

Scalable Graph Neural Networks for Mesh-Based Fluid Flow Modeling

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Data-Intensive Computing and AI/ML Applications at Scale
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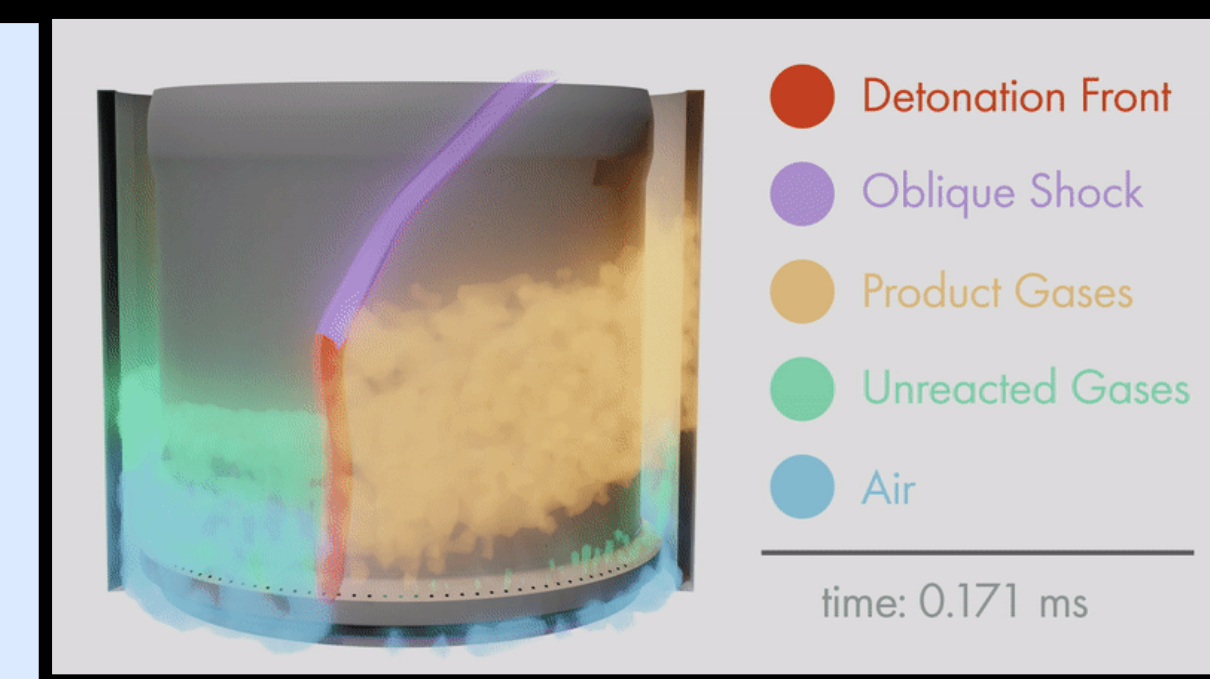
Interpretable Scientific Machine Learning for Mesh-Based Simulations with Graph Neural Networks

With: Romit Maulik (Argonne/Penn State)
Varun Shankar (CMU), Venkat Viswanathan (CMU)

Research Objectives

Goal: surrogate models for **full-scale** unsteady fluid simulations (e.g., propulsion applications)

Objective 1: Enable complex geometry compatibility.



Solver: UMReactingFlow (APCL, UM)
Visualization: Michelle Lehmann (ORNL)

Objective 2: Ensure interpretable latent spaces, fine-tuned to modeling task (reconstruction, forecasting).

