



## An Algebraic Sparsified Nested Dissection Algorithm using Low-Rank Approximations

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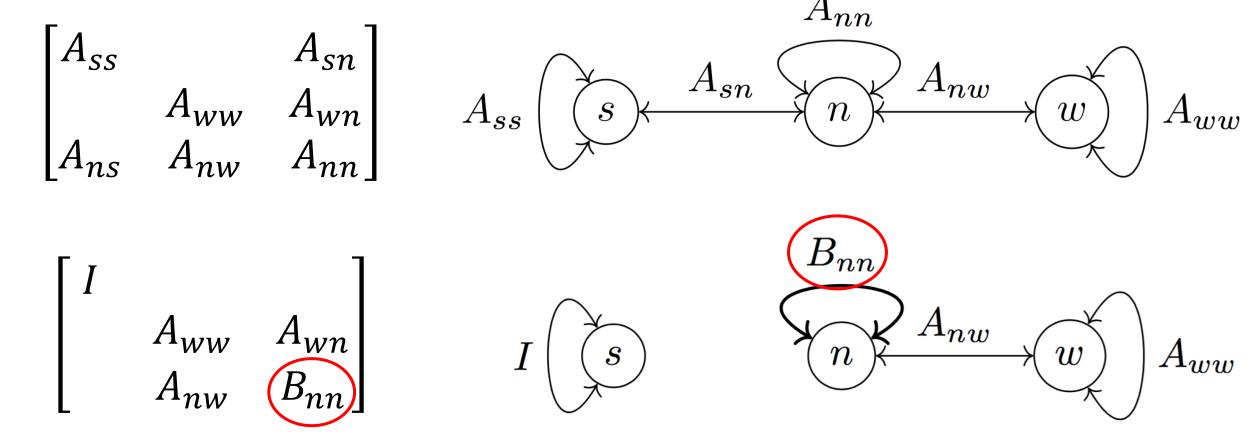
#### Linear Systems

We want to solve Ax = b

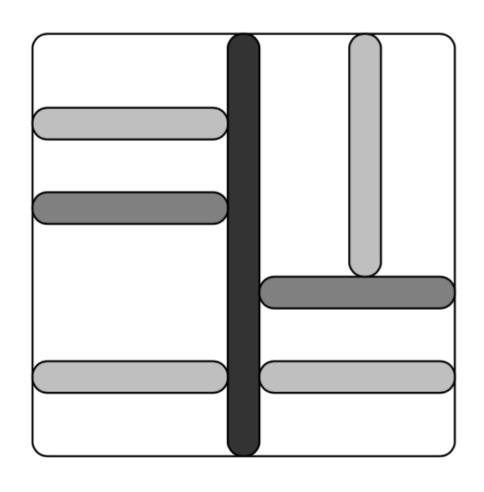
Iterative methods **Direct Methods Approximate Factorizations** ILU / ND + H-(Sparse) LU + Ordering + Custom Preconditioner algebra ... - Robust Cheap - Tunable accuracy Specific Accurate - Tunable cost Generic - Relatively generic Costly

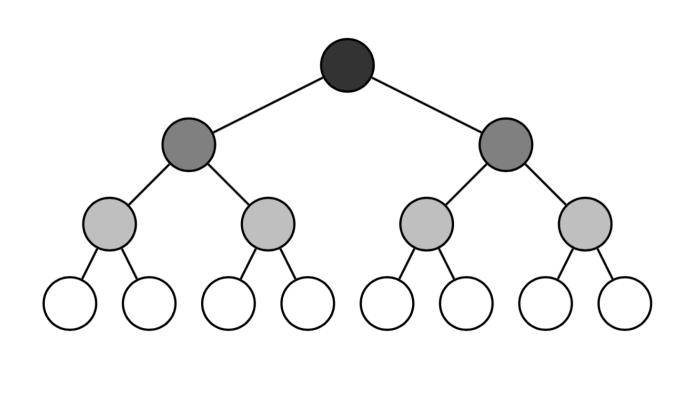
Our approach is heavily inspired by K. L. Ho and L. Ying, Hierarchical interpolative factorization for elliptic operators: differential equations, Communications on Pure and Applied Mathematics, 69 (2016), pp. 1415–1451

