Beyond Simulation
AI's Role in Future Crash Studies

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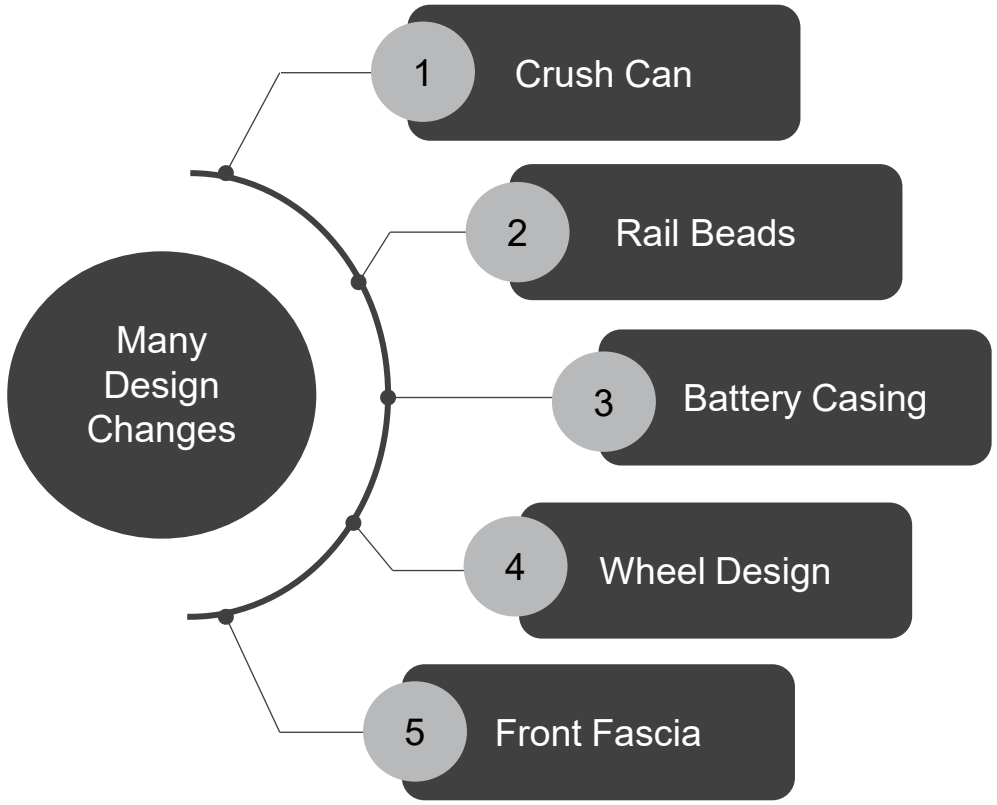
Agenda

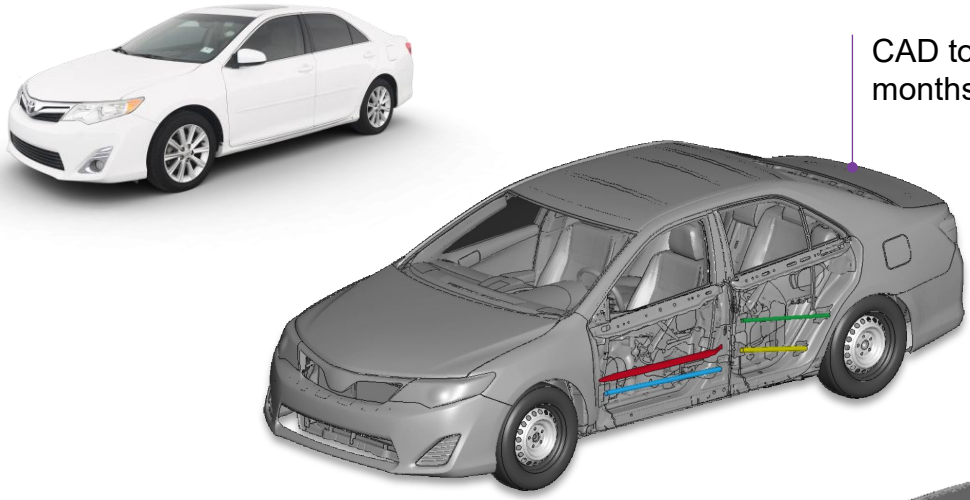
- Challenges in Crash Modeling
- Objective
- **SimAI**
- **GeomAI**
- Case Study
- Q&A

Challenges in Crash Modeling

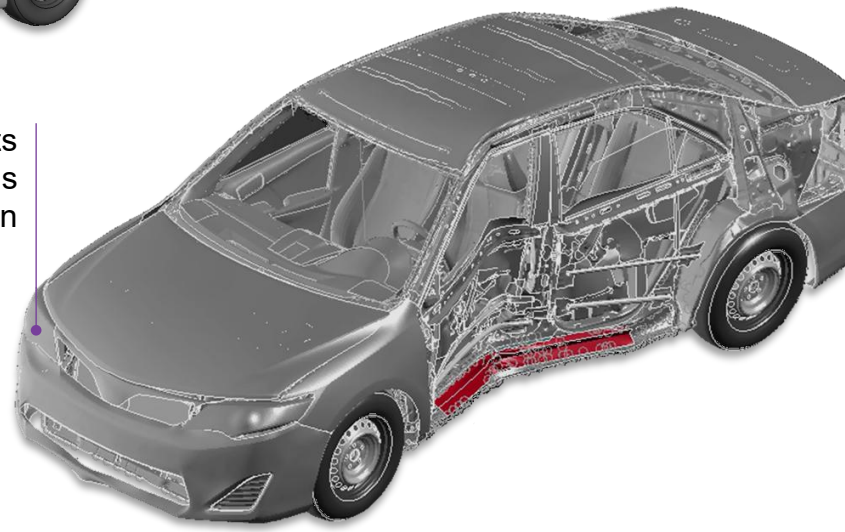
Objectives

challenges in crash modeling





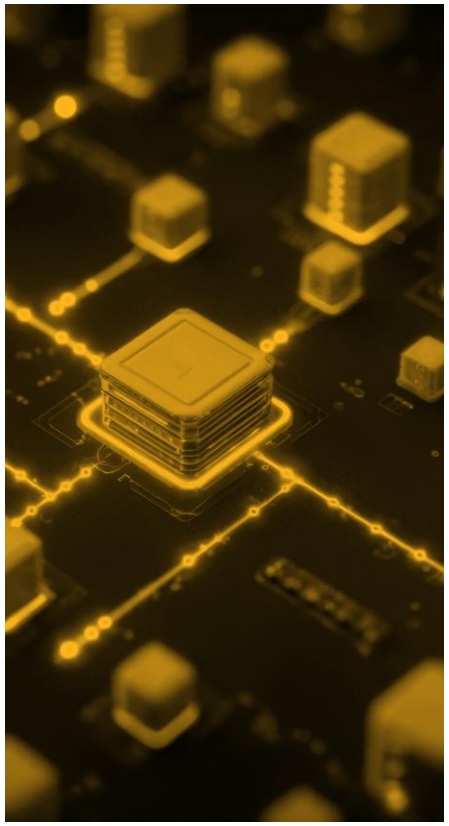
CAD to FE takes months



40 to 50 million elements
700 to 1000 CPUs
25 to 30 hours per simulation

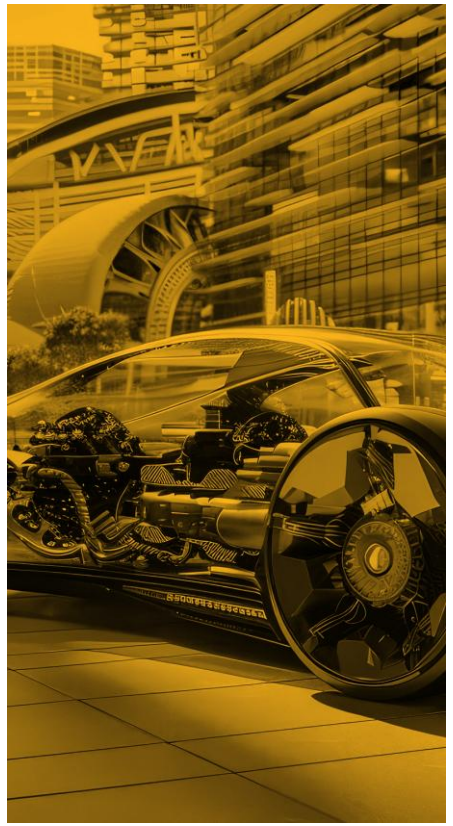
CAE models cannot keep up with all the design changes for a given program

objectives
in crash modeling



learn
from existing data

build
accurate predictive models



generalize
for early design prediction

APPLIED ARTIFICIAL INTELLIGENCE

SimAI

The Physics AI Engine

SimAI
training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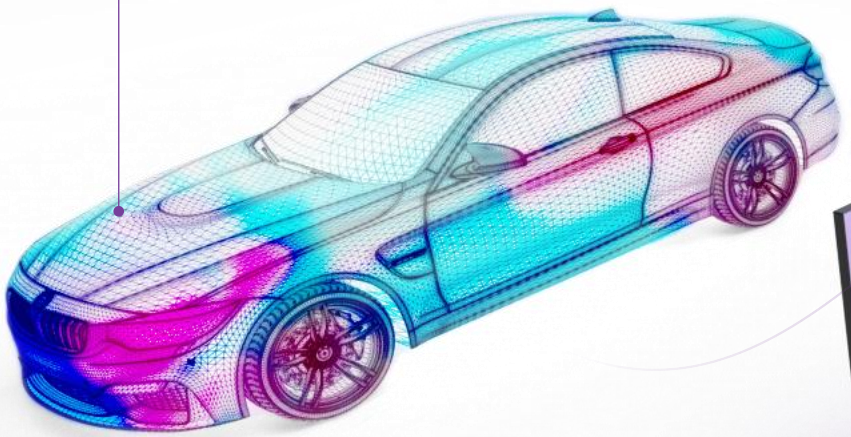
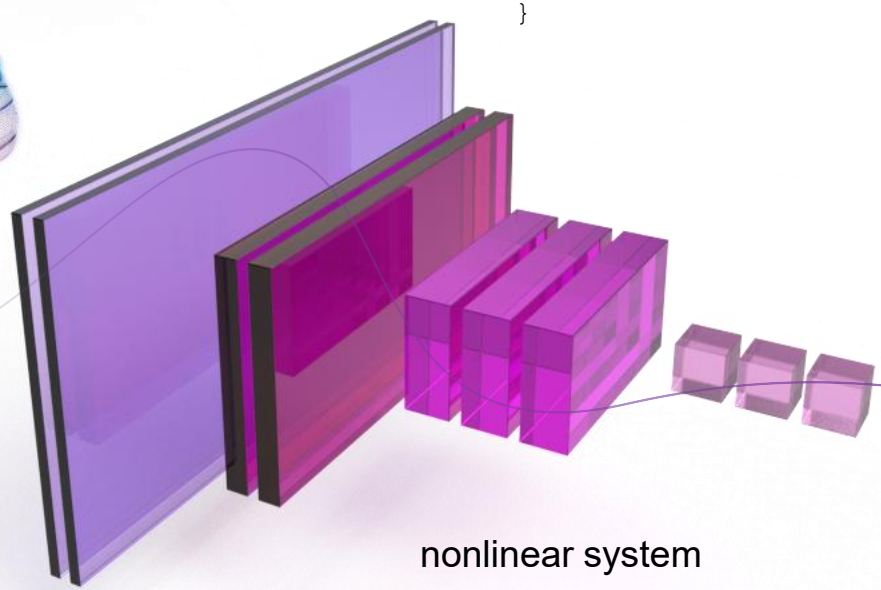
scalar inputs
surface inputs
volume inputs



no parameters



nonlinear system

nonlinear space

SimAI inference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}
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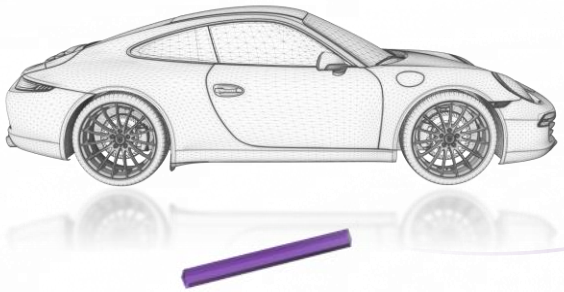
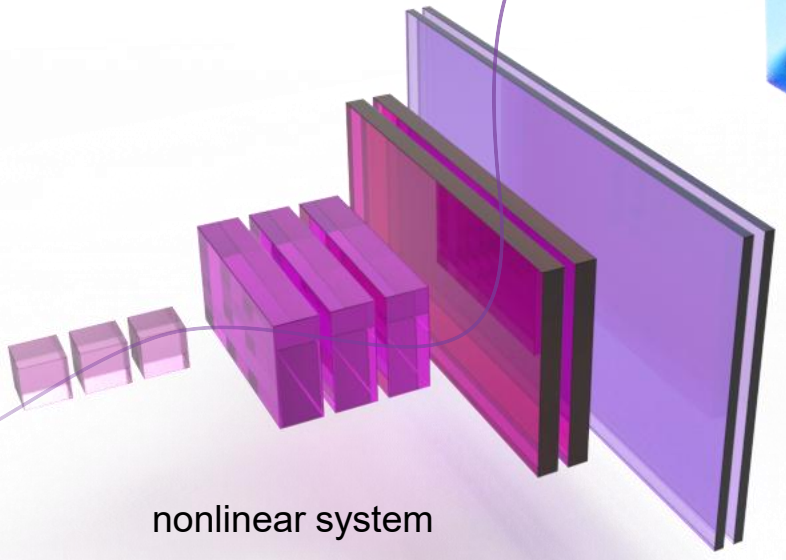
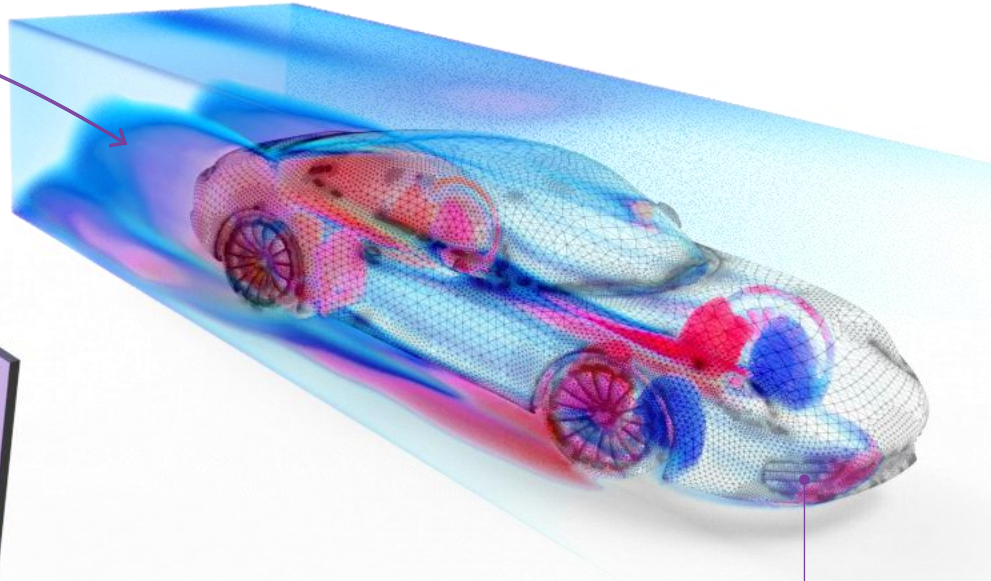
unseen design



