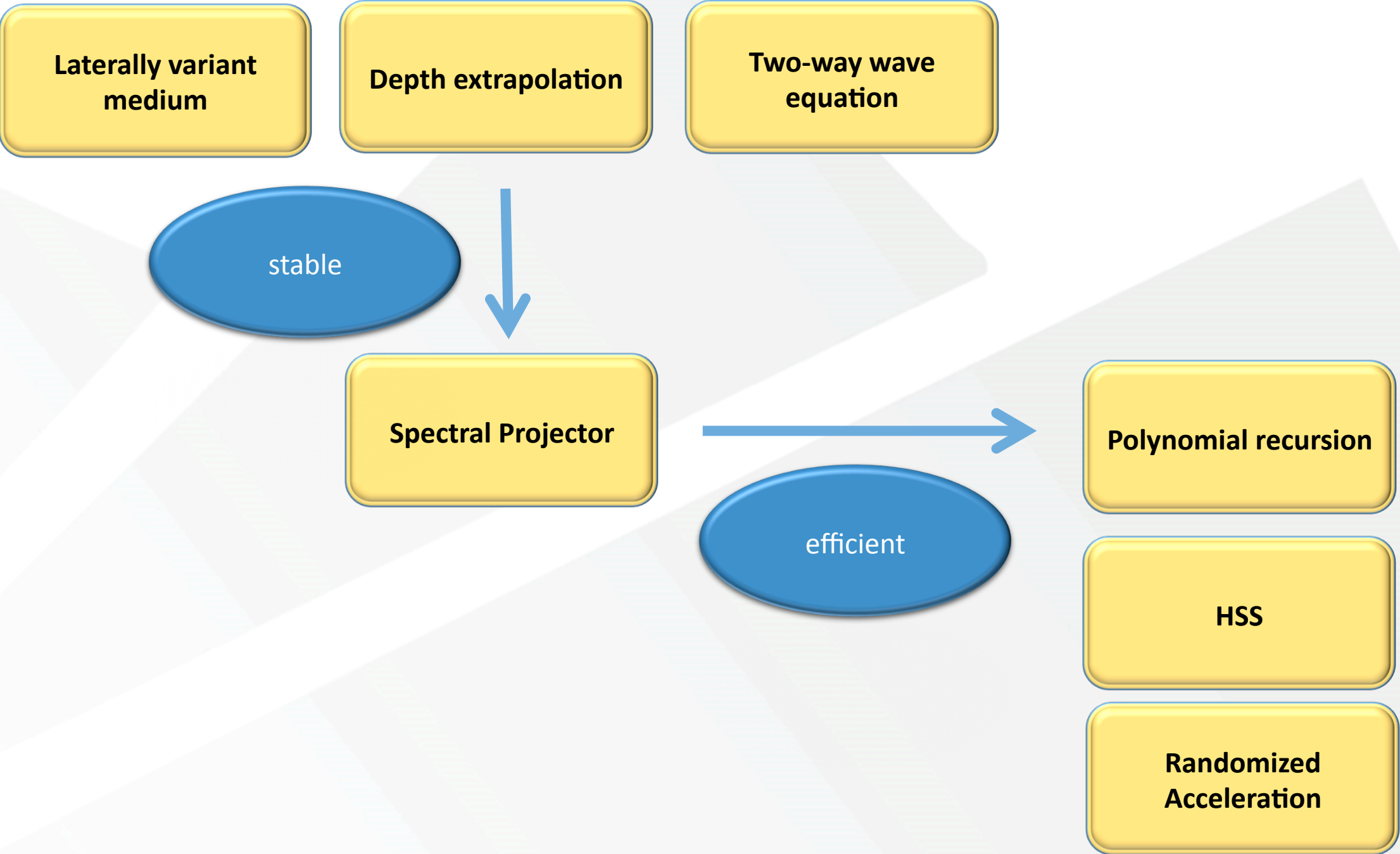




RANDOMIZED HSS ACCELERATION FOR FULL-WAVE-EQUATION DEPTH MIGRATION

Lina Miao, Polina Zheglova, and Felix Herrmann,
University of British Columbia



PROBLEM FORMULATION

$$p_{tt} = v(z, x)^2(p_{xx} + p_{zz})$$

$$p(x, 0, t) = 0, \quad t \leq 0$$

$$\begin{cases} p(x, z, 0) = f(x) \\ p_t(x, z, 0) = g(x) \end{cases}$$

Fourier Transform

$$\hat{p}_{zz} = \left[- \left(\frac{\omega}{v(x, z)} \right)^2 - D_{xx} \right] \hat{p} \equiv L\hat{p}$$

$$\begin{cases} \hat{p}(x, z, \omega) = q(x, z, \omega) \\ \hat{p}_z(x, z, \omega) = q_z(x, z, \omega) \end{cases}$$

Two way wave-equation
as an initial value problem

Unstable with evanescent
wave components

PROBLEM FORMULATION

$$\begin{aligned} p_{tt} &= v(z, x)^2 (p_{xx} + p_{zz}) \\ p(x, 0, t) &= 0, \quad t \leq 0 \\ \begin{cases} p(x, z, 0) = f(x) \\ p_t(x, z, 0) = g(x) \end{cases} \end{aligned}$$

Fourier Transform

$$\begin{aligned} \hat{p}_{zz} &= \left[- \left(\frac{\omega}{v(x, z)} \right)^2 - D_{xx} \right] \hat{p} \equiv L\hat{p} \\ \begin{cases} \hat{p}(x, z, \omega) = q(x, z, \omega) \\ \hat{p}_z(x, z, \omega) = q_z(x, z, \omega) \end{cases} \end{aligned}$$

Spectral Projector $\mathcal{P}$

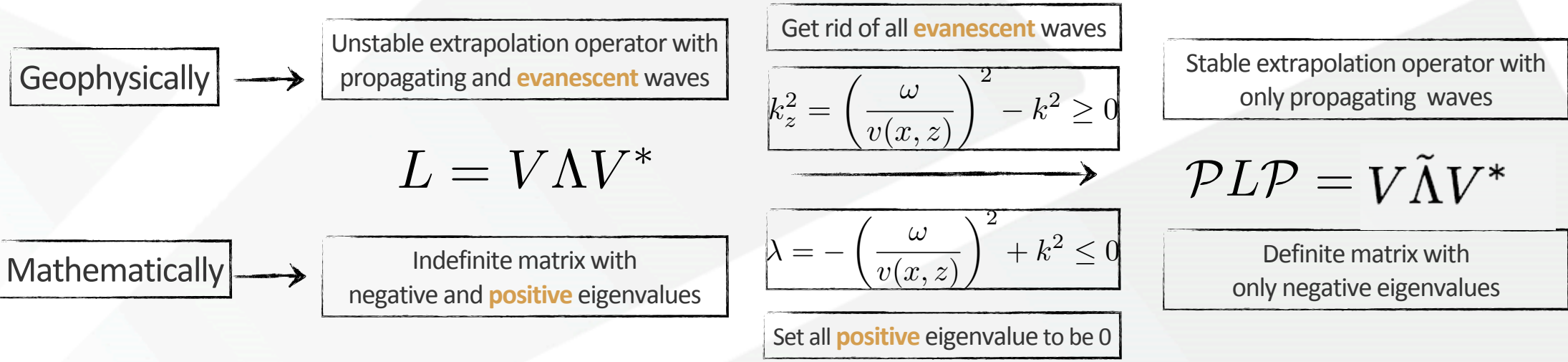
$$\begin{aligned} \hat{p}_{zz} &= \mathcal{P} L \mathcal{P} \hat{p} \\ \begin{cases} \hat{p}(x, z_n, \omega) = q(x, z_n, \omega) \\ \hat{p}_z(x, z_n, \omega) = q_z(x, z_n, \omega) \end{cases} \end{aligned}$$

Two way wave-equation
as an initial value problem

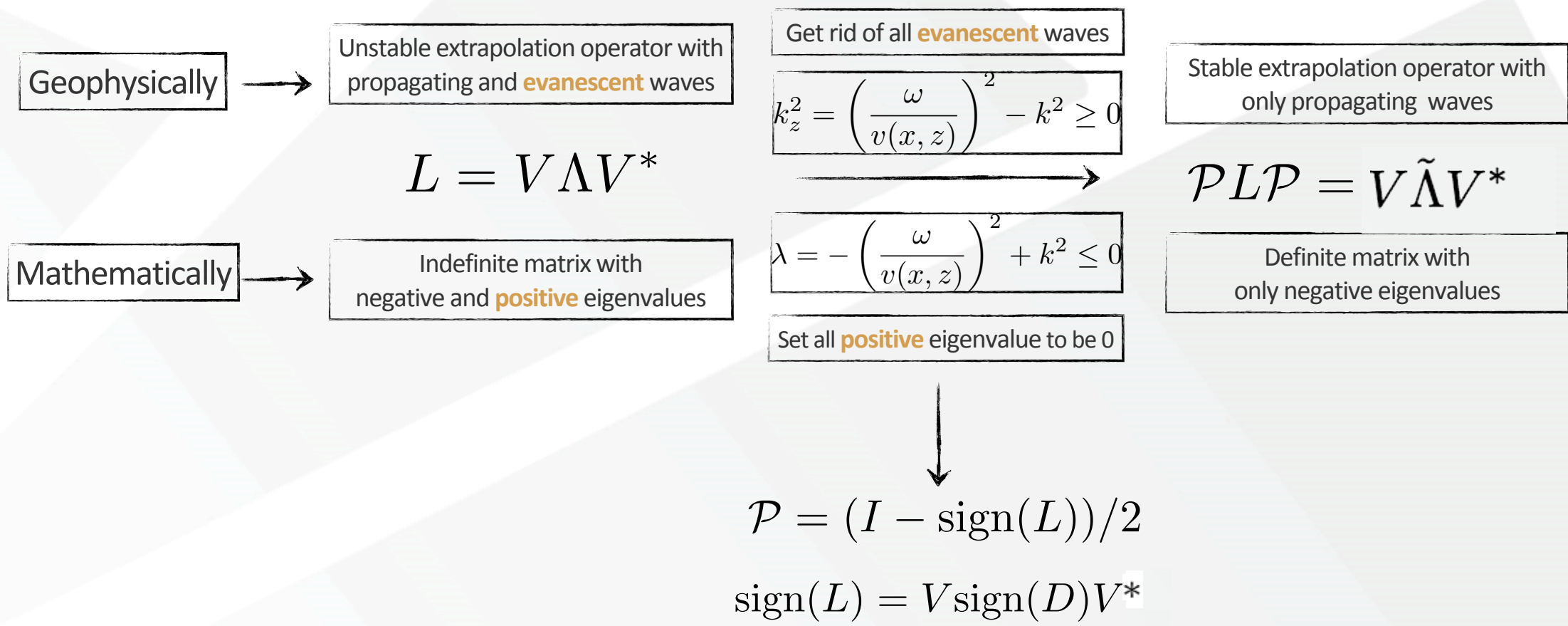
Unstable with evanescent
wave components

