Learning Three-dimensional Flow for Interactive Aerodynamic Design

Nobuyuki Umetani[1], Bernd Bickel[2]

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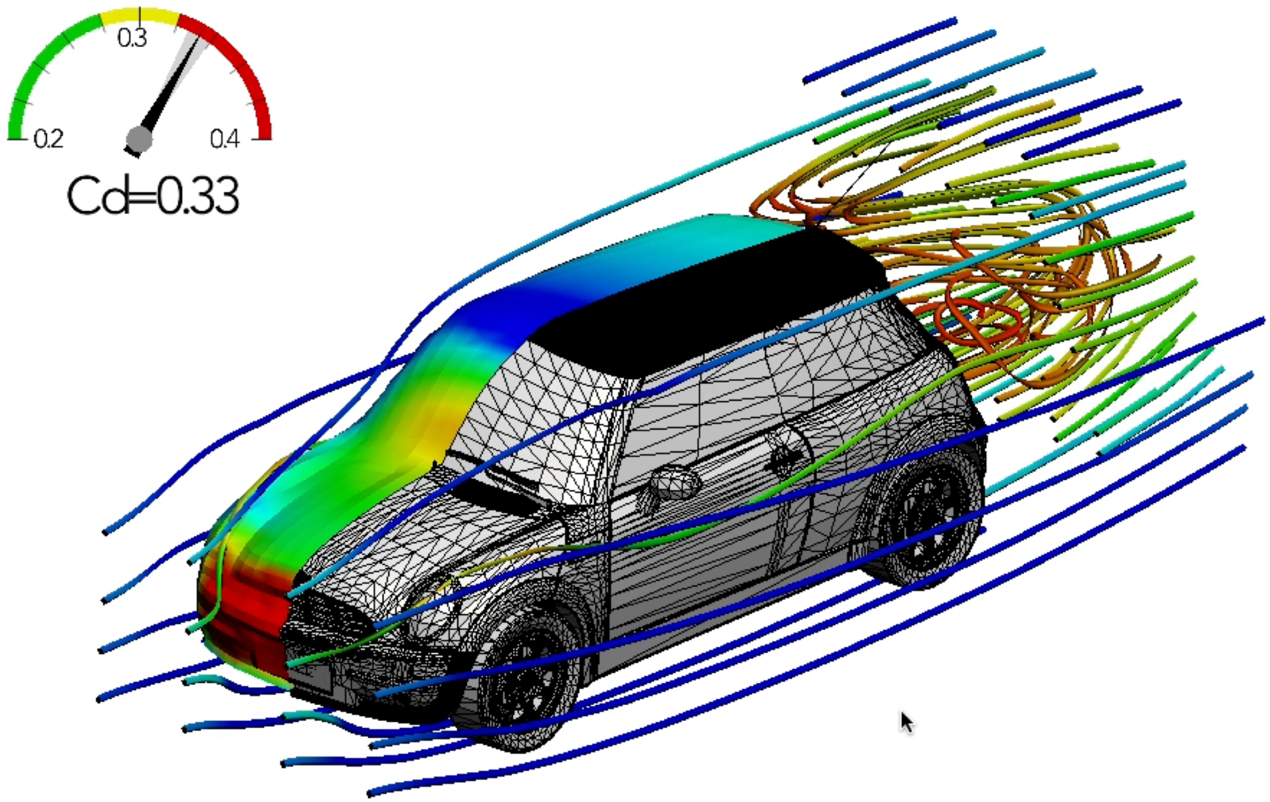
Motivation

- Predicting aerodynamics at an interactive rate



Aerodynamics is Important











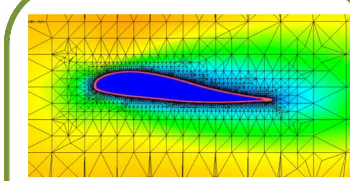
Images from Shutterstock and PixaBay

Computational Fluid Dynamics

- Traditional workflow is expensive & slow

input

3D shape

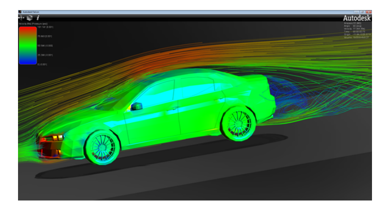


mesh generation

$$
\begin{aligned}
\rho\left(\frac{\partial \mathbf{u}}{\partial t} + \mathbf{u}\cdot\nabla\mathbf{u} - \mathbf{f}\right) - \mu\nabla^2\mathbf{u} + \nabla p &= \mathbf{0} \\
\nabla\cdot\mathbf{u} &= 0
\end{aligned}
$$

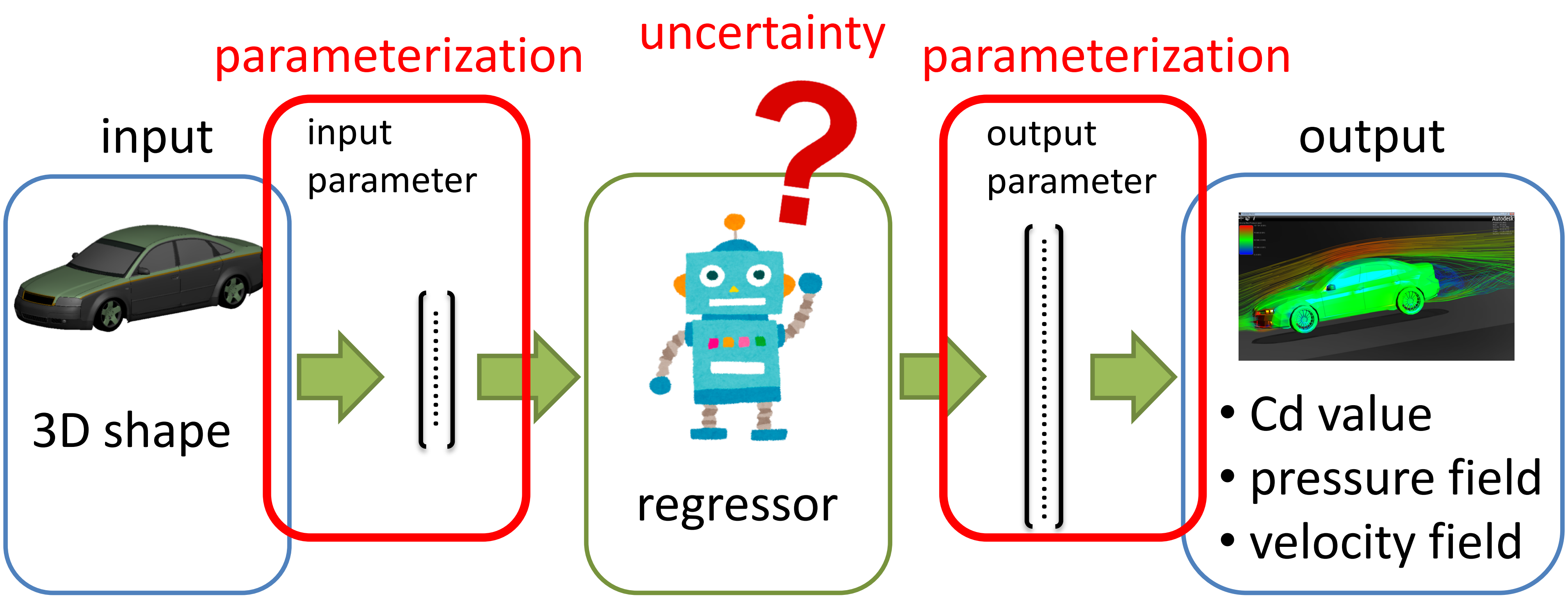
NS equation

output



- Cd value
- pressure field
- velocity field

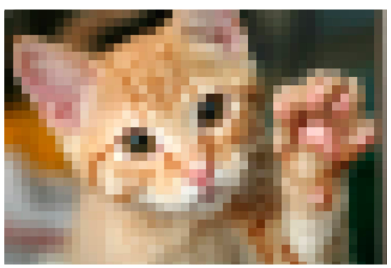
Replacing CFD with ML



Parameterization Problem

- Shape need to be represented by fixed dimensional vector/tensor

2D Image



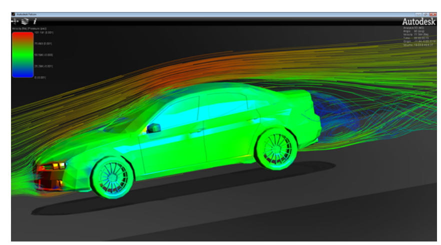
$$\begin{pmatrix} 53.3 \\ \vdots \\ 236.1 \\ \vdots \\ 67.2 \end{pmatrix}$$

3D shape

?

$$\begin{pmatrix} 53.3 \\ \vdots \\ 236.1 \\ \vdots \\ 67.2 \end{pmatrix}$$

3D field

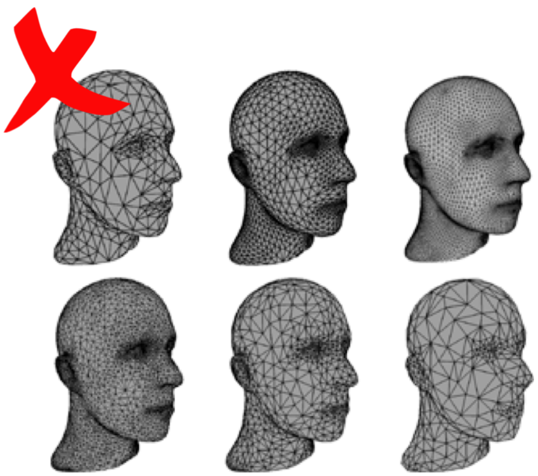


?

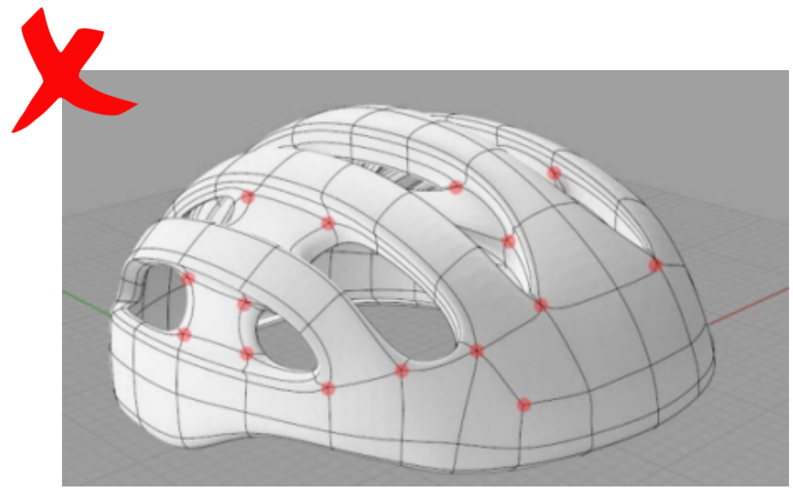
$$\begin{pmatrix} 53.3 \\ \vdots \\ 236.1 \\ \vdots \\ 67.2 \end{pmatrix}$$

Parameterization Problem

- Triangle mesh / NURBS are not suitable for ML
  - – Topology / #points are not constant



