

RQZ: A rational QZ method for the generalized eigenvalue problem

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KU Leuven - University of Leuven - Department of Computer Science - NUMA Section

In this talk we will discuss:

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- ◇ Shift & *pole* introduction and swapping
- ◇ Rational Krylov
- ◇ Subspace iteration

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Generalized eigenvalue problems

- ◇ Given A & B : $n \times n$ matrices, either \mathbb{R} or \mathbb{C}
- ◇ Computation of the triplets $(\alpha, \beta, \mathbf{x})$ that satisfy $\beta A \mathbf{x} = \alpha B \mathbf{x}$
- ◇ Procedure:
 1. Reduce the pencil to a *manageable* form
 2. Iterate to generalized Schur form
 3. Recover eigenvectors
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Hessenberg, Hessenberg form

$$\begin{bmatrix}
 h_{11} & h_{12} & h_{13} & \cdots & h_{1n} \\
 h_{21} & h_{22} & h_{23} & \cdots & h_{2n} \\
 0 & h_{32} & h_{33} & \cdots & h_{3n} \\
 \vdots & \ddots & \ddots & \ddots & \vdots \\
 0 & \cdots & 0 & h_{n,n-1} & h_{nn}
 \end{bmatrix}$$

Upper Heisenberg Matrix

source: spikedmath.com/573.html

Hessenberg, Hessenberg form

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Hessenberg, Hessenberg form

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A

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B

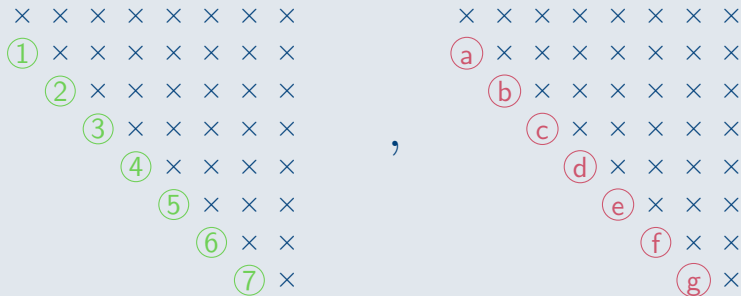
Hessenberg, Hessenberg form

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 \end{array}$$

 A B

$$\text{poles } \Xi = \left(\begin{array}{c} \times \\ \times \end{array} \right) \subset \bar{\mathbb{C}}$$

Hessenberg, Hessenberg form



$$A \quad B$$

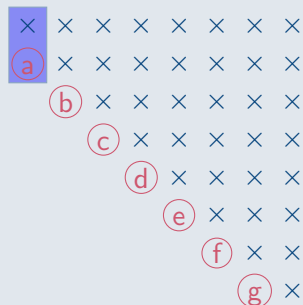
$$\text{poles } \Xi = \left(\frac{\textcircled{1}}{\textcircled{a}}, \frac{\textcircled{2}}{\textcircled{b}}, \dots \right) \subset \bar{\mathbb{C}}$$

Introducing a shift



A

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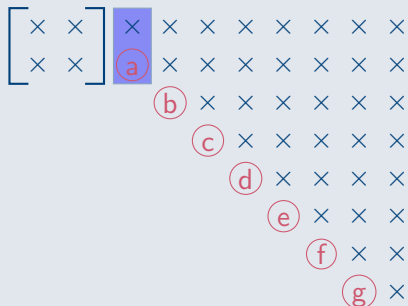


B

Introducing a shift



A



B

$$\begin{matrix} \times \\ \textcircled{1} \end{matrix} \neq \gamma \begin{matrix} \times \\ \textcircled{a} \end{matrix} !$$

