

# Projection Methods for Generalized Eigenvalue Problems

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# Outline

- 1 Introduction
- 2 Assessing Solution Accuracy
- 3 GEP Solvers
- 4 Projection Methods for Large, Sparse Generalized Eigenvalue Problems
- 5 Conclusion

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# The Generalized Eigenvalue Problem (GEP)

## Definition

Let  $K, M \in \mathbb{C}^{n,n}$ . Finding  $x \in \mathbb{C}^n \setminus \{0\}$  and  $\lambda \in \mathbb{C}$  so that

$$Kx = \lambda Mx$$

is called a *generalized eigenvalue problem*.

$K$  is called *stiffness matrix*,  $M$  is called *mass matrix*.

$(\lambda, x)$  is called an *eigenpair*.

# Matrix Properties

- $K$ ,  $M$  arise from finite element discretization
- $K$ ,  $M$  Hermitian positive semidefinite (HPSD)
- $M$  may be diagonal

# Solution Properties

Regular matrix pencils, HPSD matrices

- The matrices can be simultaneously diagonalized by a non-unitary congruence transformation
- $0 \leq \lambda \leq \infty$

# Singular Matrix Pencils

## Example

$$K = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, M = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}.$$

- $(K - \lambda M)e_2 = 0$  has a solution for all values of  $\lambda$
- $(K, M)$  is called *singular*

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# Requirements for Practical Accuracy Measures

- Can be calculated numerically stable
- Quickly computable
- Structure preserving
- Computes relative errors

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# Polynomial Norms

## Definition (Adhikari, Alam, and Kressner, 2011)

Let  $K, M \in \mathbb{C}^{n,n}$ , let  $\omega \in \mathbb{R}^2$ ,  $\omega > 0$ , let  $P(t) = K - tM$ . We define the matrix polynomial norm  $\|P\|_{\omega,p,q}$  as follows:

$$\|P\|_{\omega,p,q} := \|[1/\omega_1 \|K\|_p, 1/\omega_2 \|M\|_p]\|_q.$$

# Structured Backward Error for Hermitian GEPs

## Definition

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$$\Delta P(t) := \Delta K - t\Delta M.$$

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### Definition

Let  $(\tilde{\lambda}, \tilde{x})$  be an approximate eigenpair of the Hermitian matrix pencil  $(K, M)$ . Then the *structured* backward error of  $(\tilde{\lambda}, \tilde{x})$  is defined as

$$\eta_{\omega,p,q}^H(\tilde{\lambda}, \tilde{x}) := \min\{\|\Delta P\|_{\omega,p,q} : P(\tilde{\lambda})\tilde{x} + \Delta P(\tilde{\lambda})\tilde{x} = 0, \Delta P = \Delta P^*\}.$$

# Structured Backward Error for Hermitian GEPs

## Calculation

### Theorem (Adhikari and Alam, 2011, Theorem 3.10)

Let  $(\tilde{\lambda}, \tilde{x})$  be an approximate eigenpair of the Hermitian matrix pencil  $(K, M)$ , where  $\tilde{\lambda}$  is real finite and  $\|\tilde{x}\|_2 = 1$ . Let  $r = K\tilde{x} - \tilde{\lambda}M\tilde{x}$ , let  $\omega_{rel} = [\|K\|_F, \|M\|_F]$ . Then

$$\eta_{\omega_{rel}, F, 2}^H(\tilde{\lambda}, \tilde{x}) = \min \left\| \left[ \frac{\|\Delta K\|_F}{\|K\|_F}, \frac{\|\Delta M\|_F}{\|M\|_F} \right] \right\|_2 = \sqrt{\frac{2\|r\|_2^2 - |r^*\tilde{x}|^2}{\|K\|_F^2 + |\tilde{\lambda}|^2\|M\|_F^2}},$$

where  $(K + \Delta K)\tilde{x} = \tilde{\lambda}(M + \Delta M)\tilde{x}$ .

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# Solvers for GEPs with HPSD Matrices

## Standard Eigenvalue Problem (SEP) Reduction (SR)

$K$  Hermitian,  $M$  HPD:

- Compute Cholesky decomposition  $LL^* := M$
- Solve  $L^{-1}KL^{-*}x_L = \lambda x_L$
- Revert basis change:  $x := L^{-T}x_L$



# Solvers for GEPs with HPSD Matrices

## SEP Reduction with Deflation (SR+D)

$K$  Hermitian,  $M$  HPSD:

- Deflate infinite eigenvalues from matrix pencil
- Apply SEP reduction to deflated pencil

