

What can AI do for High-Performance Computing?

Corentin Lapeyre

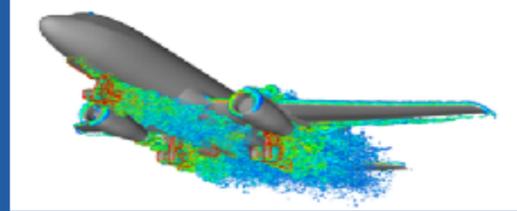
Research Scientist, CERFACS

“High performance AI in the industry” Workshop

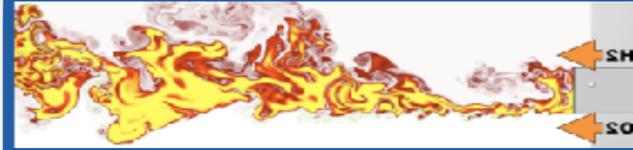
2022.06.15



Propulsion



Aerodynamics and Aeroacoustics



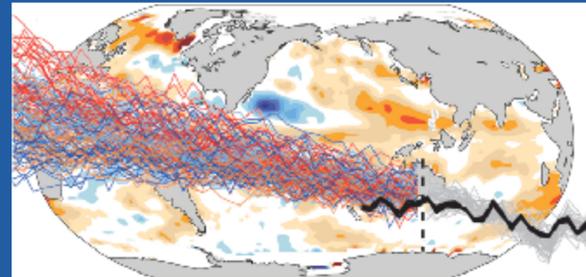
Hydrogen combustion



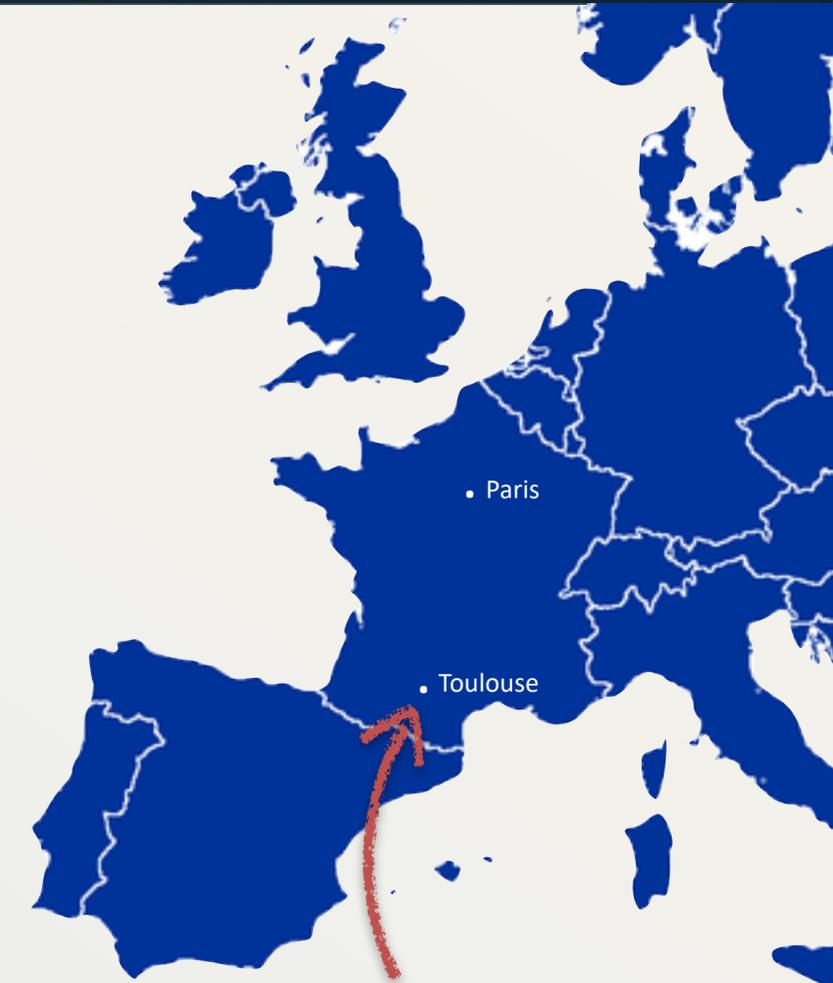
Environment and Safety



Climate - air transport interactions



Climate Variability and Predictability



CERFACS

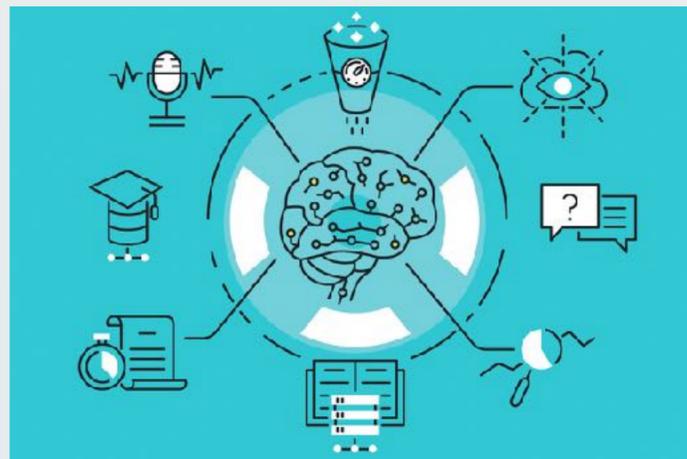
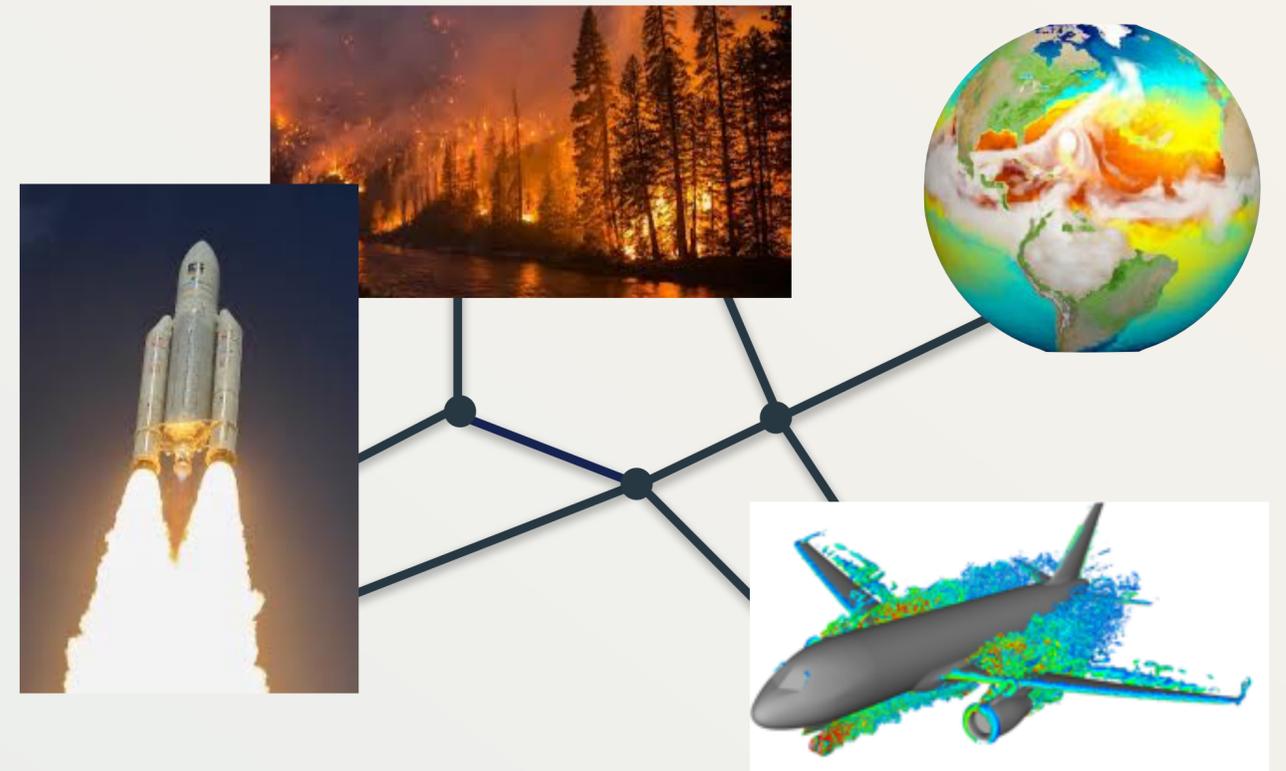
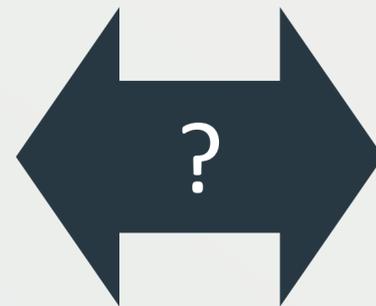


