

Preconditioning for nonsymmetric Toeplitz matrices with application to time-dependent PDEs

Andy Wathen
Oxford University, UK



joint work with
Jen Pestana (University of Strathclyde),
Elle McDonald (Oxford University)

$$\mathbf{Ax} = \mathbf{b}$$

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But

A, H, I, M, O, T, U, V, W, X, Y

must be symmetric matrices (Parlett convention)!

$$\mathbf{Bx} = \mathbf{b}$$

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This makes a **big** difference!

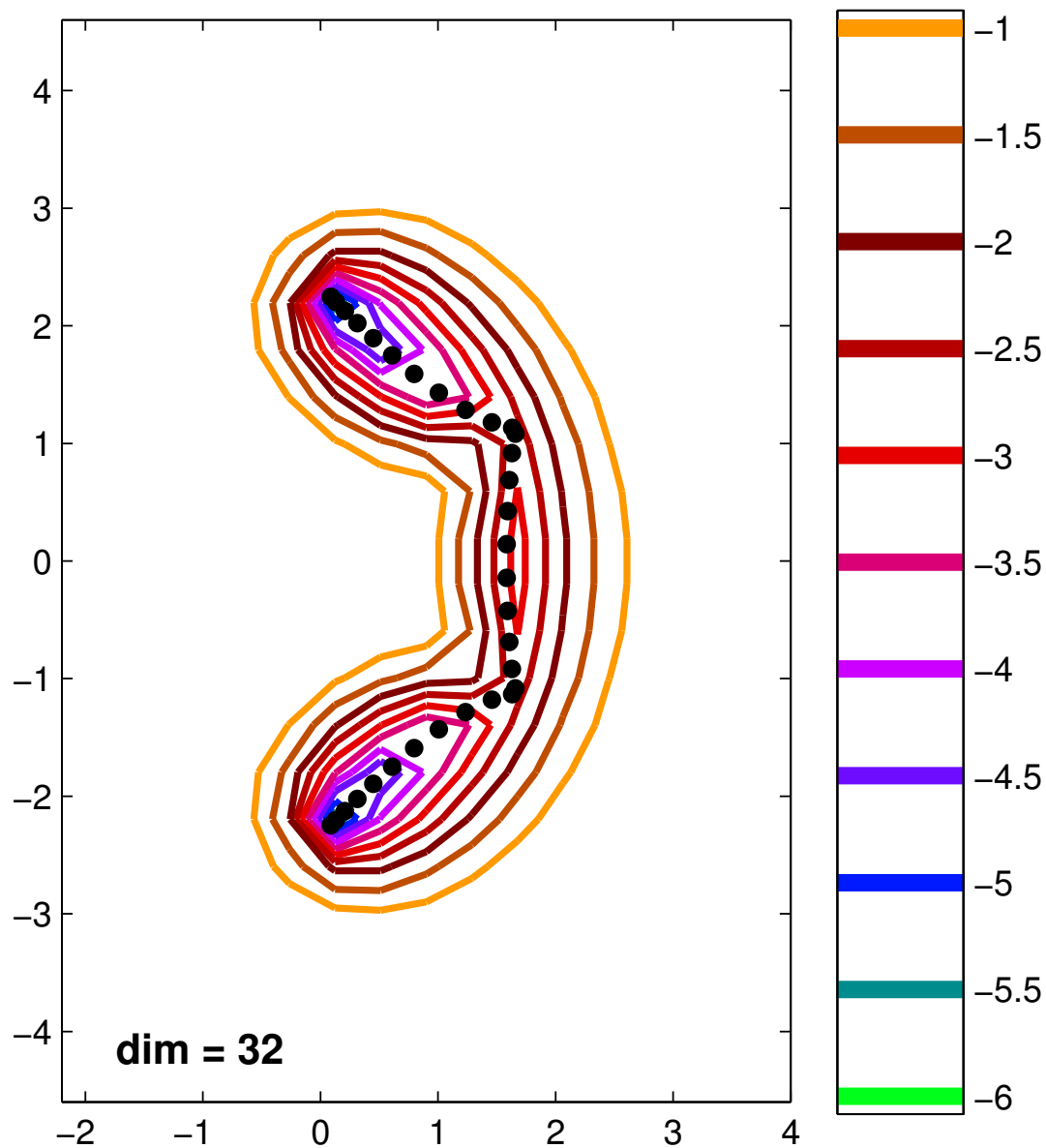
$$\mathbf{A} = \begin{bmatrix}
 2 & -1 & 0 & \dots & 0 & 2 \\
 -1 & 3 & \ddots & 0 & 1 & 0 \\
 0 & \ddots & \ddots & \cdot & \ddots & \vdots \\
 \vdots & \ddots & \cdot & \ddots & \ddots & 0 \\
 0 & 1 & 0 & \ddots & 3 & -1 \\
 2 & 0 & \dots & 0 & -1 & 2
 \end{bmatrix} \text{ is nice, symmetric}$$

