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Research Statement

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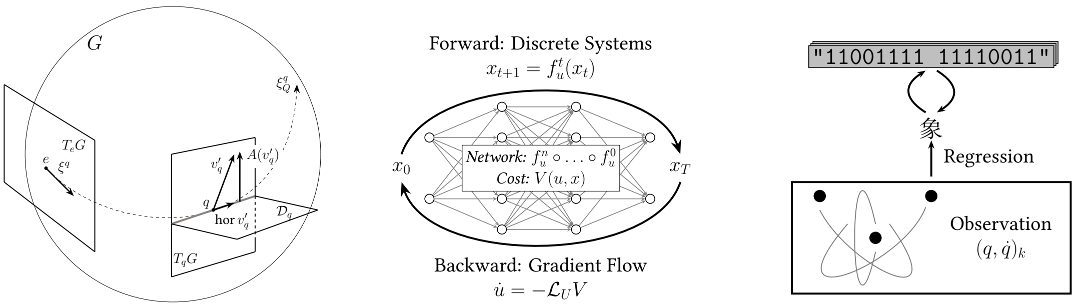
Most of my previous research experience has been in robotics, where I worked on projects involving mechanics, control theory, and dynamical systems. During this time, I also witnessed the rise of AI in almost every aspect enabled by the growth of computational power. Yet many modern AI models remain "non-transparent boxes" where we lack understanding. This motivated my overarching research goal: to bridge mathematical structures with machine learning, so that we can not only leverage the power of AI but also know why it works.

The first direction I am passionate about is *Physically Inspired Machine Learning*, which describes how dynamical systems can be learned from data inspired by theories of differential equations and geometry. This naturally leads to my second area of interest, *Neural Dynamical Systems* where I seek to incorporate geometric structures and dynamical system properties into network design. More generally, I outline additional open topics in the section *Future Research Directions*, where I welcome interdisciplinary collaboration. This include exploring how structure-preserving architectures can enhance engineering systems such as robotics, computer vision and language models, and investigate how logic and symbolic representations arise and interact within machine learning.



(a) Physically Inspired ML (b) Neural Dynamical Systems (c) Future Research Directions

Figure 1: My research interests in three parts.

Physically Inspired Machine Learning

My research background in robotics has provided me with significant insights into mechanics and dynamical systems. From mechanics of material [1] (my undergraduate research where we modeled the mechanics of a series of volumetric soft actuator), to Lagrangian mechanics (my undergraduate thesis in modeling and simulating an overconstrained legged robot based on Lagrangian mechanics), to computational dynamical systems [2]. In this work, I learned about how to represent the evolution of a system by discretizing the dynamics and over-approximate reachable sets with zonotopes, and then optimize and plan trajectories with constraints provided by obstacles. These experiences motivated my shift toward studying mathematical representations of physical systems.

So I took a further step into control systems, differential equations, and geometric mechanics. I developed my interest in understanding systems within the framework of differential geometry [3, 4], which also led to my interest in geometric machine learning. After studying *Nonholonomic Mechanics*, I became fascinated by the challenges that nonholonomic constraints pose in machine learning. Unlike constraints on the configuration space, they do not generate a Lagrangian submanifold. Motivated by this challenge, I conducted independent research on learning nonholonomic systems [5]. This work parameterized the unknown constraint of the system, rearranged the dynamics into Hamel's formalism, and trained the dynamics in a neural ODE fashion. The learned dynamics respects the momentum equation, and preserves symmetry over a chosen subgroup (Figure 1 (a) illustrates a nonholonomic system on Lie group G).

Looking ahead, I am interested in expanding this research, such as learning with discretized systems on the entire vector field [6], and developing systematic approaches to learning Lagrangian and Hamiltonian systems [7, 8], PDEs [9, 10], and systems with dissipation [11].

Neural Dynamical Systems

Another question of interest is, *if a neural network can learn a dynamical system, can a dynamical system represent a neural network?* As models scale up in size, this question becomes critical in interpretability, design and control. In our work [5], we incorporated Lie bracket structures in parameterized Hamel equations to describe systems that evolve on a moving basis, and proved that there is a local minimum for the training problem. I am interested in exploring more connections between the two subjects.

There are already different intersections. For example, if we look at the forward direction of a neural network, each layer can be represented by a flow f, the number of layers can be seen as a discretized time step, and the weights are control inputs to the function [12] (Figure 1 (b)). Early work has shown that stable structures such as symplecticity in *Residual Networks* are discovered by treating the network as a Hamiltonian system. There are also network designs that directly learn conservative systems [13, 14] using symplectic structures. More recent architectures, such as the *Transformer* network, can be interpreted as interactive particle systems [15]. Topological properties of deep neural networks were also found to parallel the differential-geometric *Ricci flow* [16, 17]. I am also curious to find out infinite dimensional geometric structure [18] in operator learning.

From a training perspective, weight updates in backpropagation generally take the form of gradient flow $\dot{u} = -\nabla V_u = -\mathcal{L}_U V$, where u denotes the weight of the network, and V_u is the loss. Therefore, one might ask how to design a network with the steepest gradient descent [19], with safety features [20], or a network that converges stably to its minima [21, 22]. Answering these research questions will help improve network efficiency.

Future Research Directions

Although the previous sections focus on theoretical questions, these ideas have numerous engineering applications. For example, with symmetry in deep learning, one can create an equivariant robot policy [23], a diffusion policy [24], an efficient reinforcement learning policy [25]. What network structures from the previous sections can we use to enhance efficiency and interpretability in *reinforcement learning*, *imitation learning*, or *vision-language models* is an interesting interdisciplinary research topic.

I have also maintained a strong interest in symbolic computation (Figure 1 (c)) (during my graduate research, I developed a symbolic dynamics program to compute robot dynamics for system identification). While working on learning nonholonomic systems [5], I realized that I was solving a symbolic question (finding the right equation) numerically (with neural network output dynamics). Indeed, not only math symbols are symbols, human languages are also symbols–evidence includes that words are usually represented by vectors in language models [26]; some purely symbolic attention models have demonstrated mathematician-like problem solving abilities [27]; some symbolic regression could help rediscovering physical functions [28]. We constructed our ideas through our languages and symbols, and we think in these symbols.

Therefore, I am curious to explore the potential relations between dimensionality reduction and symbolic representation [29, 30]. Furthermore, this research question can help to develop insights in neuro-symbolic schemes [31] in machine learning.

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