Between Physics and Data

A Critical Examination of AI's Role in Simulation Driven Product Development

Maths-4-Innov-Action, March 24th 2026
College de France

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Agenda

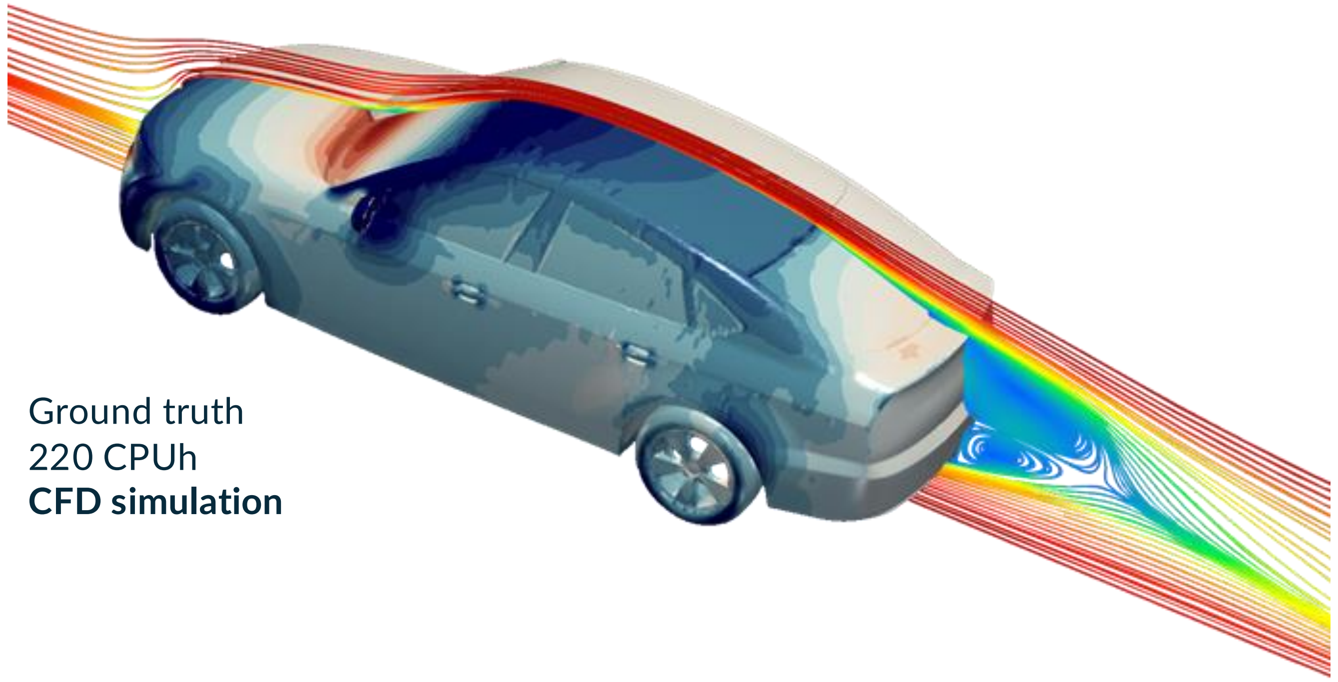
Introduction
Trends and their motivation

Physics <-> Data
Learning the relationship

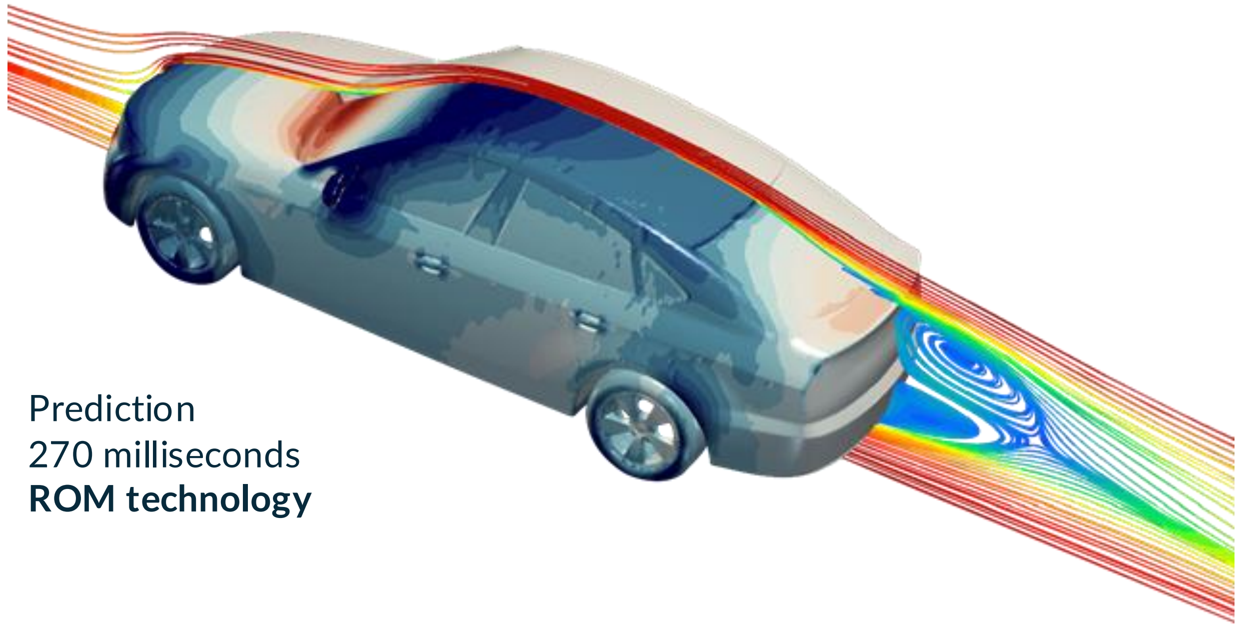
Conclusions

Our topic

Models accelerated by data that capture full solution @ lower cost



Ground truth
220 CPUh
CFD simulation



Prediction
270 milliseconds
ROM technology

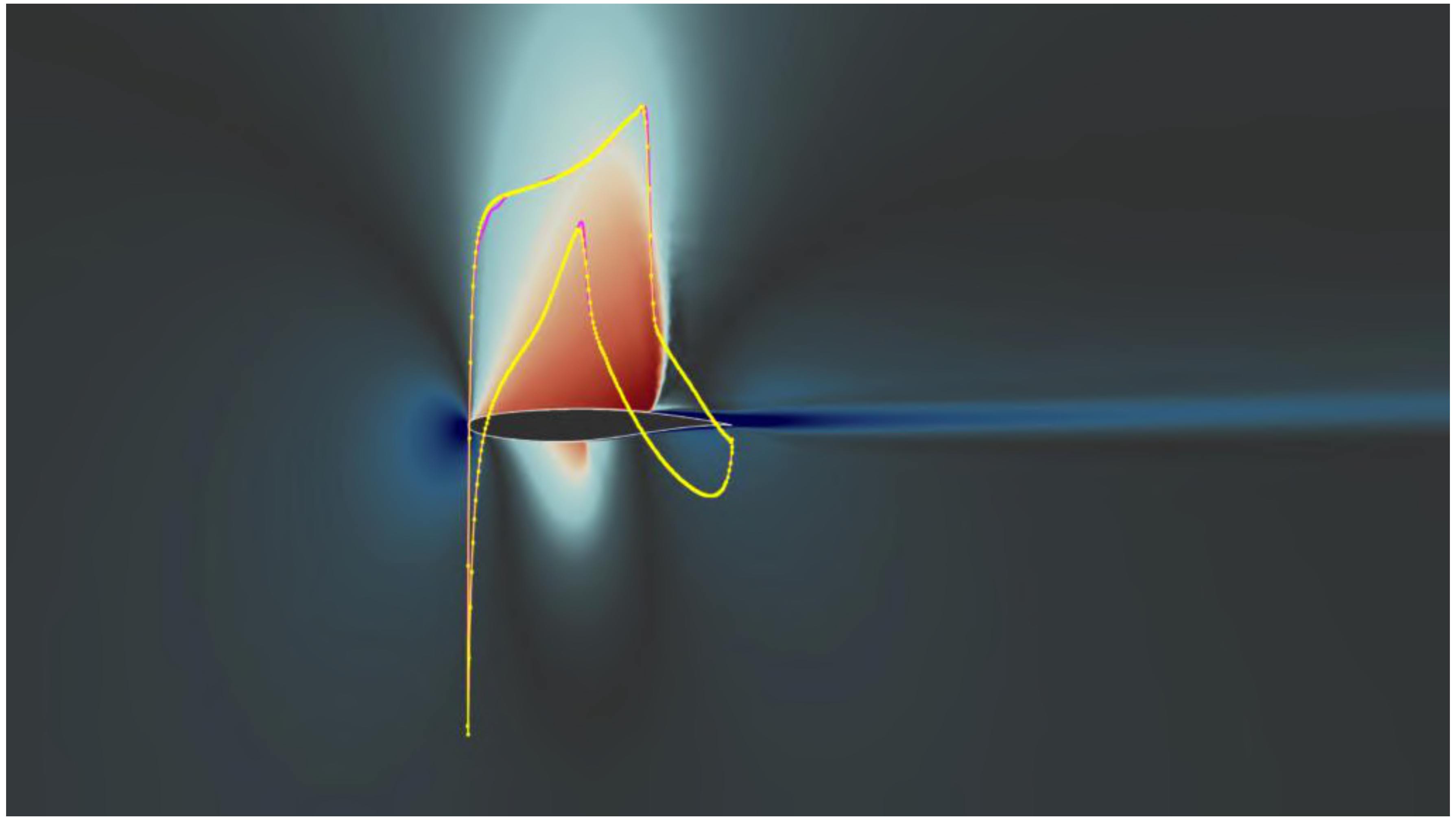
Why AI technology

Non-parametric

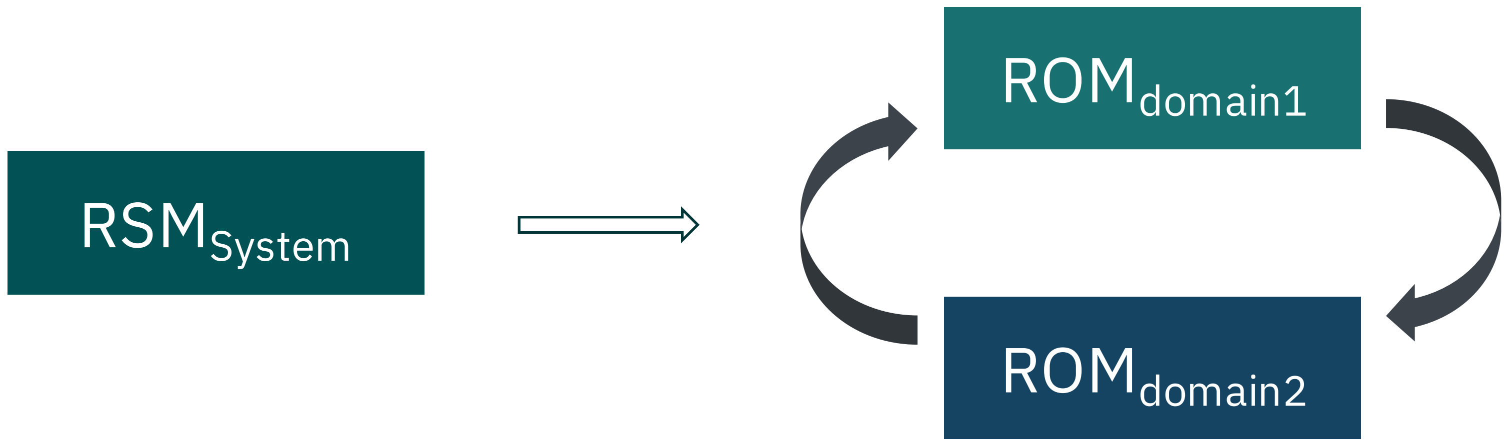
- CAD can be an input
- Loading curve can be an input

Full Order Insights

- Inspection of full solution
- Derive QoI at any time



Why AI technology

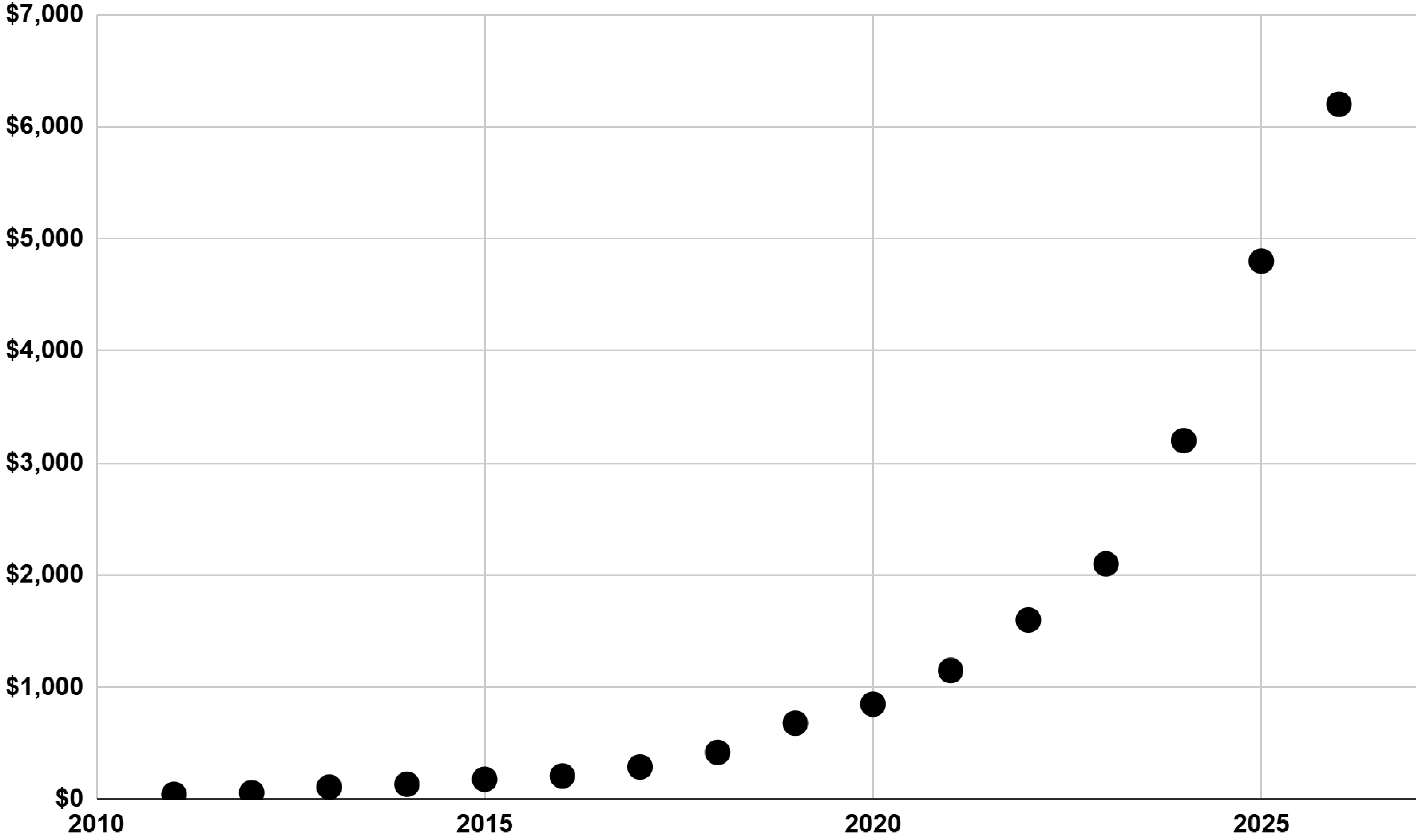


Accelerate HiFi MDAO

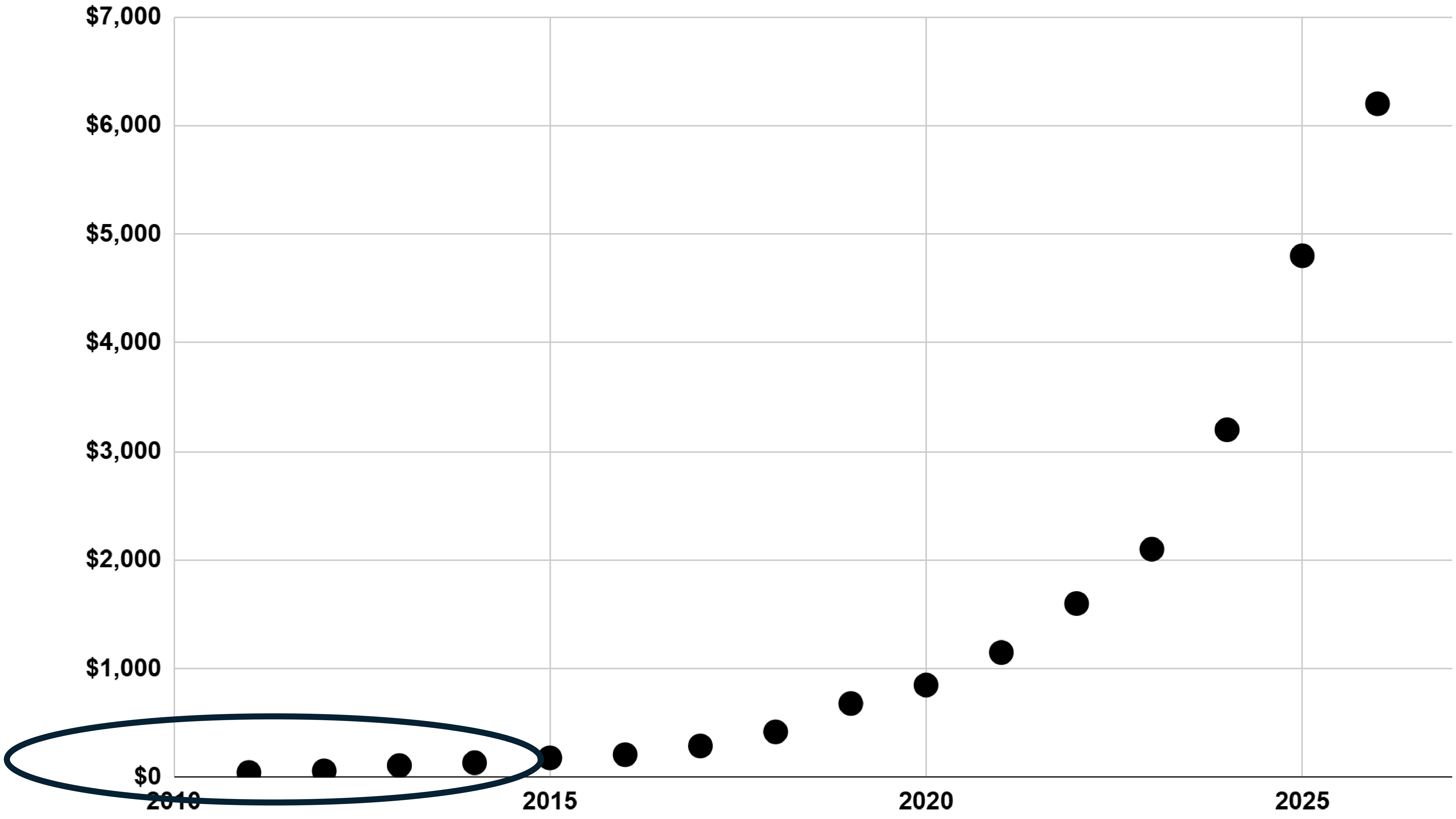
- Derive ROM for each discipline
- Couple ROMs
- Enable HiFi-based system simulation

A story from 2011 and a very different story from 2025...

Yearly deals in simulation related AI [M$]



From Reduced order models to foundational models



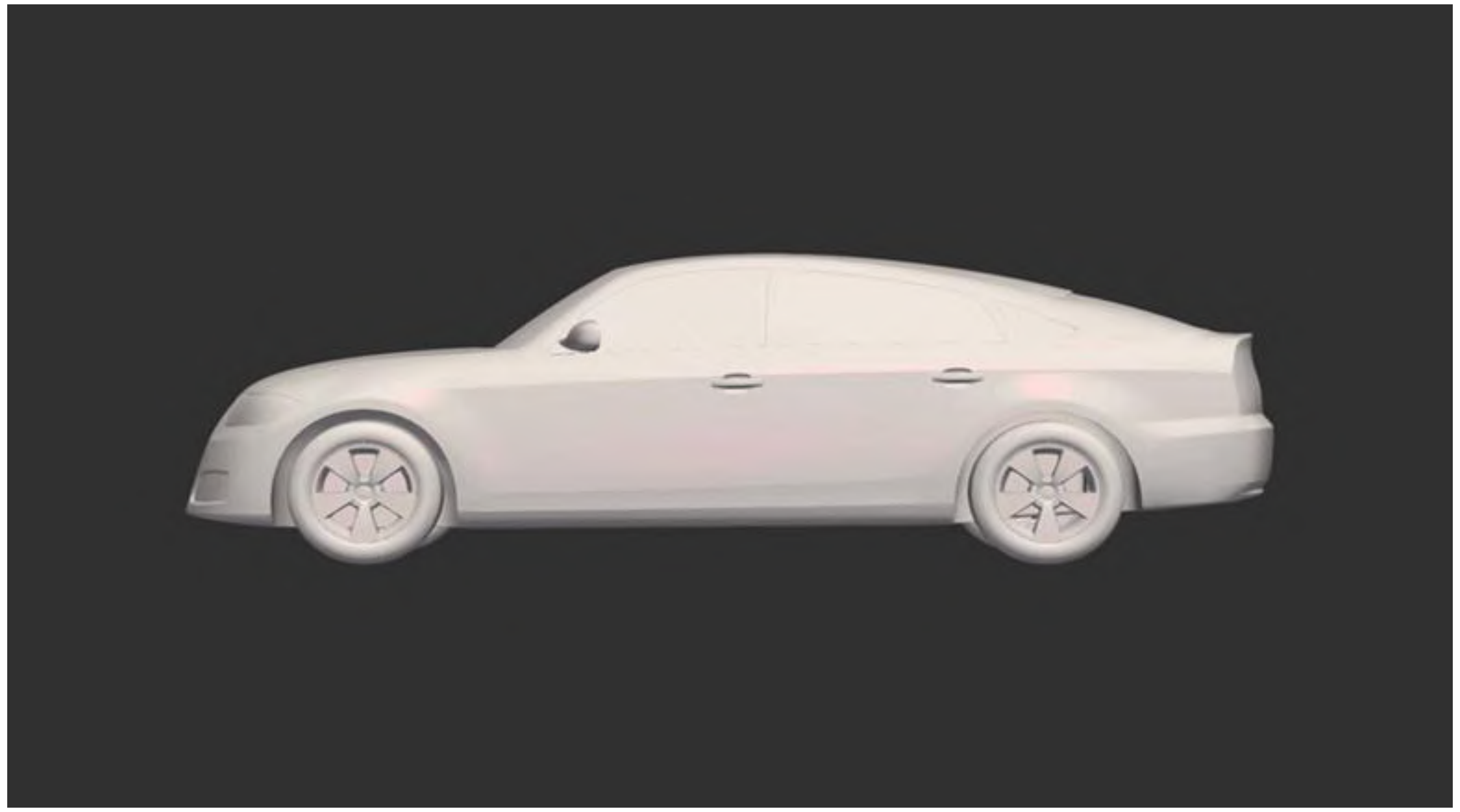
Reduced Order Models

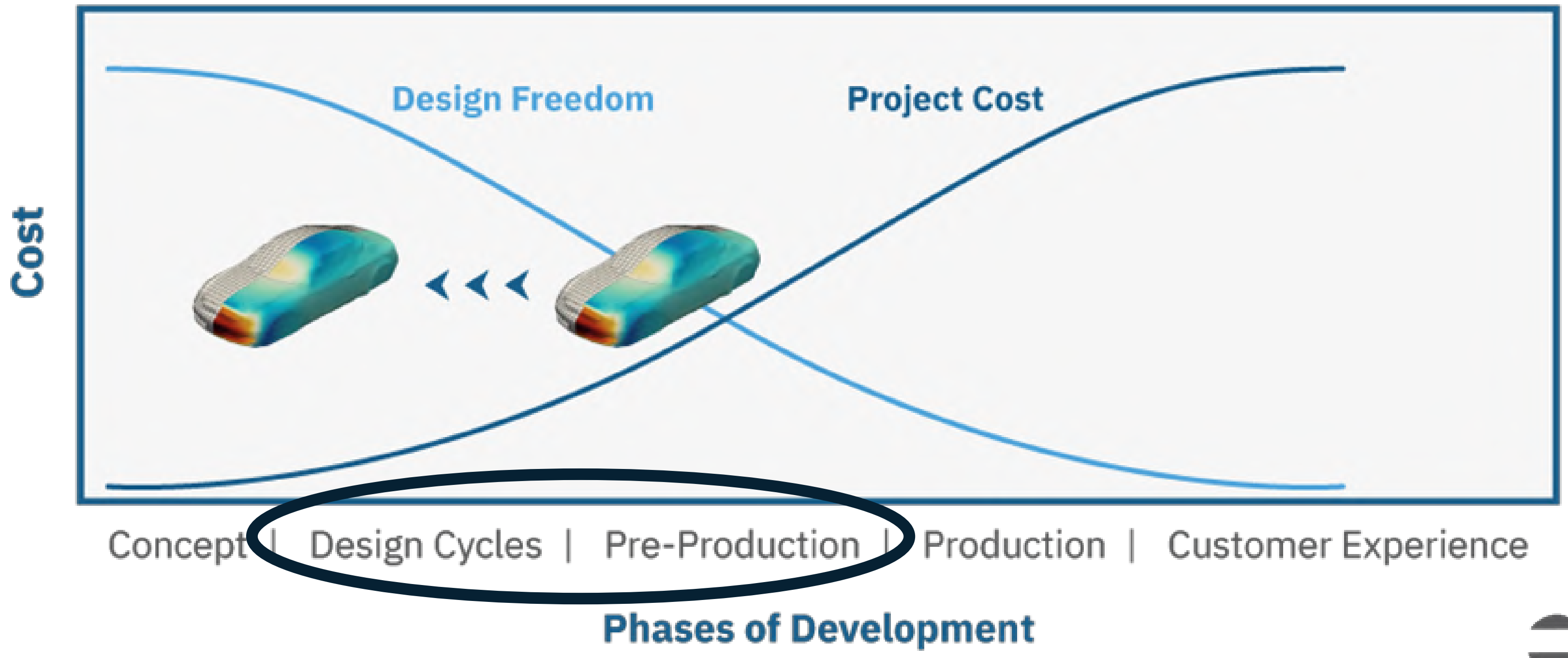
since 2000 “Accelerate multi-query tasks”

- Linear encoders, **+solver** +regression
- Training data owned by user & **generated for task**
- in-distribution by construction

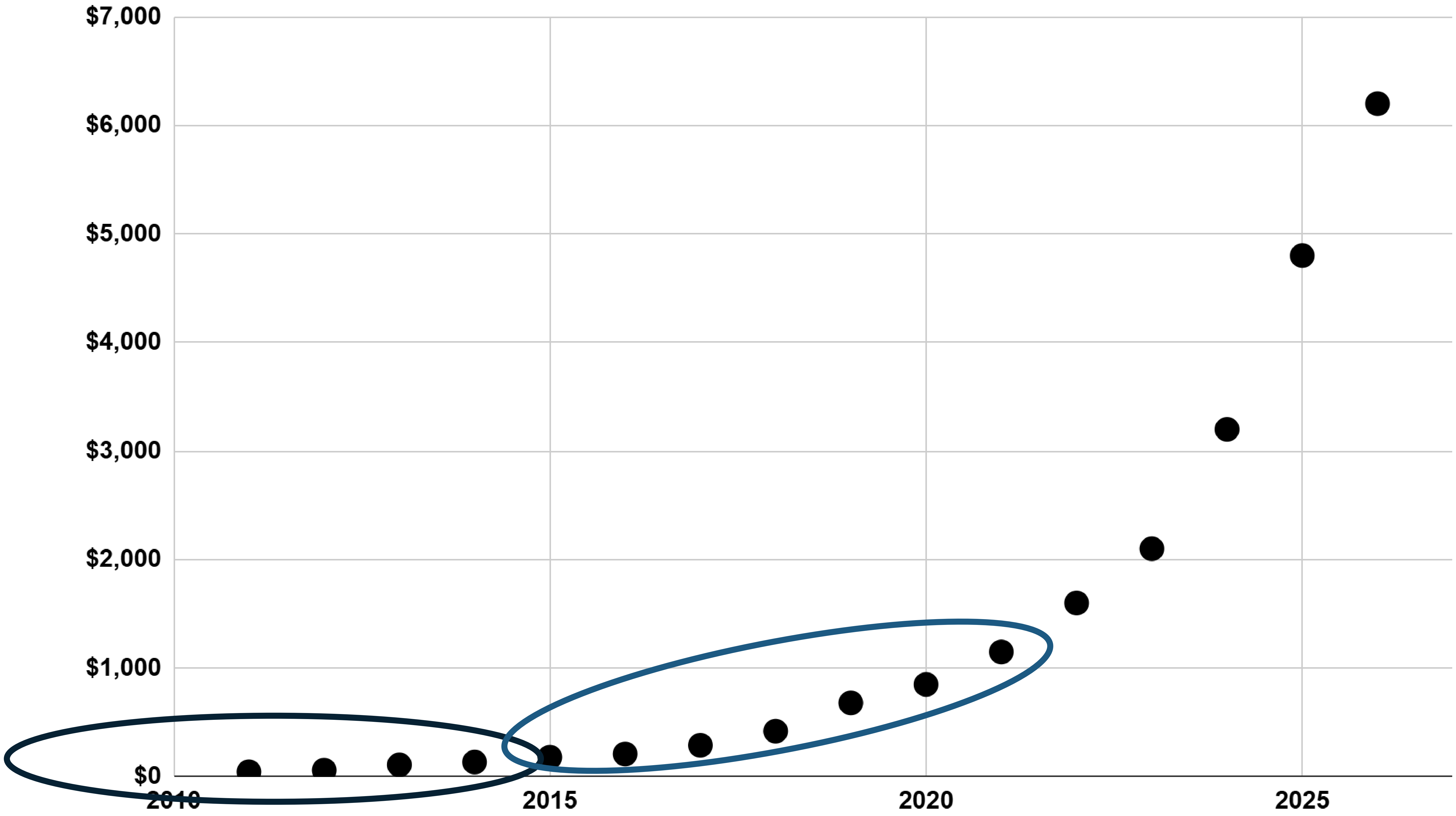
- Shift left paradigm
- Requires a data warehouse

- **Parsimonious**
- **Very intrusive & very complex**





From Reduced order models to foundational models



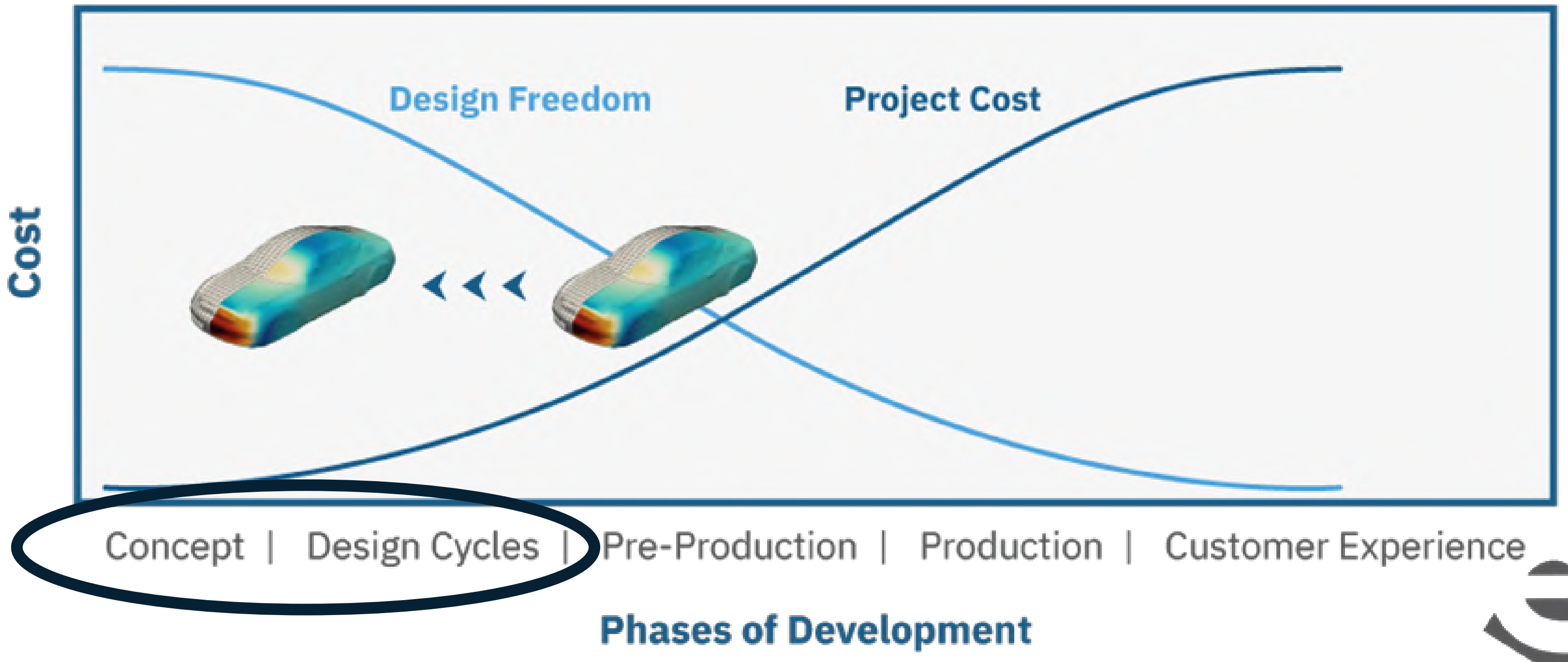
Deep Learning

since 2015 “Reuse historical data”

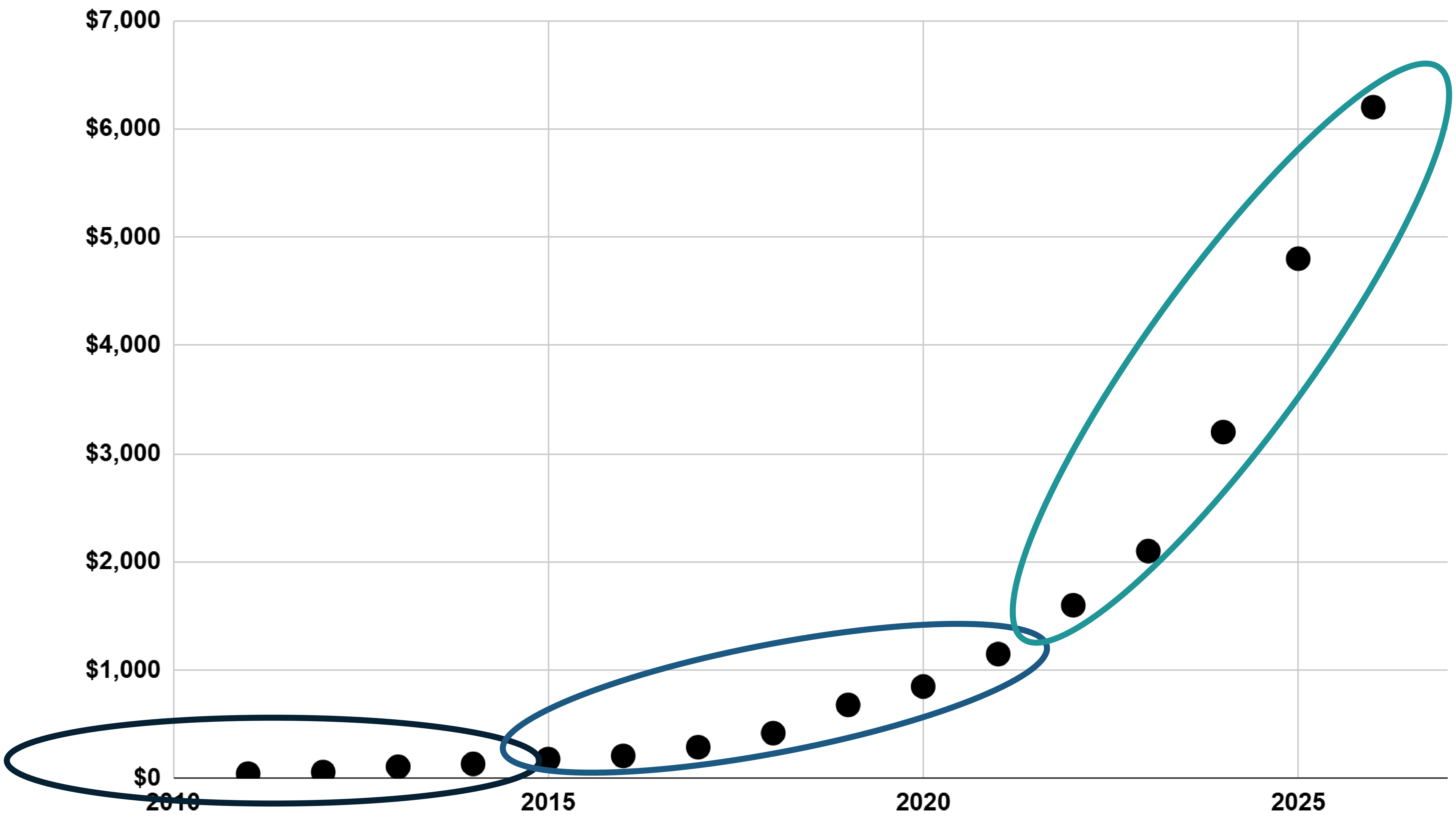
- **Non-linear encoders,** e.g. Graph Convolutionary NN
- Training data owned by company & **made available**
- out-of-distribution requires extra data-generation

- Push right paradigm
- Requires a data lake

- **Data- intensive**
- **Non-intrusive & not complex**
- **Infrastructural challenge**
- **Data management**



From Reduced order models to foundational models

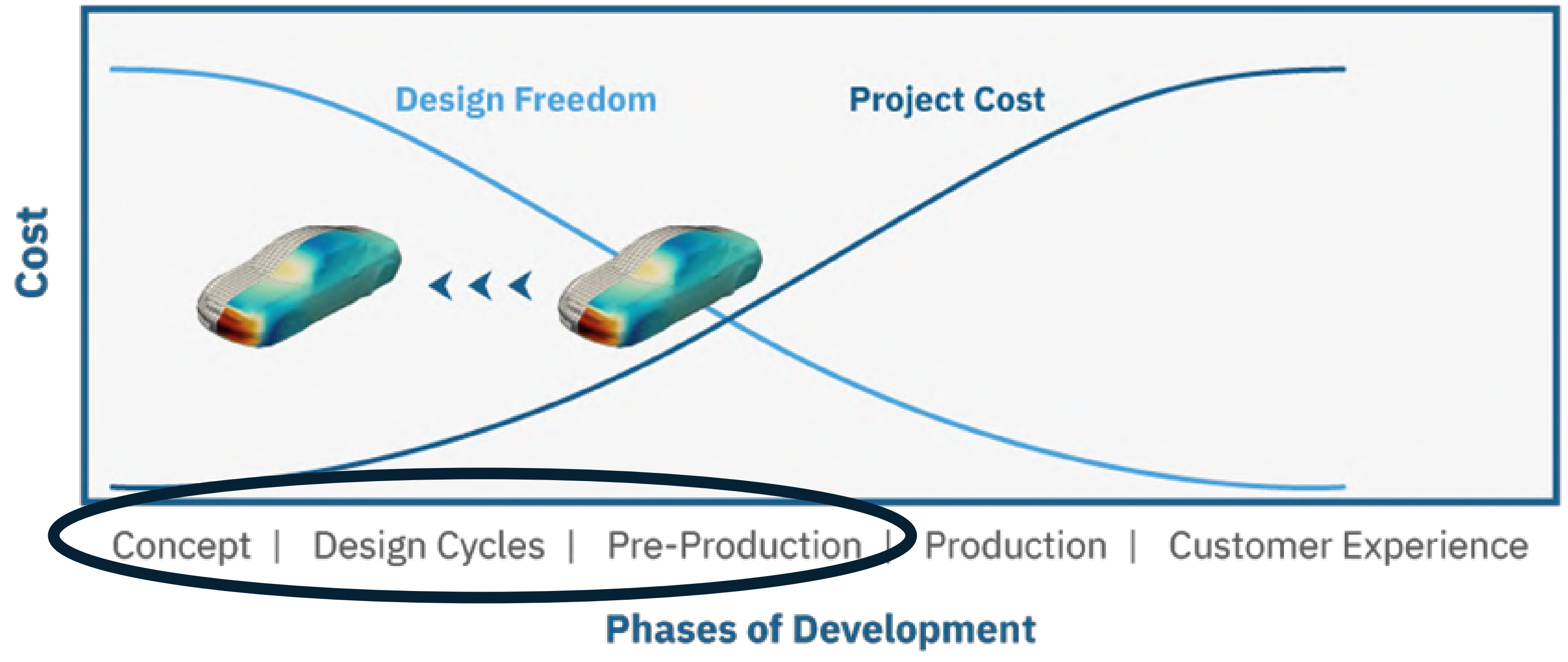


Foundational models

since 2023 “Substitute solver”

- Geometric Deep Learning, transformers
- **Training data owned by AI provider** (+ small sets for transfer learning)
- **Generalization**

- Huge data requirement
- **Large scale projects**



Physics <-> Data

One of these for each item listed on your agenda slide

The role of physics in data-driven approaches

	Training (Offline)	Prediction (Online)
Vanilla solver	*Data for calibration*	-
Reduced Order Model	Data	(modified) Solver
Full data driven	Data	ML
Physics Informed Neural Networks	(simplified) Solver	ML

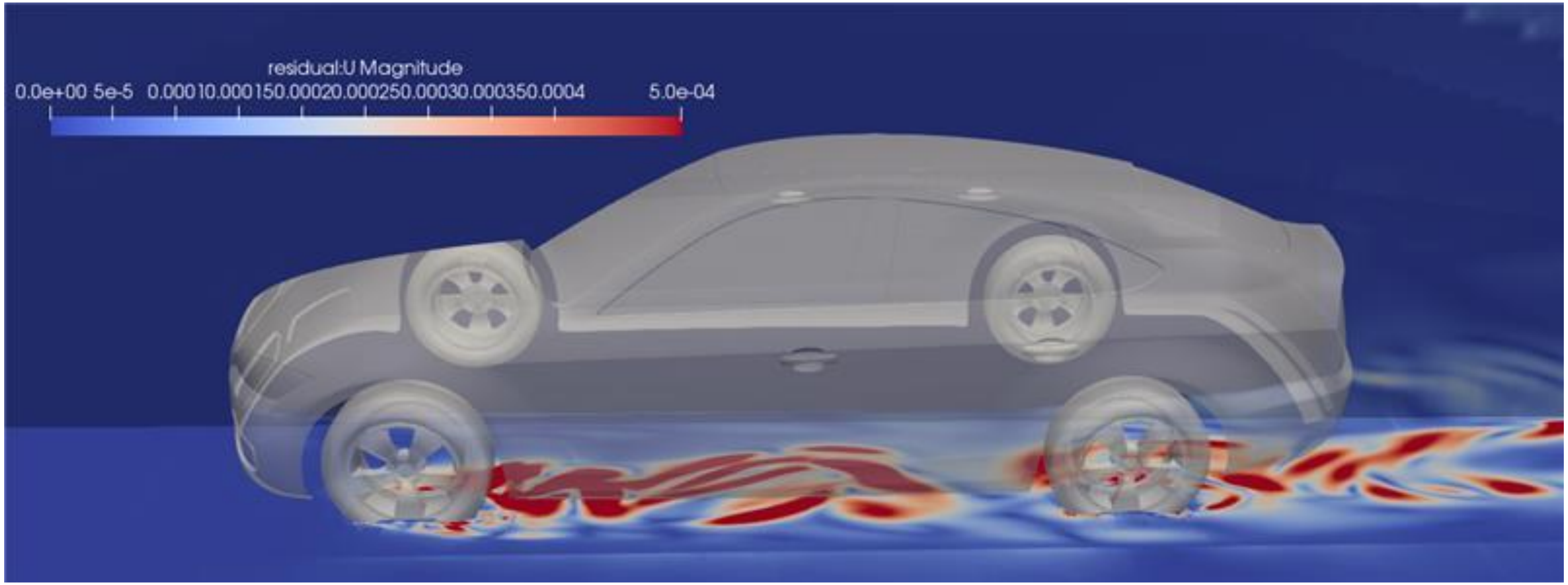
Residuals are an implicit representation of data

Res(Data) = 0

Difficult coexistence of ML and physics

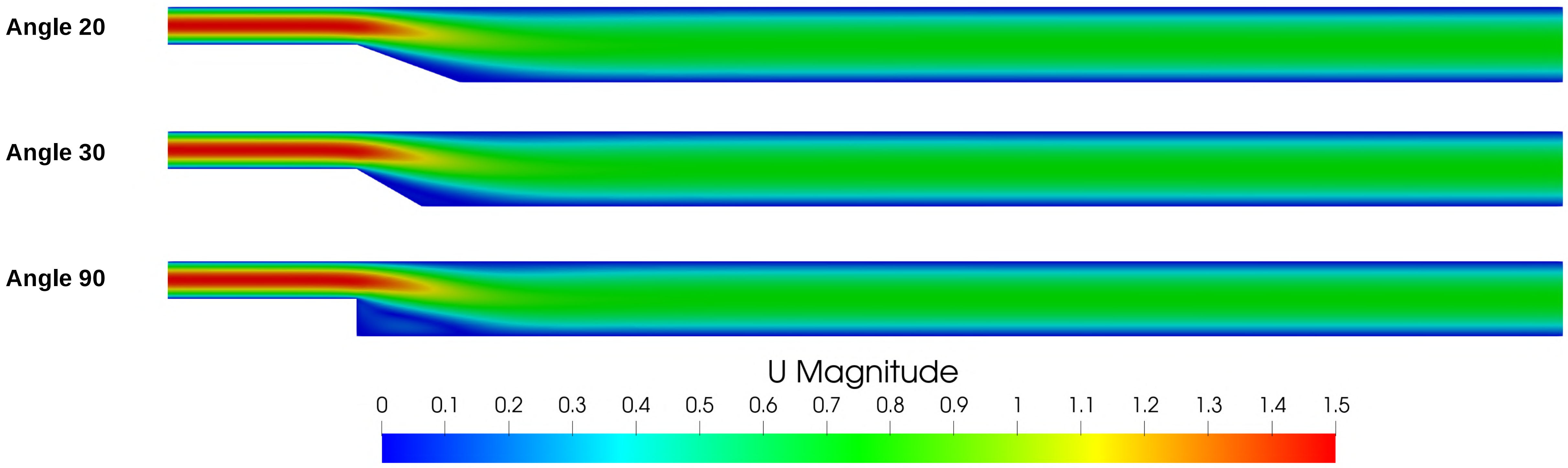
Available data

- Badly converged steady-state solutions
- Averaged results of resolved transient (storage $O(10^3)$)
- None are solutions to solver

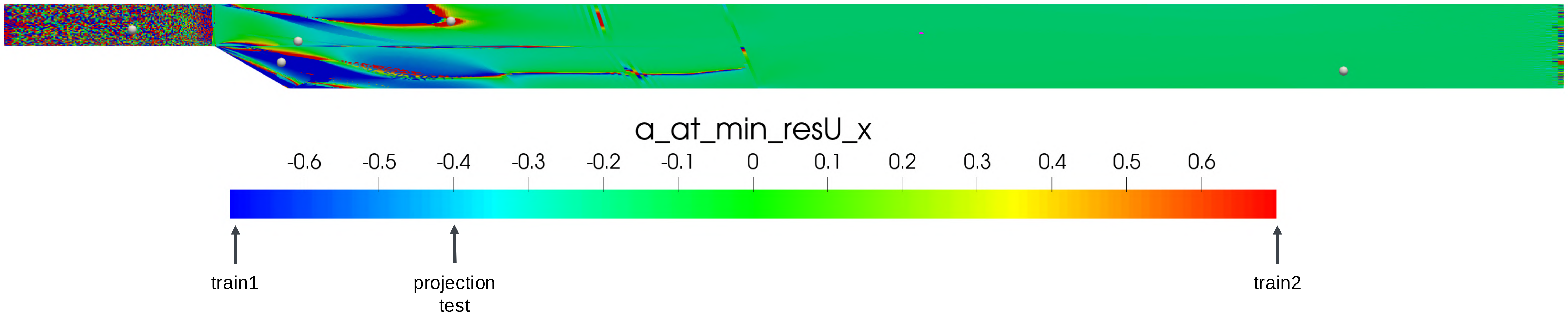


Residuals as loss function

Laminar backward facing step
OpenFOAM
2 training / 1 testing snapshot



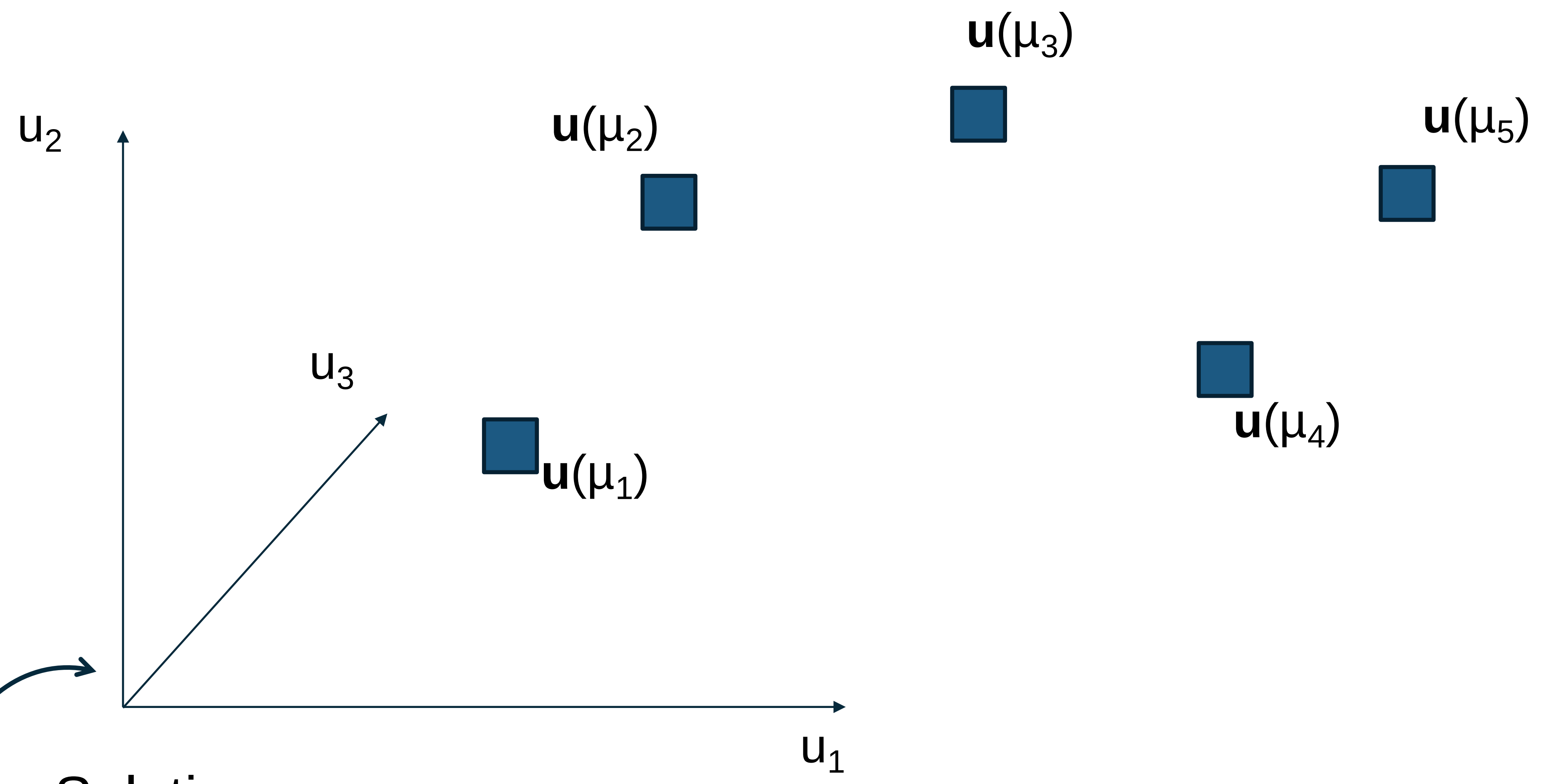
Point-wise minimization of cell residual



Solution space

Dimension N_{mesh}

- very coarse computational model
- one parameter

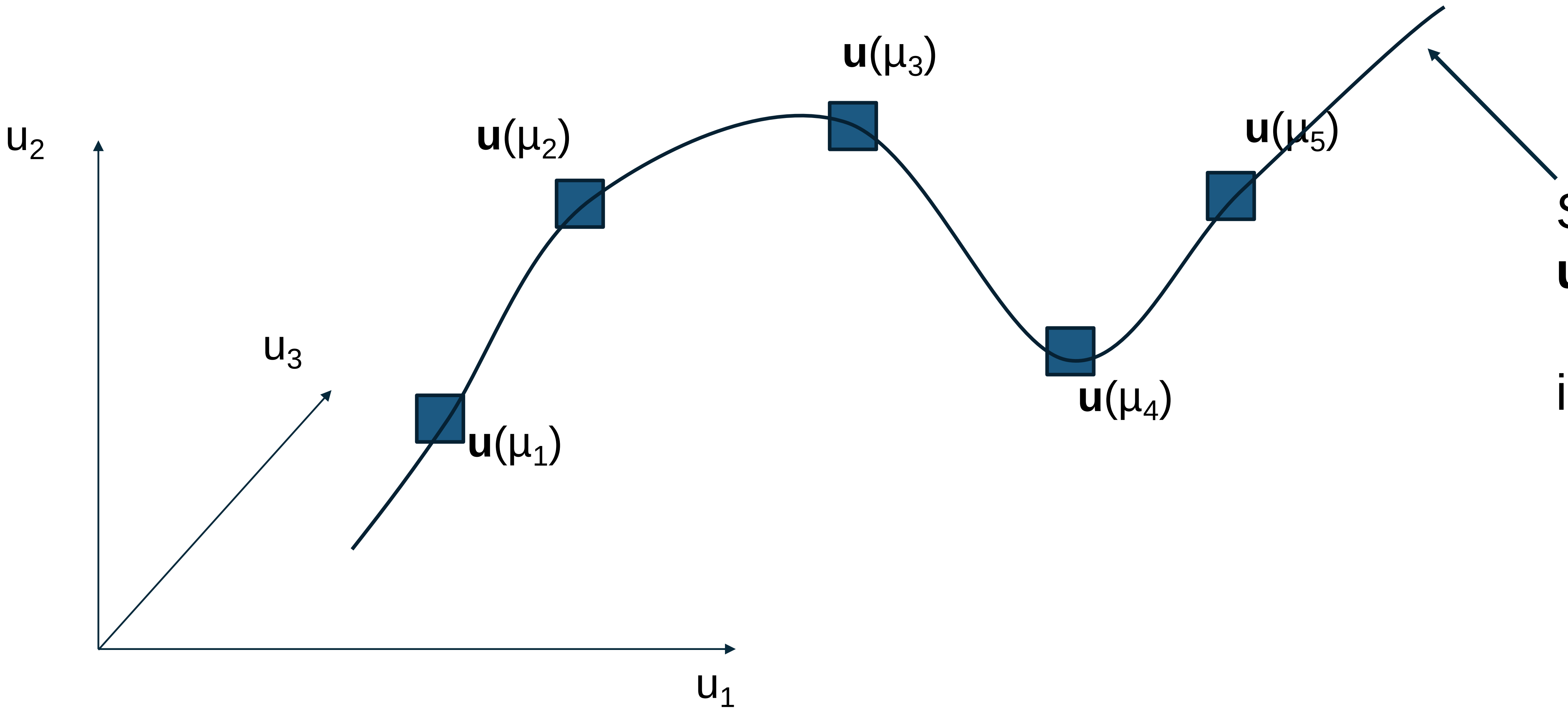


Solution space
$\mathbf{u} = (u_1, u_2, u_3)$

in this case, 3D

Solution manifold

Dimension N_{param}

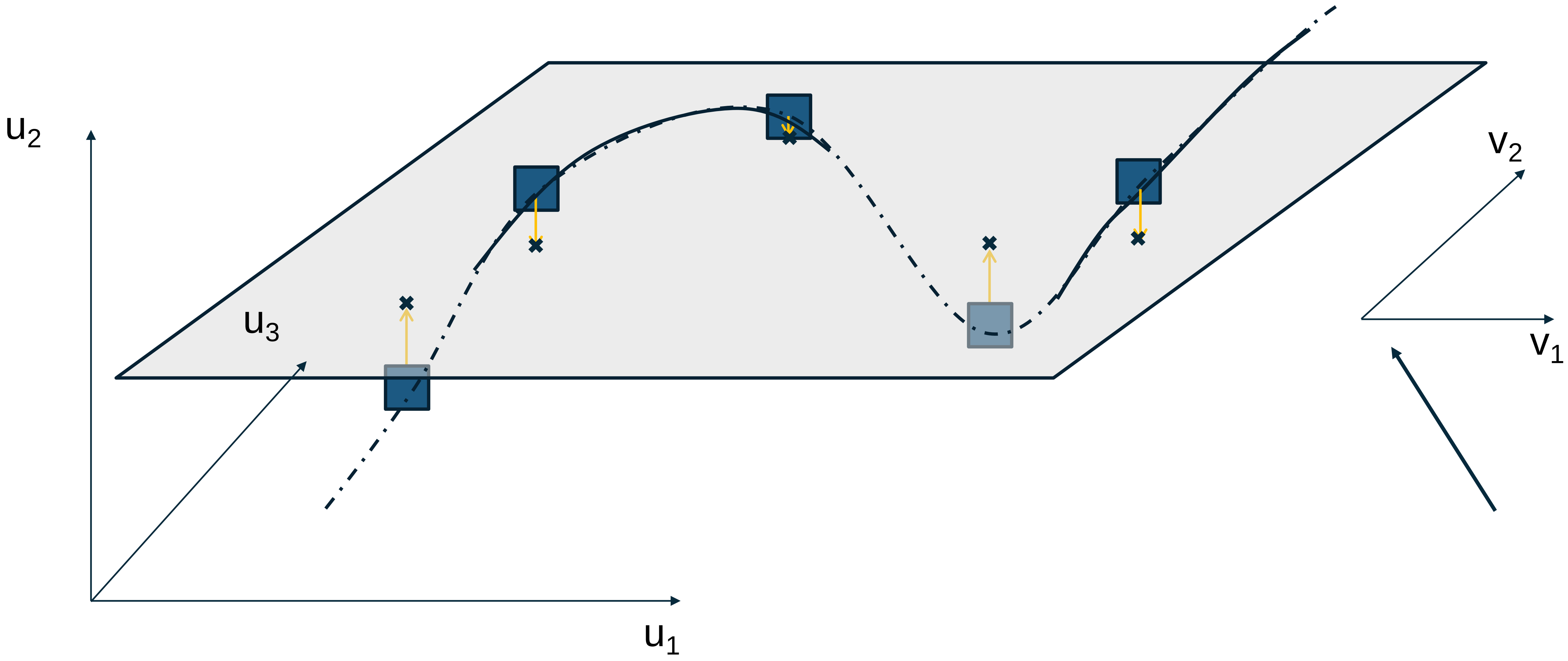


Solution manifold
$\mathbf{u} = f(\mu)$

in this case, 1D = N_{param}

Reduced space

A subspace that embeds well the solution manifold

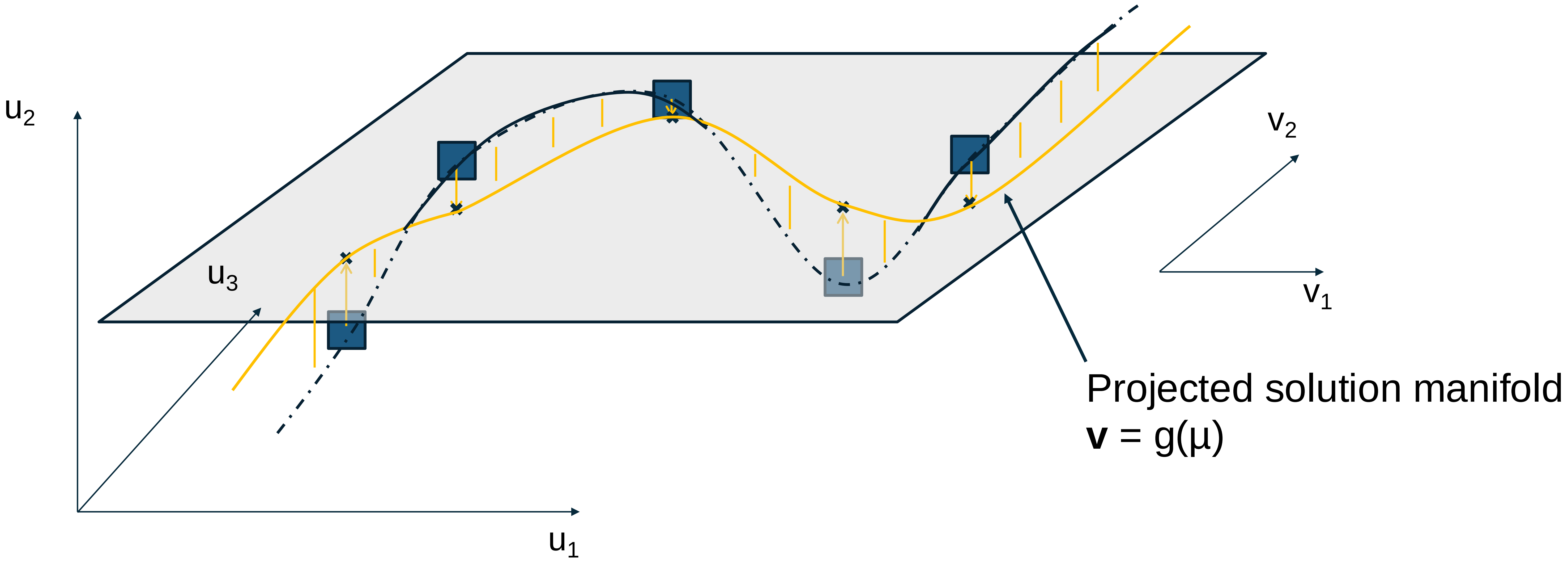


Linear solution subspace
$\mathbf{v} = (v_1, v_2)$

in this case, 2D

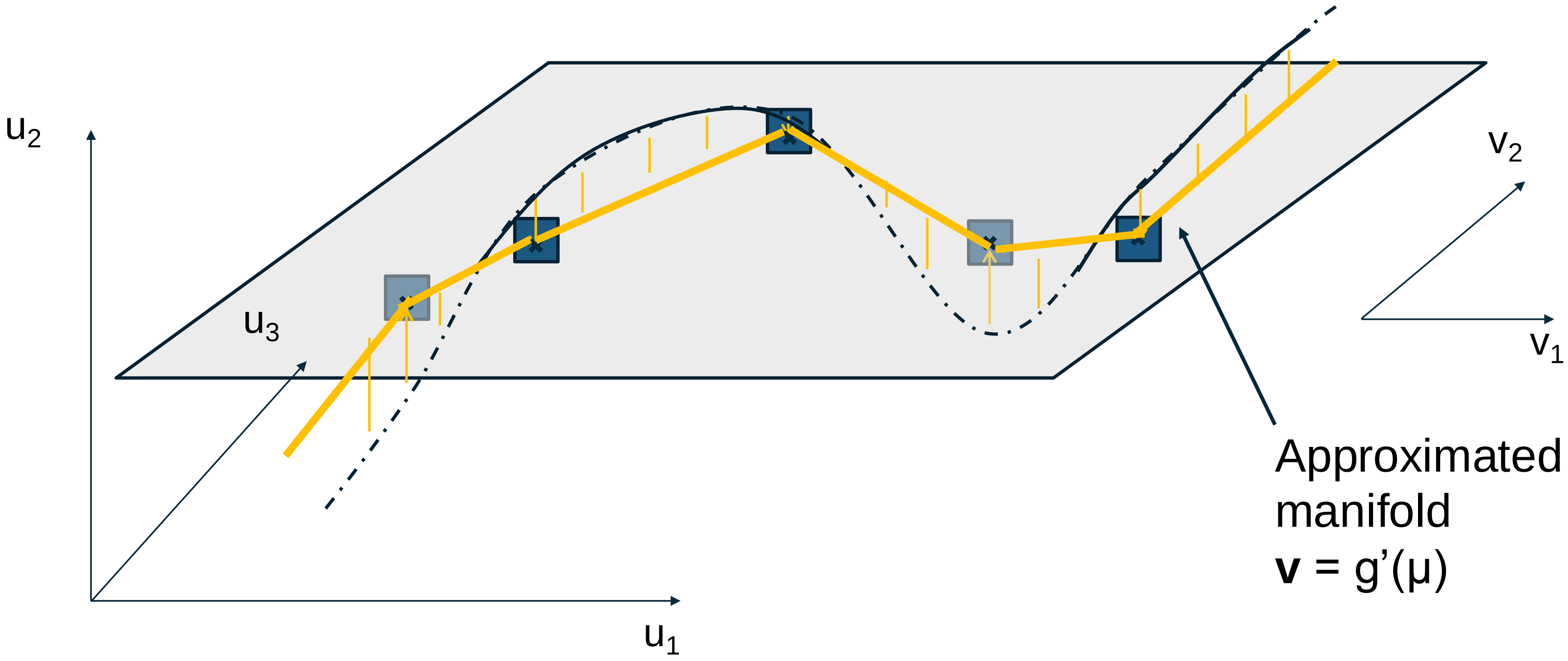
Projected solution manifold

The representation of the manifold in the solution subspace



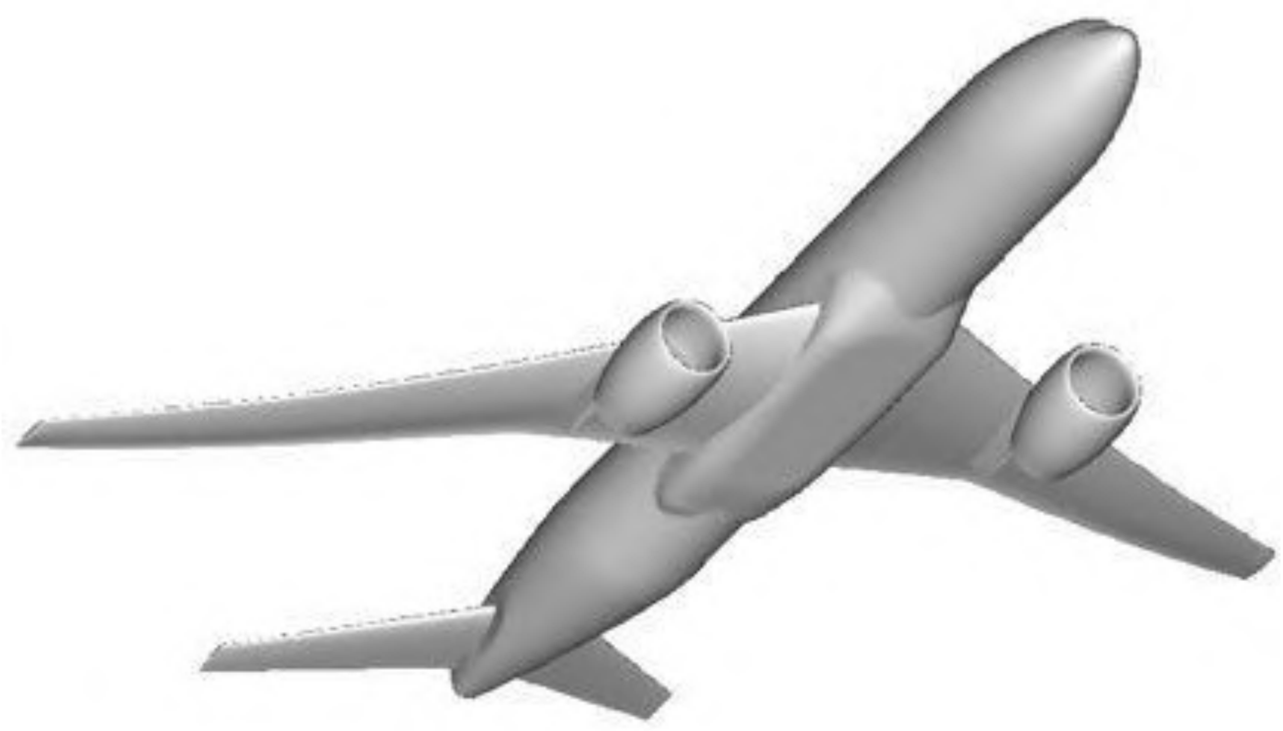
Approximated solution manifold

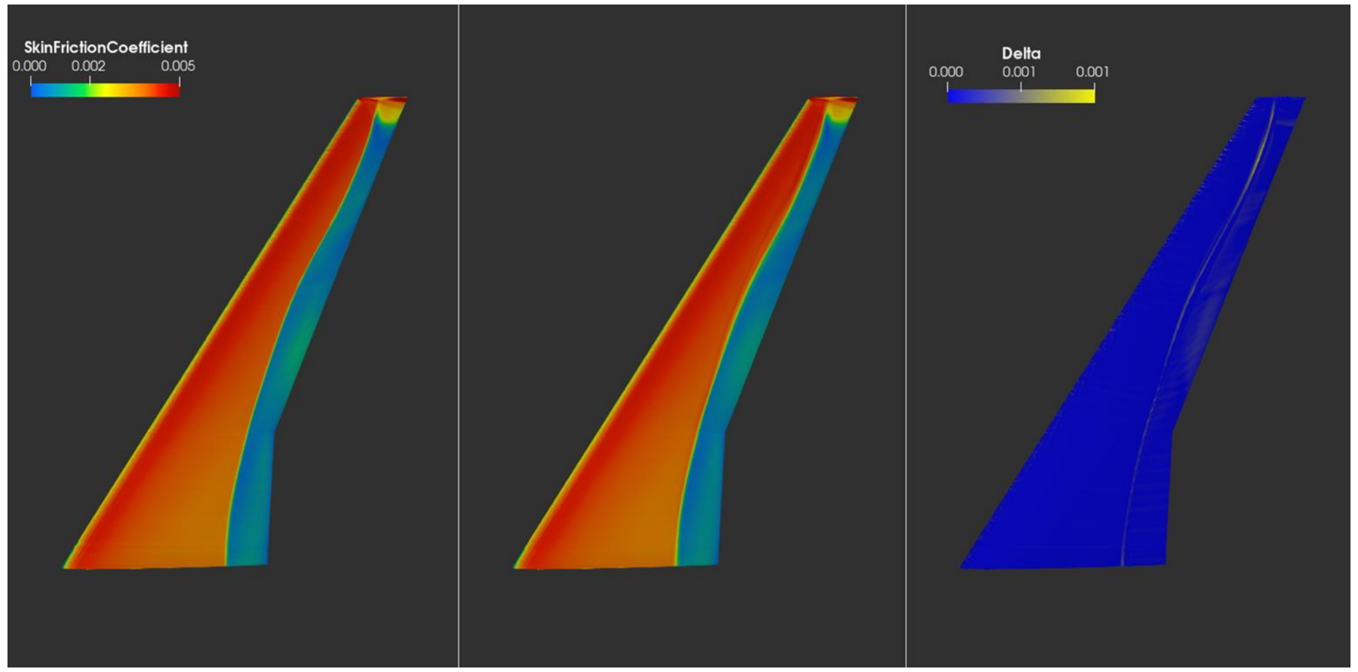
A 1sr order approximation

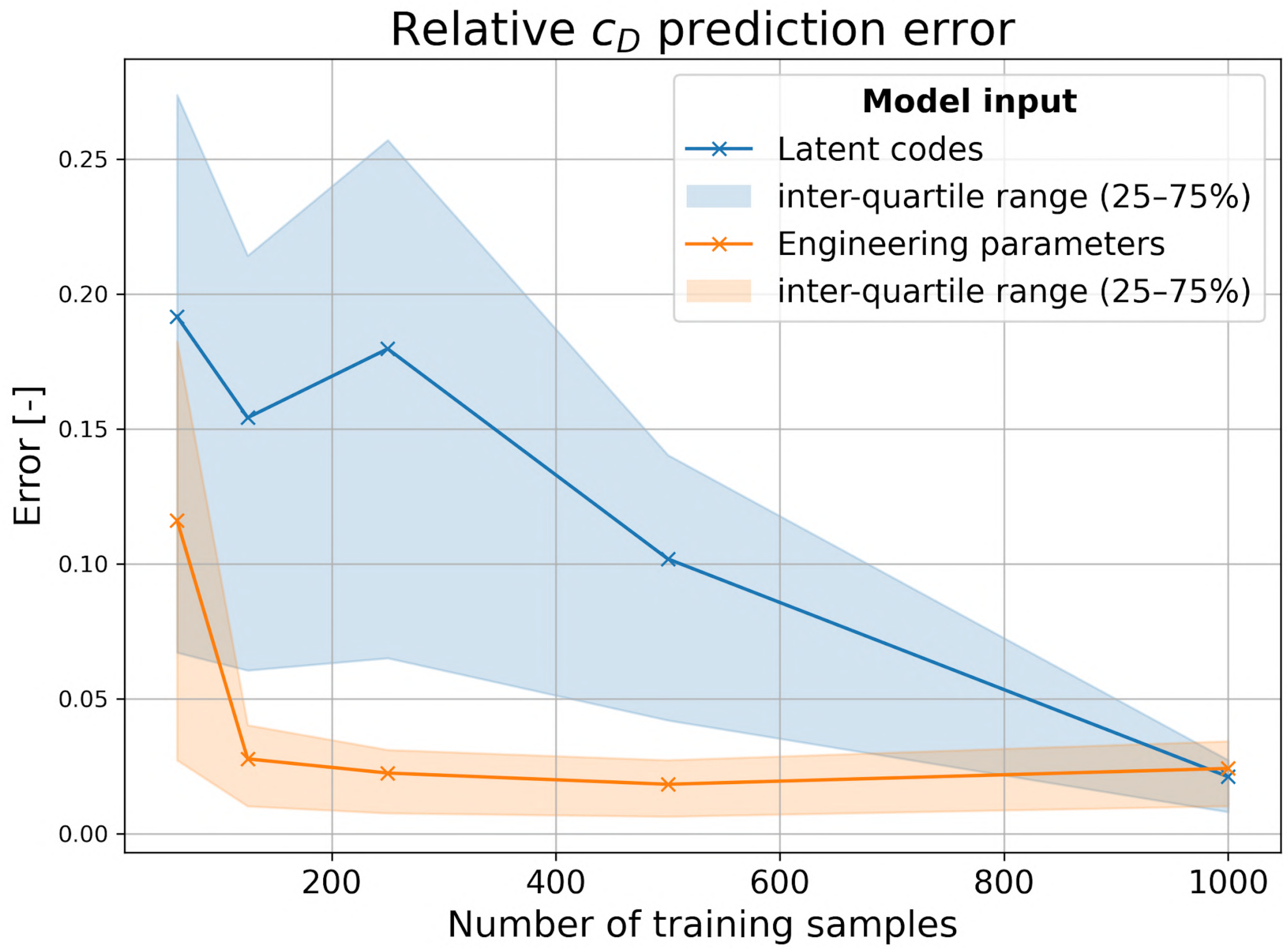


Approximated solution manifold
v = g'(μ)

Comparison




SkinFrictionCoefficient
0.000 0.002 0.005
Delta
0.000 0.001 0.001


Relative c_D prediction error
Model input
Latent codes
inter-quartile range (25–75%)
Engineering parameters
inter-quartile range (25–75%)
Error [-]
0.00
0.05
0.10
0.15
0.20
0.25
200
400
600
800
1000
Number of training samples

A major difference....

Reduced space

- core of ROMs
- independent of parameters

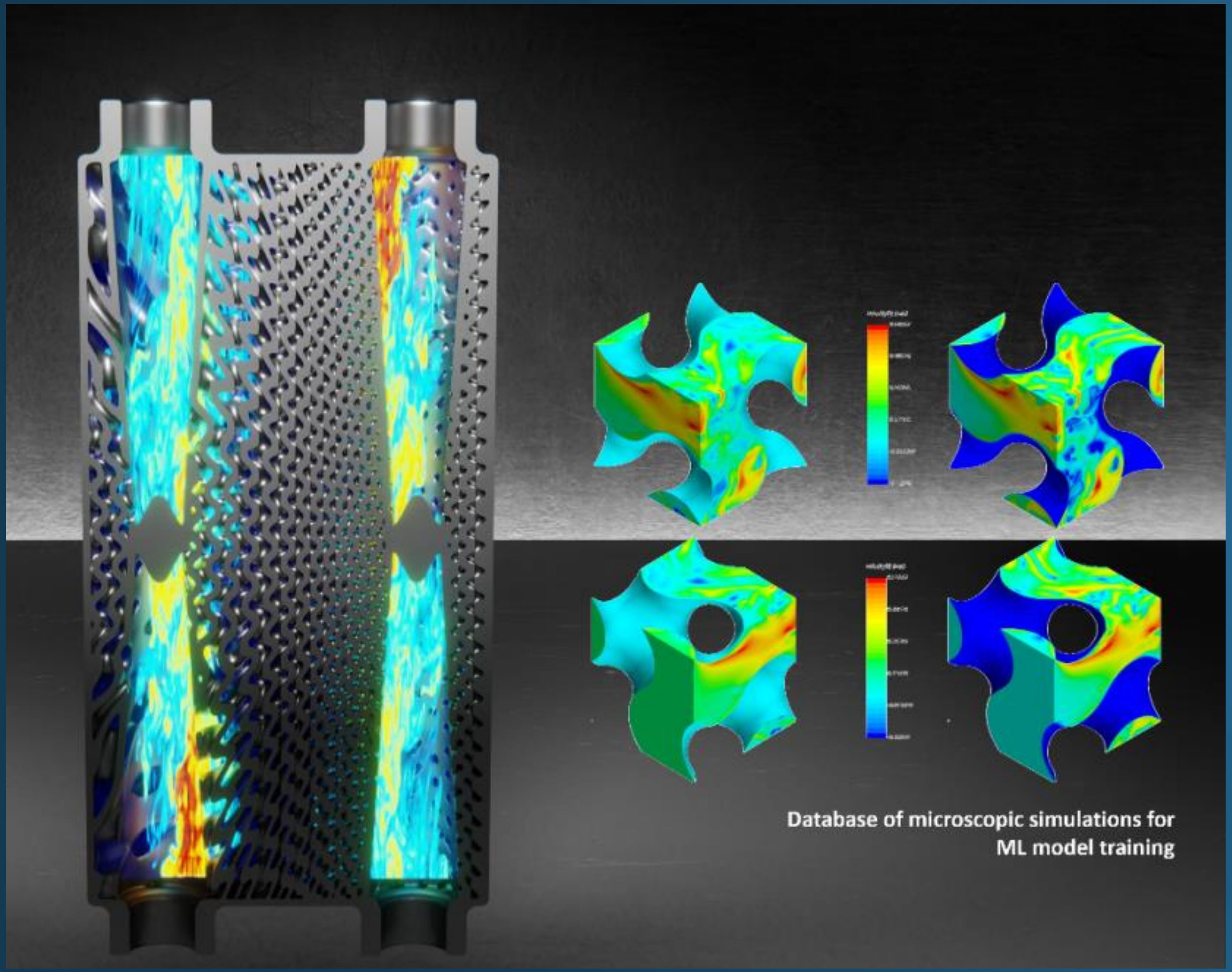
- accuracy
  - dictated by representation capability of RS.

Approximate manifold

- core of ML
- rely on parameters for definition of neighborhood

- accuracy
  - order of interpolation
  - spacing of data in parameter space
  - Affected by curse of dimensionality

Take-away points



Reduced Order Models

Less affected by CoD -> parsimonious in data
Enabler for multi-disciplinary, multi-scale problems

Intrusive -> exclusive to owners of code
Difficulty to span across use cases

DL for foundational models

Potential to generalize across different cases
Require huge amount of data to do so

Opportunity to capital intensive ventures
Barrier to all others

Thank you!

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