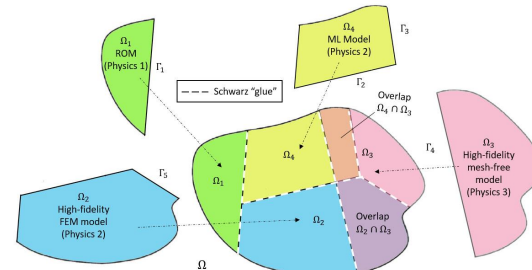
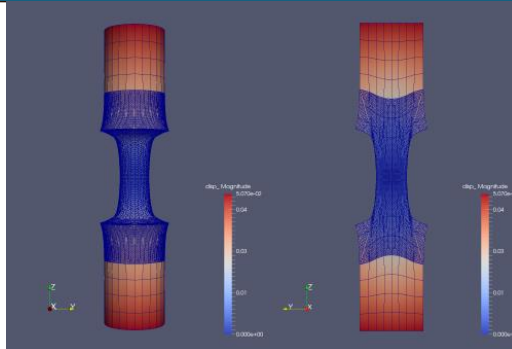
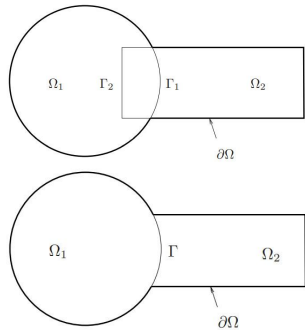


# Towards adaptive hybrid models via domain decomposition and the Schwarz alternating method



Irina Tezaur<sup>1</sup>, Chris Wentland<sup>1</sup>, Francesco Rizzi<sup>2</sup>, Joshua Barnett<sup>3</sup>,  
Alejandro Mota<sup>1</sup>

<sup>1</sup>Sandia National Laboratories, <sup>2</sup>NexGen Analytics, <sup>3</sup>Cadence Design Systems

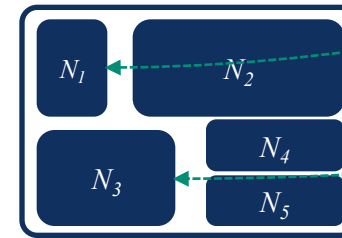
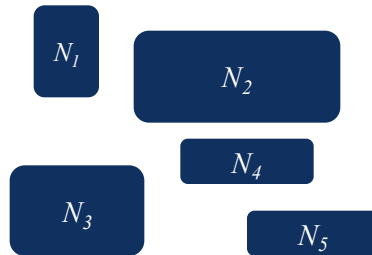
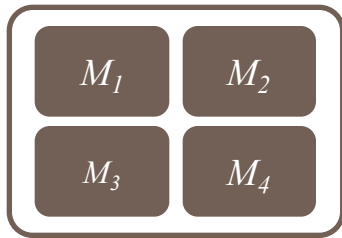
2025 Joint Mathematics Meetings (JMM 2025)  
Seattle, WA. Jan. 8-11, 2025

SAND2024-16987C

# Motivation: Multi-scale & Multi-physics Coupling



There exist established **rigorous mathematical theories** for **coupling** multi-scale and multi-physics components based on **traditional discretization methods** (“Full Order Models” or FOMs).



## Complex System Model

- PDEs, ODEs
- Nonlocal integral
- Classical DFT
- Atomistic, ...

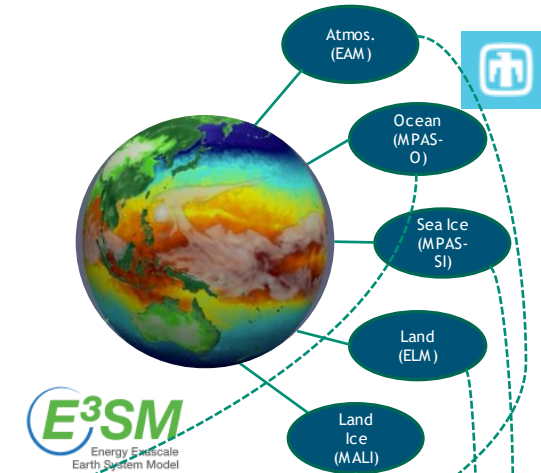
## Traditional Methods

- Mesh-based (FE, FV, FD)
- Meshless (SPH, MLS)
- Implicit, explicit
- Eulerian, Lagrangian...

## Coupled Numerical Model

- Monolithic (Lagrange multipliers)
- Partitioned (loose) coupling
- Iterative (Schwarz, optimization)

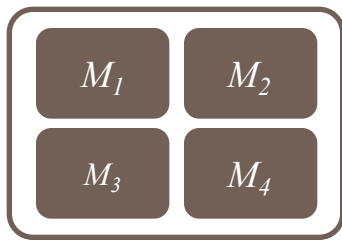
**E<sup>3</sup>SM**  
Energy-Euscale  
Earth System Model



# Motivation: Multi-scale & Multi-physics Coupling

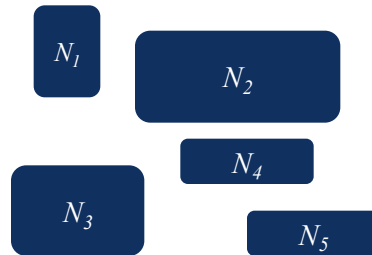


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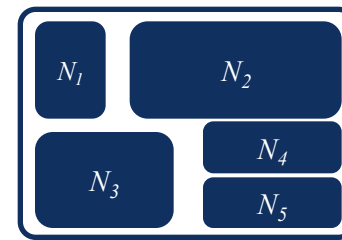
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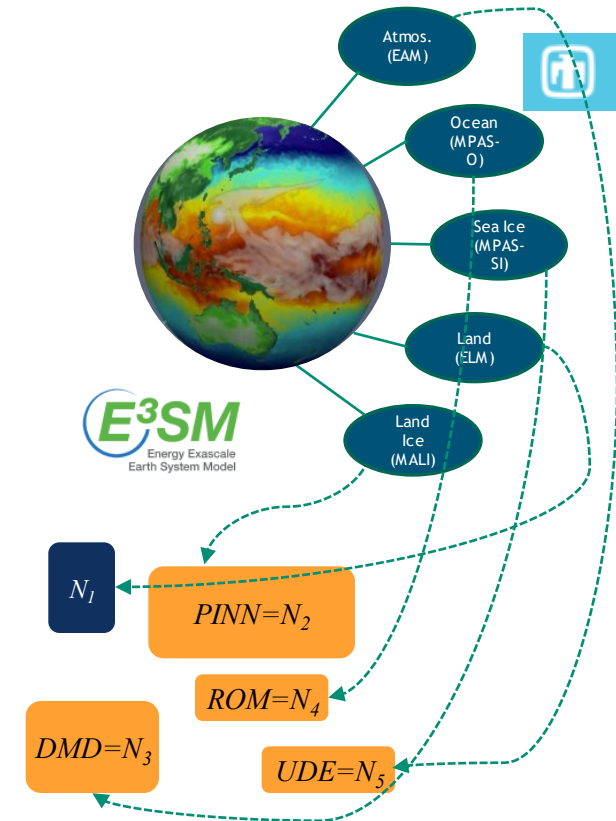
## Traditional Methods

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## Coupled Numerical Model

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- Iterative (Schwarz, optimization)



## Traditional + Data-Driven Methods

- PINNs
- Neural ODEs
- Projection-based ROMs, ...

Unfortunately, existing algorithmic and software infrastructures are **ill-equipped** to handle plug-and-play integration of **non-traditional, data-driven models!**



# Flexible Heterogeneous Numerical Methods (fHNM) and Multi-faceted Mathematics for Predictive Digital Twins (M2dt) Projects



$$\int \mathcal{M}^2 dt$$

## Principal research objective:

- Discover mathematical principles guiding the assembly of standard and data-driven numerical models in stable, accurate and physically consistent ways.

## Principal research goals:

- “Mix-and-match” standard and data-driven models from three-classes
  - **Class A:** projection-based reduced order models (ROMs) *This talk.*
  - **Class B:** machine-learned models, i.e., Physics-Informed Neural Networks (PINNs)
  - **Class C:** flow map approximation models, i.e., dynamic model decomposition (DMD) models
- Ensure well-posedness & physical consistency of resulting heterogeneous models.
- Solve such heterogeneous models efficiently.

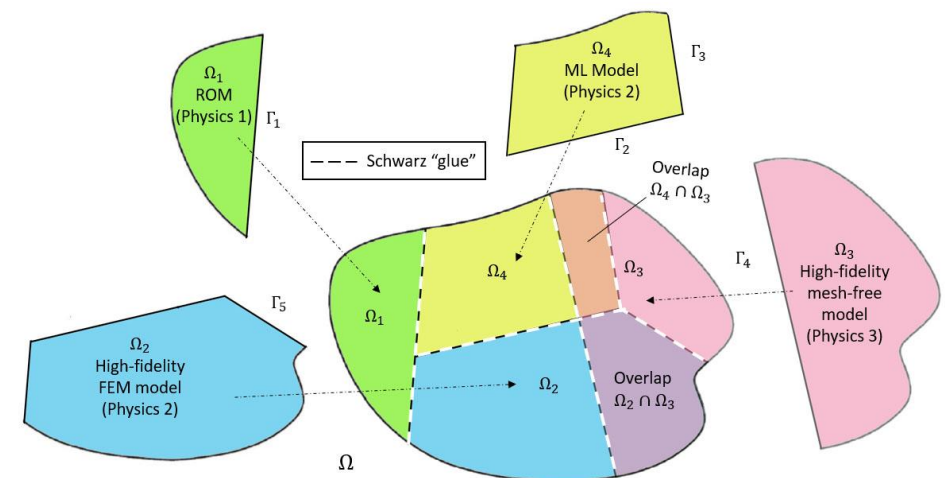


Office of Science

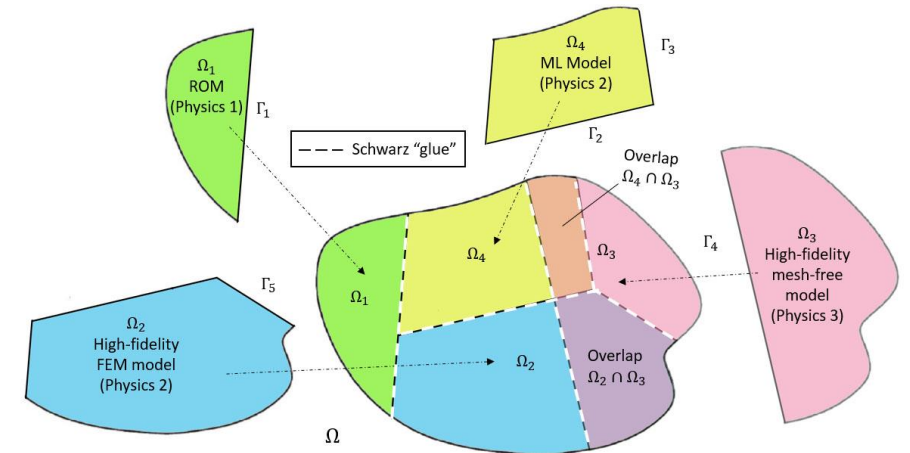
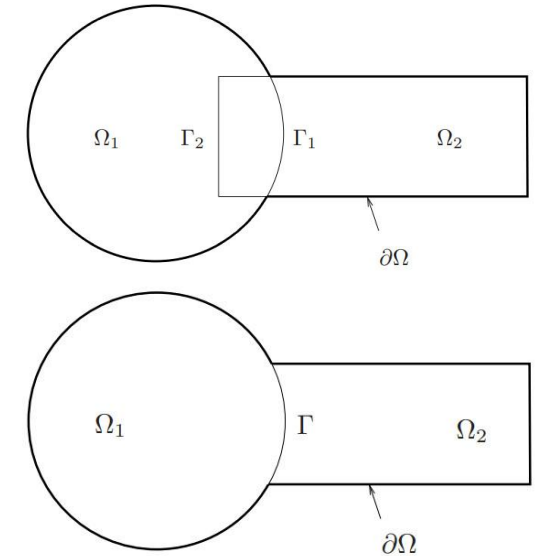


## Three coupling methods:

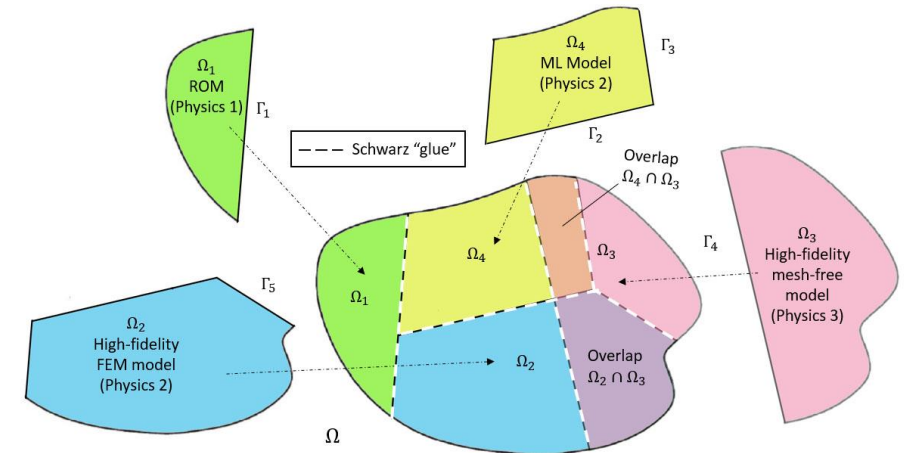
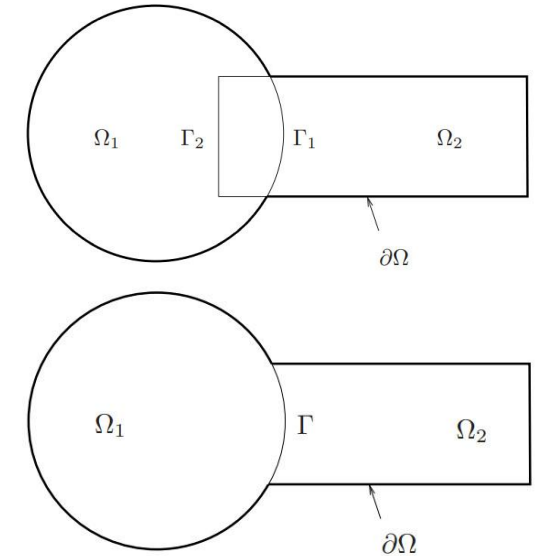
- Alternating Schwarz-based coupling *This talk.*
- Optimization-based coupling
- Coupling via generalized mortar methods



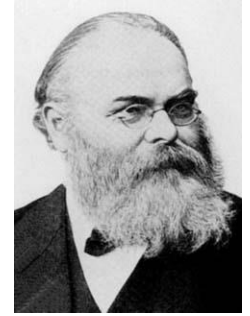
- The Schwarz Alternating Method for Domain Decomposition-Based Coupling
- Extension to FOM\*-ROM# and ROM-ROM Coupling
- Numerical Examples
  - 2D Shallow Water Equations (SWE)
  - 2D Burgers' Equations
  - 2D Euler Equations
- Ongoing/Future Work & Summary



- **The Schwarz Alternating Method for Domain Decomposition-Based Coupling**
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  - 2D Euler Equations
- Ongoing/Future Work & Summary



# 7 Schwarz Alternating Method for Domain Decomposition



H. Schwarz (1843-1921)



- Proposed in 1870 by H. Schwarz for solving Laplace PDE on irregular domains.

**Crux of Method:** if the solution is known in regularly shaped domains, use those as pieces to iteratively build a solution for the more complex domain.

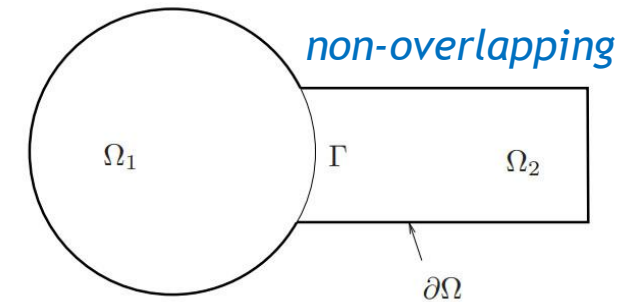
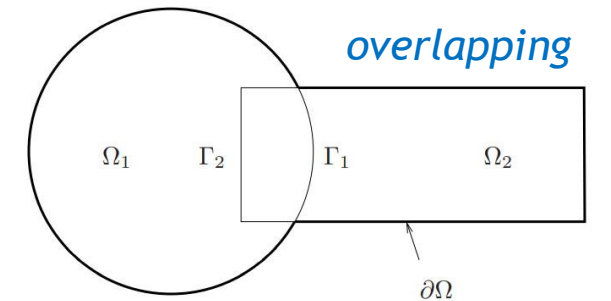
## Basic Schwarz Algorithm

### *Initialize:*

- Solve PDE by any method on  $\Omega_1$  w/ initial guess for transmission BCs on  $\Gamma_1$ .

### *Iterate until convergence:*

- Solve PDE by any method on  $\Omega_2$  w/ transmission BCs on  $\Gamma_2$  based on values just obtained for  $\Omega_1$ .
- Solve PDE by any method on  $\Omega_1$  w/ transmission BCs on  $\Gamma_1$  based on values just obtained for  $\Omega_2$ .

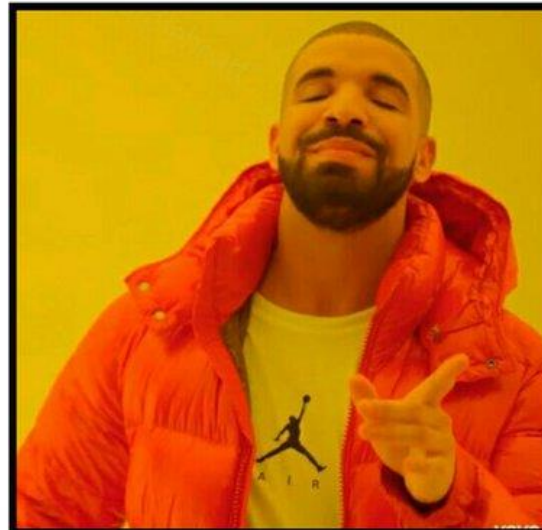


- Schwarz alternating method most commonly used as a **preconditioner** for Krylov iterative methods to solve linear algebraic equations.

**Idea behind this work:** using the Schwarz alternating method as a **discretization method** for solving multi-scale or multi-physics partial differential equations (PDEs).



**AS A *PRECONDITIONER***  
**FOR THE LINEARIZED**  
**SYSTEM**



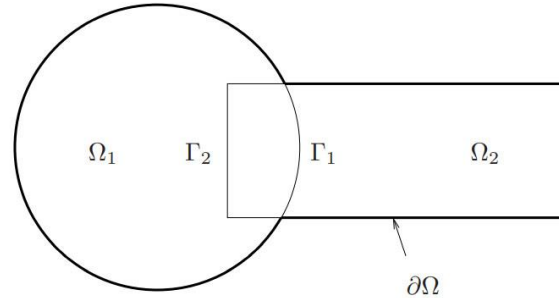
**AS A *SOLVER*** FOR THE  
**COUPLED**  
**FULLY NONLINEAR**  
**PROBLEM**



## Overlapping Domain Decomposition

$$\begin{cases} N(\mathbf{u}_1^{(n+1)}) = f, & \text{in } \Omega_1 \\ \mathbf{u}_1^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_1 \setminus \Gamma_1 \\ \mathbf{u}_1^{(n+1)} = \mathbf{u}_2^{(n)} & \text{on } \Gamma_1 \end{cases}$$

$$\begin{cases} N(\mathbf{u}_2^{(n+1)}) = f, & \text{in } \Omega_2 \\ \mathbf{u}_2^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_2 \setminus \Gamma_2 \\ \mathbf{u}_2^{(n+1)} = \mathbf{u}_1^{(n+1)} & \text{on } \Gamma_2 \end{cases}$$



$$\text{Model PDE: } \begin{cases} N(\mathbf{u}) = \mathbf{f}, & \text{in } \Omega \\ \mathbf{u} = \mathbf{g}, & \text{on } \partial\Omega \end{cases}$$

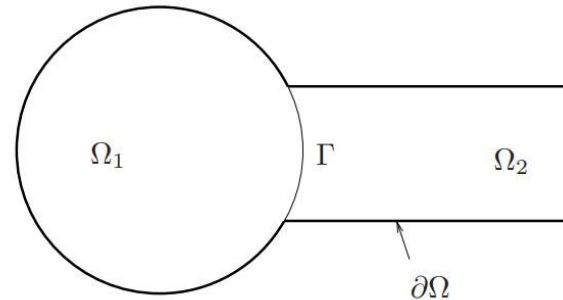
- Dirichlet-Dirichlet transmission BCs [Schwarz 1870; Lions 1988; Mota *et al.* 2017; Mota *et al.* 2022]

## Non-overlapping Domain Decomposition

$$\begin{cases} N(\mathbf{u}_1^{(n+1)}) = f, & \text{in } \Omega_1 \\ \mathbf{u}_1^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_1 \setminus \Gamma \\ \mathbf{u}_1^{(n+1)} = \lambda_{n+1}, & \text{on } \Gamma \end{cases}$$

$$\begin{cases} N(\mathbf{u}_2^{(n+1)}) = f, & \text{in } \Omega_2 \\ \mathbf{u}_2^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_2 \setminus \Gamma \\ \nabla \mathbf{u}_2^{(n+1)} \cdot \mathbf{n} = \nabla \mathbf{u}_1^{(n+1)} \cdot \mathbf{n}, & \text{on } \Gamma \end{cases}$$

$$\lambda_{n+1} = \theta \mathbf{u}_2^{(n)} + (1 - \theta) \lambda_n, \text{ on } \Gamma, \text{ for } n \geq 1$$



- Relevant for multi-material and multi-physics coupling
- Alternating Dirichlet-Neumann transmission BCs [Zanolli *et al.* 1987]
- Robin-Robin transmission BCs also lead to convergence [Lions 1990]
- $\theta \in [0,1]$ : relaxation parameter (can help convergence)

### Multiplicative Overlapping Schwarz

$$\begin{cases} N(\mathbf{u}_1^{(n+1)}) = f, & \text{in } \Omega_1 \\ \mathbf{u}_1^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_1 \setminus \Gamma_1 \\ \mathbf{u}_1^{(n+1)} = \mathbf{u}_2^{(n)} & \text{on } \Gamma_1 \end{cases}$$

$$\begin{cases} N(\mathbf{u}_2^{(n+1)}) = f, & \text{in } \Omega_2 \\ \mathbf{u}_2^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_2 \setminus \Gamma_2 \\ \mathbf{u}_2^{(n+1)} = \mathbf{u}_1^{(n+1)} & \text{on } \Gamma_2 \end{cases}$$

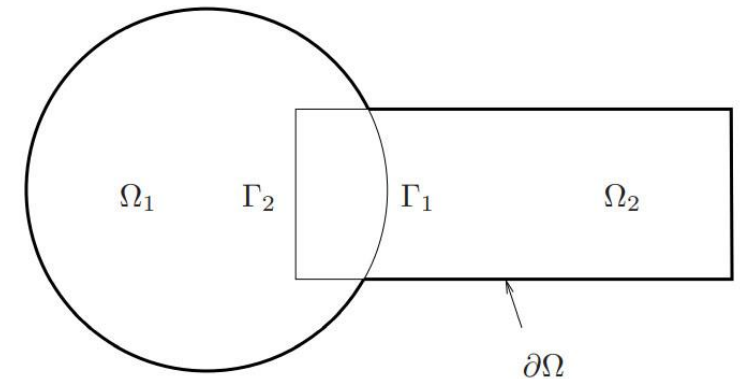
### Additive Overlapping Schwarz

$$\begin{cases} N(\mathbf{u}_1^{(n+1)}) = f, & \text{in } \Omega_1 \\ \mathbf{u}_1^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_1 \setminus \Gamma_1 \\ \mathbf{u}_1^{(n+1)} = \mathbf{u}_2^{(n)} & \text{on } \Gamma_1 \end{cases}$$

