

Full-Waveform Inversion with Gauss-Newton-Krylov Method

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Full-Waveform Inversion (FWI)

Given experiment data \mathbf{P} .

With the misfit functional: $E[\mathbf{m}] = \frac{1}{2} \|\mathbf{P} - \mathbf{F}[\mathbf{m}]\|_2^2$

Optimization Problem: Find

$$\hat{\mathbf{m}} = \arg \min_{\mathbf{m} \in \mathcal{M}} E[\mathbf{m}] \quad \text{subject to} \quad \mathbf{F}[\mathbf{m}] = \mathbf{D}\mathbf{U}[\mathbf{m}]$$

the (forward) modeling wavefields \mathbf{U} restricted to the receivers by \mathbf{D} .

- Lailly, 1983
- Tarantola, 1984, 1986, 1987
- Pratt and co-authors, 1996, 1998, 1999, 2003

Frequency domain FWI

Forward model: Helmholtz equation

$$\mathbf{H}[\omega, \mathbf{m}] \mathbf{U} = \mathbf{Q}, \quad \mathbf{m} = (m_1 \dots m_M)^T$$

- \mathbf{H} : the Helmholtz matrix, function of angular freq ω
- $\mathbf{Q} = [\mathbf{q}_1 \dots \mathbf{q}_{n_s}]$: the source matrix, with n_s shots
- $\mathbf{U} = [\mathbf{u}_1 \dots \mathbf{u}_{n_s}]$: the wavefield matrix

Impediments

- Fast, scalable solver for the forward and adjoint systems
 - iterative method with
 - Preconditioning with shifted Laplacian [E. et al. (2006), Riyanti et al., (2006)]
 - Multilevel Krylov method [E. & Nabben (2009), E. & Herrmann (2008)]
- Multidimensional experiments (shots, frequencies): more data than model
 - Data reduction via frequency subsampling [Sirgue & Pratt (2004), Mulder & Plessix (2004)]
 - Compressive Sampling (CS) framework : data reduction via *shot* and *frequency* subsampling
 - compressive wavefield computation [Lin, Herrmann (2007), Herrmann, E. & Lin (2009)]
 - extension to compressive imaging
- Fast minimization solver (GN-type: Hessian)
 - Gauss-Newton method with implicit computation of Hessian

Our solution

- Gauss-Newton with implicit Hessian (Gauss-Newton-Krylov, GNK)
- Dimensionality reduction
 - [Herrmann, E. & Lin (2009)]
 - [Tim Lin: Compressive simultaneous full-waveform simulation, this meeting, SM1]

$$\left\{ \begin{array}{l} \mathbf{Q} = \mathbf{D}^* \underbrace{\mathbf{s}}_{\text{single shots}} \\ \mathbf{H}\mathbf{U} = \mathbf{Q} \\ \mathbf{y} = \mathbf{R}\mathbf{M}\mathbf{D}\mathbf{U} \end{array} \right. \iff \left\{ \begin{array}{l} \underline{\mathbf{Q}} = \underline{\mathbf{D}}^* \underbrace{\mathbf{R}\mathbf{M}\mathbf{s}}_{\text{simul. shots}} \\ \underline{\mathbf{H}}\mathbf{U} = \underline{\mathbf{Q}} \\ \underline{\mathbf{y}} = \underline{\mathbf{D}}\mathbf{U} \end{array} \right.$$

- FWI with CS

FWI with CS

The misfit functional: $\underline{E}[\mathbf{m}] = \frac{1}{2} \|\mathbf{RM}(\mathbf{P} - \mathbf{F}[\mathbf{m}])\|_2^2$

with \mathbf{RM} a CS-sampling matrix (reduces data size).

Optimization Problem: Find

$$\hat{\mathbf{m}} = \arg \min_{\mathbf{m} \in \mathcal{M}} \underline{E}[\mathbf{m}] \quad \text{subject to} \quad \mathbf{F}[\mathbf{m}] = \mathbf{DU}[\mathbf{m}]$$

Main contribution: [Hermann et al. (2009), EAGE]
See also: Krebs et al. (2009), this meeting

$$\underline{E}[\mathbf{m}] = \frac{1}{2} \|\underline{\mathbf{P}} - \underline{\mathbf{F}}[\mathbf{m}]\|_2^2$$

In line with this:

Sampling of overdetermined systems [Drineas, Mahoney & Muthukhrisnan (2006)]

- $\min \underline{E} \neq \min E$ but is a bounded approximation.

Outline

- Newton method: Hessian
 - Implicit computation of the GN Hessian
 - Extension to CS framework
 - Reduced numbers of shots and frequencies
 - Examples
-
- related work: in time domain [Akcelic, Biros & Ghattas (2002)]
 - PDE-constrained optimization: KKT systems, reduced systems, etc [Heinkenschloss (1991), Biros & Ghattas (2005), ...]

Newton Method

$$E[\mathbf{m} + \delta\mathbf{m}] = E[\mathbf{m}] + \mathbf{g}^T \delta\mathbf{m} + \frac{1}{2} \delta\mathbf{m}^T \mathcal{H} \delta\mathbf{m}$$

Initial model \mathbf{m}_0 ;

Update until convergence:

$$\begin{aligned} \delta\mathbf{m} &= -\mathcal{H}_{k-1}^{-1} \mathbf{g}_{k-1}; \\ \mathbf{m}_k &= \mathbf{m}_{k-1} + \gamma_{k-1} \delta\mathbf{m}; \end{aligned}$$

with

- $\mathbf{g}_{k-1} \equiv \mathbf{g}[\mathbf{m}_{k-1}]$: the gradient,
- $\mathcal{H}_{k-1} \equiv \mathcal{H}[\mathbf{m}_{k-1}]$: the Hessian,
- γ_{k-1} : the step length.

