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Interactive design of 2D car profiles with aerodynamic feedback
Supplemental materials

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1. Smoothed dirac formulation of drag coefficient

To evaluate drag with our smoothed dirac formulation, we considered two strategies to create a pressure field where points in the vicinity of the profile have similar pressure values as their closest point along the profile. The *projection* strategy consists in replacing the pressure anywhere in the domain by the pressure of the closest point on the shape. In contrast, the *diffusion* strategy produces a smoother field by solving a Laplace equation with pressure values along the profile set as Dirichlet boundary conditions.

We evaluate these two strategies by using the two resulting pressure fields to compute the drag coefficient for each profile in our dataset. We compared these approximate measures obtained with a smoothed dirac to the exact measure computed by a linear integral along the profile. Fig. 1 plots the histograms of the relative error achieved by each strategy. This evaluation reveals that the diffusion strategy gives slightly more accurate evaluations of the drag.

Moreover, the diffusion strategy produces a smooth field that is easier to regress than the discontinuous field produced by the projection strategy. We validate this intuition by a second experiment, where we trained two versions of our surrogate model, one for each strategy of propagation. For each strategy, we then compared the drag computed from the predicted field with the drag computed from the corresponding ground truth field, on our test dataset. Fig. 2 plots the histograms of the relative prediction error achieved by each strategy. The diffusion strategy again outperforms the projection strategy.

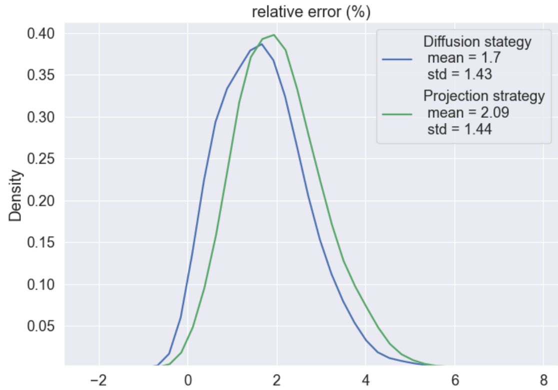

Figure 1: *Distributions of errors for the two propagation strategies we considered to compute the drag coefficient using our smoothed dirac formulation. Both strategies produce an accurate estimation of the drag compared to the exact integration along the car profile (1.7% of error for diffusion, 2% for projection, on average).*

2. Neural network architectures

Fig. 3 and 4 detail the architecture of the MLP and auto-encoder we use to implement our method. Fig. 5 details the architecture of the CNN we used for comparison.

References

[EUD17] ELFWING S., UCHIBE E., DOYA K.: Sigmoid-weighted linear units for neural network function approximation in reinforcement learning, 2017.

[LWJ*22] LIU H.-T. D., WILLIAMS F., JACOBSON A., FIDLER S., LITANY O.: Learning smooth neural functions via lipschitz regularization. In *ACM SIGGRAPH Conference Proceedings* (2022).

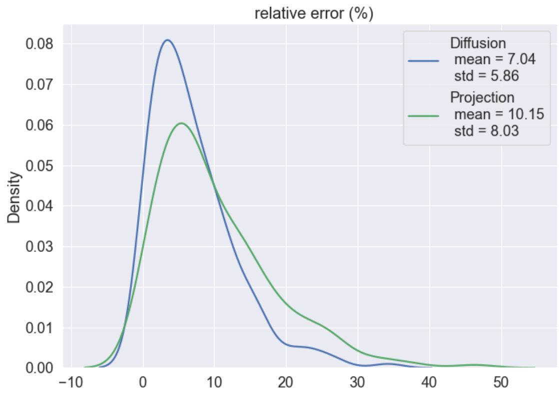

Figure 2: *Distributions of errors between drag computed on ground truth propagated pressure fields and on predicted propagated pressure fields. The pressure field propagated with the diffusion strategy is easier to regress, yielding a lower relative error between prediction and ground truth.*

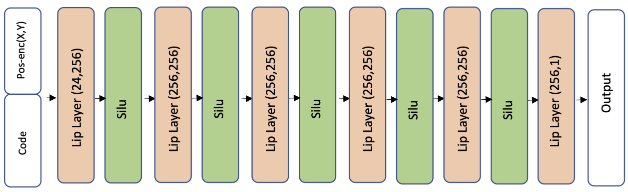

Figure 3: *Architecture of the multi-layer perceptron used to implement our surrogate model, with SiLU [?] activation functions and Lipschitz regularization [?] layers. Some variations appear between the different flavors of our networks: the MLP that predict the SDF has one layer less, and the one that predicts the pressure uses ReLU activation functions instead.*

