



Università di Bologna

## Recent advances in low-rank matrix equation solvers

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# Some matrix equations

- ▶ Sylvester matrix equation  $\mathbf{AX} + \mathbf{XB} + \mathbf{D} = \mathbf{0}$   
Eigenvalue pbs and tracking, Control, MOR, Assignment pbs, PDEs, Riccati eqn

- ▶ Lyapunov matrix equation  $\mathbf{AX} + \mathbf{XA}^\top + \mathbf{D} = \mathbf{0}$ ,  $\mathbf{D} = \mathbf{D}^\top$   
Stability analysis in Control and Dynamical systems, Signal processing, eigenvalue computations

- ▶ Multiterm matrix equation

$$\mathbf{A}_1\mathbf{XB}_1 + \mathbf{A}_2\mathbf{XB}_2 + \dots + \mathbf{A}_\ell\mathbf{XB}_\ell = \mathbf{C}$$

Control, (Stochastic) PDEs, ...

Survey article: V.S., SIAM Review 2016.

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# More matrix equations

- ▶ Systems of linear matrix equations:

$$\begin{aligned}A_2\mathbf{X} + \mathbf{X}A_1 + B^\top\mathbf{P} &= F_1 \\A_1\mathbf{Y} + \mathbf{Y}A_2 + \mathbf{P}B &= F_2 \\B\mathbf{X} + \mathbf{Y}B^\top &= F_3\end{aligned}$$

(V.S., 2019)

- ▶ Riccati equation: Find  $\mathbf{X} \in \mathbb{R}^{n \times n}$  such that

$$A\mathbf{X} + \mathbf{X}A^\top - \mathbf{X}BB^\top\mathbf{X} + C^\top C = 0$$

workhorse in Control Theory

- ▶ Tensor equation: Find  $\mathbf{X} \in \mathbb{R}^{n \times n \times n}$  such that

$$(H \otimes M \otimes A + M \otimes A \otimes H + A \otimes H \otimes M)\mathbf{x} + \mathbf{c} = 0 \quad \mathbf{x} = \text{vec}(\mathbf{X})$$

Discretization of (parameter-dependent) PDEs

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## ... Before proceeding:

which linear equation

which matrix structure

which size

- ▶ key property: **tensor product** space approximation to the continuous problem
  - Finite differences, e.g., Bickley & McNamee, 1960, Wachspress, 1963
  - Certain spectral methods, e.g., Canuto, Hussaini, Quarteroni and Zang, 1980s
  - Isogeometric Analysis (IGA)
  - Space-parameter, Space-time and Parallel-in-Time (PinT) discretizations
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- ▶ Symmetry, sparsity, etc., and also **low-rank properties of data and solution**
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# What do we expect from this ?

## Pros:

- ✓ Smaller dimensional matrices
- ✓ Preserve continuous problem's properties
- ✓ Exploit structure (e.g., symmetry)
- ✓ Reach more complex problems

## Cons:

- ✗ Extra effort to go beyond vectors
- ✗ Need to leave “comfort zone” of established NLA
- ✗ Different interpretation of your NLA data

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# The Poisson equation

$$-u_{xx} - u_{yy} = f, \quad \text{in } \Omega = (0, 1)^2 \quad + \text{Dirichlet zero b.c.}$$

FD Discretization:  $U_{i,j} \approx u(x_i, y_j)$ , with  $(x_i, y_j)$  interior nodes, so that

$$T_1 \mathbf{U} + \mathbf{U} T_1^\top = F, \quad F_{ij} = f(x_i, y_j), \quad T_1 = -\frac{1}{h^2} \text{tridiag}(1, -2, 1)$$

Lexicographic ordering:  $\mathbf{U} \rightarrow \mathbf{u} = [\mathbf{U}_{11}, \mathbf{U}_{n,1}, \mathbf{U}_{1,2}, \dots, \mathbf{U}_{n,2}, \dots]^\top$

$$A\mathbf{u} = f \quad A = I \otimes T_1 + T_1 \otimes I, \quad f = \text{vec}(F),$$