Hessian: $\mathcal{H} = [h_{i,j}]$ with

$$h_{i,j} = \frac{\partial}{\partial m_i} \left(\frac{\partial E}{\partial m_j} \right)$$
$$= \text{rowsum} \left(\frac{\partial^2 \mathbf{U}}{\partial m_i \partial m_j} - \frac{\partial \mathbf{U}}{\partial m_i} \frac{\partial \mathbf{F}}{\partial m_j} \right).$$

- Negative sign: not necessarily SP(S)D
- Fast/quadratic convergence only if close to the minimizer
- From the adjoint system: $\frac{\partial \mathbf{U}}{\partial m_i} \rightarrow \mathbf{V}$ (back-propagated)

Gauss-Newton Method

- Simplify the Hessian by setting $\frac{\partial \mathbf{U}}{\partial m_i} \frac{\partial \mathbf{F}}{\partial m_j} = 0$
 - nonlinear wave phenomena (e.g. multiples)

- Giving

$$h_{i,j}^{GN} = \text{rowsum} \left(\frac{\partial^2 \mathbf{U}}{\partial m_i \partial m_j} \right).$$

- This is associated with setting the back-propagated wavefield $\mathbf{V} = 0$ in the Hessian
- $\mathcal{H}^{GN} = [h_{i,j}^{GN}]$ is SP(S)D.

Inverting the Hessian: Krylov

$$\mathcal{H}_{k-1}^{GN} \delta \mathbf{m} = -\mathbf{g}_{k-1}$$

SP(S)D Hessian: compute $\delta \mathbf{m}$ with Conjugate Gradient (CG).
Four important steps in CG:

- compute: $\mathbf{w} := \mathcal{H}_{k-1}^{GN} \mathbf{p}$
- solution update: $\delta \mathbf{m} \leftarrow \delta \mathbf{m} + \alpha \mathbf{p}$
- residual update: $\mathbf{r} \leftarrow \mathbf{r} - \alpha \mathbf{w}$
- search dir. update: $\mathbf{p} \leftarrow \mathbf{r} + \beta \mathbf{w}$

α, β :

CG step lengths,
satisfying
orthogonal
projection

$\mathbf{p} \sim \delta^2 \mathbf{m}$: second variation (of the Lagrangian) of \mathbf{m} .

Second variation system of GN

- derived from second variations of the Lagrange minimization functional
- detailed treatment in weak (bilinear) formulation, see the abstract.

$$\text{Forward model: } \mathbf{H}[\mathbf{m}]\tilde{\mathbf{U}} = -\omega^2 \text{diag}(\mathbf{p})\mathbf{U}$$

- $\tilde{\mathbf{U}}$: second variation of \mathbf{U}

$$\text{Adjoint system/back propagation: } \mathbf{H}[\mathbf{m}]\tilde{\mathbf{V}} = \mathbf{D}^*\mathbf{D}\tilde{\mathbf{U}}$$

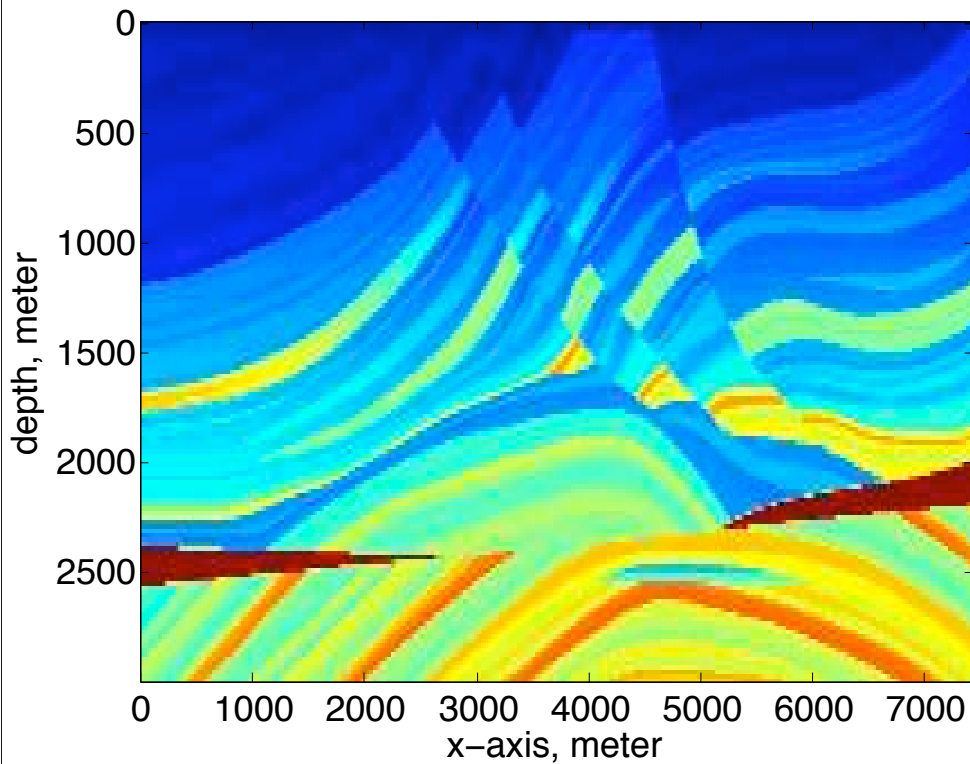
- $\tilde{\mathbf{V}}$: the second variation of \mathbf{V}