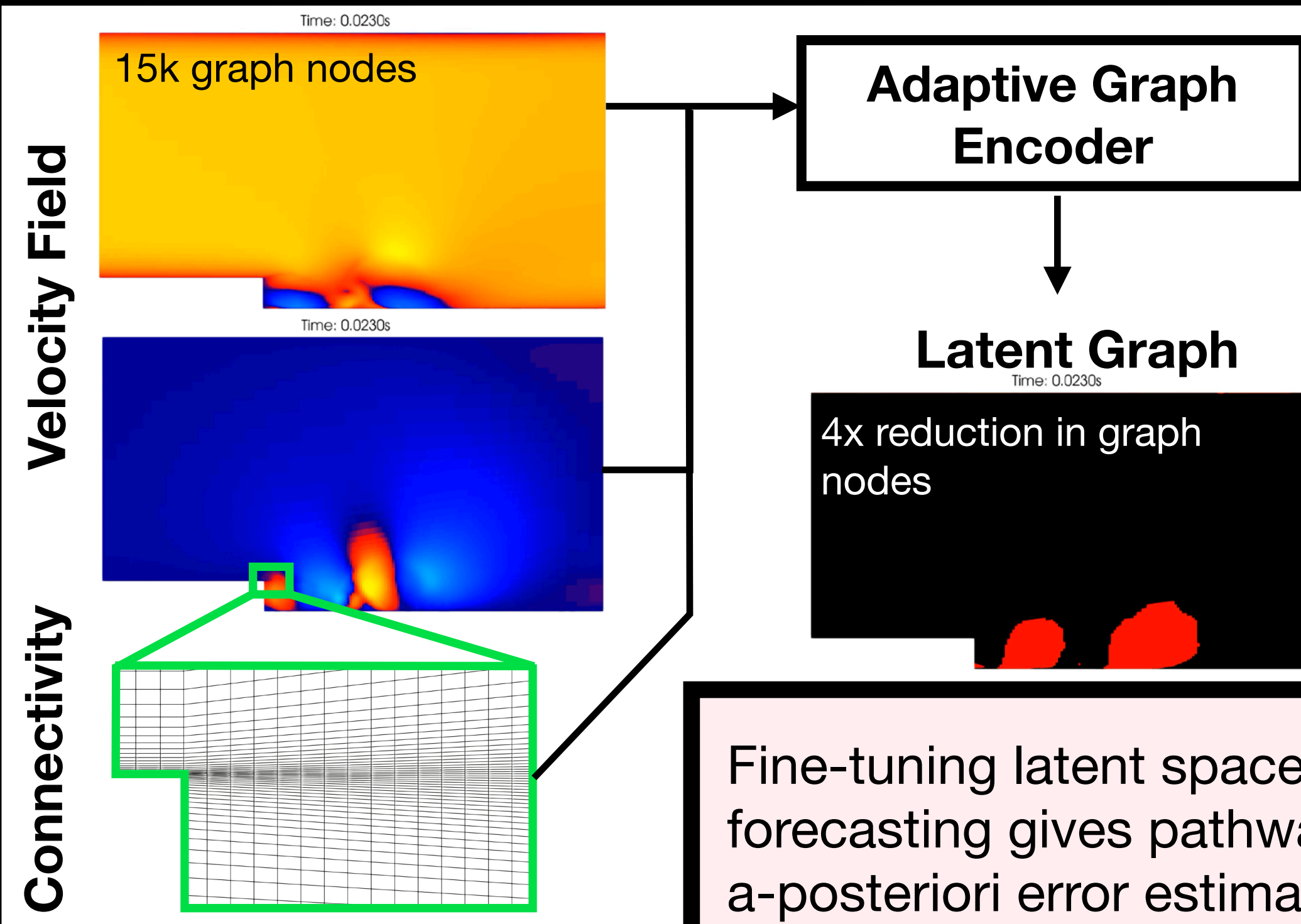
Objective 3: Develop scalable training and inference strategies.

Approach

Multiscale GNN layers: Employ **message passing** schemes at various grid resolutions to enable efficient propagation of information

Graph reduction: Top-K graph pooling strategy achieves reduction in input graph dimensionality using adaptive and learnable node subsampling

Domain decomposition: Leverage domain decomposition routines used in vetted exascale computational fluid dynamics codes (NekRS) to scale-up and train models on very large graphs

