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Impacts of artificial intelligence in Fluid Dynamics research

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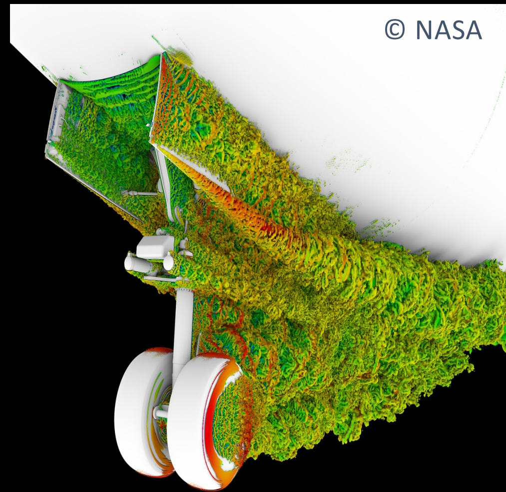
Fluid Dynamics

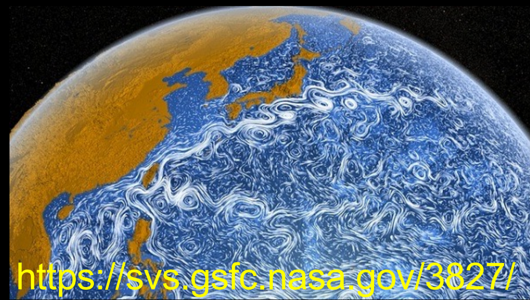
- Studies the motion of fluids and their interactions with bodies
  - under the effect of forces, temperatures or concentration differences, …
- Omnipresent in a range of scientific domains, from aerospace to health
- **Non linear, multiscale problems**
- High-fidelity Computational or Experimental Fluid Dynamics (CFD, EFD) must **resolve all scales** → very costly or impossible
- Lower-fidelity descriptions **miss part of the Physics**

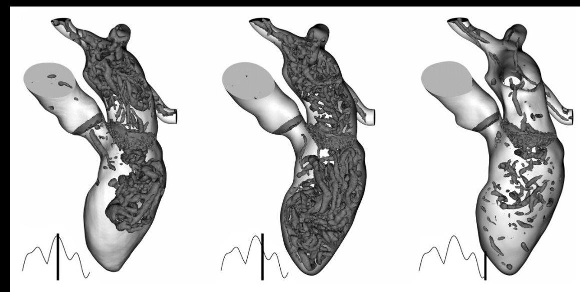
- **Transformative potential of AI in Fluid Physics**
  - Generate AI-driven flow models **at a fraction of time and cost**