Introducing a shift



A

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B

Swapping poles



A

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B

Swapping poles

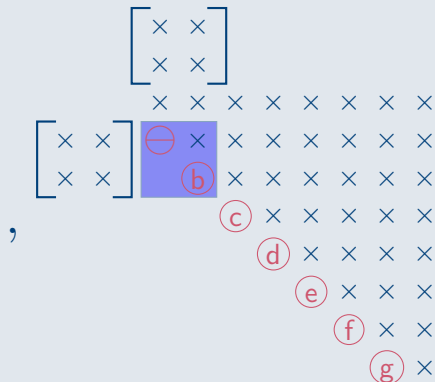
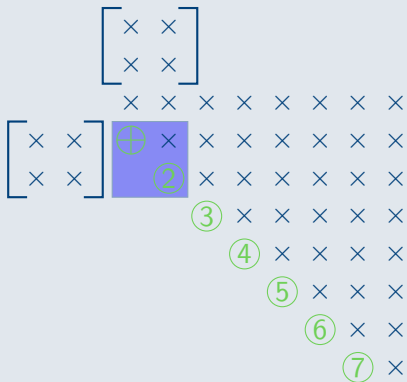
Solve coupled Sylvester equation

(cfr. reordering Schur form [Kågström and Poromaa])

$$\begin{array}{|c|} \hline \frac{\oplus}{\ominus} \neq \frac{\textcircled{2}}{\textcircled{b}} ! \\ \hline \end{array} \quad \begin{array}{|c|} \hline \frac{\oplus}{\ominus} \neq \frac{0}{0} ! \\ \hline \end{array} \quad \begin{array}{|c|} \hline \frac{\textcircled{2}}{\textcircled{b}} \neq \frac{0}{0} ! \\ \hline \end{array}$$

$$\Rightarrow Q^* = \begin{bmatrix} \times & \times \\ \times & \times \end{bmatrix}, Z = \begin{bmatrix} \times & \times \\ \times & \times \end{bmatrix}$$

Swapping poles



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A

B

Swapping poles



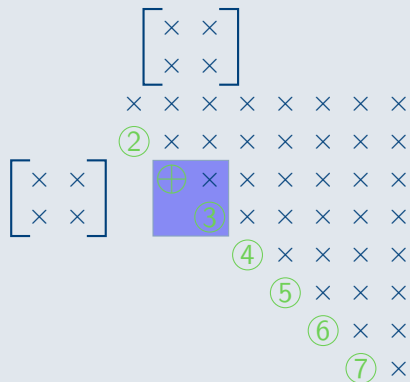
A

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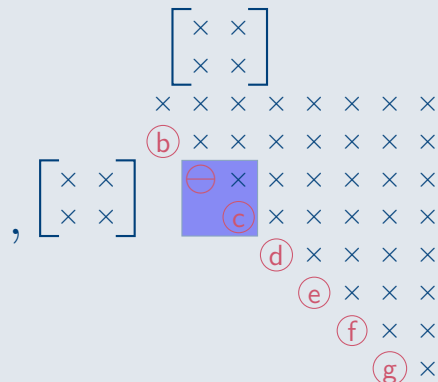


B

Swapping poles



A



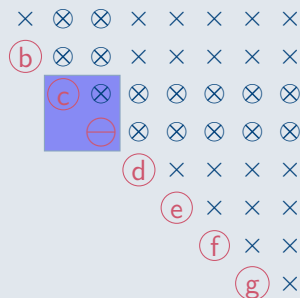
B

Swapping poles



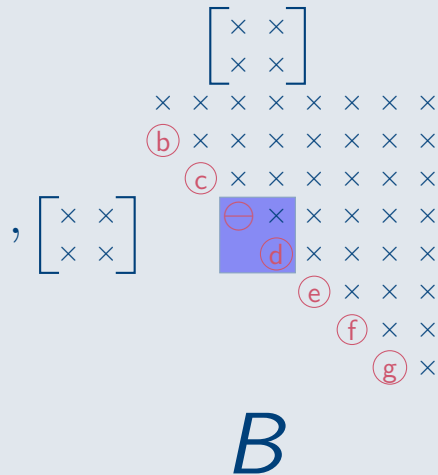
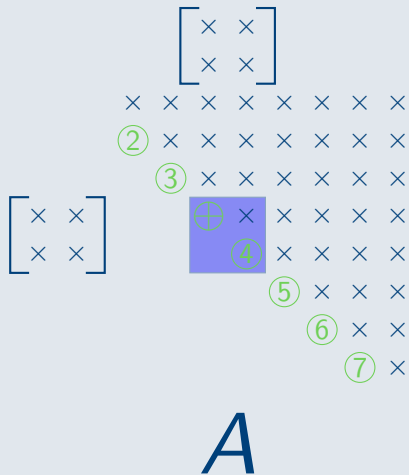
A

