

Introduction to compressive (wavefield) computations

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Motivation

“Holy grail” has been to find transforms that “near diagonalize” wavefield extrapolation operators

$$\begin{array}{c} \left[\begin{array}{|c|} \hline \text{|||||} \\ \hline \end{array} \right] = \left[\begin{array}{|c|} \hline \text{|||||} \\ \hline \end{array} \right] \left[\begin{array}{|c|} \hline \text{///} \\ \hline \end{array} \right] \left[\begin{array}{|c|} \hline \text{====} \\ \hline \end{array} \right] \\ \mathbf{W}^{\pm} = \mathbf{C}^H \hat{\mathbf{W}}^{\pm} \mathbf{C} \end{array}$$

For smooth media curvelets “remain” near diagonal.
Efforts are made to correct for curvelet dispersion.

Problems:

- wavefield extrapolation operators difficult to compute in transformed domain
- complex media tend to fill the extrapolation matrix
- hampered by large constants

Propose a different approach

Compressive wavefield computations

Near diagonality corresponds to preservation of sparsity (Hart Smit's original motivation)

Use this property to "smash" wavefield extrapolation & imaging operators

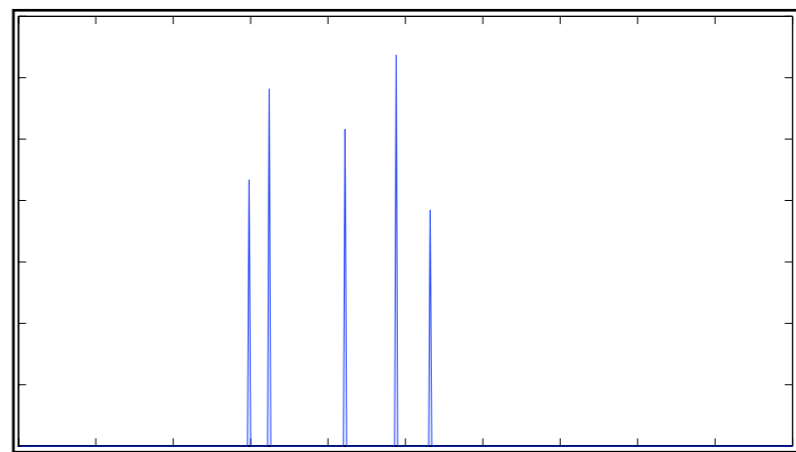
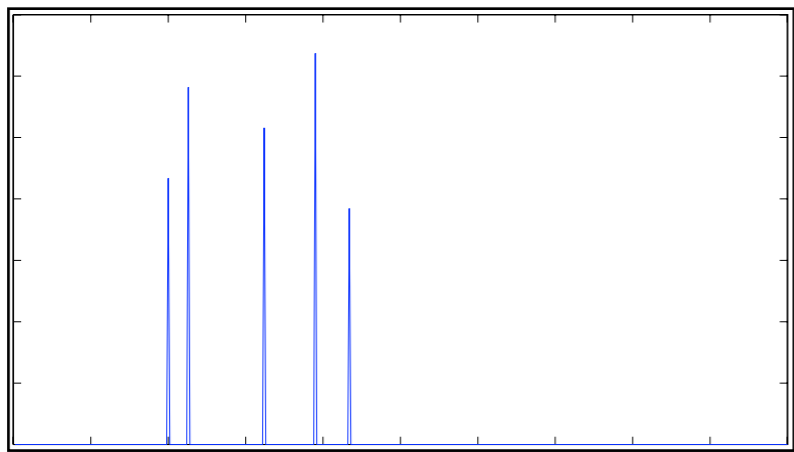
- compressively sample the solution & recover by
- exploiting sparsity &
- "incoherence" between measurement basis & sparsity representations

Smashed operators correspond to operators that are

- restricted in angular frequencies
- restricted in eigenvalues
- etc. etc.

