



AIRFRANS: High Fidelity Computational Fluid Dynamics Dataset for Approximating Reynolds-Averaged Navier–Stokes Solutions

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- ▶ **Main problem.**
Computational cost of solvers.

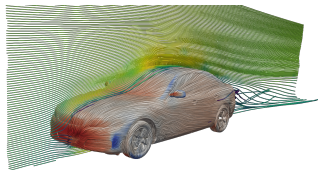


Figure 1: Velocity streamlines and pressure profile on a car body.

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- ▶ **Candidate solution.**
Data-driven approximation models.

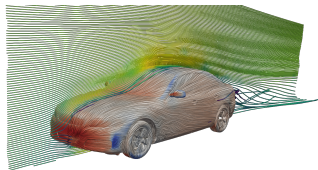


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- ▶ **Candidate solution.**
Data-driven approximation models.
- ▶ **Goal.** Make possible automated design procedure.

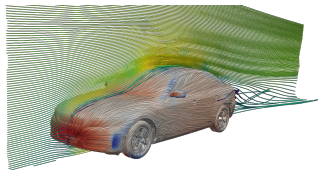


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- ▶ **Metrics and visualizations.** Metrics and visualizations are proposed to focus on relevant part of dynamics and important derived quantities.
- ▶ **Baselines.** Standard baselines are proposed based on neural networks from the Geometric Deep Learning framework.

Task definition. *Find the airfoil that maximizes the lift-over-drag ratio, and predict the velocity and pressure fields around it.*

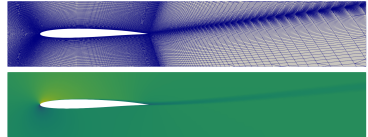
Equations to solve. Incompressible two-dimensional steady-state RANS equations

$$\begin{cases} (\bar{u} \cdot \nabla) \bar{u} = -\frac{1}{\rho} \nabla \bar{p} + (\nu + \nu_t) \Delta \bar{u} \\ \nabla \cdot \bar{u} = 0 \end{cases}$$

along with the $k - \omega$ SST model for turbulence modeling.

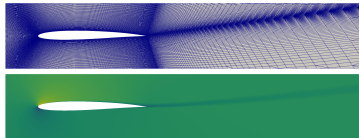
Simulation generation process

- ▶ NACA 4 and 5 digits series.



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- ▶ Parameters chosen for subsonic flights setup.



Validation of the simulations

- ▶ Simulations validated with NASA's experimental results.

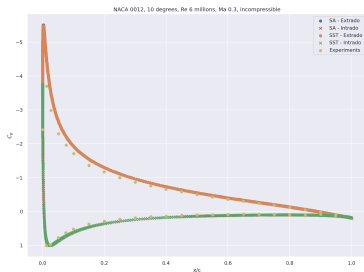


Figure 2: Coefficient of pressure at the surface for a NACA 0012.

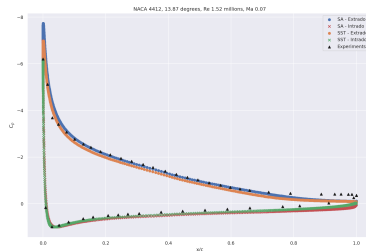


Figure 3: Coefficient of pressure at the surface for a NACA 4412.

Force coefficients validation

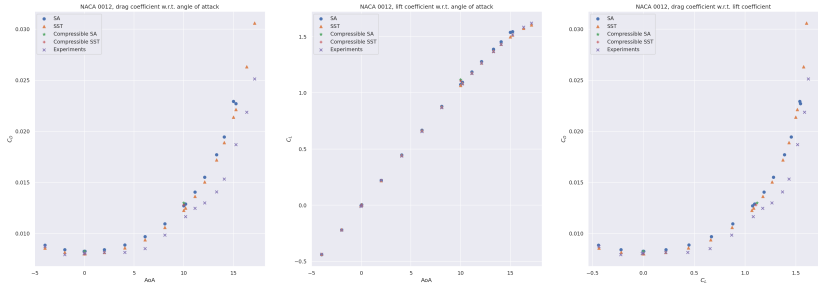


Figure 4: Force coefficients for a NACA 0012.

- ▶ **Full data regime.** 800 simulations in the training set and 200 simulations in the test set.
- ▶ **Scarce data regime.** Same test set but only 200 simulations in the training set.
- ▶ **Reynolds extrapolation regime.** Out-of-distribution Reynolds number for simulations in the test set.
- ▶ **Angles of attack extrapolation regime.** Out-of-distribution angles of attack (AoA, airflow direction) for simulations in the test set.