Stabilized initial value problem
with spectral projector

SPECTRAL PROJECTOR



SPECTRAL PROJECTOR



MATRIX SIGN FUNCTION

$$L = V \Lambda V^*$$

The diagram illustrates the decomposition of a matrix L into its singular value decomposition components. It consists of three rows of square matrices. The top row shows L , which is a dark gray square with a thin, light gray diagonal line. The middle row shows V , which is a square matrix filled with a complex, wavy, black and white pattern. The bottom row shows Λ , which is a dark gray square with a thin, light gray diagonal line. To the right of these three rows is a fourth square matrix, V^* , which is also filled with a complex, wavy, black and white pattern. The matrices are arranged in a sequence: L is followed by an equals sign, then V , followed by a multiplication sign, then Λ , followed by a multiplication sign, and finally V^* . The entire sequence is enclosed in a light gray rectangular frame.

$$\text{sign}(L) = V \text{sign}(\Lambda) V^*$$

The diagram illustrates the decomposition of the sign of a matrix L into its singular value decomposition components. It consists of three rows of square matrices. The top row shows $\text{sign}(L)$, which is a dark gray square with a thin, light gray diagonal line. The middle row shows V , which is a square matrix filled with a complex, wavy, black and white pattern. The bottom row shows $\text{sign}(\Lambda)$, which is a dark gray square with a thin, light gray diagonal line. To the right of these three rows is a fourth square matrix, V^* , which is also filled with a complex, wavy, black and white pattern. The matrices are arranged in a sequence: $\text{sign}(L)$ is followed by an equals sign, then V , followed by a multiplication sign, then $\text{sign}(\Lambda)$, followed by a multiplication sign, and finally V^* . The entire sequence is enclosed in a light gray rectangular frame.

NEWTON-SCHULZ ITERATION FOR MATRIX SIGN FUNCTION

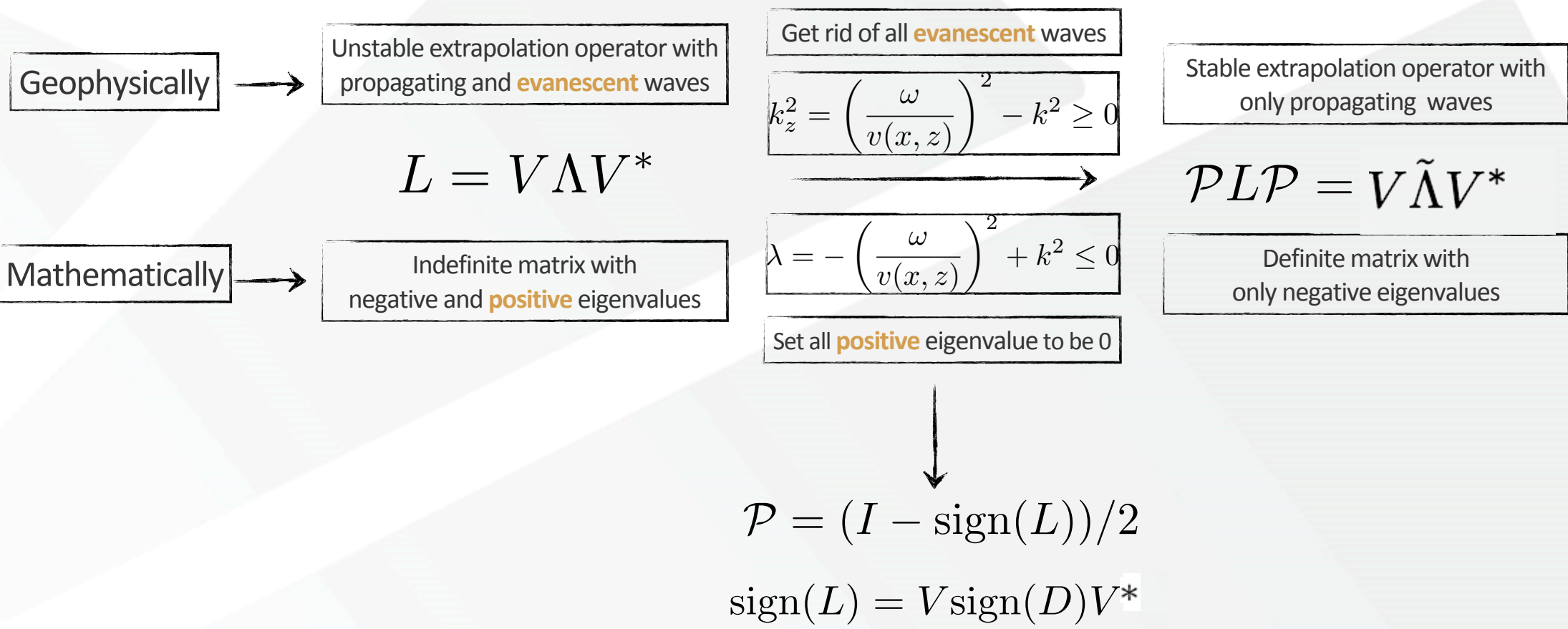
Algorithm Newton-Schulz Iteration for the Matrix Sign Function (Auslander and Tsao (1991))

Input: Self adjoint matrix L

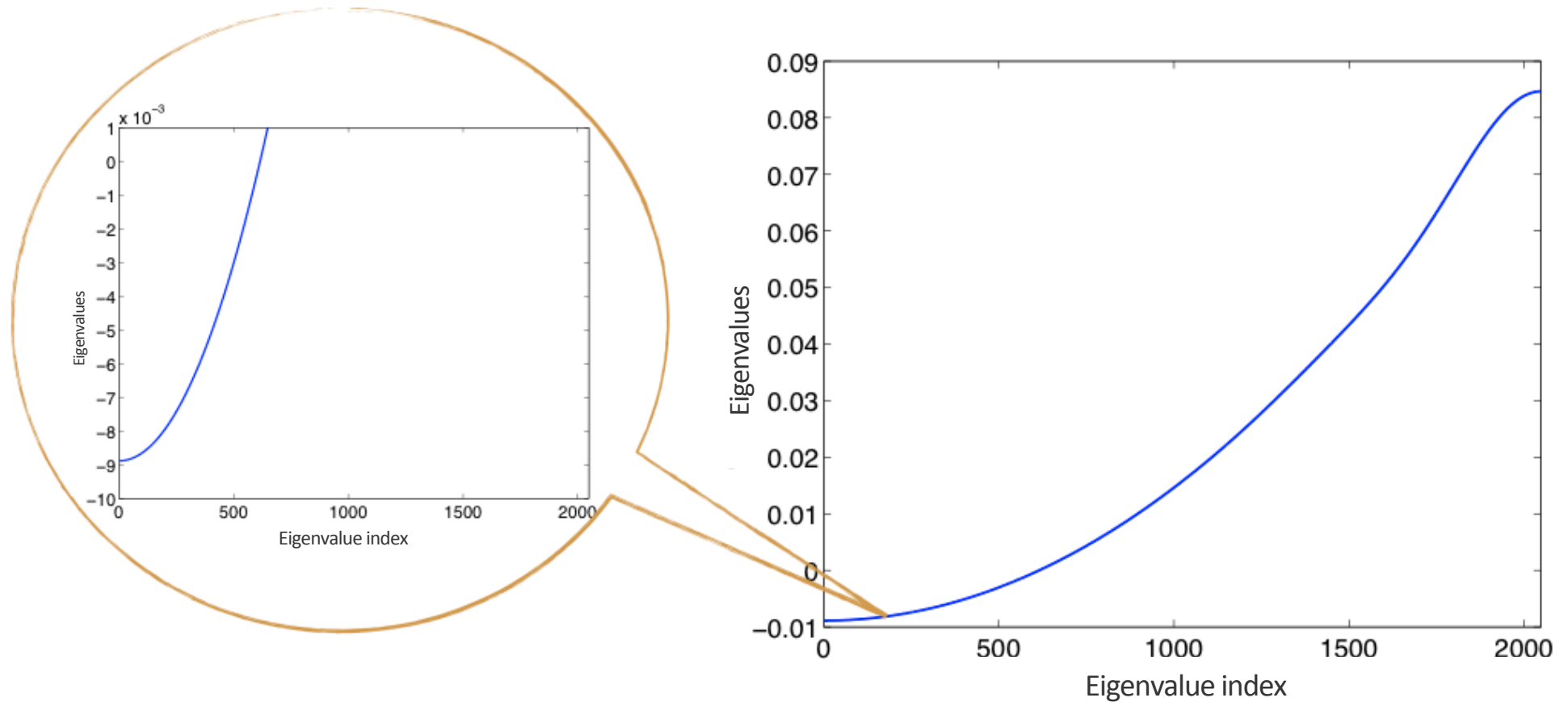
Output: $S := \text{sign}(L)$

1. Initialize $S_0 = L/||L||_2$, where $||L||_2$ stands for the 2 norm of matrix L
 2. For $k = 1.....N$, $S_{k+1} = \frac{3}{2}S_k - \frac{1}{2}S_k^3$
-

