Frequency-compensated PINNs for Fluid-dynamics Design Problems

SIEMENS
Ingenuity for life

NEURAL INFORMATION PROCESSING SYSTEMS

Tongtao Zhang, Biswadip Dey, Pratik Kakkar, Arindam Dasgupta, Amit Chakraborty

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Problem Motivation


Energy


Aerospace & Automotive


Process Control

Fluid-dynamics Simulations play a critical role in a large class of engineering problems
- Design Processes
- Planning and Control Problems

Challenge: High-fidelity simulations require significant time and compute power!
- Limited scope in design optimization can lead to sub-optimal design
- Restricted use of simulation in control and reinforcement learning

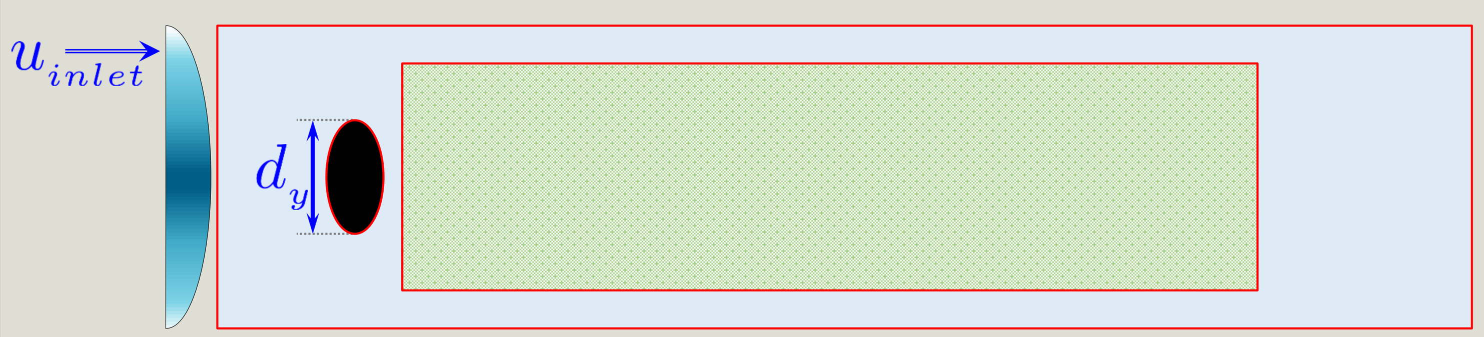
Solution: Surrogates which obey/enforce the underlying physics while predicting simulation outputs

Loss Function = Prediction Error + Physics-based Regularizer

Related Work:

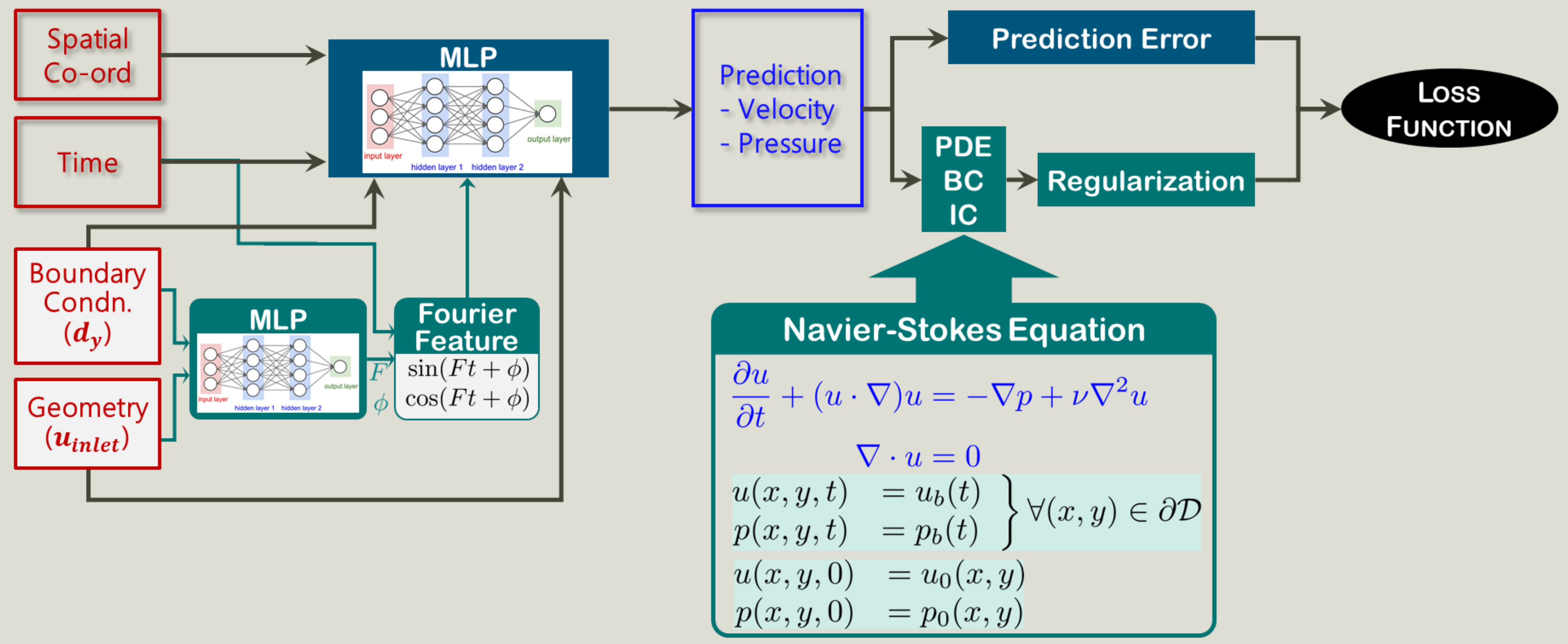
1. Raissi, Perdikaris, and Karniadakis. *Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations*. Journal of Computational Physics, 378:686–707, 2019.
2. Wang *et. al. Towards physics-informed deep learning for turbulent flow prediction*. Proc. ACM SIGKDD, 1457–1466, 2020.
3. Nabian and Meidani. Physics-driven regularization of deep neural networks for enhanced engineering design and analysis. Journal of Computing and Information Science in Engineering, 20(1), 2020.
4. Li *et. al. Fourier Neural Operator for Parametric Partial Differential Equations*. arXiv:2010.08895, 2020.

Cylinder in a Cross-flow



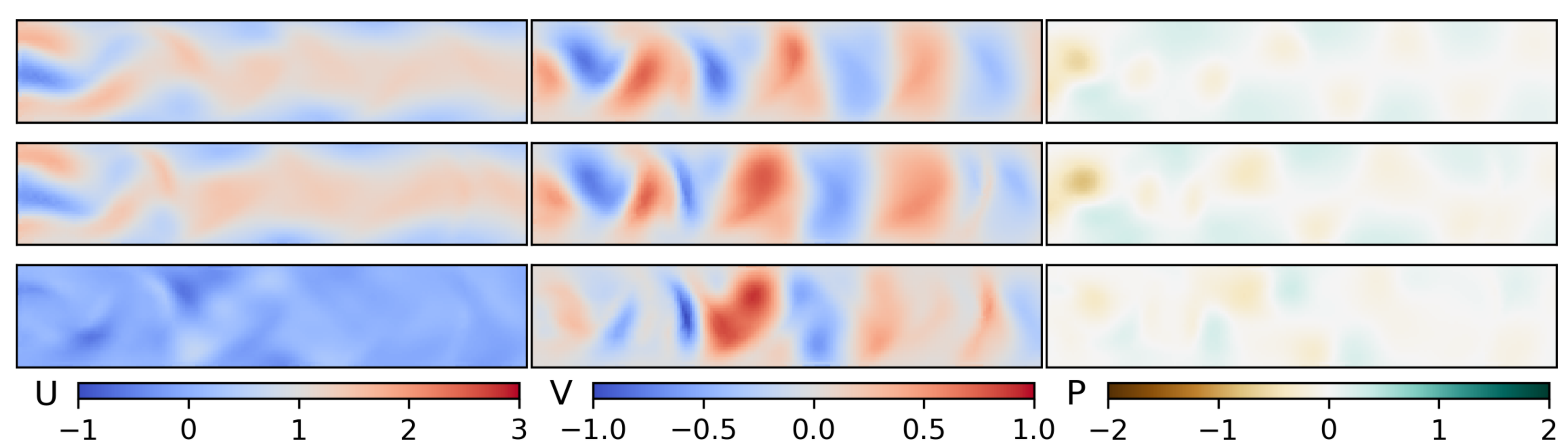
- *Reynolds number*: $\boldsymbol{Re} = \frac{u_{inlet} * d_y}{\nu}$
- *Vortex Shedding Frequency*: $0.21 * \left(1 - \frac{21}{\boldsymbol{Re}}\right) * \left(\frac{u_{inlet}}{d_y}\right)$
- Design Space
  - Parametrized Geometry: $d_y \in \mathcal{D}$
  - Parametrized Boundary Conditions: $u_{inlet} \in \mathcal{U}$
- **Objective:** Learn a surrogate that can predict flow velocity (u, v) and pressure (p) at any location (x, y) inside the shaded region □ at any time (t) for a given geometry $d_y \in \mathcal{D}$ and inlet velocity $u_{inlet} \in \mathcal{U}$.