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$$\mathbf{G} = \begin{bmatrix} 1 & -1 & 0 & \dots & \dots & \dots & 0 \\ 1 & 1 & -1 & \ddots & & & \vdots \\ 1 & 1 & 1 & -1 & \ddots & & \vdots \\ 1 & 1 & 1 & 1 & \ddots & \ddots & \vdots \\ 0 & \ddots & \ddots & \ddots & \ddots & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & -1 \\ 0 & \dots & 0 & 1 & 1 & 1 & 1 \end{bmatrix}$$

is one of Nick Trefethen's favourite *non-normal* matrices!

“Test EigTool by running the command
`eigtool(gallery('grcar', 32))`.”



Krylov subspace methods

For $\mathbf{B}\mathbf{x} = \mathbf{b}$: from \mathbf{x}_0 generate $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k, \dots\}$ using one matrix \times vector product at each iteration:

$$\mathbf{B}\mathbf{r}, \mathbf{B}(\mathbf{B}\mathbf{r}), \dots, \mathbf{B}^k\mathbf{r}, \dots$$

\Rightarrow Krylov subspace methods:

$$\mathbf{r}_k = \mathbf{p}_k(\mathbf{B})\mathbf{r}_0, \quad \mathbf{r}_k = \mathbf{b} - \mathbf{B}\mathbf{x}_k, \quad \mathbf{p}_k \in \Pi_k, \mathbf{p}_k(\mathbf{0}) = \mathbf{1}$$

so if $\mathbf{B} = \mathbf{X}\mathbf{\Lambda}\mathbf{X}^{-1}$ then $\mathbf{p}_k(\mathbf{B}) = \mathbf{X}\mathbf{p}_k(\mathbf{\Lambda})\mathbf{X}^{-1}$ so

$$\|\mathbf{r}_k\| \leq \|\mathbf{X}\| \|\mathbf{p}_k(\mathbf{\Lambda})\| \|\mathbf{X}^{-1}\| \|\mathbf{r}_0\|$$

and if $\mathbf{B} = \mathbf{B}^T$ so that $\mathbf{X}^{-1} = \mathbf{X}^T$ then this bound on convergence in $\|\cdot\|_2$ depends only eigenvalues

Krylov subspace methods

For self-adjoint problems/symmetric matrices, iterative methods of choice exist: conjugate gradients for SPD, MINRES otherwise

but many possible methods for non-self-adjoint problems/nonsymmetric matrices: GMRES , BICGSTAB , QMR , IDR , ...

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For almost all need *preconditioning*

Preconditioner \mathbf{P} such that

$$\text{“}\mathbf{P}^{-1}\mathbf{B}\mathbf{x} = \mathbf{P}^{-1}\mathbf{b}\text{”}$$

has much faster convergence with the appropriate iterative method than $\mathbf{B}\mathbf{x} = \mathbf{b}$.

Krylov subspace methods

Arises because of convergence guarantees:

- for symmetric matrices: descriptive convergence bounds based on eigenvalues \Rightarrow a priori estimates of iterations for acceptable convergence; good preconditioning ensures fast convergence.
- for nonsymmetric matrices: by contrast, to date there are no generally applicable *and descriptive* convergence bounds even for GMRES ; for any of the other nonsymmetric methods without a minimisation property, convergence theory is extremely limited \Rightarrow no good a priori way to identify what are the desired qualities of a preconditioner

A major theoretical difficulty, but heuristic ideas abound!