The action of Hessian on \mathbf{p}

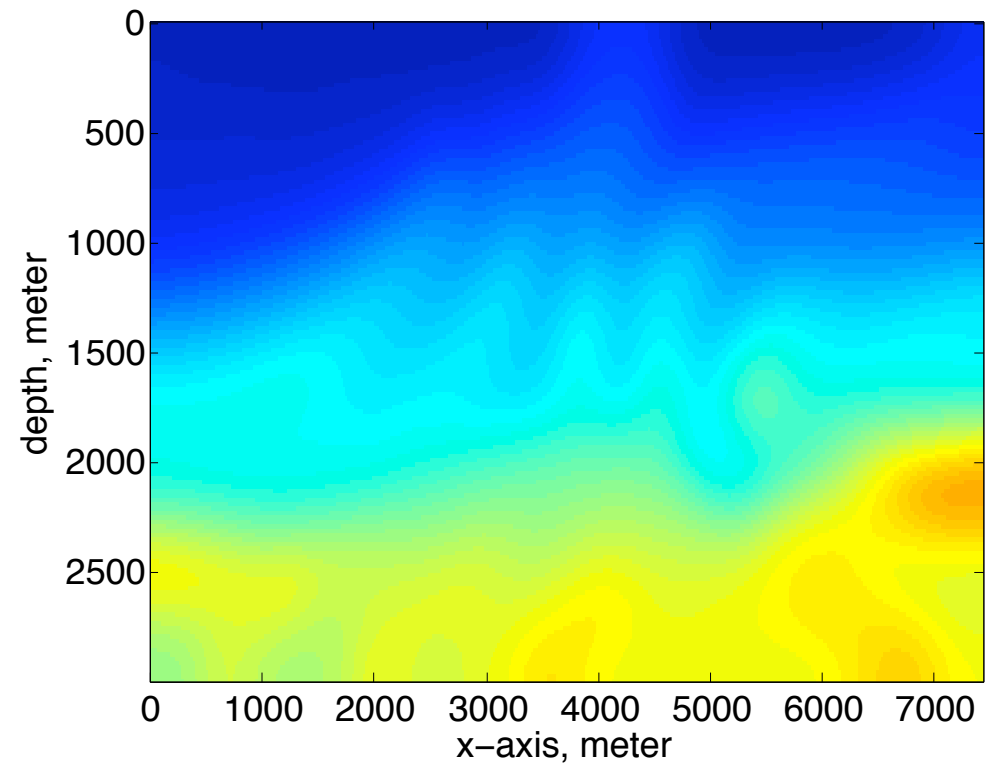
$$\mathcal{H}^{GN}\mathbf{p} := -\omega^2 \text{rowsum}(\mathbf{U} \odot \tilde{\mathbf{V}})$$

FWI: Examples

Marmousi model: 7420 x 2980 m, 372 x 150 gridpoints, 370 shots. Freqs: 3, 5, 9 Hz. 10 CG iters for the Hessian.



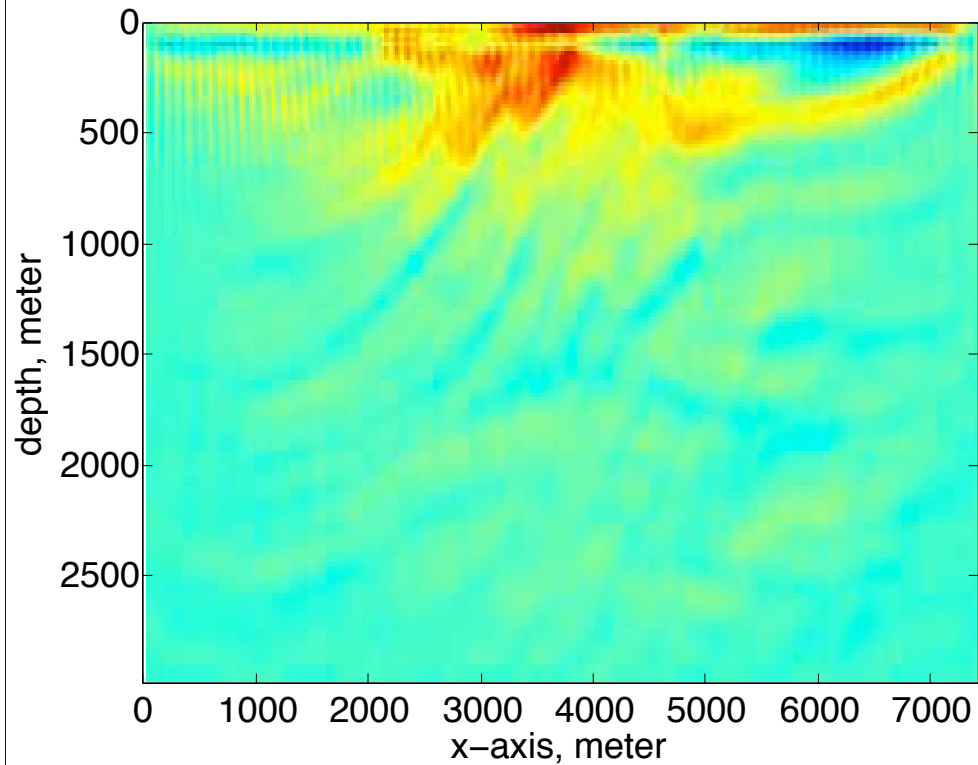
Hard model



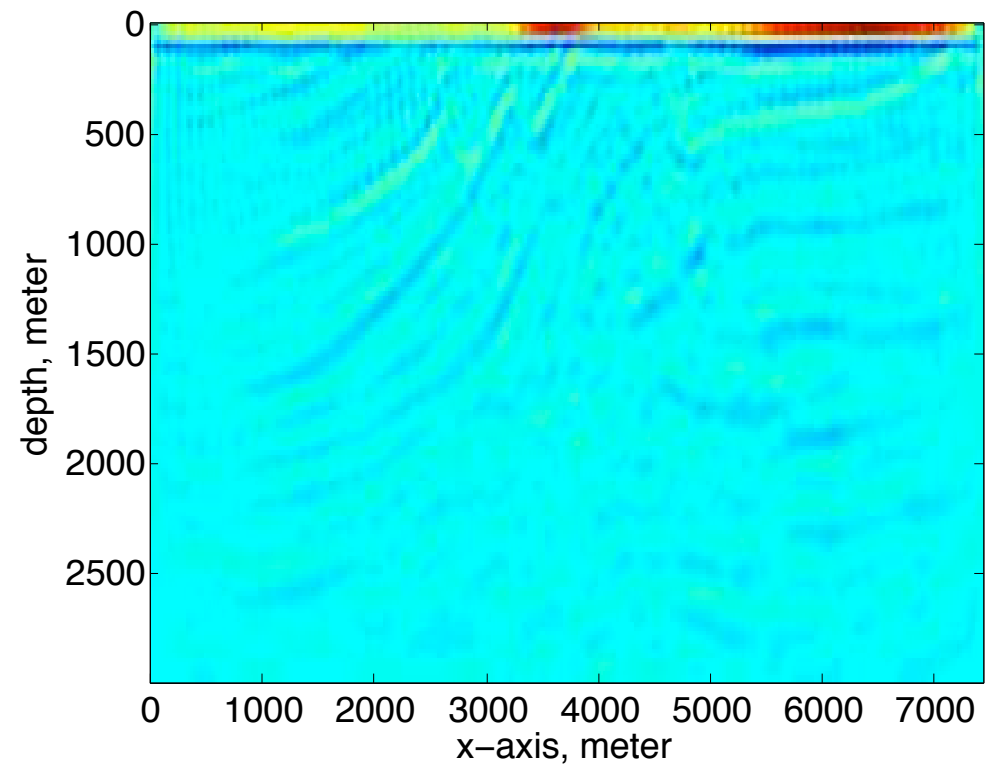
Smooth model

First Update (in $\delta\mathbf{m}$)