Proposed Solution

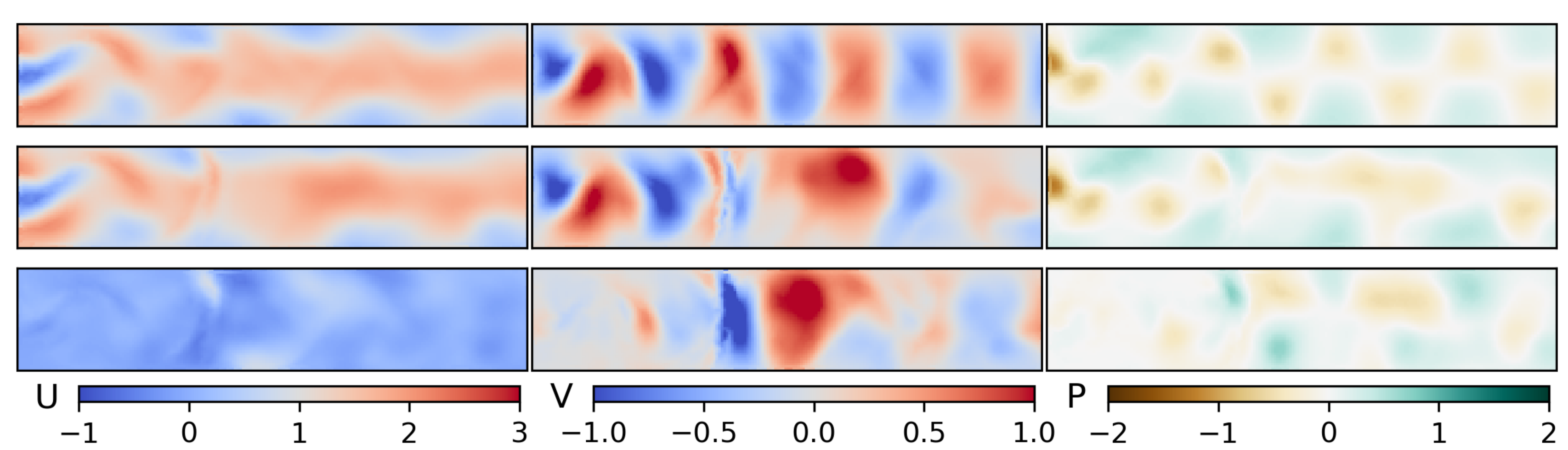


- **Our solution adopts a two-pronged approach to encode physics into the surrogate!**
  - **Regularized Loss Function –** A regularization term enforces Navier-Stokes equation along with appropriate initial and boundary conditions.
  - **Computation Graph –** Furthermore, a set of Fourier features are used to promote periodic behavior in the predicted velocity and pressure; this periodicity in the flow depends on underlying geometry and inlet velocity via the Strouhal number.
- **Training Dataset:**
  - First, 9 different design conditions are sampled from $\mathcal{D} \times \mathcal{U}$.
  - Then, *FEniCS* was used to build the ground-truth simulation dataset ($[0s, 5s]$ with $0.1s$ time resolution).

