# Geometric adaptive smoothed aggregation multigrid for DG discretisations

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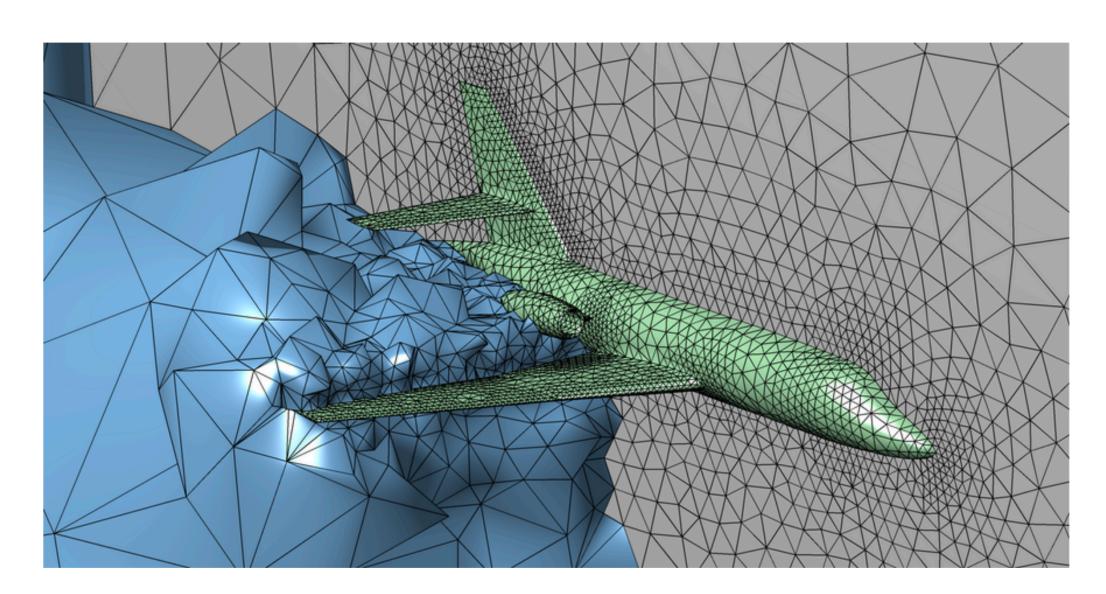
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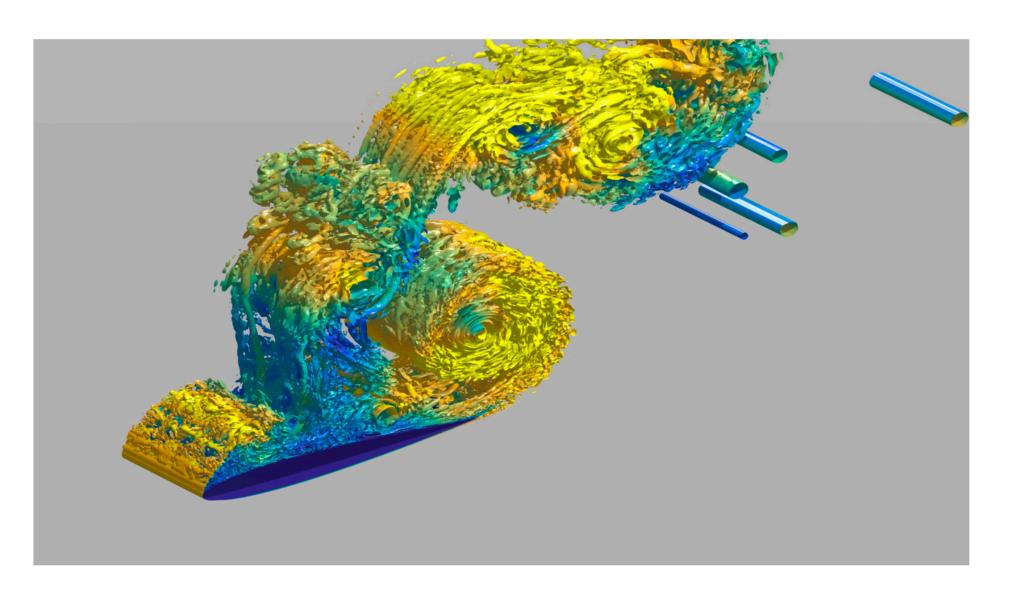


