luminary

October 9, 2026

AutoCFD5

Luminary contributions to the AI/ML TFG

Luminary: Physics AI Platform

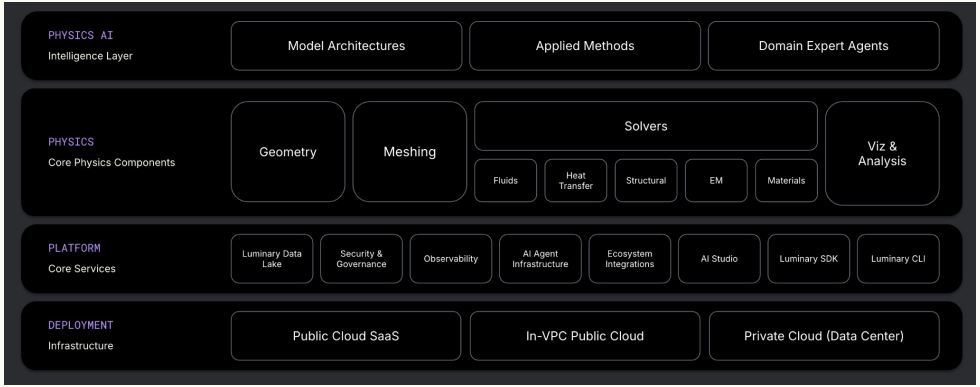
Platform for training & deploying Physics AI models

Multiple deployment form factors

Full data generation and data ingestion support

Host multiple AI model architectures
- DoMINO
- GeoTransolver
- SMART
- more coming shortly

Agentic and SDK interfaces



Luminary platform capabilities diagram

Luminary: Physics AI Platform

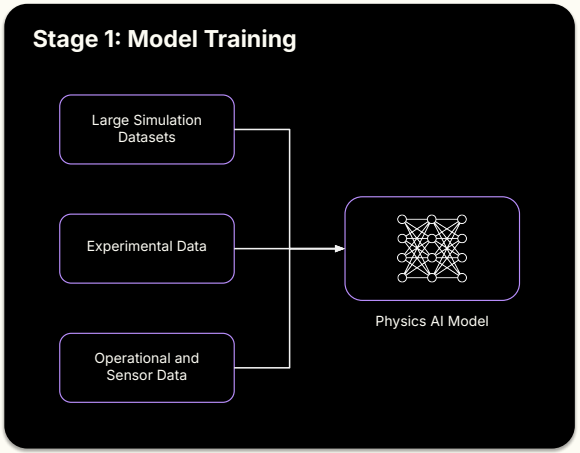
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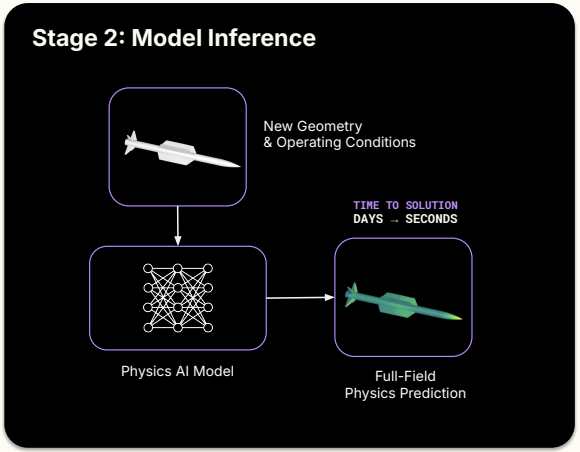
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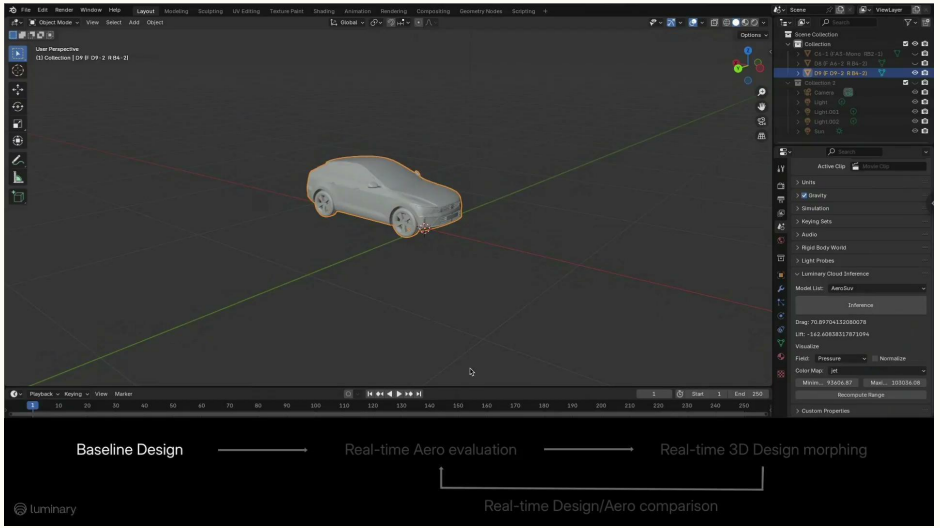
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Outline

Core Content

Base Model Architecture: Luminary-SMART with Out Of Distribution (OOD) detection & UQ

From-scratch results

Fine tuning results
- from adjacent dataset: SHIFT-SUV
- from lower-fidelity: RANS checkpoint

Quick Hits

Physics-Informed ML
- data assimilation: sparse measurement corrected predictions
- Physics-informed loss formulations

Luminary-SMART

Architecture type: Transformer based

Point cloud inputs at inference

Key benefits
- inference-time resolution independence
- scalable for training

Technical blog:
https://luminary.ai/resources/luminary-smart-the-new-state-of-the-art-model-architecture-for-large-physics-models/

SMART: Scalable Mesh-free Aerodynamic Simulations from Raw Geometries using a Transformer-based Surrogate Model

Jan Hagnberger [1] Mathias Niepert [1 2 3]

Abstract

Machine learning–based surrogate models have emerged as more efficient alternatives to numerical solvers for physical simulations over complex geometries, such as car bodies. Many existing models incorporate the simulation mesh as an additional input, thereby reducing prediction errors. However, generating a simulation mesh for new geometries is computationally costly. In contrast, mesh-free methods, which do not rely on the simulation mesh, typically incur higher errors. Motivated by these considerations, we introduce SMART, a neural surrogate model that predicts physical quantities at arbitrary query locations using only a point-cloud representation of the geometry, without requiring access to the simulation mesh. The geometry and simulation parameters are encoded into a shared latent space that captures both structural and parametric characteristics of the physical field. A physics decoder then attends to the encoder's intermediate latent representations to map spatial queries to physical quantities. Through this cross-layer interaction, the model jointly updates latent geometric features and the evolving physical field. Extensive experi-

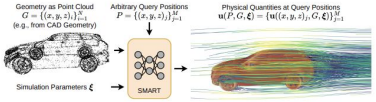


Figure 1. The proposed SMART model maps a geometry G, represented as a point cloud, and simulation parameters ξ to physical quantities (e.g., surface pressure and velocity in the volume) for arbitrary query positions P without relying on the simulation mesh.

craft bodies rely on Computational Fluid Dynamics (CFD) simulations to assess aerodynamic properties such as drag and lift coefficients. Traditional design pipelines depend on numerical solvers for these simulations, which are computationally expensive and time-consuming, significantly slowing the iterative design process.

Machine Learning (ML) is increasingly used to accelerate the solution process of Partial Differential Equations (PDEs) and physical simulations (Lu et al., 2019; Li et al., 2021; 2023c; Serrano et al., 2024; Hagnberger et al., 2026). ML-based methods offer several advantages over traditional numerical solvers, including efficient inference and applicability even when the underlying physics is partially unknown (Tompson et al., 2017; Li et al., 2021). Recent advances

