



Minimization provides a poverful tool to capture structured uncertainty in many optimization applications. This problem has recently found many new applications in machine learning and operations research, including those in generative and adversarial machine learning reinforcement learning and distributionally robust optimization

In this talk, we will focus on a special class of minimax optimization problems: nonconvexinear minimax setting. This model, though special, covers many important applications in recent years such as distributionally robust optimization with discrete probability measure, adversarial training and agnostic meta-learning. We first discuss this special model and its equivalent reformulations, identify some key challenges to tackle it, especially instochastic settings. Then, we propose two different algorithms to approximate a solution in stochastic and finite-sumsettings. We compare our algorithms with existing methods from the literature both theoretically and numerically. We also provide some numerical examples to illustrate the performance of our methods in comparison to existing methods.

Quec Tian Dirhis currently an associate professor at the Department of Statistics and Operations Research, The University of North Carolina at Chapel Hill. He obtained his Bachelor at Vietnam National University in Hanoi, and his Ph.D. from the Department of Electrical Engineering and the Optimization in Engineering Center at KU Leusen, Belgium His research mainly focuses on efficient numerical methods for and applications of continuous optimization and related problems, including convex and nonconvex optimization, stochastic programming and minimax problems. He currently serves as an associate editor of the Computational Optimization and Applications (COAP) and Mathematical Programming Computation (MPC), journals.