    → **Replace costly simulators and experiments with AI emulators**

    → **Supplement incomplete experiments or models** by **learning from data**







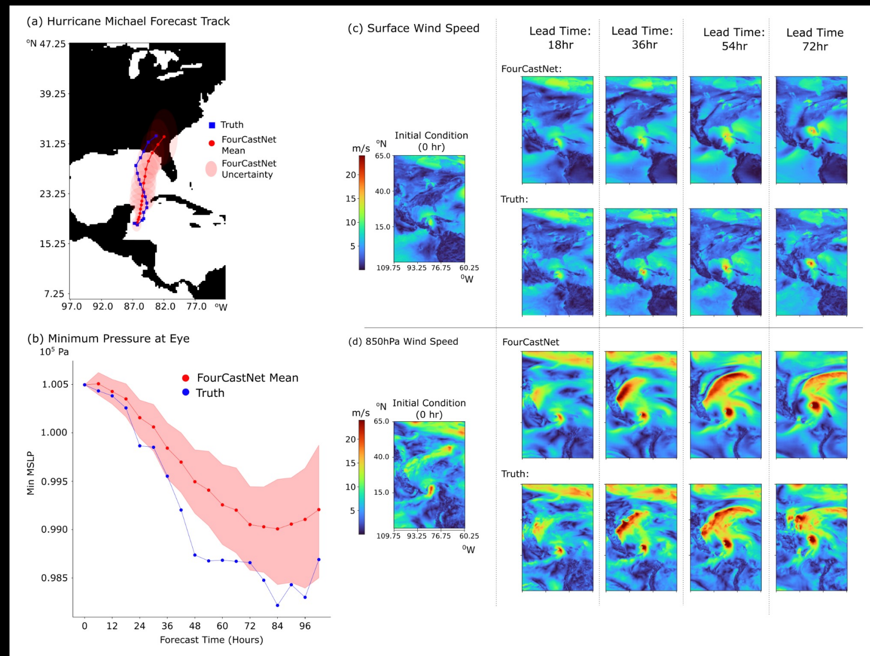
Nicoud et al., 2021

AI emulators of costly simulators

Major advances in **Weather and Climate models**

- **Neural operators** learn the solution operator
  - FourCastNet (NVIDIA): Fourier ForeCasting Neural Network
  - Aurora (Msoft)
- Accurate short to medium-range global predictions at 0.25° resolution (about 25 Km)
- Dramatic reduction of CPU cost (factor 1000)

Caveat: trained on large amounts of historical data for the same environment (Planet Earth)



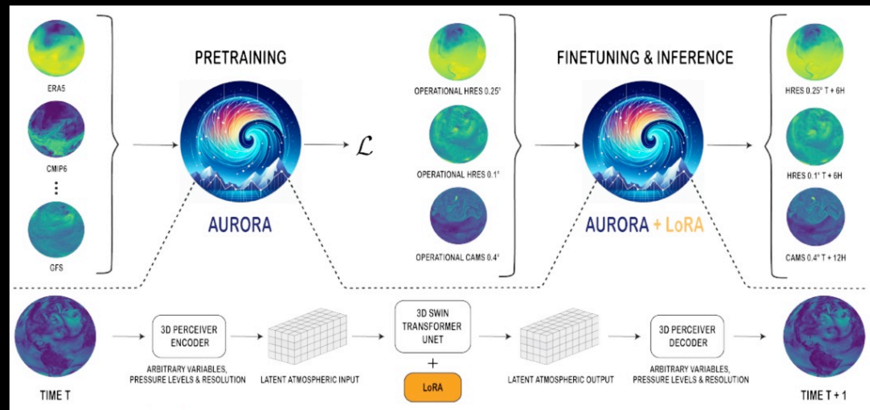
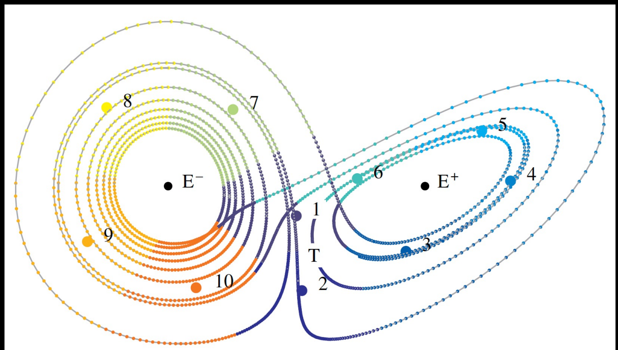


Figure 1: **Aurora is a 1.3 billion parameter foundation model for high-resolution forecasting of weather and atmospheric processes.** Aurora is a flexible 3D Swin Transformer with 3D Perceiver-based encoders and decoders. At pretraining time, Aurora is optimised to minimise a loss $\mathcal{L}$ on multiple heterogeneous datasets with different resolutions, variables, and pressure levels. The model is then fine-tuned in two stages: (1) short-lead time fine-tuning of the pretrained weights (2) long-lead time (rollout) fine-tuning using Low Rank Adaptation (LoRA). The fine-tuned models are then deployed to tackle a diverse collection of operational forecasting scenarios at different resolutions.

