We consider the tradeoffs between statistical accuracy and computational complexity for two kinds of regularized regression. First, we consider approximating L2 regularized regression by using hard-thresholding of the sample covariance. Under appropriate conditions, the approximation will be the solution to a symmetric diagonally dominant system, solvable in nearly linear time. We analyze the predictive risk of this family of estimators as a function of the threshold and regularization parameters, deriving a family of estimators that provide a tuneable tradeoff between statistical risk and computational efficiency.

In our second setting, we consider inference and hypothesis testing for L1-penalized linear regression. Recent work has shown how this estimator can be debiased by adding a term proportional to the subgradient of L1 norm at the solution point. We propose a variant where the sample covariance is again replaced with a hard-thresholded version. We derive a computational speed-up, but this time we show that asymptotically there is no loss of power.