

### Structured Preconditioners for Saddle Point Problems

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Motivational Application

Constrained minimization problem

minimize 
$$J(u) = \frac{1}{2} \langle Au, u \rangle - \langle f, u \rangle$$

subject to Bu = g  $A \quad n \times n$  symmetric,  $B \ m \times n, \ m \leq n$  $\downarrow$ 

Lagrange multipliers approach

Karush-Kuhn-Tucker (KKT) system



- Computational Fluid Dynamics
- Elasticity problems
- Mixed (FE) formulations of II and IV order elliptic PDEs
- Linearly Constrained Programs
- Linear Regression in Statistics
- Weighted Least Squares (Image restoration)



$$\begin{bmatrix} A & B^T \\ B & 0 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} f \\ g \end{bmatrix}$$

• A sym. pos.semidef., B full rank

$$\begin{bmatrix} A & B^T \\ B & -C \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} f \\ g \end{bmatrix}$$

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A sym,

$$\mathcal{M}x = b$$
  $\mathcal{M}$  sym. indef.

With n positive and m negative real eigenvalues

### Typical Sparsity pattern (3D problem)



• 
$$\mathcal{M} = \begin{bmatrix} A & B^T \\ B & 0 \end{bmatrix}$$
  $0 < \lambda_n \leq \cdots \leq \lambda_1$  eigs of  $A$   
 $0 < \sigma_m \leq \cdots \leq \sigma_1$  sing. vals of  $B$ 

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• (Rusten & Winther 1992)  $\Lambda(\mathcal{M})$  subset of

$$\left[\frac{1}{2}(\lambda_n - \sqrt{\lambda_n^2 + 4\sigma_1^2}), \frac{1}{2}(\lambda_1 - \sqrt{\lambda_1^2 + 4\sigma_m^2})\right] \quad \cup \quad \left[\lambda_n, \frac{1}{2}(\lambda_1 + \sqrt{\lambda_1^2 + 4\sigma_m^2})\right]$$

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• (Silvester & Wathen 1994),  $0 \le \sigma_m \le \cdots \le \sigma_1$ 

$$\lambda_n - \lambda_{\max}(C) - \sqrt{(\lambda_n + \lambda_{\max}(C))^2 + 4\sigma_1^2}$$

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More results for special cases (e.g. Perugia & S. 2000)

General preconditioning strategy

• Find  $\mathcal{P}$  such that

$$\mathcal{M}\mathcal{P}^{-1}\hat{u} = b \qquad \hat{u} = \mathcal{P}u$$

is easier (faster) to solve than  $\mathcal{M}u = b$ 

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- A look at efficiency:
  - Dealing with  $\mathcal{P}$  should be cheap
  - Storage for  $\ensuremath{\mathcal{P}}$  should be low
  - Properties (algebraic/functional) exploited

Structure preserving preconditioning

Idealized case:

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$$\mathcal{P} = \begin{bmatrix} A & 0\\ 0 & B^T A^{-1} B \end{bmatrix} \Rightarrow \mathcal{MP}^{-1} \text{ eigs } 1, \frac{1}{2} \pm \frac{\sqrt{5}}{2}$$

### MINRES converges in at most 3 iterations

(Murphy, Golub & Wathen, 2002)

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#### MINRES converges in at most 3 iterations

(Murphy, Golub & Wathen, 2002)

★ A nonsing.,  $C \neq 0$ :

$$\mathcal{P} = \begin{bmatrix} A & B \\ 0 & B^T A^{-1} B + C \end{bmatrix} \Rightarrow \mathcal{M} \mathcal{P}^{-1} = \begin{bmatrix} I & 0 \\ B^T A^{-1} & I \end{bmatrix}$$

GMRES converges in at most 2 iterations

# **Block diagonal Preconditioner**

$$\mathcal{P} = \left[ \begin{array}{cc} \widetilde{A} & 0 \\ 0 & \widetilde{C} \end{array} \right]$$

sym. pos. def.

Rusten Winther (1992), Silvester Wathen (1993-1994), Klawonn (1998) Fischer Ramage Silvester Wathen (1998...), . . .

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 $\lambda \neq 0$  eigs of  $\mathcal{P}^{-\frac{1}{2}}\mathcal{M}\mathcal{P}^{-\frac{1}{2}}$ ,

$$\lambda \in [-a, -b] \cup [c, d]$$



$$\mathcal{Q} = \begin{bmatrix} \widetilde{A} & B \\ B^T & -C \end{bmatrix}$$

Axelsson (1979), Ewing Lazarov Lu Vassilevski (1990), Braess Sarazin (1997) Golub Wathen (1998) Vassilevski Lazarov (1996), Lukšan Vlček (1998-1999), Perugia S. Arioli (1999), Keller Gould Wathen (2000) Perugia S. (2000), Gould Hribar Nocedal (2001), Rozloznik S. (2002), Durazzi Ruggiero (2003), Axelsson Neytcheva (2003), ...