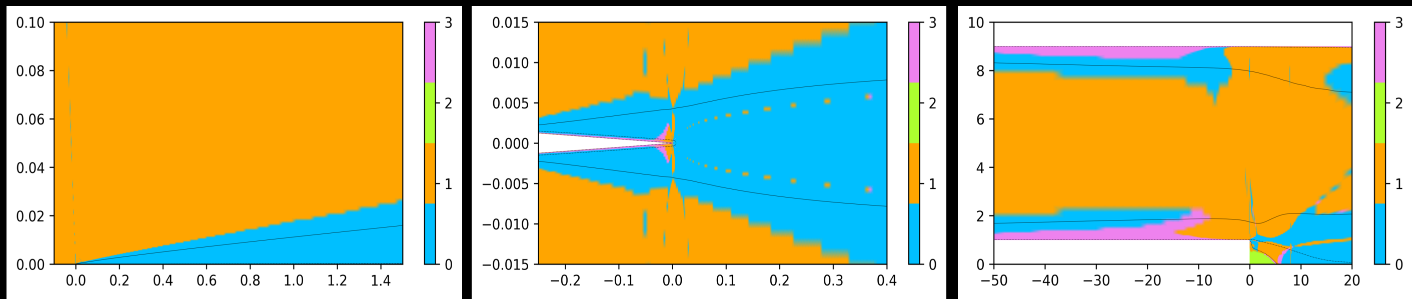
Learn and recognize physical processes

- **Identify** common flow processes within and across flows
- Represent processes in a suitable feature space
- Reconstruct complex environments from simpler components

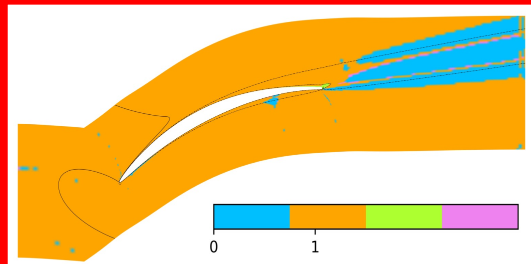
Challenge: invariant and interpretable features to describe relevant processes



Clustering of time dynamics (Kaiser et al., JFM, 2014)