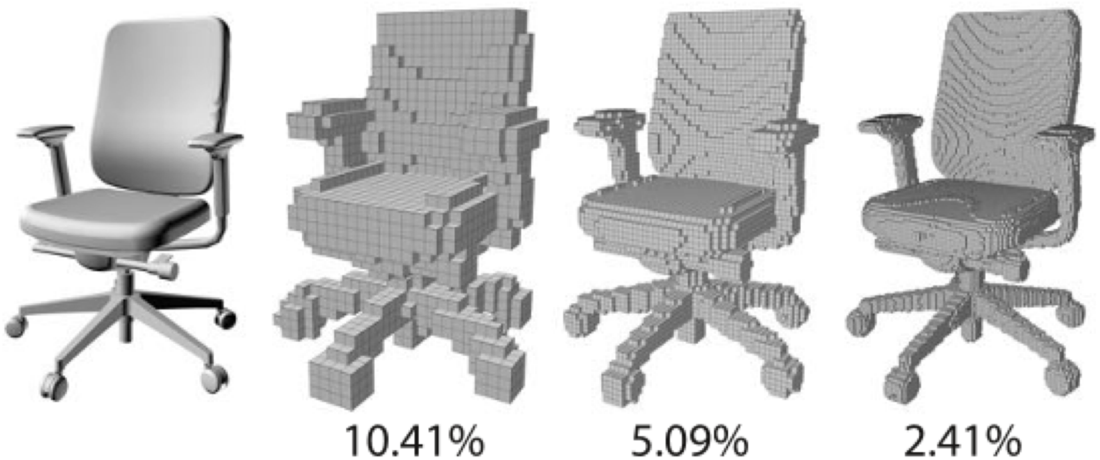
Triangle mesh



NURBS

Related Work: Voxel Model

- Difficult to handle detailed 3D shape



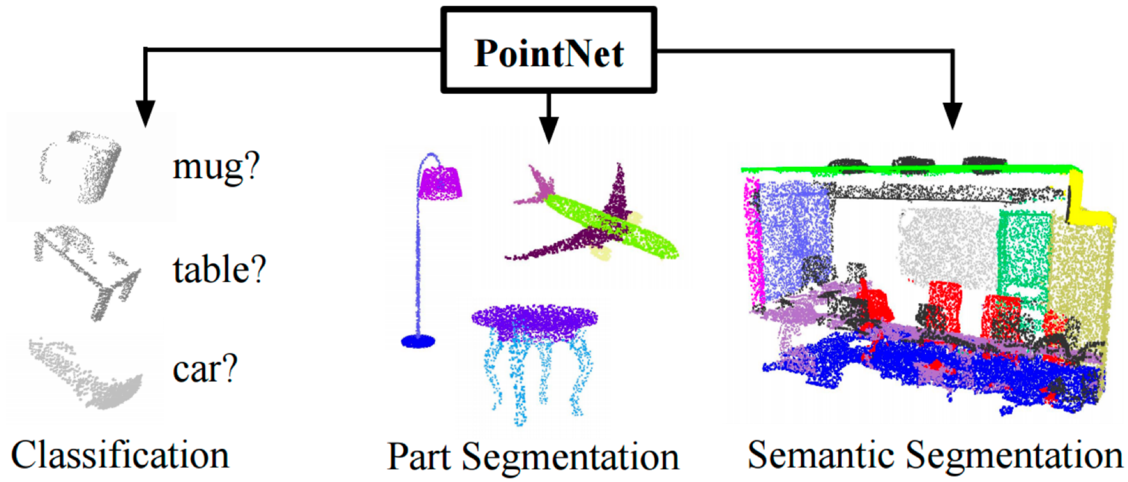
[FPNN, Li et al., 2017]

[3D GAN, 2016] [Girdhar et al., 2016] [O-CNN, Wang et al., 2017]

[liu et al., 2017] [OctNet, Riegler et al., 2017]

Related Work: Point-based Model

- Ordering of the point is not consistent



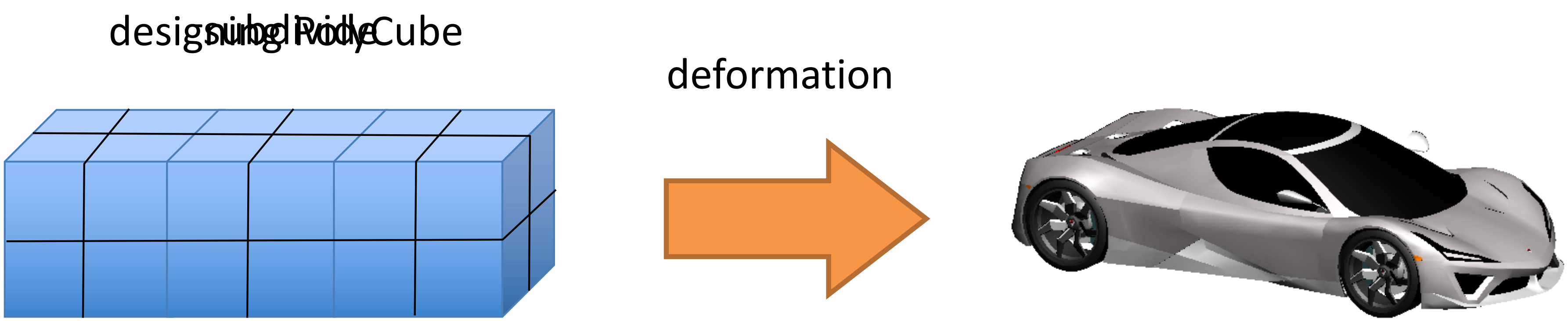
[PointNet, Qi et al, 2017]

[PointNet++, Qi et al, 2017]   [Gadelha et al.,2017]

[DeformNet, Kurenkov et.al, 2017]   [Fan et al, 2017]

Our Approach: Mesh Representation

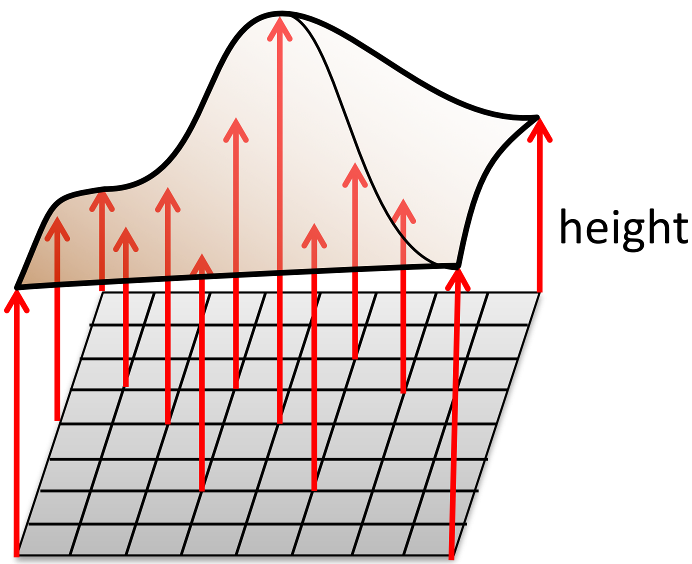
- PolyCube as a template quad mesh
- Deforming the quad mesh into the input shape



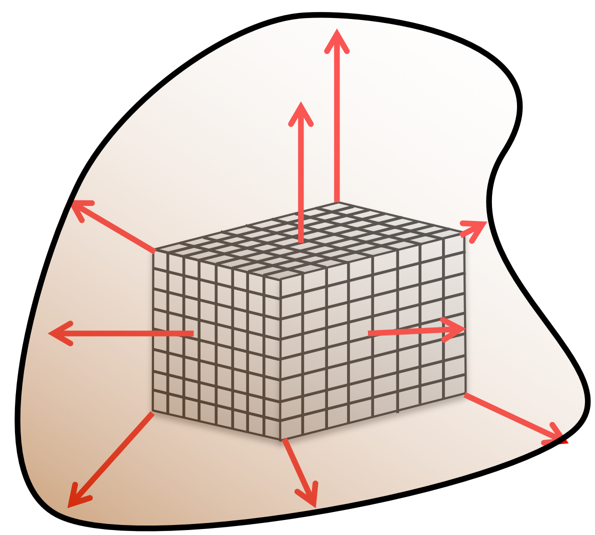
3D Shape as "Height Field"

- "Height field" from a PolyCube in normal directions

[Umetani 2018], Normal Meshes [Guskov et al. 2000]



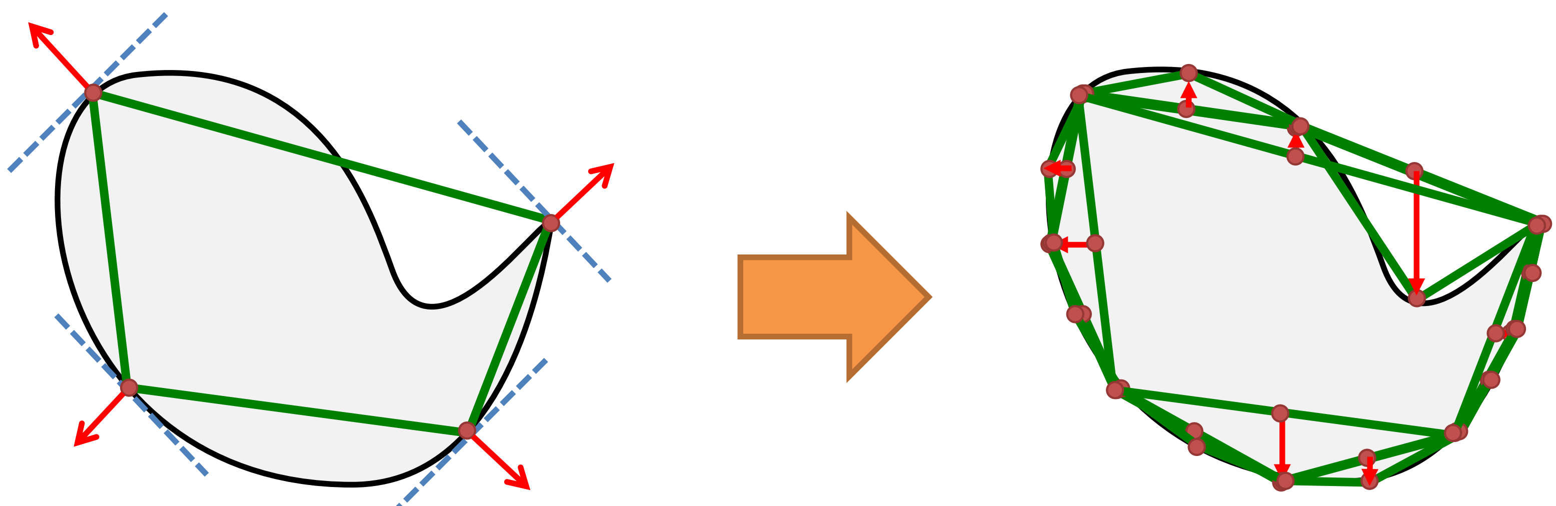
2.5 dimensional



3 dimensional

Hierarchical Projection

- We repeat subdivision and projection
- Key observation: concave shape is locally convex

