Delft University of Technology

Project: Reduced Order Models for Fluid Flow With Generative Adversarial Networks (GANs)

Supervisor(s):
Alexander Heinlein

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Project Description

Computational fluid dynamics (CFD) simulations are a numerical tool to model and analyze the behavior of fluid flow. However, **accurate simulations are generally very costly because they require high grid resolutions**.

Therefore, there is high demand for reduced order models which reduce the computational costs of computing fluid flow fields. In this project, **generative adversarial networks (GANs) [3] based on convolutional neural networks (CNNs) should be employed to train such a reduced order model**; the project is in the spirit of [1, 2] where autoencoder type convolutional neural networks have been employed to compute a reduced order model.

In order to train the network model, parametrized flow data is first generated by **solving the stationary Navier-Stokes equations**

$$\begin{aligned} -\nu\Delta u + (u\cdot\nabla)\,u + \nabla p &= 0 \text{ in } \Omega, \\ \nabla\cdot u &= 0 \text{ in } \Omega, \end{aligned} \tag{1}$$

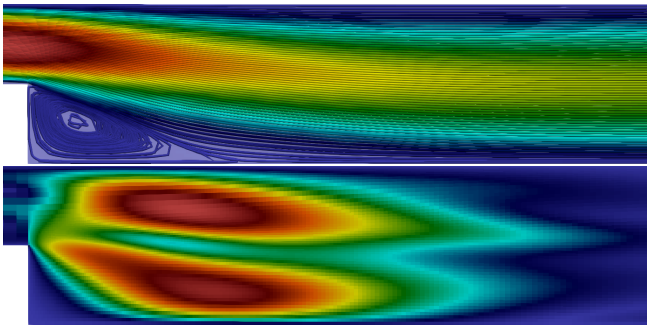

Figure 1: Mean (left) and standard deviation (right) of the flow field for a variation of the viscosity.

with certain boundary conditions on $\partial\Omega$, kinematic viscosity $\nu > 0$, velocity u, and pressure p on a computational domain Ω.

Certain parameters, such as the viscosity or the boundary conditions, should then be varied and a **reduced order neural network model be trained to approximate the resulting flow fields.**

Tasks

- Install and familiarize with the software packages:
  - The open-source CFD software OpenFOAM[1].
  - The Python machine learning libraries TensorFlow 2.0[2] and Keras[3].
- Implement and train a GAN based on CNNs for a simple data set; see, e.g., the *TensorFlow Tutorial on Deep Convolutional Generative Adversarial Network*[4].
- Set up a software pipeline based on OpenFOAM to automatically generate fluid flow data depending on certain parameters, such as viscosity, inflow velocity, etc.
- Based on the previous tasks, train a GAN for predicting flow flow fields based on certain input parameters.
- Optimization of the model and comparison against the reference data.

Contact

If you are interested in this project and/or have further questions, please contact Alexander Heinlein, a.heinlein@tudelft.nl.

References

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[1] https://www.openfoam.org
[2] https://www.tensorflow.org
[3] https://keras.io
[4] https://www.tensorflow.org/tutorials/generative/dcgan

[2] M. Eichinger, A. Heinlein, and A. Klawonn. Stationary flow predictions using convolutional neural networks. In F. J. Vermolen and C. Vuik, editors, *Numerical Mathematics and Advanced Applications ENUMATH 2019*, pages 541–549, Cham, 2021. Springer International Publishing. ISBN 978-3-030-55874-1. doi: 10.1007/978-3-030-55874-1_53.

[3] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial networks, 2014.