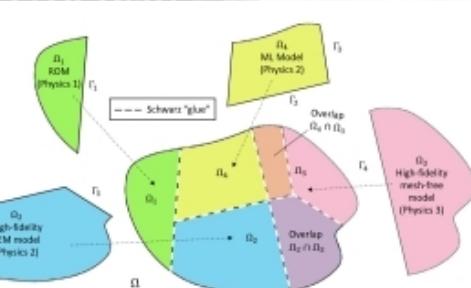
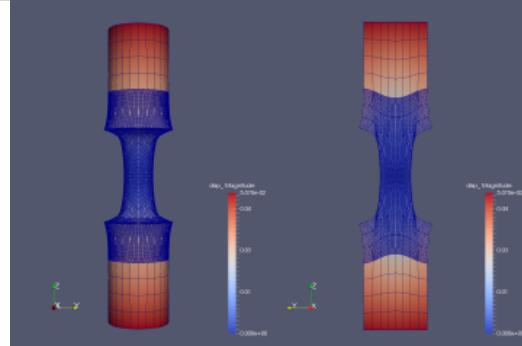
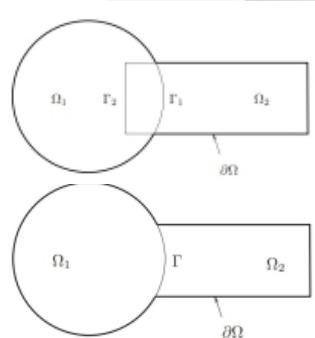




# Flexible domain decomposition-based couplings of conventional and data-driven models via the Schwarz alternating method



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

2<sup>nd</sup> AMS-UNI International Joint Meeting  
Palermo, Italy. July 23-26, 2024



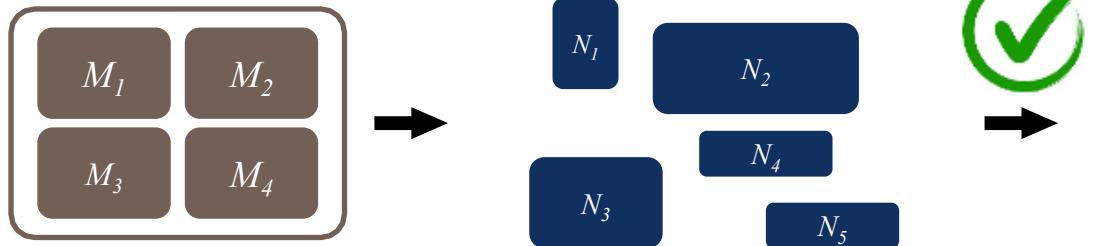
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# Motivation: multi-scale & multi-physics coupling



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

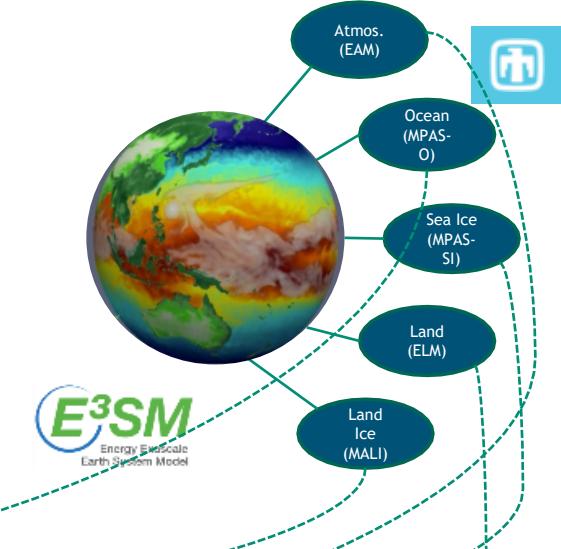
- PDEs, ODEs
- Nonlocal integral
- Classical DFT
- Atomistic, ...

## Traditional Methods

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

## Coupled Numerical Model

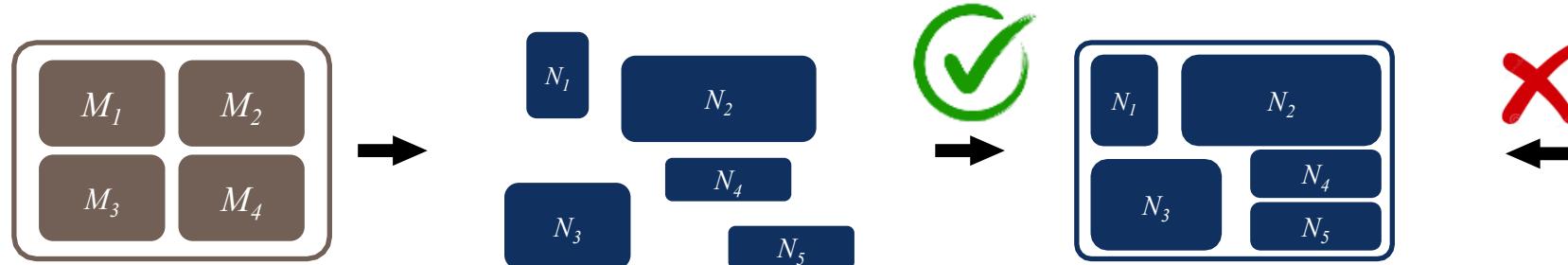
- Monolithic (Lagrange multipliers)
- Partitioned (loose) coupling
- Iterative (Schwarz, optimization)



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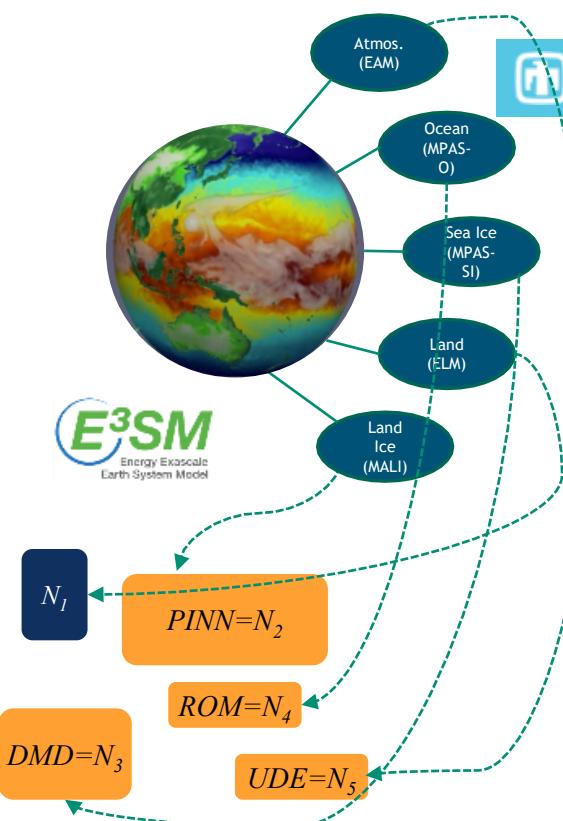
## Coupled Numerical Model

- Monolithic (Lagrange multipliers)
- Partitioned (loose) coupling
- 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!**



## Principal research objective:

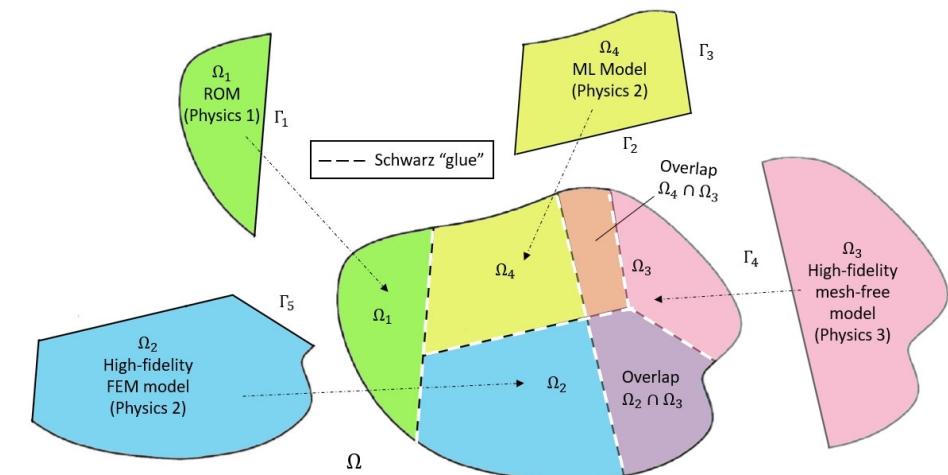
- Discover mathematical principles guiding the assembly of standard and data-driven numerical models in stable, accurate and physically consistent ways.

## 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.

## Three coupling methods:

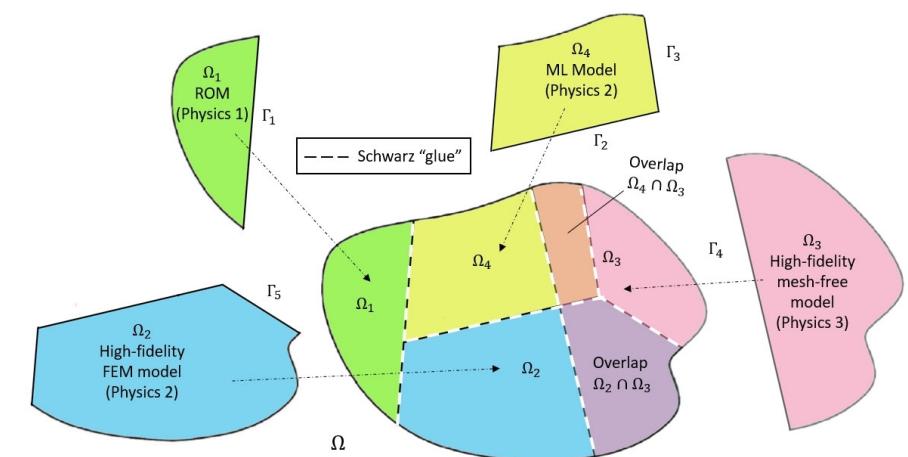
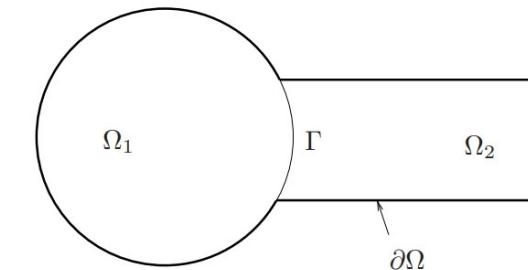
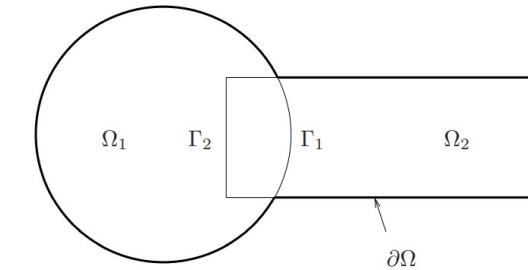
- Alternating Schwarz-based coupling *This talk.*
- Optimization-based coupling
- Coupling via generalized mortar methods



# Outline



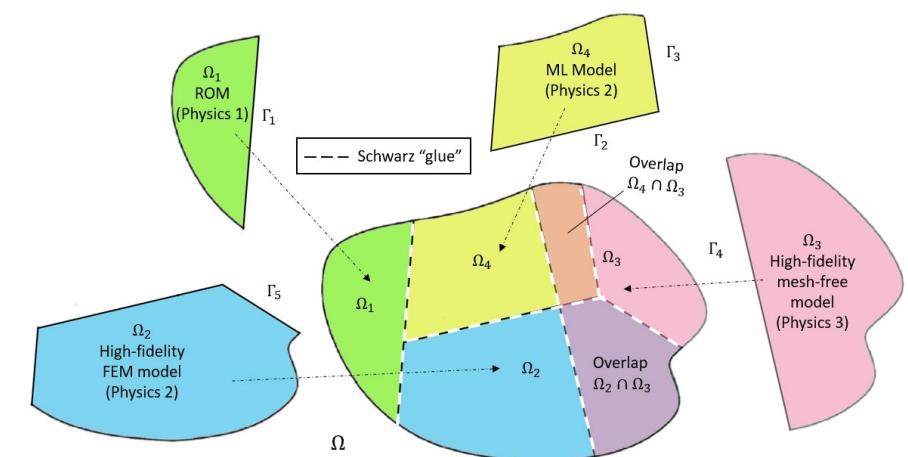
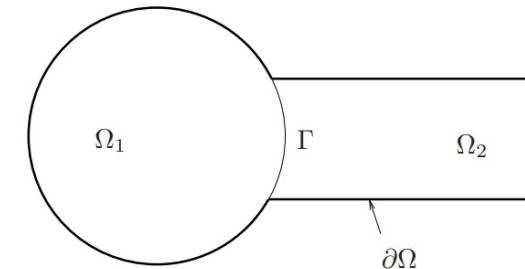
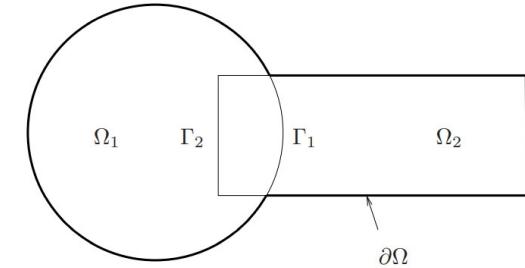
- The Schwarz Alternating Method for Domain Decomposition-Based Coupling
- Extension to FOM\*-ROM<sup>#</sup> and ROM-ROM Coupling
- Numerical Examples
  - 2D Burgers Equation
  - 2D Shallow Water Equations
  - Teaser: 2D Euler Equations Riemann Problem
- Summary & Future Work



# 6 Outline



- The Schwarz Alternating Method for Domain Decomposition-Based Coupling
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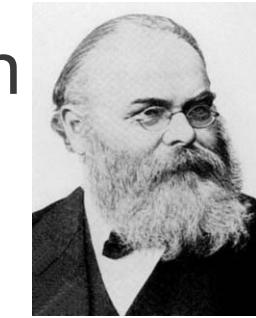


# 7 Schwarz Alternating Method for Domain Decomposition



- 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.



H. Schwarz (1843-1921)

## Basic Schwarz Algorithm

### Initialize:

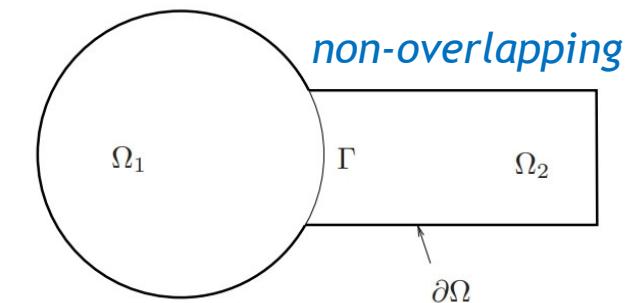
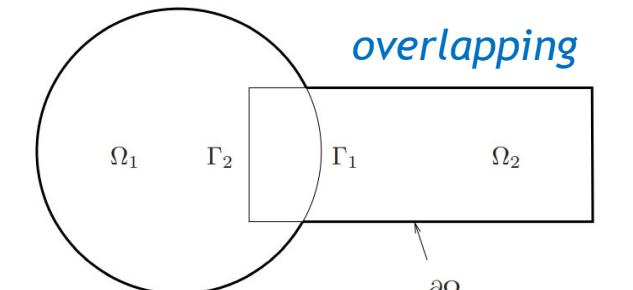
- Solve PDE by any method on  $\Omega_1$  w/ initial guess for transmission BCs on  $\Gamma_1$

.