Gradient Method



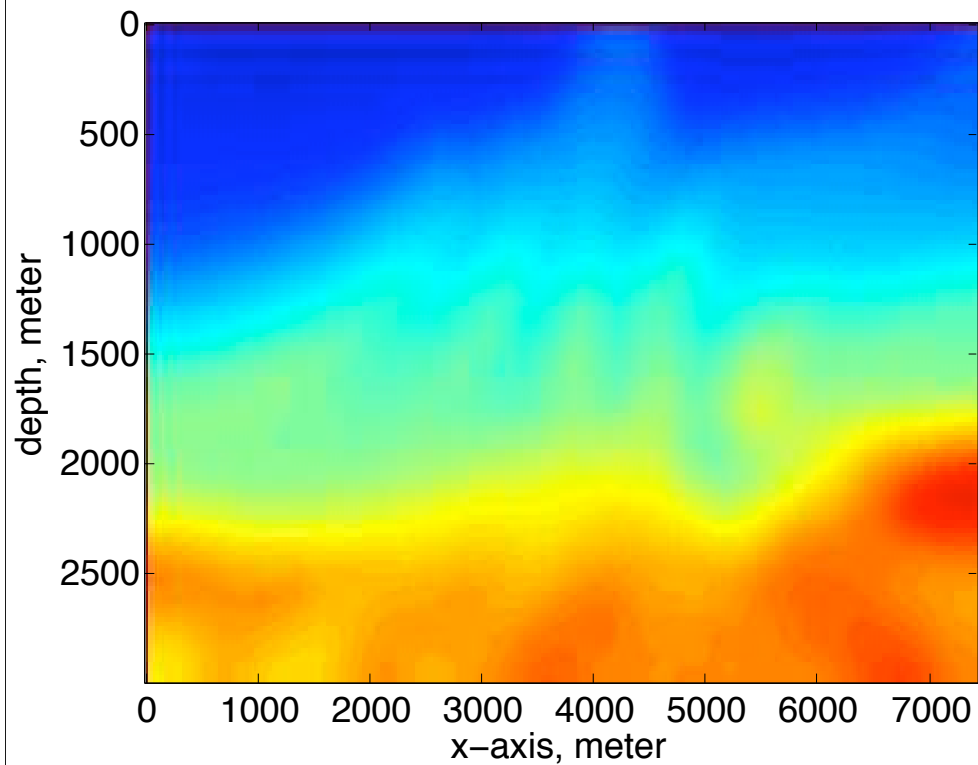
GNK



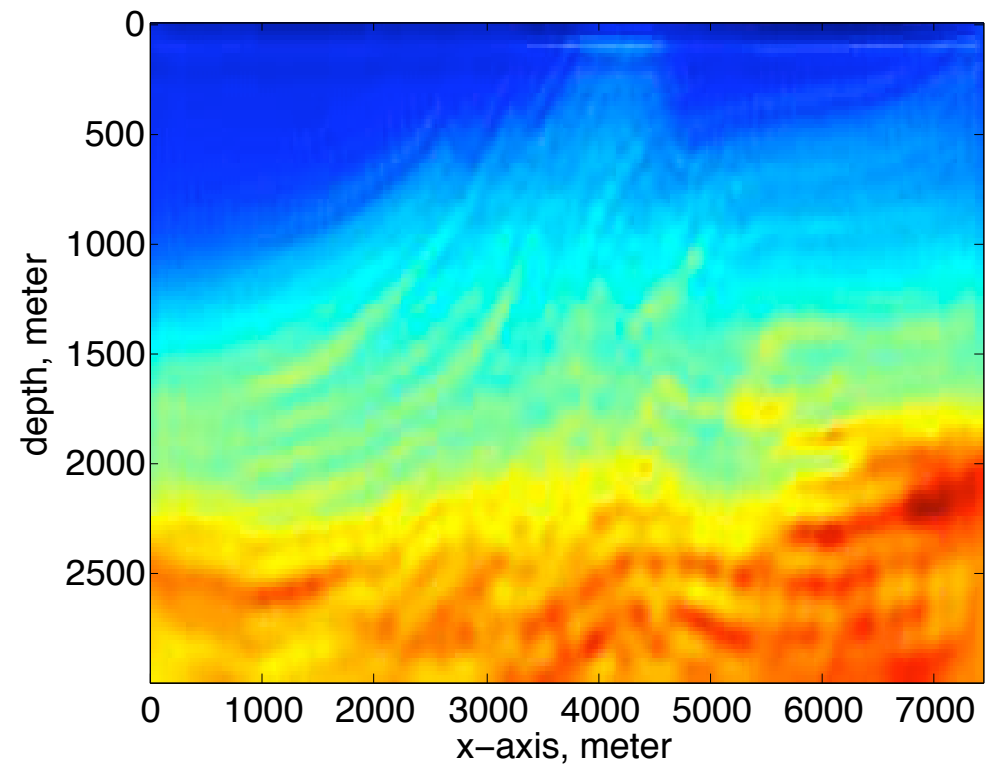
Note: different scale (by 10^3)

