do**

    $w, g = \Phi(s_t)$

    Robot y_t, $\dot{y}_t$ from s_t (pos, vel)

    for $m = 1, \ldots, M$ (integration steps) **do**

      Estimate $\dot{x}_m$ via (2) and update x_m

      Estimate $\ddot{y}_{t+m}, \dot{y}_{t+m}, y_{t+m}$ via (4), (5)

      $a_{t+n} = g(y_{t+m}, y_{t+m-1})$

      Apply action a_{t+n} to get s_{t+n+1}

      Store transition (s, a, s', r)

    end for

    Compute Policy gradient ∇_θ

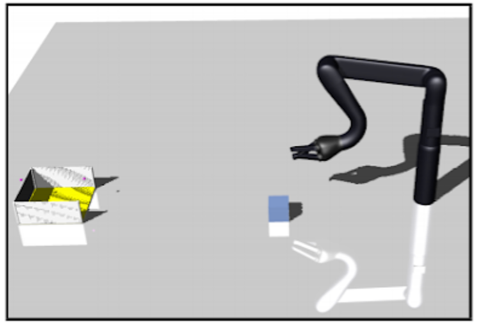
    $\theta \leftarrow \theta + \eta \nabla_\theta J$

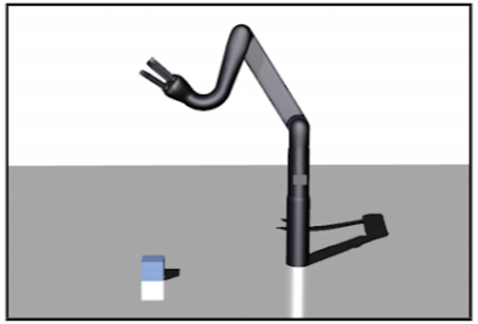
  end for

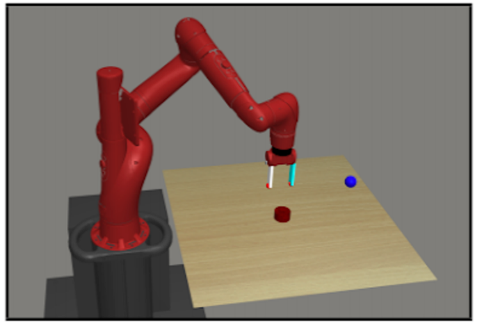
end for

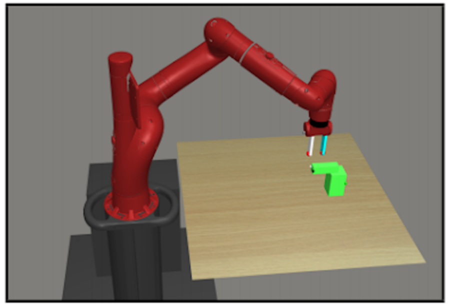
Results

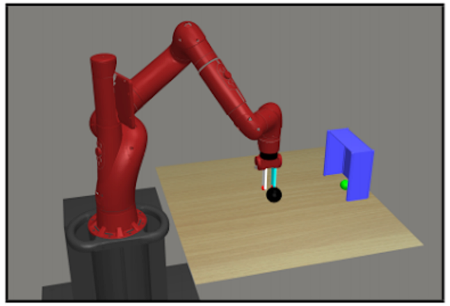
Reinforcement Learning

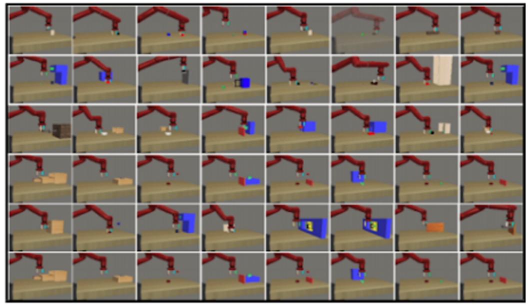

(a) Throwing


(b) Picking

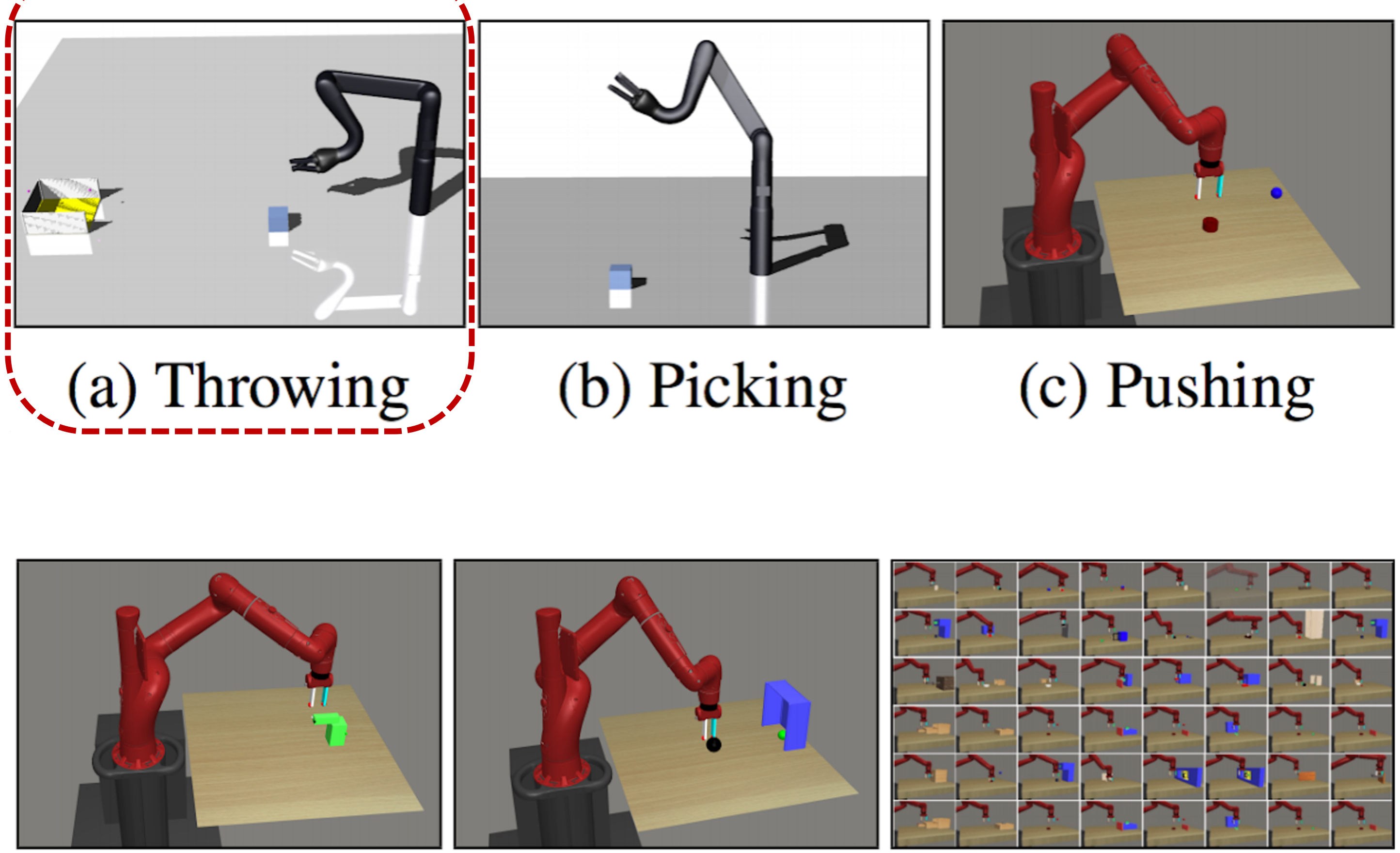

(c) Pushing


(d) Faucet Open


(e) Soccer


(f) 50 Tasks

Reinforcement Learning



(a) Throwing (b) Picking (c) Pushing

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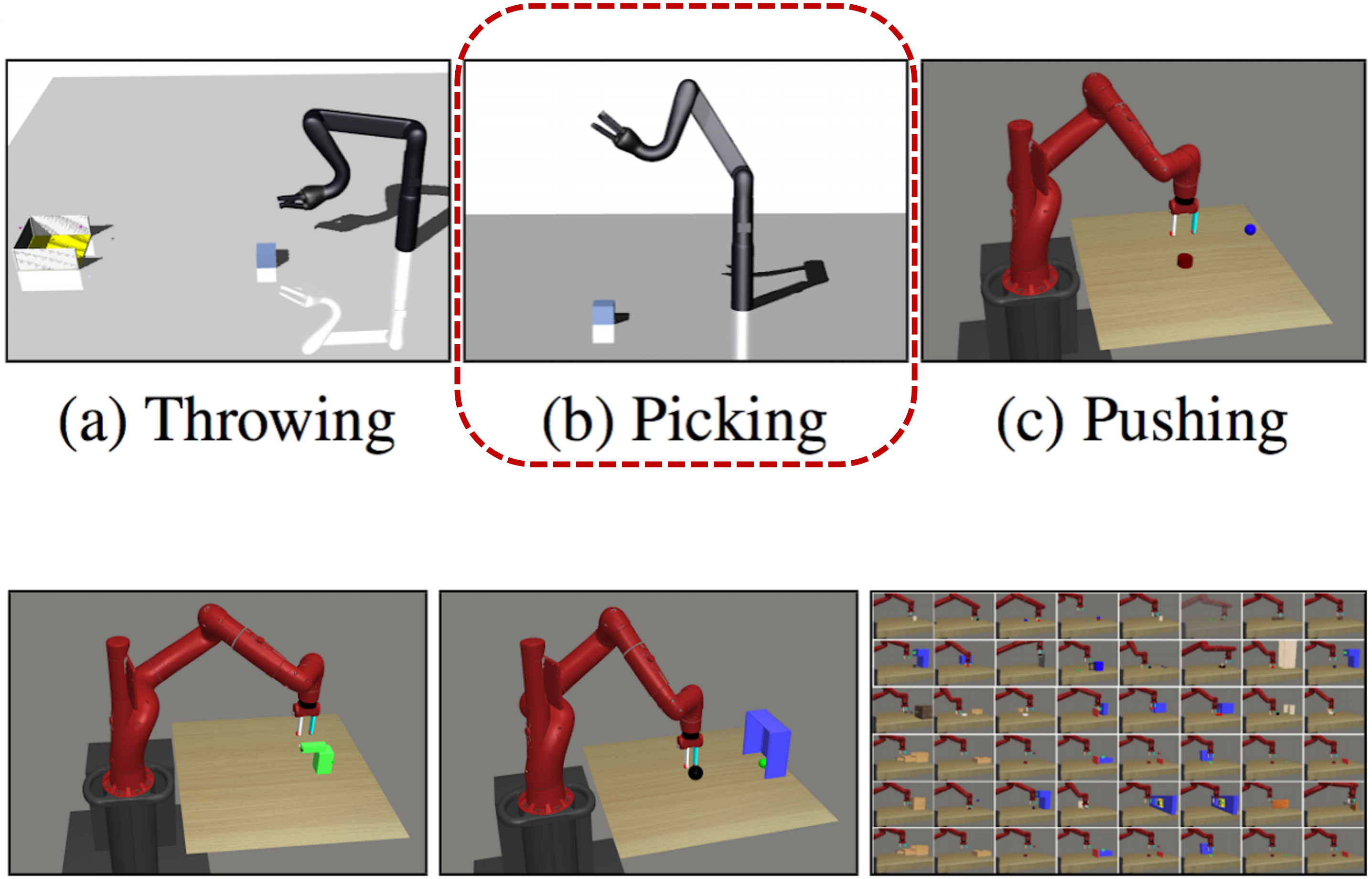
Reinforcement Learning