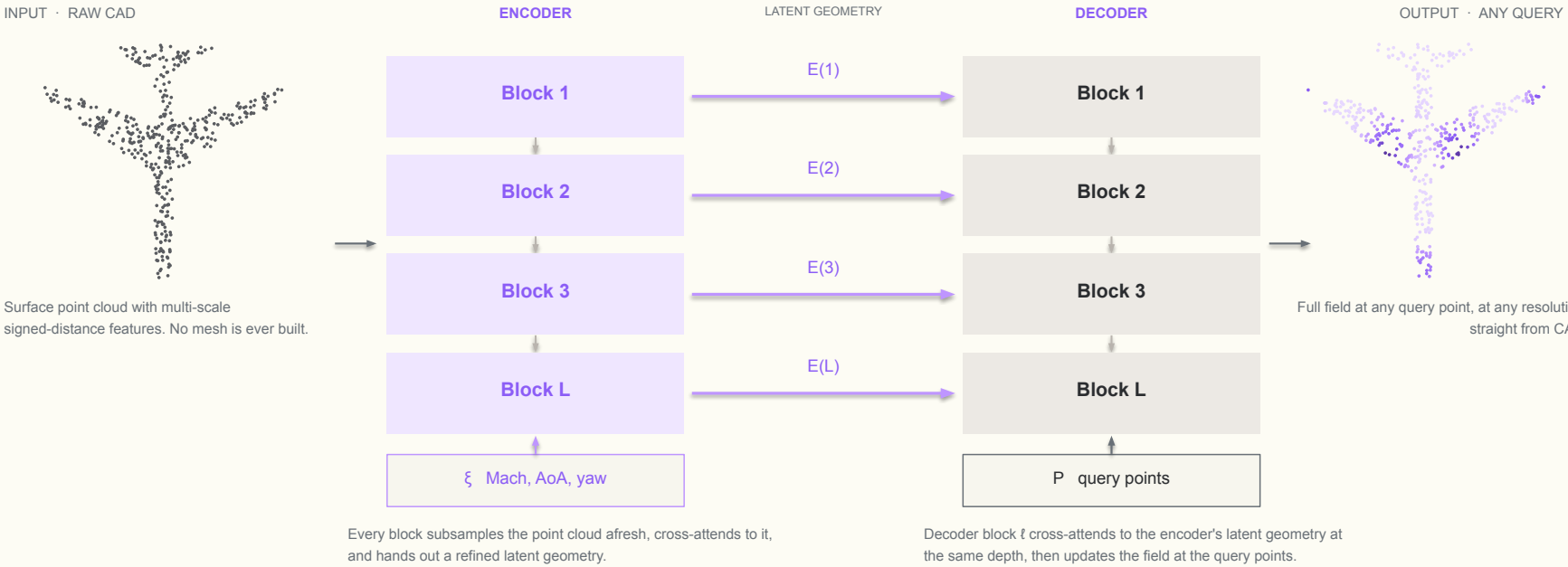
SMART architecture paper

Architecture after Hagnberger and Niepert, arXiv:2601.18707. Luminary-SMART is a clean-room implementation, production-hardened with UQ, OOD detection and multi-physics support.

Base Model Architecture

Luminary-SMART

Learnable tokens re-sample the raw point cloud at every layer, so there is no fixed discretization left for the network to memorize.



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Raw geometry

CAD geometry model (BREP or Discrete)

→

Point cloud

Surface points with multi-scale signed-distance features

→

Geometry tokens

K learnable tokens re-sample the point set at every layer

→

L× encoder

Geometry cross-attention; FiLM modulation by ξ

→

L× decoder

Block ℓ attends to encoder block ℓ's latent geometry

→

Fields at queries

Any resolution. Queries stay independent

01

No mesh at inference

The model never sees a simulation mesh, so it cannot learn one. Query it directly on raw CAD.

02

Queries are independent

No attention across query points. Evaluate one point or fifty million; tile the domain and the answer is identical.

03

Parameters are native

Flow parameters can modulate the network itself, so one model can spans operating envelopes.

Architecture after Hagnberger and Niepert, arXiv:2601.18707. Luminary-SMART is a clean-room implementation, production-hardened with UQ, OOD detection and multi-physics support.

From scratch results

Expected Insight: as we train on more data, the score gets better

Sampling: 16k surface, 64k volume points

Hardware: 2xH100, 500 epochs, 16 hours (full)

What is the Overall Score hiding?



From scratch results

Overall Score breakdown:

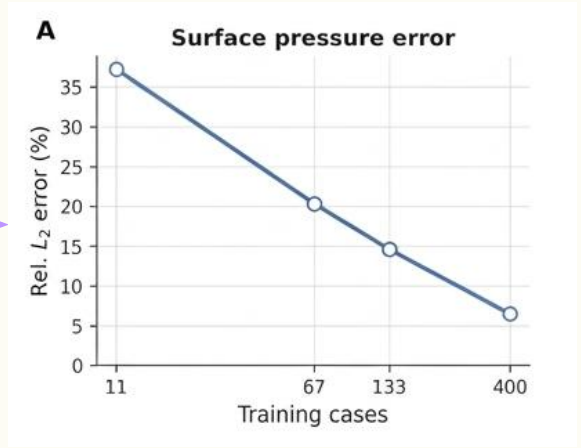
COMPONENT	super_scarce 11 train · 50 test	scarce 67 train · 50 test	medium 133 train · 50 test	full 400 train · 50 test
Fields score	0.00 of 50 pts	0.00 of 50 pts	4.31 of 50 pts	19.16 of 50 pts
Surface pressure	0.00 37.26% error	0.00 20.33% error	0.41 14.59% error	8.53 6.47% error
Surface wall shear	0.00 45.19% error	0.00 21.96% error	1.80 16.41% error	5.13 9.73% error
Volume velocity	0.00 43.95% error	0.00 21.36% error	0.00 15.74% error	0.00 12.16% error
Volume pressure	0.00 39.54% error	0.00 16.54% error	2.11 11.83% error	5.49 6.76% error
Forces score	2.82 of 25 pts	5.20 of 25 pts	14.94 of 25 pts	24.33 of 25 pts
Drag Cd	0.00 R² −1.764	3.49 R² 0.233	7.35 R² 0.490	14.64 R² 0.976
Lift Cl	0.00 R² −1.993	0.00 R² −0.134	3.16 R² 0.632	4.75 R² 0.950
Pitching moment CmPitch	2.82 R² 0.564	1.70 R² 0.341	4.43 R² 0.885	4.94 R² 0.988
Fixed profiles score	20.66 of 25 pts	23.67 of 25 pts	24.15 of 25 pts	24.86 of 25 pts
Velocity profiles (16 lines)	12.21 R² 0.814	14.31 R² 0.954	14.66 R² 0.978	14.91 R² 0.994
Cp cuts (4 cuts)	8.45 R² 0.845	9.36 R² 0.936	9.49 R² 0.949	9.95 R² 0.995
Overall score	23.48 of 100	28.87 of 100	43.40 of 100	68.35 of 100

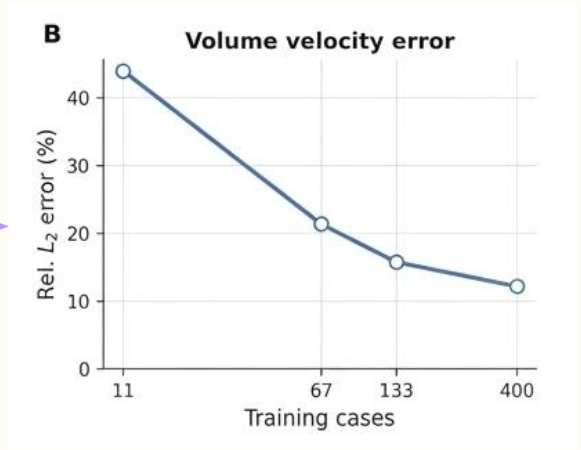


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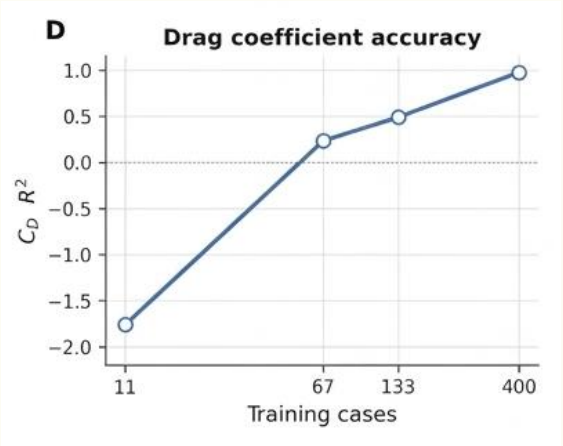


