



COMBINING MACHINE LEARNING WITH COMPUTATIONAL FLUID DYNAMICS USING OPENFOAM AND SMARTSIM

DATA-DRIVEN MODELING SPECIAL INTEREST GROUP

Information about the Data-Driven SIG:

https://wiki.openfoam.com/Data_Driven_Modelling_Special_Interest_Group

We organize hackathons on combining ML+CFD in OpenFOAM

<https://github.com/OFDataCommittee/OFMLHackathon>

Combining CFD and ML with OpenFOAM and SmartSim

<https://github.com/OFDataCommittee/openfoam-smartsim>

<https://doi.org/10.1007/s11012-024-01797-z>

[OpenFOAM-SmartSim as an OpenFOAM Module](#)

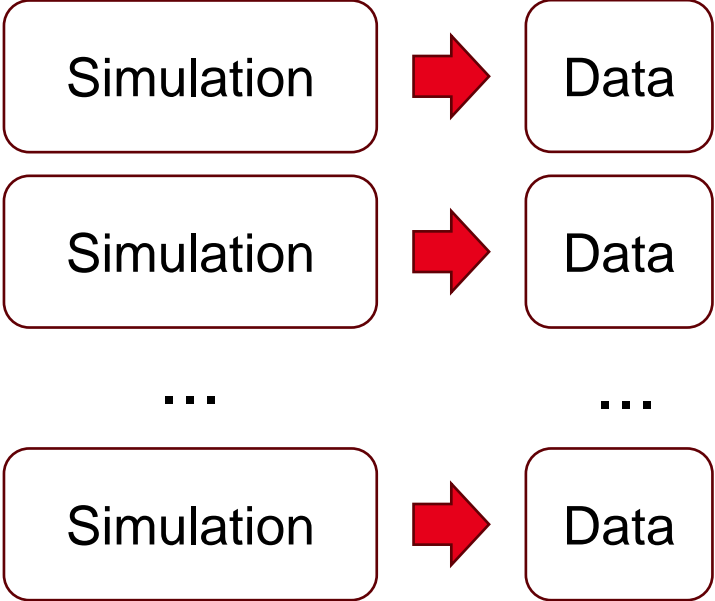
[OpenFOAM + SmartSim OFW18 Training](#)

Open  FOAM

SMART 

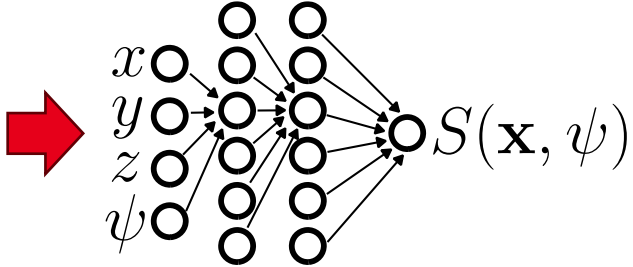
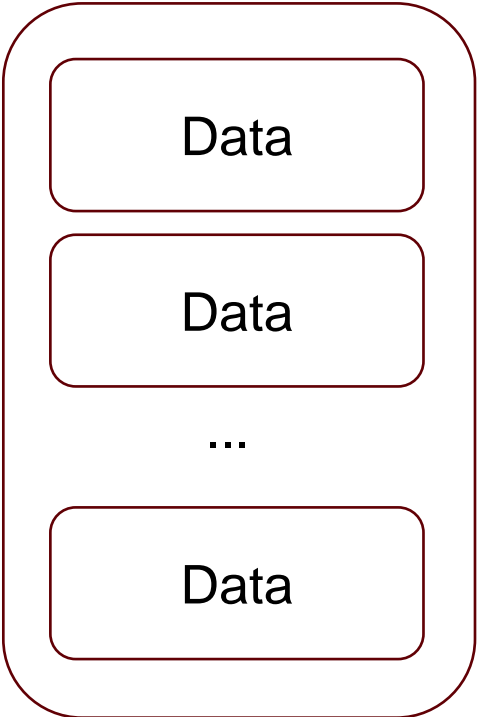
ML+CFD DATA PATTERNS I