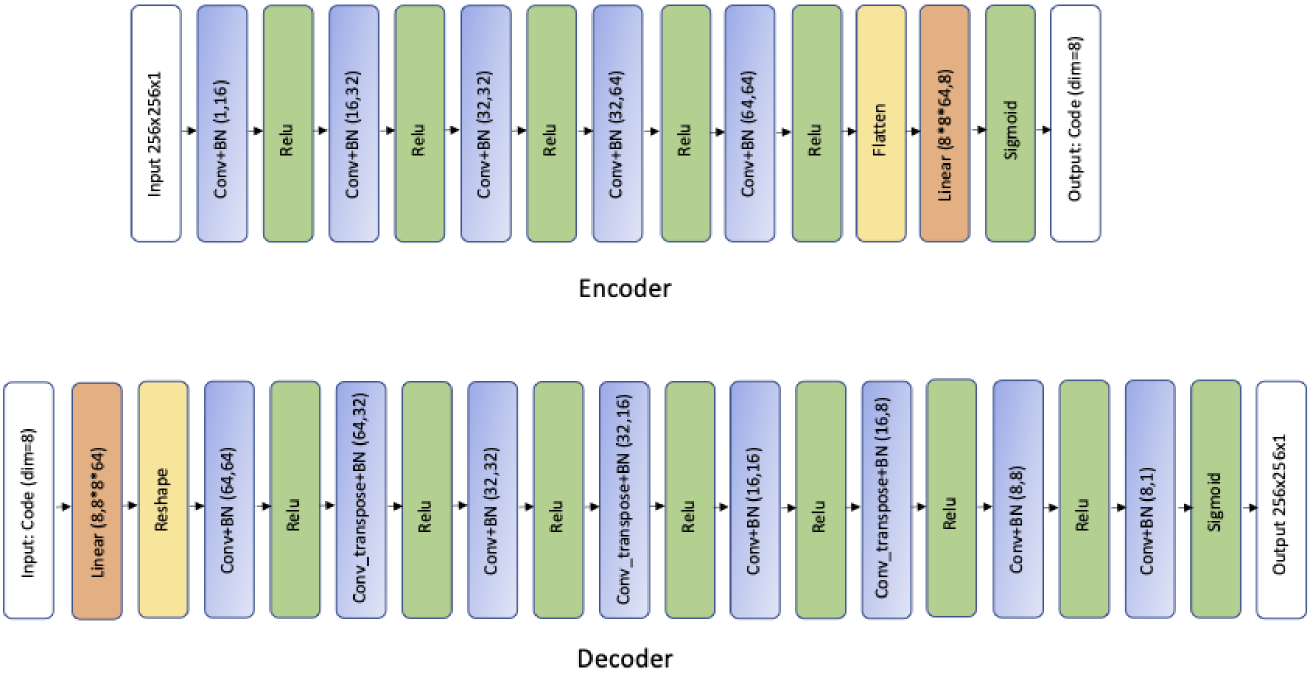

Figure 4: *Architecture of the autoencoder of car profiles.*

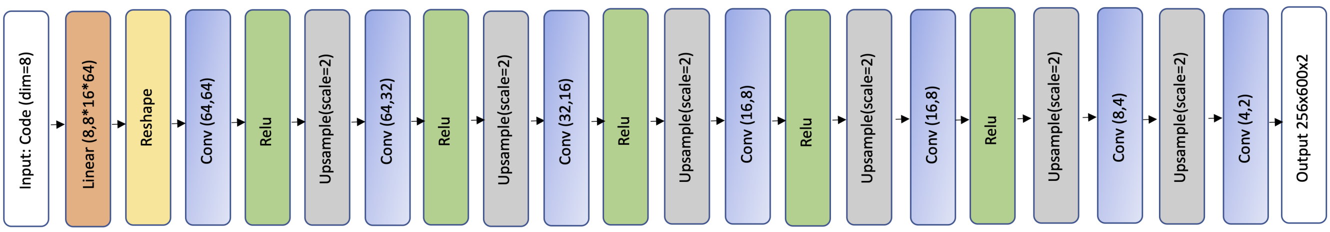

Figure 5: *Architecture of the CNN we used as a baseline for comparison, which we trained to predict pressure and signed distance fields necessary for drag computation.*