Can Neural ODE learn correctly?

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In this talk, I will introduce Neural ODEs—a powerful framework that blends traditional numerical methods with deep learning by using them to define loss functions. One of the core applications of this approach is uncovering the underlying dynamics of a system from discrete observational data. For autonomous differential systems of the form $\frac{dx}{dt} = f(x)$, the key idea is to approximate the unknown function $f(x)$ with a trainable neural network. By numerically integrating this system, we can then measure the mismatch between model predictions and observed data at selected time points.

In the first part of my presentation, I'll explore structural aspects of the learned dynamics, with a focus on rotational behavior and emerging patterns. I'll compare one-step and multi-step integration methods, highlighting that while minimizing the loss function often yields promising results, it doesn't always guarantee an accurate representation of the system's true behavior. I'll share our insights and conclude this section by proposing practical criteria for choosing numerical integrators that better preserve the intrinsic structure of the original dynamics.

The second part will examine the influence of noise on model learning. I'll show how different noise levels can distort the inferred dynamics and compare the performance of models trained on noisy versus clean data.