Statement of Purpose
Qasim Wani

I intend to pursue a lifelong career in Computer Science research, focusing on applying Machine Learning techniques to address challenges in robustness and distribution shift. I believe Deep Learning models that utilize structural dependencies in data will be critical to achieving generalization.

My motivation for pursuing a research role in Machine Learning stems primarily from three research experiences over the past year: resilient reinforcement learning with Prof. Ming Jin, structure learning with Prof. Ruoxi Jia, and interpretable Graph Neural Networks at Qualcomm. All these projects share a common theme: Can we somehow utilize the underlying data and problem structure to build a more robust generalizable model?

Robust Machine Learning. My research interests in robustness and applied ML led me to Prof. Ming Jin's research group, where I have worked over the past year. Over this summer, our group had the opportunity to participate in the CityLearn challenge, an annual research competition to develop a multi-agent Reinforcement Learning (RL) algorithm that optimizes a coordination strategy for a distributed control system such as a power grid.[1] Unfortunately, RL baselines don't work well in the real world despite recent performances due to the complexity of the environment and sparsity in the reward signal. To combat this, researchers have used classical interpretable optimization methods. However, the primary disadvantage of this approach is its inability to adapt to dynamic environments, raising safety and assurance concerns.

I addressed this issue by developing a novel zeroth-order implicit reinforcement learning framework that combines the synergetic strength of optimization and RL. Our RL agent aims to iteratively adapt to the parameters within the policy, a convex optimization model, of dynamically changing environment conditions. This is a paradigm shift from traditional representations of policies: linear functions and neural networks. Constrained by allotted training time, I implemented a gradient-free approach due to its low per iteration cost. This proved to be a challenge since there was no immediate way of guiding the agent (i.e., searching for optimal parameters of the optimization model) while maintaining convergence on various baselines. I addressed this problem by designing a guided random search algorithm that leverages structural information of the environment to accelerate convergence. By utilizing the exponential convergence criterion [1] and the sampling properties of a homogeneous Markov chain, we demonstrated that this strategy is guaranteed to converge to an optimal solution. Ultimately, **our method won the CityLearn competition, beating the second-place solution by 120%.** My work as the leading co-author is currently under review at AISTATS.[2]

As a result of this achievement, I am currently working on a gradient-based algorithm that incorporates an actor-critic framework, improving our zeroth-order approach. This line of research showcases the effectiveness of encoding structural information into a problem to build a robust, interpretable, and safe ML solution. However, a key question arises—what happens if you don't have the domain knowledge to encode structural information into a problem?

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[1] Learn more about the CityLearn challenge: www.citylearn.net
[2] Khattar, V.; **Wani, Q.**; Kaushik, H.; Chang, Z.; and Jin, M. *Zeroth-Order Implicit Reinforcement Learning for Sequential Decision Making in Distributed Control Systems*. 2021. Preprint: tinyurl.com/ZO-iRL

Structure Learning. I undertook the challenge of understanding and assuring arbitrary data under Prof. Jia's guidance. A data point might be important at times if it's in the presence/absence of other data points. Since most real-world datasets are extremely dense, higher-order interactions between data points may reveal interesting revelations such as determining the most influential subset responsible for a specific prediction. I implemented this idea by designing a graph-based algorithm where the goal is to generate a subgraph with the highest utility between corresponding edges. We define the utility of an edge as an evaluation metric such as accuracy, which quantifies dependencies between data points. I designed this utility function as a neural network with inputs representing a node and output the predicted accuracy.

It's straightforward to construct an arbitrary subgraph—randomly connect *n* nodes with *k* edges. The standard approach is to go through all possible permutations of a graph and report the subgraph with the highest utility among all edges. However, as we scale to larger real-world datasets, this strategy will turn out to be computationally inefficient. Taking inspiration from Max Chickering [2], I tackled this problem by developing a greedy algorithm that only adds an edge/node to a subgraph *G* if it maximizes overall utility. Though computationally efficient, this approach can lead to a suboptimal graph. To combat this, I introduced a Monte-Carlo subroutine such that the procedure of adding a new edge/node is an unbiased estimator of the best edge/node selection. Upon testing this method on various Computer Vision datasets such as CIFAR and MNIST, we showed that **picking the right subset (60x size reduction) can reduce training time by 10 times and improve test accuracy up to 8%.** This work culminated in first author submission to ICML 2022.[3]

Future Goals. Over the next few years, I aim to continue studying approaches to construct generalizable models that take advantage of data's inherent structural connections. Given my experience building scalable software and ML research, I am confident in my ability to deliver high-impact ML products based on core research that can exponentially impact society in the near future.

References

[1] Aldous, David J. "Exchangeability and related topics."École d'Été de Probabilités de Saint-Flour XIII—1983. Springer, Berlin, Heidelberg, 1985. 1-198.

[2] Chickering, David Maxwell. "Optimal structure identification with greedy search." Journal of machine learning research 3. Nov (2002): 507-554.

[3] **Wani, Q.**; Foruhandeh, M.; Jia, R. *Utility based Graphical Structure Learning for Deep Neural Networks*. 2021. Preprint: tinyurl.com/structure-learning