Generate Training Data



Wait

Train the Model



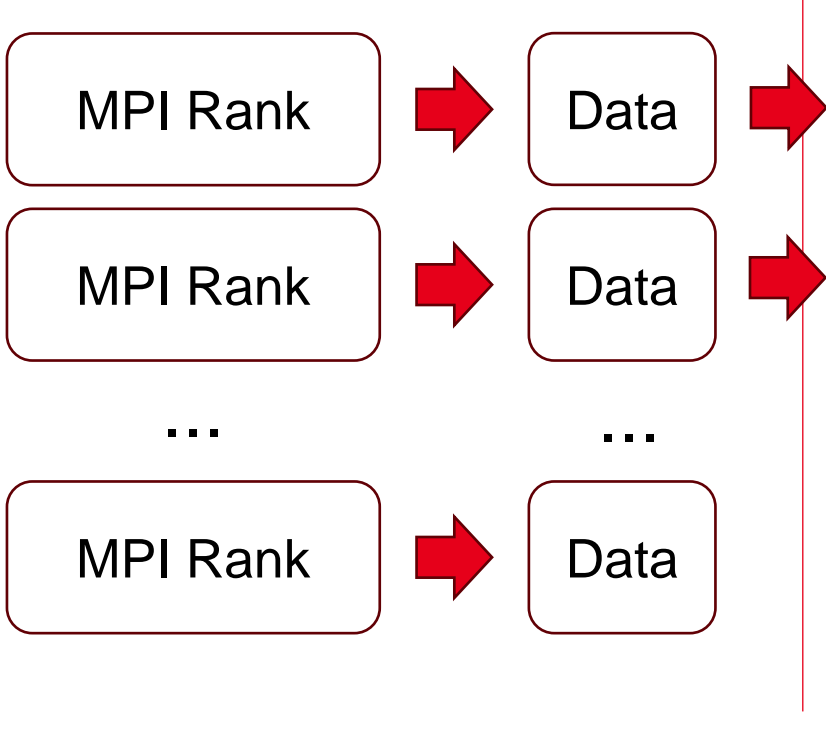
Wait

Use the Model

$$\begin{aligned} \partial_t \psi + \nabla \cdot (v\psi) \\ -\nabla \cdot (\Gamma\psi) = S(x, \psi) \end{aligned}$$

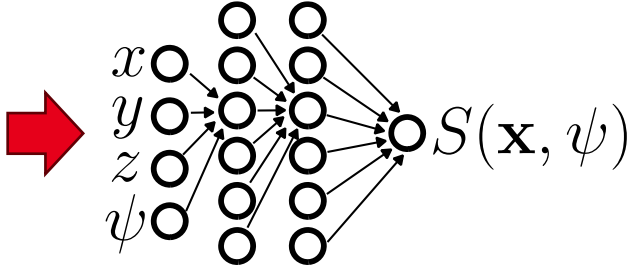
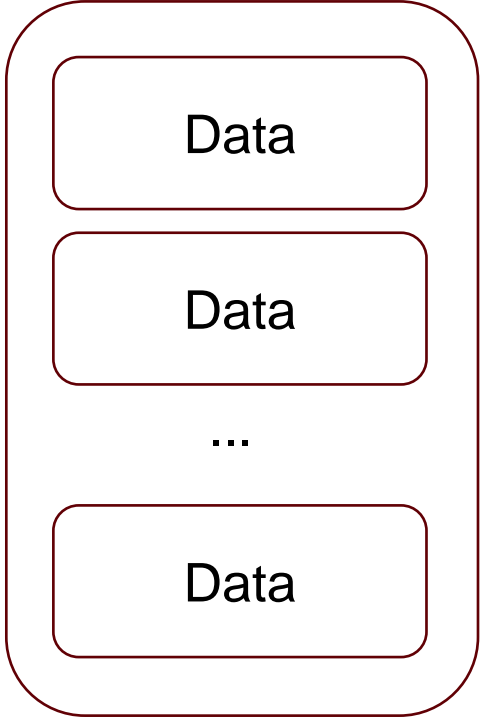
ML+CFD DATA PATTERNS II