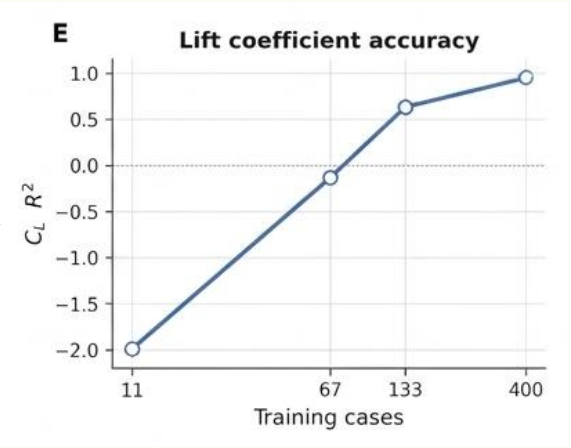


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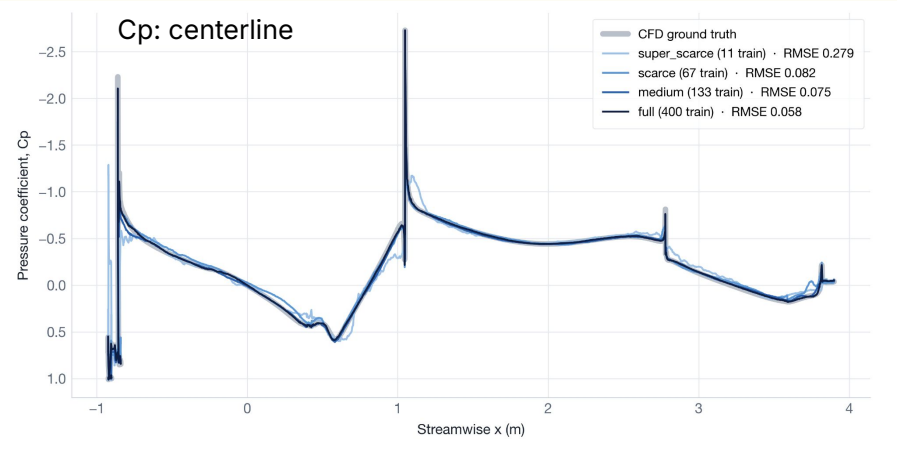
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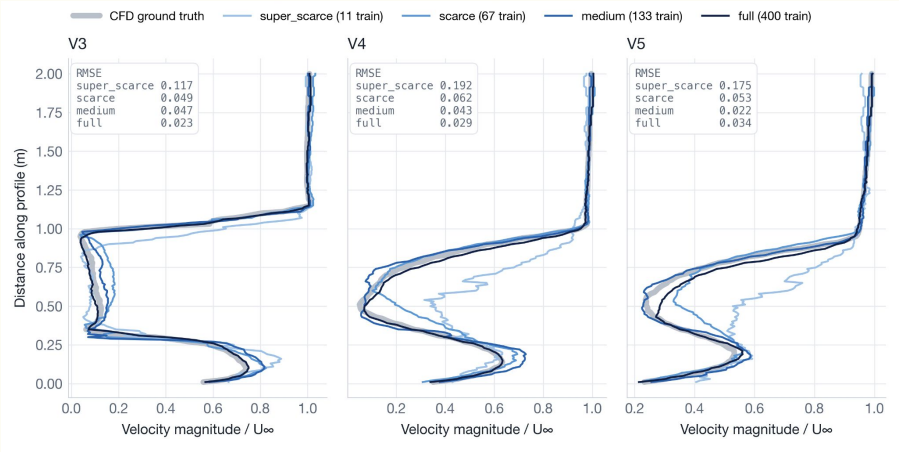




From scratch results

Run 382: from test set, median error across metrics





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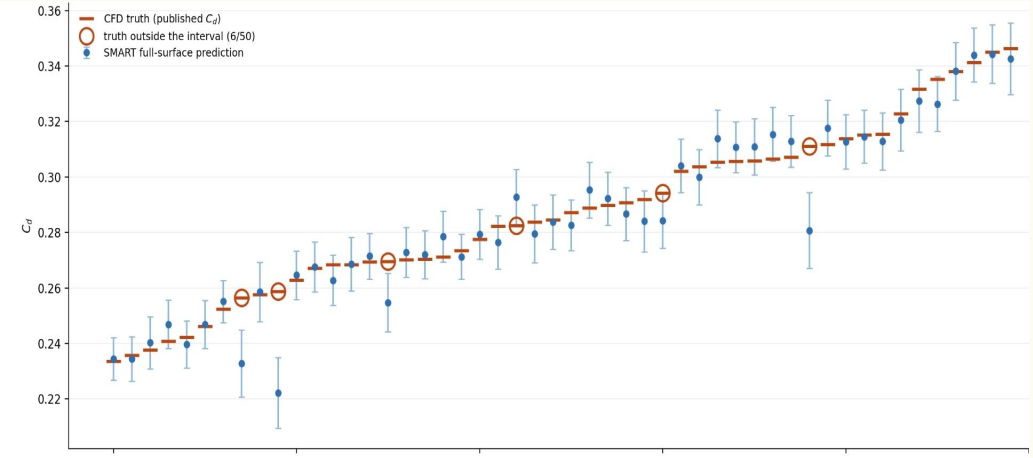
Uncertainty Quantification: Per Sample Fields

We generate prediction intervals using a parallel MLP branch with post-training Conformal calibration [1, 2, 3].

This gives prediction intervals on predicted fields (pressure, shear stresses, etc) and scalars (Cd, Cl, etc).

Both training and inference of the UQ branch are < 1% of the SMART model.

Guaranteed coverage both marginal and per-sample.



Per-sample Cd Predictions with 90% error bars on the 50 held out cases. Coverage 44/50.

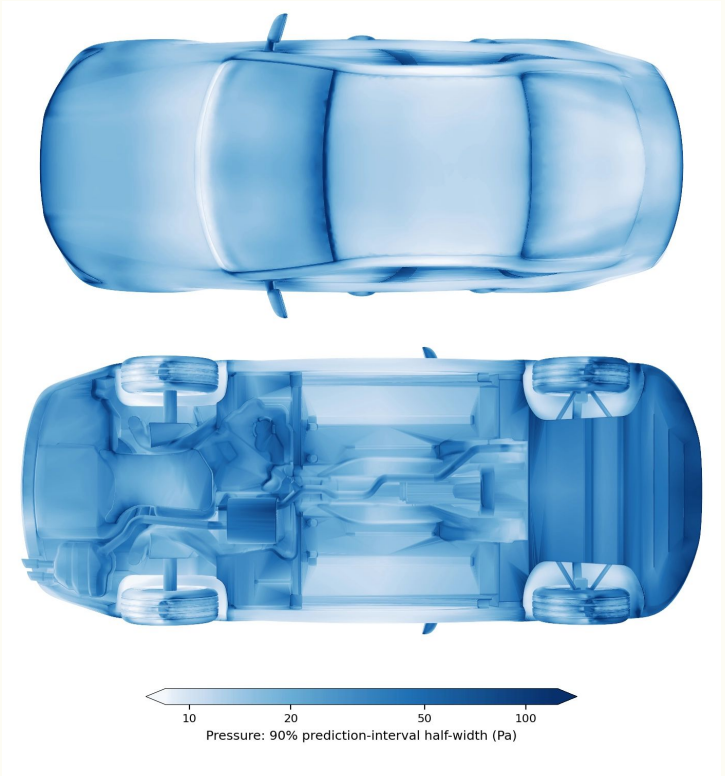
[1] M. C. Kennedy and A. O'Hagan, "Predicting the output from a complex computer code when fast approximations are available," Biometrika 87(1):1–13, 2000. doi:10.1093/biomet/87.1.1
[2] H. Papadopoulos, A. Gammerman and V. Vovk, "Normalized nonconformity measures for regression conformal prediction," Proc. 26th IASTED Int. Conf. on Artificial Intelligence and Applications (AIA 2008), pp. 64–69, 2008.
[3] J. Lei, M. G'Sell, A. Rinaldo, R. J. Tibshirani and L. Wasserman, "Distribution-free predictive inference for regression," JASA 113(523):1094–1111, 2018. arXiv:1604.04173

Uncertainty Quantification: Per Sample Fields

Guaranteed 90% (target value user specifiable) coverage per-sample.

Insights can drive architecture development or even point to data augmentation needs.

Sensibly Adaptive: Prediction intervals *wider* at grill & bonnet leading edge, wheel arches, windscreen header, A-pillars; *narrower* at roof, doors, etc.



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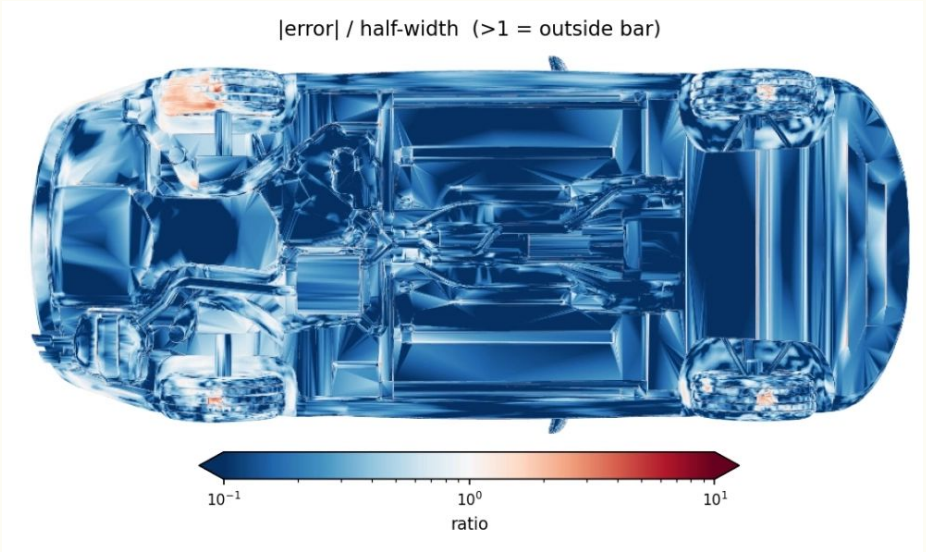


Figure: Coverage of Field UQ predictions. Covered denoted by blue, red denotes not covered at 90% prediction intervals.

