

A physics-informed machine learning approach to super-resolution of 4D-flow MRI in the left ventricle

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Clinical Motivation: Impact of Cardiovascular Disease

- WHO estimates that cardiovascular disease (CVD) kills >17 million yearly worldwide
 - Heart failure is a major contributor to CVD
- Estimated yearly cost of CVD is **\$219 billion** in US alone
 - In UK, this figure currently stands at **£7.4 billion**
 - Additional indirect costs incur **£15.8 billion**



CVD in USA:

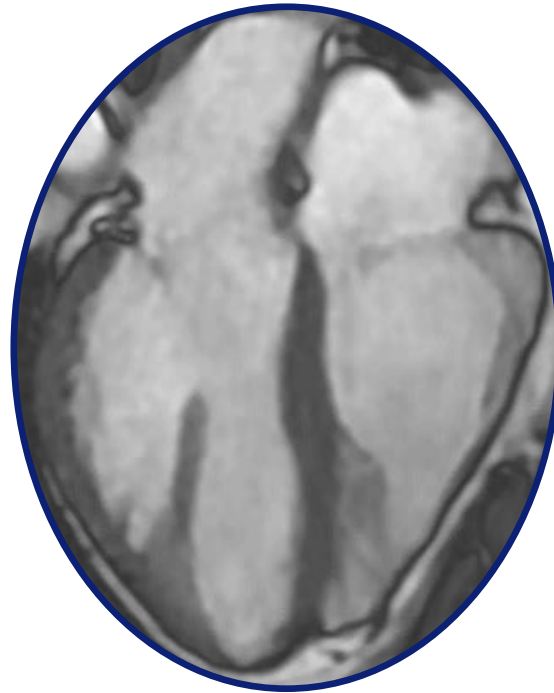
- **\$219 billion**
- **655,000 deaths**



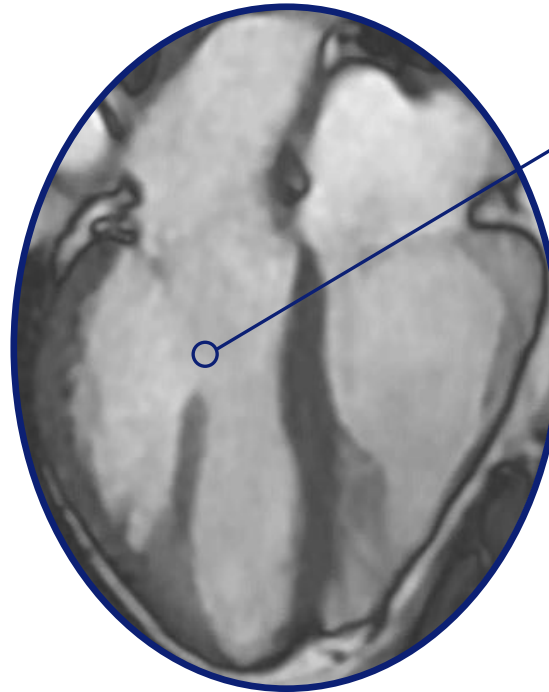
CVD in UK:

- **£23 billion**
- **160,000 deaths**

Haemodynamics in the Heart Chambers

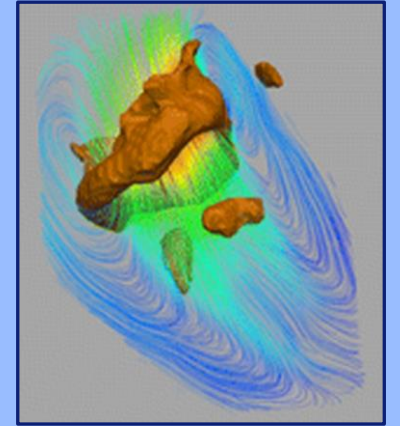


Haemodynamics in the Heart Chambers



Vorticity

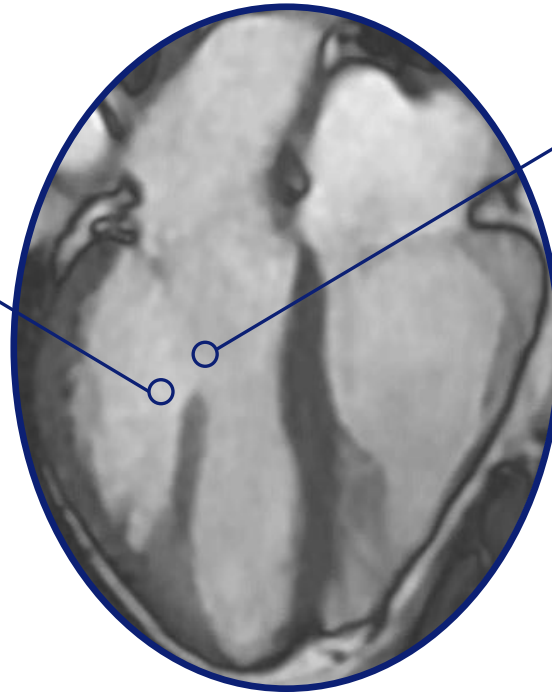
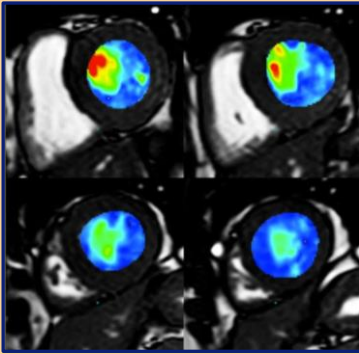
Demirkiran et al.
(2022)



Haemodynamics in the Heart Chambers

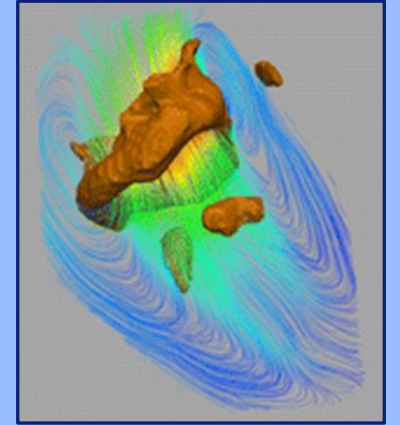
Kinetic energy

Garg et al.
(2018)



Vorticity

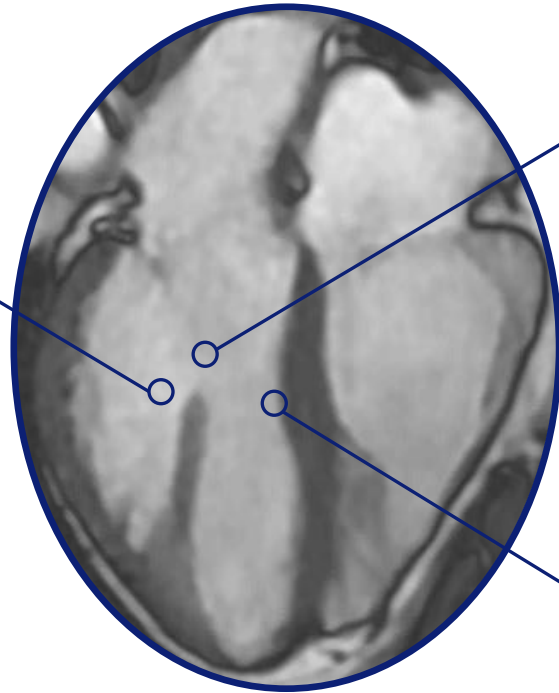
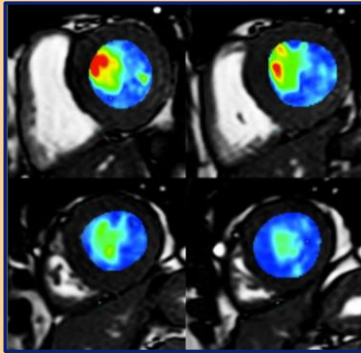
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Haemodynamics in the Heart Chambers

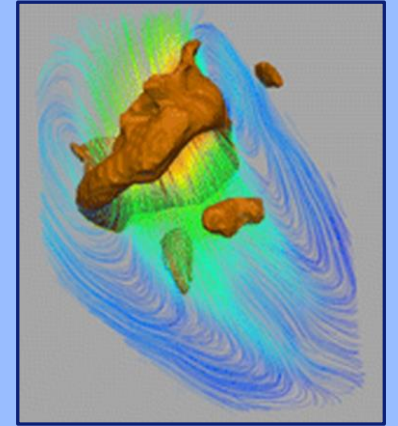
Kinetic energy

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(2018)



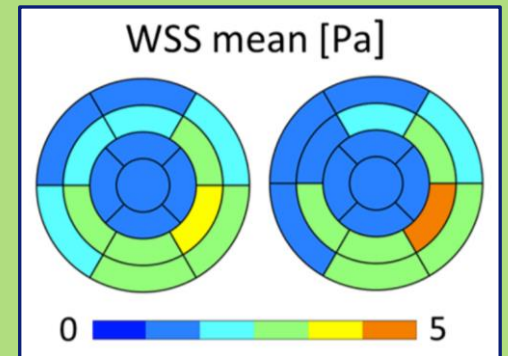
Vorticity

Demirkiran et al.
(2022)



Wall shear stress

Canè et al.
(2022)