Generate Training Data



Don't wait

Train the Model Incrementally

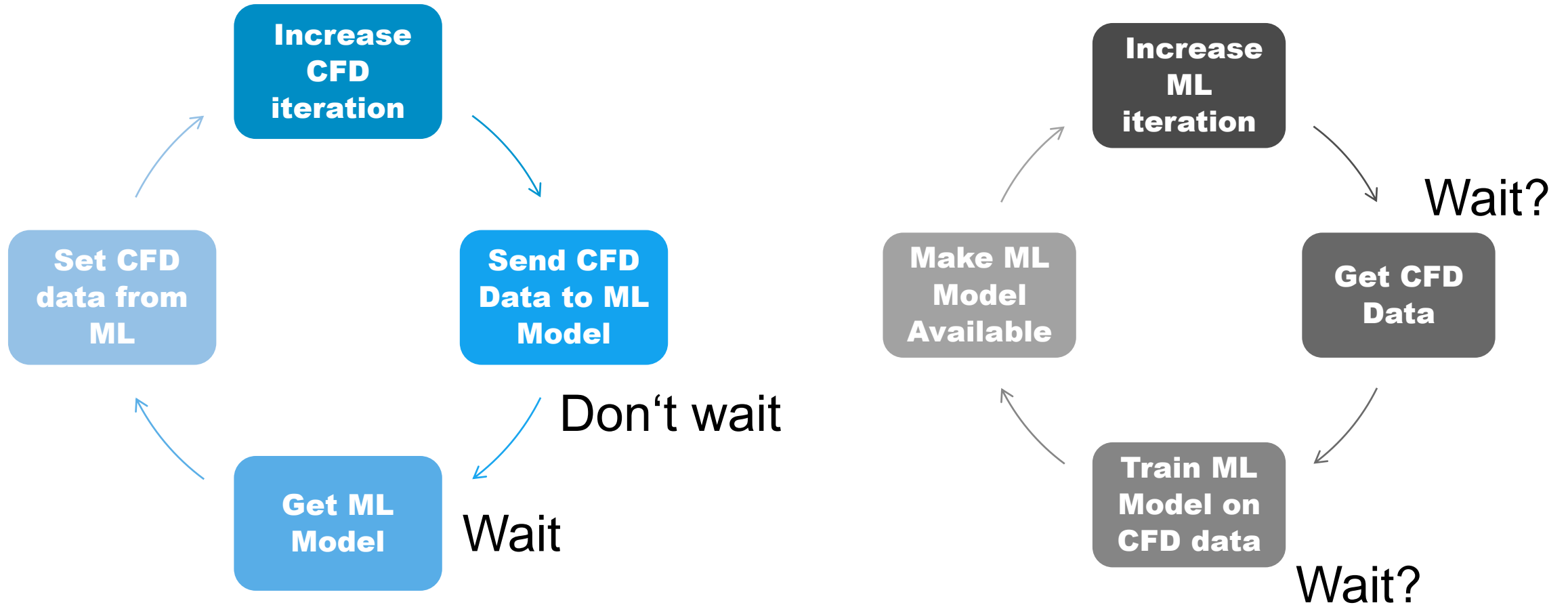


Wait

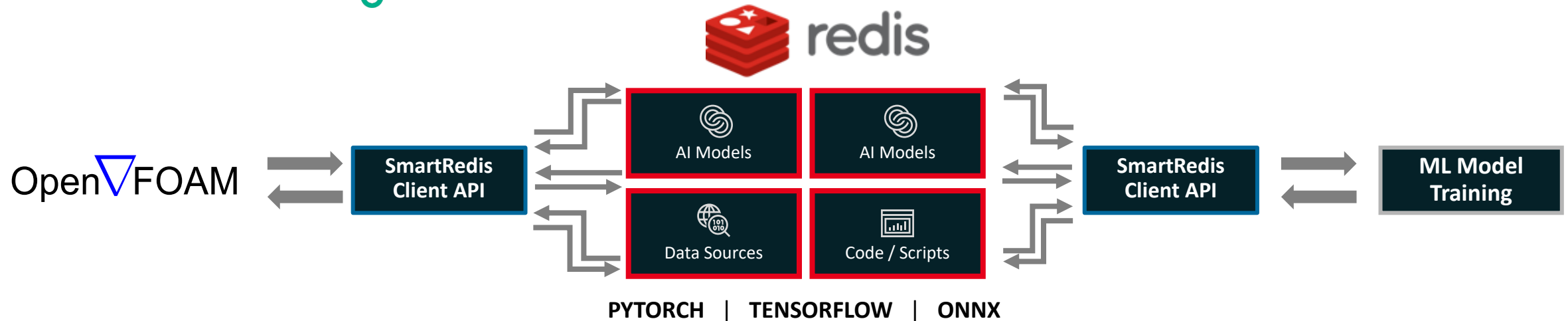
Use the Model

$$\begin{aligned} \partial_t \psi + \nabla \cdot (v\psi) \\ -\nabla \cdot (\Gamma\psi) = S(x, \psi) \end{aligned}$$