150 researchers

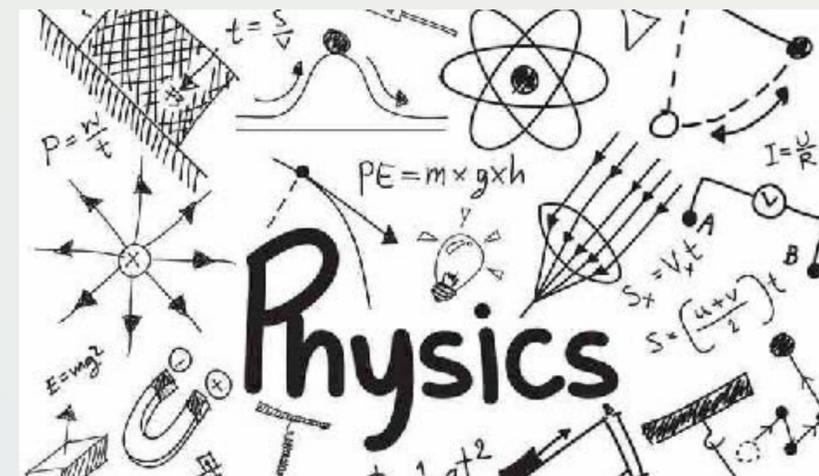


20 training sessions / y





Machine Learning





A tool for engineers and scientists

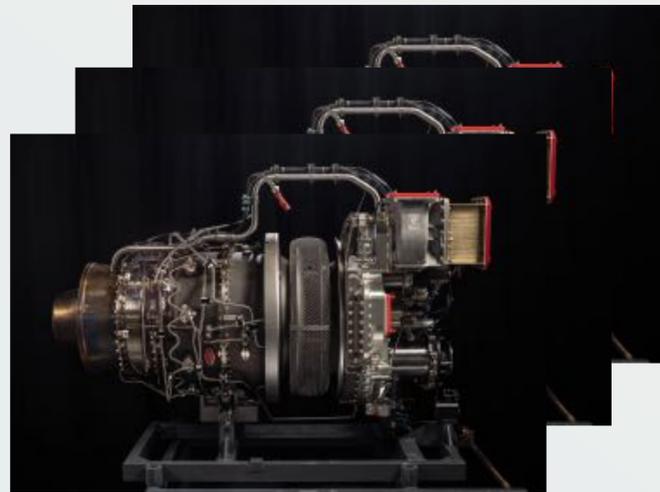
Data Valorization

- ▶ Predictive Maintenance
- ▶ Real time systems

Surrogate models

- ▶ From real world data
- ▶ From simulations





Test Data



Flight Data



Maintenance Data

Large industrial datasets require Data Engineering

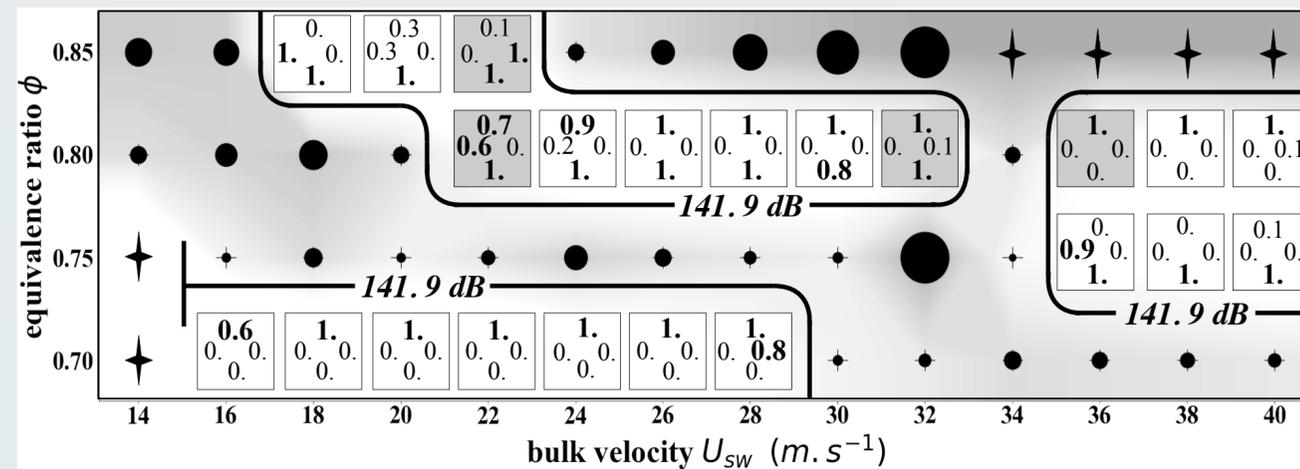
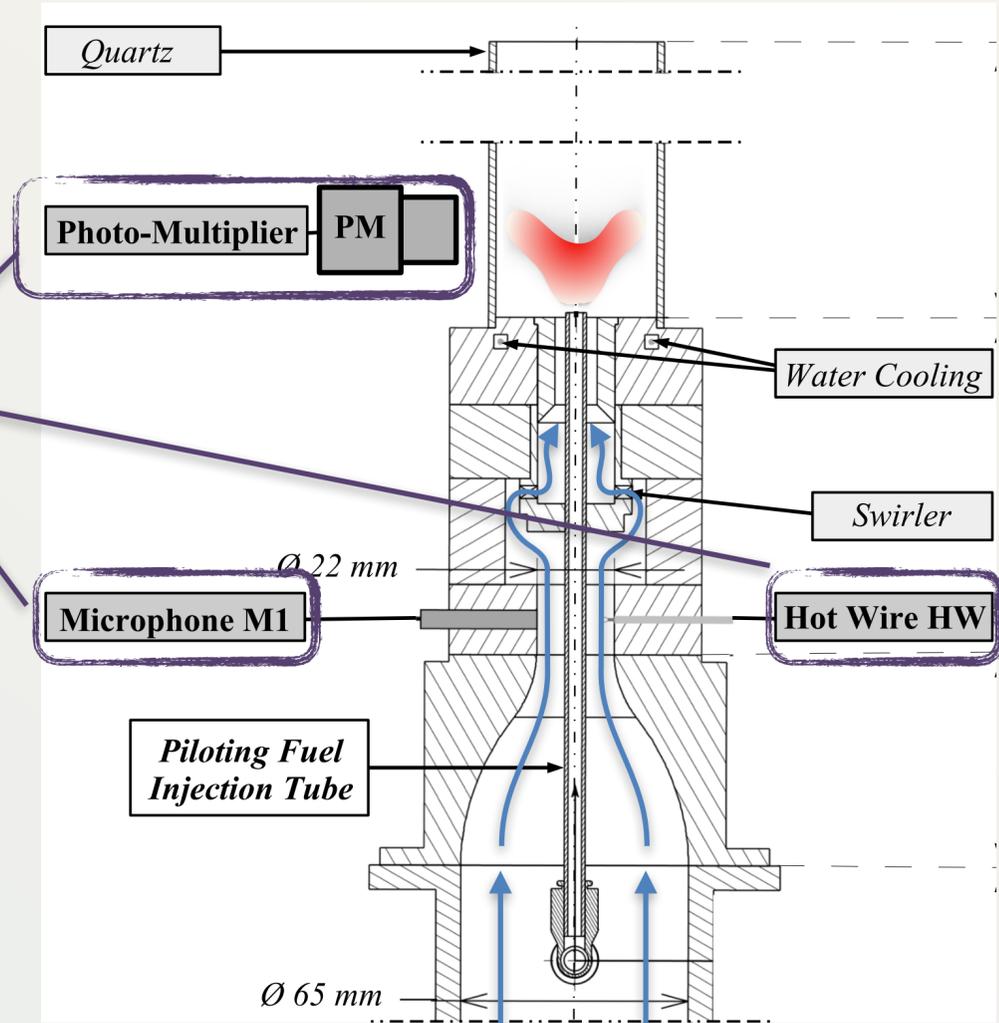
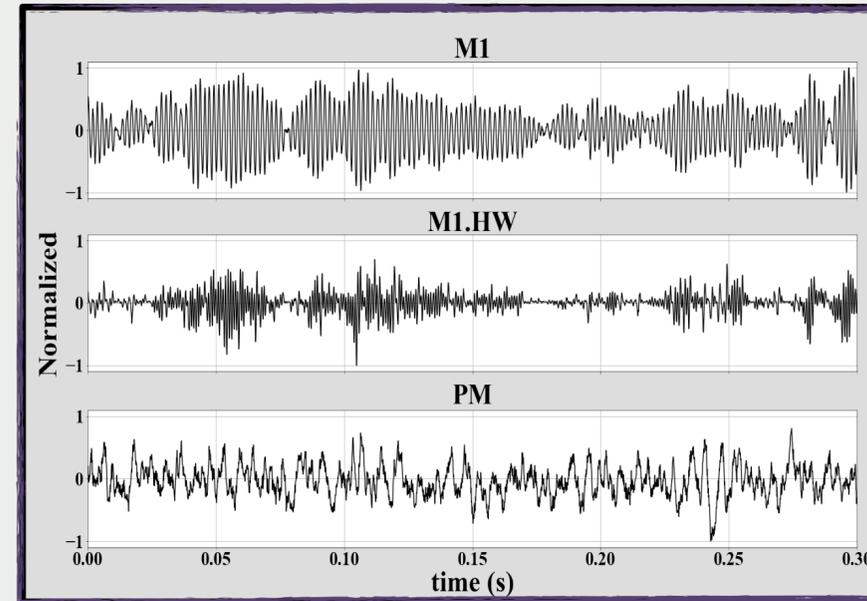
Collection, cleaning & labelling, access



Research Data is often underused

Fieldwork campaign organized by Prof. Martin Wooster (Dept of Geog. University College London) in Kruger National Park, 2014 South Africa.
Work performed at Cerfacs by R. Paugam, N. Cazard, M. Rochoux