#### Sparse Linear Systems



#### Nested Dissection





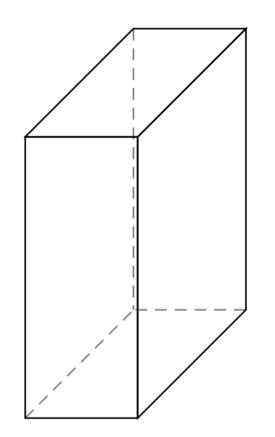
#### Nested Dissection

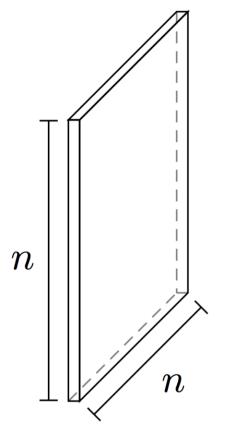
Issue: separators are small, but still too big on typical 3D problems

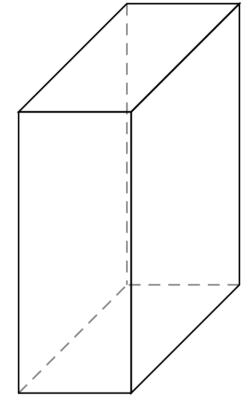
 $N = n^3$ 

Separator:  $n^2$ 

Fact. cost:  $n^{2\cdot 3} = N^2$ 







#### Sparsification I

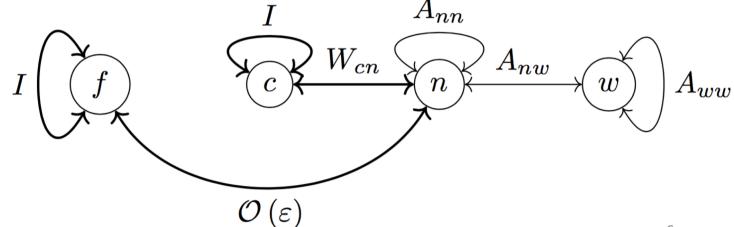
(1) We start with

$$\begin{bmatrix} I & A_{sn} \\ A_{ww} & A_{wn} \\ A_{ns} & A_{nw} & A_{nn} \end{bmatrix}$$

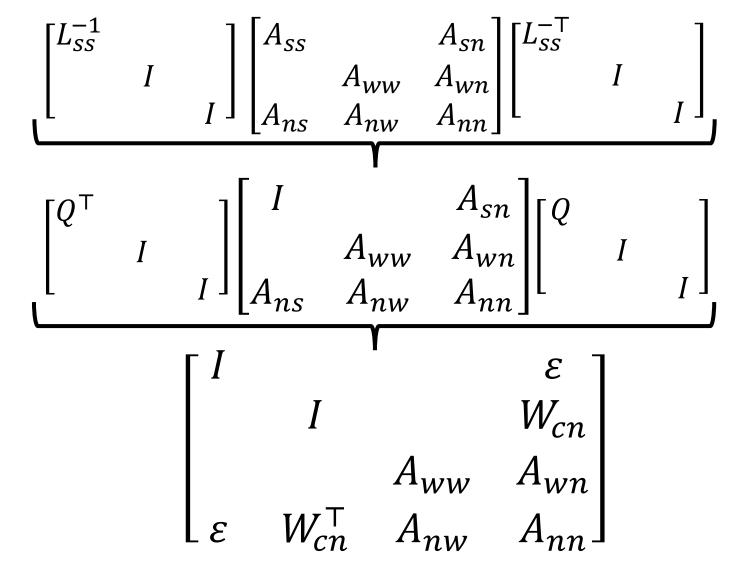
(2) We then approximate

$$A_{sn} = Q_{sc}W_{cn} + \varepsilon$$
$$Q^{\mathsf{T}}s = f \cup c$$

(3) We end up with



#### Sparsification I



#### Sparsification II

(1) We start with

$$egin{bmatrix} A_{SS} & A_{Sn} \ A_{WW} & A_{WN} \ A_{nS} & A_{nW} & A_{nn} \end{bmatrix}$$