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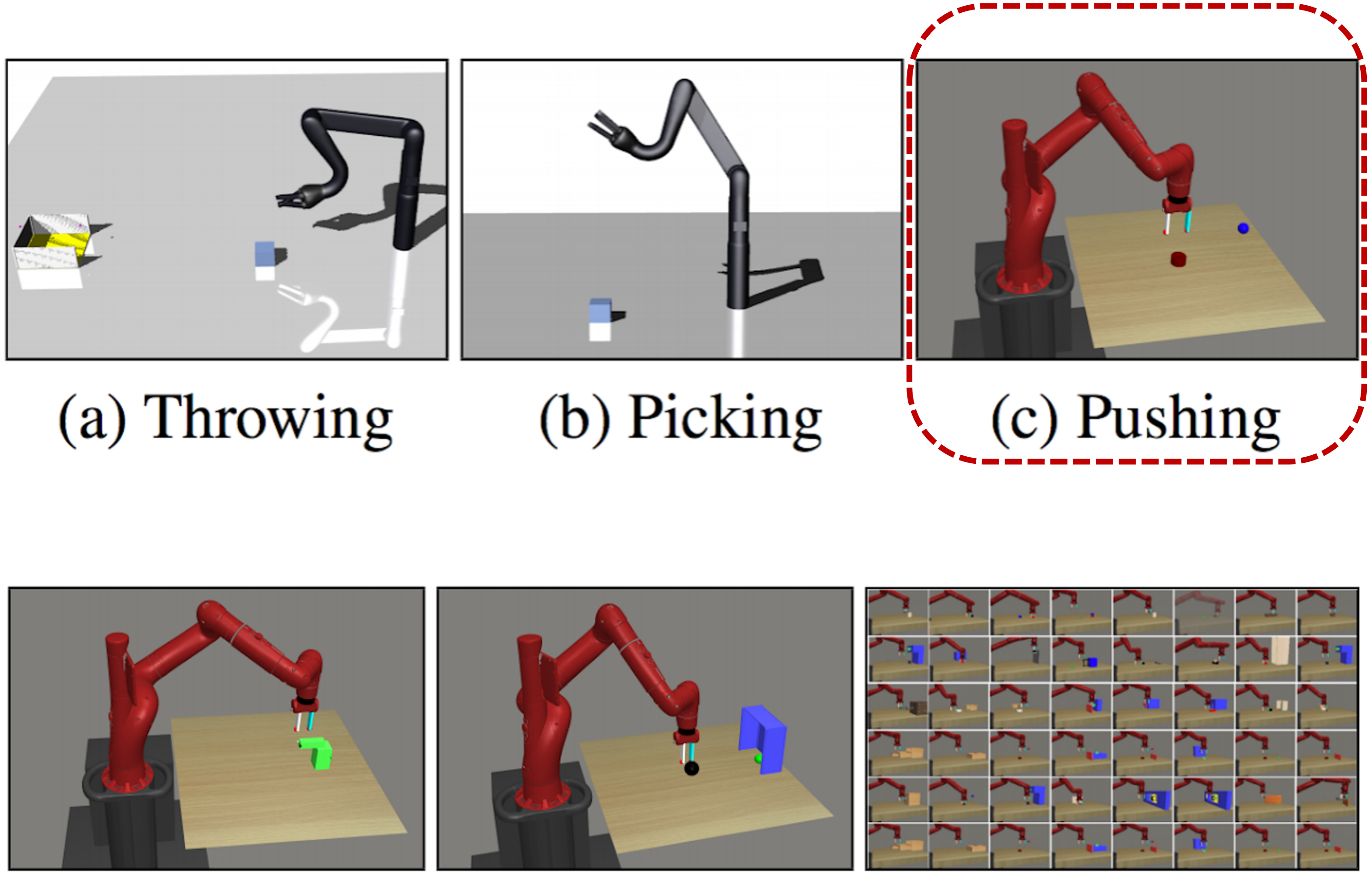

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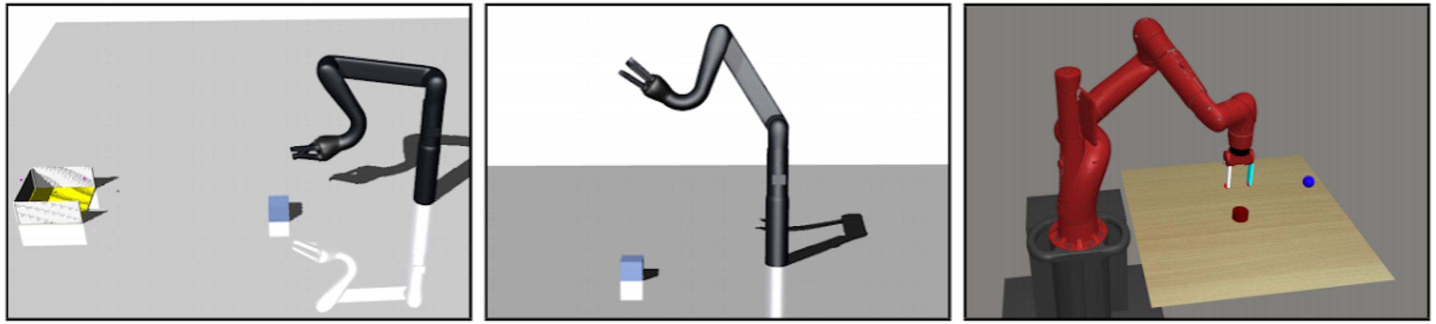

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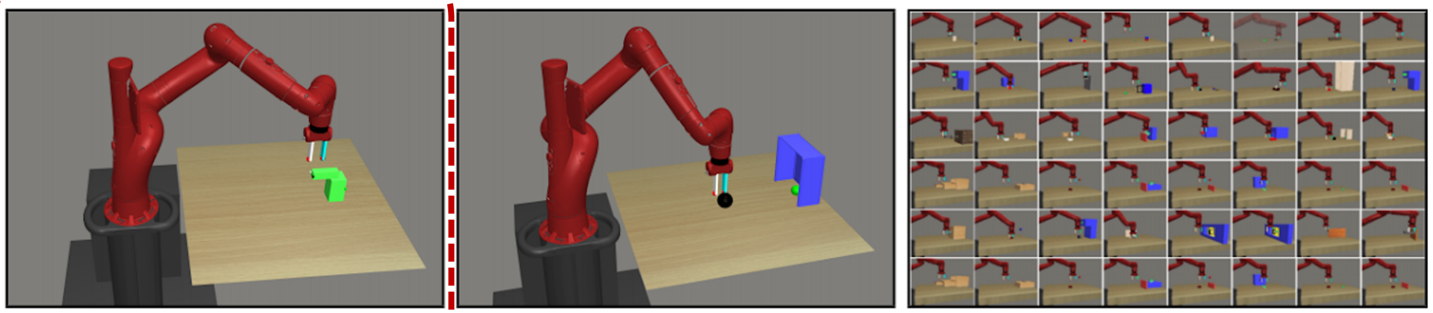

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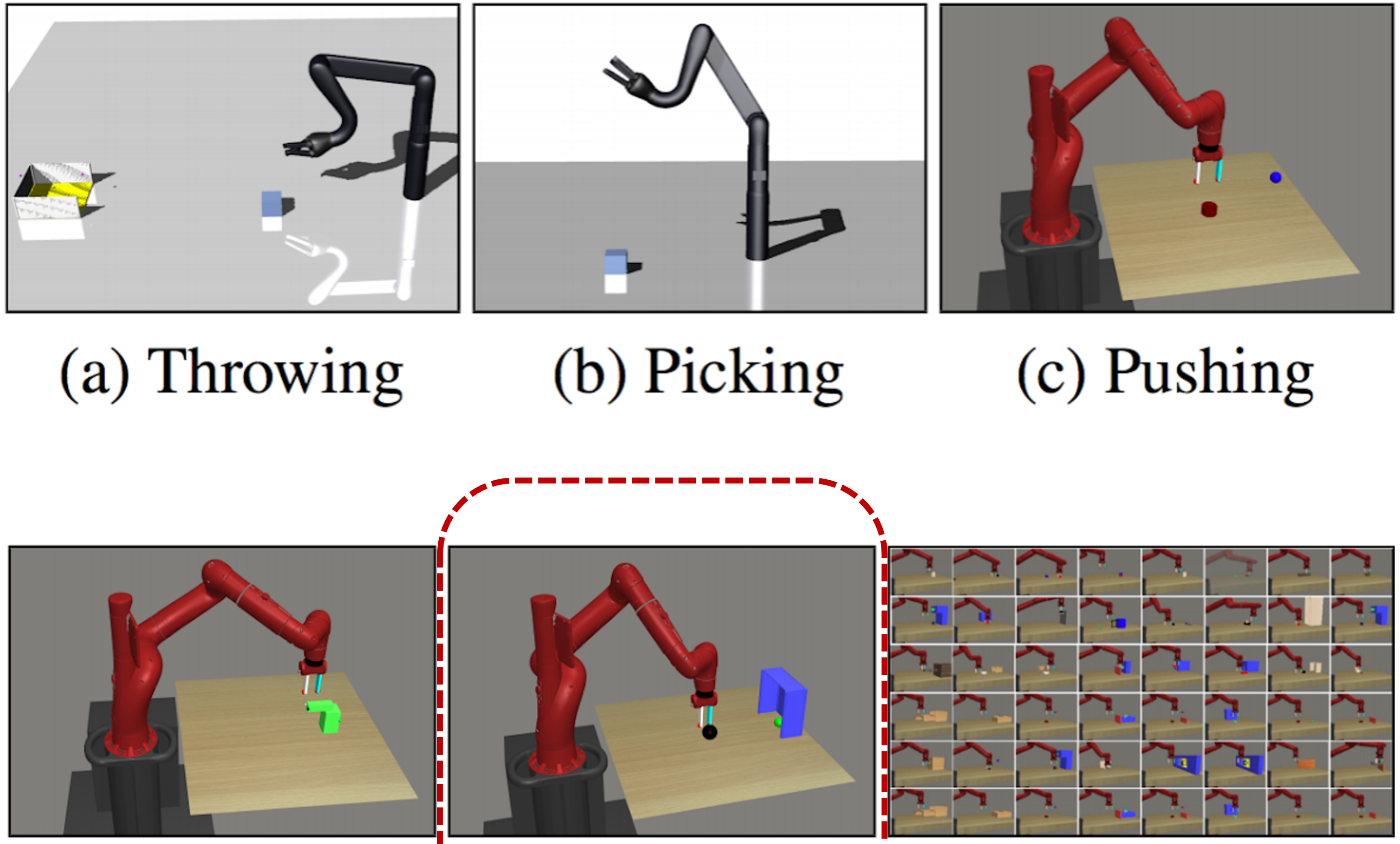