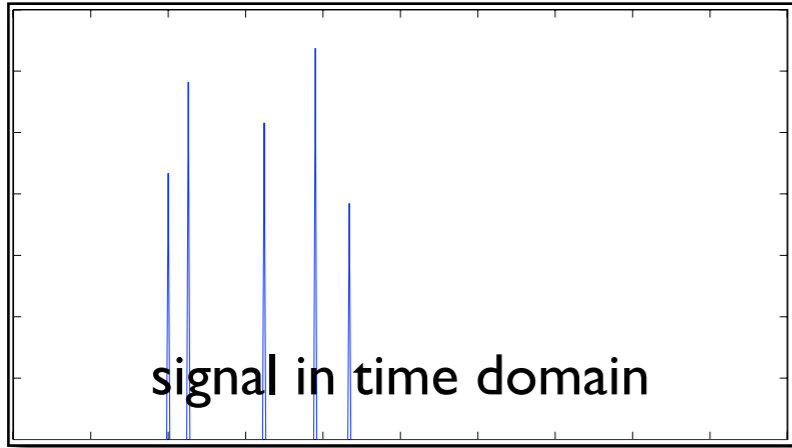
Our approach

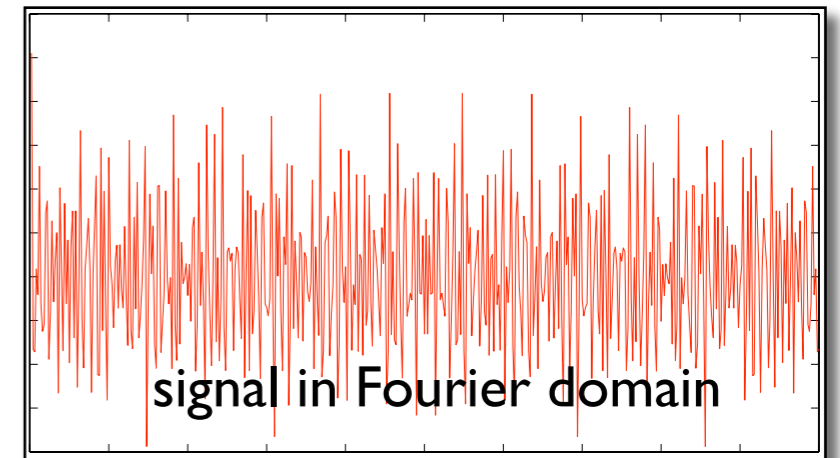
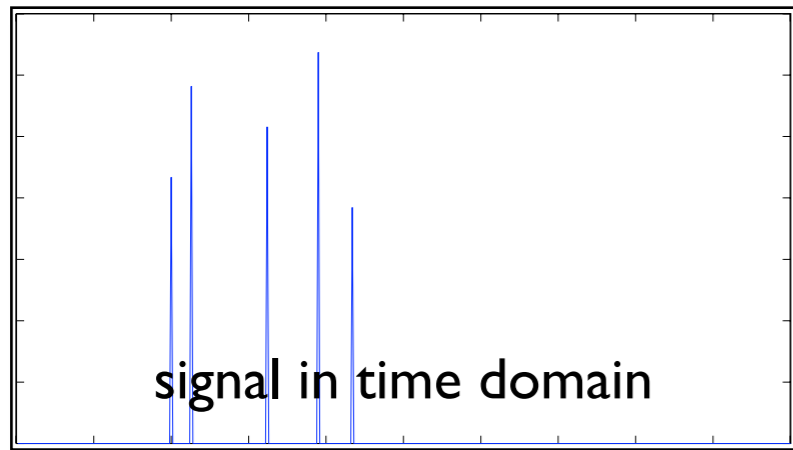
- Consider a related, but simpler problem: shifting (or translating) signal

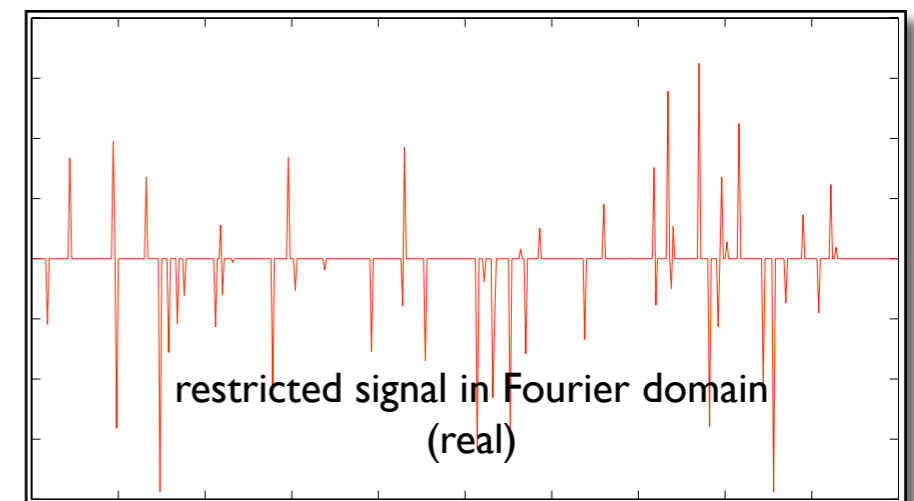
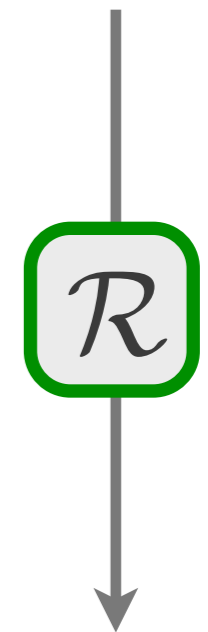
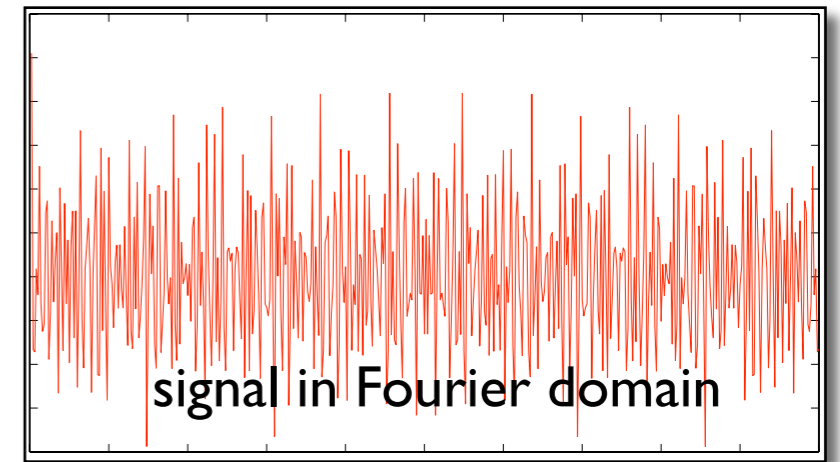
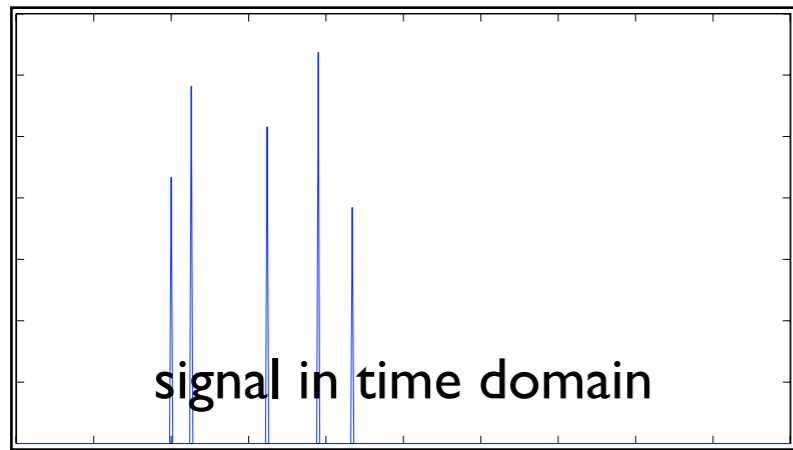


