

New insights into one-norm solvers from the Pareto curve

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Ewout van den Berg

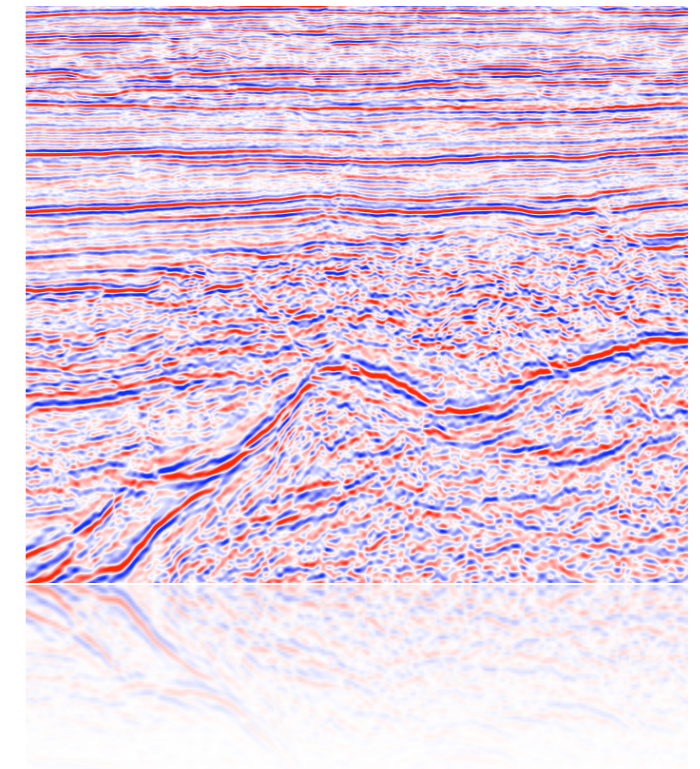
Michael P. Friedlander

Felix J. Herrmann

Seismic Laboratory for Imaging & Modeling

Department of Earth & Ocean Sciences

The University of British Columbia



SLIM consortium meeting
Background on sparsity-promoting solvers
Wednesday, February 20th, 2008 - 10:00 AM

Problem statement

- underdetermined system of linear equations

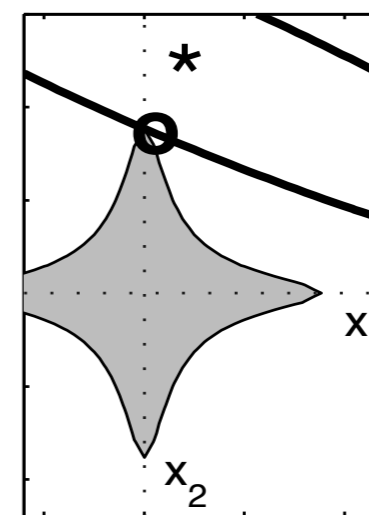
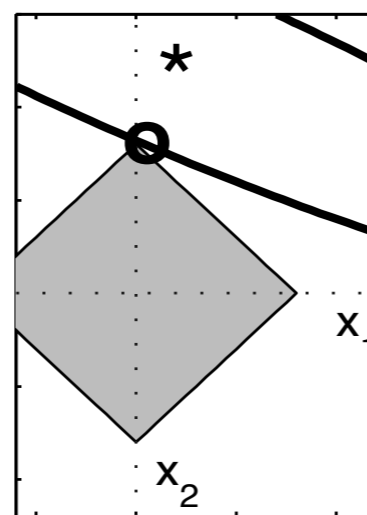
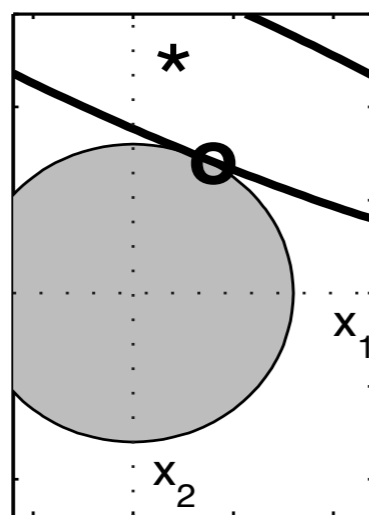
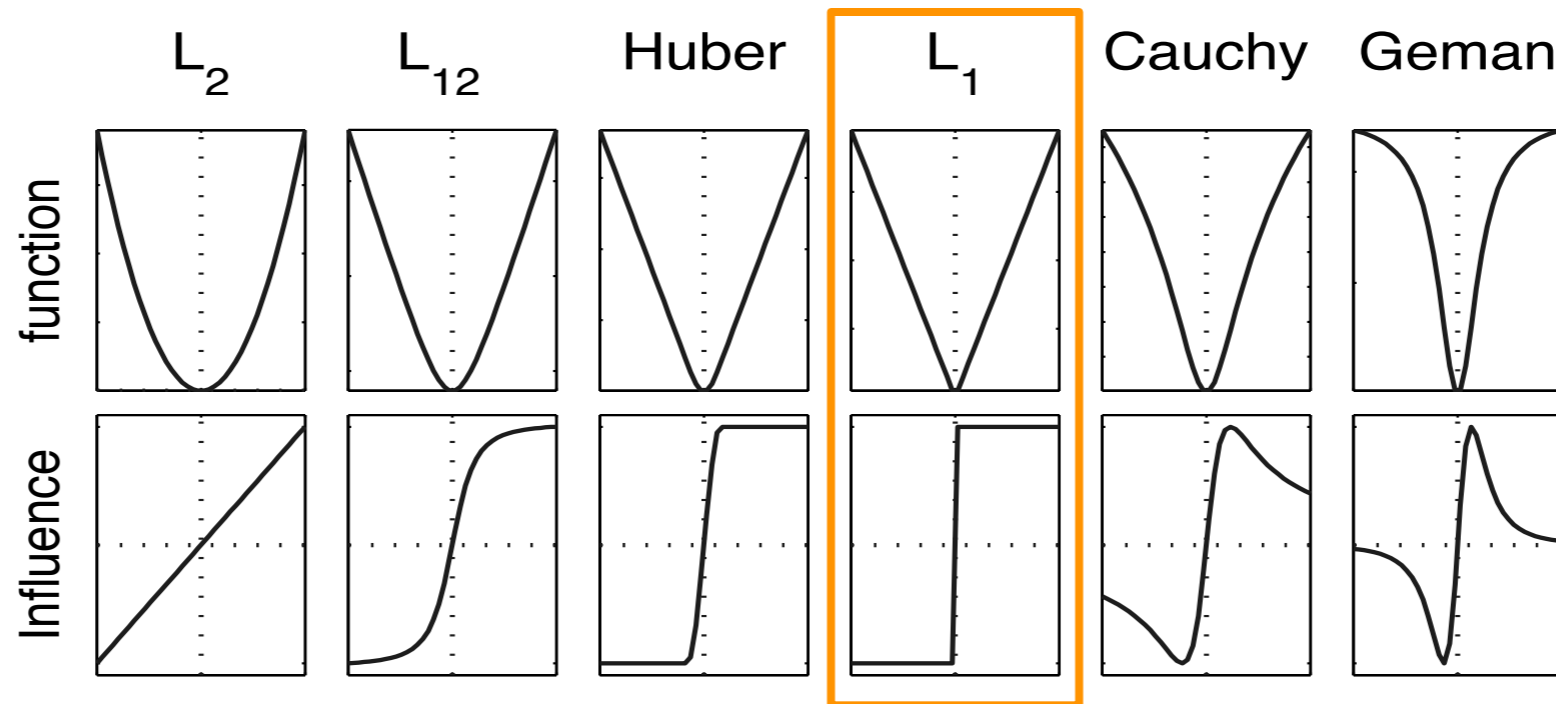
- setup

The diagram illustrates the equation $\mathbf{y} = \mathbf{A} \mathbf{x}_0 + \mathbf{n}$. The vector \mathbf{y} is labeled 'data'. The matrix \mathbf{A} is labeled 'modeling operator'. The vector \mathbf{x}_0 is labeled 'coefficients (sparse vector)'. The vector \mathbf{n} is labeled 'noise'. The matrix \mathbf{A} is represented by a grid of 10 columns and 15 rows.

