

# Control of the search space size and solving linear systems in the FEAST algorithm

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Joint work with

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<http://www.sppexa.de>

<http://blogs.fau.de/essex/>



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Iterative solution

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# Symmetric eigenvalue problem


We aim at solving the problem:

**Given:**  $A \in \mathbb{R}^{n \times n}$ ,  $A = A^*$ ,  
an interval

$$I_\lambda = [\underline{\lambda}, \bar{\lambda}].$$

**Sought:**  $X \in \mathbb{R}^{n \times m}$ ,  $m \leq n$ ,  $X^*X = I$ ,  $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_m)$  such that

$$AX = X\Lambda \text{ and all } \lambda_j \in [\underline{\lambda}, \bar{\lambda}].$$

-  Solve the (partial) symmetric eigenproblem. Find all eigenvalues in a given interval.

(Everything can be generalized to complex matrices and to a pair  $(A, B)$  with  $B$  hpd.)



# Framework: Rayleigh-Ritz approach

- ▶ Choose a subspace  $\mathcal{U} = \text{span}(\mathbf{U})$ ,  $\mathbf{U} \in \mathbb{C}^{n \times m}$ .
- ▶ Compute the **Rayleigh quotients**  $A_{\mathbf{U}} := \mathbf{U}^* \mathbf{A} \mathbf{U}$ ,  $B_{\mathbf{U}} := \mathbf{U}^* \mathbf{B} \mathbf{U}$ .



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- ▶ Compute eigenpairs  $(\tilde{\Lambda}, \tilde{\mathbf{W}})$  of  $\mathbf{A}_U \tilde{\mathbf{W}} = \mathbf{B}_U \tilde{\mathbf{W}} \tilde{\Lambda}$ .
- ▶ Form **Ritz pairs**  $(\tilde{\Lambda}, \mathbf{U} \tilde{\mathbf{W}})$  of  $\mathbf{A} \mathbf{X} = \mathbf{B} \mathbf{X} \tilde{\Lambda}$ .



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- ▶ Form **Ritz pairs**  $(\tilde{\Lambda}, \mathbf{U} \tilde{\mathbf{W}})$  of  $\mathbf{A} \mathbf{X} = \mathbf{B} \mathbf{X} \tilde{\Lambda}$ .

... and hope that  $(\tilde{\Lambda}, \mathbf{U} \tilde{\mathbf{W}})$  are good approximations to some eigenpairs.

Otherwise, set  $\mathbf{U} := \mathbf{U} \tilde{\mathbf{W}}$  and iterate.





E. Polizzi, Phys. Rev. B, 2009, 79, 115112

In FEAST: The subspace

$$U := \frac{1}{2\pi i} \int_{\mathcal{C}} (zB - A)^{-1} dz BY$$

is used.

- ▶  $\mathcal{C}$  = curve in complex plane surrounding  $I_{\lambda}$ .
- ▶  $Y$  = starting base of (possibly) random vectors.

It follows

$$\frac{1}{2\pi i} \int_{\mathcal{C}} (zB - A)^{-1} B dz = \text{orth. projector onto } \text{span}(X)$$



# The FEAST Algorithm: Skeleton

**Input:**  $I_\lambda := [\underline{\lambda}, \bar{\lambda}]$ , an estimate  $\tilde{m}$  of the number of eigenvalues in  $I_\lambda$ .