More generally, w/separable coefficients (and convection-diffusion)

$$\begin{aligned} \phi(x, y)u_{xx} + \psi(x, y)u_{yy} = f & \Rightarrow A_1 \mathbf{U} M_1 + M_2 \mathbf{U} A_2 = F \\ & (M_2^{-1} A_1) \mathbf{U} + \mathbf{U} (A_2 M_1^{-1}) = \hat{F} \end{aligned}$$

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# Numerical solution of the Sylvester equation

$$AU + UB = F$$

Various settings:

- ▶ Tiny  $A$  and  $B$ : Kron will do!
- ▶ Small  $A$  and  $B$ : Bartels-Stewart algorithm (Computes the Schur form of  $A$  and  $B$ )
- ▶ Large  $A$  and  $B$ : Iterative solution ( $F$  low rank)
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# All-at-once heat equation

$$u_t + \ell(u) = f \quad u(0) = 0 \quad (\text{for convenience})$$

Variational formulation

$$\text{find } u \in U : \quad b(u, v) = \langle f, v \rangle \quad \text{for all } v \in V$$

where  $U := H_{(0)}^1(\mathcal{I}; X') \cap L_2(\mathcal{I}, X)$ ,  $X := H_0^1(\Omega)$ ,  $V := L_2(\mathcal{I}; X)$

$$b(u, v) := \int_0^\tau \int_\Omega u_t(t, x) v(t, x) dx dt + \int_0^\tau a(u(t), v(t)) dt$$

$$\langle f, v \rangle := \int_0^\tau \int_\Omega f(t, x) v(t, x) dx dt.$$

**Discretization:** Petrov-Galerkin method with trial and test spaces  $U_\delta \subset U$ ,  $V_\delta \subset V$

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with  $U_\delta := S_{\Delta t} \otimes X_h$ ,  $V_\delta = Q_{\Delta t} \otimes X_h$  where

$S_{\Delta t}$  : piecewise linear FE on  $\mathcal{I}$

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$X_h$  : any conformal space, e.g., p.w. linear FE

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# The final linear system

$$B_\delta^\top u_\delta = f_\delta$$

where

$$\begin{aligned} [B_\delta]_{(k,i),(\ell,j)} &= (\dot{\sigma}^k, \tau^\ell)_{L_2(\mathcal{I})} (\phi_i, \phi_j)_{L_2(\Omega)} + (\sigma^k, \tau^\ell)_{L_2(\mathcal{I})} \mathbf{a}(\phi_i, \phi_j), \\ [f_\delta]_{(\ell,j)} &= (\mathbf{f}, \tau^\ell \otimes \phi_j)_{L_2(\mathcal{I}; H)} \end{aligned}$$

that is,  $B_\delta = D_{\Delta t} \otimes M_h + C_{\Delta t} \otimes K_h$

**Remark:** We approximate  $f_\delta$  to achieve full tensor-product structure

Resulting generalized Sylvester equation:

$$M_h \mathbf{U}_\delta D_{\Delta t} + K_h \mathbf{U}_\delta C_{\Delta t} = F_\delta, \quad \text{with } F_\delta = [g_1, \dots, g_P][h_1, \dots, h_P]^\top$$

$$F_\delta \text{ matrix of low rank} \quad \Rightarrow \quad \mathbf{U}_\delta \text{ approx by low rank matrix } \tilde{\mathbf{U}}_\delta$$

(Julian Henning, Davide Palitta, V. S., Karsten Urban, 2021)



## A simple example

$\Omega = (-1, 1)^3$ , with homogeneous Dirichlet boundary conditions

$\mathcal{I} = (0, 10)$  and initial conditions  $u(0, x, y, z) \equiv 0$

$f(t, x, y, z) := 10 \sin(t)t \cos(\frac{\pi}{2}x) \cos(\frac{\pi}{2}y) \cos(\frac{\pi}{2}z)$  ( $F_\delta$  is thus low rank)