- examples

- wavefield reconstruction with $\mathbf{A}=\mathbf{RS}^H$ [Sacchi et al '98], [Xu et al '05], [Zwartjes and Sacchi, 2007], [Herrmann and Hennenfent, 2007] & talks by J. Johnson and J. Yan
- denoising with $\mathbf{A}=\mathbf{S}^H$ [many references!] & talks by R. Neelamani and V. Kumar
- (deconvolution with $\mathbf{A}=\mathbf{KS}^H$ [Hennenfent et al., 2005] & talk by V. Kumar)

Sparse solution via one-norm



Approaches

- quadratic programming [many references!]

$$\text{QP}_\lambda : \min_{\mathbf{x}} \frac{1}{2} \|\mathbf{y} - \mathbf{Ax}\|_2^2 + \lambda \|\mathbf{x}\|_1$$

- basis pursuit denoise [Chen et al., 1995]

$$\text{BP}_\sigma : \min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{y} - \mathbf{Ax}\|_2 \leq \sigma$$

- LASSO [Tibshirani, 1996]

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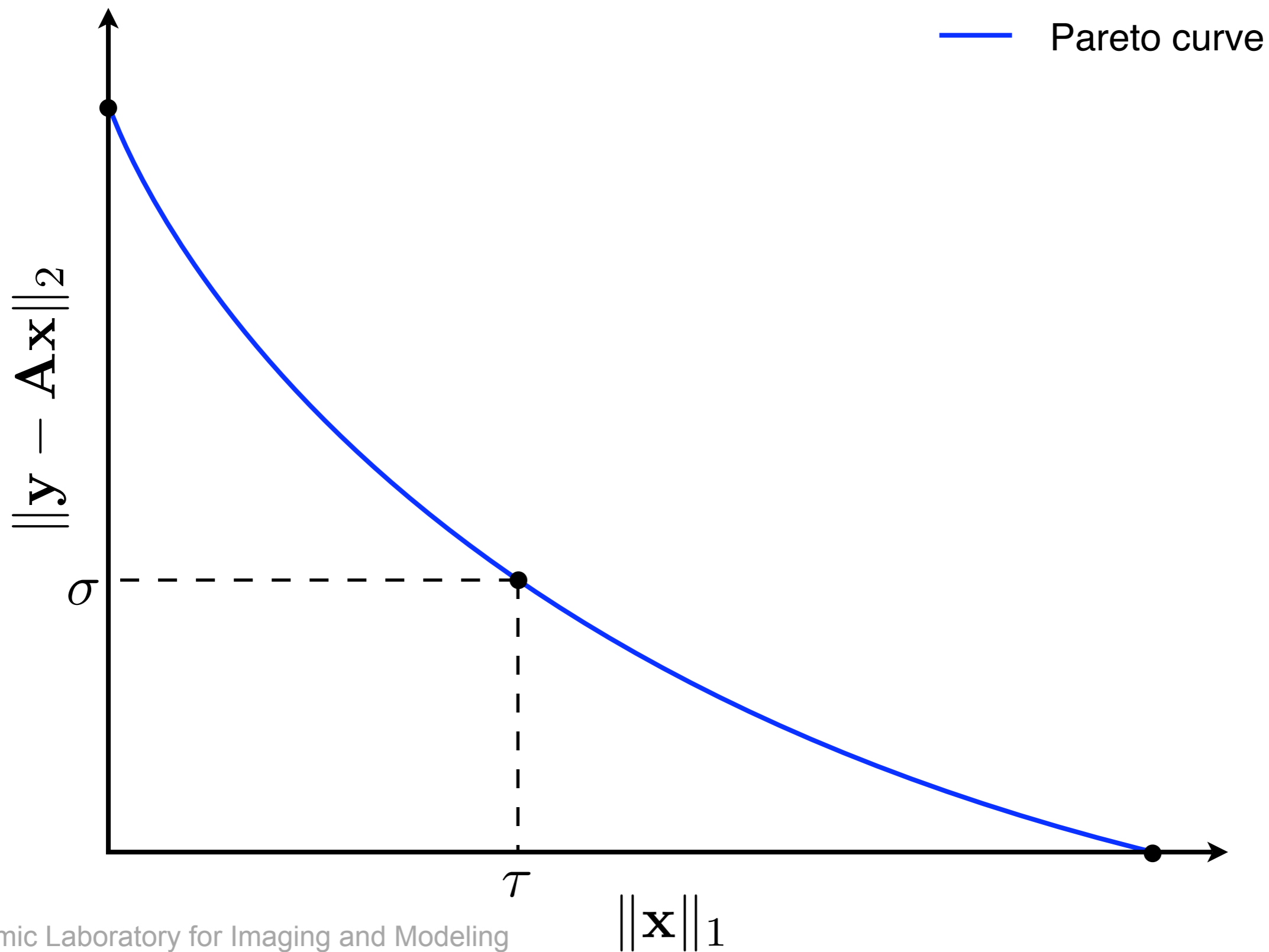
Solvers

- quadratic programming
 - iteratively re-weighted least-squares (IRLS) [Gersztenkorn et al., 1986]
 - iterative soft thresholding (IST) [Daubechies et al., 2004]
 - extensions of IST [Figueiredo and Nowak, 2003], [Herrmann and Hennenfent, 2008]
 - primal-dual interior method for convex objectives (PDCO)
- basis pursuit denoise
 - iterative soft thresholding with cooling (ISTc) [Herrmann and Hennenfent, 2008]
 - spectral projected-gradient for l_1 -norm (SPG/ l_1) [van den Berg and Friedlander, 2007]
 - log-barrier methods for second-order cone programming
 - homotopy methods [Osborne et al., 2000], [Donoho and Tsaig, 2006]
- LASSO
 - projected gradient [Daubechies et al., 2007], [van den Berg and Friedlander, 2007]