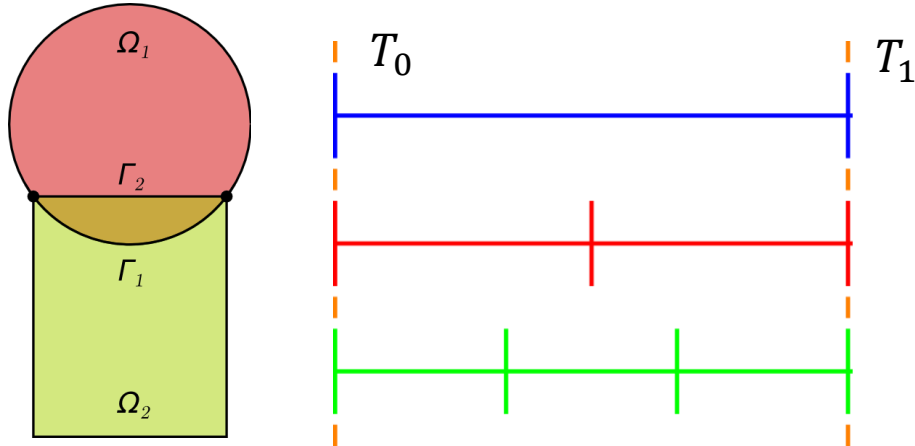
$$\begin{cases} N(\mathbf{u}_2^{(n+1)}) = f, & \text{in } \Omega_2 \\ \mathbf{u}_2^{(n+1)} = \mathbf{g}, & \text{on } \partial\Omega_2 \setminus \Gamma_2 \\ \mathbf{u}_2^{(n+1)} = \mathbf{u}_1^{(n)} & \text{on } \Gamma_2 \end{cases}$$

*Model PDE:*

$$\begin{cases} N(\mathbf{u}) = f, & \text{in } \Omega \\ \mathbf{u} = \mathbf{g}, & \text{on } \partial\Omega \end{cases}$$



- **Multiplicative Schwarz:** solves subdomain problems **sequentially** (in serial)
- **Additive Schwarz:** advance subdomains in **parallel**, communicate boundary condition data later
  - Typically requires a few more **Schwarz iterations**, but does not degrade **accuracy**
  - **Parallelism** helps balance additional **cost** due to Schwarz iterations
  - Applicable to both **overlapping** and **non-overlapping** Schwarz



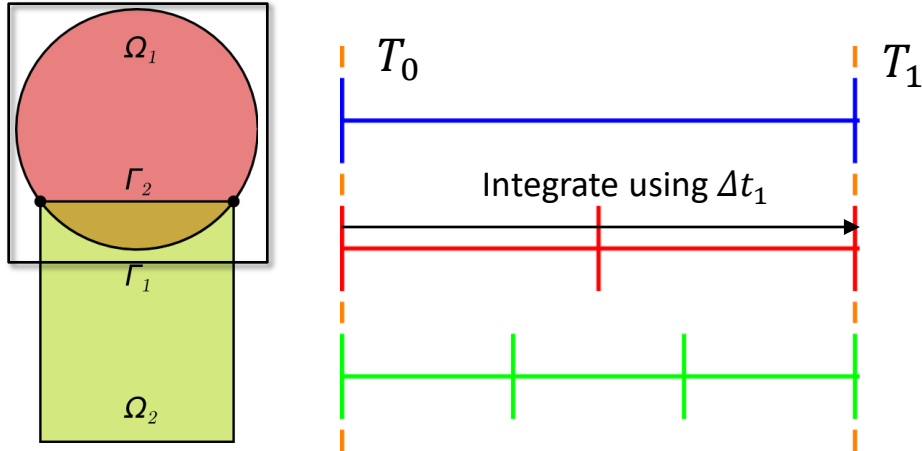
Controller time stepper

Time integrator for  $\Omega_1$

Time integrator for  $\Omega_2$

**Step 0:** Initialize  $i = 0$  (controller time index).

$$\text{Model PDE: } \begin{cases} \dot{\mathbf{u}} + N(\mathbf{u}) = \mathbf{f}, & \text{in } \Omega \\ \mathbf{u}(\mathbf{x}, t) = \mathbf{g}(t), & \text{on } \partial\Omega \\ \mathbf{u}(\mathbf{x}, 0) = \mathbf{u}_0, & \text{in } \Omega \end{cases}$$



Controller time stepper

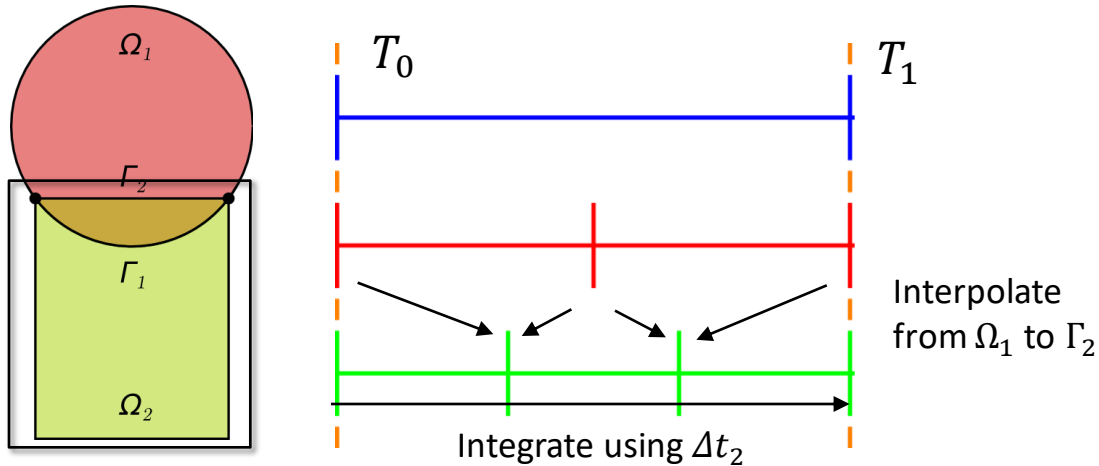
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Controller time stepper

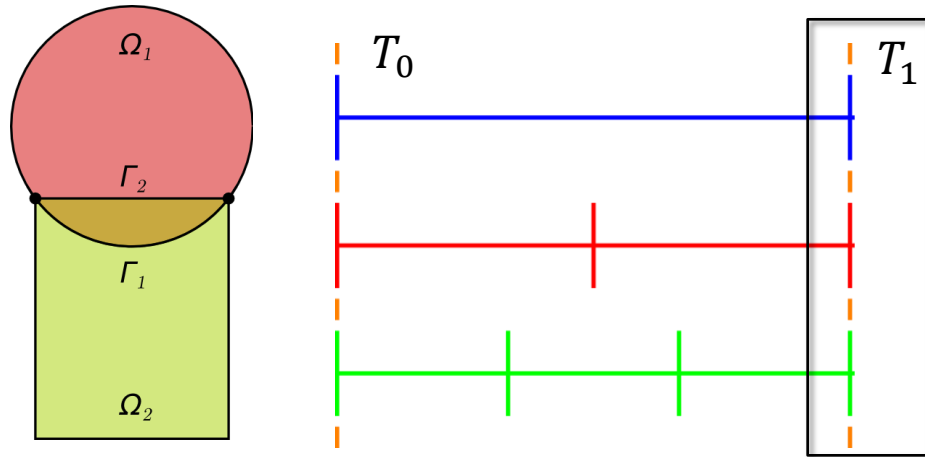
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Controller time stepper

Time integrator for  $\Omega_1$ Time integrator for  $\Omega_2$ 

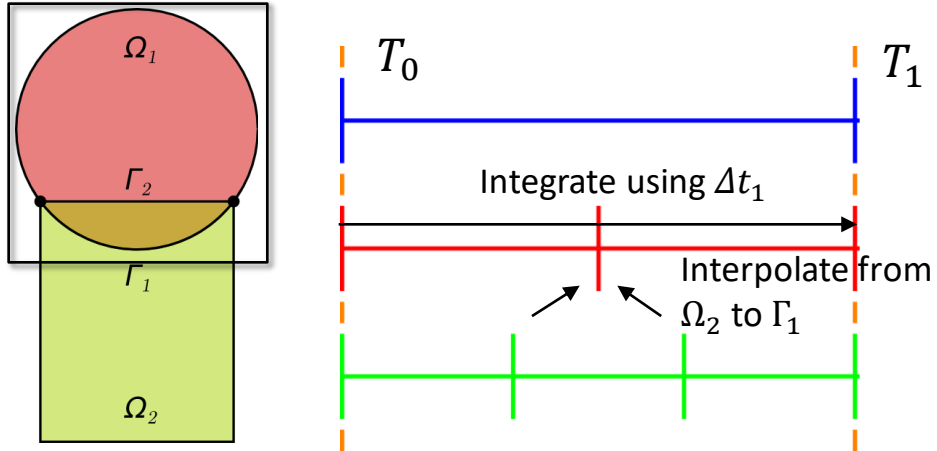
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Controller time stepper

Time integrator for  $\Omega_1$ Time integrator for  $\Omega_2$ 

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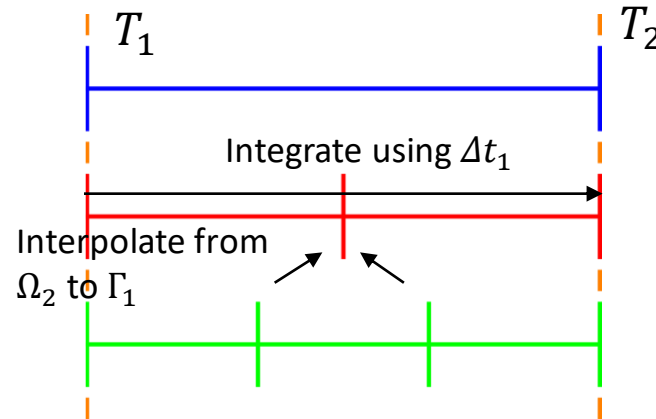
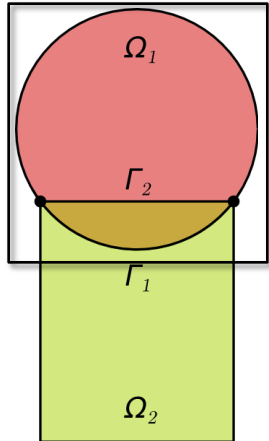
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**Step 3:** Check for convergence at time  $T_{i+1}$ .

➤ If unconverted, return to Step 1.

$$\text{Model PDE: } \begin{cases} \dot{\mathbf{u}} + N(\mathbf{u}) = \mathbf{f}, & \text{in } \Omega \\ \mathbf{u}(\mathbf{x}, t) = \mathbf{g}(t), & \text{on } \partial\Omega \\ \mathbf{u}(\mathbf{x}, 0) = \mathbf{u}_0, & \text{in } \Omega \end{cases}$$



Controller time stepper

Time integrator for  $\Omega_1$

Time integrator for  $\Omega_2$

Can use *different integrators* with *different time steps* within each domain!

**Step 0:** Initialize  $i = 0$  (controller time index).

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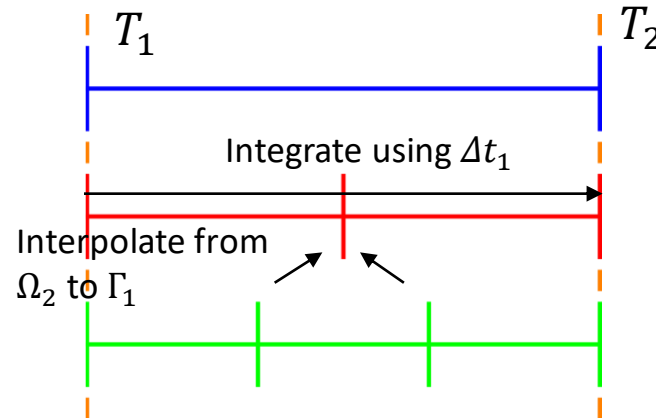
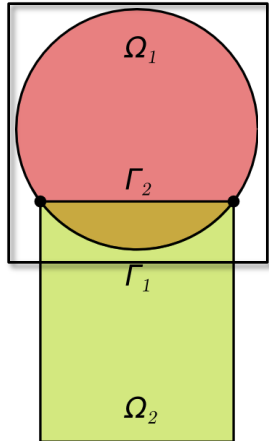
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- If unconverged, return to Step 1.
- If converged, set  $i = i + 1$  and return to Step 1.

$$\text{Model PDE: } \begin{cases} \dot{\mathbf{u}} + N(\mathbf{u}) = \mathbf{f}, & \text{in } \Omega \\ \mathbf{u}(x, t) = \mathbf{g}(t), & \text{on } \partial\Omega \\ \mathbf{u}(x, 0) = \mathbf{u}_0, & \text{in } \Omega \end{cases}$$





Controller time stepper

Time integrator for  $\Omega_1$ Time integrator for  $\Omega_2$ 

Time-stepping procedure is **equivalent** to doing Schwarz on **space-time domain** [Mota *et al.* 2022].

**Step 0:** Initialize  $i = 0$  (controller time index).

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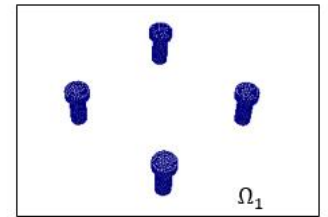
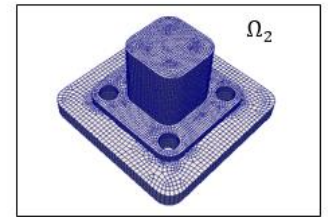
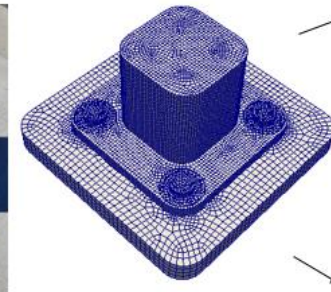


### Model Solid Mechanics PDEs:

$$\text{Quasistatic: } \text{Div } \mathbf{P} + \rho_0 \mathbf{B} = \mathbf{0} \quad \text{in } \Omega$$

$$\text{Dynamic: } \text{Div } \mathbf{P} + \rho_0 \mathbf{B} = \rho_0 \ddot{\varphi} \quad \text{in } \Omega \times I$$

- Coupling is *concurrent* (two-way).
- *Ease of implementation* into existing massively-parallel HPC codes.
- *Scalable, fast, robust* (we target *real* engineering problems, e.g., analyses involving failure of bolted components!).
- Coupling does not introduce *nonphysical artifacts*.
- *Theoretical* convergence properties/guarantees<sup>1</sup>.
- “*Plug-and-play*” framework:
  - Ability to couple regions with *different non-conformal meshes*, *different element types* and *different levels of refinement* to simplify task of *meshing complex geometries*.
  - Ability to use *different solvers/time-integrators* in different regions.



 Albany-LCM<sup>2</sup>



<sup>1</sup> Mota *et al.* 2017; Mota *et al.* 2022. <sup>2</sup> <https://github.com/sandialabs/LCM>.

# Schwarz for Multiscale FOM-FOM Coupling in Solid Mechanics<sup>1</sup>

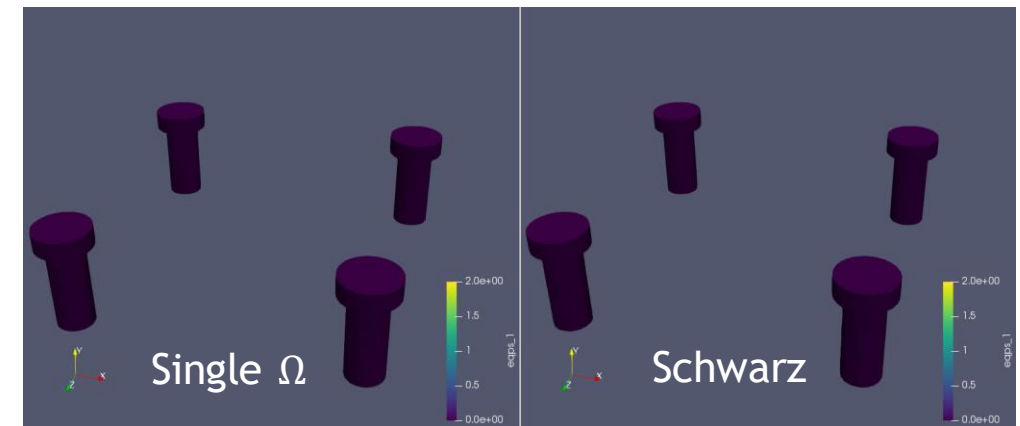
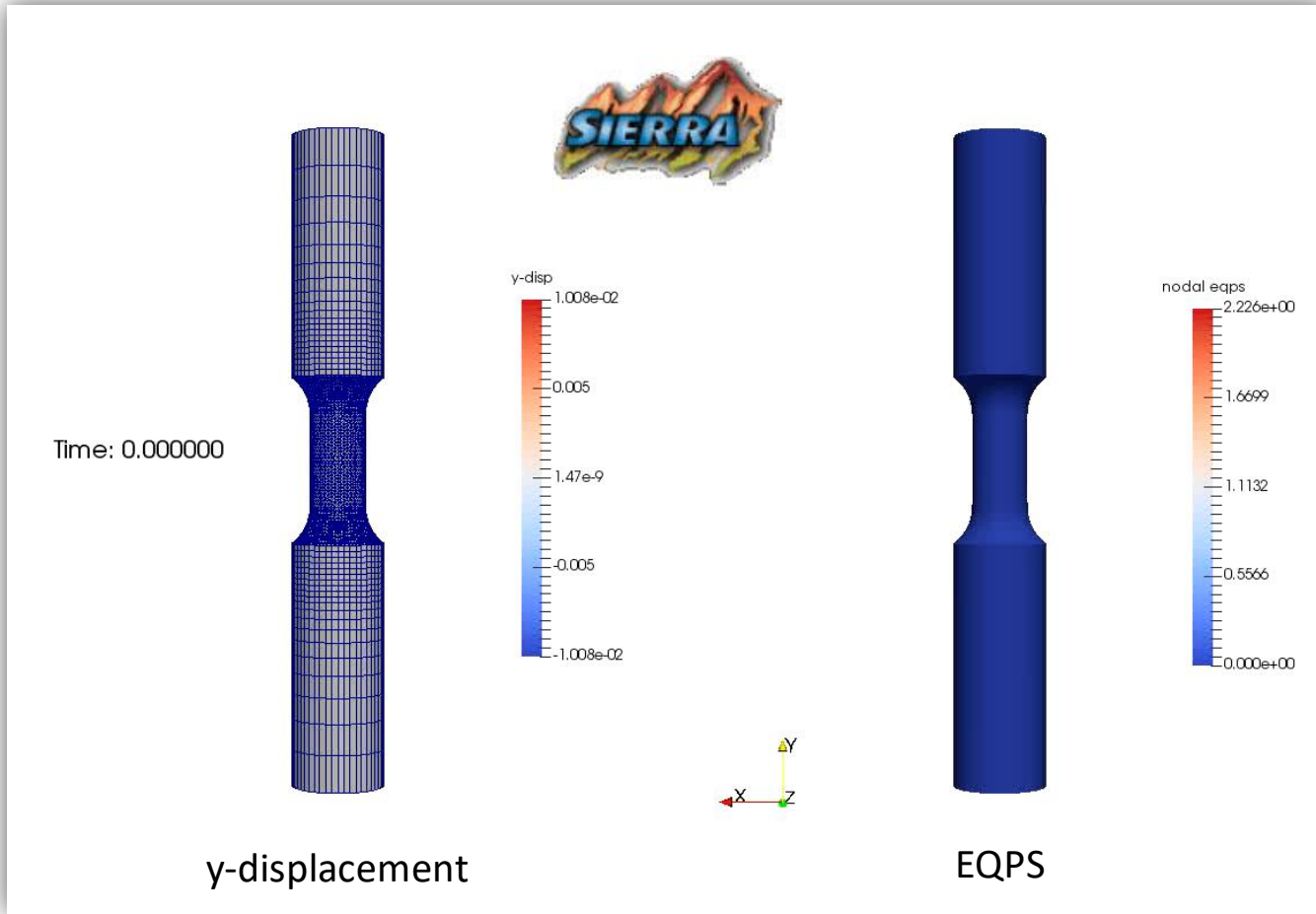
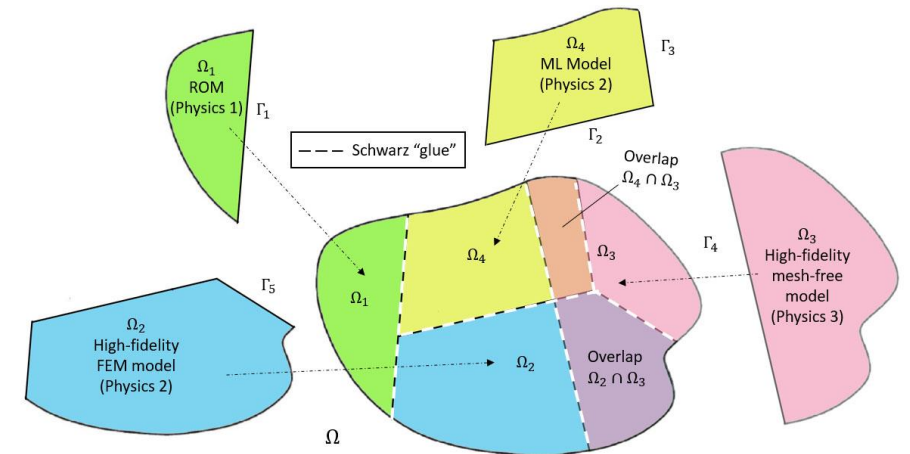
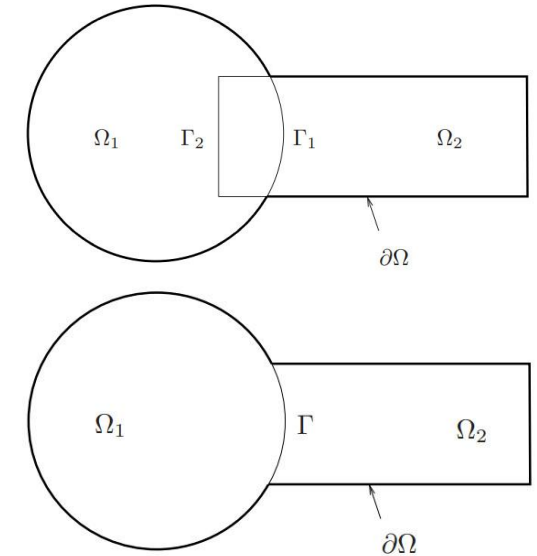


Figure above: tension specimen simulation coupling composite TET10 elements with HEX elements in Sierra/SM.

Figures right: bolted joint simulation coupling composite TET10 elements with HEX elements in Sierra/SM.

<sup>1</sup> Mota *et al.* 2017; Mota *et al.* 2022.

