The Smooth-Lasso estimator

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In several high dimensional numerical experiments, one has to estimate a sparse and smooth regression vector, *i.e.,* a vector with many zero components, and with its successive nonzero components varying slowly. In such situations, we propose the Smooth-Lasso, a Lasso-type method which exploits both sparsity and smoothness of the underlying model. The Smooth-Lasso outperforms known methods as the Lasso and even the Elastic-Net in several settings. In this talk we illustrate this superiority in theory: we show that under specific assumptions, the Smooth-Lasso can estimate the ℓ_2-estimation error (distance with the true parameter under the ℓ_2-norm), with a better rate of convergence than the usual nonparametric rate of convergence. These assumptions bring into play large correlations between successive variables that make the Lasso fail to recover the true parameter. Moreover, a simulation study is conducted and shows that when we consider the estimation accuracy, the Smooth-Lasso performs better than the Lasso, the Elastic-Net, and the Fused-Lasso, specifically when the regression vector is smooth.