Velocity after the first update

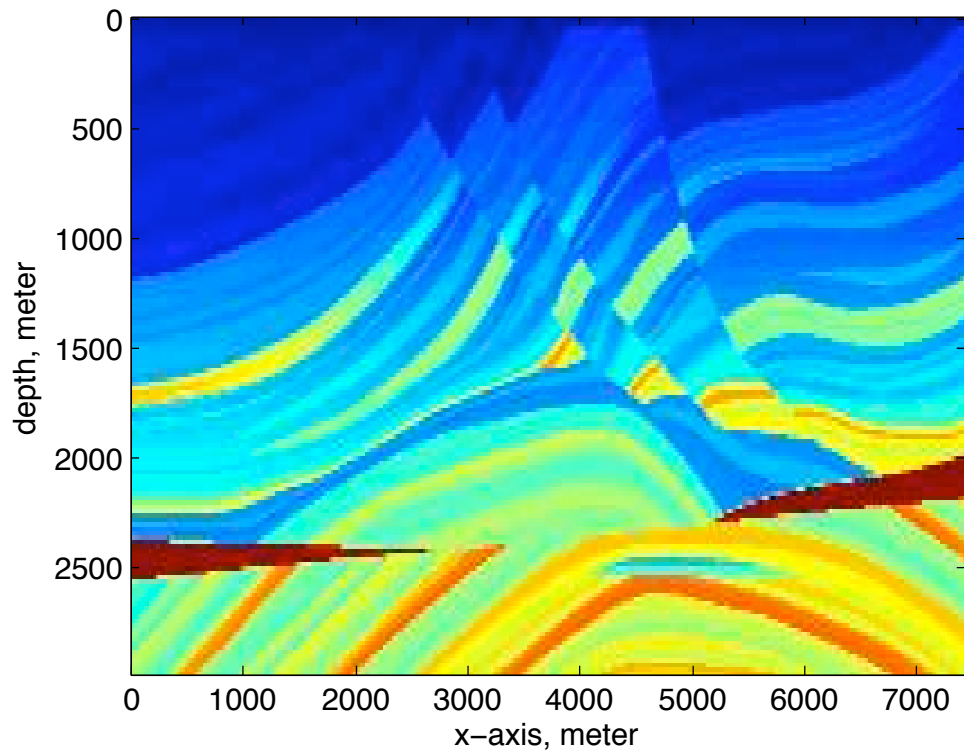
Gradient Method



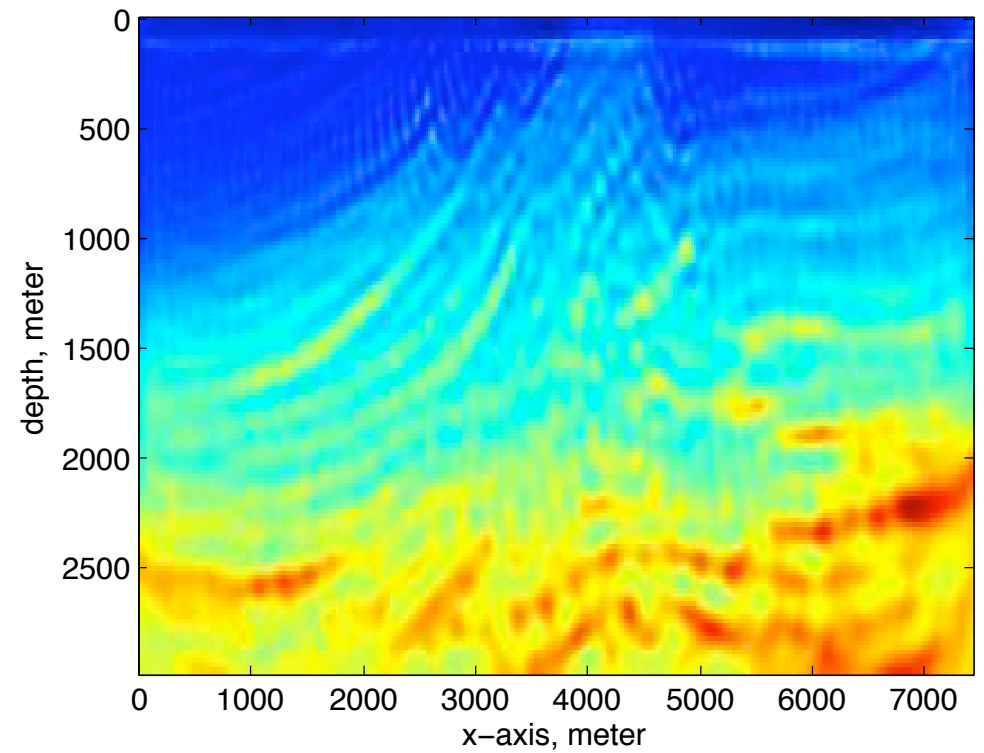
GNK



After 5 iterations



Hard model



Inverted Result

FWI with compressive simultaneous source (CFWI)

Minimization problem:

$$\hat{\mathbf{m}}_R = \arg \min_{\mathbf{m} \in \mathcal{M}} \frac{1}{2} \|\mathbf{RM}(\mathbf{P} - \mathbf{F})\|_2^2$$

RM :

- CS-sampling matrix
- turns single shots into randomized simultaneous shots
- subsamples the shots (fewer shots) and frequencies

Simultaneous shots:

Beasley, Chambers & Jiang (1998), Beasley (2008)

Berkhout (2008)

Neelamani, Krohn, Krebs, Deffenbaugh & Romberg (2008)

Herrmann, E. & Lin (2009)

Gradient method of CFWI

Minimize functional:

$$\begin{aligned} E &= \frac{1}{2} \|\mathbf{RM}(\mathbf{P} - \mathbf{DU})\|_2^2 \\ &= \frac{1}{2} (\mathbf{RM}(\mathbf{P} - \mathbf{DU}))^T \overline{\mathbf{RM}(\mathbf{P} - \mathbf{DU})} \end{aligned}$$

Gradient update: $\mathbf{g}_R = \text{rowsum} \left(\mathbf{J}^T \overline{\mathbf{RM}(\mathbf{P} - \mathbf{DU})} \right)$

with the Jacobian $\mathbf{J} \equiv \mathbf{J}(\mathbf{RMDU})$.

$$\mathbf{g}_R = -\text{rowsum} \left(\mathbf{J} \odot \overline{\mathbf{RM}(\mathbf{P} - \mathbf{DU})} \right)$$

Using wavefield-source equivalence [Herrmann, E., & Lin, 2009]

Gradient update $\delta \mathbf{m} = \mathbf{g} = \underline{\mathbf{J}}^T (\underline{\mathbf{P}} - \underline{\mathbf{D}}\underline{\mathbf{U}})$

with

- $\underline{\mathbf{J}} \equiv \underline{\mathbf{J}}(\underline{\mathbf{D}}\underline{\mathbf{U}})$: the (compressed) Jacobian w.r.t. to the compressed simultaneous sources
- $\underline{\mathbf{P}}$: data obtained with simultaneous shot