# Background

#### Discontinuous Galerkin (DG) methods

- Variant of Finite Element method allowing for discontinuities along element boundaries, with Finite Volume fluxes used for stabilisation
- Popular for discretisation of convection-diffusion equations in fluids and beyond
- High-order accurate, suitable for use on unstructured meshes in 2D/3D
- However, expensive to apply in practice, more work required to resolve large complex linear systems





#### Linear solvers

- One advantage of DG block sparsity patterns
- Some examples of popular solvers
  - General purpose: block Jacobi/block Gauss-Seidel
  - Hyperbolic: Incomplete LU factorisations
  - Elliptic: Multigrid
- However many techniques scale optimally OR cannot be applied general purpose for large classes of equations
- More work needed

#### Convection-diffusion equation

Model equation for this talk:

$$\mathbf{v} \cdot \nabla u - \mu \Delta u = f$$

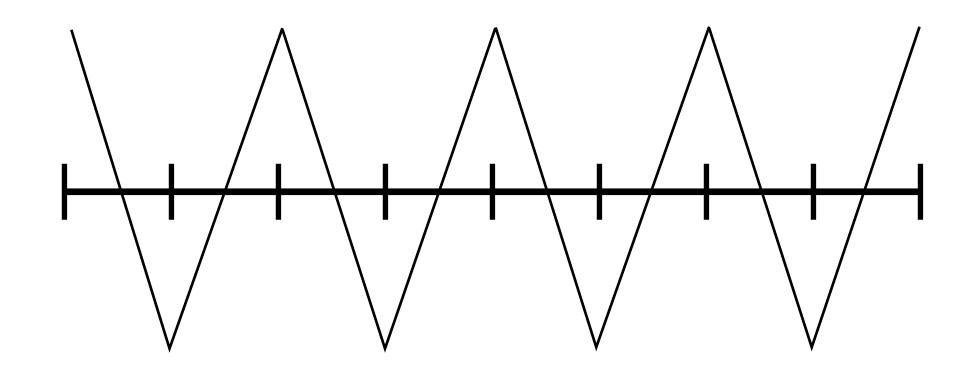
After discretisation gives general linear system of form:

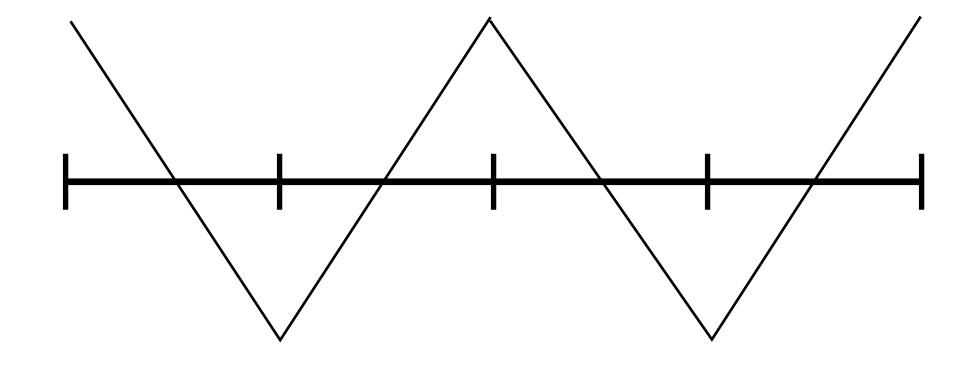
$$Au = f$$

- Challenges with this system:
  - Mesh of underlying domain is unstructured
  - Equation has both hyperbolic and elliptic character
  - Equations might be stiff

#### Multigrid (MG) methods

- Originally designed for elliptic equations on structured domains
- Main idea:
  - Recursively solve linear algebra problem on nested hierarchy
  - Successive levels resolve distinct high frequencies
  - Achieve asymptotically optimal linear O(N) runtime





#### Multigrid (MG) methods

- Ingredients in general MG method:
  - Restriction  $R_k^{k+1}$ 
    - Transfer of residual from higher to lower level
  - Smoother  $S_k$ 
    - Relax high frequency modes at each level, e.g. Jacobi, Gauss-Seidel
  - Interpolation  $T_{k+1}^k$ 
    - Transfer of solution from lower to higher level