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Can this be improved? Yes

There is a lot of exploration to be performed

- incorporate geometry parameters
- Score as validation loss
- Network & hyperparameter optimizations
- model development informed by UQ

Baseline 500 epochs	Geo-parameter conditioning 750 epochs · lr 1e-5	Change points
19.16 of 50 pts	23.70 of 50 pts	+4.54 pts
8.53 6.47% error	9.45 5.55% error	+0.92 −0.92 pp error
5.13 9.73% error	5.49 9.02% error	+0.36 −0.71 pp error
0.00 12.16% error	1.83 10.53% error	+1.83 −1.63 pp error
5.49 6.76% error	6.93 4.61% error	+1.44 −2.15 pp error
24.33 of 25 pts	24.41 of 25 pts	+0.08 pts
14.64 R² 0.976	14.77 R² 0.984	+0.12 +0.008 R²
4.75 R² 0.950	4.66 R² 0.932	−0.09 −0.017 R²
4.94 R² 0.988	4.98 R² 0.997	+0.05 +0.009 R²
24.86 of 25 pts	24.88 of 25 pts	+0.02 pts
14.91 R² 0.994	14.92 R² 0.995	+0.01 +0.000 R²
9.95 R² 0.995	9.96 R² 0.996	+0.01 +0.001 R²
68.35 of 100	73.00 of 100	+4.65 pts

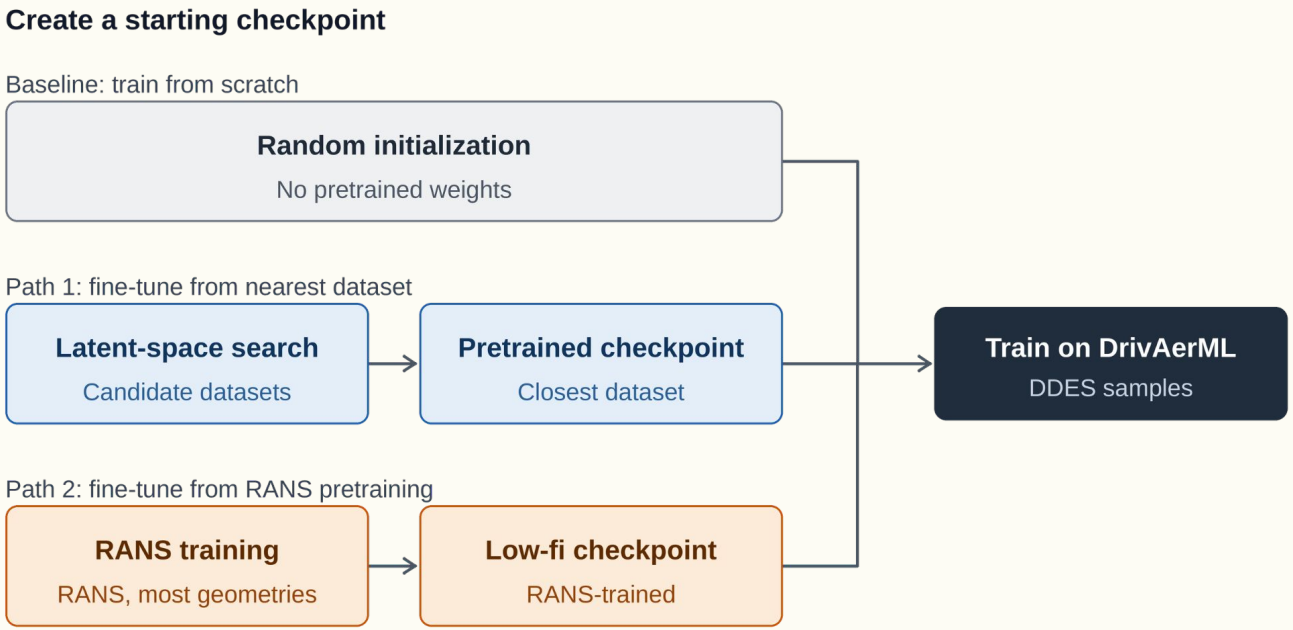
ongoing experiments since submission

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Can this be accelerated?

Fine Tuning: two flavors

Goal: accelerate time and/or cost to acceptable-accuracy



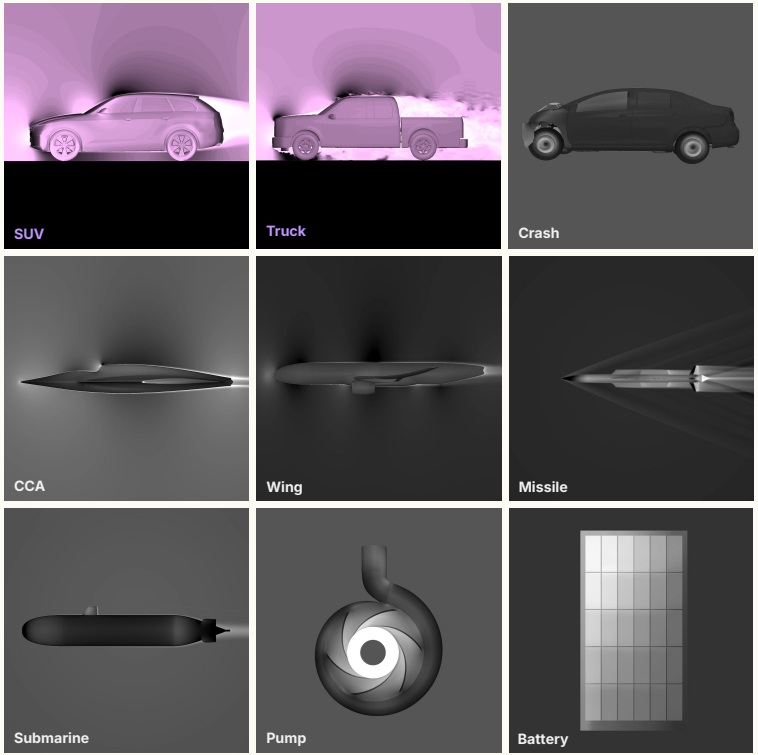
Fine Tuning: from a related dataset

open-source SHIFT datasets:
https://huggingface.co/luminary-shift

other useful datasets of course exist

checkpoint produced from potential
geometric and flow condition differences

latent space assessments of similarity of datasets



Luminary SHIFT open-source datasets

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differences	SHIFT-SUV	DrivAerML
wheel BCs	rotating wall	static wall
floor treatment	translating floor patches	single no slip-slip transition line
inflow velocity	31.3 m/s	38.9 m/s
underbody	smooth (EV)	detailed

summary of major differences in modeling approaches between source and target datasets

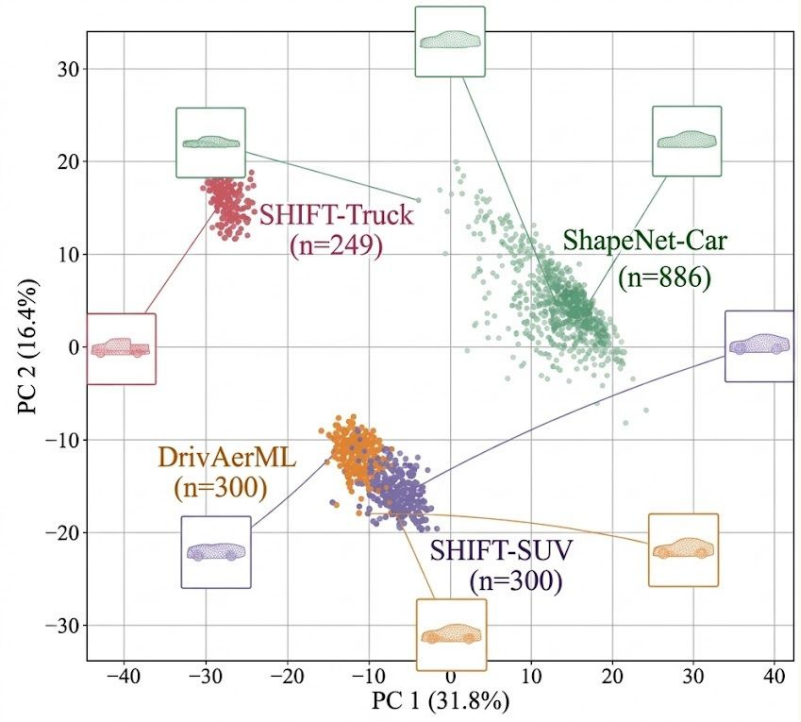
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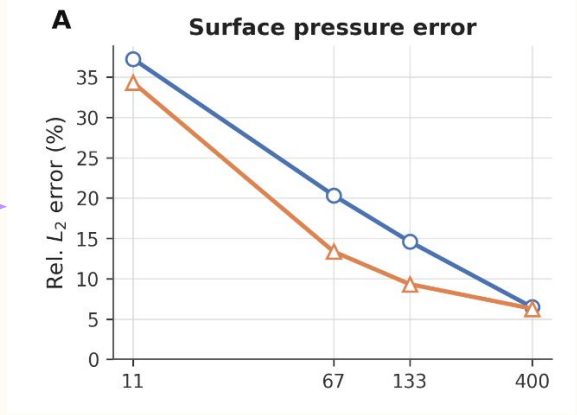
SMART **geometry** latent space visualization of different automotive geometry datasets