# The Generalized Singular Value Decomposition (GSVD)

## Definition (MC, §6.1.6, Bai, 1992, §2)

Let  $n, r \in \mathbb{N}$ ,  $n \geq r$ , let  $A, B \in \mathbb{C}^{n,r}$ . Then there are unitary matrices  $U_1, U_2 \in \mathbb{C}^{n,n}$ ,  $Q \in \mathbb{C}^{r,r}$ , nonnegative diagonal matrices  $\Sigma_1, \Sigma_2 \in \mathbb{R}^{n,r}$ , and an upper-triangular matrix  $R \in \mathbb{C}^{r,r}$  such that

$$\begin{bmatrix} A \\ B \end{bmatrix} = \begin{bmatrix} U_1 & 0 \\ 0 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 \\ \Sigma_2 \end{bmatrix} \begin{bmatrix} 0 & R \end{bmatrix} Q^*.$$

It holds that

$$\Sigma_1 = \begin{matrix} r & & \\ & C & \\ n-r & & 0 \end{matrix}, \Sigma_2 = \begin{matrix} r & & \\ & S & \\ n-r & & 0 \end{matrix},$$

where  $C^2 + S^2 = I_r$ . If  $A$  and  $B$  are real, then all matrices may be taken to be real.

## Theorem (Bai, 1992, §4.2, §4.3)

Let  $A, B \in \mathbb{C}^{n,n}$ , let  $\text{rank}[A^*, B^*] = n$ , let

$$\begin{bmatrix} A \\ B \end{bmatrix} = \begin{bmatrix} U_1 & 0 \\ 0 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 \\ \Sigma_2 \end{bmatrix} RQ^*$$

be the GSVD of  $(A, B)$  and let  $QR^{-*} = [x_1, x_2, \dots, x_n]$ . Then we solved implicitly the generalized eigenvalue problem

$$A^*Ax_i = \lambda_i B^*Bx_i,$$

where  $\lambda_i = c_{ii}^2/s_{ii}^2$ ,  $i = 1, 2, \dots, n$ . If  $A$  and  $B$  are real, then all matrices can be taken to be real.

Note  $(\infty, x)$  is an eigenpair of  $(A^*A, B^*B)$  iff  $(0, x)$  is an eigenpair of  $(B^*B, A^*A)$ .

# Solvers for GEPs with HPSD Matrices

## GSVD Reduction

- Compute  $A$  such that  $K = A^*A$
- Compute  $B$  such that  $M = B^*B$
- Compute GSVD of  $(A, B)$ 
  - Compute GSVD directly, or
  - use QR factorizations and a CS decomposition (QR+CSD)
- Compute eigenpairs

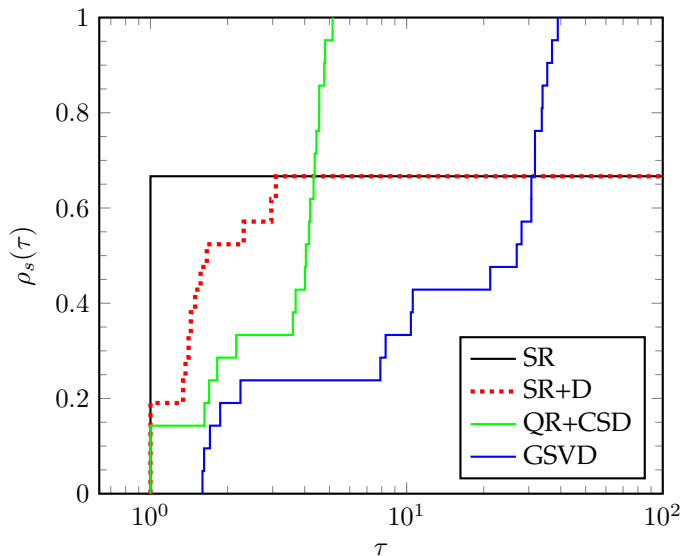
# Solvers for GEPs with HPSD Matrices

## Properties

Solver	QZ	SR	SR+D	GSVD
Backward stable	✓		(✓)	✓
Computes eigenvectors		✓	✓	✓
Preserves symmetry		✓	✓	✓
Preserves definiteness		(✓)	(✓)	✓
Handles singular pencils	✓		(✓)	✓
$(K, M)$ , $(M, K)$ equivalent	✓			✓

# Solvers for GEPs with HPSD Matrices

Performance Profile (Single Precision)



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# Projection Method

## Definition (Saad, 2011, §4.3)

Given a subspace  $\mathcal{S} \subseteq \mathbb{C}^n$ , an orthogonal *projection method* for an eigenvalue problem tries to approximate an eigenpair  $(\tilde{\lambda}, \tilde{x})$  so that  $\tilde{x} \in \mathcal{S}$  and  $K\tilde{x} - \tilde{\lambda}M\tilde{x} \perp \mathcal{S}$  for some given inner product in which orthogonality is defined.



# A Multilevel Eigensolver

## Assumptions

- The user seeks eigenpairs (in contrast to eigenvalues),
- mass and stiffness matrix are given explicitly,
- mass and stiffness matrix are HPSD,
- the matrix pencil is regular, and
- GEPs on the block diagonal deliver good approximations to the eigenpairs.