### 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).

# How We Use the Schwarz Alternating Method



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



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

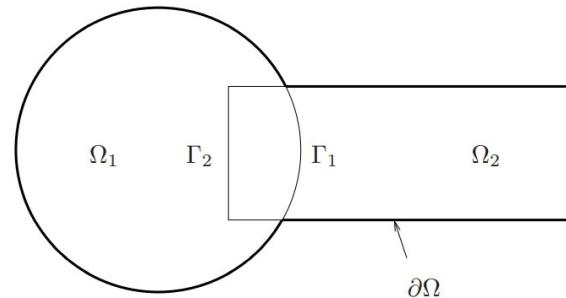
# Spatial Coupling via (Multiplicative) Alternating Schwarz



## Overlapping Domain Decomposition

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

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



Model PDE:

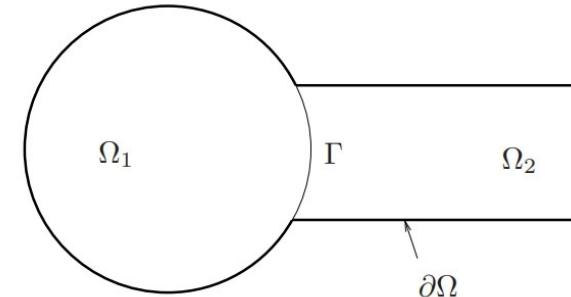
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- Dirichlet-Dirichlet transmission BCs [Schwarz 1870; Lions 1988; Mota *et al.* 2017; Mota *et al.* 2022]

## Non-overlapping Domain Decomposition

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$$\lambda_{n+1} = \theta \varphi_2^{(n)} + (1 - \theta) \lambda_n \text{ on } \Gamma, \text{ for } n \geq 1$$

- 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)

# Additional Parallelism via Additive Schwarz



## Multiplicative Overlapping Schwarz

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

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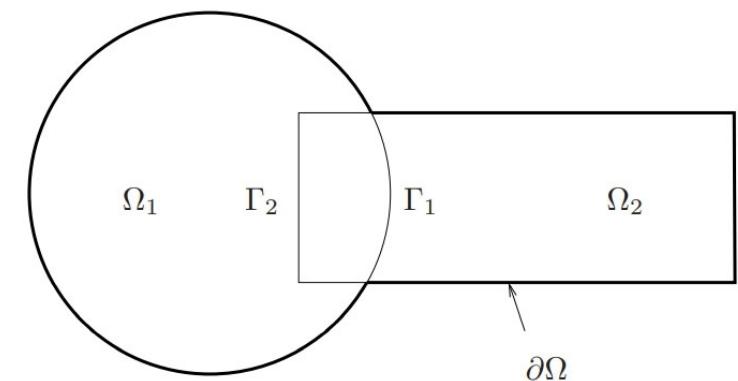
## Additive Overlapping Schwarz

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

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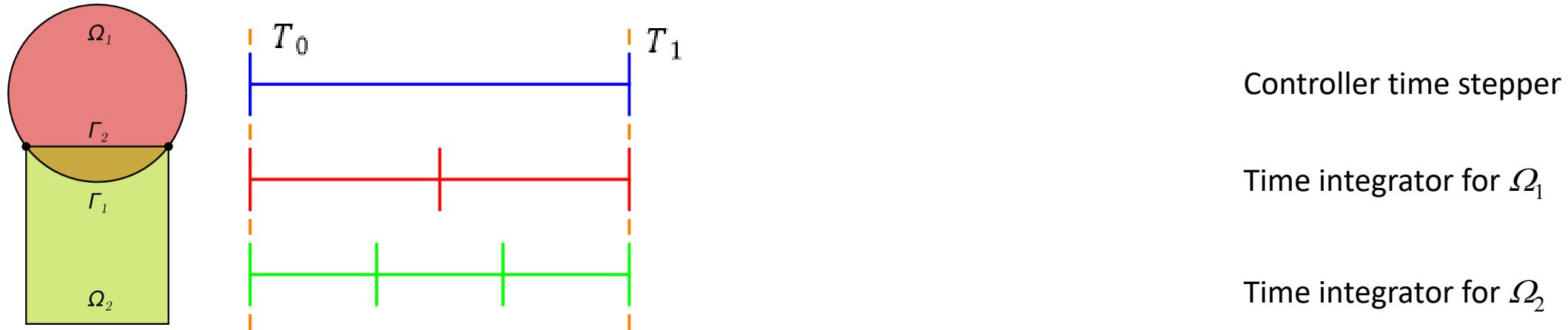
*Model PDE:*

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



- **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

# Time-Advancement Within the Schwarz Framework

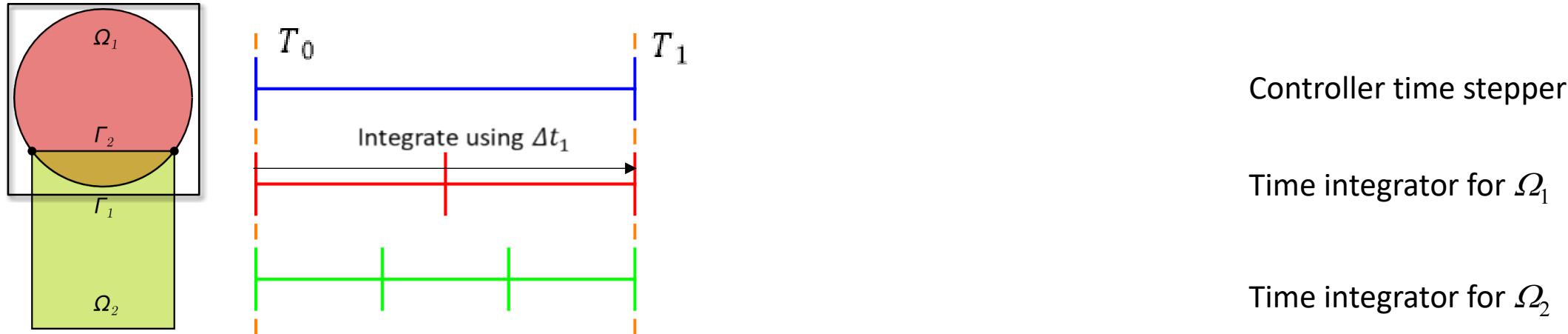


**Step 0:** Initialize  $i = 0$  (controller time index).

**Model PDE:**

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

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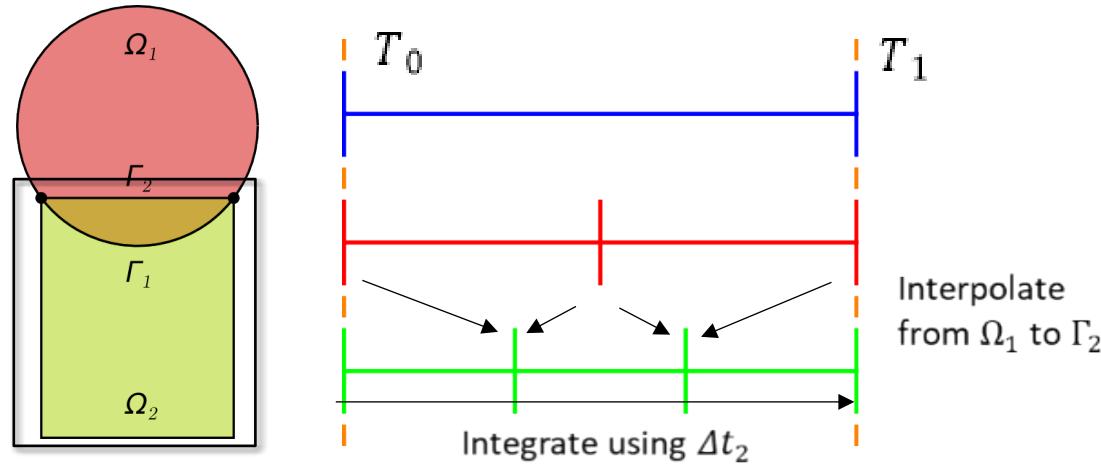


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# Time-Advancement Within the Schwarz Framework



Controller time stepper

Time integrator for  $\Omega_1$

Time integrator for  $\Omega_2$

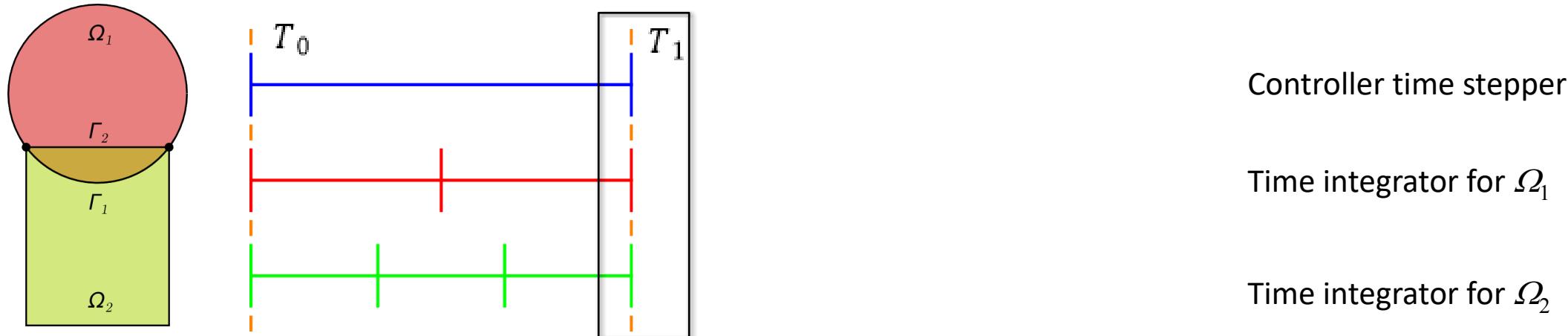
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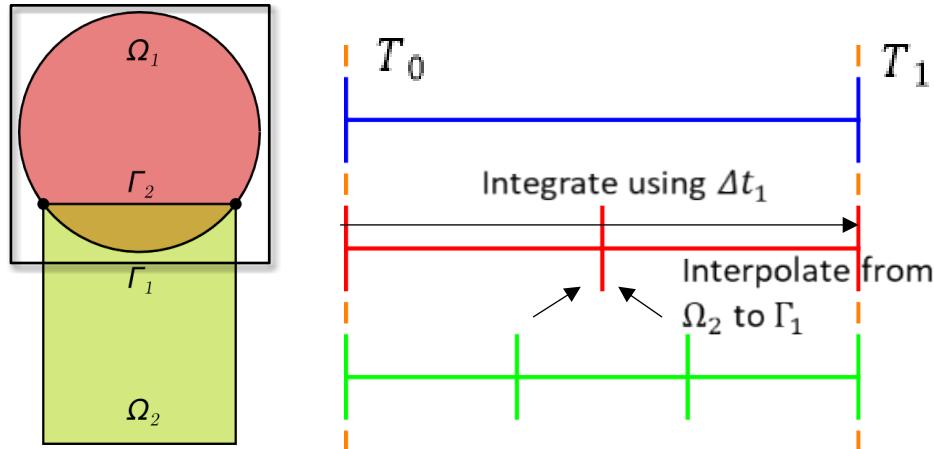
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Controller time stepper

Time integrator for  $\Omega_1$

Time integrator for  $\Omega_2$

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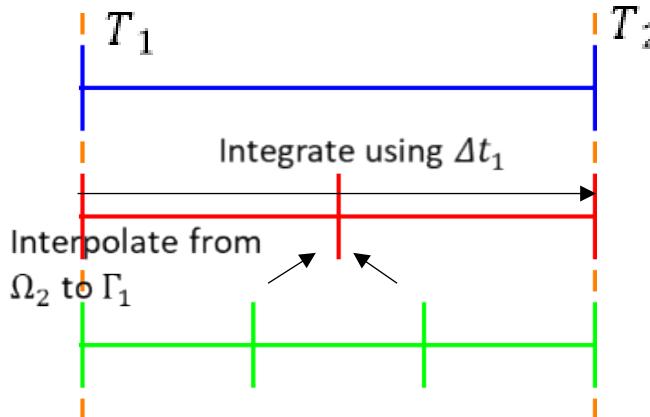
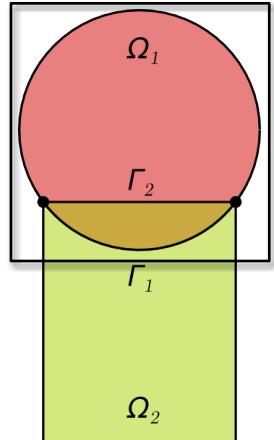
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➤ If unconverged, return to Step 1.

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# Time-Advancement Within the Schwarz Framework



Controller time stepper

Time integrator for  $\Omega_1$

Time integrator for  $\Omega_2$

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

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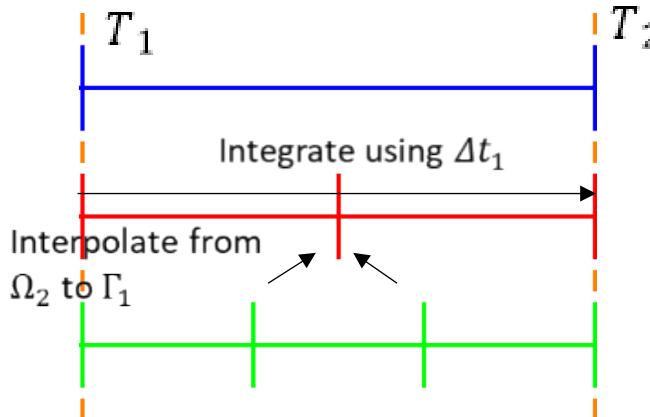
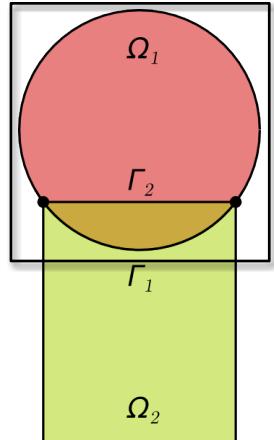
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- If unconverged, return to Step 1.
- If converged, set  $i = i + 1$  and return to Step 1.

**Model PDE:** 
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# Time-Advancement Within the Schwarz Framework



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].