(2) We then approximate

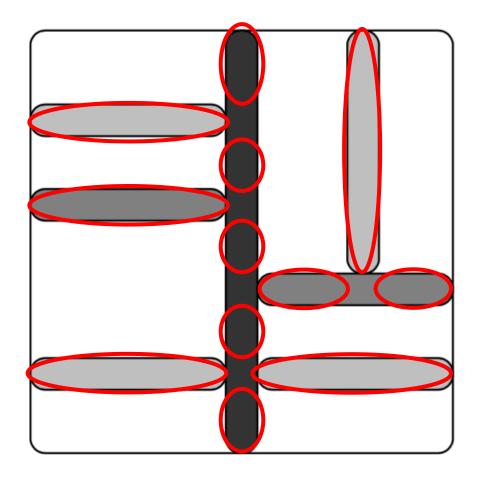
$$A_{sn} = {T_{fc} \choose I} A_{cn} + \varepsilon$$
$$s = f \cup c$$

(3) We end up with

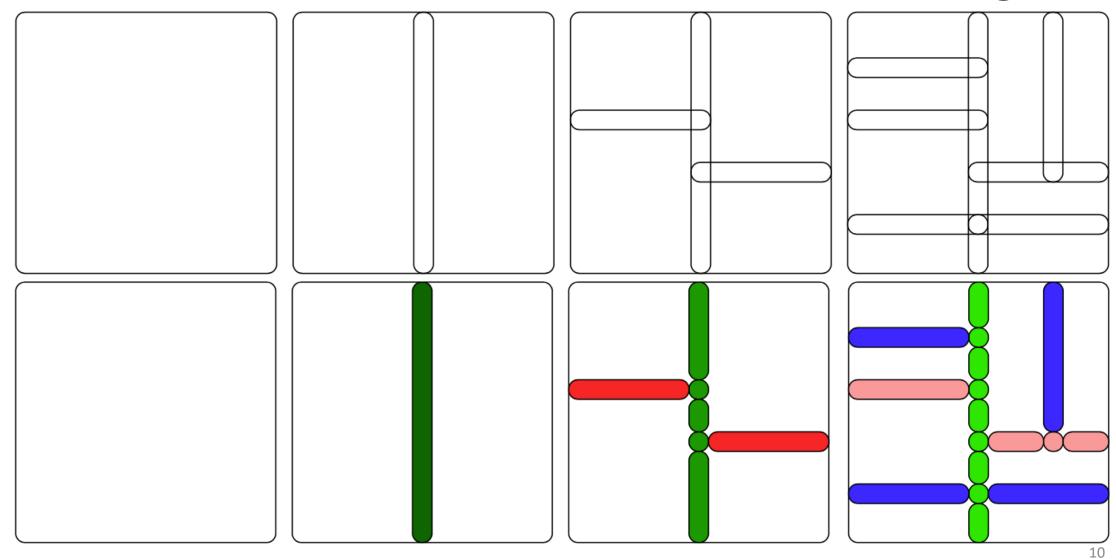
$$\begin{bmatrix} C_{ff} & C_{fc} & \varepsilon \\ C_{cf} & A_{cc} & A_{cn} \\ & A_{ww} & A_{wn} \\ \varepsilon & A_{nc} & A_{nw} & A_{nn} \end{bmatrix} C_{f,f} \underbrace{\begin{pmatrix} C_{f,c} & A_{cn} & A_{nw} \\ C_{f,c} & C_{f,c} & C_{f,c} & A_{cn} & A_{nw} \\ C_{f,f} & C_{f,c} & C_{f,c} & C_{f,c} & C_{f,c} \\ C_{f,c} & C_{f,c} & C_{f,c} & C_{f,c} & C_{f,c} \\ C_{f,c} & C_{f,c} & C_{f,c} & C_{f,c} & C_{f,c} \\ C_{f,c} & C_{f,c} & C_{f,c} & C_{f,c} \\ C_{f,f} & C_{f,f} & C_{f,f} & C_{f,c} \\ C_{f,f} & C_{f,f} & C_{f,f} & C_{f,f} \\ C_{f,f} & C_{f,f} \\ C_{f,f} & C_{f,f} & C_{f$$