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B

Swapping poles

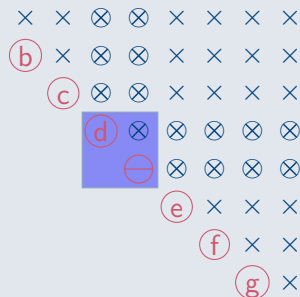


Swapping poles



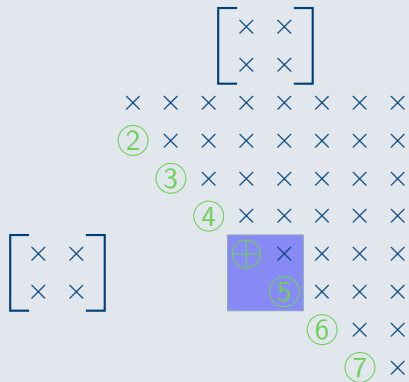
A

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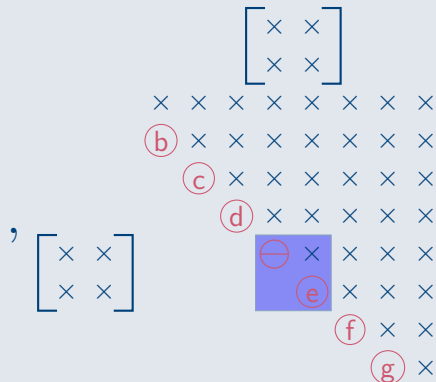


B

Swapping poles



A



B

Swapping poles



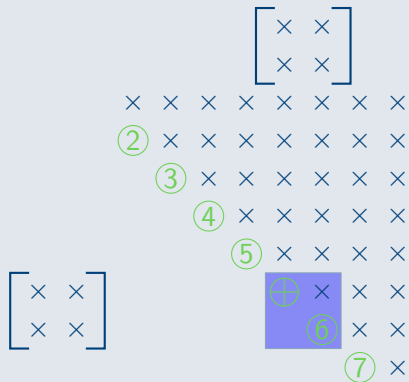
A

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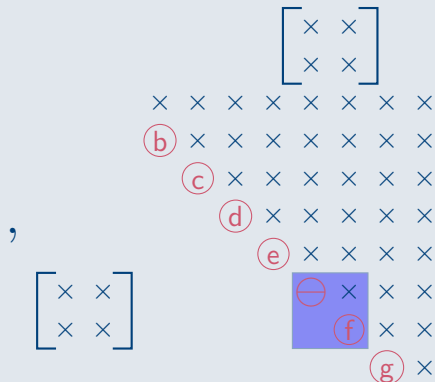


B

Swapping poles

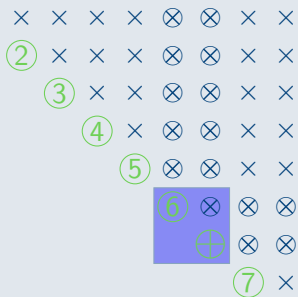


A



B

Swapping poles



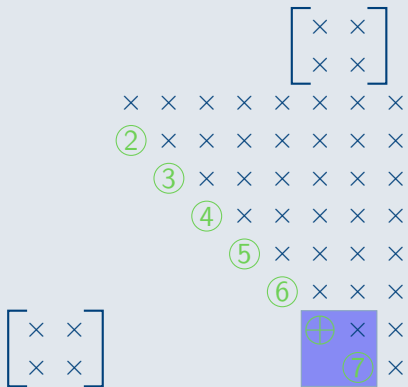
A

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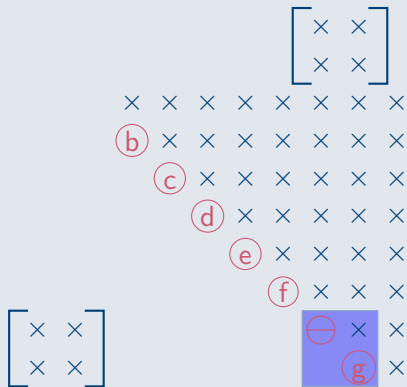
B