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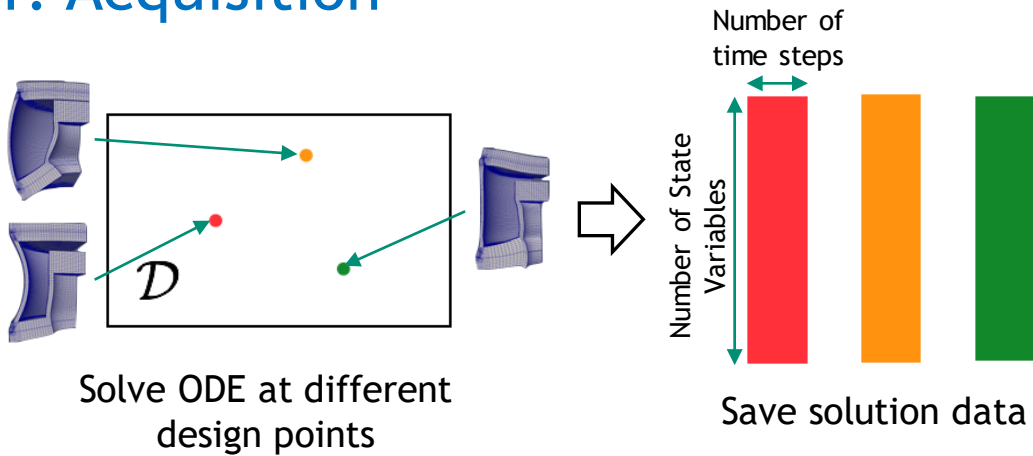
# Projection-Based Model Order Reduction via the POD/LSPG\* Method



Full Order Model (FOM):  $\frac{du}{dt} = f(\mathbf{u}; t, \boldsymbol{\mu})$

\* Least-Squares Petrov-Galerkin

## 1. Acquisition



## 2. Learning

Proper Orthogonal Decomposition (POD):

$$\mathbf{X} = \begin{bmatrix} \text{red} \\ \text{orange} \\ \text{green} \end{bmatrix} = \boldsymbol{\Phi} \mathbf{U} \quad \Sigma \quad \mathbf{V}^T$$

ROM = projection-based Reduced Order Model

## 3. Projection-Based Reduction

Choose ODE temporal discretization

$$\frac{du}{dt} = f(\mathbf{u}; t, \boldsymbol{\mu})$$

$$\Downarrow$$

$$\mathbf{r}^n(\mathbf{u}^n; \boldsymbol{\mu}) = \mathbf{0}, \quad n = 1, \dots, T$$

Reduce the number of unknowns

$$\mathbf{u}(t) \approx \tilde{\mathbf{u}}(t) = \boldsymbol{\Phi} \hat{\mathbf{u}}(t)$$

Minimize residual

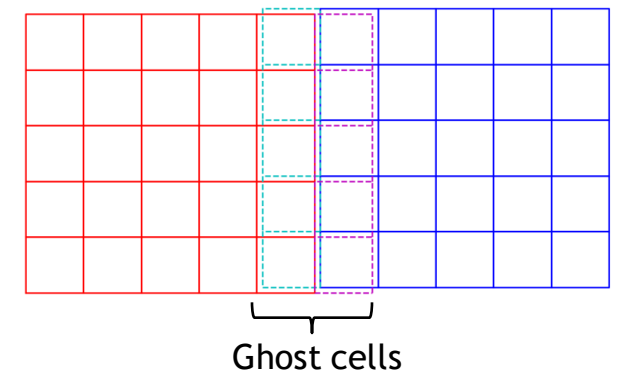
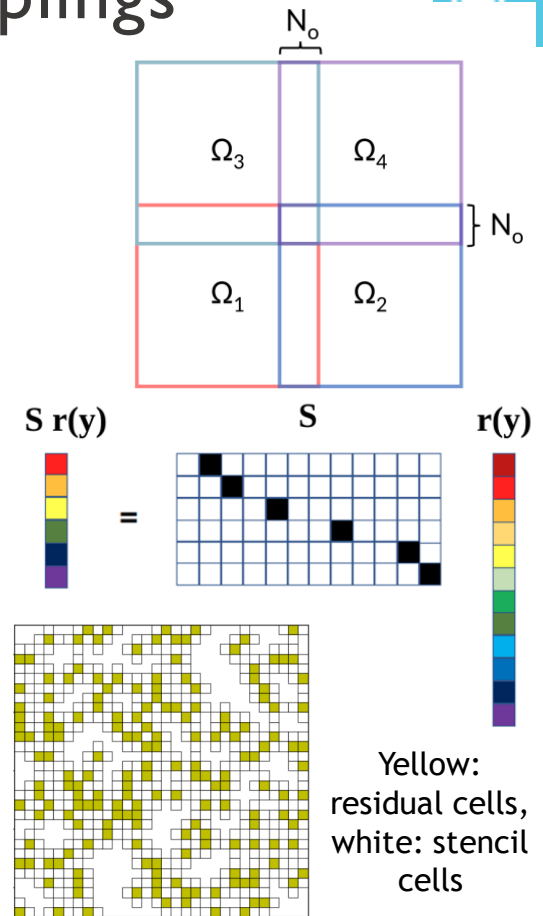
$$\underset{\hat{\mathbf{v}}}{\text{minimize}} \left\| \begin{bmatrix} \mathbf{S} \\ \mathbf{r}^n(\boldsymbol{\Phi} \hat{\mathbf{v}}; \boldsymbol{\mu}) \end{bmatrix} \right\|_2$$

Hyper-reduction/sample mesh

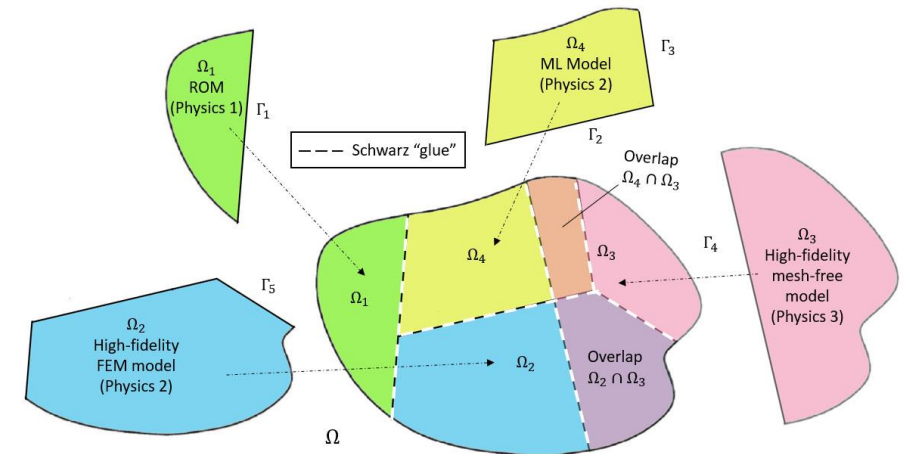
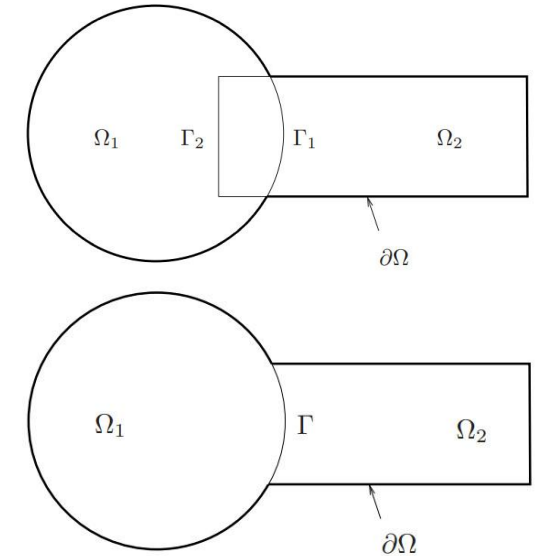
HROM = Hyper-reduced ROM

# Schwarz Extensions to FOM-ROM and ROM-ROM Couplings

- Perform **FOM** simulation on a spatial domain  $\Omega$  and **collect  $s$  snapshots**
- Create **domain decomposition** of  $\Omega$  into  $d$  **overlapping or non-overlapping subdomains**  $\Omega_i$  with  $N_o$  overlap cells (could be 0).
- Compute **POD basis**  $\Phi_i$  on each  $\Omega_i$  by restricting the snapshots to  $\Omega_i$ .
- For nonlinear problems, compute **sample mesh**  $S_i$  on each  $\Omega_i$ .
  - **Collocation**: minimize the residual at a small subset of DOFs  $N_s \ll N$ .
  - **Key question: how to sample Schwarz boundaries given fixed budget of sample mesh points?**
- **Construct POD/LSPG ROM** in each subdomain  $\Omega_i$ , **transmit Schwarz BCs**, apply Schwarz iteration procedure.
  - **Key question: how to impose Schwarz BCs in ROMs?**
    - ❖ BCs imposed **approximately** by **fictitious ghost cells**, as FOMs are based on cell-centered finite volume (CCFV) discretizations
  - To maximize efficiency, we employ **additive Schwarz** with OpenMPI parallelism (1 thread/subdomain)

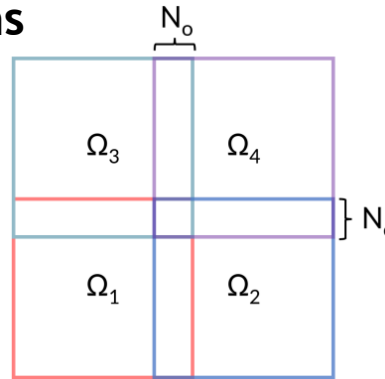
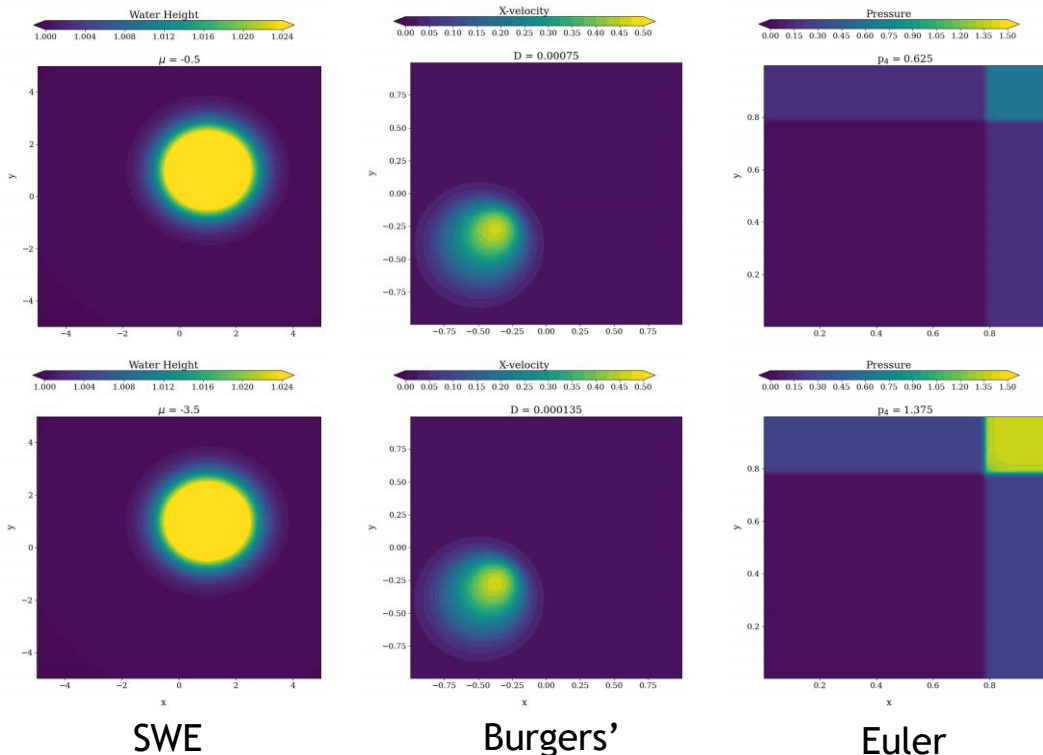


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# 3 Parametrized Hyperbolic Conservation Law Test Cases

- Nonlinear hyperbolic fluid systems in Pressio/Pressio demo-apps\*
  - 2D shallow water equations (SWE), vary Coriolis parameter ( $\mu$ )
  - 2D viscous Burgers' equations, vary diffusion parameter ( $D$ )
  - 2D Euler equations, vary upper right pressure ( $p_4$ ) in IC
- Wave/shock propagation across interfaces  $\Rightarrow$  high Kolmogorov  $n$ -width
- FOM discretization: first-order CCFV method, 300x300 mesh, BDF1
- Consider decompositions of  $\Omega$  into four subdomains



**All results  
predictive: 5  
training points, 4  
(interpolative)  
testing points**

**SWE**

$$\frac{\partial h}{\partial t} + \frac{\partial hu}{\partial x} + \frac{\partial hv}{\partial y} = 0$$

$$\frac{\partial(hu)}{\partial t} + \frac{\partial}{\partial x} \left( hu^2 + \frac{1}{2}gh^2 \right) + \frac{\partial(huv)}{\partial y} = -\mu v$$

$$\frac{\partial(hv)}{\partial t} + \frac{\partial(hvu)}{\partial x} + \frac{\partial}{\partial y} \left( hv^2 + \frac{1}{2}gh^2 \right) = \mu u$$

**Burgers'**

$$\frac{\partial u}{\partial t} + \frac{1}{2} \left( \frac{\partial u^2}{\partial x} + \frac{\partial uv}{\partial y} \right) = D \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right)$$

$$\frac{\partial v}{\partial t} + \frac{1}{2} \left( \frac{\partial uv}{\partial x} + \frac{\partial v^2}{\partial y} \right) = D \left( \frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \right)$$

**Euler**

$$\frac{\partial \rho}{\partial t} + \frac{\partial \rho u}{\partial x} + \frac{\partial \rho v}{\partial y} = 0$$

$$\frac{\partial(\rho u)}{\partial t} + \frac{\partial}{\partial x} (\rho u^2 + p) + \frac{\partial(\rho uv)}{\partial y} = 0$$

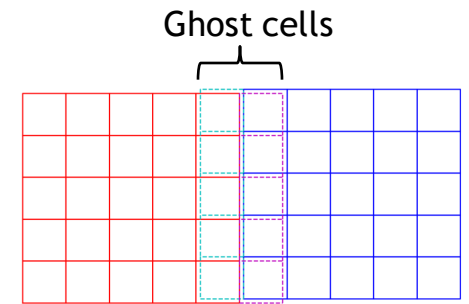
$$\frac{\partial(\rho v)}{\partial t} + \frac{\partial(\rho vu)}{\partial x} + \frac{\partial}{\partial y} (\rho v^2 + p) = 0$$

$$\frac{\partial(\rho E)}{\partial t} + \frac{\partial}{\partial x} ((E + p)u) + \frac{\partial}{\partial y} ((E + p)v) = 0$$

\* <https://pressio.github.io>,  
<https://github.com/cwentland0/pressio-demoapps-schwarz>

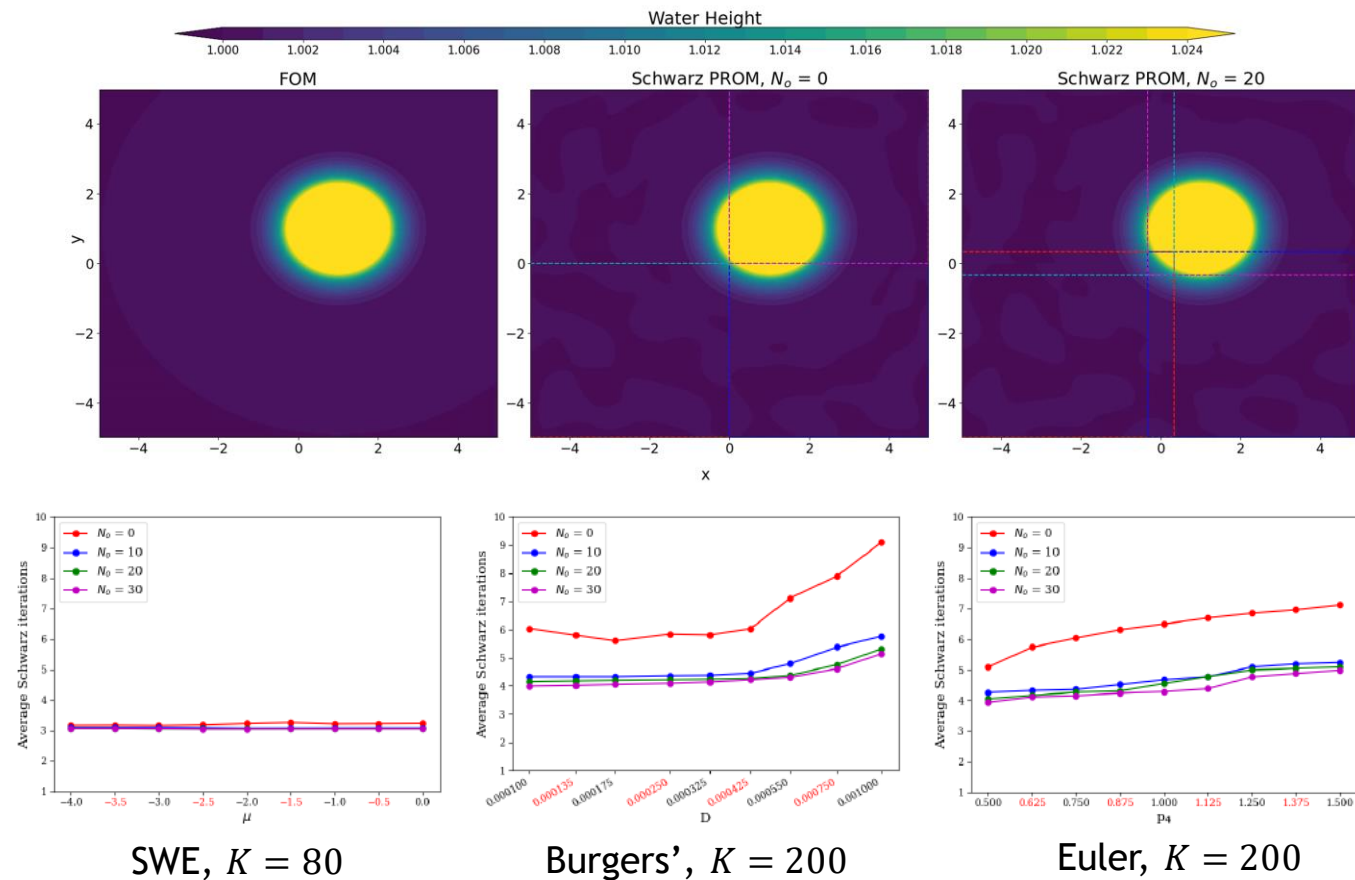


# Unsampled ROMs: Impact of Subdomain Overlap



**Key result: non-overlapping Schwarz iteration converges without a degradation in accuracy when using Dirichlet-Dirichlet Schwarz BCs!**

- This result is **not true** in general [Barnett et al., 2022; Mota et al., 2017; Mota et al. 2022]!
  - Generally need **alternating Dirichlet-Neumann** or **Robin-Robin BCs** for non-overlapping Schwarz convergence.
  - Dirichlet-Dirichlet works here due to **implied overlap** introduced into otherwise non-overlapping DD by ghost cells.
- More Schwarz iterations** are required for convergence with no overlap (as expected)
- Non-overlapping incurs **negligible convergence penalty** for smooth problems (SWE)
- Non-overlapping Schwarz **avoids duplicate calculations** in overlap region
- It becomes **more difficult to transmit shock** across non-overlapping interface (Burgers, Euler)

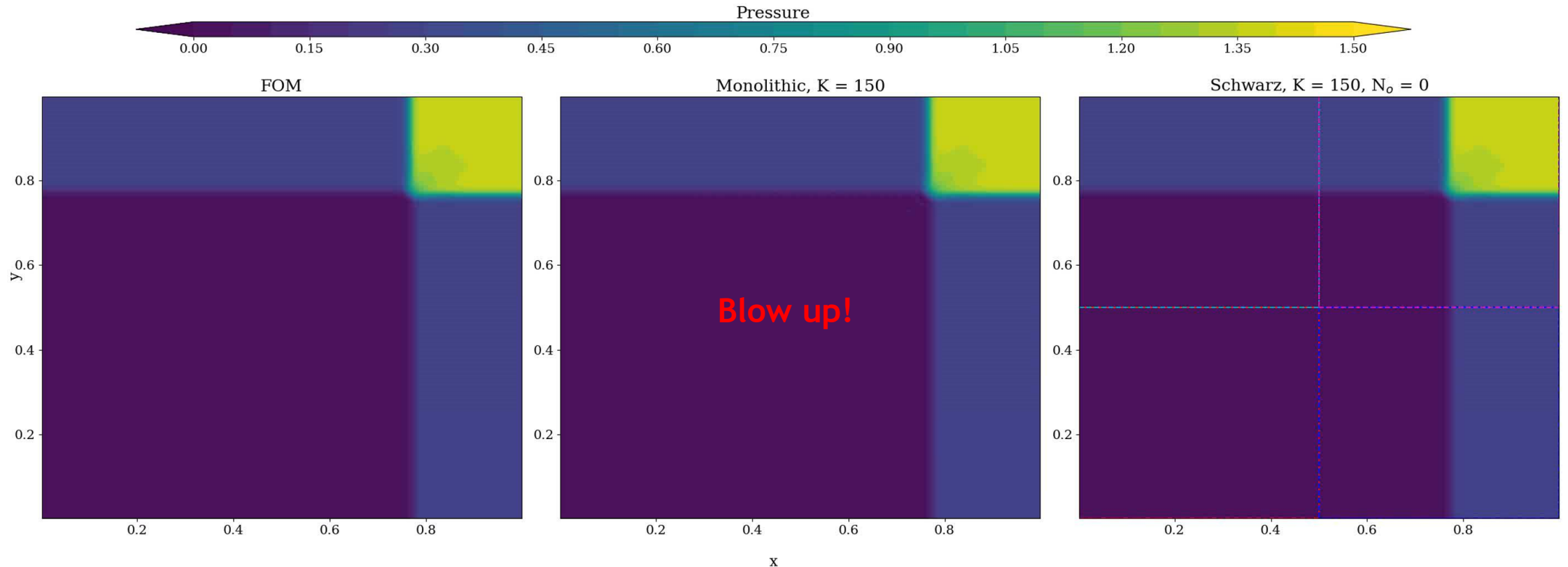


Red parameter values are predictive.

# Unsampled ROMs: Stabilization Effects



**Key result: domain decomposition + Schwarz coupling can stabilize an otherwise unstable monolithic solution**

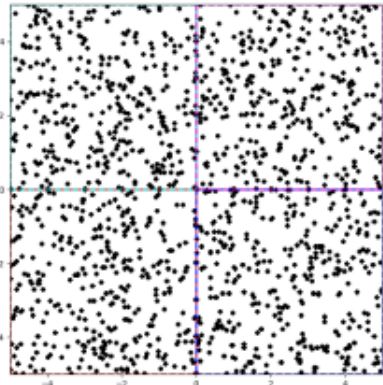


*Movie above: monolithic vs. decomposed ROM for Euler problem with  $p_4 = 1.375$  (predictive regime).*

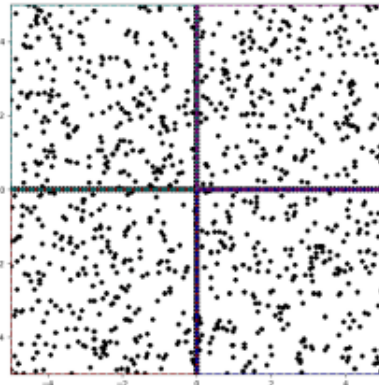
# Hyper-reduced ROMs: Impact of Boundary Sampling



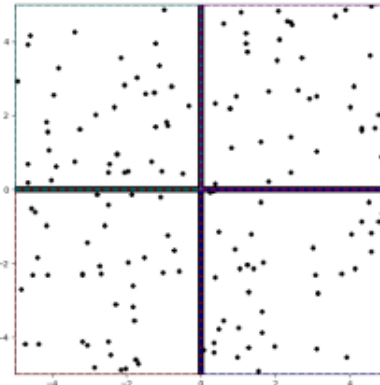
**Key result:** given a fixed “budget” of sample mesh points, there is a (problem-dependent) optimal number of sample mesh points to allocate to the Schwarz boundaries vs. the subdomain interiors.