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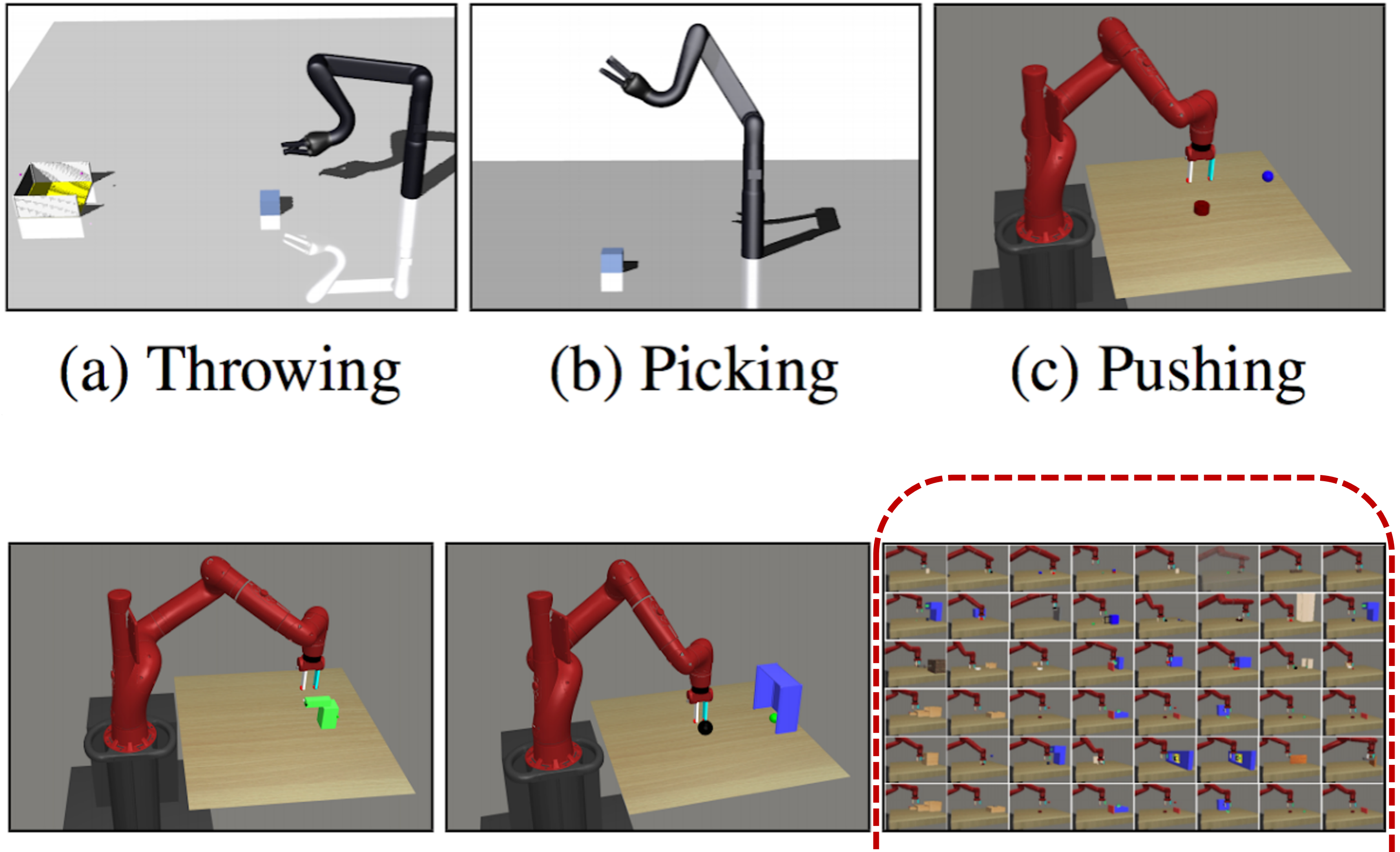

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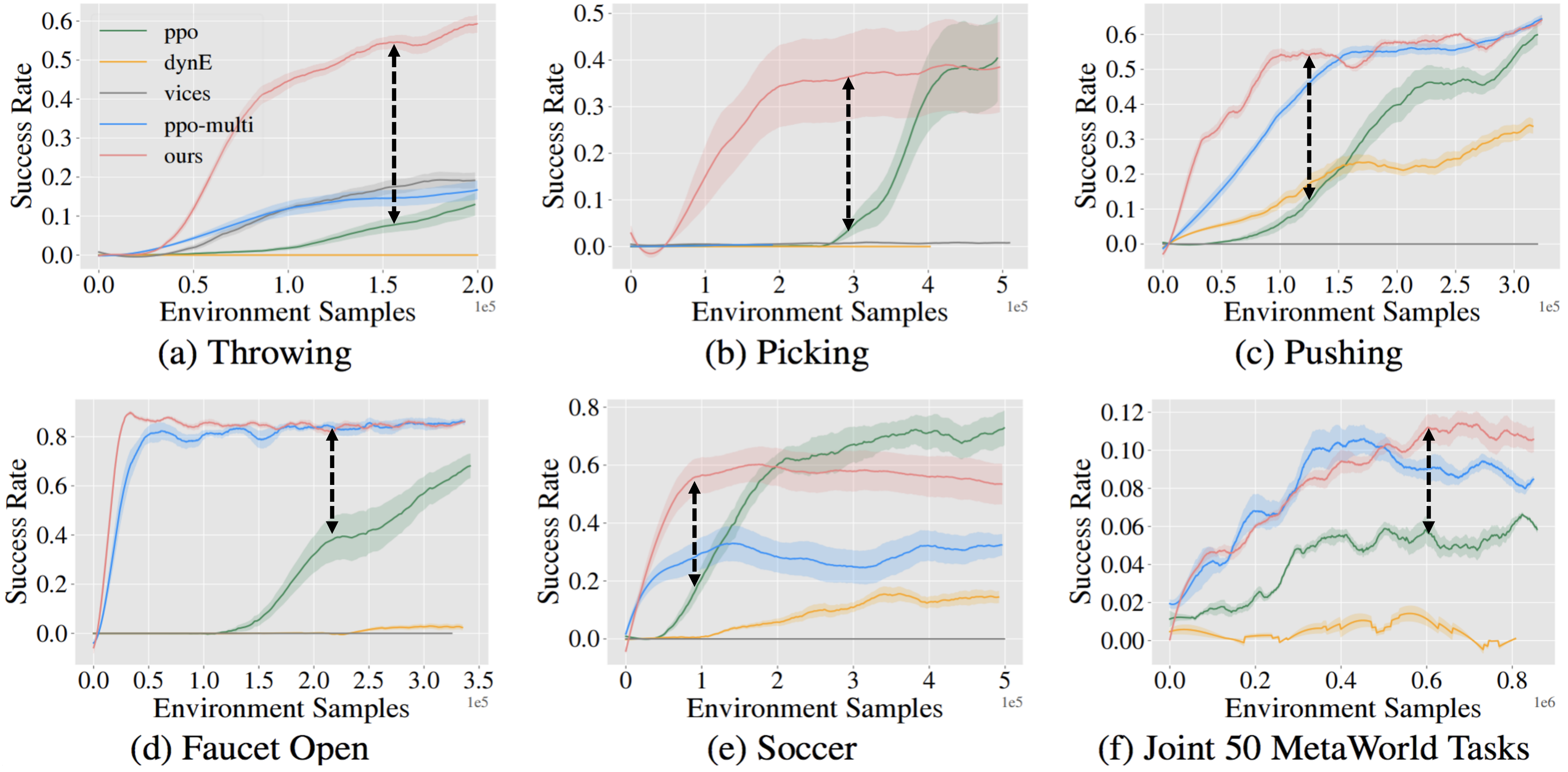
RL: Results



ppo
dynE
vices
ppo-multi
ours
Success Rate
Environment Samples
1e5
1e6
(a) Throwing
(b) Picking
(c) Pushing
(d) Faucet Open
(e) Soccer
(f) Joint 50 MetaWorld Tasks

