Project Plan

1. Motivate the Project

Solving a high dimensional model with huge degrees of freedom is really computationally expensive. In this case, using a reduced order model (ROM) to approximate corresponding high fidelity model retaining as much as possible is the goal of this project. The ROM should have decent prediction capability as the high fidelity one. ROM can speed up many orders of magnitude resulting and predicting, so it can be used for multi-query problems and for real-time calculations.

Long short term memory network (LSTM), as one of the recurrent neural networks, has a great prediction performance on time-dependent deterministic problems. It has been widely used in stocks price prediction, translation and speech recognition. The 'memory' possessed by these neural networks may have particular importance for model reduction and might be used for large scale problems. For example, these methods lead to the prospect of being able to resolve the flows within a building while simultaneously resolving the flows within an entire city. This project will develop the LSTM network with the possible extension of using domain decomposition Methods to gain further reduction in computational cost.

1. Literature Review

The project can be divided meanly into three parts. The first part is using existing

1. Xiao, Dunhui & Heaney, Claire & Mottet, Laetitia & Fang, F & Lin, William & Navon, Ionel & Guo, Y & Matar, Omar & Robins, A.G. & Pain, Chris. (2018). A reduced order model for turbulent flows in the urban environment using machine learning. Building and Environment. 148. 10.1016/j.buildenv.2018.10.035.

Really similar to the job I have to do, the difference is that is not using LSTM and not combining domain decomposition.

1. A domain decomposition non-intrusive reduced order model for turbulent flows

* NIROM with domain decomposition, using GBR.

1. A domain decomposition method for the non-intrusive reduced-order modelling of fluid flow

Current subdomain and the surrounding subdomains. Detailed method on what to do with domain decomposition.

1. Model identification of reduced order fluid dynamics systems using deep learning

* LSTM is used to construct a set of hypersurfaces representing the reduced fluid dynamic system. The input of LSTM is the POD basis of size P.
* Also some method on evaluating the performance of the model. The time step choosing and splitting of training and validation set.

1. Deep convolutional recurrent autoencoders for learning low-dimensional feature dynamics of fluid systems

data-driven model reduction.

Using AE and CNN. Dimensionality reduction via convolutional autoencoders.

Learning feature dynamics by LSTM.

1. Data-driven computational mechanics

* Using data-driven methods in other areas. How to keep good performance and how it works.

1. Computational mechanics enhanced by deep learning

* Using deep learning method or the FEM stiffness matrices.

1. Smart finite elements: A novel machine learning application

* Utilizes machine learning to generate a direct relationship between the element state and its forces, which avoids the complex task of finding the internal displacement field and eliminates the need for numerical iterations.
* Not tied with any particular ML method.

1. Model-Free Data-Driven inelasticity

* Using the data-driven method in a completely different domain, while it has lots of benefits.

## Milestones and the Dates

Details are in the Gantt chart below:

