Schwarz methods, Schur complements, preconditioning and numerical linear algebra

and numerical linear algebra

Michal Outrata supervised by Martin J. Gander

#### **Outline**

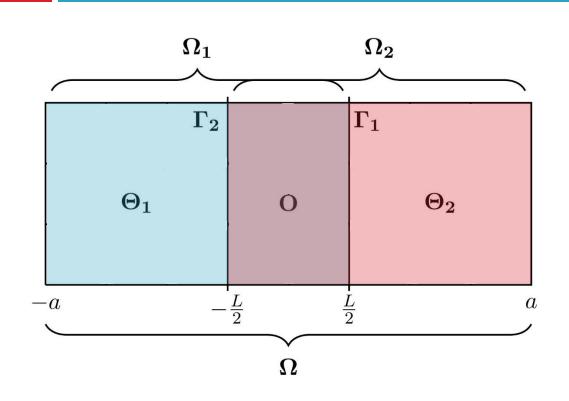
Model problem and set-up

Schwarz methods and DS

Schwarz methods and ABC

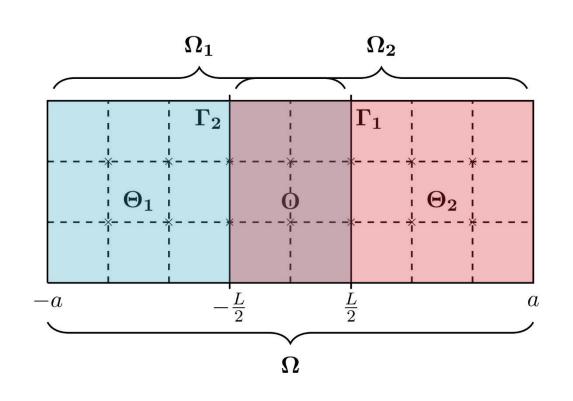
IRK preconditioners

## Model problem



$$\Delta u = f \quad \text{in } \Omega,$$
 $u = g \quad \text{on } \partial \Omega$ 

## Model problem

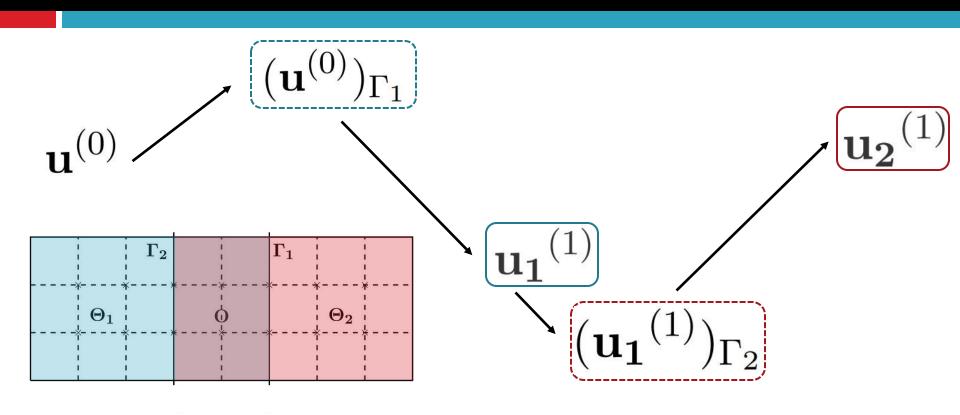


 $L\mathbf{u} = \mathbf{f}$ 

blackboard (diag D)

## **Schwarz methods**

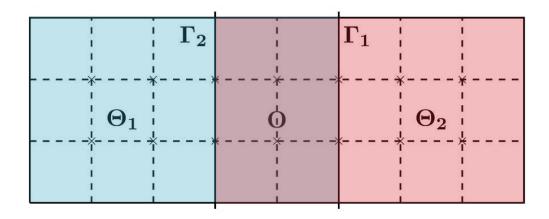
## **Schwarz methods**



## Schwarz methods

$$\begin{bmatrix} 1 & I & & \\ I & \ddots & \ddots & \\ & \ddots & \ddots & I \\ & & I & D \end{bmatrix} \mathbf{u}_1^{(n)} = \mathbf{b}_1^{(n)}$$

$$\frac{1}{h^2} \begin{bmatrix} D & I & & \\ I & \ddots & \ddots & \\ & \ddots & \ddots & I \\ & & I & D \end{bmatrix} \mathbf{u}_2^{(n)} = \mathbf{b}_2^{(n)}$$



$$\frac{1}{h^2} \begin{bmatrix} D & I & & & \\ I & \ddots & \ddots & & \\ & \ddots & D & I \\ & & I & D - S_1^{\star} \end{bmatrix} \mathbf{u}_1^{(n)} = \mathbf{b}_1^{(n)}$$

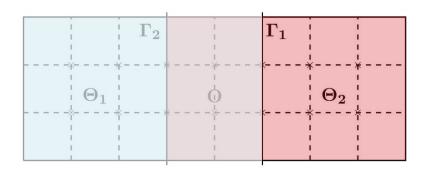
$$\frac{1}{h^2} \begin{bmatrix} D - S_2^{\star} & I & & \\ I & \ddots & \ddots & \\ & & \ddots & D & I \\ & & I & D \end{bmatrix} \mathbf{u}_2^{(n)} = \mathbf{b}_2^{(n)}$$

$$\begin{bmatrix}
\frac{1}{h^2} \begin{bmatrix} D & I & & & \\ I & \ddots & \ddots & & \\ & \ddots & D & I \\ & & I & D - S_1^{\star} \end{bmatrix} \mathbf{u}_1^{(n)} = \mathbf{b}_1^{(n)} \\
\begin{bmatrix}
\frac{1}{h^2} \begin{bmatrix} D - S_2^{\star} & I & & & \\ I & \ddots & \ddots & & \\ & & \ddots & D & I \\ & & & I & D \end{bmatrix} \mathbf{u}_2^{(n)} = \mathbf{b}_2^{(n)}$$

$$\frac{1}{h^2} \begin{bmatrix} D - S_2^{\star} & I & & \\ I & \ddots & \ddots & \\ & & \ddots & D & I \\ & & I & D \end{bmatrix} \mathbf{u}_2^{(n)} = \mathbf{b}_2^{(n)}$$

$$S_1^{\star} := E_{\Gamma_1}^T L_{\Theta_2}^{-1} E_{\Gamma_1}$$

$$S^{\star} := E_{\Gamma_1}^T L_{\Theta_2}^{-1} E_{\Gamma_1}$$



$$\frac{1}{h^2} \begin{bmatrix} D & I & & & \\ I & \ddots & \ddots & & \\ & \ddots & D & I \\ & & I & D - S_1 \end{bmatrix} \mathbf{u}_1^{(n)} = \mathbf{b}_1^{(n)}$$

