ESTECO
INTERNATIONAL
USERS' MEETING

um
2026

Geometric Deep Learning for Surrogate Modeling

Laura Balasso
Research Engineer

Luca Muscarà
Application Engineer

Agenda

Surrogate modeling for geometrically varying domains
Challenges in real-world scenarios

Modular non-parametric surrogate framework
Implicit geometry representation

Use case - DrivAer
Numerical setup and parametrization

End-to-End Deep Learning Approach
Integral values and fields predictions

Conclusions

Surrogate modeling for geometrically varying domains

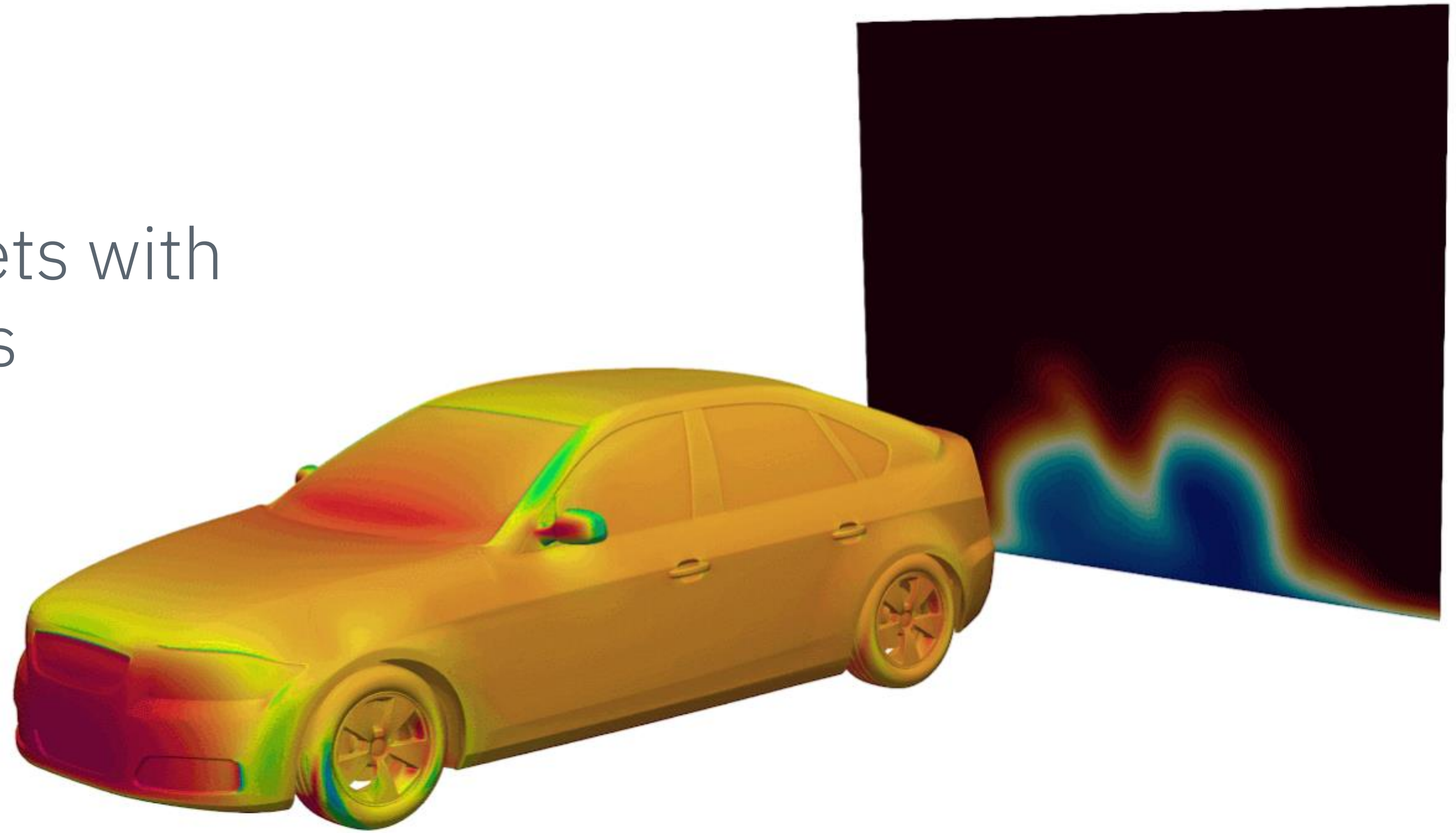
Problem Setting

Surrogate models are widely used to accelerate many-query or real time processes like design exploration, optimization and uncertainty quantification.

However, some real-world scenarios may introduce additional challenges in presence of **geometrically varying domains**.

- **Geometric parameterization:**
  Geometries may originate from legacy datasets with inconsistent or unavailable parameterizations

- **Mesh representation:**
  Meshes may lack point-to-point correspondence, or even differ in topology



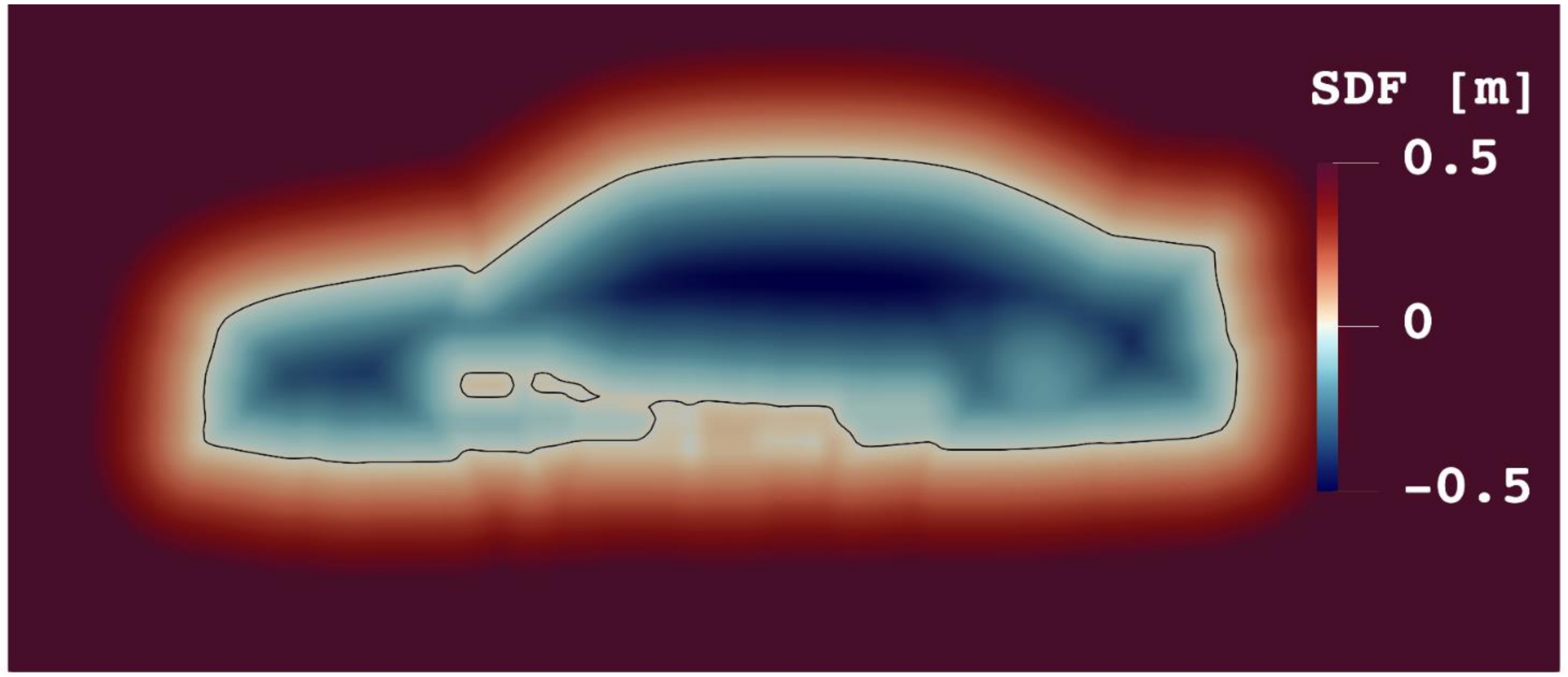
um 2026

A modular non-parametric surrogate framework

Goal: geometric deep learning techniques to develop a **mesh- and parametrization-free framework**

Our approach:

- implicitly represents geometries through their **Signed Distance Functions** (SDFs)