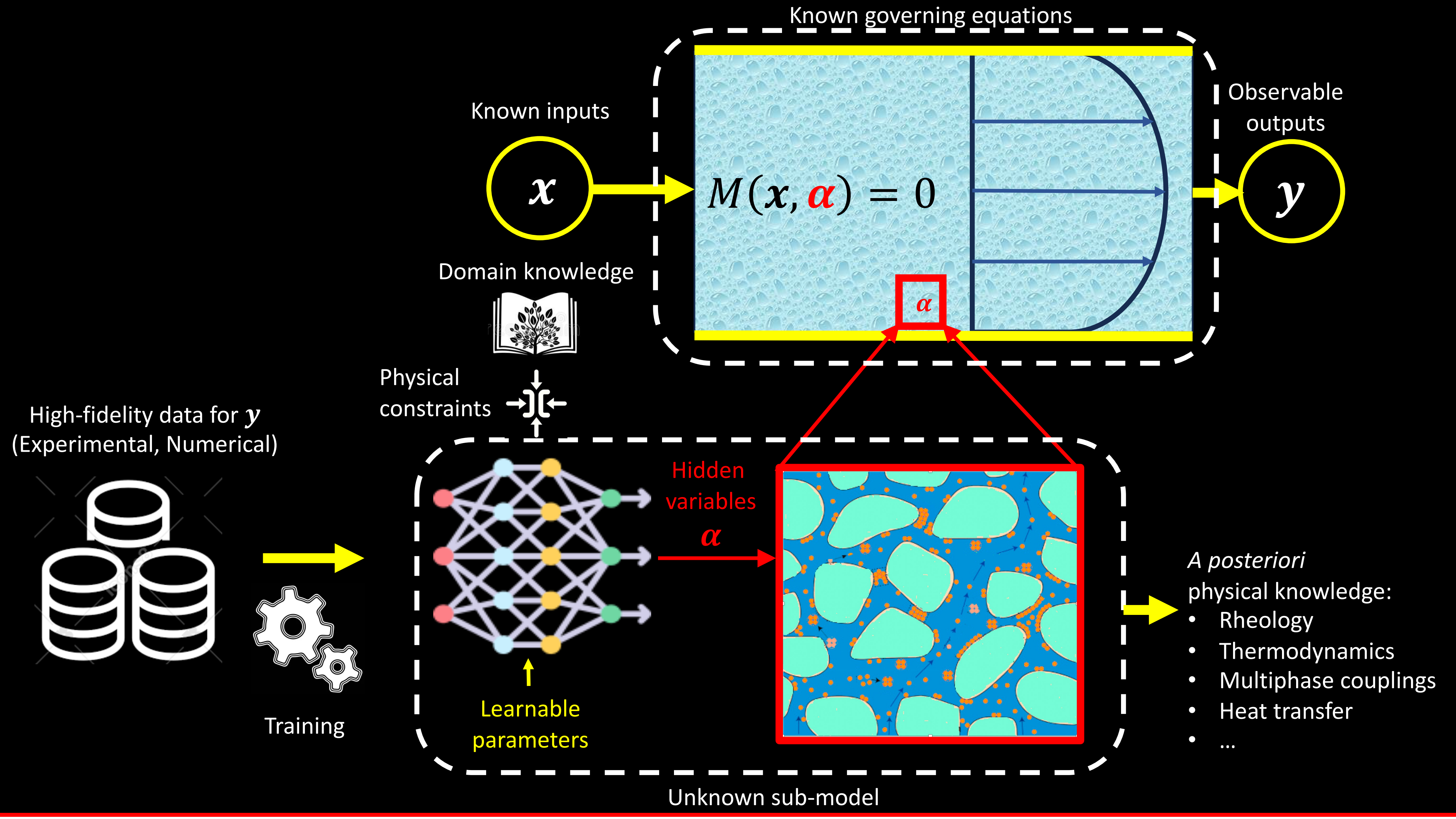
Train



Test

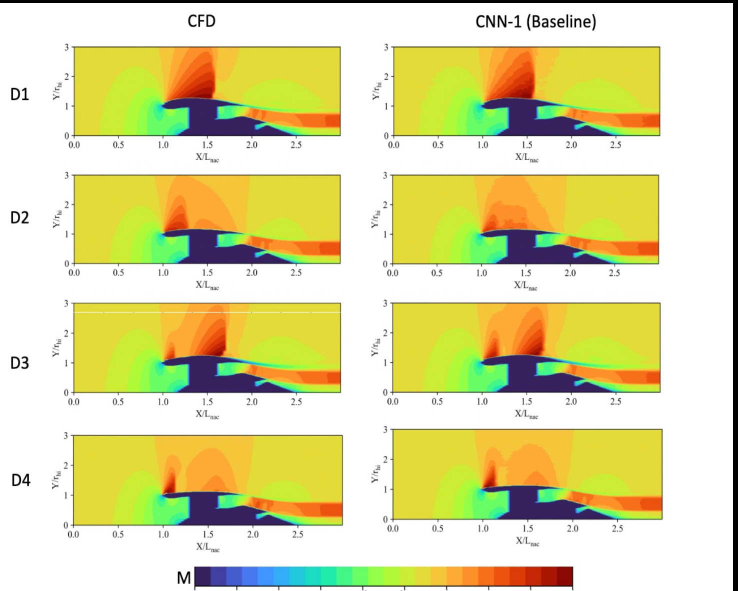
Identification of spatial dynamics across flows (Roques et al. 2025)

Infer constitutive laws from observations

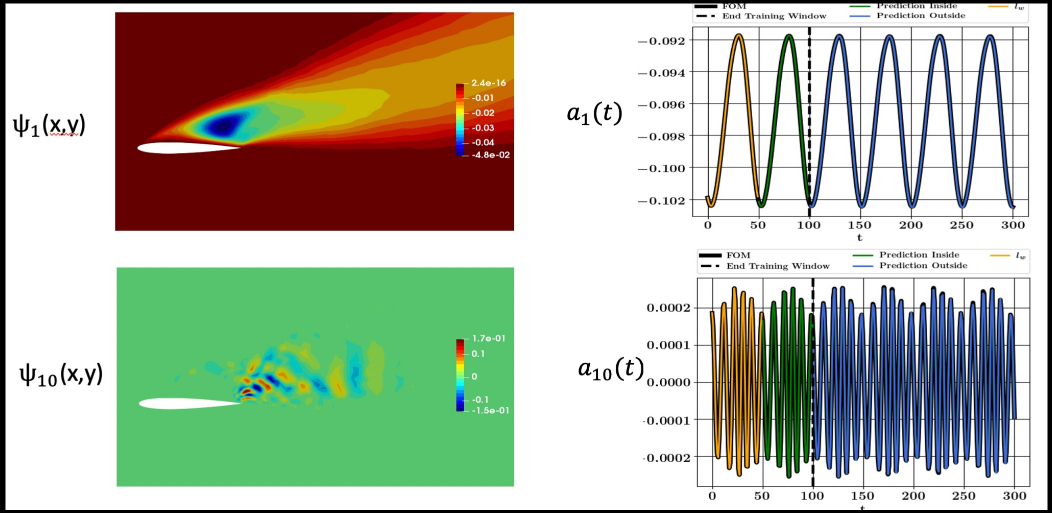


Optimize, characterize, control

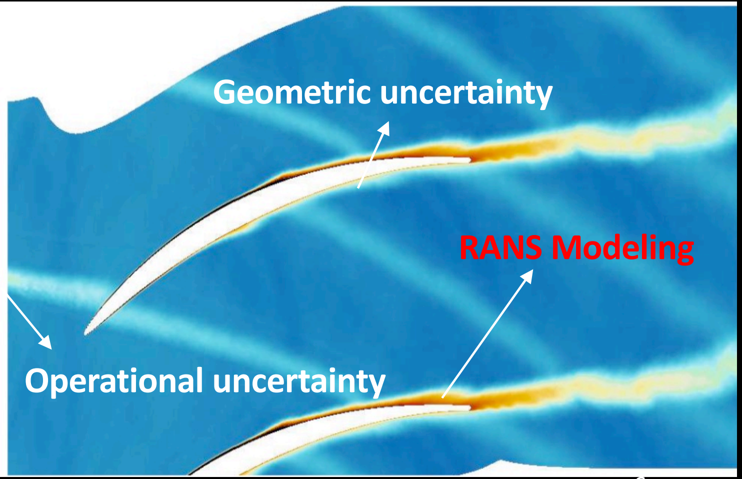
- Automated design and optimization
- Uncertainty quantification
- Digital Twins and real-time simulation