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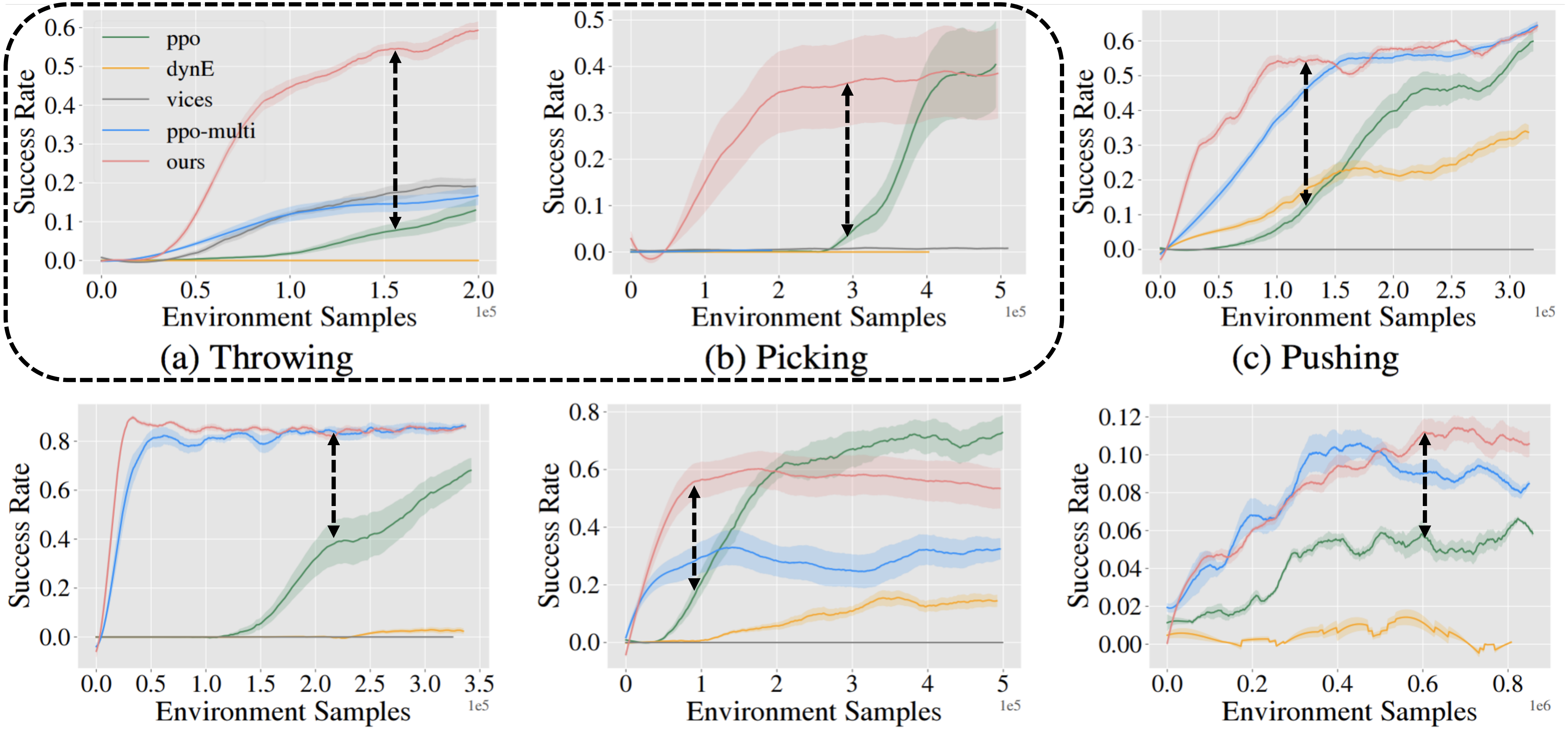

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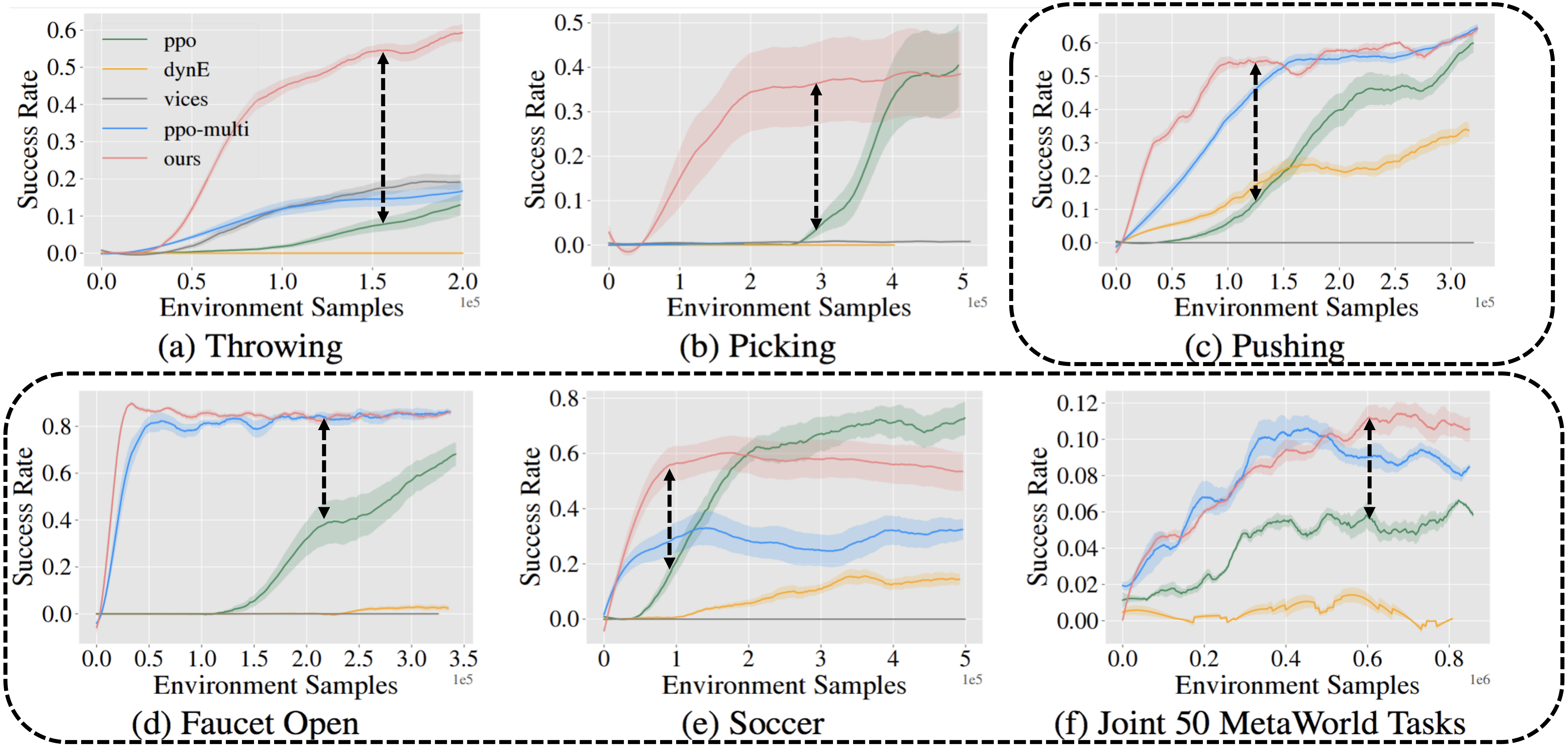
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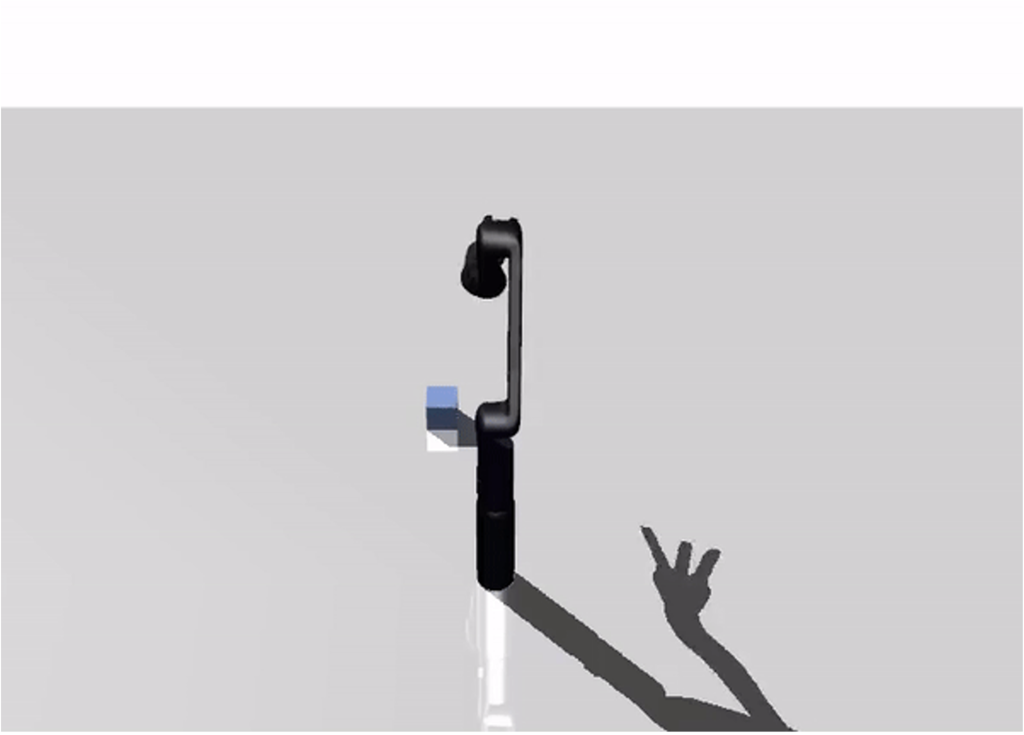
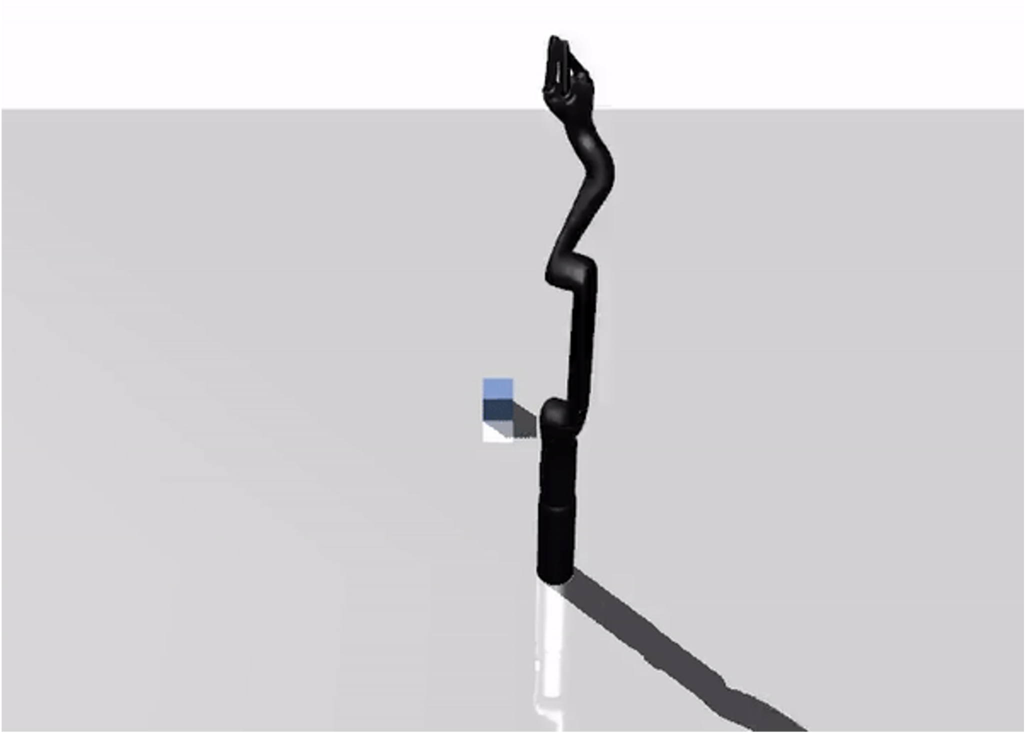
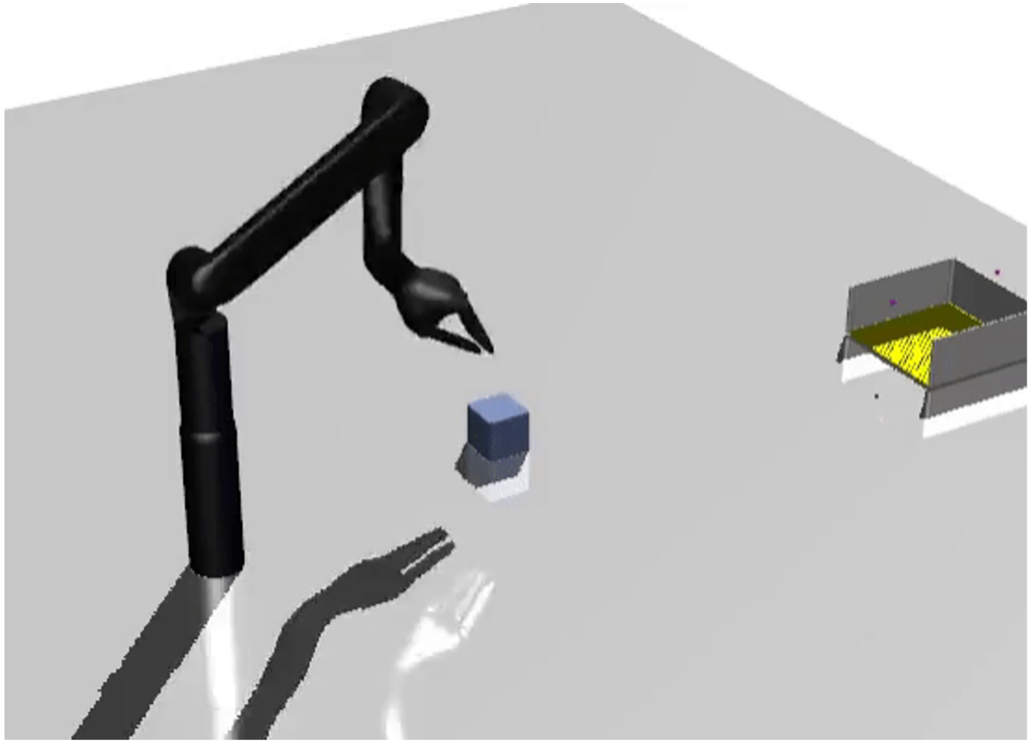
NDP (ours)