- ▶ **Candidate models.** MLP, GraphSAGE, PointNet, and Graph U-Net (GUNet).

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- ▶ **Regressed fields.** Unknowns of the RANS equations.

Model	Volume				Surface
	$\bar{u}_x (\times 10^{-2})$	$\bar{u}_y (\times 10^{-2})$	$\bar{\beta} (\times 10^{-2})$	$\nu_y (\times 10^{-2})$	$\bar{\beta} (\times 10^{-1})$
MLP	1.65±0.03	1.45±0.07	3.90±0.57	5.01±0.76	2.19±0.53
GraphSAGE	1.46±0.13	1.45±0.12	4.70±0.80	6.11±0.79	1.95±0.34
PointNet	3.11±0.30	2.78±0.39	3.29±1.05	5.58±2.36	1.83±0.41
Graph U-Net	1.75±0.19	1.83±0.18	3.39±0.84	4.30±1.00	1.47±0.35

Figure 5: Comparison of the mean squared error on the normalized fields in the scarce data regime.

- **Spearman's correlation.** Preservation of the rank of the force coefficients is primary.

Model	Relative error		Spearman's correlation	
	C_D	C_L	ρ_D	ρ_L
MLP	2.95±0.14	0.66±0.16	-0.24±0.08	0.923±0.026
GraphSAGE	3.50±1.00	0.39±0.10	-0.14±0.18	0.981±0.006
PointNet	8.35±1.39	0.59±0.13	-0.05±0.27	0.949±0.019
Graph U-Net	6.87±1.80	0.42±0.13	-0.10±0.23	0.976±0.009

Figure 6: Comparison of the Spearman's rank correlation and mean relative error for the predicted drag and lift coefficients in the scarce data regime.

Force coefficients visualization

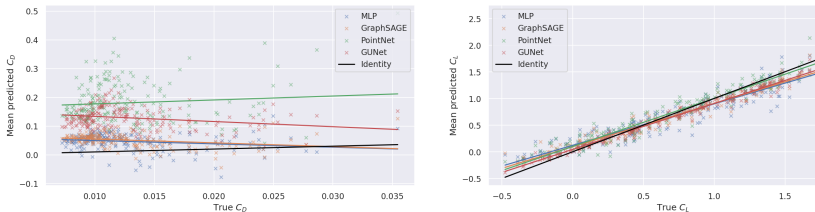


Figure 7: Predicted drag (left) and lift (right) coefficients with respect to the true ones.

Surface profiles visualization

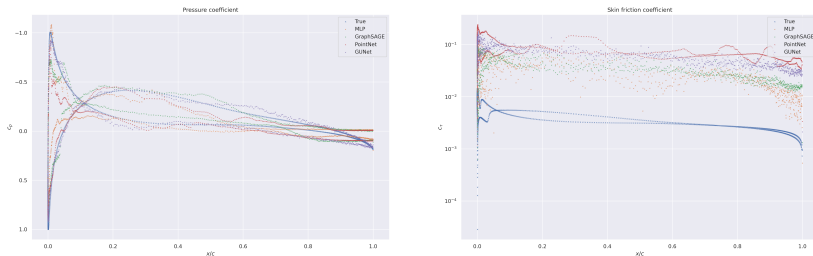


Figure 8: Comparison of the predicted pressure coefficient c_p and the skin friction coefficient c_τ profiles on a random geometry with respect to the true ones.

Boundary layers visualization

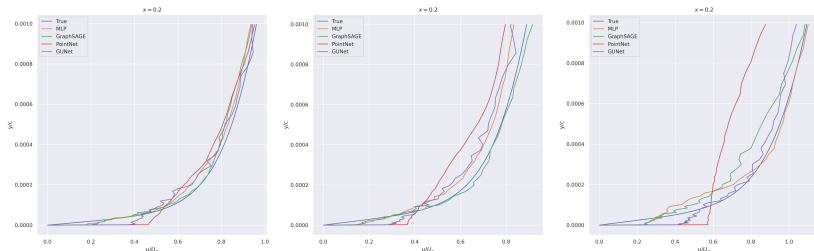


Figure 9: Comparison of the predicted boundary layers profiles on three random test geometries at abscissas $x = 0.2$.

- ▶ Spearman's rank correlation close to 1 for both force coefficients.
- ▶ Relative errors lower than 5% for both force coefficients.
- ▶ Accurate fitting of the boundary layers and the far fields.

- ▶ **For reproducing the results.**
<https://github.com/Extrality/AirfRANS>
- ▶ **For running new simulations.**
https://github.com/Extrality/NACA_simulation

