Speaker: Cynthia RUSH

Using AMP to Characterize the Optimal Type 1 Error and Power Trade-off for Sorted L1 Penalized Estimation (SLOPE)

Sorted L1 regularization has been incorporated into many methods for solving high-dimensional statistical estimation problems. In particular, SLOPE is a relatively new convex optimization procedure for high-dimensional linear regression that uses a sorted L1 penalty: the larger the rank of the fitted coefficient, the larger the penalty. This non-separable penalty renders many existing techniques invalid or inconclusive in analyzing the SLOPE solution. In this talk, we propose using approximate message passing or AMP to provably solve the SLOPE problem in the regime of linear sparsity under Gaussian random designs. This algorithmic approach allows one to approximate the SLOPE solution via the much more amenable AMP iterates, and a consequence of this analysis is an asymptotically exact characterization of the SLOPE solution. We will show how the AMP analysis can be used to characterize the optimal SLOPE trade-off between the false discovery proportion and true positive proportion or, equivalently, between measures of type I error and power, which, in turn, shows that SLOPE improves variable selection compared to other common penalized regression methods like the LASSO. This is joint work with Zhiqi Bu, Jason Klusowski, and Weijie Su based on a series of papers: https://arxiv.org/abs/1907.07502 and https://arxiv.org/abs/2105.13302.