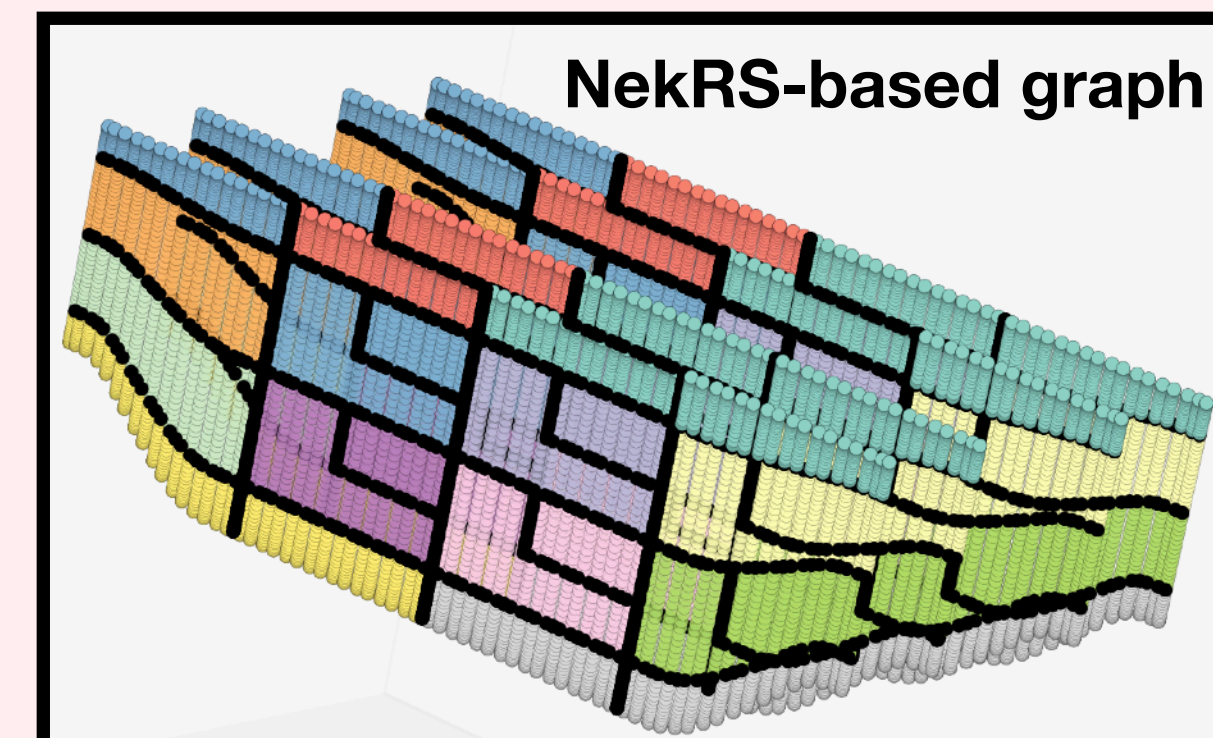


Fine-tuning latent spaces for forecasting gives pathways for a-posteriori error estimation for surrogate models.

Ongoing work: distributed GNN operations using NekRS, and forecasting stability.