## Geometric multigrid (GMG)

- Hierarchy is formed using mesh discretisation, generally nested mesh constructions are used
- Direct polynomial injection generally used for interpolation operator, restriction taken to be its adjoint

$$R_k^{k+1} = \left(T_{k+1}^k\right)^T$$

• BUT, hard to form on unstructured meshes, some approaches include element agglomeration<sup>1</sup>, mesh decimation, non-nested triangulations







<sup>1</sup>Yulong Pan, Per-Olof Persson. Agglomeration-based geometric multigrid solvers for Compact Discontinuous Galerkin discretisations on unstructured meshes. *J. Comp. Phys.*, Vol 454, 110906, April 2022. https://arxiv.org/abs/2012.08024

#### Algebraic multigrid (AMG)

- Introduced as an alternative to geometric multigrid methods
- Multigrid hierarchy is constructed blind to the underlying mesh, instead hierarchy is formed using only entries of the matrix
- Help ease the problem of constructing unstructured mesh hierarchies
- Two main variants: Classical Ruge-Stuben and Smoothed Aggregation AMG

- However, reliance on the matrix means its entries must be readily accessible
- Can be difficult to make fully matrix free

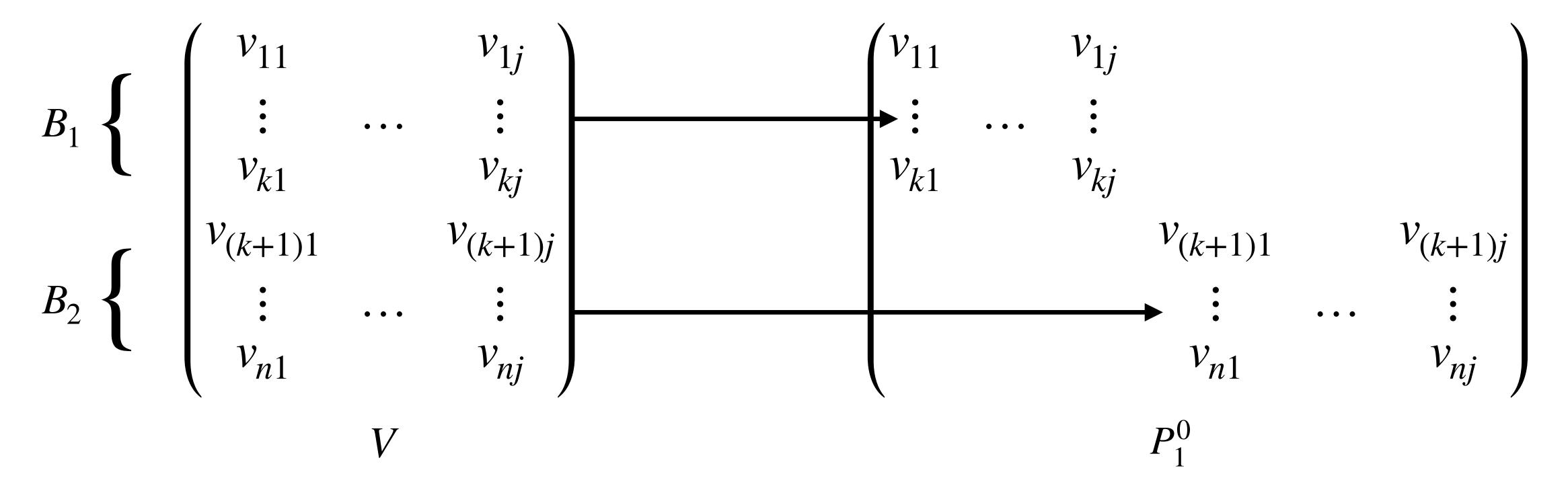
## Smoothed aggregation (SA)

- Introduced in Vanek et al., Algebraic multigrid by smoothed aggregation for second and fourth order. (1996)
- Fundamentally a method of constructing interpolation/restriction operators for AMG

- Assume given matrix A, two partitions  $B_1, B_2$  of its degrees of freedom defining next level in MG hierarchy
  - Also assume given a set of vectors  $V = \{v_1, \dots, v_j\}$  representing the column space of the next level in AMG hierarchy