Sureshbabu et al., 2023



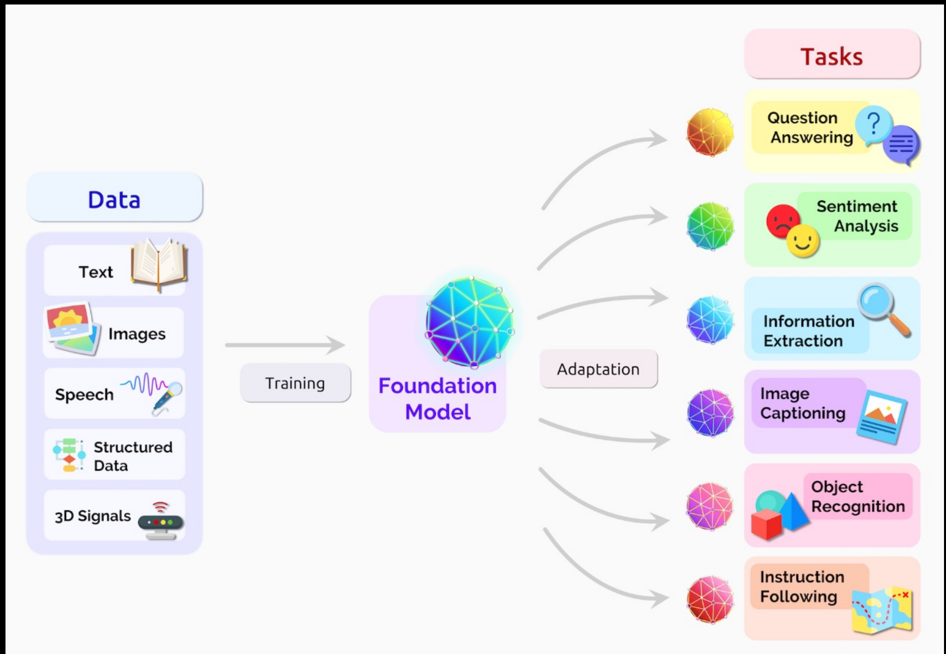
Sayadi et al., 2020



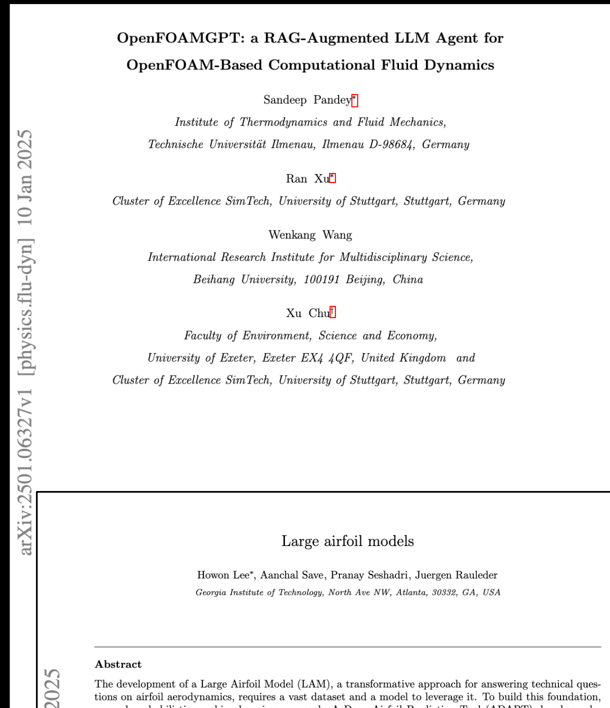
De Zordo Banliat et al., 2020

Large Language models for fluids

- Pretrained on large datasets, **fine-tuned** on fluid-related datasets
  - Historical data, pre-existing simulations and experiments, manuals, literature, user forums..
- A measure of human oversight remains critical to ensure correctness and adapt to evolving context



Bommasani et al., 2022



arXiv:2501.06327v1 [physics.flu-dyn] 10 Jan 2025

OpenFOAMGPT: a RAG-Augmented LLM Agent for OpenFOAM-Based Computational Fluid Dynamics

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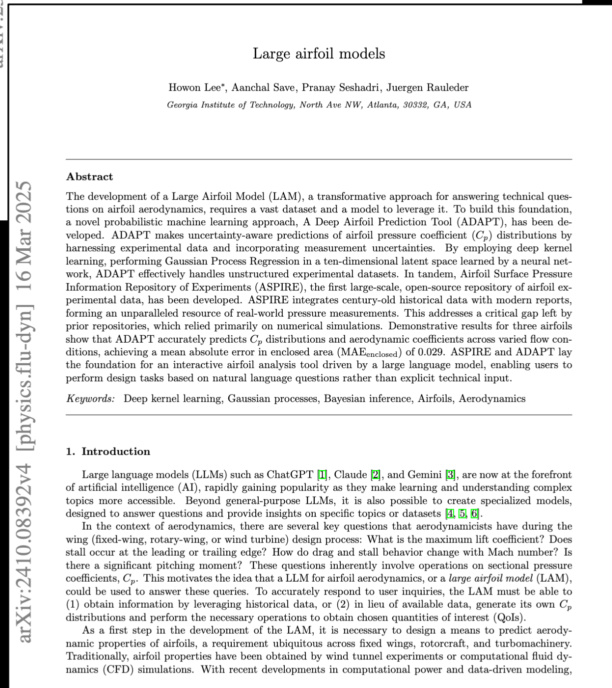

