As optimization stands at the interaction of "human intelligence" and "machine intelligence", its great theoretical and practical impact endow us with unprecedented opportunities and challenges. With a solid foundation in mathematics and expertise in computer science, I am inspired to explore innovative algorithms to address real-world problems in dynamic environments. Driven by this passion, I hope to pursue a Ph.D. degree in Operations Research to develop efficient methods and push the boundaries.

As an undergraduate mathematics major, I have long been fascinated by optimization and its potential to tackle complex problems. This enduring interest deepened when I took graduate-level courses with Prof. Yinyu Ye and Prof. Ellen Vitercik at Stanford and earned the first-place grade in both classes. Immersed in advanced theories and their applications, I gained a rigorous understanding of dual algorithms and data-sharing models. This experience solidified my passion in optimization and motivated me to explore cutting-edge advancements.

Building on this foundation, I collaborated with Prof. Ye and Vitercik focusing on an online linear programming (OLP) problem for decision-making in resource allocation. Existing methods are constrained by time-consuming computations or low precision, resulting in cumulative delays and resource inefficiencies in real-world scenarios. To address these limitations, I developed an innovative two-path algorithm which introduced a feedback loop to periodically update the decision-making process with up-to-date online learning results. This novel structure kept the algorithm responsive to dynamic environments and adaptive to new information with reduced computational costs. It outperformed classic methods with 20-fold higher optimality and 100-fold speed increase. To analyze the algorithm, I delved into the latest literature to not only understand the mathematical derivations but also explore the shared intuition behind these analyses. I discovered that achieving optimal decisions required incorporating dynamic resource utilization into convergence analysis, while attaining efficient computation relied on iteratively refining solutions using gradient information. I adhered to these key insights as guiding principles to structure my analysis and ultimately constructed a cohesive mathematical framework integrating resolving and subgradient methods unprecedentedly. For the first time, I demonstrated our algorithm achieved a logarithmic regret, the best-known result in current OLP literature. With solid theoretical support, I established a "wait-less" online framework for decision-making and achieved an effective balance between decision optimality and computation efficiency, enabling users to set the optimality level based on the availability of their computational resources. We plan to submit this work to *Operations Research* soon.

Alongside my pursuit of online decision-making, I collaborated with Prof. Madeleine Udell to explore challenges in regularized empirical risk minimization (ERM) problems from modern machine learning. I focused on an ill-conditioned, non-smooth, and large-scale convex optimization problem, where existing methods suffer from slow convergence and substantial computational costs. To overcome these obstacles, I extensively explored recent works in ERM to pinpoint relevant techniques and quickly understand their key underlying principles. With this foundation, I developed a robust algorithm to balance optimality and non-smooth regularization. I leveraged sketching-based preconditioning for a low-rank Hessian approximation and designed a scaled proximal mapping to stabilize gradient updates. By analyzing how these techniques reduce stochastic variance, I constructed a comprehensive mathematical framework and demonstrated the linear convergence of our algorithm both locally and globally. In addition, I implemented the algorithm in a well-organized codebase with clear annotations, facilitating effective collaboration to extend it to a GPU-compatible version. Our algorithm surpassed commonly used methods, improving the convergence rate by 50% and achieving a 100-fold enhancement in optimality. This approach established an efficient and robust framework for ill-conditioned composite machine-learning problems involving lasso regressions and empowered users with the flexibility to select precision levels based on their computational resources. We intend to submit this work to *SIMODS* soon.

Beyond developing innovative mathematical frameworks, I have actively engaged in academic events by presenting my works and I am honored to receive recognition from the OR community. During my undergraduate studies, I collaborated with Prof. Asaf Cohen on a machine-learning-driven optimization problem. I developed a Deep Galerkin Method (DGM) to tackle the mean-field control problem, leveraging neural networks to approximate optimal solutions for high-dimensional non-linear PDEs and demonstrating robust adaptability to dynamic environments. I gave a talk at the departmental REU summer research seminar and aroused great enthusiasm of peers and faculty. We further proved the numerical approximator achieved a uniform convergence to the true solution. With these achievements, I was selected to present this work at the INFORMS 2024 Annual Conference in Seattle, where our approach sparked substantial interest among attendees and inspired insightful discussions of practical extensions.

These valuable experiences refined my understanding of optimization and cultivated my ability to identify an impactful problem, grasp valuable ideas, and turn it into systematic research. As my career goal, I hope to explore how advanced mathematical skills and modern machine-learning techniques could revolutionize optimization theories and their applications to unlock new possibilities for solving complex real-impact problems. Specifically, I am interested in developing robust frameworks for large-scale optimization, decision-making under uncertainty, and machine learning models to improve the efficiency and welfare of society. These pursuits strengthened my determination to become a researcher in the future. In the long term, I aspire to develop my own understanding of optimization as a researcher in OR community and contribute to broadening its impact across a wide range of areas.