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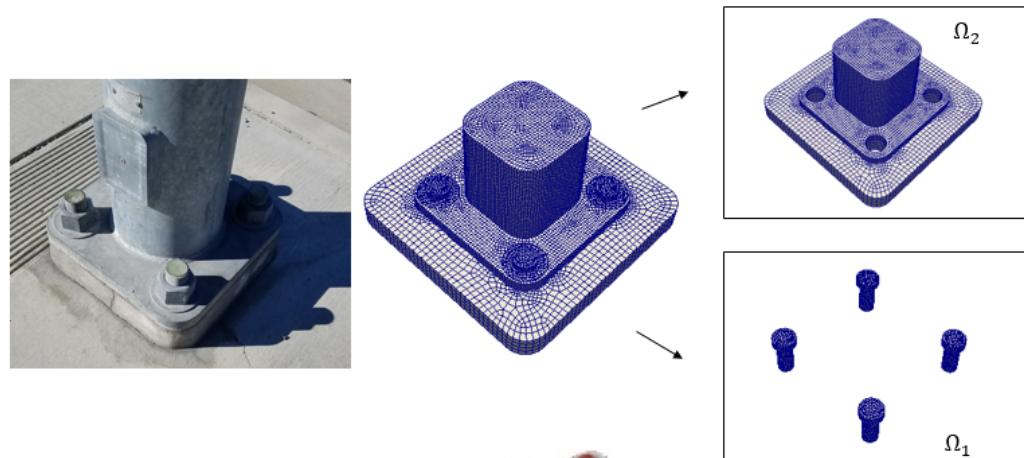
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*Model Solid Mechanics PDEs:*

- 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.
- ***“Plug-and-play” framework:***

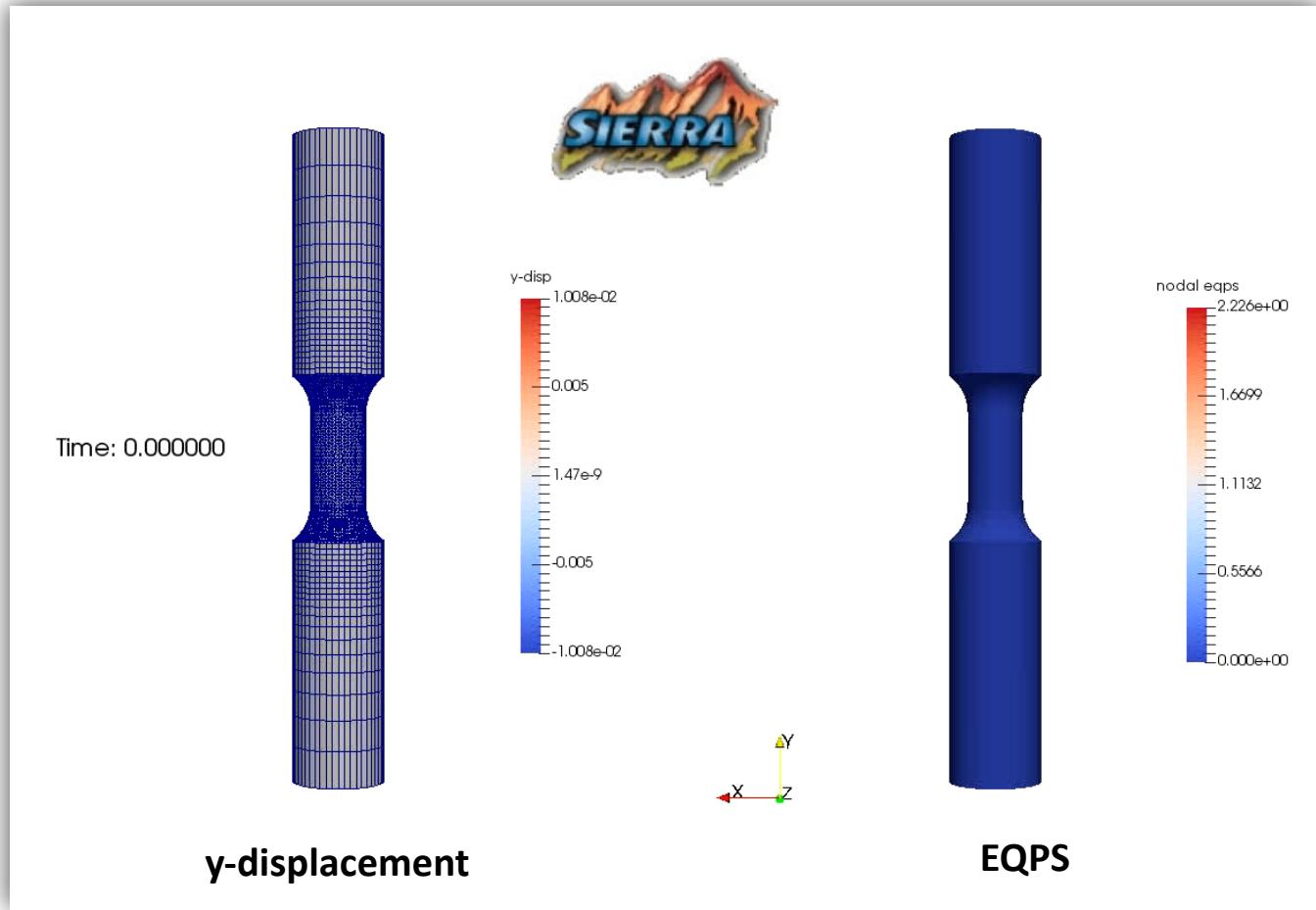
Quasistatic:  $\operatorname{Div} \mathbf{P} + \rho_0 \mathbf{B} = \mathbf{0}$  in  $\Omega$

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



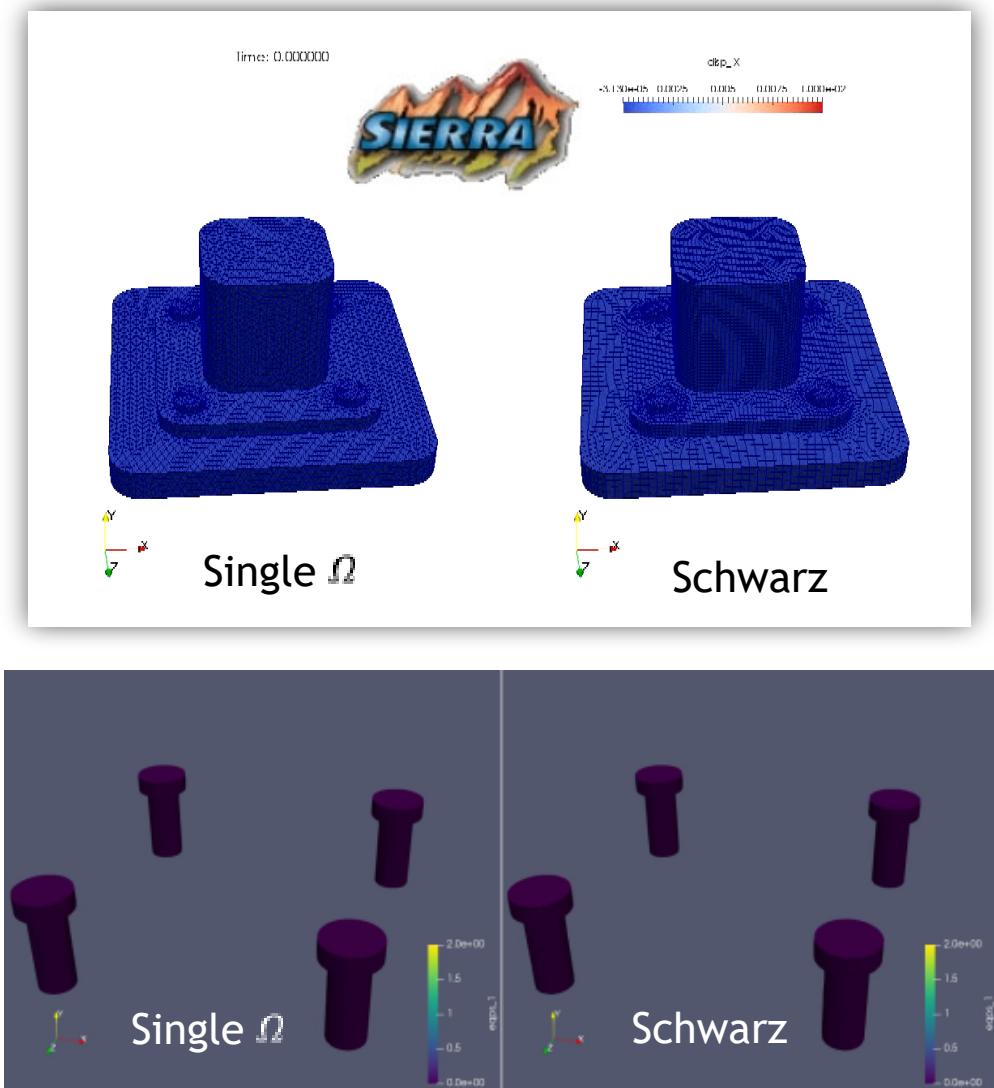
- Ability to couple regions with ***different non-conformal meshes, different element types and different levels of refinement*** to simplify task of ***meshing complex geometries***.
- Ability to use ***different solvers/time-integrators*** in different regions.

# 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.

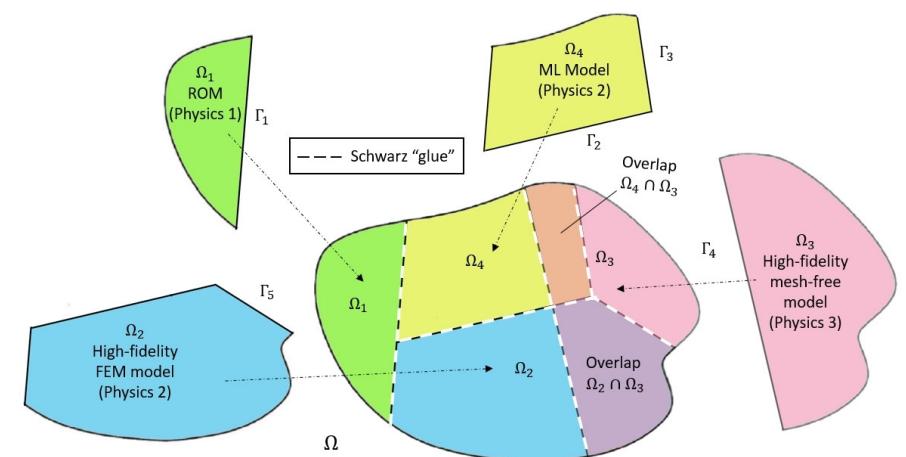
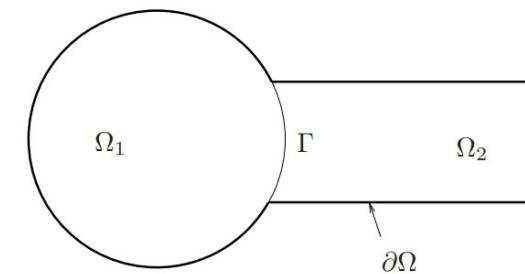
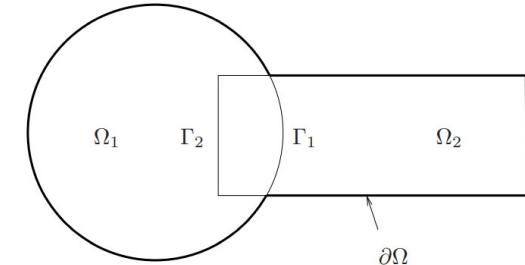
*Figures right:* bolted joint simulation coupling composite TET10 elements with HEX elements in Sierra/SM.



# Outline



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- Summary & Future Work



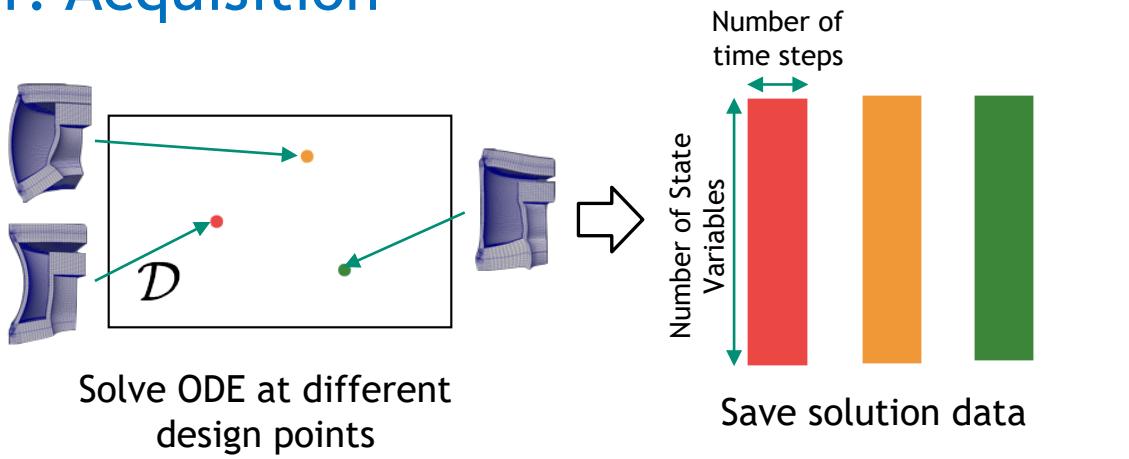
# Projection-Based Model Order Reduction via the POD/LSPG\* Method



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

\* Least-Squares Petrov-Galerkin

## 1. Acquisition



## 2. Learning

Proper Orthogonal Decomposition (POD):

$$\mathbf{X} = \begin{matrix} \text{Red Bar} \\ \text{Orange Bar} \\ \text{Green Bar} \end{matrix} = \begin{matrix} \text{Brown Matrix} \\ \text{Blue Matrix} \end{matrix} \Sigma \begin{matrix} \text{Blue Matrix} \\ \text{Light Blue Matrix} \end{matrix}$$

ROM = projection-based Reduced Order Model

## 3. Projection-Based Reduction

Choose ODE temporal discretization

$$\frac{du}{dt} = f(u; t, \mu) \downarrow r^n(u^n; \mu) = 0, n = 1, \dots, T$$

Reduce the number of unknowns

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

Minimize residual

$$\min_{\hat{v}} \| \mathbf{A} \begin{pmatrix} \text{Red Bar} \\ \text{Orange Bar} \\ \text{Green Bar} \end{pmatrix} - \mathbf{r}^n(\Phi \hat{v}; \mu) \|_2$$

Hyper-reduction/sample mesh

HROM = Hyper-reduced ROM

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



## *Choice of domain decomposition*

- Overlapping vs. non-overlapping domain decomposition?
  - Non-overlapping more flexible but typically requires more Schwarz iterations
- FOM vs. ROM subdomain assignment?
  - Do not assign ROM to subdomains where they have no hope of approximating solution

## *Snapshot collection and reduced basis construction*

- Are subdomains simulated independently in each subdomains or together?