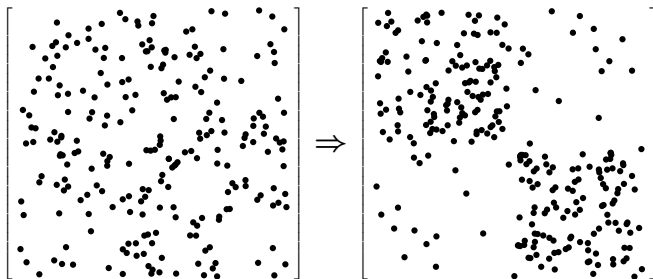
# A Multilevel Eigensolver

## Idea

Recursively decompose the GEP into many small GEPs

# A Multilevel Eigensolver

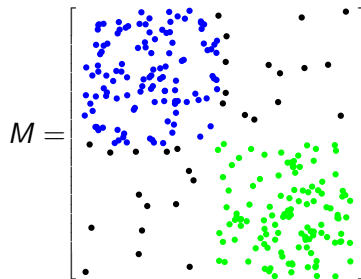
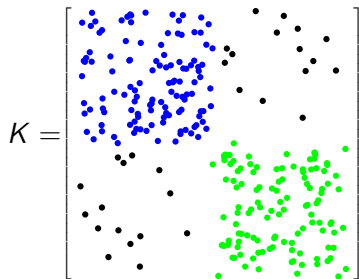
## Step 1: Partitioning



Minimize weight of off-diagonal entries (graph bisection)

# A Multilevel Eigensolver

## Step 2: Recursion



Compute eigenpair approximations in block diagonal GEPs



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# Additional Thesis Topics

- Singular matrix pencils
- A new fast and stable GEP solver for HPSD matrices
- Improving numerical stability
- Numerical experiments with multilevel eigensolver (TODO)

# Conclusion

- Structured backward errors can be computed quickly for GEPs with Hermitian matrices
- GSVD-based solvers are fast and robust in practice
- In our tests the more robust the GEP solver, the slower the GEP solver



Thank you for your attention.  
Questions?

# References I

- Adhikari, B. and R. Alam (2011). "On backward errors of structured polynomial eigenproblems solved by structure preserving linearizations". In: *Linear Algebra and its Applications* 434.9, pp. 1989–2017. ISSN: 0024-3795. DOI: 10.1016/j.laa.2010.12.014.
- Adhikari, B., R. Alam, and D. Kressner (2011). "Structured eigenvalue condition numbers and linearizations for matrix polynomials". In: *Linear Algebra and its Applications* 435.9, pp. 2193–2221. ISSN: 0024-3795. DOI: 10.1016/j.laa.2011.04.020.
- Bai, Z. (1992). *The CSD, GSVD, Their Applications and Computations*. IMA Preprint Series 958. Minneapolis, MN, USA: University of Minnesota. HDL: 11299/1875.
- Dolan, E. D. and J. J. Moré (2002). "Benchmarking optimization software with performance profiles". In: *Mathematical Programming* 91.2, pp. 201–213. ISSN: 0025-5610. DOI: 10.1007/s101070100263.
- Golub, G. H. and C. F. Van Loan (2012). *Matrix Computations*. 4th ed. Baltimore, MD, USA: Johns Hopkins University Press. ISBN: 978-1-4214-0794-4.
- Higham, N. J. (2002). *Accuracy and Stability of Numerical Algorithms*. 2nd ed. Philadelphia, PA, USA: Society for Industrial and Applied Mathematics. ISBN: 978-0-89871-521-7. DOI: 10.1137/1.9780898718027.
- Mehrmann, V. and H. Xu (2015). "Structure preserving deflation of infinite eigenvalues in structured pencils". In: *Electronic Transactions on Numerical Analysis* 44, pp. 1–24. ISSN: 1068-9613. URL: <http://etna.mcs.kent.edu/volumes/2011-2020/vol144/>.
- Nakatsukasa, Y. (2012). "On the condition numbers of a multiple eigenvalue of a generalized eigenvalue problem". In: *Numerische Mathematik* 121.3, pp. 531–544. ISSN: 0029-599X. DOI: 10.1007/s00211-011-0440-x.

# References II

Saad, Y. (2011). *Numerical Methods for Large Eigenvalue Problems. Revised Edition.* Classics in Applied Mathematics 66. Philadelphia, PA, USA: Society for Industrial and Applied Mathematics. ISBN: 978-1-61197-072-2. DOI: 10.1137/1.9781611970739.

Stathopoulos, A. (2005). *Locking issues for finding a large number of eigenvectors of hermitian matrices.* Tech. rep. WM-CS-2005-09. Revised June 2006. Williamsburg, VA, USA: College of William & Mary.