nonlinear space

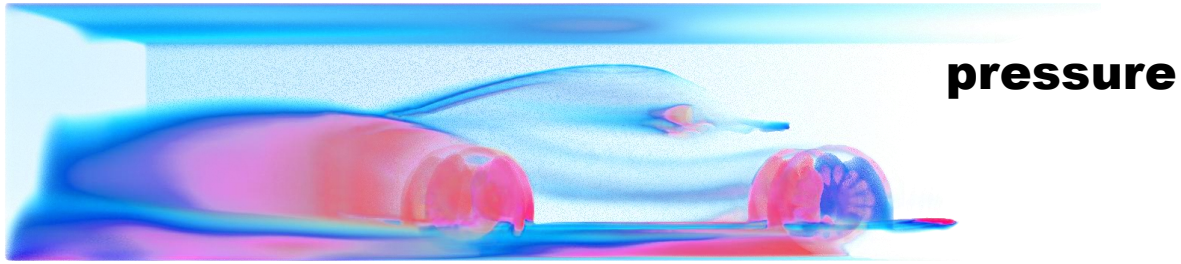


nonlinear system

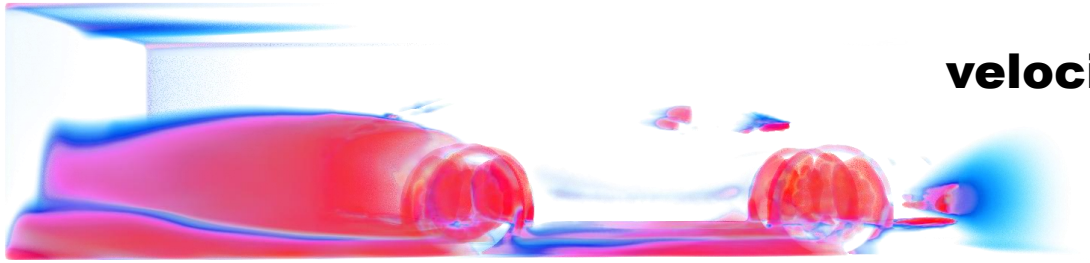


continuous function with infinite resolution to be collocated

SimAI
stacked model

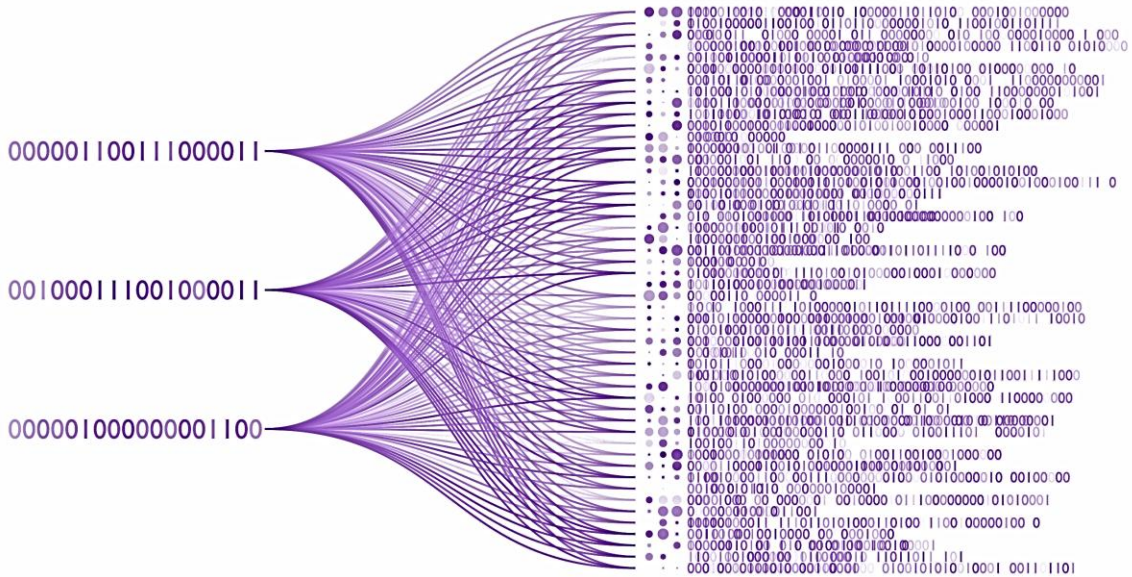


pressure



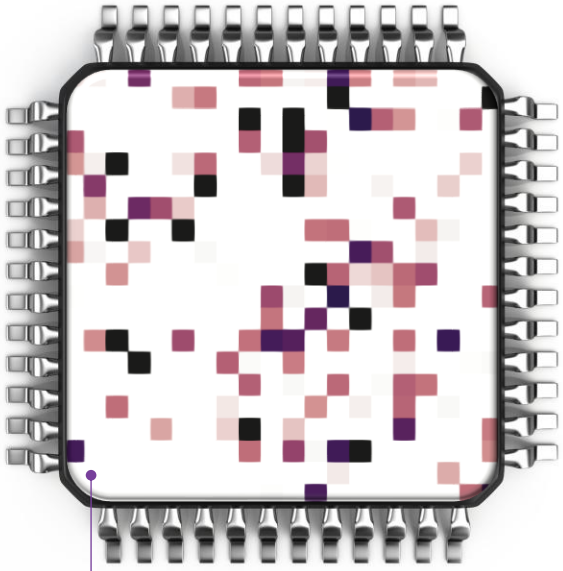
velocity

vorticity

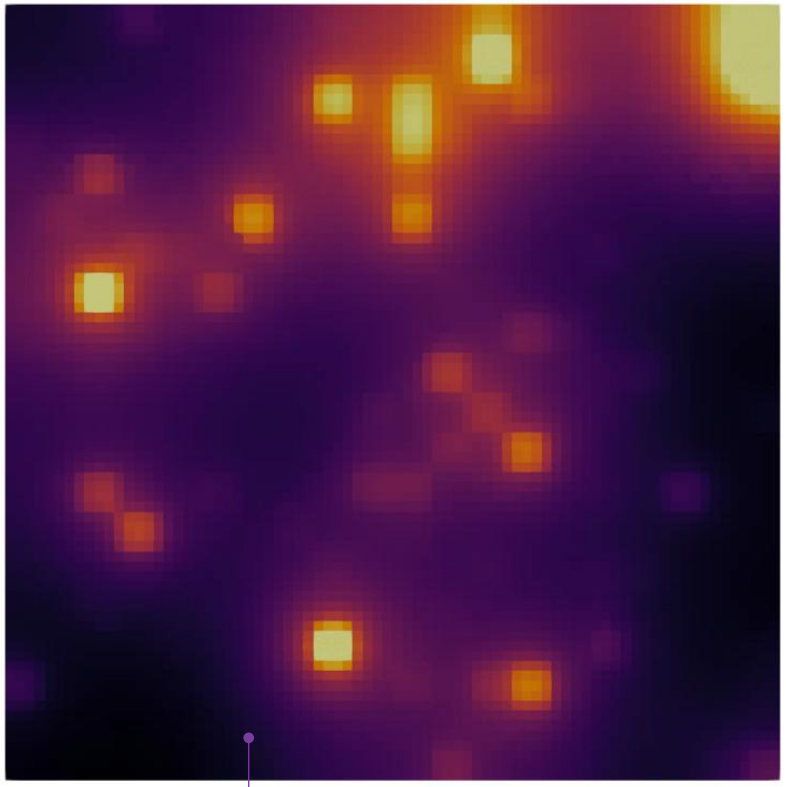


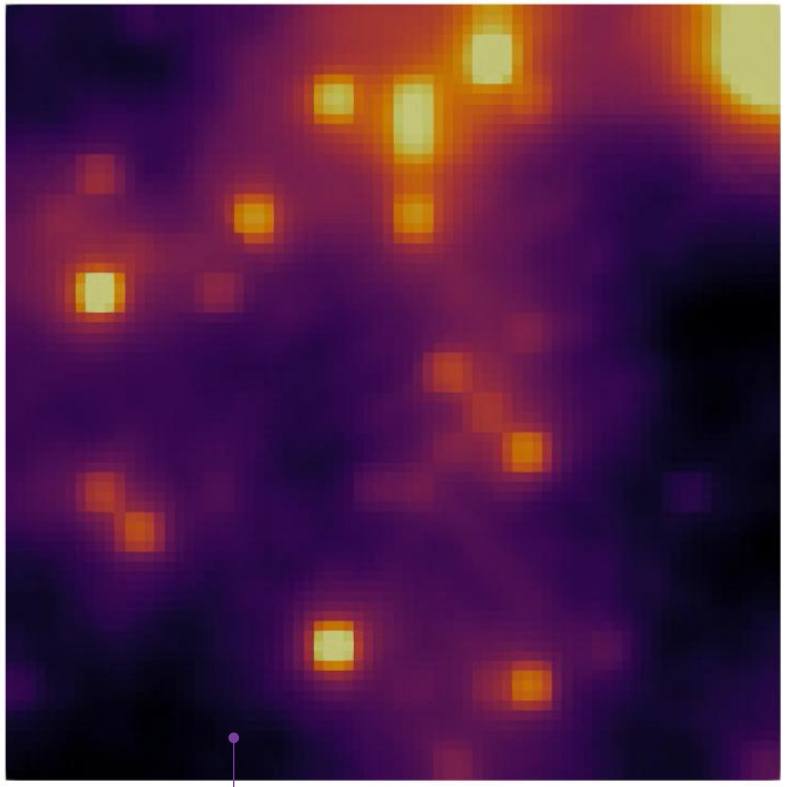
Because all are governed by the same physics.

Δ 0.5 %



source distribution





steady state

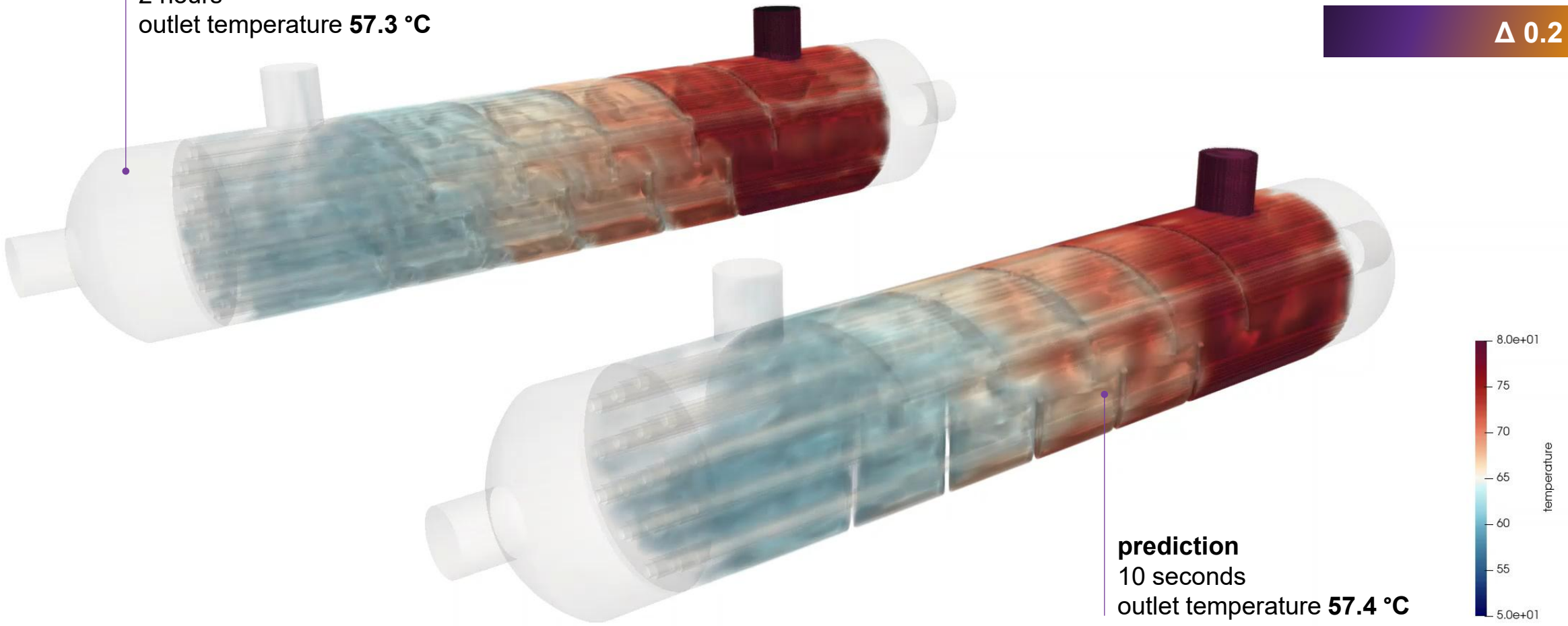
validating on the basics

simulation
30 minutes
maximum temperature **130.1 °C**

prediction
5 seconds
maximum temperature **130.7 °C**

simulation
2 hours
outlet temperature **57.3 °C**

Δ 0.2 %

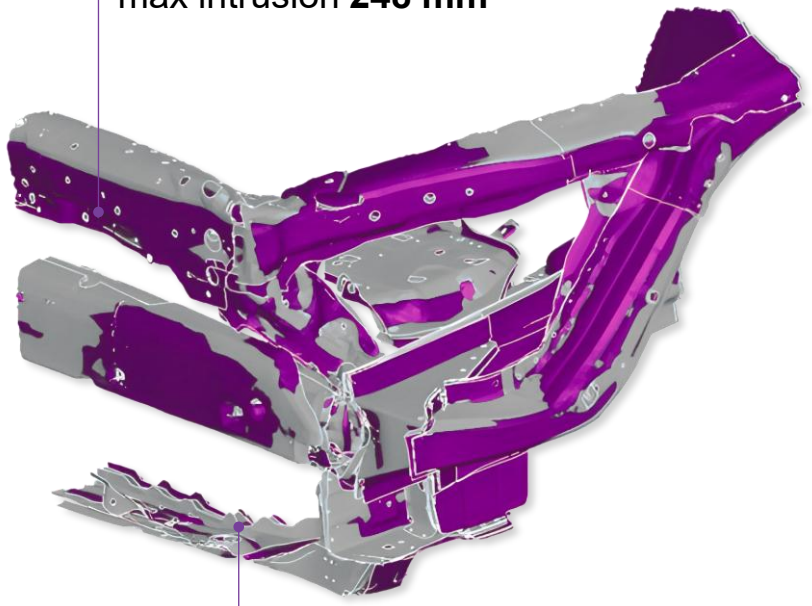


prediction
10 seconds
outlet temperature **57.4 °C**

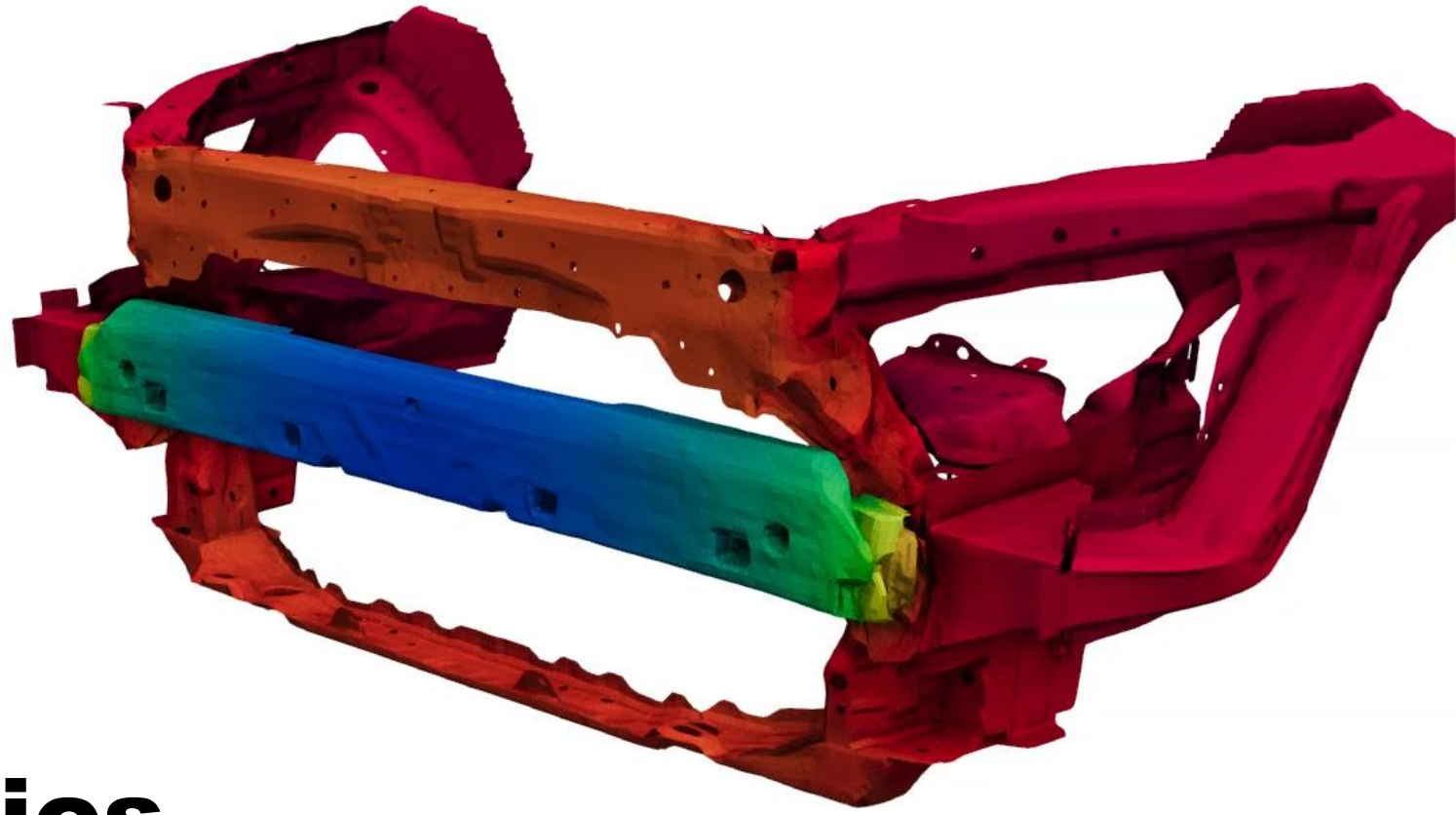
conjugate heat transfer

evolving from single physics to fully coupled multiphysics

simulation
30 minutes
max intrusion **248 mm**



prediction
30 seconds
max intrusion **250 mm**



explicit dynamics

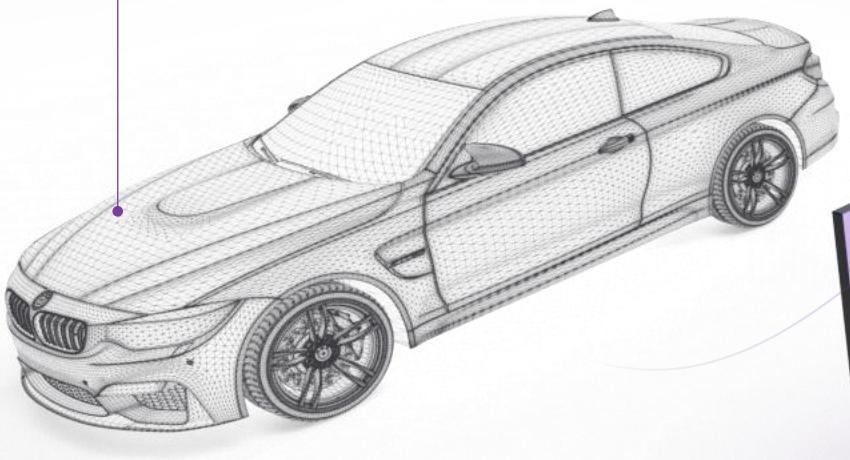
and advancing from simple drop test to complex crash simulation

GeomAI

The Geometry AI Engine

GeomAI
training

mesh



no parameters

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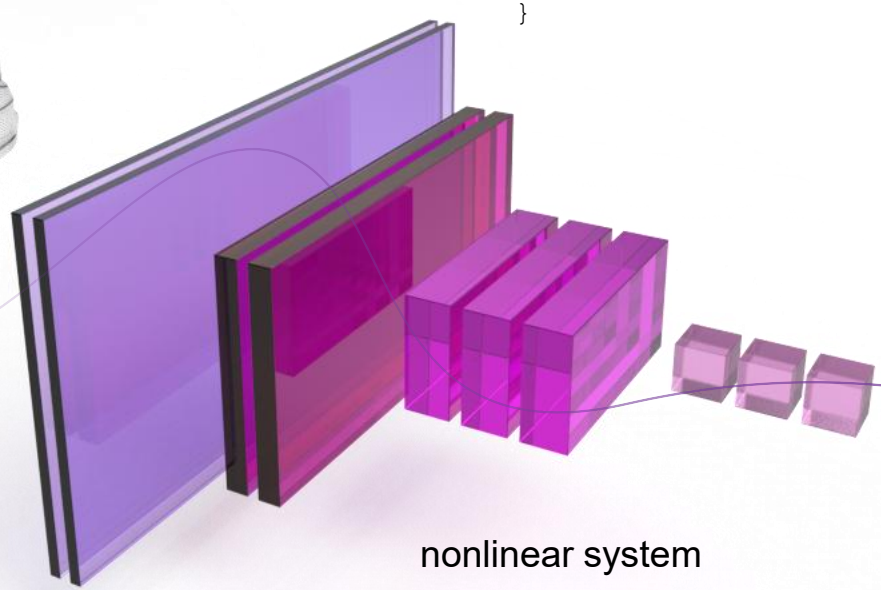

nonlinear system

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  "lp 5": 0.021,
  "lp 6": 0.299,
  ...
}
```

latent parameters

GeomAI
inference


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  "PCA": false,
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}
```