ML+CFD DATA PATTERNS III

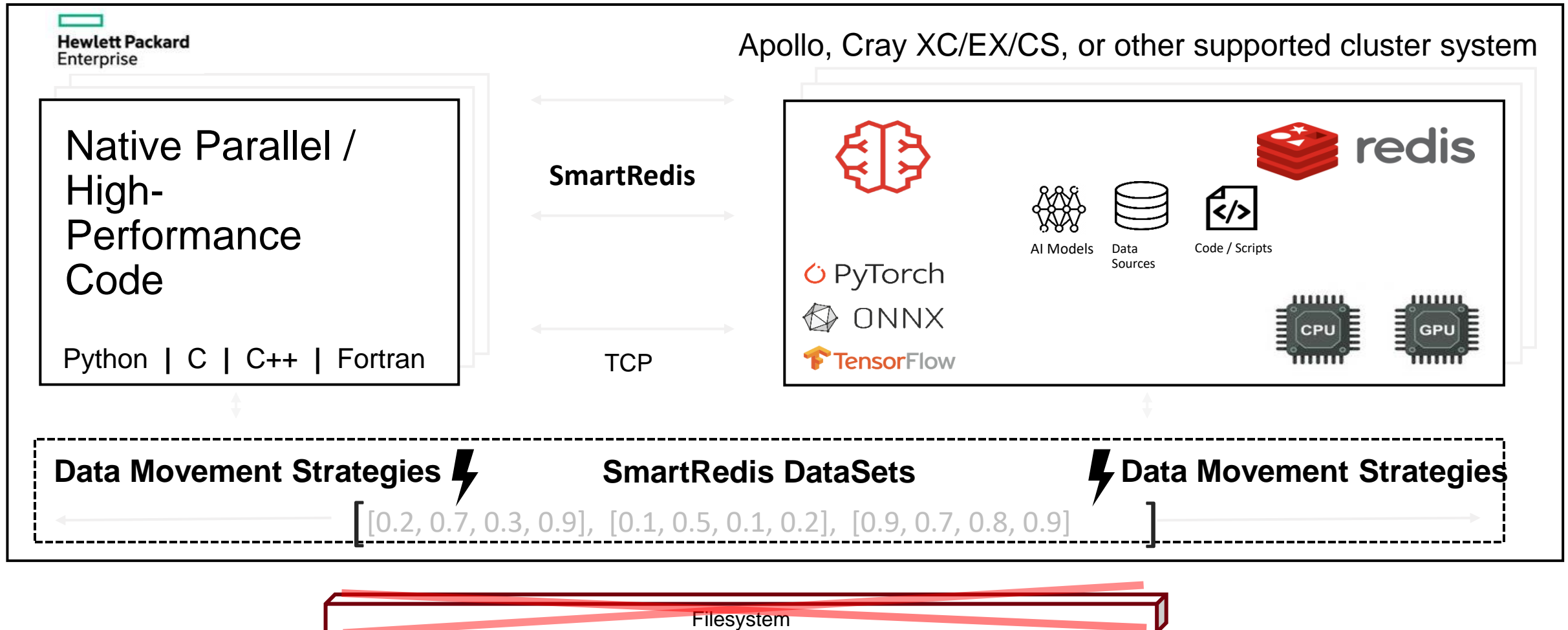


OPENFOAM + SMARTSIM + ML



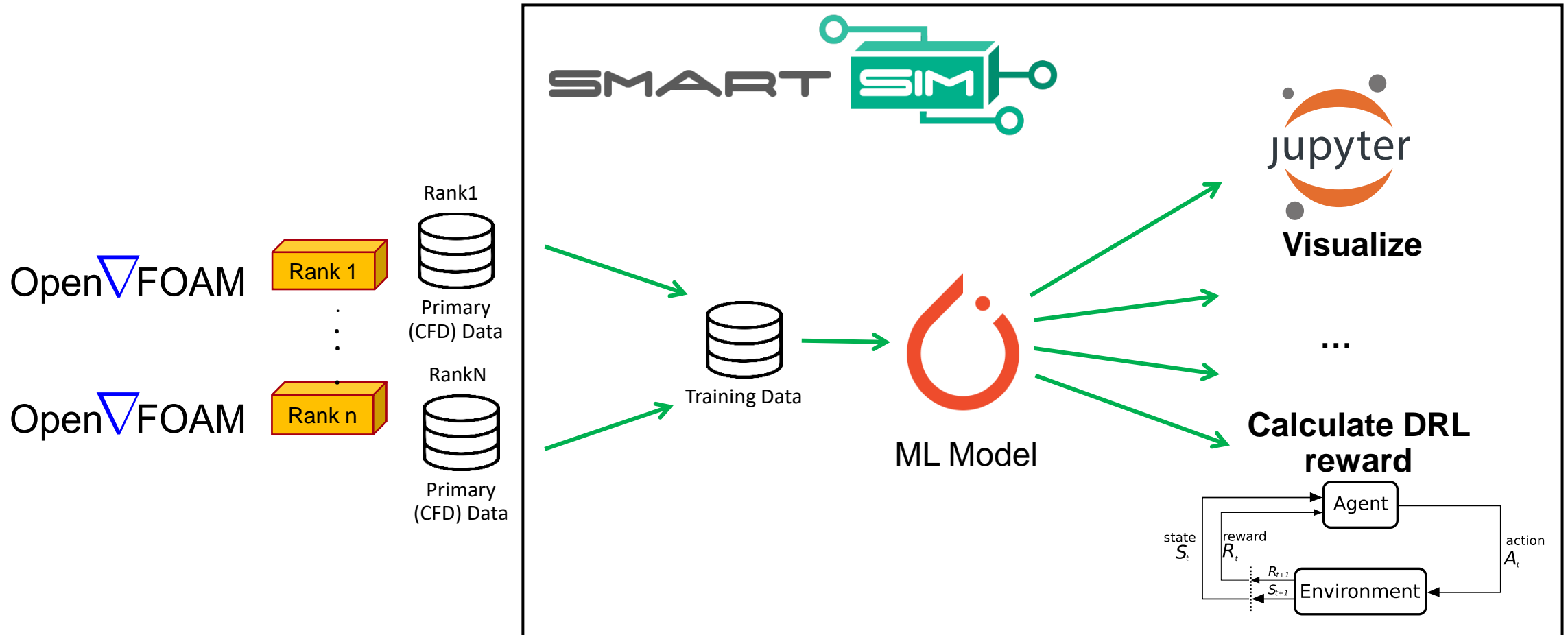
- **SmartSim Orchestrator:** implementing the computational workflow.
 - Jupyter Notebook or Python script – straightforward API.
- **SmartRedis Database:** CFD data, trained model, model inference.
 - Straightforward API in C++ (!!) and Python.

SMART REDIS DATABASE



ONLINE POST-PROCESSING

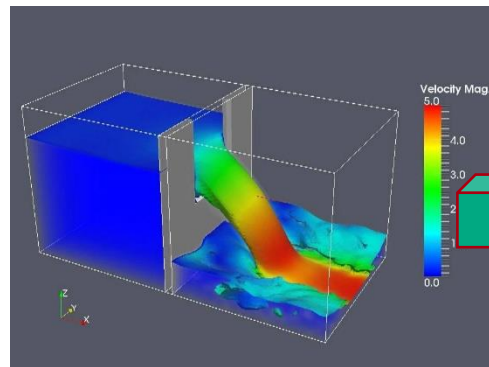
On-line Machine Learning while the simulation is running.