Impact & Ongoing Work

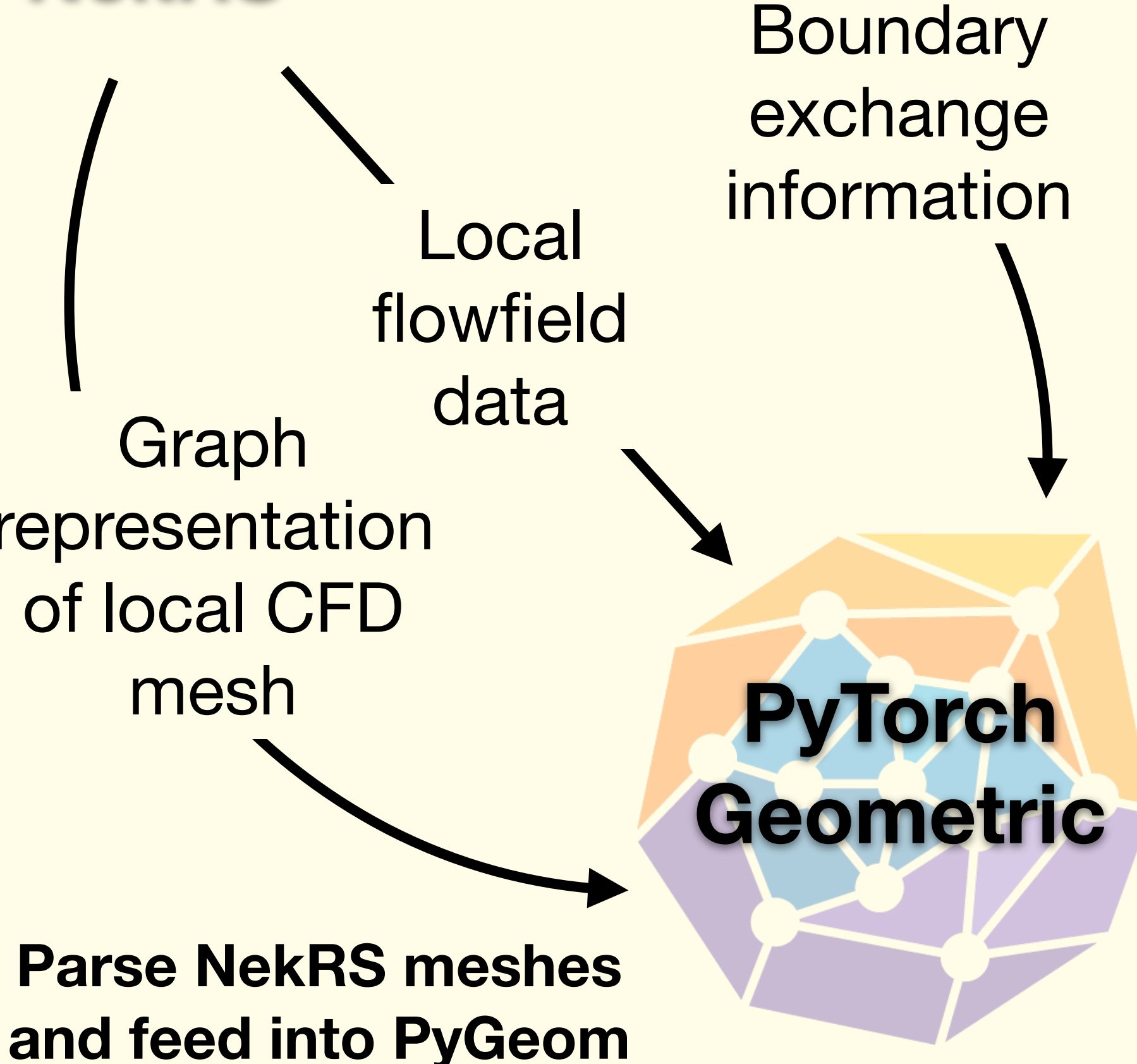
Interpretable GNN layers address key limitation in SOTA — latent spaces can now be accessed and mapped to physical phenomena.



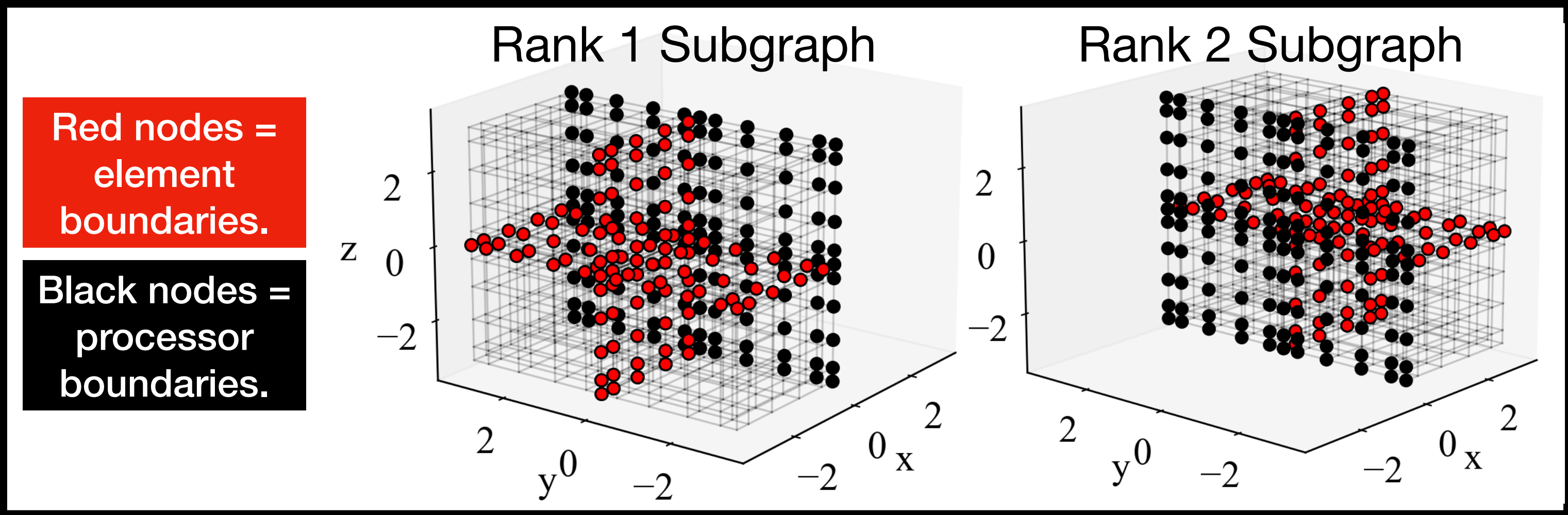
Scaling Up GNN Operations: Interfacing with NekRS

