Post-Regularization Confidence Bands for High-Dimensional Nonparametric Models with Local Sparsity Graphical Models

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Abstract

We propose a novel high dimensional nonparametric model named ATLAS which is a generalization of the sparse additive model. The ATLAS model assumes the high dimensional regression function can be locally approximated by a sparse additive function, while such an approximation may change from the global perspective. We aim to estimate high dimensional function using a novel kernel-sieve hybrid regression estimator that combines the local kernel regression with the B-spline basis approximation. We show the estimation rate of true function in the supremum norm. We also propose two types of confidence bands for true function. Both procedures proceed in two steps: (1) a novel bias correction method is applied to remove the shrinkage introduced by the model selection penalty and (2) quantiles of the normalized de-biased estimator are approximated by quantiles of the limiting distribution or a Gaussian multiplier bootstrap. We further show that the covering probability of the bootstrap confidence bands converges to the nominal one at a polynomial rate.

(Joint work with Junwei Lu and Han Liu.)