Computing the Jacobian

Compressed forward model: $\underline{\mathbf{H}}\underline{\mathbf{U}} = \underline{\mathbf{Q}}$

$$\Rightarrow \frac{\partial \underline{\mathbf{U}}}{\partial m_i} = -\underline{\mathbf{H}}^{-1} \frac{\partial \underline{\mathbf{H}}}{\partial m_i} \underline{\mathbf{U}}.$$

$$\delta \mathbf{m} = -\text{rowsum} \left(\underline{\mathbf{U}}^T \left[\frac{\partial \underline{\mathbf{H}}^T}{\partial m_1} \cdots \frac{\partial \underline{\mathbf{H}}^T}{\partial m_M} \right] \overbrace{\underline{\mathbf{H}}^{-T} (\underline{\mathbf{P}} - \underline{\mathbf{D}}\underline{\mathbf{U}})}^{\underline{\mathbf{V}}} \right)$$

$\underline{\mathbf{V}}$: backpropagated wavefield ass. with $\underline{\mathbf{Q}} = \mathbf{R}\mathbf{M}\mathbf{Q}$.

The GN Hessian can be derived in the similar way!

Complexity Analysis

Gauss-Newton-Krylov (GNK)

□ Gradient : forward + back-propagation $n_f n_s n^2 \log n$

□ Hessian : forward + back-propagation per CG iteration

$$n_{CG} n_f n_s n^2 \log n$$

□ Overall :

$$n_{CG} n_f n_s n^2 \log n$$

Compressive FWI with GNK:

$$n_{CG} n'_f n'_s n^2 \log n$$

$$n'_f \ll n_f, \quad n'_s \ll n_s$$

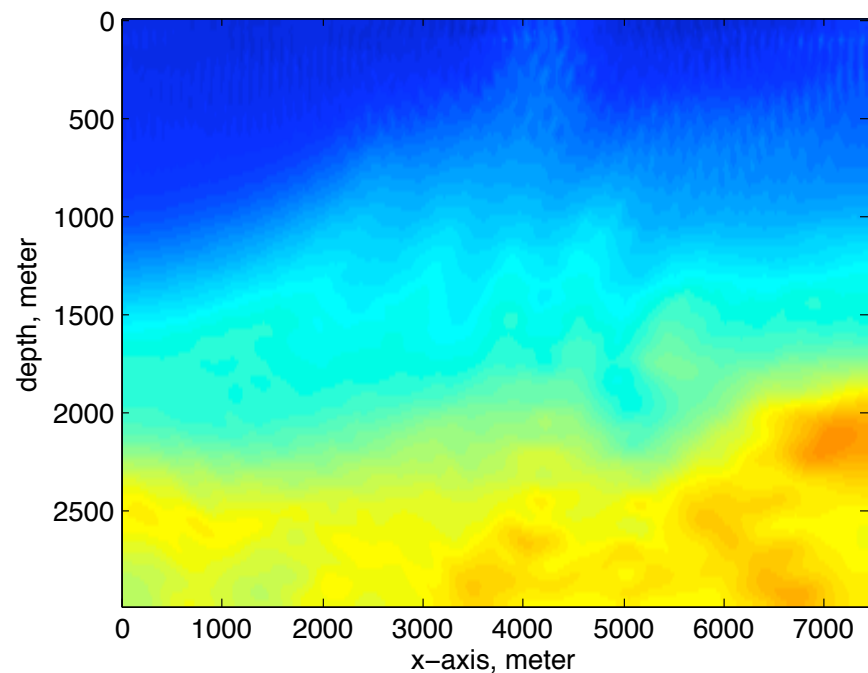
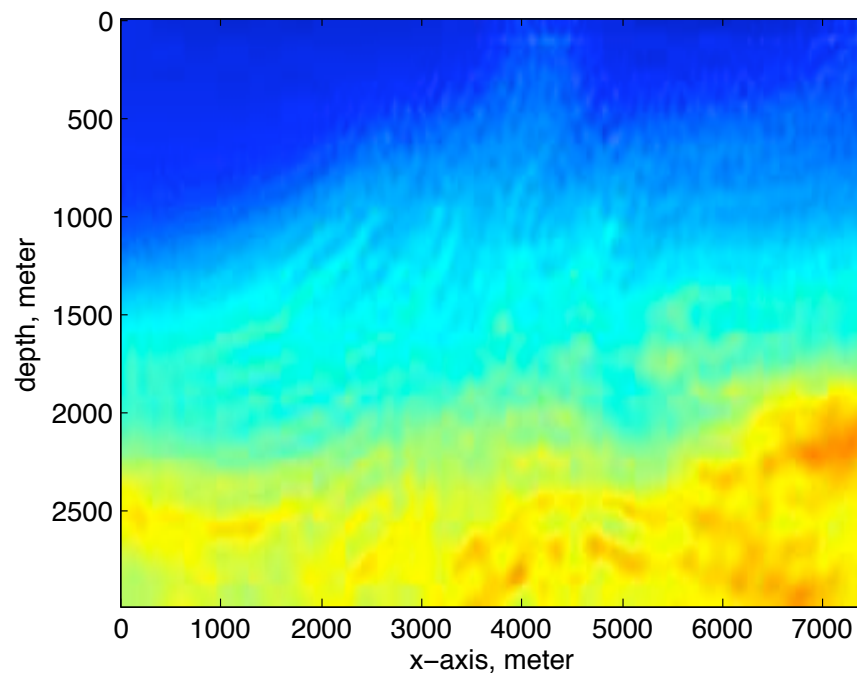
Construction of **RM** negligible compared to FWI