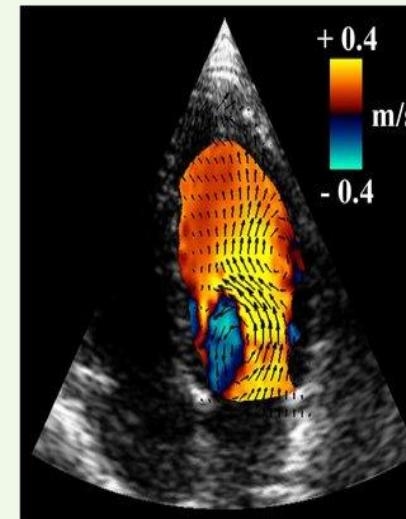
Quantifying Haemodynamics in the Heart

CFD

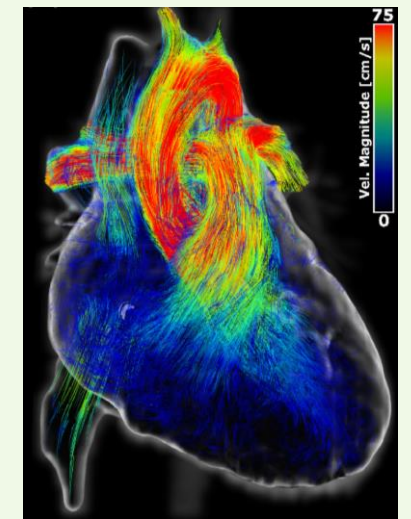


Imaging

Doppler echocardiography

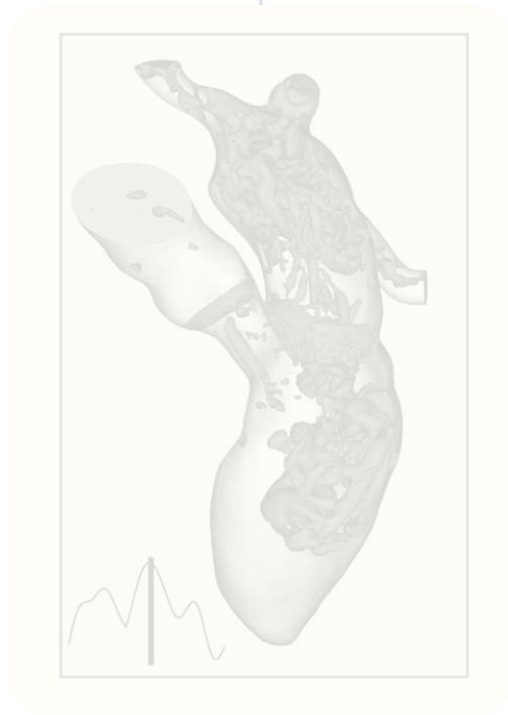


4D-flow MRI



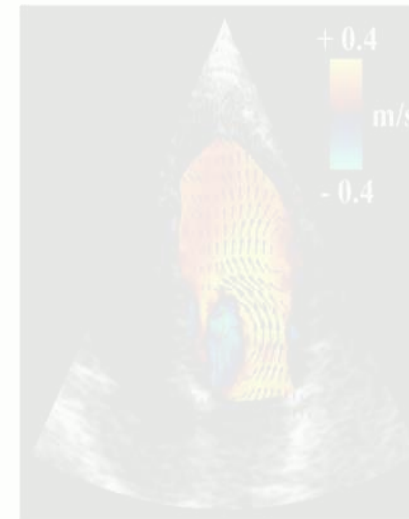
Quantifying Haemodynamics in the Heart

CFD

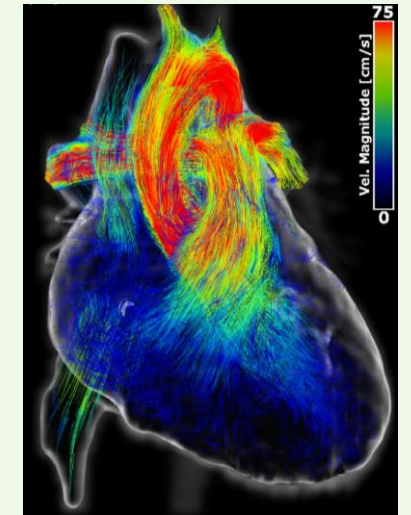


Imaging

Doppler echocardiography



4D-flow MRI



Quantifying Haemodynamics in the Heart

CFD

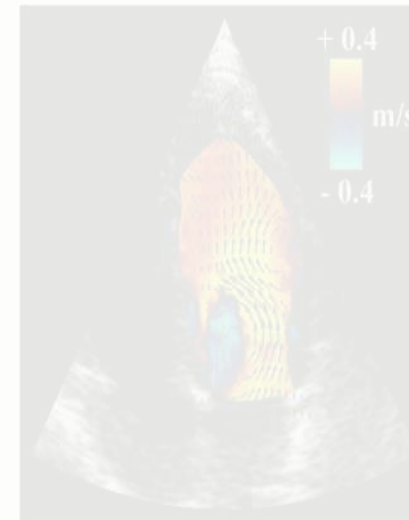
Low spatial resolution:
2.5 – 3mm³

Noise artifacts:
Non-Gaussian spatial distribution

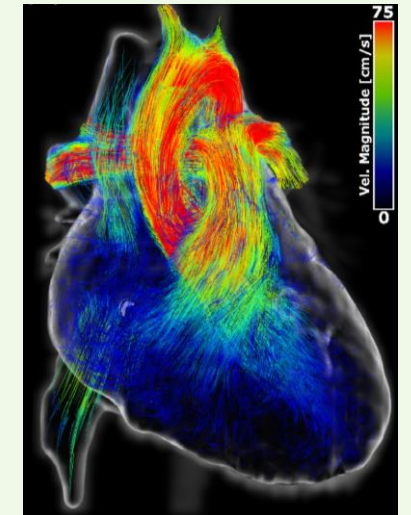
Temporal averaging:
Over scan duration

Imaging

Doppler echocardiography



4D-flow MRI



Quantifying Haemodynamics in the Heart

CFD

Low spatial resolution:
2.5 – 3mm³

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Over scan duration

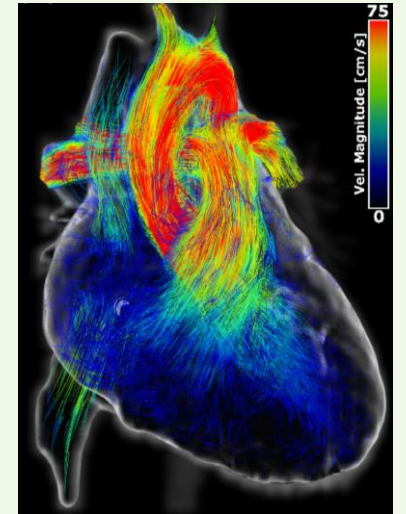
Poor accuracy of derivatives:
Relevant variables such as vorticity and stresses

Near-wall flow not captured well

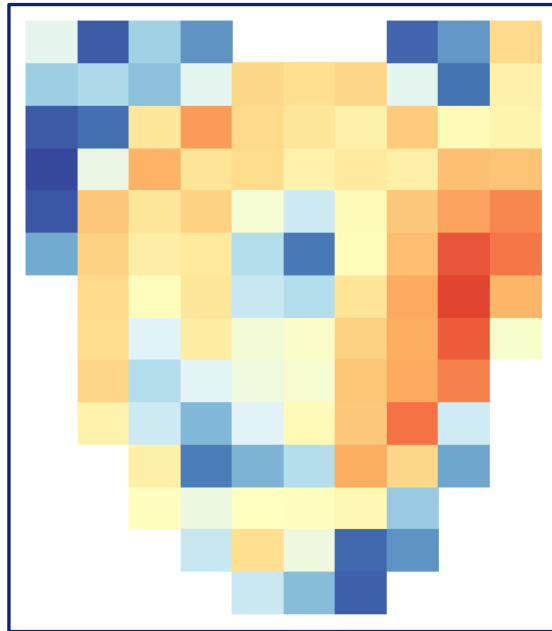
Small-scale flow features missed:
Particularly important in analysis of vortex
dissipation