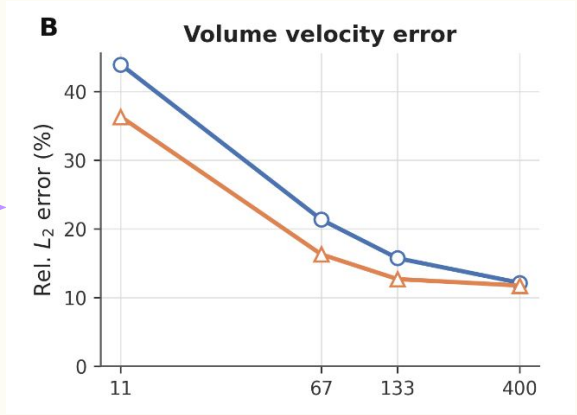
Fine Tuned: Standard Splits

From SHIFT-SUV

Overall Score breakdown:

COMPONENT	super_scarce 11 train · 50 test	scarce 67 train · 50 test	medium 133 train · 50 test	full 400 train · 50 test
Fields score	**0.00** of 50 pts	**5.44** of 50 pts	**14.22** of 50 pts	**20.36** of 50 pts
Surface pressure	0.00 34.33% error	1.64 13.36% error	5.68 9.32% error	8.72 6.28% error
Surface wall shear	0.00 40.29% error	1.61 16.79% error	3.92 12.17% error	5.37 9.26% error
Volume velocity	0.00 36.34% error	0.00 16.30% error	0.00 12.70% error	0.29 11.76% error
Volume pressure	0.00 30.77% error	2.20 11.69% error	4.62 8.06% error	5.98 6.03% error
Forces score	**1.27** of 25 pts	**19.99** of 25 pts	**22.93** of 25 pts	**24.17** of 25 pts
Drag Cd	0.00 R^2 −0.112	13.26 R^2 0.884	13.88 R^2 0.925	14.69 R^2 0.979
Lift Cl	0.00 R^2 −1.014	2.87 R^2 0.573	4.26 R^2 0.853	4.61 R^2 0.922
Pitching moment CmPitch	1.27 R^2 0.254	3.86 R^2 0.773	4.78 R^2 0.957	4.87 R^2 0.975
Fixed profiles score	**21.90** of 25 pts	**24.47** of 25 pts	**24.71** of 25 pts	**24.87** of 25 pts
Velocity profiles (16 lines)	13.21 R^2 0.880	14.73 R^2 0.982	14.85 R^2 0.990	14.92 R^2 0.995
Cp cuts (4 cuts)	8.70 R^2 0.870	9.74 R^2 0.974	9.86 R^2 0.986	9.95 R^2 0.995
Overall score	**23.17** of 100	**49.90** of 100	**61.85** of 100	**69.41** of 100



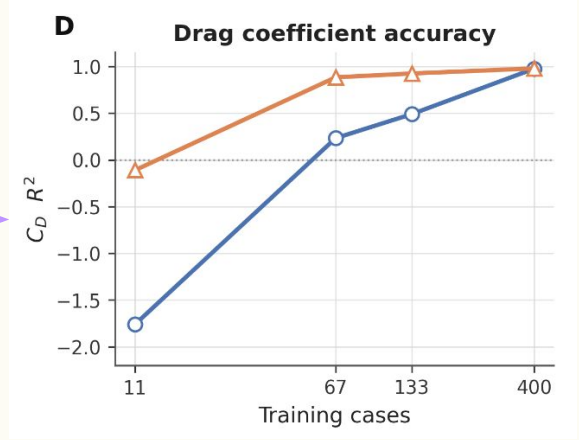


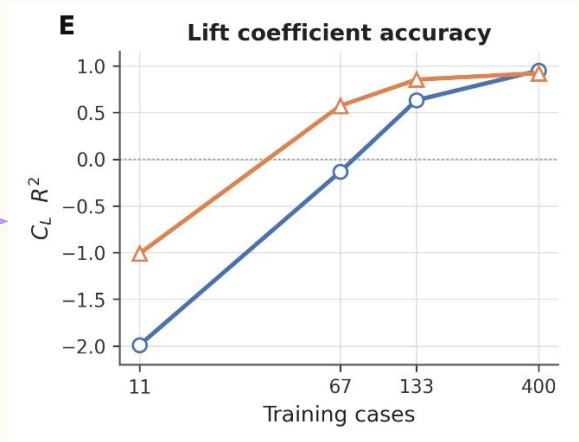
Fine Tuned: Standard Splits

From SHIFT-SUV

Overall Score breakdown:

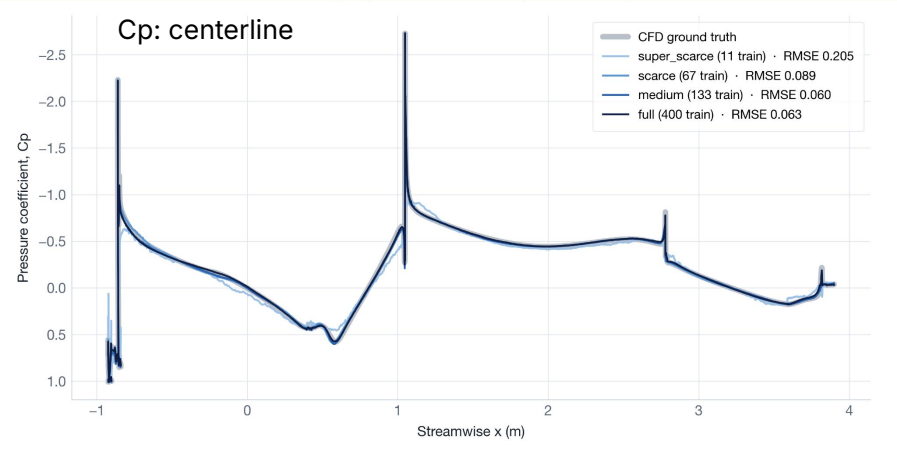
COMPONENT	super_scarce 11 train · 50 test	scarce 67 train · 50 test	medium 133 train · 50 test	full 400 train · 50 test
Fields score	0.00 of 50 pts	5.44 of 50 pts	14.22 of 50 pts	20.36 of 50 pts
Surface pressure	0.00 34.33% error	1.64 13.36% error	5.68 9.32% error	8.72 6.28% error
Surface wall shear	0.00 40.29% error	1.61 16.79% error	3.92 12.17% error	5.37 9.26% error
Volume velocity	0.00 36.34% error	0.00 16.30% error	0.00 12.70% error	0.29 11.76% error
Volume pressure	0.00 30.77% error	2.20 11.69% error	4.62 8.06% error	5.98 6.03% error
Forces score	1.27 of 25 pts	19.99 of 25 pts	22.93 of 25 pts	24.17 of 25 pts
Drag Cd	0.00 R^2 −0.112	13.26 R^2 0.884	13.88 R^2 0.925	14.69 R^2 0.979
Lift Cl	0.00 R^2 −1.014	2.87 R^2 0.573	4.26 R^2 0.853	4.61 R^2 0.922
Pitching moment CmPitch	1.27 R^2 0.254	3.86 R^2 0.773	4.78 R^2 0.957	4.87 R^2 0.975
Fixed profiles score	21.90 of 25 pts	24.47 of 25 pts	24.71 of 25 pts	24.87 of 25 pts
Velocity profiles (16 lines)	13.21 R^2 0.880	14.73 R^2 0.982	14.85 R^2 0.990	14.92 R^2 0.995
Cp cuts (4 cuts)	8.70 R^2 0.870	9.74 R^2 0.974	9.86 R^2 0.986	9.95 R^2 0.995
Overall score	23.17 of 100	49.90 of 100	61.85 of 100	69.41 of 100

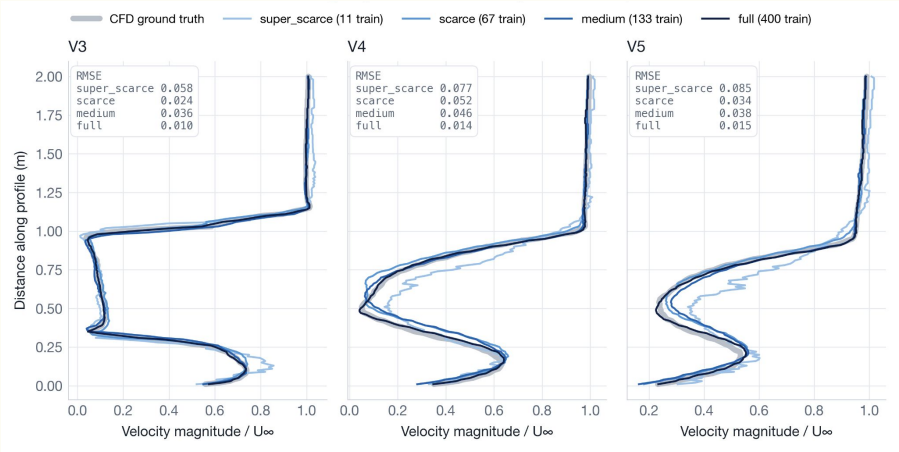




From SHIFT-SUV

Run 382: from test set, median error across metrics





Fixed profiles score	**20.66** of 25 pts	**23.67** of 25 pts	**24.15** of 25 pts	**24.86** of 25 pts
Velocity profiles (16 lines)	**12.21** R^2 0.814	**14.31** R^2 0.954	**14.66** R^2 0.978	**14.91** R^2 0.994
Cp cuts (4 cuts)	**8.45** R^2 0.845	**9.36** R^2 0.936	**9.49** R^2 0.949	**9.95** R^2 0.995
Overall score	**23.48** of 100	**28.87** of 100	**43.40** of 100	**68.35** of 100