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

- Strong vs. weak BC enforcement?
  - Strong BC enforcement difficult for some models (e.g., cell-centered finite volume, PINNs)
- Optimizing parameters in Schwarz BCs for non-overlapping Schwarz?

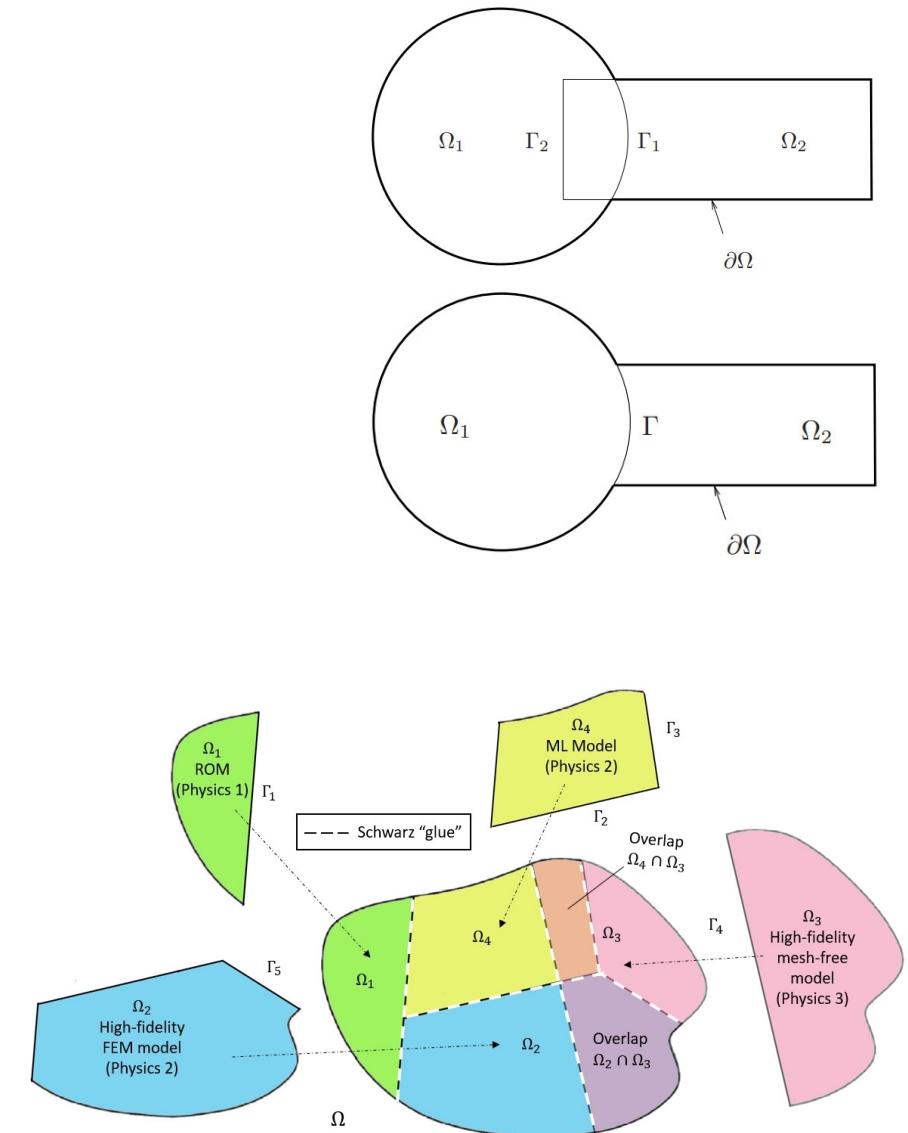
## *Choice of hyper-reduction*

- What hyper-reduction method to use?
  - Application may require particular method (e.g., ECSW for solid mechanics problems)
- How to sample Schwarz boundaries in applying hyper-reduction?
  - Need to have enough sample mesh points at Schwarz boundaries to apply Schwarz

# Outline



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

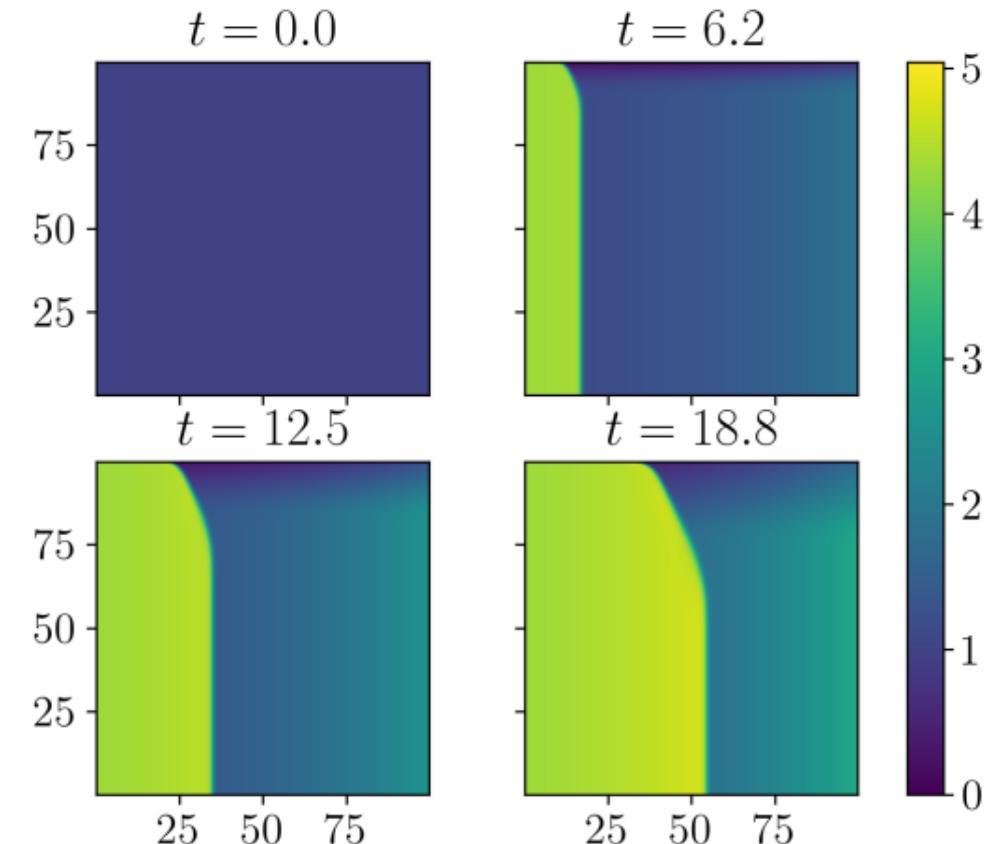
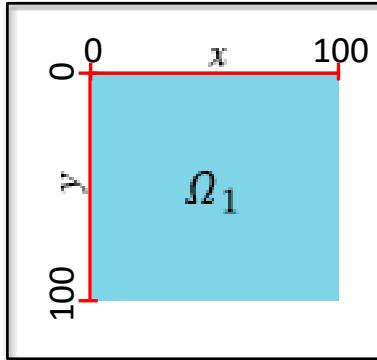


# 2D Inviscid Burgers Equation



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

$$\begin{aligned}\frac{\partial u}{\partial t} + \frac{1}{2} \left( \frac{\partial (u^2)}{\partial x} + \frac{\partial (uv)}{\partial y} \right) &= 0.02 \exp(\mu_2 x) \\ \frac{\partial v}{\partial t} + \frac{1}{2} \left( \frac{\partial (vu)}{\partial x} + \frac{\partial (v^2)}{\partial y} \right) &= 0 \\ u(0, y, t; \mu) &= \mu_1 \\ u(x, y, 0) &= v(x, y, 0) = 1\end{aligned}$$



## Problem setup:

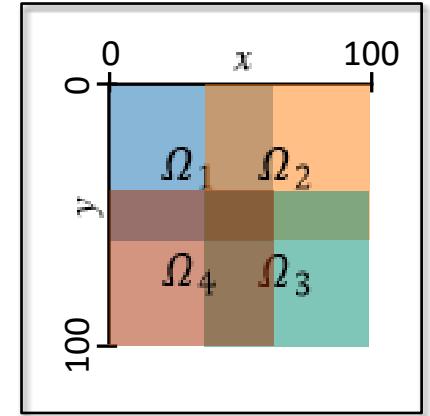
- $\Omega = (0, 100)^2$ ,  $t \in [0, 25]$
- Two parameters  $\mu = (\mu_1, \mu_2)$ . **Training:** uniform sampling of  $=[4.25, 5.50] \times [0.015, 0.03]$  by a  $3 \times 3$  grid. **Testing:** query unsampled point  $\mu = [4.75, 0.02]$

## FOM discretization:

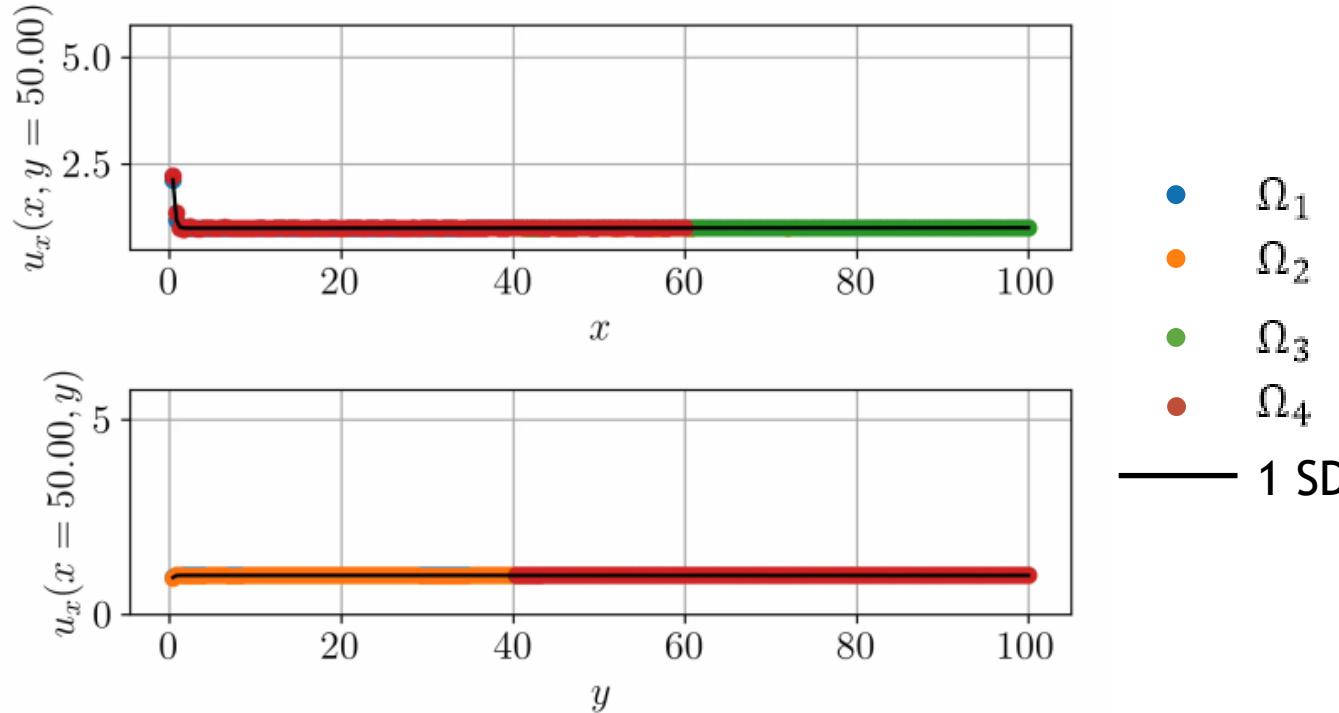
- Spatial discretization given by a **Godunov-type scheme** with  $N = 250$  elements in each dimension
- Implicit **trapezoidal method** with fixed  $\Delta t = 0.05$

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

No  
Image



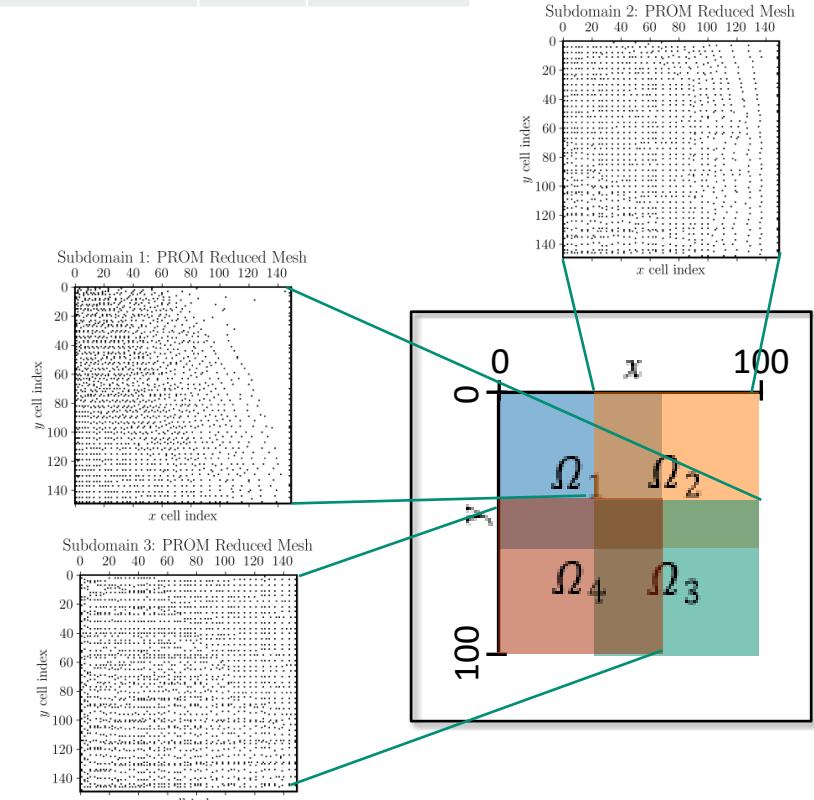
# FOM-HROM-HROM-HROM Coupling



- 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  $\Omega_1$
- 2.26x speedup achieved over all-FOM coupling

