"I would love to incorporate deep learning into the design, manufacturing, and operations of our aircraft. But I need some guarantees."-an Aerospace Director while visiting Caltech

With the unprecedented advances of modern machine learning comes the tantalizing possibility of smart data-driven autonomous systems across a broad range of real-world settings. However, in high-stakes tasks such as robotic control in hazardous environments and health care, we must confront several key challenges before the widespread deployment of machine learning: (1) Real-world systems have complex and time-varying uncertainties, which require robust and adaptive learning methods. (2) High-stakes tasks need control-theoretic guarantees such as safety and stability, which require a framework to unify learning and control theoretical results. (3) In order to be useful, such a theory needs to enable tractable system design.

In light of these challenges, my research vision is to lay the groundwork for learning and control that enables the long-term autonomy of complex real-world systems, such as space exploration and medical robots. In pursuit of this vision, my research agenda is centered around **establishing a unified algorithmic and theoretical framework that can simultaneously reason over trade-offs in learning and control and using that theory to enable tractable system design to unlock new capabilities in autonomous systems**. The proposed unified framework supported by rigorous yet practical theory advances the state of the art in that complex problems can be simplified greatly in a modularized way, making it much easier to reason about high-level goals. To that end, my Ph.D. and future research have three goals spanning the entire spectrum from theory to applications:

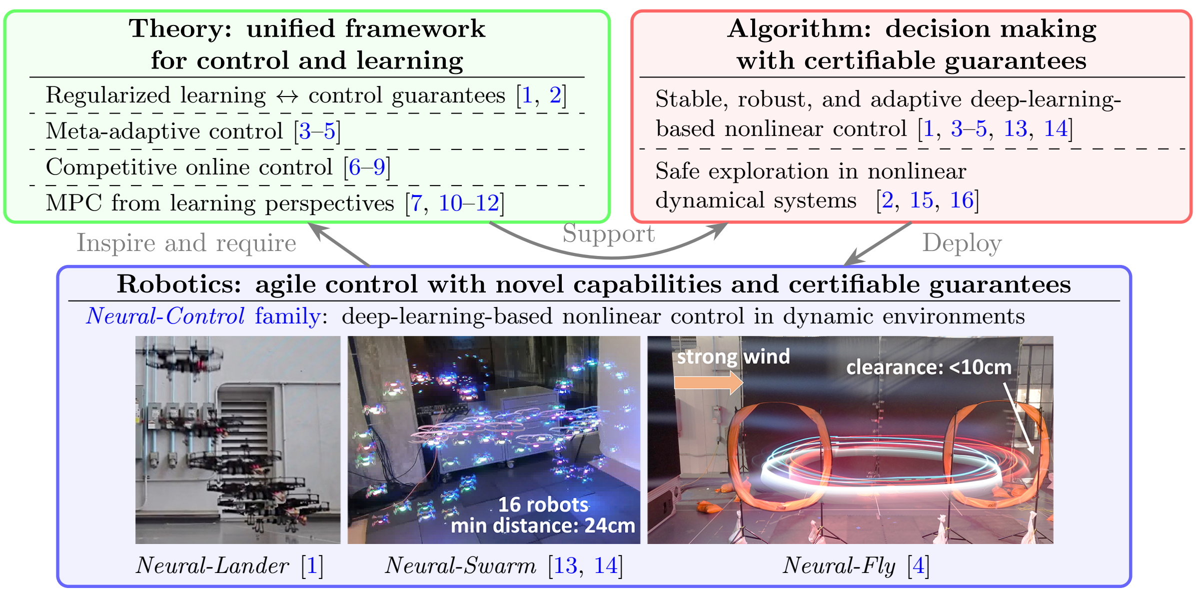

Figure 1: The connection between my three goals and an overview of my Ph.D. research.