## Smoothed aggregation (SA)

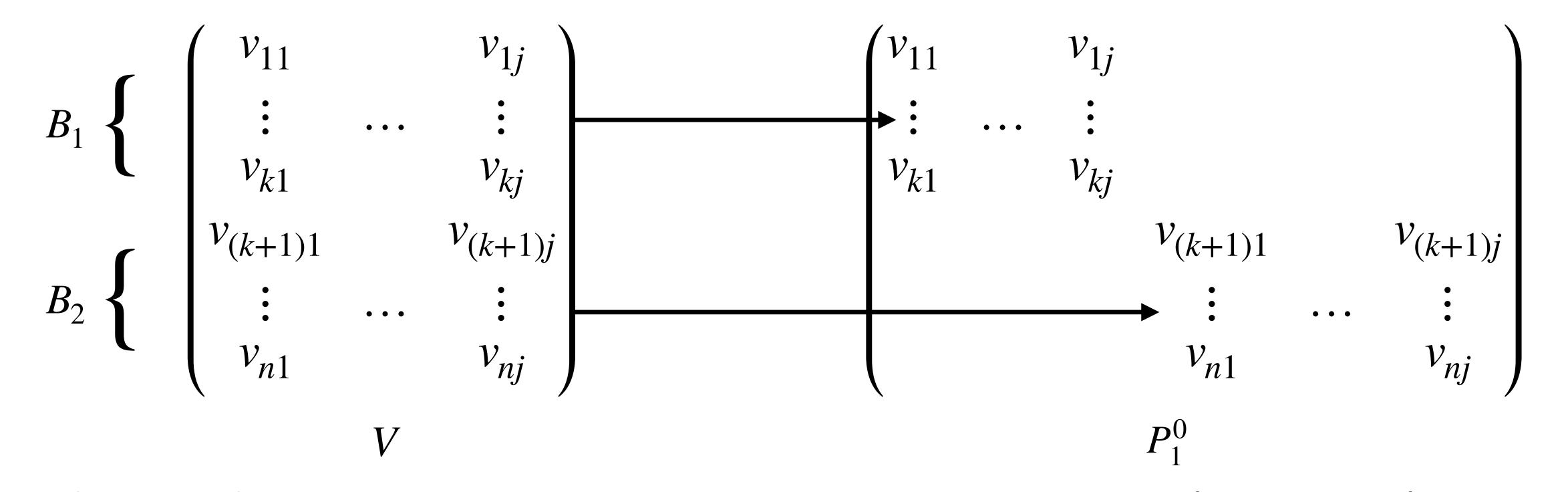
- Assume given matrix A, two partitions  $B_1, B_2$  of its degrees of freedom
  - Also given a set of vectors  $V=\{v_1,\ldots,v_j\}$  representing the column space of the next level in AMG hierarchy



ullet Coarse modes V are split according to partitions in block diagonal matrix

## Smoothed aggregation (SA)

ullet Coarse modes V are split according to partitions in block diagonal matrix



• To finish defining prolongation operator, smoothing is applied (e.g. Jacobi)

$$T_1^0 = S_0 P_1^0$$

Smooth out high frequency modes introduced by partitioning

#### GMG vs AMG

#### Geometric MG

- Mesh hierarchies
- Difficult to generalise on unstructured meshes
- Matrix A not explicitly necessary

#### Algebraic MG

- ullet Algebraic hierarchies inferred from A
- Entirely blind to underlying mesh
- Matrix A needed explicitly

 Is there a way to combine the two to obtain fast method suitable for unstructured meshes?

#### Further challenges

- MG difficult to generalise to both hyperbolic and elliptic equations
  - Some previous work include L-AIR solvers (Southworth et al. 2017)
- MG methods are also sensitive to choice of DG numerical flux
  - In particular for Laplacian, different constructions required for Interior Penalty (IP) vs Local DG (LDG) fluxes (Fortunato et al. 2019)
- Can also struggle on stiff systems

<sup>\*</sup>Apologies for the myriad abbreviations, we know there are a lot of them in this field unfortunately