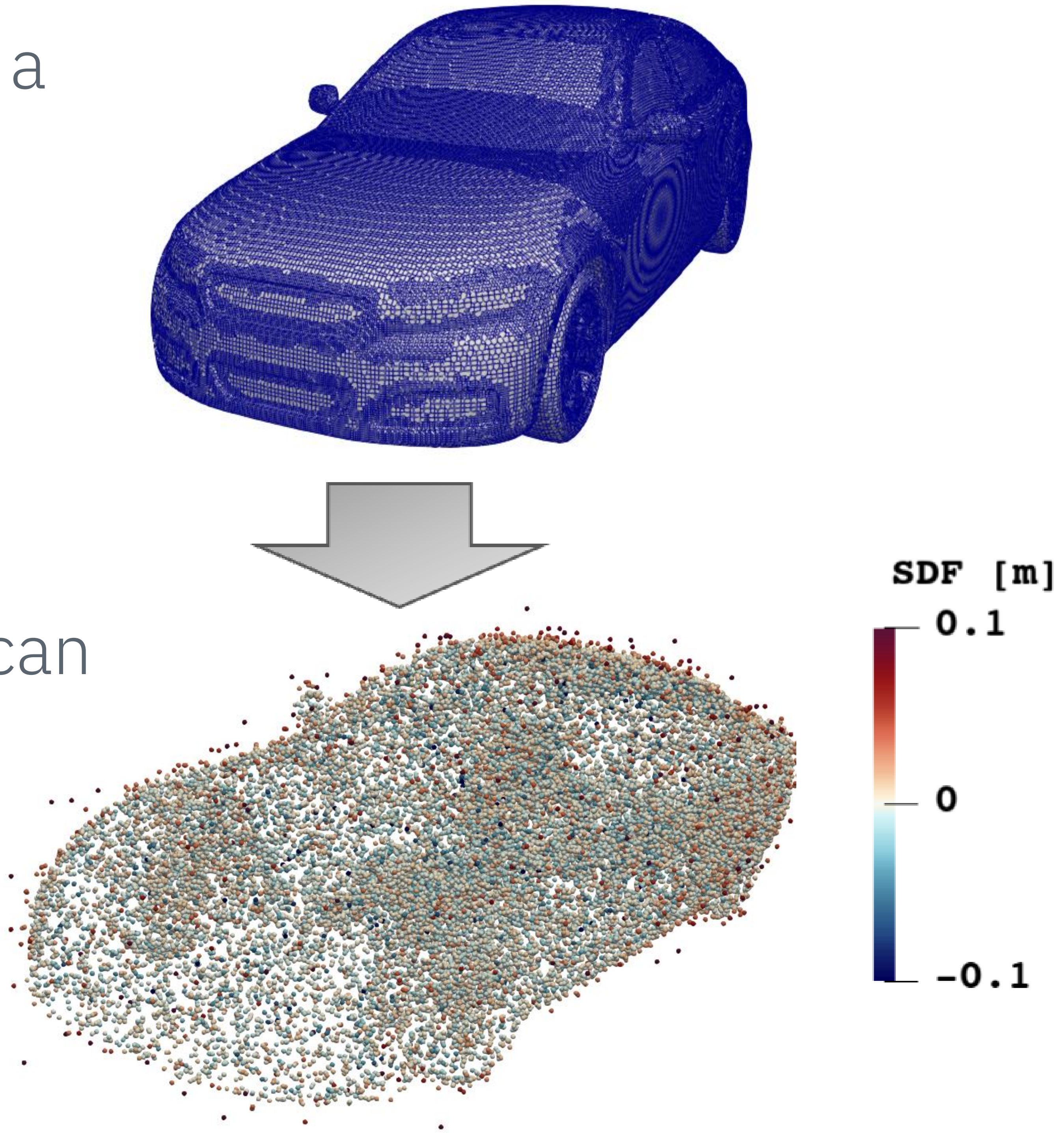
um 2026

A modular non-parametric surrogate framework

Goal: geometric deep learning techniques to develop a **mesh- and parametrization-free framework**

Our approach:

- implicitly represents geometries through their **Signed Distance Functions** (SDFs)
- enables a **mesh-independent** representation that can be generated **directly from CAD models**

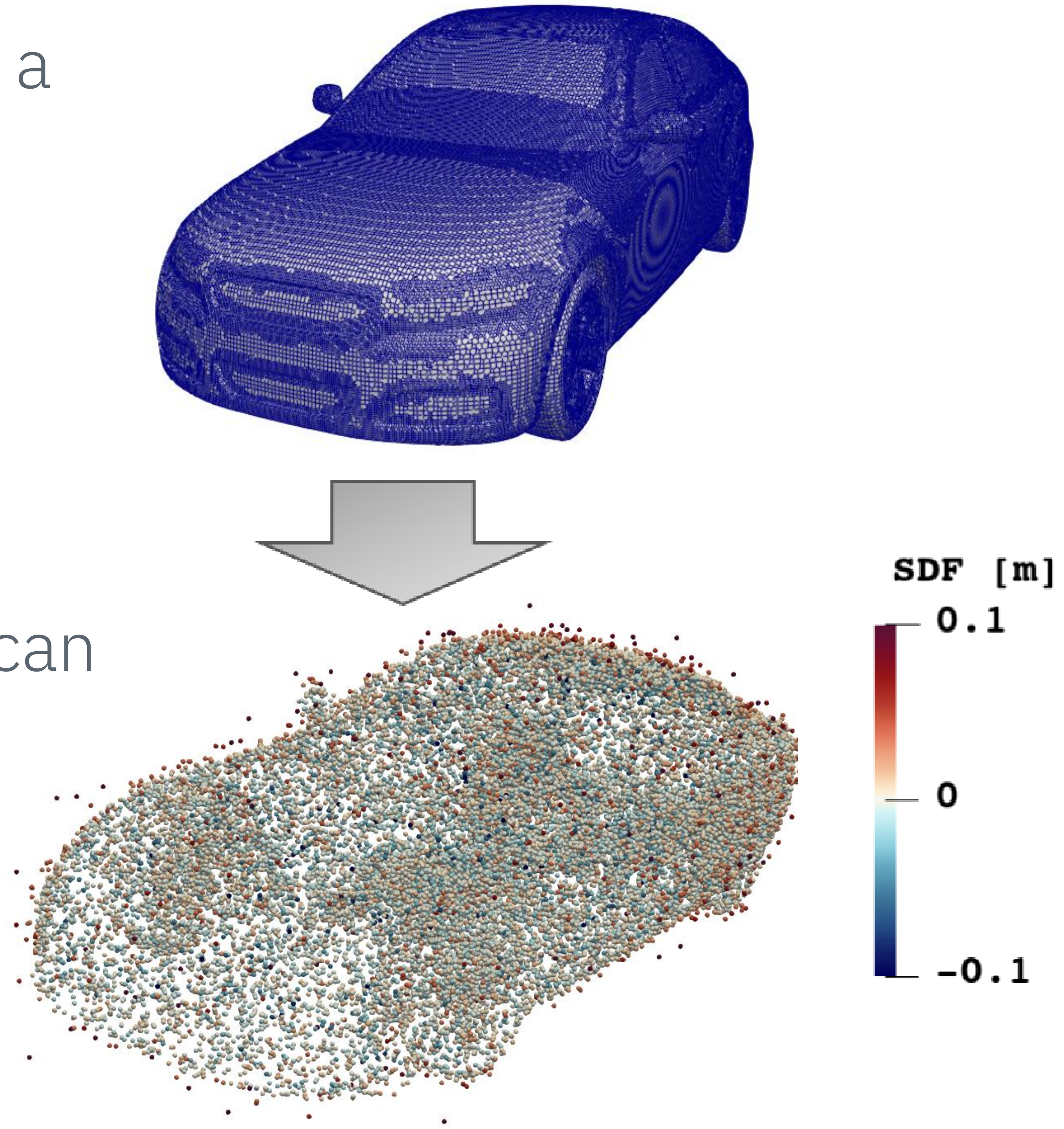


A modular non-parametric surrogate framework

Goal: geometric deep learning techniques to develop a **mesh- and parametrization-free framework**

Our approach:

- implicitly represents geometries through their **Signed Distance Functions** (SDFs)
- enables a **mesh-independent** representation that can be generated **directly from CAD** models
- **learns a compact latent parametrization** directly from the SDFs

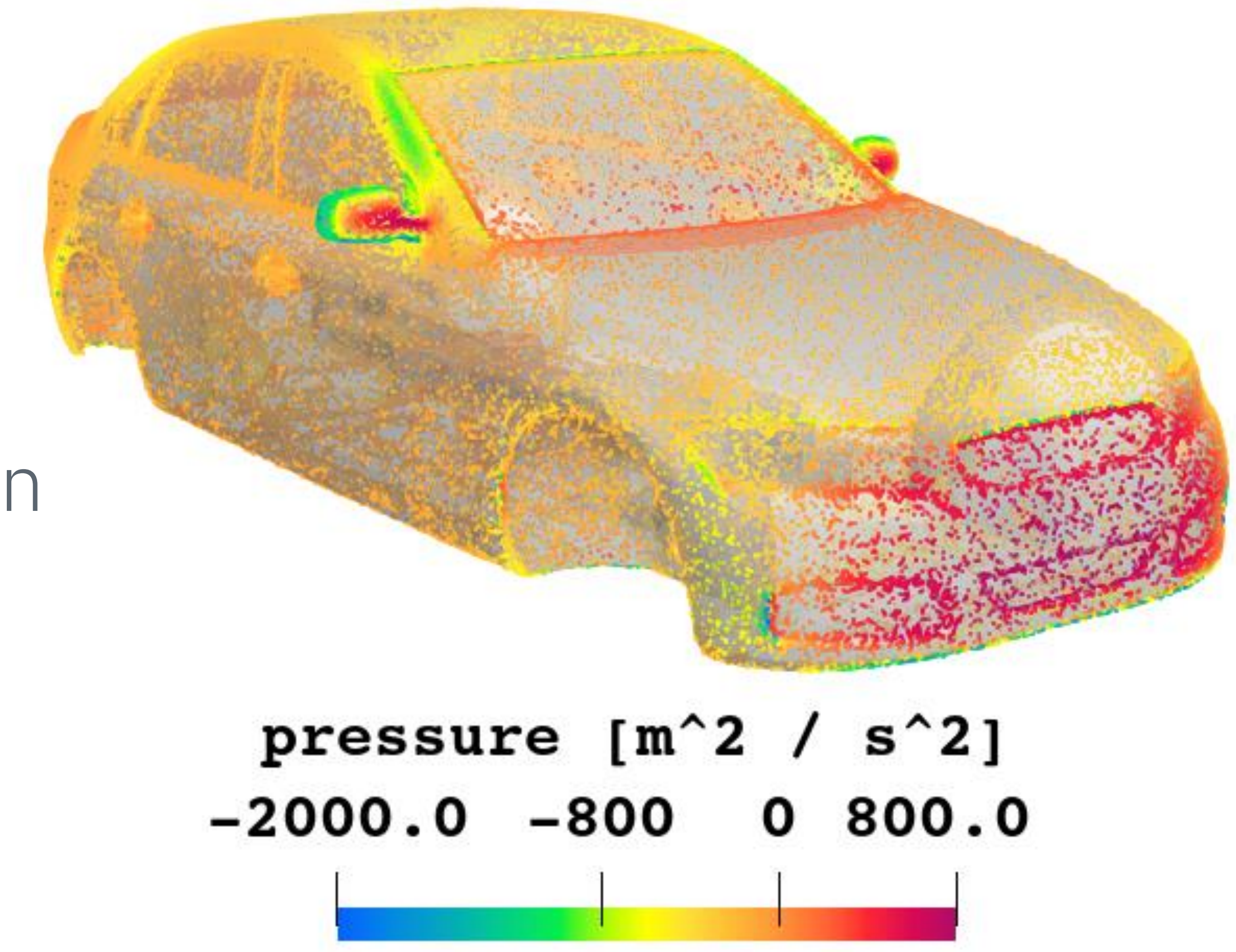


A modular non-parametric surrogate framework

Goal: geometric deep learning techniques to develop a **mesh- and parametrization-free framework**

Our approach:

- implicitly represents geometries through their **Signed Distance Functions** (SDFs)
- enables a **mesh-independent** representation that can be generated **directly from CAD** models
- **learns a compact latent parametrization** directly from the SDFs
- **predicts solution fields** at arbitrary space/time locations from the latent representations



Implicit geometry representation

Main idea: a deep neural network learns a compact shape encoding from the Signed Distance Function representation of the geometry.