ML FOR TURBULENCE PREDICTION IN OPENFOAM

- Use a machine-learning model to reduce my time-to-solution.

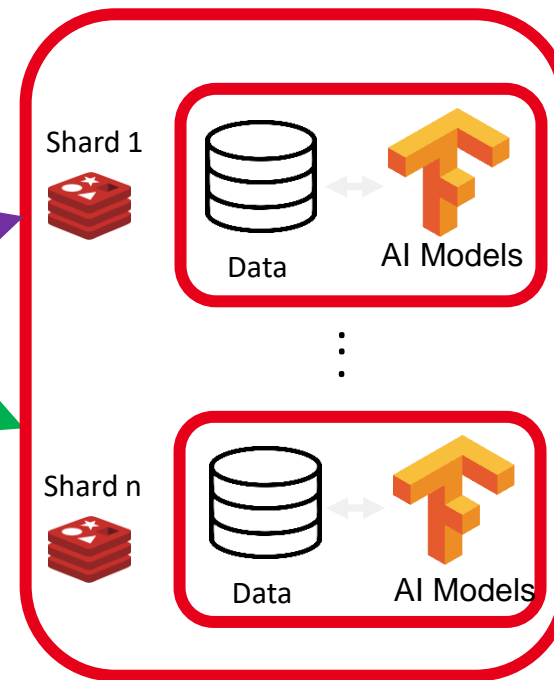
OpenFOAM



OpenFOAM
Simulation

Tensors
(i.e. Fortran Arrays)



SmartRedis



“Orchestrator”

Datastore and inference engine

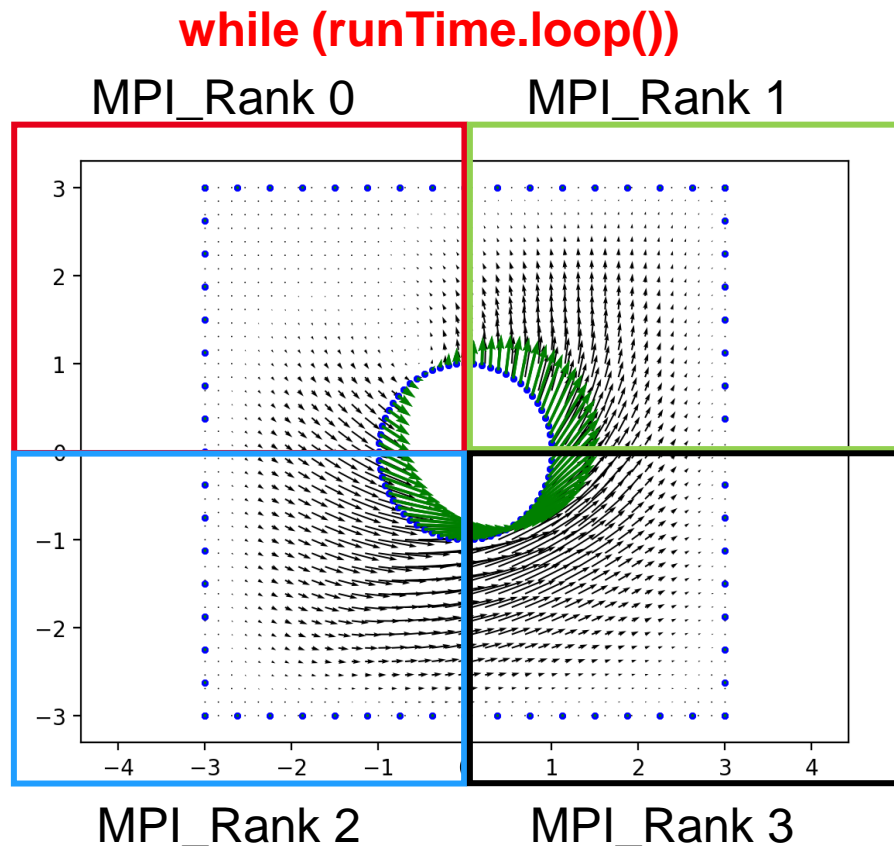
- **Tensorflow model** provides a pre-conditioned state that **reduces** number of solver **iterations**
- **Multi-stage workflow in one Python script**
 - Mesh decomposition
 - ML training
 - ML inference
 - Solver Integration
 - Analysis
 - Visualization

-  ML inference results to simulation
-  Data to Orchestrator

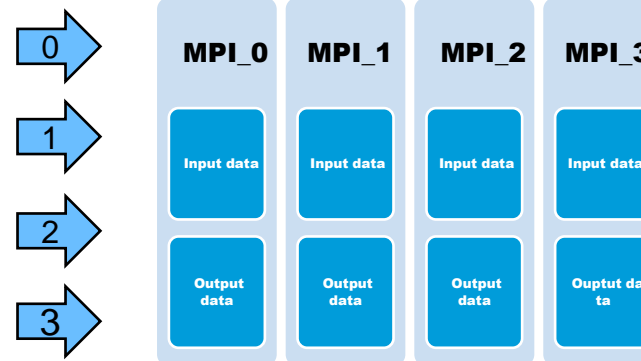
Code repo: <https://github.com/CrayLabs/smartsim-openFOAM>