## Geometric adaptive SA multigrid for DG

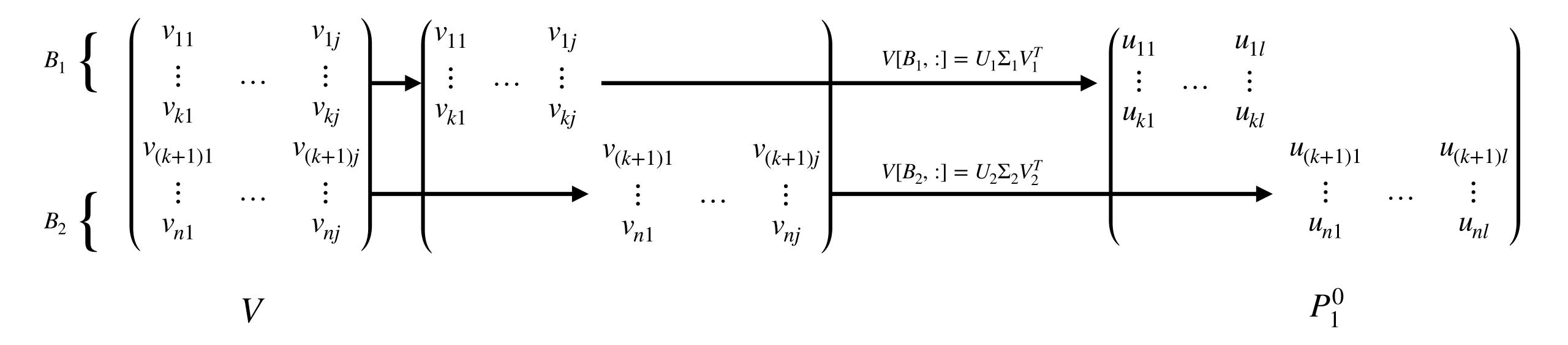
# Adaptive smoothed aggregation ( $\alpha$ SA)

- Introduced by Brezina et al. Adaptive smoothed aggregation ( $\alpha$ SA) multigrid. (2005)
- In original SA algorithm, coarse modes V are given a priori based off expected low frequency modes of Laplacian (e.g. constant mode)
  - Doesn't necessarily generalise to other problems
- Idea of  $\alpha$ SA: adaptively find coarse modes by applying MG smoother on some random vectors
- Why? The leftover modes should span the column space of the next level of the hierarchy!

# Adaptive smoothed aggregation ( $\alpha$ SA)

- 1. Assume given matrix A, and partitions of its degrees of freedom  $B_1, \ldots B_m$
- 2. Define smoother S e.g. Jacobi,  $S = I \omega D^{-1}A$ ,  $\omega = 2/3$ , D = diagonal of A
- 3. Form random matrix with random Gaussian entries  $(b_1 \dots b_r)$
- 4. Apply S to each random vector p times to obtain coarse space vectors V
- 5. Partition V according to  $B_1, \ldots B_m$
- 6. Apply SVD to each diagonal block to filter which modes to keep
- 7. Form prolongation operator as before

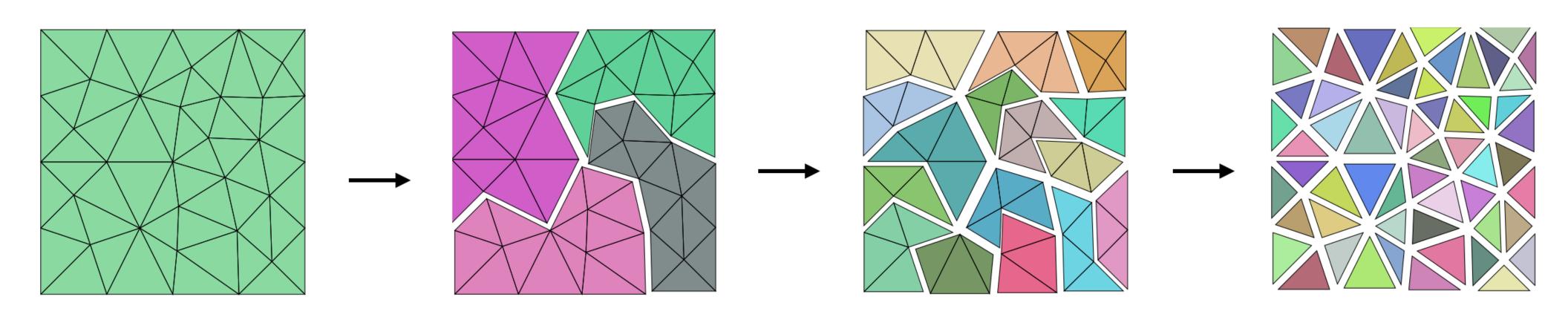
# Adaptive smoothed aggregation ( $\alpha$ SA)



- Additional SVD step to filter out relevant modes in each block
- Difference in  $lpha {\sf SA}$  vs  ${\sf SA}$  lies in how V is formed
  - Pre-determined in SA, adaptive found via smoothing random vectors in  $\alpha$ SA
- Partitions  $B_1, \ldots B_m$  are formed using standard AMG techniques, which we will not delve into in this talk

