Chair of Aerodynamics and Fluid Mechanics
TUM School of Engineering and Design
Technical University of Munich

Manifold Learning in Fluid Mechanics

Bachelor's Thesis

The idea of advancing physical systems on reduced data manifolds has been a pursuit in research, with ever-evolving approaches, for a long time. What begin with the use of asymptotics to reduce the dimension, evolved into attempting to identify the dominant modes, or applying linear algebra-based decompositions. In recent years one utilizes machine learning models for this task. Beginning with autoencoders, and evolving into generative models with variational autoencoders, generative adversarial networks, and neural ordinary differential equations all striving to learn a lower-dimensional latent space to either induce a reduction, or perform propagation in time, on the found latent space. All of this is in fluid dynamics, and physics in general, driven by our knowledge of the existence of such lower-dimensional manifolds which our problems live on, but we are nearly always unable to find these manifolds with confidence. Manifold-learning approaches this problem by combining aspects from the aforementioned models with insights from energy-based models to learn the shape of the data manifold, a tractable bijective chart between the lower-dimensional latent space, and the data manifold, and a tractable probability density over the manifold. To enable such scheme manifold learning has to utilize a non-probabilistic distance measure, whose use has been pioneered in the training of energy-based models.

In this thesis, we will dive deeper into the manifold learning approach with Fluid dynamics data to explore its potential for Fluid dynamics problems and their generative modeling to understand its potential on problems of ever-increasing difficulty. A key focus in this endeavour will be the computational tractability of the M-flow model training.

Tasks:

- Begin with the codebase of *"Flows for Simultaneous Manifold Learning and Density Estimation"*, familiarize yourself with its codebase, to then extend & apply it to Fluid dynamics problems of ever-increasing difficulty
  - Burgers
  - Kolmogorov Flows
- Alter the training scheme to more efficiently train M-flow models on our problems
  - Extend the codebase where necessary with components from PyTorch packages for normalizing flows, GANs, and energy-based models

Requirements:

- Ability to work independently
- Curiosity to experiment with machine learning approaches
- Coursework in Probability theory / Probabilistic modeling is beneficial.
- First attempts at playing with PyTorch are beneficial.

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