ONLINE ML MESH MOTION

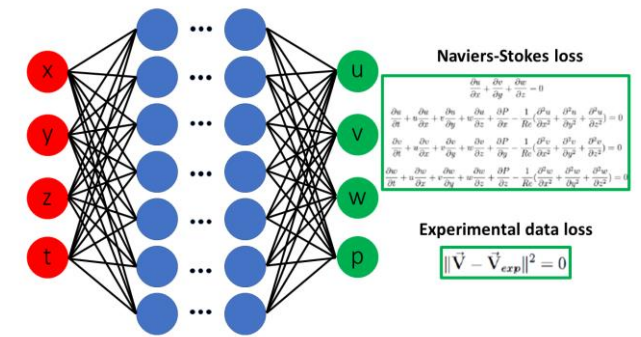
- Use a machine-learning model to approximate mesh-motion displacements.



Training Data



- Agglomerates training data.
- Trains on other resources.



Physics-Informed Neural Network
Riccardo Munafò, [CC BY-SA 4.0](https://creativecommons.org/licenses/by-sa/4.0/)

- **Online training and inference requires synchronization with the CFD algorithm.**



OPENFOAM FIELDS ARE INTERPRETABLE AS TENSORS

```
template<class T>
class UList
{
    // Private Data

    //- Number of elements in UList
    label size_;

    //- Vector of values of type T
    T* __restrict__ v_;
};
```

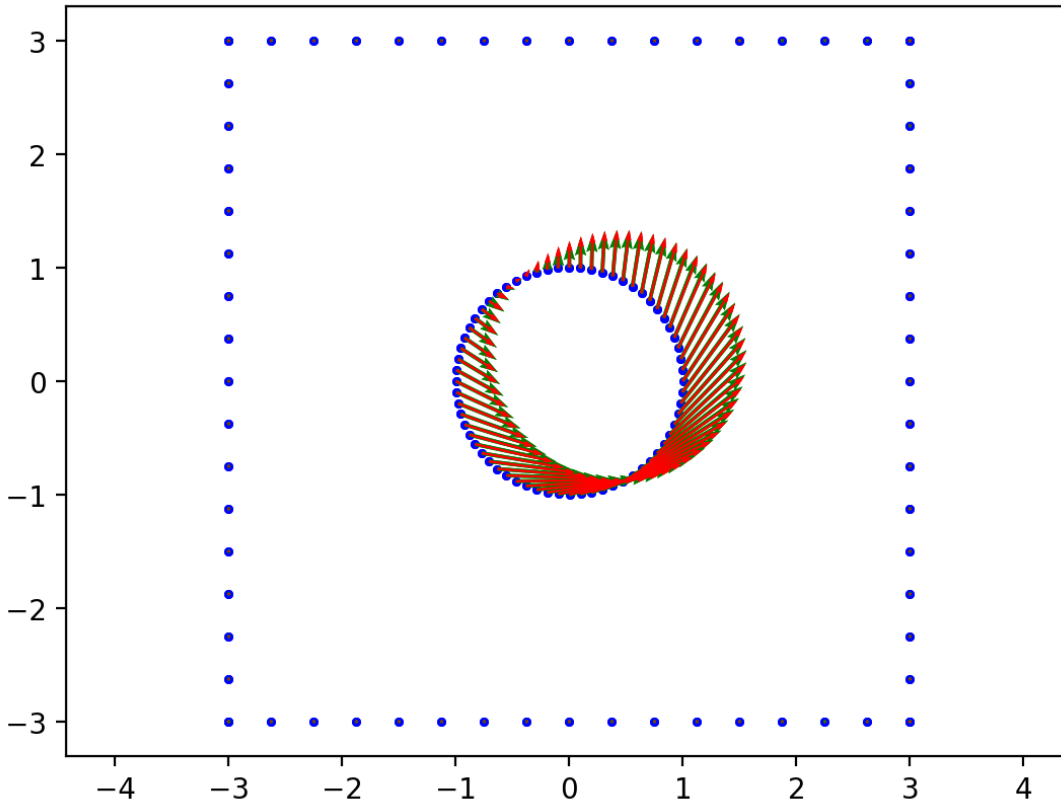
- All OpenFOAM Fields are ULists.
- UList<T> is a wrapper for T*
- Fields provide cdata() to reinterpret them as (void*).
- This is necessary not only for interpreting OpenFOAM fields as SmartRedis tensors, but also tensors in Machine Learning Frameworks.



ONLINE MACHINE LEARNING FOR MESH MOTION

ONLINE ML MESH MOTION

- **User story:** I want to use a machine-learning model to approximate mesh-motion displacements.