Imaging

4D-flow MRI

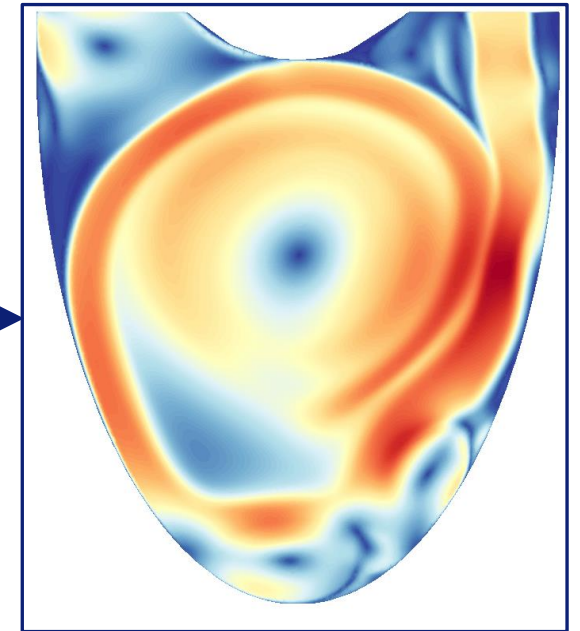


Improving 4D-Flow MRI – Super-Resolution



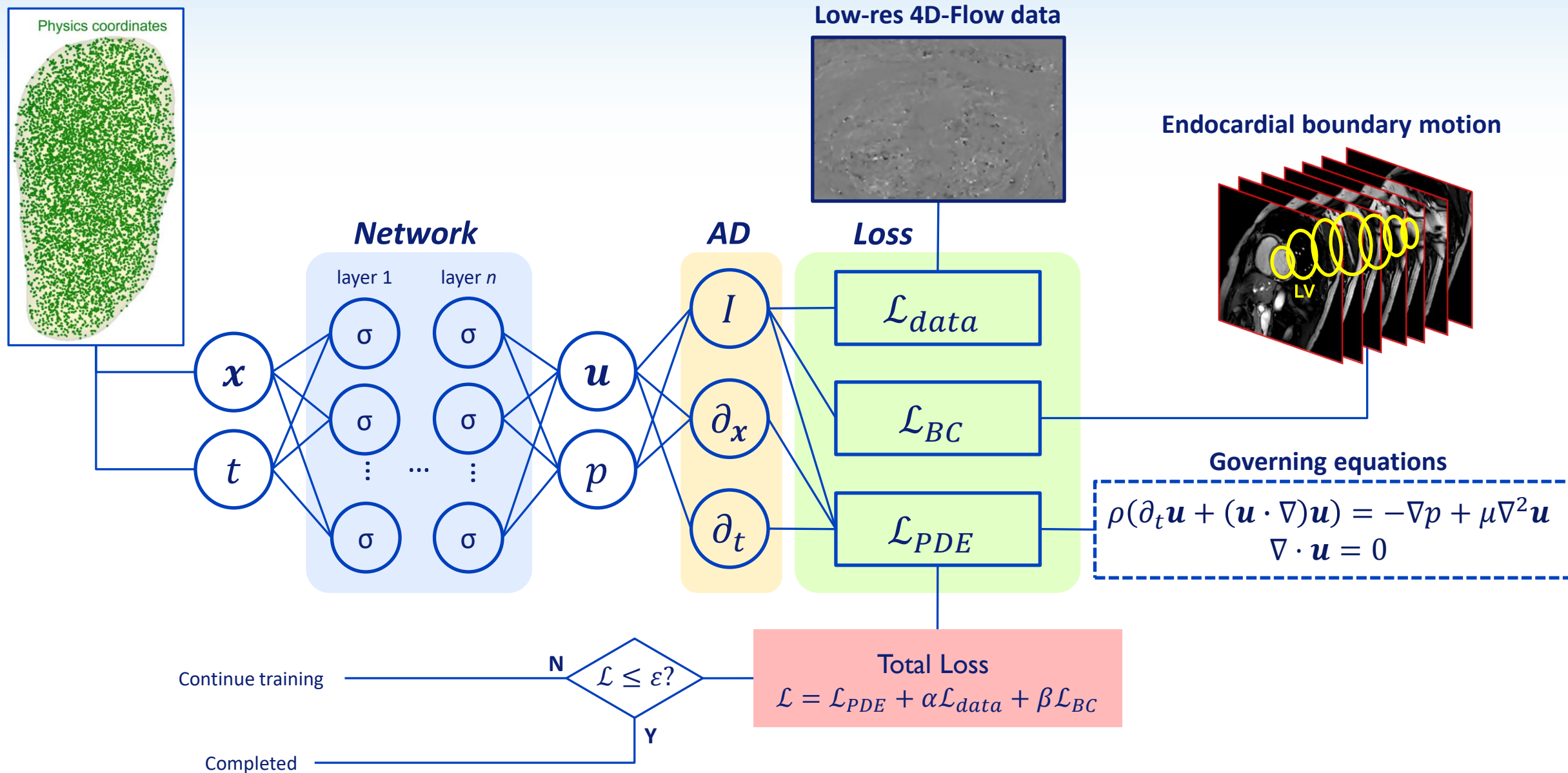
Low-resolution, corrupted velocity data

Model

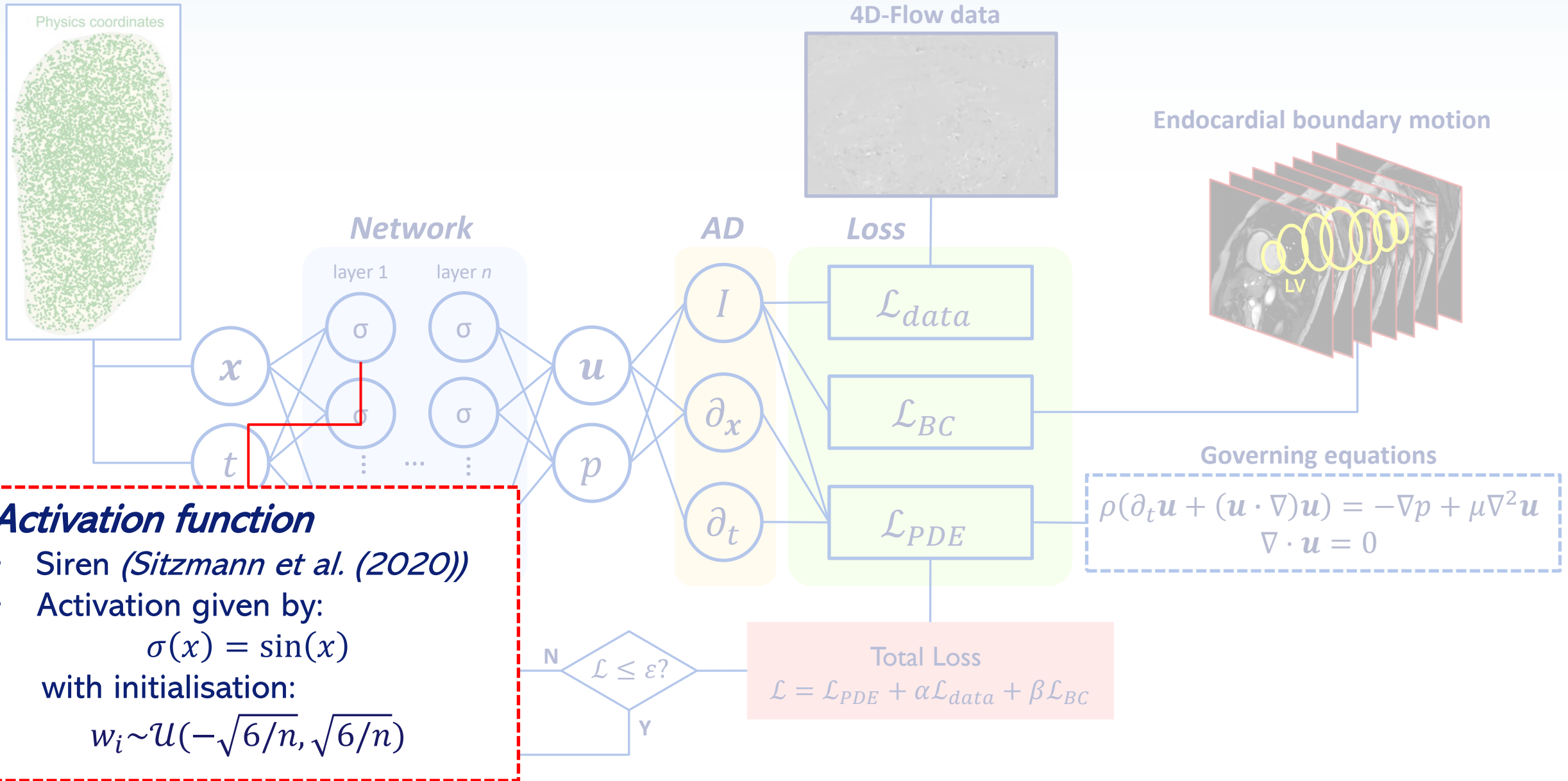


High-resolution velocity field

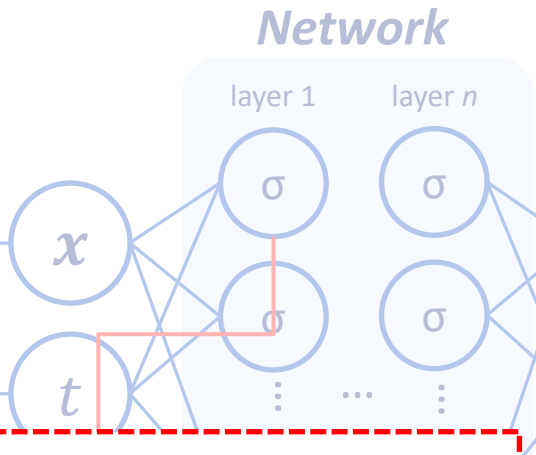
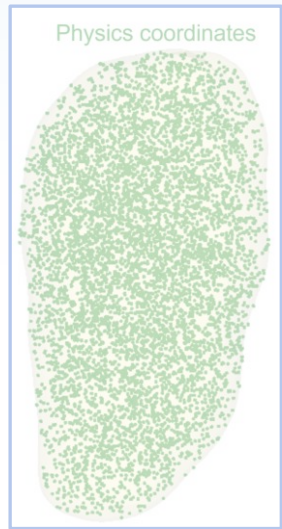
Our Super-Resolution Model – Physics-Informed Neural Network