#### What do we sparsify?

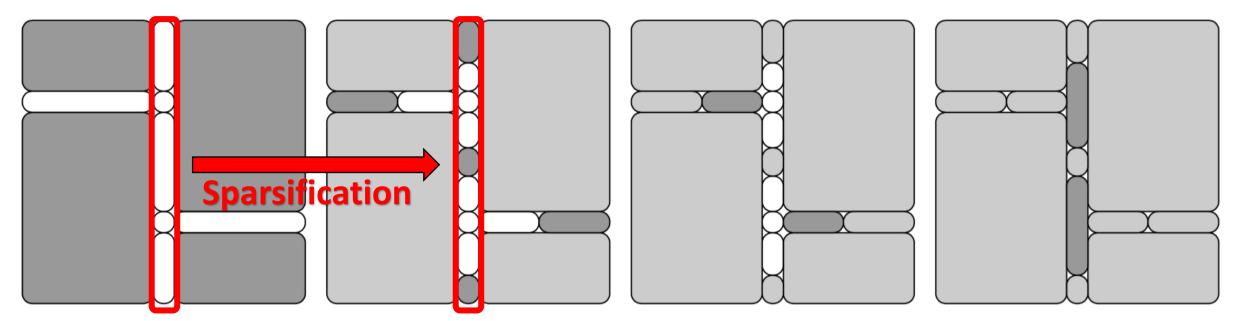
Interfaces between eliminated-interiors

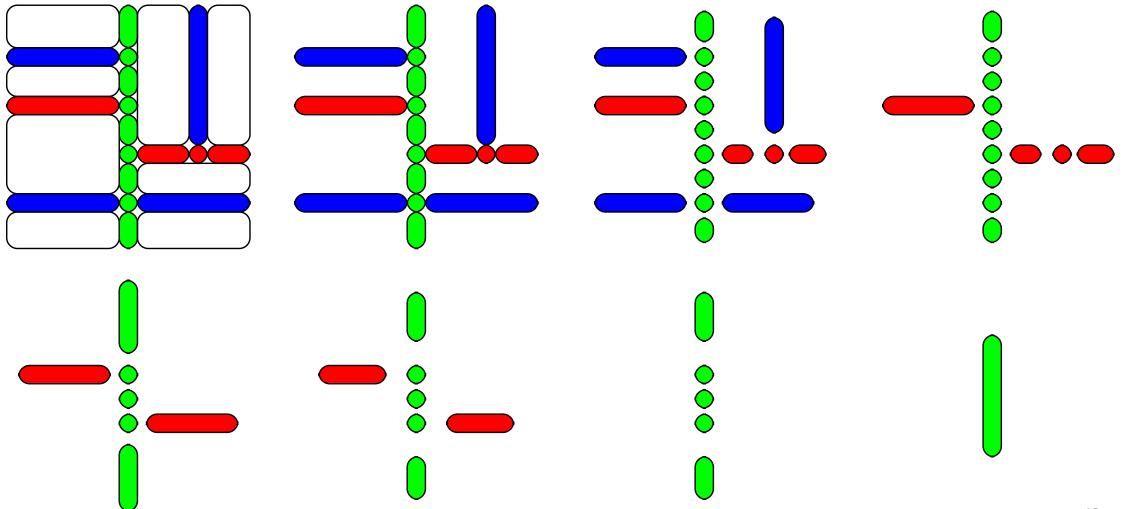


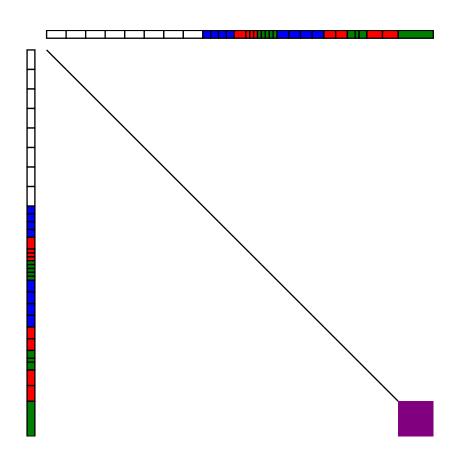
#### How do we find those interfaces? Coloring