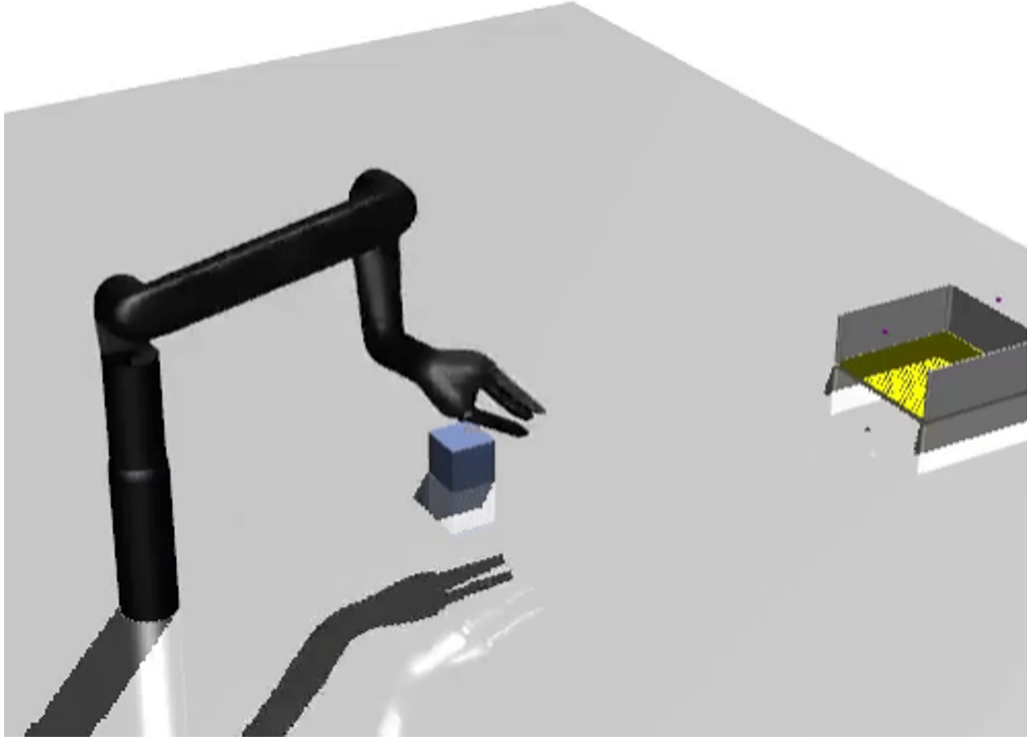
PPO-Multi (Baseline)



NDP (ours)

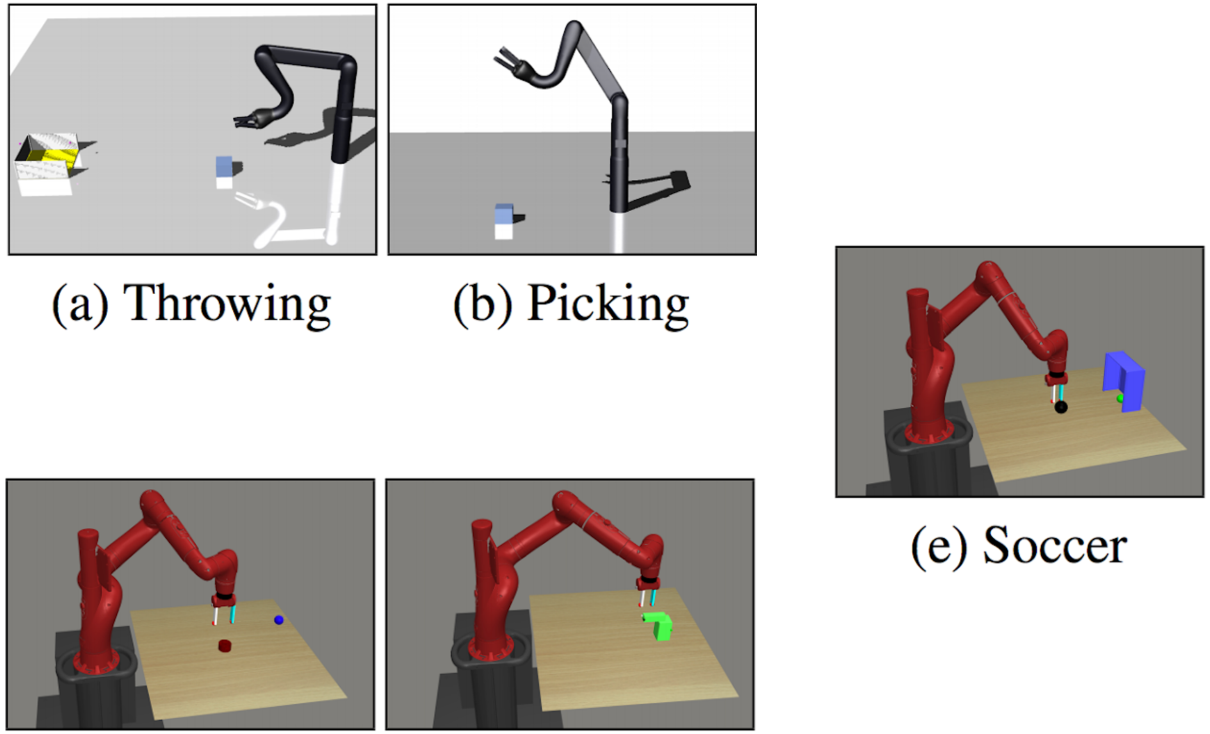


PPO-Multi (Baseline)



Imitation Learning

Method	NN	**NDP (ours)**
Throw	0.528 ± 0.262	$\mathbf{0.642 \pm 0.246}$
Pick	$\mathbf{0.672 \pm 0.074}$	0.408 ± 0.058
Push	0.002 ± 0.004	$\mathbf{0.208 \pm 0.049}$
Soccer	0.885 ± 0.016	$\mathbf{0.890 \pm 0.010}$
Faucet	0.532 ± 0.231	$\mathbf{0.790 \pm 0.059}$