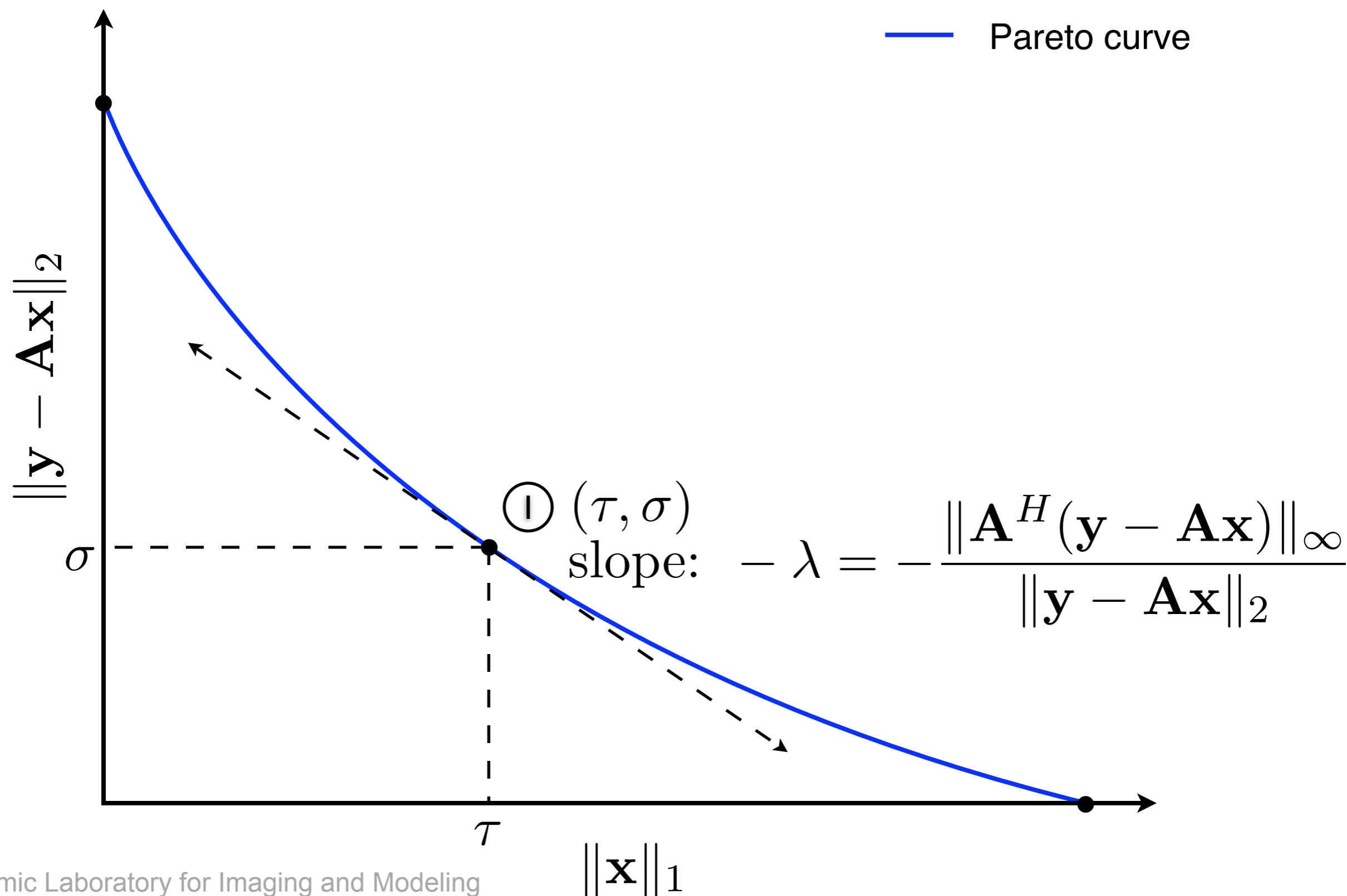
Connection & comparison

- context
 - ONE problem
 - THREE approaches
 - MANY solvers...
- Pareto curve
 - defined as the **optimal tradeoff** between $\|\mathbf{y}-\mathbf{Ax}\|_2$ and $\|\mathbf{x}\|_1$
 - **establishes the connection** between the three approaches
 - **exposes the behavior** of one-norm solvers
 - used to **evaluate the performance** of one-norm solvers