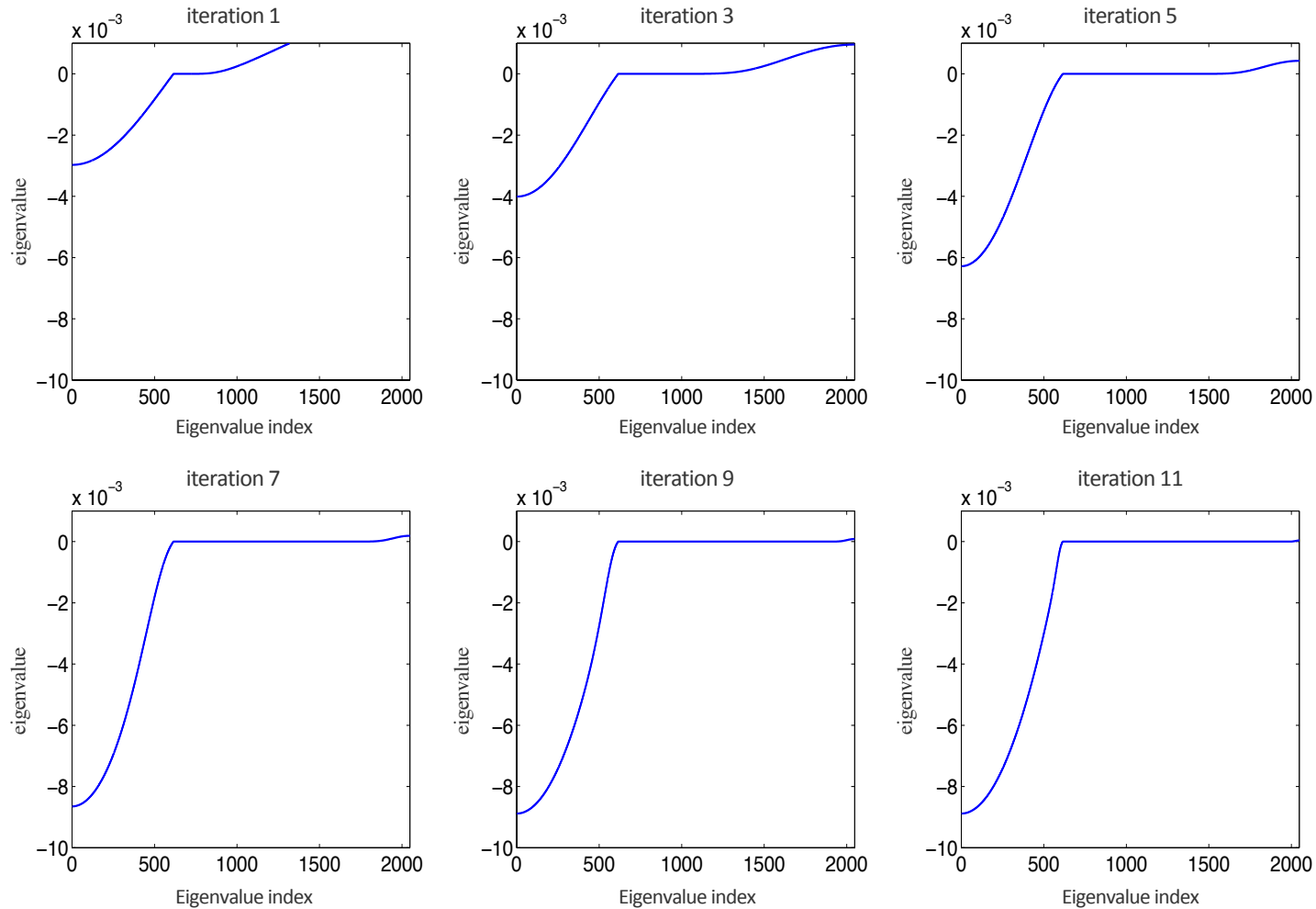
SPECTRAL PROJECTOR



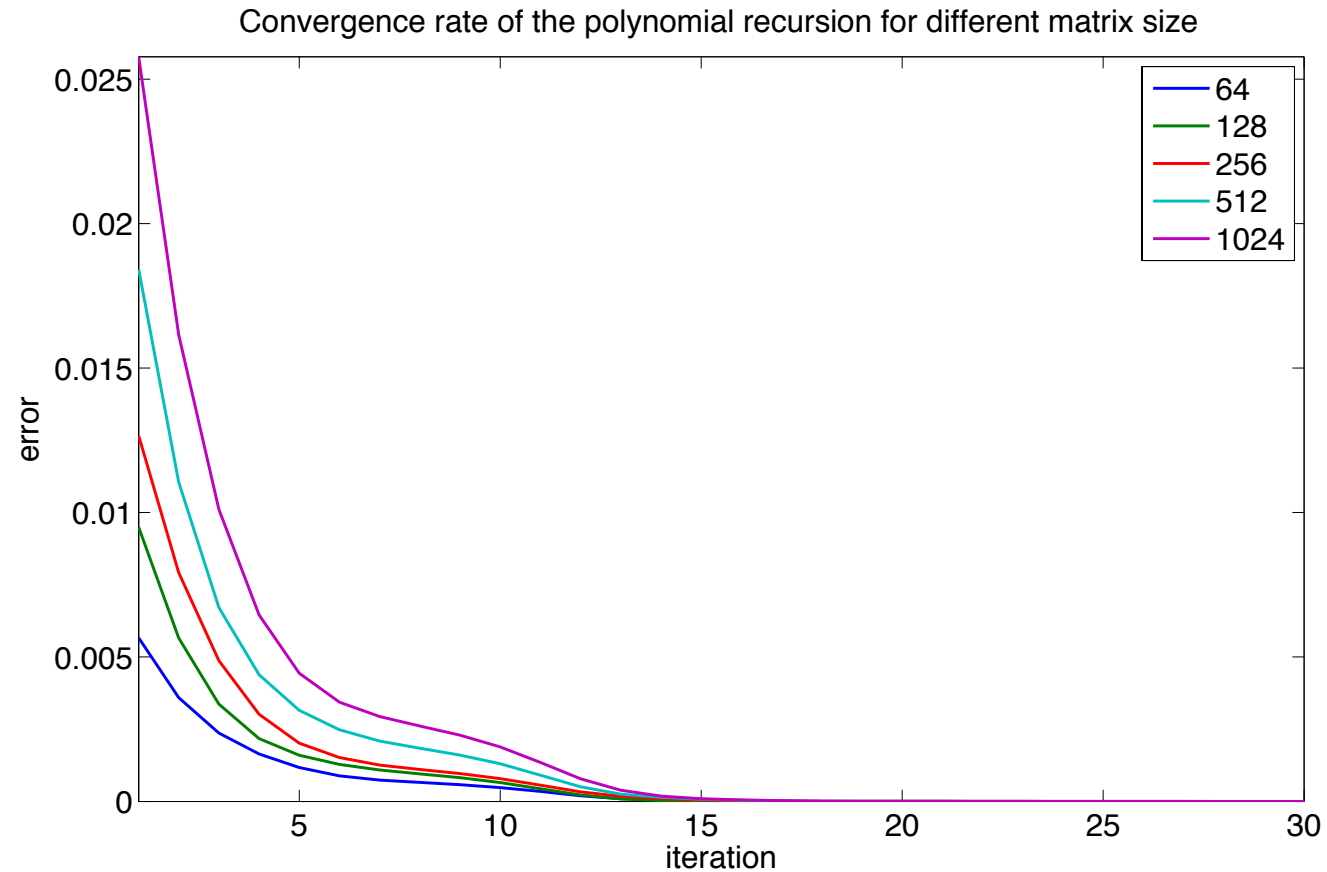
SPECTRAL PROJECTOR (MATRIX SIGN FUNCTION) VIA POLYNOMIAL RECURSION



SPECTRAL PROJECTOR (MATRIX SIGN FUNCTION) VIA POLYNOMIAL RECURSION



SIGN FUNCTION COMPUTATION VIA POLYNOMIAL RECURSION



NEWTON-SCHULZ ITERATION FOR MATRIX SIGN FUNCTION

Algorithm Newton-Schulz Iteration for the Matrix Sign Function (Auslander and Tsao (1991))

