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Extending the capabilities of data-driven reduced-order models to make predictions for unseen scenarios

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Reduced-order modelling aims to approximate a high-dimensional system by a low-dimensional system that should be faster to solve and accurate enough for the desired purpose. Non-intrusive or data-driven reduced-order models (ROMs) most commonly learn the evolution of the system by exploiting machine learning [1, 2]. We present an approach for data-driven reduced-order modelling based on a sub-sampling technique and domain decomposition, the combination of which enables predictions to be made for unseen scenarios with larger-sized domains than were used in training. To find the low-dimensional space, a convolutional autoencoder is used, as this type of network can compress information more efficiently than traditional approaches [3]. For the prediction, an adversarial network is used, which attempts to keep the predictions realistic [4].

The method is applied to chaotic time-dependent air flow past buildings at a moderate Reynolds number in 2D. After training, we apply the data-driven ROM to a domain that has twice the area of the domain used for training and with a different arrangement of buildings. Statistical properties of the flows from the data-driven ROM are compared with those from the CFD model in order to establish the success of the method.

The method presented here shows great potential for increasing the generalisation of data-driven reduced-order models. We believe that this approach is generic and could be applied to other problems, for example, other turbulent flows or porous media flows.

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