Robotics: Agile Control with Novel Capabilities and Certifiable Guarantees

My Ph.D. focused on reliable agile robot control with new capabilities which have not been achieved by either pure control or learning methods. In particular, the *Neural-Control* family (Fig. 1) demonstrates state-of-the-art flight control performance in the presence of unknown unsteady aerodynamics. Beyond flight control, the *Neural-Control* idea has been successfully adopted by many other researchers (e.g., for legged, underwater, soft robots), companies, and national agencies, including JPL and DARPA. For the first time, *Neural-Lander* [1] enables agile maneuvers only a few millimeters from the ground; *Neural-Swarm* [13] enables close-proximity flights (minimum distance 24cm) of a heterogeneous aerial swarm (16 drones), while prior works have to keep a safe distance of 60cm even with 2-3 drones; *Neural-Fly* [4] achieves accurate adaptive tracking with an average error down to 3cm in gusty wind conditions up to 6m/s, which improves baselines by one order of magnitude. All these systems run Deep Neural Networks (DNNs) onboard in the control loop but with safety, stability, and robustness guarantees.

As depicted in Fig. 1, the connection between these robotic capabilities and the unified theoretical and algorithmic framework is two-fold: (1) The unified framework allows tractable, efficient, and safe real-world deployment due to its modularity and end-to-end guarantees. For instance, *Neural-Lander/Fly* only needs 5/12-minute training data. (2) Pushing the boundaries of agile robot control requires and inspires new unified perspectives on control and learning. For example, for agile maneuvers in time-varying wind conditions, we have to extract common representations shared by all conditions, which requires and inspires the novel *meta-adaptive control* framework [3, 4]. In the following sections, I systematically introduce the unified framework and illustrate why it is *necessary* and *sufficient* for unlocking new capabilities in real-world autonomous systems.

Theory: Bridge Learning and Control in a Unified Framework

My theoretical interests are driven by the quest for a unified framework to characterize and safeguard learned control systems. My work is distinctive in three ways. First, it studies how to integrate advanced concepts such as deep learning and nonlinear control, for which unified learning- and control-theoretic analysis is still in its infancy. Second, my work studies how to reconcile fairly fragmented analyses between the two fields (e.g., what does exponentially stable control imply about online regret?), which will deepen the fundamental connections and enable more efficient translation between the two fields. Third, my work allows tractable real-world implementations with novel capabilities.

From statistical learning with regularized DNNs to nonlinear stability and safety. From both computational and statistical standpoints, the learning methods must incorporate prior physics in real-world dynamical systems. For example, the *Neural-Control* family in Fig. 1 only learns complex aerodynamics which is hard to model using classic approaches. A central question in this diagram is how to leverage the structure in prior physics and translate statistical learning results to stability and safety results in control. In [1], I connected generalization bounds of properly spectrally regularized DNNs with input-to-state stability (ISS) bounds in nonlinear control. We found that poorly regularized DNNs without desired Lipschitz properties can cause drones to crash because small noise may destroy local stability. Together with domain shift experts, we then generalized this idea to sequential control problems, by connecting uncertainty bounds under domain shift with safety bounds [2, 16]. These results not only provide sufficient conditions for stable and safe learning-based nonlinear control but also enable roboticists to reason more cleanly between learning and control performance.

Meta-adaptive control. In order to have rapidly adaptable autonomous systems operating in changing environments (e.g., varying wind conditions for drones), it is crucial to extract common representations from all environments. However, existing theoretical results focus on either representation/meta-learning with i.i.d. data (i.e., no dynamics) or adaptive control in a single environment. Therefore, I proposed a novel *meta-adaptive control* framework, where meta-learning optimizes a representation shared by all environments. Then the representation is seamlessly used as basis functions for adaptive nonlinear control in low-dimensional space [3, 4]. *Meta-adaptive control* provides both new theoretical results (the first end-to-end non-asymptotic guarantee for multi-task nonlinear control [3]) and new capabilities in robotics [4], both beyond a simple stack of meta-learning and adaptive control.

