

# Bounds on Eigenvalues of Symmetric Interval Matrices

Milan Hladík<sup>1</sup>   David Daney<sup>2</sup>   Elias P. Tsigaridas<sup>2</sup>

<sup>1</sup> Department of Applied Mathematics  
Charles University, Prague

<sup>2</sup> INRIA  
Sophia Antipolis, France

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## Applications

- Mechanics and engineering:
  - robotics;
  - automobile suspension systems;
  - mass structures;
  - vibrating systems.
- principal component analysis;
- global optimization.

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## Definition

Let  $A \in \mathbb{R}^{n \times n}$  be a real symmetric matrix. It has  $n$  real eigenvalues

$$\lambda_1(A) \geq \lambda_2(A) \geq \cdots \geq \lambda_n(A).$$

## Notation

An interval matrix

$$\mathbf{A} := [\underline{A}, \bar{A}] = \{A \in \mathbb{R}^{n \times n} \mid \underline{A} \leq A \leq \bar{A}\}.$$

The midpoint and the radius of  $\mathbf{A}$

$$A_c := \frac{1}{2}(\underline{A} + \bar{A}), \quad A_\Delta := \frac{1}{2}(\bar{A} - \underline{A}).$$

A symmetric interval matrix

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## Aim

For each  $i$  determine bounds for the set of the  $i$ -th eigenvalues

$$\lambda_i(\mathbf{A}^S) := \{\lambda_i(A) \mid A \in \mathbf{A}^S\}.$$

## History

- Deif, 1991: exact bound under restrictive assumptions;
- Hertz, 1992: exponential formula for  $\bar{\lambda}_1(\mathbf{A}^S)$  and  $\underline{\lambda}_n(\mathbf{A}^S)$ ;
- Qiu et al., 1996: approximation;
- Rohn, 2005: simple formulae for outer estimation;
- Kolev, 2006: outer estimation for general case with non-linear dependencies;
- Leng & He, 2007: outer estimation;
- Yuan et al., 2008: inner estimation;
- Hladík & Daney & Tsigaridas, 2009: outer estimation.

## Theorem (Rohn, 2005)

*We have*

$$\lambda_i(\mathbf{A}^S) \subseteq [\lambda_i(A_c) - \rho(A_\Delta), \lambda_i(A_c) + \rho(A_\Delta)].$$

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- Easy and cheap to compute;
- good starting point;
- all intervals the same width.

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*We have*

$$\bar{\lambda}_1(\mathbf{A}^S) \leq \lambda_1(|\mathbf{A}|).$$

## Proposition

Let  $i \in \{1, \dots, n\}$ . Then there is some matrix  $A \in \mathbf{A}^S$  with diagonal entries  $A_{j,j} = \bar{A}_{j,j}$  such that  $\lambda_i(A) = \bar{\lambda}_i(\mathbf{A}^S)$ .

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## Consequence

For each  $i \in \{1, \dots, n\}$ ,

$$\bar{\lambda}_i(\mathbf{A}^S) = \bar{\lambda}_i(\mathbf{A}_r^S),$$

where

$$\mathbf{A}_r^S := \{A \in \mathbf{A}^S \mid A_{j,j} = \bar{A}_{j,j} \ \forall j = 1, \dots, n\}.$$

## Theorem (Interlacing property, Cauchy, 1829)

Let  $A \in \mathbb{R}^n$  be a symmetric matrix and let  $A_i$  be a matrix obtained from  $A$  by removing the  $i$ -th row and column. Then

$$\lambda_1(A) \geq \lambda_1(A_i) \geq \lambda_2(A) \geq \lambda_2(A_i) \geq \cdots \geq \lambda_{n-1}(A_i) \geq \lambda_n(A).$$

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## Generalization to symmetric interval matrices

$$\bar{\lambda}_1(\mathbf{A}^S) \geq \bar{\lambda}_1(\mathbf{A}_i^S) \geq \bar{\lambda}_2(\mathbf{A}^S) \geq \bar{\lambda}_2(\mathbf{A}_i^S) \geq \cdots \geq \bar{\lambda}_{n-1}(\mathbf{A}_i^S) \geq \bar{\lambda}_n(\mathbf{A}^S),$$

and

$$\underline{\lambda}_1(\mathbf{A}^S) \geq \underline{\lambda}_1(\mathbf{A}_i^S) \geq \underline{\lambda}_2(\mathbf{A}^S) \geq \underline{\lambda}_2(\mathbf{A}_i^S) \geq \cdots \geq \underline{\lambda}_{n-1}(\mathbf{A}_i^S) \geq \underline{\lambda}_n(\mathbf{A}^S).$$

