"I am passionate about improving and expanding human life by establishing theoretical foundations and offering faithful real-world solutions in sequential decision making and data science."

As scientific and engineering disciplines are increasingly driven by unprecedentedly massive amounts of data, data science is becoming a cornerstone in expanding human life and societal benefits. One intrinsic bottleneck is that data acquisition is limited due to expensive, time-consuming, or high-stakes concerns. Consequently, *sample efficiency* becomes an imperative principle in method design, particularly in a multitude of *sample-starved* application scenarios such as healthcare, robotics, and autonomous driving.

To tackle with sample efficiency and other task-specific challenges, my research [1–17] thrives at understanding and designing provable sample-efficient algorithms, and seeking practical solutions for disparate applications in the wild. Specifically, relying on tools from high-dimensional statistics, large-scale optimization, machine learning, and signal processing, I 1) develop methodology for sequential decision making problems in reinforcement learning (RL); 2) seek theory-inspired and physics-driven solutions for real-world data-driven applications, in collaboration with civil engineering, high-performance computing, robotics, mechanical engineering and industry, summarized as below:

	RL	Application-driven data science
Theory: provable sample efficiency	Online RL [3]; Offline RL [7,8] Robust RL [1,6]	Blind deconvolution [11]
Applications	Offline RL [2,5]; Robust RL [4] Curriculum RL [9]	Multi-agent systems [14] ; Radar sensing [10,17] Image stitching [12,13]; Internet of things [15,16]

Methodology for Reinforcement Learning

As a fast-growing subfield of artificial intelligence, RL has achieved remarkable success in a variety of domains such as games [18], large language model alignment [19,20], healthcare [21,22], and robotics and control [23,24].

Provable sample-efficient RL. Contemporary RL can be extremely sample-starved with the unknown environments of unprecedentedly large dimensionality. Sample efficiency, to make the best use of available samples, inevitably lies at the core of RL. To understand and tackle the sample efficiency challenges, a recent body of works has made substantial progress by developing a finite-sample theoretical framework [25, 26] to analyze the algorithms of interest in terms of sample requirement. Despite the remarkable strides in advancing provable sample efficiency, the existing RL theory still falls short in either statistical understanding or algorithmic optimality in a wide range of RL problems. To address these open questions, my research breaks down the sample barriers of extensive sets of RL problems by designing provable near-optimal algorithms, including but not limited to online RL [3], offline RL [7,8], and robust RL [1,6]. We characterize the statistical performance of RL algorithms mainly through the lens of sample complexity — namely, the number of samples needed for an algorithm to output a policy whose resultant value function is at most ε away from optimal, with high probability.

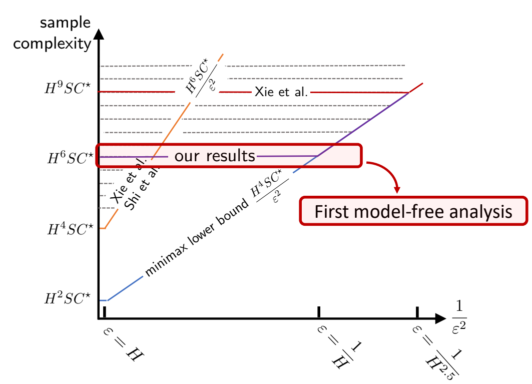
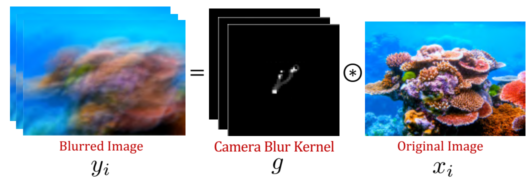


Figure 1: For instance, here is the result of model-free offline RL. RL is formulated as a finite-horizon Markov decision process with S states, A actions, and effective horizon length H (S, A, H are finite but can be large).

Practical well-performing RL. Enabling RL in diverse application scenarios requires to circumvent disparate challenges, such as limited data quality, uncertainty, and task-specific constraints. My research provides practical RL solutions for real-world tasks: achieving optimal control and playing video games by learning from a history dataset — offline RL [2, 5]; seeking safe control and autonomous driving solutions against risky spurious correlation — robust RL [4]; and generalizing to new tasks through optimal transport framework — curriculum RL [9].

Application-Driven Data Science

Provable nonconvex optimization for sample-efficient signal processing. Multi-channel sparse blind deconvolution (MSBD) aims to simultaneously recover a filter (g) and the unknown sparse inputs ($\{x_i\}$) to the filter from the observations of their convolution ($\{y_i\}$). This problem finds applications in understanding neural or seismic recordings [27, 28] as well as image debluring. It is notoriously challenging due to *shift and scaling ambiguities* and large dimensionality. My research [11] proposes a computationally efficient nonconvex optimization approach for MSBD based on simple manifold gradient descent (MGD) with theoretical guarantees for its global convergence, along with a significantly reduced sample complexity compared to prior art [29], both empirically and theoretically.



Solutions to real-world applications. Through collaborations with interdisciplinary researchers in different domains such as civil engineering, robotics institutions, and industry, I am motivated to discover and enable data-driven applications that are meaningful to people and societal benefits. My work makes progress on: 1) micro hand gesture recognition by ultrasonic active sensing [17]; 2) robust image stitching framework for strain measurement and panoramic photo [12, 13]; 3) and multiple occupant localization in smart buildings by vibration sensing systems [15, 16].

Future Plan

The significance of understanding and improving provable sample efficiency in RL and data science is far beyond what I studied here. To advance the fundamental theoretical study as well as applications, my future research shall include the following thrusts.

Towards principled and provable robust RL. While standard RL has been heavily investigated recently, its use can be significantly hampered in practice due to the sim-to-real gap [30], leading to a pressing need to enhance robustness in RL. The discovery of provable sample efficiency in robust RL appears very recently, where the existing statistical understanding and algorithmic optimality are far from adequate for both theory and practice. Our techniques that recently uncover a surprising fact — robust RL is not necessarily easier nor harder to learn than standard RL [1, 6] — show tremendous promise to both improving fundamental understanding and designing optimal sample-efficient algorithms in numerous robust RL problems.

Empowering real-world applications of science and industry. In light of data's penetration into contemporary applications, my research aims to design principled data-driven methods for societal benefits. Especially, I am eager to collaborate and explore promising application scenarios of RL and data science in fundamental science such as protein discovery in biology and simulation of fluid dynamics; in daily life such as recommendation systems for social media, resource allocation for power grid, and safe and robust autonomous driving.

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