Beyond no-regret: competitive online control. The recent progress in learning-theoretic analyses for online control begs the question: What learning-theoretic guarantees do we need for real-world systems? Existing results focus on linear systems with classic no-regret guarantees. However, no-regret policies compare with the optimal static controller in a specific class (typically linear policy class), which could be arbitrarily suboptimal in real-world nonlinear or time-varying systems [6]. Therefore, I proposed *competitive online control*, which uses stronger metrics beyond regret, i.e., competitive ratio and dynamic regret (competitive difference). Those metrics directly compare with the global optimum, thus naturally suitable for real-world systems. We have designed competitive policies in time-varying [6–8, 12] and nonlinear [8] systems, via novel reductions from online optimization to control. Moreover, we show new fundamental limits via novel lower bounds, e.g., the impact of delay [8].

Understand MPC from learning perspectives. Another critical question is begged in online learning and control: Do established control methods have strong learning guarantees? In particular, Model Predictive Control (MPC) has been one of the most successful methods in industrial control since the 1980s. However, many learning theorists are studying RL algorithms, but few are analyzing MPC and why it is so powerful. To close this gap, we proved the first non-asymptotic guarantee for MPC [10], showing that MPC is *near-optimal* in the sense of dynamic regret in online LQR control with predictable disturbance. Then we extended to settings with inexact predictions [11, 12] and LTV systems [7], in the *competitive online control* framework. These results found common ground for learning and control theory and imply fundamental algorithmic principles.

Algorithm: Reliable Decision Making Methods with Certifiable Guarantees

My algorithmic goal is to translate our improved theoretical understand (in particular, the established unified abstractions for learning and control) into tractable algorithms that inherit both the flexibility and accuracy of learning and the certifiable guarantees of control.

Stable, robust, and adaptive deep-learning-based nonlinear control. As a powerful yet obscure black box, deep learning must incorporate principled regularizations for reliable and tractable real-world implementations. First, I used Lipschitz-constrained DNNs to learn the residual dynamics, where the constraint is specified by the established unified framework between regularized learning and nonlinear stability. Such control-theoretic regularizations ensure the stability and robustness of deep-learning-based nonlinear controllers [1, 13, 14]. Our training methods also improve generalization to unseen data [1, 2, 13]. The second type of regularization for learning is *invariance*. In *Neural-Swarm* [13, 14], I leveraged the *permutation-invariance* of swarm dynamics to develop Heterogeneous Deep Sets for learning swarm interactions in a decentralized manner, which enables generalization from 1-3 robots in training to 5-16 in testing. In *Neural-Fly* [4], based on the *meta-adaptive control* framework, I proposed the Domain Adversarially Invariant Meta-Learning (DAIML) algorithm, which uses an adversarial regularizer to train a *domain-invariant* representation for online adaptation. These principled regularizations are critical for efficient and safe real-world deployment (e.g., Fig. 1).

Safe exploration in nonlinear dynamical systems. Safety-critical tasks such as space exploration and agile drone landing are challenging because (1) there is no expert collecting data, and (2) there exists non-trivial domain shift (e.g., sim2real, exploring to unseen states). Therefore, we have to quantify uncertainty and design safe learning and exploration methods. Built on the connection between uncertainty bounds and safety bounds in the unified framework, we proposed the first safe exploration algorithm with robust end-to-end learning and control guarantees under domain shift, in both deterministic [2] and stochastic [16] settings. The key idea is to derive uncertainty bounds from distributionally robust learning and use them in robust trajectory optimization. Collaborating with vision experts at NVIDIA, I also developed a fast uncertainty quantification algorithm for object pose estimation under sim2real shift, which enables safe and robust robotic manipulation [15].

Future Directions

My future work is centered around the end-to-end impact in autonomous systems: developing unified yet tractable frameworks which yield useful theory, practical algorithms, and novel real-world capabilities. Concretely, my future work includes the following thrusts.