Swapping poles



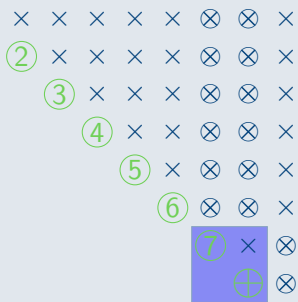
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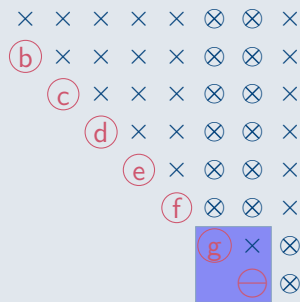
B

Swapping poles



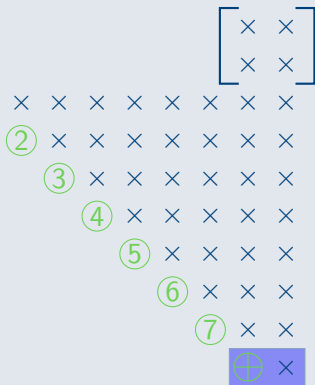
A

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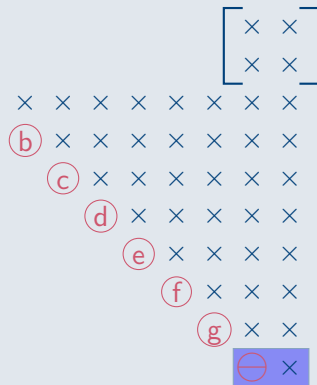
B

Introducing a pole



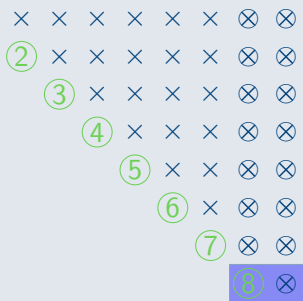
A

$$\boxed{\oplus \times \neq \gamma \ominus \times !}$$



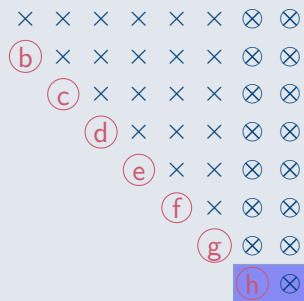
B

Introducing a pole



A

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B

The algorithm in a nutshell:

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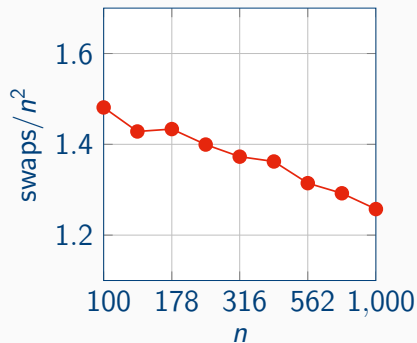
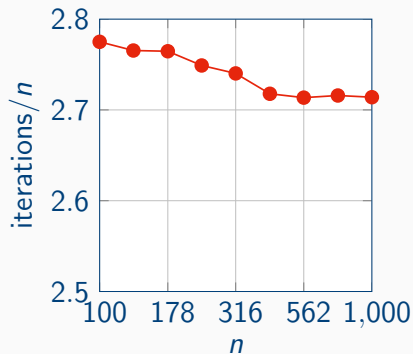
The algorithm in a nutshell:

1. Introduce shift at the top
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3. Introduce pole at the end

Poles at ∞ ($\times = 0$) \rightarrow QZ method: Bulge exchange interpretation [Watkins]