$$\frac{1}{h^2} \begin{bmatrix} D - S_2 & I & & \\ I & \ddots & \ddots & \\ & \ddots & D & I \\ & & I & D \end{bmatrix} \mathbf{u}_2^{(n)} = \mathbf{b}_2^{(n)}$$

$$S^{\star} \to S$$

$$\begin{bmatrix} \frac{1}{h^2} \begin{bmatrix} D & I & & & \\ I & \ddots & \ddots & & \\ & \ddots & D & I \\ & & I & D - S_1 \end{bmatrix} \mathbf{u}_1^{(n)} = \mathbf{b}_1^{(n)} \\ \end{bmatrix} \begin{bmatrix} \frac{1}{h^2} \begin{bmatrix} D - S_2 & I & & \\ I & \ddots & \ddots & \\ & & \ddots & D & I \\ & & & I & D \end{bmatrix} \mathbf{u}_2^{(n)} = \mathbf{b}_2^{(n)} \\ \end{bmatrix}$$

$$\frac{1}{h^2} \begin{bmatrix} D - S_2 & I & & \\ I & \ddots & \ddots & \\ & \ddots & D & I \\ & & I & D \end{bmatrix} \mathbf{u}_2^{(n)} = \mathbf{b}_2^{(n)}$$

$$S^* \to S \qquad ||S - S^*||$$

$$\begin{bmatrix}
\frac{1}{h^2} \begin{bmatrix} D & I & & & \\ I & \ddots & \ddots & & \\ & \ddots & D & I \\ & & I & D - S_1 \end{bmatrix} \mathbf{u}_1^{(n)} = \mathbf{b}_1^{(n)} \\
\begin{bmatrix}
\frac{1}{h^2} \begin{bmatrix} D - S_2 & I & & \\ I & \ddots & \ddots & \\ & & \ddots & D & I \\ & & & I & D \end{bmatrix} \mathbf{u}_2^{(n)} = \mathbf{b}_2^{(n)}$$

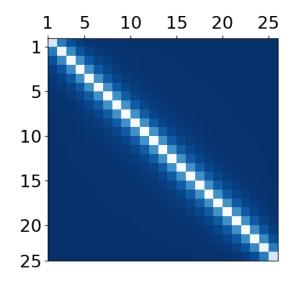
$$\frac{1}{h^2} \begin{bmatrix} D - S_2 & I & & \\ I & \ddots & \ddots & \\ & & \ddots & D & I \\ & & I & D \end{bmatrix} \mathbf{u}_2^{(n)} = \mathbf{b}_2^{(n)}$$

$$S^* \to S \qquad ||S - S^*|| \qquad \rho^{\operatorname{discr}}(S)$$

DS = data-sparse formats low-rank & HODLR

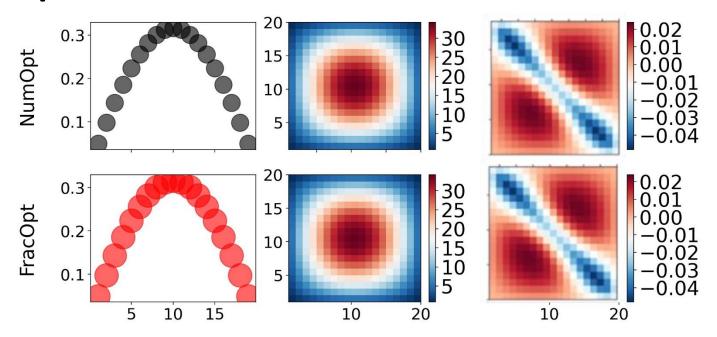
$$S_1^{\star} := E_{\Gamma_1}^T L_{\Theta_2}^{-1} E_{\Gamma_1}$$

