From Structured Sparsity to Causal Effects: GSLOPE, PCGLASSO, and SLOPE-Based Doubly Robust Inference

This talk presents three applications of structured convex regularization in high-dimensional inference. GSLOPE estimates sparse precision matrices while identifying groups of equal or similar entries, whereas PCGLASSO provides scale-invariant estimation of sparse partial-correlation matrices. By recovering conditional-dependence structures, these methods can reduce the search space and provide useful building blocks for causal graph learning. I will also discuss the potential of SLOPE-based doubly robust methods for estimating causal treatment effects.