$N_d = 30$



$N_d = 3$



$N_d = 1$

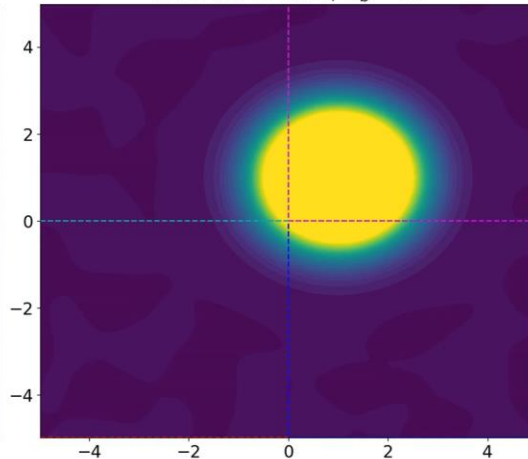
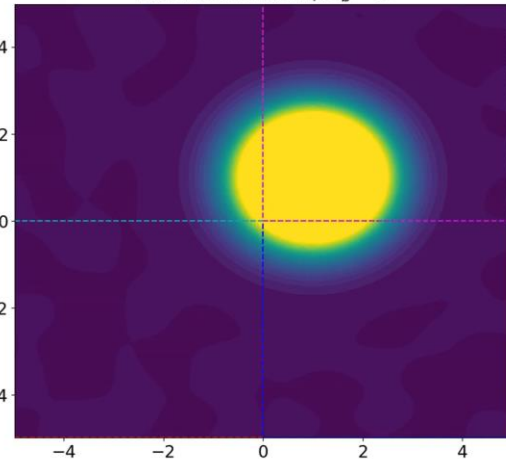
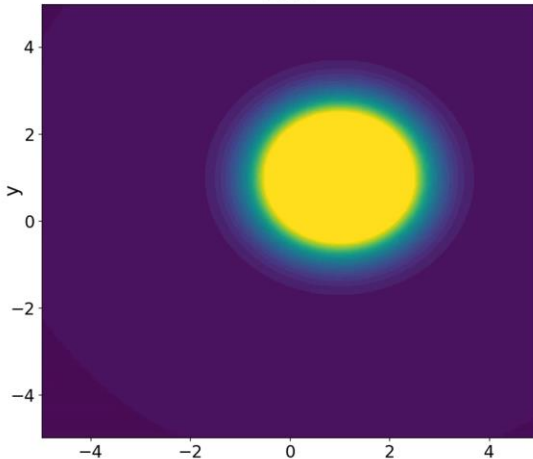
- $N_d =$  fixed interval at which Schwarz boundaries are sampled
- For a fixed budget of sample mesh points  $N_S$ , boundary points draw points away from interior (figure left)
- Failure to deliberately sample the Schwarz boundary will also always lead to instabilities (movie left)



FOM

Schwarz HPROM,  $N_b = 5$

Schwarz HPROM,  $N_b = 10$

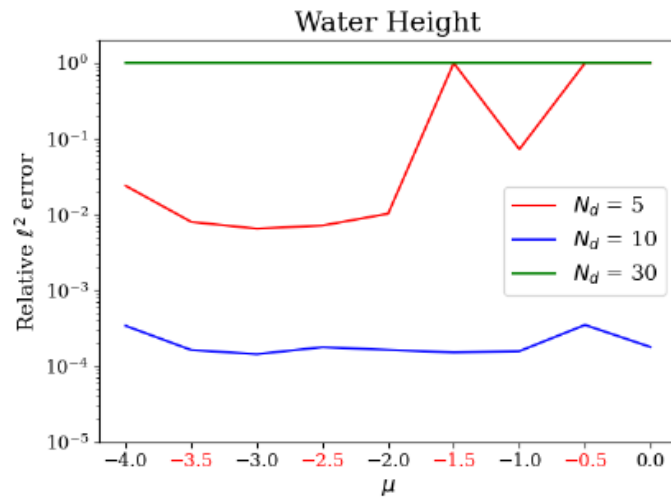


# Hyper-reduced ROMs: Impact of Boundary Sampling

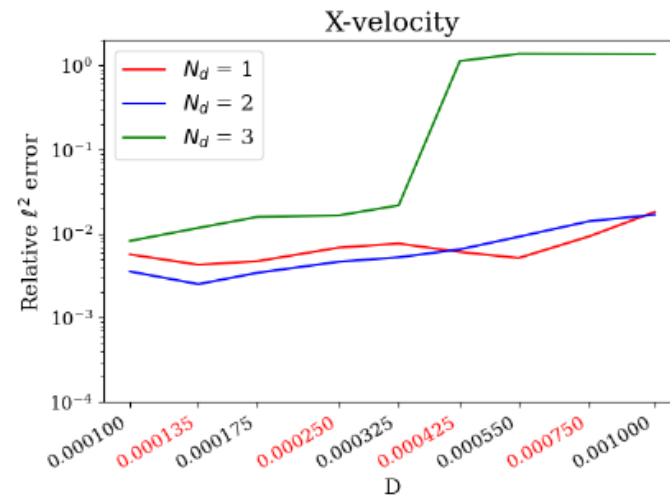


**Key result:** given a fixed “budget” of sample mesh points, there is a (problem-dependent) optimal number of sample mesh points to allocate to the Schwarz boundaries vs. the subdomain interiors.

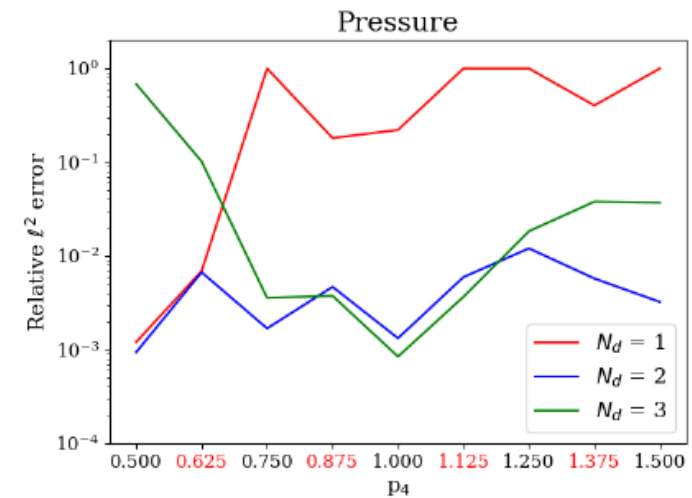
- There is a delicate balance of ensuring BC transmission together with an accurate interior solutions
- More extensive boundary sampling is required for problems with shocks (Burgers, Euler)



SWE,  $N_S = 0.5\%N$



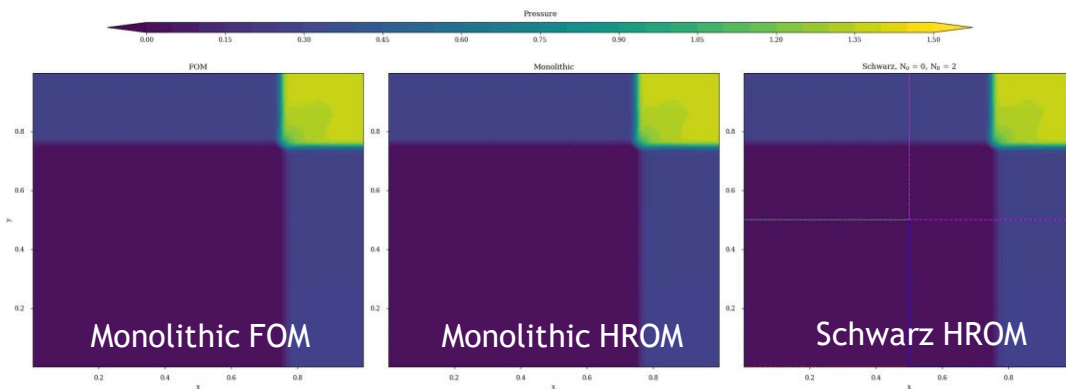
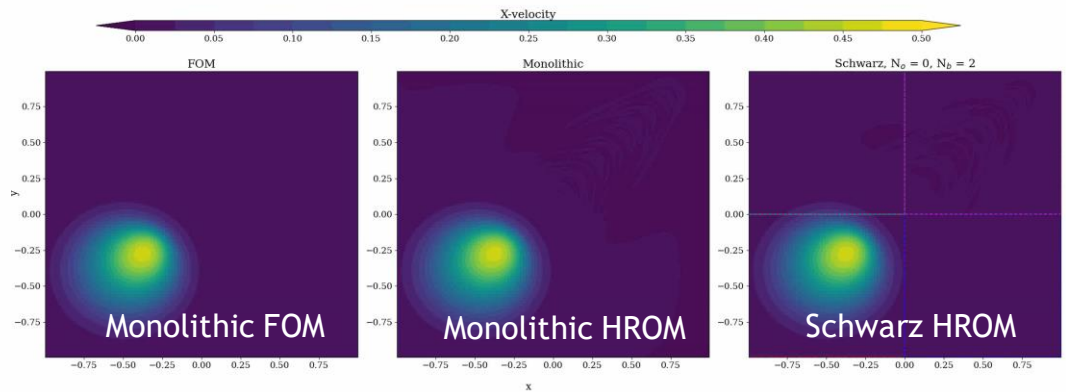
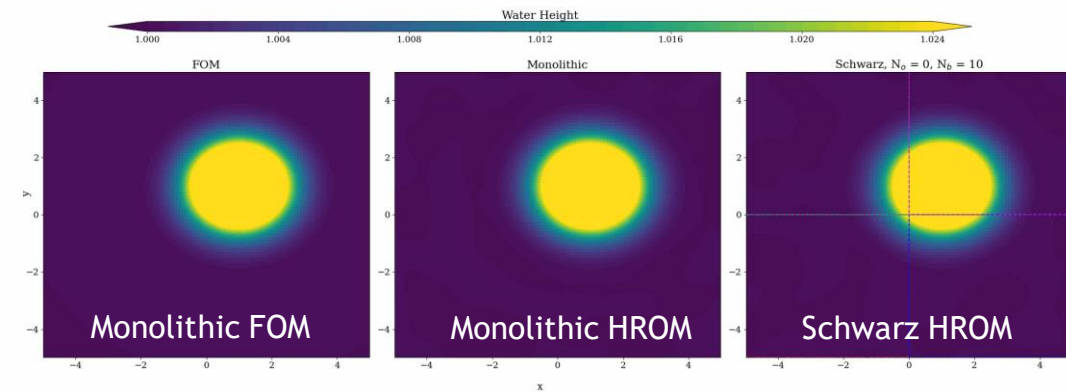
Burgers',  $N_S = 3.75\%N$



Euler,  $N_S = 5\%N$

Red parameter values are predictive.

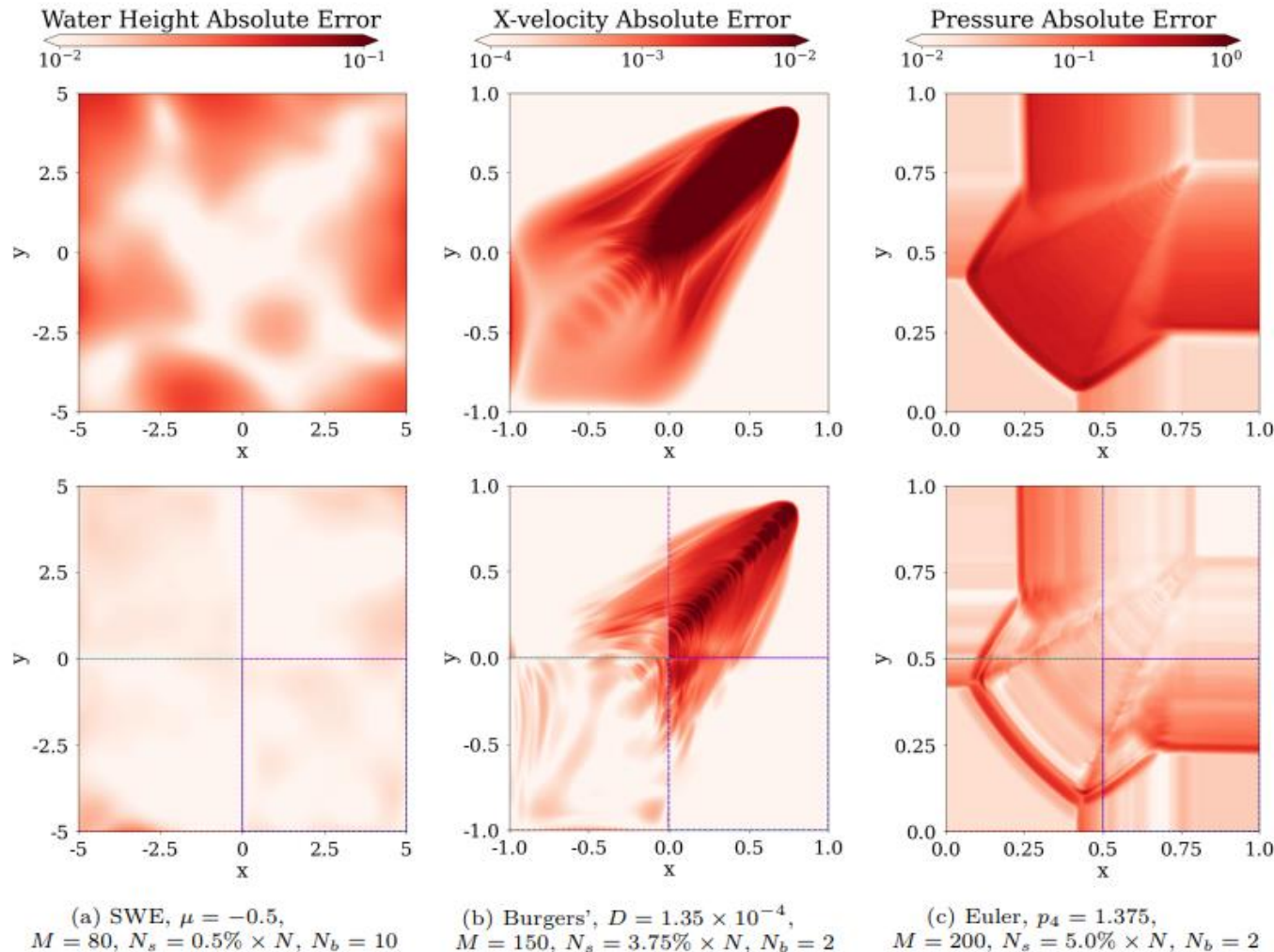
# Hyper-reduced ROMs: Accuracy



**Key result:** predictive hyper-reduced ROMs (HROMs) with non-overlapping Dirichlet-Dirichlet Schwarz coupling are indistinguishable from corresponding monolithic ROMs/FOMs.

*Top row: SWE*  
*Middle row: Burgers'*  
*Bottom row: Euler*

**Key result:** Decomposed ROMs achieve **lower error** for the same trial basis size  $K$  and have **no artifacts** at Schwarz boundaries.



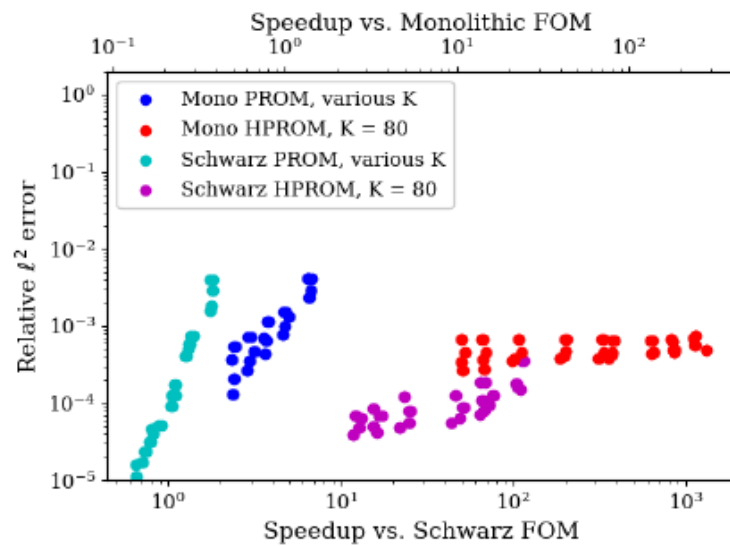
*Left figure:* average absolute spatial error fields for representative monolithic (top) and decomposed (bottom) hyper-reduced ROM with no overlap. Subdomain interfaces are marked with dashed lines.

# Hyper-reduced ROMs: Computational Cost

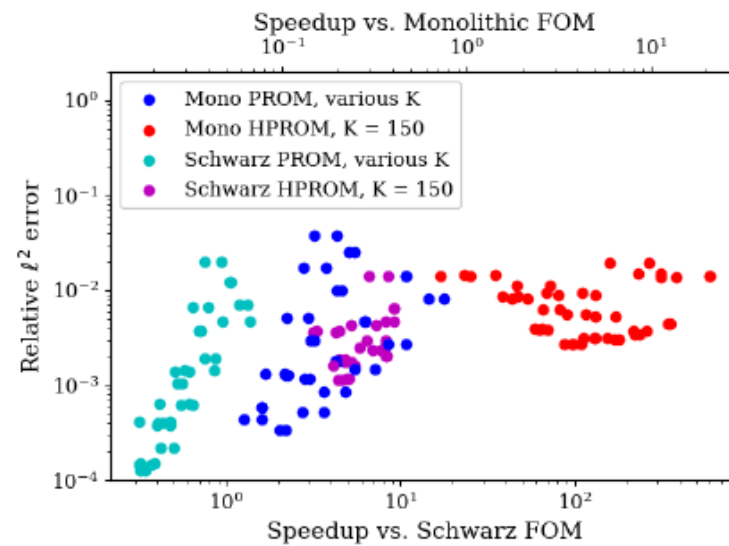


**Key result:** additive Schwarz enables speed-ups over corresponding coupled Schwarz FOM and sometimes over monolithic FOM.

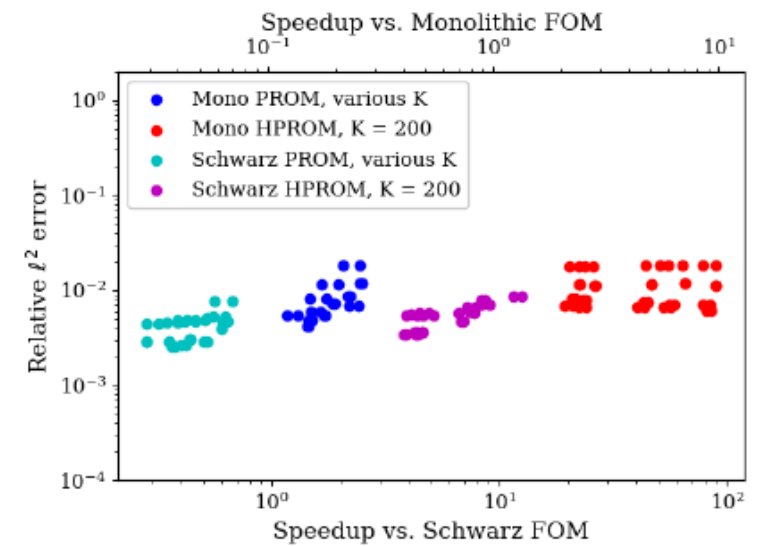
- Hyper-reduced ROMs generally achieve cost savings w.r.t. corresponding coupled Schwarz FOM
- **Cost savings using Schwarz ROMs over corresponding monolithic FOM are possible for SWE problem**
  - **Coupled Schwarz FOMs are often only viable options for Sandia analysts due to meshing challenges**
  - **Next step: try to improve this via adaptive Schwarz ROMs**



SWE



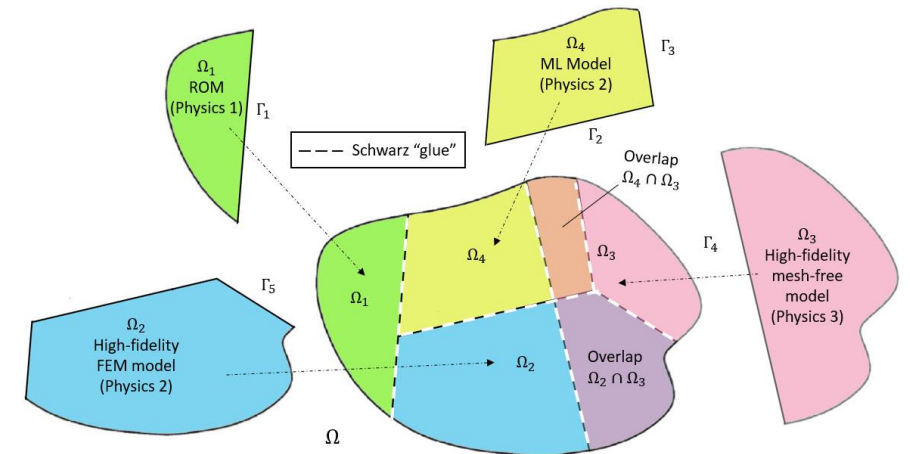
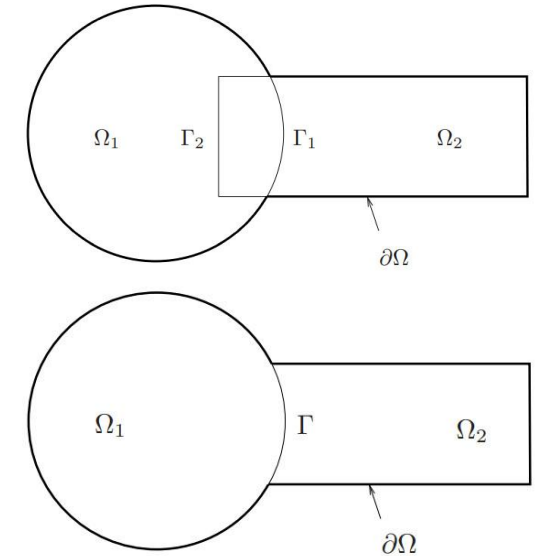
Burgers'



Euler

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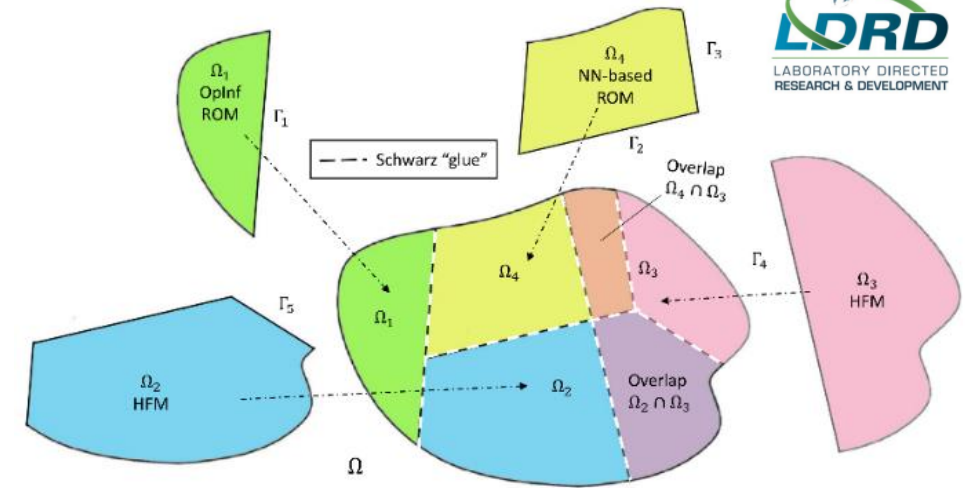
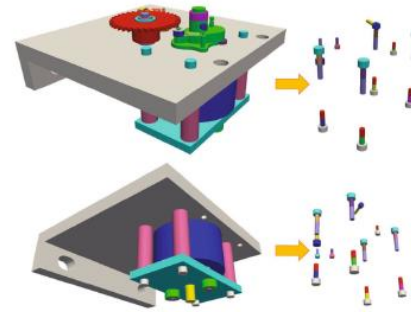


# New Project: Adaptive Hybrid modElS via domAin Decomposition (AHEAD)

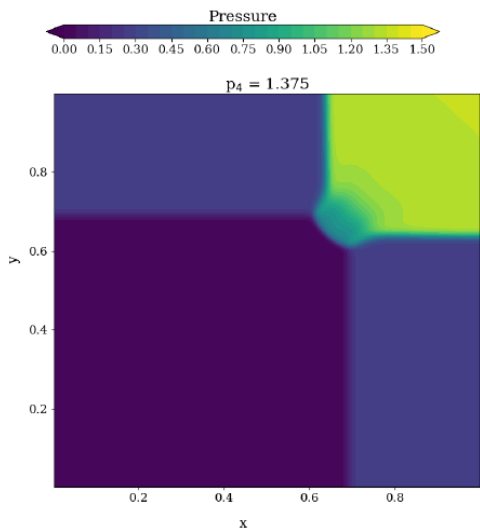


## Goals (for solid mechanics exemplars):

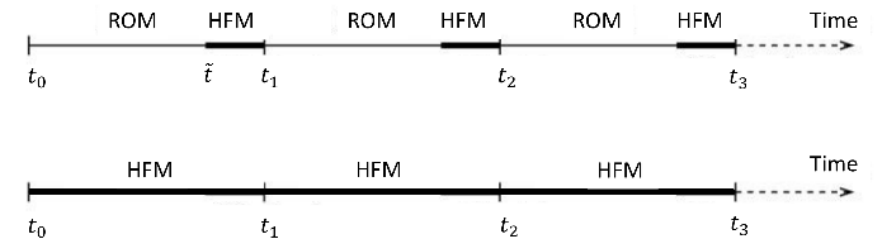
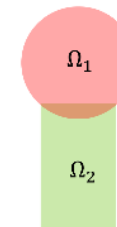
- Simplify meshing via Schwarz + DD
- Extend Schwarz to non-intrusive ROMs (Operator Inference, NN)
- Development of automated criteria to determine appropriate use of less refined or reduced-order models without sacrificing accuracy, enabling real-time transitions between different model fidelities



Example sample DD and ROM/HFM assignment.