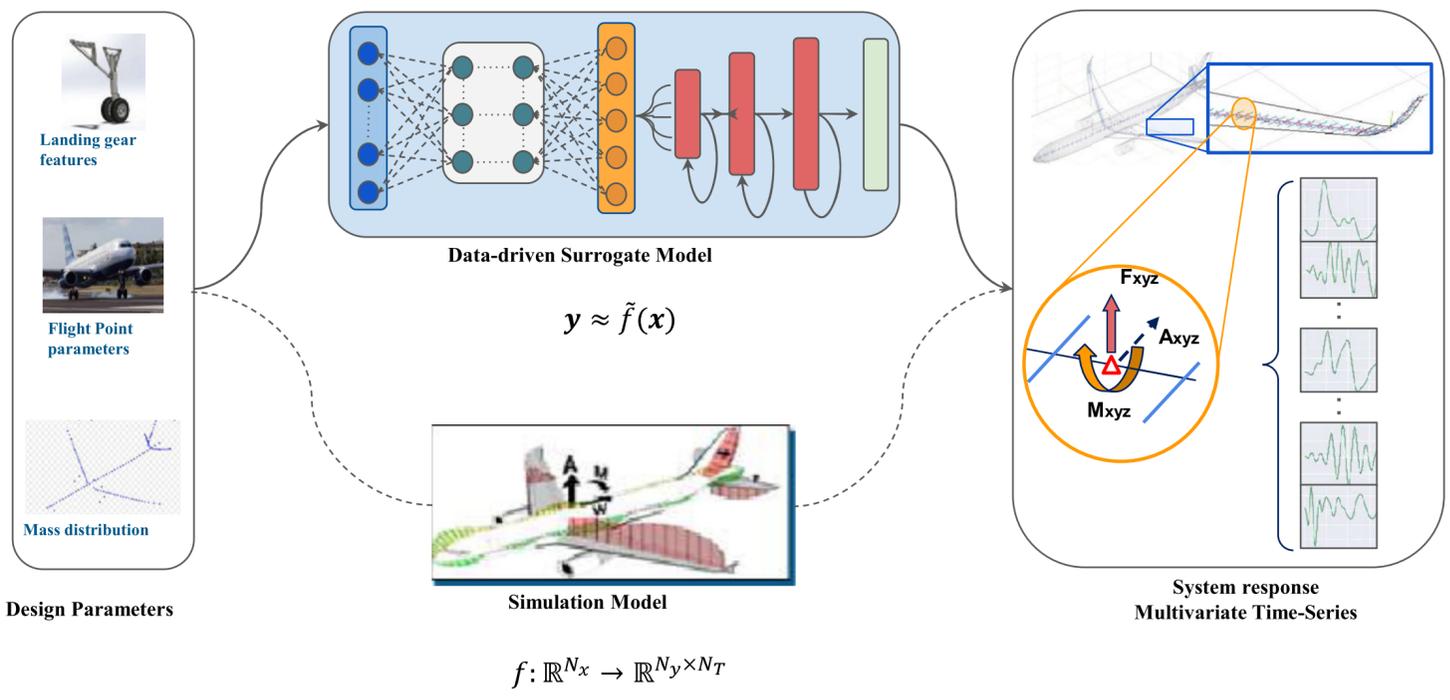
High-frequency sampling time-series



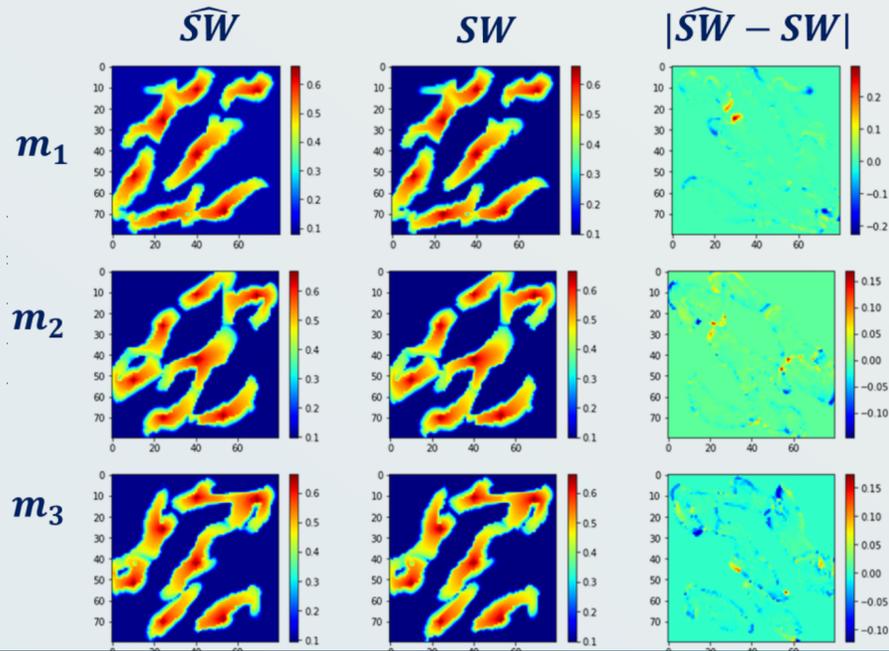
Edge AI

Realtime Predictions (< 100 ms)

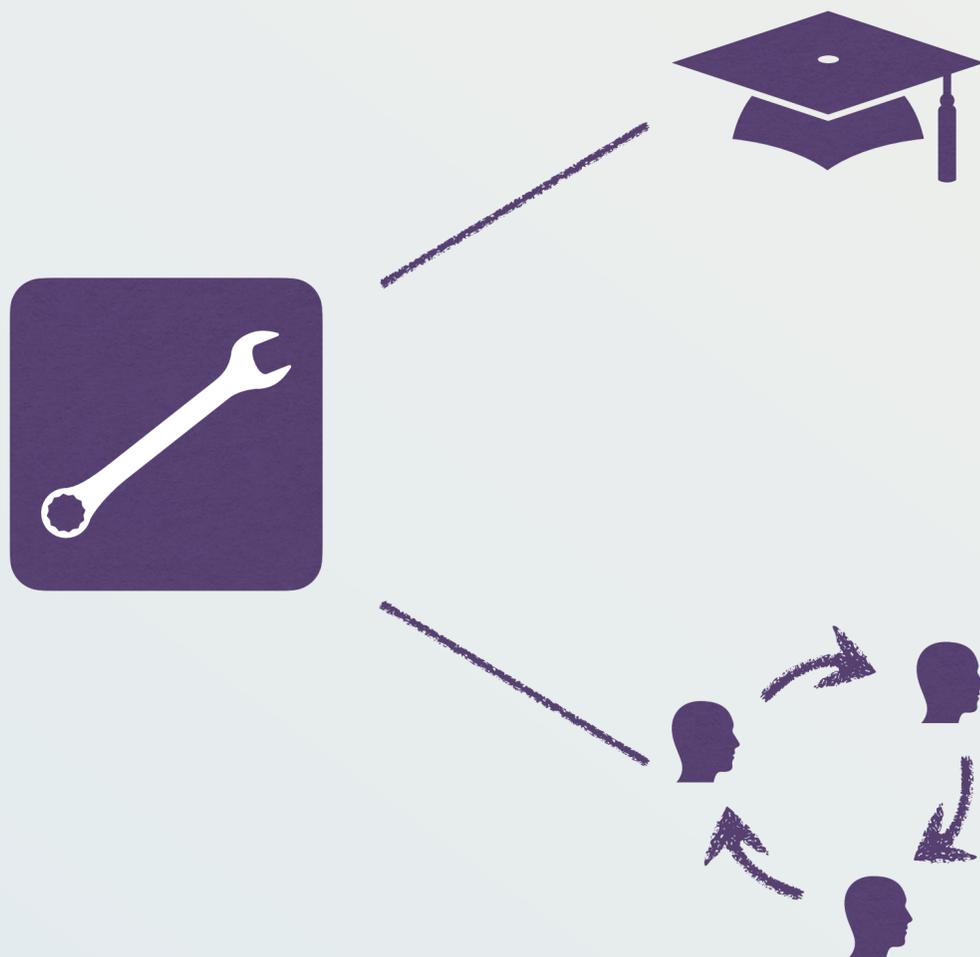
Lapeyre, C. J. *et al.* (2019). Reconstruction of Hydraulic Data by Machine Learning. *SimHydro 2019*, Nice, France, June 12-14, *arXiv:1903.01123*.



Lazzara, M. *et al.* "Surrogate modelling for an aircraft dynamic landing loads simulation using an LSTM AutoEncoder-based dimensionality reduction approach." *Aerospace Science and Technology* (2022): 107629.



Yewgat, A. *et al.* "IMEX-AUNET: Deep Learning proxy for multi-phase subsurface flow". Submitted to *31st ACM International Conference on Information and Knowledge Management*, Atlanta, Georgia, USA, Oct. 17-22 2022



Training (scientists and engineers alike)