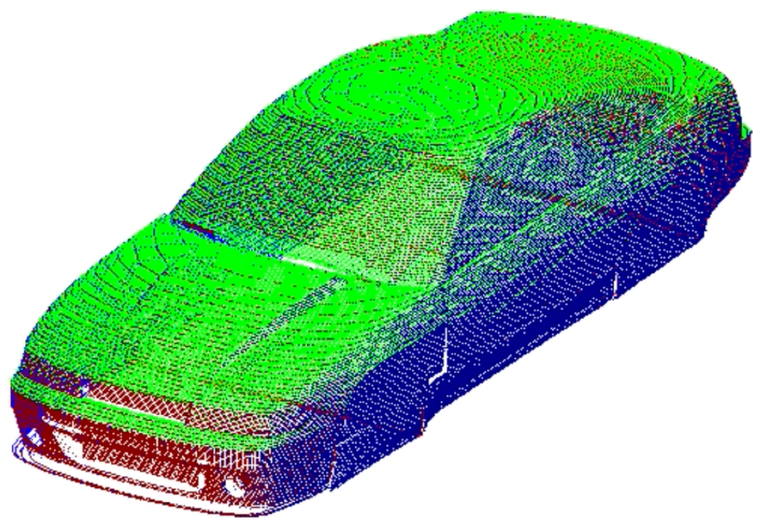


initialization

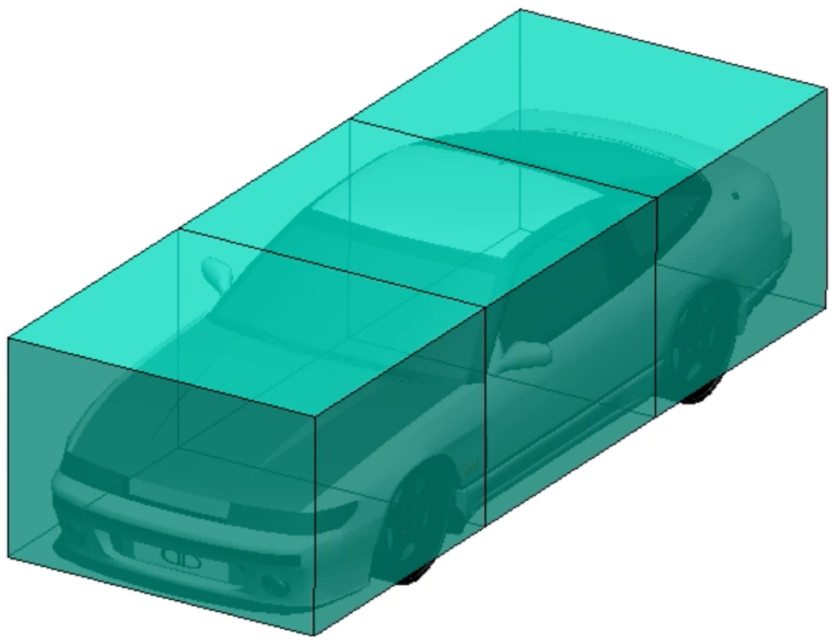
subdivision & projection

Parameterization Example

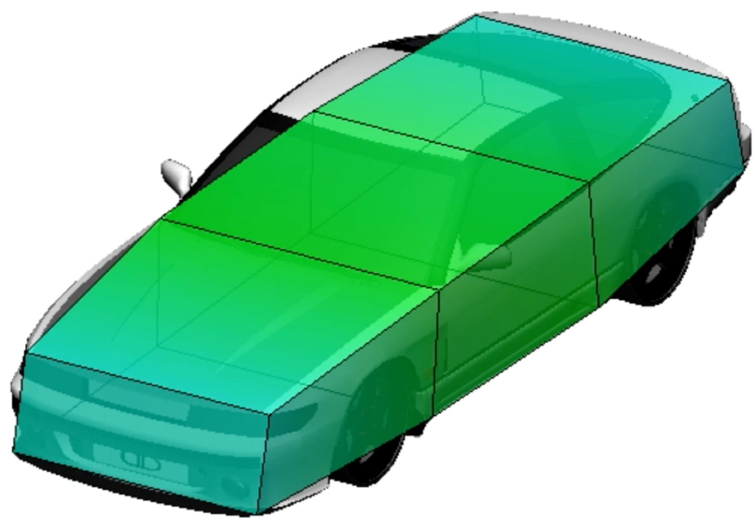
Parameterization Example



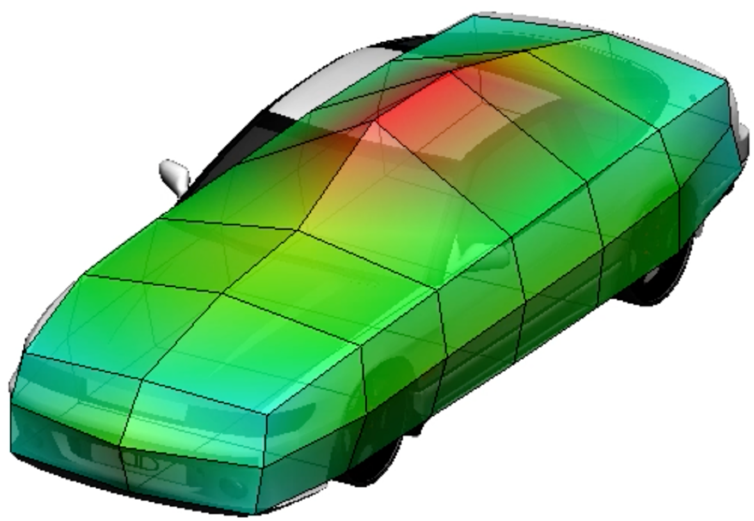
Parameterization Example



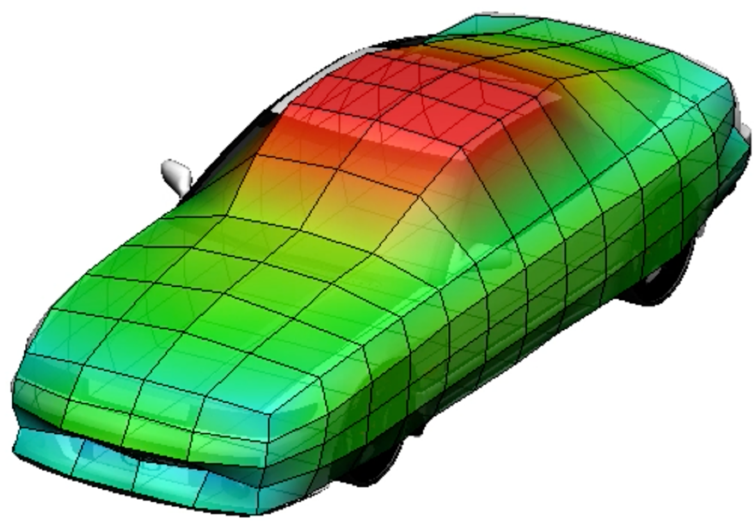
Parameterization Example



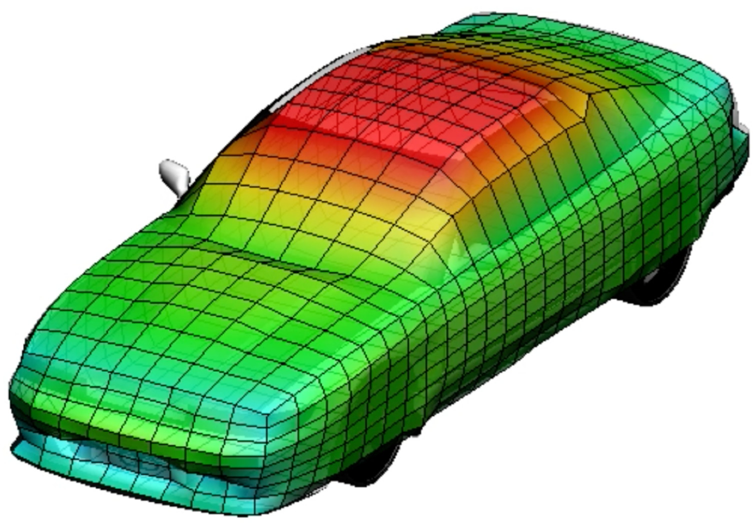
Parameterization Example



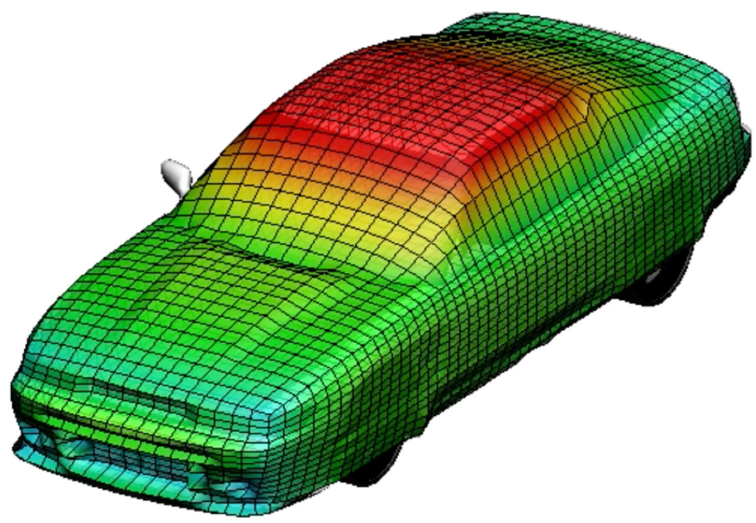
Parameterization Example



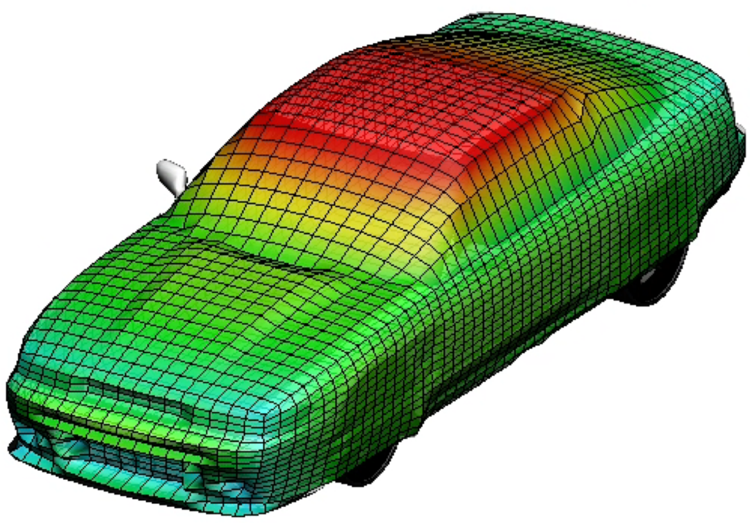
Parameterization Example



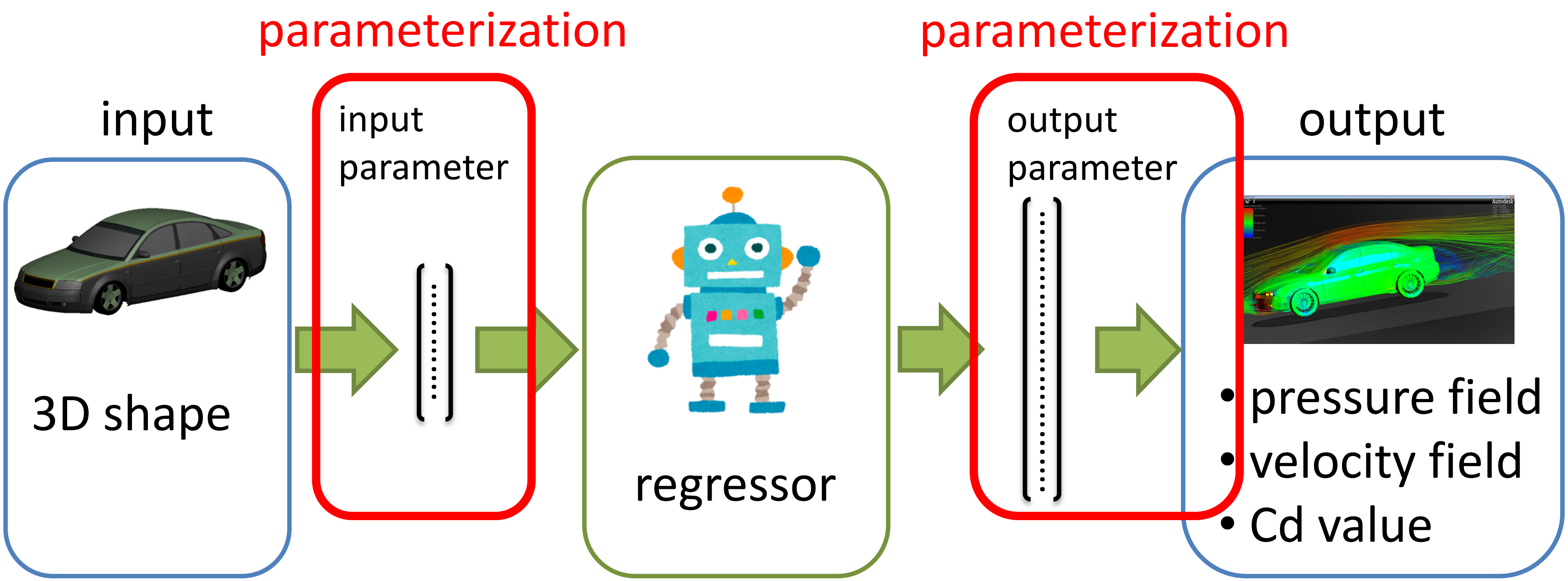
Parameterization Example



Parameterization Example

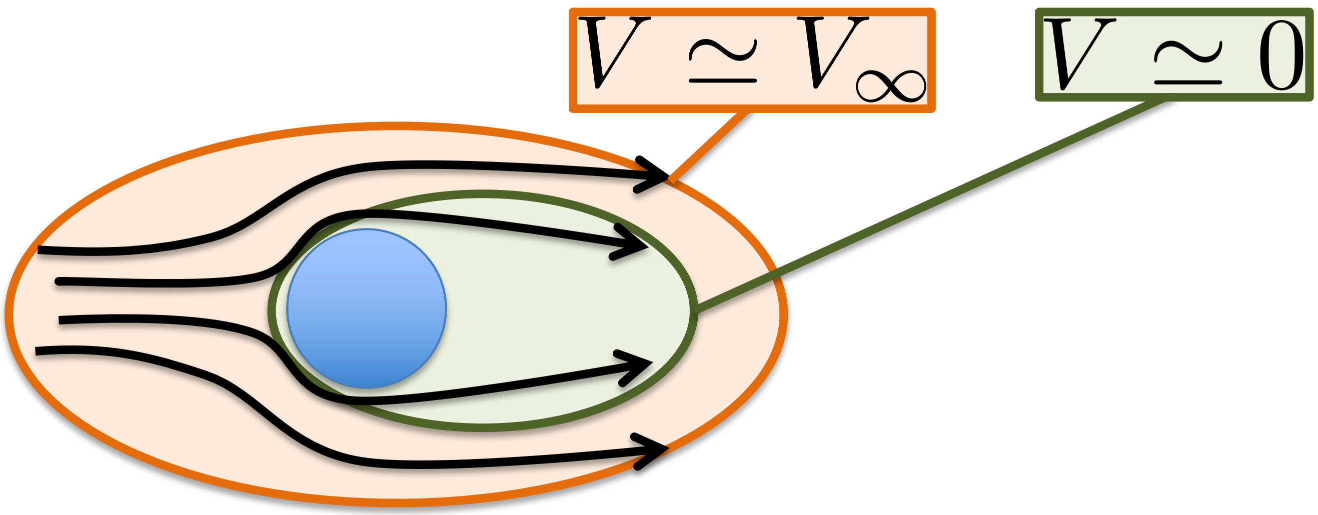


Overview of Our Approach



Challenge for Velocity Field Learning

- Velocity changes rapidly at the boundary



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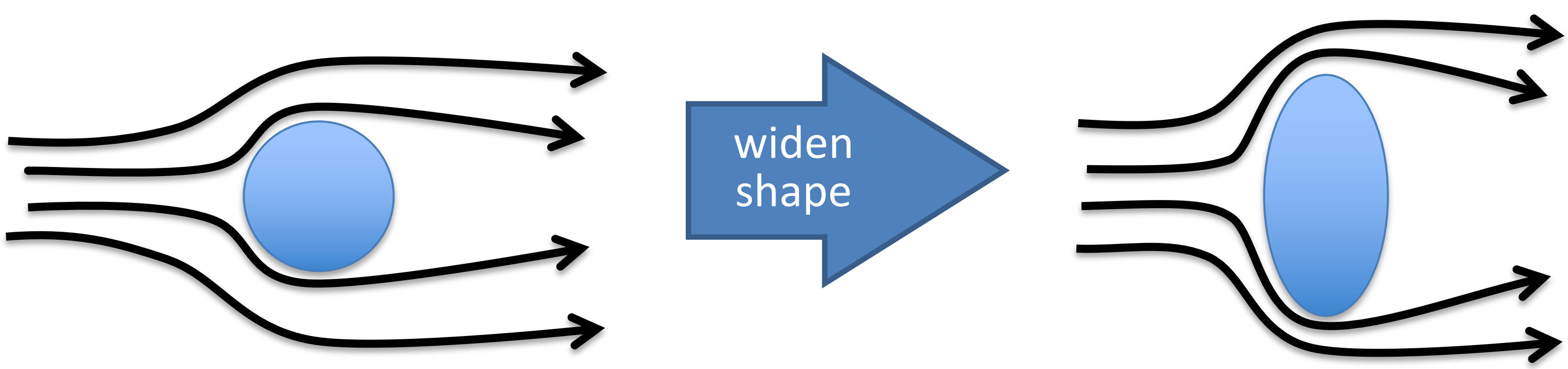

Challenge for Velocity Field Learning

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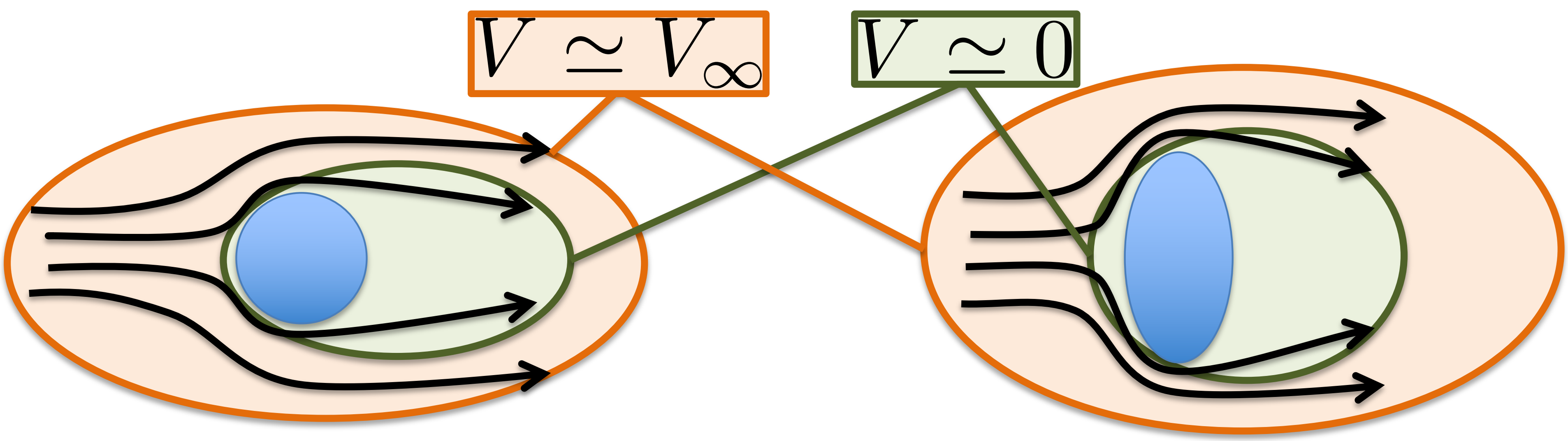
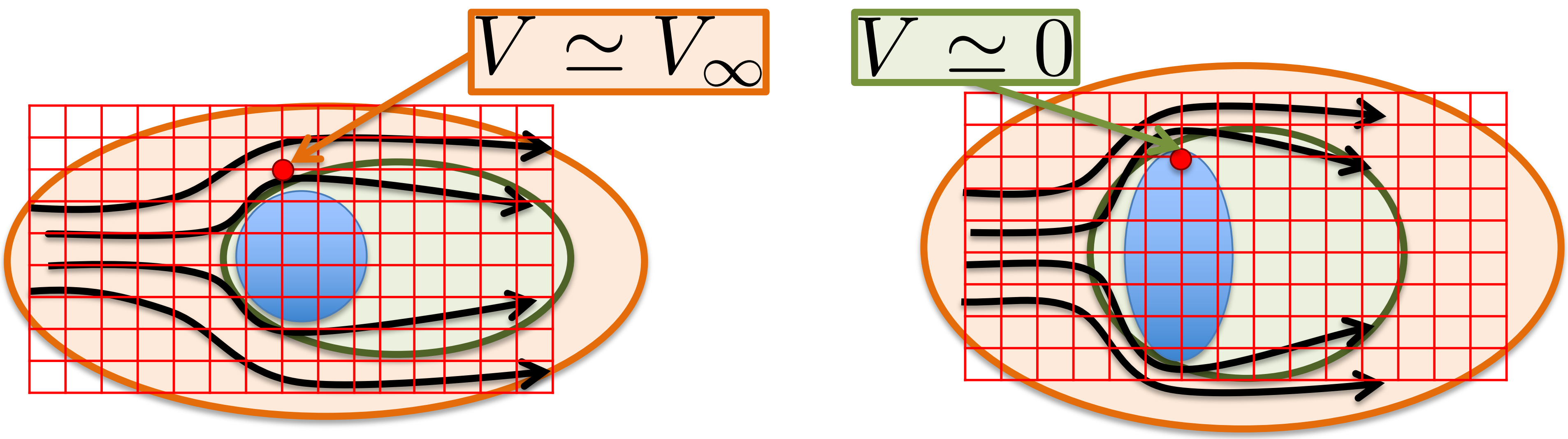


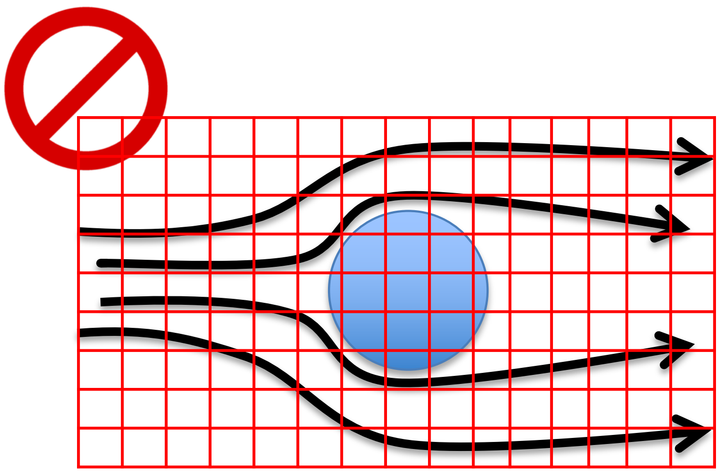
Challenge for Velocity Field Learning

- Regular grid has too much nonlinearity



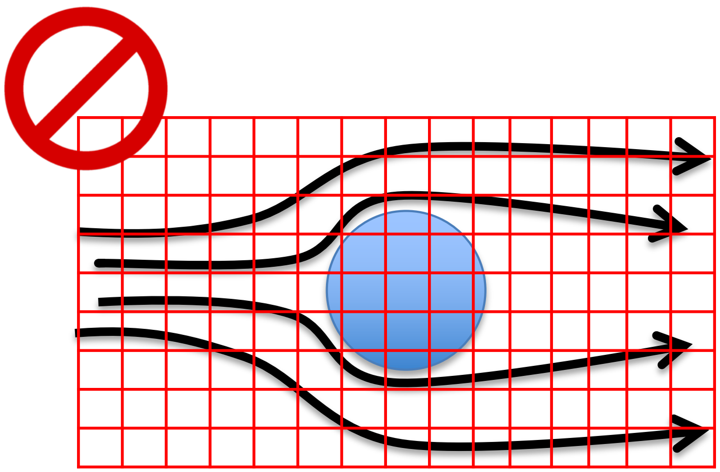
Parameterization of the Velocity Field

We cannot use fixed grid

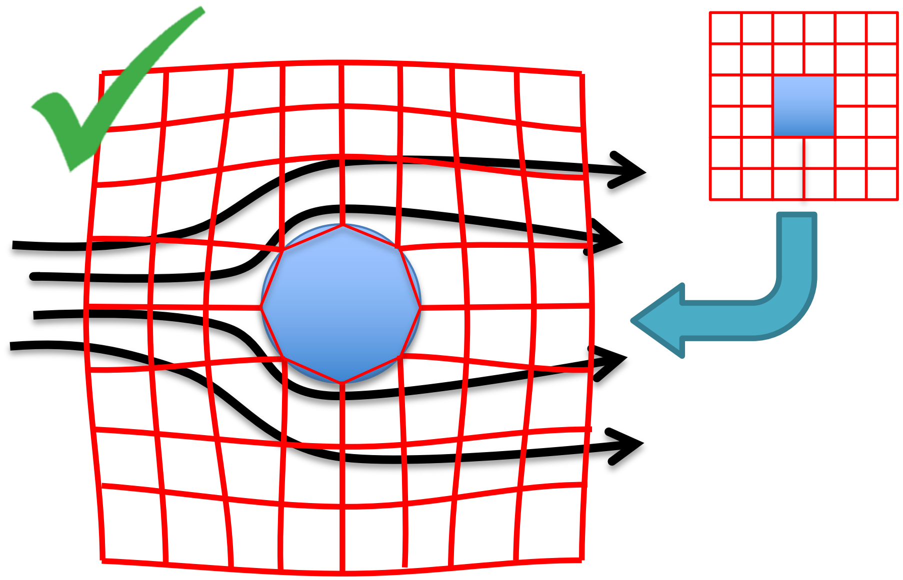


Parameterization of the Velocity Field

We cannot use fixed grid



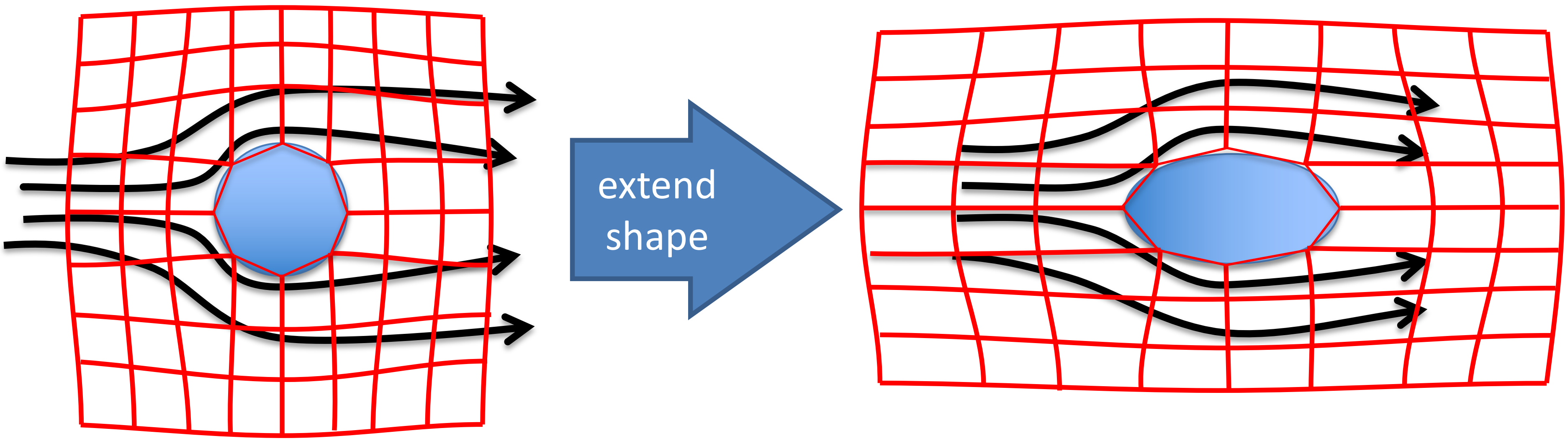
We use conformable grid



Parameterization of the Velocity Field

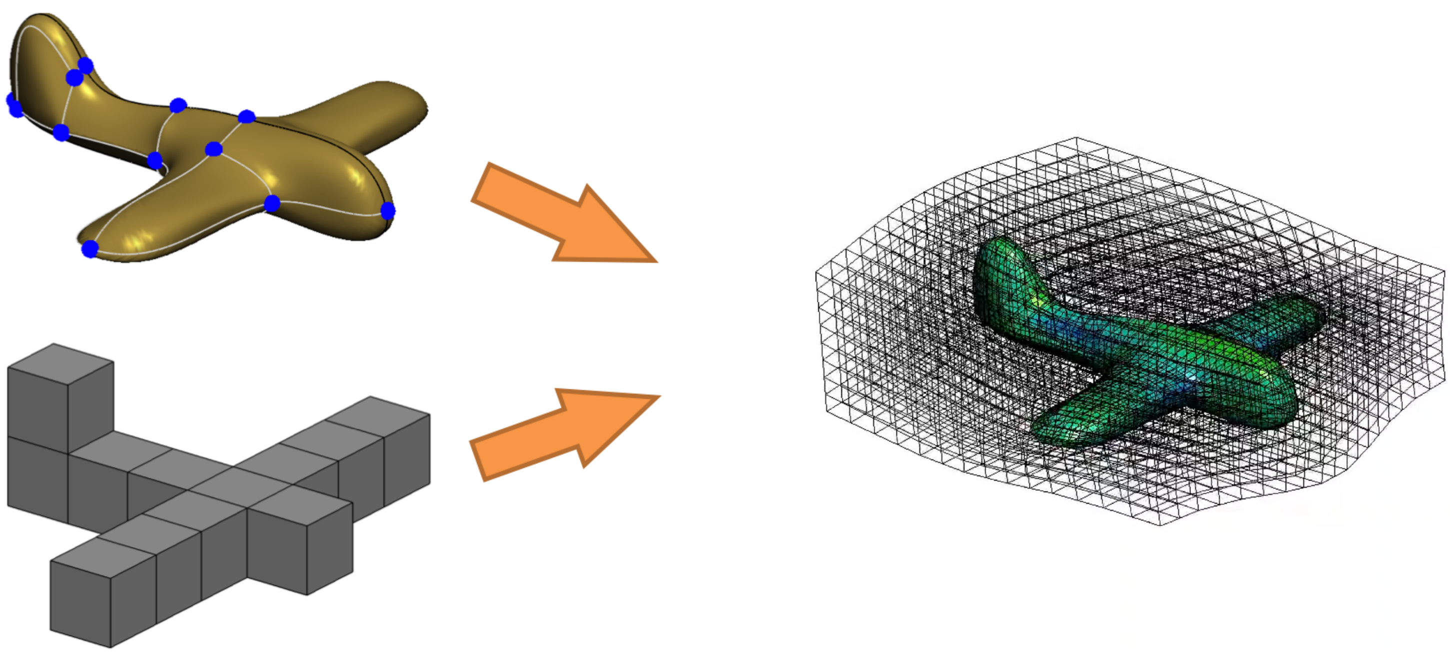
- Continuous representation of velocity field ☺

3D Mean Value Coordinate [Tao et al, 2005]



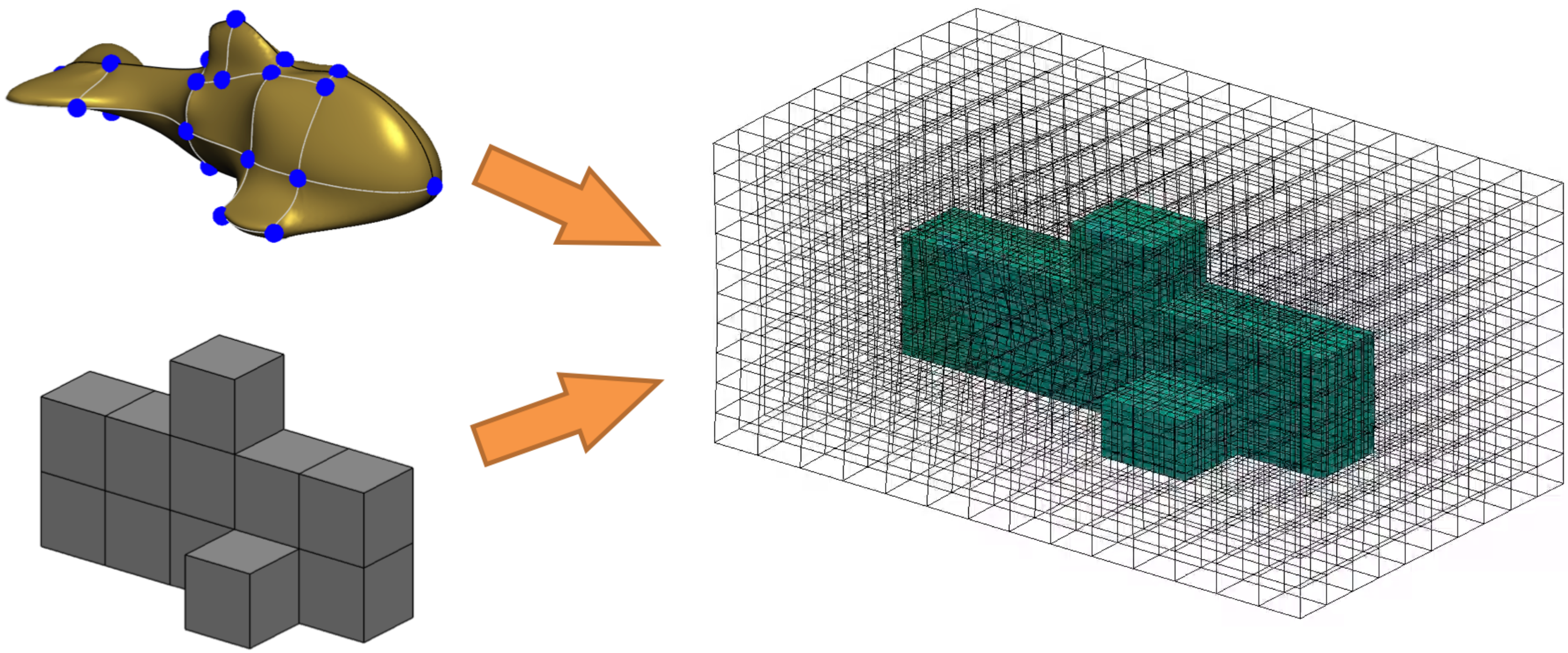
Parameterization Result

Airplane

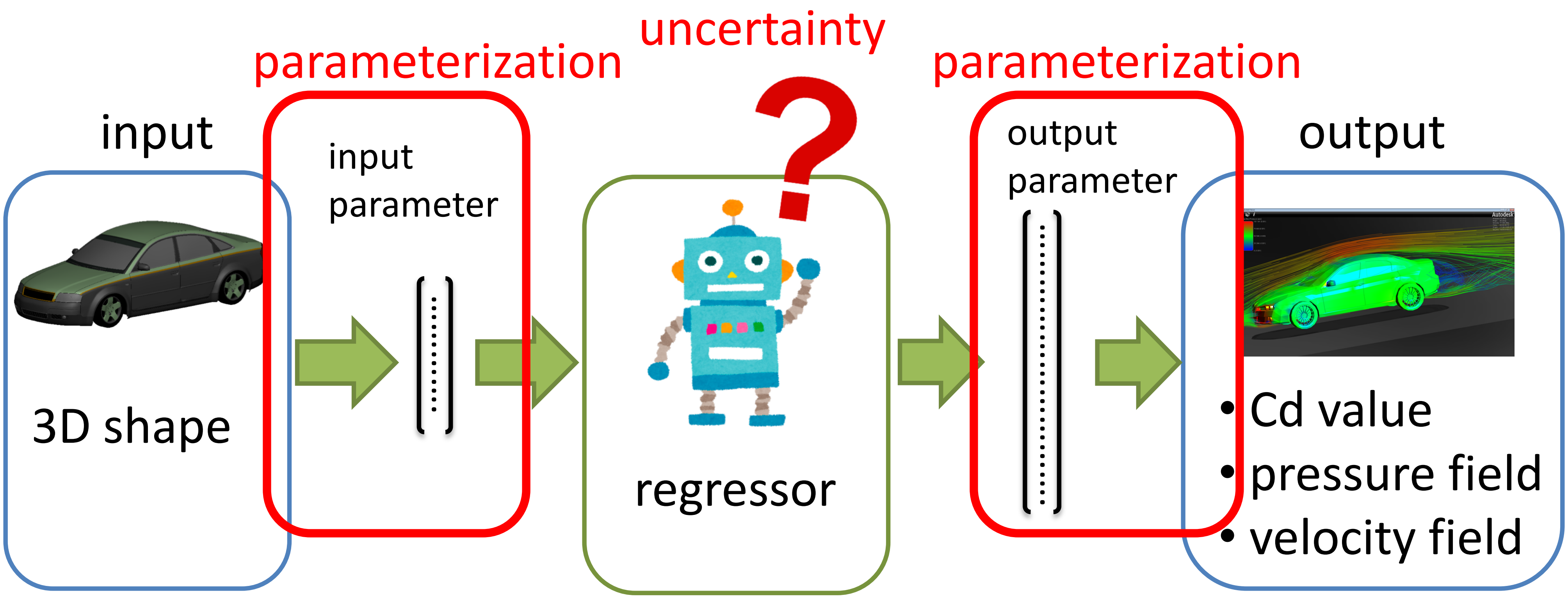


Parameterization Result

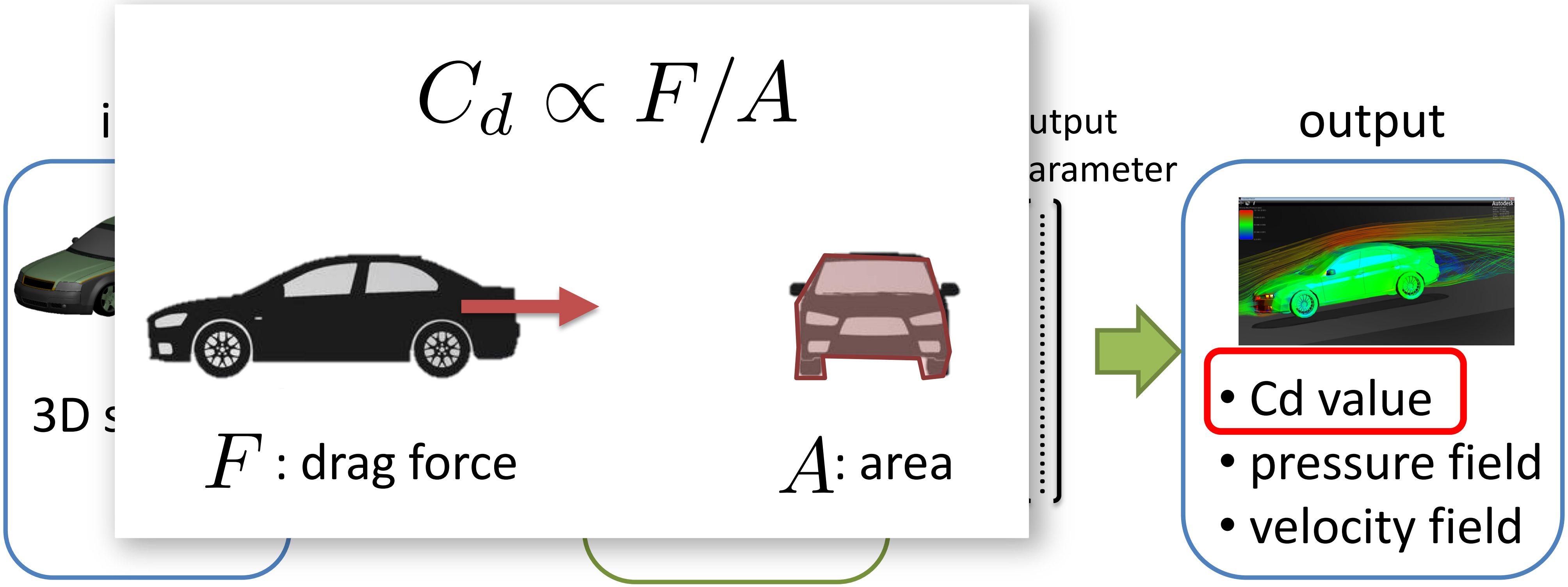
Dolphin



Challenges


uncertainty
parameterization
parameterization
input
input parameter
3D shape
regressor
output parameter
output
• Cd value
• pressure field
• velocity field

Challenges



$C_d \propto F/A$
F : drag force
A: area
output
• Cd value
• pressure field
• velocity field