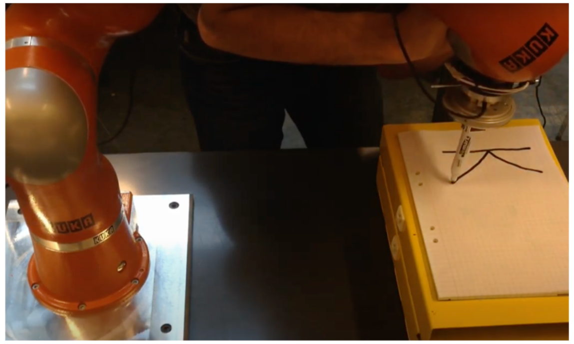
(a) Throwing (b) Picking (c) Pushing (d) Faucet Open (e) Soccer

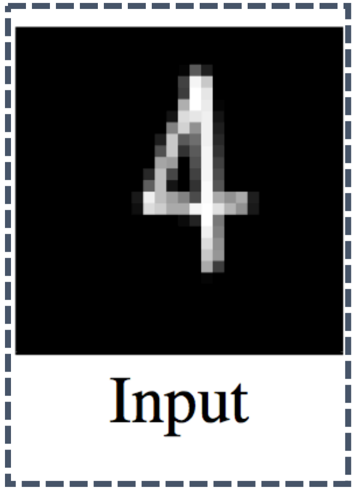
NDPs from Images

Digit Writing

Image of desired digit

Output: end-effector positions

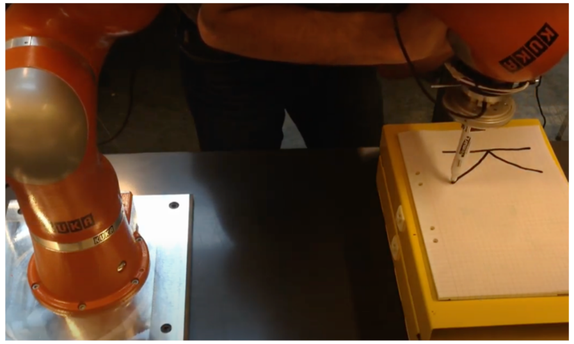


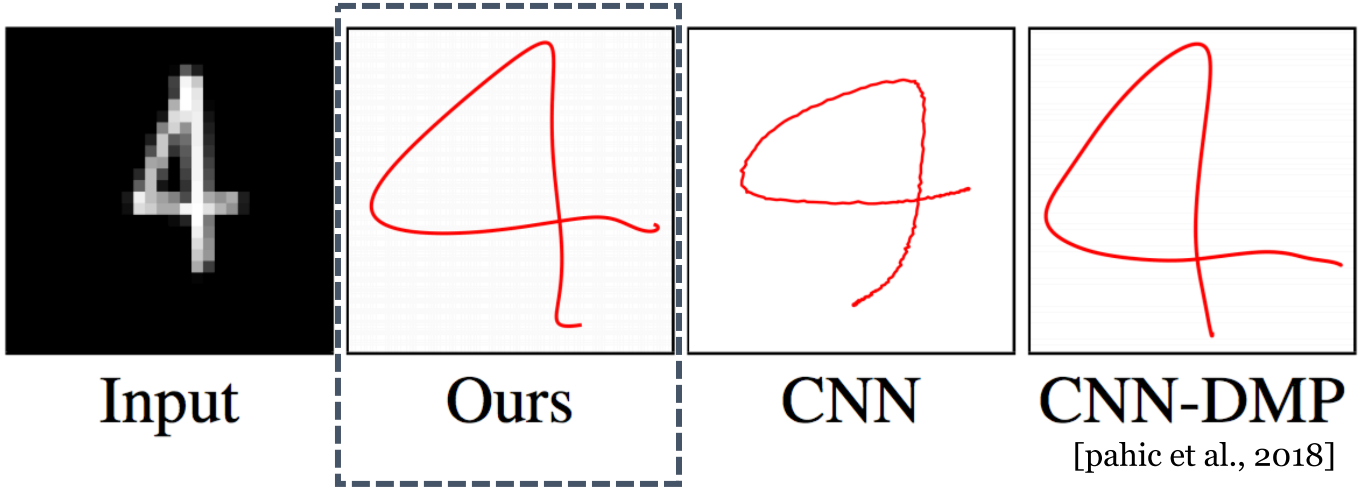


Digit Writing

Image of desired digit

Output: end-effector positions

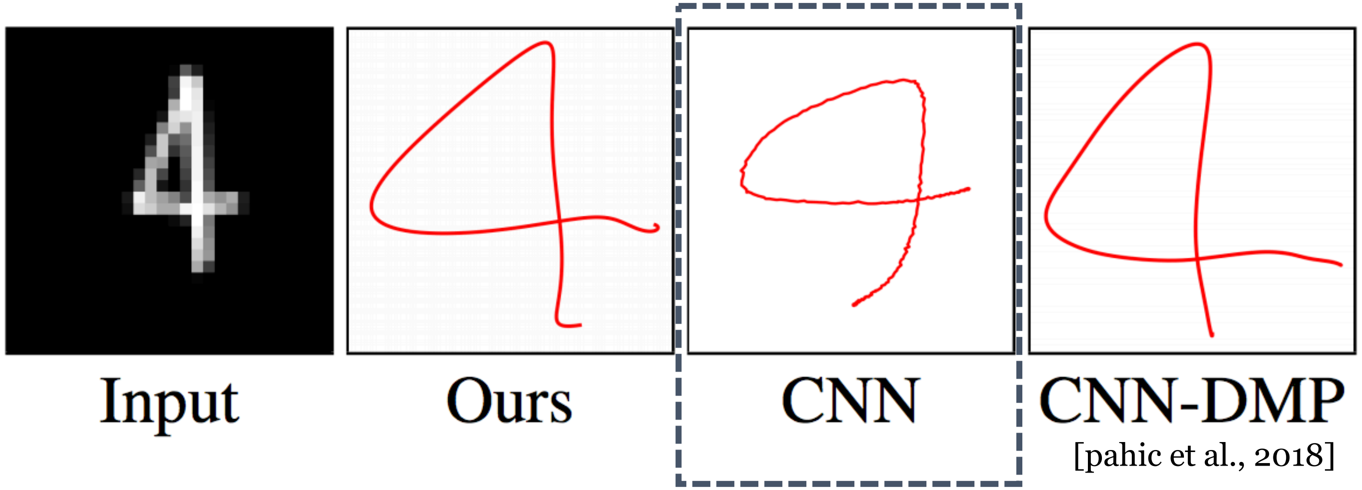


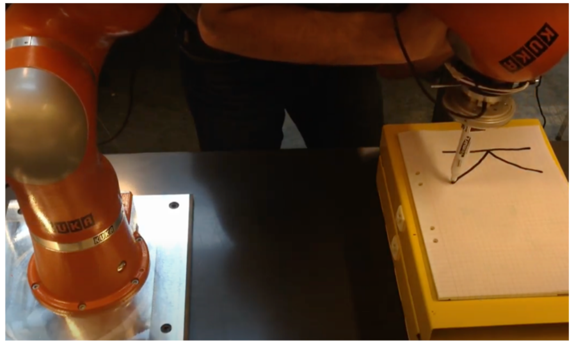


Digit Writing

Image of desired digit

Output: end-effector positions

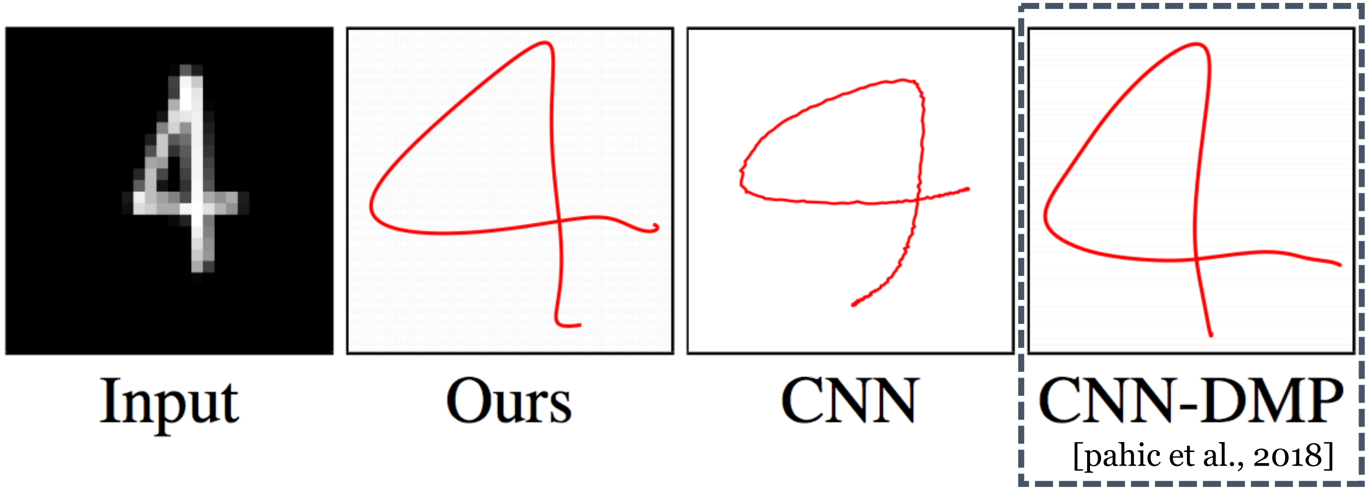


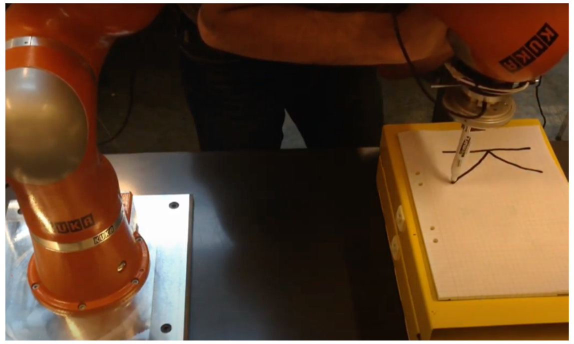


Digit Writing

Image of desired digit

Output: end-effector positions