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{
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}
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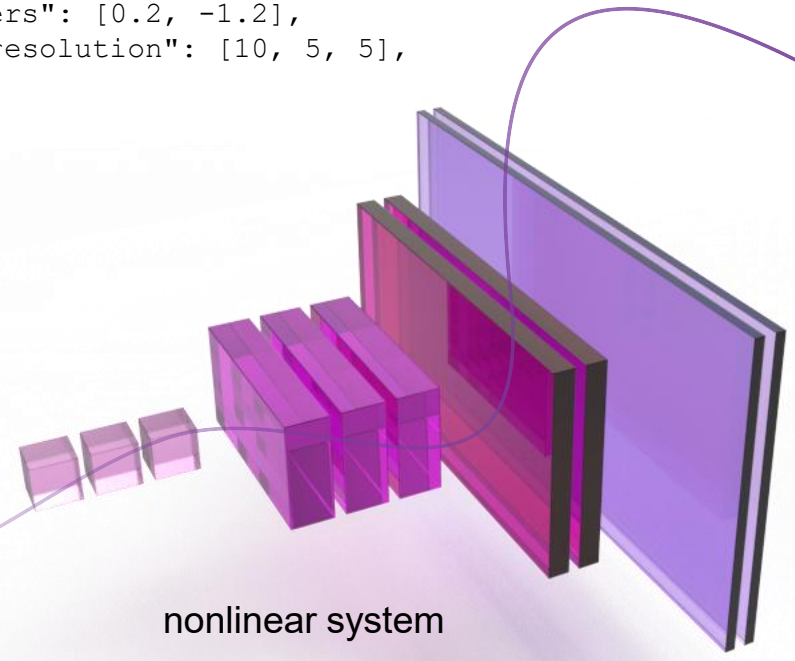
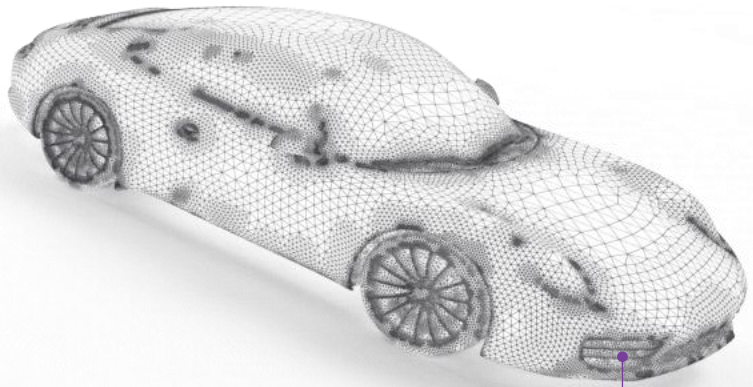
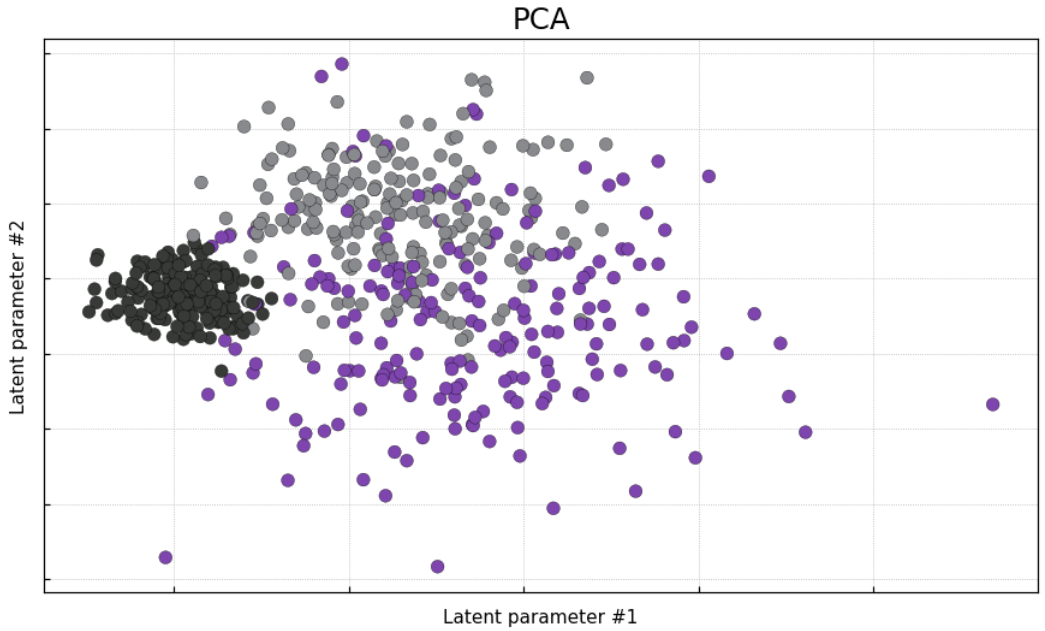


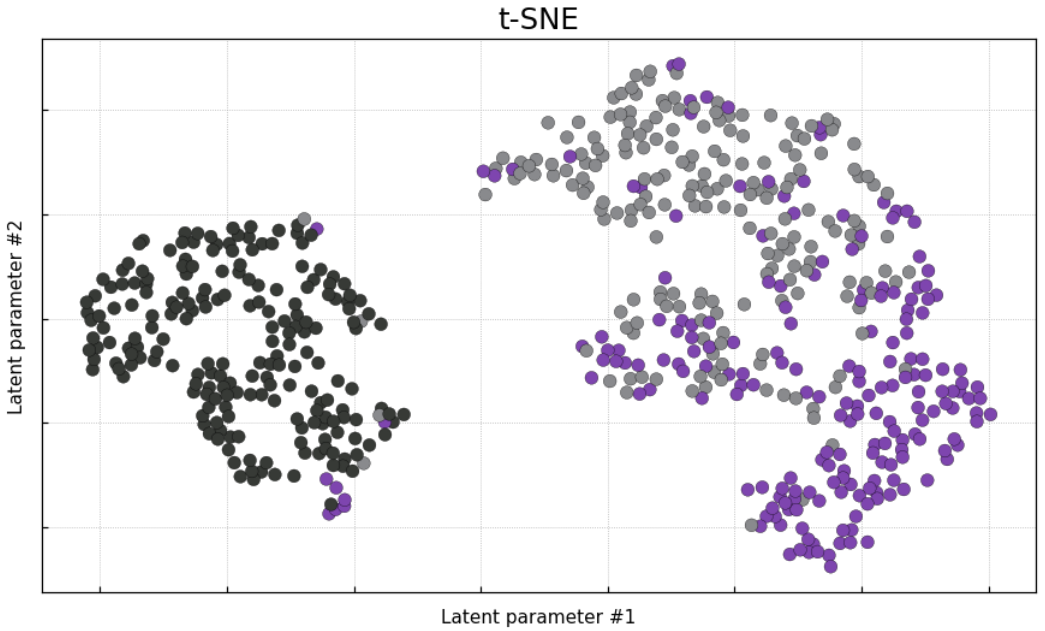
nonlinear system

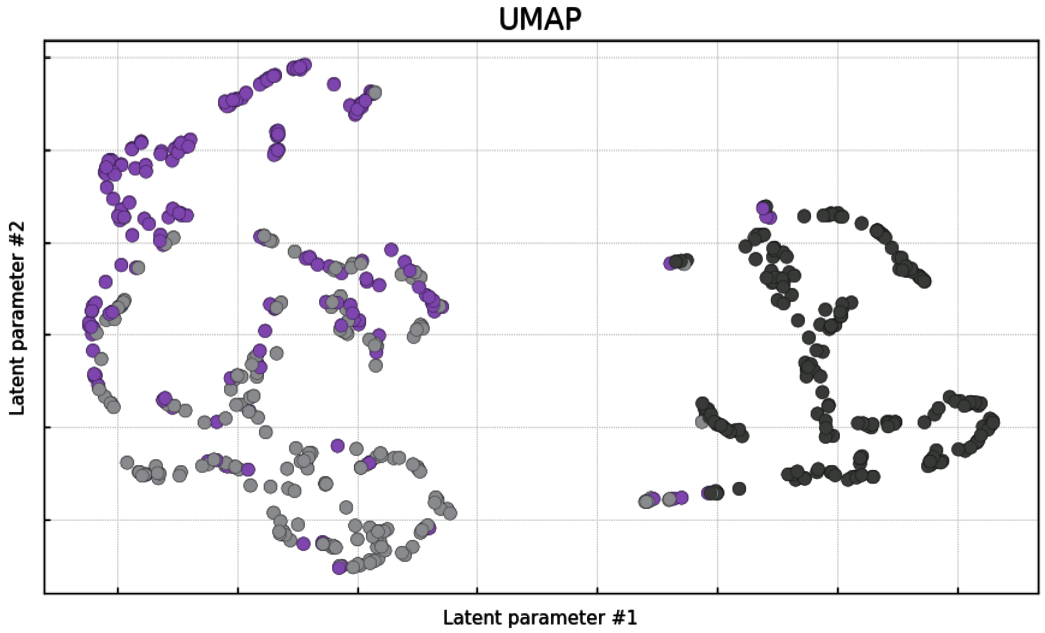
latent parameters

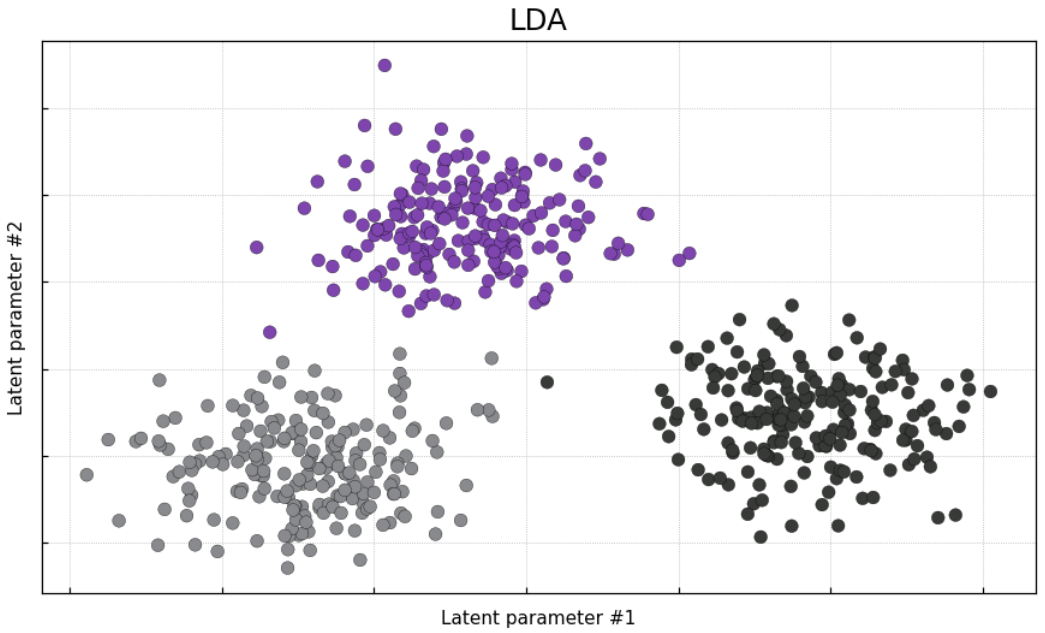


implicit representation reconstructed into a high-resolution mesh

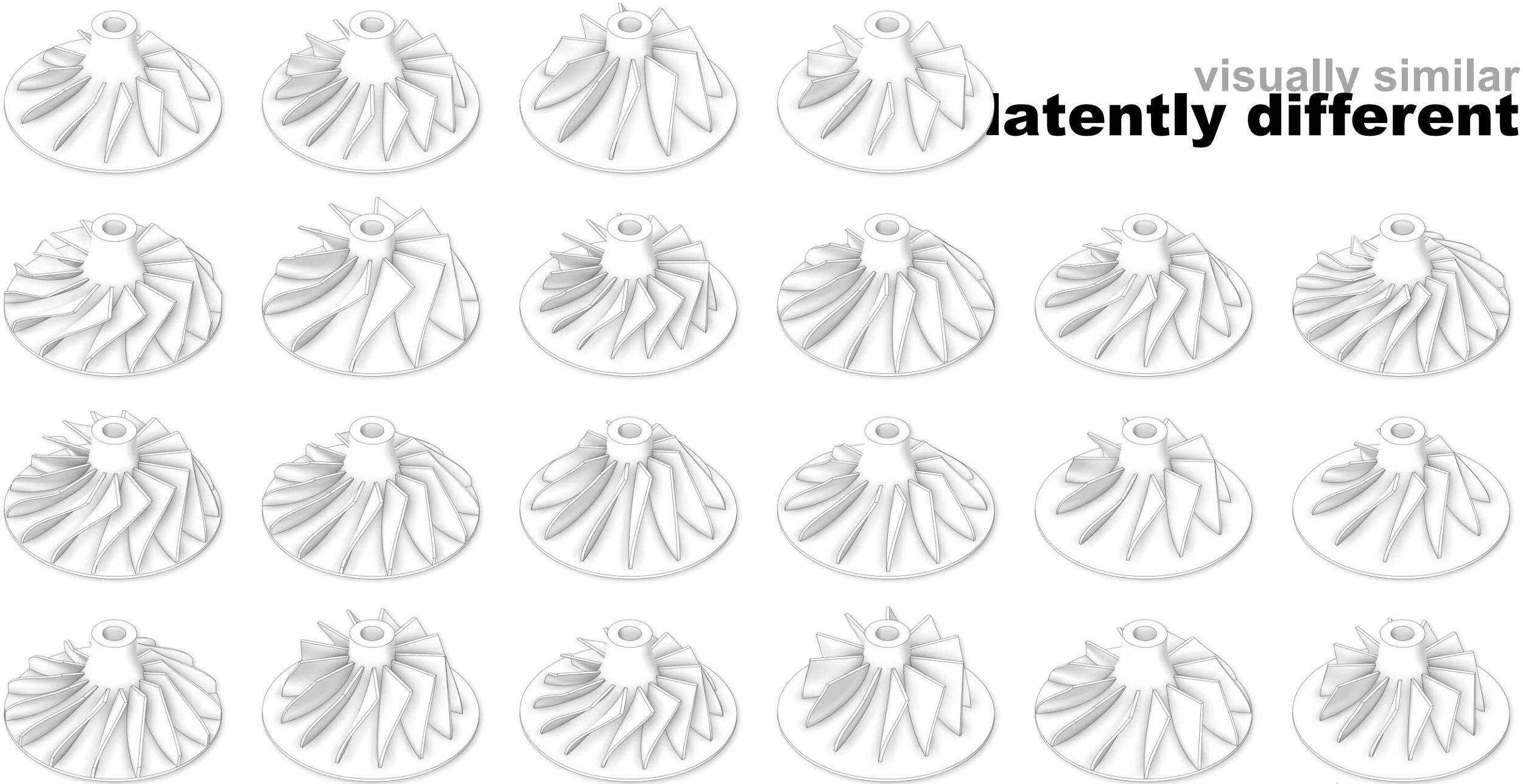






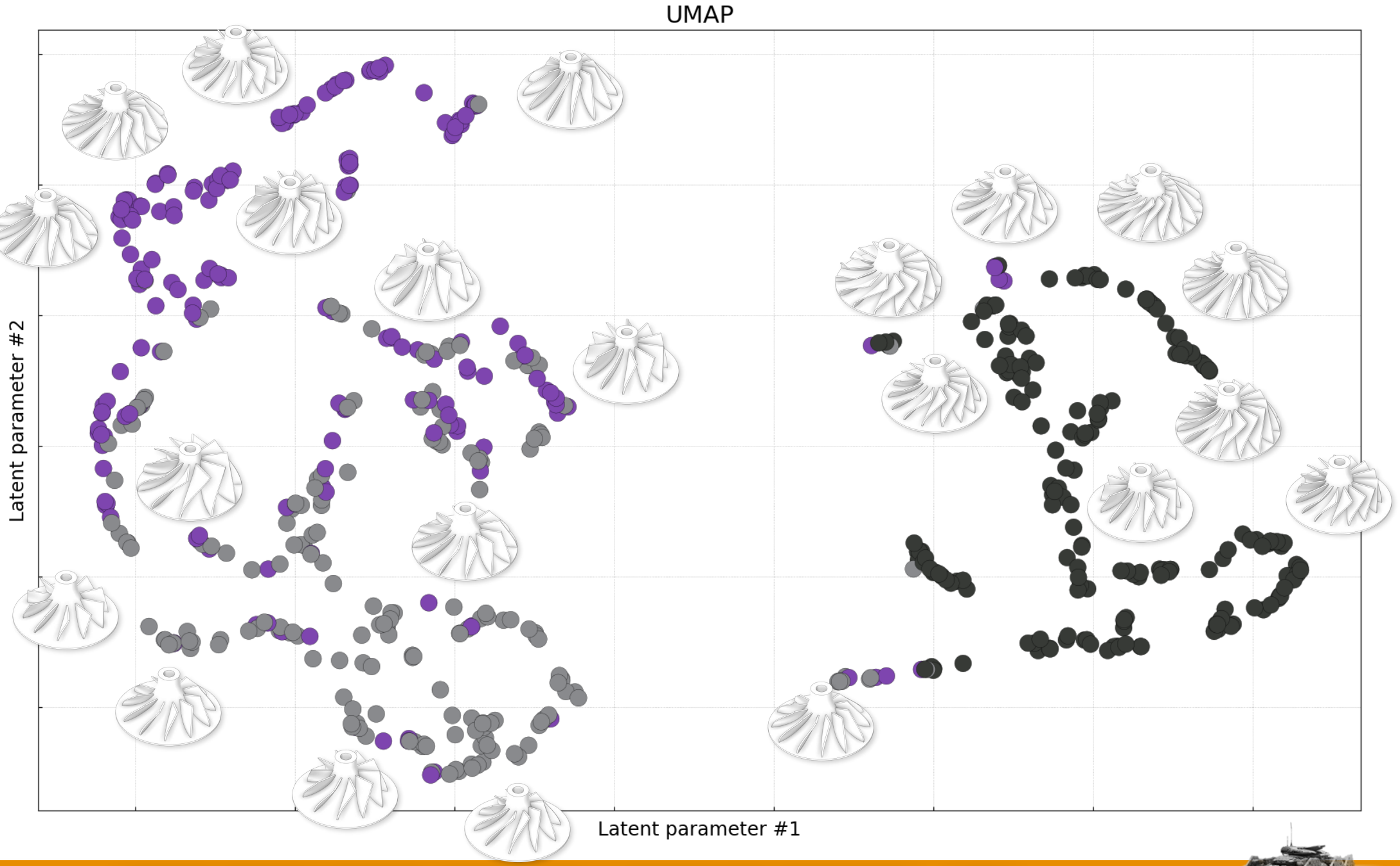


Several techniques are available for visualizing design similarity, including Principal Component Analysis (**PCA**), t-distributed Stochastic Neighbor Embedding (**t-SNE**), Uniform Manifold Approximation and Projection (**UMAP**), and Linear Discriminant Analysis (**LDA**).