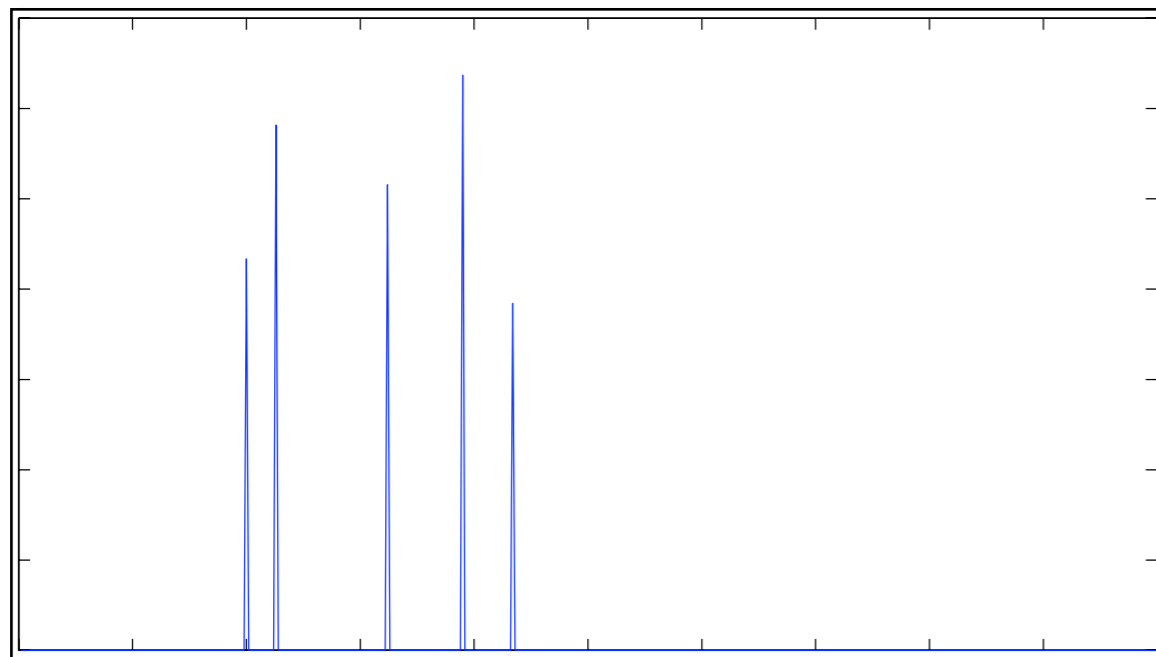
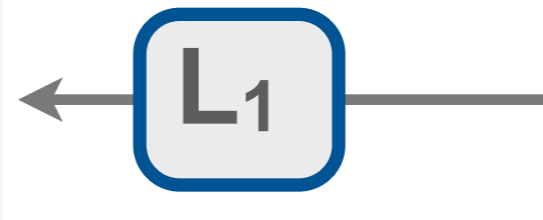
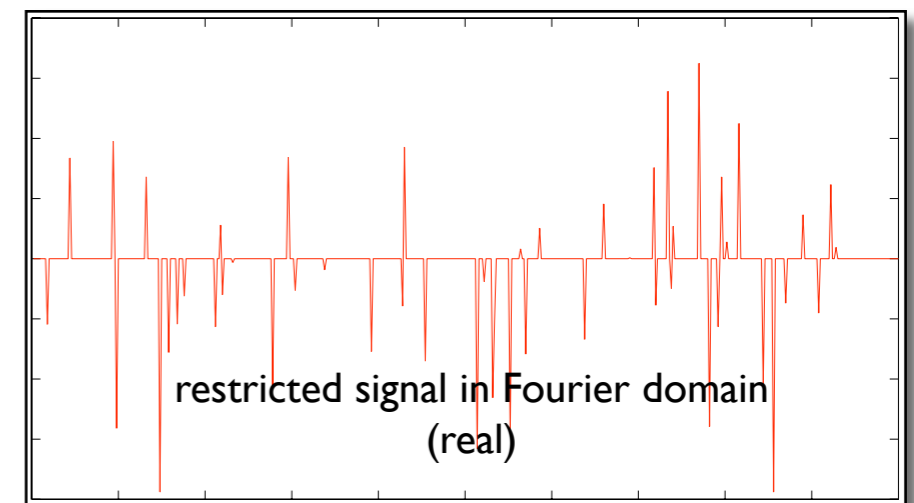
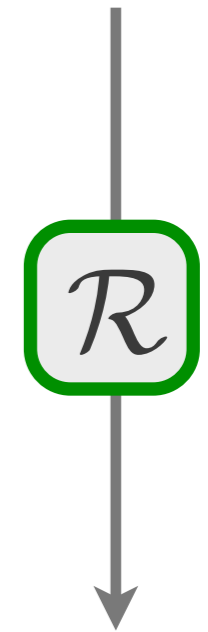
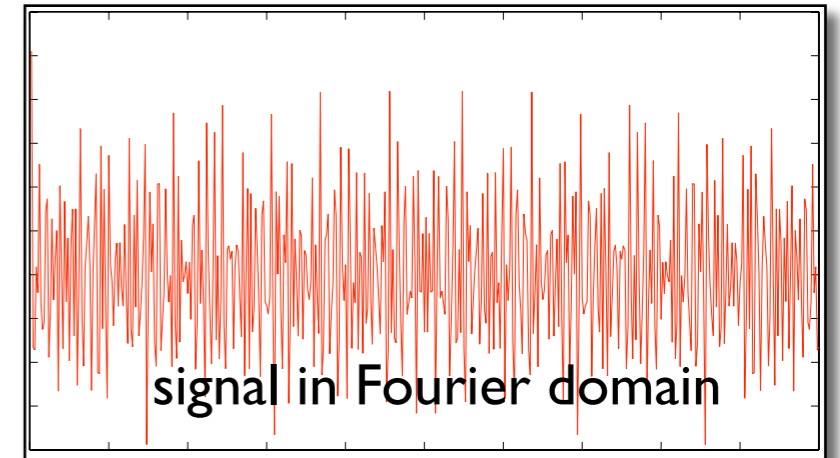
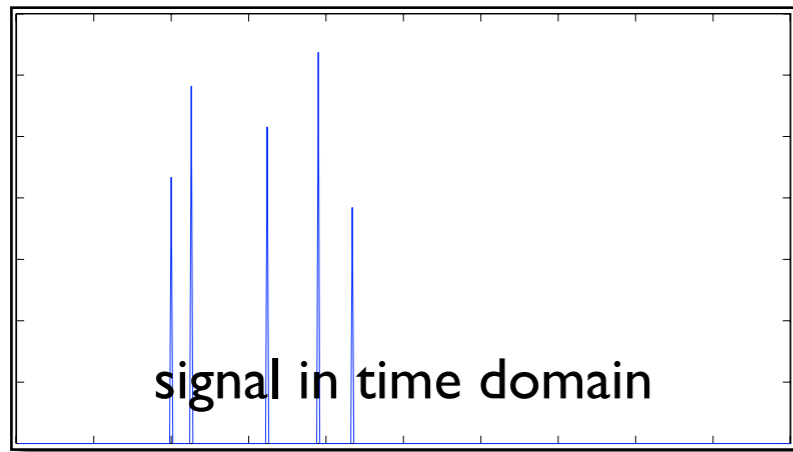
- operator is $\mathbf{S} = e^{-j \frac{\Delta x}{2\pi}} \mathbf{D}$
- \mathbf{D} is differential operator

$$\mathbf{D} = \begin{bmatrix} & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \end{bmatrix}$$

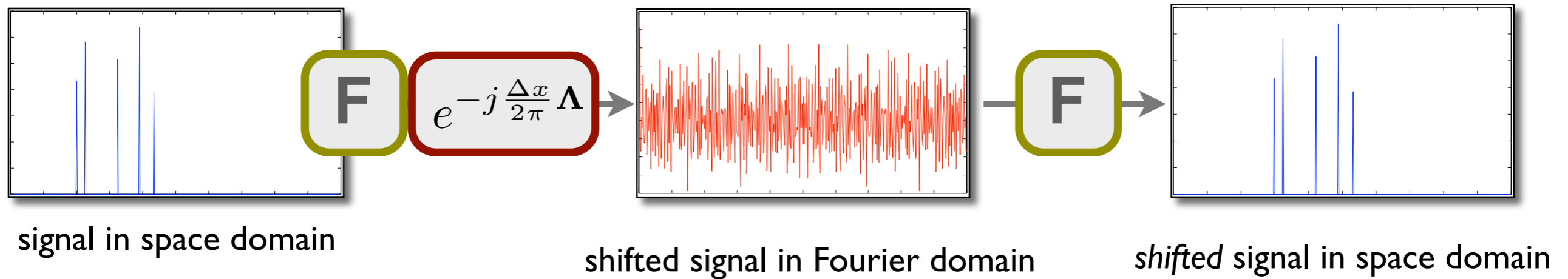




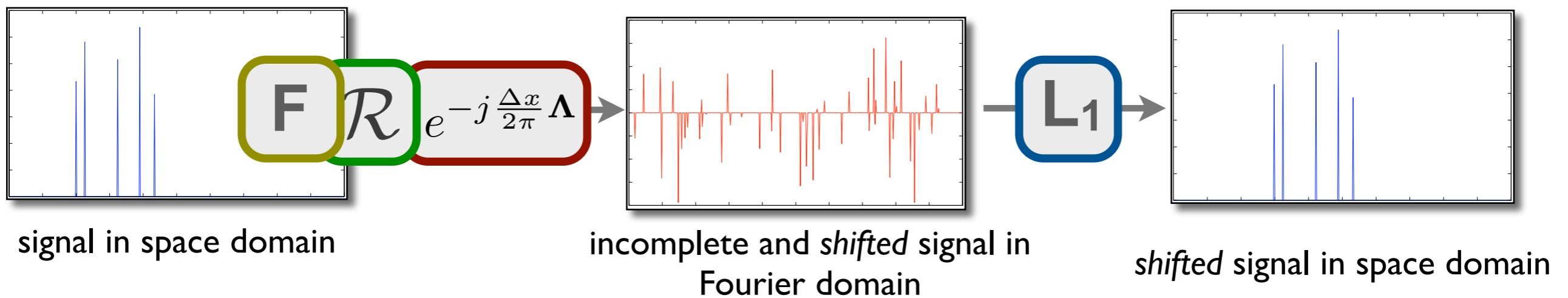




Straightforward Computation



Compressed Processing



Compressive imaging

Seismic data is highly redundant.

Relies on redundancy to reduce SNR.

Based on multidimensional *correlations* of extrapolated wavefields.

Correlations are 'poor man's inverses.

Opens the possibility to leverage *compressive* sampling

- extend the *focal* transform to include *compressive* sampling
- reduce the computational burden of computing the gradient in adjoint state methods

Tensor extension of compressive sampling



Compressive sampling

Based on linear “forward” model

$$\begin{aligned} \mathbf{y} &= \mathbf{RMf}_0 \\ &= \underbrace{\mathbf{RMS}^H}_{\mathbf{A}} \mathbf{x}_0 \end{aligned}$$

with

\mathbf{R} = flat restriction matrix

\mathbf{M} = measurement basis

\mathbf{S}^H = synthesis matrix

\mathbf{y} = \mathbf{RMf}_0 (measured data)

\mathbf{f}_0 = original function

\mathbf{x}_0 = transform-domain representation.

Tensor CS

“Wavefield deconvolution” at heart of

- focal transform
- imaging (*prior* to applying imaging conditions)

Can be formulated as a CS problem

$$\begin{aligned}\mathbf{P} &= \Delta \mathbf{P} \mathbf{P}_0 \\ \mathbf{Y} &= \underbrace{\mathbf{R} \Delta \mathbf{P} \mathbf{S}^H}_{\mathbf{A}} \mathbf{x}_0\end{aligned}$$

- for the focal transform
- multiple right-hand sites
- \mathbf{R} is a 2-D picking matrix

Special case of more general **tensor** formulation of CS for matrices ...

Tensor CS

Use Kronecker product and the vector identity

$$\begin{aligned} \mathbf{U}\mathbf{V}\mathbf{W} &= \mathbf{Z} \\ (\mathbf{W}^H \otimes \mathbf{U})\text{vec}(\mathbf{V}) &= \text{vec}(\mathbf{Z}) \end{aligned}$$

