**Practicality meets Optimality: Real-Time Statistical Inference under Complex Constraints**

**Sen Na**, University of California, Berkeley, CA, USA.

Email: senna@berkeley.edu

## Biography

Sen Na is currently a postdoctoral researcher in the Department of Statistics and the International Computer Science Institute at UC Berkeley. He received a Ph.D. degree in statistics from the University of Chicago.

Sen Na is broadly interested in the mathematical foundations of data science, with topics including high-dimensional statistics, graphical models, semiparametric models, optimal control, and large-scale and stochastic nonlinear optimization. He is also interested in the broad applications of machine learning methods in scientific fields such as biology, neuroscience, and engineering. His research has been recognized by the prestigious Harper Dissertation Fellowship from UChicago, and he has been selected as one of the Young Researchers in ORIE by Cornell University.

## Abstract

Constrained estimation problems are prevalent in applications in statistics, machine learning, and engineering. These problems encompass constrained generalized linear models, constrained deep neural networks, physics-inspired machine learning, algorithmic fairness, and optimal control. However, many existing estimation methods under hard constraints rely on either projection or regularization, which may theoretically exhibit optimal efficiency but are impractical or unreasonably fail in reality. This talk aims to bridge the significant gap between practice and theory for constrained estimation problems.

In the first part of the talk, I will introduce the key methodology called Stochastic Sequential Quadratic Programming to bridge the gap. We will see that the SQP method can serve as the workhorse for modern scientific machine learning problems and resolve the failure modes of prevalent regularization-based methods. I will also introduce how to make SQP adaptive and scalable using modern line search, trust region, and dimension reduction techniques, and demonstrate how to debias it to handle inequality constraints in an online fashion.

In the second part of the talk, I will focus on theory and practice. Regarding the theory, I will emphasize both the consistency and efficiency of the estimators obtained by SQP. Specifically, I will show that SQP asymptotically exhibits normal behavior with an optimal covariance in the Hájek and Le Cam sense. Significantly, the covariance does not deteriorate even when we apply modern techniques driven by practical concerns. Different online covariance estimators are also provided. The talk concludes with numerous experiments on benchmark nonlinear problems, constrained GLMs, and real datasets, illustrating the effectiveness of SQP.