ISYE 7406 - Spring 2023 Project Proposal
Lid Driven Cavity Flow: A Physics Informed Neural Network Approach vs. Traditional Statistical Model

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1 Problem Description

Computational fluid dynamics (CFD) is the process of mathematically modeling a physical phenomenon involving fluid flow and solving it numerically using computers. From winning race cars to commercial aircraft that people fly in every day, CFD is a fundamental process in the pipeline from idea to design, while saving millions in costs. Rather than building multiple versions and prototyping (which is exceedingly expensive), engineers today will simply run a series of models to find the best design and then iterate this into a final product. The main issue with this is depending on the detail and length of the simulation, even the most basic simulations will either cost many thousands of dollars on a high performance computing (HPC) cluster, or take a very long time to run on a standard desktop or laptop (usually in terms of weeks to months).

In the separate field of machine learning, neural networks and other non-explicitly programmed algorithms are estimated to be an industry in the billions. This has led to an explosion in interest and growth into the field, with researchers and scientists applying neural networks to more applications than just image identification. While these statisical models can capture nonlinear effects very well, they often require hundreds or millions of examples to fit a model, where generalization of new data is not always guaranteed. Conversely, in CFD, data is often measured in terms of gigabytes to petabytes, so sifting through this data for meaning or trying to feed more than a few examples to a neural network can be extremely prohibitive (time and cost). This leads to the introduction of physics informed neural networks (PINNs). This is where the loss function of the optimization is substituted for a part of physics (in this study, the continuity equation), in order for the model to adhere to physics better. This has led to models that adhere to physics applications much better with less data, converge to a solution faster, and put "guard rails" on models that attempt to predict vastly different phenomena that might be practical. Furthermore, traditional statistical models that are feasibly equipped to predict non-linear events will also be studied (such as SVM kernels, KNN, and others from this data mining class).

1.1 Problem Setup

In this study a classic fluid mechanics problem will be observed with an application of PINNs and other statistical models, specifically the Lid-driven cavity flow problem (or sometime referenced as the driven cavity flow problem). This is a 2 dimensional application of the Navier-Stokes equation with the simplifications of being in 2 dimensions, steady-state, incompressible fluid flow, at lower Reynolds number (≤ 2000). This is a well studied test case with many permutations such as nonlinear gridding, spectral methods and different optimization algorithms for faster convergence, however this is all outside the scope of this study. The algorithm used as baseline is the SIMPLE (Semi-Implicit Method for Pressure Linked Equations) algorithm. For the baseline examples to reproduce Reynolds numbers between roughly 300-1,900. A PINN will then be trained with the same grid size and continuity equation as the optimization function. A comparison between the baseline and machine learned approaches will then be quantitatively compared. This will then give a further insight into the usefulness of PINNs (and versus other traditional algorithms from this class), and how generalizable something like this could become in the future development in this field of study.

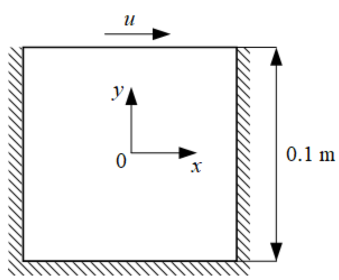

Figure 1: Open Lidded Cavity Flow Free Body Diagram

1.2 Data

For this project proposal, the data will be generated using openFOAM which will need conversion and reading from the open source openFOAM data format to something python readable by PyTorch and scikit learn.

The other possible approach for generating the data will be FlowPy (in pure python)

1.3 Scientific Research Questions

The overall theme of these questions are if statistical models could help traditional computational methods be either faster (skip the long computational times via prediction) or produce results similar to empirical/computational methods for extrapolation (data from slower speed flows, accurately predict higher flow problems)

1. Can Physics Informed Neural Network (PINNs) be properly taught to generalize a canonical non-linear problem in fluid mechanics.
2. Would more traditional algorithms better generalize to non-linear physics effects
3. Do any statistical models predict or produce accurate results compared to expensive computational methods
4. Are there any features that can be mined from the data or derived that can better produce more accurate prediction results