A Deep Learning Framework for Constrained Shape Optimization

Case study of airfoil optimization

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1. Motivation

2. Models

3. Results

4. Conclusion

Outline

Industrial Engineering Shape Design Procedure

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Concept Design → Design Refinement → Design Finalization

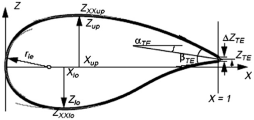
"Fuzzy" global optimization

local optimization

How hard is it to tell which shape induces greater drag?

Limitations with current surrogate modeling techniques

- Surrogate model is sensitive to shape parameterization schemes
- Shape parameterization is hand engineered and arbitrary
- Data and model cannot be transferred across different parameterization schemes
- Models are blindly doing pure input to output mapping, without incorporating any physical knowledge



A way of parameterizing the airfoil [3]

Objective of this Study

Develop a deep learning based framework that:

- Does not require hand-crafted shape parameterization.
- Is able to generate novel shapes.
- Is able to enforce shape constraints.
- Is able to provide surrogate model for optimization.

Case Study:

- Constrained Optimization of an Airfoil

Outline

Overview of this study

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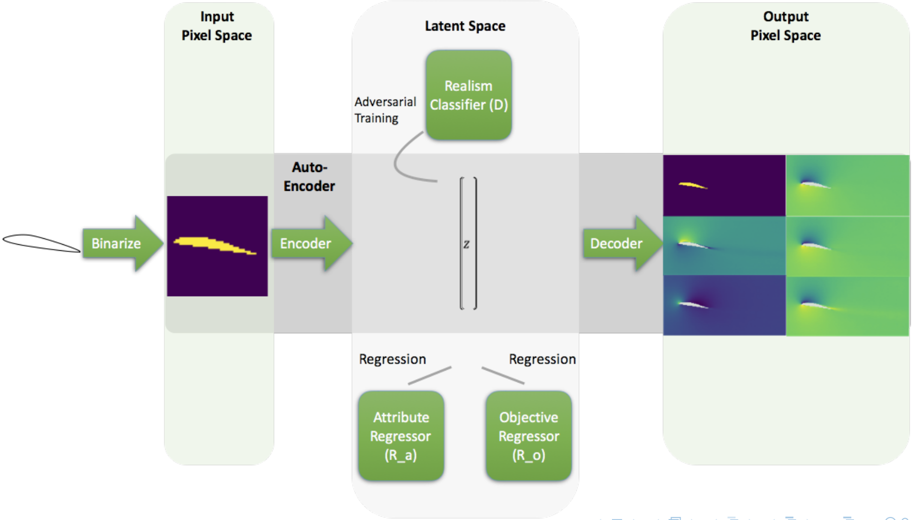
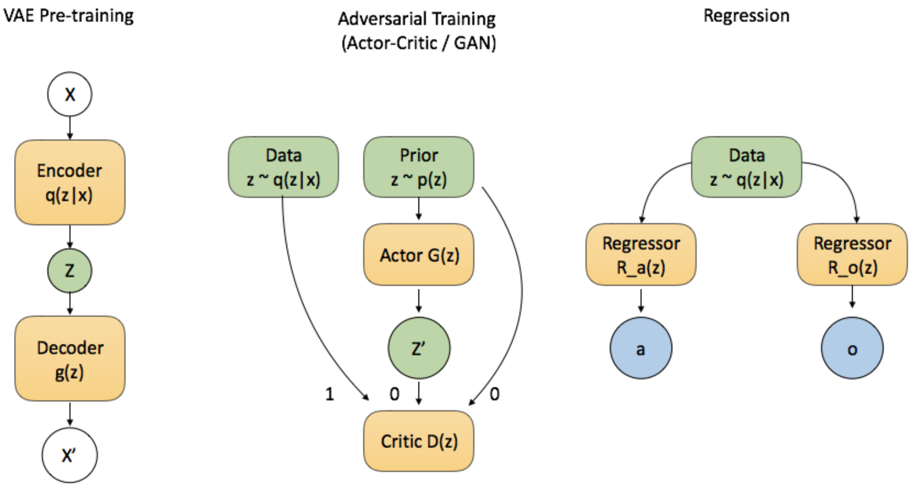


Overview of models



Source of Data: Airfoils

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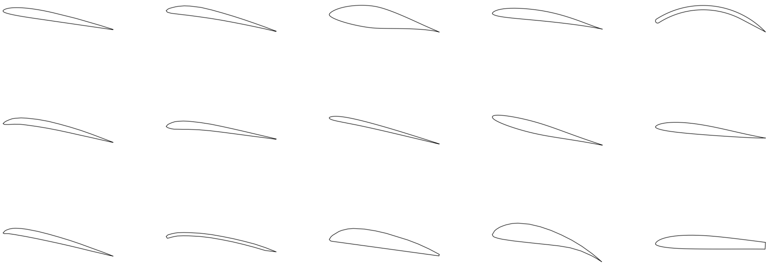

Sample of airfoil dataset in airfoil database consisting of 1636 airfoils. Each airfoil is normalized to cord length of 1. Each airfoil is randomly rotated with an angle of attack $\theta \in [0, 15]$ deg. For each sample, the recorded shape attributes are max thickness (%), max camber (%), angle of attack θ and cross-sectional area.