Caution: shift $\notin \Xi$ to avoid slower convergence

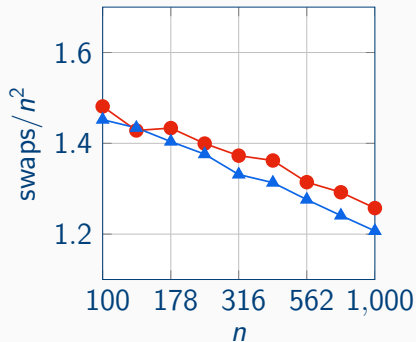
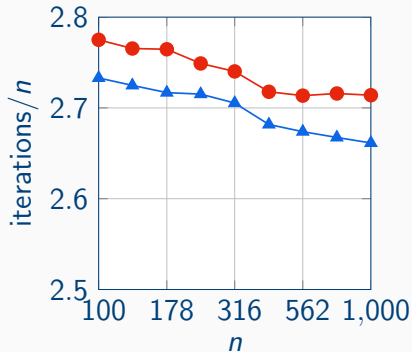
Is it worth it?



—●— QZ

Data: 9 random matrix pairs, $n \in [100, 1000]$, reduced to H-T, averaged over 10 runs

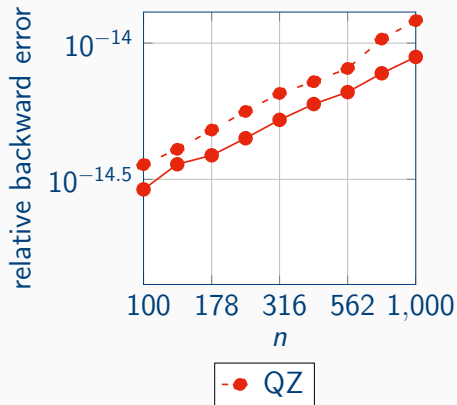
Is it worth it?



—●— QZ; —▲— RQZ

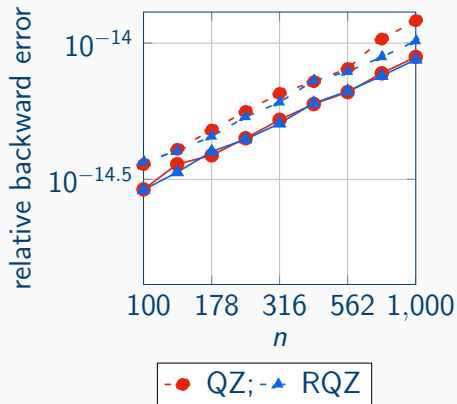
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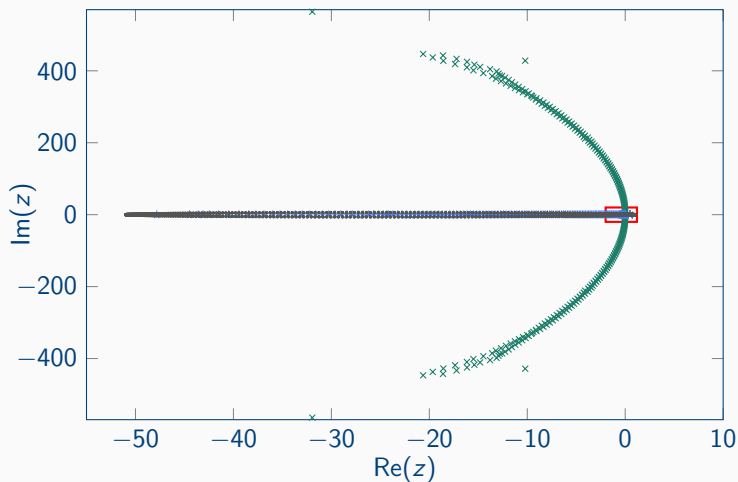
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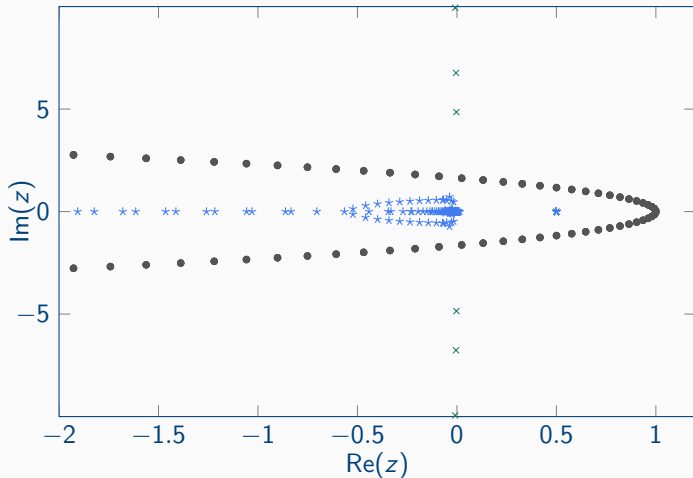
Numerical example 2: Reduction to Hessenberg, Hessenberg