## Algorithm (Interlacing approach, direct version for upper bounds)

- ①  $\mathbf{B}^S := \mathbf{A}^S$ ;
- ② for  $k = 1, \dots, n$  do
  - ① compute upper bound  $\lambda_1^u(\mathbf{B}^S)$ ;
  - ②  $\lambda_k^u(\mathbf{A}^S) := \lambda_1^u(\mathbf{B}^S)$ ;
  - ③ select the most promising index  $i \in \{1, \dots, n - k + 1\}$ ;
  - ④ remove the  $i$ -th row and the  $i$ -th column from  $\mathbf{B}^S$ ;
- ③ put  $I := \emptyset$ ; for  $k = 1, \dots, n$  do
  - ① select the most promising index  $i \in \{1, \dots, n\} \setminus I$ , and put  $I := I \cup \{i\}$ ;
  - ② create  $\mathbf{B}^S$  from  $\mathbf{A}^S$  by restriction on index set  $I$ ;
  - ③ compute  $\lambda_1^u(\mathbf{B}^S)$ ;
  - ④  $\lambda_{n-k+1}^u(\mathbf{A}^S) := \min \{ \lambda_{n-k+1}^u(\mathbf{A}^S), \lambda_1^u(\mathbf{B}^S) \}$ ;
- ④ return upper bounds  $\lambda_k^u(\mathbf{A}^S)$ ,  $k = 1, \dots, n$ .

## Selection of the most promising index $i$

Two basic possibilities:

- More computations, but sharper bounds

$$i := \arg \min_{j=1, \dots, n-k+1} \lambda_1^u(\mathbf{B}_j^S),$$

## Selection of the most promising index $i$

Two basic possibilities:

- More computations, but sharper bounds

$$i := \arg \min_{j=1, \dots, n-k+1} \lambda_1^u(\mathbf{B}_j^S),$$

- Less computations, but less sharper bounds

$$i := \arg \min_{j=1, \dots, n-k+1} \sum_{r, s \neq j} |\mathbf{B}_{r,s}|^2.$$

## Theorem (Weyl, 1912)

Let  $A, B \in \mathbb{R}^{n \times n}$  be symmetric matrices. Then

$$\lambda_{r+s-1}(A+B) \leq \lambda_r(A) + \lambda_s(B) \quad \forall r, s \in \{1, \dots, n\}, \quad r+s \leq n+1,$$

$$\lambda_{r+s-n}(A+B) \geq \lambda_r(A) + \lambda_s(B) \quad \forall r, s \in \{1, \dots, n\}, \quad r+s \geq n+1.$$

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## Generalization to symmetric interval matrices

Considering  $A := A_c$  and  $B \in [-A_\Delta, A_\Delta]^S$  we get

$$\bar{\lambda}_{r+s-1}(\mathbf{A}^S) \leq \lambda_r(A_c) + \bar{\lambda}_s([-A_\Delta, A_\Delta]^S) \quad \forall r, s: r+s \leq n+1,$$

$$\underline{\lambda}_{r+s-n}(\mathbf{A}^S) \geq \lambda_r(A_c) + \underline{\lambda}_s([-A_\Delta, A_\Delta]^S) \quad \forall r, s: r+s \geq n+1.$$

## Algorithm (Interlacing approach, indirect version)

- 1 Compute eigenvalues  $\lambda_1(A_c) \geq \dots \geq \lambda_n(A_c)$ ;
- 2 compute bounds  $\lambda_1^u([-A_\Delta, A_\Delta]^S), \dots, \lambda_n^u([-A_\Delta, A_\Delta]^S)$ ;
- 3 for  $k = 1, \dots, n$  do
  - 1  $\lambda_k^u(\mathbf{A}^S) := \min_{i=1, \dots, k} \{ \lambda_i(A_c) + \lambda_{k-i+1}^u([-A_\Delta, A_\Delta]^S) \}$ ;
- 4 return upper bounds  $\lambda_k^u(\mathbf{A}^S), k = 1, \dots, n$ .

## Theorem

Let  $\lambda^0 \notin \lambda_i(\mathbf{A}^S)$ , and define  $\mathbf{M}^S := \mathbf{A}^S - \lambda^0 I$ . Then  $(\lambda^0 + \lambda) \notin \lambda_i(\mathbf{A}^S)$  for all real  $\lambda$  satisfying

$$|\lambda| < \frac{1 - \frac{1}{2} \rho(|I - QM_c| + |I - QM_c|^T + |Q|M_\Delta + M_\Delta|Q|^T)}{\frac{1}{2} \rho(|Q| + |Q|^T)},$$

where  $Q \in \mathbb{R}^{n \times n}$ ,  $Q \neq 0$ , is an arbitrary matrix.

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## Remark

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## Remark

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## Proof.