$$S_1^{\star} := E_{\Gamma_1}^T L_{\Theta_2}^{-1} E_{\Gamma_1}$$



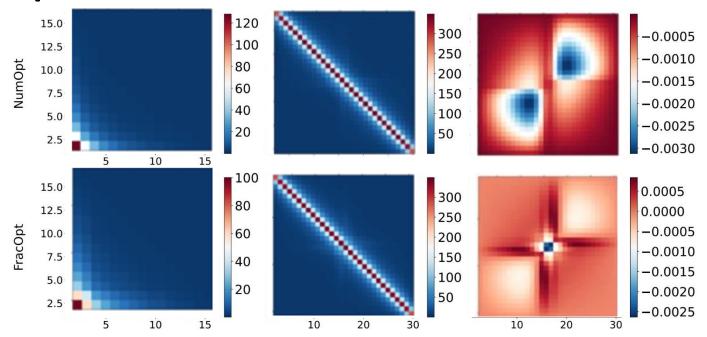
data-sparse formats: low-rank

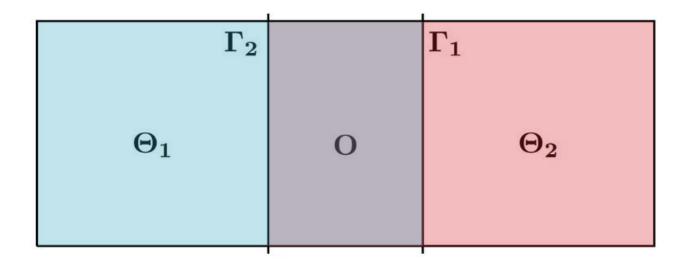
## data-sparse formats: low-rank

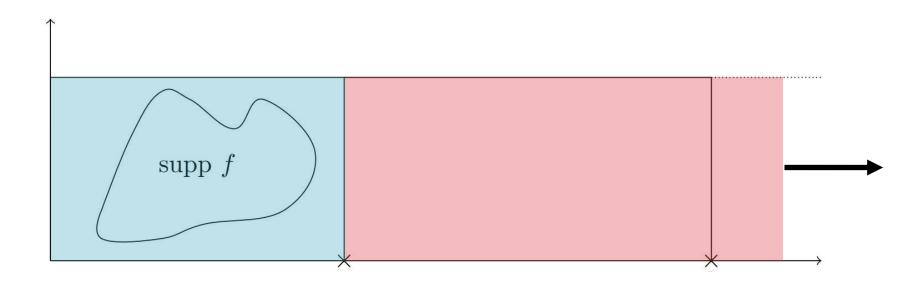


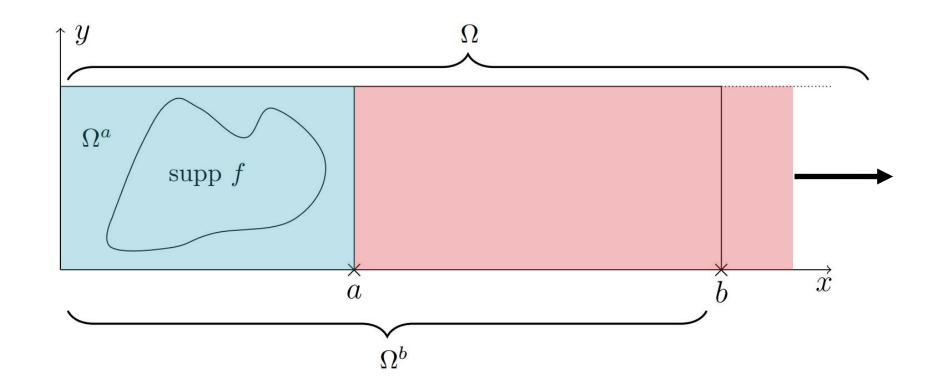
data-sparse formats: HODLR

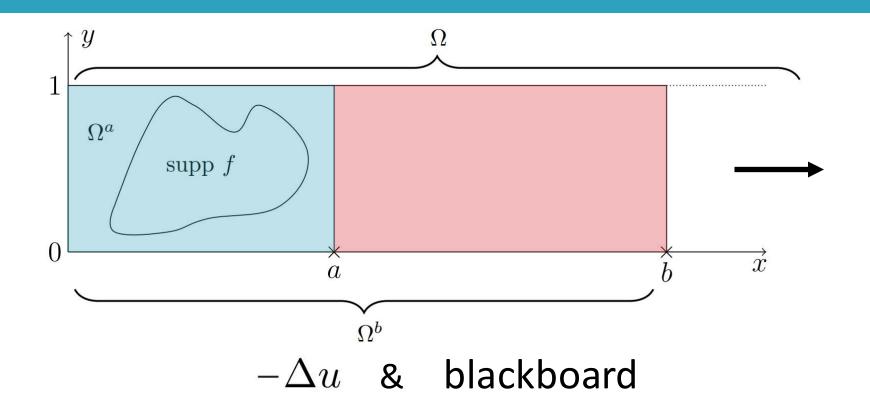
## data-sparse formats: HODLR











$$L^a \mathbf{u}^a = \mathbf{f}^a$$
  $L^b \mathbf{u}^b = \mathbf{f}^b$   $L \mathbf{u} = \mathbf{f}$ 

where  $D_i = D$  (blackboard)

$$L^a\mathbf{u}^a=\mathbf{f}^a$$
  $L^b\mathbf{u}^b=\mathbf{f}^b$   $L\mathbf{u}=\mathbf{f}$   $\begin{pmatrix} D_1 & -I & & & \\ -I & \ddots & \ddots & & & \\ & \ddots & D_{N^a-1} & -I & & \\ & & -I & D_{N^a} \end{pmatrix} \begin{pmatrix} D_1 & -I & & & \\ -I & \ddots & \ddots & & \\ & \ddots & D_{N^{b-1}} & -I & & \\ & & & -I & D_{N^b} \end{pmatrix} \begin{pmatrix} h^2L^b & & & \\ & -I & & & \\ & & -I & D_{N^{b+1}} & \ddots & \\ & & \ddots & & \ddots & \end{pmatrix}$ 

where  $D_i = D$  (blackboard)

$$L^a\mathbf{u}^a = \mathbf{f}^a \qquad L^b\mathbf{u}^b = \mathbf{f}^b \qquad L\mathbf{u} = \mathbf{f}$$
 $\begin{pmatrix} D_1 & -I & & & \\ -I & \ddots & \ddots & & \\ & \ddots & D_{N^a-1} & -I & \\ & & -I & D_{N^a} \end{pmatrix} \begin{pmatrix} D_1 & -I & & & \\ -I & \ddots & \ddots & & \\ & \ddots & D_{N^a-1} & -I & & \\ & & & -I & D_{N^b+1} & \ddots & \\ & & & \ddots & \ddots & \end{pmatrix}$ 

 $T_{N^a}^b$  (blackboard)

$$L^{a}\mathbf{u}^{a} = \mathbf{f}^{a}$$
  $L^{b}\mathbf{u}^{b} = \mathbf{f}^{b}$   $L\mathbf{u} = \mathbf{f}$ 

$$\begin{pmatrix} D_{1} & -I & & & \\ -I & \ddots & \ddots & & \\ & \ddots & D_{N^{a-1}} & -I \\ & & -I & D_{N^{a}} \end{pmatrix} \begin{pmatrix} D_{1} & -I & & & \\ -I & \ddots & \ddots & & \\ & \ddots & D_{N^{a-1}} & I \\ & & & -I & I \end{pmatrix} \begin{pmatrix} D_{1} & -I & & & \\ -I & \ddots & \ddots & & \\ & \ddots & D_{N^{a-1}} & I \\ & & & & -I & I \end{pmatrix}$$

 $T_{N^a}^b, T_{N^a}^\infty$  (blackboard)

$$L^{a}\mathbf{u}^{a} = \mathbf{f}^{a} \qquad L^{b}\mathbf{u}^{b} = \mathbf{f}^{b} \qquad L\mathbf{u} = \mathbf{f}$$

$$\begin{pmatrix} D_{1} & -I & & & \\ -I & \ddots & \ddots & & \\ & \ddots & D_{N^{a-1}} & -I \\ & & -I & D_{N^{a}} \end{pmatrix} \begin{pmatrix} D_{1} & -I & & & \\ -I & \ddots & \ddots & & \\ & \ddots & D_{N^{a-1}} & -I \\ & & & -I & T_{N^{a}}^{b} \end{pmatrix} \begin{pmatrix} D_{1} & -I & & & \\ -I & \ddots & \ddots & & \\ & \ddots & D_{N^{a-1}} & -I \\ & & & -I & T_{N^{a}}^{\infty} \end{pmatrix}$$

What is the effect of increasing b?