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

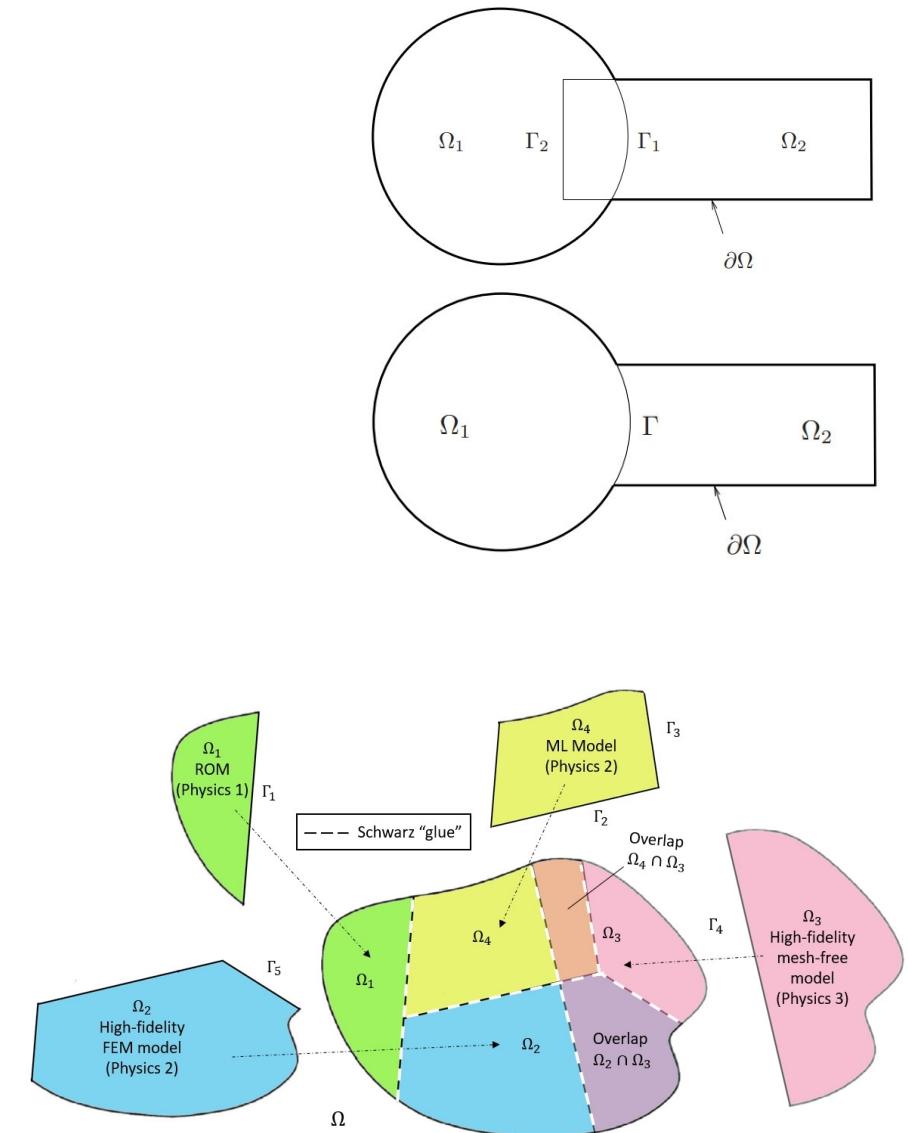
Subdomains	99% SV Energy		
	M	MSE (%)	CPU time (s)
$\Omega_1$	—	0.0	95
$\Omega_2$	120	0.26	26
$\Omega_3$	60	0.43	17
$\Omega_4$	66	0.34	21
<b>Total</b>			<b>159</b>



# Outline



- The Schwarz Alternating Method for Domain Decomposition-Based Coupling
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  - 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).

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

## 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>)

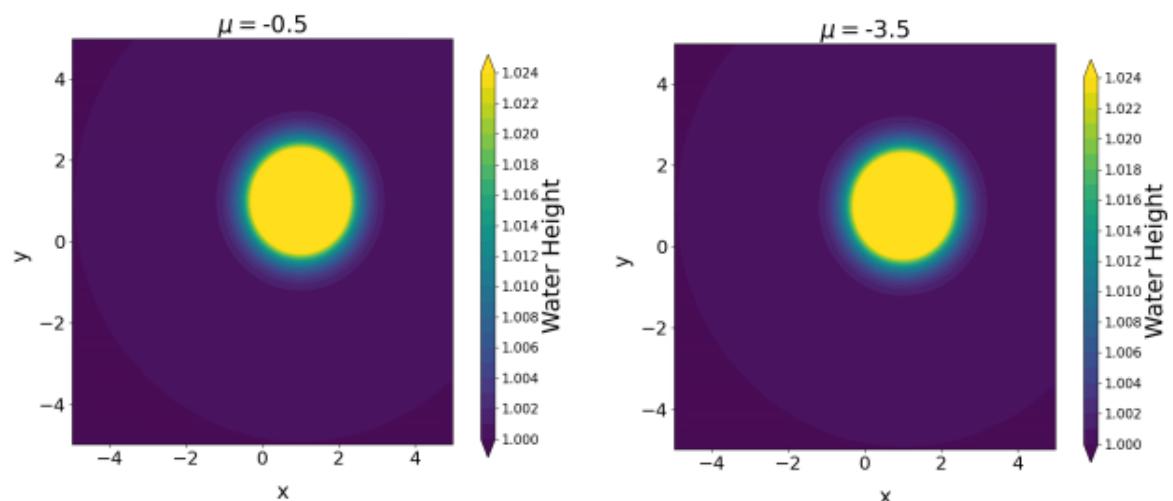


Figure above: FOM solutions to SWE for  $\mu = -0.5$  (left) and  $\mu = -3.5$  (right).

# Schwarz Coupling Details

## 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
  - ⇒ 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

Green: different from Burgers' problem

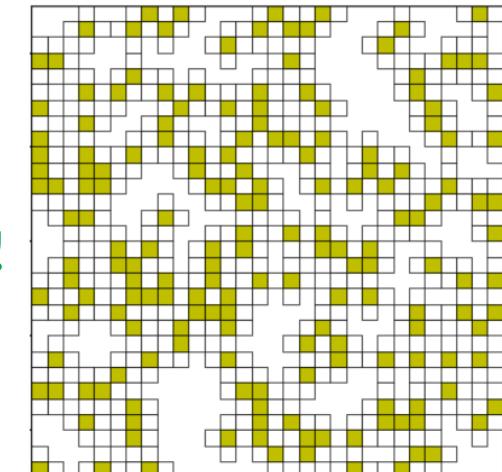
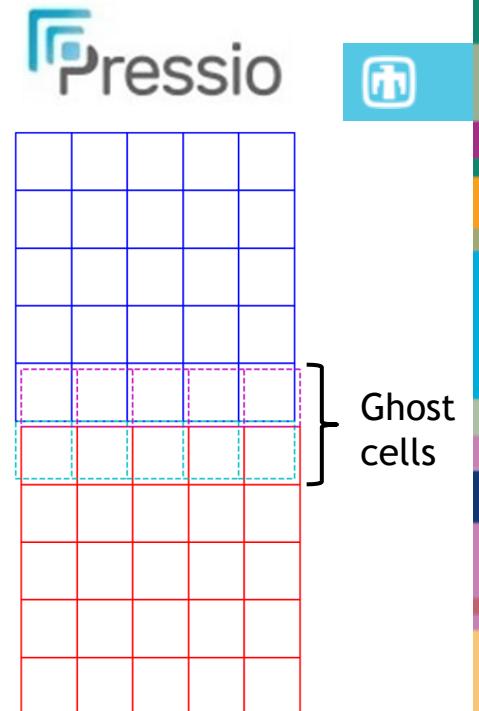
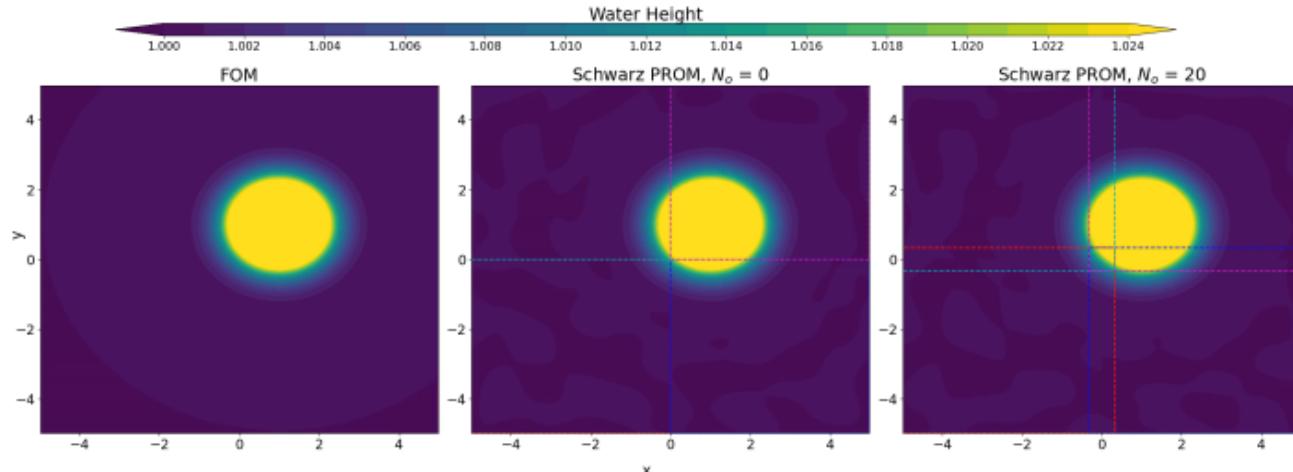


Figure above: sample mesh (yellow) and stencil (white) cells

# Schwarz All-ROM Domain Overlap Study

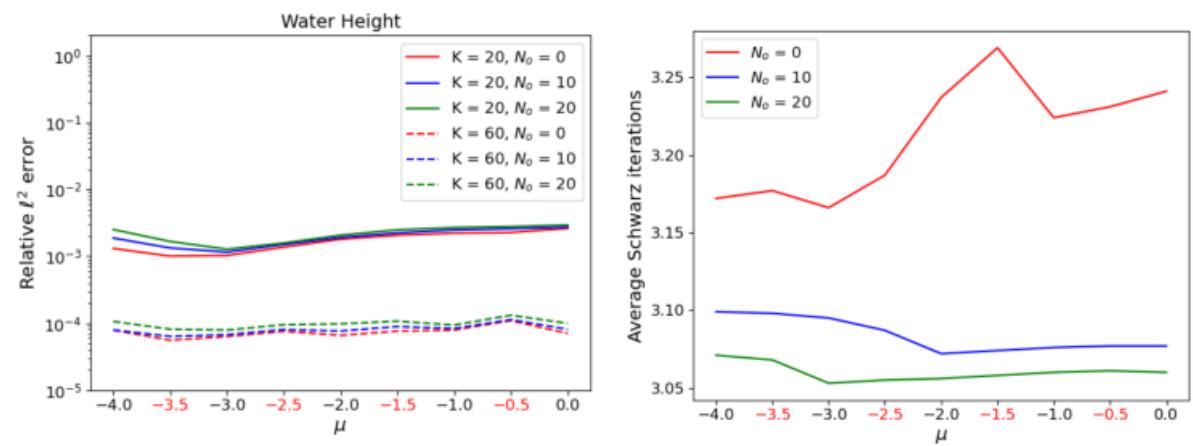


Study of Schwarz convergence for all-ROM coupling as a function of  $N_o :=$  cell width of overlap region (not including ghost cells).



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.

- 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.

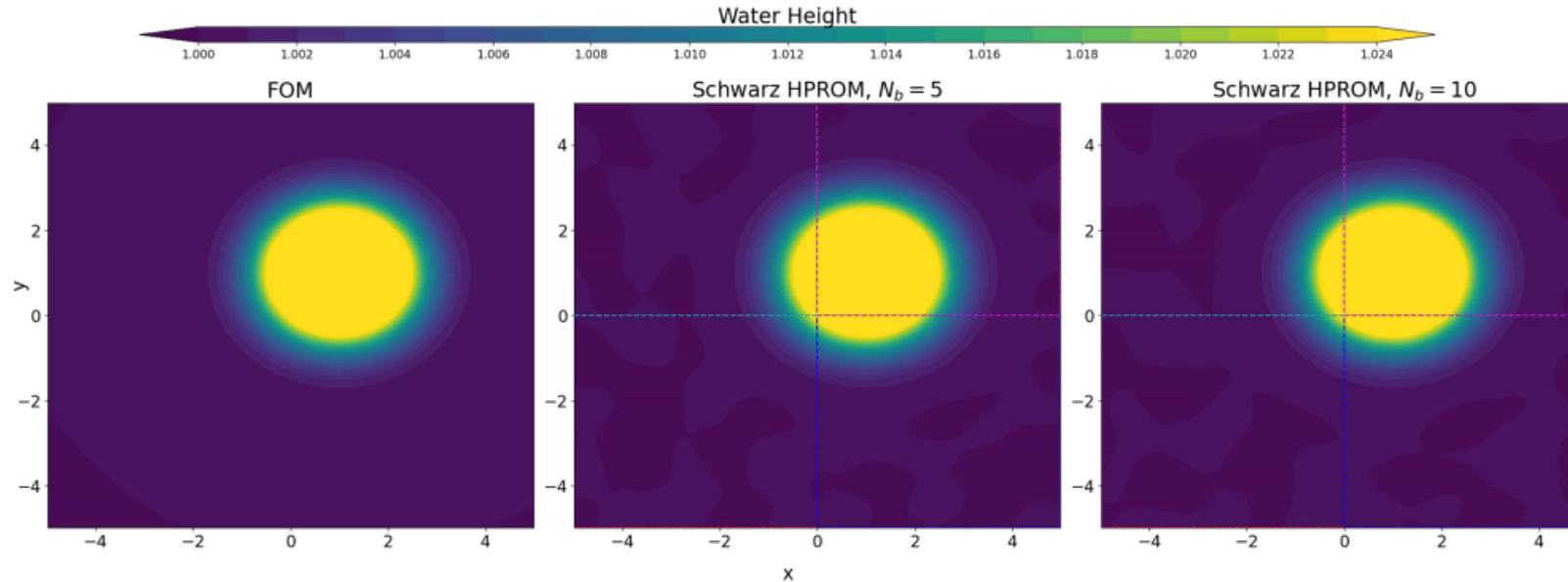
- Schwarz iterations decrease (very roughly) with  $N_o^{0.25}$  (figure, right) whereas evaluating  $r(q)$  scales with  $N_o^2$ 
  - ⇒ there is no reason not to do non-overlapping coupling for this problem

# Schwarz Boundary Sampling for All-HROM Coupling

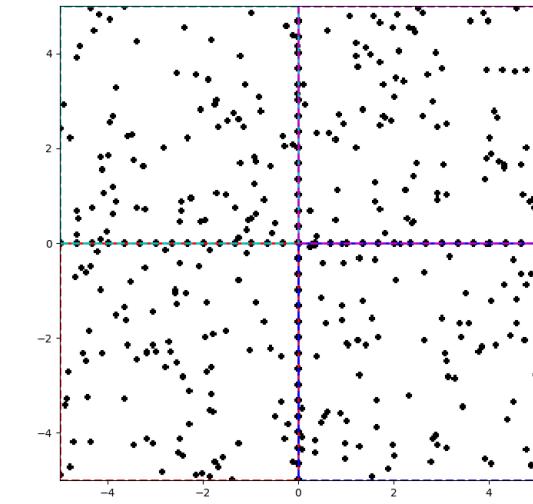


**Key question:** how many Schwarz boundary points need to be included in sample mesh when performing HROM coupling?

- Naive/sparsely-sampled Schwarz boundary results in **failure** to transmit coupling information during Schwarz