**Output**  $\hat{m} \leq \tilde{m}$  eigenpairs with eigenvalue in  $I_\lambda$ .

**Perform:**

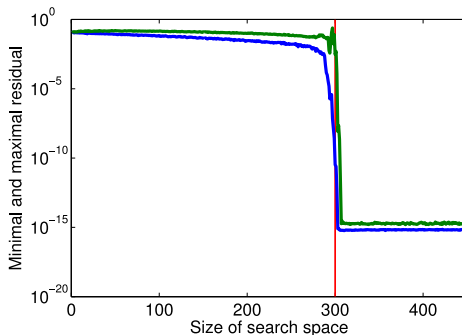
1. Choose  $Y \in \mathbb{C}^{n \times \tilde{m}}$  of full rank and compute
$$U := \frac{1}{2\pi i} \int_{\mathcal{C}} (zB - A)^{-1} B dz Y,$$
2. Form  $A_U := U^*AU$ ,  $B_U := U^*BU$ ,
3. Solve size- $\tilde{m}$  eigenproblem  $A_U \tilde{W} = B_U \tilde{W} \tilde{\Lambda}$ ,
4. Compute  $(\tilde{\Lambda}, \tilde{X} := U \cdot \tilde{W})$ ,
5. If no convergence: go to Step 1 with  $Y := \tilde{X}$ .



# Problem: How to choose search space size $\tilde{m}$ ?

**Experiment:** Choose  $I_\lambda = [\underline{\lambda}, \bar{\lambda}]$  such that it contains the  $m = 300$  lowest eigenvalues of size  $1059$ -matrix. Let  $\tilde{m}$  vary,  $\tilde{m} = 1, \dots, 450$ .

Residuals vs. search space size  $\tilde{m}$ :



K., Di Napoli, Galgon, Lang, Bientinesi: *Dissecting the FEAST algorithm for generalized eigenproblems*, 2013



# Problem: How to choose search space size $\tilde{m}$ ?

Do not choose **too small!**

Determine a good choice for  $\tilde{m} \Leftrightarrow$  Count eigenvalues in  $I_\lambda$

Leads to stopping criterion:

“all” eigenpairs found  $\Rightarrow$  Stop Algorithm



# Counting eigenvalues

- ▶  $\text{rank}(U) = m =$  number of eigenvalues in  $I_\lambda$
- ▶ In exact arithmetic:  $U$  has singular values 0 or 1
- ▶ numerical rank?



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- ▶  $\text{rank}(U) = m =$  number of eigenvalues in  $I_\lambda$
- ▶ In exact arithmetic:  $U$  has singular values 0 or 1
- ▶ numerical rank?
- ▶ It can be shown: If  $m \leq \tilde{m}$  we have  $m = \#$  of singular values of  $U$  that are  $\geq 1/2$  (Tang & Polizzi, 2013).
- ▶ Number  $1/2$  depends on implementation (integration scheme). E.g., valid for Gauß–Legendre integration, midpoint rule of even order.



# Counting eigenvalues: SVD of $U$

SVD  $U = W\Sigma V^*$  with  $\Sigma = \text{diag}(\sigma_1, \dots, \sigma_m, 0, \dots, 0)$

$\Rightarrow \text{span}(W(:, 1 : m)) = \text{span}(U)$

$\Rightarrow$  Found the correct subspace, but cost =  $\mathcal{O}(n^2 \cdot \tilde{m})$

SVD of  $B_U = U^*BU$ :

$\Rightarrow B_U = V\Sigma^*\Sigma V^*$  with  $V \in \mathbb{R}^{\tilde{m} \times \tilde{m}}$ , orthogonal. No order  $n$  cost.

$\Rightarrow U' = U \cdot V(:, 1 : m)$  spans the wanted space  $\rightsquigarrow \mathcal{O}(n \cdot m)$ .



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This means the dimension and a basis of the search space can be computed.

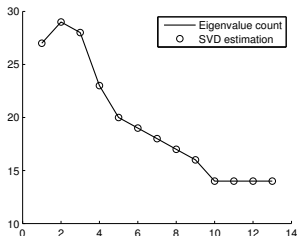
Proceed with a subspace slightly larger than  $m$ .