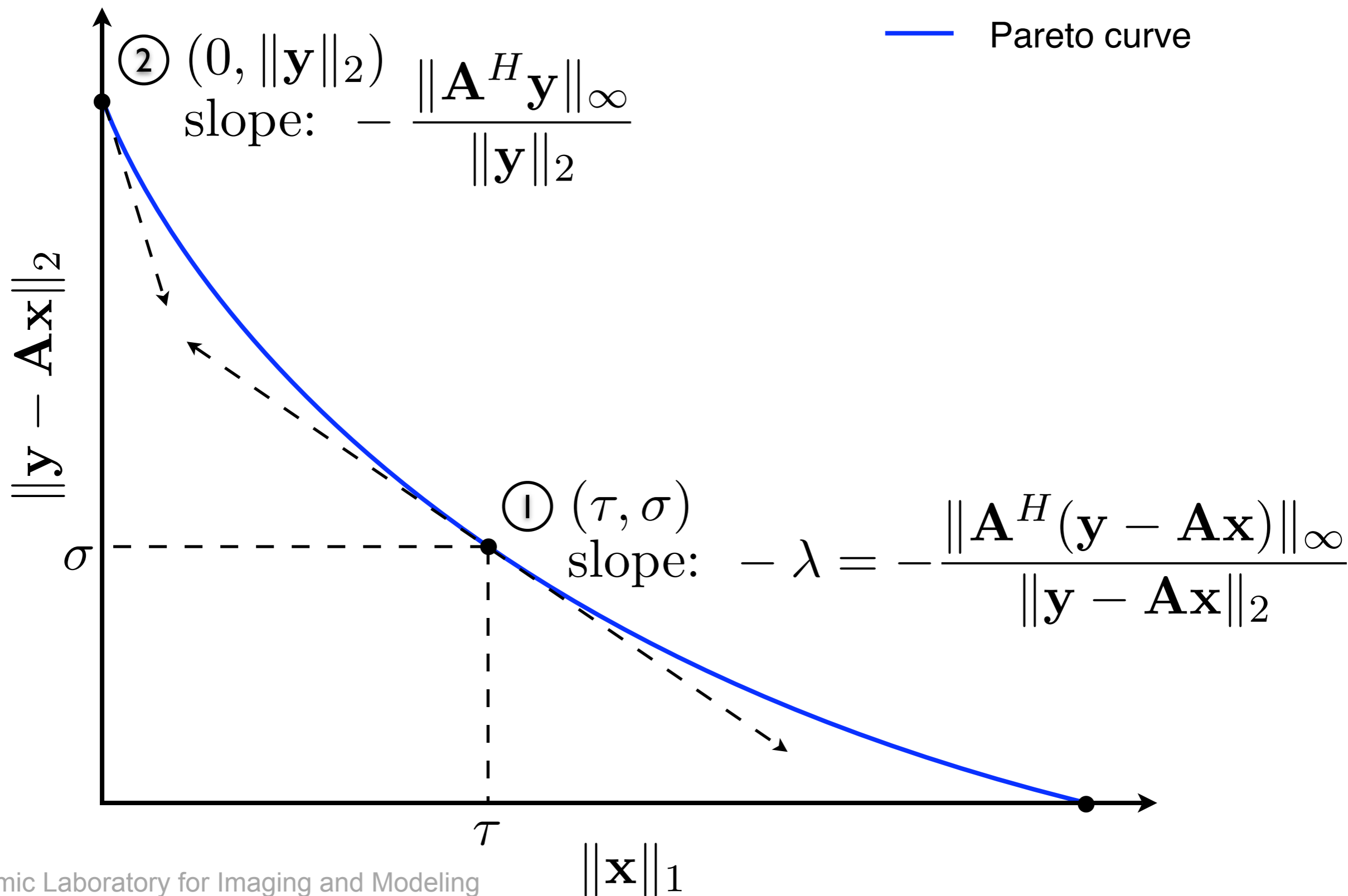
Pareto curve



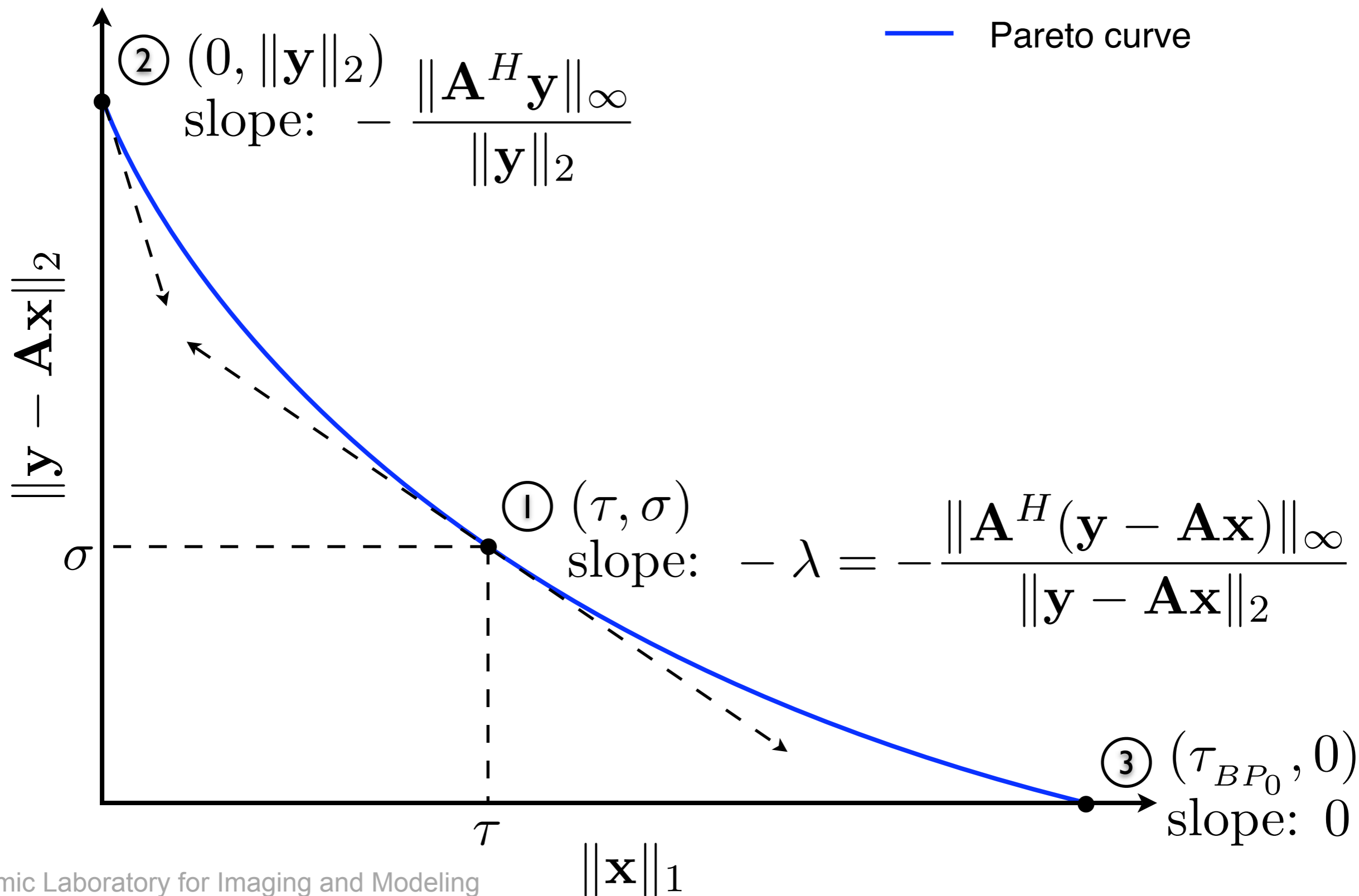
Pareto curve



Pareto curve



Pareto curve



Pareto curve

- useful properties [van den Berg and Friedlander, 2007]
 - convex & decreasing
 - continuously differentiable
 - negative slope given by

$$\lambda = \frac{\|\mathbf{A}^H (\mathbf{y} - \mathbf{A}\mathbf{x})\|_\infty}{\|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2}$$

- consequence
 - good approximation to the Pareto curve obtained with VERY few interpolating points

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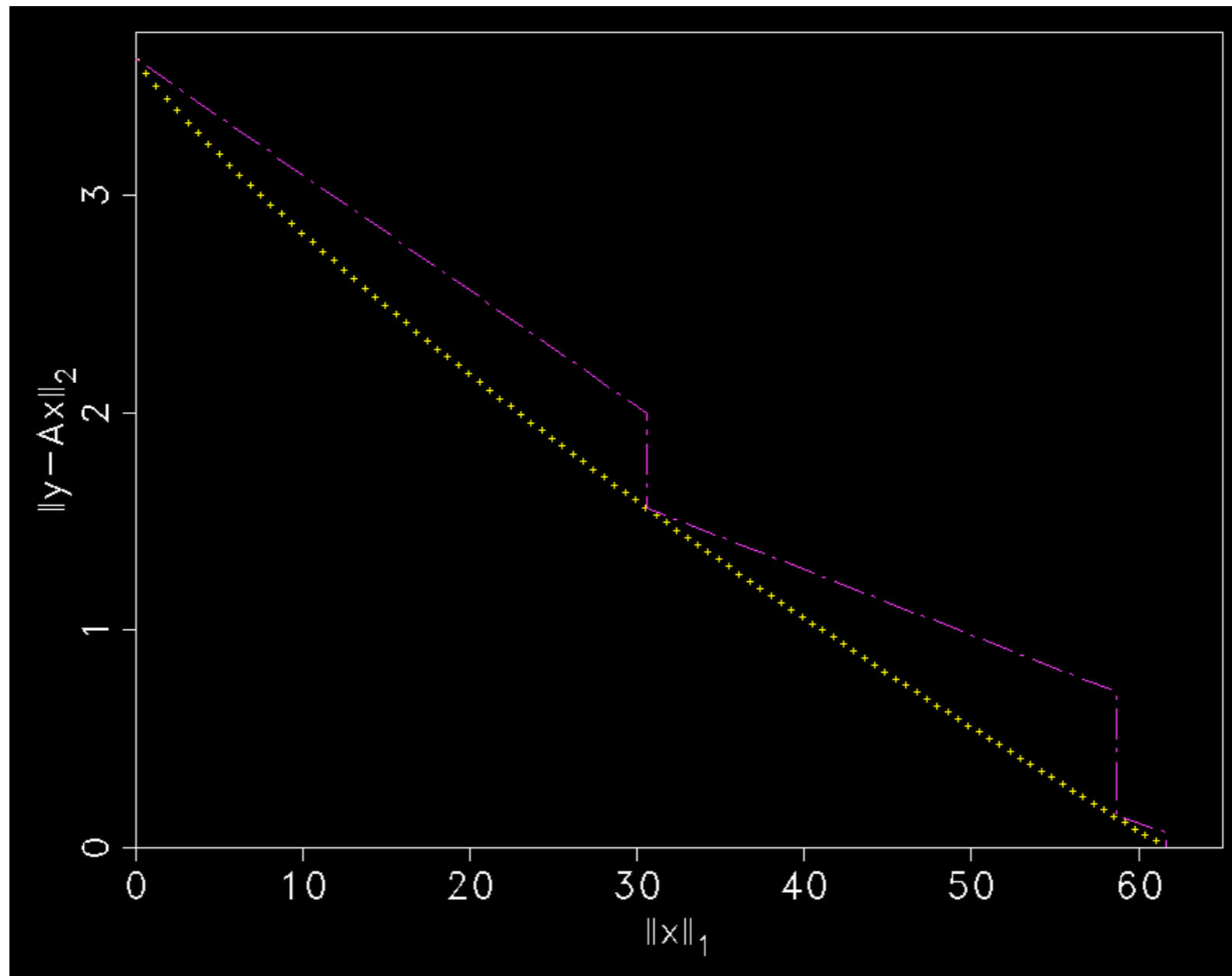
key point for large-scale
geophysical applications

Comparison of one-norm solvers

- solution path
 - track the evolution of the data misfit versus the one norm of successive solver iterates

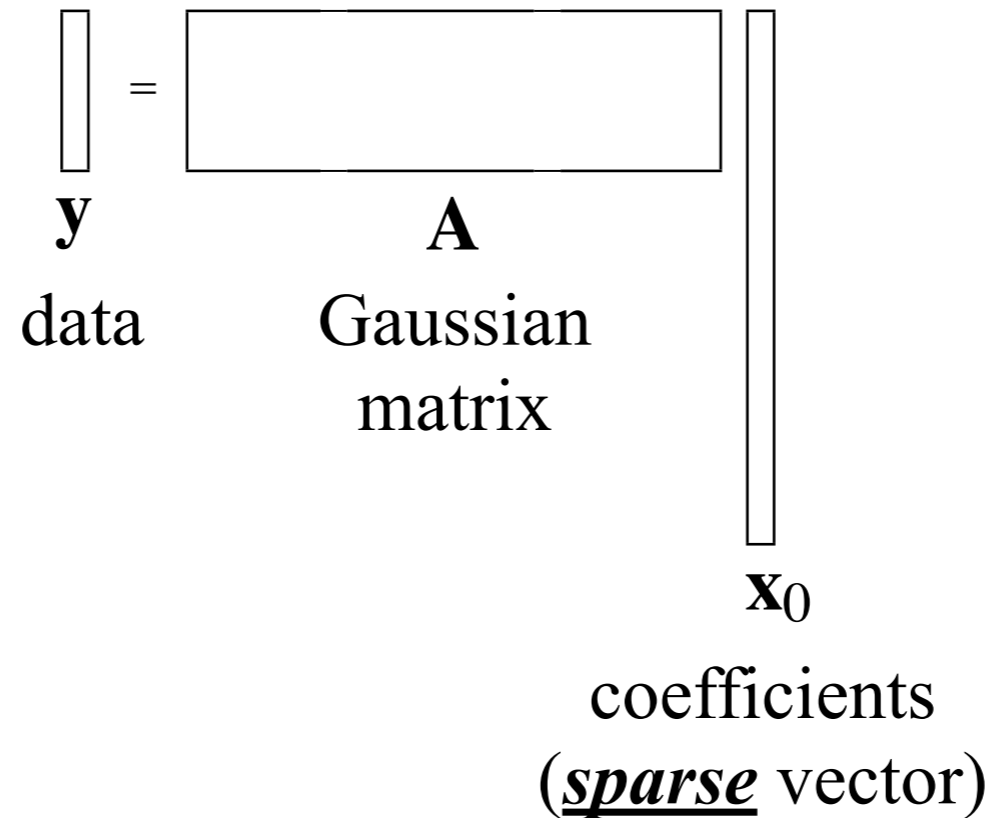
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Benchmark problem