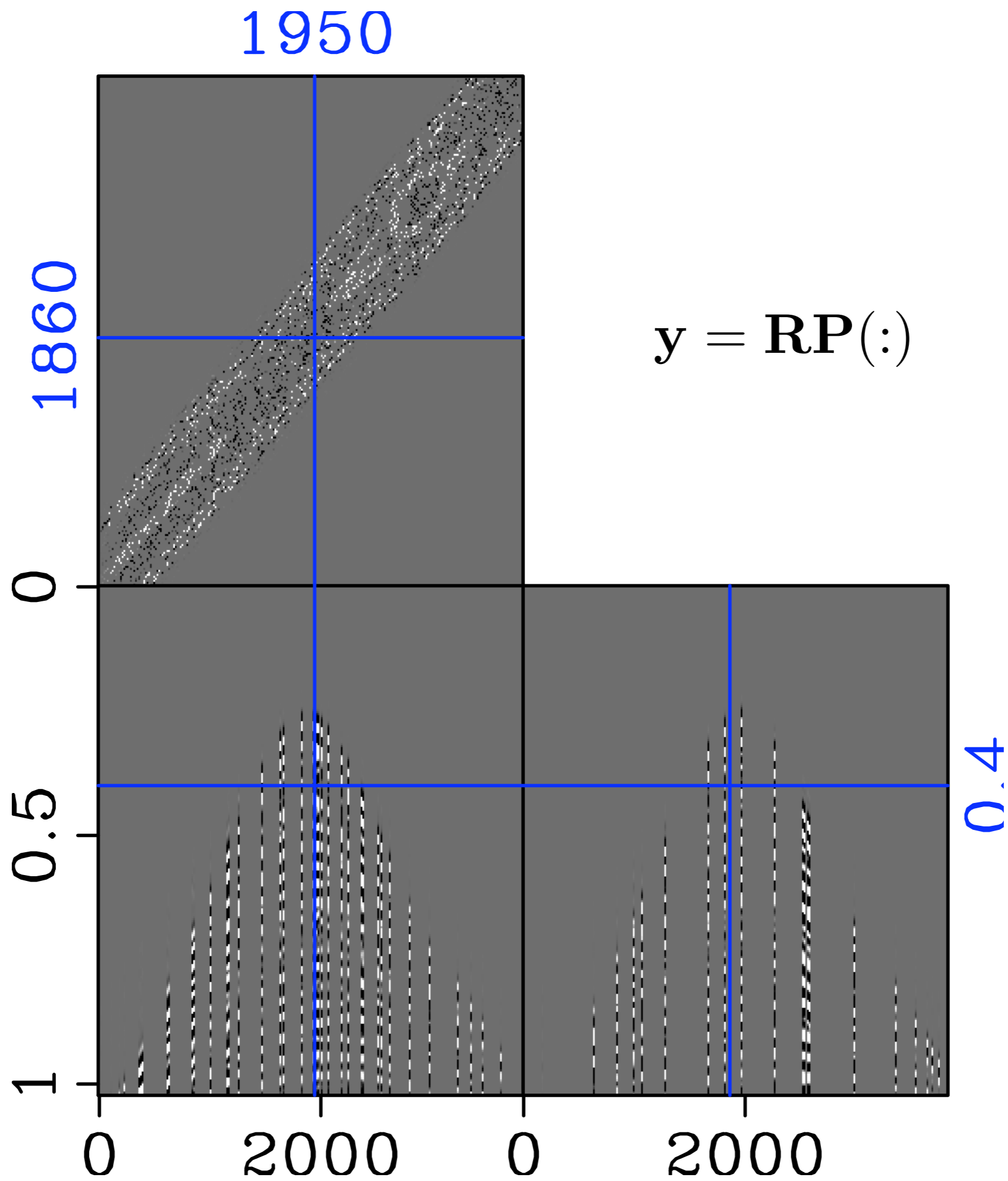
yielding the “forward model” for CS

$$\mathbf{y} = \overbrace{(\mathbf{R}_1\mathbf{M}_1 \otimes \mathbf{R}_2\mathbf{M}_2)\Delta\mathbf{P}\mathbf{C