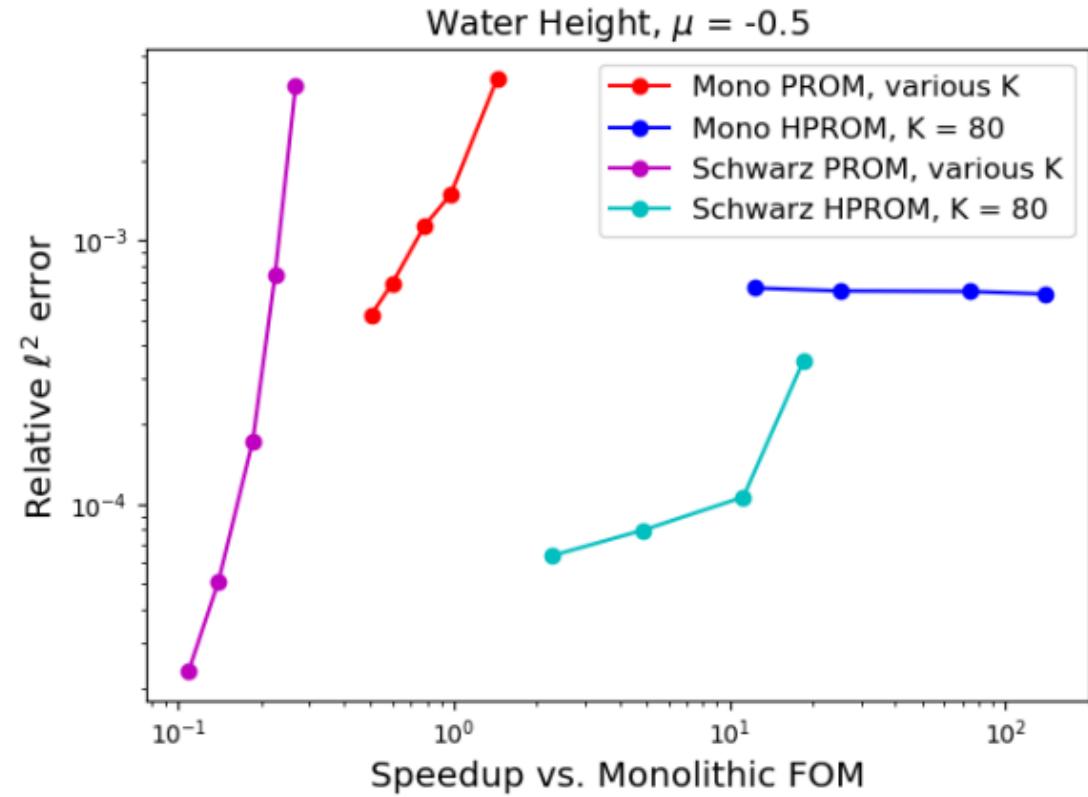
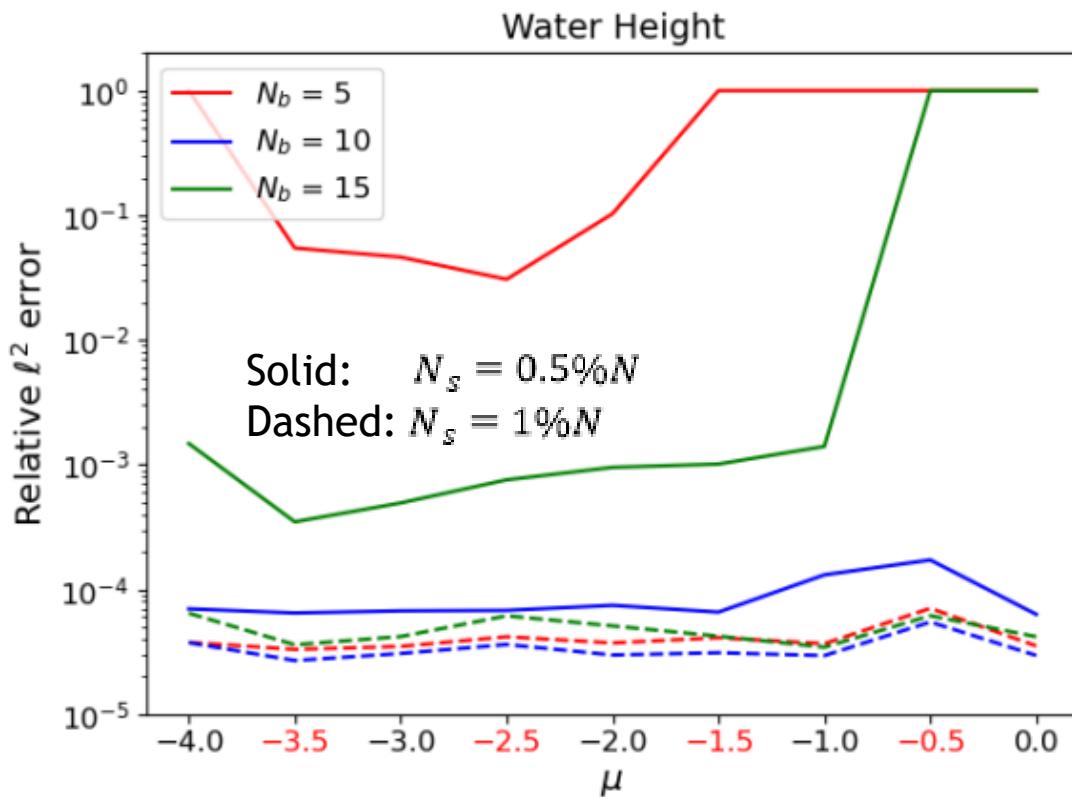
*Movie above:* FOM (left), all HROM with  $N_b = 5\%$  (middle) and all HROM with  $N_b = 10\%$  (left). ROMs have  $K = 100$  modes and  $N_s = 0.5\%N$  sample mesh points.



*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 **~10% boundary sampling** (movie above, right-most frame)

# Coupled HROM Performance

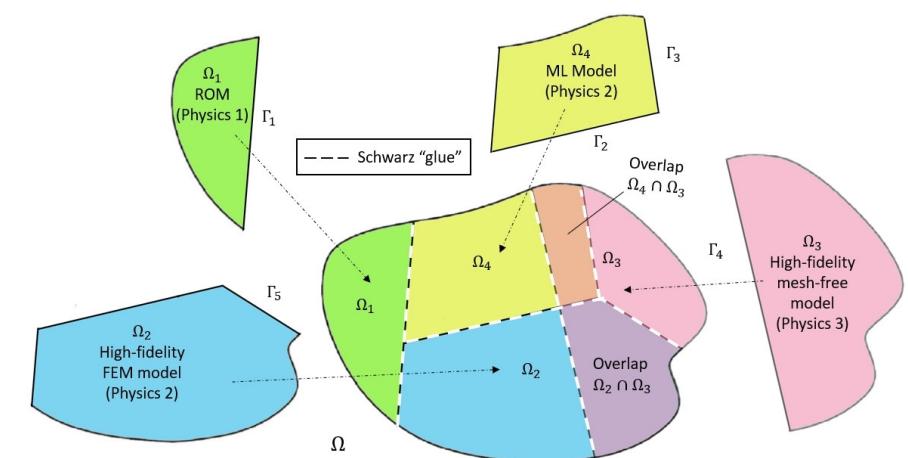
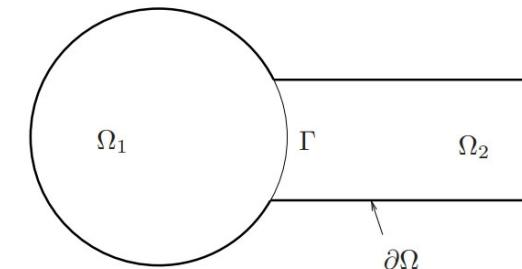
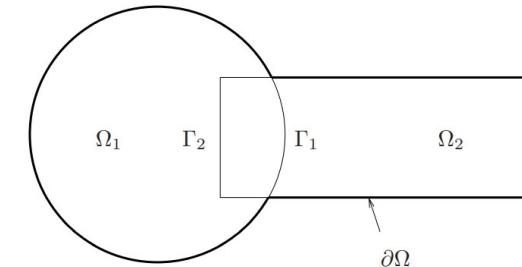


- For a fixed ROM dimension, Schwarz delivers **lower error and comparable cost!**
- There are noticeable **cost savings** relative to monolithic FOM!
- Accuracy similar for **predictive  $\mu$**  (red) and **non-predictive  $\mu$**  (black) cases.

# Outline

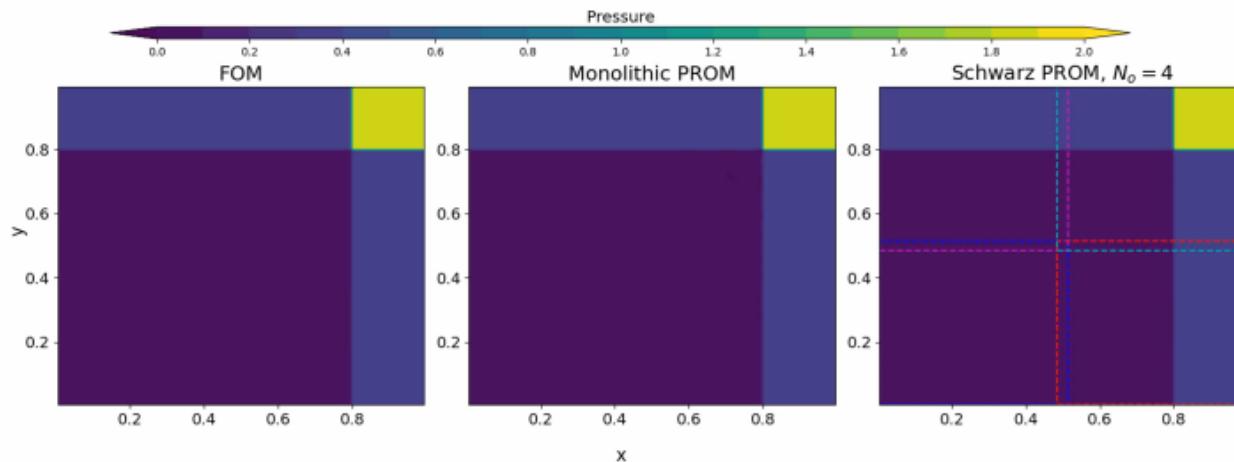


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# Teaser: 2D Euler Equations Riemann Problem

$$\begin{aligned}
 \frac{\partial}{\partial t} \begin{pmatrix} \rho \\ \rho u \\ \rho v \\ \rho E \end{pmatrix} + \frac{\partial}{\partial x} \begin{pmatrix} \rho u \\ \rho u^2 + p \\ \rho u v \\ (E + p)u \end{pmatrix} + \frac{\partial}{\partial y} \begin{pmatrix} \rho v \\ \rho u v \\ \rho v^2 + p \\ (E + p)v \end{pmatrix} = \mathbf{0} \\
 p = (\gamma - 1) \left( \rho E - \frac{1}{2} \rho (u^2 + v^2) \right)
 \end{aligned}$$



## 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  $N = N = 100$  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:

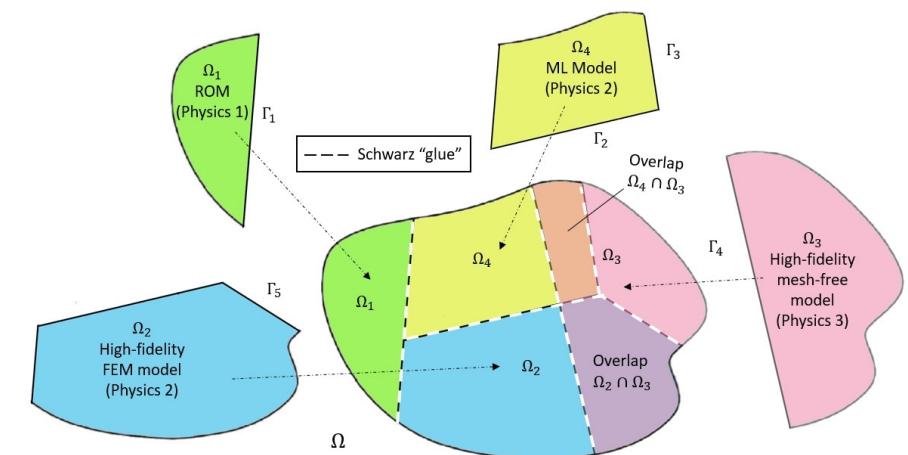
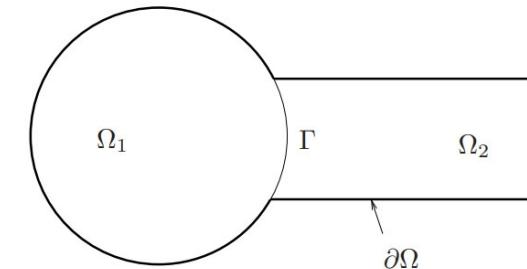
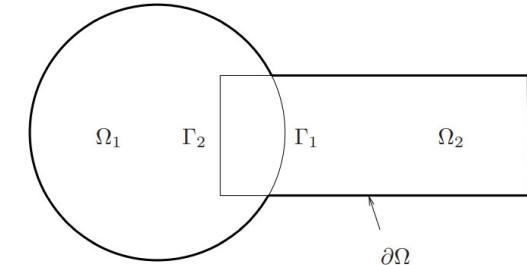
- Schwarz can **stabilize** unstable monolithic ROM for fixed dimension  $K$  (above)
- Since shock traverses all parts of domain, achieving **speedups** with Schwarz is **more difficult**

\*Schulz-Rinne, 1993.