- setup



- objective

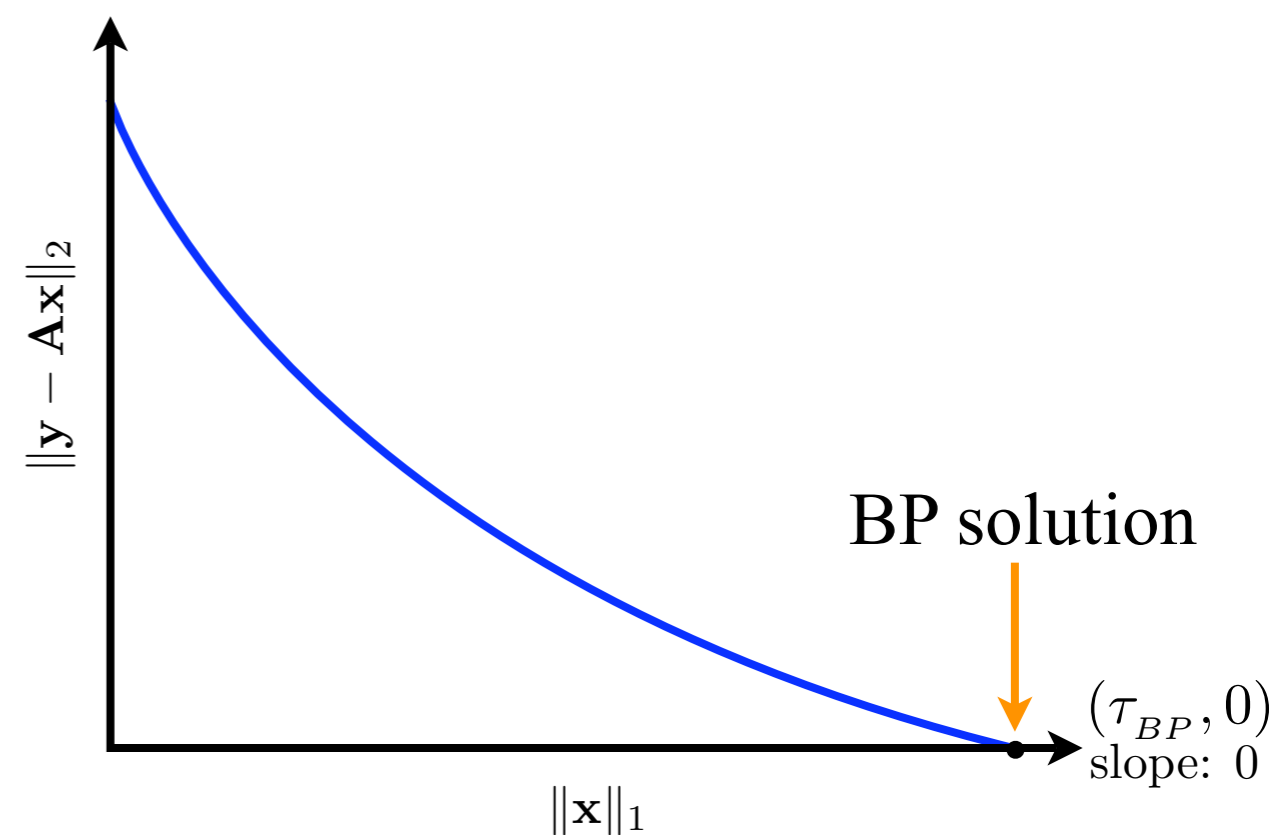
- basis pursuit (BP) solution

$$\tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \mathbf{y} = \mathbf{A}\mathbf{x}$$