}^H}^{\mathbf{A}} \text{vec}(\mathbf{x}_0)$$

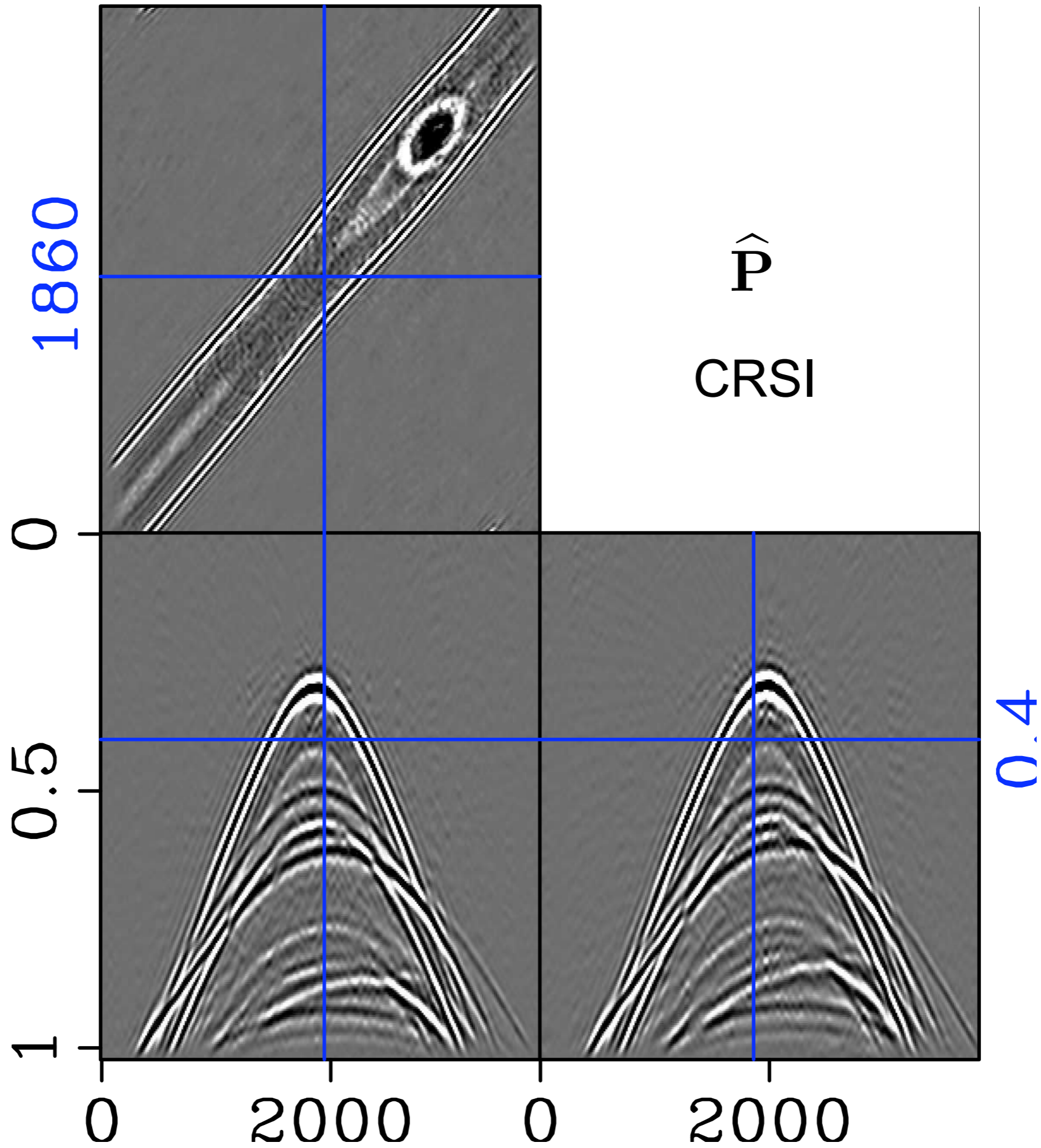
$$\mathbf{y} = (\mathbf{R}_1\mathbf{M}_1 \otimes \mathbf{R}_2\mathbf{M}_2)\text{vec}(\mathbf{P})$$

