Universal Physics Transformers (UPT) A Framework For Efficiently Scaling Neural Operators



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TLDR

- Current neural operators research largely focuses on small-scale problems (1K-10K inputs)
 Interesting problems often have 100 thousands or millions of inputs
- We introduce a framework for efficient neural operators
 - Reduced latent space modeling
 - Applicable to Eulerian and Lagrangian data
 - Leverage scalability of transformers



Datapoints





















Background: Reduced Order Modeling

- Uncompressed representation: 400 2D vectors
- Abstract representation: "four swirls"





Transient Flow Simulations





Current Landscape of Neural Operators

- Existing neural operator architectures don't scale well
 - Architectures that can't handle large inputs
 - No input compression





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Architecture

• Encoder

- Aggregate information into supernodes
- ° Exchange global information
- ° Reduce into a small latent space
- Approximator
 - Propagate latent space forward in time
- Decoder
 - Decode the latent space at arbitrary query positions





Results: Transient Flow Simulations

- Self-generated computational fluid dynamics (CFD) dataset
- 10K simulations (8K train, 1K validation, 1K test)
- Adaptive meshing (between 29K and 59K mesh points)
- 2D problem





Results: Transient Flow Simulations

• UPTs easily outperform competition





UPTs for Lagrangian Simulations

• UPTs can model the underlying velocity field extremely well







Thanks for your attention!



Project Page + Code https://ml-jku.github.io/UPT



Paper https://arxiv.org/abs/2402.12365



Tutorial https://github.com/BenediktAlkin/upt-tutorial