Key Ingredients



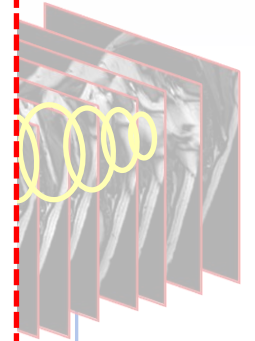
Key Ingredients



Reasoning

- Spectral bias:
 - PINNs with standard activations suffer – difficulty capturing high-frequency solution modes
 - Small-scale flow features not captured
 - Siren addresses this
- Ventricular flow
 - Transitional
 - Across range of length and time scales
 - Important to capture these features

Boundary motion



Activation function

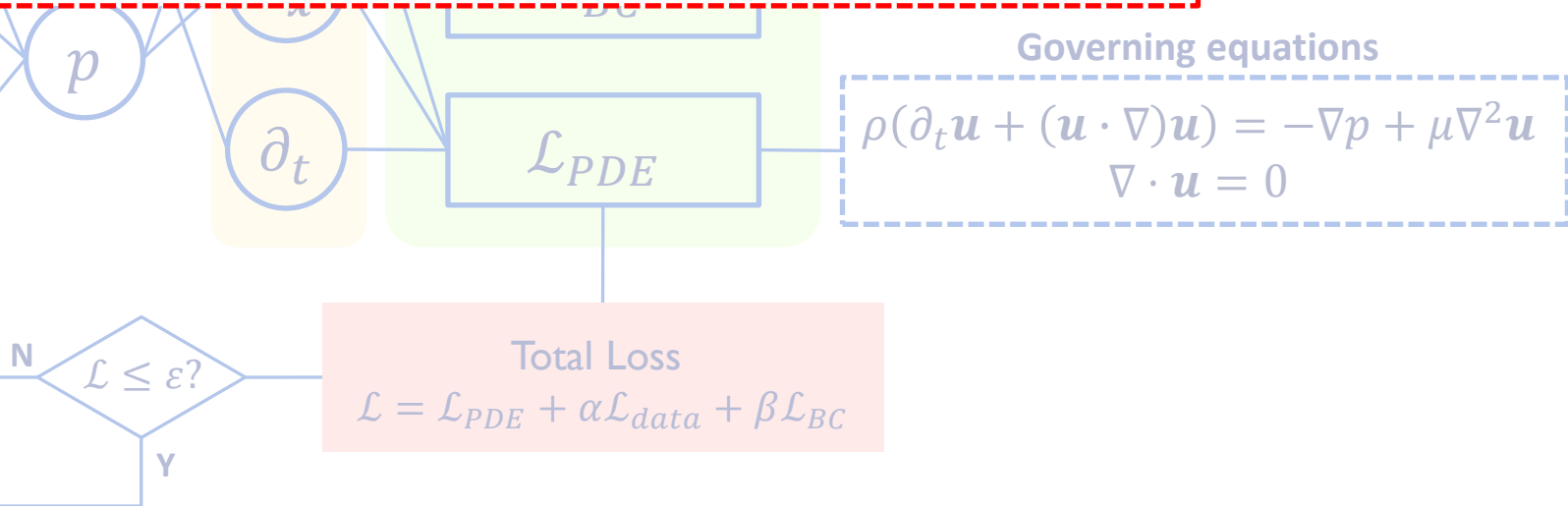
- Siren (*Sitzmann et al. (2020)*)

- Activation given by:

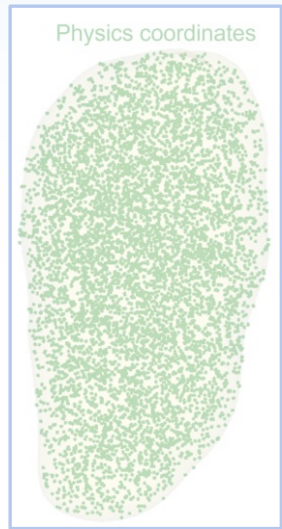
$$\sigma(x) = \sin(x)$$

with initialisation:

$$w_i \sim \mathcal{U}(-\sqrt{6/n}, \sqrt{6/n})$$



Key Ingredients



Dynamic loss weighting

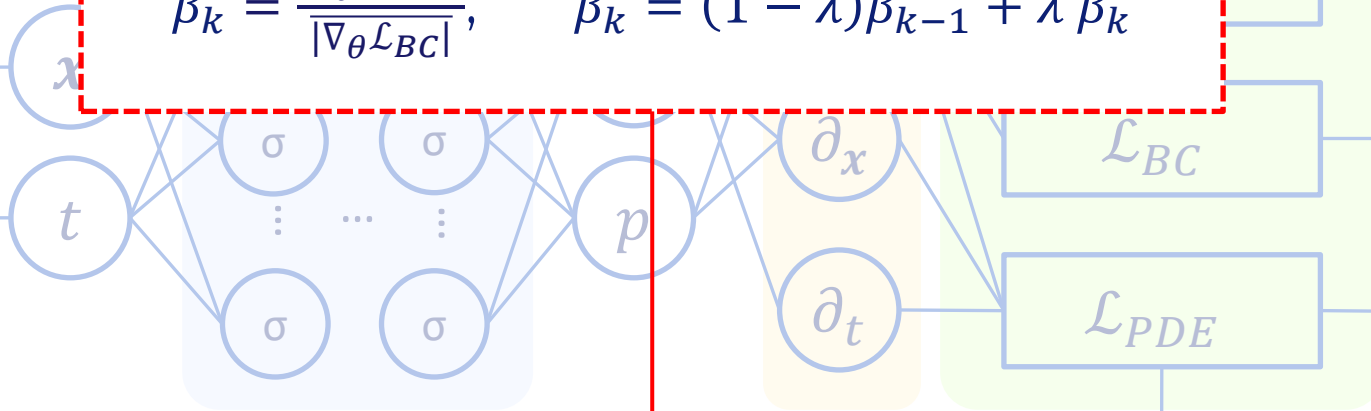
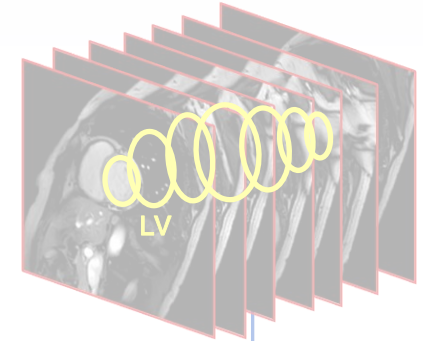
- Scheme proposed in *Jin et al. (2021)*
- Weights updated as:

$$\hat{\alpha}_k = \frac{|\nabla_{\theta} \mathcal{L}_{PDE}|}{|\nabla_{\theta} \mathcal{L}_{data}|}, \quad \alpha_k = (1 - \lambda)\alpha_{k-1} + \lambda \hat{\alpha}_k$$

$$\hat{\beta}_k = \frac{|\nabla_{\theta} \mathcal{L}_{PDE}|}{|\nabla_{\theta} \mathcal{L}_{BC}|}, \quad \beta_k = (1 - \lambda)\beta_{k-1} + \lambda \hat{\beta}_k$$

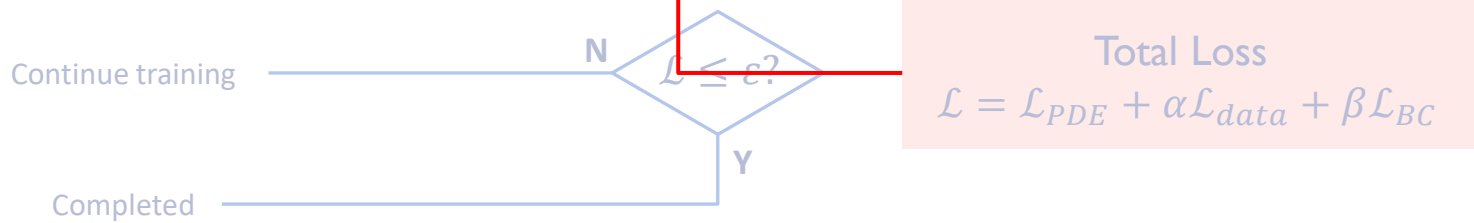


Endocardial boundary motion

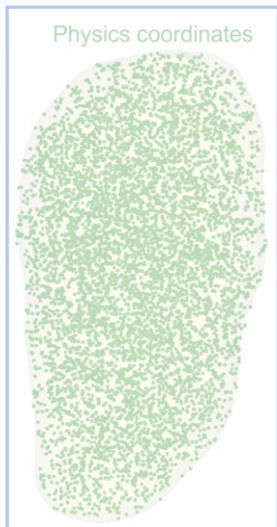


Governing equations

$$\rho(\partial_t \mathbf{u} + (\mathbf{u} \cdot \nabla) \mathbf{u}) = -\nabla p + \mu \nabla^2 \mathbf{u}$$
$$\nabla \cdot \mathbf{u} = 0$$