Based on the Beack–Rump sufficient condition on regularity of an interval matrix  $\mathbf{B}$ :  $\rho(|I - QB_c| + |Q|B_\Delta) < 1$ . □

## Algorithm (Filtering $\lambda_i(\mathbf{A}^S)$ from above)

- ① Compute an initial approximation  $\lambda \supseteq \lambda_i(\mathbf{A}^S)$ ;
- ②  $t := 0$ ;
- ③  $\mu := \varepsilon \lambda_{\Delta} + 1$  ( $\varepsilon > 0$  is given);
- ④ while  $\mu > \varepsilon \lambda_{\Delta}$  and  $t < T$  do
  - ①  $t := t + 1$ ;
  - ②  $\mathbf{M}^S := \mathbf{A}^S - \bar{\lambda}I$ ;
  - ③ compute  $Q := M_c^{-1}$ ;
  - ④  $\mu := \frac{2 - \rho(|I - QM_c| + |I - QM_c|^T + |Q|M_{\Delta} + M_{\Delta}|Q|^T)}{\rho(|Q| + |Q|^T)}$ ;
  - ⑤ if  $\mu > 0$  then  $\bar{\lambda} := \bar{\lambda} - \mu$ ;
  - ⑥ if  $\bar{\lambda} < \underline{\lambda}$  then return  $\lambda := \emptyset$ ;
- ⑤ return  $\lambda$ .

## Example

$$\mathbf{A}^S = \begin{pmatrix} [0, 2] & [-7, 3] & [-2, 2] \\ [-7, 3] & [4, 8] & [-3, 5] \\ [-2, 2] & [-3, 5] & [1, 5] \end{pmatrix}^S.$$

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	$[\lambda_1^l(\mathbf{A}^S), \lambda_1^u(\mathbf{A}^S)]$	$[\lambda_2^l(\mathbf{A}^S), \lambda_2^u(\mathbf{A}^S)]$	$[\lambda_3^l(\mathbf{A}^S), \lambda_3^u(\mathbf{A}^S)]$
Rohn	$[-2.2298, 16.0881]$	$[-6.3445, 11.9734]$	$[-8.9026, 9.4154]$
Direct	$[4.0000, 15.3275]$	$[-2.5616, 6.0000]$	$[-8.9026, 2.0000]$
Indirect	$[-0.7436, 16.0881]$	$[-3.3052, 10.4907]$	$[-8.9026, 6.3760]$
Best initial	$[4.0000, 15.3275]$	$[-2.0000, 6.0000]$	$[-8.3759, 2.0000]$
Filtering	$[4.0000, 15.3275]$	$[-2.0000, 6.0000]$	$[-7.9186, 2.0000]$
Optimal	$[?, 15.3275]$	$[?, ?]$	$[-7.8184, ?]$
Inner	$[5.6056, 15.3275]$	$[0.8301, 6.0000]$	$[-7.8184, 1.0000]$

## Example (Qiu et al., 1996)

$$\mathbf{A}^S = \begin{pmatrix} [2975, 3025] & [-2015, -1985] & 0 & 0 \\ [-2015, -1985] & [4965, 5035] & [-3020, -2980] & 0 \\ 0 & [-3020, -2980] & [6955, 7045] & [-4025, -3975] \\ 0 & 0 & [-4025, -3975] & [8945, 9055] \end{pmatrix}^S$$

# Numerical experiments

## Example (Qiu et al., 1996)

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	$[\lambda_1^l(\mathbf{A}^S), \lambda_1^u(\mathbf{A}^S)]$	$[\lambda_2^l(\mathbf{A}^S), \lambda_2^u(\mathbf{A}^S)]$	$[\lambda_3^l(\mathbf{A}^S), \lambda_3^u(\mathbf{A}^S)]$	$[\lambda_4^l(\mathbf{A}^S), \lambda_4^u(\mathbf{A}^S)]$
R	[12560.630, 12720.433]	[6984.557, 7144.361]	[3309.947, 3469.750]	[825.260, 985.063]
D	[8945.000, 12720.227]	[4945.000, 9055.000]	[2924.505, 6281.722]	[825.260, 3025.000]
I	[12560.630, 12720.433]	[6984.557, 7144.361]	[3309.947, 3469.750]	[825.260, 985.063]
B	[12560.630, 12720.227]	[6990.762, 7138.180]	[3320.286, 3459.432]	[837.064, 973.199]
F	[12560.813, 12720.227]	[6999.786, 7129.272]	[3332.716, 3447.463]	[841.533, 968.585]
O	[12560.838, 12720.227]	[7002.283, 7126.828]	[3337.078, 3443.313]	[842.925, 967.108]

R ... Rohn, D ... direct, I ... indirect, B ... best initial, F ... filtering, O ... optimal

## Definition

Let  $\mathbf{A} \subset \mathbb{R}^{m \times n}$ , its singular value sets are

$$\sigma_i(\mathbf{A}) := \{\sigma_i(A) \mid A \in \mathbf{A}\}, \quad i = 1, \dots, q := \min\{m, n\}.$$

# Singular values

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## Jordan–Wielandt matrix

Singular values of  $A \in \mathbb{R}^{m \times n}$  are identical with the  $q$  largest eigenvalues of

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## Generalization to interval matrices

Singular value sets of  $\mathbf{A} \subset \mathbb{R}^{m \times n}$  are equal to the  $q$  largest eigenvalue sets of

$$\begin{pmatrix} 0 & \mathbf{A}^T \\ \mathbf{A} & 0 \end{pmatrix}^S.$$