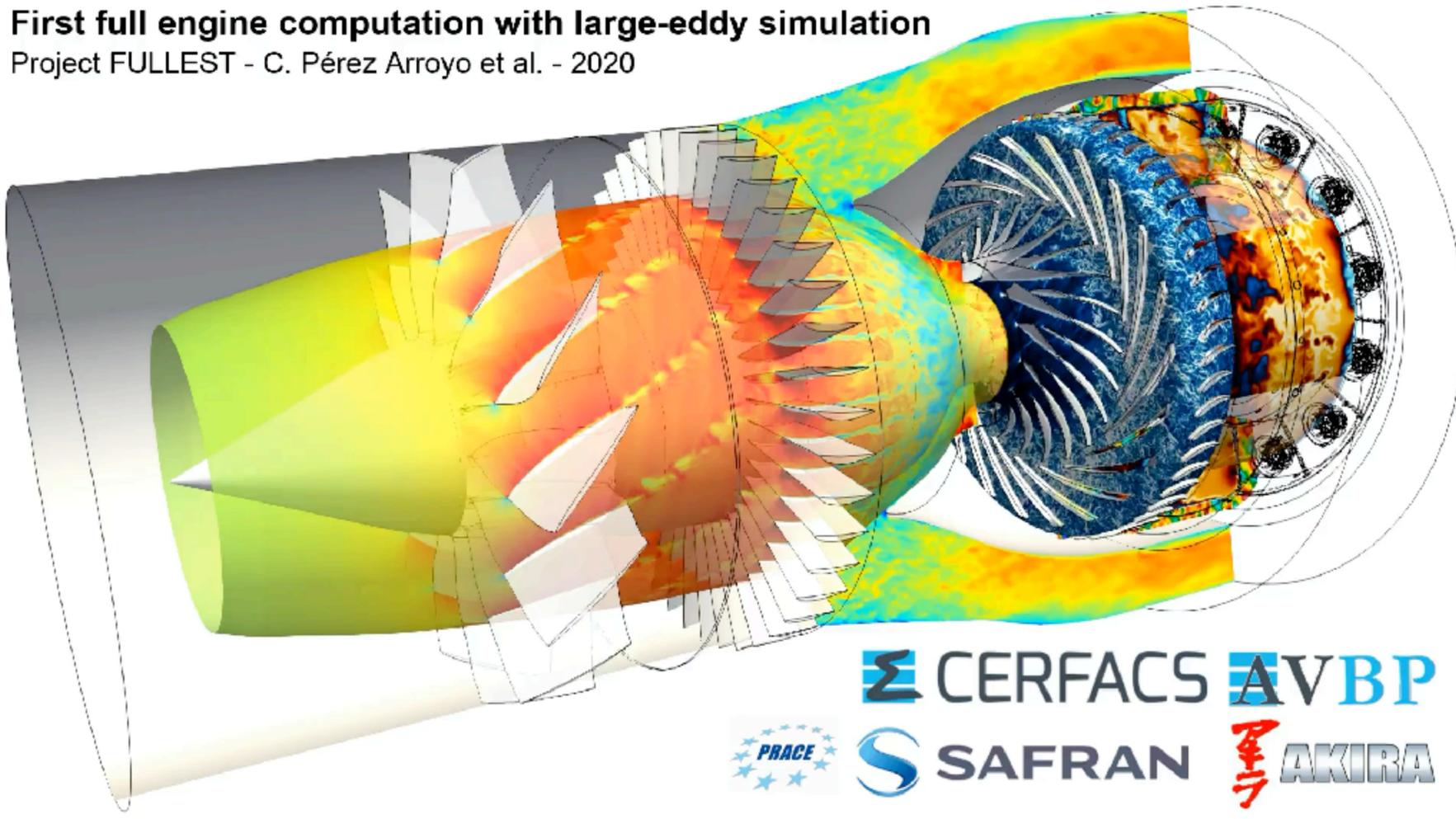
Interdisciplinary collaboration

Domain Experts

Data Engineers

Data Scientists

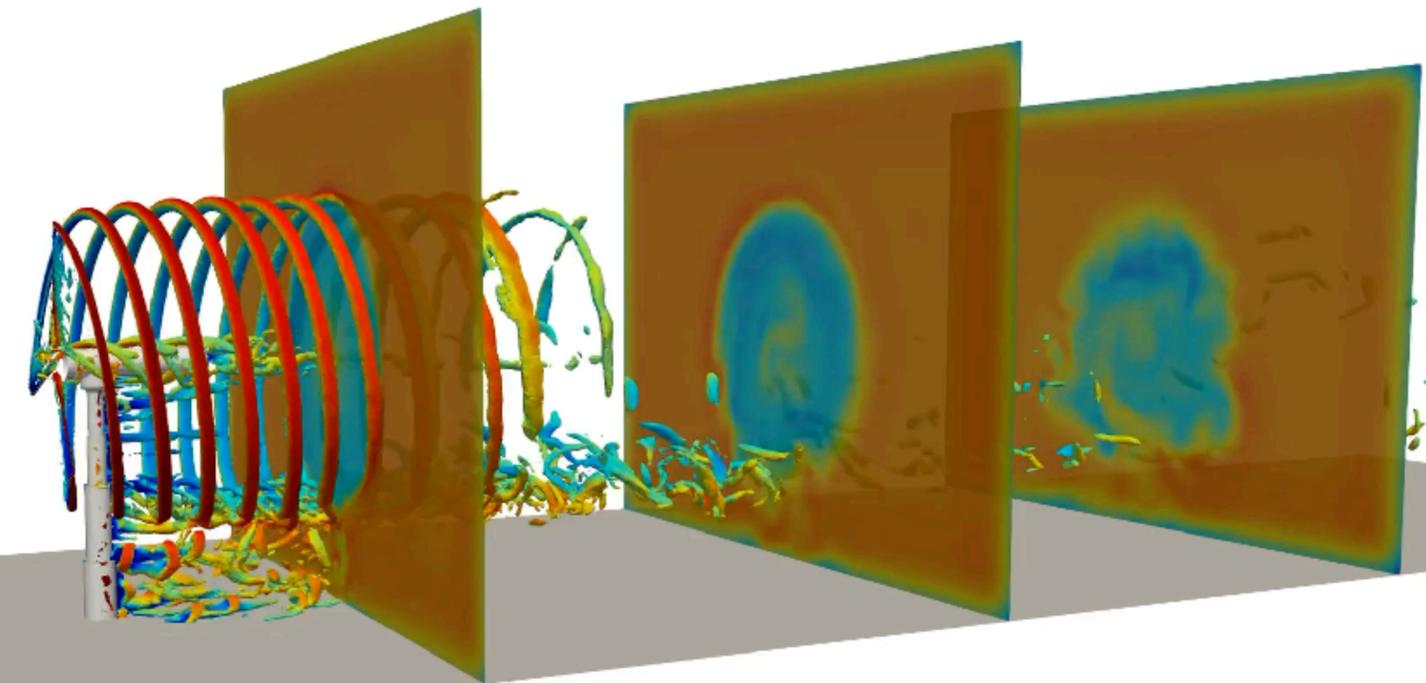
First full engine computation with large-eddy simulation
Project FULLEST - C. Pérez Arroyo et al. - 2020



High Performance

Time: 3.769196

Computational Fluid Dynamics



DNS

LES

RANS

DL

ML
System
Models

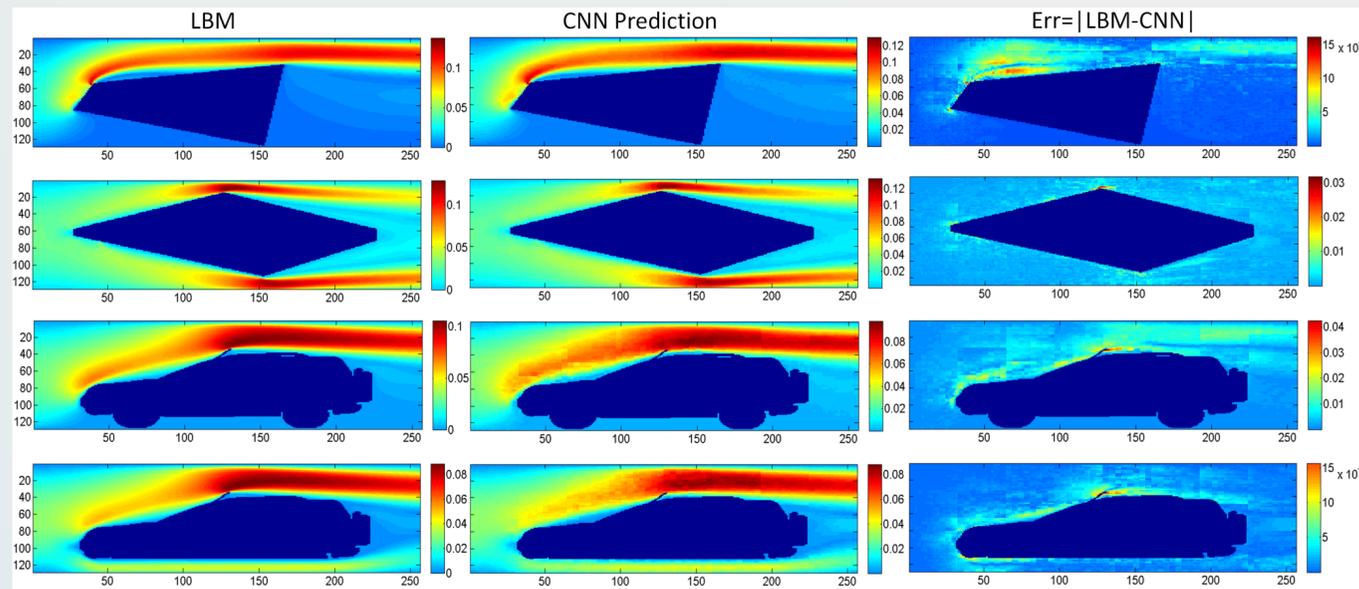
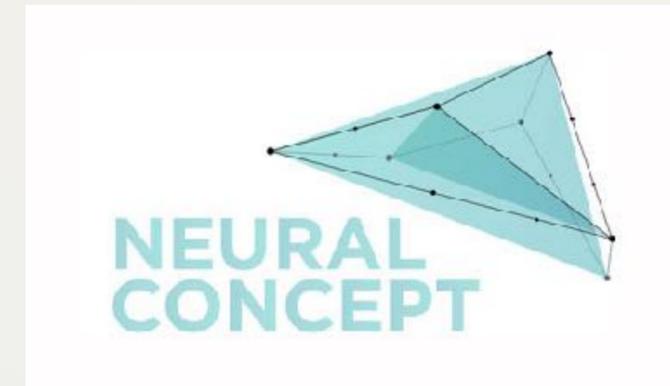
Accuracy

Good tradeoffs

ML for low-cost models

DL as a RANS surrogate

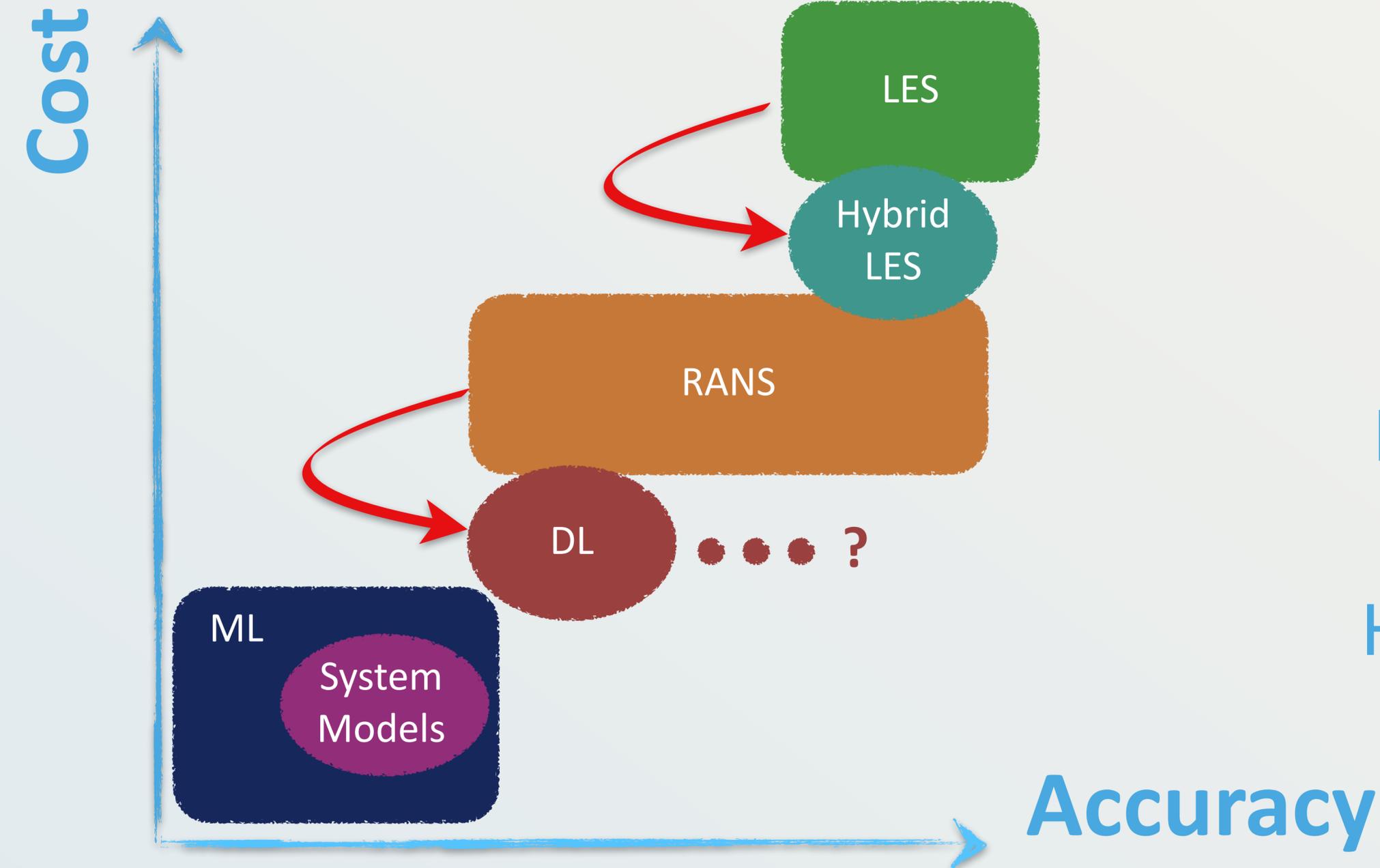
Do we always need CFD?



