I grew up in an underdeveloped part of China, but fortunately, with several great teachers. My mother is a passionate math teacher in a junior high school, my grandmother was in an elementary school teaching Chinese literature, and my granduncle teaches electrodynamics in a college. Since kindergarten, they have been sharing their stories with their students with me. Such a family environment makes me firmly believe that education is the most critical enabler and catalyst of personal growth and social progress. To me, the role of teaching is three-fold: (1) Teaching can educate students on fundamental knowledge and skills which lay foundations in their careers; (2) Beyond lecturing skills, good teachers teach students learning methods and critical thinking such that every student can develop a unique and diverse way to influence the world; (3) As Richard Feynman said, "*If you want to master something, teach it.*" Teaching is not necessarily from teachers to students. Teachers should also learn from students by incorporating their feedback, new perspectives, and colorful ideas (see examples in my teaching and mentoring experience).

Teaching and Mentoring Experience

At Caltech, I was fortunate to have several opportunities to teach undergraduate and graduate students from very diverse backgrounds. I have been a teaching assistant for the graduate course *CS 165: Foundations of Machine Learning and Statistical Inference* (with Prof. Anima Anandkumar). In this course, I was responsible for not only regular TA tasks (e.g., grading homework and exams) but also developing recitation classes about foundations in probability, optimization, and linear algebra. I also helped students shape their course projects (some of them eventually appeared in top machine learning conferences). I have also been a guest lecturer for the graduate course *CS 159: Advanced Topics in Machine Learning* (with Prof. Yisong Yue), where I gave highly interdisciplinary learning and control lectures. These valuable experiences taught me the importance of solid foundations, diversity, and interdisciplinarity (see more discussions in my teaching philosophy).

I also had the opportunity to mentor six undergraduates (via Caltech SURF and WAVE programs) and three Caltech graduate students, many of whom are from underrepresented groups. Under my guidance, we have conducted research projects in machine learning, control theory, and robotics. Many mentored students continued research in various graduate programs (including MIT, Caltech, Columbia, and Stony Brook). One important lesson I learned from interacting with my mentees is that their diverse and novel ideas/perspectives are often complementary and extremely valuable for my research. For example, an undergraduate's game-theoretic view on online control plays a crucial role in our project (published at NeurIPS'20). Another undergraduate's great idea about how to visualize wind conditions in a wind tunnel also helped my agile drone control project (see a cool photo using his idea).

Teaching Philosophy

Building solid foundations to enable long-term careers for students. The benefit of building solid foundations and understanding fundamental concepts is two-fold. (1) Those foundations allow students to simplify complex problems in a modularized way, making it much easier to reason about high-level goals. When I taught *Foundations of Machine Learning and Statistical Inference*, I designed several recitation classes to help students recap concepts in probability, linear algebra, and optimization. Those concepts directly guided students in developing and sharpening their machine learning projects. (2) Those foundations allow students to understand the fundamental limits of complex methods. For example, in *Foundations of Machine Learning and Statistical Inference*, I used the Cramér–Rao bound to teach students the limit on variance for any unbiased estimators. In *Advanced Topics in Machine Learning*, I taught students the fundamental trade-off between robustness and performance for any controllers. Those fundamental limits help students ask pertinent research questions and avoid potential pitfalls.

Interdisciplinarity and diversity. One takeaway from my Ph.D. journey is the importance of viewing a problem through different lenses. In teaching (especially for interdisciplinary classes), it is critical to teach one concept from different perspectives and encourage students to study one subject in a diverse manner. For example, when teaching adaptive control theory, I will also introduce online learning perspectives. When teaching model-based reinforcement learning, I will also teach how optimal control literature addresses the same problem. A diverse set of research aspects enables students with different knowledge structures and backgrounds to exchange ideas, which often cultivates new research thrusts.

Student-centered teaching and mentoring. Teaching and mentoring should be student-centered from the following perspectives. (1) Everyone has a different and unique background, so it is essential to teach students in a specific and tailored manner with empathy. For example, when I mentored an undergraduate (with a strong background in game theory but little background in control) for an online control project, I designed a gentle curriculum for him to learn control theory and helped him connect the online control problem to game theory. (2) Incorporating feedback and listening from students/mentees is extremely important. Teaching has been an active and lifelong learning process for me. I have gained massive improvement from my mentees' feedback.

Teaching Plan

Standard learning, control, and robotics classes. I feel confident and comfortable teaching standard introductory or more advanced classes in learning, control, and robotics. For example, I can teach statistical learning, deep learning, and online learning. For control, I am interested in teaching linear systems, nonlinear control, optimal control, and adaptive control. For robotics, I can teach introductory robotics, kinematics/dynamics, and motion planning. A strong focus for these courses would be balancing "classic" and "modern" results (e.g., deep learning before and after the overparameterization era) and ensuring students understand fundamental concepts clearly.

Interdisciplinary learning and control classes. I am excited to develop and teach an interdisciplinary class that unifies control and learning. Based on my Ph.D. research experience, I believe I am in the proper position to teach learning experts control theory and vice versa. In particular, there are two types of such classes in my mind: (1) a course about learning-based or data-driven control and (2) a course about safe learning in autonomous systems. The goal is not only introducing machine learning advances to autonomous systems and/or introducing control-theoretic knowledge (e.g., safety/stability) to learning algorithms, but also deeply connecting fundamental concepts and theoretical results in learning and control. For example, how generalization bounds relate to control stability and how no-regret online learning connects to the convergence of adaptive control.

A project-based "Neural-Control" robotics class. My Ph.D. research shows that integrating both learning and control advances translated to new capabilities in agile robotic control (e.g., the *Neural-Control* family for agile flight control). Therefore, I am eager to develop and teach a novel (potentially undergraduate-level) project-based class focusing on "Neural-Control" in robotics. The goal is to encourage and advise students to apply state-of-the-art deep learning and control algorithms to real-world robotic systems (e.g., using the open-source Crazyflie platform). Moreover, I am looking forward to collaborating with faculty in areas such as human-robot interaction, perception, and network systems, to add more dimensions to the course.