$N_h$	$N_t$	RKSM				CN Time(s)	
		Its	$\mu_{\text{mem}}$	$\text{rank}(\tilde{U}_\delta)$	Time(s)	Direct	Iterative
41 300	300	13	14	9	25.96	123.43	59.10
	500	13	14	9	30.46	143.71	78.01
	700	13	14	9	28.17	153.38	93.03
347 361	300	14	15	9	820.17	14705.10	792.42
	500	14	15	9	828.34	15215.47	1041.47
	700	14	15	7	826.93	15917.52	1212.57

- ♣ Memory allocations in CN are for full problem
- ♣ Sylvester-oriented method: overall Space and Time independence

# The multiterm matrix equation problem

$$A_1 \mathbf{X} B_1 + A_2 \mathbf{X} B_2 + \dots + A_\ell \mathbf{X} B_\ell = C$$

$A_i \in \mathbb{R}^{n \times n}$ ,  $B_i \in \mathbb{R}^{m \times m}$ ,  $\mathbf{X}$  unknown matrix

- ▶ Kronecker form and back on track
- ▶ Fixed point iterations (an “evergreen” ...)
- ▶ Projection-type methods  $\Rightarrow$  low rank approximation
- ▶ Ad-hoc problem-dependent procedures
- ▶ etc.

A sample of these methodologies on different problems:

- ♣ Stochastic PDEs
- ♣ PDEs on polygonal domains, IGA, spectral methods, etc
- ♣ Space-time PDEs
- ♣ All-at-once PDE-constrained optimization problem
- ♣ Bilinear control problems
- ♣ ....

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# “Ultraweak” variational formulations of the wave equation

$$\ddot{u}(t) + A u(t) = f(t) \text{ in } V', \quad t \in I \text{ a.e.}, \quad u(0) = u_0 \in H, \quad \dot{u}(0) = u_1 \in V'.$$

initial state in, say,  $L_2(\Omega)$ , initial velocity in, say,  $H^{-1}(\Omega)$  (very low regularity)  
 $\Rightarrow$  weakly smooth solution

$$b(u_\delta, v_\delta) = g(v_\delta) \quad \forall v_\delta \in \mathbb{V}_\delta$$

with

$$b(u_\delta, v_\delta) := (u_\delta, \ddot{v}_\delta + A v_\delta)_{\mathcal{H}}, \quad g(v_\delta) := (f_\delta, v_\delta)_{\mathcal{H}} + \langle u_1, v_\delta(0) \rangle - (u_0, \dot{v}_\delta(0))_H,$$

\* Test space  $\mathbb{V}_\delta$ : proper piecewise quadratic splines in time and conformal (e.g. piecewise quadratic) finite elements in space,

\* Trial space  $\mathbb{U}_\delta$ : adjoint operator  $B^* = \partial_{tt} + A$  applied to test basis functions

(Julian Henning, Davide Palitta, V. S., Karsten Urban, 2022)

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# The resulting linear system

In the optimal inf-sup case,  $\mathbb{B}_\delta = \mathbf{Q}_{\Delta t} \otimes \mathbf{M}_h + \mathbf{N}_{\Delta t} \otimes \mathbf{N}_h^\top + \mathbf{N}_{\Delta t}^\top \otimes \mathbf{N}_h + \mathbf{M}_{\Delta t} \otimes \mathbf{Q}_h$ ,

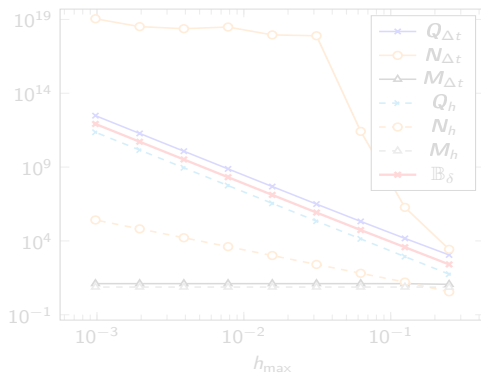
$$\mathbb{B}_\delta \mathbf{u}_\delta = \mathbf{g}_\delta \quad \mathbb{B}_\delta \text{ spd for } A = -\Delta$$