ROM	FOM
ROM	ROM



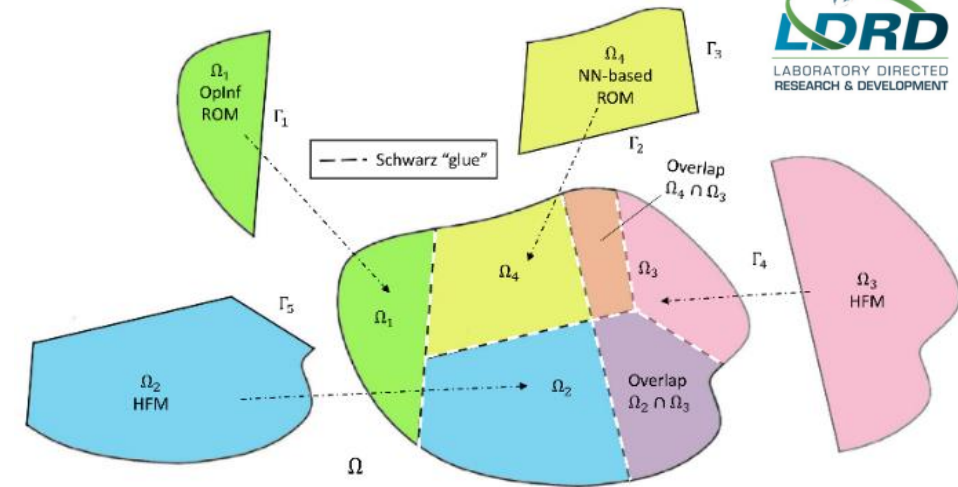
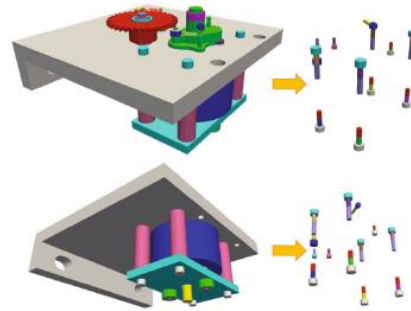
On-the-fly model switching in our DD workflow.

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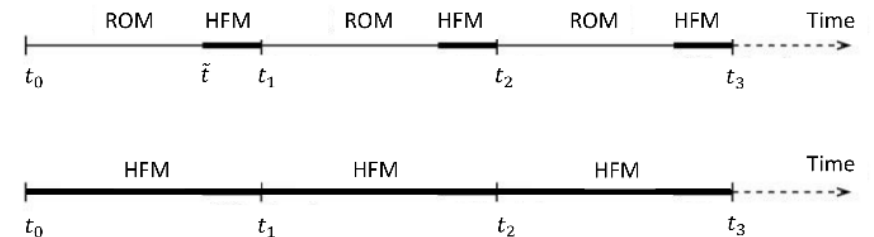
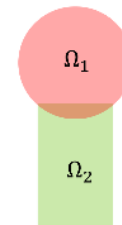
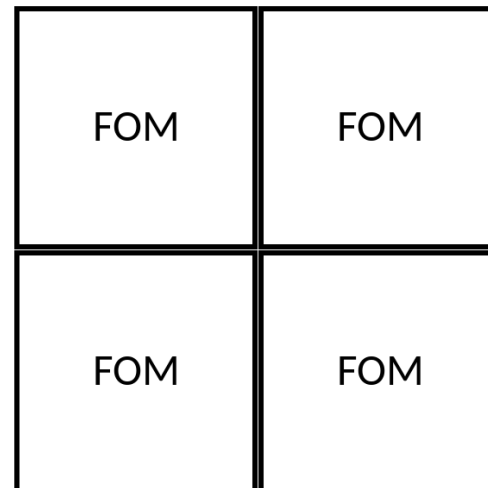
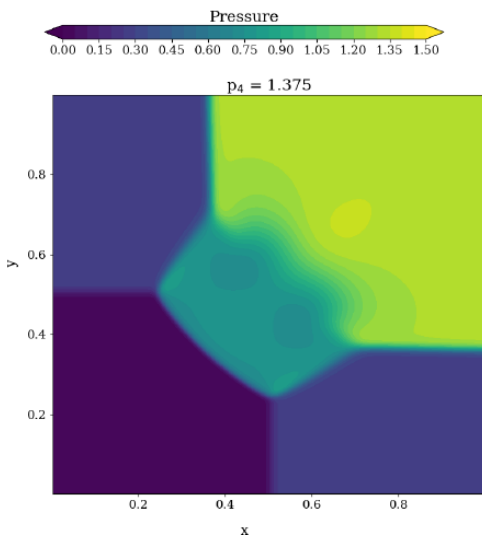


## Goals (for solid mechanics exemplars):

- Simplify meshing via Schwarz + DD
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Example sample DD and ROM/HFM assignment.



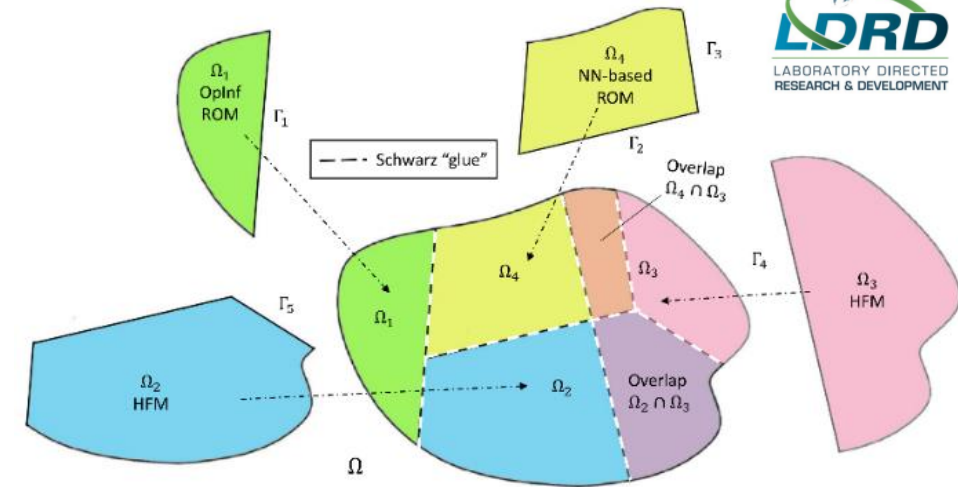
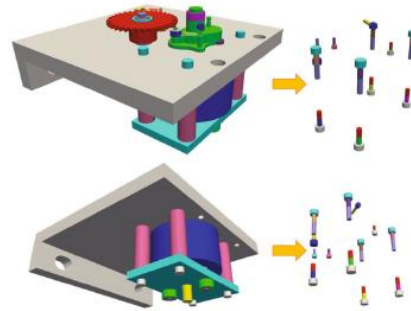
On-the-fly model switching in our DD workflow.

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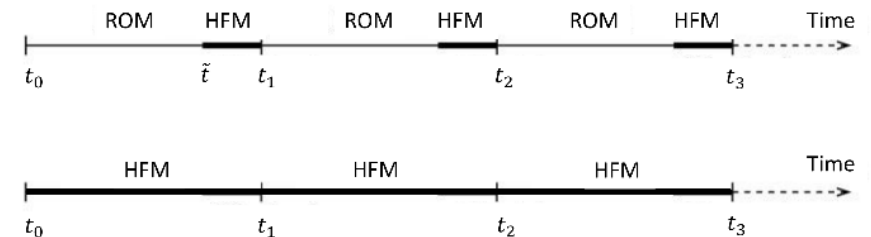
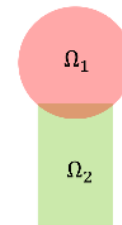
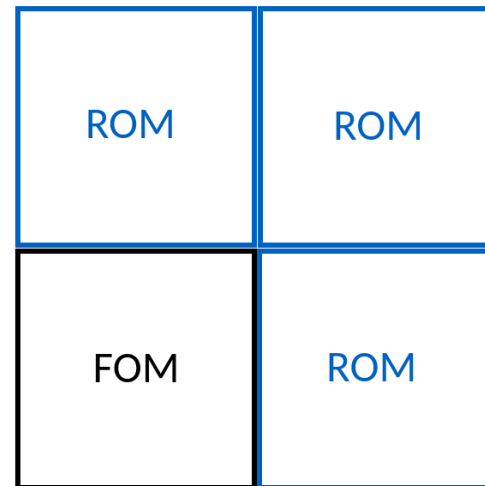
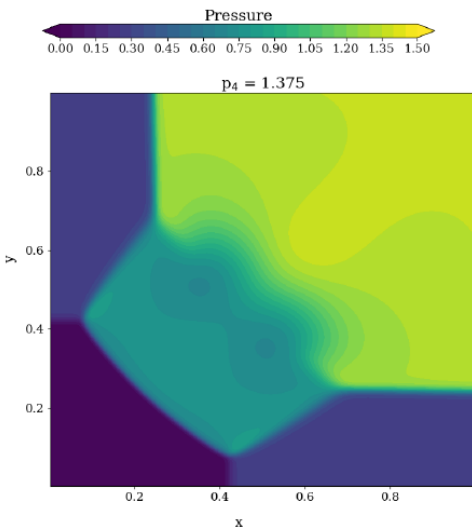


## Goals (for solid mechanics exemplars):

- Simplify meshing via Schwarz + DD
- Extend Schwarz to **non-intrusive ROMs** (Operator Inference, NN)
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Example sample DD and ROM/FOM assignment.



On-the-fly model switching in our DD workflow.

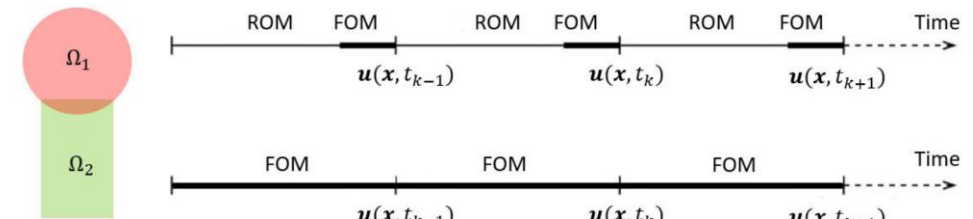
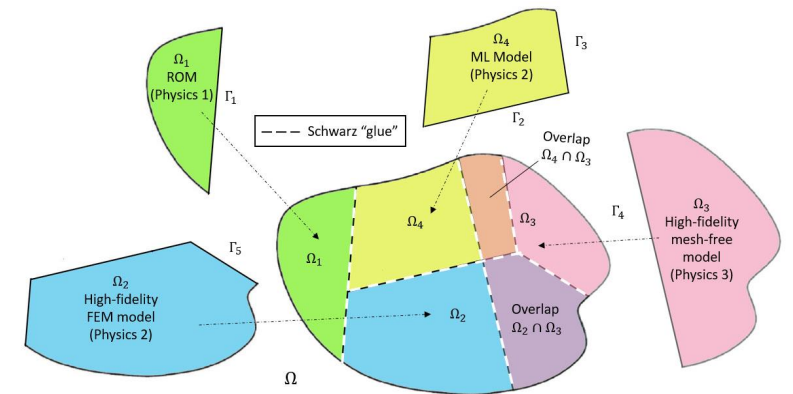


## Summary:

- Schwarz has been **demonstrated** for coupling of FOMs and (H)ROMs
- **Computational gains** can be achieved by coupling **HROMs** and using the **additive Schwarz** variant
- Interesting new results regarding **interface sampling** & **non-overlapping transmission BCs** for CCFV

## Ongoing & future work:

- Extension to **other applications** (fasteners, laser welds)
- **Rigorous analysis** of why Dirichlet-Dirichlet BC “work” when employing non-overlapping Schwarz with discretizations that employ ghost cells
- Learning of “**optimal**” transmission conditions to ensure structure preservation
- Extension of Schwarz to enabling coupling of **non-intrusive ROMs** (e.g., Oplnf, Neural Networks)
- Development of **automated criteria** to determine appropriate use of less refined or reduced-order models without sacrificing accuracy, enabling **real-time transitions** between different model fidelities → **New project: AHEAD LDRD**



# Team & Acknowledgments



Irina Tezaur



Chris Wentland



Francesco Rizzi



Joshua Barnett



Alejandro Mota



Will Snyder  
*Former Intern from  
Virginia Tech  
[Schwarz + PINNs]*



Ian Moore  
*Intern from  
Virginia Tech  
[Schwarz + Oplnf]*



Eric Parish



Anthony Gruber

AHEAD/M2dt



U.S. DEPARTMENT OF  
**ENERGY**

Office of Science



[1] A. Mota, I. Tezaur, C. Alleman. “The Schwarz Alternating Method in Solid Mechanics”, *Comput. Meth. Appl. Mech. Engng.* 319 (2017), 19-51.

[2] A. Mota, I. Tezaur, G. Phlipot. “The Schwarz Alternating Method for Dynamic Solid Mechanics”, *Comput. Meth. Appl. Mech. Engng.* 121 (21) (2022) 5036-5071.

[3] J. Barnett, I. Tezaur, A. Mota. “The Schwarz alternating method for the seamless coupling of nonlinear reduced order models and full order models”, ArXiv pre-print, 2022. <https://arxiv.org/abs/2210.12551>

[4] W. Snyder, I. Tezaur, C. Wentland. “Domain decomposition-based coupling of physics-informed neural networks via the Schwarz alternating method”, ArXiv pre-print, 2023. <https://arxiv.org/abs/2311.00224>

[5] A. Mota, D. Koliesnikova, I. Tezaur. “A Fundamentally New Coupled Approach to Contact Mechanics via the Dirichlet-Neumann Schwarz Alternating Method”, ArXiv pre-print, 2023. <https://arxiv.org/abs/2311.05643>

[6] C. Wentland, F. Rizzi, J. Barnett, I. Tezaur. “The role of interface boundary conditions and sampling strategies for Schwarz-based coupling of projection-based reduced order models, ArXiv pre-print, 2024.

<https://arxiv.org/abs/2410.04668>

*This talk!*

[7] Pressio: <https://pressio.github.io>

[8] Pressio demo-apps: <https://github.com/Pressio/pressio-demoapps>



[9] Pressio demo-apps + Schwarz: <https://github.com/cwentland0/pressio-demoapps-schwarz> (copyright assertion in progress)

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[www.sandia.gov/~ikalash](http://www.sandia.gov/~ikalash)

**Students:** we have available a summer internship on ROM at Sandia! If interested, please email your CV to Irina.

## Start of Backup Slides

# 2D Inviscid Burgers Equation



Popular analog for fluid problems where **shocks** are possible, and particularly **difficult** for conventional projection-based ROMs

$$\frac{\partial u}{\partial t} + \frac{1}{2} \left( \frac{\partial(u^2)}{\partial x} + \frac{\partial(uv)}{\partial y} \right) = 0.02 \exp(\mu_2 x)$$

$$\frac{\partial v}{\partial t} + \frac{1}{2} \left( \frac{\partial(vu)}{\partial x} + \frac{\partial(v^2)}{\partial y} \right) = 0$$

$$u(0, y, t; \boldsymbol{\mu}) = \mu_1$$

$$u(x, y, 0) = v(x, y, 0) = 1$$

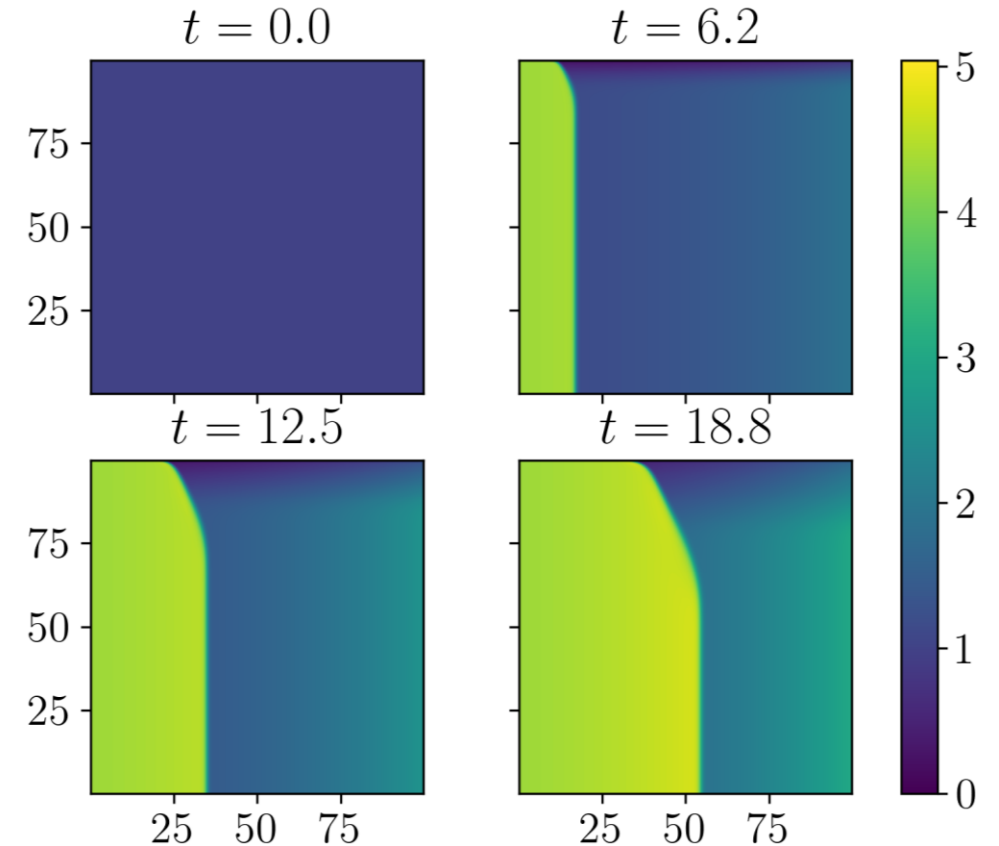
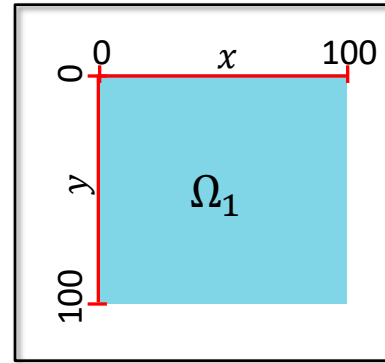


Figure above: solution of  $u$  component at various times

## Problem setup:

- $\Omega = (0, 100)^2$ ,  $t \in [0, 25]$
- Two parameters  $\boldsymbol{\mu} = (\mu_1, \mu_2)$ . **Training:** uniform sampling of  $\mu_1 \times \mu_2 = [4.25, 5.50] \times [0.015, 0.03]$  by a  $3 \times 3$  grid. **Testing:** query unsampled point  $\boldsymbol{\mu} = [4.75, 0.02]$

## FOM discretization:

- Spatial discretization given by a **Godunov-type scheme** with  $N = 250$  elements in each dimension
- Implicit **trapezoidal method** with fixed  $\Delta t = 0.05$



# Schwarz Coupling Details

## Choice of domain decomposition

- Overlapping DD of  $\Omega$  into 4 subdomains coupled via multiplicative Schwarz
- Solution in  $\Omega_1$  is most difficult to capture by ROM

## Snapshot collection and reduced basis construction

- Single-domain FOM on  $\Omega$  used to generate snapshots/POD modes

## Enforcement of boundary conditions (BCs) in ROM at Schwarz boundaries

- BCs imposed strongly via Method 1 of [Gunzburger *et al.*, 2007] at indices  $i_{\text{Dir}}$

$$q(t) \approx \bar{q} + \Phi \hat{q}(t)$$

- POD modes made to satisfy homogeneous DBCs:  $\Phi(i_{\text{Dir}}, :) = \mathbf{0}$
- BCs imposed by modifying  $\bar{q}$ :  $\bar{q}(i_{\text{Dir}}) \leftarrow \chi_q$

## Choice of hyper-reduction

- Energy Conserving Sampling & Weighting (ECSW) method for hyper-reduction
- All points on Schwarz boundaries are included in the sample mesh