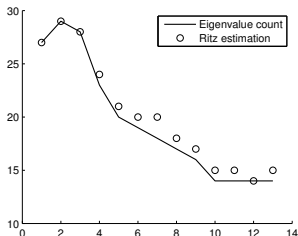


# Counting eigenvalues: example

## SVD count




## Number of Ritz values in $I_\lambda$



1 Point on abscissa  $\equiv$  1 interval  $I_\lambda$

○ = count from respective method

line = exact count

 Ritz count is almost for free and not too bad. It does **not** deliver the subspace. Typically overestimates.



# Counting eigenvalues: alternatives

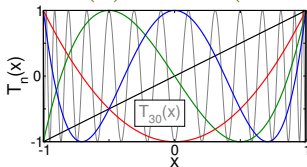
## Chebyshev polynomials

two-term recurrence

$$T_n(x) = \cos(n \arccos x)$$

$$T_0(x) = 1, \quad T_1(x) = x,$$

$$T_{n+1}(x) = 2xT_n(x) - T_{n-1}(x)$$



## Expansion of functions

for example: density of states  
(DOS)  $\hat{=}$  eigenvalue count

$$\rho(\omega) \propto \mu_0 + 2 \sum_{n=1} \mu_n T_n(\omega)$$

with coefficients  
(moments) of the matrix  $A$

$$\begin{aligned} \mu_n &= \int_{-1}^1 \rho(\omega) T_n(\omega) d\omega \\ &= x^* T_n(A) x \end{aligned}$$



# Counting eigenvalues: alternatives

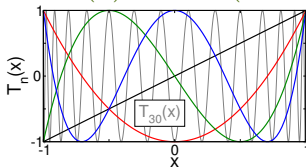
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## Expansion of functions

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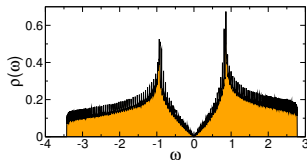
(DOS)  $\hat{=}$  eigenvalue count

**idea:** use as input for FEAST

further technical details: [Weiße, Wellein, Alvermann, Fehske, Rev. Mod. Phys. 78, 275 \(2006\)](#).

cf. recent report

[\(Di Napoli et al., 2013\)](#)



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Central task: Solution of

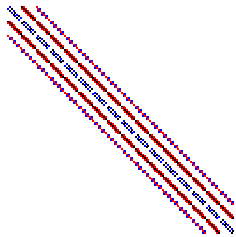
$$(zB - A)V = BY.$$

Matrix  $(zB - A)$  is

- ▶ large and sparse **Cholesky LU**
- ▶ non-Hermitian ( $z$  complex) **Cholesky CG**
- ▶ complex valued
- ▶ often ill-conditioned **GMRES GMRES??**



# Problems from Graphene nanoribbons



some lead to **banded** systems  $\Rightarrow$  special banded **direct** solver.

See (Hockney & Jesshope, 1988) and (Lawrie & Sameh, 1984).



# Results with banded solver

- ▶ Matrix size  $n \approx 1.2M$ , ratio  $\frac{\text{nnz}}{n^2} \approx 0.001\%$  (12 nonzero entries per row).
- ▶ Graphene II with gap around zero.

Matrix	est.	found	iters.
Graphene I	535	535	7
▶ Graphene II ( $\ell$ )	492	492	4
Graphene II (r)	546	546	8
Graphene III	574	572	25

- ▶ Eigenpair residuals:  $10^{-9} \dots 10^{-16}$
- ▶ Linear system residuals:  $10^{-10} \dots 10^{-16}$



# General (non-banded) problems

Problem large & sparse: **Iterative** method needed.