arXiv:2410.08392v4 [physics.flu-dyn] 16 Mar 2025

Large airfoil models

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Abstract

The development of a Large Airfoil Model (LAM), a transformative approach for answering technical questions on airfoil aerodynamics, requires a vast dataset and a model to leverage it. To build this foundation, a novel probabilistic machine learning approach, A Deep Airfoil Prediction Tool (ADAPT), has been developed. ADAPT makes uncertainty-aware predictions of airfoil pressure coefficient (C_p) distributions by harnessing experimental data and incorporating measurement uncertainties. By employing deep kernel learning, performing Gaussian Process Regression in a ten-dimensional latent space learned by a neural network, ADAPT effectively handles unstructured experimental datasets. In tandem, Airfoil Surface Pressure Information Repository of Experiments (ASPIRE), the first large-scale, open-source repository of airfoil experimental data, has been developed. ASPIRE integrates century-old historical data with modern reports, forming an unparalleled resource of real-world pressure measurements. This addresses a critical gap left by prior repositories, which relied primarily on numerical simulations. Demonstrative results for three airfoils show that ADAPT accurately predicts C_p distributions and aerodynamic coefficients across varied flow conditions, achieving a mean absolute error in enclosed area ($\mathrm{MAE}_{\mathrm{enclosed}}$) of 0.029. ASPIRE and ADAPT lay the foundation for an interactive airfoil analysis tool driven by a large language model, enabling users to perform design tasks based on natural language questions rather than explicit technical input.

Keywords: Deep kernel learning, Gaussian processes, Bayesian inference, Airfoils, Aerodynamics

1. Introduction

Large language models (LLMs) such as ChatGPT [1], Claude [2], and Gemini [3], are now at the forefront of artificial intelligence (AI), rapidly gaining popularity as they make learning and understanding complex topics more accessible. Beyond general-purpose LLMs, it is also possible to create specialized models, designed to answer questions and provide insights on specific topics or datasets [4, 5, 6].

In the context of aerodynamics, there are several key questions that aerodynamicists have during the wing (fixed-wing, rotary-wing, or wind turbine) design process: What is the maximum lift coefficient? Does stall occur at the leading or trailing edge? How do drag and stall behavior change with Mach number? Is there a significant pitching moment? These questions inherently involve operations on sectional pressure coefficients, C_p. This motivates the idea that a LLM for airfoil aerodynamics, or a *large airfoil model* (LAM), could be used to answer these queries. To accurately respond to user inquiries, the LAM must be able to (1) obtain information by leveraging historical data, or (2) in lieu of available data, generate its own C_p distributions and perform the necessary operations to obtain chosen quantities of interest (QoIs).

As a first step in the development of the LAM, it is necessary to design a means to predict aerodynamic properties of airfoils, a requirement ubiquitous across fixed wings, rotorcraft, and turbomachinery. Traditionally, airfoil properties have been obtained by wind tunnel experiments or computational fluid dynamics (CFD) simulations. With recent developments in computational power and data-driven modeling,

Challenges

Machine Learning models **not generalizable** outside their training sets

- Need for context-aware generalization techniques
  - → Learn **commonalities** among different flows
  - → Use context information to **predict unseen flows**
  - → Include inductive biases from **physical principles**
- Careful selection of training data to avoid biases
- Data availability? Intellectual property?
  - → Health data, military and dual-use applications…
- Human supervision and critical analysis remains essential
  - → AI assistant, not AI researcher!