Title: FDR Control via SLOPE Method

Abstract:

The Sorted L-One Penalized Estimator (SLOPE) is defined as the solution to the convex optimization problem

$$\hat{b} = arg\min_{b}\left(-l(b) + \sum_{i=1}^{p} \lambda_i |b|_{(i)}\right) \quad , \tag{1}$$

where $l(b)$ denotes the log-likelihood function, $\{\lambda_i\}_{i=1}^{p}$ is a positive non-increasing sequence of tuning parameters, and $|b|_{(i)}$ denotes the i-th largest element of the vector $(|b_1|, \ldots, |b_p|)$'.

In the generalized linear model (GLM) framework, SLOPE performs variable selection by identifying predictors corresponding to non-zero components of $\hat{b}$.

In this talk, we present theoretical results showing that SLOPE (asymptotically) controls the false discovery rate (FDR) in GLMs under suitable regularity conditions. We consider both the low-dimensional setting, where the number of predictors (p) is fixed while the sample size (n) tends to infinity, and the high-dimensional setting, where (p) may grow substantially faster than (n). The theoretical findings are illustrated through simulation studies.