Recent years have witnessed a surging interest in deploying **real robots**, potentially leveraging **data-driven methods** in different real-world circumstances. Rather than virtual assistance like ChatGPT or DALL·E, using real robots would face significant challenges such as *stringent safety requirements*, *high robustness against uncertainty*, and *limited computational resources*. Developing a trustworthy autonomous system is key to enabling wonderful real robots like Mini Cheetah to operate reliably in challenging environments. Captivated by Isaac Asimov's robot novels from a young age, I've always wondered: ***Can we create real robotic systems that can move and interact with humans and environments stably, safely and robustly?*** To create such robots, we need to (i) develop hands-on expertise on **real robotic hardware systems**, (ii) develop **a trustworthy perception, planning, and control framework**, and (iii) potentially leverage **data-driven methods**, which are already quite successful in various applications in vision and language. Through my past, present, and future research, I want to answer this question.

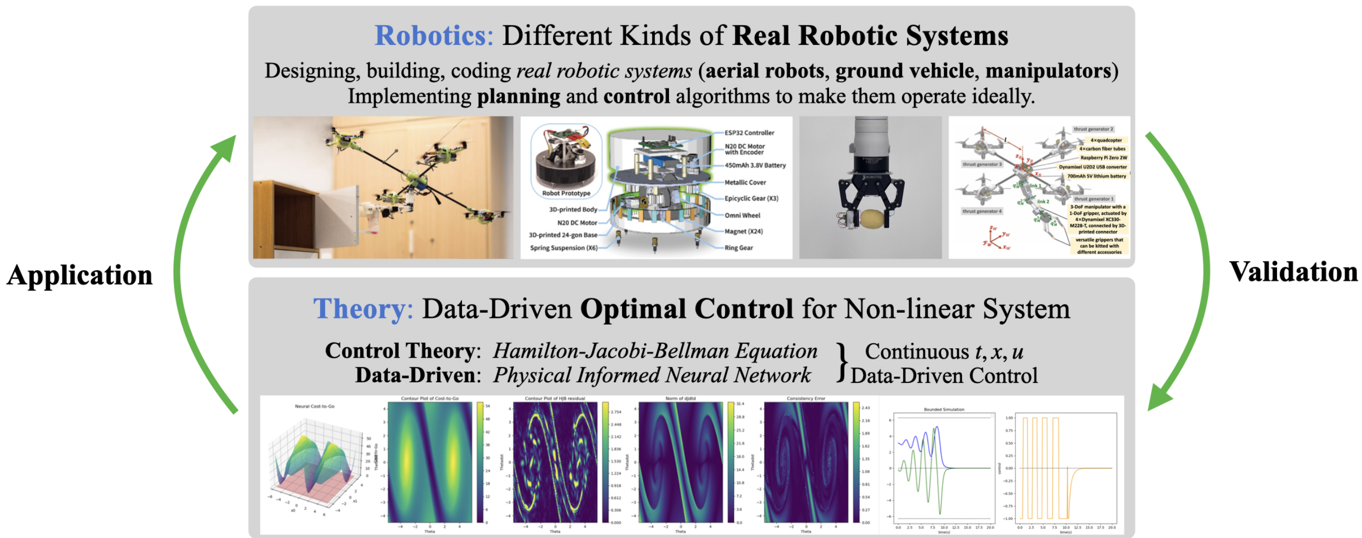

Figure 1: The connection between the two main parts of my undergraduate research.

My past research (shown in Figure 1) has done some exploration in answering this question, especially in domains of *real robots*, *control*, and *planning*. I worked as a research intern in robotics lab of the Chinese State Key Laboratory for Cross-Media AGI, led by Dr. Hangxin Liu and Prof. Song-Chun Zhu on various projects about **developing different real robotic systems, including *aerial robots*, *ground vehicles*, and *manipulators* in both hardware and software to tackle different tasks**. Regarding **aerial robots**, I led the project of *developing an unmanned aerial manipulator (UAM) system that could complete sequential manipulation in household environments interacting with articulated objects*. The UAM system consisted of an unmanned aerial vehicle (UAV) and an attached manipulator. To create a UAM system for such manipulation tasks, consider the size of the robot, the first thing is to improve the agility of the system for nimble maneuvers and expand its reachable workspace for interaction, where the underactuation of traditional multirotors became a significant bottleneck. To address this, I **designed and built *a novel overactuated UAM*** from scratch, using four omnidirectional thrust generators with 2-DoF passive gimbal joints to enable the system's capability of independently tracking position and orientation while maintaining high thrust efficiency. With this agile hardware system, the next problem was motion planning for sequential manipulation, where coordinated whole-body motions of both the flying vehicle and its manipulator are necessary, especially during interaction. Current planning frameworks for mobile manipulators fell short because they typically planned the motion of these two components *independently* rather than *in coordination*. To tackle this, I chose to **for the first time apply a *Virtual Kinematic Chain (VKC)* based motion planner on such aerial robot**, connected the flying vehicle, manipulator, and manipulated object, and conducted planning on this kinematic chain. Leveraging this representation, the system could alleviate unnecessary intermediate goals and improve coordination. After obtaining trajectories from the VKC-based planner, I **designed and implemented a *hierarchical control framework* for trajectory tracking**. Combining *feedback linearization* with optimization methods that exploited control redundancy to minimize the *downwash effect* caused by airflow, this approach achieved good performance in both simulation and real-world experiments. This series of work led to two papers at the International Conference on Intelligent Robots and Systems (IROS). The downwash-aware control allocation optimization was published in a paper at **IROS 2022**, and the whole UAM project won ***the Best Paper Finalist on Mobile Manipulation*** **at IROS 2023**.