Key Ingredients



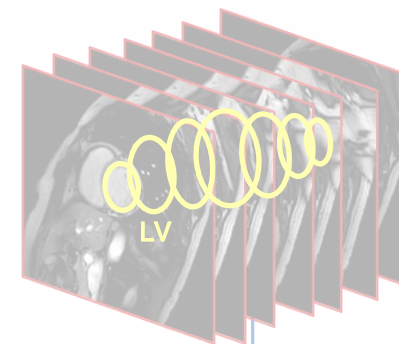
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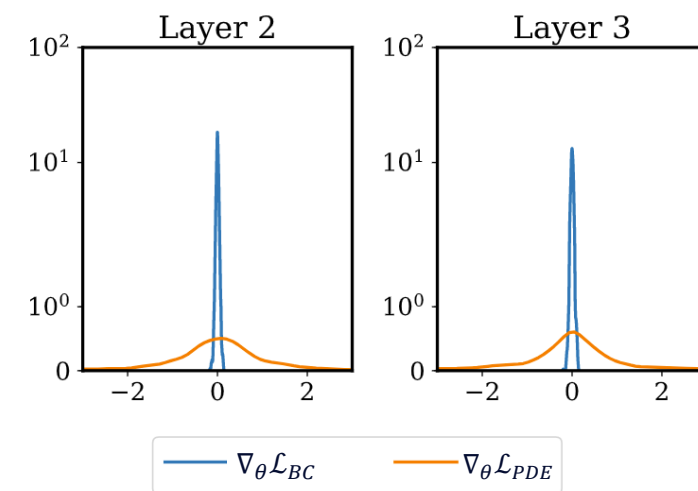
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Endocardial boundary motion



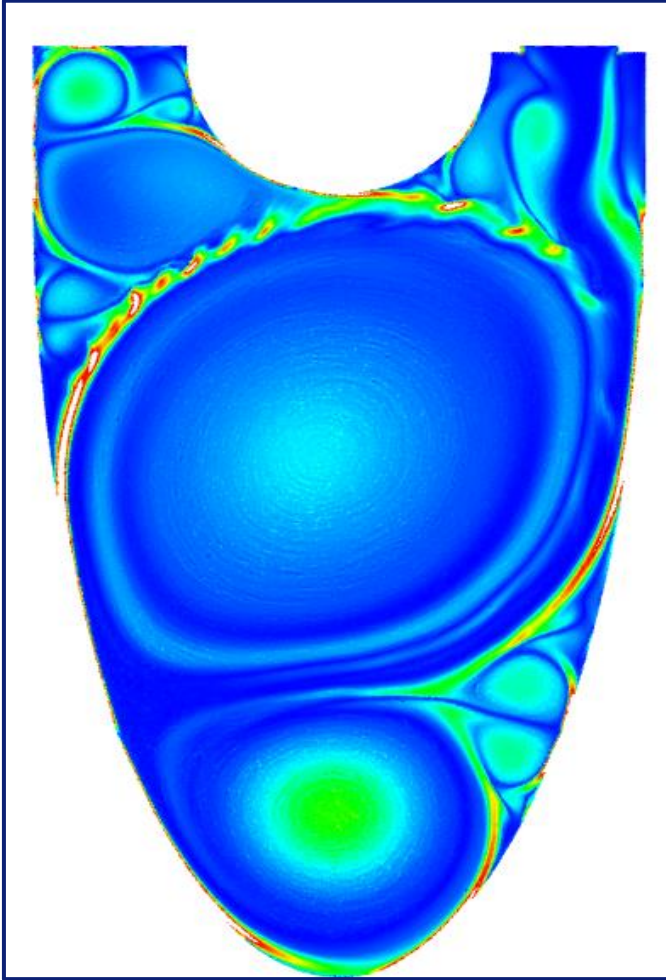
Reasoning

- Different loss terms provide different gradient contributions
- Term contributing smaller gradients may not be satisfied during training
- E.g. boundary condition loss in figure
- More complex PDEs (like Navier-Stokes equations) tend to contribute larger gradients

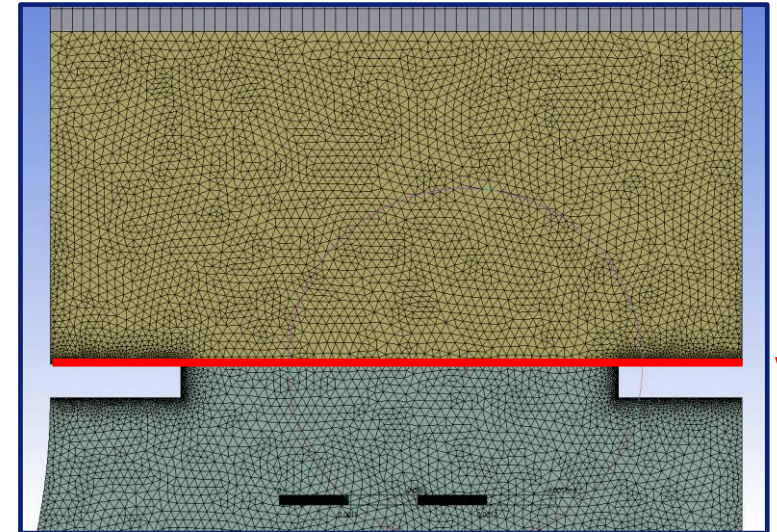
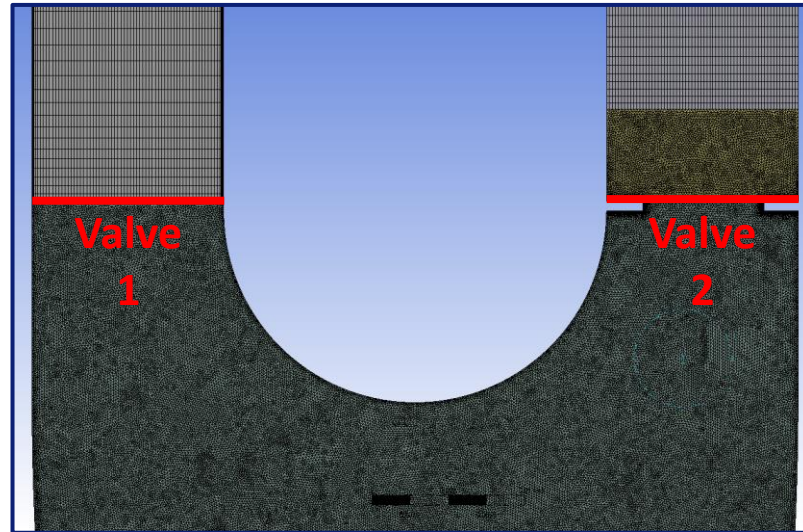


Experiments: 2D Idealised Ventricle

- Synthetic study designed to validate model
- Simplified, 2D CFD-generated ventricle
 - Flow driven by moving boundary
 - Highly-resolved mesh
 - Small adaptive time-step
 - Results in complex flow simulated