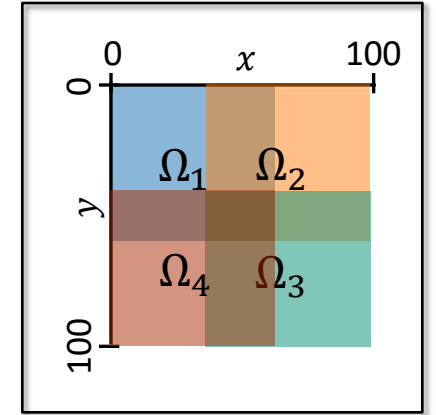


Figure above: 4 subdomain overlapping DD

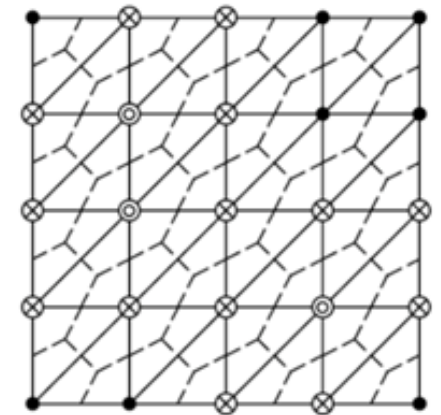
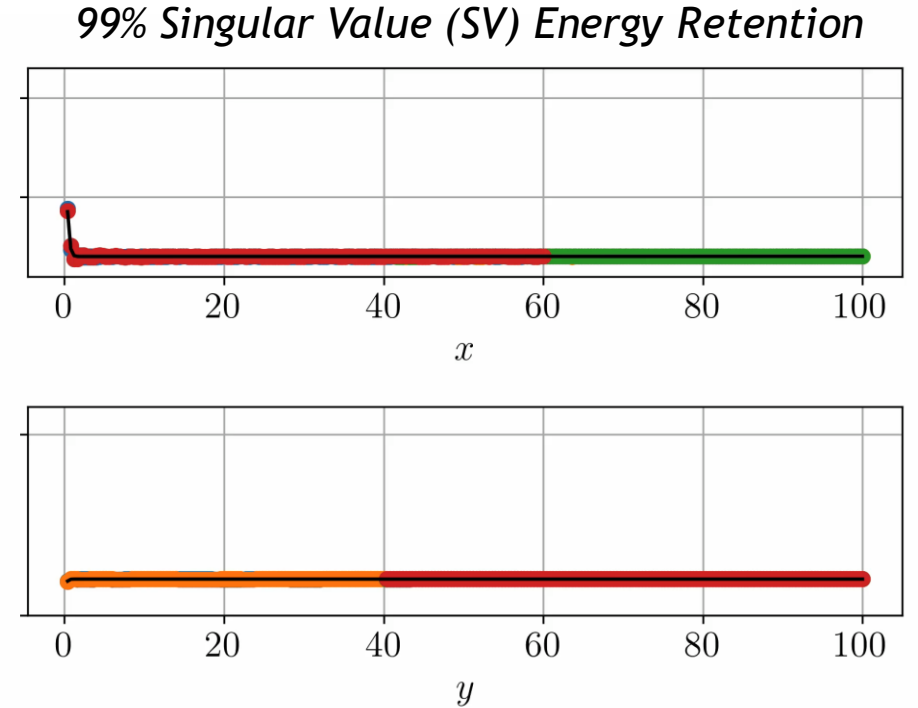
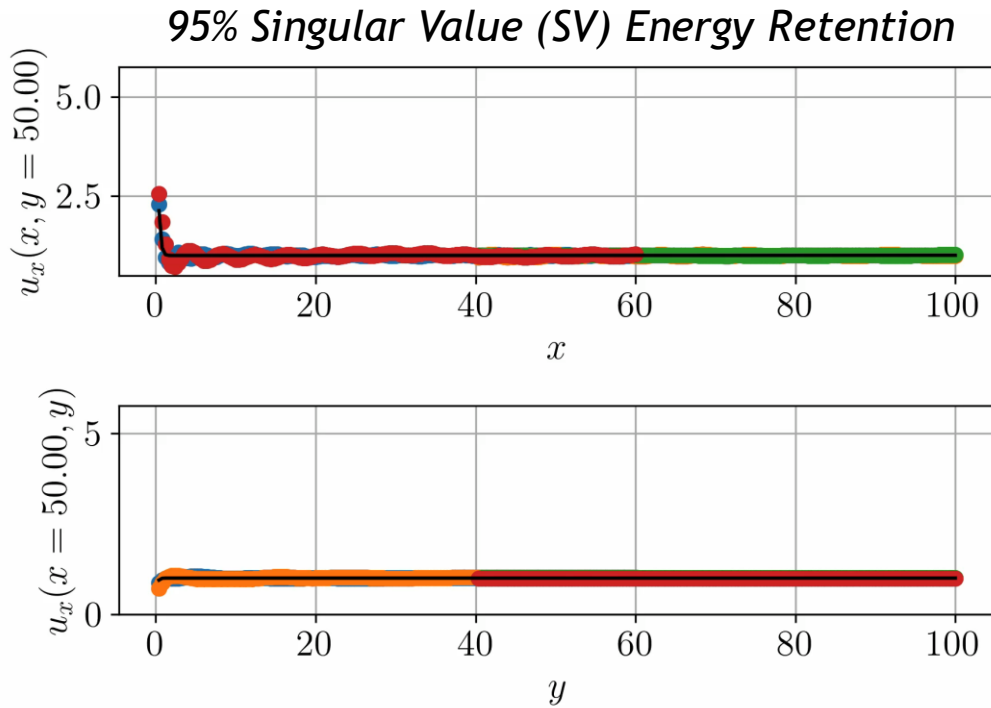
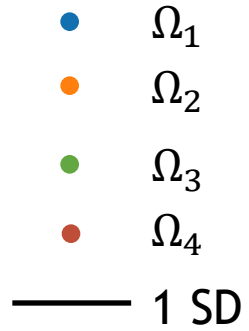


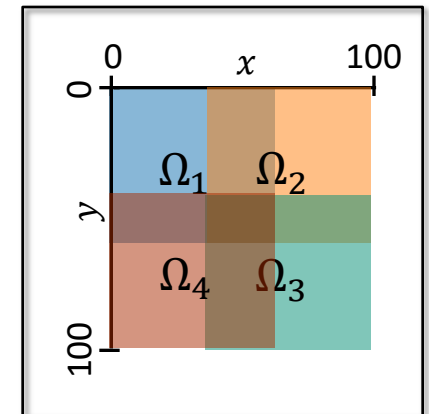
Figure above:  
ECSW augmented  
reduced mesh

# All-ROM Coupling

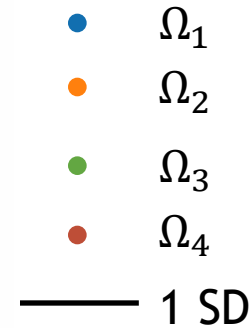
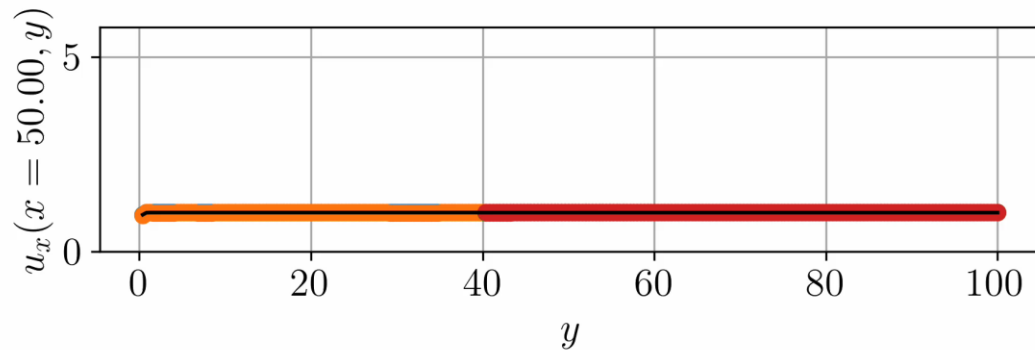
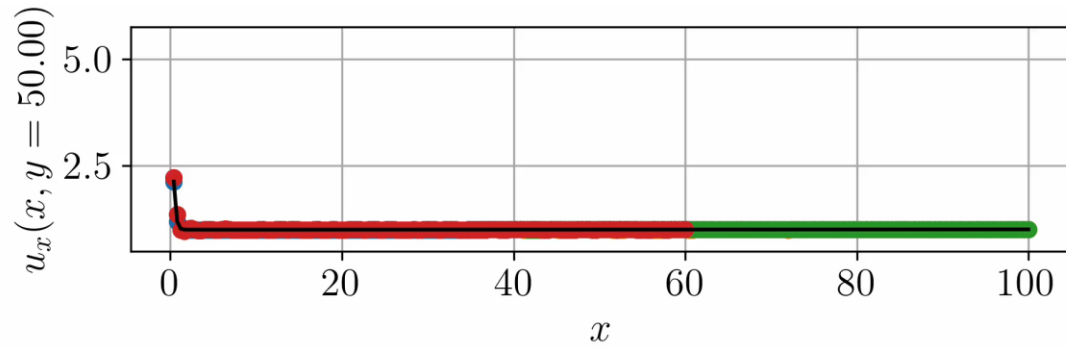


- Method converges in **only 3 Schwarz iterations** per controller time-step
- Errors  $O(1\%)$  or less
- 1.47 $\times$  speedup** over all-FOM coupling for 95% SV energy retention case

Subdomains	95% SV Energy			99% SV Energy		
	$M$	MSE (%)	CPU time (s)	$M$	MSE (%)	CPU time (s)
$\Omega_1$	57	1.1	85	146	0.18	295
$\Omega_2$	44	1.2	56	120	0.18	216
$\Omega_3$	24	1.4	43	60	0.16	89
$\Omega_4$	32	1.9	61	66	0.25	100
<b>Total</b>			<b>245</b>			<b>700</b>



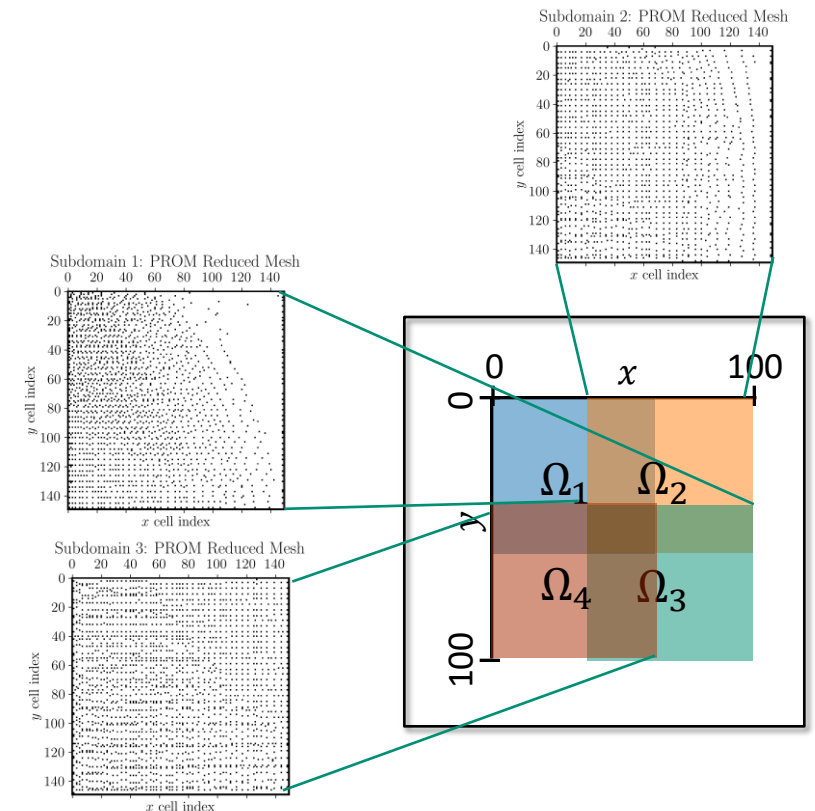
# FOM-HROM-HROM-HROM Coupling



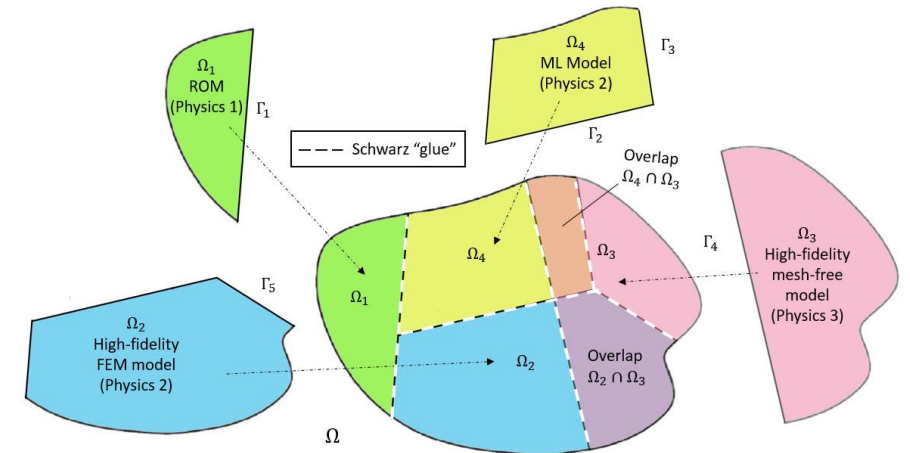
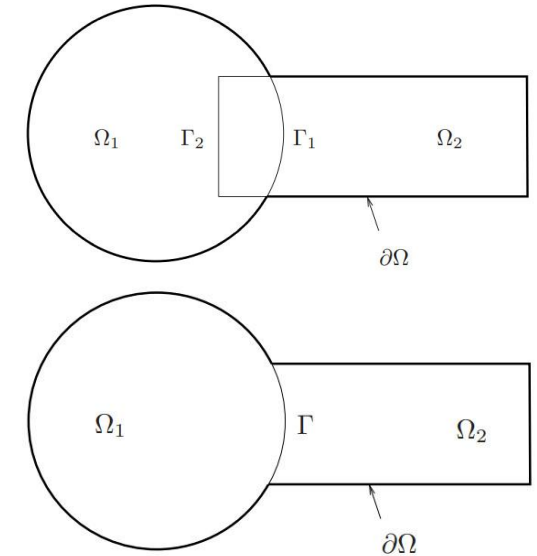
- FOM in  $\Omega_1$  as this is “hardest” subdomain for ROM
- HROMs in  $\Omega_2, \Omega_3, \Omega_4$  capture 99% snapshot energy
- Method converges in 3 Schwarz iterations per controller time-step
- Errors  $O(0.1\%)$  with 0 error in  $\Omega_1$
- $2.26\times$  speedup achieved over all-FOM coupling

Further speedups possible via code optimizations, additive Schwarz and reduction of # sample mesh points.

Subdomains	99% SV Energy		
	$M$	MSE (%)	CPU time (s)
$\Omega_1$	—	0.0	95
$\Omega_2$	120	0.26	26
$\Omega_3$	60	0.43	17
$\Omega_4$	66	0.34	21
<b>Total</b>			<b>159</b>



- The Schwarz Alternating Method for Domain Decomposition-Based Coupling
- Extension to FOM\*-ROM# and ROM-ROM Coupling
- Numerical Examples
  - 2D Burgers Equation
  - 2D Shallow Water Equations
  - Teaser: 2D Euler Equations Riemann Problem
- Summary & Future Work



# 2D Shallow Water Equations (SWE)



Hyperbolic PDEs modeling **wave propagation** below a pressure surface in a fluid (e.g., atmosphere, ocean).

$$\begin{aligned} \frac{\partial h}{\partial t} + \frac{\partial(hu)}{\partial x} + \frac{\partial(hv)}{\partial y} &= 0 \\ \frac{\partial(hu)}{\partial t} + \frac{\partial}{\partial x} \left( hu^2 + \frac{1}{2}gh^2 \right) + \frac{\partial}{\partial y} (huv) &= -\mu v \\ \frac{\partial(hv)}{\partial t} + \frac{\partial}{\partial x} (huv) + \frac{\partial}{\partial y} \left( hv^2 + \frac{1}{2}gh^2 \right) &= \mu u \end{aligned}$$

## Problem setup:

- $\Omega = (-5,5)^2$ ,  $t \in [0, 10]$ , Gaussian initial condition
- **Coriolis parameter**  $\mu \in \{-4, -3, -2, -1, 0\}$  for training, and  $\mu \in \{-3.5, -2.5, -1.5, -0.5\}$  for testing

## FOM discretization:

- Spatial discretization given by a first-order **cell-centered finite volume** discretization with  $N = 300$  elements in each dimension
- Implicit first order temporal discretization: **backward Euler** with fixed  $\Delta t = 0.01$
- Implemented in **Pressio-demoapps** (<https://github.com/Pressio/pressio-demoapps>)

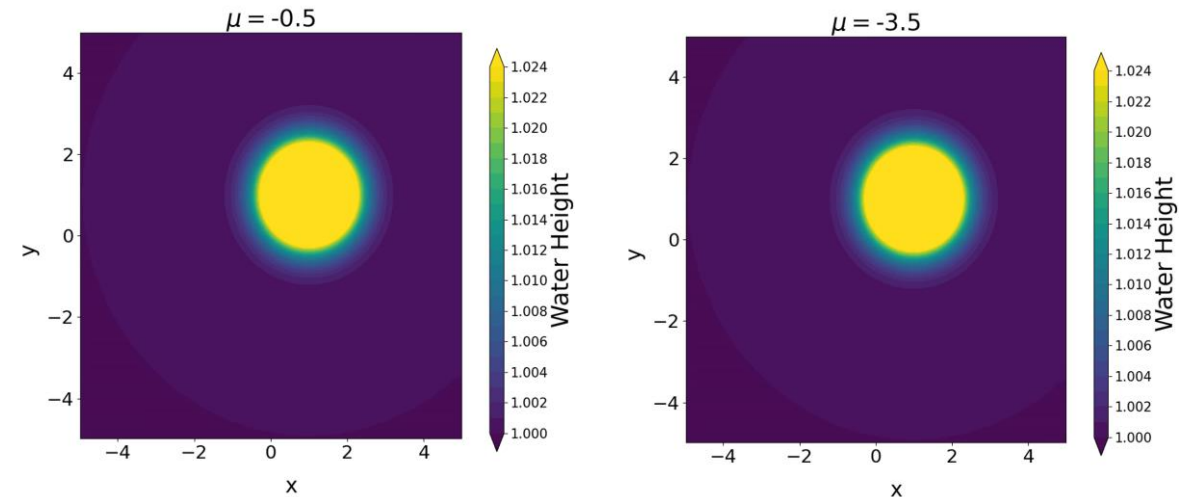


Figure above: FOM solutions to SWE for  $\mu = -0.5$  (left) and  $\mu = -3.5$  (right).

# Schwarz Coupling Details

**Green:** different from Burgers' problem

## Choice of domain decomposition

- **Non-overlapping** DD of  $\Omega$  into 4 subdomains coupled via **additive Schwarz**
  - **OpenMP parallelism** with 1 thread/subdomain
- **All-ROM** or **All-HROM** coupling via Pressio\*

## Snapshot collection and reduced basis construction

- **Single-domain FOM** on  $\Omega$  used to generate snapshots/POD modes

## Enforcement of boundary conditions (BCs) in ROM at Schwarz boundaries

- BCs are imposed **approximately** by fictitious ghost cell states
  - Implementing Neumann and Robin BCs is **challenging**
- **Ghost cells** introduce some overlap even with non-overlapping DD
  - $\Rightarrow$  **Dirichlet-Dirichlet non-overlapping Schwarz** is stable/convergent!

## Choice of hyper-reduction

- **Collocation** for hyper-reduction: min residual at small subset DOFs
- Assume **fixed budget of sample mesh points** at Schwarz boundaries

\*<https://github.com/Pressio/pressio-demoapps>

Figure right: non-overlapping DD w/ ghost cells creating overlap

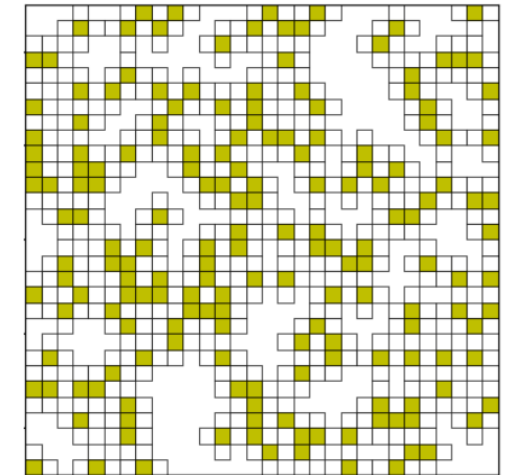
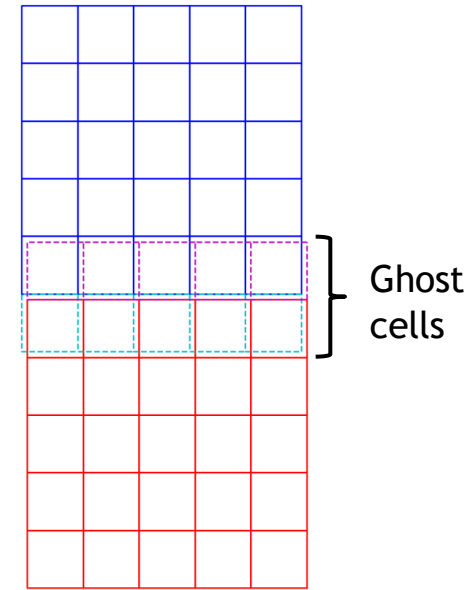
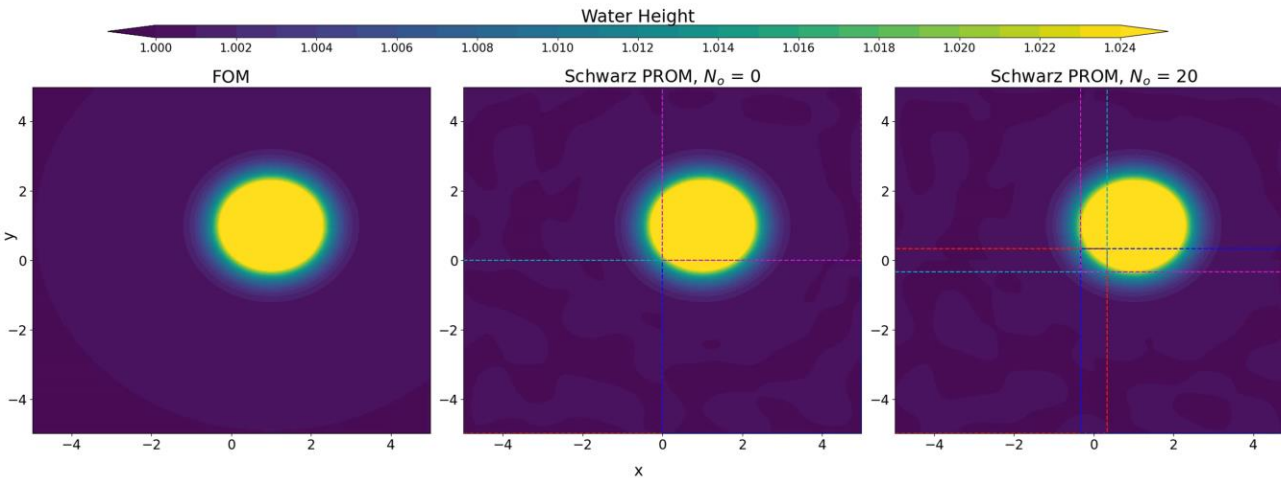


Figure above: sample mesh (yellow) and stencil (white) cells

# Schwarz All-ROM Domain Overlap Study



Study of Schwarz convergence for all-ROM coupling as a function of  $N_o :=$  cell width of overlap region (not including ghost cells).

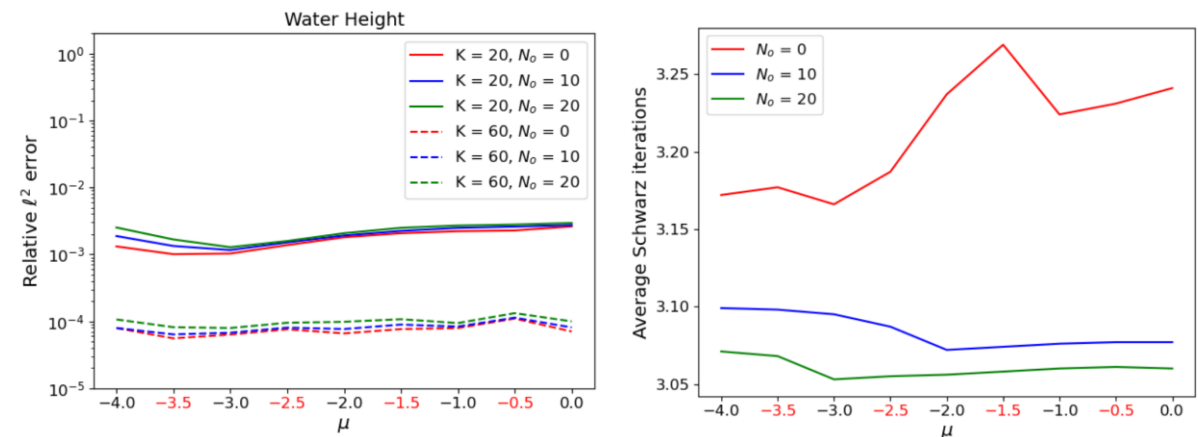


Movie above: FOM (left), 4 subdomain ROM coupled via non-overlapping Schwarz (middle), and 4 subdomain ROM coupled via overlapping Schwarz (right) for predictive SWE problem with  $\mu = -0.5$ . All ROMs have  $K = 80$  POD modes.