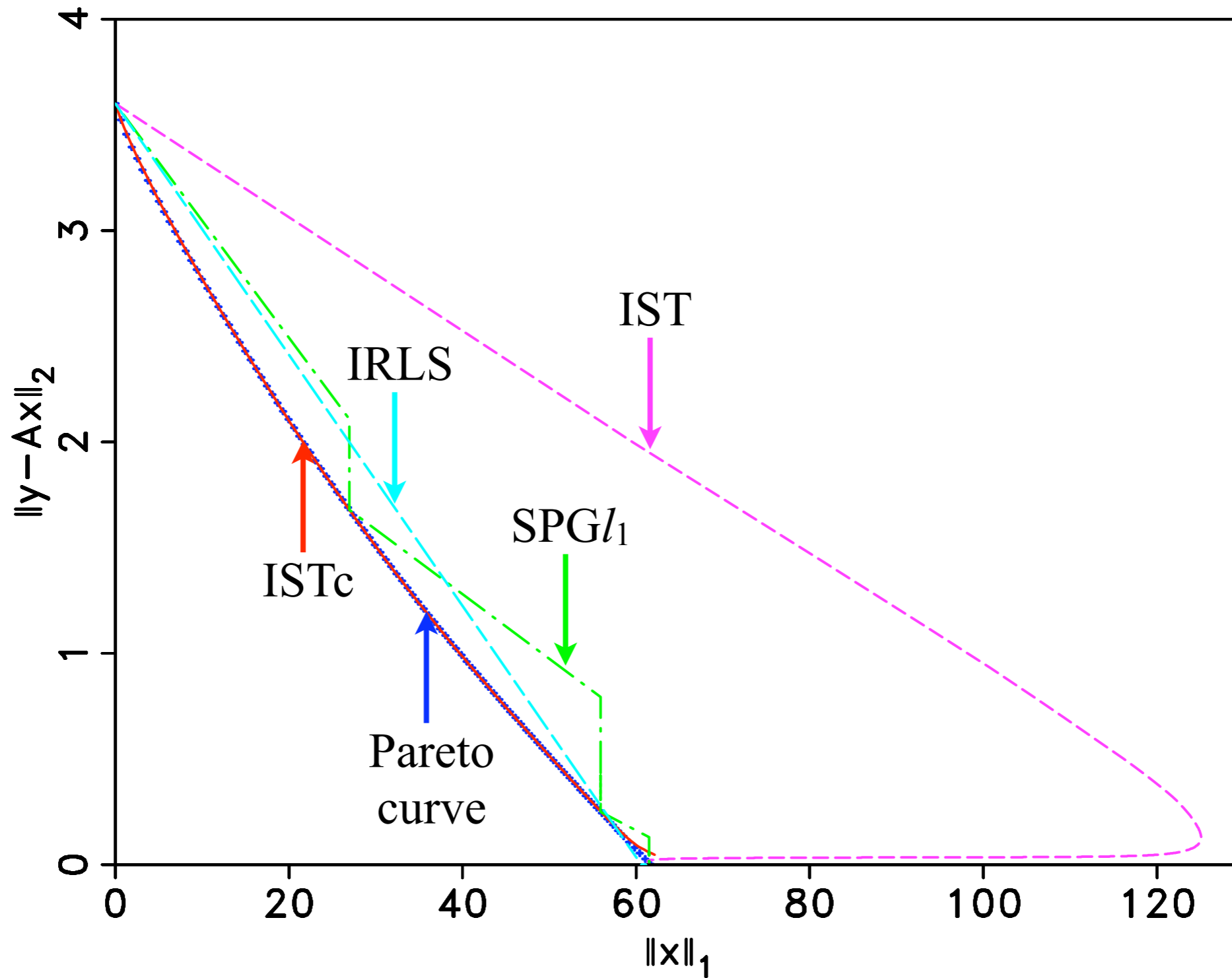
Basis pursuit

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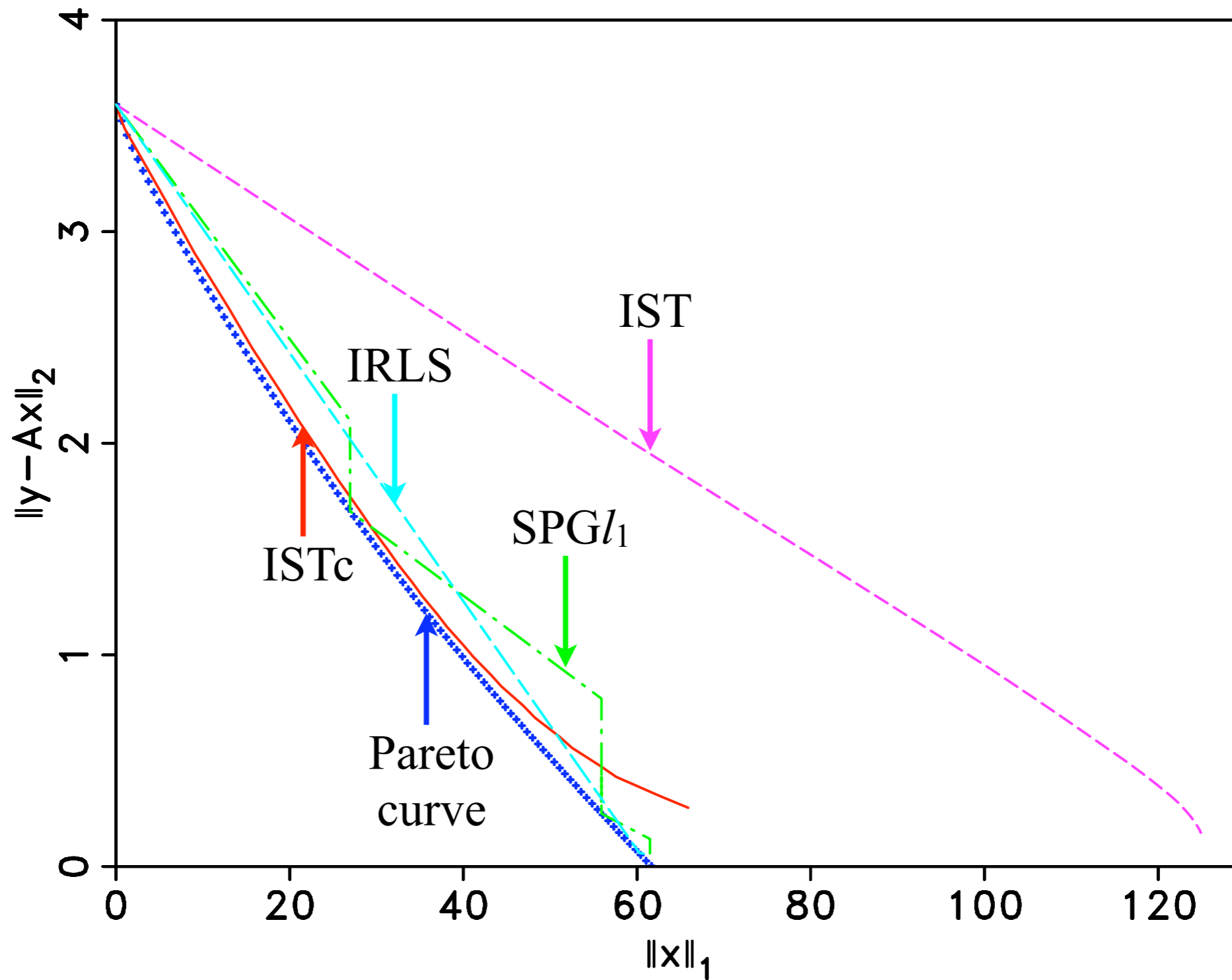
- challenging problem for solvers that attack QP_λ
 - solution only attained in the limit as $\lambda \rightarrow 0$
- applications
 - interpolation of noise-free wavefields
 - noise-free deconvolution



Solution paths: large-enough # of iterations



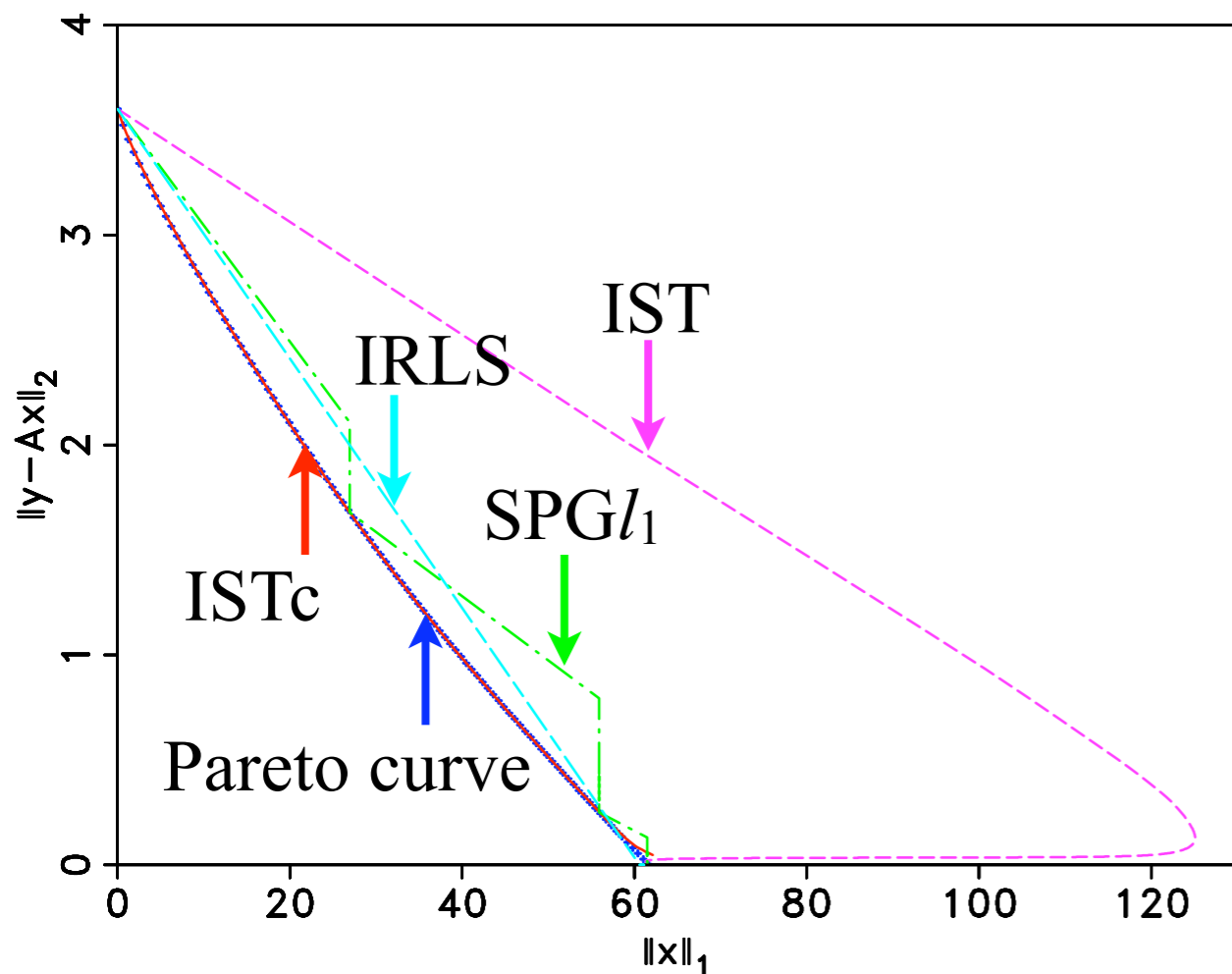
Solution paths: (very) limited # of iterations