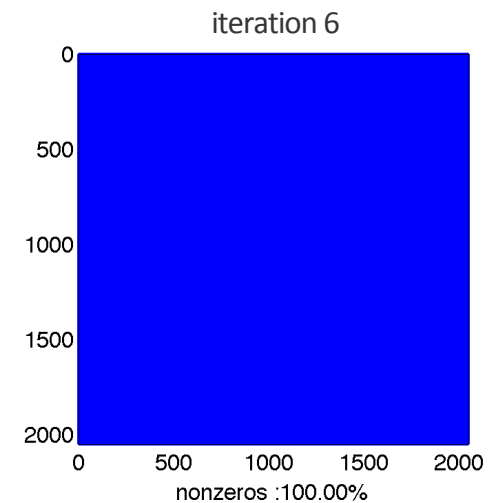
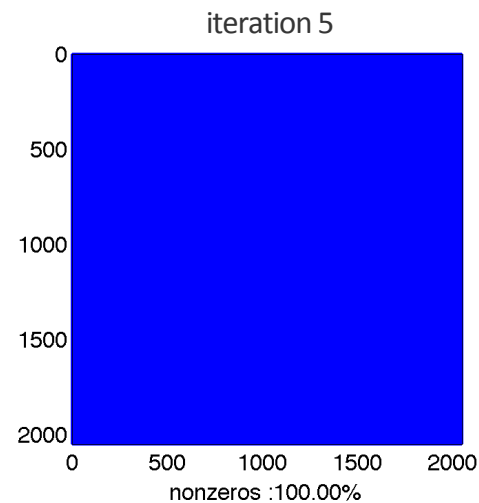
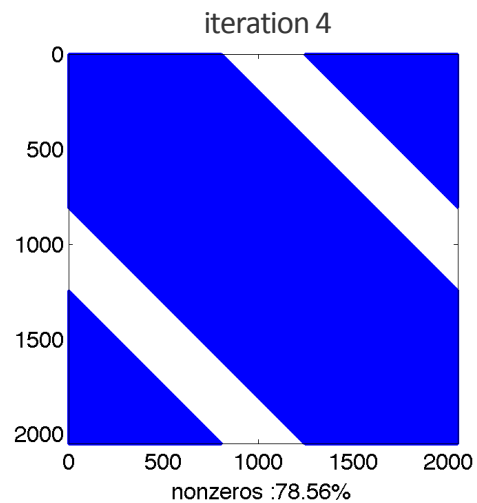
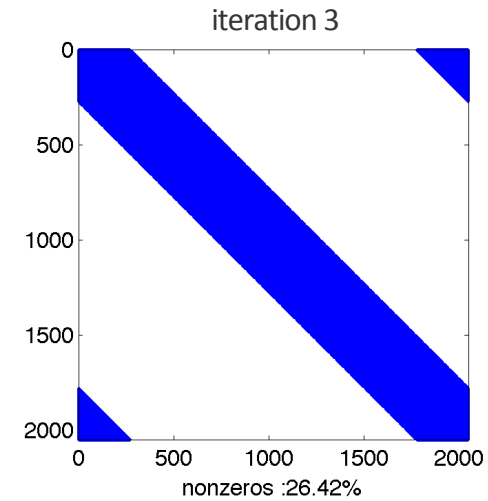
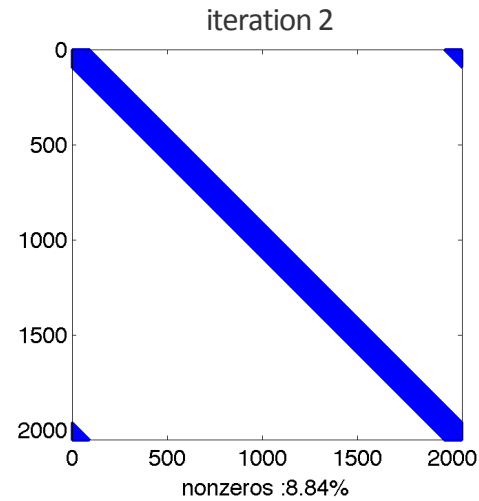
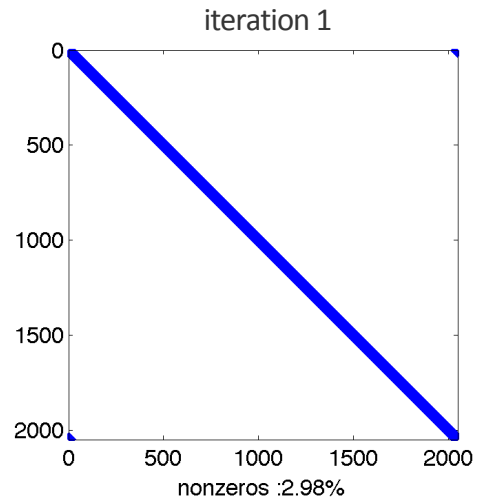
Input: Self adjoint matrix L

Output: $S := \text{sign}(L)$

1. Initialize $S_0 = L/||L||_2$, where $||L||_2$ stands for the 2 norm of matrix L

2. For $k = 1.....N$, $S_{k+1} = \frac{3}{2}S_k - \frac{1}{2}S_k^3$

MATRIX SPARSITY IN THE POLYNOMIAL RECURSION

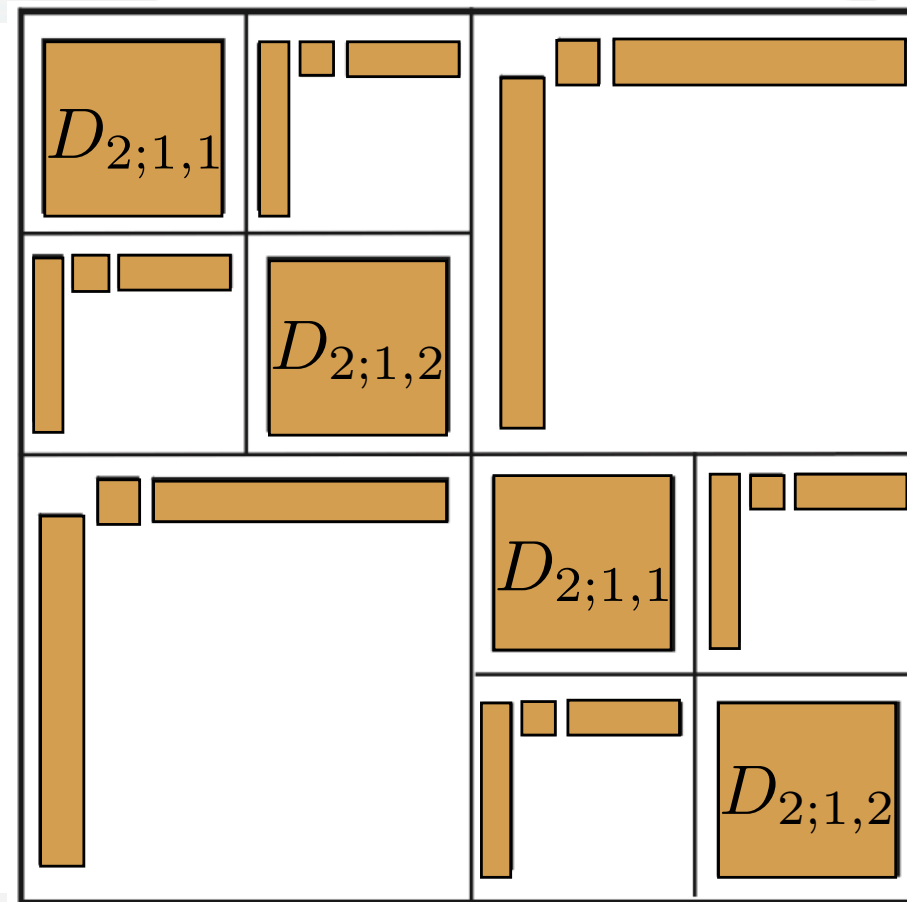


HIERARCHICALLY SEMI-SEPARABLE MATRIX REPRESENTATION

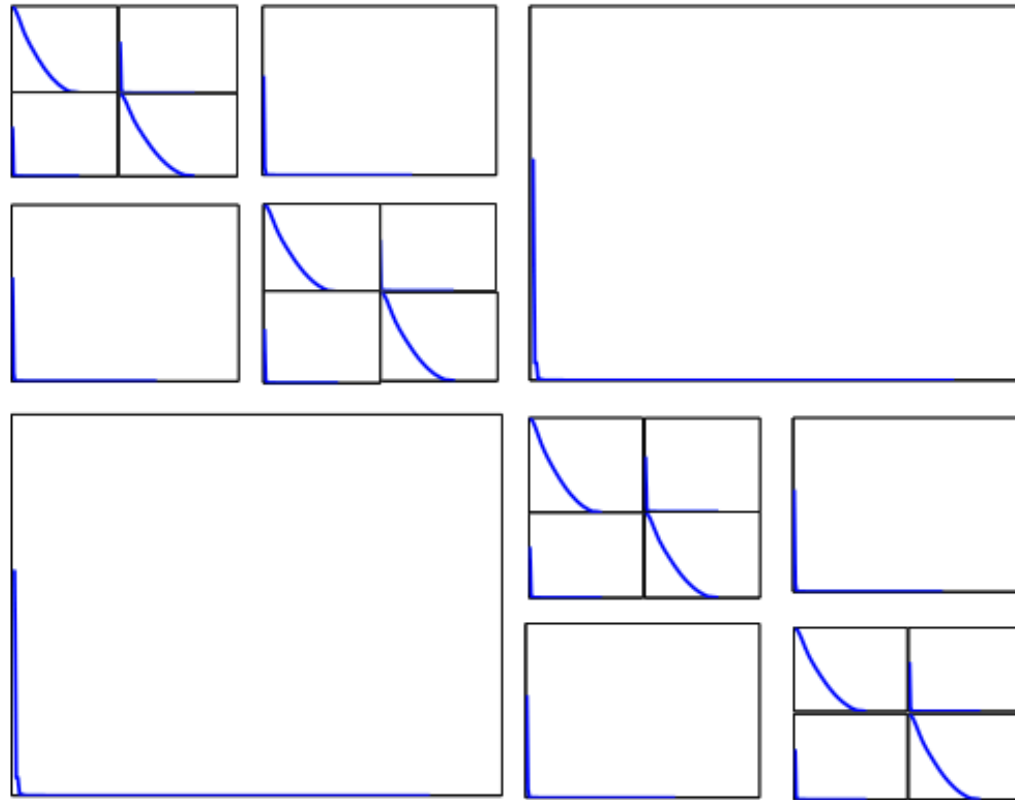
$$A = \begin{pmatrix} A_{1;1,1} & A_{1;1,2} \\ A_{1;2,1} & A_{1;2,2} \end{pmatrix}$$

$$\mathbf{A} = \begin{pmatrix} D_{1;1,1} & (USV^*)_{1;1,2} \\ (USV^*)_{1;2,1} & D_{1;2,2} \end{pmatrix}$$

$$\mathbf{A} = \begin{pmatrix} \begin{pmatrix} D_{2;1,1} & (USV^*)_{2;1,2} \\ (USV^*)_{2;2,1} & D_{2;2,2} \end{pmatrix} & (USV^*)_{1;1,2} \\ (USV^*)_{1;2,1} & \begin{pmatrix} D_{2;1,1} & (USV^*)_{2;1,2} \\ (USV^*)_{2;2,1} & D_{2;2,2} \end{pmatrix} \end{pmatrix}$$