Source of Data: Aerodynamics Simulation

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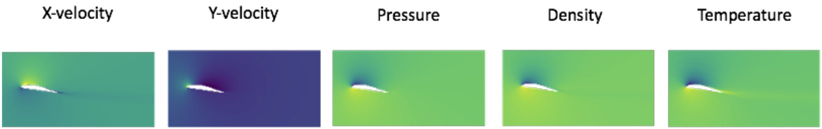

The figure above shows one simulated shape sample. The flow channels are two components of velocity, pressure, density and temperature. Flow simulation is performed under Mach 0.15 using Open Source simulator OpenFOAM. The simulation results are resampled onto a 256×512 grid

Semi-supervised Variational Autoencoder (VAE)

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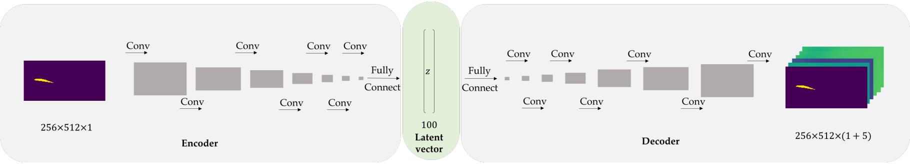
- Consists of convolutional, up-convolutional, and fully connected layer.
- Bottleneck of size 100 forces the extraction of a feature vector of length 100.
- $loss = ||x - Dec(Enc(x))||_2 + D_{KL}(z||\hat{z})$ where $\hat{z} \sim \mathcal{N}(0, 1)$
- $D_{KL}(z||\hat{z}) = -\Sigma_i z(i) \log \frac{z(i)}{\hat{z}(i)}$ We use KL Divergence to measure how closely the latent vector resembles a unit Gaussian



Latent Space Learning: Adversarial Training

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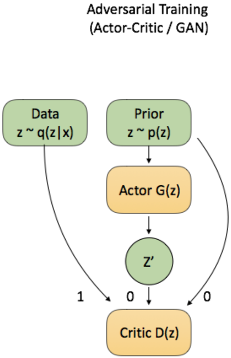

- Train two separate networks against each other, namely an actor (a.k.a. Generator G) and a critic (a.k.a. Discriminator D). Equilibrium of the 2-player game allows D to efficiently distinguish real and fake data distributions.
- $\mathcal{L}_D = \mathbb{E}_{z\sim p(z)}(-log(1 - D(z))) + \mathbb{E}_{z\sim G(p(z))}(-log(1 - D(z))) + \mathbb{E}_{z\sim q(z)}(-log(D(z)))$
- $\mathcal{L}_G = \mathbb{E}_{z\sim G(p(z))}(-log(D(z)))$

Latent Space Learning: Regression

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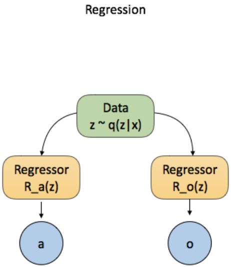

- Use Multilayer Perceptron (MLP) as nonlinear regressor for attributes (R_a) and objectives (R_o).
- $\mathcal{L}_{R_a} = \sum_{i=1}^{N}(R_a(z_i) - a_i)^2$
- $\mathcal{L}_{R_o} = \sum_{i=1}^{N}(R_o(z_i) - o_i)^2$

Constrained Optimization of Shapes

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Use $R_o(z)$, $R_a(z)$ as function approximators for objectives and attributes. Denote the portion of R_a subject to equality constraints as R_a^{eq}. Denote the portion of R_a subject to inequality constraints as R_a^{ieq}.
Relax the constrained optimization problem as follows. Given m attribute equality constraints $\mathbf{c} \in \mathbb{R}^m$ and n inequality bounds $\mathbf{d} \in \mathbb{R}^n$, minimize the objective function $R_o(z)$:

$$
\begin{aligned}
\underset{z}{\textit{minimize}} \quad & R_o(z) \\
\textit{subject to} \quad & R_a^{eq}(z) = \mathbf{c}, \ \text{equality constraints} \\
& R_a^{ieq}(z) \geq \mathbf{d}, \ \text{inequality constraints}
\end{aligned}
$$

