

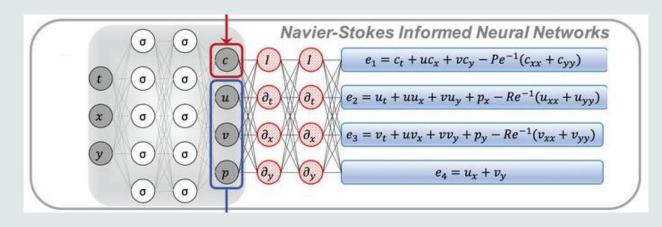




In the Fluid Dynamics framework we often meet problems involving **PDEs** which cannot be solved analitically.



A rising computational technique employs **Neural Networks** to reconstruct **pressure** and **velocity** of the fluid, the main unknowns in this field.



A simple test case

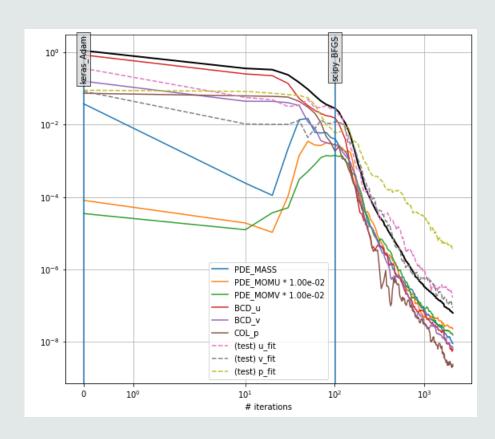
- Reconstructing the pressure is the main difficulty, since it is difficult to have its measures; for this reason, we started from the **Colliding Flows** benchmark case, whose analytical solution is known, and trained our Neural Network giving only the information on the mean value of the pressure and the BCs for the velocities.
- The reference library for the automatic differentiation is **nisaba**, a Python Library built on the top of Tensorflow.

$$\Omega = (-1,1) \times (-1,1)$$

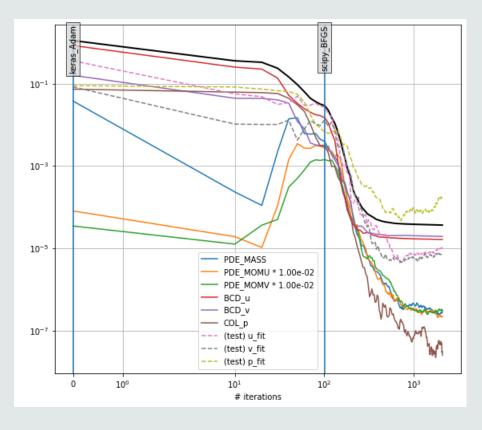
$$\begin{cases}
-\Delta \mathbf{u} + \nabla p = \mathbf{f} = 0 & \text{in } \Omega \\
\text{div } \mathbf{u} = 0 & \text{in } \Omega \\
\mathbf{u} = \mathbf{g} = (20xy^3, 5x^4 - 5y^4)^T \text{ on } \partial \Omega
\end{cases}$$



The results

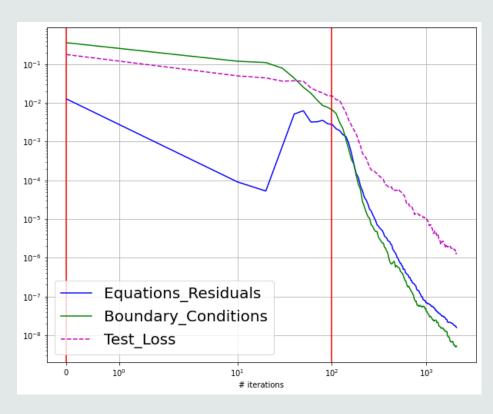


2000 epochs, **no noise** on data

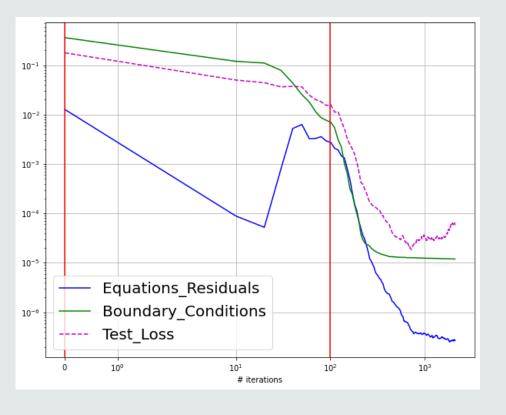


2000 epochs, with noise on data

The results







2000 epochs, with noise on data



Our goal is to apply this strategy to a complex, real problem: the **Coronary Flow Assessment**, fundamental to evaluate **coronary artery disease**.

In this case, there is no hope for an analytical solution!



In recent papers, it has been shown that ML algorithms provide information in a more **reproducible** manner and with **improved diagnostic accuracy** in comparison to the traditional methods.

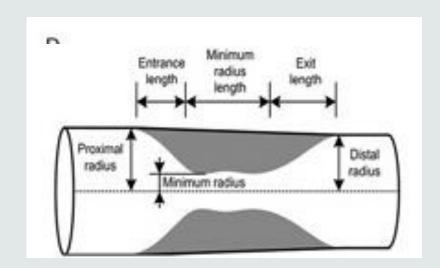




• To train our Neural Network, we plan to exploit two types of information:

Geometrical Data

(eg: branch length, vessel radius...)



<u>Data on velocity</u> (provided by medical imaging)