In the **ground vehicle** project, I helped develop *a modular single-wheeled mobile robot (WMR) system* that could self-reconfigure to perform omni-directional movement and collaborative object transportation. I addressed problems of *hardware design and implementation* of the WMRs. The main challenge was *how to make WMRs successfully, precisely, and* *solidly dock and move collaboratively with transported objects*. I designed a structure with two separate parts connected by a planetary gear system. The docking mechanism was made of a magnet array, and other parts are also carefully designed to provide flexible moving capability and other functions. This work was published at **IROS 2023**. The **manipulator project** was about *tactile sensing*. In this project, I helped in designing and building an enhanced version of the classic GelSight sensor to acquire a better three-axis force sensing capability. I accumulated valuable experience in programming commercial manipulators and designing different experiments to validate the capability of the wireless sensor by integrating it on the gripper as the end effector. This work was published in Robotics and Automation Letters **(RA-L) 2023**.

I accumulated countless valuable hands-on experience in these **hardware-related robot projects**. These experiences have granted me invaluable insights that highlighted the safety, stability, and robustness issues of real-world applications. To make real robots operate robustly, stably, and safely, *a trustworthy perception, planning, and control framework is necessary*. Such challenges motivated me to delve into theory-based control. Since July 2023, I've started to work as a visiting undergraduate researcher in Boston at the School of Engineering and Applied Sciences (SEAS) at Harvard University, advised by Prof. Heng Yang. I worked on several data-driven control problems, one of them being **theory-based data-driven optimal control problems**. In most real robot control, *linearization controllers* are prevalent. However, not only are the parameters hard to tune, but in underactuated systems, these linear methods are theoretically challenging. Another way is using *trajectory optimization methods*, such as *Model Predictive Control (MPC)* or other shooting and collocation methods. Still, since I care about the case where the spaces of time, state, and control are all continuous, the (non-convex) optimization problem is challenging to solve. Aimed at designing *applicable and trustworthy control systems that could be deployed in real robots*, I took inspiration from the *Q learning algorithm* in reinforcement learning (RL). I chose to use a **neural network** to represent the *value function* (always named *cost-to-go function* in control communities) in continuous time as the solution to infinite horizon **Hamilton-Jacobi-Bellman (HJB) Equation**. By borrowing the idea of *physics-informed neural network (PINN)*, I used a neural network to solve this partial differential equation (PDE) and synthesize real-time controllers. One of the biggest challenges is the lack of boundary conditions. Since the boundary condition is undetermined, there are *infinite solutions* to such PDE. The **viscosity solution** is the only one that I want, but it is hard to reach through the "vanilla" training process. I designed different methods to regulate the training process, such as *semi-definiteness*, *values at the termination states*, and the *integration calculation* along the trajectories determined by the corresponding controller. I also used a valid controller (*e.g.* energy-pumping) as a heuristic and warm start to stabilize the training process towards the optimal controller. I obtained a reasonable approximation only using a *multi-layer perceptron (MLP)*, and the control performance is considerable. One significant bottleneck of this method is that the value function will become more non-smooth or even quasi-discontinuous in *control-saturated systems* (such as the spiral lines shown in the bottom of figure 1), so the preciseness and control performance of the neural network approximations would decrease. To tackle the problems in these cases, I'm working on using this data-driven method and the results as good initial guesses for optimization-based control such as MPC or integrating with other numerical PDE solving techniques and Pontryagin Minimum Principle to yield more precise approximations with certificates and facilitate the analysis of value functions of non-linear systems. Besides, I am also actively exploring combining continuous-time HJB training with discrete-time fitted value iteration to seek the guarantee of convergence to optimality in a subspace of the parameter, inspired by the success of representation learning.

In my future research, I wish to continue delving deeper into *creating trustworthy real robots that could assist humans and interact with environments, potentially leveraging data-driven methods*, aiming at realizing reliable and safe autonomy and freeing the hands of human beings. Specifically, inspired by my previous projects, I'm currently interested in **creating data-driven control and planning algorithms with safety and robustness guarantees and applying them to real robots**. My previous experiences have shown that optimality is difficult for learning-based approaches due to the underlying non-smoothness or quasi-discontinuity. Nevertheless, one step back from *equality* to *inequality* could be promising, notably given recent advancements in learning-based control offering *Lyapunov stability* or *Control Barrier Function safety* certificates and similar works towards *robustness*. Besides, recently several data-driven methods such as *Diffuser* and *vision-based control* have become popular in the robotics field, but further analysis regarding safety and robustness needs more attention to deploy on real robots. I'm excited about these and wish to design and finally apply trustworthy data-driven methods on different real robot platforms in challenging environments. My past experiences are comprehensive in different fields, equipping me with a versatile skill set that makes me well-prepared for various research opportunities. My extensive hands-on experience with real robots has not only honed my engineering skills but also provided me with a practical understanding of implementing and optimizing autonomous systems. I have also accumulated rich experience in the theoretical tools for problem solving, especially in control theory and using machine learning. I'm confident that this unique blend of practical and theoretical expertise can be instrumental and valuable in my future research and explorations. I hope to pursue a Ph.D. and continue to invesxtigate the creation of trustworthy real robotic systems that could interact with humans and environments, with the ultimate goal of becoming a lifelong researcher as a faculty in academia.