Guo, Xiaoxiao, Wei Li, and Francesco Iorio. "Convolutional neural networks for steady flow approximation." *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*. 2016.



...



Good tradeoffs

ML for low-cost models

DL as a RANS surrogate

Hybrid LES: faster, better high fidelity?



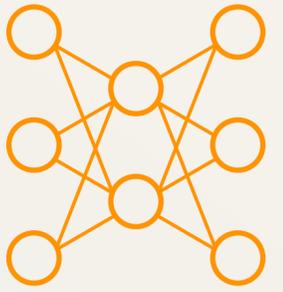
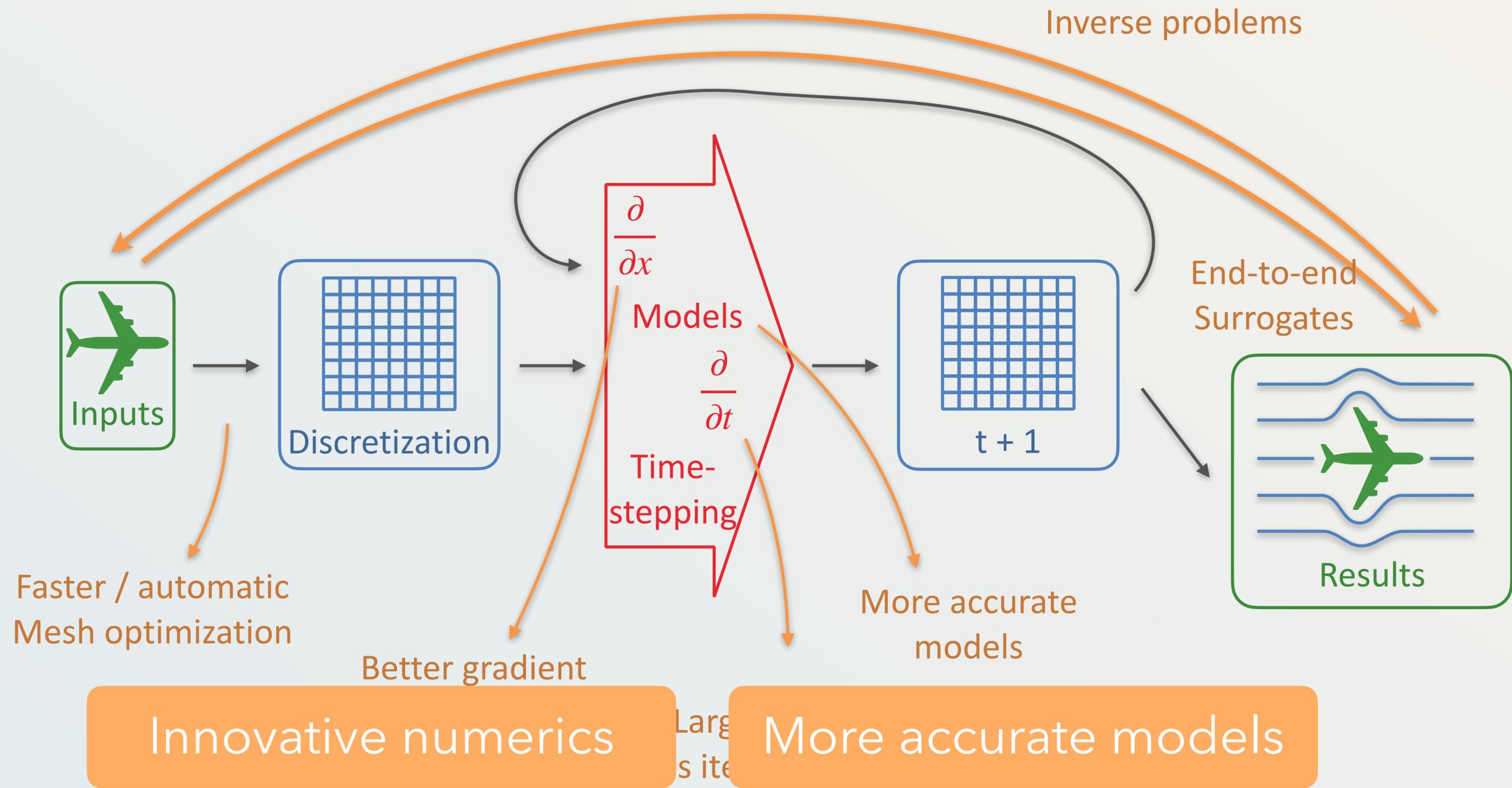
Hybrid High-Fidelity Simulation

More accurate models

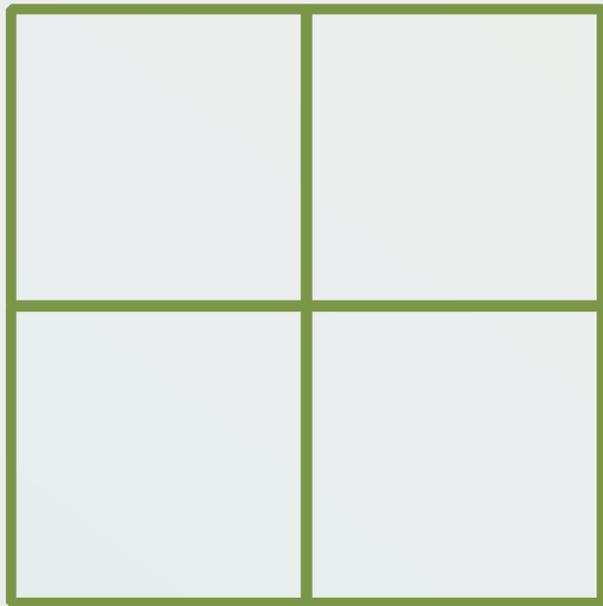
Innovative numerics

- ▶ Better Preconditioners
- ▶ New discretisation schemes

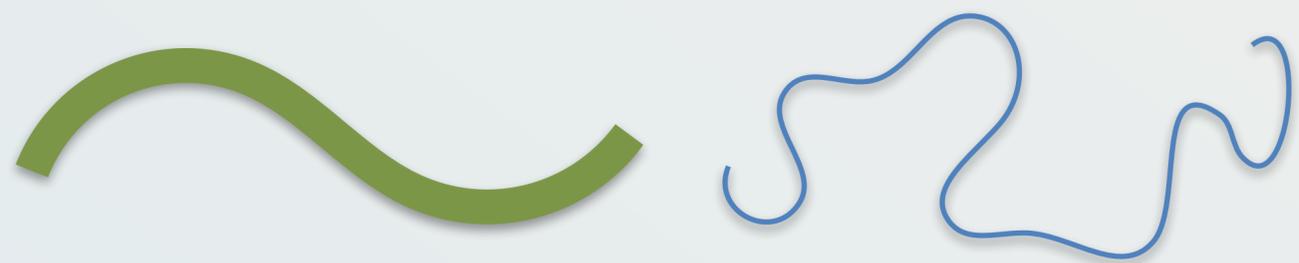
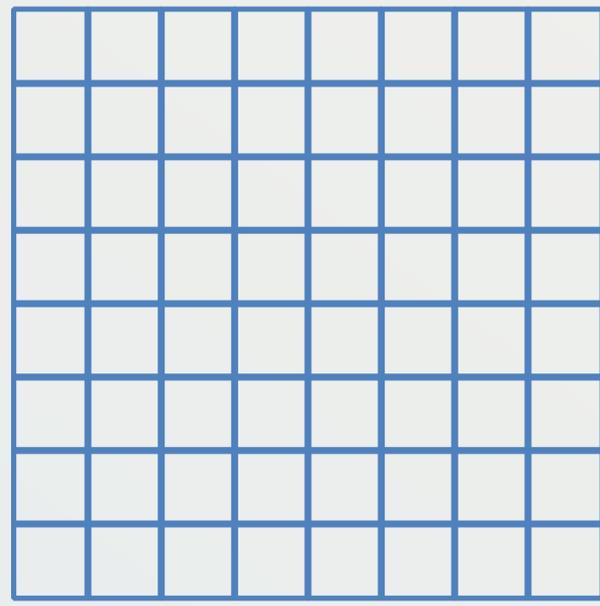




