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Physics-Aware Convolutional Neural Networks for Computational Fluid Dynamics Simulations

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CFD simulations are very costly to compute and have to be repeated if the geometry changes even slightly. Recently there have been a number of attempts to speed up this process using neural networks. Among these is the use of Convolutional Neural Networks (CNN) as surrogate models for CFD simulations with varying geometries; see, e.g., [1]. Here, the model is trained on images of high-fidelity simulation results. However, the generation of training data is expensive and this approach usually requires a large data set. Thus, it is of interest to be able to train a CNN in the absence of abundant training data with the help of physical constraints. First results have already been achieved for the heat equation on a fixed geometry and flow problems in parameterizable geometries; see [2, 3]. In this talk, we present a physics-aware approach to train CNNs as surrogate models for CFD simulations in varying geometries. The employed CNN takes an imags of the geometry as input and returns images of the associated CFD simulation results, i.e., velocity and pressure, as output. Our CNN architecture is based on the structure of U-Net [4]. Since the model is trained on pixel images, it can be applied to a variety of different geometries. We show results for two-dimensional flows around obstacles of varying size and placement and in non-rectangular geometries, esp. arteries and aneurysms.

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