Why do we need both Physics-based Regularization and Fourier Features? Results from Ablation Studies

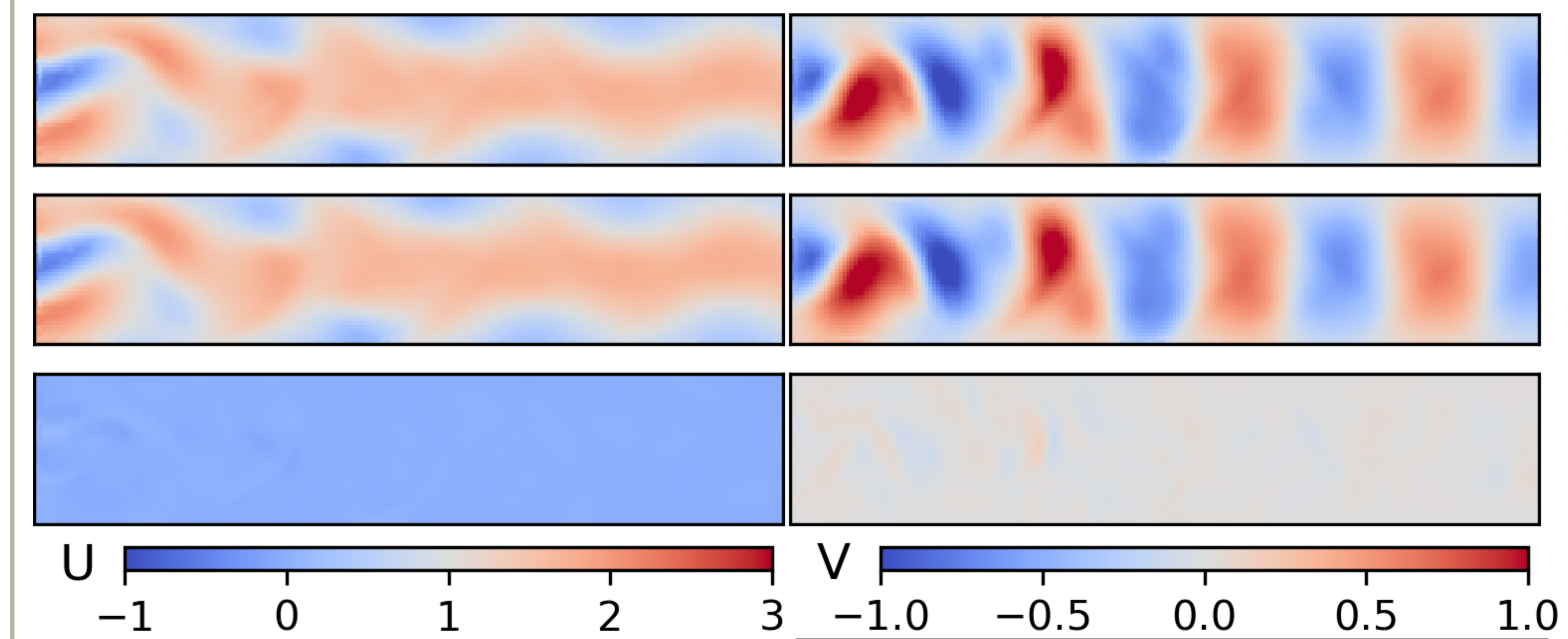


Physics-informed Regularization, But NO Fourier Feature

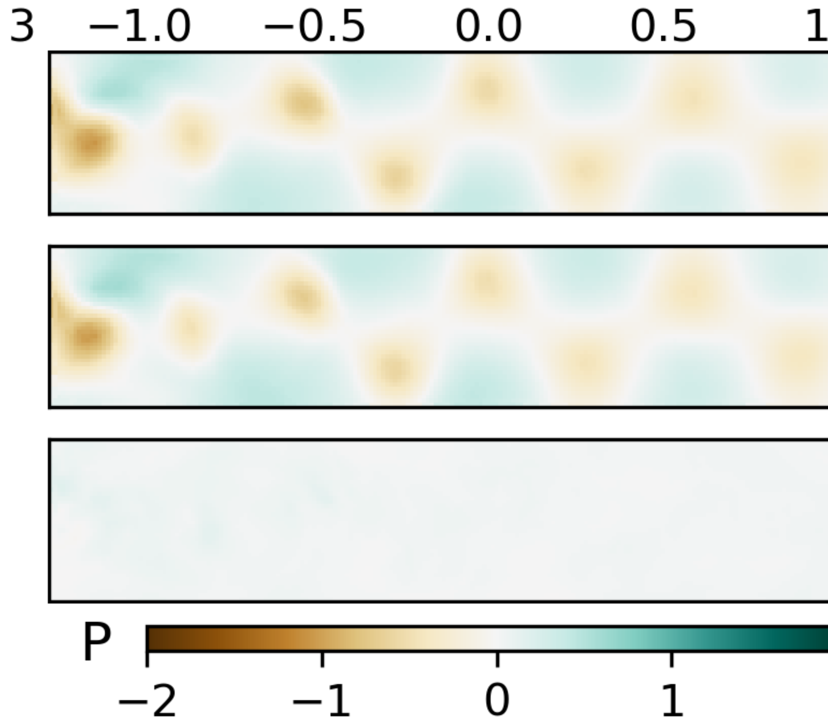


Fourier Features are Used, But NO Physics-informed Regularization