# Outline



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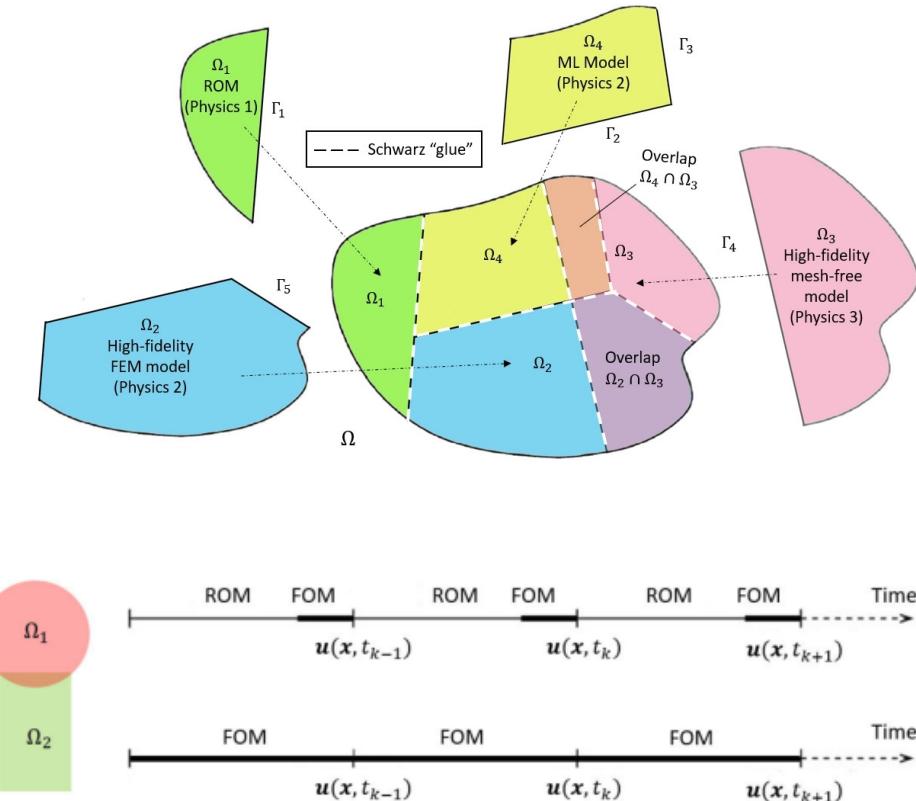
## Summary:

- Schwarz has been demonstrated for coupling of FOMs and (H)ROMs
- Computational gains can be achieved by coupling (H)ROMs and using the additive Schwarz variant

Pressio

## 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., DMD, 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



# Team & Acknowledgments



Irina Tezaur



Chris Wentland



Francesco Rizzi



Joshua Barnett



Alejandro Mota



Sandia  
National  
Laboratories



Will Snyder



Ian Moore



# References



- [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.  
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- [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>

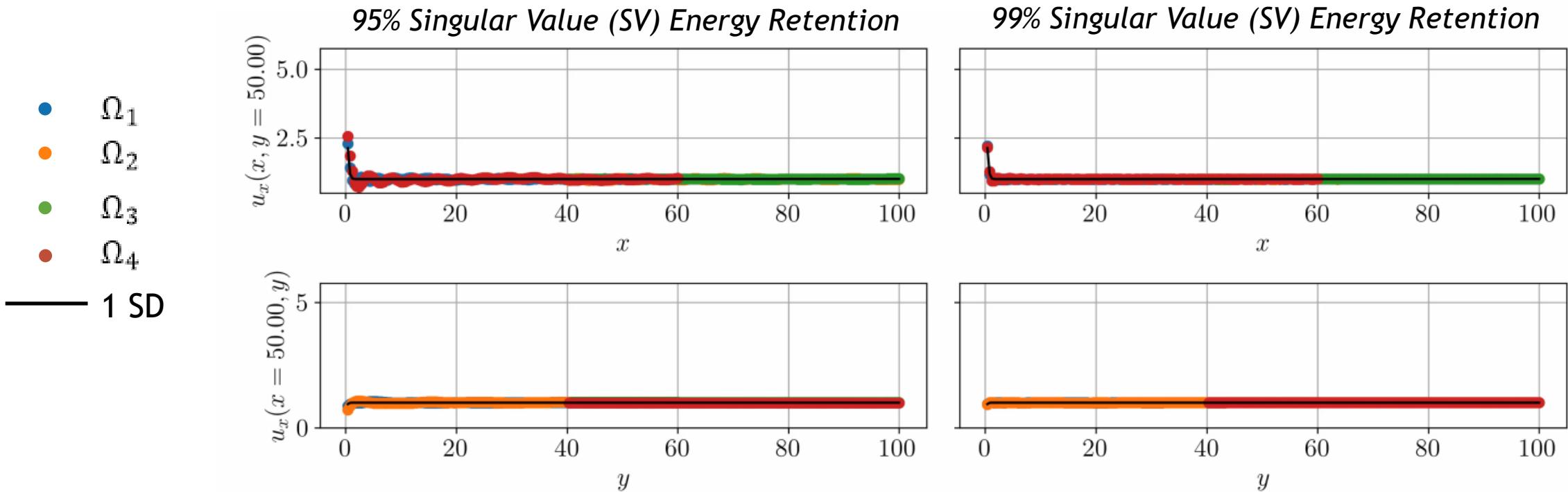
*Email:* [ikalash@sandia.gov](mailto:ikalash@sandia.gov)

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



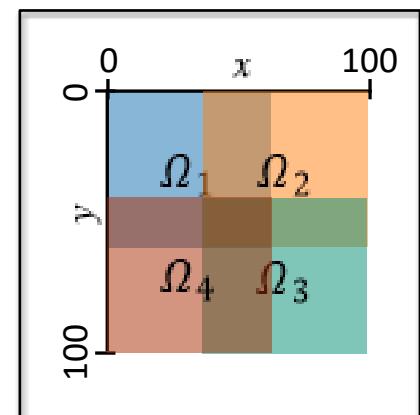
## Start of Backup Slides

# All-ROM Coupling



- Method converges in **only 3 Schwarz iterations** per controller time-step
- Errors  $O(1\%)$  or less
- 1.47x 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 (%)
$\Omega_1$	57	1.1	85	146	0.18
$\Omega_2$	44	1.2	56	120	0.18
$\Omega_3$	24	1.4	43	60	0.16
$\Omega_4$	32	1.9	61	66	0.25
Total			245		700



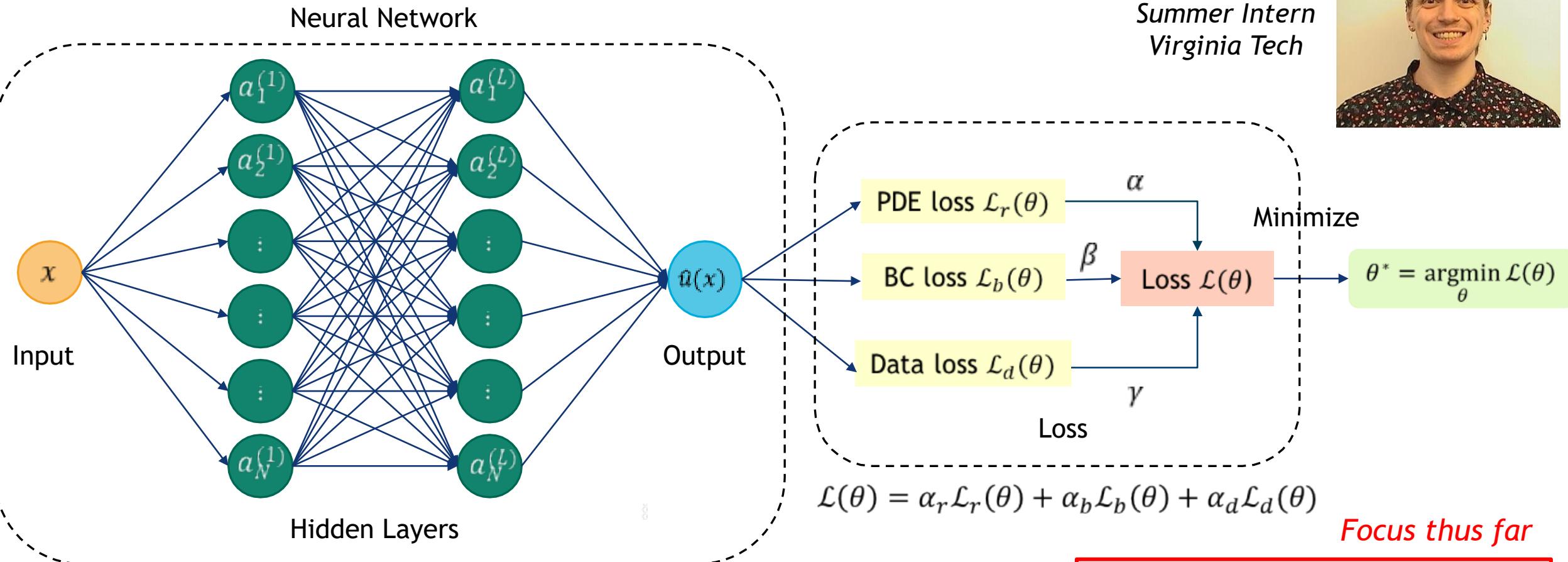


The Schwarz alternating method has been developed for concurrent multi-scale coupling of conventional and data-driven models.

- ☺ 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



*Focus thus far*

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

Related work: Li et al., 2019, Li et al., 2020, Wang et al., 2022.

**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

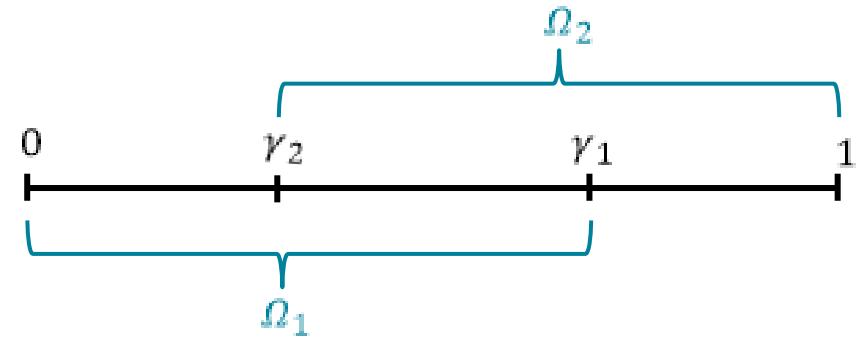


1D steady advection-diffusion equation on  $\Omega = [0,1]$ :

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

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:**

$$\begin{aligned}\mathcal{L}_{r,i}(\theta) &= MSE\left(-\nu \nabla_x^2 NN_{\Omega_i}(x, \theta) + \nabla_x NN_{\Omega_i}(x, \theta) - 1\right) \\ \mathcal{L}_{b,i}(\theta) &= MSE\left(NN_{\Omega_i}(\partial\Omega, \theta)\right) + MSE\left(NN_{\Omega_i}(\gamma_i, \theta) - NN_{\Omega_j}(\gamma_i, \theta)\right)\end{aligned}$$

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

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

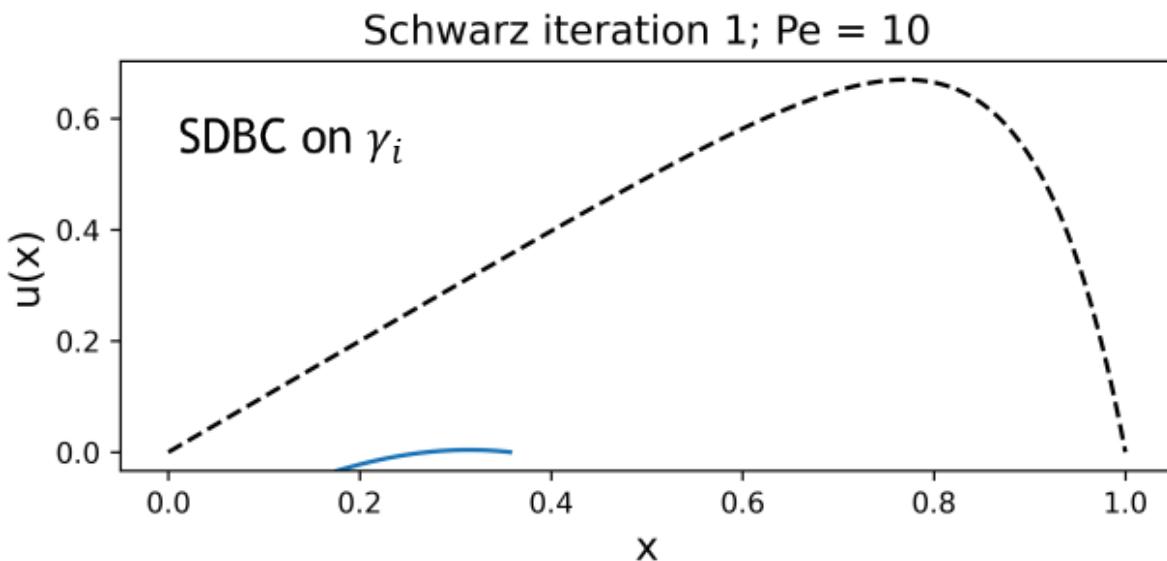
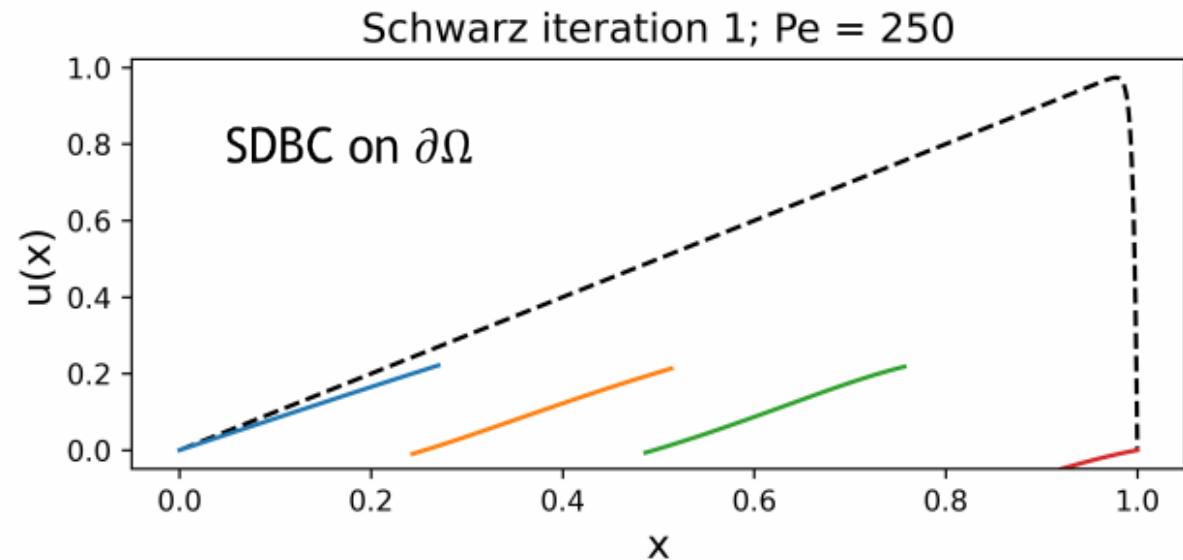
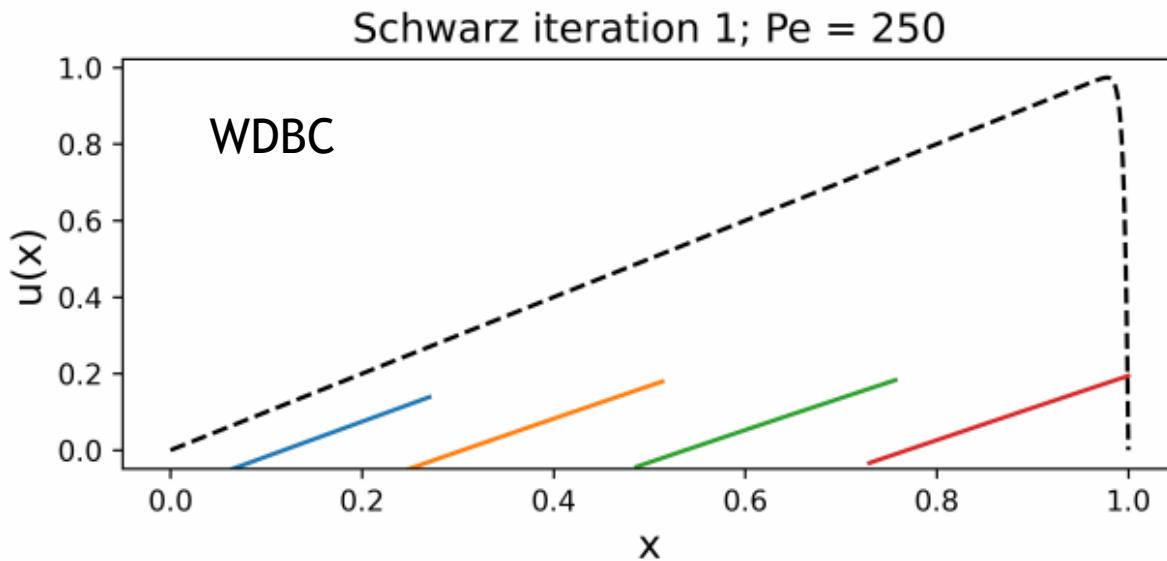
Communicate Dirichlet data between neighboring subdomains