 $T_{N^a}^b$ :

$$\hat{T}_i^b = Q \frac{D}{h^2} Q^T - Q \frac{(T_{i+1}^b)^{-1}}{h^4} Q^T = \frac{\Lambda}{h^2} - \frac{(\hat{T}_{i+1}^b)^{-1}}{h^4}$$

 $T_{N^a}^b$ :

$$\hat{T}_{i}^{b} = Q \frac{D}{h^{2}} Q^{T} - Q \frac{(T_{i+1}^{b})^{-1}}{h^{4}} Q^{T} = \frac{\Lambda}{h^{2}} - \frac{(\hat{T}_{i+1}^{b})^{-1}}{h^{4}}$$

$$\hat{t}_{i}^{b}(\lambda) = \frac{1}{h^{2}} \left(\lambda - \frac{1}{h^{2} \hat{t}_{i+1}^{b}(\lambda)}\right)$$

 $T_{N^a}^b$  :

$$\begin{split} \hat{T}_i^b &= Q \frac{D}{h^2} Q^T - Q \frac{(T_{i+1}^b)^{-1}}{h^4} Q^T = \frac{\Lambda}{h^2} - \frac{(\hat{T}_{i+1}^b)^{-1}}{h^4} \\ \hat{t}_i^b(\lambda) &= \frac{1}{h^2} \left( \lambda - \frac{1}{h^2 \hat{t}_{i+1}^b(\lambda)} \right) \end{split}$$

$$\hat{t}_i^b(\lambda) = \frac{1}{h^2} \left( \lambda - \frac{1}{\lambda - \frac{1}{h^2 \hat{t}_{i+2}^b}} \right)$$

 $T_{N^a}^b$  :

$$T_{N^a}^b$$
 :

$$\hat{t}_{N^a}^b(\lambda) = \frac{1}{h^2} \left( \lambda - \frac{1}{\lambda - \frac{\ddots}{\lambda - \frac{1}{\lambda}}} \right)$$

 $N^b-N^a$ levels; blackboard



$$\hat{T}_{N^a}^{\infty}(\lambda) = \lim_{b \to +\infty} \hat{T}_{N^a}^b(\lambda)$$

 $T_{N^a}^\infty$  :

$$\hat{T}_{N^a}^{\infty}(\lambda) = \lim_{b \to +\infty} \hat{T}_{N^a}^b(\lambda) \qquad \hat{t}_{N^a}^{\infty}(\lambda) = \lim_{b \to +\infty} \hat{t}_{N^a}^b(\lambda)$$

$$T_{N^a}^\infty$$
 :

$$\hat{T}_{N^a}^{\infty}(\lambda) = \lim_{b \to +\infty} \hat{T}_{N^a}^b(\lambda) \qquad \hat{t}_{N^a}^{\infty}(\lambda) = \lim_{b \to +\infty} \hat{t}_{N^a}^b(\lambda)$$

$$T_{N^a}^{\infty}$$
: 
$$\hat{t}_i^b(\lambda) = \frac{1}{h^2} \left( \lambda - \frac{1}{h^2 \hat{t}_{i+1}^b(\lambda)} \right)$$

$$\hat{T}_{N^a}^{\infty}(\lambda) = \lim_{b \to +\infty} \hat{T}_{N^a}^b(\lambda) \qquad \hat{t}_{N^a}^{\infty}(\lambda) = \lim_{b \to +\infty} \hat{t}_{N^a}^b(\lambda)$$

$$\widehat{T_{N^a}^{\infty}}: \quad \widehat{t}_i^b(\lambda) = \frac{1}{h^2} \left(\lambda - \frac{1}{h^2 \widehat{t}_{i+1}^b(\lambda)}\right)$$

$$\widehat{t}_{N^a}^{\infty}(\lambda) = \frac{1}{h^2} \left(\lambda - \frac{1}{h^2 \widehat{t}_{N^a}^{\infty}(\lambda)}\right)$$

Schwarz methods & ABC 
$$\hat{T}_{N^a}^\infty(\lambda) = \lim_{b \to +\infty} \hat{T}_{N^a}^b(\lambda) \qquad \hat{t}_{N^a}^\infty(\lambda) = \lim_{b \to +\infty} \hat{t}_{N^a}^b(\lambda)$$

$$T_{N^a}(\lambda) = \lim_{b \to +\infty} T_{N^a}(\lambda) \qquad t_{N^a}(\lambda) = \lim_{b \to +\infty} t_{N^a}(\lambda)$$

$$\hat{t}_i^b(\lambda) = \frac{1}{h^2} \left(\lambda - \frac{1}{h^2 \hat{t}_{i+1}^b(\lambda)}\right)$$

$$\hat{t}_{N^a}^\infty(\lambda) = \frac{1}{h^2} \left(\lambda - \frac{1}{h^2 \hat{t}_{N^a}^\infty(\lambda)}\right)$$

$$\hat{t}_{i}^{b}(\lambda) = \frac{1}{h^{2}} \left( \lambda - \frac{1}{h^{2} \hat{t}_{i+1}^{b}(\lambda)} \right)$$

$$\hat{t}_{Na}^{\infty}(\lambda) = \frac{1}{h^{2}} \left( \lambda - \frac{1}{h^{2} \hat{t}_{Na}^{\infty}(\lambda)} \right)$$

$$\hat{t}_{Na}^{\infty}(\lambda) = \frac{1}{h^{2}} \left( \lambda - \frac{1}{\lambda - \frac{1}{h^{2} \hat{t}_{Na}^{\infty}(\lambda)}} \right)$$

$$\hat{t}_{N^a}^{\infty}: \qquad \hat{t}_{N^a}^{\infty}(\lambda) = \frac{1}{h^2} \left( \lambda - \frac{1}{\lambda - \frac{\cdot}{\lambda - \frac{1}{\lambda - \frac{1}{\lambda}}}} \right)$$

blackboard

$$\hat{t}_{N^a}^{\infty}(\lambda) = \frac{1}{h^2} \left( \lambda - \frac{1}{h^2 \hat{t}_{N^a}^{\infty}(\lambda)} \right)$$

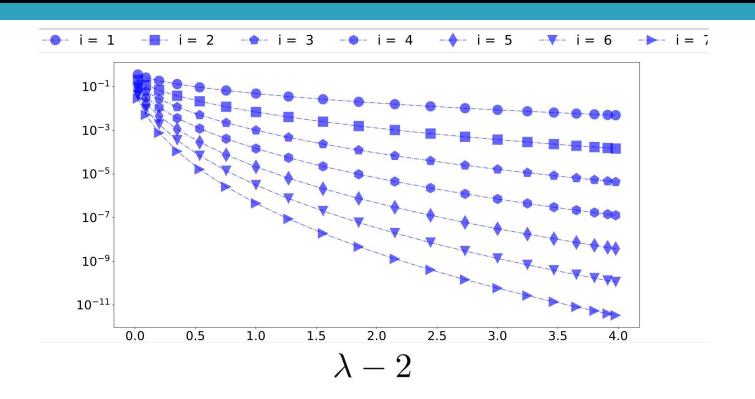
 $T_{N^a}^\infty$  :