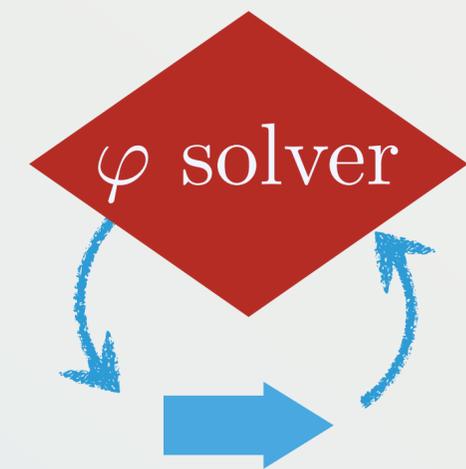
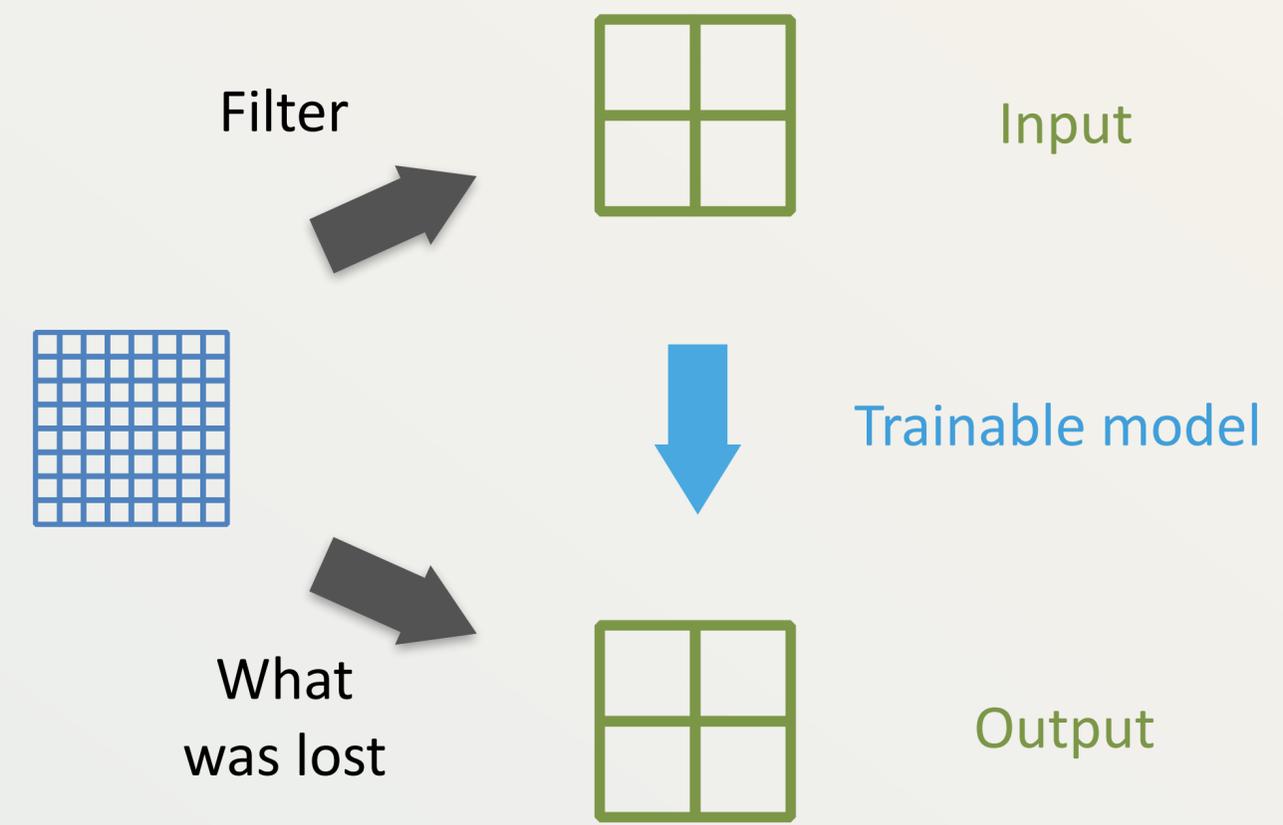
What I can pay for



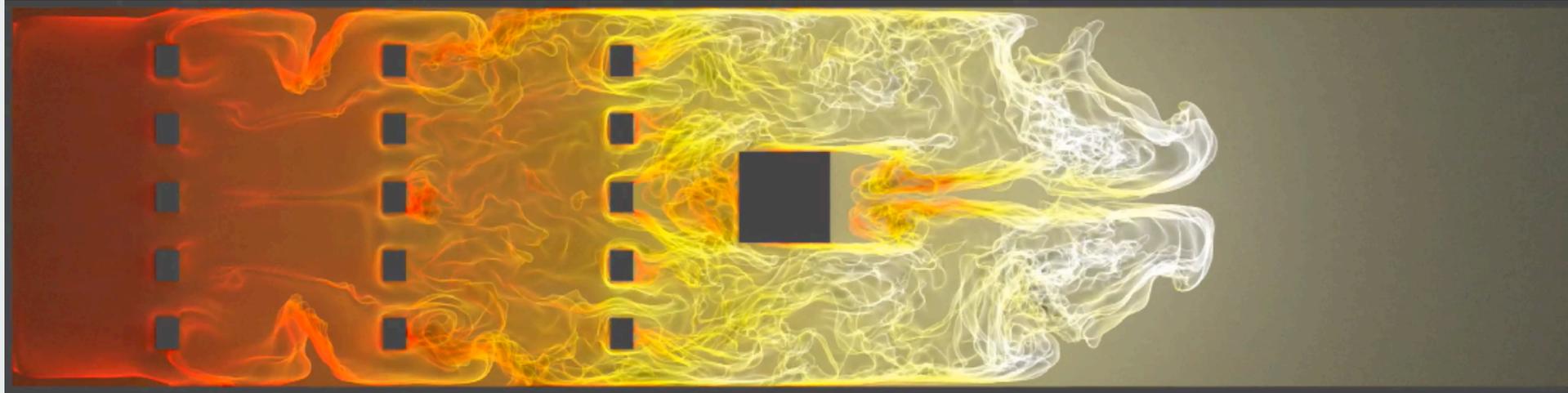
Fully resolved physics



What's missing?

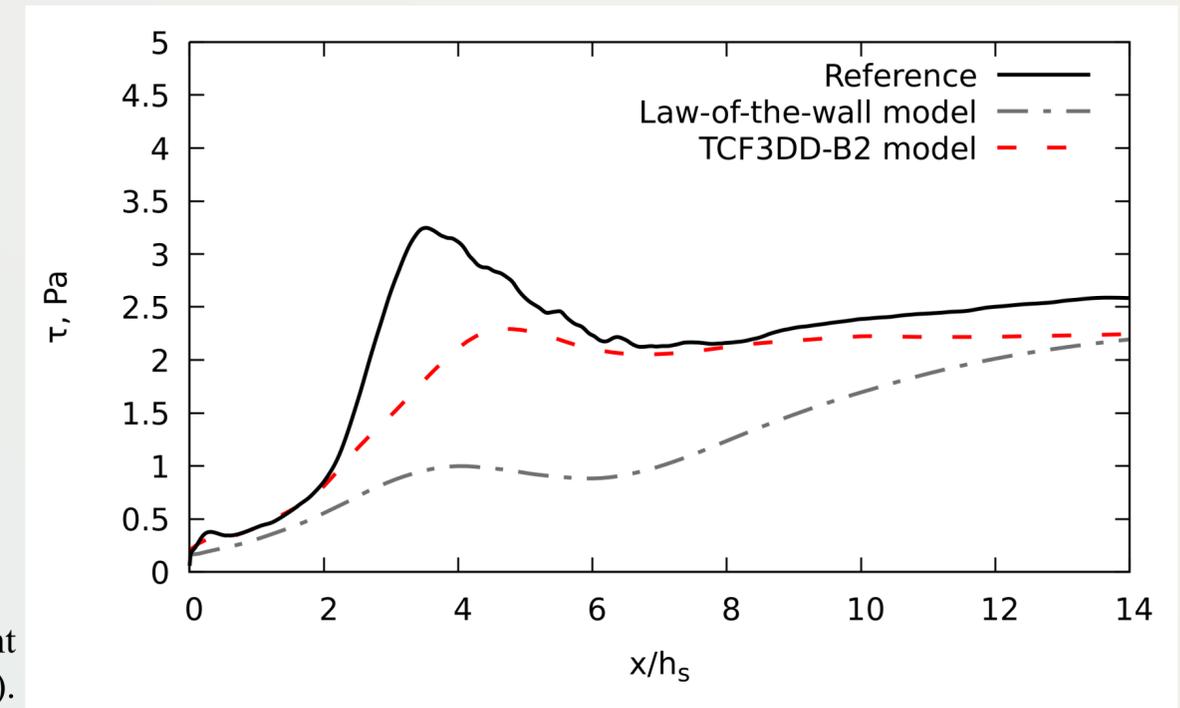


ML / DL based model for on-the-fly use

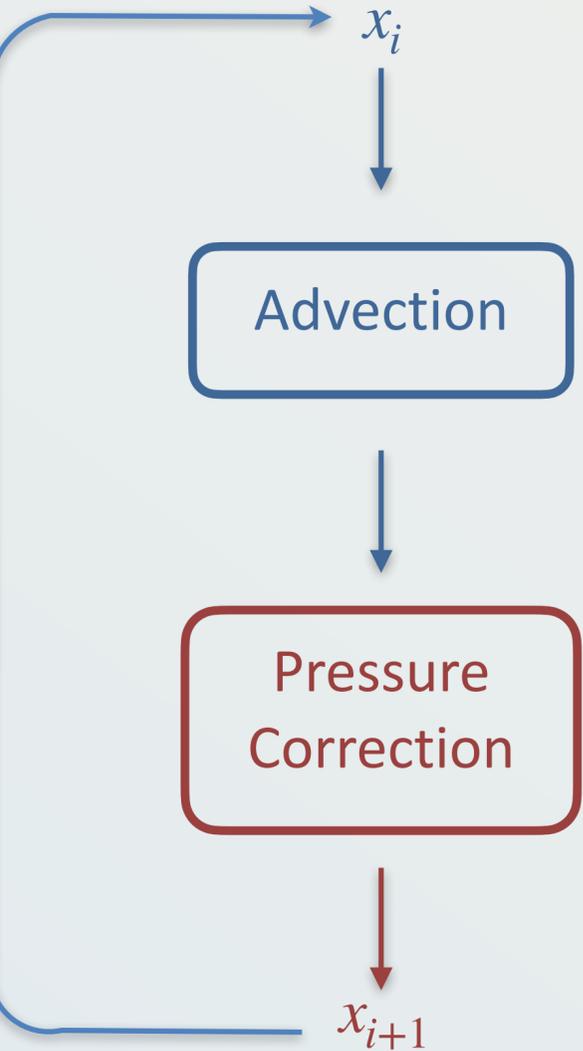


Xing, Victor, et al. "Generalization Capability of Convolutional Neural Networks for Progress Variable Variance and Reaction Rate Subgrid-Scale Modeling." *Energies* 14.16 (2021): 5096.

Dupuy, D. et al. "Data-driven wall modelling for turbulent separated flows." Submitted to *Physical Review Fluids* (2022).