Given Dirichlet (fixed value) conditions for mesh motion on mesh boundary patches $\{\partial\Omega_k\}_k$

- We use displacements $\delta(x, t) \in \Omega$

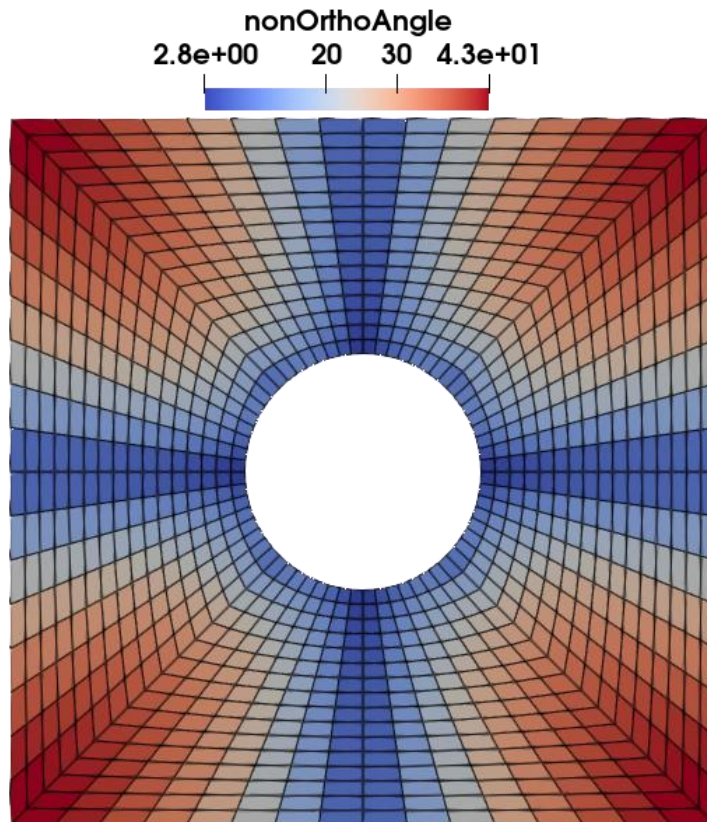
Approximate displacements in the solution domain as

$$\tilde{\delta}(x, t, \theta)$$

with θ as model parameters.

PDE-BASED MESH MOTION

- Why use a machine-learning model for mesh-motion?



PDE-based mesh motion like the Laplacian mesh motion

$$\nabla \cdot (\lambda \nabla \delta) = 0$$

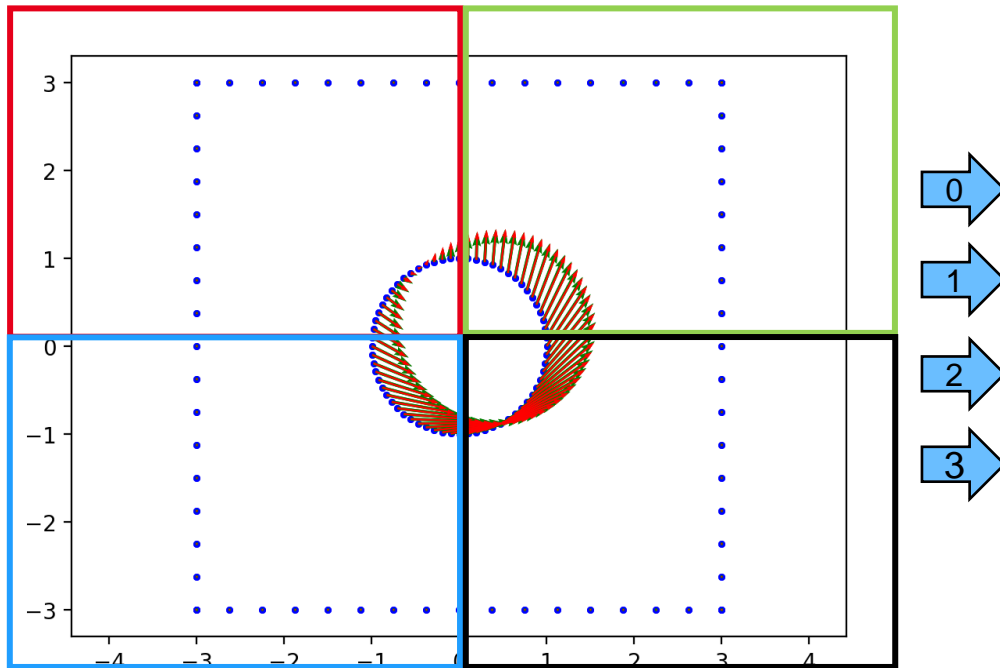
$$\delta(x, t) = d(x, t), \forall x \in \{\partial\Omega_k\}_{\{k \in K\}}$$

- Approximatively solves the PDE on a deforming mesh with increasingly deteriorating quality (e.g. non-orthogonality).
- Approximation or interpolation-based mesh motion is smoother and can potentially deliver higher mesh quality for stronger deformations.

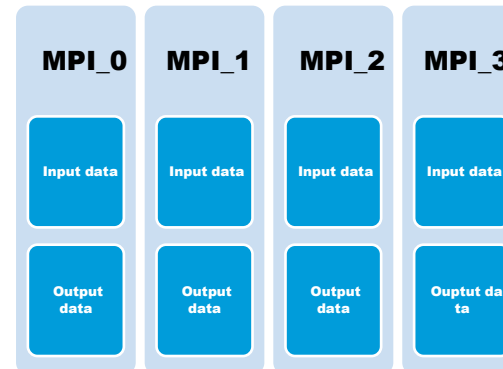
De Boer, A., Van der Schoot, M. S., & Bijl, H. (2007). Mesh deformation based on radial basis function interpolation. *Computers & structures*, 85(11-14), 784-795.