The situation is more severe than this:

Theorem (*Greenbaum, Ptak and Strakos, 1996*)

Given any set of eigenvalues and any monotonic convergence curve, then for any \mathbf{b} there exists a matrix \mathbf{B} having those eigenvalues and an initial guess \mathbf{x}_0 such that GMRES for $\mathbf{B}\mathbf{x} = \mathbf{b}$ with \mathbf{x}_0 as starting vector will give that convergence curve.

In fact more extreme negative results than this exist.

One way to address such questions:
look for (non-standard) inner products in which a problem
might be self-adjoint

One way to address such questions:
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might be self-adjoint

such inner products exist for a real nonsymmetric matrix \mathbf{B}
if and only if \mathbf{B} is diagonalizable and has real eigenvalues

but preconditioners still would have to have self-adjointness
in any relevant non-standard inner product!!

Recently (*Pestana & W, 2015*) we have made progress for real nonsymmetric Toeplitz (constant diagonal) matrices regardless of nonnormality with a very simple observation: If \mathbf{B} is a real Toeplitz matrix then

$$\underbrace{\begin{bmatrix} a_0 & a_{-1} & \cdot & \cdot & a_{1-n} \\ a_1 & a_0 & a_{-1} & \cdot & \cdot \\ \cdot & a_1 & a_0 & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & a_{-1} \\ a_{n-1} & \cdot & \cdot & a_1 & a_0 \end{bmatrix}}_{\mathbf{B}} \underbrace{\begin{bmatrix} 0 & 0 & \cdot & 0 & 1 \\ 0 & \cdot & 0 & 1 & 0 \\ \cdot & 0 & 1 & 0 & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 1 & 0 & \cdot & 0 & 0 \end{bmatrix}}_{\mathbf{Y}}$$

is the real *symmetric* (Hankel) matrix

$$\begin{bmatrix} a_{1-n} & \cdot & \cdot & a_{-1} & a_0 \\ \cdot & \cdot & a_{-1} & a_0 & a_1 \\ \cdot & \cdot & a_0 & a_1 & \cdot \\ a_{-1} & \cdot & \cdot & \cdot & \cdot \\ a_0 & a_1 & \cdot & \cdot & a_{n-1} \end{bmatrix}$$

Thus MINRES can be robustly applied to \mathbf{BY} — it is symmetric but generally indefinite — and its convergence will depend only on eigenvalues.

BUT preconditioning? – needs to be symmetric and positive definite for MINRES

Fortunately it is well known that many Toeplitz matrices are well approximated by related circulant matrices, \mathbf{C} (*Strang, 1986, Chan, 1988, Trefethen, 1990, Tyrtyshnikov, 1996/7*) which are diagonalised by an FFT in $O(n \log n)$ work: $\mathbf{C} = \mathbf{F}^* \mathbf{\Lambda} \mathbf{F}$.

For many Toeplitz matrices we have that the Strang or Optimal (Chan) circulant \mathbf{C} satisfy

$$\mathbf{C}^{-1} \mathbf{B} = \mathbf{I} + \mathbf{R} + \mathbf{E}$$

where \mathbf{R} is of small rank and \mathbf{E} is of small norm

\Rightarrow eigenvalues clustered around 1 except for a few outliers

For example, the Strang circulant for the standard Toeplitz matrix (as above) is

$$\underbrace{\begin{bmatrix}
 a_0 & a_{-1} & \dots & a_{-\lfloor \frac{n}{2} \rfloor} & a_{\lfloor \frac{n-1}{2} \rfloor} & \dots & a_2 & a_1 \\
 a_1 & a_0 & a_{-1} & \dots & a_{-\lfloor \frac{n}{2} \rfloor} & a_{\lfloor \frac{n-1}{2} \rfloor} & \dots & a_2 \\
 \dots & a_1 & a_0 & \ddots & \dots & a_{-\lfloor \frac{n}{2} \rfloor} & \ddots & \vdots \\
 a_{\lfloor \frac{n}{2} \rfloor} & \dots & \ddots & \ddots & \ddots & \dots & \ddots & a_{\lfloor \frac{n-1}{2} \rfloor} \\
 a_{-\lfloor \frac{n-1}{2} \rfloor} & \ddots & \dots & \ddots & \ddots & \ddots & \dots & a_{-\lfloor \frac{n}{2} \rfloor} \\
 \vdots & \ddots & a_{\lfloor \frac{n}{2} \rfloor} & \dots & \ddots & a_0 & a_{-1} & \dots \\
 a_{-2} & \dots & a_{-\lfloor \frac{n-1}{2} \rfloor} & a_{\lfloor \frac{n}{2} \rfloor} & \dots & a_1 & a_0 & a_1 \\
 a_{-1} & a_{-2} & \dots & a_{-\lfloor \frac{n-1}{2} \rfloor} & a_{\lfloor \frac{n}{2} \rfloor} & \dots & a_1 & a_0
 \end{bmatrix}}_C$$