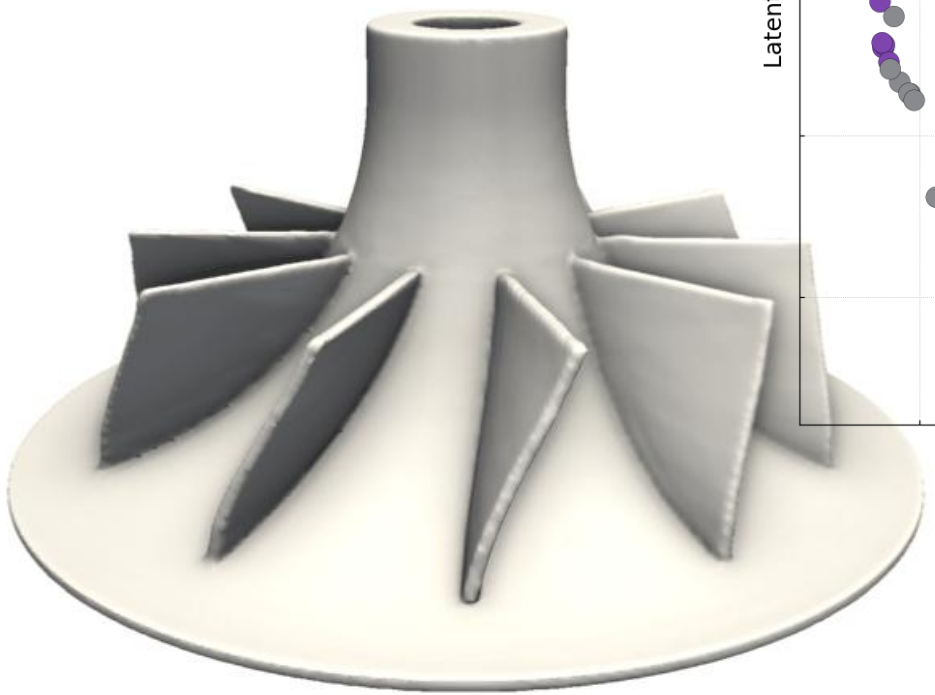


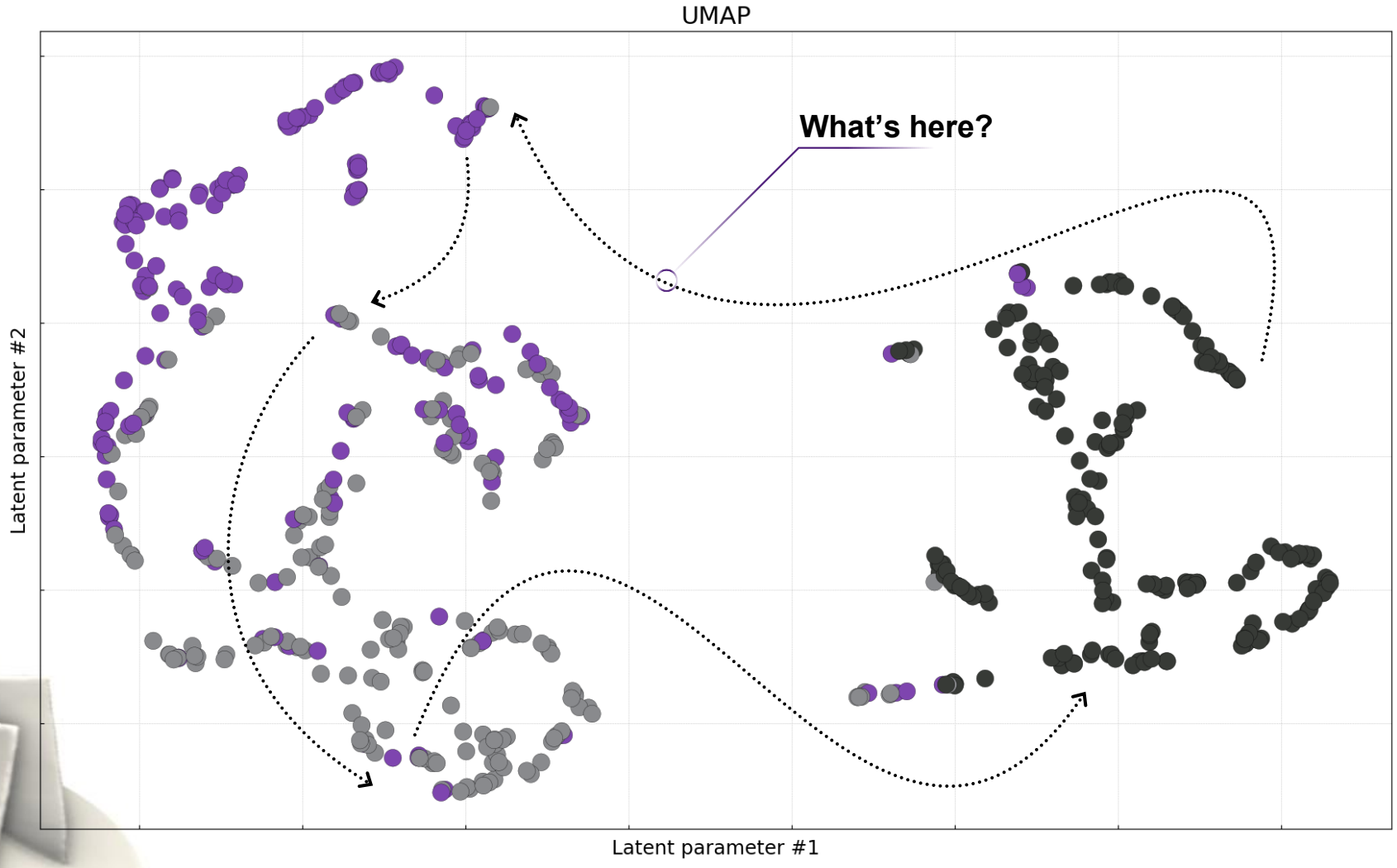
visually similar

latently different


UMAP
Latent parameter #2
Latent parameter #1

latent space sweep

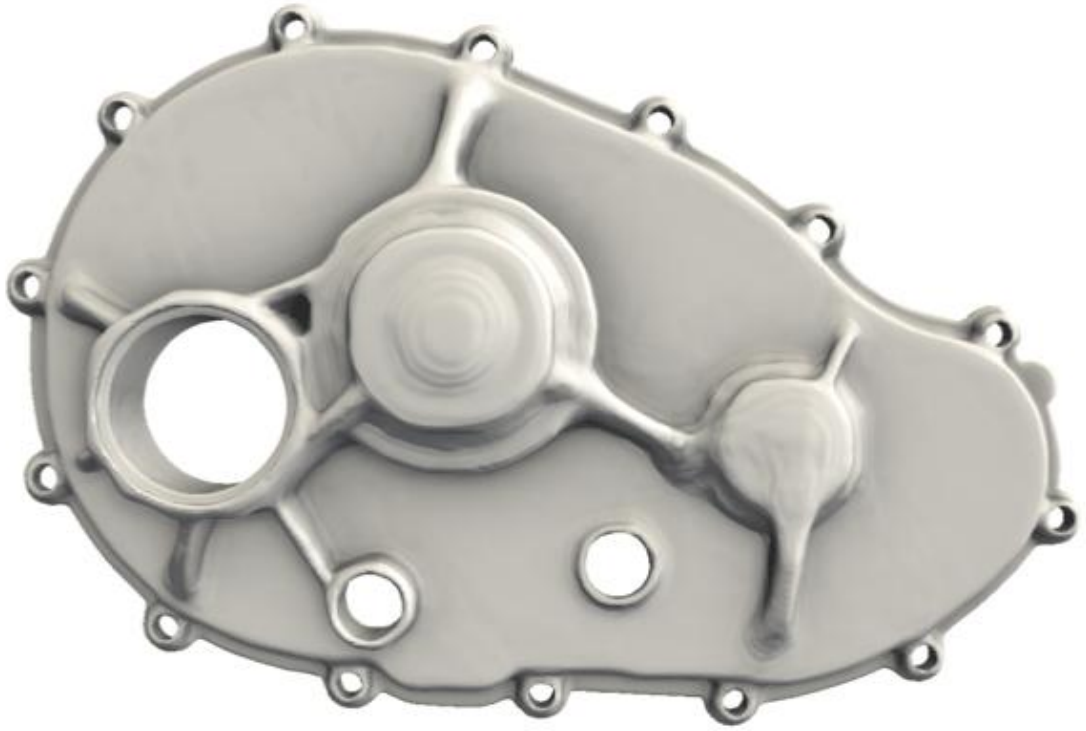




Enabling effective exploration of the latent space to **uncover novel designs** hidden within existing ones.

impeller

working with scanned and reconstructed data

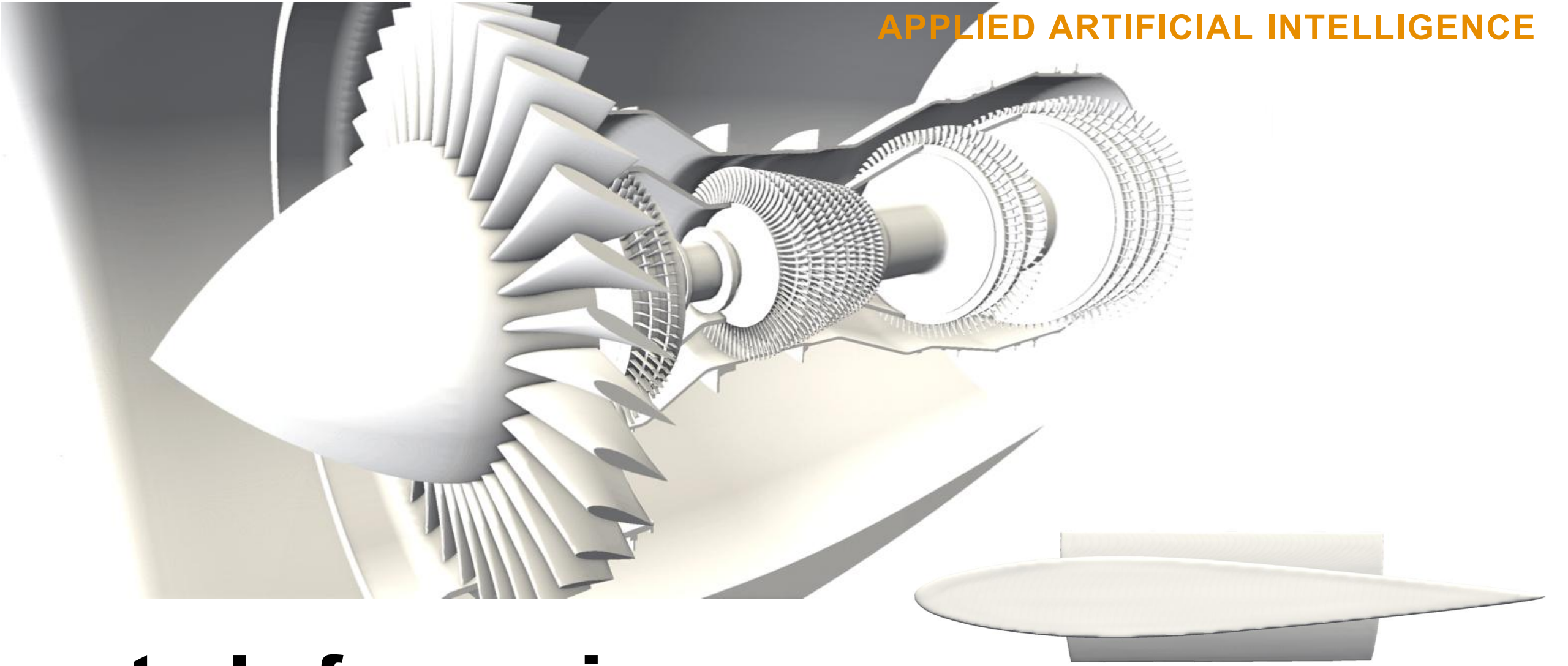


transmission housing

with results from topology optimization

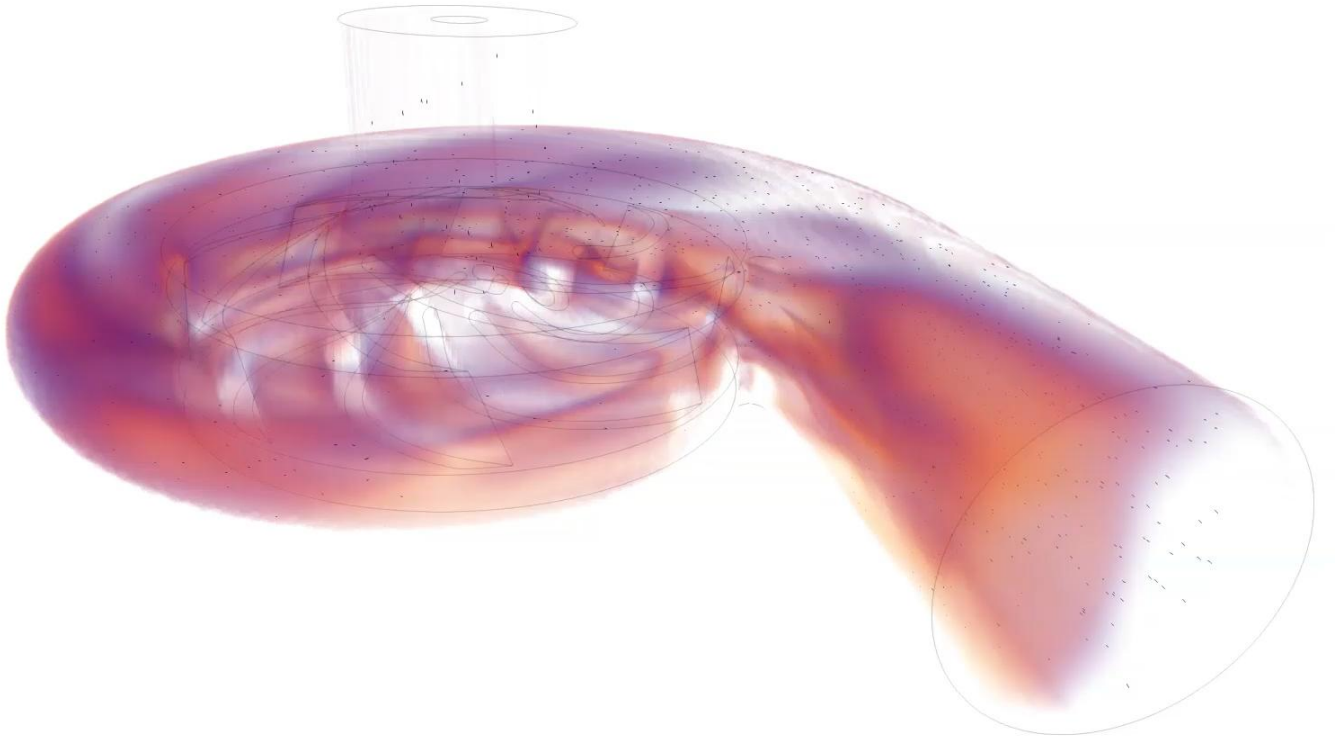
heatsink

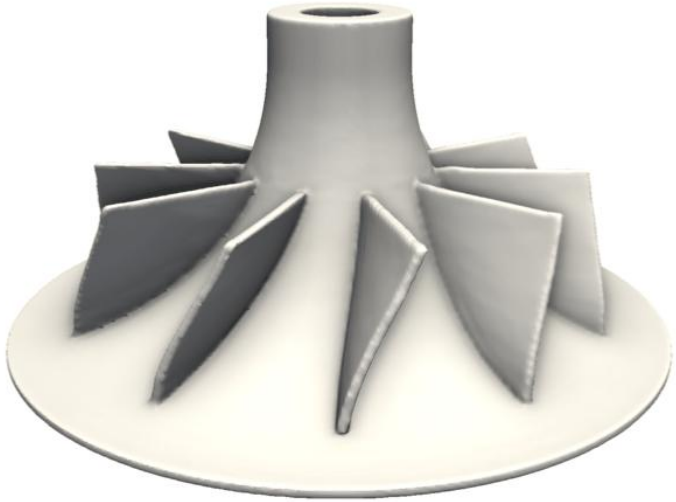
even when balancing conflicting objectives such as temperature and pressure drop



turbofan engine

and finally integrating everything back into complex, high-performance assemblies





