Peeling for L0-Regularized Least-Squares

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L0-Regularized Least-Squares

Framework

Sparse linear models

- Linear regression with a sparse optimizer
- Applications in signal processing, machine learning, statistics, etc...

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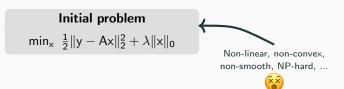
 $\ell_0 \text{-regularized least-squares} \\ \min_{\mathbf{x}} \ \ \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda \|\mathbf{x}\|_0$

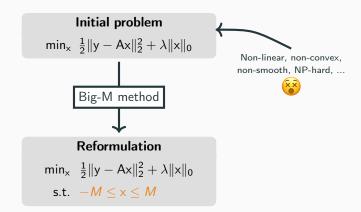
Ingredients

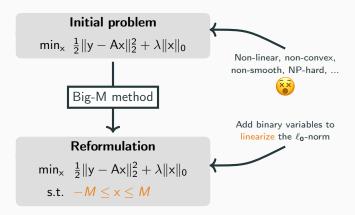
- Least-squares loss to ensure the linear model fitting
- ℓ_0 -norm that counts the non-zeros in x
- \bullet Tradeoff parameter $\lambda>0$ to control the sparsity

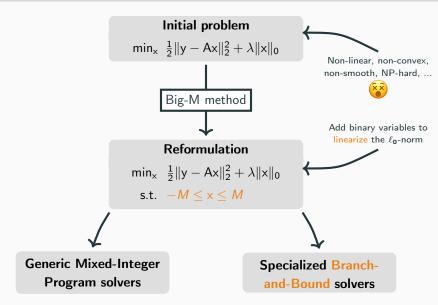
Initial problem

$$\min_{\mathbf{x}} \ \tfrac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda \|\mathbf{x}\|_0$$









Branch-and-Bound

Branch-and-Bound algorithms

Branch-and-Bound

"Enumerate all candidate solutions and discard sub-optimal ones."



Main principles

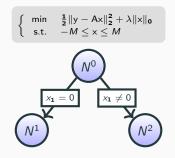
Branching: Divide the search space

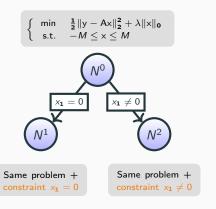
Bounding: Test whether a region can contain optimal solutions

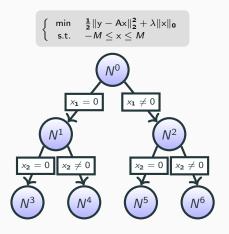
Pruning: Discard regions without optimal solutions

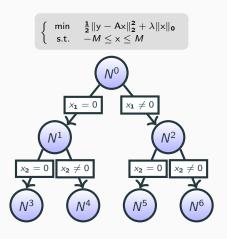
$$\left\{ \begin{array}{ll} \min & \frac{1}{2}\|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\mathbf{2}}^{2} + \lambda \|\mathbf{x}\|_{\mathbf{0}} \\ \text{s.t.} & -M \leq \mathbf{x} \leq M \end{array} \right.$$



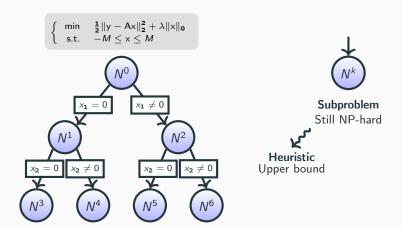


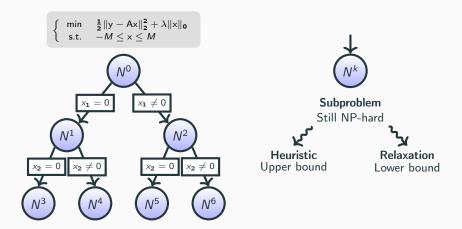


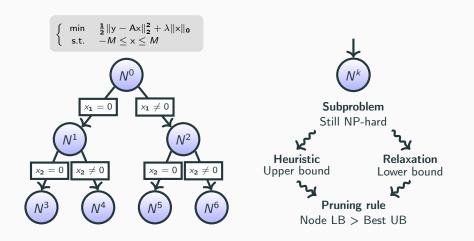


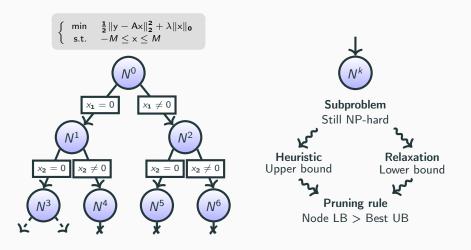










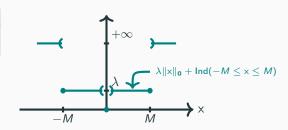


Node problem

$$\left\{ \begin{array}{ll} \min & \frac{1}{2}\|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\mathbf{2}}^{2} + \lambda \|\mathbf{x}\|_{\mathbf{0}} \\ \text{s.t.} & -M \leq \mathbf{x} \leq M \end{array} \right.$$

