

HIERARCHICAL NEURAL DYNAMIC POLICIES

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How can we build *generalizable* policies for *real world dynamic tasks*?

Dynamical systems in robotics literature have been used to perform dynamic tasks (e.g. DMPs [Schaal, 2002])



[Moulling et al., 2013]



[Steinmetz, 2014]

DMP Structure

$$\tilde{y} = \alpha(\beta(g - y) - \tilde{y}) + f(x)$$

$$f(x, g) = \frac{\sum \psi_i w_i}{\sum \psi_i} x(g - y_0)$$

NDPs

NDPs [Bahl et al., 2020] embed DMPs in policy networks

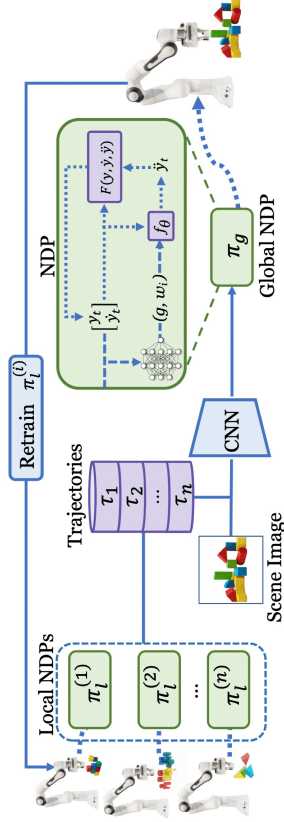
NDPs reason the space of trajectory shapes and goals

NDPs operate in a space of smooth & plausible trajectories

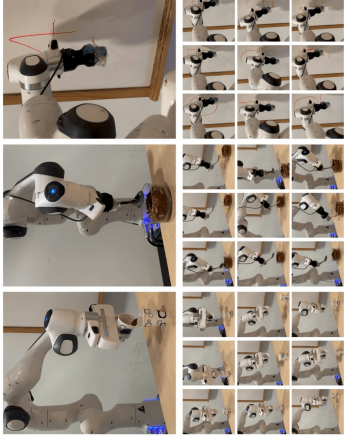
Single dynamical systems tend to overfit to single trajectories

How can we leverage dynamical systems to handle diversity in the task and handle unstructured data?

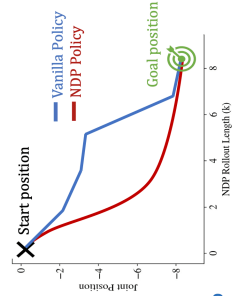
Local-to-Global Structure: Hierarchical Neural Dynamical Policies (H-NDPs)



- Train local NDPs on individual task regions from state space
- Distill into a global NDP that operates from raw images only



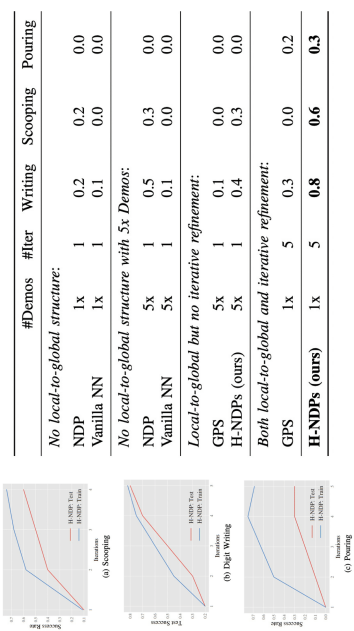
H-NDPs can perform *real-world* dynamic tasks from *raw images* only and *generalize* to novel settings.



For videos and paper!
<https://shikharbahl.github.io/hierarchical-ndps/>

Learning from Demonstrations

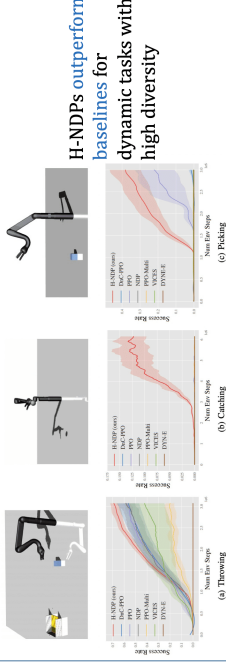
We perform a large scale, systematic evaluation in the real world



H-NDPs show strong performance against state-of-the-art baselines



Reinforcement Learning



H-NDPs outperform baselines for dynamic tasks with high diversity