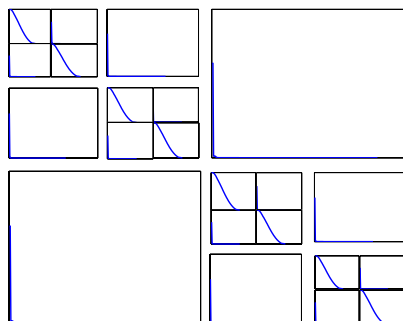


MATRIX SPECTRUM WITH HSS PARTITION

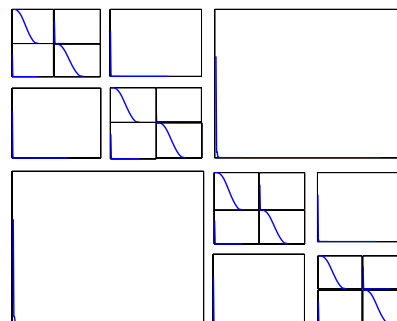


MATRIX SPECTRUM WITH HSS PARTITION IN NEWTON-SCHULZ ITERATION

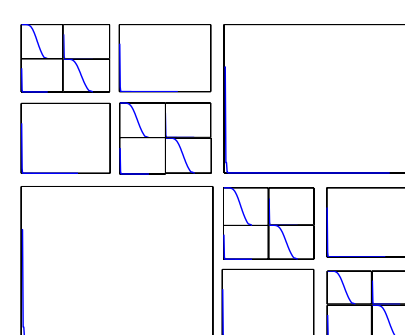
iter:1



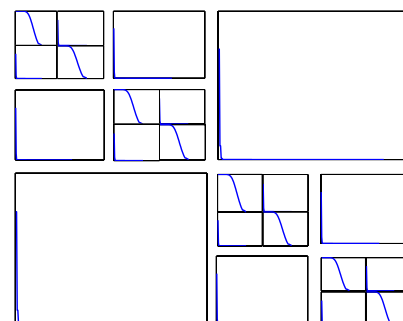
iter:2



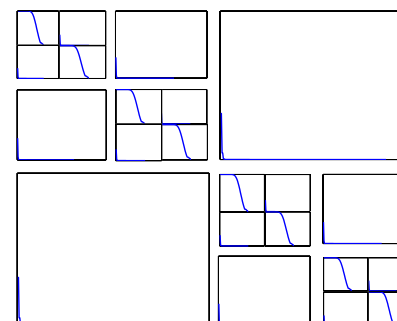
iter:3



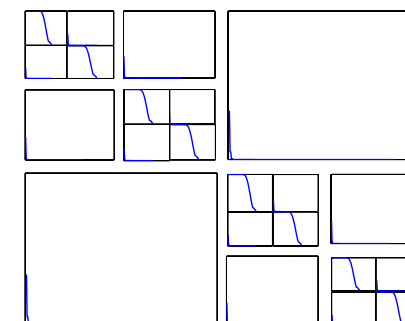
iter:4



iter:5



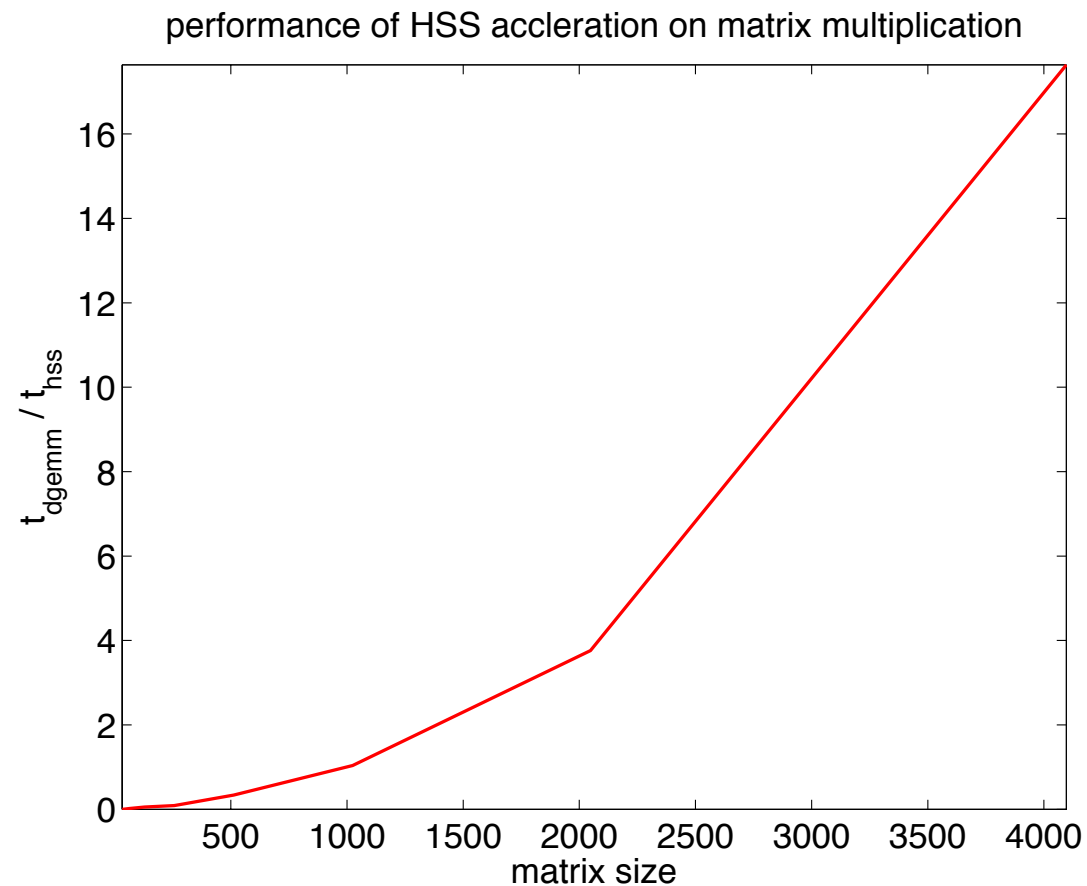
iter:6



COMPLEXITY ANALYSIS OF HSS OPERATIONS

Operation	Complexity with HSS	Complexity without HSS
Matrix-Vector Multiplication	$\mathcal{O}(nk^2)$	$\mathcal{O}(n^2)$
Matrix-Matrix Multiplication	$\mathcal{O}(nk^3)$	$\mathcal{O}(n^3)$
Matrix addition	$\mathcal{O}(nk^2)$	$\mathcal{O}(n^2)$
Compression	$\mathcal{O}(nk^3)$	Not Applicable
LU Decomposition	$\mathcal{O}(nk^3)$	$\mathcal{O}(n^3)$
Inverse	$\mathcal{O}(nk^3)$	$\mathcal{O}(n^3)$
Transpose	$\mathcal{O}(nk)$	$\mathcal{O}(n^2)$
Construct HSS (Xia (2012))	$\mathcal{O}(n^2r)$	Not Applicable

COMPUTATION OF MATRIX-MATRIX MULTIPLICATION WITH HSS

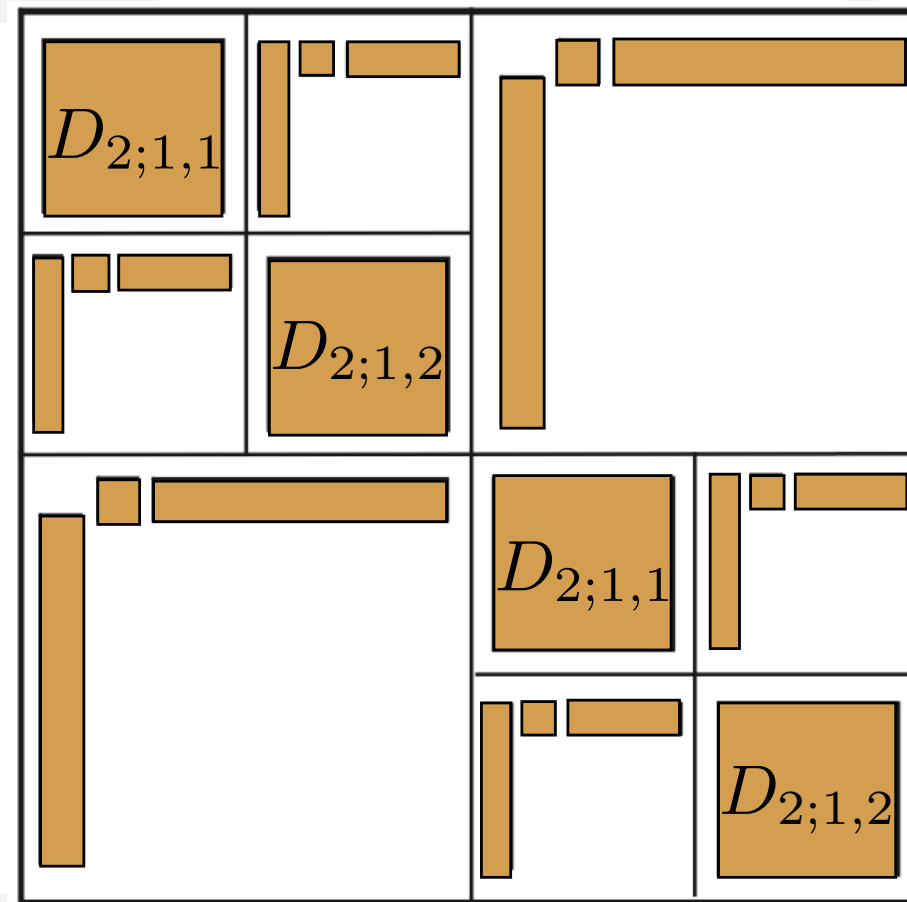


HIERARCHICALLY SEMI-SEPARABLE MATRIX REPRESENTATION

$$A = \begin{pmatrix} A_{1;1,1} & A_{1;1,2} \\ A_{1;2,1} & A_{1;2,2} \end{pmatrix}$$

