Research Statement

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Suppose we wanted to order pizza online from our home. In order to achieve this, we can assume our credit card information and our home address is saved in the pizza vendors database. It is then a simple matter of clicking ”order” and the pizza arrives at our doorstep. There are no extra actions or hassle. It is as simple as clicking a button and we get our pizza. This is analogous to finding the global optimum in convex optimization problems where the arrival of the pizza is the reaching to a global optimum.

Next, suppose your location is undetermined - for example, you’re in a park or out on the road. To get pizza, we can no longer simply click ”order” as the delivery person does not know our exact location. So what is the next best thing we do? We approximate by having the person deliver the pizza to a nearby landmark, or we give extra information such as details for how to identify us in a crowd, or you integrate the pizza apps with GPS. This is analogous to solving non-convex problems given extra conditions such as proper initialization or projection to a ”trust region”. My research interest, metaphorically speaking, is to have pizza delivered to us when our location is undetermined *without any extra information*. I want to find theory that can help solve non-convex optimization in ”one click”, without regularization.

This is important because a large part of optimization problems in nature are non-convex with the convex problems being the minority. Being able to solve non-convex problems ”easily” holds tremendous applications in machine learning, physics, computer science, and mathematics. Recent years have seen progress in theoretical guarantees for solving non-convex problems without any form regularization. One example is the development of the Wirtinger Flow algorithm to solve phase retrieval. This method requires an initial guess and then proceeds to use gradient descent without projecting the iterates to a ”trust region”. Another example of theoretical investigation of a non-convex problem is low rank matrix recovery. A recent paper from Princeton provides a polynomial time complexity for vanilla gradient descent using a suitable initializer. I am interested in studying theoretical properties of low rank matrix recovery and this is supported my background of working with non-convex problems.

Phase Retrieval (current research)- Phase Retrieval is an example of a non-convex quadratic program with quadratic constraints. In the real-valued case, it is a combinatorial problem of determining the missing signs of Ax, which is known to be NP-hard. Despite this observation, recent years have seen the development of new algorithms that solve phase retrieval problems effectively. Unfortunately, because of the lack of publicly available real-world data, the lack of a common software interface for different algorithms, and a knowledge gap between practitioners and theoreticians, only little work has been devoted to compare and evaluate newer phase retrieval methods. So we created Phasepack, comprehensive library that compiles all the algorithms within a uniform interface. I am first author on the paper on Phasepack which has been submitted to the IEEE proceedings of the 51^{st} Asilomar Conference on Signals, Systems and Computers, 2017. The project and the paper can be found on my homepage.

Low Rank Matrix Recovery Without Lifting (current research)- Another example of intractability associated with non-convexity is low rank matrix recovery where a solution is obtained by *lifting* the problem to a higher parameter space. To elaborate, lifting expresses a system of quadratic measurements as a system of linear equations whose solution is a matrix that obeys a rank constraint. However, working with matrices instead of vectors in higher dimensions generally means incurring large storage costs. As part of my MS thesis, I am trying to solve the problem of low rank matrix recovery without lifting i.e. in the natural parameter space. We observed that Phasemax (Goldstein and Studor, 2016) solves phase retrieval by recovering solutions in the same space as the input without lifting to higher dimensions. Consequently, it is a better alternative to current lifting solutions for solving SDP’s. Initial sketches of my proof look promising and I am currently in the process of formalizing this.