Fine Tuning: from a related dataset

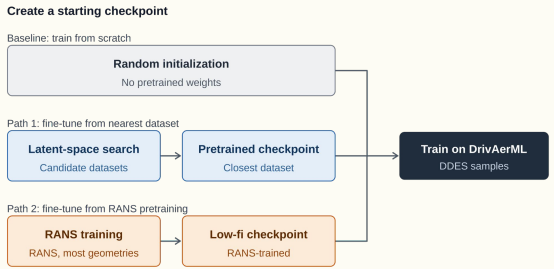
open-source SHIFT datasets:
https://huggingface.co/luminary-shift

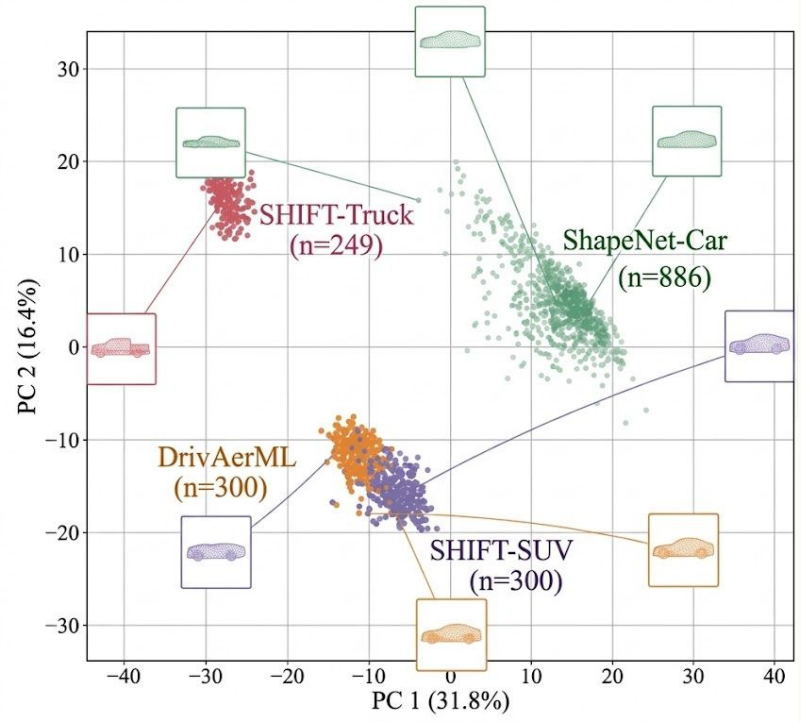
other useful datasets of course exist

checkpoint produced from potential
geometric and flow condition differences

latent space assessments of similarity of datasets

What if you don't have a related dataset?





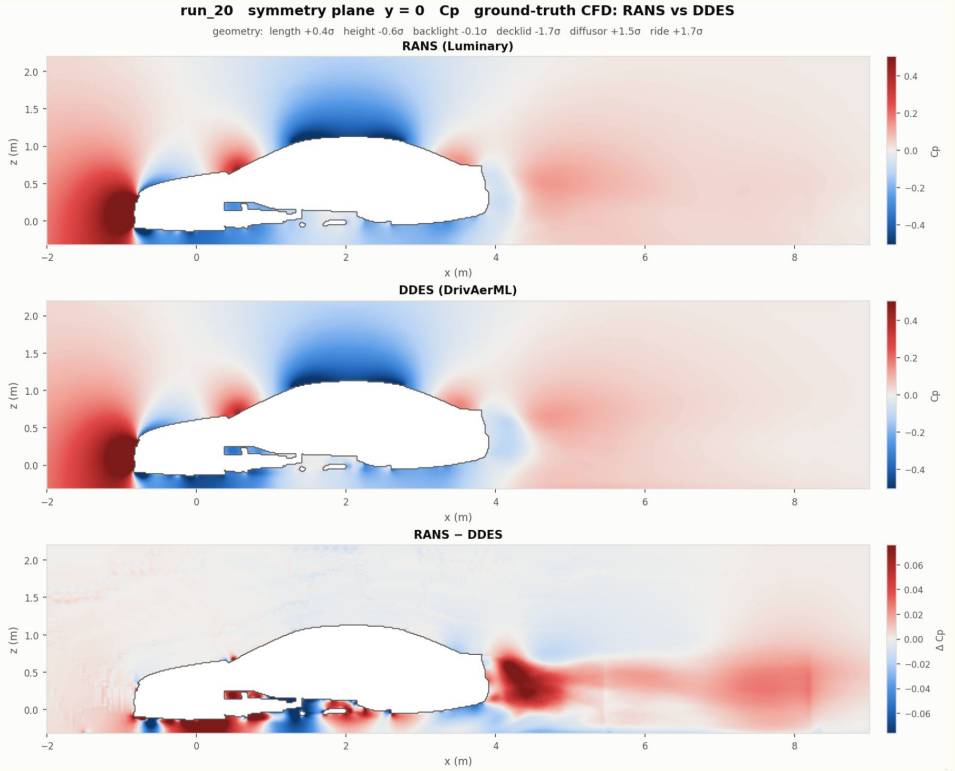
SMART **geometry** latent space visualization of different automotive geometry datasets

From RANS results

Pretraining Dataset:

RANS results (Luminary solver) run on 337 of the DrivAerML sample geometries

81 samples for Validation set; no overlap with Test set



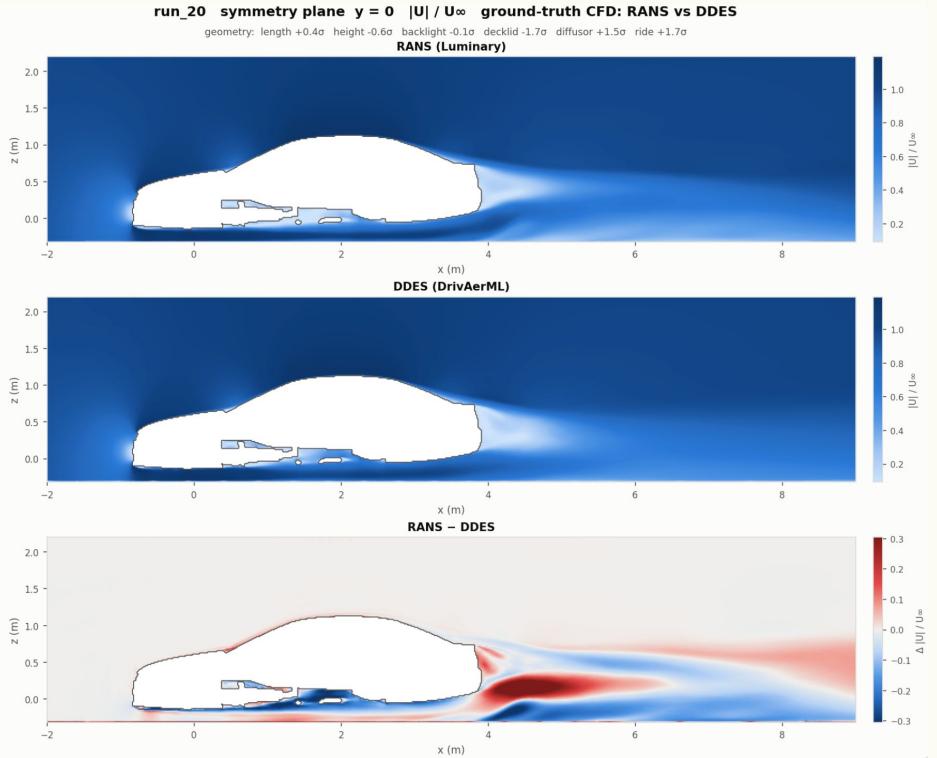
Cp contours

From RANS results

Pretraining Dataset:

RANS results (Luminary solver) run on 337 of the DrivAerML sample geometries

81 samples for Validation set; no overlap with Test set



velocity magnitude contours

From RANS results

Pretraining Dataset:

RANS results (Luminary solver) run on 337 of the DrivAerML sample geometries

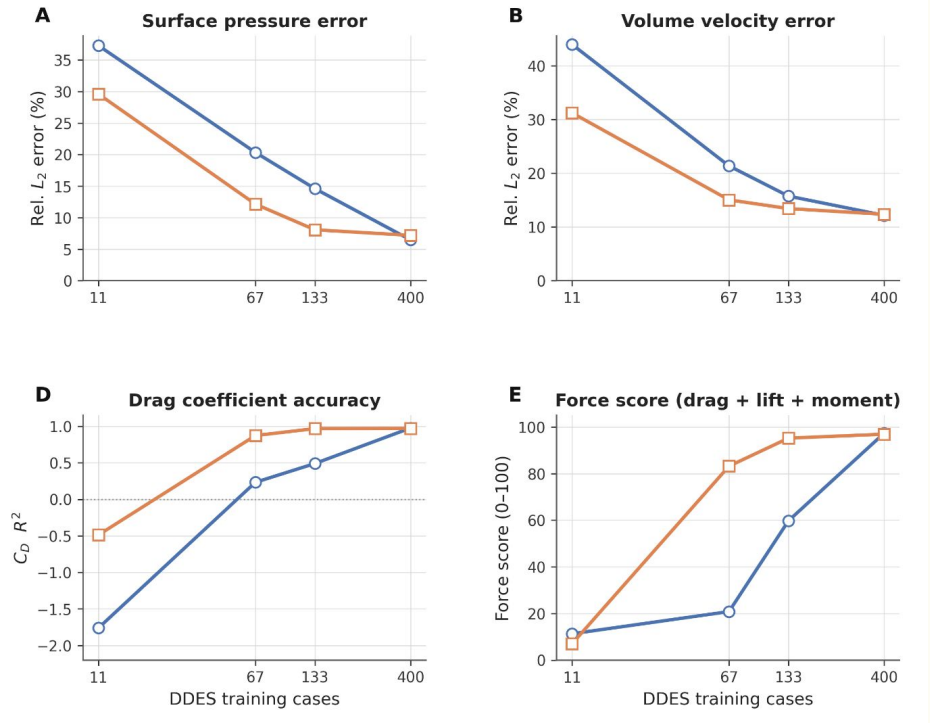
81 samples for Validation set; no overlap with Test set

Notable Observations

Checkpoint data is better associated with geometry and flow conditions of relevance

RANS helps most where the flow is hardest to learn from a small DDES budget: wake and underbody probes

Cost of generating and training the RANS checkpoint implies a cross-over point of cost vs. benefit



From RANS results

Pretraining Dataset:

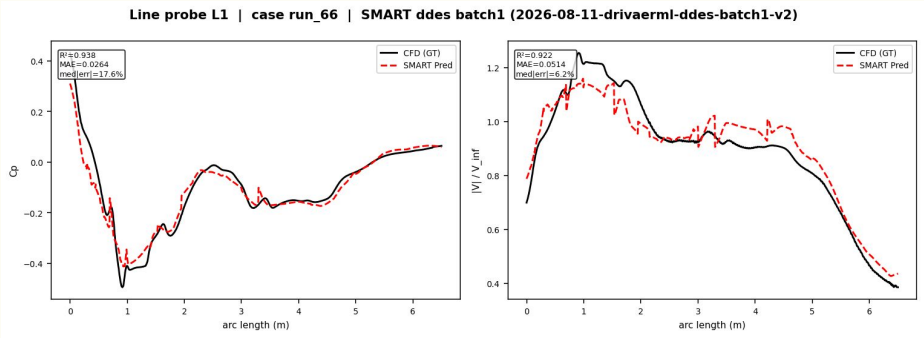
RANS results (Luminary solver) run on 337 of the DrivAerML sample geometries

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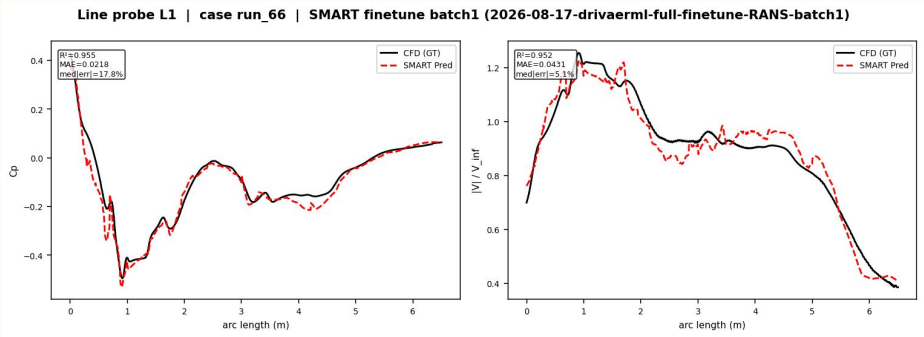
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baseline



RANS fine tuned

From RANS results

Pretraining Dataset:

RANS results (Luminary solver) run on 337 of the DrivAerML sample geometries

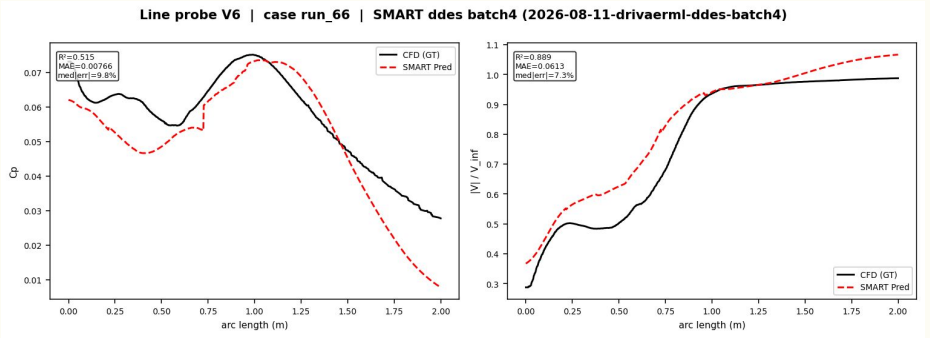
81 samples for Validation set; no overlap with Test set

Notable Observations

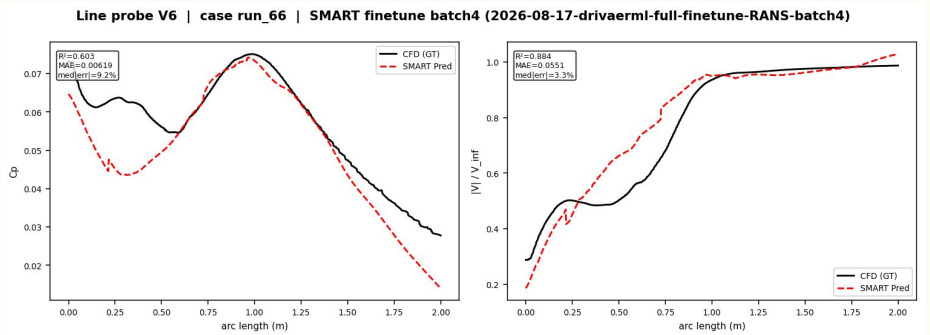
Checkpoint data is better associated with geometry and flow conditions of relevance

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baseline



RANS fine tuned

luminary

Quick Hits

One minute mentions



Data assimilation

Correcting an AI flow surrogate with sparse experimental data for AutoCFD Case 2a

Can a small amount of experimental data correct the surrogate, without rerunning CFD?

SMART SURROGATE

Fast & full-field

Predicts the whole flow in seconds, but carries surrogate errors relative to CFD.

EXPERIMENT

True, but sparse

Real pressure taps and velocity probes, measured only at a few hundred points.

CFD RERUN

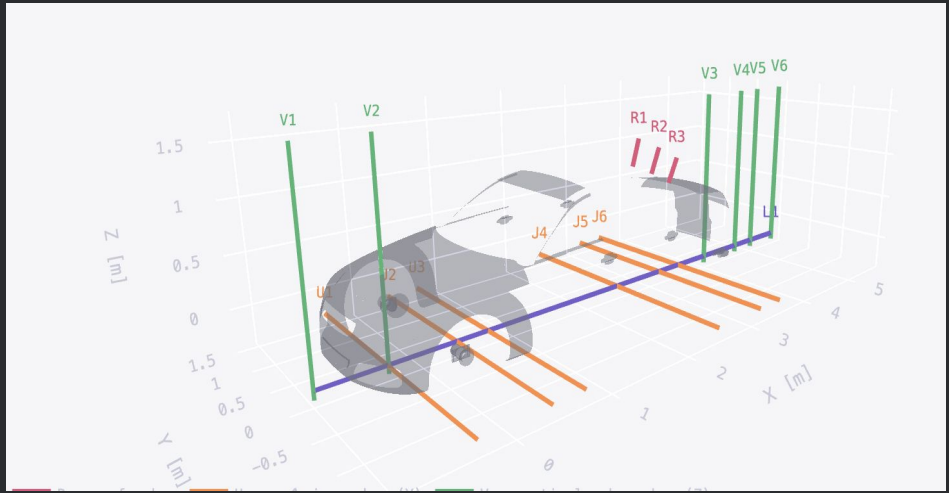
Slow & imperfect

Hours of compute per design change, and still carries physics modeling errors vs. reality.