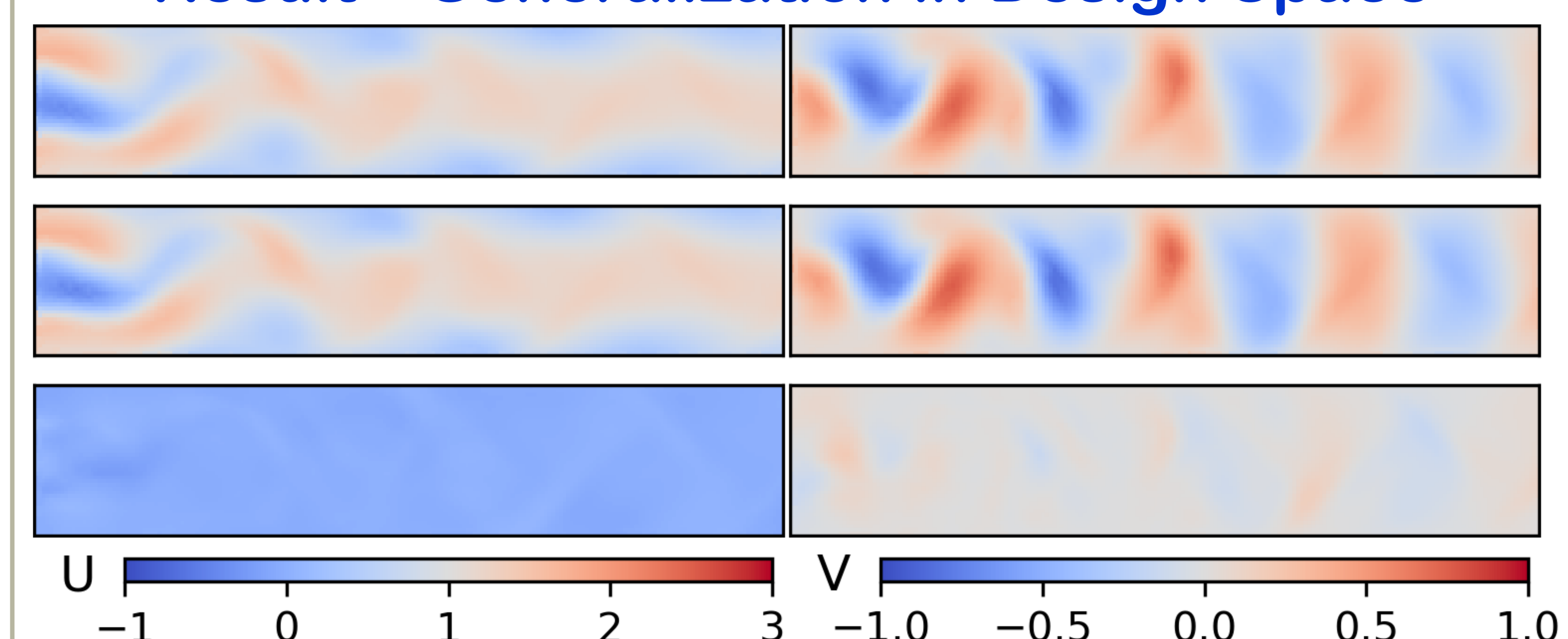
Result – Generalization in Time



- Time Resolution: $0.05s$
- Geometry – $d_y = \mathbf{0.11}$
- Inlet Velocity – $u_{inlet} = \mathbf{1.0}$



Result – Generalization in Design Space



- Geometry – $d_y = \mathbf{0.11}$
- Inlet Velocity – $u_{inlet} = \mathbf{0.8}$
- Time Resolution: $0.1s$