- Schwarz iterations decrease (very roughly) with  $N_o^{0.25}$  (figure, right) whereas evaluating  $r(q)$  scales with  $N_o^2$

➤  $\Rightarrow$  there is no reason not to do non-overlapping coupling for this problem

- Dirichlet-Dirichlet coupling with no-overlap ( $N_o = 0$ ) performs well with no convergence issues (movie, left) and errors comparable to Dirichlet-Dirichlet coupling with overlap (figure below, left)



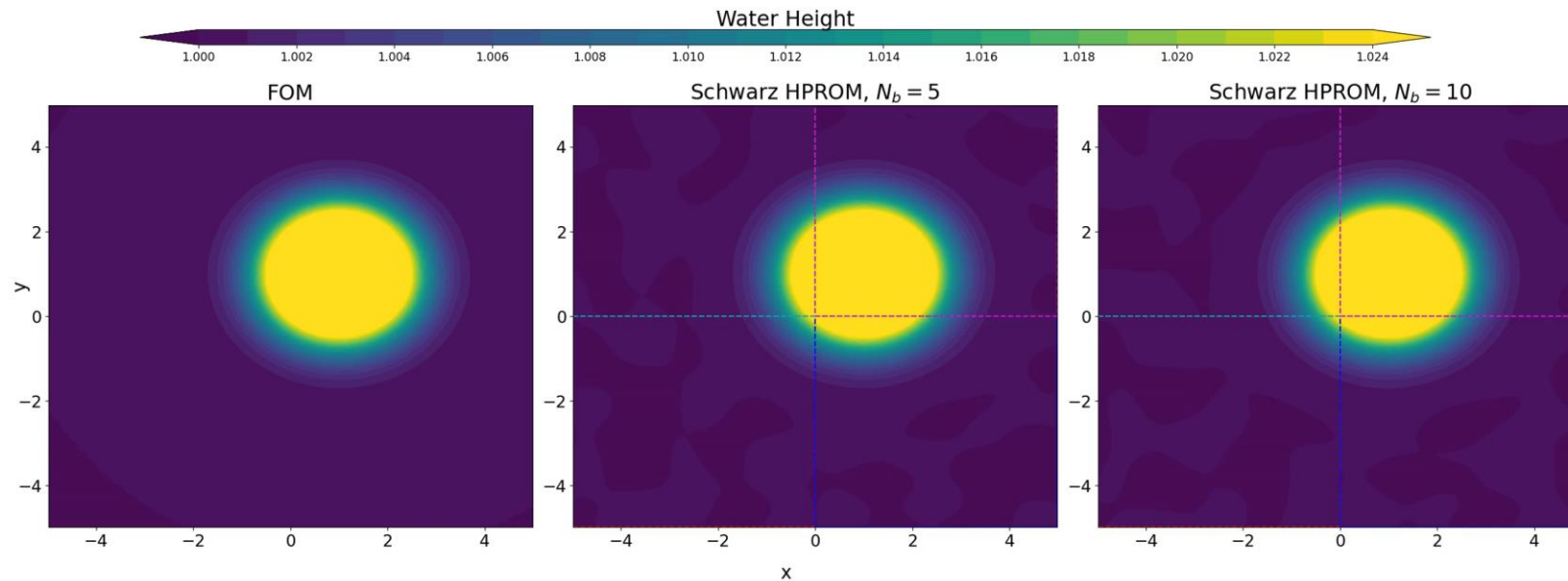
Figures above: relative error and average # Schwarz iterations as a function of  $\mu$  and  $N_o$ . Black  $\mu$ : training, red  $\mu$ : testing.

# Schwarz Boundary Sampling for All-HROM Coupling



**Key question:** how many Schwarz boundary points need to be included in **sample mesh** when performing HROM coupling?

- Naïve/sparse-sampled Schwarz boundary results in **failure** to transmit coupling information during Schwarz



Movie above: FOM (left), all HROM with  $N_b = 5\%$  (middle) and all HROM with  $N_b = 10\%$  (right). ROMs have  $K = 100$  modes and  $N_s = 0.5\%N$  sample mesh points.

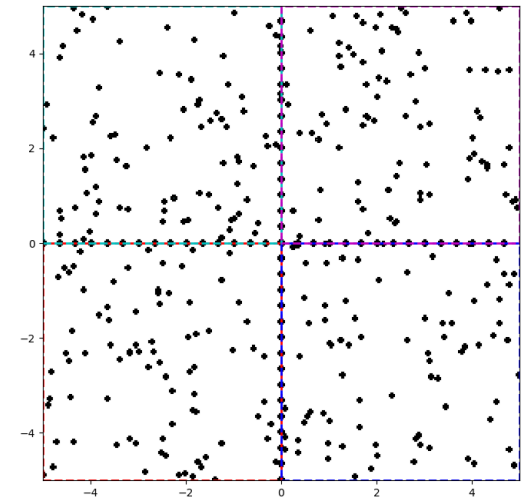
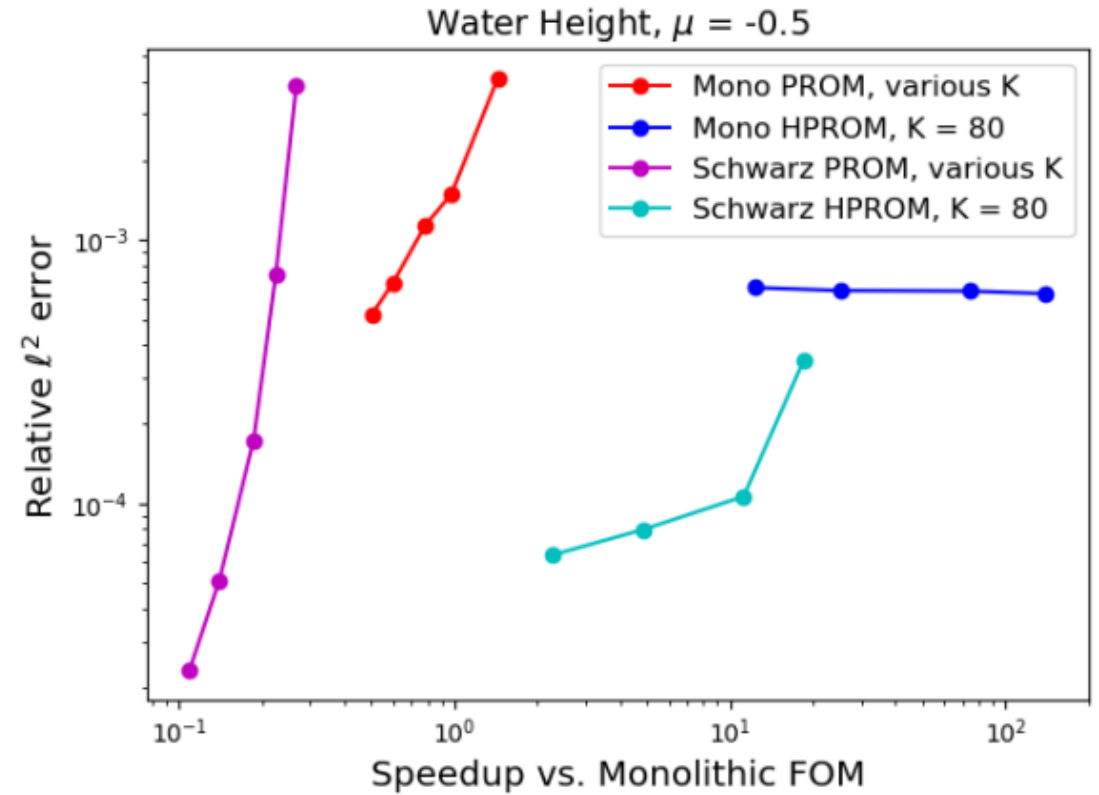
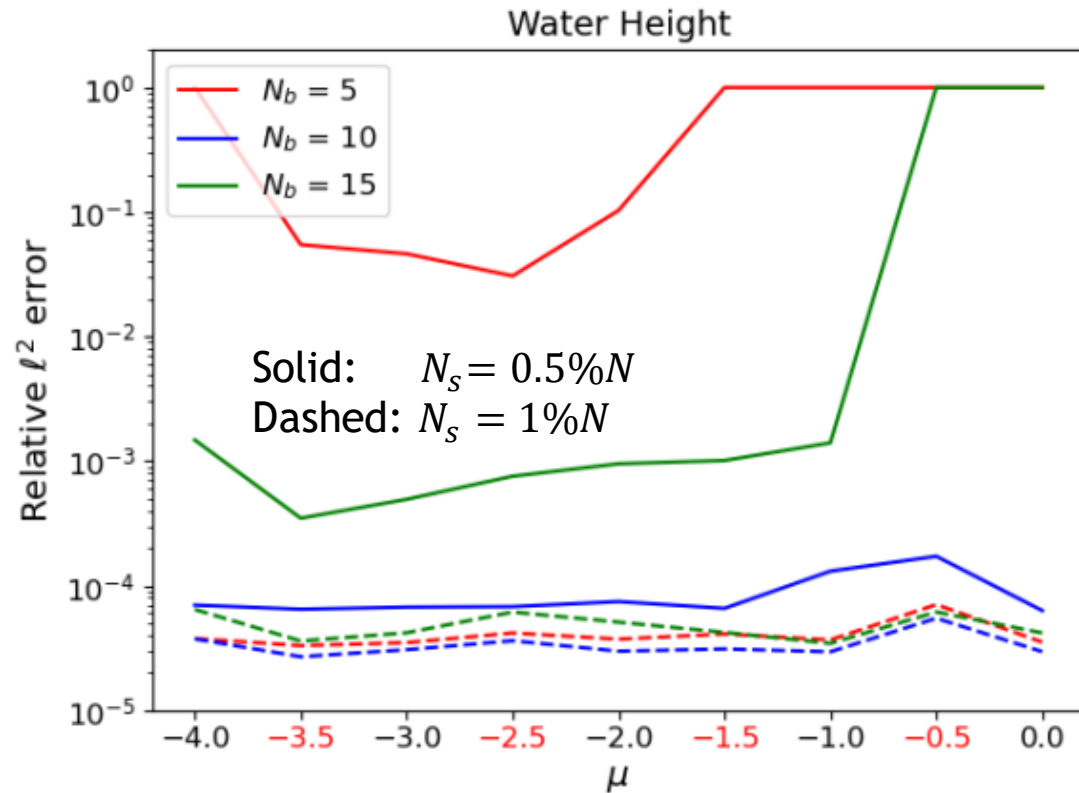


Figure above: example sample mesh with sampling rate  $N_b = 10\%$

- Including too many Schwarz boundary points ( $N_b$ ) in sample mesh given fixed budget of  $N_s$  sample mesh points may lead to too few sample mesh points in interior
- For SWE problem, we can get away with  $\sim 10\%$  boundary sampling (movie above, right-most frame)



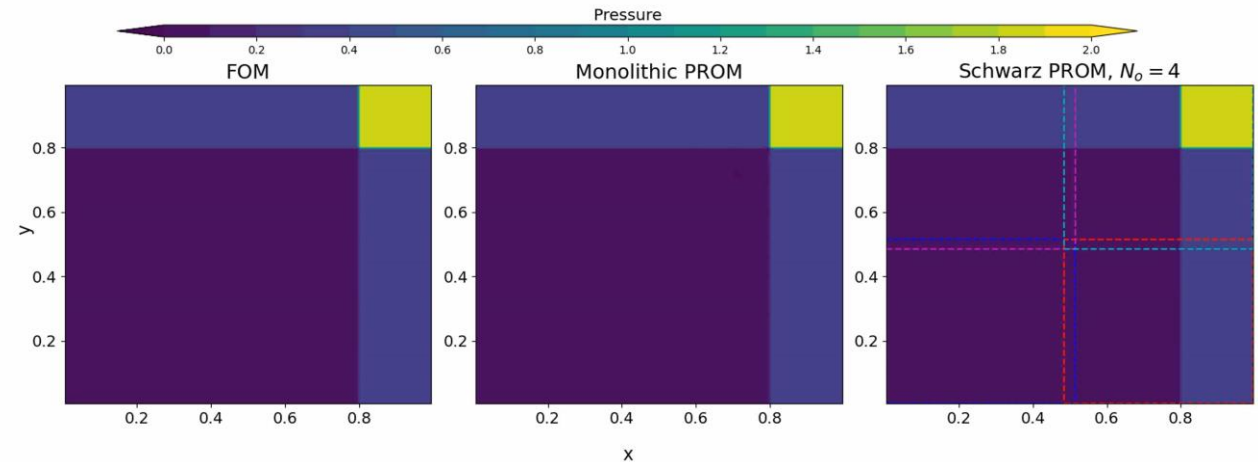
# Coupled HRROM Performance



- For a fixed ROM dimension, Schwarz delivers **lower error and comparable cost!**
- There are noticeable **cost savings** relative to monolithic FOM!
- Accuracy similar for **predictive  $\mu$**  (red) and **non-predictive  $\mu$**  (black) cases.

$$\frac{\partial}{\partial t} \begin{pmatrix} \rho \\ \rho u \\ \rho v \\ \rho E \end{pmatrix} + \frac{\partial}{\partial x} \begin{pmatrix} \rho u \\ \rho u^2 + p \\ \rho uv \\ (E + p)u \end{pmatrix} + \frac{\partial}{\partial y} \begin{pmatrix} \rho v \\ \rho uv \\ \rho v^2 + p \\ (E + p)v \end{pmatrix} = \mathbf{0}$$

$$p = (\gamma - 1) \left( \rho E - \frac{1}{2} \rho (u^2 + v^2) \right)$$



### Problem setup:

- $\Omega = (0,1)^2$ ,  $t \in [0, 0.8]$ , homogeneous Neumann BCs
- Fix  $\rho_1 = 1.5$ ,  $u_1 = v_1 = 0$ ,  $p_3 = 0.029$
- Vary  $p_1$ ; IC from compatibility conditions\*
  - Training:  $p_1 \in [1.0, 1.25, 1.5, 1.75, 2.0]$
  - Testing:  $p_1 \in [1.125, 1.375, 1.625, 1.875]$

### FOM discretization:

- Spatial discretization given by a first-order cell-centered finite volume discretization with  $N = 300$  or  $N = 100$  elements in each dimension
- Implicit first order temporal discretization: backward Euler with fixed  $\Delta t = 0.005$
- Implemented in Pressio-demoapps (<https://github.com/Pressio/pressio-demoapps>)

### Preliminary results:

- Schwarz can **stabilize** unstable monolithic ROM for fixed dimension  $K$  (above)
- Since shock traverses all parts of domain, achieving **speedups** with Schwarz is **more difficult**

\*Schulz-Rinne, 1993.



The **Schwarz alternating method** has been developed for concurrent multi-scale coupling of **conventional** and **data-driven models**.

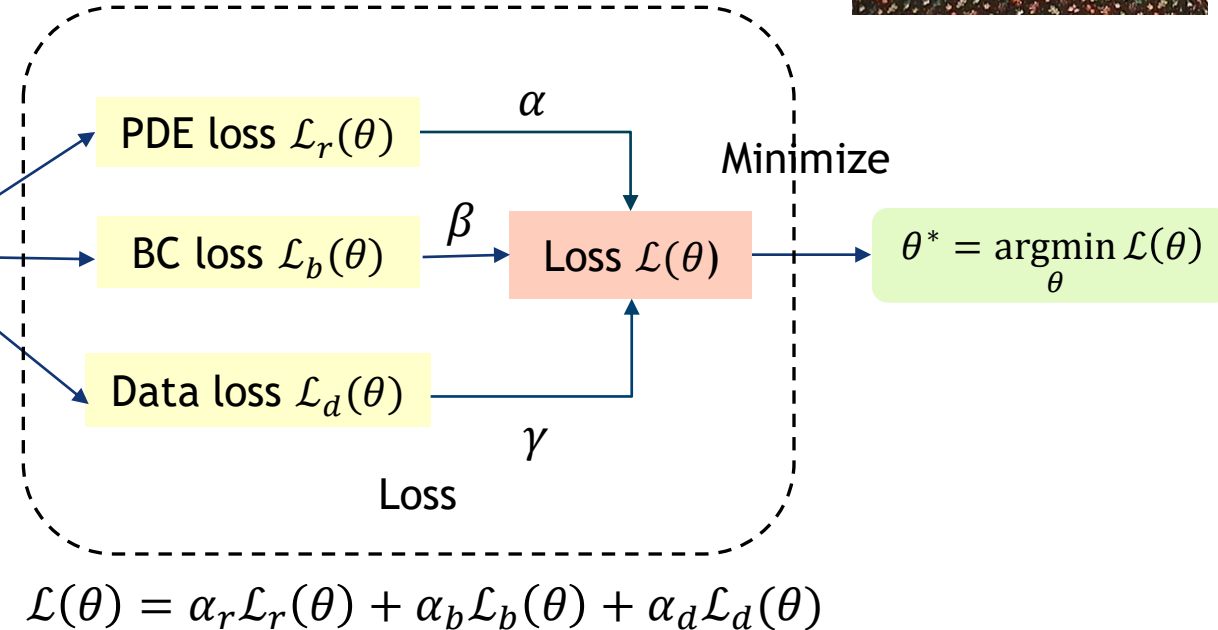
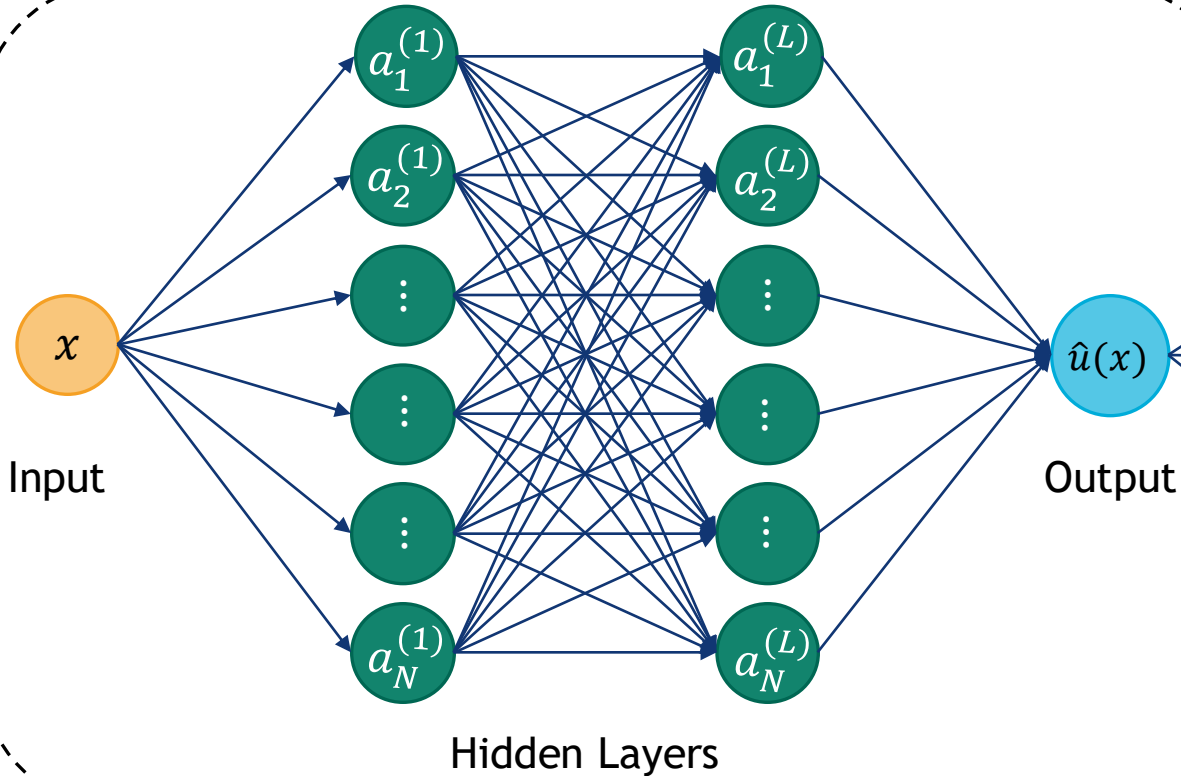
- ☺ Coupling is *concurrent* (two-way).
- ☺ *Ease of implementation* into existing massively-parallel HPC codes.
- ☺ “*Plug-and-play*” *framework*: simplifies task of meshing complex geometries!
  - ☺ Ability to couple regions with *different non-conformal meshes*, *different element types* and *different levels of refinement*.
  - ☺ Ability to use *different solvers (including ROM/FOM)* and *time-integrators* in different regions.
- ☺ *Scalable, fast, robust* on *real* engineering problems
- ☺ Coupling does not introduce *nonphysical artifacts*.
- ☺ *Theoretical* convergence properties/guarantees.

# Bonus: PINN-PINN and PINN-FOM coupling

Will Snyder  
Summer Intern  
Virginia Tech



Neural Network



*Focus thus far*

**Goal:** investigate the use of the Schwarz alternating method as a means to couple **Physics-Informed Neural Networks (PINNs)**

**Scenario 1:** use Schwarz to train subdomain PINNs (offline)

**Scenario 2:** use Schwarz to couple pre-trained subdomain PINNs/NNs (online)

# Bonus: PINN-PINN coupling

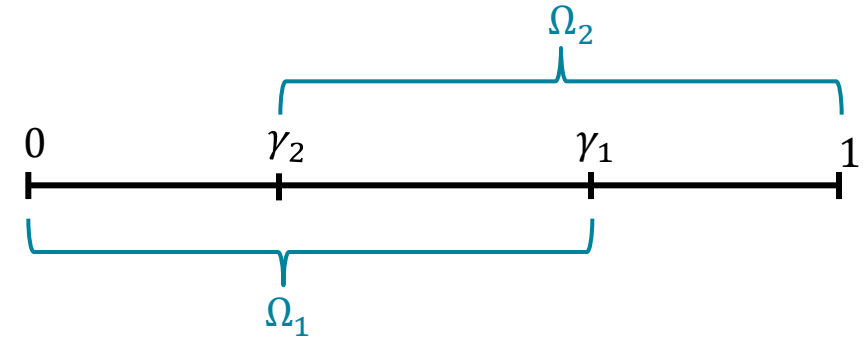


1D steady advection-diffusion equation on  $\Omega = [0,1]$ :

$$u_x - \nu u_{xx} = 1, \quad u(0) = u(1) = 0$$

PINNs are notoriously difficult to train for higher Peclet numbers!

Can Schwarz help?