Cd Value is Important

- Car design is strongly influenced by the Cd value

1951

Citroen 2CV

Cd=0.51

1980

Ford Mercury

Cd=0.36

1995

Ford Falcon

Cd=0.31

2005

Ford Fusion

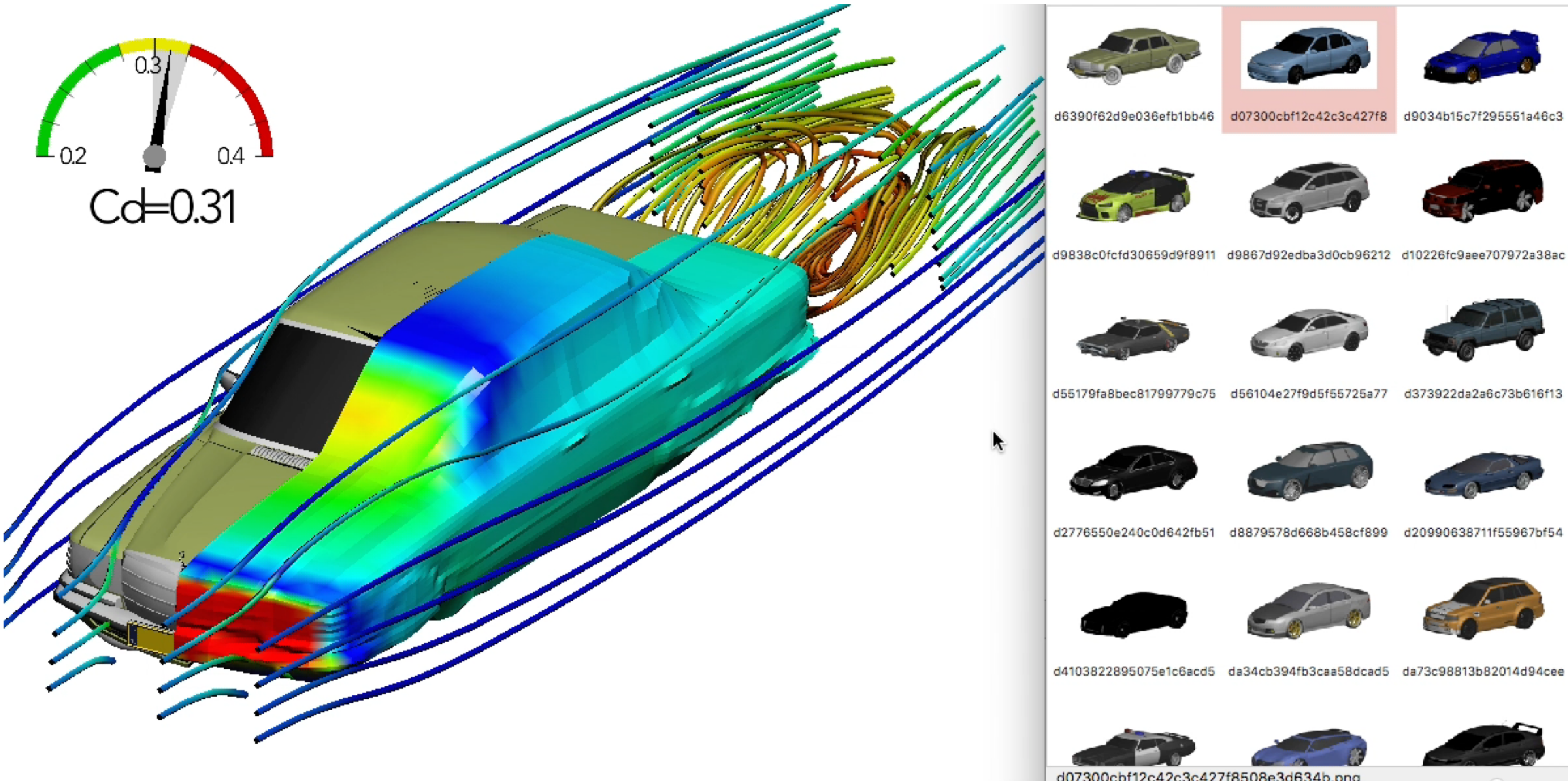
Cd=0.275

2017

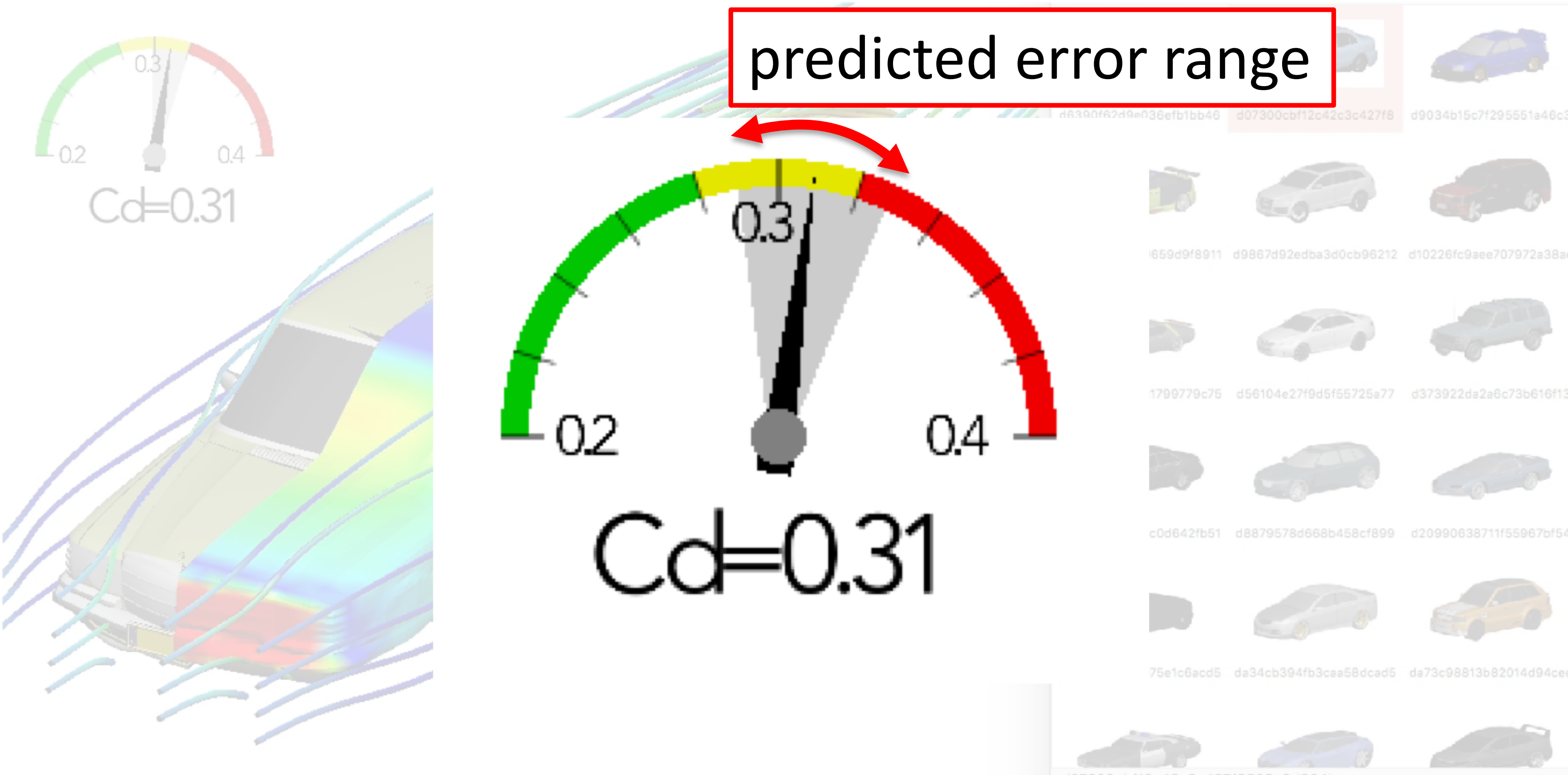
Tesla Model3

Cd=0.23

Preview of Result



Preview of Result



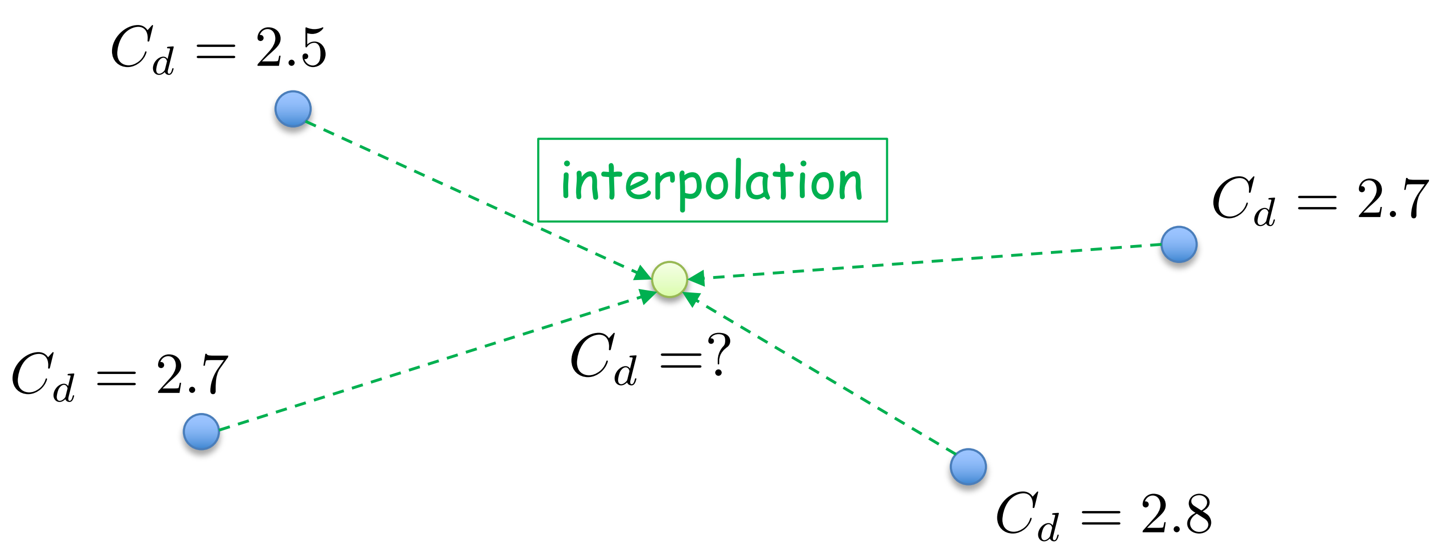
Regression: Gaussian Process(GP)

- GP: non-parametric Bayesian regression model
  - Handles nonlinearity well ☺
  - Learning from few samples without over–fitting ☺
  - Prediction of error ☺

Regression: Gaussian Process(GP)

- GP: non-parametric Bayesian regression model

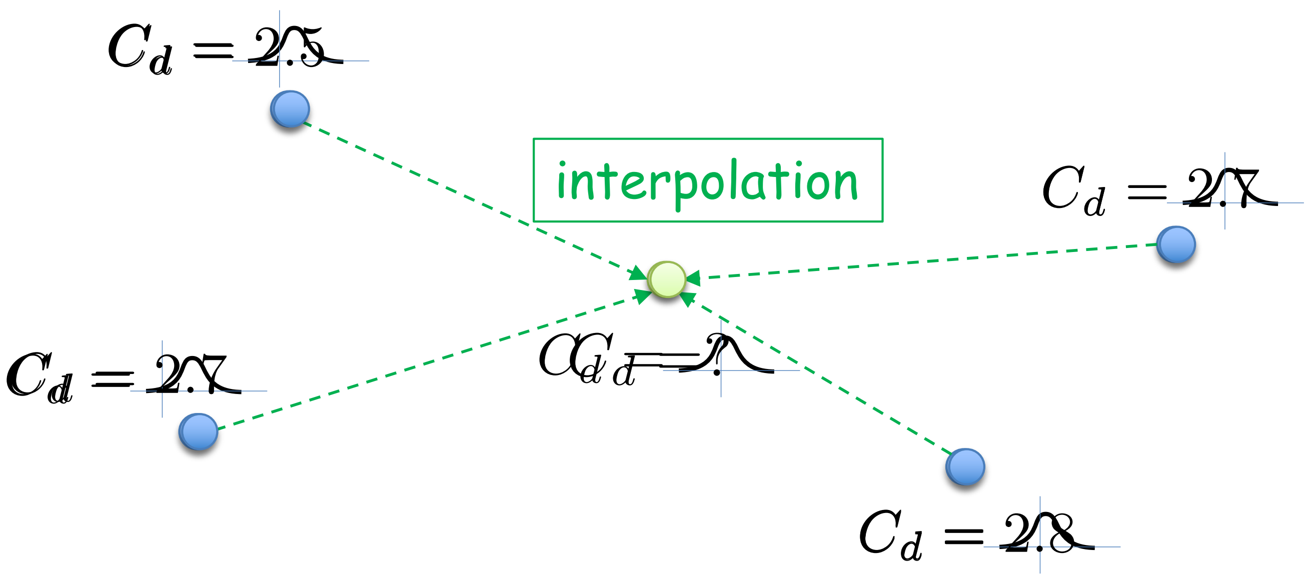
Interpolation weight is determined by distances



Regression: Gaussian Process(GP)

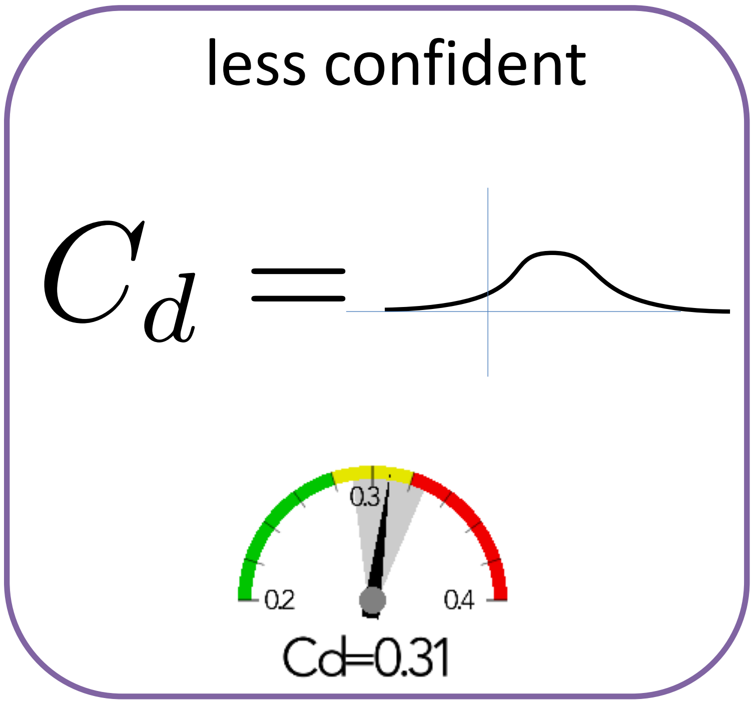
- GP: non-parametric Bayesian regression model

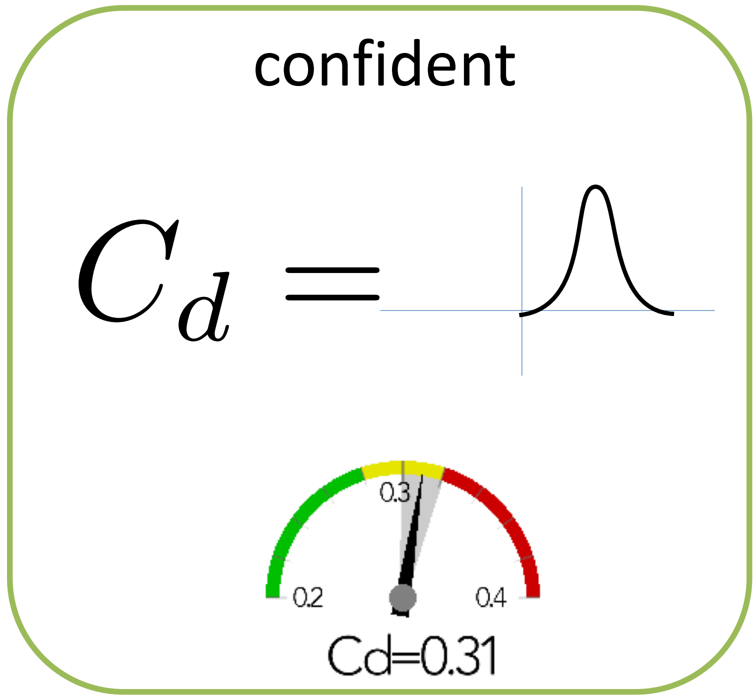
Covariance (similarity of the distributions) is determined by distances



Regression: Gaussian Process(GP)

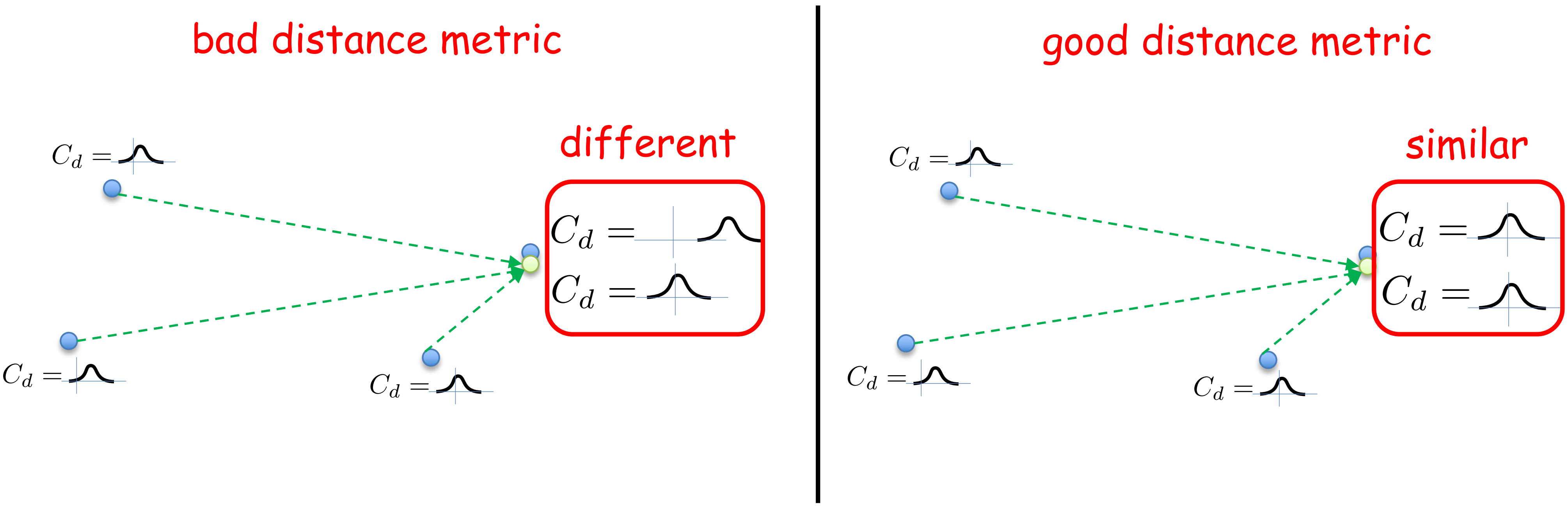
- Standard deviation gives how "confident" the prediction is