SimAI

show me **a shape**, I will reveal its **performance instantly**

GeomAI

show me **shapes**, I will **design more**

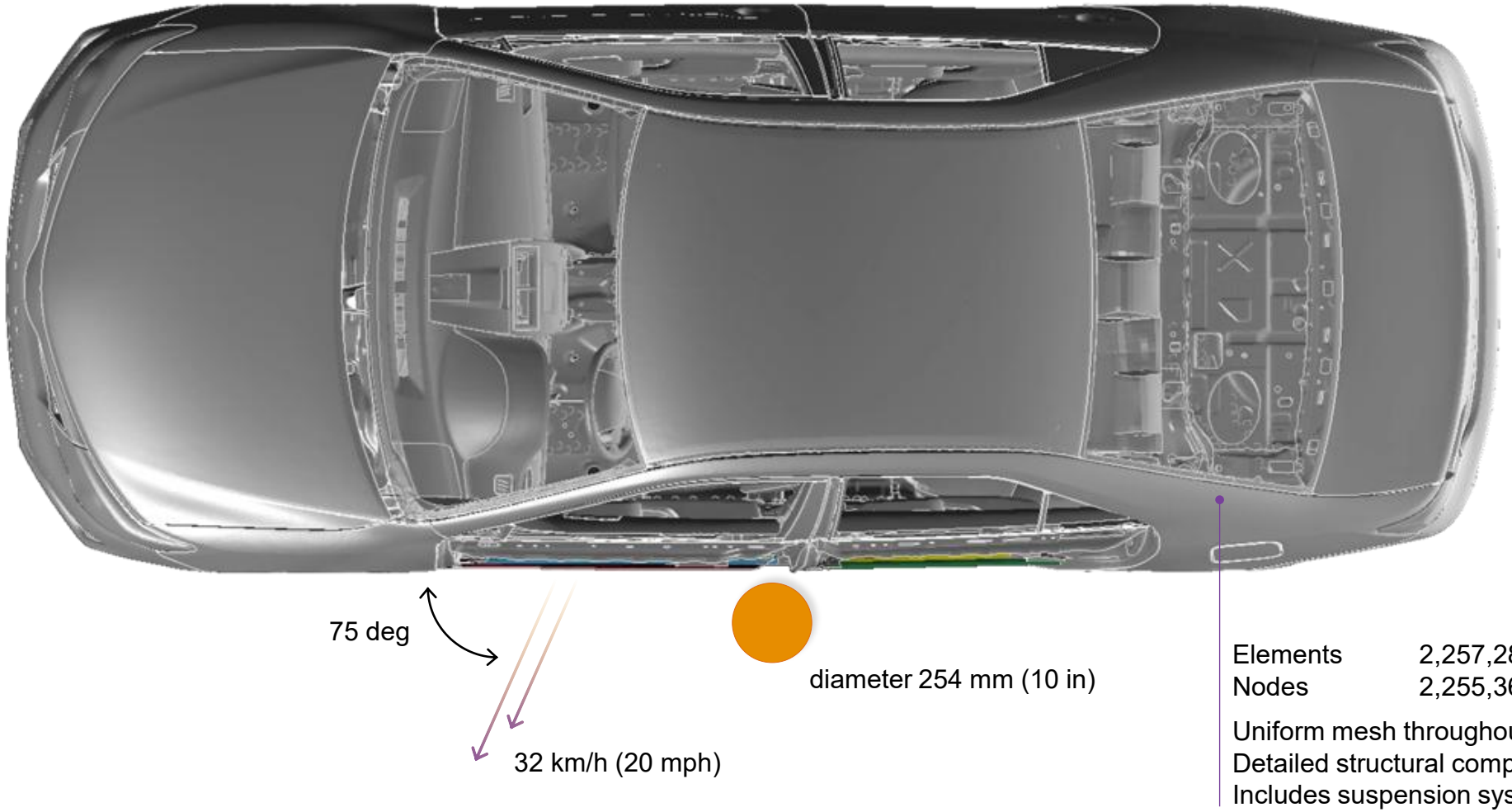
Case Study

Pole Impact

FE model

2012 Toyota Camry (CCSA V5a)

Model source: https://www.ccsa.gmu.edu/models/2012-toyota-camry

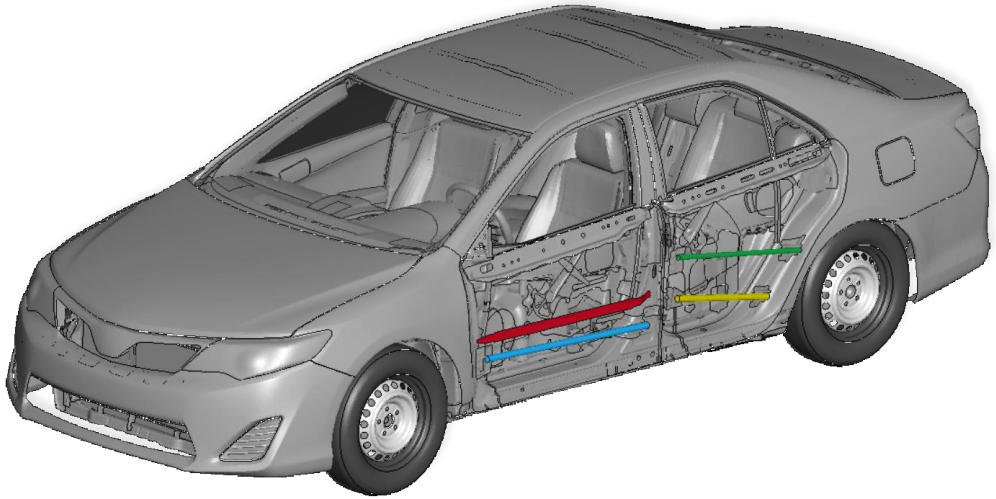


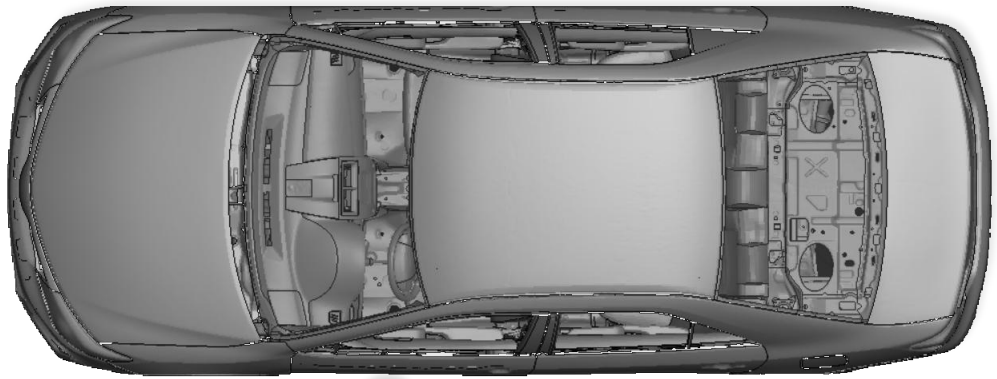
Elements	2,257,280
Nodes	2,255,361

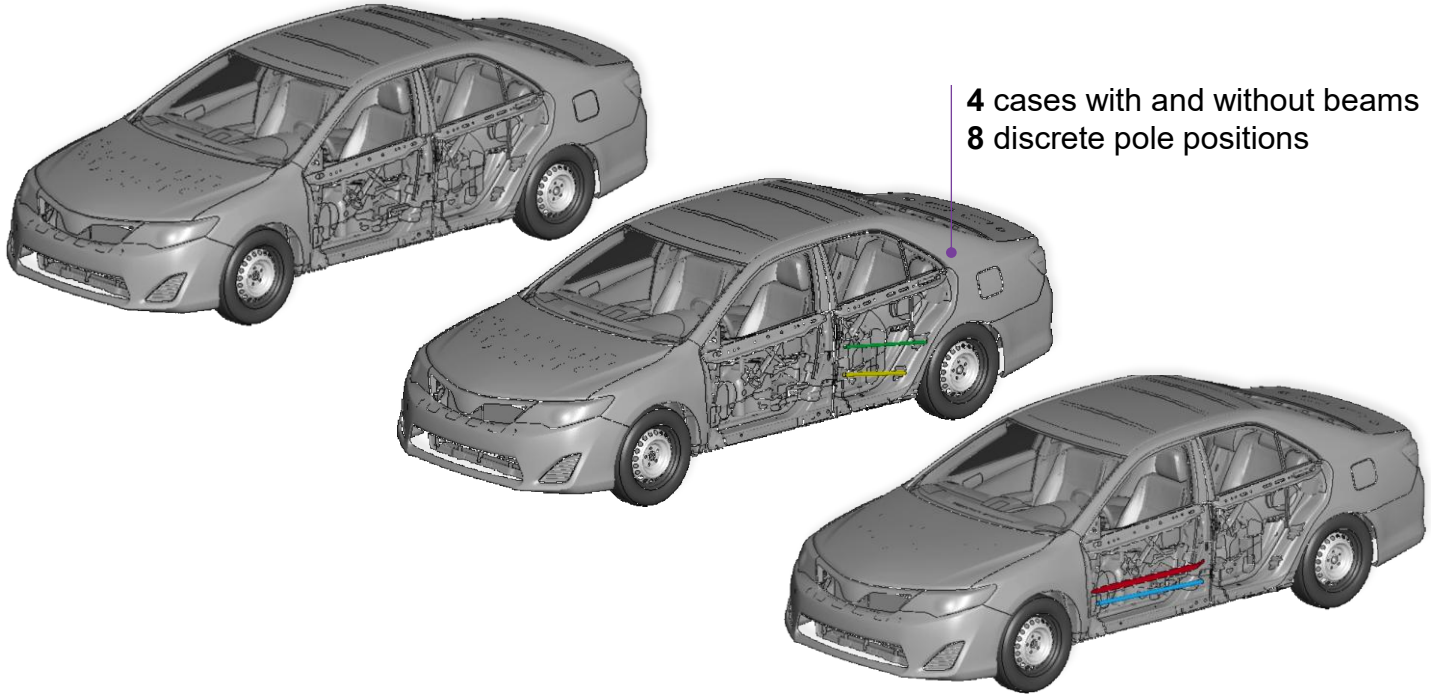
Uniform mesh throughout
Detailed structural components and interior
Includes suspension system

dataset A

pole and door beam variation







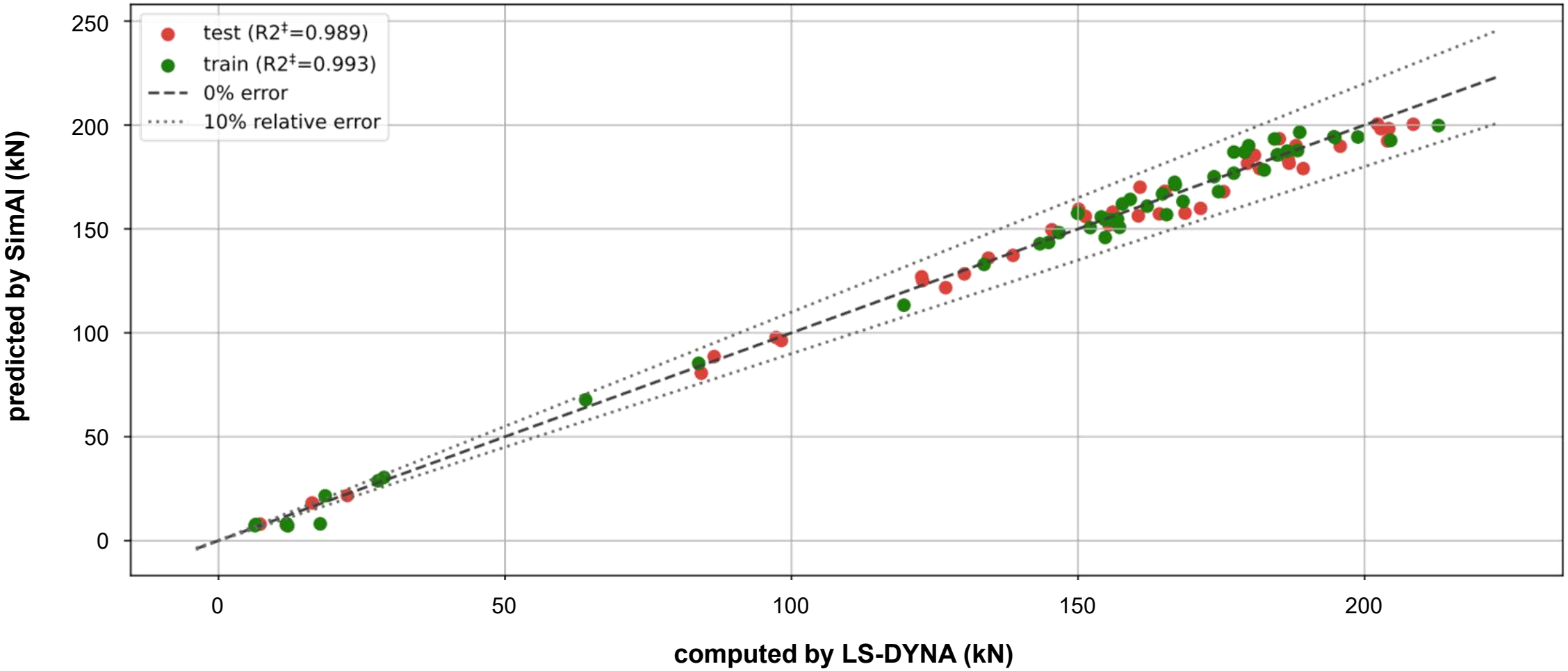
4 cases with and without beams
8 discrete pole positions

dataset size

training	**28** cases × **20** states per case
test	**4** cases × **20** states per case