Overlapping DD:  $\Omega = \Omega_1 \cup \Omega_2$  with boundary  $\partial\Omega = \{0,1\}$

## Schwarz PINN training algorithm:

Loop over subdomains  $\Omega_i$  until convergence of Schwarz method

Train PINN in  $\Omega_i$  with loss  $\mathcal{L}_i(\theta) = \alpha \mathcal{L}_{r,i}(\theta) + \beta \mathcal{L}_{b,i}(\theta) + \gamma \mathcal{L}_{d,i}(\theta)$

Communicate Dirichlet data between neighboring subdomains

Update boundary data on  $\gamma_i$  from neighboring subdomains

If strong enforcement of Dirichlet BC (SDBC), set  $\hat{u}_{\Omega_i}(x, \theta) = NN_{\Omega_i}(x, \theta)$

If weak enforcement of Dirichlet BC (WDBC), set  $\beta = 0$  and  $\hat{u}_{\Omega_i}(x, \theta) = v(x)NN_{\Omega_i}(x, \theta) + \psi(x)\hat{u}_{\Omega_j}(\gamma_j, \theta)$

where  $v(x)$  is chosen s.t.  $v(0) = v(\gamma_i) = v(1) = 0$  and  $\psi(x)$  is chosen s.t.  $v(\gamma_i) = 1$

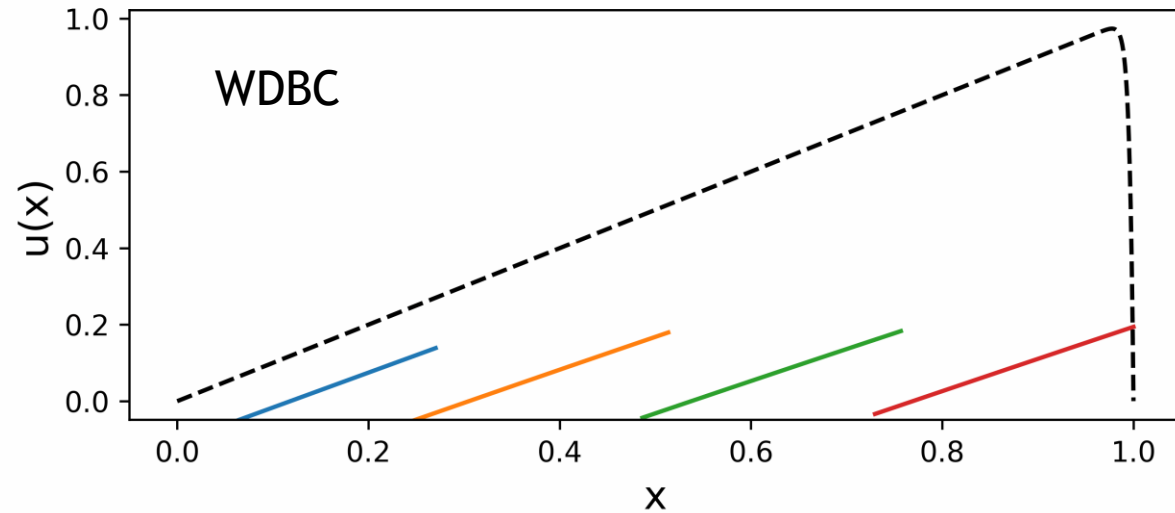
$$\mathcal{L}_{r,i}(\theta) = \text{MSE}(-\nu \nabla_x^2 NN_{\Omega_i}(x, \theta) + \nabla_x NN_{\Omega_i}(x, \theta) - 1)$$

$$\mathcal{L}_{b,i}(\theta) = \text{MSE}(NN_{\Omega_i}(\partial\Omega, \theta)) + \text{MSE}(NN_{\Omega_i}(\gamma_i, \theta) - NN_{\Omega_j}(\gamma_i, \theta))$$

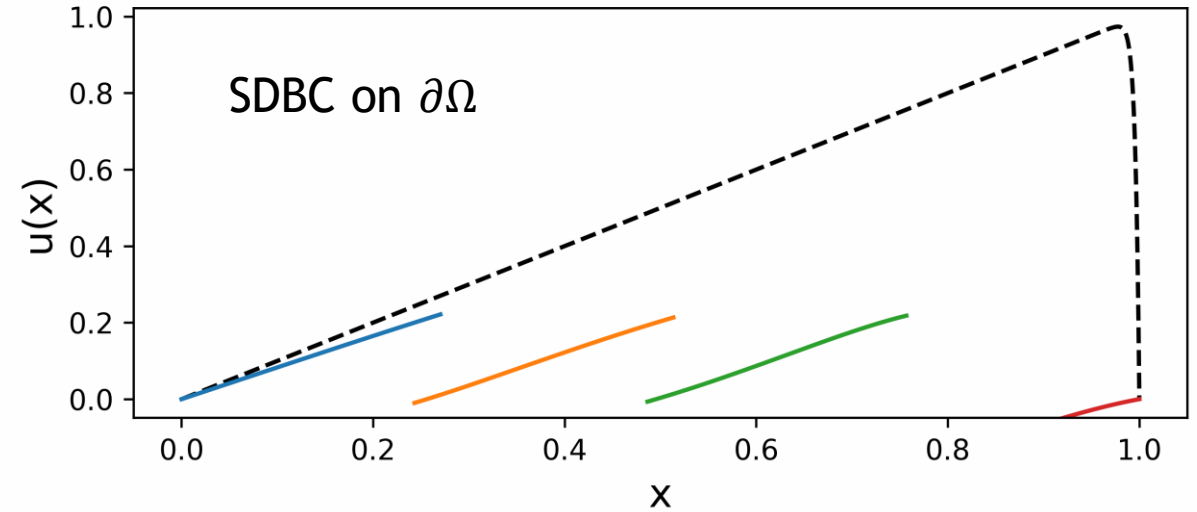
# Bonus: PINN-PINN coupling



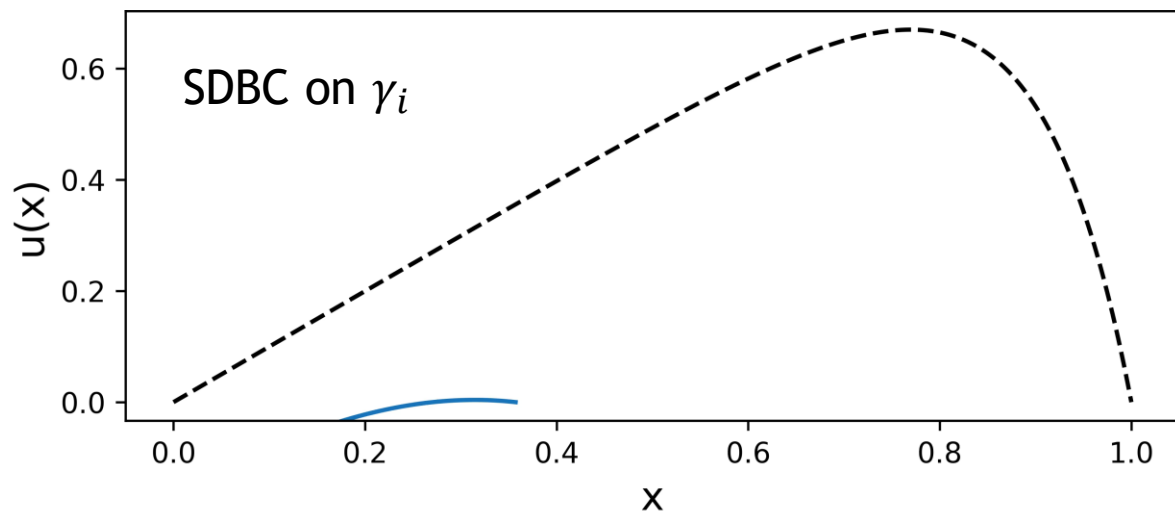
Schwarz iteration 1; Pe = 250



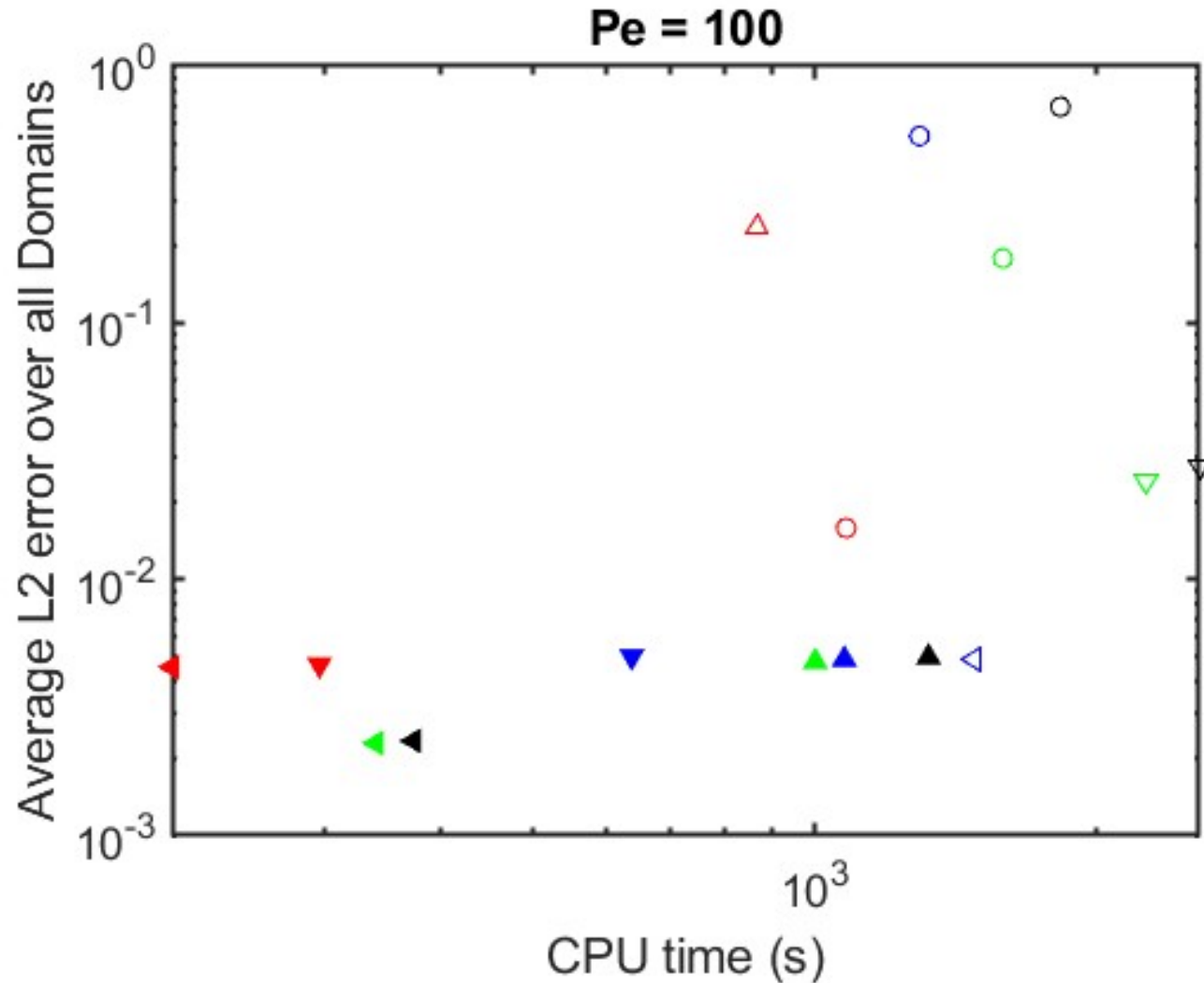
Schwarz iteration 1; Pe = 250



Schwarz iteration 1; Pe = 10

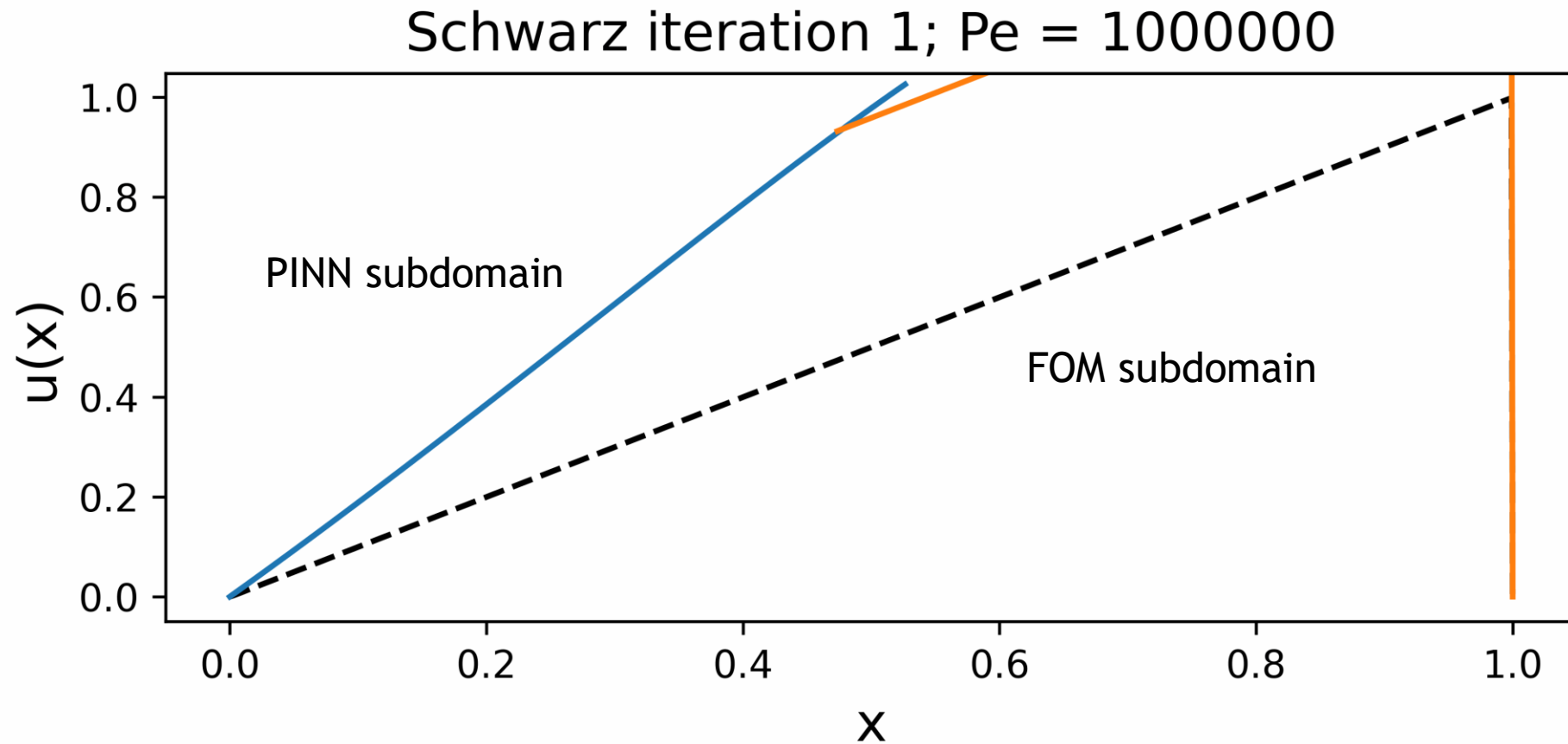


- How **Dirichlet boundary conditions** are handled has a large impact on PINN convergence
- Convergence not improved in general with **increasing overlap**
- Increasing # **subdomains** in general will increase CPU time



- 2  $\Omega$ , no snapshots, WDBC (unconverged)
- ▼ 2  $\Omega$ , no snapshots, SDBC
- △ 2  $\Omega$ , snapshots, WDBC (unconverged)
- ◄ 2  $\Omega$ , snapshots, SDBC
- 3  $\Omega$ , no snapshots, WDBC (unconverged)
- ▼ 3  $\Omega$ , no snapshots, SDBC
- ▲ 3  $\Omega$ , snapshots, WDBC
- ◁ 3  $\Omega$ , snapshots SDBC (unconverged)
- 4  $\Omega$ , no snapshots, WDBC (unconverged)
- ▽ 4  $\Omega$ , no snapshots, SDBC (unconverged)
- ▲ 4  $\Omega$ , snapshots, WDBC
- ◄ 4  $\Omega$ , snapshots SDBC
- 5  $\Omega$ , no snapshots, WDBC (unconverged)
- ▽ 5  $\Omega$ , no snapshots, SDBC (unconverged)
- ▲ 5  $\Omega$ , snapshots, WDBC
- ◄ 5  $\Omega$ , snapshots, SDBC

- Using **SDBC**s and **data loss** helps with PINN/NN convergence and accuracy



- PINN-FOM coupling gives rapid PINN convergence for arbitrarily high Peclet numbers
- PINN-FOM couplings works with both WDBC and SDBC configurations



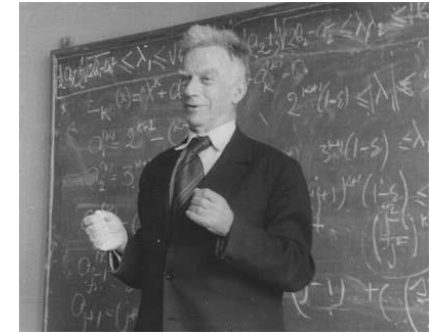
# Theoretical Foundation

Using the Schwarz alternating as a **discretization method** for PDEs is natural idea with a sound **theoretical foundation**.

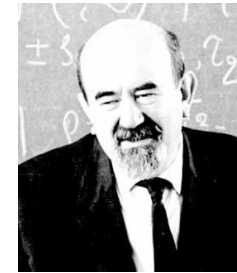
- **S.L. Sobolev (1936)**: posed Schwarz method for **linear elasticity** in variational form and **proved method's convergence** by proposing a convergent sequence of energy functionals.
- **S.G. Mikhlin (1951)**: **proved convergence** of Schwarz method for general linear elliptic PDEs.
- **P.-L. Lions (1988)**: studied convergence of Schwarz for **nonlinear monotone elliptic problems** using max principle.
- **A. Mota, I. Tezaur, C. Alleman (2017)**: proved **convergence** of the alternating Schwarz method for **finite deformation quasi-static nonlinear PDEs** (with energy functional  $\Phi[\varphi]$ ) with a **geometric convergence rate**.

$$\Phi[\varphi] = \int_B A(\mathbf{F}, \mathbf{Z}) dV - \int_B \mathbf{B} \cdot \boldsymbol{\varphi} dV$$

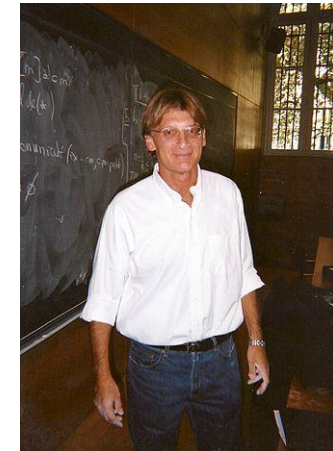
$$\nabla \cdot \mathbf{P} + \mathbf{B} = \mathbf{0}$$



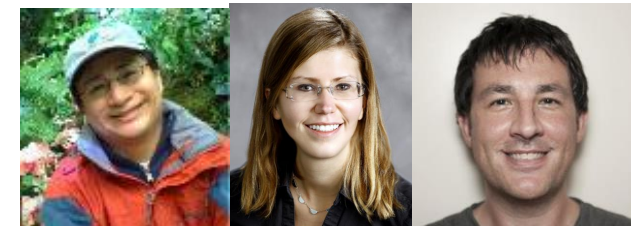
S.L. Sobolev (1908 – 1989)



S.G. Mikhlin  
(1908 – 1990)



P.- L. Lions (1956-)



A. Mota, I. Tezaur, C. Alleman





- Like for quasistatics, dynamic alternating Schwarz method converges provided each single-domain problem is **well-posed** and **overlap region** is **non-empty**, under some **conditions** on  $\Delta t$ .
- **Well-posedness** for the dynamic problem requires that action functional  $S[\boldsymbol{\varphi}] := \int_I \int_{\Omega} L(\boldsymbol{\varphi}, \dot{\boldsymbol{\varphi}}) dV dt$  be **strictly convex** or **strictly concave**, where  $L(\boldsymbol{\varphi}, \dot{\boldsymbol{\varphi}}) := T(\dot{\boldsymbol{\varphi}}) + V(\boldsymbol{\varphi})$  is the Lagrangian.
  - This is studied by looking at its second variation  $\delta^2 S[\boldsymbol{\varphi}_h]$
- We can show assuming a **Newmark** time-integration scheme that for the **fully-discrete** problem:

$$\delta^2 S[\boldsymbol{\varphi}_h] = \mathbf{x}^T \left[ \frac{\gamma^2}{(\beta \Delta t)^2} \mathbf{M} - \mathbf{K} \right] \mathbf{x}$$

- $\delta^2 S[\boldsymbol{\varphi}_h]$  can always be made positive by choosing a **sufficiently small**  $\Delta t$
- Numerical experiments reveal that  $\Delta t$  requirements for **stability/accuracy** typically lead to automatic satisfaction of this bound.

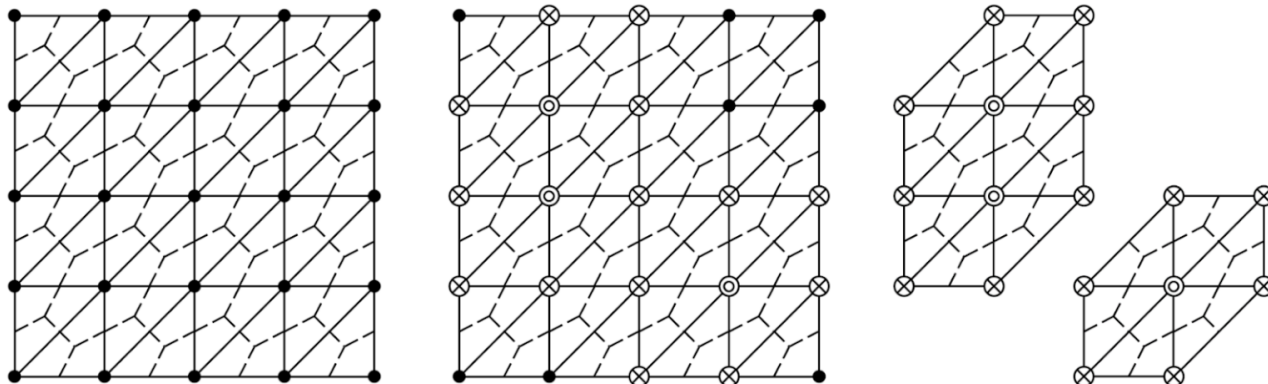
# Energy-Conserving Sampling and Weighting (ECSW)



- **Project-then-approximate** paradigm (as opposed to approximate-then-project)

$$\begin{aligned} r_k(q_k, t) &= W^T r(\tilde{u}, t) \\ &= \sum_{e \in \mathcal{E}} W^T L_e^T r_e(L_e \tilde{u}, t) \end{aligned}$$

- $L_e \in \{0,1\}^{d_e \times N}$  where  $d_e$  is the **number of degrees of freedom** associated with each mesh element (this is in the context of meshes used in first-order hyperbolic problems where there are  $N_e$  mesh elements)
- $L_{e+} \in \{0,1\}^{d_e \times N}$  selects degrees of freedom necessary for **flux reconstruction**
- Equality can be **relaxed**



Augmented reduced mesh:  $\odot$  represents a selected node attached to a selected element; and  $\otimes$  represents an added node to enable the full representation of the computational stencil at the selected node/element

# ECSW: Generating the Reduced Mesh and Weights



- Using a subset of the same snapshots  $u_i, i \in 1, \dots, n_h$  used to generate the **state basis**  $V$ , we can train the reduced mesh
- Snapshots are first **projected** onto their associated basis and then **reconstructed**

$$c_{se} = W^T L_e^T r_e \left( L_e + \left( u_{ref} + V V^T (u_s - u_{ref}) \right), t \right) \in \mathbb{R}^n$$

$$d_s = r_k(\tilde{u}, t) \in \mathbb{R}^n, \quad s = 1, \dots, n_h$$

- We can then form the **system**

$$\mathbf{C} = \begin{pmatrix} c_{11} & \dots & c_{1N_e} \\ \vdots & \ddots & \vdots \\ c_{n_h 1} & \dots & c_{n_h N_e} \end{pmatrix}, \quad \mathbf{d} = \begin{pmatrix} d_1 \\ \vdots \\ d_{n_h} \end{pmatrix}$$

- Where  $\mathbf{C}\xi = \mathbf{d}$ ,  $\xi \in \mathbb{R}^{N_e}$ ,  $\xi = \mathbf{1}$  must be the solution
- Further relax the equality to yield **non-negative least-squares problem**:

$$\xi = \arg \min_{x \in \mathbb{R}^n} \|\mathbf{C}x - \mathbf{d}\|_2 \text{ subject to } x \geq \mathbf{0}$$

- Solve the above optimization problem using a **non-negative least squares solver** with an **early termination condition** to promote sparsity of the vector  $\xi$