CFWI: Examples, GNK Iter #1

90% subsampled

37 randomized simul. shots

37 periodic shots



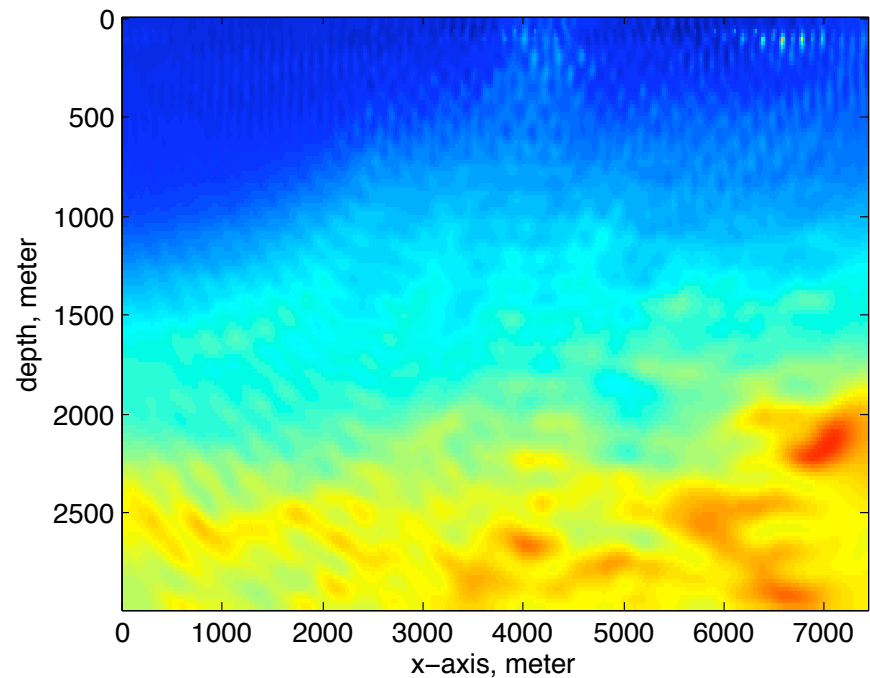
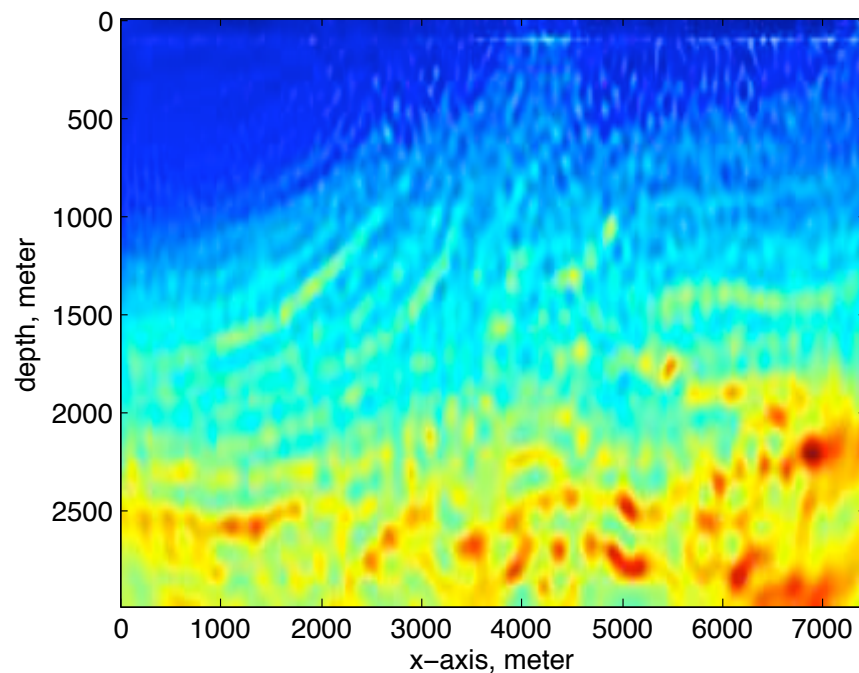
Noisy image --> recover the image via sparsity promoting

CFWI: Examples, GNK Iter #5

90% subsampled

37 randomized simul. shots

37 periodic shots

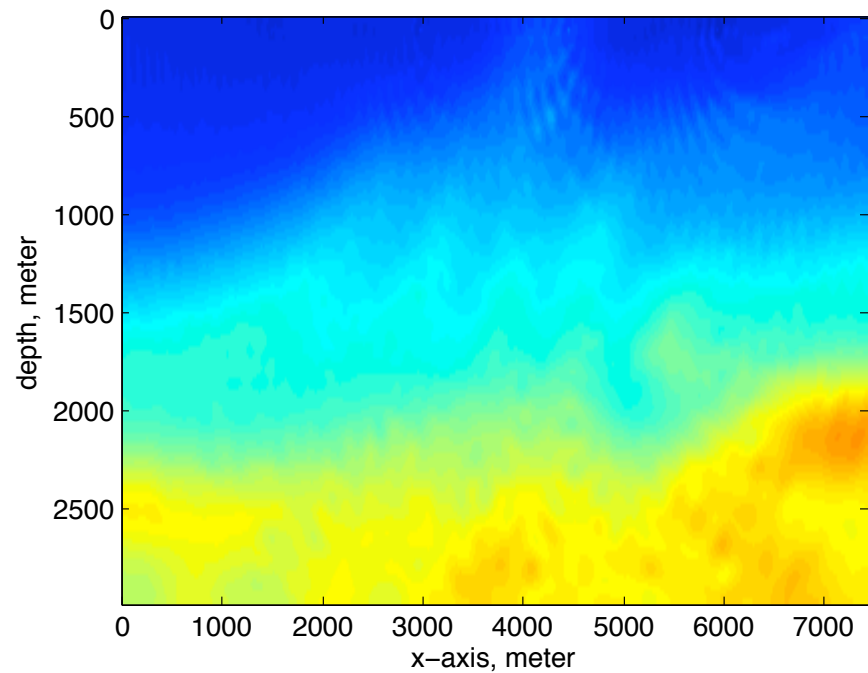
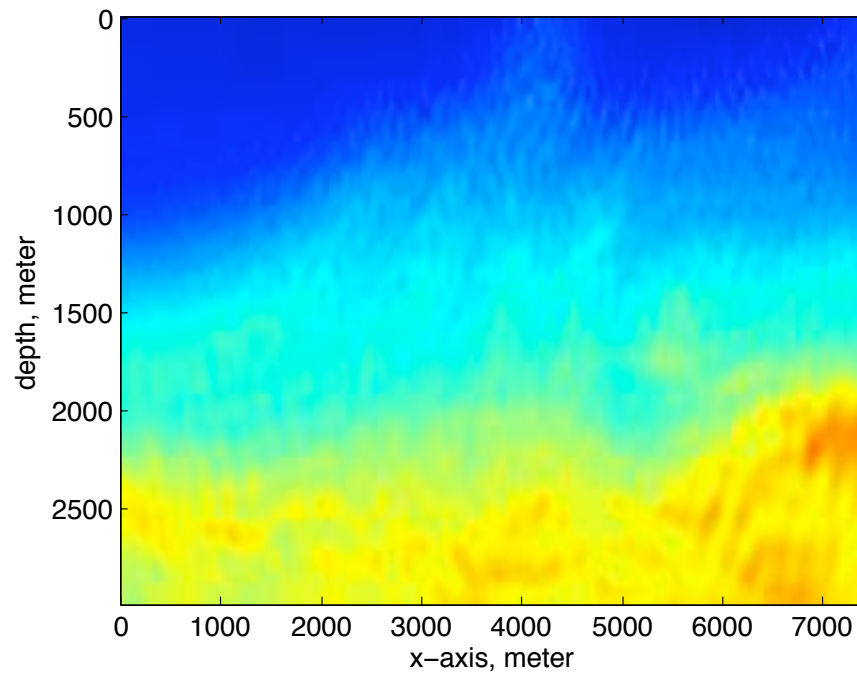