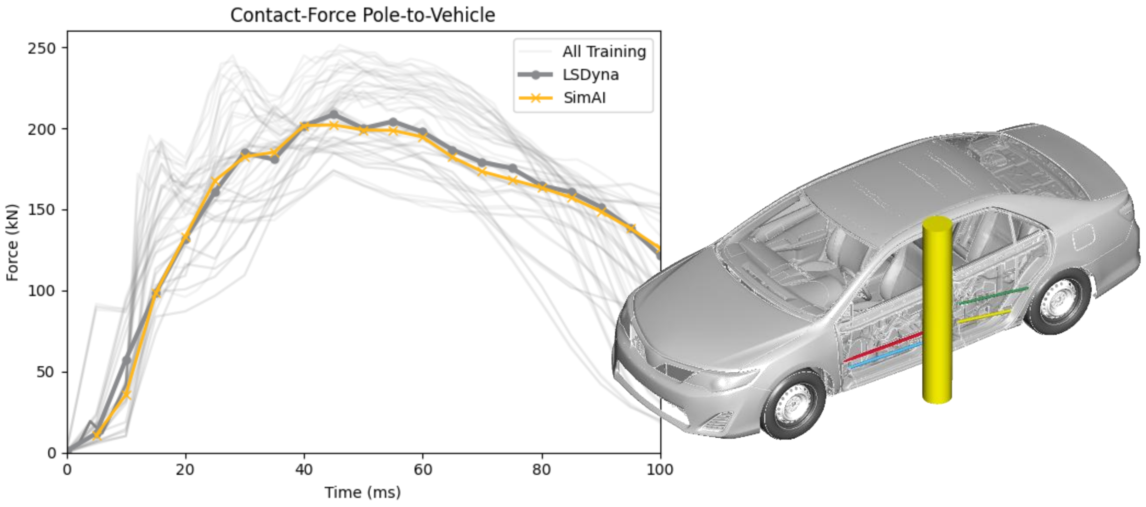
dataset A

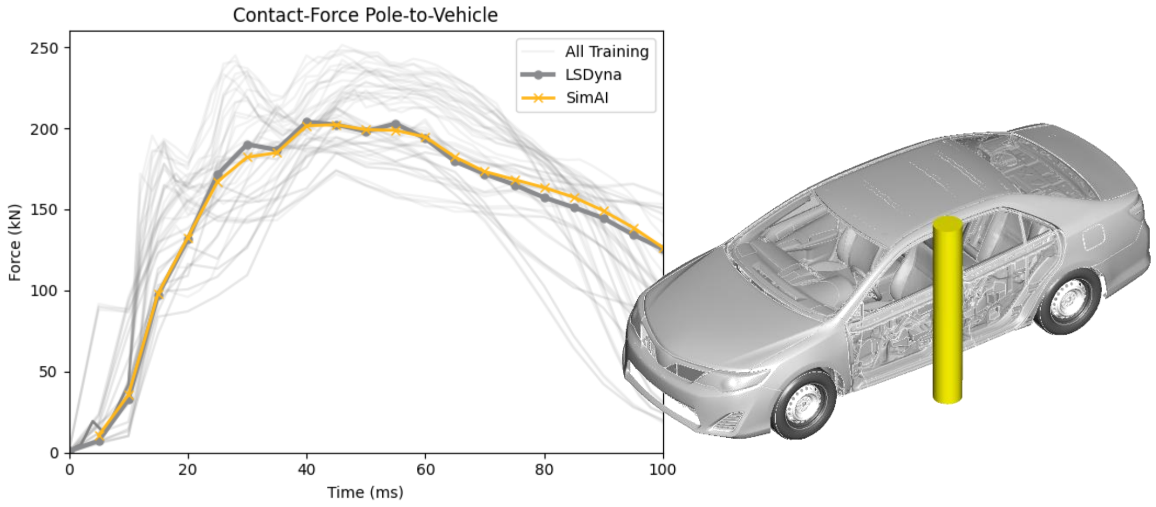
contact force pole-to-vehicle

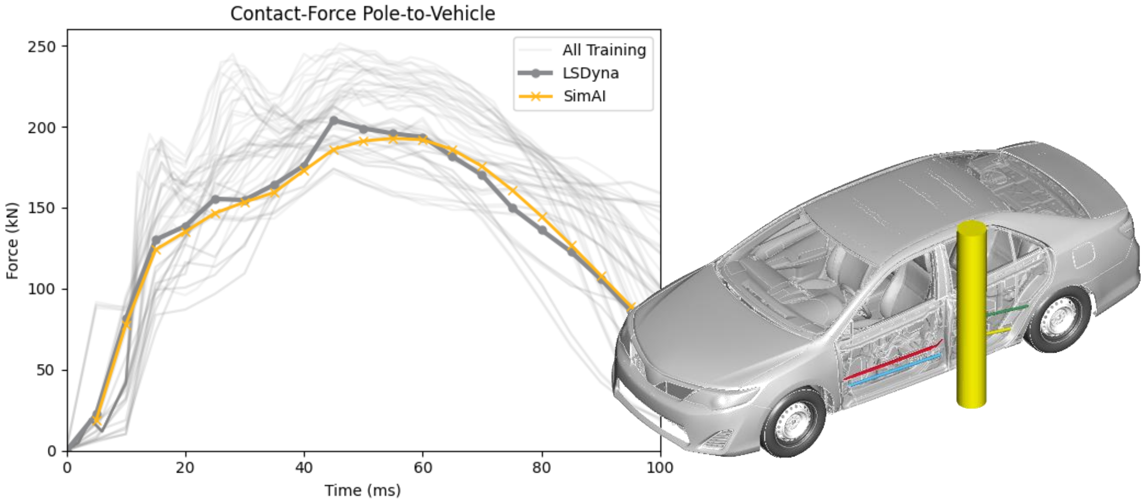


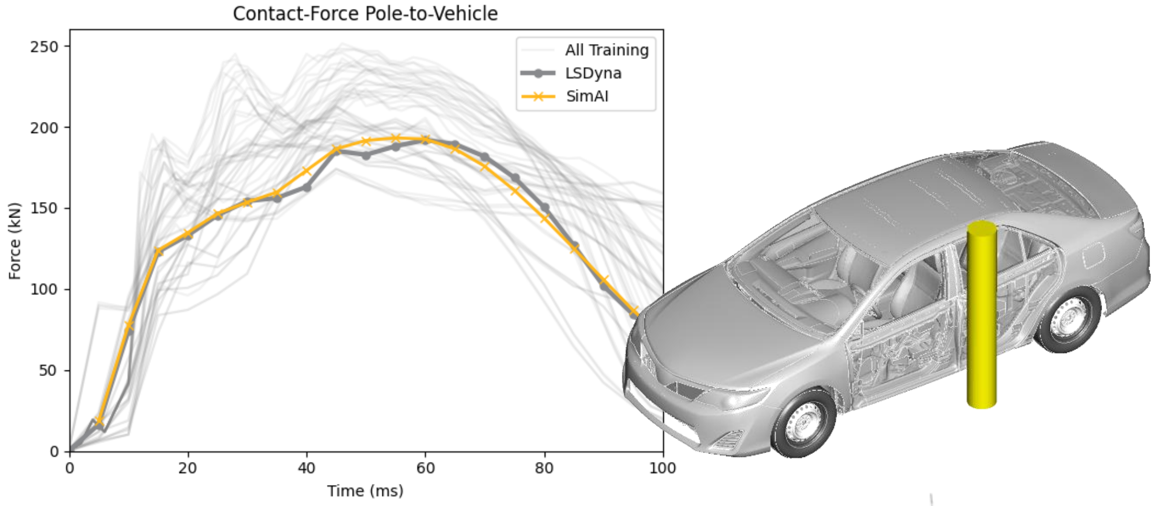
unseen data

pole and door beam variation



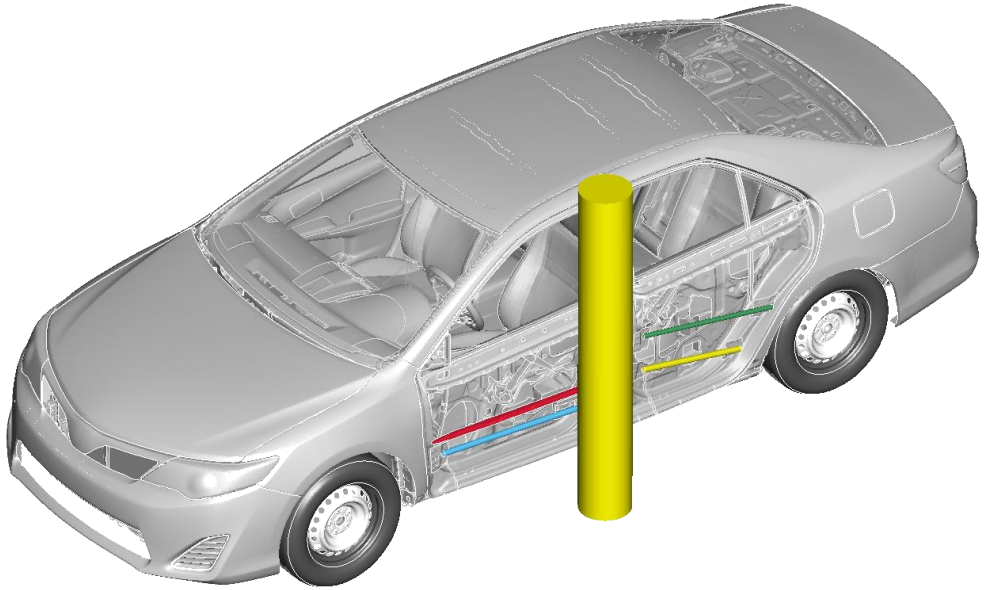




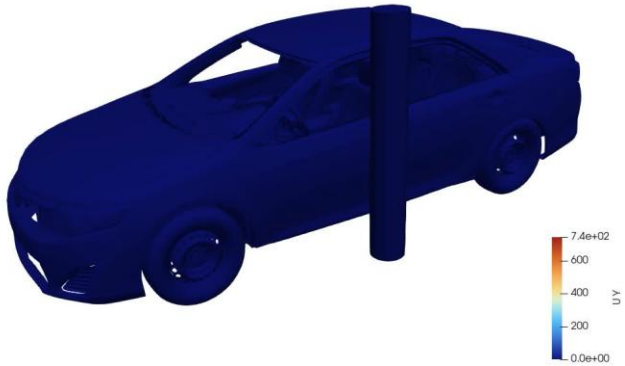


unseen data

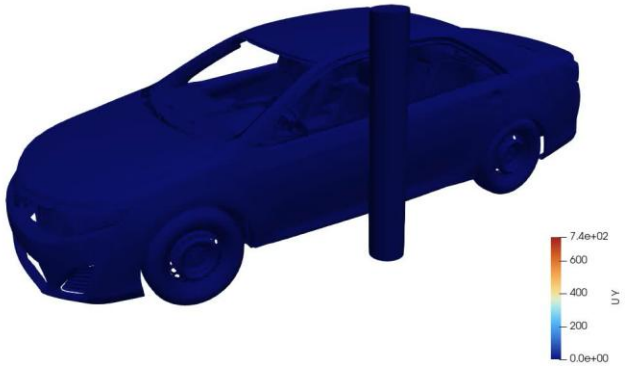
pole and door beam variation

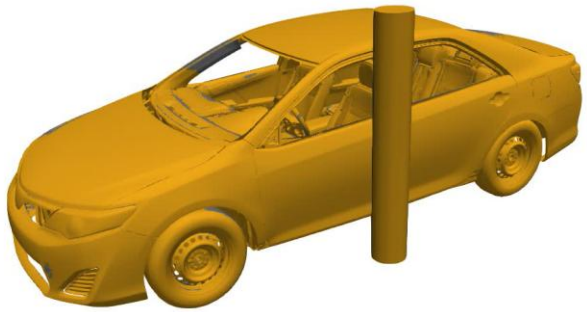


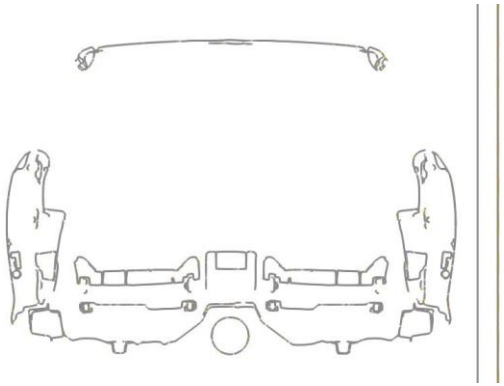
LS-DYNA

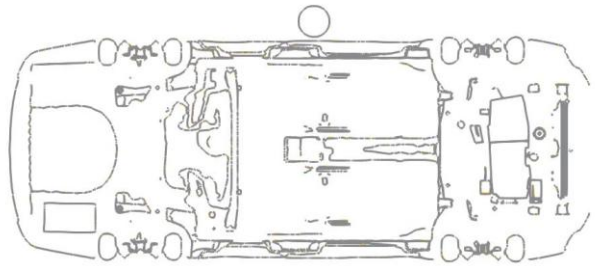


SimAI



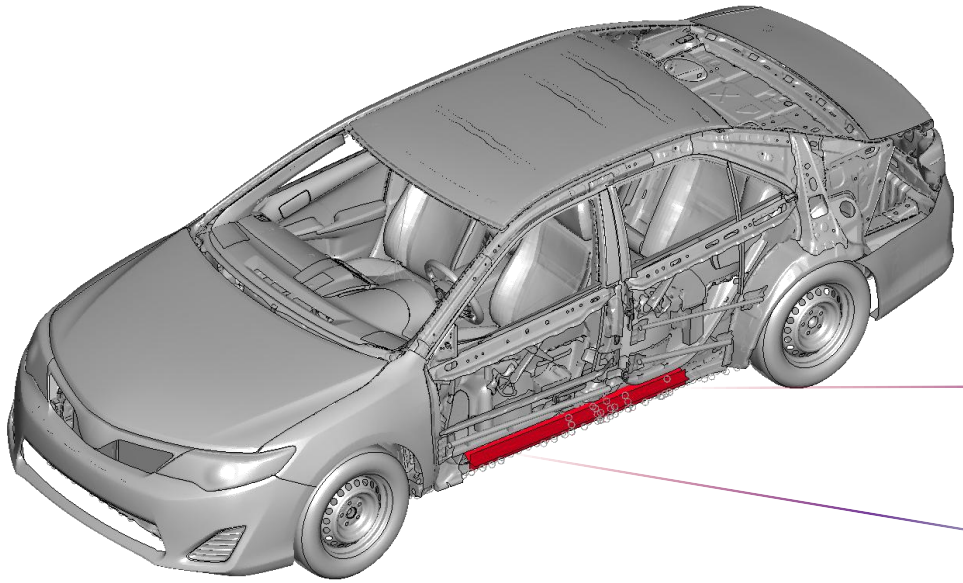


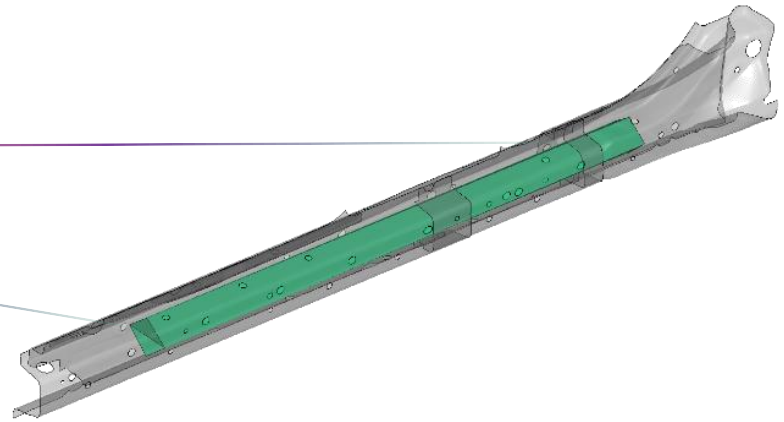


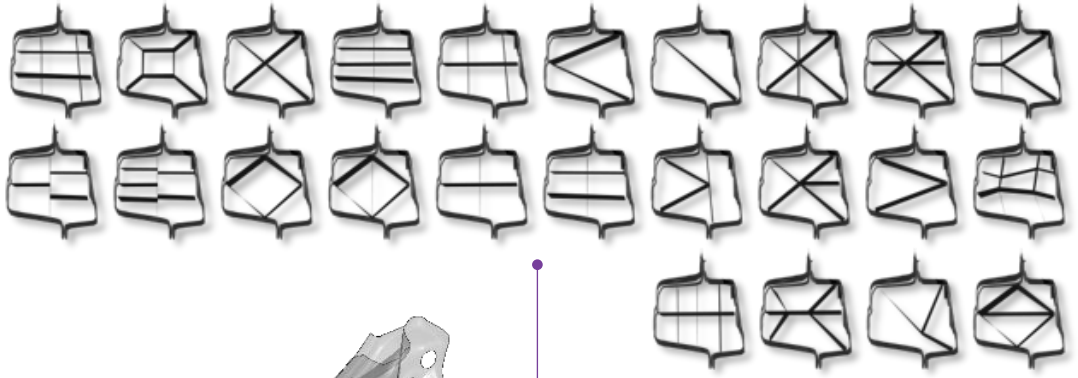


dataset B

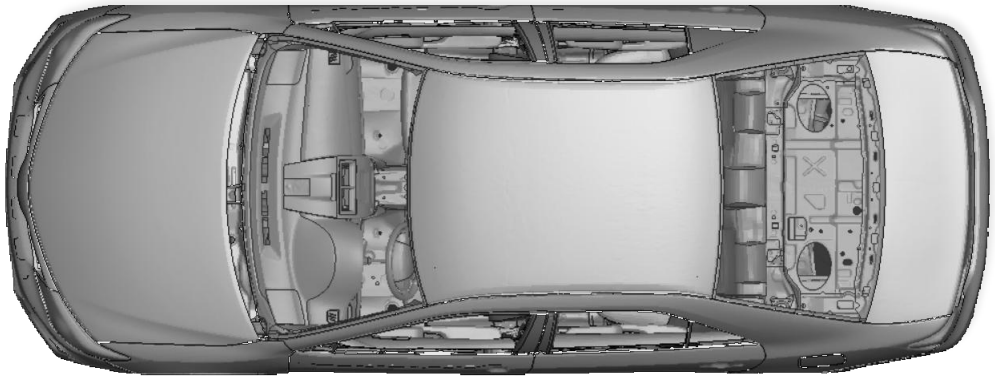
rocker inlay profile variation







24 unique rocker inlay profiles

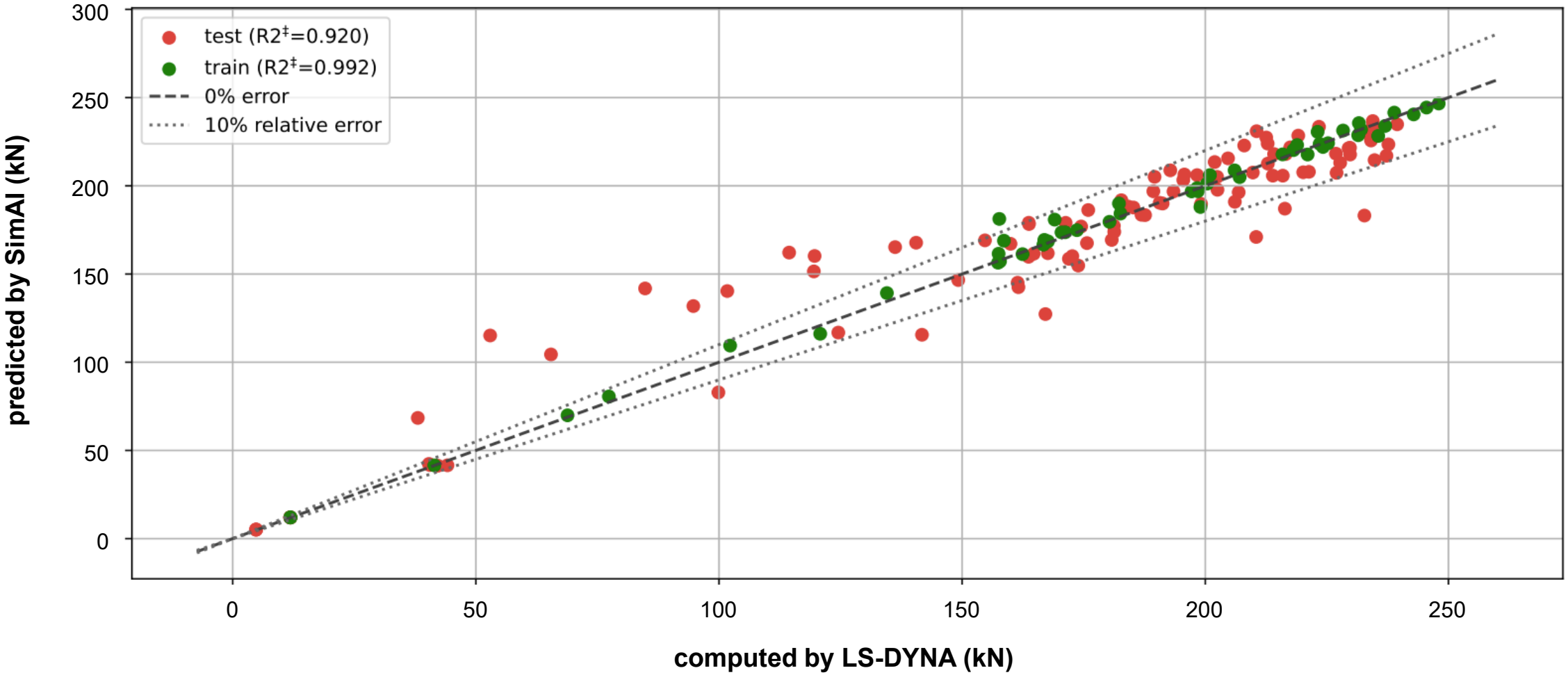


dataset size

training	**20** cases × **25** states per case
test	**4** cases × **25** states per case