$$\mathbf{A} = \begin{pmatrix} D_{1;1,1} & (USV^*)_{1;1,2} \\ (USV^*)_{1;2,1} & D_{1;2,2} \end{pmatrix}$$

$$\mathbf{A} = \begin{pmatrix} \begin{pmatrix} D_{2;1,1} & (USV^*)_{2;1,2} \\ (USV^*)_{2;2,1} & D_{2;2,2} \end{pmatrix} & (USV^*)_{1;1,2} \\ (USV^*)_{1;2,1} & \begin{pmatrix} D_{2;1,1} & (USV^*)_{2;1,2} \\ (USV^*)_{2;2,1} & D_{2;2,2} \end{pmatrix} \end{pmatrix}$$



RANDOMIZED HSS ALGORITHM

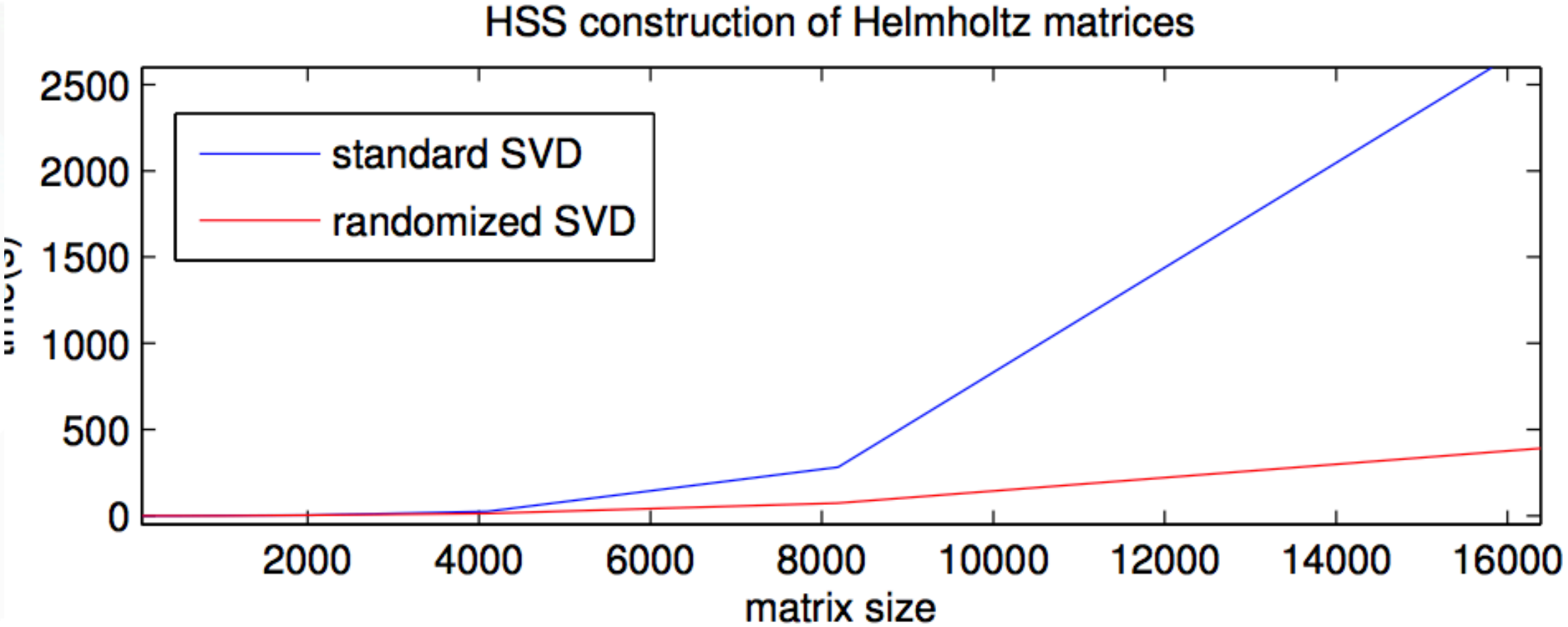
Algorithm The basic rSVD algorithm (Tygert and Rokhlin (2007))

Input: An $m \times n$ matrix A with rank k , $k \leq n \leq m$

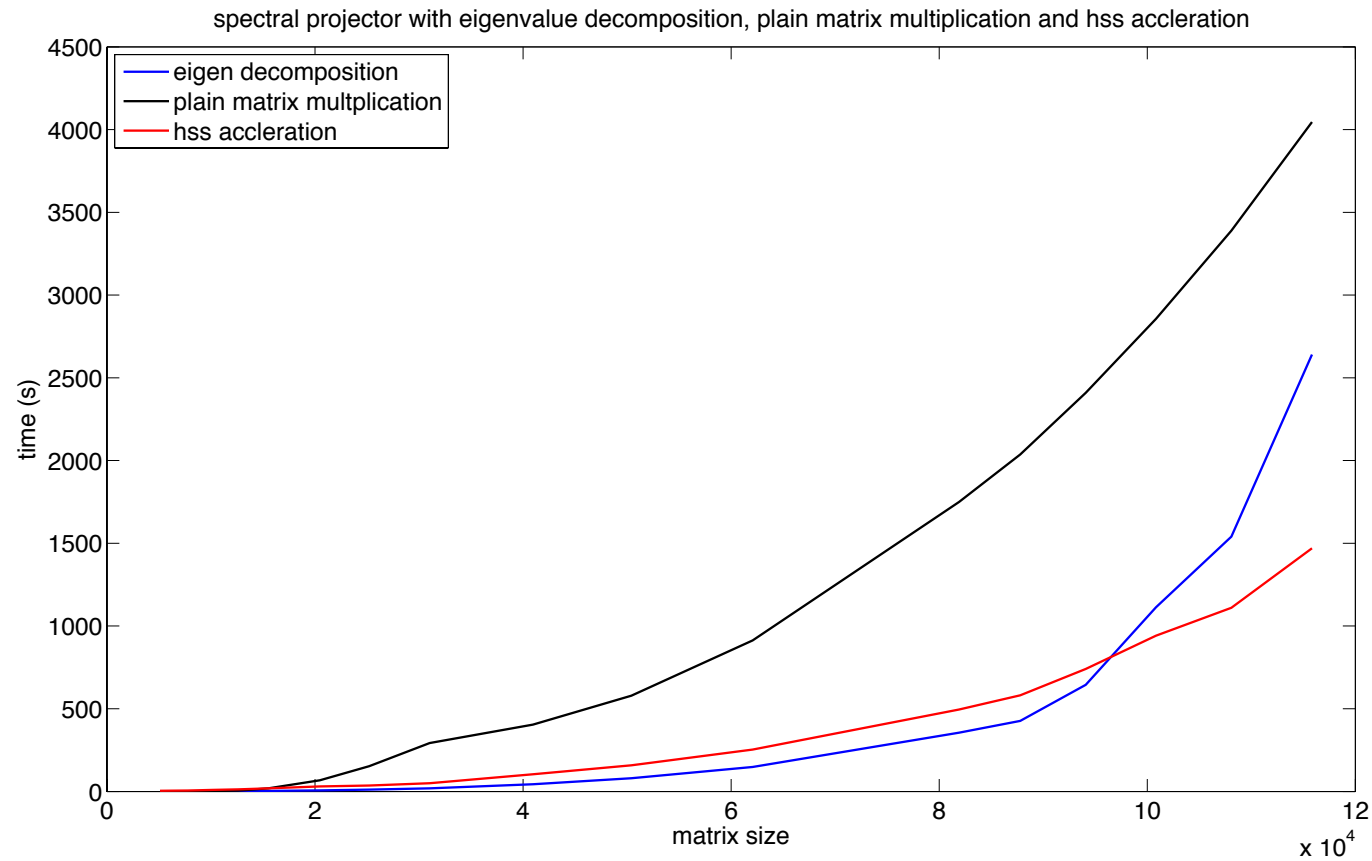
output: The randomized SVD of A , U, Σ, V