OPENFOAM DATA STRUCTURE

OpenFOAM



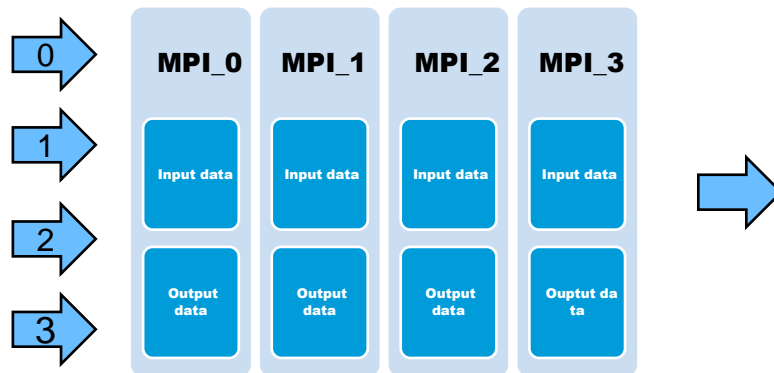
0
1
2
3



- Each MPI rank sends its own data to increase efficiency.
- We don't need MPI process boundary data.
- We don't need empty patches.
- Boundary field of a pointField stores a list of all boundary patches – zero length for those not on the MPI Rank.
- Input data are datasets:
 - `point_patch_timeStep_rank`
 - `displ_patch_timeStep_rank`

runTime++;

DATASETS AND AGGREGATION LISTS

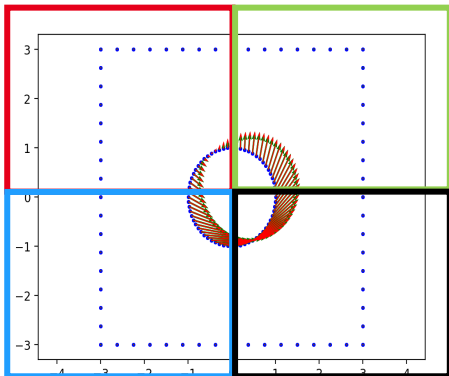


- Input data are datasets:
 - `point_patch_timeStep_rank`
 - `displ_patch_timeStep_rank`
- **What does this look like for 30 patches and 50 MPI ranks?**
 - How to check if this data is available in SmartRedis?
- **Dataset: agglomerate over patches**
 - `pointsDataset_timeStep_rank`
 - `displacementsDataSet_timeStep_rank`
- **Aggregation list: agglomerate datasets over time steps**
 - If we know `MPI_Comm_size` and the time index, we know if all the data is available in SmartRedis. **How?**

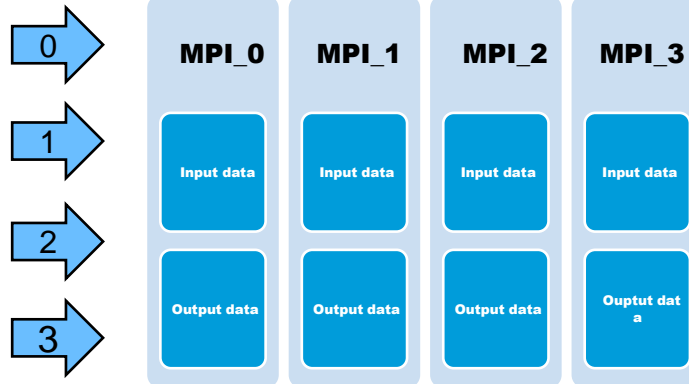
SYNCHRONISE TIME STEPS

OpenFOAM

runTime++;



redis



SMART SIM

runTime++;

• Aggregation list length

• $MPI_Comm_size * timeIndex$

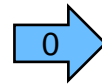
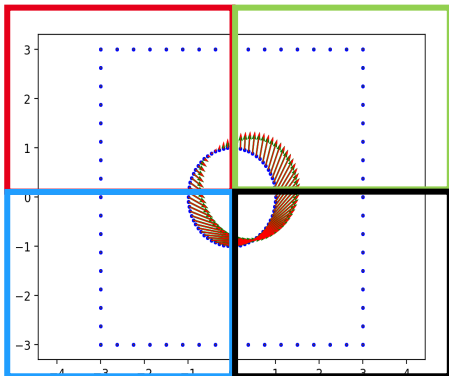
```
client.poll_list_length("displacementsDatasetList",
    time_index * num_mpi_ranks,
    10, 1000);
```

• Is there anything else?

SYNCHRONISE TIME STEPS

OpenFOAM

runTime++;



runTime++;

•How does SmartSim Python script know that the OpenFOAM simulation has ended?

```
if client.poll_key("end_time_index", 10, 100):
    print ("End time reached.")
    break
```

ONLINE ML MESH MOTION

- Let's look at some source code.