Convert to Unconstrained Optimization

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Further relax the constrained optimization problem into unconstrained optimization problem by utilizing penalty weights.

$$\underset{z}{minimize} \qquad \mathcal{L}_{opt}(z)$$

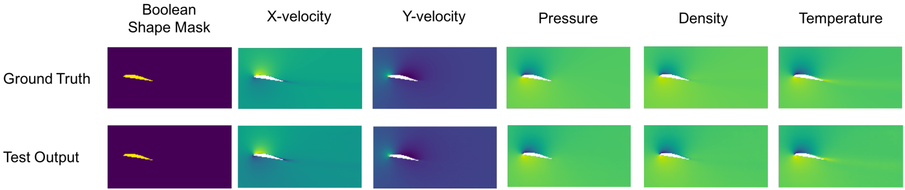
where

$$\begin{aligned} \mathcal{L}_{opt}(z) :=& R_o(z) + \lambda_{eq}||R_a^{eq}(z) - \mathbf{c}||^2 + \lambda_{ieq}\mathcal{I}(R_a^{ieq}(z) \leq \mathbf{d}) \\ &+ \lambda_r(-log(D(z))) \end{aligned}$$

where $\lambda_{eq}, \lambda_{ieq}, \lambda_r$ represent the penalty constant for equality, inequality and realism constraints. $\mathcal{I}$ is the indictor function that returns number of logical True entries.

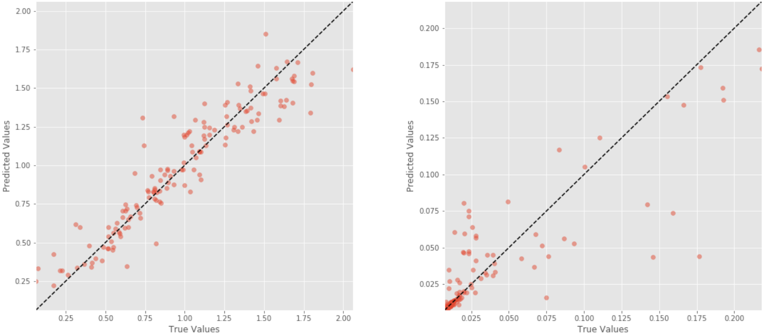
Outline

Results: Reconstruction Performance



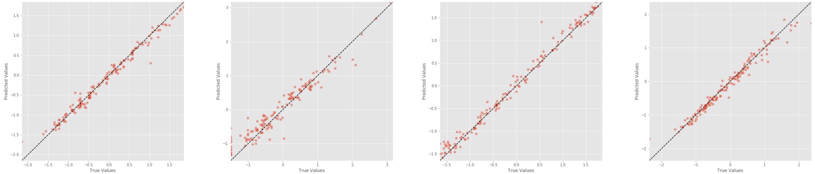
A random held-out test sample. Reconstructed shapes and flow fields closely resembles the original shapes, indicating that flow-related shape information is well preserved in the bottleneck feature vector.

Results: Predictive Performance on Objectives (Lift) $R^2 = 87.6\%$ (Drag) $R^2 = 75.2\%$



Plot of True (abscissa) vs Predicted (ordinate) values. Left shows a plot of lift predictions, Right shows a plot of drag predictions. Drag performance is more difficult due to nonhomogeneous distribution of training data.

Results: Predictive Performance on Attributes



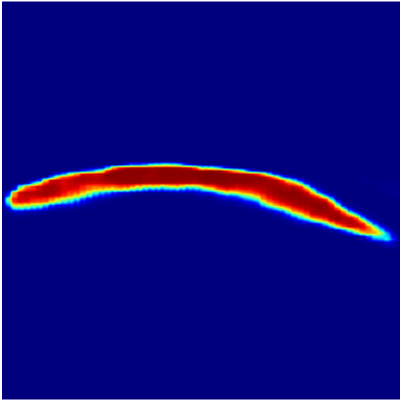
True vs prediction plot. Left to right: max thickness, max camber, angle of attack, area

Prediction Accuracies

Attributes	Max Thickness	Max Camber	Angle of Attack	Area
Test R^2	0.9794	0.9386	0.9902	0.9841

Latent Space Shape Manipulation

Morphing by linear interpolation of latent vectors



Outline

Conclusion and Continual Work

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So Far:

- We have formulated a deep learning based model for constrained shape optimization.
- Our surrogate model takes in raw shape information and does not require any hand-engineered shape parameterization, allowing for more efficient feature selections.
- The latent space of VAE has nice properties allowing continuous shape manipulations. Attribute and objective information can be effectively recovered in the latent space.

Work to be continued:

- Constrained shape generation
- Shape optimization

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Thank you. Questions?