Distance Metric Optimization

- Distance metric is optimized for maximizing likelihood of the training data

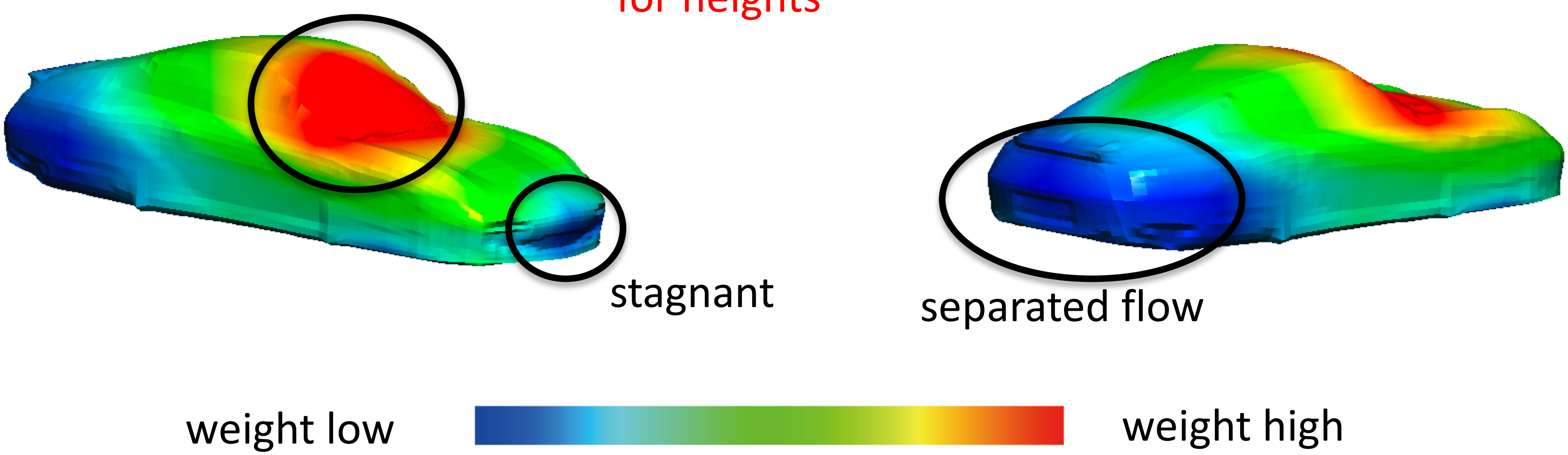


The Weights in the Distance Metric

$$Distance(\mathbf{h_0}, \mathbf{h_1}) \propto ||\boxed{\mathbf{w}}\boxed{(\mathbf{h_0} - \mathbf{h_1})}||$$

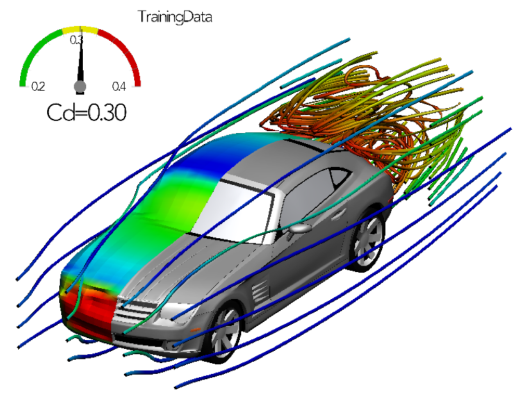
height difference

distributed weight
for heights



Training Data

- 889 CFD simulation for car shapes from ShapeNet

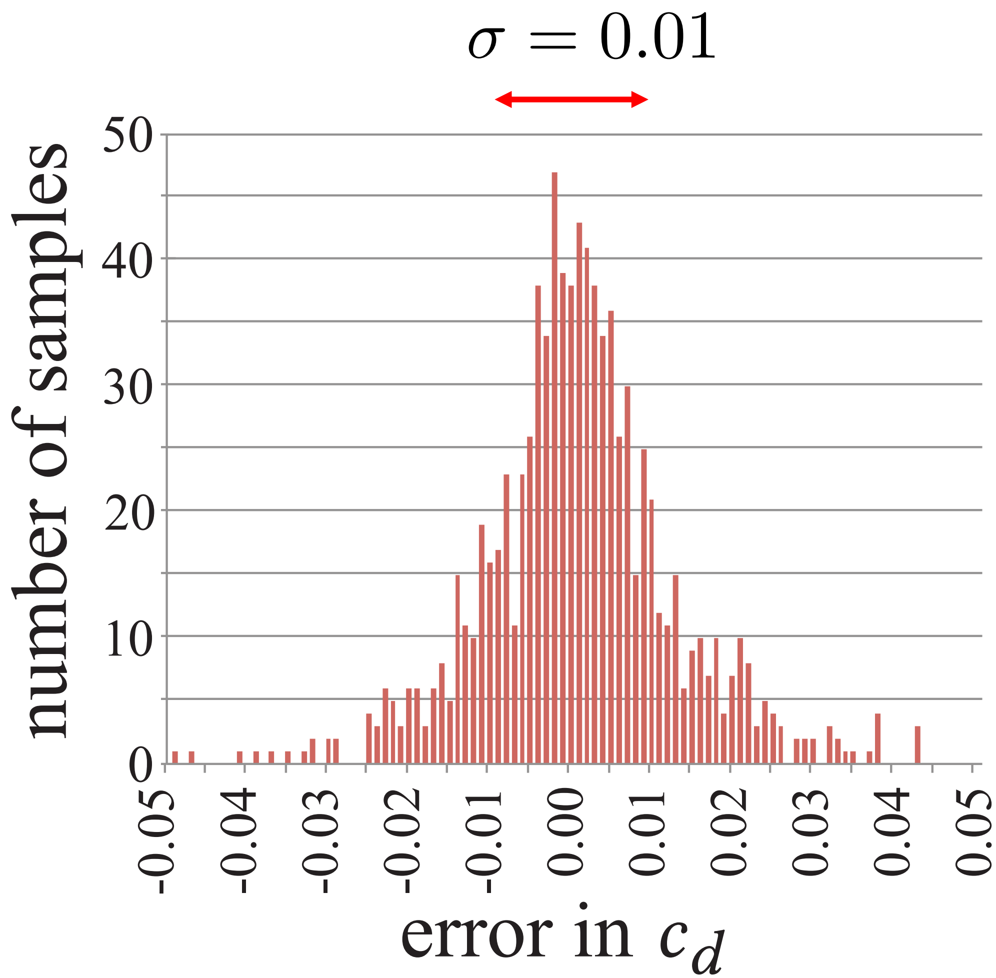


- Each simulation takes 3 hours computed on Amazon AWS

- All data available

http://www.nobuyuki-umetani.com/

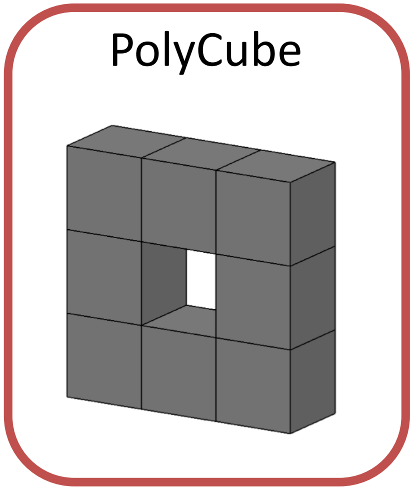
Accuracy

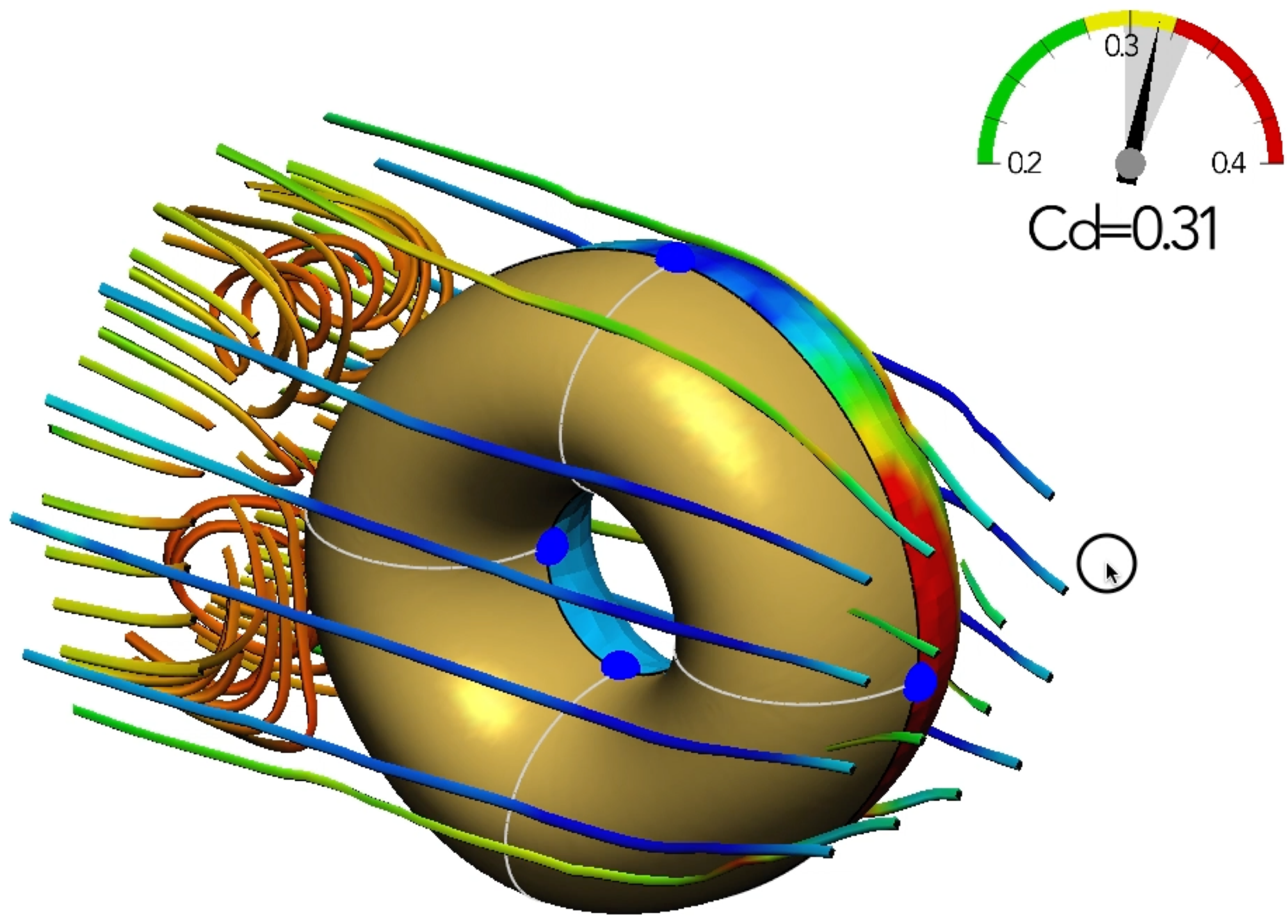


$\sigma = 0.01$
50
40
30
20
10
0
number of samples
-0.05
-0.04
-0.03
-0.02
-0.01
0.00
0.01
0.02
0.03
0.04
0.05
error in c_d

Live Demo!

Shape with Genus One Topology





3D Printed Hood Ornament

Limitations

- Prediction limited by training data
- Highly concave shape

side mirror

spoiler

Future Work

- Convolution operation on the PolyCube
- Application to more complex phenomena
  - thermal convection, acoustics

Acknowledgement

- Anonymous reviewers
- Alec Jacobson, Ryan Schmidt, Eitan Grinspun

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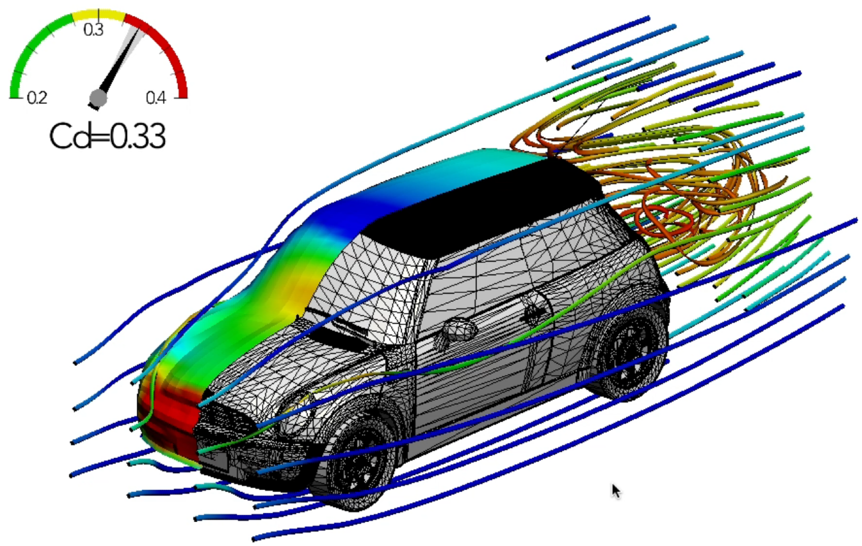
- European Research Council (ERC) No 715767 -- MATERIALIZABLE

Learning Three-dimensional Flow for Interactive Aerodynamic Design



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