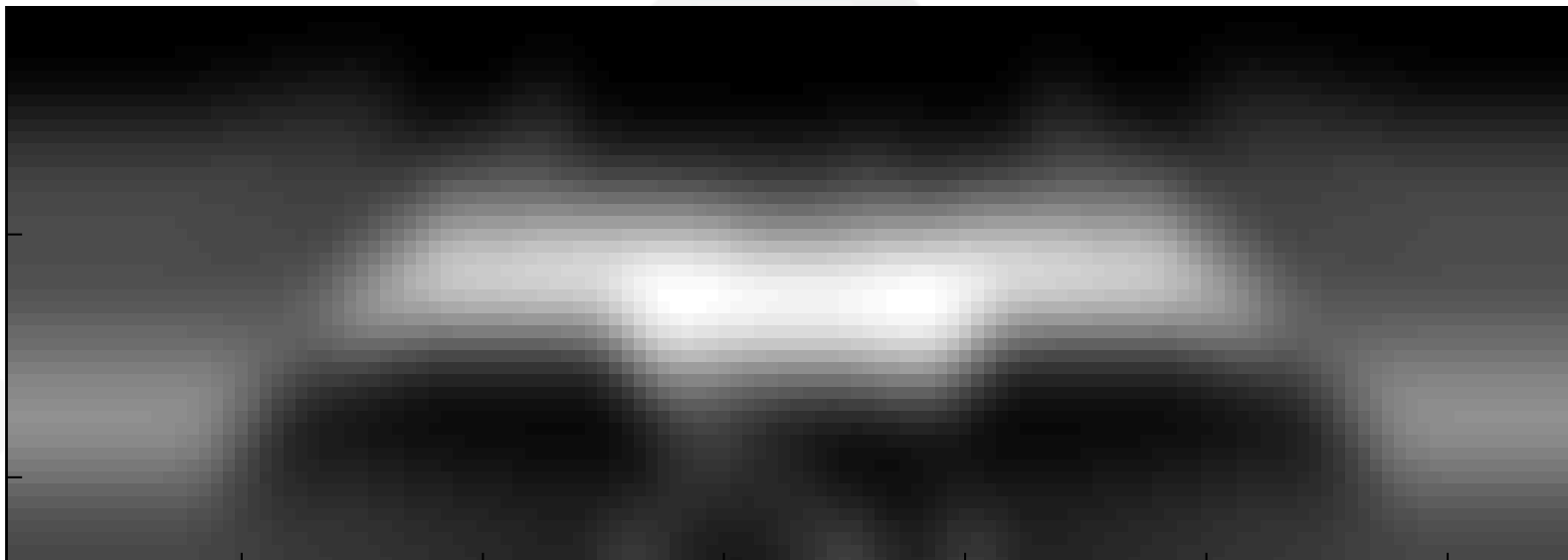
1. Form $P_{m \times (k+20)} = A_{m \times n} R_{n \times (k+20)}$; R is random
 2. Form $Q_{m \times k}$, the matrix whose columns consist of the left singular vectors corresponding to the k greatest singular values of $P_{m \times (k+20)}$
 3. Form $S_{n \times k} = A_{n \times m}^T Q_{m \times k}$
 4. Compute the SVD : $T_{k \times k} \Sigma_{k \times k} V_{k \times n}^T$ of $S_{k \times n}^T$
 5. Form $U_{m \times k} = Q_{m \times k} T_{k \times k}$
-