Data: MHD matrix pair from MatrixMarket, $n = 1280$



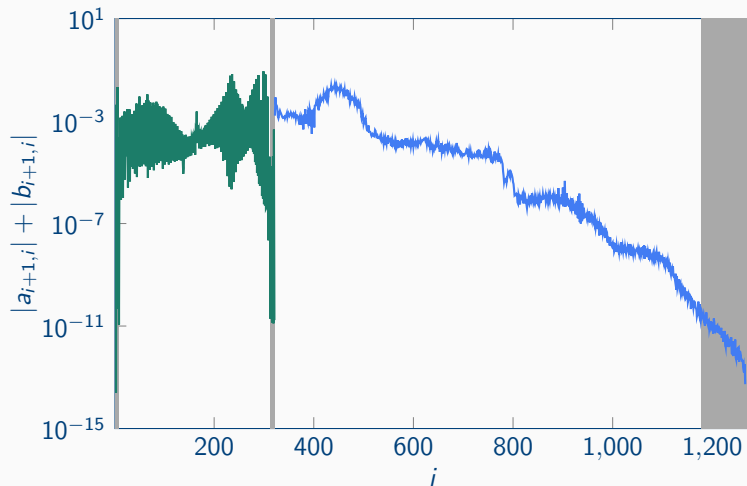
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A word on the theory

Definition: Properness

The Hessenberg, Hessenberg pair (A, B) is called *proper* (or *irreducible*) if:

1. $\begin{array}{|c|} \times \\ \hline 1 \end{array} \neq \gamma \begin{array}{|c|} \times \\ \hline a \end{array}$

2. $\frac{\times}{\times} \neq \frac{0}{0}$

3. $\begin{array}{|c|} \oplus \\ \times \\ \hline \end{array} \neq \gamma \begin{array}{|c|} \ominus \\ \times \\ \hline \end{array}$

Why and how does RQZ work?

Krylov subspaces

1. Krylov subspace: $\mathcal{K}_i(M, \mathbf{v}) = \mathcal{R}(\mathbf{v}, M\mathbf{v}, \dots, M^{i-1}\mathbf{v})$

Why and how does RQZ work?

Krylov subspaces

1. Krylov subspace: $\mathcal{K}_i(M, \mathbf{v}) = \mathcal{R}(\mathbf{v}, M\mathbf{v}, \dots, M^{i-1}\mathbf{v})$
2. rational Krylov subspace: $\mathcal{K}_i^{\text{rat}}(M, \mathbf{v}, \Xi = (\xi_1, \dots, \xi_{i-1})) = q_{\Xi}(M)^{-1} \mathcal{K}_i(M, \mathbf{v})$

Why and how does RQZ work?

Krylov subspaces

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Theorem

If (A, B) is a proper Hessenberg pair with poles $(\xi_1, \dots, \xi_{n-1})$ then for $i = 1, \dots, n-1$:

$$\mathcal{K}_i^{\text{rat}}(AB^{-1}, \mathbf{e}_1, (\xi_1, \dots, \xi_{i-1})) = \mathcal{K}_i^{\text{rat}}(B^{-1}A, \mathbf{e}_1, (\xi_2, \dots, \xi_i)) = \mathcal{R}(\mathbf{e}_1, \dots, \mathbf{e}_i) = \mathcal{E}_i$$

Why and how does RQZ work?

Theorem: Implicit Q (and Z)

Given a pair (A, B) , the matrices Q and Z that transform it to proper Hessenberg form,

$$(\hat{A}, \hat{B}) = Q^* (A, B) Z,$$

are determined *essentially unique* if $Q\mathbf{e}_1$ and the poles are fixed.

Why and how does RQZ work?