Vorticity contour plot of CFD results

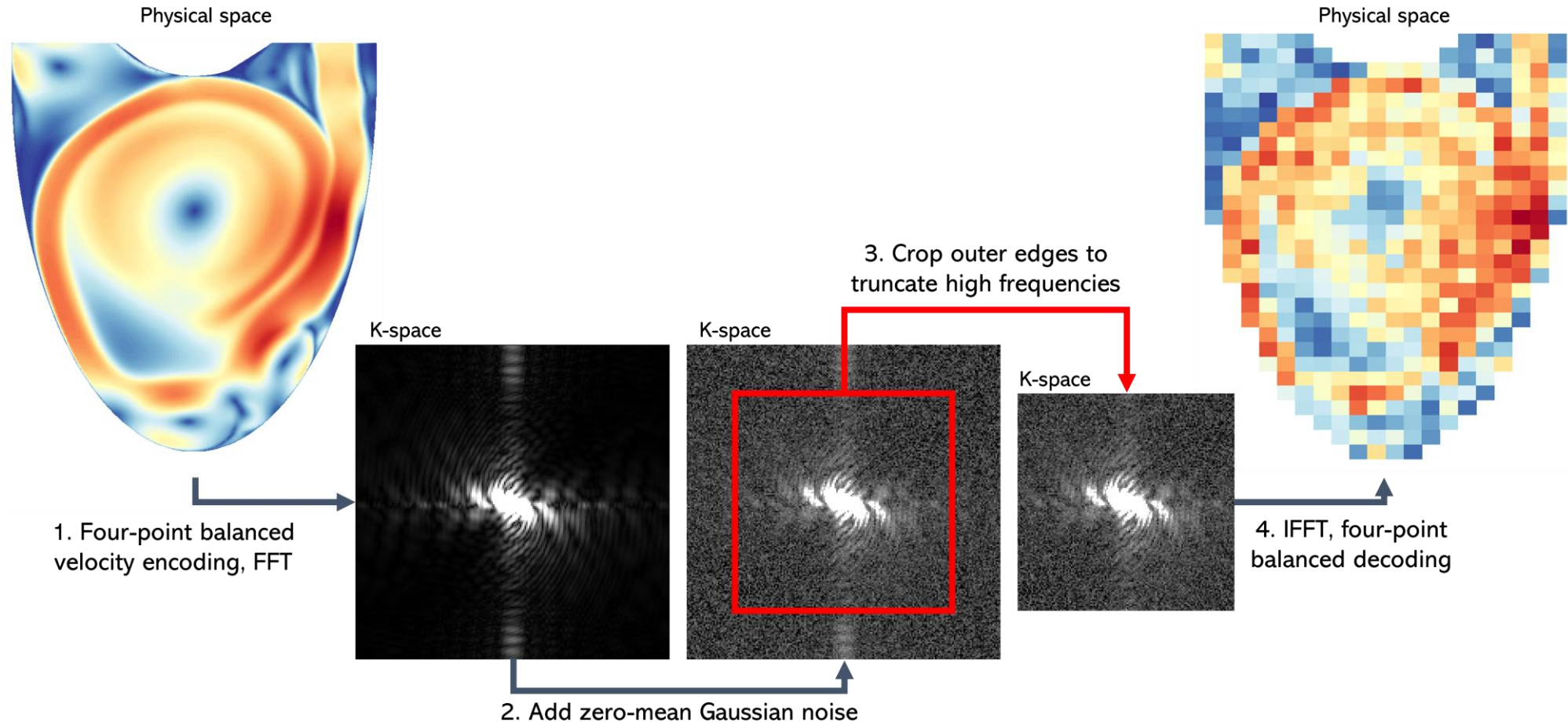


Mesh details

Valve
2

2D Idealised Ventricle: Synthetic Data Generation

- Downsample data to match 4D-flow characteristics

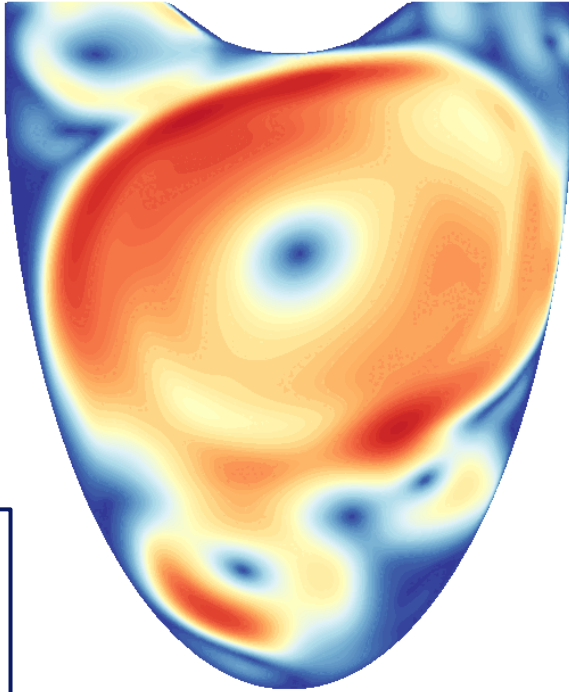


2D Idealised Ventricle: Setup

- Network width: **900** neurons
- Network depth: **9** layers
- Dropout rate: **0.55**
- Number of epochs: **30**
- Initial learning rate: 1×10^{-5} (annealing based on plateau of validation loss)
- Optimiser: **ADAM**
- Total collocation (physics) sample count: **5,986,116**
- Total wall data sample count: **346,572**
- Total training time: **<3 hours**

