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# Screen & Relax for Sparse Support Identification

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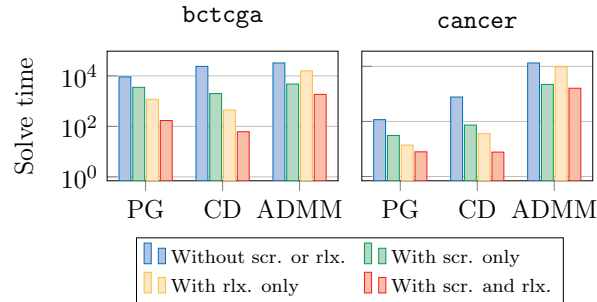
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Sparse representations arise in many application fields such as machine learning and signal processing. They usually result from the resolution of some convex optimization problem of the form  $\mathbf{x}^* \in \arg \min_{\mathbf{x}} f(\mathbf{x}) + \lambda g(\mathbf{x})$ , where  $f(\cdot)$  is a loss function,  $g(\cdot)$  is a sparsity-inducing regularization [1] and  $\lambda > 0$  is a tradeoff parameter. The latter problem can be addressed with first-order optimization methods such as Proximal Gradient (PG), Coordinate Descent (CD) or Alternating Direction Method of Multipliers (ADMM). A popular strategy to exploit the problem structure is to enhance these algorithms with *screening tests* to detect the position of *zeros* in  $\mathbf{x}^*$ . This allows shrinking the problem dimensionality and saving computational resources during the resolution [2]. We propose a complementary strategy, dubbed *relaxing*, to detect the position of *non-zeros* in  $\mathbf{x}^*$ . We then leverage this knowledge to perform second-order iterations on the latter subset of entries, thus expecting improvements in the convergence rate.

The adjacent figure shows the improvements allowed by screening and relaxing on two large-scale datasets, namely `bctgca` and `cancer`, drawn from the `HDRM` database. We set  $f(\cdot)$  as a Least-squares and Logistic loss, respectively, and  $g(\cdot)$  as an Elastic-net regularization. For each dataset, we solve the corresponding problem for 20 logarithmically spaced values of  $\lambda$  to span different working regimes and we report the overall solution time. We observe an acceleration factor up to three orders of magnitude when implementing both screening and relaxing tests compared to a vanilla implementation of PG, CD and ADMM, which assesses the interest for the presented ‘‘Screen & Relax’’ strategy.



## References

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- [2] Xiang, Z. J. et al. (2016). Screening tests for lasso problems. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39(5), 1008-1027.