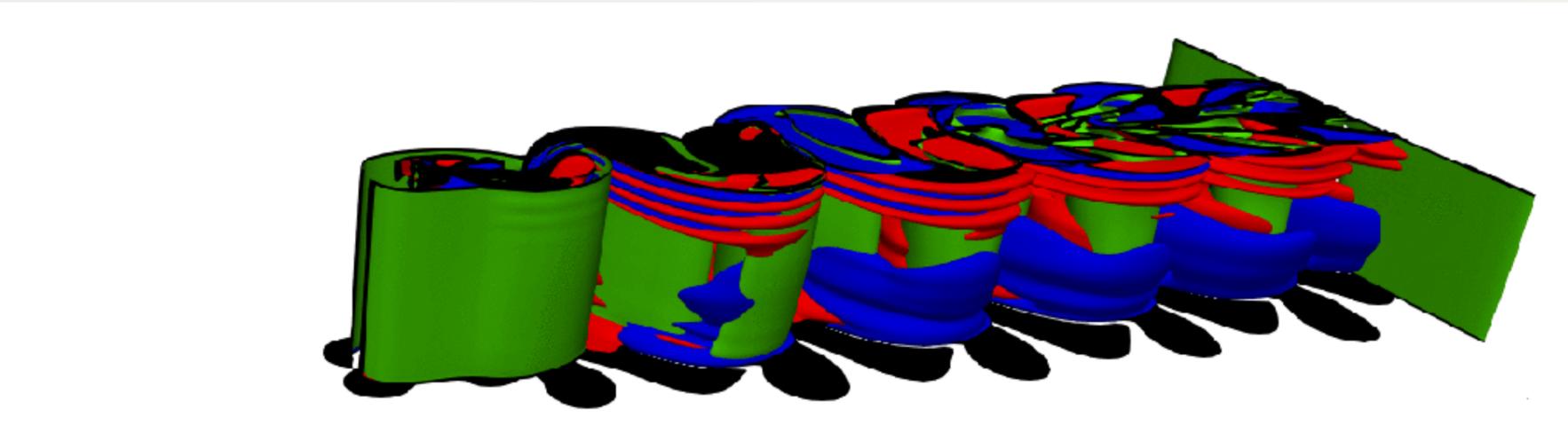
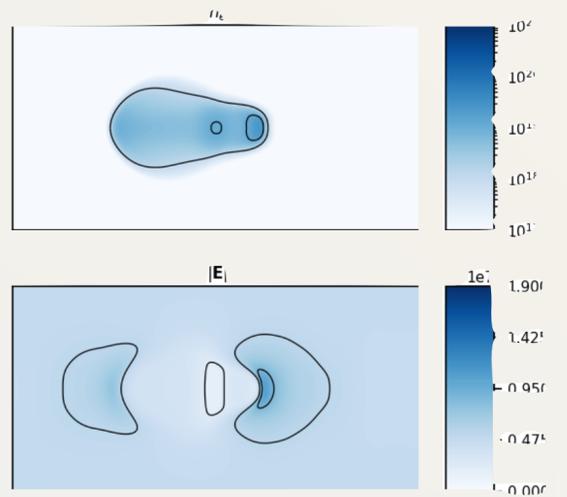
Preconditioners



> fast classical solver

> neural network initial guess
Iterative solver converges to precision if needed

Plasma solver

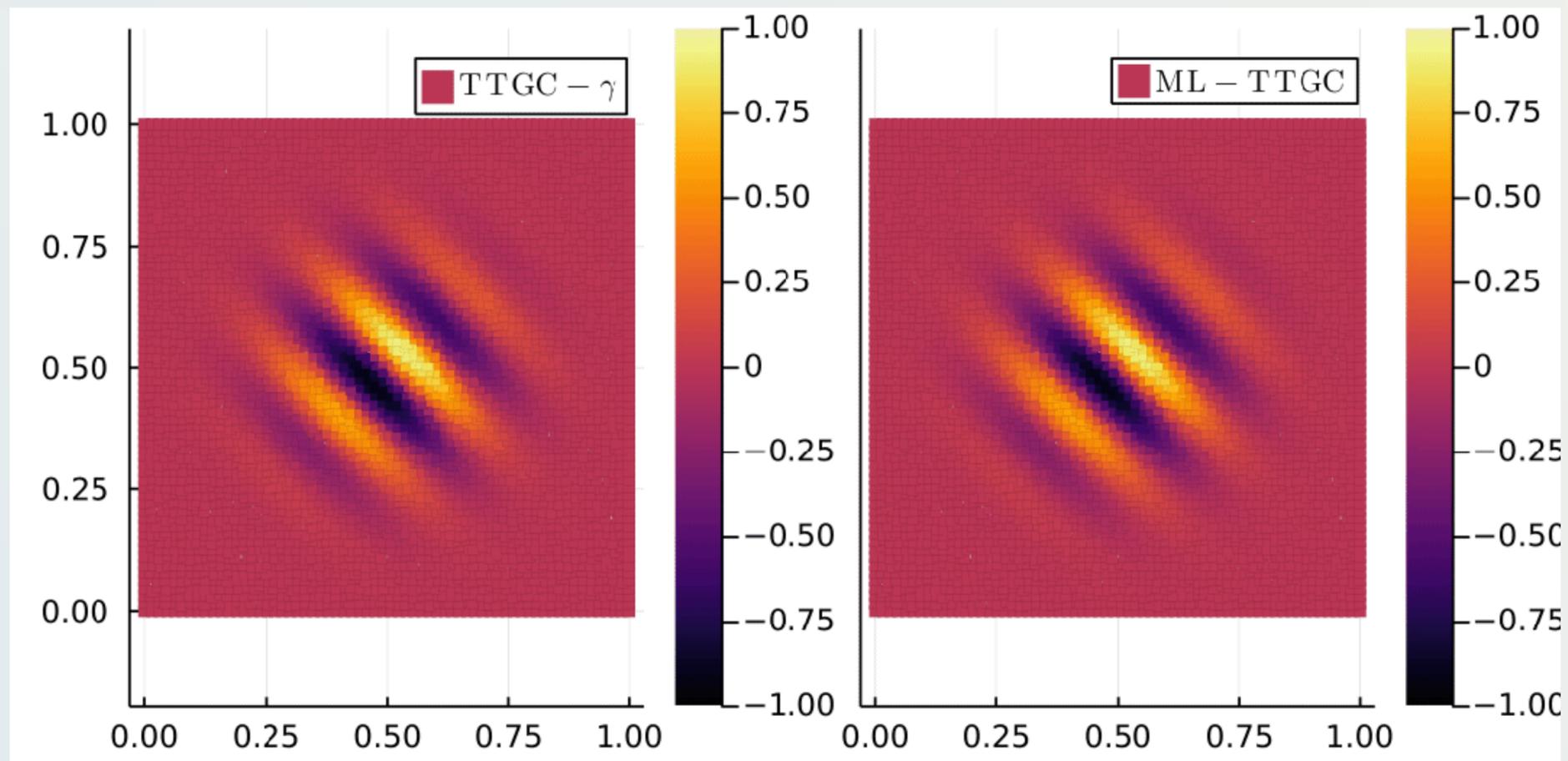


Incompressible flow solver

Cheng, L., Illarramendi, E. A., Bogopolsky, G., Bauerheim, M., & Cuenot, B. (2021). Using neural networks to solve the 2D Poisson equation for electric field computation in plasma fluid simulations. arXiv preprint arXiv:2109.13076.

Ajuria Illarramendi, E., Alguacil, A., Bauerheim, M., Misdariis, A., Cuenot, B., & Benazera, E. (2020). Towards an hybrid computational strategy based on Deep Learning for incompressible flows. In AIAA AVIATION 2020 FORUM (p. 3058).

Drozda, L. *et al.* (2021). Data-driven Taylor-Galerkin finite-element scheme for convection problems.
The Symbiosis of Deep Learning and Differential Equations - Neurips 2021 Workshop