CFWI: Examples, GNK Iter #1

99% subsampled

4 randomized simul. shots

4 periodic shots

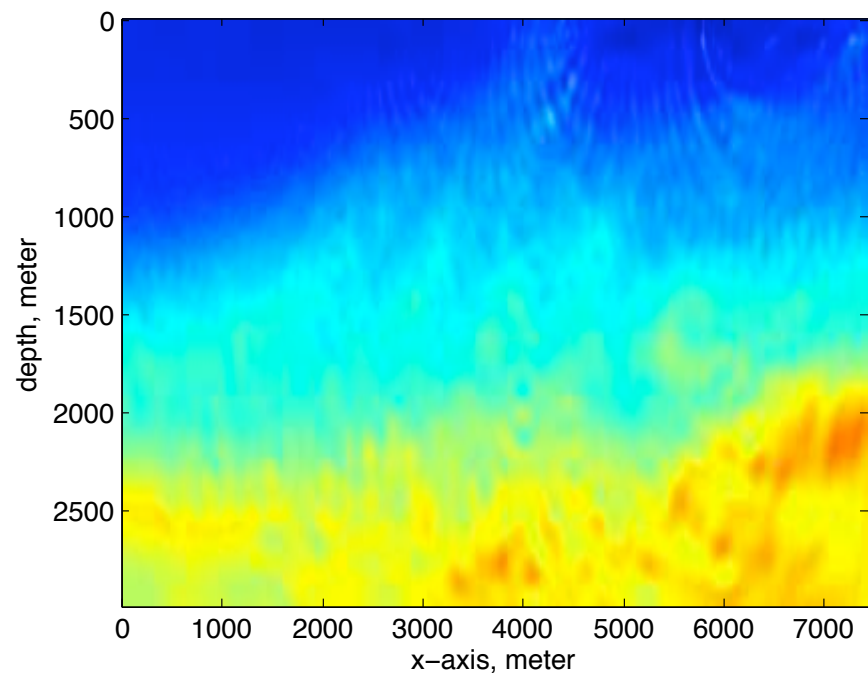
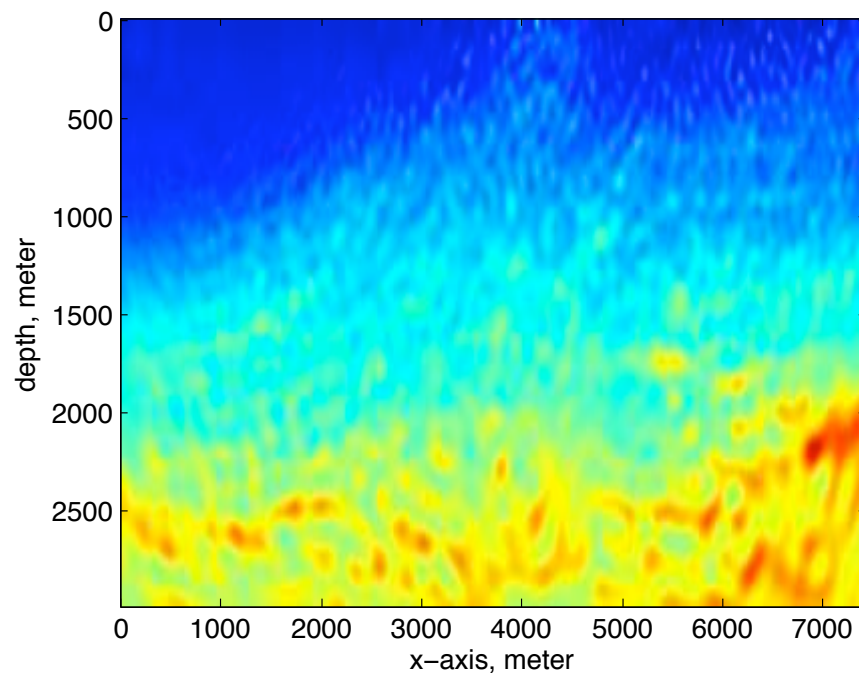


CFWI: Examples, GNK Iter #5

99% subsampled

4 randomized simul. shots

4 periodic shots



Conclusion

- Viable inversion of GN Hessian with Krylov method
 - Accuracy of the inversion of Hessian depends on the number of iterations --> better FWI result
 - Faster convergence of CG by preconditioners
 - Implicit BFGS-type preconditioner
 - Curvelet-based preconditioner [Herrmann, Brown, E. & Moghaddam (2009)]
 - Memory-friendly algorithm (gradient and Hessian can be computed on the fly)
 - With scalable implicit solver for forward and adjoint systems, matrix-free algorithm [E., Oosterlee & Vuik (2006), E. & Nabben (2009), E. & Herrmann (2008)]
- Natural extension to compressive FWI
 - Similar results but less computational work
 - In the CS framework: l1 inversion

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