where

$$[\mathbf{Q}_{\Delta t}]_{\ell,k} := (\ddot{\varrho}^\ell, \ddot{\varrho}^k)_{L_2(I)}, \quad [\mathbf{M}_{\Delta t}]_{\ell,k} := (\varrho^\ell, \varrho^k)_{L_2(I)}, \quad [\mathbf{N}_{\Delta t}]_{\ell,k} := (\ddot{\varrho}^\ell, \varrho^k)_{L_2(I)},$$

$$[\mathbf{Q}_h]_{j,i} := (A\phi_j, A\phi_i)_{L_2(\Omega)}, \quad [\mathbf{M}_h]_{j,i} := (\phi_j, \phi_i)_{L_2(\Omega)}, \quad [\mathbf{N}_h]_{j,i} := (A\phi_j, \phi_i)_{L_2(\Omega)}.$$

$$[\mathbf{g}_\delta]_\nu = (f, \varphi_\nu)_\mathcal{H} + \langle \mathbf{u}_1, \varphi_\nu(0) \rangle_{V' \times V} - (\mathbf{u}_0, \dot{\varphi}_\nu(0))_H \quad \text{plus quad formulas}$$



# The resulting linear system

In the optimal inf-sup case,  $\mathbb{B}_\delta = \mathbf{Q}_{\Delta t} \otimes \mathbf{M}_h + \mathbf{N}_{\Delta t} \otimes \mathbf{N}_h^\top + \mathbf{N}_{\Delta t}^\top \otimes \mathbf{N}_h + \mathbf{M}_{\Delta t} \otimes \mathbf{Q}_h$ ,

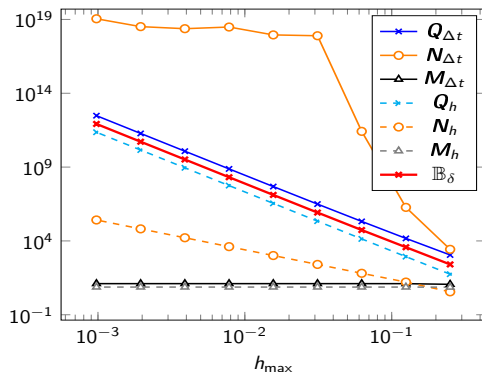
$$\mathbb{B}_\delta \mathbf{u}_\delta = \mathbf{g}_\delta \quad \mathbb{B}_\delta \text{ spd for } A = -\Delta$$

where

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# The resulting linear system

For  $\mathbb{B}_\delta = \mathbf{Q}_{\Delta t} \otimes \mathbf{M}_h + (\mathbf{N}_{\Delta t} + \mathbf{N}_{\Delta t}^\top) \otimes \mathbf{N}_h^\top + \mathbf{M}_{\Delta t} \otimes \mathbf{Q}_h$ ,

$$\mathbb{B}_\delta \mathbf{u}_\delta = \mathbf{g}_\delta \quad (*)$$

► Structure-aware Preconditioned “matrix-oriented” Conjugate gradients

- Robust preconditioning  $\mathbb{K}_\delta^\top \mathbb{M}_\delta^{-1} \mathbb{K}_\delta$  ( $\mathbb{M}_\delta := \mathbf{M}_{\Delta t} \otimes \mathbf{M}_h$  and  $\mathbb{K}_\delta := \mathbf{N}_{\Delta t} \otimes \mathbf{M}_h + \mathbf{M}_{\Delta t} \otimes \mathbf{N}_h$ )
- (cheaper) Sylvester preconditioning  $\mathbb{P} = \mathbf{Q}_{\Delta t} \otimes \mathbf{M}_h + \mathbf{M}_{\Delta t} \otimes \mathbf{Q}_h$

► Galerkin method

Transform (\*) into linear multiterm matrix equation:

$$\mathbf{M}_h \mathbf{U} \mathbf{Q}_{\Delta t}^\top + \mathbf{N}_h^\top \mathbf{U} (\mathbf{N}_{\Delta t}^\top + \mathbf{N}_{\Delta t}) + \mathbf{Q}_h \mathbf{U} \mathbf{M}_{\Delta t} = \mathbf{G}, \quad \mathbf{G} = \mathbf{G}_1 \mathbf{G}_2^\top$$