Locally-tuned
numerical schemes



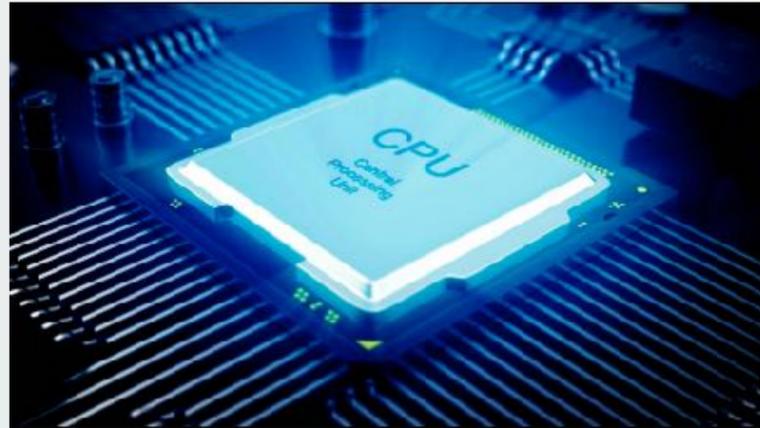
HPC for Hybrid Simulation

CPU/GPU architectures

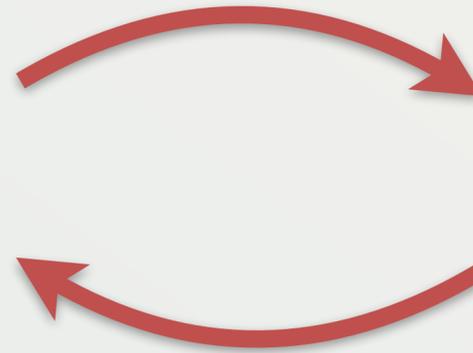
Mesh issues

- Interpolation strategies
- Innovative network architectures





Physical fields



Predictions



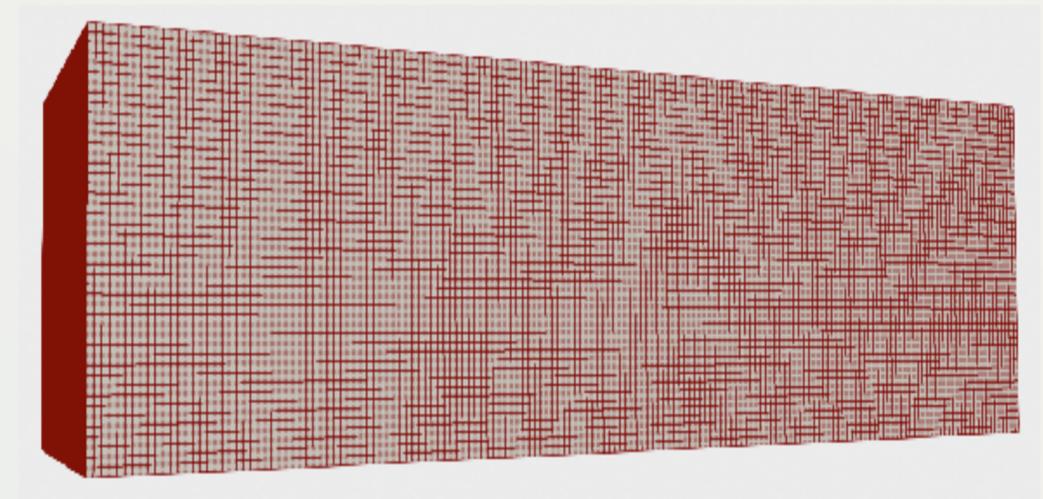
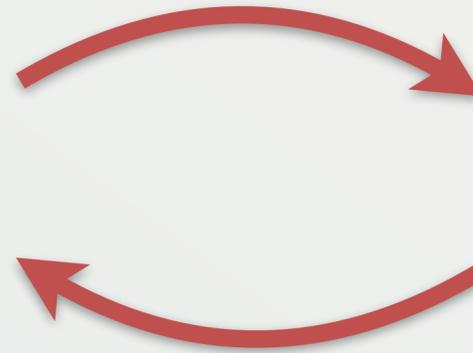
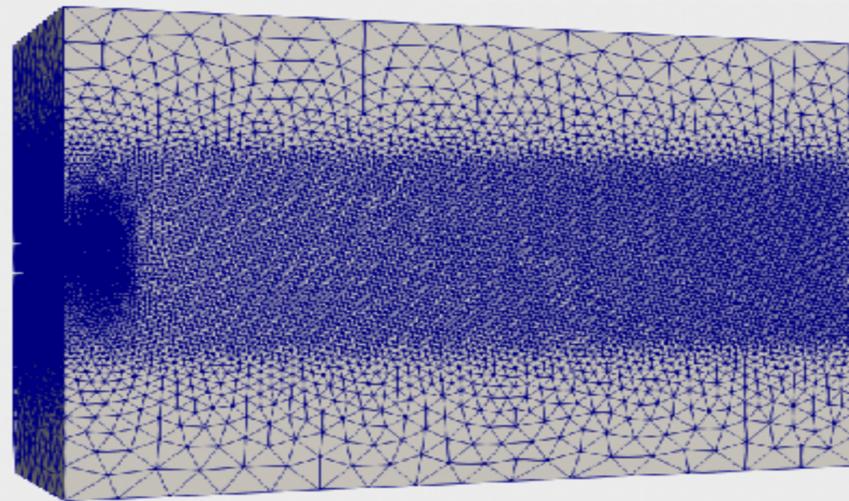
$$\frac{Du}{Dt} = -\nabla p + \mu \nabla^2 u + \rho F$$

CPU : Navier-Stokes solver
(e.g. AVBP)



GPU : Neural Net
(TensorFlow)

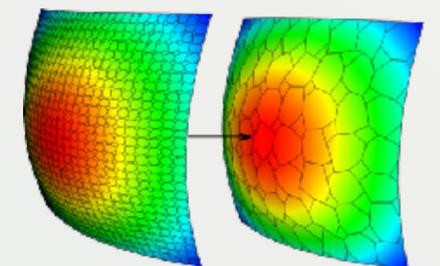


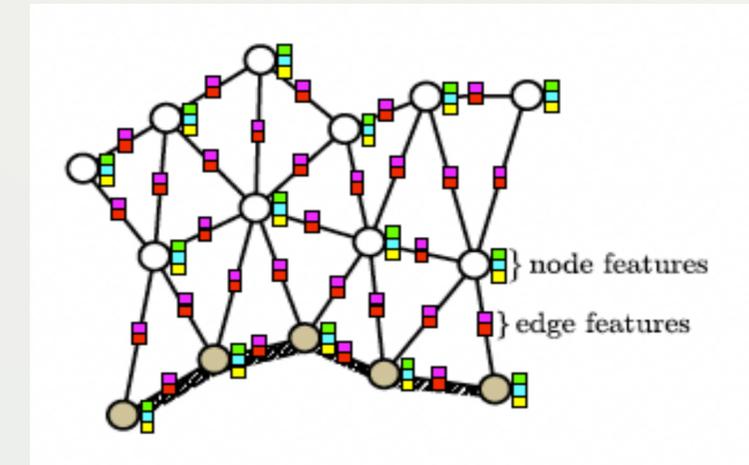
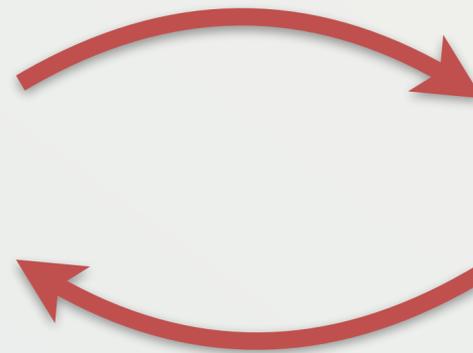
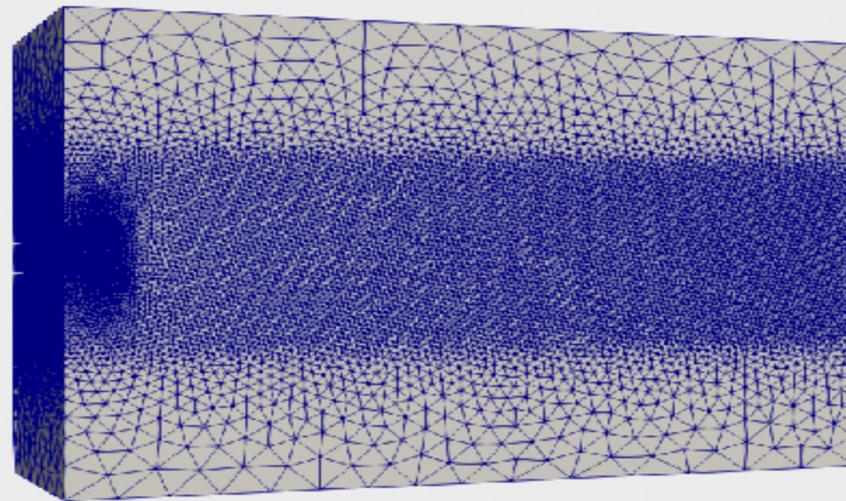


Unstructured mesh

CNN: Pixels / Voxels

Mesh mismatch => on-the-fly interpolation (CWIPI library)





Unstructured mesh

GNN: Same mesh

Direct use of *Mesh Graph Networks* can alleviate interpolation

Serhani, A., Xing, V., Dupuy, D., Lapeyre, C., Staffelbach, G. (2022). High-performance hybrid coupling of a CFD solver to deep neural networks. 33rd Parallel CFD International Conference, May 25-27, Alba, Italy.



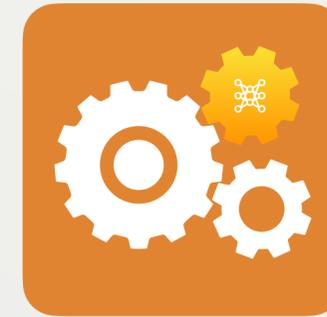
Training

Interdisciplinary
collaboration



Training

Interdisciplinary
collaboration



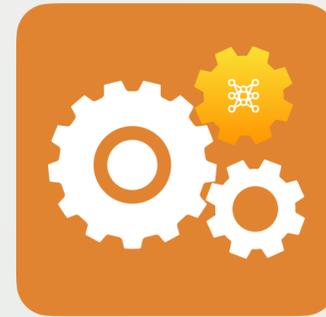
Hybrid simulation:

AI inside CFD



Training

Interdisciplinary
collaboration



Hybrid simulation:

AI inside CFD



Hybrid HPC:

CPU / GPU / ...?

Recent Papers

- Lazzara, M., Chevalier, M., Colombo, M., Garay Garcia, J., Lapeyre, C., Teste, O. (2022). Surrogate modelling for an aircraft dynamic landing loads simulation using an LSTM AutoEncoder-based dimensionality reduction approach. *Aerospace Science and Technology*, 126, 107629.
- Yewgat, A., Busby, D., Chevalier, M. et al. (2022). Physics-constrained deep learning forecasting: an application with capacitance resistive model. *Comput Geosci*.
- Besombes, C. *et al.* (2021). Producing realistic climate data with GANs. *Nonlinear Processes in Geophysics*, 28, 347–370.
- Xing V. *et al.* (2021). Generalization Capability of Convolutional Neural Networks for Progress Variable Variance and Reaction Rate Subgrid-Scale Modeling. *Energies* 14(16):5096.
- Cellier, A. *et al.* (2021). Detection of precursors of combustion instability using convolutional recurrent neural networks. *Combustion and Flame*, Volume 233, 111558.
- Lapeyre, C.J. *et al.* (2019). Training convolutional neural networks to estimate turbulent sub-grid scale reaction rates. *Combustion and Flame*, 203, 255-264.

Recent Conferences

- Serhani, A., Xing, V., Dupuy, D., Lapeyre, C., Staffelbach, G. (2022). High-performance hybrid coupling of a CFD solver to deep neural networks. 33rd Parallel CFD International Conference, May 25-27, Alba, Italy.
- ElMontassir, R., Lapeyre, C., Pannekoucke, O. (2022). Hybrid Physics-AI Approach for Cloud Cover Nowcasting. ECMWF Machine Learning Workshop.
- Drozda, L., Mohanamurthy, P., Realpe, Y., Lapeyre, C., Adler, A., Daviller, G., & Poinso, T. (2021). Data-driven Taylor-Galerkin finite-element scheme for convection problems. *The Symbiosis of Deep Learning and Differential Equations - Neurips 2021 Workshop*
- Yewgat, A., Busby, D., Chevalier, M., Lapeyre, C. & Teste, O. (2020) Deep-CRM: A New Deep Learning Approach for Capacitance Resistive Models. 17th European Conference on the Mathematics of Oil Recovery, September 14-17 2020.
- Lapeyre, C. J., Cazard, N., Roy, P. T., Ricci, S., & Zaoui, F. (2019). Reconstruction of Hydraulic Data by Machine Learning. *SimHydro 2019*, Nice, France, June 12-14, arXiv:1903.01123.
- Ronan Paugam, Melanie Rochoux, Nicolas Cazard, Corentin Lapeyre, William Mell, Joshua Johnston, and Martin Wooster: Computing High Resolution Fire Behavior Metrics from Prescribed Burn using Handheld Airborne Thermal Camera Observations. *The 6th International Fire Behaviour and Fuels Conference*, Marseilles, May 2019.