**Candidate 1:** Special tailored method for systems

$$(R + \mathbf{i}S)(x + \mathbf{i}y) = \varphi + \mathbf{i}\psi$$

$$R = R^T, S = S^T, \text{ real}$$

(Axelsson & Kucherov, 2000)

- ▶  $(zB - A)V = BY$  can be brought to this form.
- ▶ Leads to **real** systems of size  $2n$ .
- ▶ Not efficient enough in practice





# General (non-banded) problems

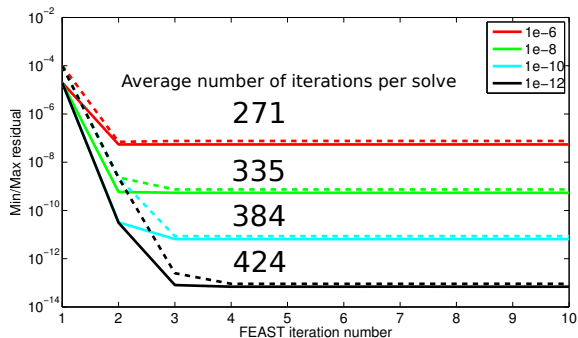
Problem large & sparse: **Iterative** method needed.

**Candidate 2: CARP-CG**

(cf. Talk of Jonas Thies, Code also by Jonas)

**Experiment:** Graphene,  $n = 4,200$ ,  $m = 17$  interior eigenpairs

Achievable residuals  $\|Ax - x\lambda\|$ :



$$\max_{z_j} \kappa(z_j | -A) = 1097.$$



**Example 1:** Graphene,  $n = 84,000$ , sought  $m = 102$  eigenpairs from interior.

**Average:** 567 iterations/solve.

- ▶  $\text{tol}_{\text{lin}} = 10^{-10}$
- ▶  $\|Ax - x\lambda\| = 10^{-7} \dots 10^{-10}$  (convergence criterion:  $10^{-7}$ ).
- ▶ Orthogonality  $\max_{i \neq j} |x_i^* x_j| = 10^{-15}$ .

**Example 2:** Graphene,  $n = 176,000$ , sought  $m = 201$  eigenpairs from interior.

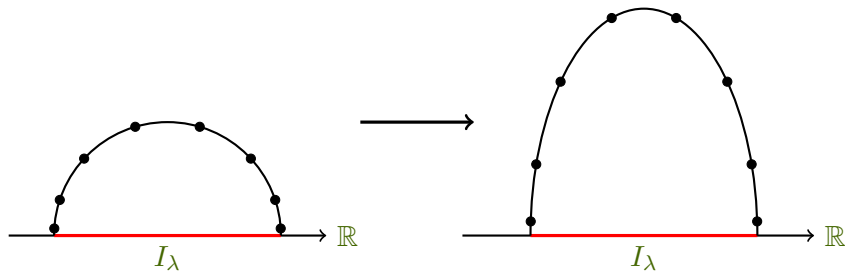
**Average:** 655 iterations/solve.

- ▶  $\text{tol}_{\text{lin}} = 10^{-10}$
- ▶  $\|Ax - x\lambda\| = 10^{-8} \dots 10^{-10}$  (convergence criterion:  $10^{-7}$ ).
- ▶ Orthogonality  $\max_{i \neq j} |x_i^* x_j| = 10^{-15}$ .



# Other contours

**Idea:** Bring integration points away from real axis.



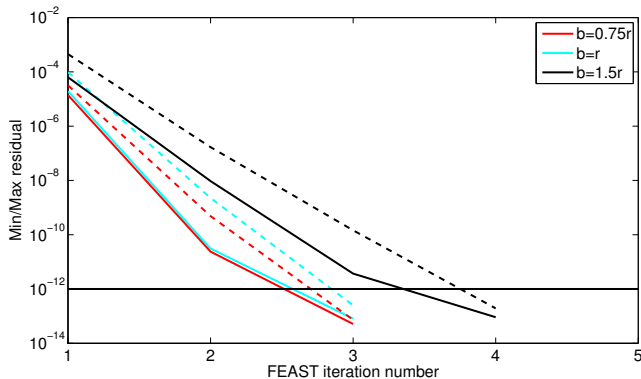
$$\text{Use } U = \frac{1}{2\pi i} A \int_C \frac{1}{z} (zI - A)^{-1} dz$$



# Use of ellipse: Results

**Experiment:** Graphene,  $n = 4,200$ ,  $m = 17$  interior eigenpairs

$r$  = main semi axis, second semi axis  $b = \alpha r$ , vary  $\alpha$



Required  $\|Ax - x\lambda\| \leq 10^{-12}$ .