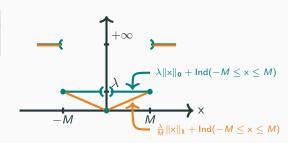
Node problem

$$\begin{cases} \min & \frac{1}{2} \| y - Ax \|_{2}^{2} + \lambda \| x \|_{0} \\ s.t. & -M \le x \le M \end{cases}$$



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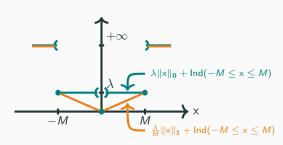
Node problem

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Relaxation

$$\begin{aligned} & \min \quad & \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\mathbf{2}}^{2} + \frac{\lambda}{M} \|\mathbf{x}\|_{\mathbf{1}} \\ & \text{s.t.} \quad & -M \leq \mathbf{x} \leq M \end{aligned}$$



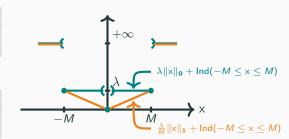


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Relaxation

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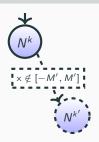
Dilemma in the choice of M

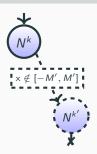
Large value of M to recover interesting solutions Small value of M to build strong relaxations

Our solution: Peeling

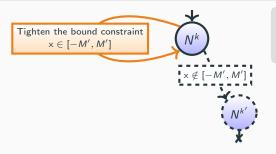
Start with M large and refine it locally along branches

Peeling

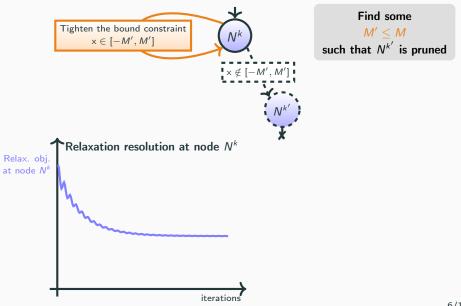


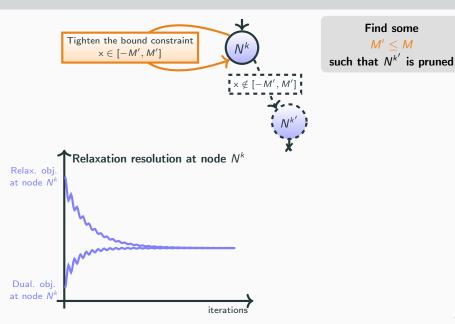


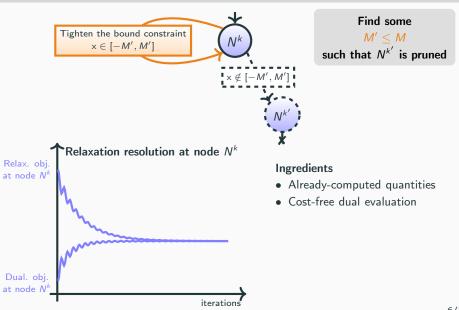
Find some $\frac{M' \leq M}{\text{such that } N^{k'} \text{ is pruned}}$

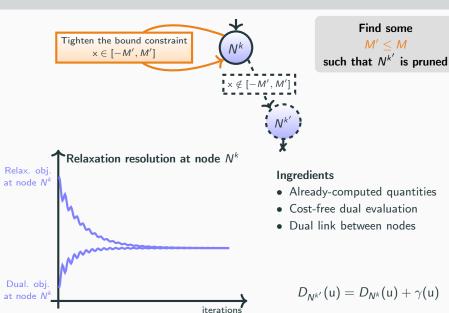


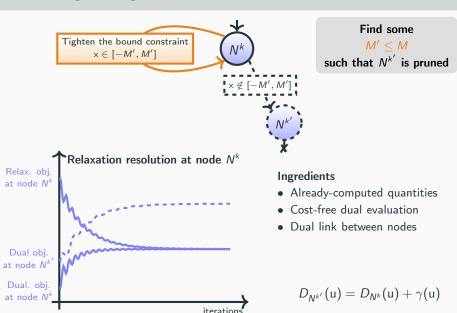
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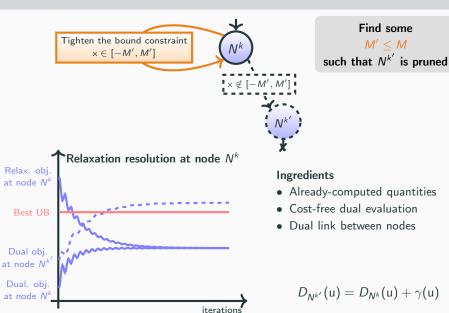