With: Romit Maulik, Riccardo Balin,
Saumil Patel, Ramesh Balakrishnan,
Venkat Vishwanath

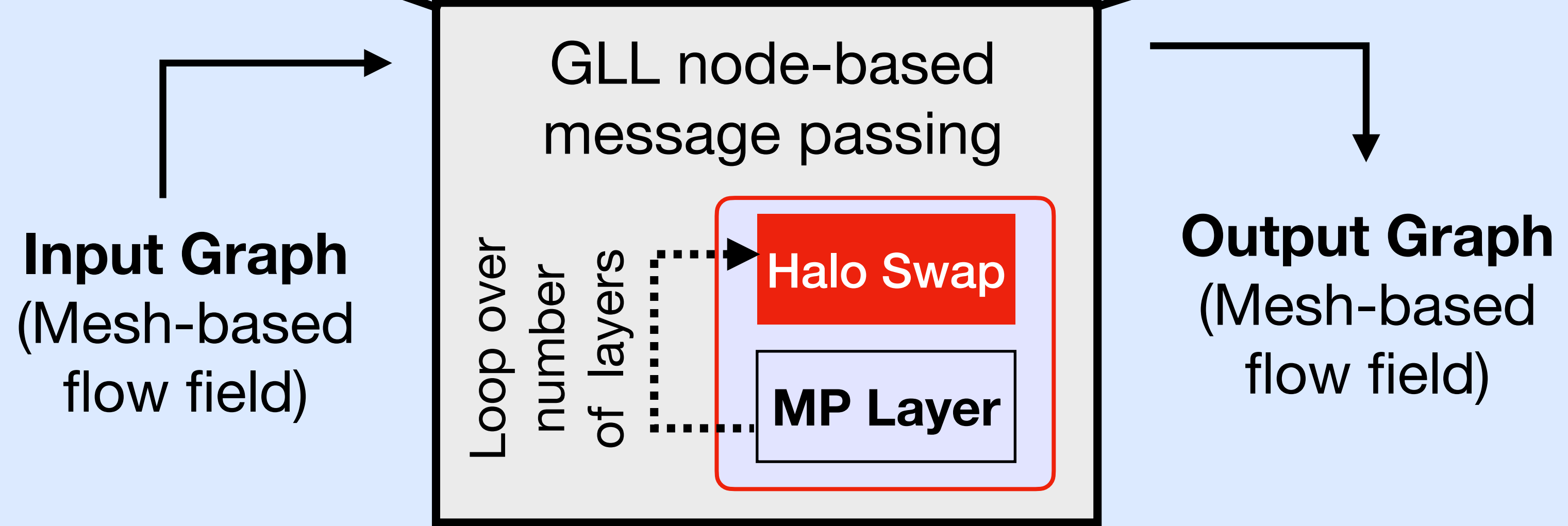
NekRS



Partitioned NekRS-based graph



Graph Neural Network



GNN scope: node-level regression tasks (e.g., forecasting).
Offline training demonstration in progress.