

### Research Vision

Current methodologies in robot learning face two critical challenges that limit the capabilities of cyberphysical systems: expressing intentions as learning objectives (the intent-to-behavior gap) and maintaining controller behavior when moving from simulation to reality (the sim-to-real gap). These challenges are particularly acute in resource-constrained systems, where failures can lead to damage and where computational efficiency is paramount. My research introduces principled foundations for bridging these gaps through structured objective specification. By combining insights from programming languages, machine learning, and embedded systems, I enable practitioners to directly express their intentions while ensuring learned behaviors remains robust and efficient when deployed on real platforms—demonstrated through applications ranging from general-purpose robot control to state-of-the-art performance on racing quadrotors.

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### Research Impact and Current Work

**Foundational Sim-to-Real Transfer:** In RE+AL, my first research paper demonstrated the first RL-based controllers to outperform well-tuned PID controllers on real racing quadrotors. Building on this, my recent work on anchor critics allows for on-the-fly NN optimization, achieving near-50% power reduction while maintaining stable flights.

**Reliable Real-World Deployment:** Through CAPS (Conditioning for Action Policy Smoothness), I developed a general regularization technique achieving 80% power reduction while maintaining performance on real robots. This work has become a cornerstone reference in efficient reinforcement learning with over 80 citations.

**Efficient Control for Resource-Constrained Robots:** By breaking actor-critic symmetry, I demonstrated that neural network controllers can be dramatically reduced in size (up to 99% reduction in weights, averaging 77% across tasks) while maintaining performance, enabling deployment on heavily resource-constrained platforms.

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### Future Research Program and Impact

My research agenda focuses on establishing Expressive Reinforcement Learning as a new subfield bridging programming languages and robot learning. I am developing Algebraic Policy Specification (APS), a novel domain-specific language that generalizes traditional reward composition to enable direct expression of complex behavioral objectives. Initial results show a 600% improvement in sample efficiency compared to state-of-the-art methods. In the short term (2-5 years), I will create frameworks for composable reward specification that generalize across different robotics domains while maintaining computational efficiency. Long-term, this work will establish theoretical foundations for a new generation of robot learning systems that can faithfully translate high-level intentions into reliable behaviors.

I am committed to broader impacts through education and mentorship. My teaching experience spans core computer science courses, where I've developed innovative materials like PyBullet simulations for teaching control fundamentals. Through programs like AI4ALL and the F1Tenth Racing Team, I actively mentor diverse students while bridging academia and industry through open-source tools, ensuring real-world impact while fostering an inclusive research environment.