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$$\mathcal{Q}^{-1} = \begin{bmatrix} I & -B^T \\ 0 & I \end{bmatrix} \begin{bmatrix} I & 0 \\ 0 & -(\mathbf{B}\mathbf{B^T} + \mathbf{C})^{-1} \end{bmatrix} \begin{bmatrix} I & 0 \\ -B & I \end{bmatrix}$$

Polyak 1970, ..., Fischer & Ramage & Silvester & Wathen 1997, Bai & Golub & Ng 2003, Sidi 2003, Benzi & Golub 2004, S. & Benzi 2004, ...

$$\Lambda(\mathcal{M}_{-})$$
 in  $\mathbb{C}^{+}$ 

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• More refined spectral information possible

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$$\Lambda(\mathcal{M}_{-})$$
 in  $\mathbb{C}^{+}$ 

- More refined spectral information possible
- New classes of preconditioners
- General framework for spectral analysis of some inexact preconditioners



- $A \quad n \times n$  sym. semidef. matrix,  $B \quad m \times n$ ,  $m \leq n$ 
  - $\mathcal{M}_{-}$  has at least n m real eigenvalues



Spectral properties of  $\mathcal{M}_{-}$ 

• Let  $C = \beta I$ . If  $\lambda_{\min}(A + \beta I) \ge 4 \lambda_{\max}(B^T A^{-1}B + \beta I)$ , then all eigenvalues of  $\mathcal{M}_-$  are real.

A  $n \times n$  sym. semidef. matrix,  $B \quad m \times n$ ,  $m \leq n$ 

•  $\mathcal{M}_{-}$  has at least n-m real eigenvalues

- $A \quad n \times n$  sym. semidef. matrix,  $B \quad m \times n$ ,  $m \leq n$ 
  - $\mathcal{M}_{-}$  has at least n-r
  - Let  $C = \beta I$ . If  $\lambda_{\min}(A + \beta I) \ge 4 \lambda_{\max}(B^T A^{-1} B + \beta I)$ , then all eigenvalues of  $\mathcal{M}_{-}$  are real.
  - Let C be sym. Let  $\lambda \in \Lambda(\mathcal{M}_{-})$ . If  $\Im(\lambda) \neq 0$ , then

 $\lambda_{\max}(C)$  $|\mathfrak{I}(\Lambda)| \geq o_{\max}(D).$ 

If  $\Im(\lambda) = 0$  then

 $2\min\{\lambda_{\min}(A), \lambda_{\min}(C)\} \le \lambda \le (\lambda_{\max}(A) + \lambda_{\max}(C)).$ 

cf. Sidi 2003 for C=0

# Spectral properties of $\mathcal{M}_{-}$

$$n$$
 real eigenvalues

$$\frac{1}{2}(\lambda_{\min}(A) + \lambda_{\min}(C)) \le \Re(\lambda) \le \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\min}(C)) \le \Re(\lambda) \le \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(C)) \le \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) \le \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) \le \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) \le \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) \le \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) \le \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) \le \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}(A) \le \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\max}(A) + \lambda_{\max}($$

#### Hermitian Skew-Hermitian

Preconditioning

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Use the preconditioner

$$\mathcal{R} = \frac{1}{2\alpha} (\mathcal{H} + \alpha I) (\mathcal{S} + \alpha I) \qquad \alpha \in \mathbb{R}, \ \alpha > 0$$

Bai & Golub & Ng 2003, Benzi & Gander & Golub 2003, Benzi & Golub 2004, S. & Benzi 2004

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Sharp spectral bounds for C = 0 (S. & Benzi 2004)



$$\mathcal{P}^{-1} \begin{bmatrix} A & B^T \\ B & -C \end{bmatrix} \longrightarrow \begin{bmatrix} \widetilde{A} & \widetilde{B}^T \\ -\widetilde{B} & \widetilde{C} \end{bmatrix} \qquad \widetilde{A} \ge 0, \ \widetilde{C} \ge 0$$

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Inexact Constraint Preconditioner

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- Inexact Constraint Preconditioner
- Hermitian Skew-Hermitian Preconditioner ( $C = \beta I$ )

$$\mathcal{P}^{-1} \begin{bmatrix} A & B^T \\ B & -C \end{bmatrix} \longrightarrow \begin{bmatrix} \widetilde{A} & \widetilde{B}^T \\ -\widetilde{B} & \widetilde{C} \end{bmatrix} \qquad \widetilde{A} \ge 0, \ \widetilde{C} \ge 0$$

- Inexact Constraint Preconditioner
- Hermitian Skew-Hermitian Preconditioner ( $C = \beta I$ )
- Indefinite Block diagonal Preconditioner

$$\left[\begin{array}{cc} \widehat{A} & 0\\ 0 & -\widehat{C} \end{array}\right]$$

cf. Fischer et al. 1997



• Performance of preconditioners is problem dependent



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- Ad-Hoc preconditioners usually designed (information from application problem)



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- Visit http://www.dm.unibo.it/~simoncin