RANDOMIZED HSS

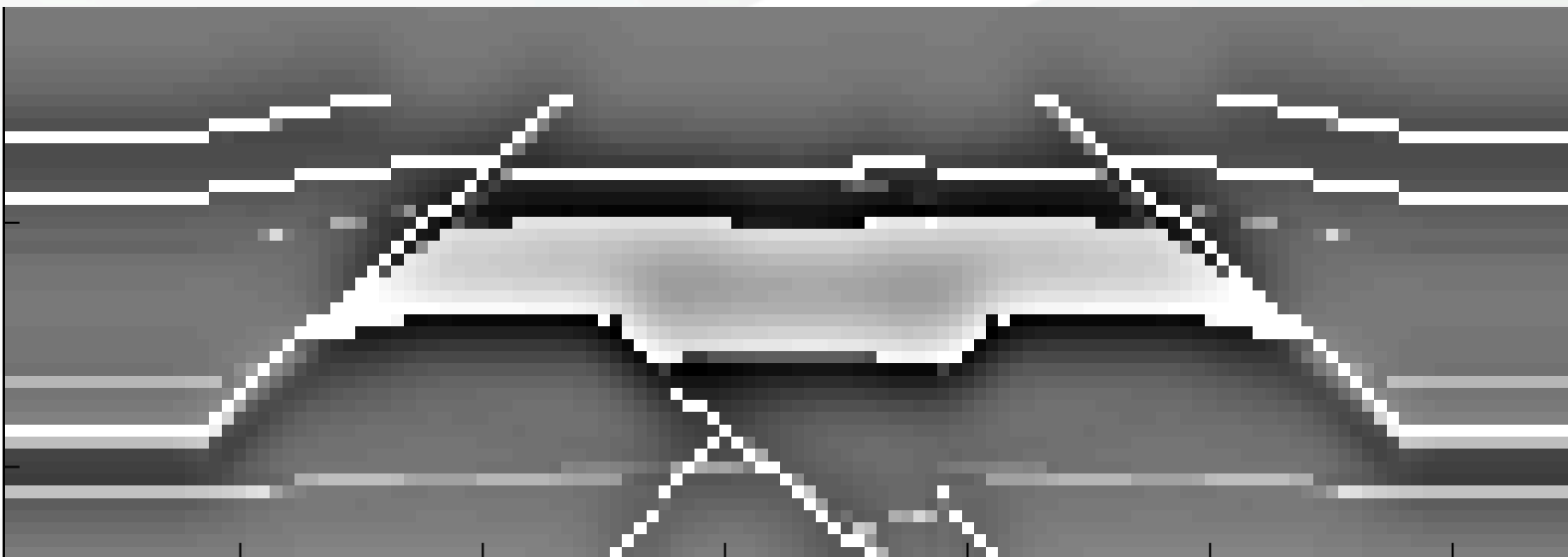


COMPUTATION OF SPECTRAL PROJECTOR WITH HSS

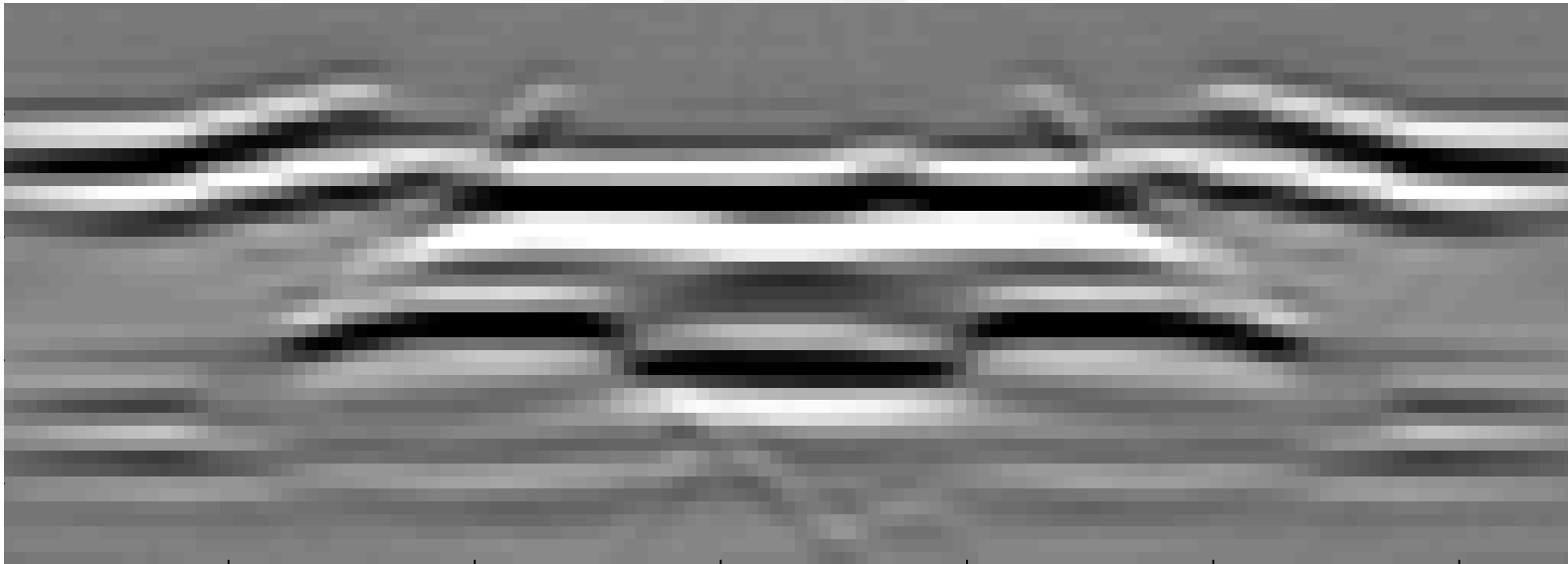




m_0



dm



two-way wave-equation depth migration

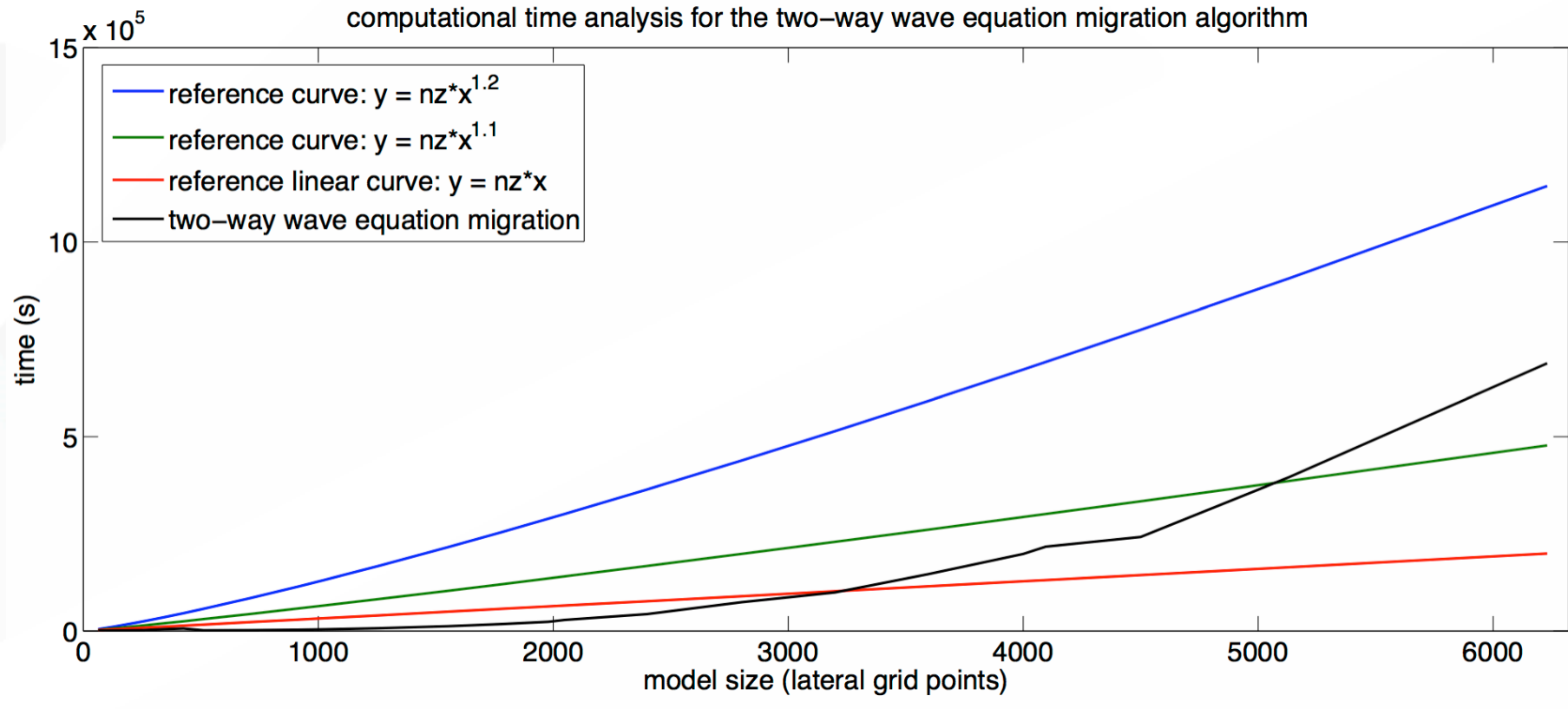


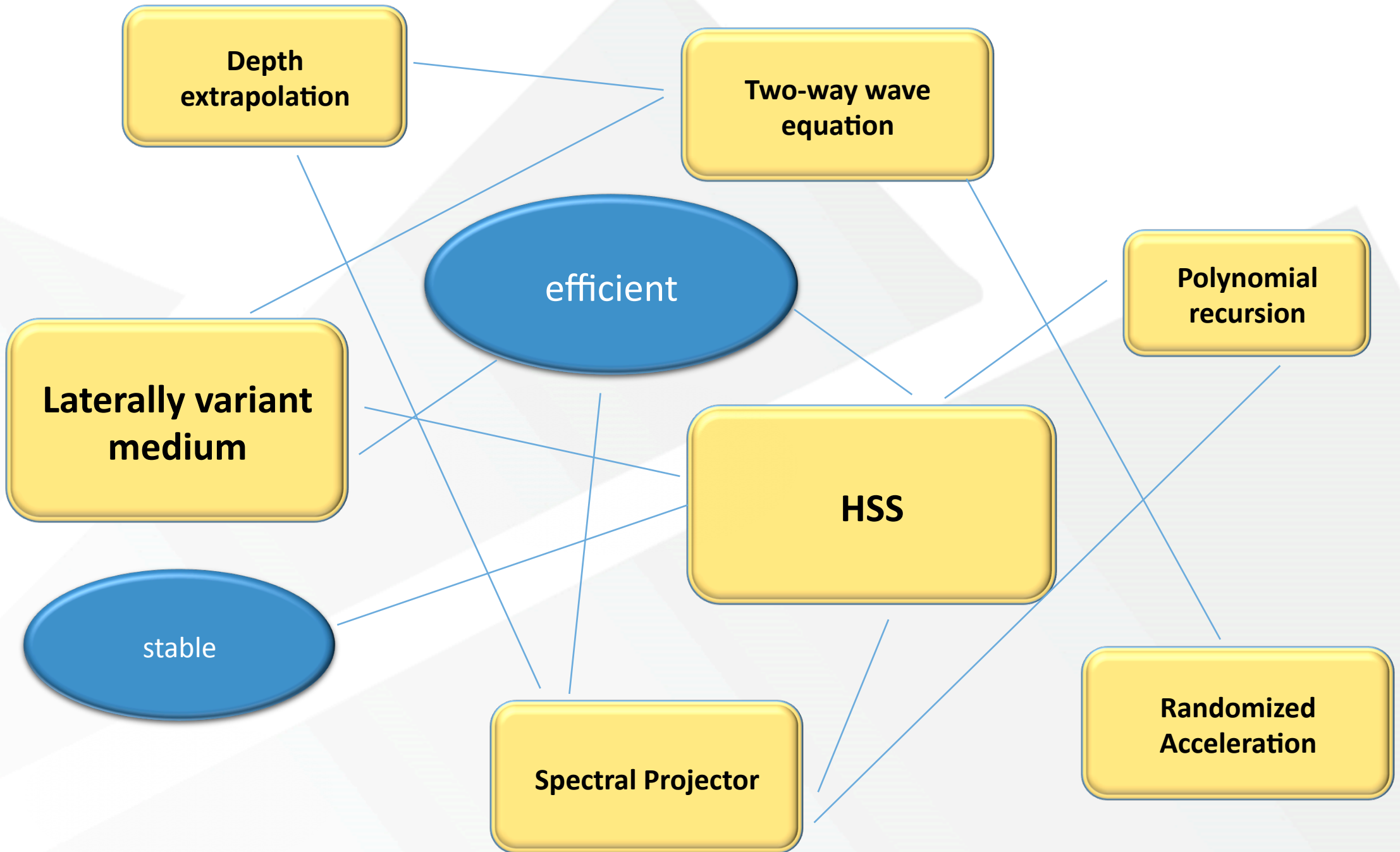
Reverse time migration

MIGRATION TIME COMPLEXITY

Operation	Complexity
rSVD	$\mathcal{O}(n)$
HSS construction	$\mathcal{O}(n)$
HSS matrix matrix addition	$\mathcal{O}(n)$
HSS matrix matrix multiplication	$\mathcal{O}(n)$
HSS matrix scalar multiplication	$\mathcal{O}(n)$
Depth extrapolation (Sandberg and Beylkin (2009))	$\mathcal{O}(n)$
The two-way wave equation depth extrapolation migration	$\mathcal{O}(n_\omega n_z n)$

MIGRATION TIME COMPLEXITY





**Laterally variant
medium**

Depth extrapolation

**Two-way wave
equation**

stable



Spectral Projector



efficient

Polynomial recursion

HSS

**Randomized
Acceleration**

CONCLUSION

- **Spectral projector** computed with **polynomial recursion** using **randomized HSS techniques** provides an **efficient two-way** wave equation based **depth extrapolation** migration for **laterally variant medium**.
- Better image quality with the steep events (90 degrees) compared to reverse time migration (RTM).

ACKNOWLEDGEMENT

- This work was in part financially supported by the Natural Sciences and Engineering Research Council of Canada Discovery Grant (22R81254) and the Collaborative Research and Development Grant DNOISE II (375142-08). This research was carried out as part of the SINBAD II project with support from the following organizations: BG Group, BGP, BP, CGG, Chevron, ConocoPhillips, ION, Petrobras, PGS, Statoil, Total SA, WesternGeco, and Woodside.

REFERENCE

Auslander, L., and A. Tsao, 1991, On parallelizable eigensolvers: Citeseer.

Chandrasekaran, S., P. Dewilde, M. Gu, W. Lyons, and T. Pals, 2006, A fast solver for hss representations via sparse matrices: SIAM Journal on Matrix Analysis and Applications, 29, 67–81.

Halko, N., P.-G. Martinsson, and J. A. Tropp, 2011, Finding structure with randomness: Probabilistic algorithms for constructing approximate matrix decompositions: SIAM review, 53, 217–288.

Kenney, C. S., and A. J. Laub, 1995, The matrix sign function: Automatic Control, IEEE Transactions on, 40, 1330–1348. Kosloff, D. D., and E. Baysal, 1983, Migration with the fullacoustic wave equation: Geophysics, 48, 677–687.

Lyons, W., 2005, Fast algorithms with applications to pdes: PhD thesis, UNIVERSITY of CALIFORNIA.

Sandberg, K., and G. Beylkin, 2009, Full-wave-equation depth extrapolation for migration: Geophysics, 74, WCA121– WCA128.

Sheng, Z., P. Dewilde, and S. Chandrasekaran, 2007, Algorithms to solve hierarchically semi-separable systems: Operator Theory: Advances and Applications, 176, 255–294.

Tygert, M., and Rokhlin, 2007, A randomized algorithm for approximating the svd of a matrix.

Wapenaar, K., and J. L. Grimbergen, 1998, A discussion on stability analysis of wave field depth extrapolation: Presented at the 1998 SEG Annual Meeting.

Xia, J., 2012, On the complexity of some hierarchical structured matrix algorithms: SIAM Journal on Matrix Analysis and Applications, 33, 388–410.