Where is the experimental data?



surface pressure taps



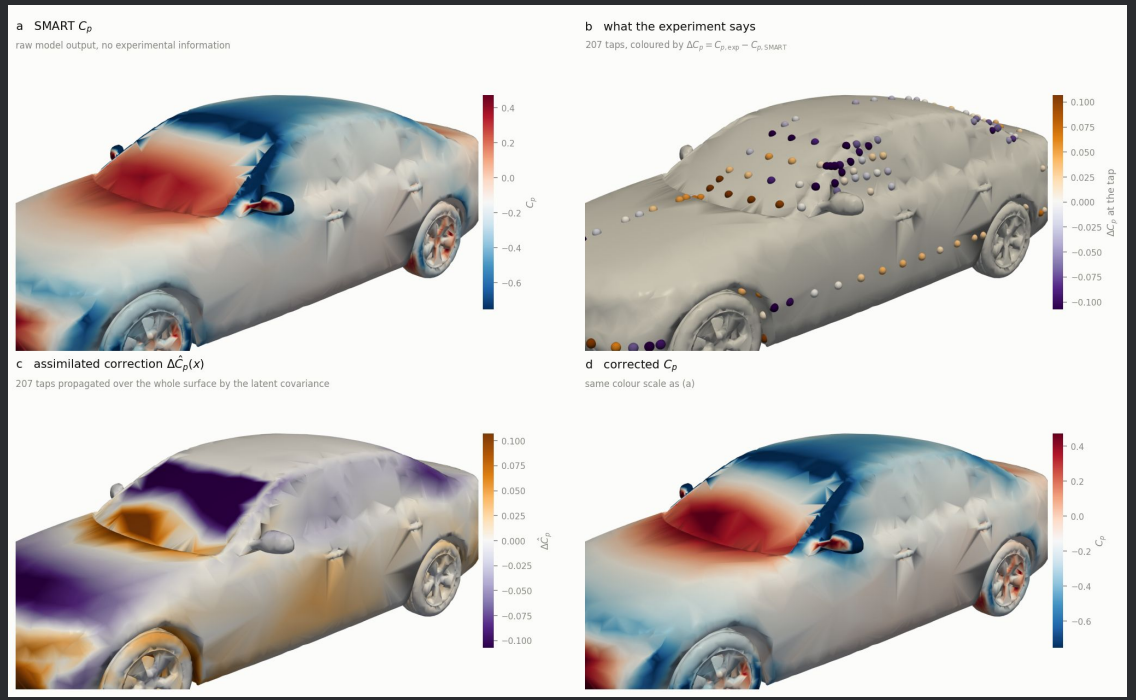
volumetric velocity probe rakes

Corrected field predictions

Correction is learning both
- spatial correlation or error
- error magnitude

Assimilation not alignment: too few data points (only this geometry) to be able to generalize across samples

Spatial density of experiment sufficient to learn correlations



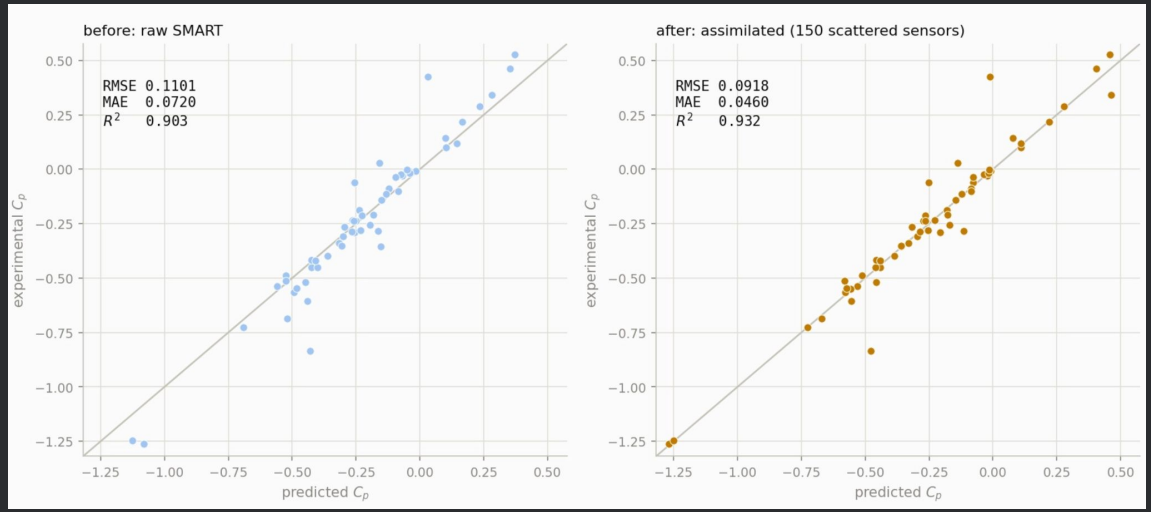
surface field correction

Corrected field predictions

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Spatial density of experiment sufficient to learn correlations



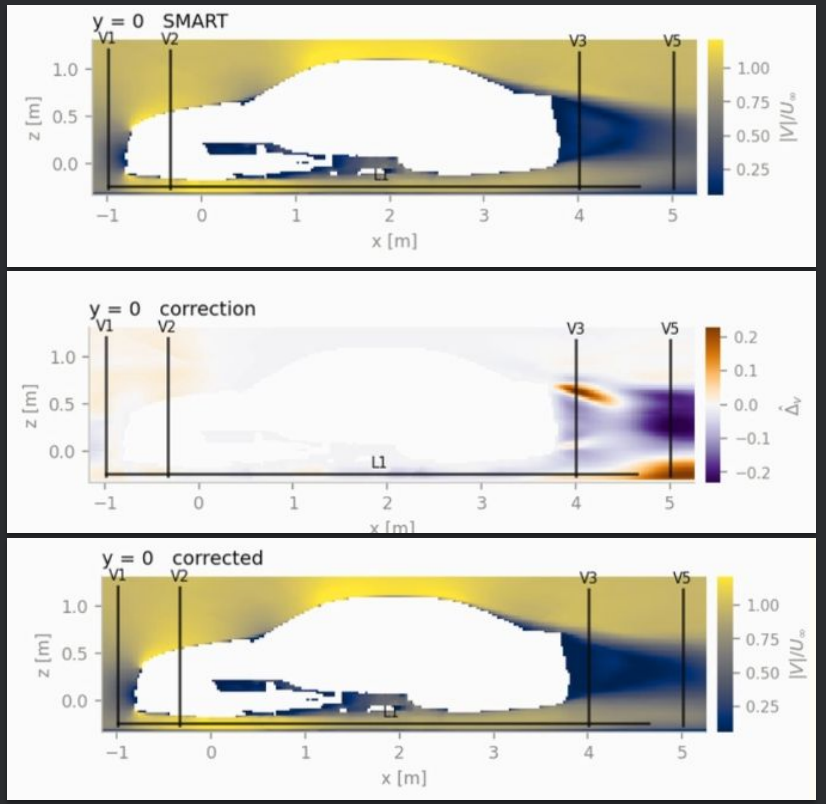
Case 2a: 150 sensors used to train the correlation, 57 held out taps shown here

Corrected field predictions

Correction is learning both
- spatial correlation or error
- error magnitude

Assimilation not alignment: too few data points (only this geometry) to be able to generalize across samples

Spatial density of experiment sufficient to learn correlations



volume field correction (in plane)

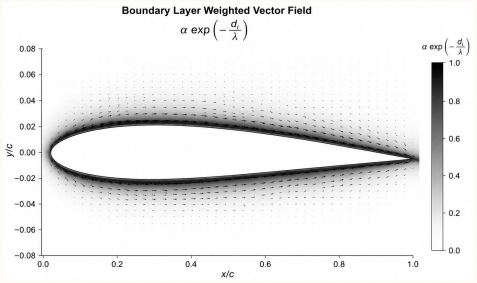
Intuition informed losses

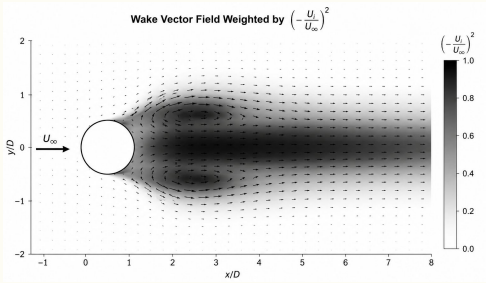
Focusing spatial attention mechanisms

Physics Informed Loss Formulations

Concept: Focus spatial attention on Boundary Layer & Wake regions, & less on free stream, etc.

Not A PINN: regions & weights mathematically defined using *supervision*





Boundary layer

Wake

$$w_i = 1 + \alpha\left(\exp\left(\frac{-d_i}{\lambda}\right)\right) + \beta \max\left(0, \left(-\frac{U_i}{U_\infty}\right)^2\right)$$

Physics Informed Loss Formulations

Concept: Focus spatial attention on Boundary Layer & Wake regions, & less on free stream, etc.

Not A PINN: regions & weights mathematically defined using *supervision*.

Result: Improved accuracy over all targets on DrivAerML, as well as other test cases.

Model	Val loss	Volume rel-L2 |V|	Volume rel-L2 p
Baseline	0.2044	0.1528	0.1162
PILF	0.1991	0.1495	0.1030

Please reach out

memory@luminary.ai