For level  $\ell$ , from leaves to top Eliminate interiors at level  $\ell$ (Scale &) Sparsify interfaces at level  $\ell$ 







We effectively build a preconditioner *P* such that

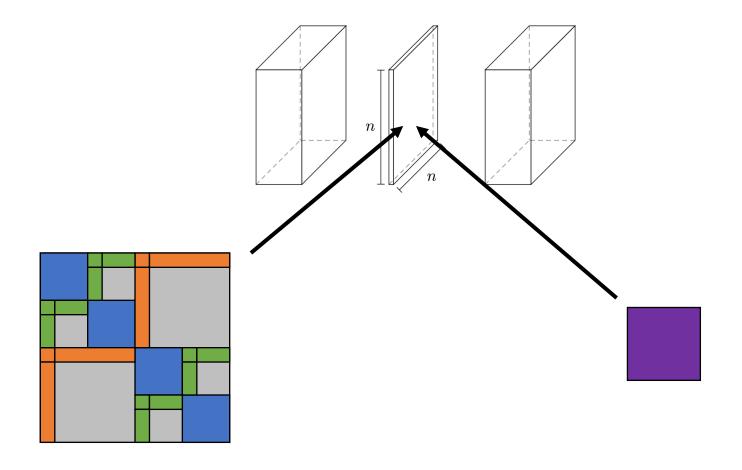
$$P^{\mathsf{T}}AP \approx I + \varepsilon$$

Where *P* is a sequence (product) of

- Eliminations
- (Scalings)
- Sparsifications

We then use P as a preconditioner for CG

#### Different from fast-algebra techniques



#### Sparsification I & II

$$\begin{bmatrix} A_{ss} & A_{sn} \\ A_{ww} & A_{wn} \\ A_{ns} & A_{nw} & A_{nn} \end{bmatrix} \quad A_{sn} = \begin{pmatrix} T_{fc} \\ I \end{pmatrix} A_{cn} + \varepsilon$$

$$A_{sn} = {\binom{T_{fc}}{I}} A_{cn} + \varepsilon$$

$$\begin{bmatrix} I & A_{sn} \\ A_{ww} & A_{wn} \\ A_{ns} & A_{nw} & A_{nn} \end{bmatrix}$$

$$\begin{bmatrix} I & A_{sn} \\ A_{ww} & A_{wn} \\ A_{ns} & A_{nw} & A_{nn} \end{bmatrix} \quad A_{sn} = \begin{pmatrix} T_{fc} \\ I \end{pmatrix} A_{cn} + \varepsilon$$

$$A_{sn} = Q_{sc} W_{cn} + \varepsilon$$

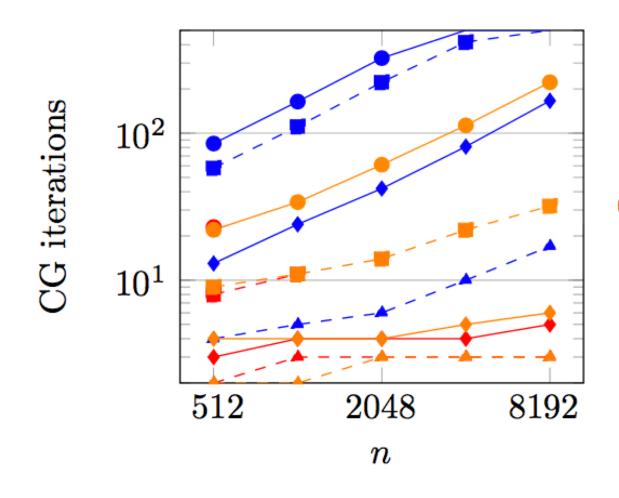
#### Orthogonal, with scaling, stays SPD