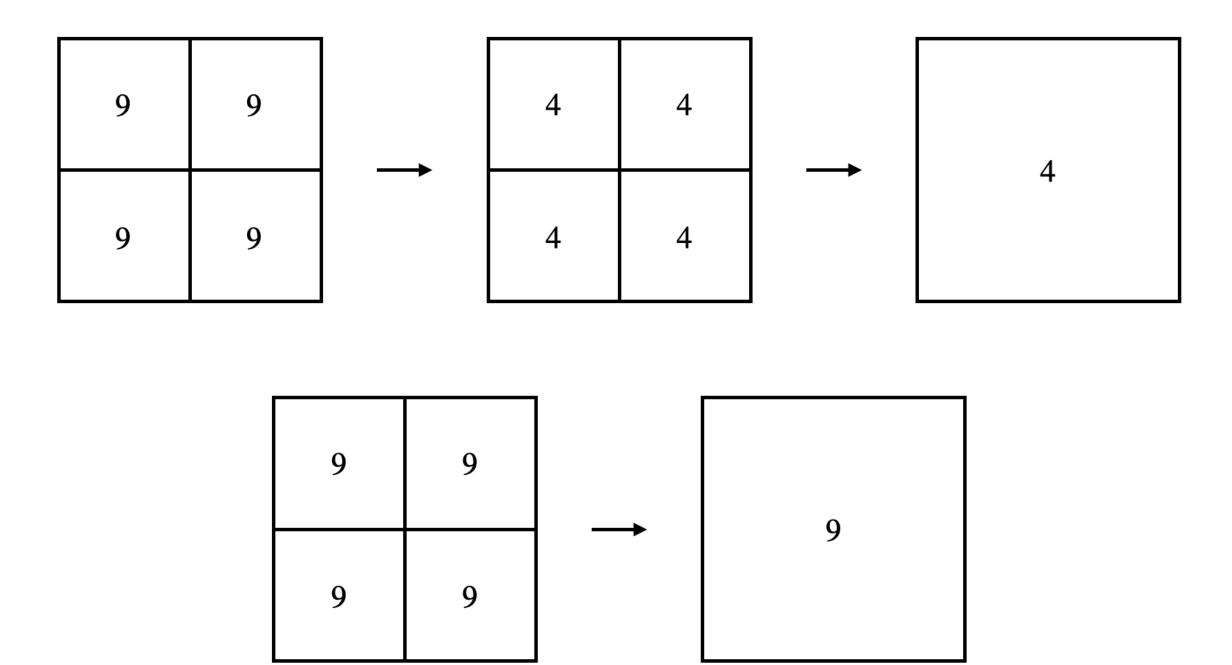
#### Geometric aSA for DG

- Main idea: Form mesh partitions  $B_1, \ldots B_m$  using mesh information
- To form each partition block  $B_i$ , agglomerate elements together using graph partitioning algorithms (e.g. METIS)
- Advantage: Removes explicit dependence on matrix A,  $\alpha$ SA construction allows for generalisation to unstructured meshes
  - Combine advantages of GMG and smoothed aggregation AMG



#### h- vs h\*- multigrid

- Two types of geometric coarsening possible in DG
  - Inter-element h-multigrid, by combining elements via agglomeration
  - Intra-element h\*-multigrid, by coarsening modes within each element (akin to standard p-multigrid)



#### Geometric $\alpha$ SA for DG

- Overall algorithm (assume given matrix  $A^k$  and mesh), at each level k:
  - 1. Form mesh partitions for next level via agglomeration
  - 2. Form smoother  $S_k$ , and apply to random Gaussian vectors  $\boldsymbol{b}_j^k$
  - 3. Partition random vectors and form prolongation  $T_{k+1}^k$  using  $\alpha {\sf SA}$  procedure
  - 4. Form restriction operator  $R_k^{k+1} = (T_{k+1}^k)^T$
  - 5. Form operator at next level  $A^{k+1} = R_k^{k+1} A^k T_{k+1}^k$
  - 6. Go to next level k+1