General neurosymbolic learning for data-efficient decision making in complex environments. My Ph.D. research found that more data is needed as tasks get more involved (Fig. 2). *Neural-Lander* needs 15K data points (5-min flight) [1]; Moving to the multi-environment case, *Neural-Fly* needs 36K points (12-min) [4]; For the heterogeneous swarm case, *Neural-Swarm* needs 1.4M

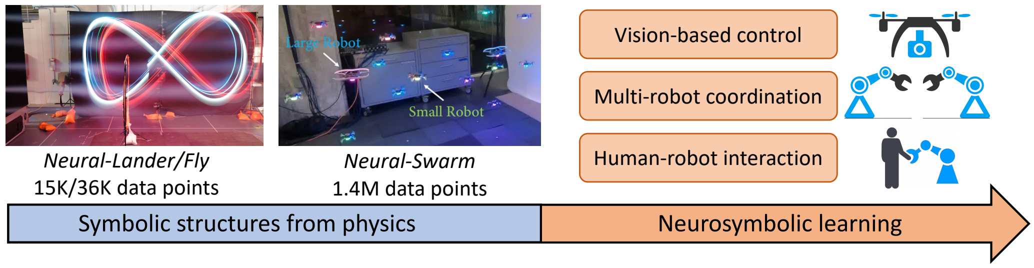

Figure 2: From my Ph.D. research to future research (more data required from left to right).

points [13]. One key observation is that **having symbolic structures in black box learning is critical for learning in autonomous systems.** For example, if we learn the full dynamics instead of the residual for drone landing, we need 1hour of data instead of 5min. Encoding permutation invariance and task invariance also greatly improves sample efficiency for *Neural-Swarm* and *-Fly* respectively. However, these structures are from physics and relatively straightforward to discover. Neurosymbolic learning is required when moving to more complex scenarios, including vision-based control, multi-robot coordination, and human-robot interaction (depicted in Fig. 2). For these settings, data is often very high-dimensional, and there is no clear symbolic prior such as the nominal dynamics in *Neural-Lander*. Therefore I am eager to develop a principled neurosymbolic learning framework that discovers symbolic priors from data and integrates these priors with control theory. For instance, in vision-based control, we can discover *causal* structures by learning a low-dimensional representation that causally relates to the control task, then integrating these structures with robust and optimal control theory. Another example is multi-robot coordination with uncertainty: consider three drones carrying a payload in strong winds. Drones need to share common information (e.g., wind effect) and negotiate potential conflicts (e.g., which drone moves first). We need to disentangle the shared and conflict parts and incorporate them using game theory and hierarchical planning.

Provably safe lifelong learning in real-world autonomous systems. As one of the most challenging open problems in AI, lifelong learning considers systems that can continually learn many tasks over a lifetime. Lifelong learning already poses several fundamental problems (e.g., catastrophic forgetting), let alone considering the safety-critical real-world setting (e.g., aircraft control with self-improvement over a lifetime). Note that my work *meta-adaptive control* [3, 4] can be viewed as a "one-shot" and supervised approximation of lifelong learning, where a representation shared by several tasks is learned first (with supervision) and then adapted by adaptive control. Towards unsupervised and continual lifelong learning with safety guarantees, my goal is to systematically address the following questions: How to distill knowledge from previous tasks without supervision? How to design an "event-triggered" mechanism to selectively and safely transfer the distilled knowledge to new tasks?

Theoretical foundations in learning and control. My research will continue investigating the intersection of learning and control theory, including: (1) Encoding control-theoretic knowledge to reinforcement learning. Most popular RL algorithms (e.g., TRPO, SAC) are *universal* for all tasks. In contrast, drastically different nonlinear control methods are developed for different systems/tasks, and their successes highly rely on structures inside these systems/tasks. I aim to encode these structures in RL algorithms in a principled manner. (2) Sample complexity analysis for nonlinear systems. Existing sample complexity results for dynamical systems focus on linear dynamics, but most real-world systems are highly nonlinear. Significantly more challenges appear from nonlinearity. For example, it is often intractable to characterize the closed-loop behavior of the optimal policy. My work serves as an initial step by considering LTV systems [7] and some particular classes of nonlinear systems [3, 8]. (3) Hierarchical and layered learning and control. Having different levels of abstractions is crucial for autonomous systems, but how to design each level in a data-driven manner is unclear. As an initial step, my work *meta-adaptive control* [3, 4] builds on a 2-layer structure. I plan to study general algorithmic principles and convergence properties in general multi-layer learning and control settings.

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