$$\begin{bmatrix} I & A_{sn} \\ A_{ww} & A_{wn} \\ A_{ns} & A_{nw} & A_{nn} \end{bmatrix} \qquad A_{sn} = Q_{sc}W_{cn} + Q_{sf}W_{fn}$$

$$S_{nn} = A_{nn} - W_{cn}^{\mathsf{T}} W_{cn} - W_{cf}^{\mathsf{T}} W_{cf}$$

Approximate Schur Complement over (n,n)

## Low-Rank Compression: three variants (2D Laplacians)

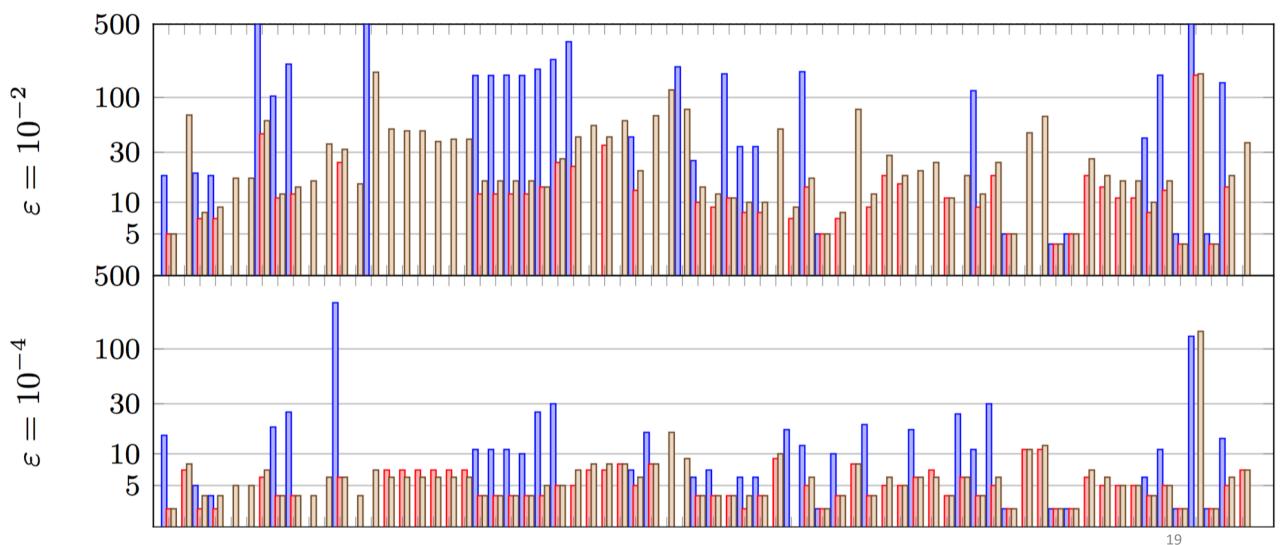


Interpolative, no scaling
Interpolative, with scaling
Orthogonal, with scaling

$$\varepsilon = 10^{-1} \to 10^{-6}$$

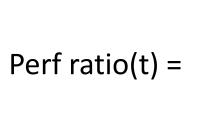
### SPD problems from SuiteSparse

Interpolative, no scaling
Interpolative, with scaling
Orthogonal, with scaling

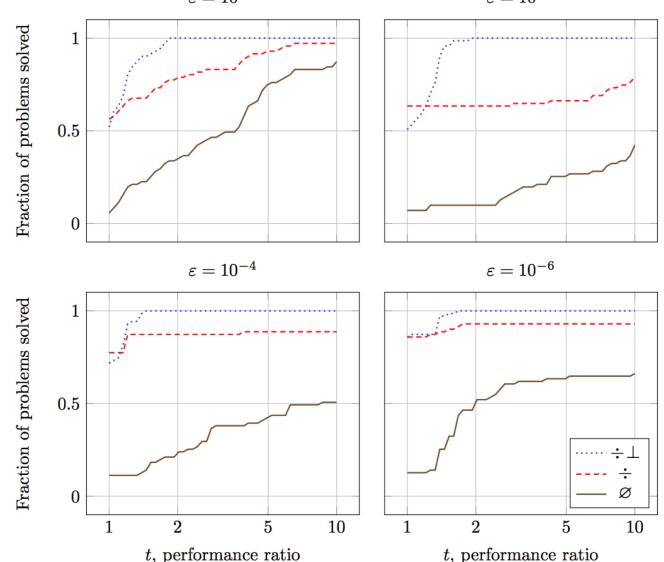


# SPD problems from SuiteSparse $_{\varepsilon=10^{-2}}^{\text{Interpolative, the scaling}}$ Orthogonal, with scaling

Interpolative, no scaling Interpolative, with scaling

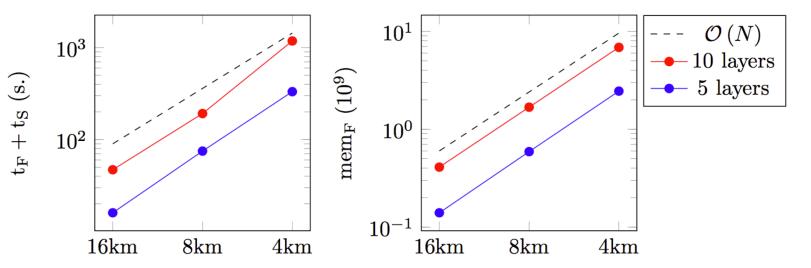


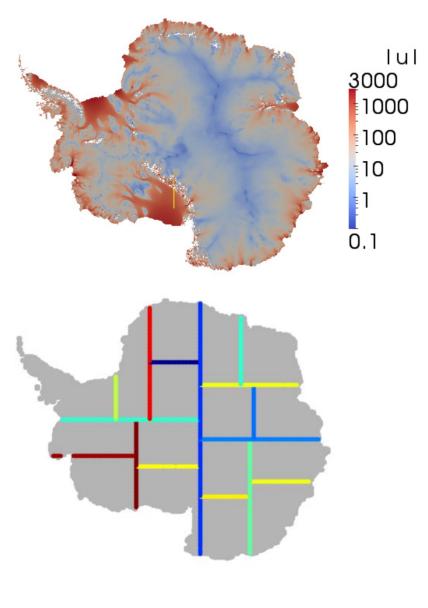
$$\frac{\#\left\{p\in P\left|\frac{CGpv}{CG_p^*}\leq t\right\}\right\}}{\#P}$$



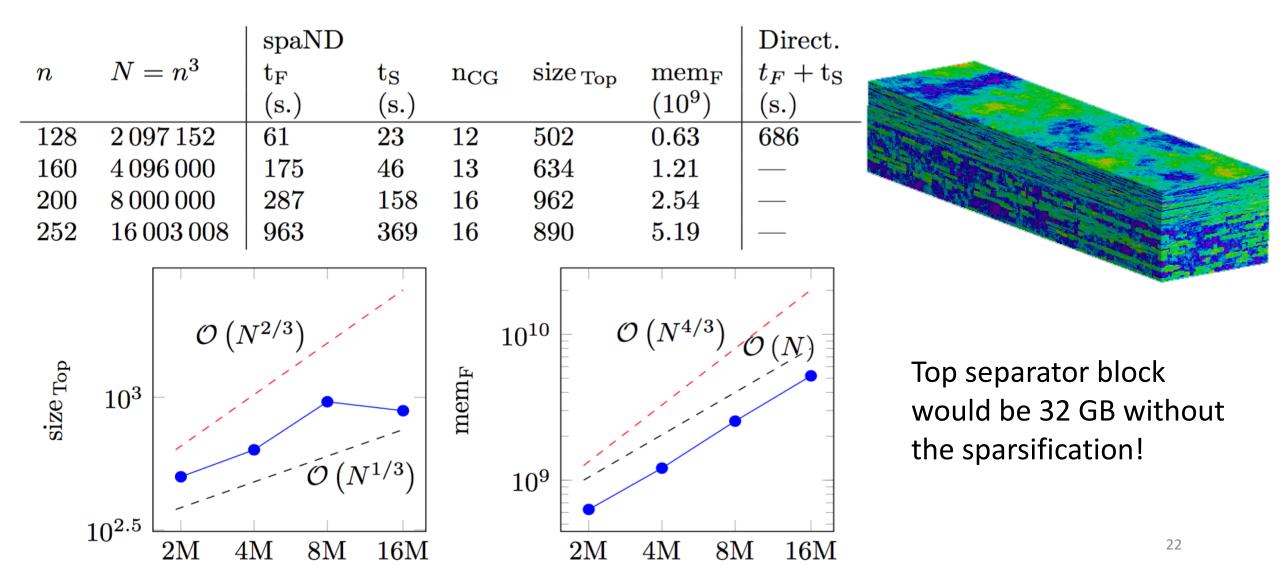
#### Ice-Sheet modeling $\kappa(A) > 10^{11}$