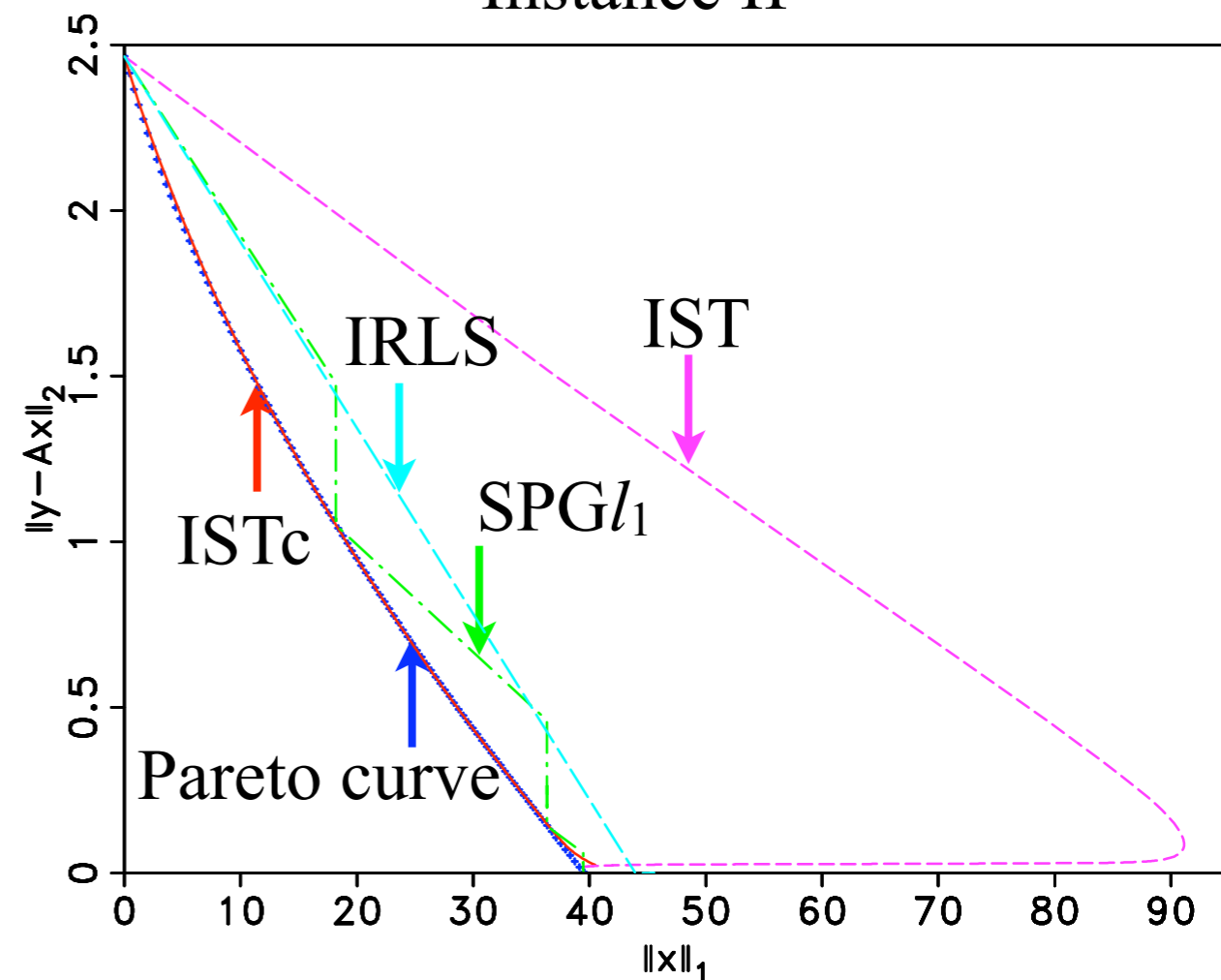
Exposing solvers' weakness

- sensitivity test
 - new instance of benchmark problem
 - same solvers tuning parameters as previous instance