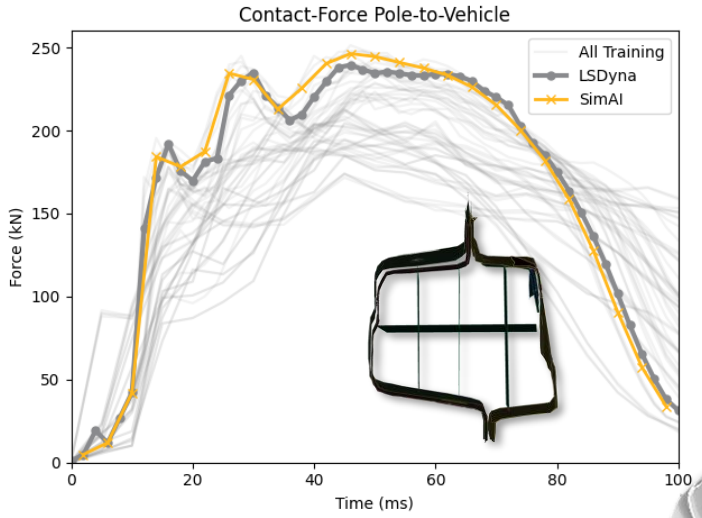
dataset B

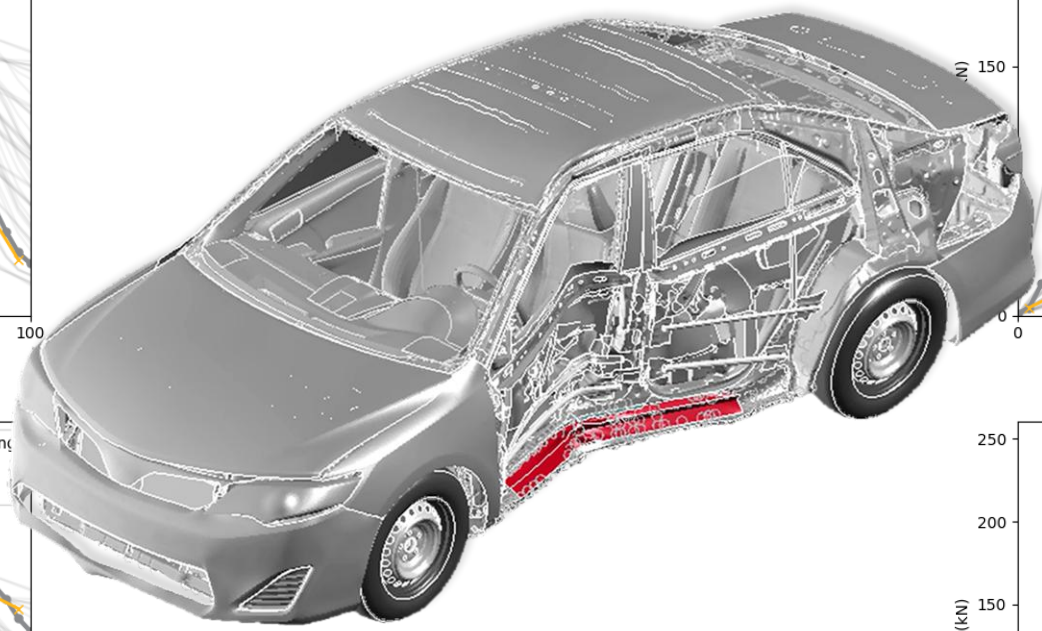
contact force pole-to-vehicle

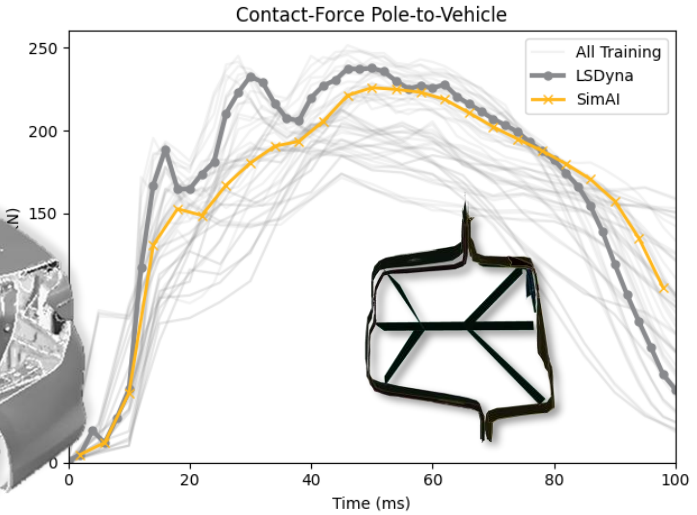


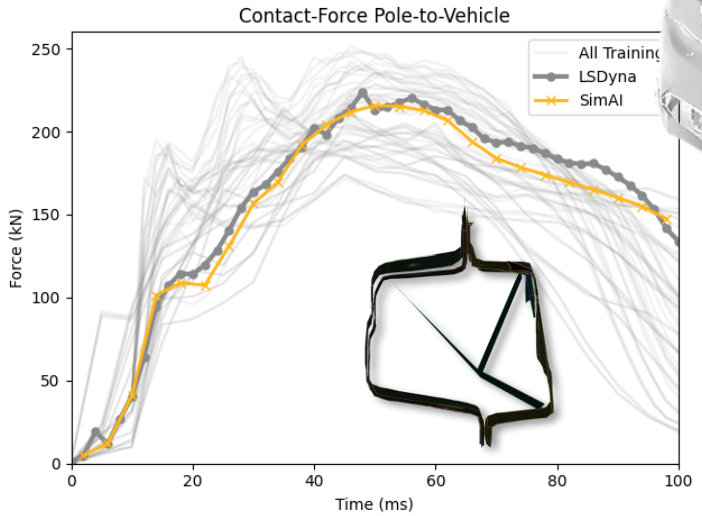
unseen data

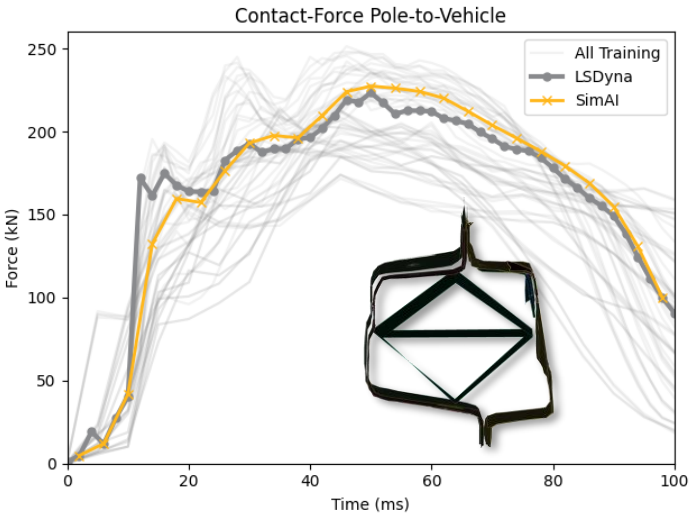
rocker inlay profile variation





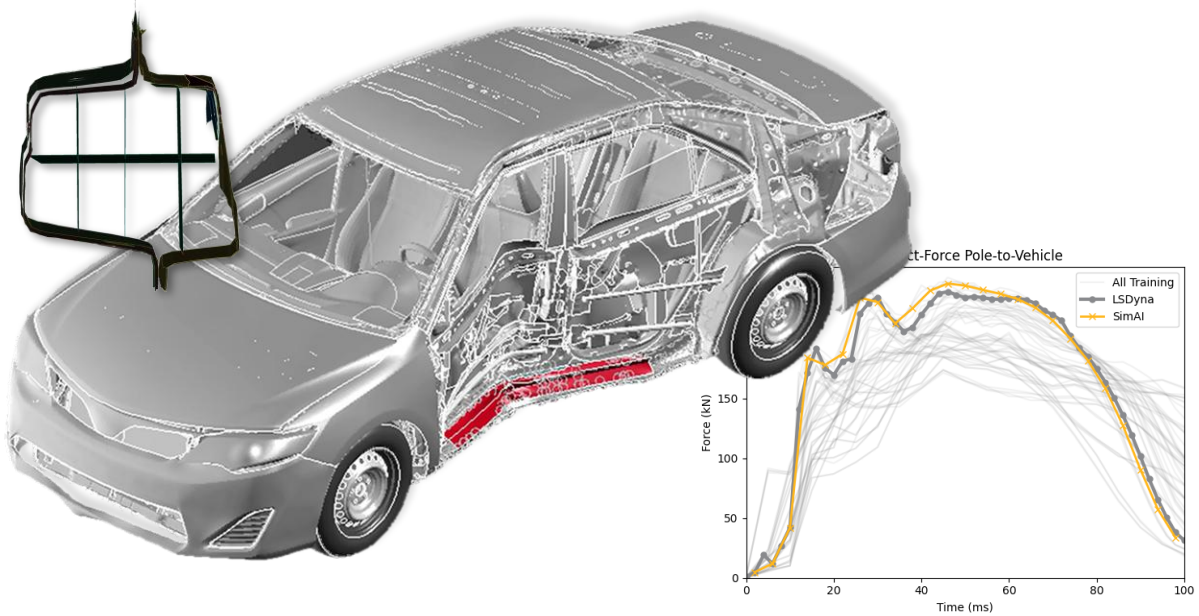




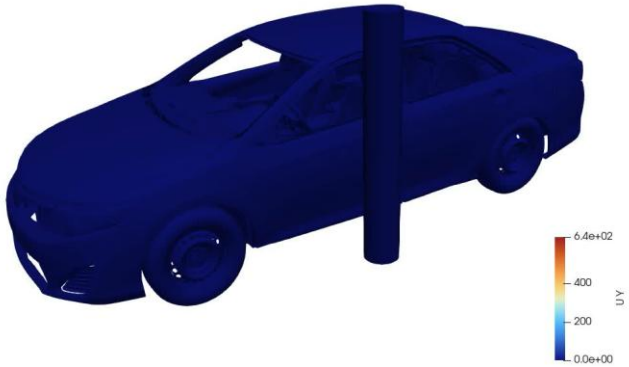


unseen data

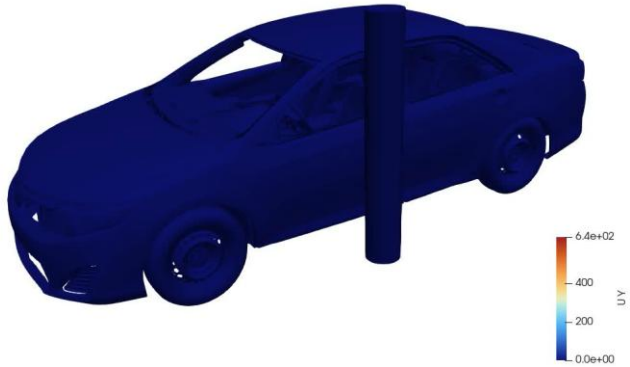
rocker inlay profile variation

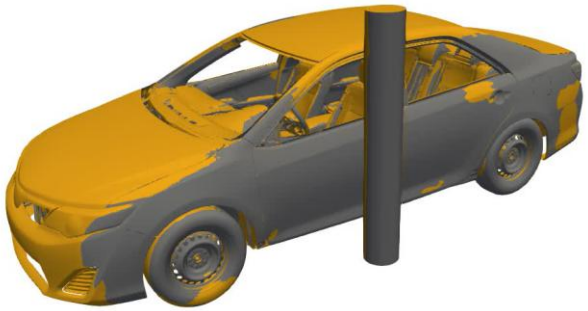


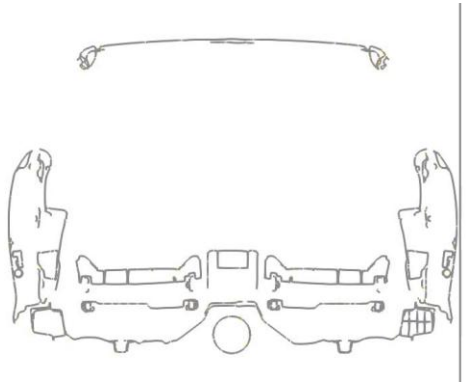
LS-DYNA

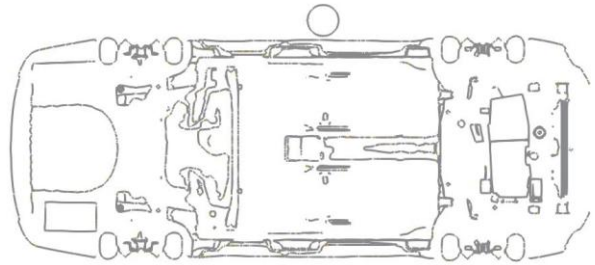


SimAI







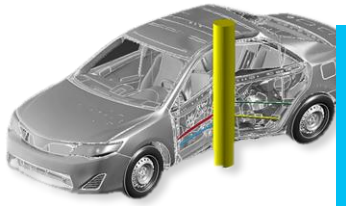


Case Study

Building a Domain-specific Foundation Model

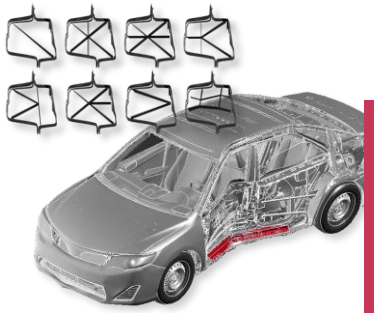
dataset A + B

building a domain-specific foundation model



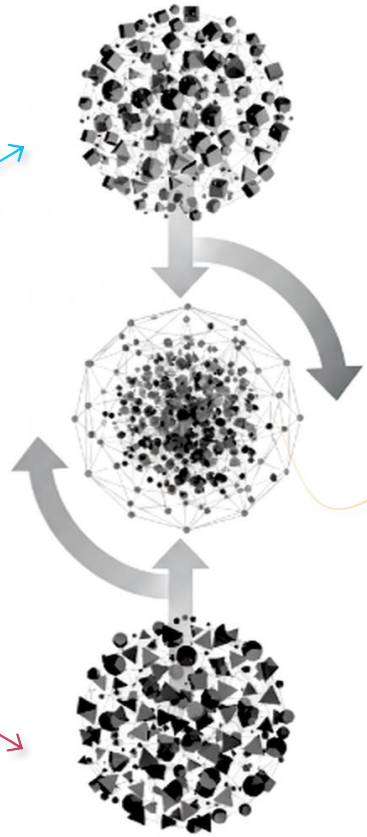
IN
variable pole position
variable door beams