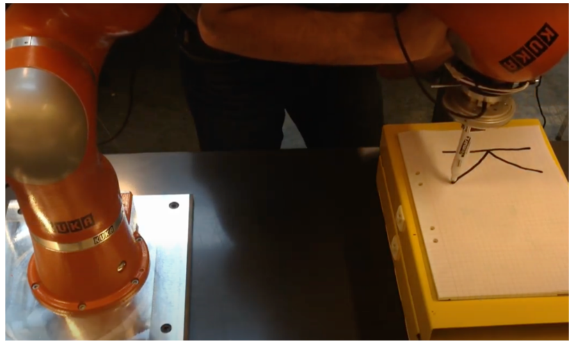


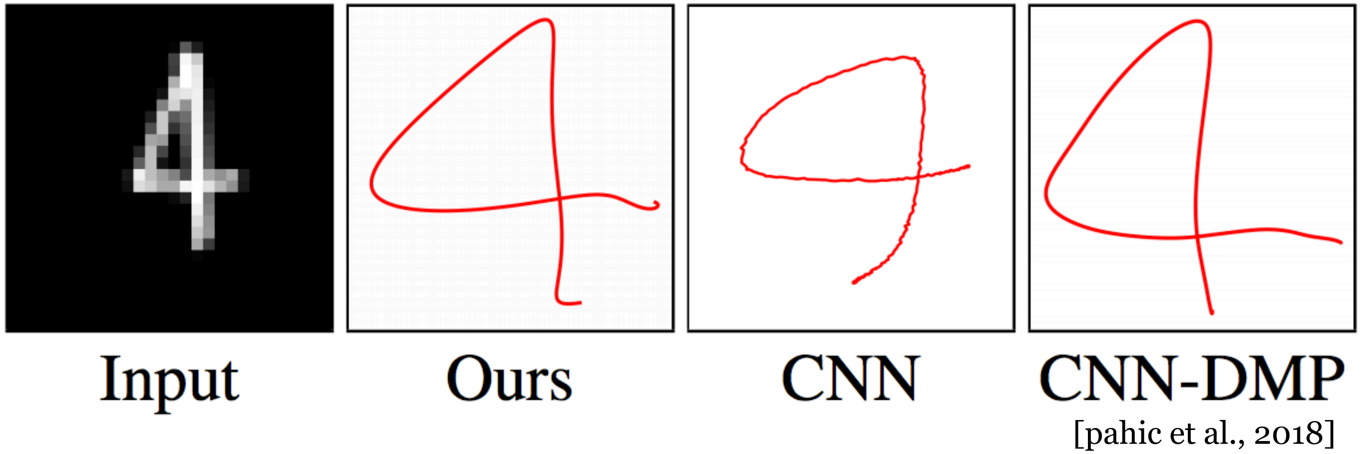


Digit Writing

Image of desired digit

Output: end-effector positions



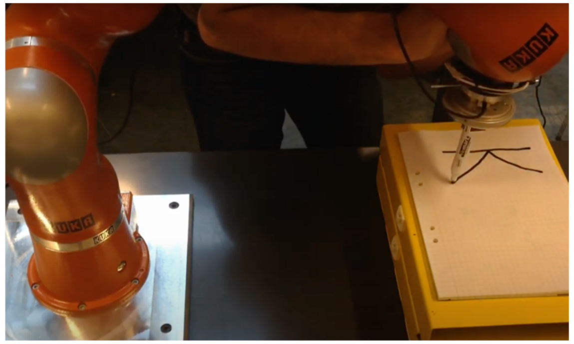


NDP has smoother and more accurate reconstruction

Digit Writing

Image of desired digit

Output: end-effector positions



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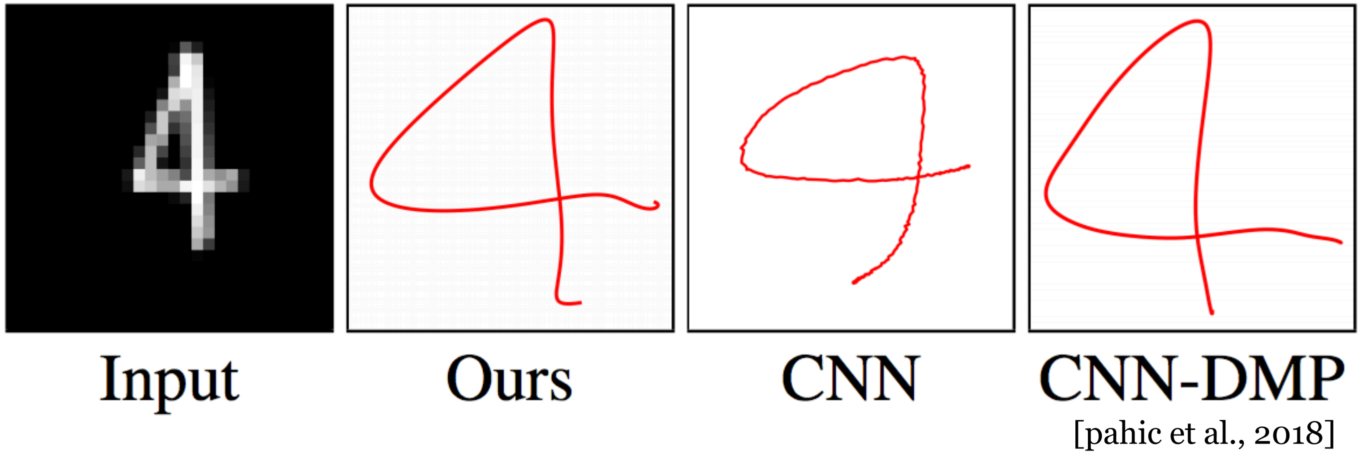
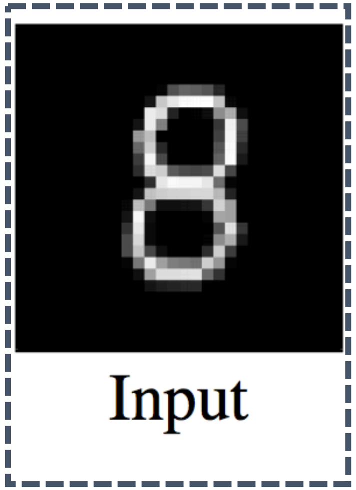
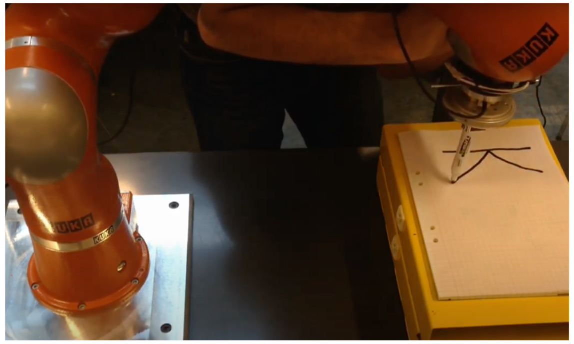




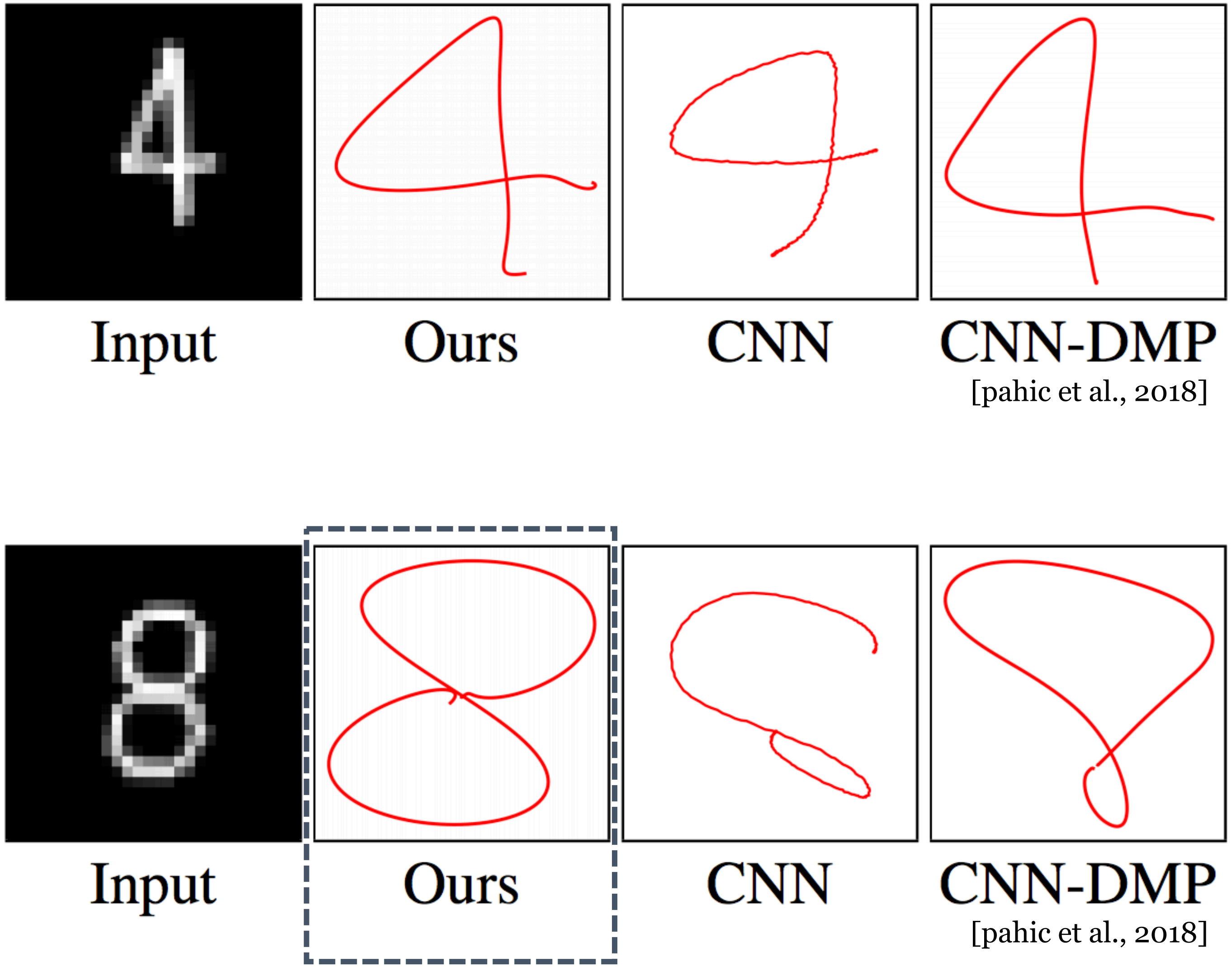
Digit Writing

Image of desired digit

Output: end-effector positions



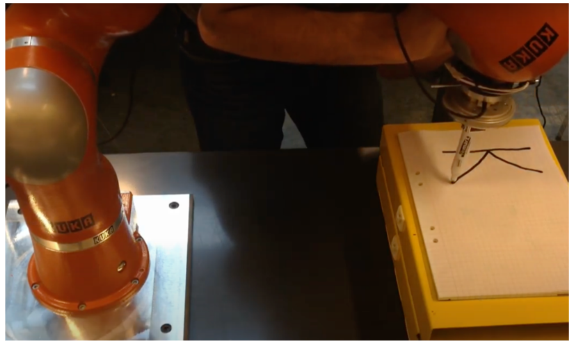
NDP has smoother and more accurate reconstruction