Nested subspace iteration

An RQZ step with shift ϱ on a pencil with poles $(\xi_1, \dots, \xi_{n-1})$ and new pole ξ_n performs nested subspace iteration for $i = 1, \dots, n-1$ accelerated by

$$\begin{aligned}\mathcal{R}(\mathbf{q}_1, \dots, \mathbf{q}_i) &= (A - \varrho B)(A - \xi_i B)^{-1} \mathcal{E}_i \\ \mathcal{R}(\mathbf{z}_1, \dots, \mathbf{z}_i) &= (A - \xi_{i+1} B)^{-1} (A - \varrho B) \mathcal{E}_i.\end{aligned}$$

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What does this mean?

- QR step with shift ϱ on entire space

Why and how does RQZ work?

Nested subspace iteration

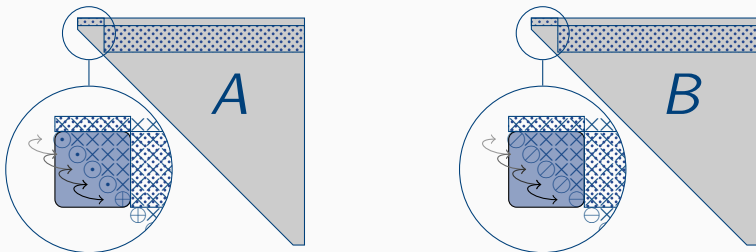
An RQZ step with shift ϱ on a pencil with poles $(\xi_1, \dots, \xi_{n-1})$ and new pole ξ_n performs nested subspace iteration for $i = 1, \dots, n-1$ accelerated by

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What does this mean?

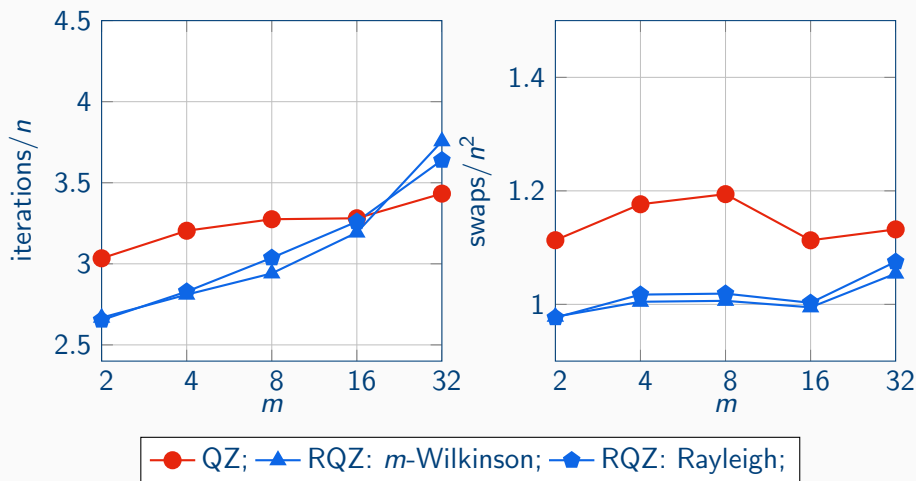
- QR step with shift ϱ on entire space
- RQ steps with tightly packed shifts Ξ on selected subspaces

Tightly packed shifts

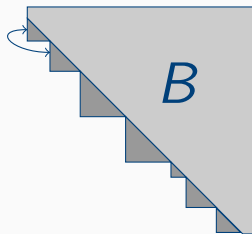
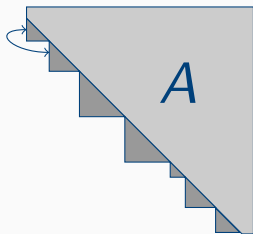


→ More cache efficient implementations (Level 3 BLAS)

Tightly packed shifts



Block Hessenberg



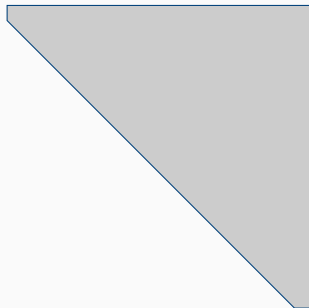
→ complex conjugate shifts and poles in real arithmetic for real pencils

Aggressive Early deflation

The performance of the QR algorithm can be significantly improved by an aggressive early deflation technique ([Braman, Byers and Mathias]) and similar techniques have been developed for the QZ method ([Kågström and Kressner]).