	spaND					Direct
N	$\mathbf{t_F}$	$\mathbf{t_{S}}$	$n_{\rm CG}$	$\operatorname{size}_{\operatorname{Top}}$	$\mathrm{mem}_{\mathrm{F}}$	$ m t_F + t_S$
	(s.)	(s.)			$(10^9)$	(s.)
5 layers						
$629544~(16~{\rm km})$	13	3	7	76	0.14	22
$2521872~(8~{\rm km})$	55	20	8	89	0.59	206
$10096080~(4~{\rm km})$	217	115	10	100	2.45	1578
10 layers						
$1154164\ (16\ \mathrm{km})$	39	8	7	136	0.41	90
$4623432~(8~{\rm km})$	148	44	8	148	1.68	710
$18509480~(4~{\rm km})$	798	384	10	159	6.86	_



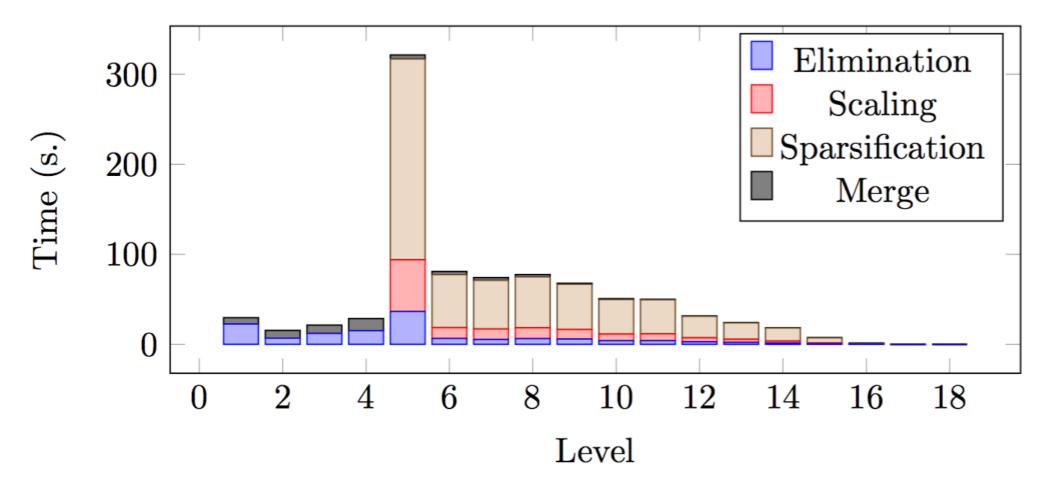


#### The SPE problem



#### Profiling: main cost is RRQR

Optimum is to skip sparsification for levels 1 to 4



#### Acknowledgements & Funding

#### • References:

• K. L. Ho and L. Ying, Hierarchical interpolative factorization for elliptic operators: differential equations, Communications on Pure and Applied Mathematics, 69 (2016), pp. 1415–1451

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