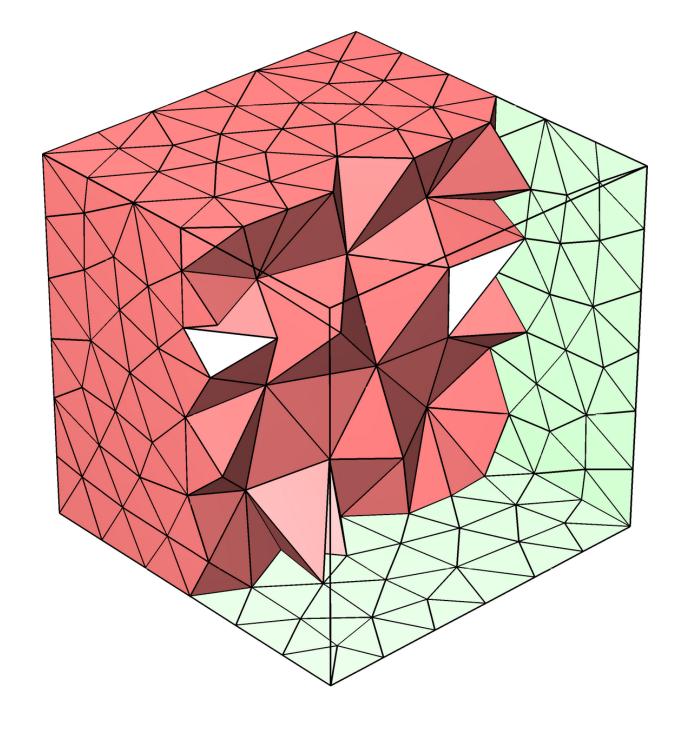
# Numerical examples

#### Poisson's equation (various numerical fluxes)

• Test problem:  $-\Delta u = f$  in 3D,  $\Omega = [-1,1]^3$ , p=1, mesh refinement

| nRef | IP | LDG | IP(pCG) | LDG(pCG) |
|------|----|-----|---------|----------|
| 1    | 7  | 7   | 6       | 6        |
| 2    | 7  | 8   | 6       | 7        |
| 3    | 7  | 9   | 6       | 7        |

#Iterations



| k | dof    | nnz       |
|---|--------|-----------|
| 0 | 32,728 | 1,835,008 |
| 1 | 5,206  | 1,706,338 |
| 2 | 882    | 310,538   |
| 3 | 100    | 9,422     |

MG hierarchy at nRef=2

#### Poisson's equation (h- vs h\*- multigrid)

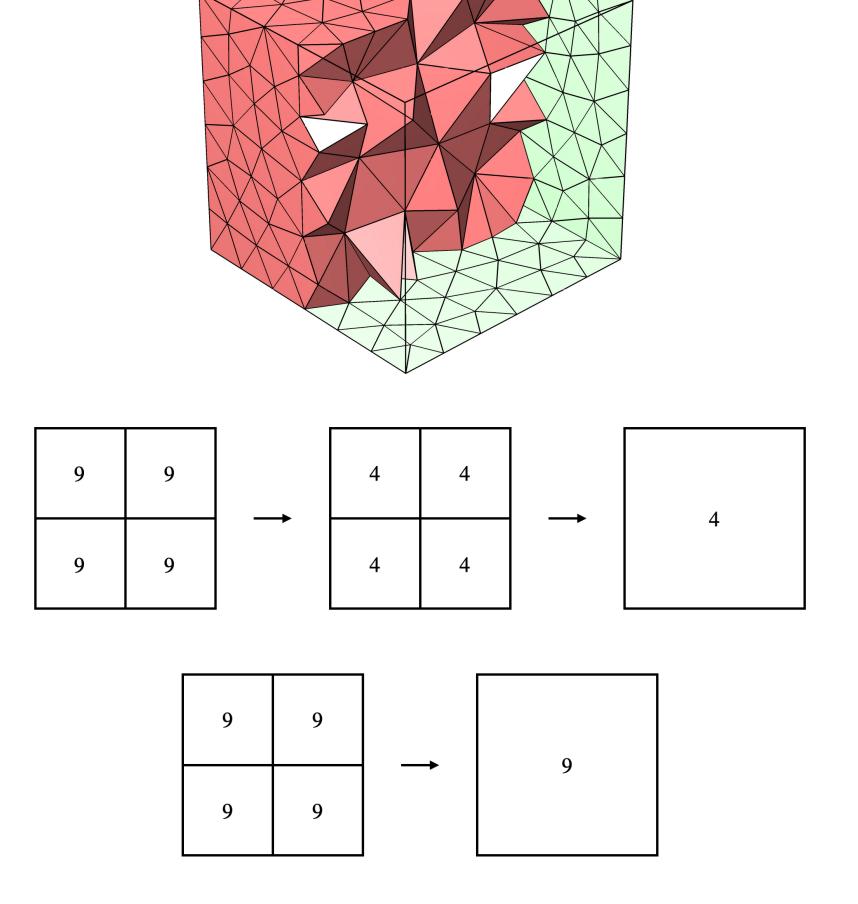
• Test problem:  $-\Delta u = f$  in 3D,  $\Omega = [-1,1]^3$ , fixed mesh, variable p

