D I S S E R T A T I O N   P R O P O S A L

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Thursday, March 1, 2018
10:00 am
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Efficient Methods for Addressing Data Uncertainty in Optimization

Optimization is a key analytical technique used in operations research for making good decisions given observed data. However, in practice, decisions must be made without full or exact information required for the optimization model. This is due to many reasons, including data measurement errors, statistical estimation errors, or missing data. In many applications, optimization with inexact data can have a large negative effect on performance. Several techniques have been developed to address data uncertainty in optimization models, including stochastic programming, robust optimization, and online optimization. Additionally, as new technologies are developed, more complex higher-dimensional optimization models become prevalent. This dissertation investigates efficient solution methodologies which scale well as the model becomes more complex.

In the first chapter, we focus on the trust-region subproblem (TRS), which is an important nonconvex optimization problem in many applications, including robust quadratic programming. We provide a second-order cone-based convexification for the TRS, which also applies to several TRS variants with conic side constraints.

In the second chapter, we study the robust optimization problem through a natural game-theoretic viewpoint as a min-max saddle point problem. We show that such an interpretation provides an iterative solution framework, which unifies two existing iterative approaches from the literature, as well as allowing us to apply scalable first-order methods to solve robust optimization problems. For robust quadratic programming, we show how to leverage the convexification of the TRS from the first chapter within our framework.

In the third chapter, we examine first-order methods in more detail through the lens of online convex optimization and regret minimization. We consider two modifications not studied previously: weighted regret and lookahead decisions. We show that these modifications allow us to exploit favourable problem structure such as smoothness and strong convexity to accelerate convergence rates. We illustrate this with applications to our robust optimization framework from the second chapter, as well as another paradigm for optimization under uncertainty called joint estimation-optimization.

In the fourth chapter, we study an application problem of estimating a non-parametric choice model. We consider the setting when empirical choice probabilities are continuously updated, which turns this into a joint estimation-optimization problem with exponentially many variables. We adapt the techniques from the third chapter to provide two first-order based solution methods with efficient convergence guarantees.

In the fifth chapter, we consider a joint prediction-optimization (JPO) problem, where unknown data for an optimization model can be estimated from given features. We propose three interesting research directions. First, we aim to prove statistical consistency for JPO methodologies and derive convergence rates. Second, we analyse the JPO problem as an adjustable optimization problem. Third, we consider tractability and desirable properties of the loss function used in JPO.