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Investigation of PDE-constrained deep neural networks for efficient flow field assimilation

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The development of data-driven surrogate models for the prediction of complex fluid phenomena, in place of more standard numerical simulations, is an ongoing challenge in various fields and may help when many-query and/or real-time simulations (e.g. uncertainty quantification, data assimilation, control...) are required. Here, we decide to investigate the potential of integrating deep neural networks (DNN), which are known to be performant in capturing transient and intermittent phenomenon with the possibility of handling translations, rotations and other invariances, in more classical numerical methods for computational fluid mechanics [1]. Inspired by recent works [2, 3], the strategy retained in this study is the one of training a DNN by leveraging some underlying physical laws of the system. The idea is to incorporate prior scientific knowledge to be used as a guideline for designing efficient deep learning models. In particular, a natural approach is to incorporate (some of) the governing partial differential equations (PDEs) of the physical model (e.g. mass/momentum/energy conservation) at the core of the DNN, i.e. in the loss/likelihood functions. We propose to investigate how this additional information effectively regularizes the minimization procedure in the training of DNN for fluid flows, and enables them to generalize well with fewer training samples. More specifically, we will report on the influence of the choice and the dimensionality of the domain of interest for data acquisition as well as subsequent training and predictions, in relation to the problem geometry, initial/boundary conditions and flow regimes. Finally, we will report on the DNNs training attempt on large direct numerical simulations database acquired for turbulent convective flow in rectangular cavity with rough bottom plate.

Figs. (1-2) present some preliminary results for an incompressible, laminar, time-dependent 2D flow past a stationary cylinder with an imposed fixed wall temperature (Reynolds and Peclet numbers: $Re=100$ and $Pec=71$). Only the simulated temperature field within the domain depicted by the $[2, 10] \times [-3, 3]$ yellow rectangle, cf. Fig. (1), is collected for several shedding cycles and used for the DNN training. In addition, numerical constraints corresponding to the advection-diffusion temperature transport equation, conservation of mass and momentum equations of the fluid are imposed to the DNN-predicted quantities during the training. Results presented at a particular instant of the time-window, cf. Fig. (2), show that hidden quantities, here, $[u, v, p]_{(t,x,y)}$, are correctly learned and predicted through the implicit encoding of the underlying PDEs.

- [1] J.N. Kutz. Deep learning in fluid dynamics. *J Fluid Mech.*, 814:1-4, 2017.
- [2] M. Raissi, P. Perdikaris, and G.E. Karniadakis. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *J. Comp. Phys.*, 378:686-707, 2019.
- [3] Y. Zhu, N. Zabaras, P. Koutsourelakis, and P. Perdikaris. Physics-constrained deep learning for high-dimensional surrogate modeling and uncertainty quantification without labeled data. *arXiv:1901.06314*, 2019.

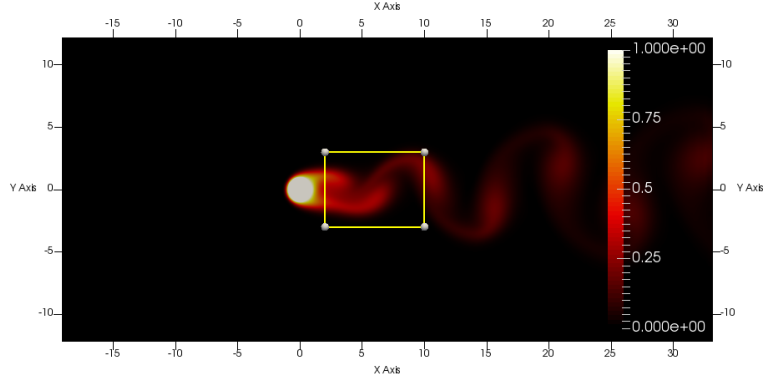


Figure 1: System considered: DNS-simulated two-dimensional flow past a heated cylinder. The simulated temperature field within the domain depicted by a $[2, 10] \times [-3, 3]$ yellow rectangle is collected for several shedding cycles and used for the DNN training.

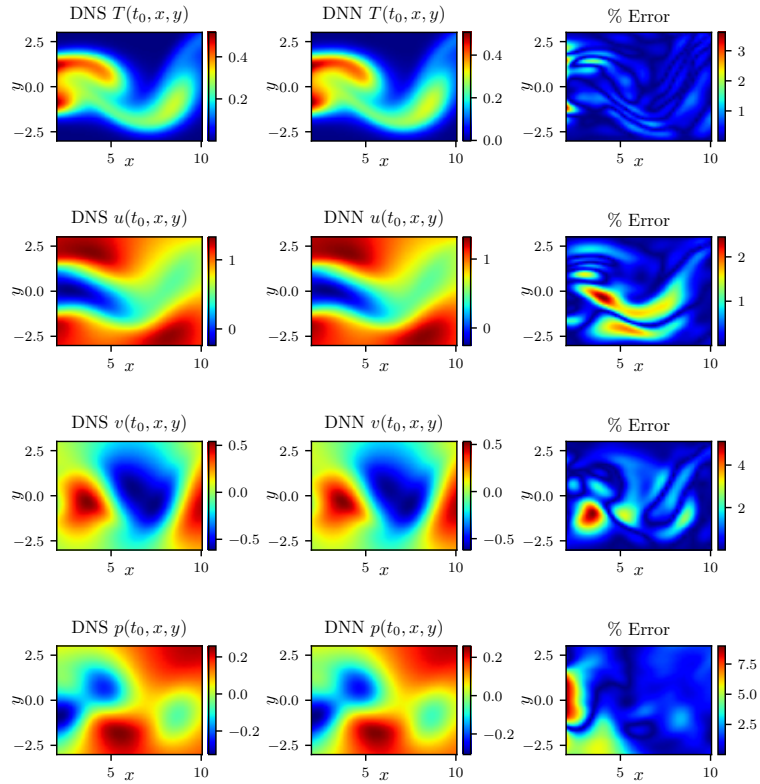


Figure 2: System predicted: reference DNS-simulated (left column) and DNN-predicted (middle column) snapshots of temperature (1st row), streamwise (2nd row) and crossflow (3rd row) velocities and pressure (last row) fields at a particular time instant t_0 . The right column represents the relative error (in percentage) normalized with the maximum value of the simulated field at that time. *Only the simulated temperature field data is used to train the DNN, which is capable of reconstructing the hidden fields with satisfactory accuracy.*