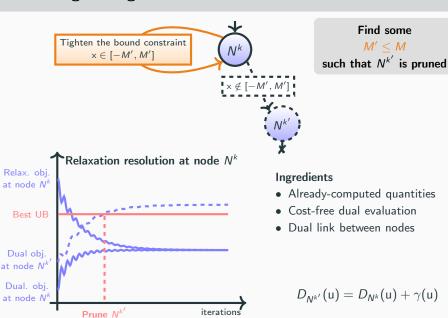




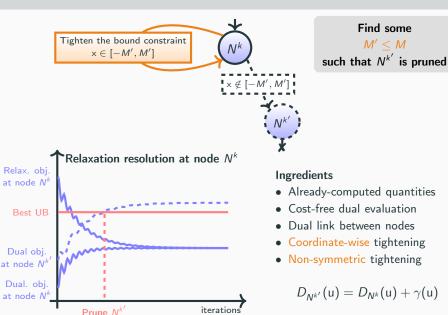




Bound tightening

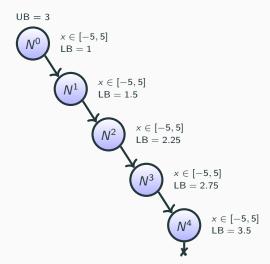


Bound tightening



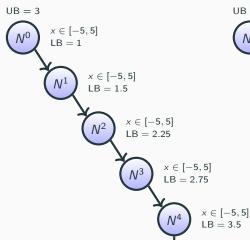
Propagation along branches

Standard BnB

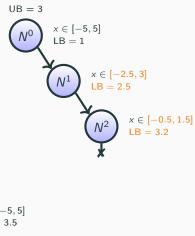


Propagation along branches

Standard BnB

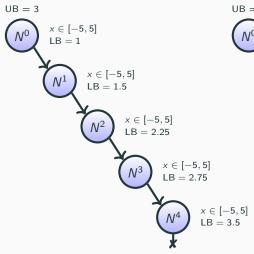


BnB with peeling

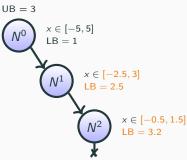


Propagation along branches

Standard BnB

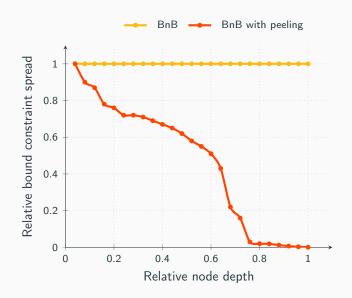


BnB with peeling



- ✔ Branches pruned early-on
- ✓ Less nodes explored
- ✔ Reduce solve time

Bound spread reduction



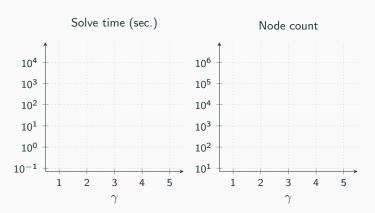


$$\min_{\mathbf{x} \in [-M,M]} \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{2}^{2} + \lambda \|\mathbf{x}\|_{0}$$

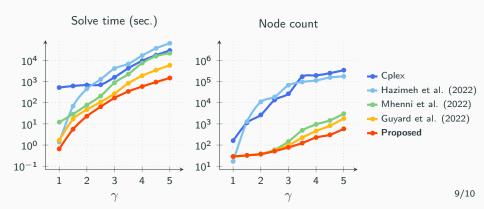
Data A **and** y : Sparse regression **Parameter** λ : Set statistically **Bound** M : $M = \gamma ||\mathbf{x}^{\star}||_{\infty}$

$$\min_{x \in [-M,M]} \frac{1}{2} ||y - Ax||_2^2 + \lambda ||x||_0$$

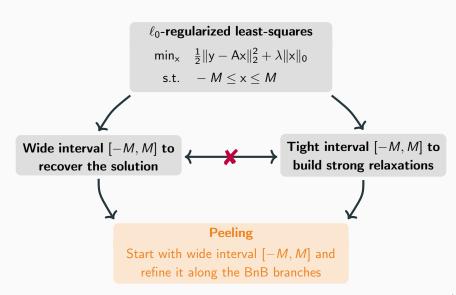
Data A **and** y : Sparse regression **Parameter** λ : Set statistically **Bound** M : $M = \gamma ||\mathbf{x}^{\star}||_{\infty}$



$$\min_{\mathbf{x} \in [-M,M]} \ \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda \|\mathbf{x}\|_0$$



Take-home message



Question time