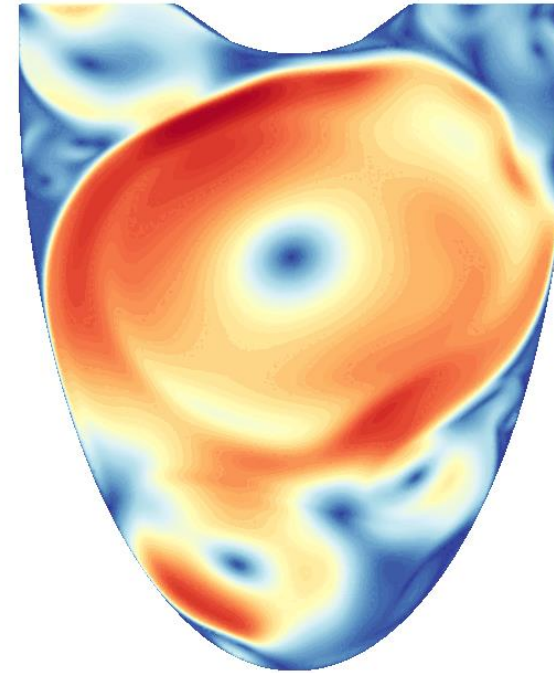
Results: Velocity Magnitude

Prediction

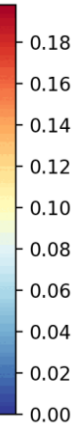


Prediction

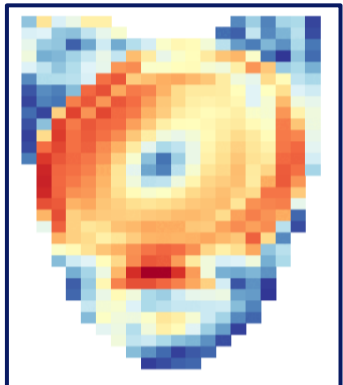
Ground_truth



Ground truth



nRMSE: **8.49%**

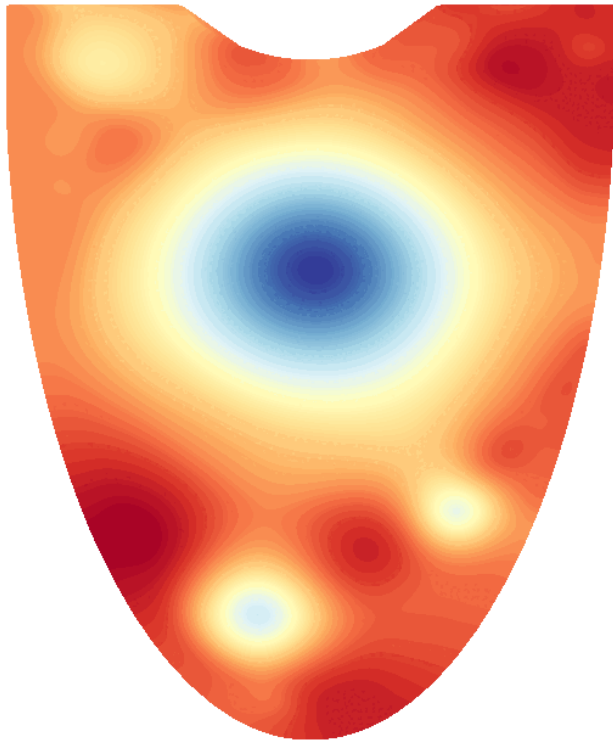


Training data

Velocity magnitude throughout cardiac cycle

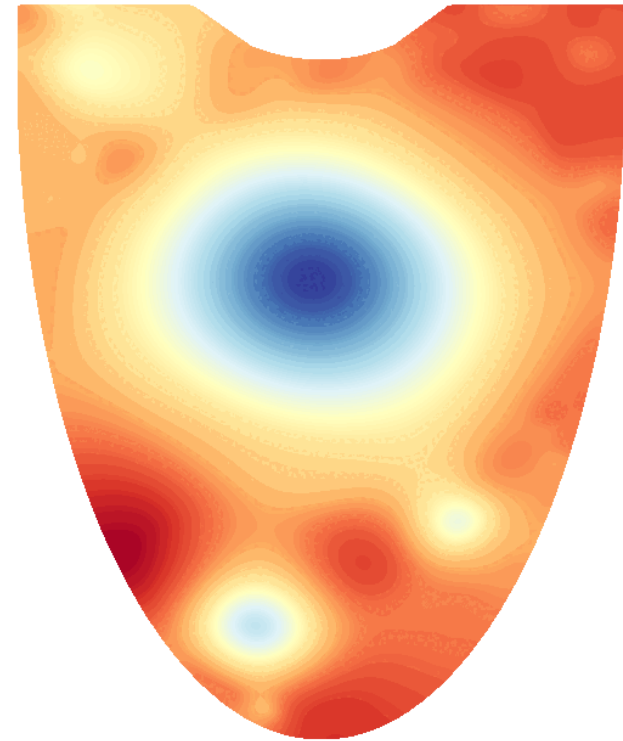
Results: Pressure

Prediction



Prediction

Ground_truth



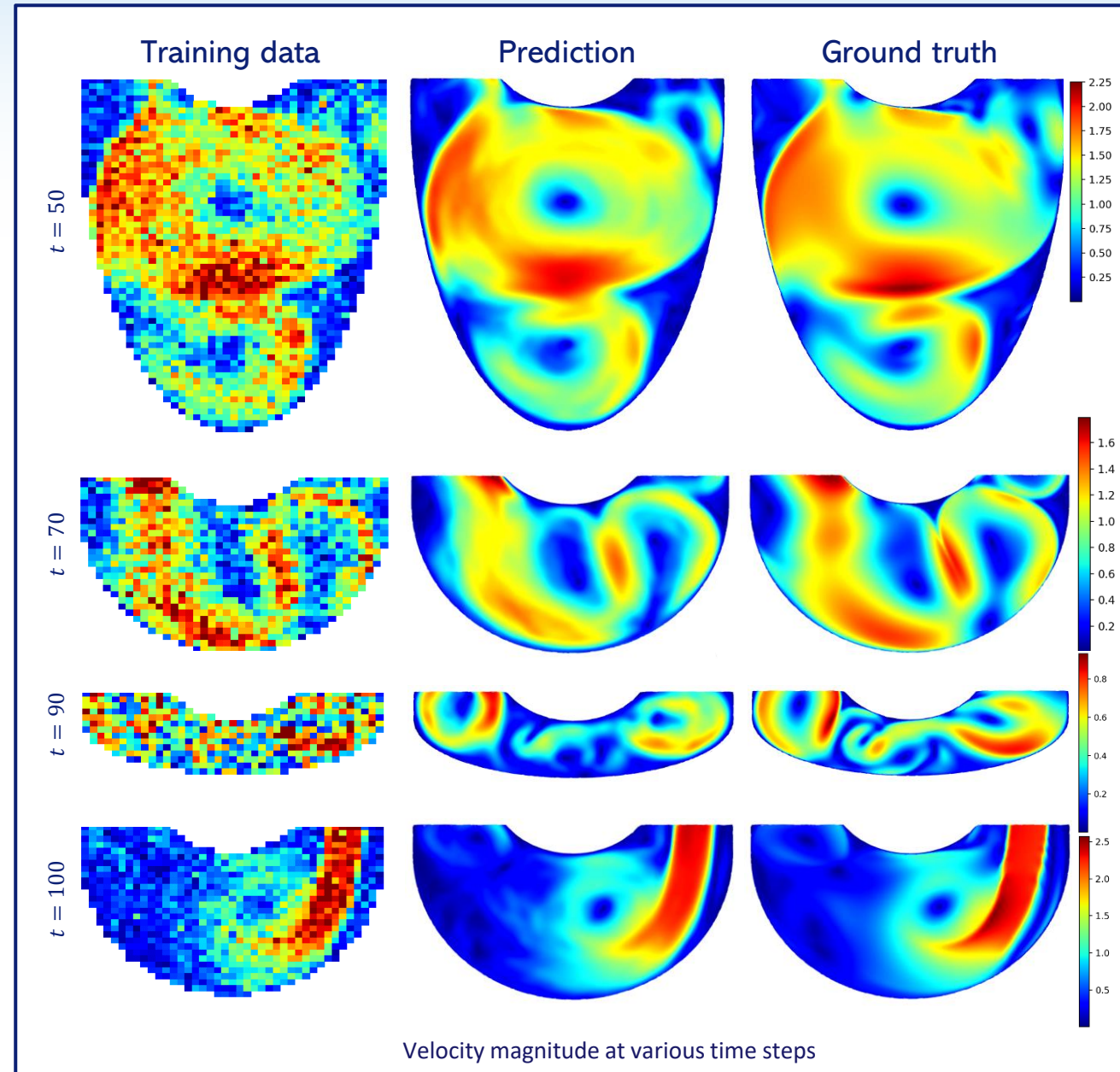
Ground truth

nRMSE: **2.66%**

Velocity magnitude throughout cardiac cycle

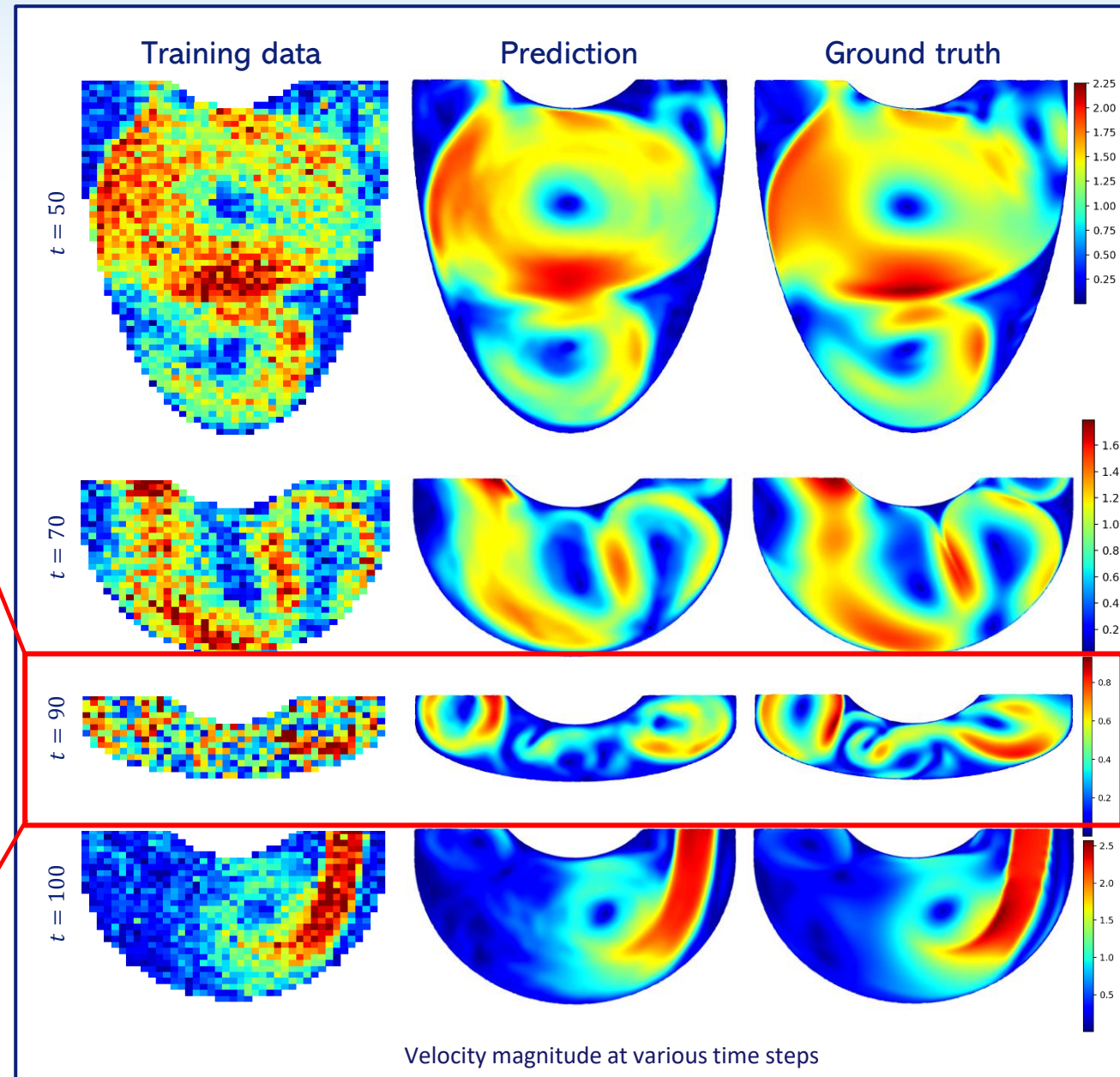
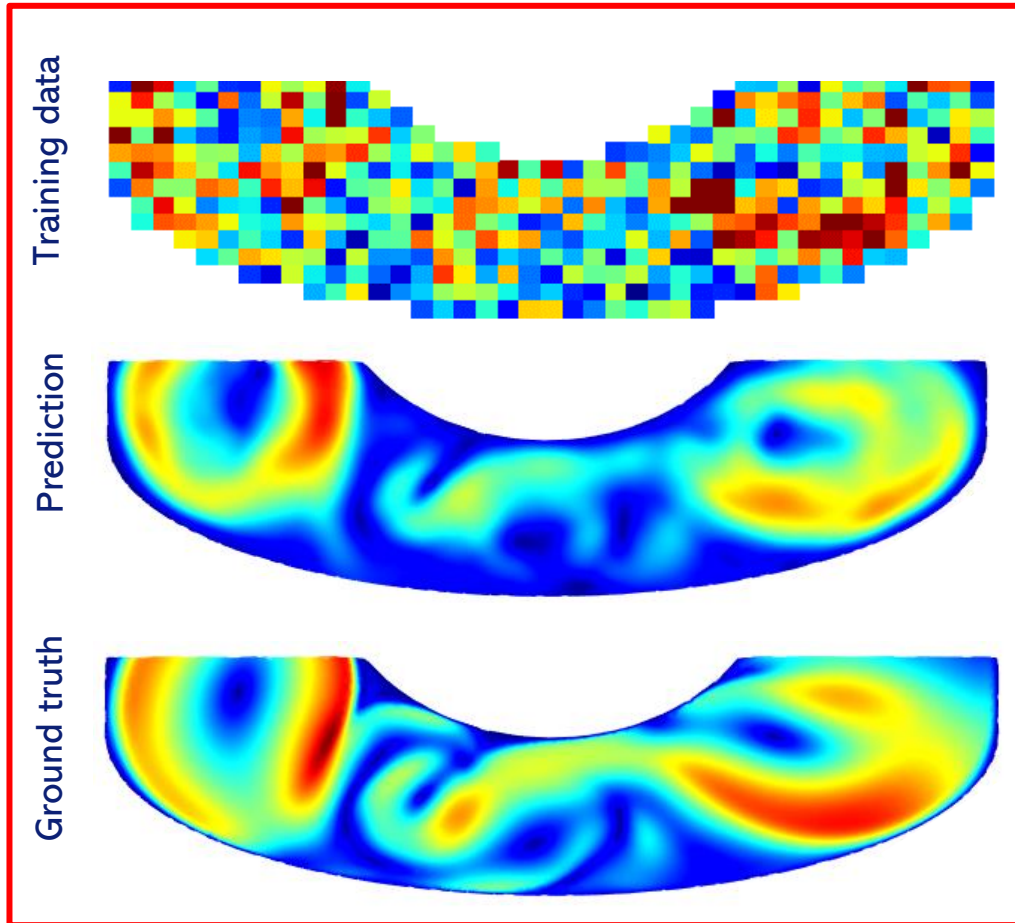
Results: Velocities