Approximate  $\mathbf{U}$  as  $\mathbf{U}_k = \mathbf{V}_k \mathbf{Y}_k \mathbf{W}_k^\top$  of low rank:

- Properly chose  $\mathbf{V}_k, \mathbf{W}_k$
- Impose Galerkin orthogonality of residual wrto  $\mathbf{W}_k \otimes \mathbf{V}_k$

This gives

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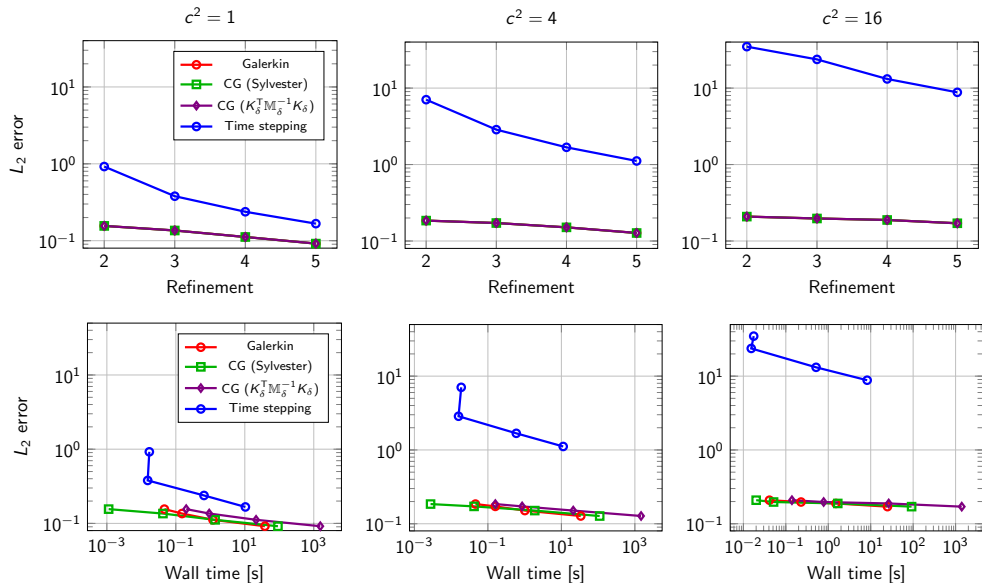
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# A numerical example. Discontinuous solution.

$A = -c^2 \Delta$  ( $c$  wave speed),  $H = L_2(\Omega)$ ,  $\Omega = (0, 1)^3$ ,  $V = H_0^1(\Omega)$

$u_0 = \mathbf{1}_{r < \sqrt{2}/5}$



# PDE-Constrained optimization problems

Functional to be minimized:

$$J(y, u) = \frac{1}{2} \int_0^T \int_{\Omega_1} (y - \hat{y})^2 dx dt + \frac{\beta}{2} \int_0^T \int_{\Omega_u} u^2 dx dt$$

★  $y$ : is the state,  $\hat{y}$  is the desired state given on a subset  $\Omega_1$  of  $\Omega$ ,

★  $u$  is the control on a subset  $\Omega_u$  of  $\Omega$ ,

(regularized by the control cost parameter  $\beta$ )

PDE constraining the functional  $J(y, u)$  (Dirichlet b.c.): for instance,

$$\begin{aligned} \dot{y} - \Delta y &= u & \text{in } \Omega_u, \\ \dot{y} - \Delta y &= 0 & \text{in } \Omega \setminus \Omega_u, \\ y &= 0 & \text{on } \partial\Omega. \end{aligned}$$

♣ All-at-once strategy (space, time, multipliers)

♣ Resulting matrix equation efficiently solved by using a tailored low-rank Galerkin method

(Alexandra Bünger, V.S., and Martin Stoll, 2021)

## Further considerations

- ▶ More structure yields improved algorithmic design. For instance,

$$AX + XB + M_1XM_2 = C$$

with  $M_1, M_2$  low rank

- ▶ *Truncated* versions of matrix-oriented Krylov methods have better chances
- ▶ 3D case leads to linear **tensor** equations: a new research area
- ▶ Matrix-oriented discretization methods for reaction-diffusion PDEs

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