Zero-Shot Transfer of Neural ODEs

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Function Encoders: A visualization





Zero-Shot RL via Function Encoders

Improving Accuracy with Neural ODEs

$$x_{t+1} = f_{\theta}\left(x_t, u_t\right)$$





Modeling a dynamical system with a MLP predicts the state *only* at discrete time points.

Modeling a dynamical system with a neural ODE predicts the state at *all* time points.

(H) $\boldsymbol{\theta} = \{\theta_1, \theta_2, \theta_3, \dots\}$ The set of possible hidden

Segment lengths, control authority, and friction are varied every episode. Transition dynamics depend on θ , e.g. $s_{t+1} = T(s_t, a_t | \theta)$

parameters is unknown

The induced dynamics function is observable each episode via data $\{s_t, a_t, T_{\theta}(s_t, a_t)\}_{t=1}^{H}$ Given data over many episodes, we can learn basis functions over the space of induced dynamics, where $g_i: S \times A \rightarrow S$

Small, online dataset

Future states of the episode

Given data over many episodes, we can learn basis functions over the space of induced dynamics, where $g_i: S \times A \rightarrow S$

Once we have learned basis functions, can we predict dynamics after collecting a small amount of online data?

Hidden-Parameter Dynamics Prediction w/ Neural ODEs

The Impact on Downstream Controllers

Example: A quadrotor carrying a package, where the weight of the package is a hidden parameter. The controller is using a learned model for model predictive control (MPC).

Learned Basis Functions and Transfer

Online Prediction

Context Representation

tyler-ingebrand.github.io/