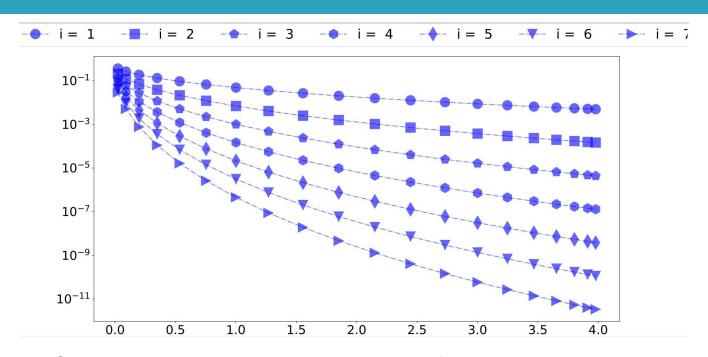
$$\hat{t}_{N^a}^{\infty}(\lambda) = \frac{1}{h^2} \left( \lambda - \frac{1}{h^2 \hat{t}_{N^a}^{\infty}(\lambda)} \right)$$

$$T_{N^a}^{\infty}$$
 :

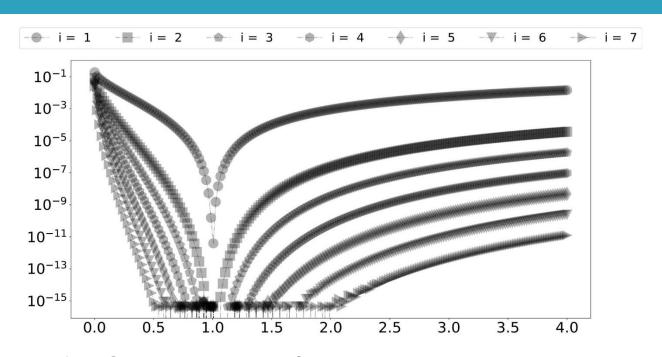
$$\hat{t}_{N^a}^{\infty}(\lambda) = \frac{\lambda + \sqrt{\lambda^2 - 4}}{2h^2}$$

blackboard





Padé approximation about endpoint



Shifted Padé approximation

$$\frac{\partial}{\partial t}u = \Delta u \quad \text{in } \Omega \times (0, T)$$

$$u = g \quad \text{on } \partial\Omega \times (0, T)$$

$$u = u_0 \quad \text{at } \partial\Omega \times \{0\}$$

$$\mathbf{u}^m = \mathbf{u}^{m-1} + \tau \sum_{i=1}^{s} b_i \mathbf{k}_i^m$$

$$\left(I_s \otimes I_n - \frac{\tau}{h^2} (A \otimes L)\right) \mathbf{k}^m = \frac{1}{h^2} (I_s \otimes L) \mathbf{u}^{m-1}$$

M

M. M. Rana, V. E. Howle, K. Long, A. Meek, and W. Milestone. A New Block Preconditioner for Implicit Runge-Kutta Methods for Parabolic PDE Problems, 2021.

factor 
$$\left(I_s \otimes I_n - \frac{\tau}{h^2} A \otimes L\right)$$

factor 
$$\left(I_s \otimes I_n - \frac{\tau}{h^2} A \otimes L\right) \approx I_s \otimes I_n - \frac{\tau}{h^2}$$
factor  $(A) \otimes L$ 

factor 
$$\left(I_s \otimes I_n - \frac{\tau}{h^2} A \otimes L\right) \approx I_s \otimes I_n - \frac{\tau}{h^2} \operatorname{factor}(A) \otimes L$$

$$I_s \otimes I_n - \frac{\tau}{h^2} D_A \otimes L =: P^{\text{diag}}$$

$$I_s \otimes I_n - \frac{\tau}{h^2} U_A \otimes L =: P^{\text{diag}}$$

$$M\left(P^{\mathrm{diag}}\right)^{-1}$$

 $sp.linalg.gmres(M, rhs, P^{diag})$ 

 $\frac{\|r_k\|}{\|r_0\|} \le \min_{\substack{\varphi(0)=1\\\deg(\varphi)\le k}} \|\varphi(M\left(P^{\operatorname{diag}}\right)^{-1})\|$ sp.linalg.gmres  $\frac{\|r_k\|}{\|r_0\|} \le \kappa(S) \min_{\substack{\varphi(0)=1\\\deg(\varphi)\le k}} \max_{\zeta_i \in \operatorname{sp}(M(P^{\operatorname{triang}})^{-1})} |\varphi(\zeta_i)|$  $\frac{\|r_k\|}{\|r_0\|} \le \kappa(S) \min_{\varphi(0)=1} \max_{\zeta \in co(sp(\cdots))} |\varphi(\zeta)|$ 

$$\|\varphi(M\left(P^{\operatorname{diag}}\right)^{-1})\|$$

$$\max_{\operatorname{sp}(M(P^{\operatorname{triang}})^{-1})} |\varphi(\zeta_i)|$$

s = 2

**Proposition.** Let s = 2 and  $a_{ij} \neq 0$ . Adopting the above notation and setting  $\operatorname{sp}(L) = \{\lambda_k\}_k$  and  $\theta_k = \frac{\tau}{h^2} \lambda_k$  we have  $\operatorname{sp}(M\left(P^{\operatorname{diag}}\right)^{-1}) = \zeta_{1,2}^{(k)}$ 

with

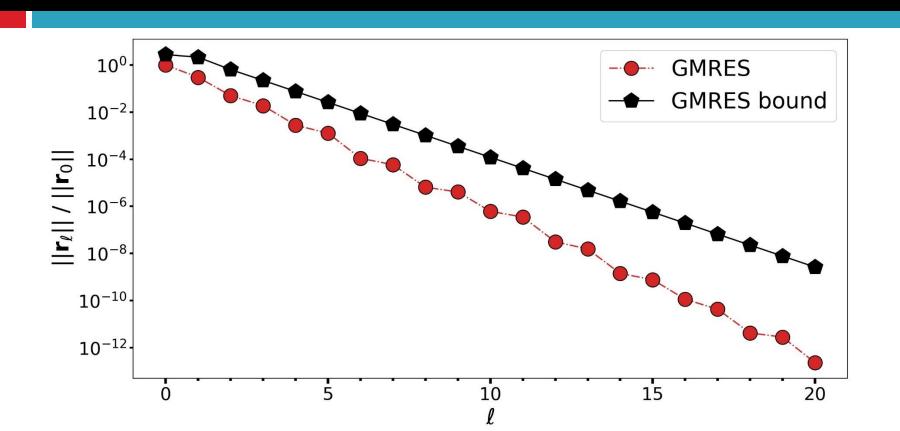
$$\zeta_{1,2}^{(k)} = 1 \pm \sqrt{\frac{a_{12}a_{21}}{(|\theta_k^{-1}| + a_{11})(|\theta_k^{-1}| + a_{22})}},$$