- Training data used
 - Spatial downsampling factor (each dim): 4
 - Temporal downsampling factor: 5
 - Signal-to-noise ratio: 6.6 (15% std dev)
- Error:
 - Velocity max-normalised RMSE: 6.5%
 - Interpolation (cubic spline) RMSE: 11.9%



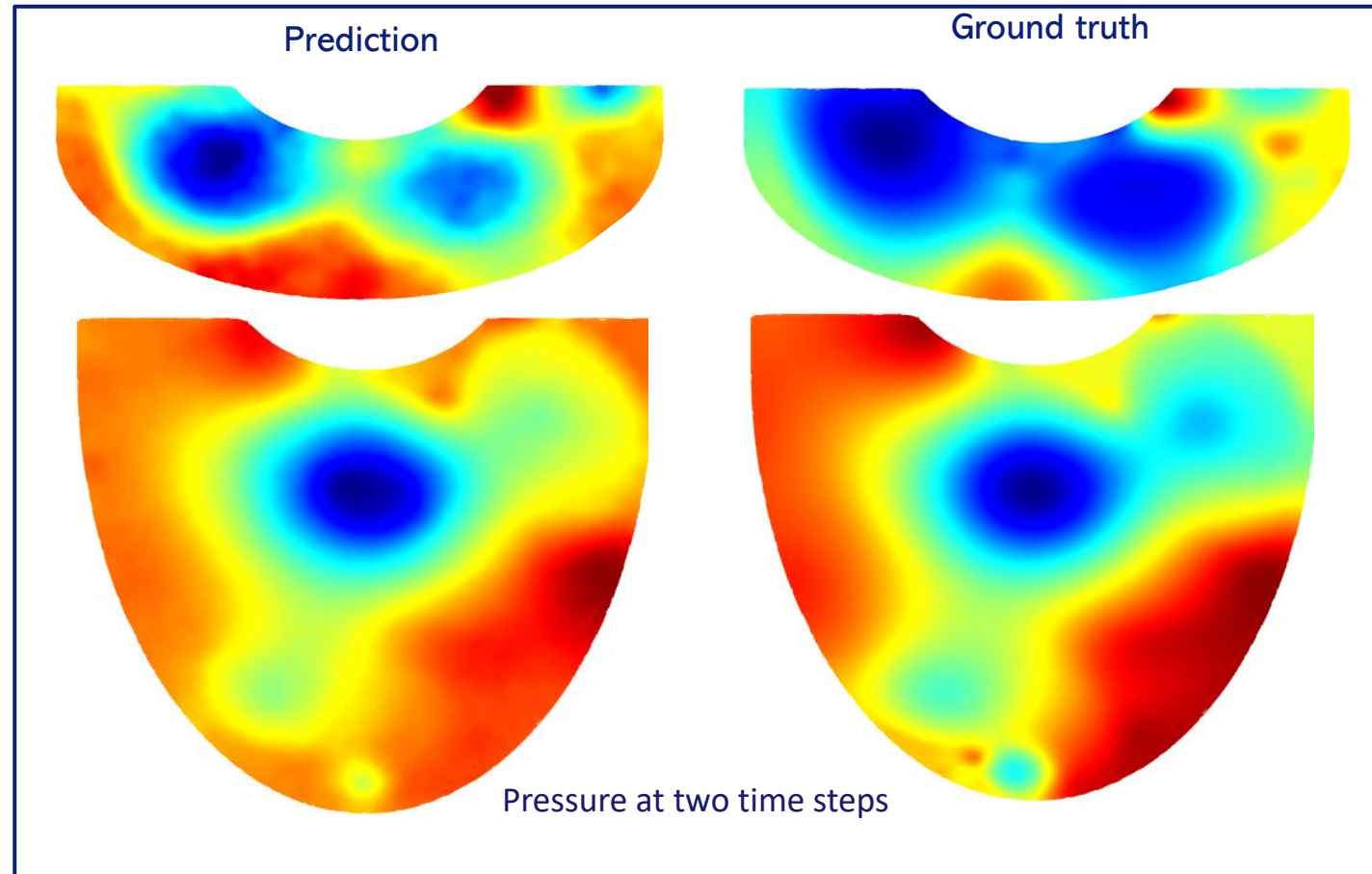
Results: Velocities

- Captures features not visible in data!



Results: Pressure

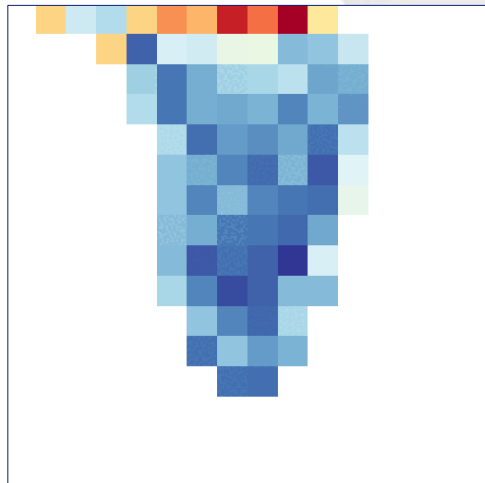
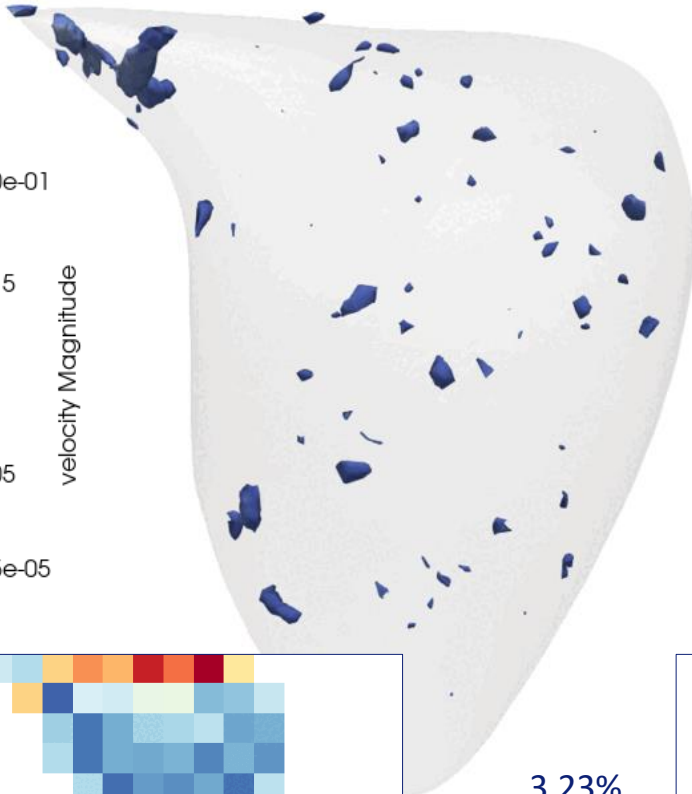
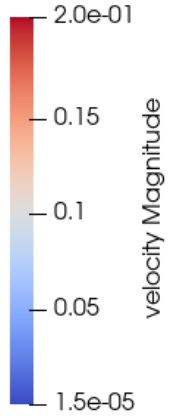
- No pressure data used in training
- Only constrained by Navier-Stokes equations!
 - Only accurate up to a constant
- Error:
 - Pressure nRMSE: **5.3%**



5x temporal upsampling

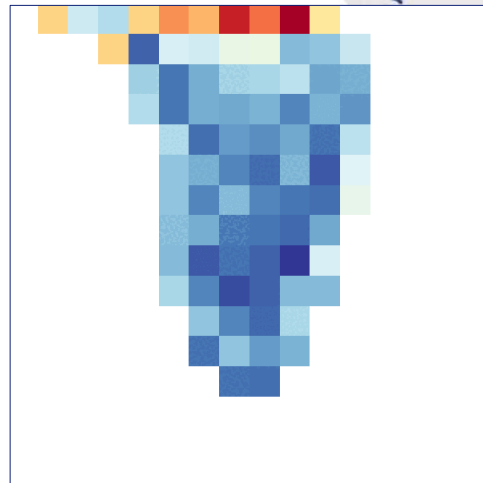
10x temporal upsampling

Ground truth



Training data

3.23%



Training data

3.56%

- Spatial downsampling rate: **8x**
- Noise: SNR **10** (10% std dev)
- Q-criterion:

$$Q = \frac{1}{2} (\|\Omega\|^2 - \|S\|^2)$$

Outlook and Challenges

- We have shown:
 - PINNs provide effective super-resolution in the presence of significant data corruption
 - We are validating this in 2D and 3D synthetic studies
- Clinical challenges:
 - Large uncertainty in boundary motion and location
 - Rigorous *in vivo* validation is required, but challenging
 - 4D-flow MRI is already the gold standard blood flow imaging modality
 - We have planned a study to acquire 4D-flow MRI at two spatial resolutions

Thank you for listening!