DEEP RESIDUAL AMBIVALENT GRAPH CONVOLUTIONAL NETWORKS FOR BIOMARKER PREDICTION IN LARGE VESSEL NETWORKS

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Introduction

1D haemodynamic partial differential equation (PDE) solvers present themselves as an excellent tool for modelling full body blood flows and pressures.

In spite of their success, however, PDE solvers are still limited by a few key areas - namely on-the-fly uncertainty quantification, ill posed problems and (potentially) expensive computational cost.

The field of haemodynamics is no exception to these limitations with a paramount need for solutions; to aid clinical judgement, account for inaccessible vessels and mitigate limited clinical resources.

Thus there is a clear need for haemodynamic models that are able to predict clinical biomarkers with minimal input data whilst conveying model confidence in an intuitive manor.

Methods

We propose a novel Deep Residual Ambivalent Graph-convolutional Network (DRAGN) to provide accurate biometric predictions with uncertainty quantification.

Bayesian inference is used as a proxy for uncertainty quantification via post-training dropout, with prediction stability obtained through multiple input perturbations - which is only possible due to the cheap evaluation of the trained neural networks.

Additionally, ill-posed problems can be handled in a similar manner through sampling unknown parameters from a distribution, reducing the time taken to obtain patient measurements and subsequently reducing clinical workload.

The network is trained on a synthetic patient database which is generated using in-house PDE haemodynamic solvers through sampling PDE input parameters from a uniform distribution and then rejecting any non-physical or non-physiological patients.

The learning objective for the network is to predict the pressure and resistivity index for a pre-specified vessel (either the carotid or femoral artery) selected from a 77 vessel network.

The network is then trained for up-to 100,000 epochs using a Latin hyper-cube sampling for parameter tuning with linear regression models to highlight areas for parameter sub-sampling.

Results

Once trained, DRAGN was able to evaluate 2000 patients per second with an inference time of 5e-4s. For pressure index metric prediction, DRAGN has a mean squared error of 9.4e-5 with the pressure index mean being 0.057.

For resistivity index metric prediction, DRAGN has a mean squared error of 0.014 with the resistivity index mean of 1.2.

DRAGN is still undergoing hyper-parameter tuning with daily performance increases.

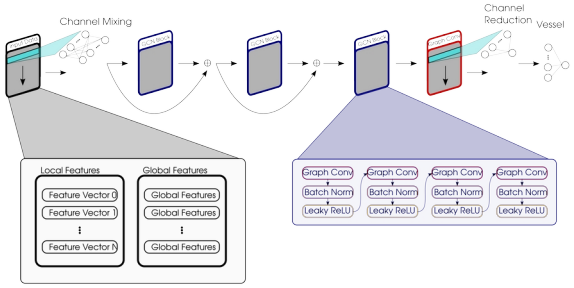

Figure 1: Schematic of the residual graph convolutional neural network architecture.

Discussion

The residual graph convolutional neural network has showcased an ability for fast and accurate biomarker prediction allowing for on-the-fly uncertainty quantification and reducing clinical measurement acquisition time - removing current clinical barriers for haemodynamic solvers.

The next steps, are to extend the neural network architecture such that it is capable of predicting transient responses (such as pressure waves) through utilising transient neural network architectures.

References

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