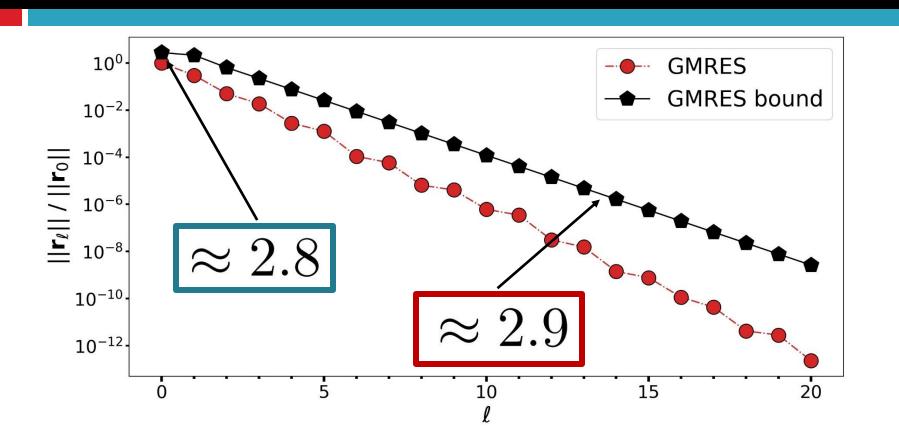
and the condition number of the eigenbasis is given by

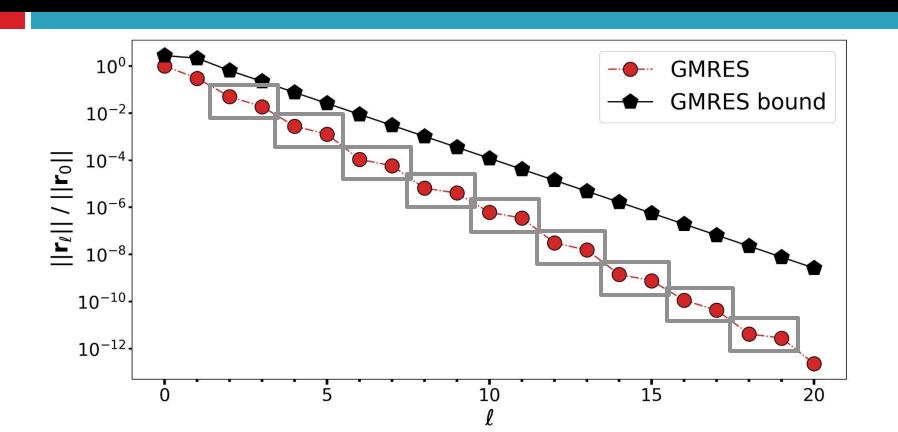
$$\kappa(S) = \max_{k=1,\dots,n} \sqrt{\frac{1 + \left| \frac{a_{21}(1 + a_{22}|\theta_k|)}{a_{12}(1 + a_{11}|\theta_k|)} \right| + \left| 1 - \left| \frac{a_{21}(1 + a_{22}|\theta_k|)}{a_{12}(1 + a_{11}|\theta_k|)} \right| \right|}{1 + \left| \frac{a_{21}(1 + a_{22}|\theta_k|)}{a_{12}(1 + a_{11}|\theta_k|)} \right| - \left| 1 - \left| \frac{a_{21}(1 + a_{22}|\theta_k|)}{a_{12}(1 + a_{11}|\theta_k|)} \right| \right|}$$

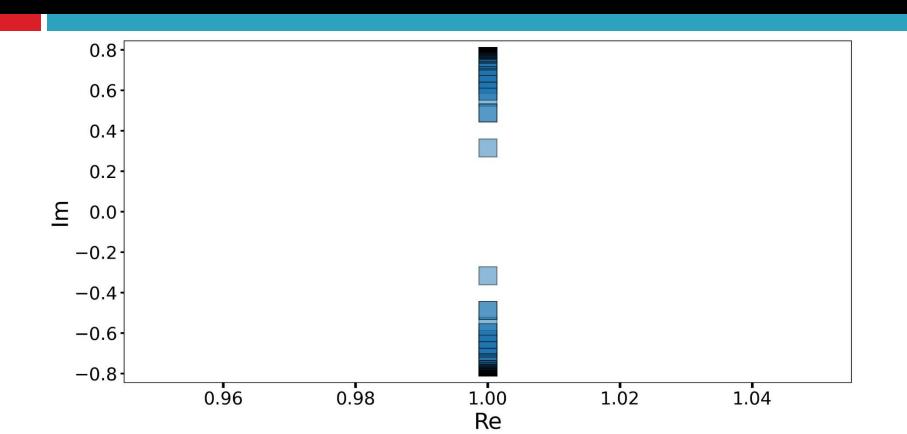
preconditioned GMRES What can we predict?

s=2







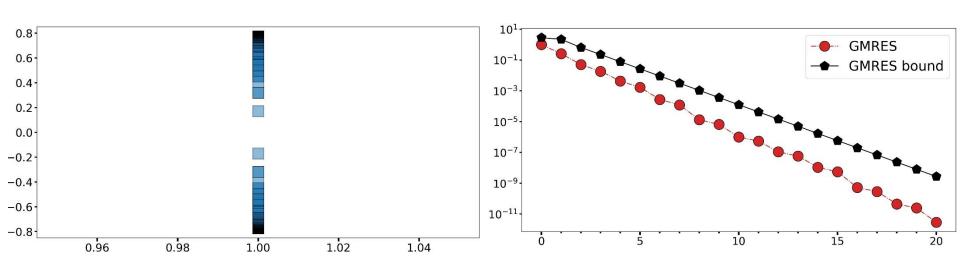


sp.linalg.gmres

$$\frac{\|r_k\|}{\|r_0\|} \le \min_{\substack{\varphi(0)=1\\\deg(\varphi)\le k}} \|\varphi(M\left(P^{\operatorname{diag}}\right)^{-1})\|$$

$$\frac{\|r_k\|}{\|r_0\|} \le \kappa(S) \min_{\substack{\varphi(0)=1\\\deg(\varphi)\le k}} \max_{\substack{\zeta_i \in \operatorname{sp}(M(P^{\operatorname{triang}})^{-1})\\\varphi(0)=1}} |\varphi(\zeta_i)|$$

$$\frac{\|r_k\|}{\|r_0\|} \le \kappa(S) \min_{\substack{\varphi(0)=1\\\varphi(0)=1}} \max_{\substack{\zeta \in \operatorname{co}(sp(\cdots))\\\varphi(0)\le k}} |\varphi(\zeta)|$$



# Conclusion

# Thank you for your attention

#### Schwarz methods



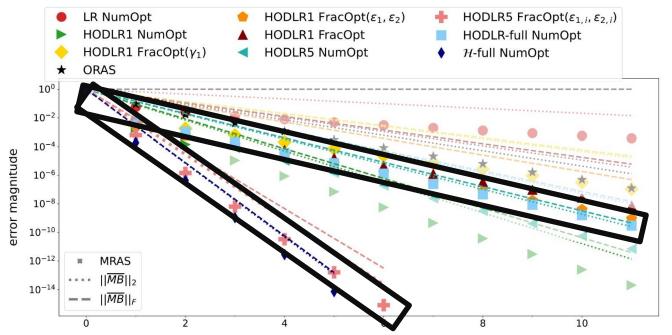
# Karl Hermann Amandus Schwarz

#### Schwarz methods & DS

data-sparse formats: convergence

#### Schwarz methods & DS

## data-sparse formats: convergence



#### Schwarz methods & ABC



Henri Eugène Padé

## References

**Theorem.** For any  $\alpha \in (-1, +\infty)$  we have

$$\sqrt{1+\alpha} = 1 + \frac{\frac{\alpha}{2}}{1 + \frac{\frac{\alpha}{2}}{2}}$$

$$2 + \frac{\frac{\alpha}{2}}{1 + \frac{\frac{\alpha}{2}}{2}}$$

$$\vdots$$

Moreover, for any n the [n+1,n]-Padé approximant of  $\sqrt{1+\alpha}$  expanded about  $\alpha = 0$  is the (2n+1)-st truncation of the continued fraction above.

#### To combine

$$\sqrt{1+\alpha} = 1 + \frac{\frac{\alpha}{2}}{1 + \frac{\alpha}{2}}$$

$$1 + \frac{\alpha}{2}$$

$$1 + \frac{\alpha}{2}$$

$$1 + \frac{\alpha}{2}$$

#### To combine

$$\sqrt{1+\alpha} = 1 + \frac{\frac{\alpha}{2}}{1 + \frac{\alpha}{2}}$$
and
$$2 + \frac{\frac{\alpha}{2}}{1 + \frac{\alpha}{2}}$$

$$\hat{c}_{N^a}^{\infty}(\lambda) = \frac{\lambda + \sqrt{\lambda^2 - 4}}{2h^2}$$

To combine

and
$$\begin{array}{c}
\sqrt{1+\alpha} = 1 + \frac{\frac{\alpha}{2}}{1 + \frac{\frac{\alpha}{2}}{2}} \\
2 + \frac{\frac{\alpha}{2}}{1 + \frac{\frac{\alpha}{2}}{2}}
\end{array}$$

things get a little calculaty

Having  $\lambda = 2 + z$  we get

Having  $\lambda = 2 + z$  we get

$$\hat{t}_{N^a}^b(z) = \frac{1}{h^2} \left( 2 + z - \frac{1}{2 + z - \frac{1}{2 + z - \frac{1}{2 + z - \frac{1}{2 + z}}}} \right)$$

Having  $\lambda = 2 + z$  we get

$$\hat{t}_{N^a}^b(z) = \frac{1}{h^2} \left( 2 + z - \frac{1}{2 + z - \frac{1}{2 + z - \frac{1}{2 + z - \frac{1}{2 + z}}}} \right)$$

$$\hat{t}_{N^a}^{\infty}(z) = \frac{1}{h^2} \left( 2 + z - \frac{1}{2 + z - \frac{1}{2 + z - \frac{1}{2 + z - \frac{1}{2}}}} \right) = \frac{1}{h^2} \left( 1 + \frac{z}{2} + \frac{z}{2} \sqrt{1 + \frac{4}{z}} \right)$$

#### Combining

$$\sqrt{1+\alpha} = 1 + \frac{\frac{\alpha}{2}}{1 + \frac{\frac{\alpha}{2}}{2}}$$

$$2 + \frac{\frac{\alpha}{2}}{1 + \frac{\frac{\alpha}{2}}{2}}$$

#### Combining

$$\sqrt{1+\alpha} = 1 + \frac{\frac{\alpha}{2}}{1+\frac{\alpha}{2}}$$
and
$$2 + \frac{z}{\sqrt{1+\frac{4}{2}}}$$

$$1 + \frac{z}{\sqrt{1+\frac{4}{2}}}$$

$$1 + \frac{z}{\sqrt{1+\frac{4}{2}}}$$

$$\hat{t}_{N^a}^{\infty}(z) = \frac{1}{h^2} \left( 1 + \frac{z}{2} + \frac{z}{2} \sqrt{1 + \frac{4}{z}} \right)$$

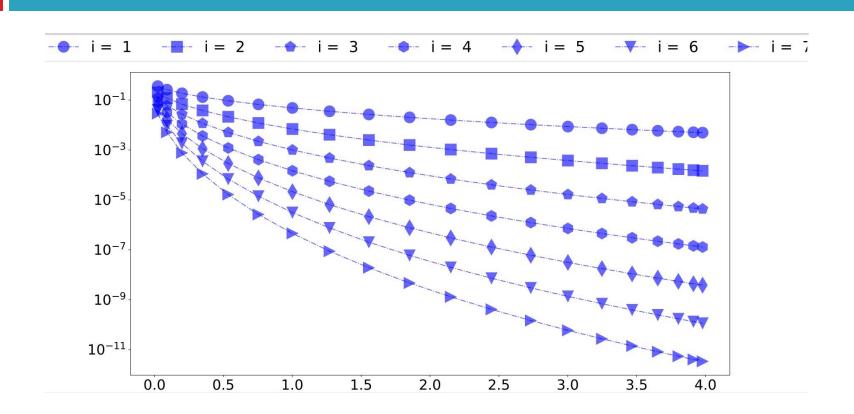
#### Combining

$$\sqrt{1+\alpha}=1+\frac{\frac{\alpha}{2}}{1+\frac{\alpha}{2}}$$
 and 
$$1+\frac{\frac{\alpha}{2}}{2+\frac{\alpha}{2}}$$
 
$$\hat{t}_{Na}^{\infty}(z)=\frac{1}{h^2}\left(1+\frac{z}{2}+\frac{1}{2}\sqrt{1+\frac{4}{z}}\right)$$
 