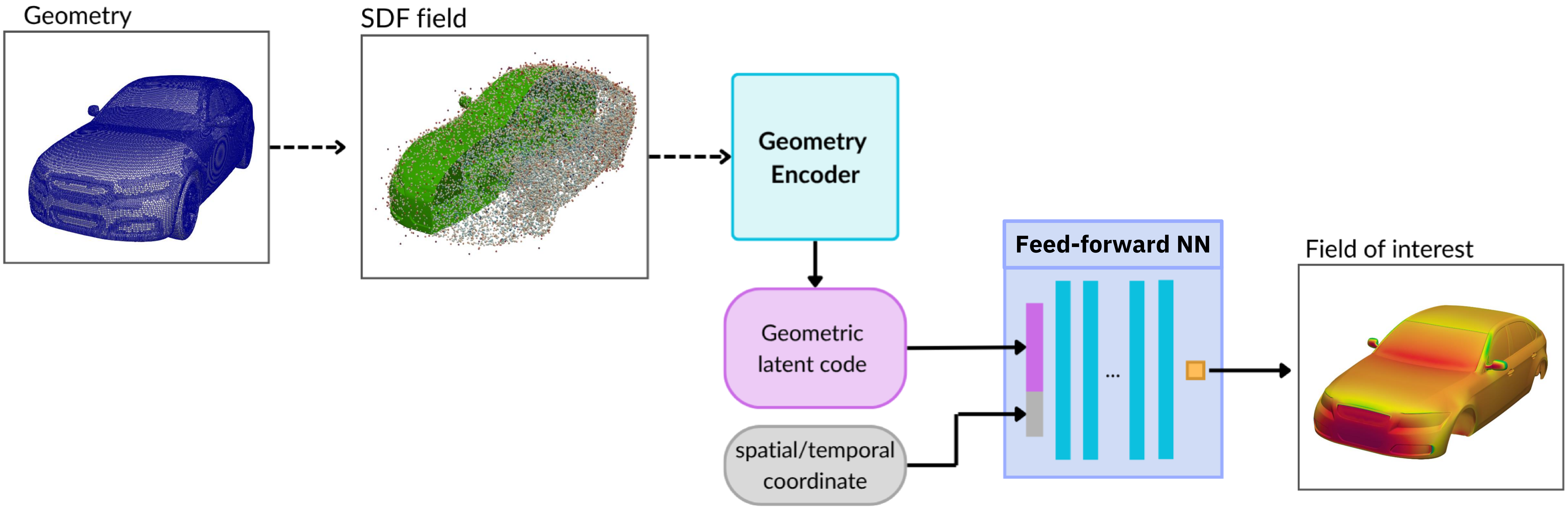
Training

- **Trained on a collection of shapes** represented as Signed Distance Functions (SDFs)
- Learns a fixed-size vector (***latent code***) that **encodes the shape of each geometry**.

Inference

- Finds the latent code **representing a new geometry**
- Solved as an **optimization problem** (almost real-time)

Complete workflow

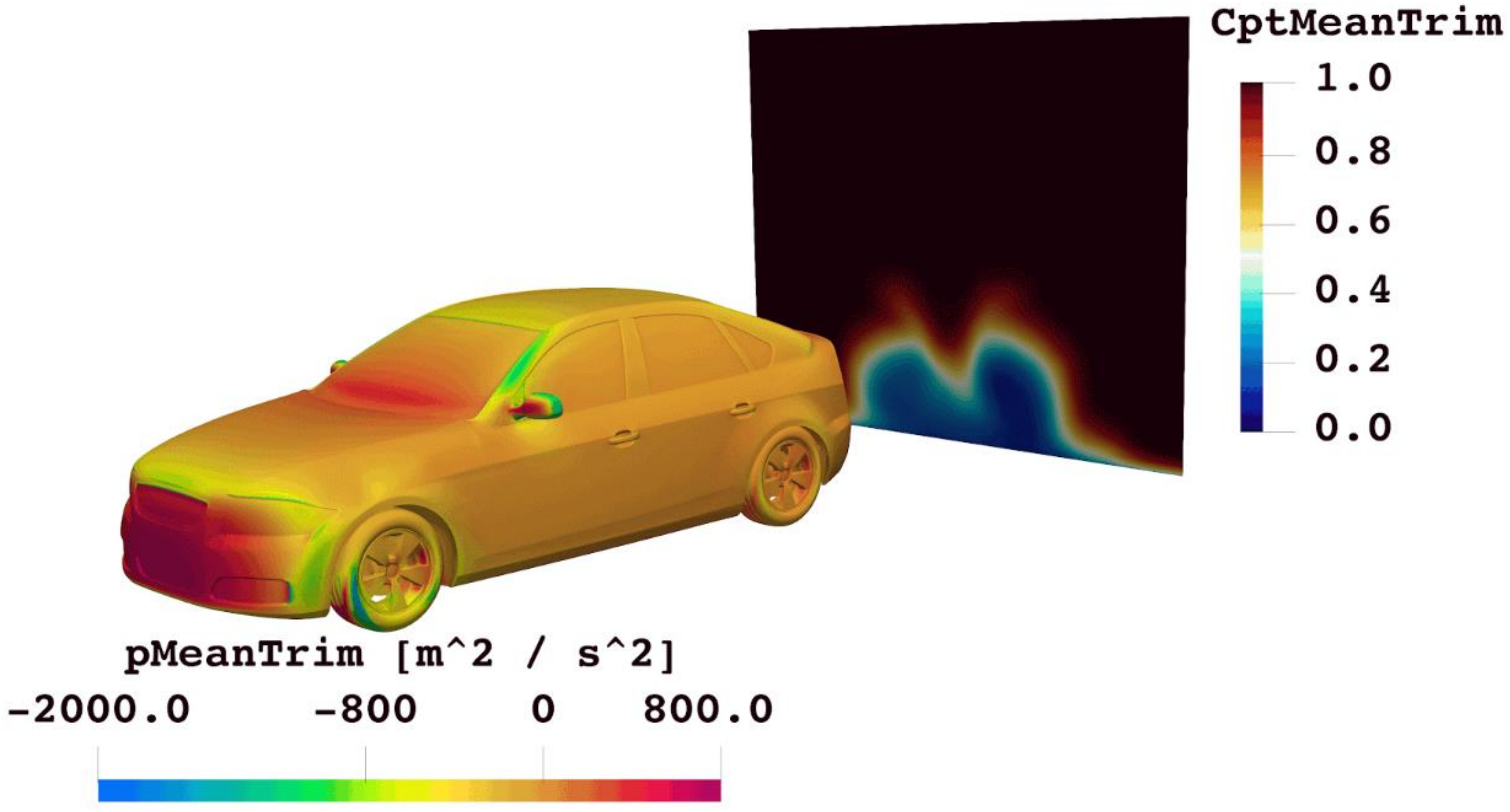


um 2026

USE CASE - DrivAer

DrivAer Notchback

Numerical Setup & Parameterization



Public Dataset available on Hugging Face:
[neashton/drivaerml · Datasets at Hugging Face]

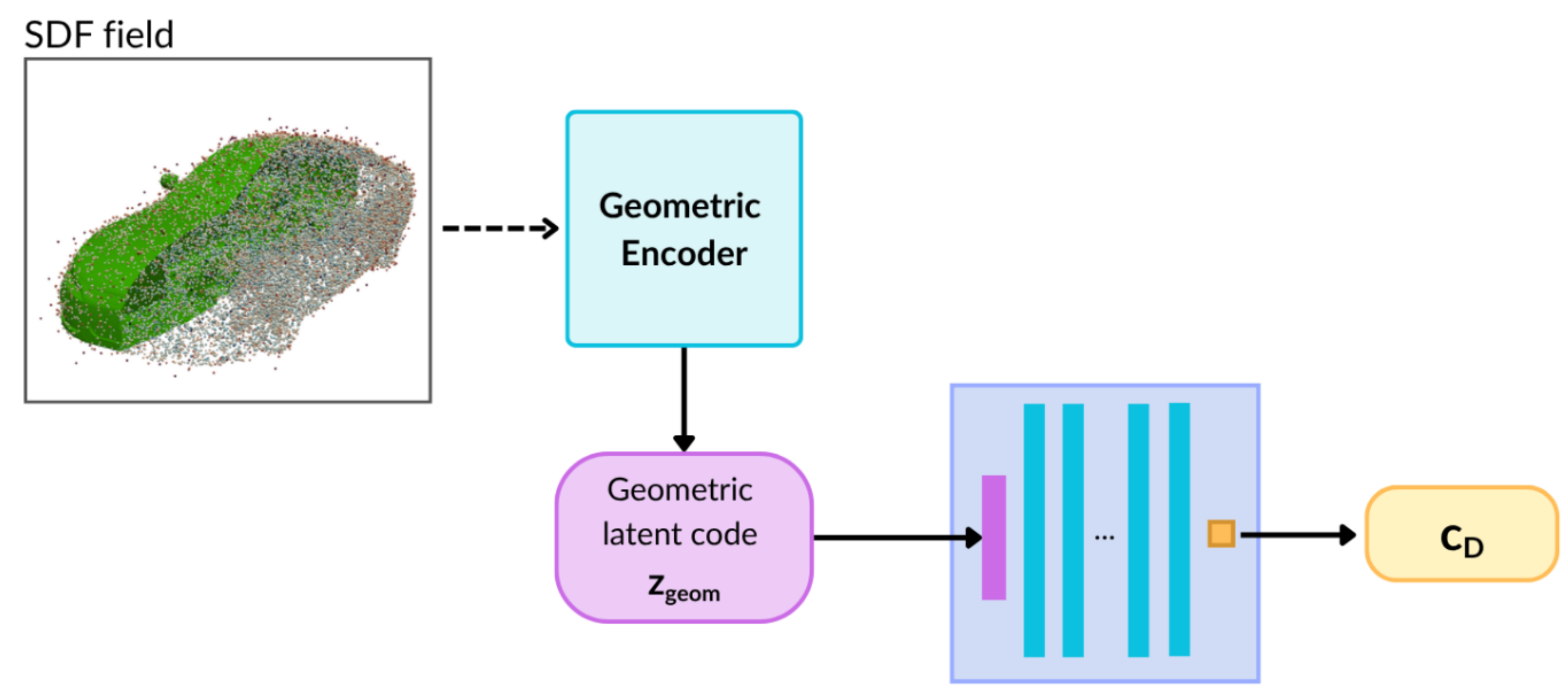
Numerical Setup	
Flow Regime	Turbulent Incompressible Flow (DDES with WF)
Mesh Size	~160 million cells
Convergence	±1.5 drag counts

Geometry & DOE	
Morphing Param.	16
DOE Samples	500 (MELS algorithm)
Runtime	**~40 h (1,536 CPU cores)**

um 2026

End-to-End Deep Learning Approach

Modular Workflow

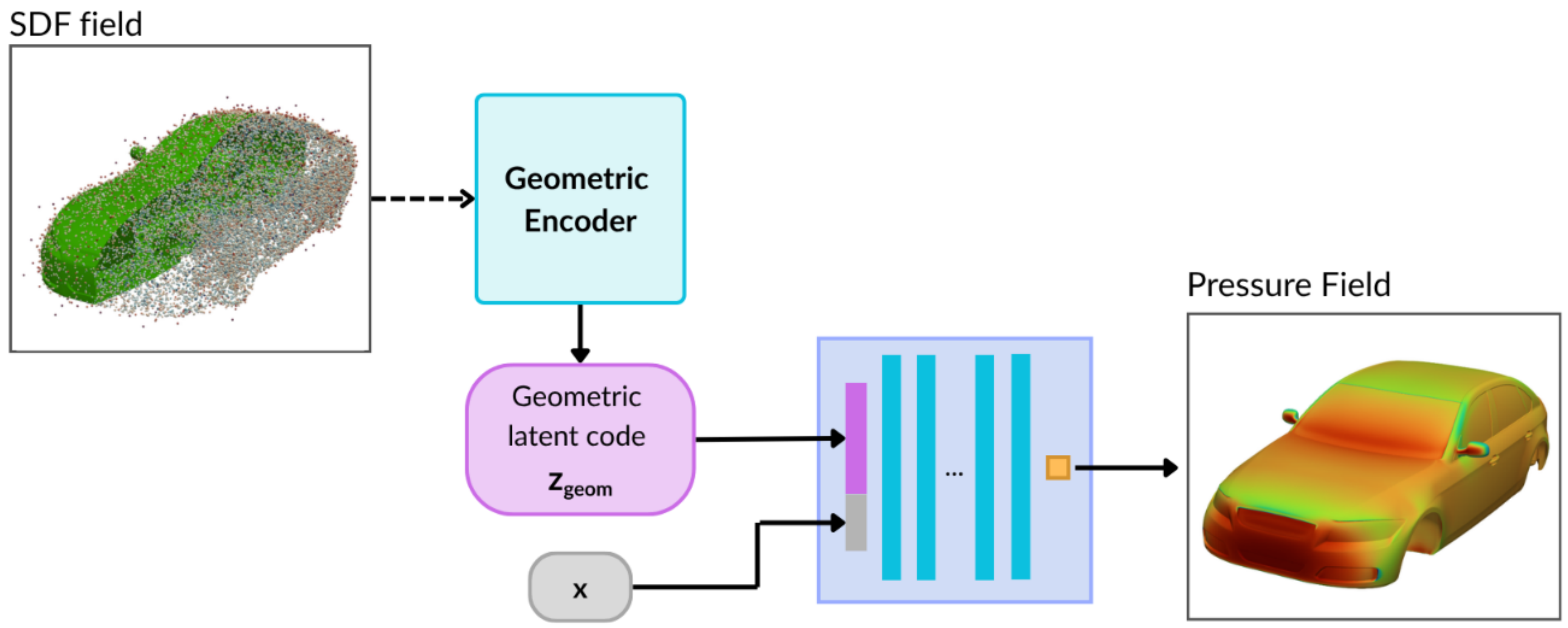


Workflow Overview

1. Integral Workflow

End-to-End Deep Learning Approach

Modular Workflow

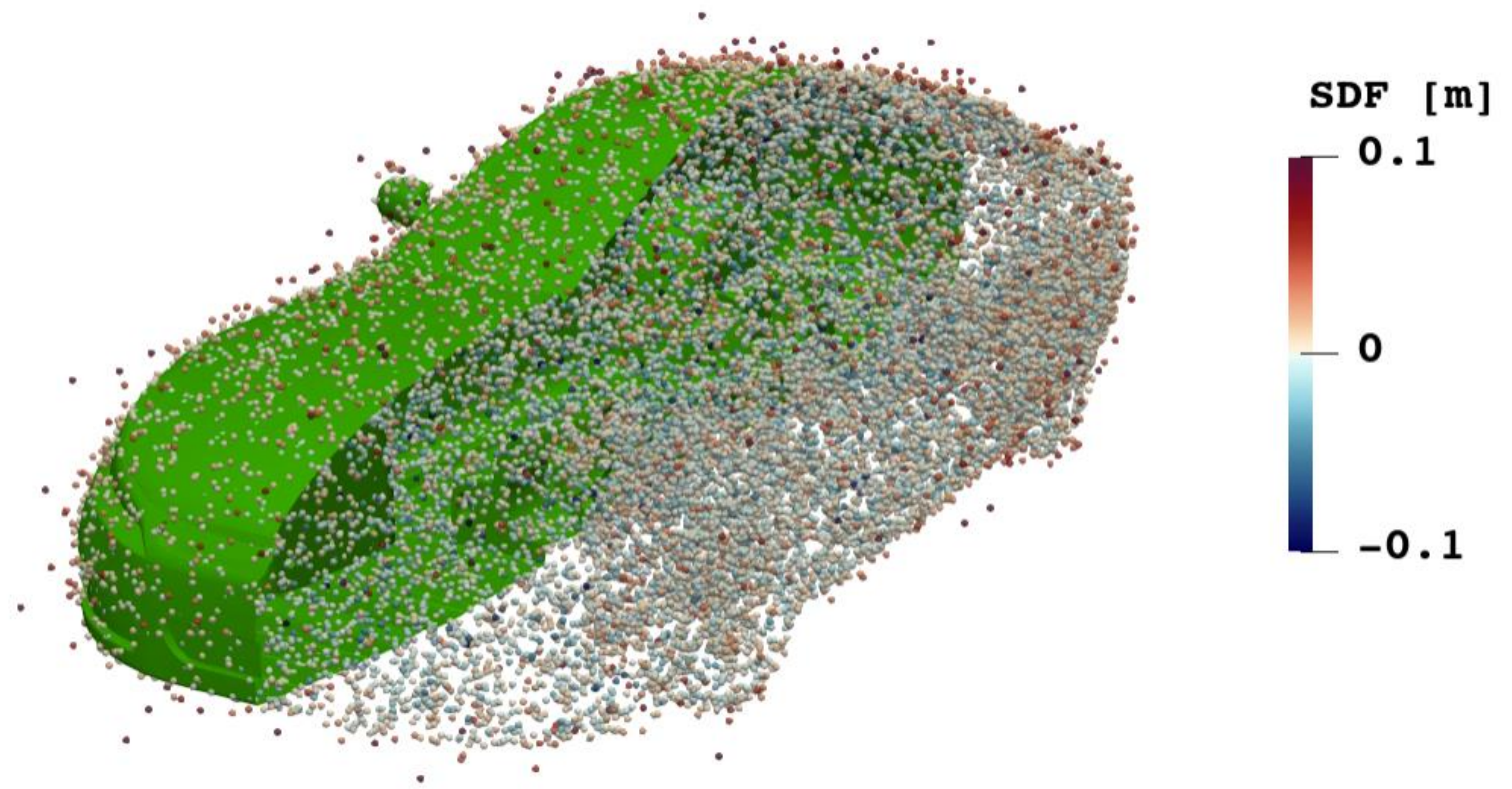


Workflow Overview

1. Integral Workflow
2. Field Workflow

Signed Distance Function

Geometry representation

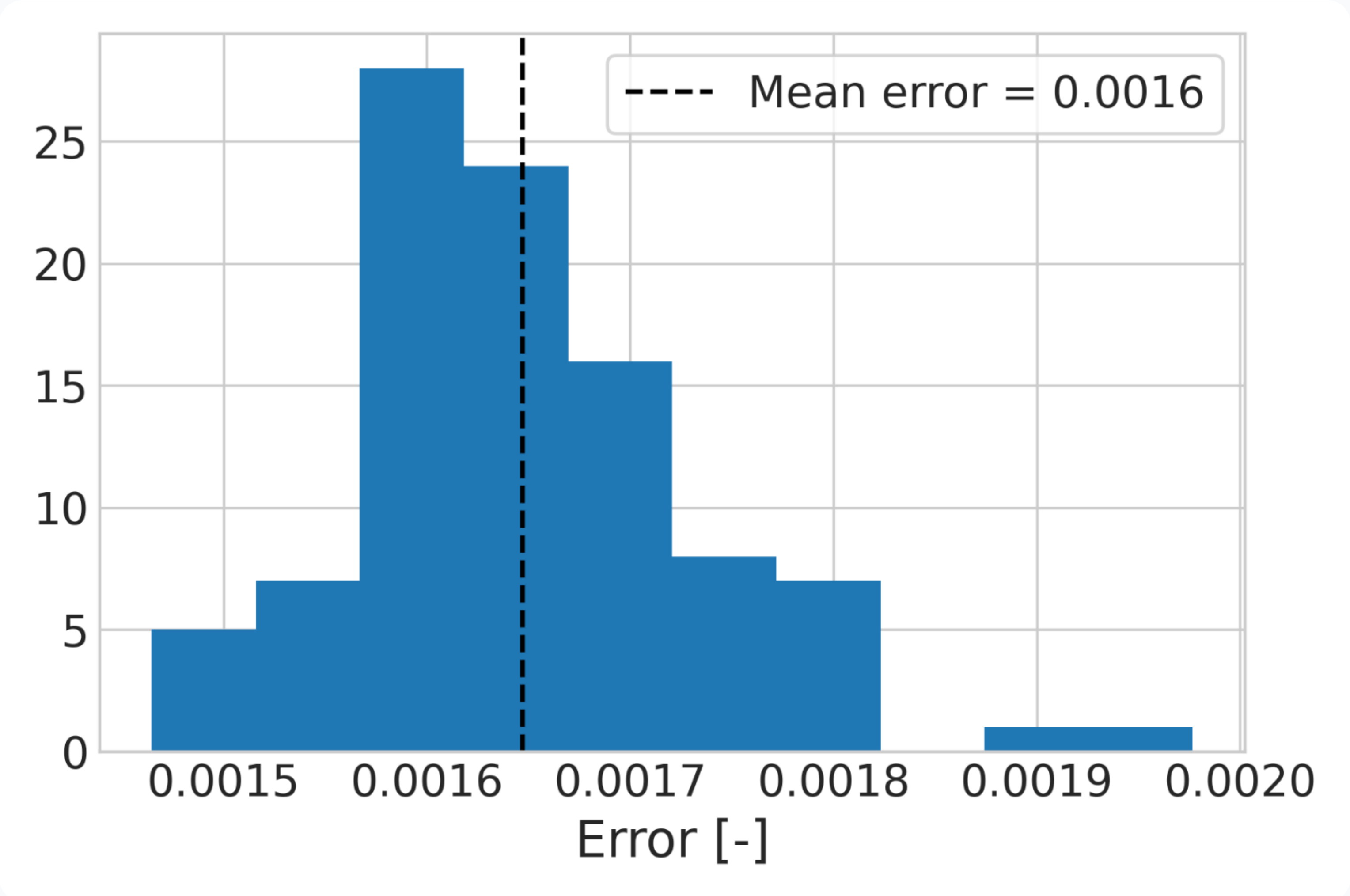


Given a point cloud, the **SDF** provides an **implicit representation** of the geometry by assigning to each point its distance from the object surface.

- **35K points** for each geometry
- dense sampling near the surface

Geometric Encoder

Test Error and Computational Performance



Distribution of mean reconstruction error on unseen samples

Training Setup

Hardware
NVIDIA A10 GPU
24 GB GDDR6, Ampere

Train / Test split
80 / 20
Samples percentage

Data Scale
~14.4M points
Processed per epoch

Model Size
1.06M
Network parameters

Performance

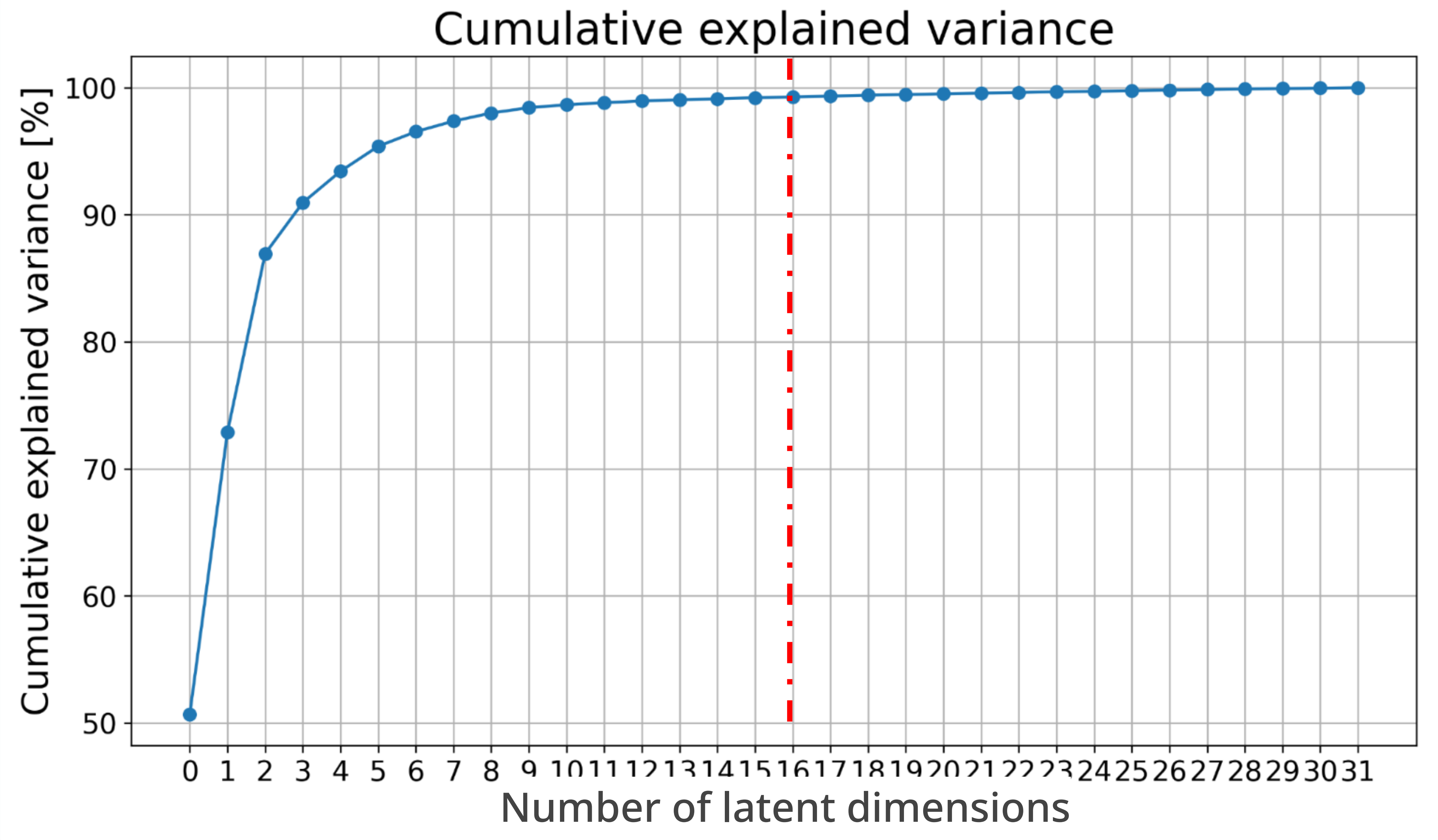
~10.28 s
per epoch

~5h 42m
total training time
(2000 epochs)

um 2026

Geometric Encoder

Dimensionality of the Learned Representation



Key Insight

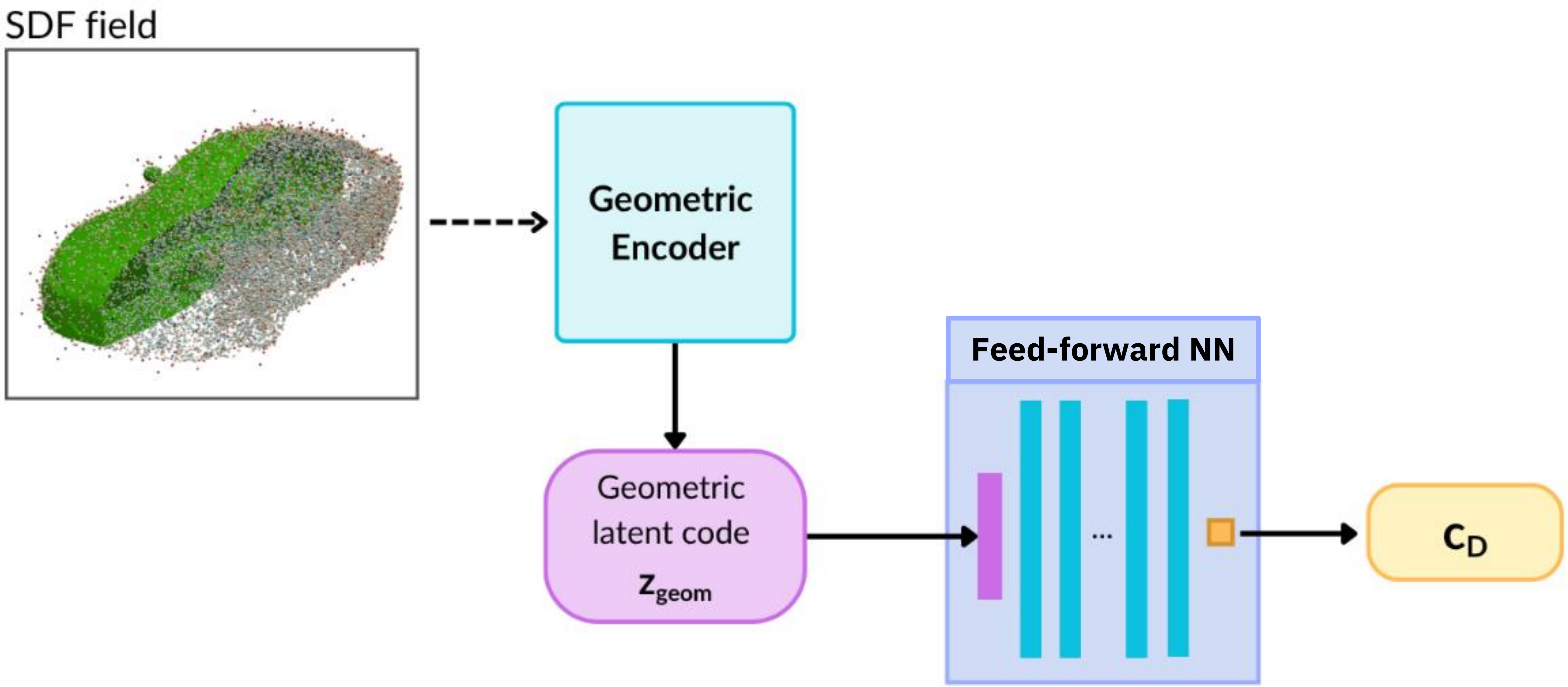
Our model reveals that **~16 latent dimensions** are needed to explain almost all the variance.

This is achieved despite the model learning a more complex **32-dimensional representation**.

um 2026

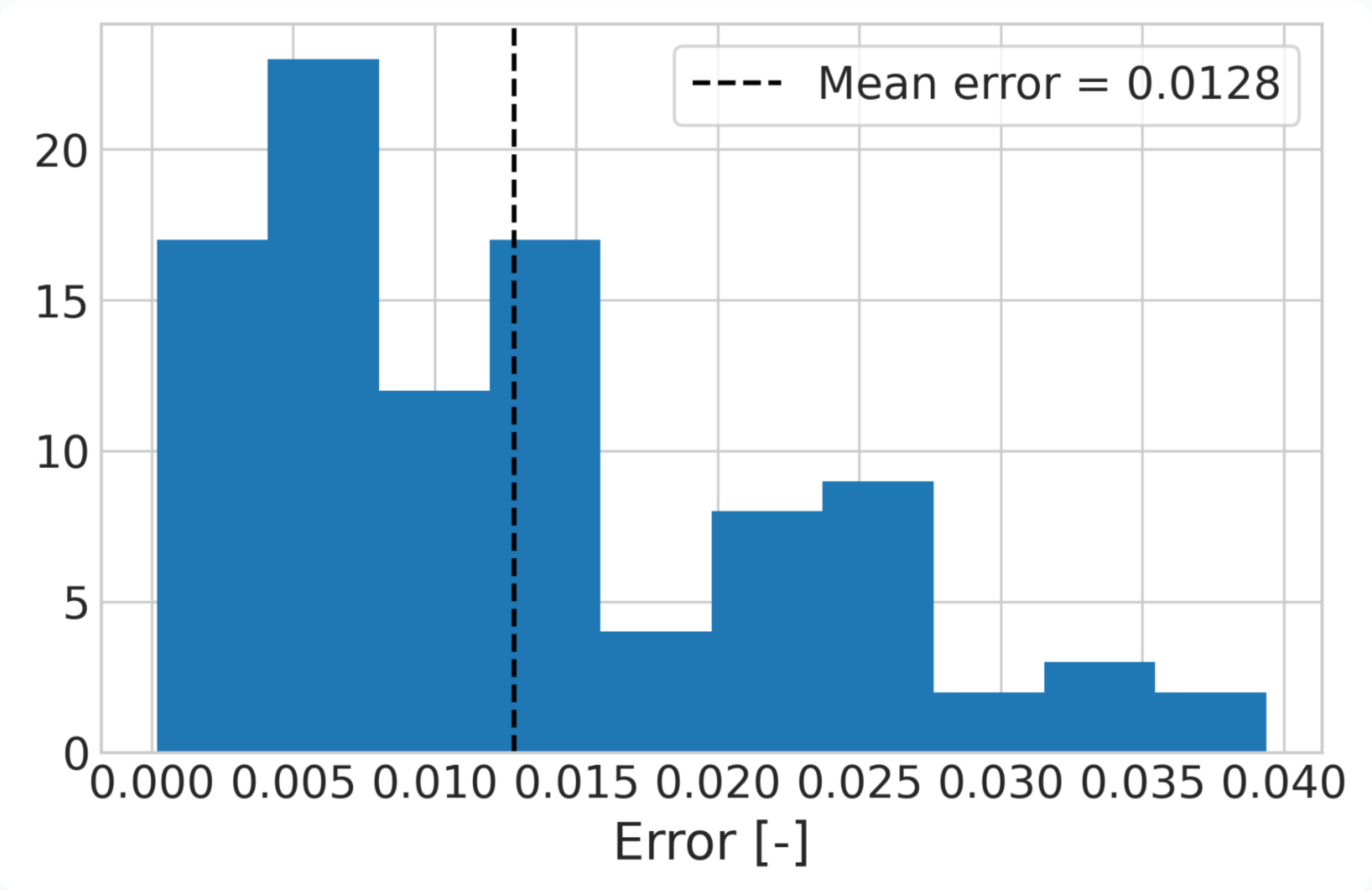
Drag Coefficient Prediction

Integral prediction Workflow



Drag Coefficient Prediction

Test Error and Computational Performance



Distribution of relative error on unseen samples

Training Setup

Hardware
CPU

Train / Test split
80 / 20
Samples percentage

Data Scale
310 cases
Processed per epoch

Model Size
593
Network parameters

Performance

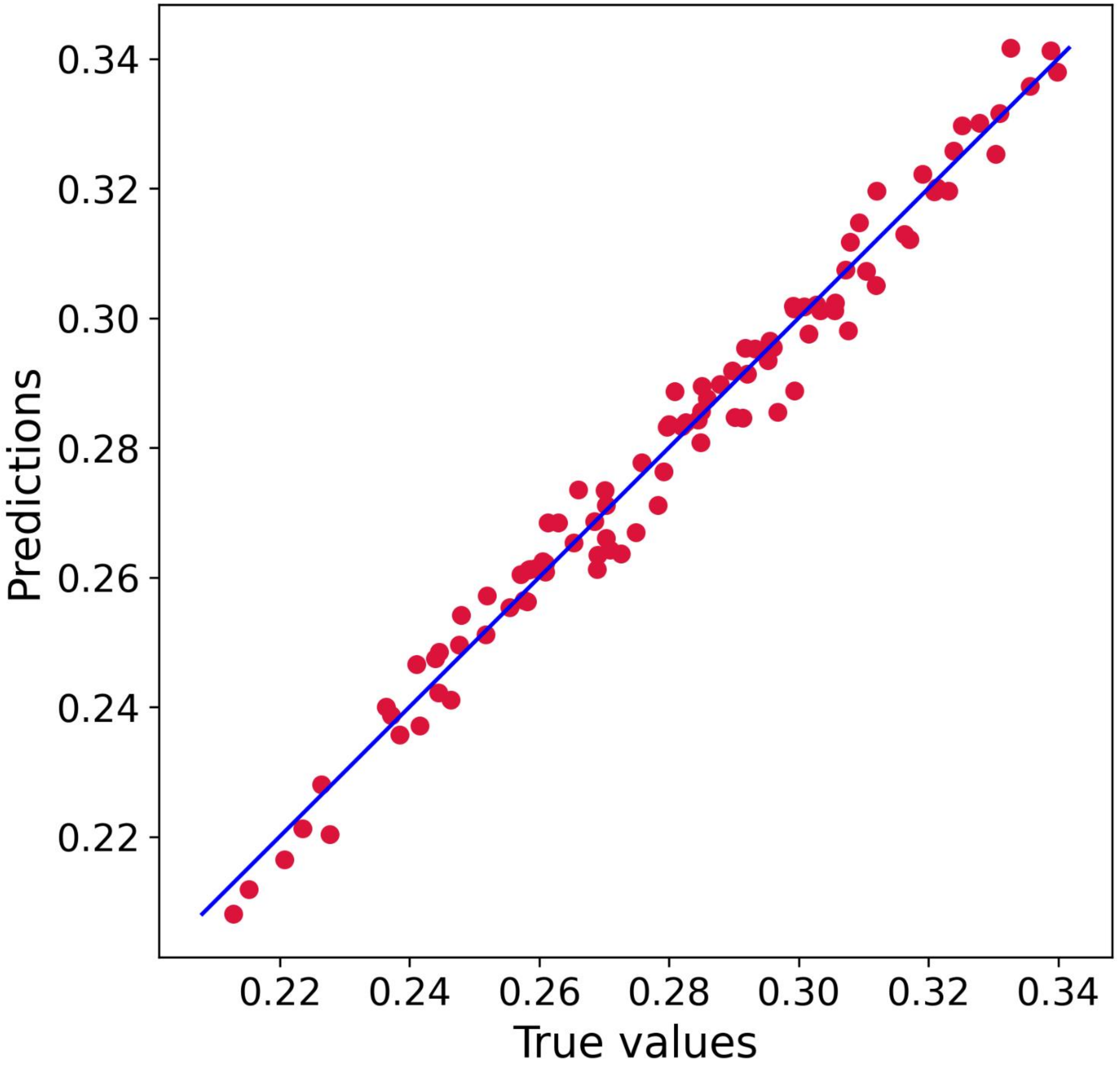
~0.1 s
per epoch

~3min 32s
total training time
(2000 epochs)

um 2026

Drag Coefficient Prediction

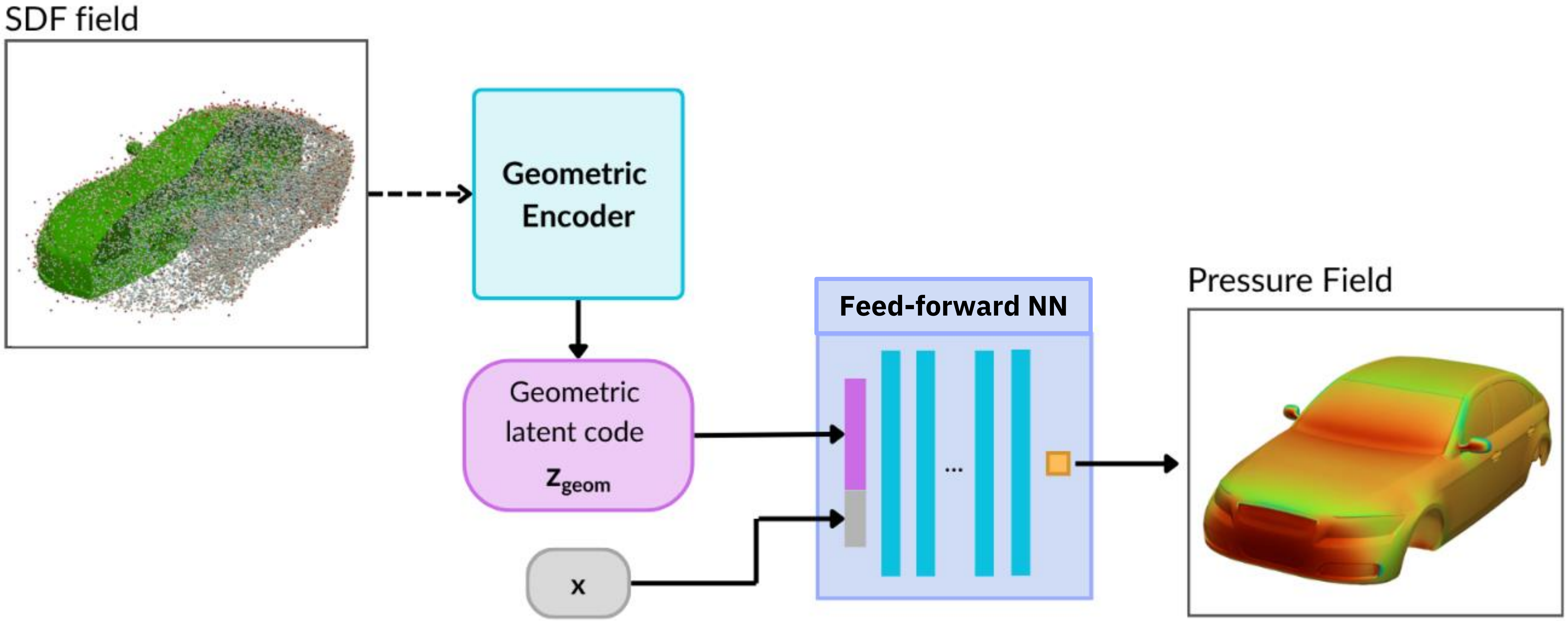
Prediction vs Ground Truth



Comparison of **Ground Truth** vs **Prediction** for the drag coefficient calculated over the test dataset.

Pressure Field Prediction

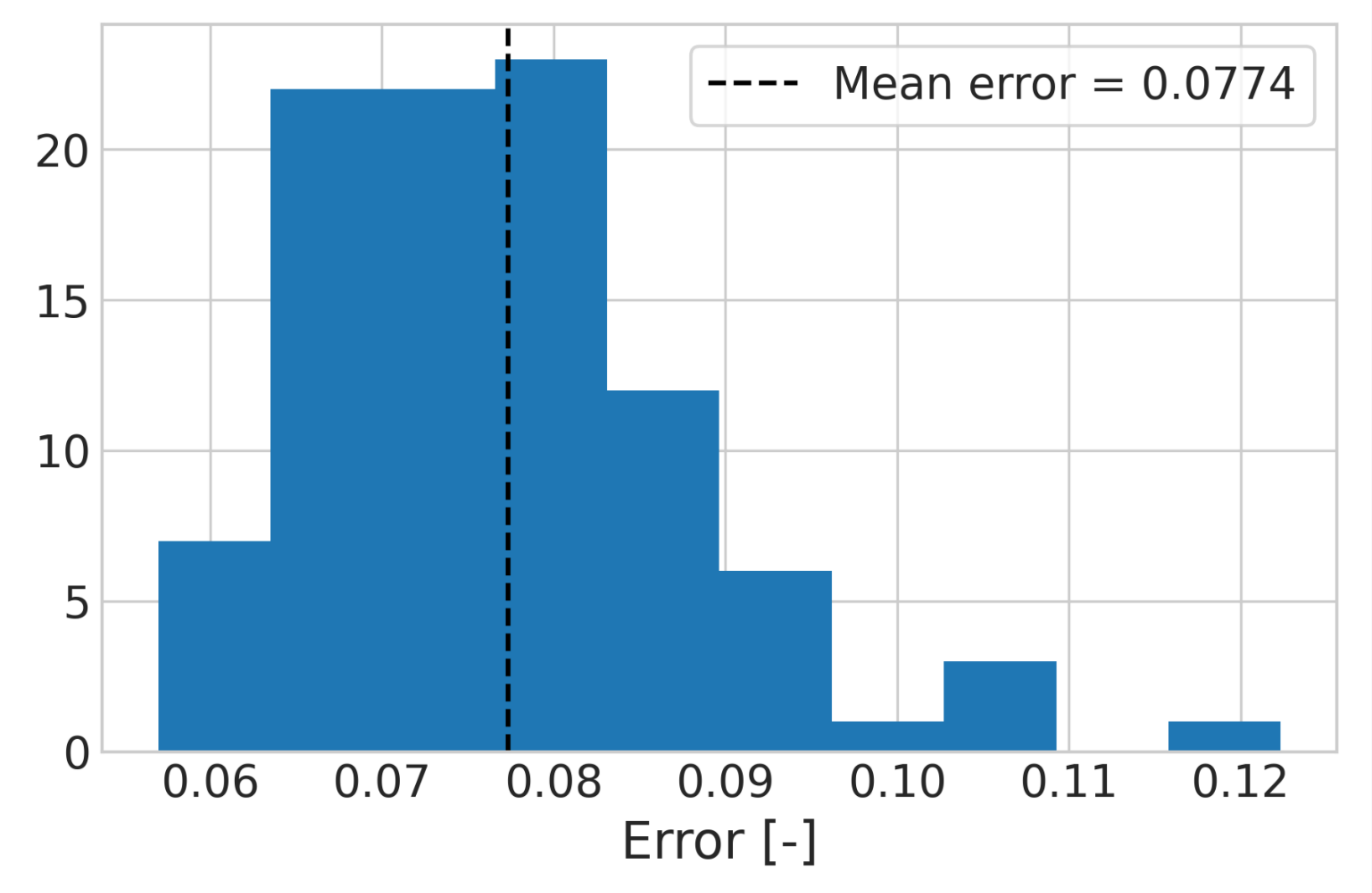
Field prediction Workflow



um 2026

Pressure Field Prediction

Test Error and Computational Performance



Distribution of mean relative error on unseen samples

Training Setup

Hardware
NVIDIA A10 GPU
24 GB GDDR6, Ampere

Train / Test split
80 / 20
Samples percentage

Data Scale
~15.5M points
Processed per epoch

Model Size
1.34M
Network parameters

Performance

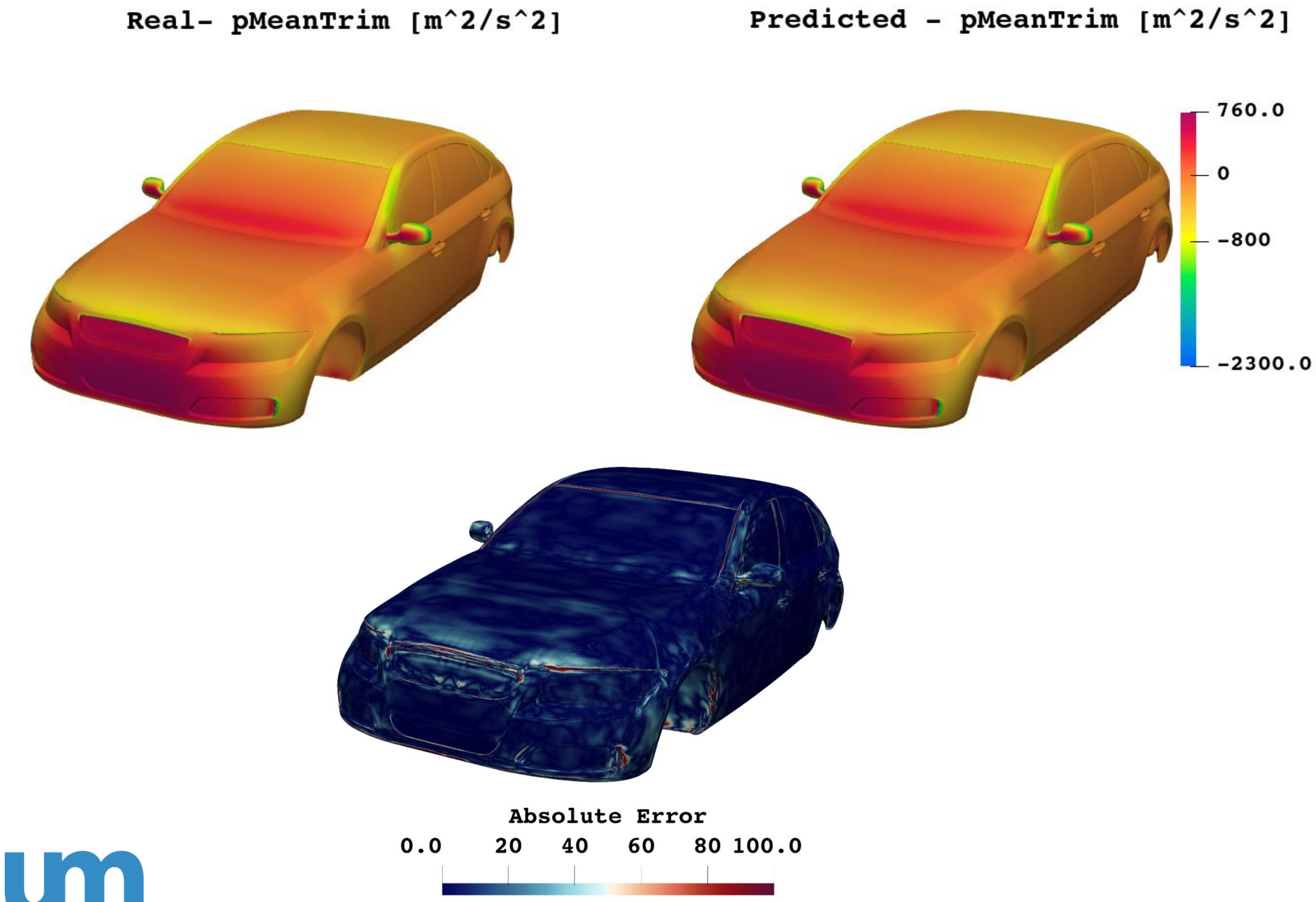
~16.11 s
per epoch

~8h 57m
total training time
(2000 epochs)

um 2026

Pressure Field Prediction

Prediction vs Ground Truth — Median Error Case

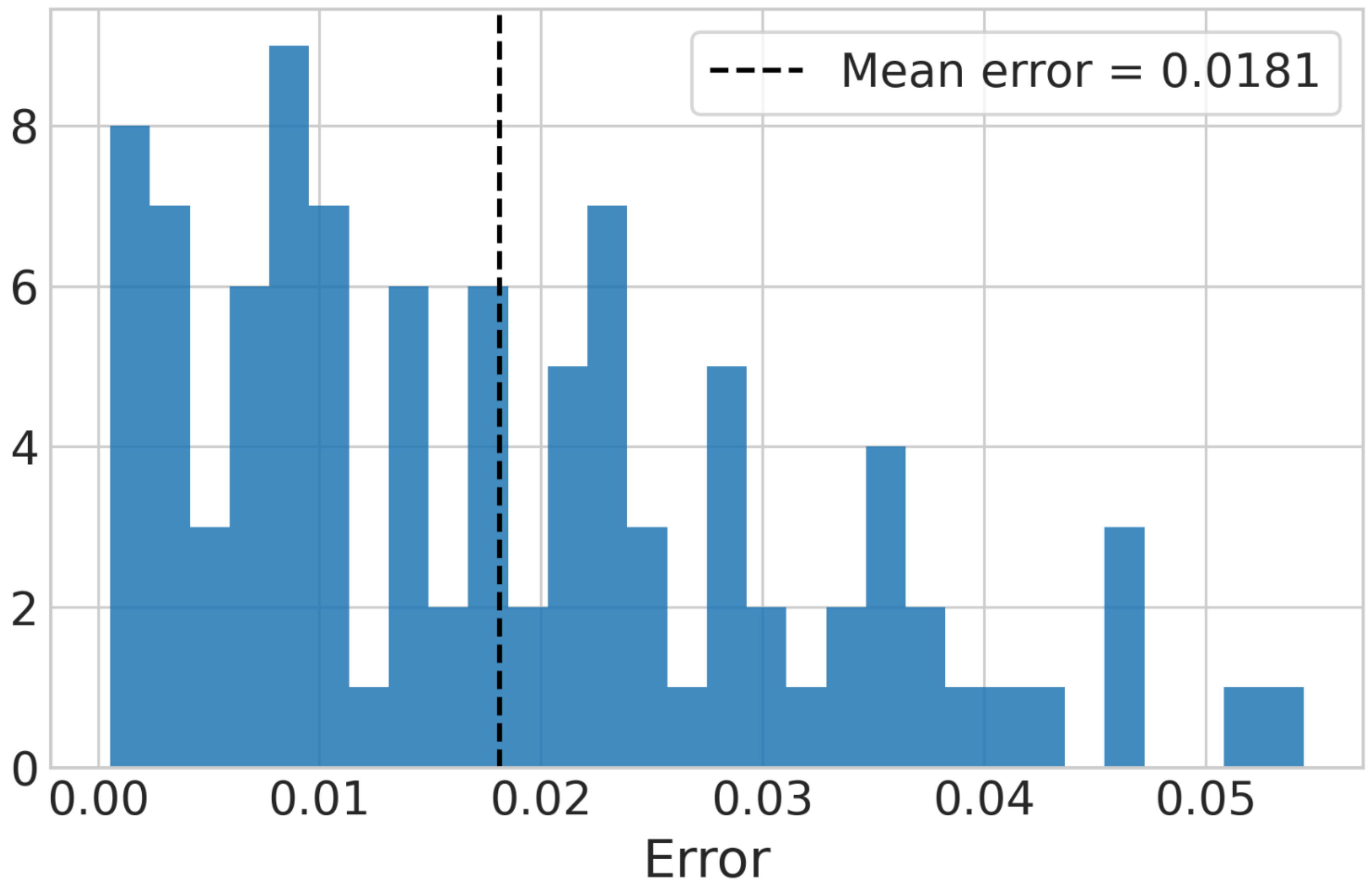


Surface pressure field comparison (**ground truth** vs **prediction**), shown for a case representative of the **median test error (≈ 7.56%).**

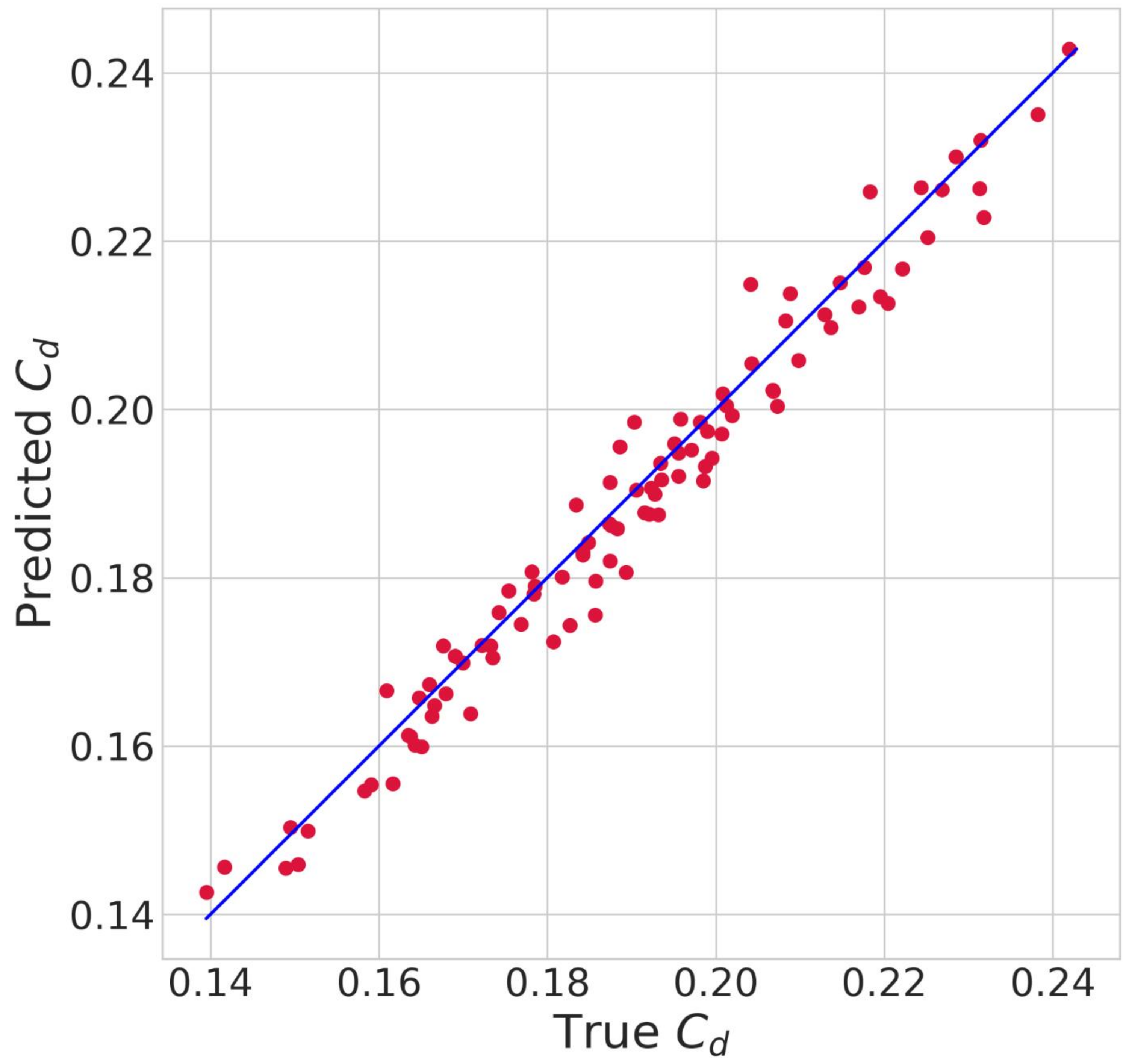
um 2026

Pressure Field Prediction → Drag Coefficient

Drag Coefficient Evaluation and Relative Errors



Distribution of relative error on unseen samples



um 2026

CONCLUSION

- We presented a **surrogate framework for geometrically varying domains** without mesh correspondence or explicit parametrization.
- SDF representations enable **compact geometry encoding** directly from point clouds.
- The workflow **accurately predicts both integral quantities and flow fields** on unseen geometries.
- Results on the DrivAer benchmark highlight the potential of geometric deep learning for industrial CFD surrogate modeling.

um
2026

Thank you

esteco.com