↓ CARP-CG iterations ↔ FEAST iterations ↑



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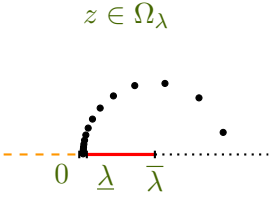
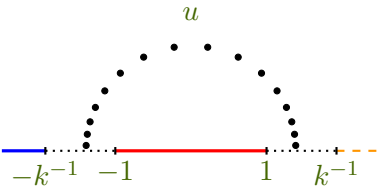
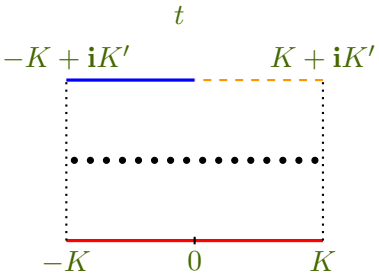
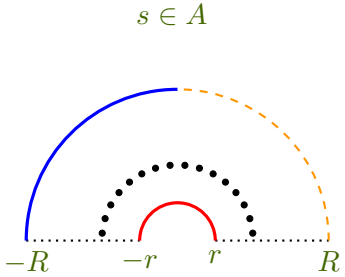
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# Outlook: Transforming the integration region

● = integration point



# Outlook: Transforming the integration region

... for computing upper eigenpairs

Adapted from (Hale *et al.*, 2008): results in

$$U = -\frac{\sqrt{\lambda\bar{\lambda}}}{\pi i k} \int_{-K+iK'/2}^{3K+iK'/2} \frac{\operatorname{cn}(t)\operatorname{dn}(t)}{(k^{-1} - \operatorname{sn}(t))^2} (z(t)B - A)^{-1} B dt Y,$$

with  $k = \frac{\sqrt{\lambda/\lambda-1}}{\sqrt{\lambda/\lambda+1}} < 1$ . Then use **midpoint** rule.



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**Theorem:** (Hale *et al.*, 2008)

Let  $\mathbf{A}, \mathbf{B}$  be real symmetric and let  $I_\lambda = [\underline{\lambda}, \bar{\lambda}] \subset (0, +\infty)$ , let  $\tilde{U}_p$  formed by **midpoint** rule, then for all  $\underline{\lambda}, \bar{\lambda} > 0$

$$\|U - \tilde{U}_p\| = \mathcal{O}\left(\exp\left(\frac{-\pi^2 p}{\log(\bar{\lambda}/\underline{\lambda}) + 3}\right)\right).$$





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$$\mathcal{O}\left(\log\left(\frac{\bar{\lambda}}{\underline{\lambda}}\right)\right) \text{ instead of } \mathcal{O}\left(\frac{\bar{\lambda}}{\underline{\lambda}}\right) \text{ solves!}$$



# Transforming the integration region: results

(A, B) from structural engineering,  $n = 1473$ , seek 300 highest eigenpairs.

Order ( $p$ )	Transformation method	Gauß–Legendre	Trapezoidal rule
4	300 eigenpairs 9 iterations 13k solves	0 eigenpairs 10 iterations 18k solves	65 eigenpairs 10 iterations 17k solves
8	300 eigenpairs 5 iterations 14k solves	0 eigenpairs 10 iterations 36k solves	68 eigenpairs 10 iterations 35k solves
16	300 eigenpairs <b>2</b> iterations 14k solves	294 eigenpairs <b>10</b> iterations 58k solves	82 eigenpairs <b>10</b> iterations 69k solves

!



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