To ensure a symmetric and positive definite preconditioner for \mathbf{BY} just use the circulant matrix

$$|\mathbf{C}| = \mathbf{F}^* |\mathbf{\Lambda}| \mathbf{F}$$

which is real symmetric and positive definite

Theorem (*Pestana & W, 2015*)

$$|\mathbf{C}|^{-1} \mathbf{BY} = \mathbf{J} + \mathbf{R} + \mathbf{E}$$

where \mathbf{J} is real symmetric and orthogonal with eigenvalues ± 1 , \mathbf{R} is of small rank and \mathbf{E} is of small norm

\Rightarrow guaranteed fast convergence because MINRES convergence only depends on eigenvalues which are clustered around ± 1 except for few outliers!

Example (Liesen & Strakoš)

$$\mathbf{B} = \begin{bmatrix} 1 & 0.01 & & & & \\ 1 & 1 & 0.01 & & & \\ & \ddots & \ddots & \ddots & & \\ & & & 1 & 1 & 0.01 \\ & & & & 1 & 1 \end{bmatrix} \in \mathbb{R}^{n \times n}$$

n	Condition number of \mathbf{B}	preconditioned MINRES iters
10	14	6
100	207	6
1000	2.6×10^6	6

n	eigenvalues of $ \mathbf{C} ^{-1}\mathbf{B}\mathbf{Y}$ (to 4 decimal places)
10	$\{-9.9107, 0.9893, -0.9640, -1.0002, -1 \times 2, 1 \times 4\}$
100	$\{-2.2803, -0.2536, 0.9919, -1.0007, -1 \times 47, 1 \times 49\}$
1000	$\{-2.1626, -1.0008, -1.8309e - 05, 0.9929, -1 \times 497, 1 \times 499\}$

Example

$$\mathbf{G} = \begin{bmatrix} 1 & -1 & 0 & \dots & \dots & \dots & 0 \\ 1 & 1 & -1 & \ddots & & & \vdots \\ 1 & 1 & 1 & -1 & \ddots & & \vdots \\ 1 & 1 & 1 & 1 & \ddots & \ddots & \vdots \\ 0 & \ddots & \ddots & \ddots & \ddots & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & -1 \\ 0 & \dots & 0 & 1 & 1 & 1 & 1 \end{bmatrix} \quad (\text{Grcar matrix})$$

n	# eigs $\neq \pm 1$ (to 12 d.p.)	preconditioned MINRES iters
10	8	10
100	8	10
1000	8	10
10000	8?	10

Example

\mathbf{B} = random (dense) Toeplitz matrices of Wiener class

n	eigenvalue inclusion	iterations
10	$[-1.018, -0.710] \cup [0.981, 1.804]$	10
100	$[-1.092, -0.856] \cup [0.912, 1.160]$	14
1000	$[-1.154, -0.708] \cup [0.864, 1.381]$	20
10000	$[-1.078, -0.980] \cup [0.922, 1.017]$	12

Block Toeplitz Matrices

$$\text{If } \mathbf{B} = \begin{bmatrix} \mathbf{B}_0 & \mathbf{B}_{-1} & \cdot & \cdot & \mathbf{B}_{1-n} \\ \mathbf{B}_1 & \mathbf{B}_0 & \mathbf{B}_{-1} & \cdot & \cdot \\ \cdot & \mathbf{B}_1 & \mathbf{B}_0 & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \mathbf{B}_{-1} \\ \mathbf{B}_{n-1} & \cdot & \cdot & \mathbf{B}_1 & \mathbf{B}_0 \end{bmatrix},$$

