Applying Dimensionality Reduction to Solutions on Finite Element Meshes with Autoencoders

Dr Claire Heaney, Prof. Christopher Pain

The Background

There is rapidly-growing interest in using autoencoders for dimensionality reduction within reduced-order models rather than Proper Orthogonal Decomposition (POD). The latter relies on a linear decomposition of coefficients and basis functions spanning a low-dimensional space, whereas the former is able to provide a low-dimensional nonlinear embedding. Although POD works well for many applications and is simple to apply, certain applications, for example, convection-dominated problems, have recently been seen to benefit from the more accurate reductions that autoencoders can provide.

When solving fluid flow problems, unstructured meshes are commonly used to represent complex geometries. In addition, for problems with evolving sharp features or discontinuities, mesh adaptivity is often used to achieve a more accurate solution than a structured mesh for the same number of degrees of freedom.

The Project

To tackle the large numbers of degrees of freedom required to solve problems of interest in computational mechanics today, such as the prediction of air flows and pollution dispersion within cities, a convolutional autoencoder (CAE) would be the network of choice for dimensionality reduction. However, CAEs are designed to be applied to structured grids. There are currently two solutions available: either a traditional CAE based on a space-filling curve (SFC) ordering [1] or graph convolutional networks [2]. The former has been demonstrated to work well for unstructured meshes and the focus of this PhD would be to extend this method and apply it to solutions on unstructured, adapted meshes.

This development would have a huge impact in reduced-order modelling, as currently many researchers are either using structured grids to solve problems which would more accurately solved on unstructured meshes, or are interpolating from the unstructured mesh to a structured grid; both of which introduces additional errors. With a SFC-CAE that could handle unstructured, adapted meshes, researchers could apply convolutional autoencoders to their data, whatever mesh had been used in the simulation.

The Candidate

The candidate should have a strong background in mathematical and computational science, a good degree in an appropriate subject (eg. mathematics, physics, computer science, engineering or earth sciences), and a strong interest in computational modelling, machine learning and code development. The student will be joining one of the largest research groups at Imperial, namely the Applied Modelling and Computation Group (AMCG), with experience in computational fluid dynamics, urban flows, flooding, multiphase flows, porous media, geothermal engineering, reservoir modelling. The candidate will have the opportunity to develop their career and profile by presenting at conferences and publishing in high impact journals.

[1] Claire E. Heaney, Yuling Li, Omar K. Matar, Christopher C. Pain (2020) *Applying Convolutional Neural Networks to Data on Unstructured Meshes with Space-Filling Curves*, *https://arxiv.org/abs/2011.14820v2*.

[2] John Tencer, Kevin Potter (2020) *A Tailored Convolutional Neural Network for Nonlinear Manifold Learning of Computational Physics Data using Unstructured Spatial Discretizations,* https://arxiv.org/abs/2006.06154.

Funding details / Application

Unfortunately, there is no funding associated with this PhD topic. Please see the following pages for advice on applying for scholarships
https://www.imperial.ac.uk/study/pg/fees-and-funding/scholarships/
https://www.imperial.ac.uk/earth-science/prosp-students/phd-opportunities/funding/

For more information about the project please contact Claire Heaney (c.heaney@imperial.ac.uk) or Christopher Pain (c.pain@imperial.ac.uk).

For details on how to apply please consult
https://www.imperial.ac.uk/earth-science/prosp-students/phd-opportunities/apply/