- so far we used **M=Id**
- possibility to measure & restrict more generally

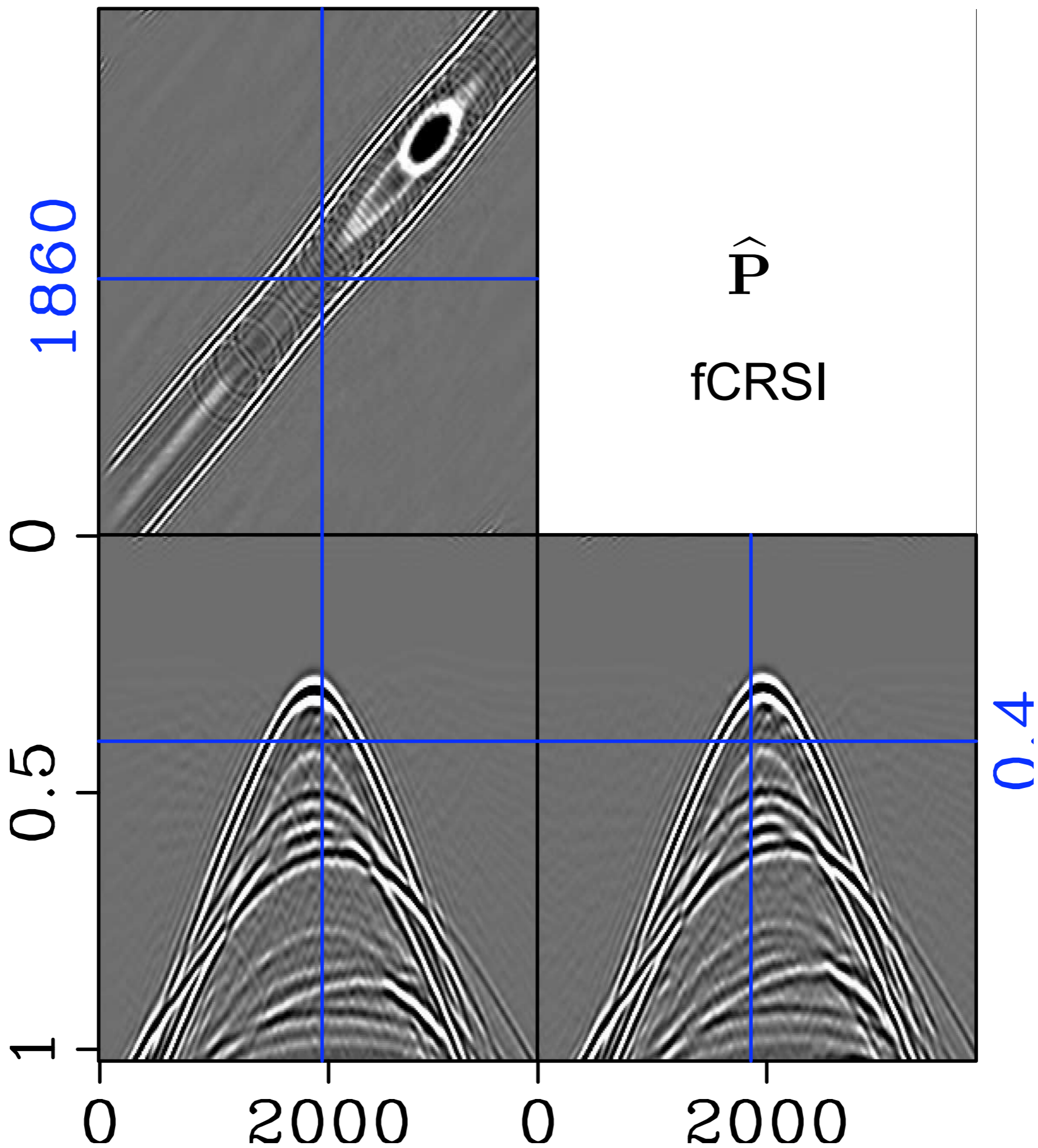
Opens possibility to image compressively compute wavefields (CCW)



1950



1950



Compressive imaging



Seismic imaging

Current paradigm:

- based on adjoint state methods for the wave equation
- predominantly implemented in finite difference => reverse-time wave-equation migration
- most time spend on **marching** wavefields
- imaging done through multidimensional **correlations**

New developments

- implicit spectral methods for Helmholtz
- new preconditioners
- compressive sensing

Propose a new nonlinear paradigm ...

Compressive seismic imaging

New paradigm: compressively

- forward propagate the source wavefield
- backward propagate the residual wavefield
- multidimensionally invert (“deconvolve”) the backward propagated wavefield from the forward propagated wavefield => image

Benefits from

- current preconditioners for Helmholtz
- reduced system size due to CS
- improved image through inversion
- intuitive divide-and-conquer
 - compressive linear wavefield extrapolation
 - nonlinear image recovery

Adjoint state methods

Migration corresponds to the Jacobian of a PDE constraint optimization problem.

Forward model:

$$\mathbf{A}[\mathbf{m}]\mathbf{u} = \mathbf{f}$$

With observed data

$$\mathbf{d} = \mathbf{D}\mathbf{u} + \mathbf{n}$$

Inverse problem

$$\min_{\mathbf{u} \in \mathcal{U}, \mathbf{m} \in \mathcal{M}} \frac{1}{2} \|\mathbf{D}\mathbf{u} - \mathbf{d}\|_2^2 \quad \text{subject to} \quad \mathbf{A}[\mathbf{m}]\mathbf{u} = \mathbf{f}$$

Adjoint state methods

Reformulate in unconstrained nonlinear LS problem

$$\min_{\mathbf{m} \in \mathcal{M}} \frac{1}{2} \|\mathbf{F}[\mathbf{m}] - \mathbf{d}\|_2^2$$

with

$$\mathbf{F}[\mathbf{m}] = \mathbf{D}\mathbf{A}^{-1}[\mathbf{m}]\mathbf{f}$$

and the gradient = migrated image

$$\nabla J(\mathbf{m}) = -\Re \left(\sum_{\omega} \sum_s \langle \mathbf{v}_s, \frac{\partial \mathbf{A}}{\partial \mathbf{m}} \mathbf{u}_s \rangle \right)$$

involving for each shot the solution of

$$\mathbf{A}[\mathbf{m}]\mathbf{u} = \mathbf{f} \quad \text{and} \quad \mathbf{A}^H[\mathbf{m}]\mathbf{v} = \mathbf{r}$$

with

$$\mathbf{r} = \mathbf{D}^H (\mathbf{F}[\mathbf{m}] - \mathbf{d})$$

Compressed adjoint state method

Replace observations by compressed observations:

$$\mathbf{y} = \mathbf{RMDu}$$

Change representation forward model:

$$\mathbf{A}[\mathbf{S}^H \mathbf{x}] \mathbf{u} = \mathbf{f}$$

yielding the inverse problem

$$\min_{\mathbf{u} \in \hat{\mathcal{U}}, \mathbf{x} \in \mathcal{X}} \frac{1}{2} \|\mathbf{RMDu} - \mathbf{y}\|_2^2 + \alpha \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{A}[\mathbf{S}^H \mathbf{x}] \mathbf{u} = \mathbf{f}$$

Compressed systems for \mathbf{R} along source & receiver & omega

$$\mathbf{A}[\mathbf{S}^H \mathbf{x}] \mathbf{u} = \mathbf{f} \quad \text{and} \quad \mathbf{A}^H[\mathbf{S}^H \mathbf{x}] \mathbf{v} = \mathbf{r}$$

with residue

$$\mathbf{r} = -\mathbf{D}^H \mathbf{M}^H \mathbf{R}^H \underbrace{(\mathbf{RMDA}^{-1} [\mathbf{S}^H \mathbf{x}] \mathbf{f} - \mathbf{y})}_{\mathbf{F}[\mathbf{S}^H \mathbf{x}]}$$

Compressed adjoint state method

Opens the way to formulate 'post-stack' imaging as

$$\min_{\mathbf{x} \in \mathcal{X}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \underbrace{\text{diag}(\mathbf{u}) \mathbf{S}^H \mathbf{x} = \mathbf{v}}_{\mathbf{A}\mathbf{x}=\mathbf{y}}$$

with descent updates on the l_1 ball

$$\mathbf{x}^{n+1} = \mathbf{S}_\alpha \left(\mathbf{x}^n + \mathbf{A}^H (\mathbf{y} - \mathbf{A}\mathbf{x}^n) \right)$$

Special case of prestack imaging

$$\min_{\mathbf{x} \in \mathcal{X}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \underbrace{(\mathbf{R}\mathbf{M}\mathbf{U}) \mathbf{S}^H \mathbf{x} = \mathbf{R}\mathbf{M}\mathbf{V}}_{\mathbf{A}\mathbf{x}=\mathbf{y}}$$

Conclusions

CS opens perspectives on compressing operators.

New field in scientific computing.

Next talks will be precursors of what to come ...

Acknowledgments

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Extensions imaging



part of SINBAD II