Update boundary data on  $\gamma_i$  from neighboring subdomains

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

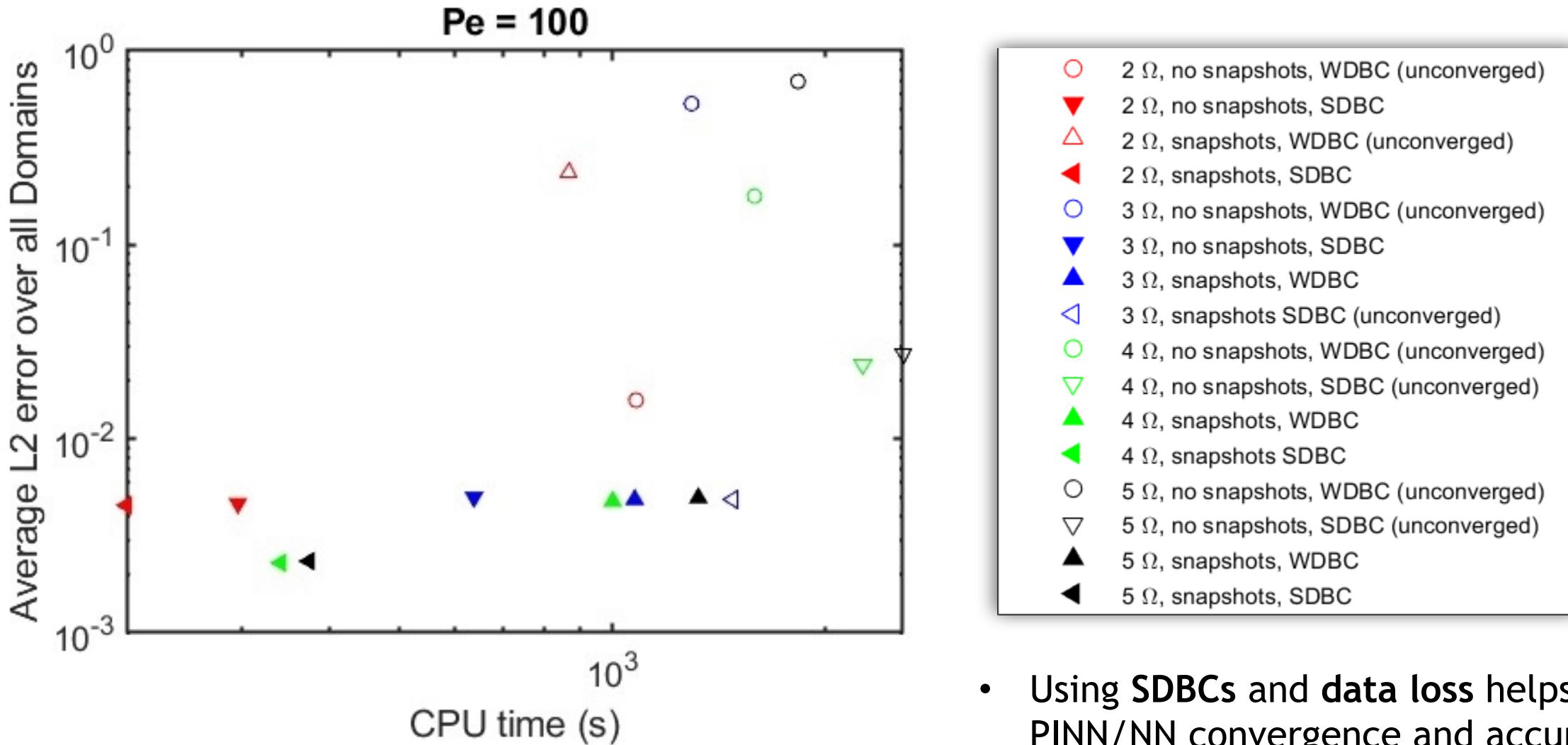
If **weak enforcement of Dirichlet BC (WDBC)**, set  $\beta = 0$  and  $\hat{u}_{\Omega_i}(x, \theta) = \nu(x)NN_{\Omega_i}(x, \theta) + \psi(x)\hat{u}_{\Omega_j}(\gamma_j, \theta)$   
where  $\nu(x)$  is chosen s.t.  $\nu(0) = \nu(\gamma_i) = \nu(1) = 0$  and  $\psi(x)$  is chosen s.t.  $\nu(\gamma_i) = 1$

# Bonus: PINN-PINN coupling

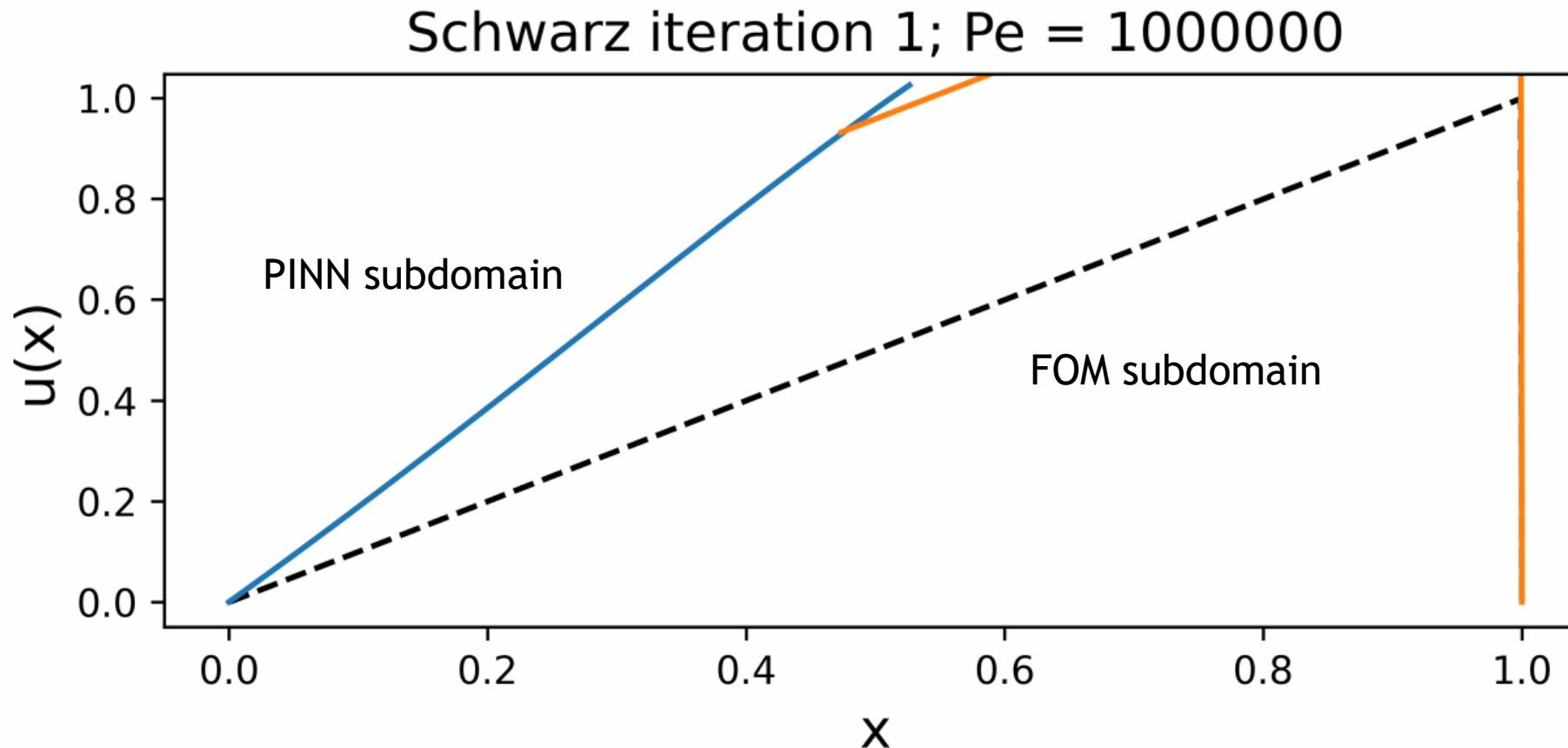


- How **Dirichlet boundary conditions** are handled has a large impact on PINN convergence
- Convergence not improved in general with **increasing overlap**
- Increasing **# subdomains** in general will increase CPU time

## Bonus: PINN-PINN coupling



## Bonus: PINN-FOM coupling



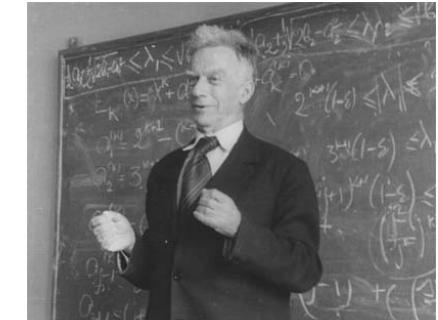
- PINN-FOM coupling gives **rapid PINN convergence for arbitrarily high Peclet numbers**
- PINN-FOM couplings works with **both WDBC and SDBC configurations**

# Theoretical Foundation

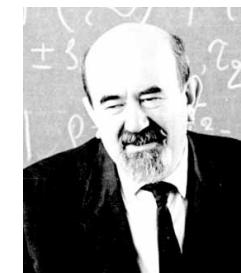


Using the Schwarz alternating as a *discretization method* for PDEs is natural idea with a sound *theoretical foundation*.

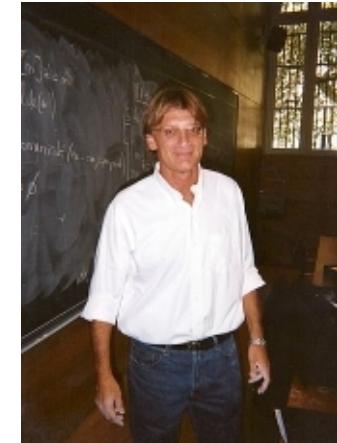
- **S.L. Sobolev (1936):** posed Schwarz method for *linear elasticity* in variational form and *proved method's convergence* by proposing a convergent sequence of energy functionals.
- **S.G. Mikhlin (1951):** *proved convergence* of Schwarz method for general linear elliptic PDEs.
- **P.-L. Lions (1988):** 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*.



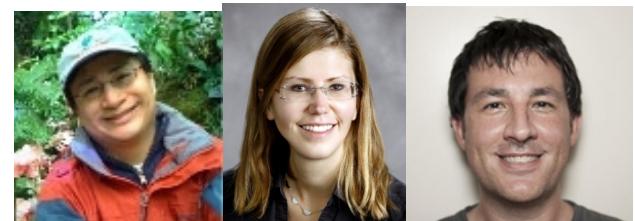
S.L. Sobolev (1908 – 1989)



S.G. Mikhlin  
(1908 – 1990)



P.-L. Lions (1956-)



A. Mota, I. Tezaur, C. Alleman

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

$$\nabla \cdot P + B = 0$$





- 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  $S[\varphi] := \int_I \int_{\Omega} L(\varphi, \dot{\varphi}) dV dt$  be ***strictly convex*** or ***strictly concave***, where  $L(\varphi, \dot{\varphi}) := T(\dot{\varphi}) + V(\varphi)$  is the Lagrangian.
  - This is studied by looking at its second variation  $\delta^2 S[\varphi_h]$
- We can show assuming a ***Newmark*** time-integration scheme that for the ***fully-discrete*** problem:

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

- $\delta^2 S[\varphi_h]$  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.

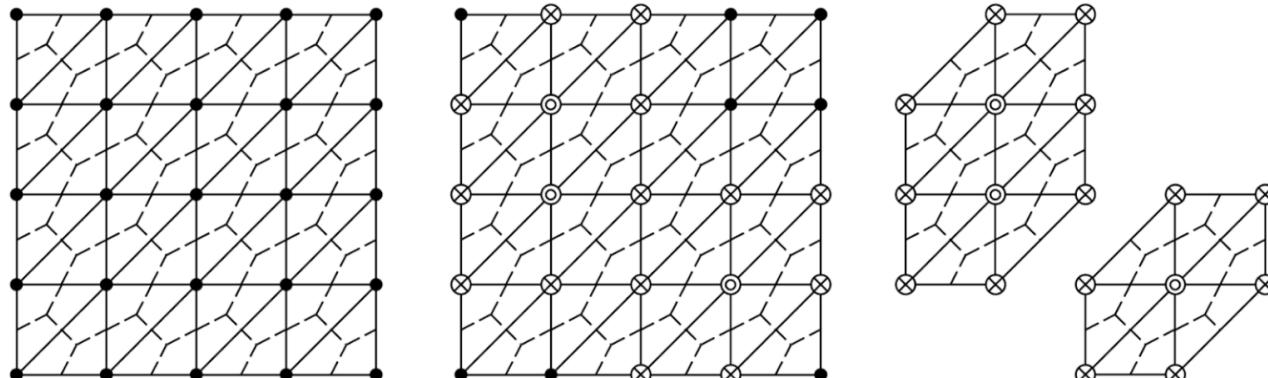
# Energy-Conserving Sampling and Weighting (ECSW)



- 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:  $\circ$  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  $\xi$