| р | h*- | h- | h*-(pCG) | h-(pCG) |
|---|-----|----|----------|---------|
| 1 | 8   | 8  | 7        | 6       |
| 2 | 8   | 9  | 6        | 7       |
| 3 | 10  | 9  | 7        | 7       |

#Iterations

| k | dof     | nnz        |
|---|---------|------------|
| 0 | 110,592 | 20,901,888 |
| 1 | 56,029  | 5,411,417  |
| 2 | 9,574   | 5,387,940  |
| 3 | 3,524   | 640,246    |

| k | dof     | nnz        |  |
|---|---------|------------|--|
| 0 | 110,592 | 20,901,888 |  |
| 1 | 18,500  | 16,494,040 |  |
| 2 | 3,104   | 2,342,854  |  |



h\*-MG hierarchy at p=2

h-MG hierarchy at p=2

#### Convection-diffusion

• Test problem:  $\mathbf{v} \cdot \nabla u - \mu \Delta u = f$  in 3D,  $\Omega = [-1,1]^3$ , p=1, mesh refinement

#Iterations - Pe = 0

| nRef | nDof      | Our method | block<br>Jacobi | AMG<br>(classical) | AMG (SA) |
|------|-----------|------------|-----------------|--------------------|----------|
| 0    | 4,188     | 9          | 184             | 38                 | 36       |
| 1    | 29,180    | 10         | 430             | 64                 | 58       |
| 2    | 214,260   | 11         | 1462            | 121                | 91       |
| 3    | 1,660,556 | 13         | 3838            | 309                | 185      |

#Iterations - Pe = 1000

| nRef | nDof      | Our method | block<br>Jacobi | AMG<br>(classical) | AMG (SA) |
|------|-----------|------------|-----------------|--------------------|----------|
| 0    | 4,188     | 10         | 46              | -                  | -        |
| 1    | 29,180    | 12         | 83              | -                  | 2473     |
| 2    | 214,260   | 12         | 279             | 719                | 507      |
| 3    | 1,660,556 | 17         | 589             | 367                | 325      |

#Iterations - Pe = 100

| nRef | nDof      | Our method | block<br>Jacobi | AMG<br>(classical) | AMG (SA) |
|------|-----------|------------|-----------------|--------------------|----------|
| 0    | 4,188     | 9          | 76              | 61                 | 66       |
| 1    | 29,180    | 10         | 181             | 57                 | 74       |
| 2    | 214,260   | 12         | 451             | 75                 | 100      |
| 3    | 1,660,556 | 16         | 892             | 173                | 172      |

#Iterations -  $Pe = \infty$ 

| nRef | nDof      | Our method | block<br>Jacobi | AMG<br>(classical) | AMG (SA) |
|------|-----------|------------|-----------------|--------------------|----------|
| 0    | 4,188     | 9          | 37              | -                  | -        |
| 1    | 29,180    | 13         | 63              | -                  | -        |
| 2    | 214,260   | 17         | 118             | -                  | -        |
| 3    | 1,660,556 | 25         | 416             | _                  | _        |

Comparison of pGMRES iterations

#### Conclusion

#### Conclusion

- Novel geometric multigrid method suitable for DG discretisations
- Applicable on unstructured meshes
- Can be applied uniformly for a variety of numerical fluxes without each requiring different treatments
- Combines aspects of GMG/AMG solvers to reduce reliance on explicit structure of matrix operators
- Excellent solver performance observed in practice for convection-diffusion problems



Yulong Pan, Michael Lindsey and Per-Olof Persson. Geometric adaptive smoothed aggregation multigrid for discontinuous Galerkin discretisations. Submitted to Journal of Computational Physics. https://arxiv.org/abs/2504.13373