$$1+\frac{\alpha}{2}$$
 
$$1+\frac{\alpha}{2}$$
 
$$1+\frac{\alpha}{2}$$
 
$$\vdots$$

becomes a little easier

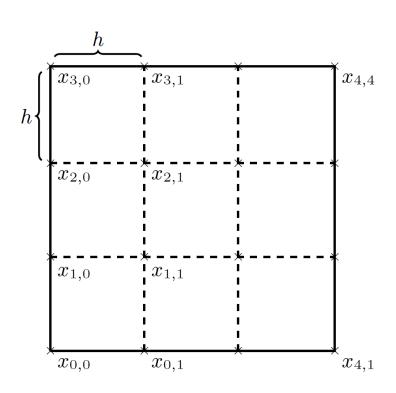
Having  $\lambda = 2 + z$  we get

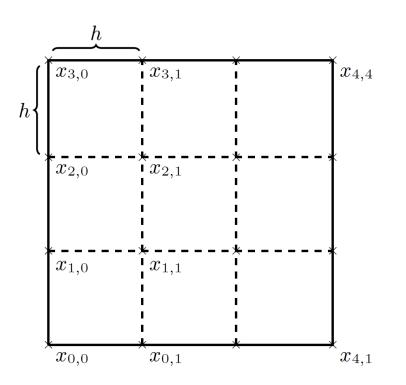
**Theorem.** The function  $\hat{t}_{Na}^b(z)$  is the [n, n]-Padé approximation about the expansion point  $z = +\infty$  of  $\hat{t}_{Na}^{\infty}(z)$ , where  $n = N^b - N^a$ .

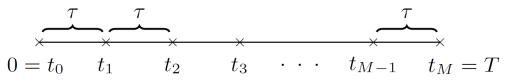


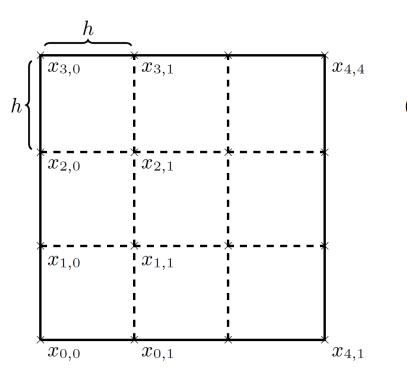
Step I:

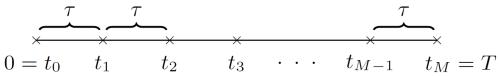
$$\Omega = (0,1) \times (0,1)$$



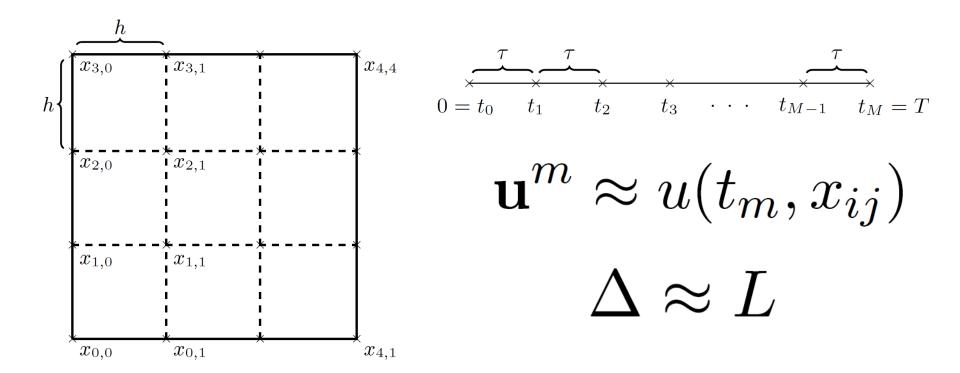








$$\mathbf{u}^m \approx u(t_m, x_{ij})$$



$$\mathbf{u}^m = \mathbf{u}^{m-1} + \tau \sum_{i=1}^{\infty} b_i \mathbf{k}_i^m$$

Step I:

$$M\left(P^{\mathrm{diag}}\right)^{-1} \sim \begin{bmatrix} X_{11} & \dots & X_{1s} \\ \vdots & \ddots & \vdots \\ X_{s1} & \dots & X_{ss} \end{bmatrix}$$

Step I:

$$M\left(P^{\mathrm{diag}}\right)^{-1} \sim \begin{bmatrix} X_{11} & \dots & X_{1s} \\ \vdots & \ddots & \vdots \\ X_{s1} & \dots & X_{ss} \end{bmatrix}$$

with 
$$X_{ij} = \operatorname{diag}\left(\xi_1^{(ij)}, \dots, \xi_n^{(ij)}\right)$$
  $\forall ij$ 

## **Preconditioner analysis**

Step II:

#### Step II:

$$X = \begin{bmatrix} X_{11} & \dots & X_{1s} \\ \vdots & \ddots & \vdots \\ X_{s1} & \dots & X_{ss} \end{bmatrix}$$
with  $X_{ij} = \operatorname{diag}\left(\xi_1^{(ij)}, \dots, \xi_n^{(ij)}\right)$ 

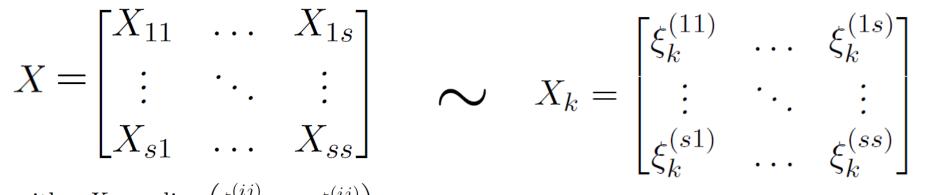
$$X \in \mathbb{R}^{ns \times ns}$$

#### Step II:

$$X = \begin{bmatrix} X_{11} & \dots & X_{1s} \\ \vdots & \ddots & \vdots \\ X_{s1} & \dots & X_{ss} \end{bmatrix}$$

with 
$$X_{ij} = \operatorname{diag}\left(\xi_1^{(ij)}, \dots, \xi_n^{(ij)}\right)$$

$$X \in \mathbb{R}^{ns \times ns}$$



**Lemma.** Let  $X \in \mathbb{R}^{ns \times ns}$  and  $X_k \in \mathbb{R}^{s \times s}$  be as above and set

eigenpair 
$$(X_k) = \left(\mu_\ell^{(k)}, \boldsymbol{s}_\ell^{(k)}\right)$$
.

Then the eigenpairs of X are equal to  $(\mu_{\ell}^{(k)}, \mathbf{s}_{\ell}^{(k)} \otimes \mathbf{e}_k)$ .