Digit Writing

Image of desired digit

Output: end-effector positions



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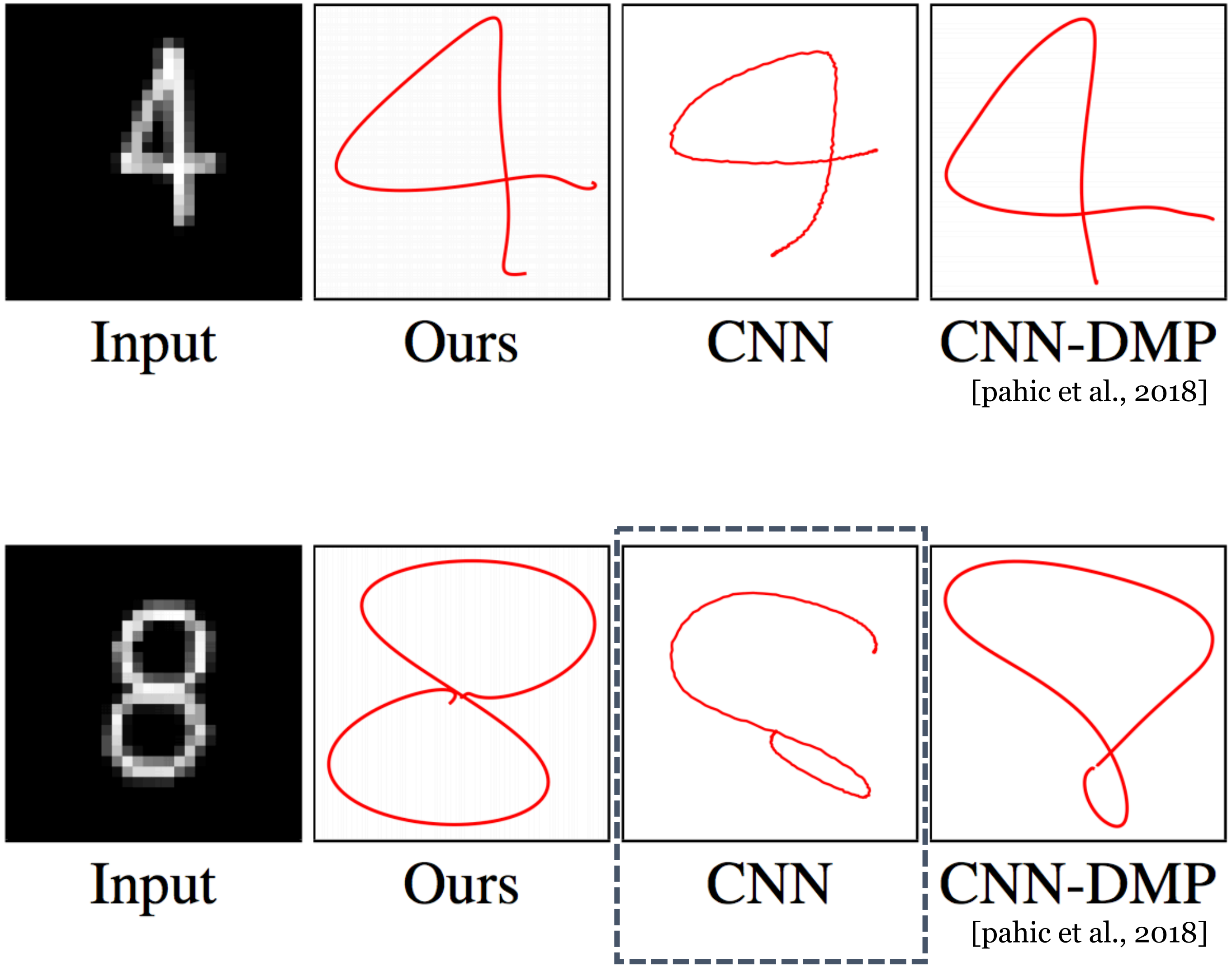
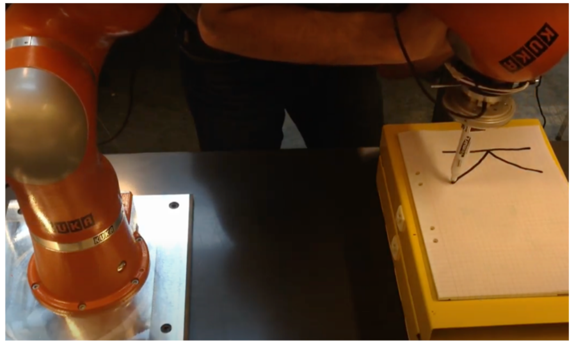


Digit Writing

Image of desired digit

Output: end-effector positions



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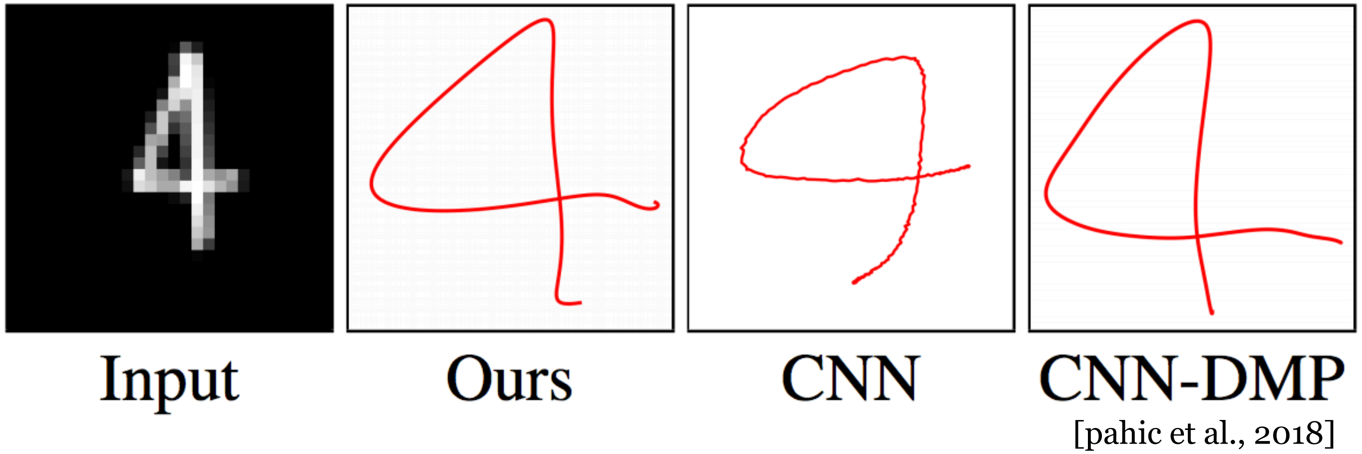
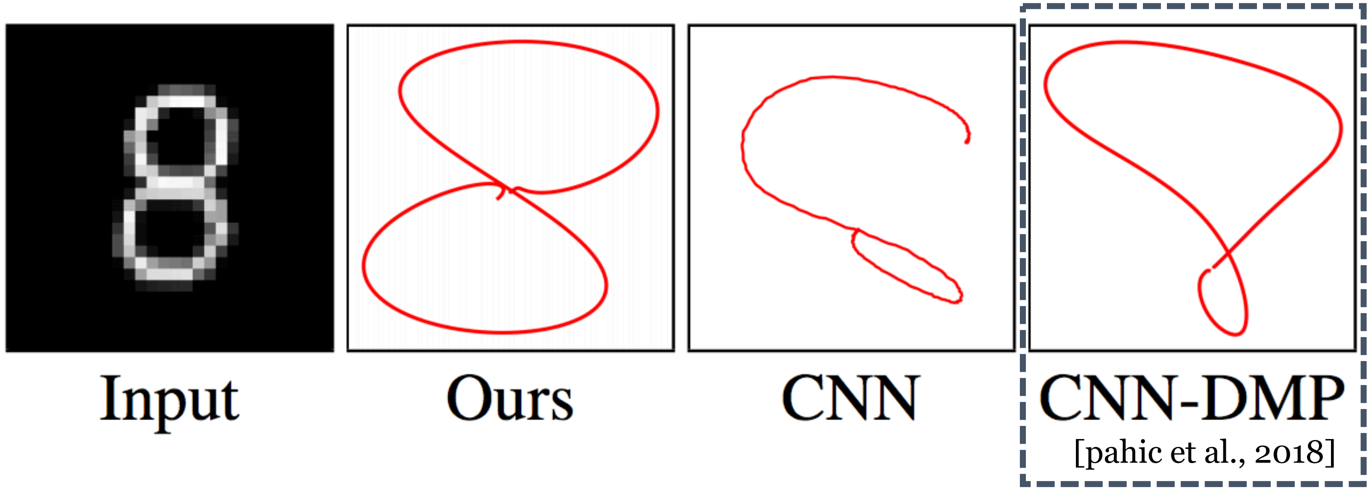




Summary

NDPs are modeled after dynamical systems in nature

Reason at a trajectory level + physically plausible paths

Keep advantages of deep learning (adaptability, learning from visual inputs, etc)

Can easily be integrated in end-to-end setups

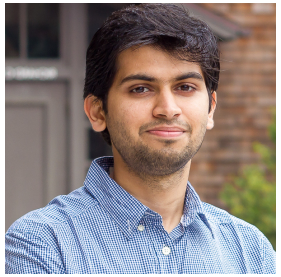
Strong performance in Reinforcement Learning and Imitation Learning, especially dynamic tasks

Thanks for Watching!

For paper and code:

shikharbahl.github.io/neural-dynamic-policy



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School of Computer Science