Instance I



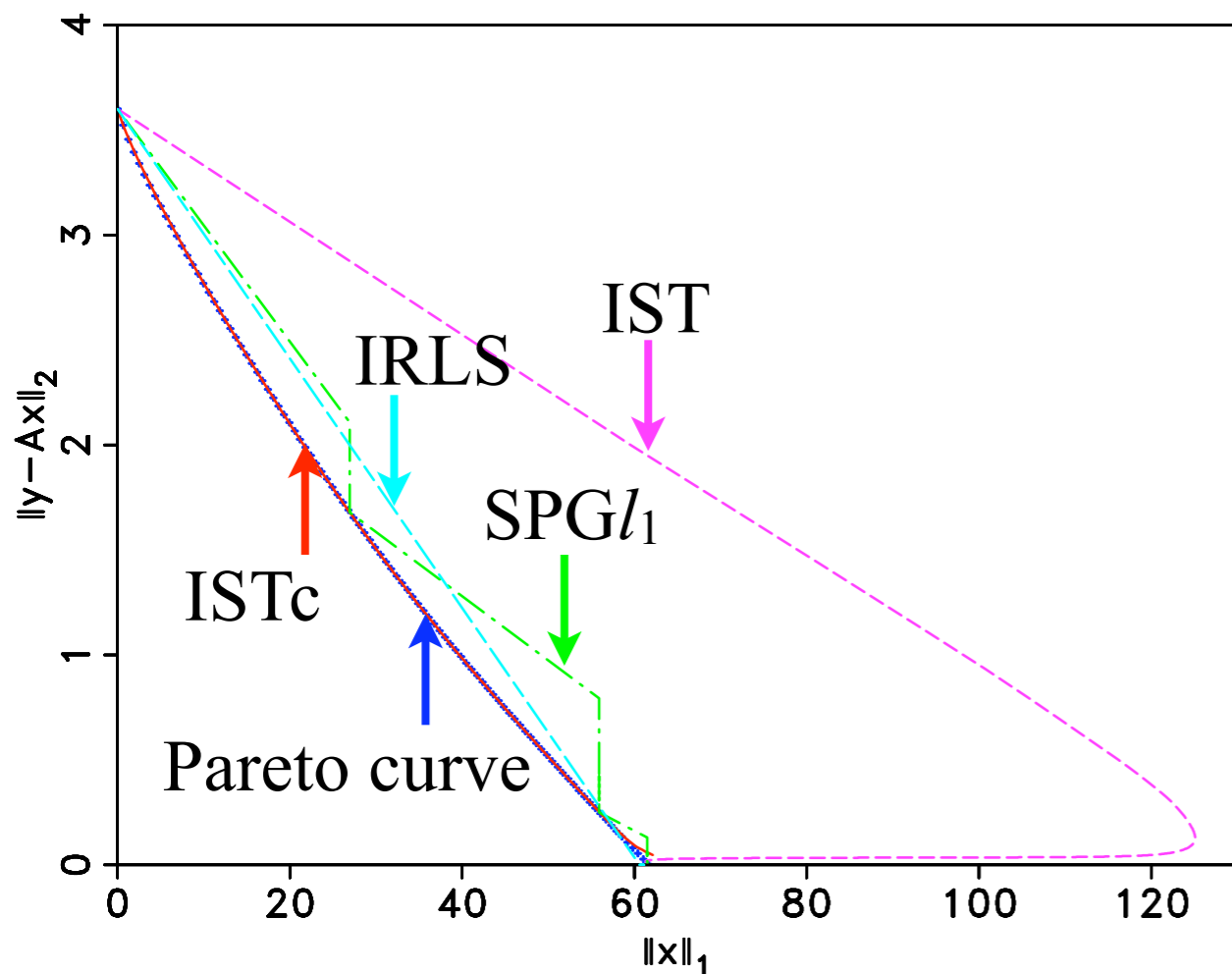
Instance II



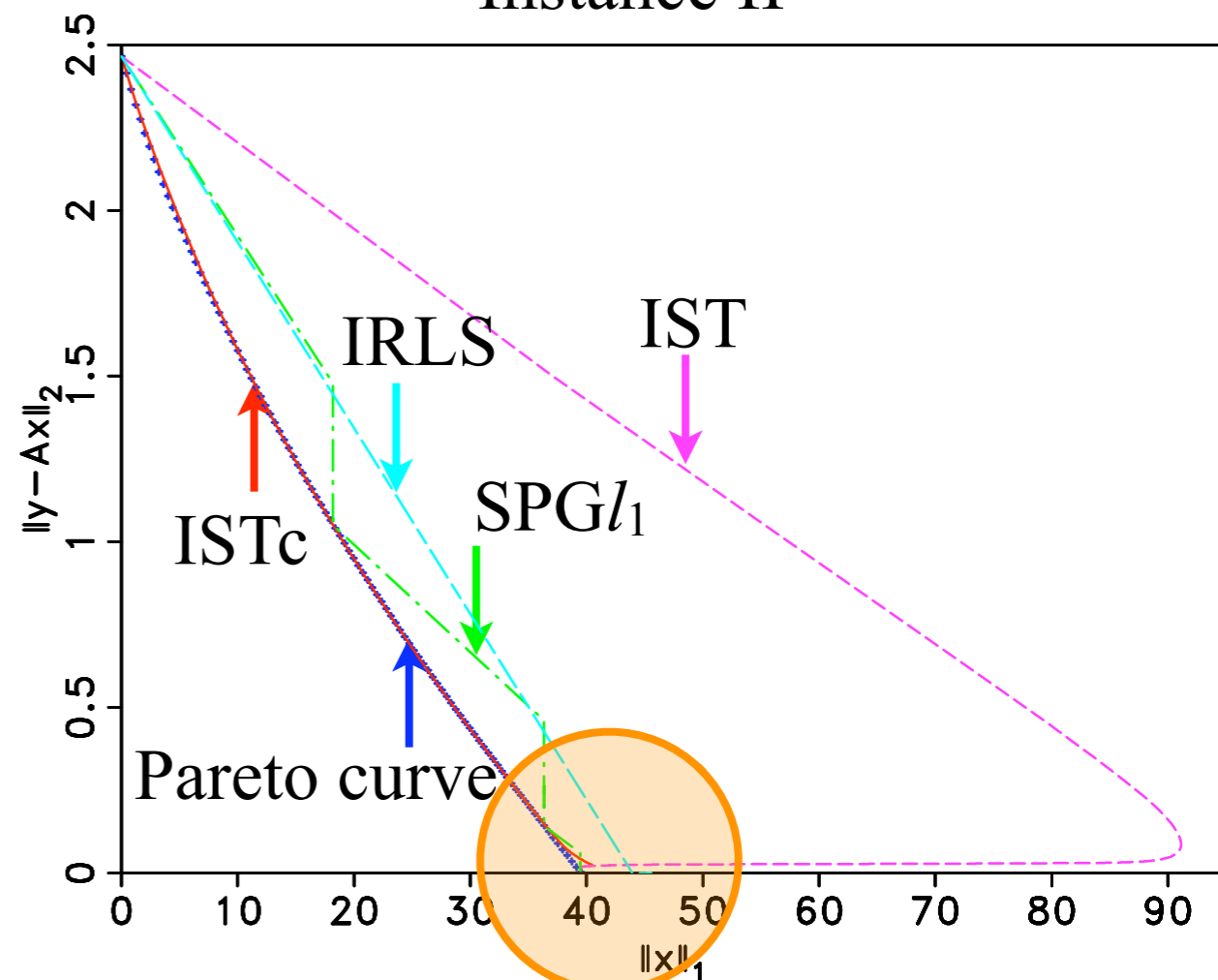
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Instance I



Instance II



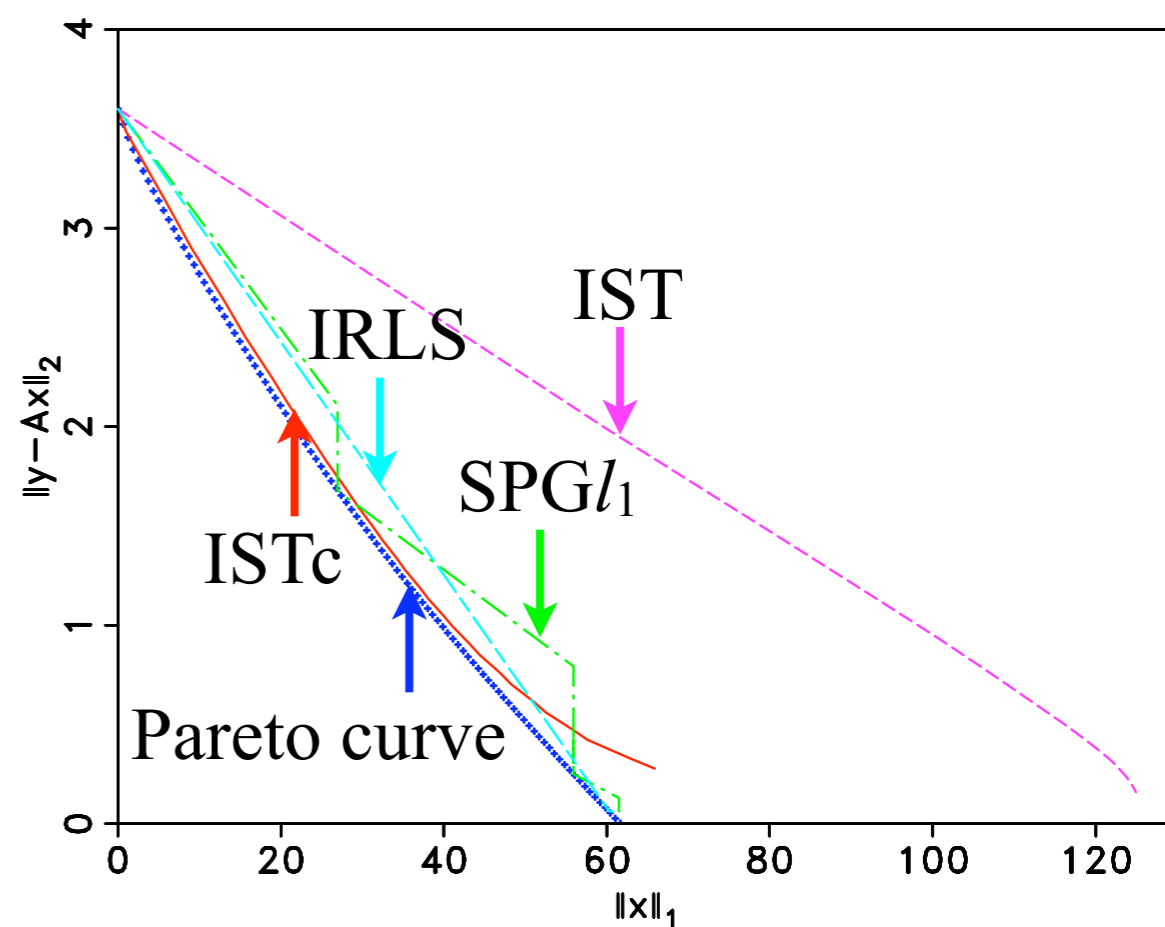
IRLS missed
BP solution

Conclusions

- Pareto curve
 - **optimal tradeoff** between $\|y-Ax\|_2$ and $\|x\|_1$
 - **establishes the connection** between QP_λ , BP_σ , and LS_T
 - **smooth**
 - good approximation to the curve obtained with VERY few interpolating points
- usage
 - explore the nature of a solver's iterations
 - informed decision on how to truncate solution process
 - **safely trade computational cost against solution accuracy**
 - evaluate the performance of one-norm solvers

Future work

- use new insights into one-norm solvers to improve them!!!
 - make SPG/ l_1 more aggressive, yet avoiding overshooting beyond the BP solution
 - keep ISTc closer the Pareto curve towards the BP solution
 - i.e., better usage of the last few iterations
- apply analysis to geophysical problems



Acknowledgments

- S. Fomel, P. Sava, and the other developers of Madagascar (rsf.sourceforge.net)
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- E. van den Berg, M. P. Friedlander, G. Hennenfent, F. J. Herrmann, R. Saab, and O. Yilmaz for Sparco (www.cs.ubc.ca/labs/scl/sparco/)

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