$\mathbf{B}_i \in \mathbb{R}^{k \times k}$ Toeplitz for all i (BTTB matrix)

$$\text{then } \mathbf{Y} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \cdot & \mathbf{0} & \mathbf{Y}_k \\ \mathbf{0} & \cdot & \mathbf{0} & \mathbf{Y}_k & \mathbf{0} \\ \cdot & \mathbf{0} & \mathbf{Y}_k & \mathbf{0} & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \mathbf{Y}_k & \mathbf{0} & \cdot & \mathbf{0} & \mathbf{0} \end{bmatrix}$$

is such that \mathbf{BY} and \mathbf{YB} are real symmetric

$$\text{If } \mathbf{B} = \begin{bmatrix} \mathbf{B}_0 & \mathbf{B}_{-1} & \cdot & \cdot & \mathbf{B}_{1-n} \\ \mathbf{B}_1 & \mathbf{B}_0 & \mathbf{B}_{-1} & \cdot & \cdot \\ \cdot & \mathbf{B}_1 & \mathbf{B}_0 & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \mathbf{B}_{-1} \\ \mathbf{B}_{n-1} & \cdot & \cdot & \mathbf{B}_1 & \mathbf{B}_0 \end{bmatrix},$$

$\mathbf{B}_i \in \mathbb{R}^{k \times k}$ real symmetric for all i (BT with symmetric blocks)

$$\text{then } \hat{\mathbf{Y}} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \cdot & \mathbf{0} & \mathbf{I}_k \\ \mathbf{0} & \cdot & \mathbf{0} & \mathbf{I}_k & \mathbf{0} \\ \cdot & \mathbf{0} & \mathbf{I}_k & \mathbf{0} & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \mathbf{I}_k & \mathbf{0} & \cdot & \mathbf{0} & \mathbf{0} \end{bmatrix}$$

is such that $\mathbf{B}\hat{\mathbf{Y}}$ and $\hat{\mathbf{Y}}\mathbf{B}$ are real symmetric

In either case we can apply a block circulant preconditioner for MINRES

Thus similar ideas apply for block Toeplitz matrices—higher dimensions—but then one has the same issues as in the symmetric case (rank of \mathbf{R} is greater)

One class of problems which are always non-symmetric:
time-dependent problems...

$\langle u_t, v \rangle = -\langle u, v_t \rangle$ so that

$$u_t = \mathcal{L}u + f$$

is non-self-adjoint even if the spatial operator \mathcal{L} is self-adjoint.

Simple example: backwards Euler for a linear(ized) problem

$$U^{n+1} + \Delta t \mathcal{L} U^{n+1} = U^n + \Delta t f^{n+1}, \quad n = 0, 1, \dots, \ell$$

All-at-once (monolithic) discretization:

$$\mathcal{A}x := \begin{bmatrix} A & 0 & \cdot & \cdot & 0 \\ B & A & 0 & \cdot & \cdot \\ \cdot & B & A & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & 0 \\ 0 & \cdot & \cdot & B & A \end{bmatrix} \begin{bmatrix} U^1 \\ U^2 \\ U^3 \\ \vdots \\ U^N \end{bmatrix} = \begin{bmatrix} U^0 + f^1 \\ f^2 \\ f^3 \\ \vdots \\ f^N \end{bmatrix}$$

$$A = I + \Delta t \mathcal{L}, \quad B = -I.$$

has block Toeplitz coefficient matrix and the ideas presented here apply

If we employ the preconditioner

$$\mathcal{P} := \begin{bmatrix} A & 0 & \cdot & \cdot & B \\ B & A & 0 & \cdot & \cdot \\ \cdot & B & A & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & 0 \\ 0 & \cdot & \cdot & B & A \end{bmatrix}$$

Theorem

$\mathcal{P}^{-1}\mathcal{A}$ is diagonalizable, has $(\ell - 1)n$ eigenvalues equal to 1 and the remaining n eigenvalues are clustered close to 1.

\Rightarrow GMRES terminates in at most $n + 1$ iterations
independent of ℓ

and \mathcal{P}^{-1} can be applied easily

Moreover: if \mathcal{A} has symmetric blocks (essentially \mathcal{L} must be self-adjoint), then one can symmetrize and use MINRES with preconditioner $|\mathcal{P}|$

Theorem

All but at most $2n$ eigenvalues are ± 1

\Rightarrow MINRES converges in a number of iterations independent of ℓ .

HAPPY BIRTHDAY IAIN

References and Acknowledgement

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