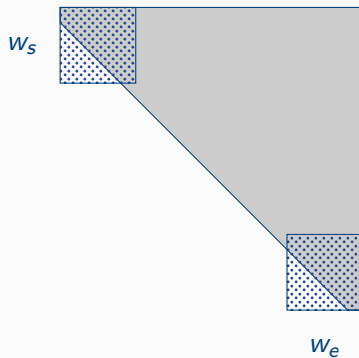
Aggressive Early deflation

A and B



Aggressive Early deflation

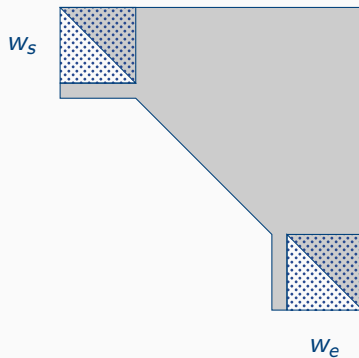
A and B



$$n \gg w_e > w_s$$

Aggressive Early deflation

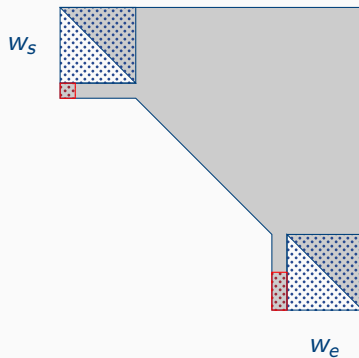
A and B



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Aggressive Early deflation

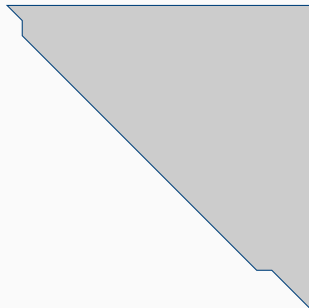
A and B



$$n \gg w_e > w_s$$

Aggressive Early deflation

A and B



Standard eigenvalue problems

- RQZ applies equivalence transformations on the pencil:

$$(\hat{A}, \hat{B}) = Q^*(A, B)Z$$

- Consequently we have two similarity transformations:

$$\hat{A}\hat{B}^{-1} = Q^*AB^{-1}Q \quad \text{and} \quad \hat{B}^{-1}\hat{A} = Z^*B^{-1}AZ$$

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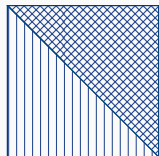
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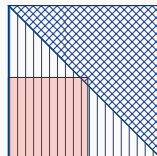
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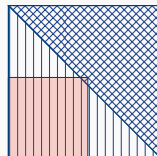
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Extended Hessenberg + diagonal = rational Hessenberg

→ my connection with this mini-symposium

Rational Krylov method

The connection between RQZ and the rational Krylov method can be used:

- to compute the Ritz values from the Hessenberg, Hessenberg recurrence pencil
- to filter and restart the rational Krylov method

Rational Krylov method

$$A V_{k+1} \underline{G}_k = B V_{k+1} \underline{H}_k$$

with:

- $\mathcal{R}(V_{k+1}) = \mathcal{K}_{k+1}^{\text{rat}}(AB^{-1}, \mathbf{v}, \Xi_{1:k})$
- $(\underline{H}_k, \underline{G}_k)$ the Hessenberg, Hessenberg recurrence pencil

Applying an RQZ step with shift ϱ , we get $\mathcal{K}_k^{\text{rat}}(AB^{-1}, \hat{\mathbf{v}}, \Xi_{2:k})$ with:

$$\hat{\mathbf{v}} = (A - \xi_1 B)^{-1} (A - \varrho B) \mathbf{v}$$

Conclusions

1. RQZ is a generalization of QZ
2. Implicit rational subspace iteration is promising
3. New shift and pole strategies can be a powerful tool to compute invariant subspaces

Further reading:

arXiv:1802.04094

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Thank you for your attention!