OUT
deformation
contact force



IN
variable rocker inlay profile

OUT
deformation
contact force

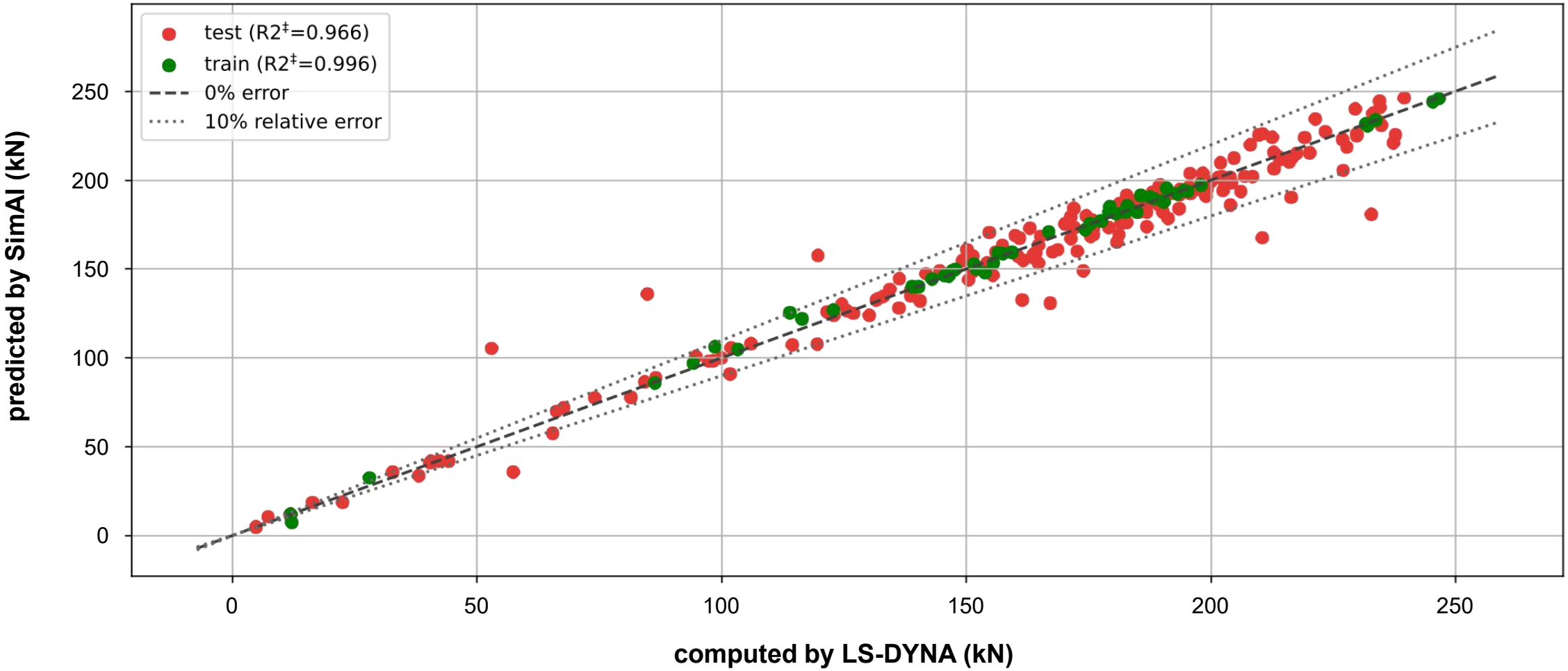


IN
variable pole position
variable door beams
variable rocker inlay profile

OUT
deformation
contact force

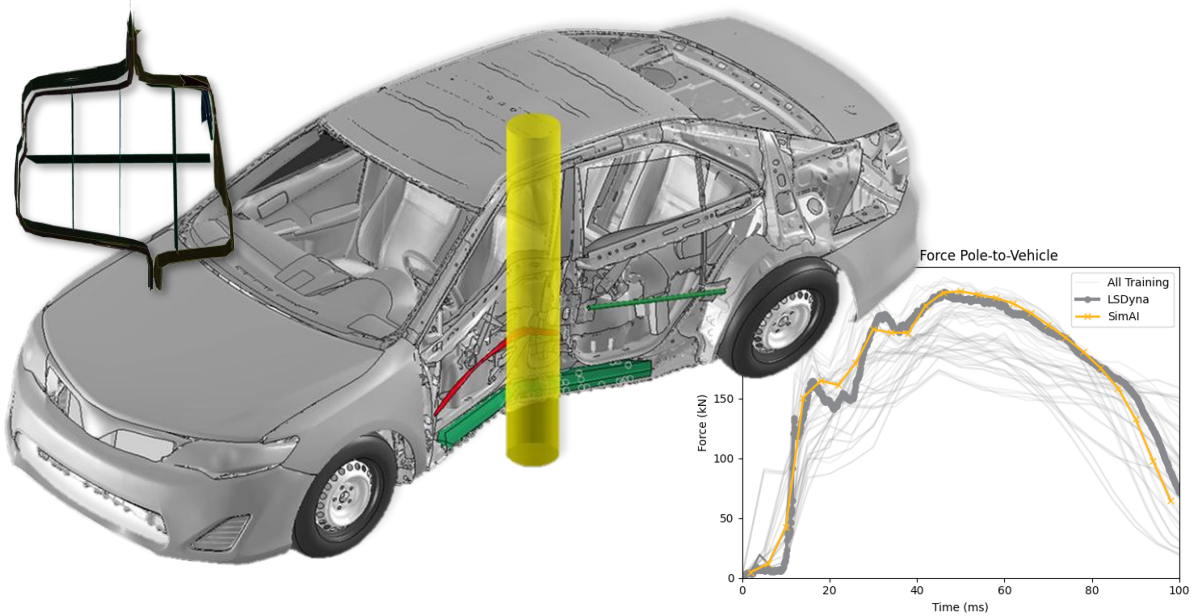
dataset A + B

contact force pole-to-vehicle

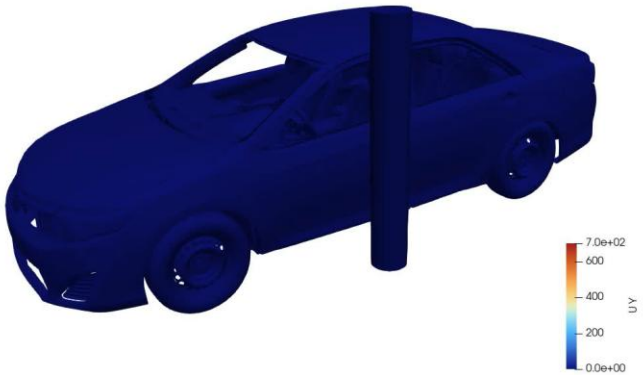


unseen data

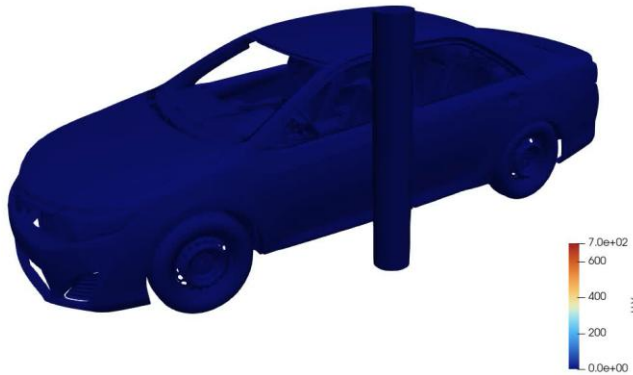
mixed variation

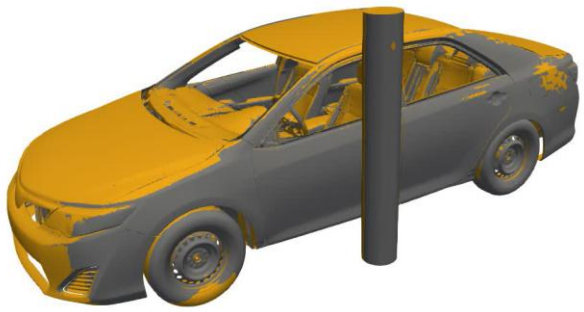


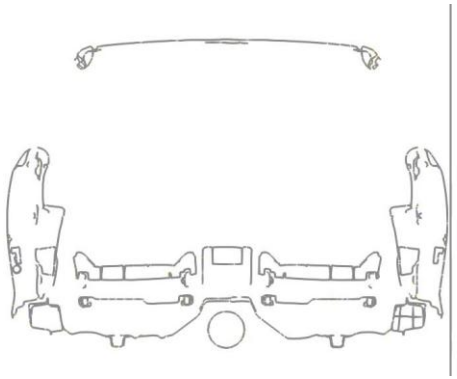
LS-DYNA

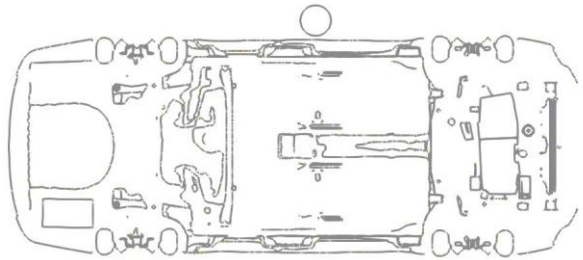


SimAI





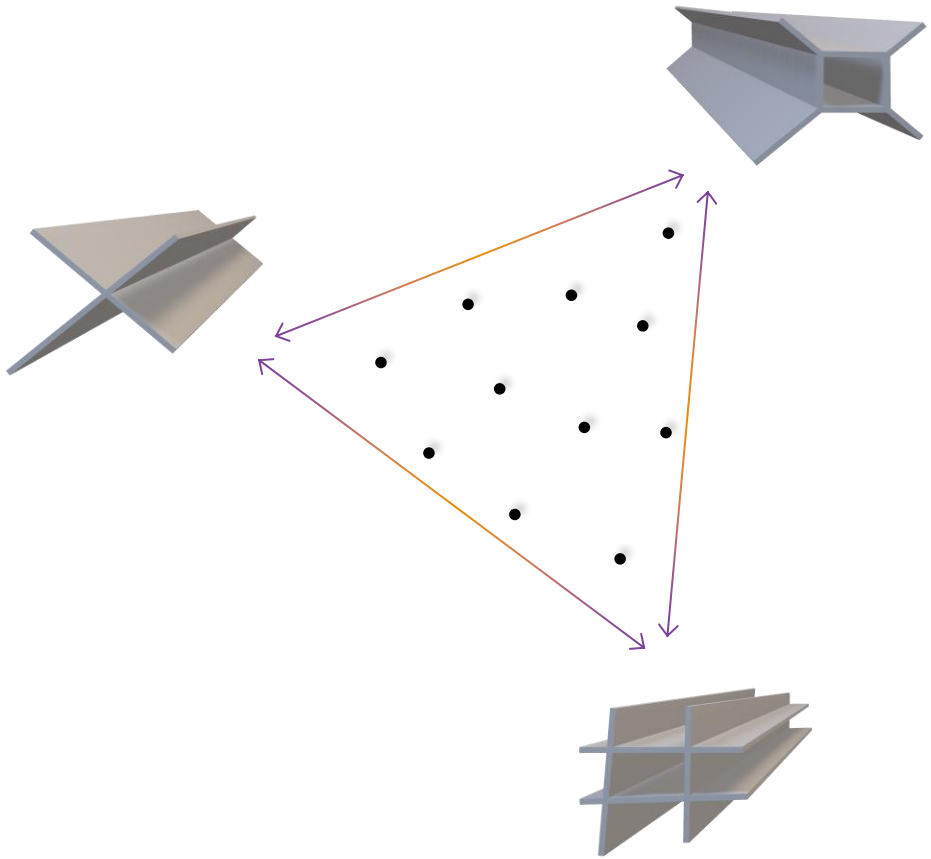




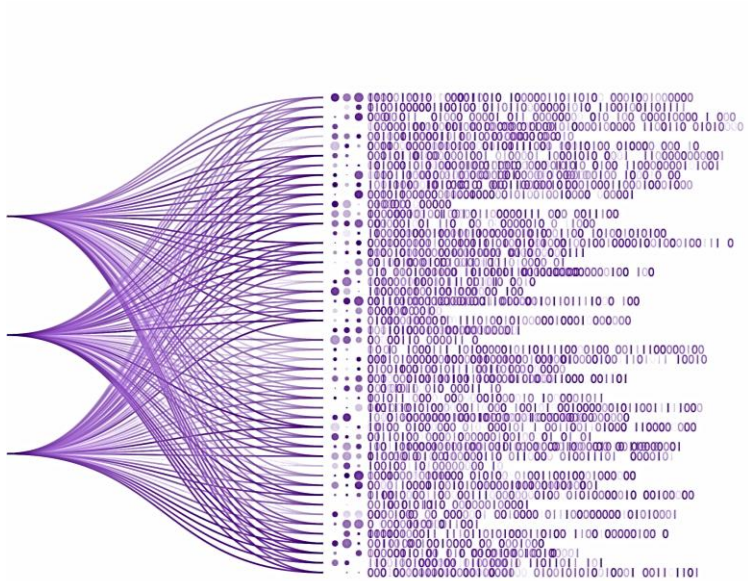
Case Study

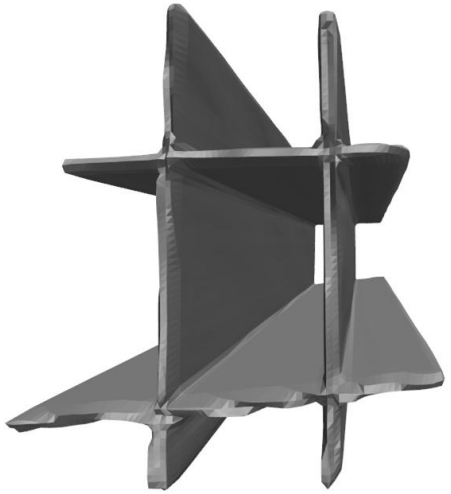
Generative AI Exploration

GeomAI
training



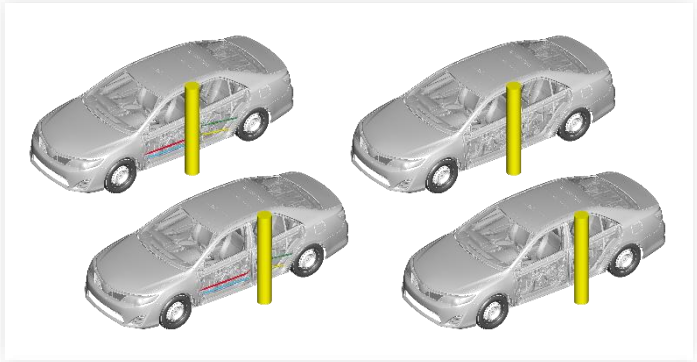
3 training samples

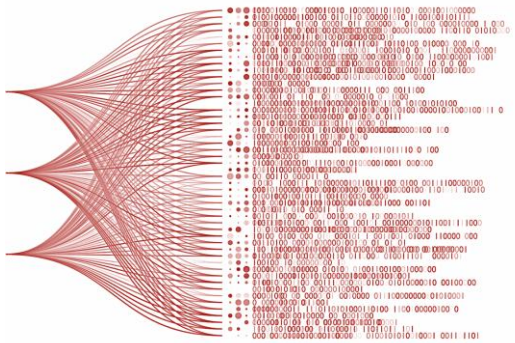


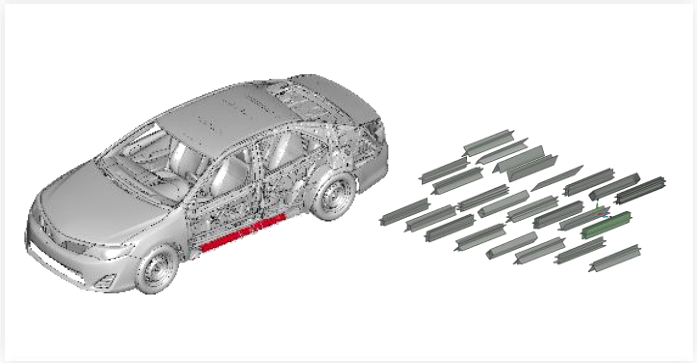


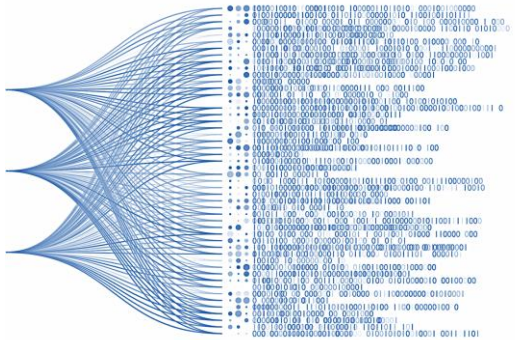
infinite number of variants

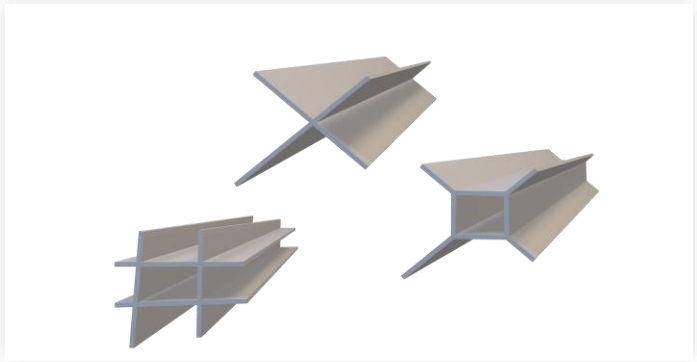
workflow
overview

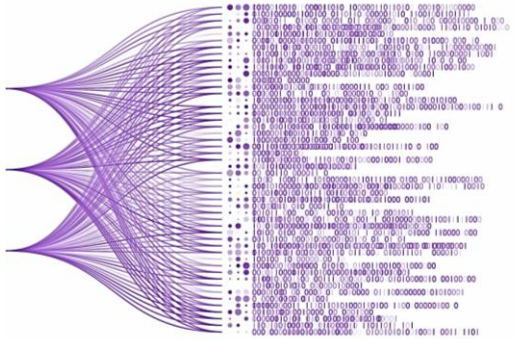




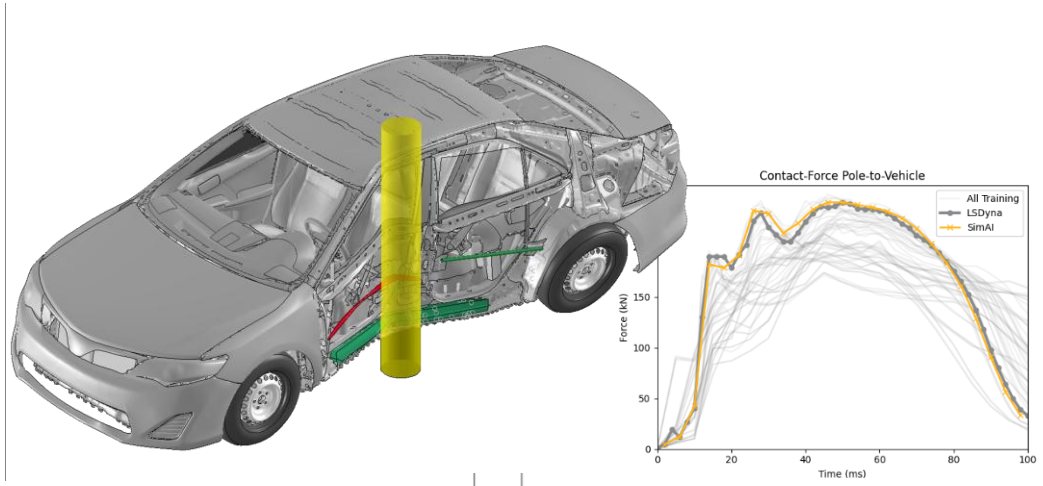


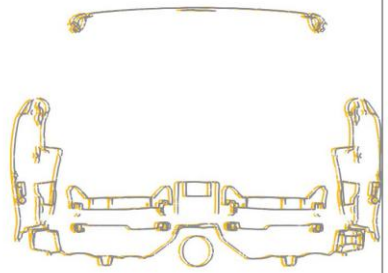


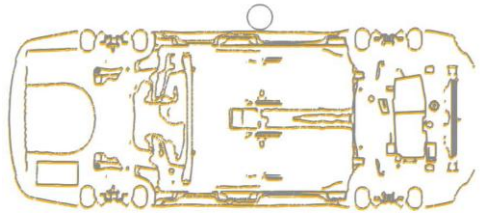


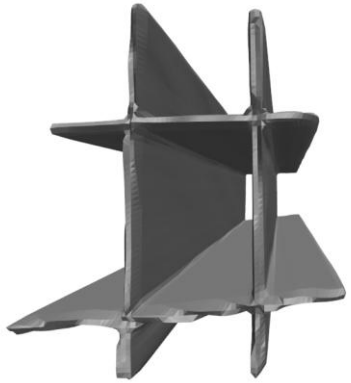


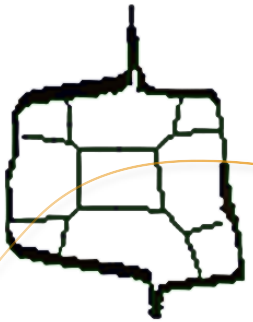
APPLIED ARTIFICIAL INTELLIGENCE



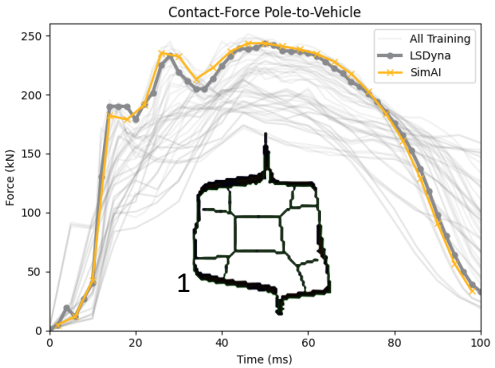


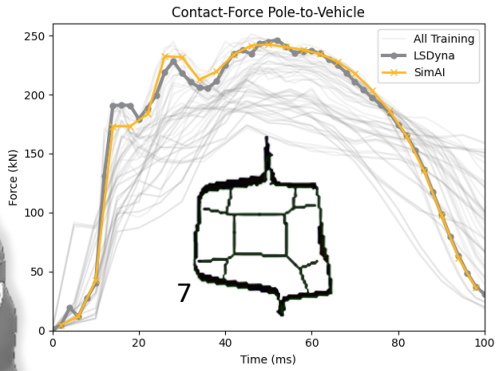


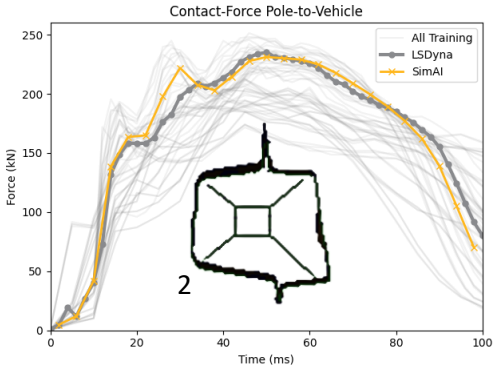


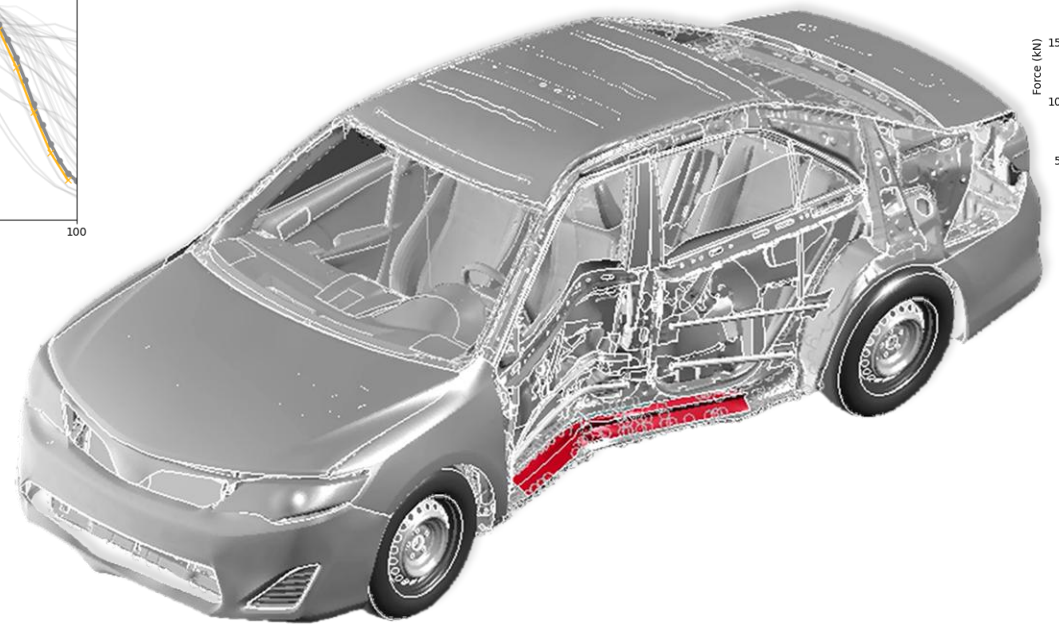


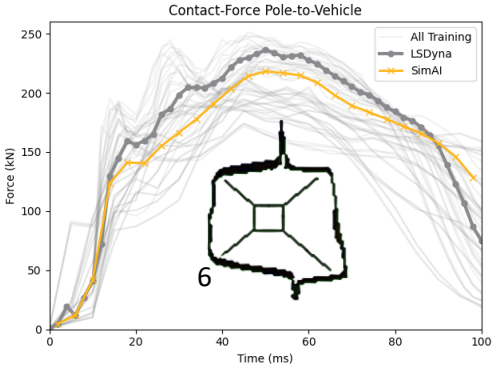
exploration
with generative AI

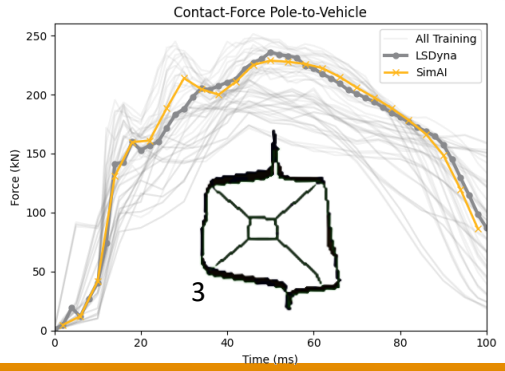


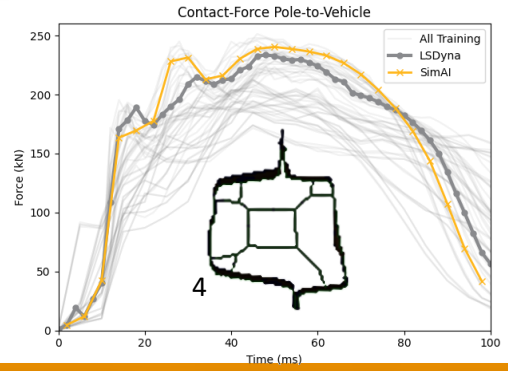


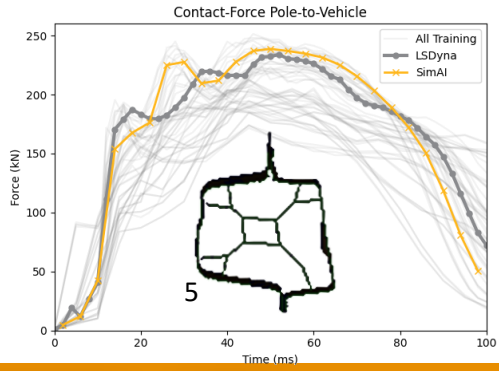






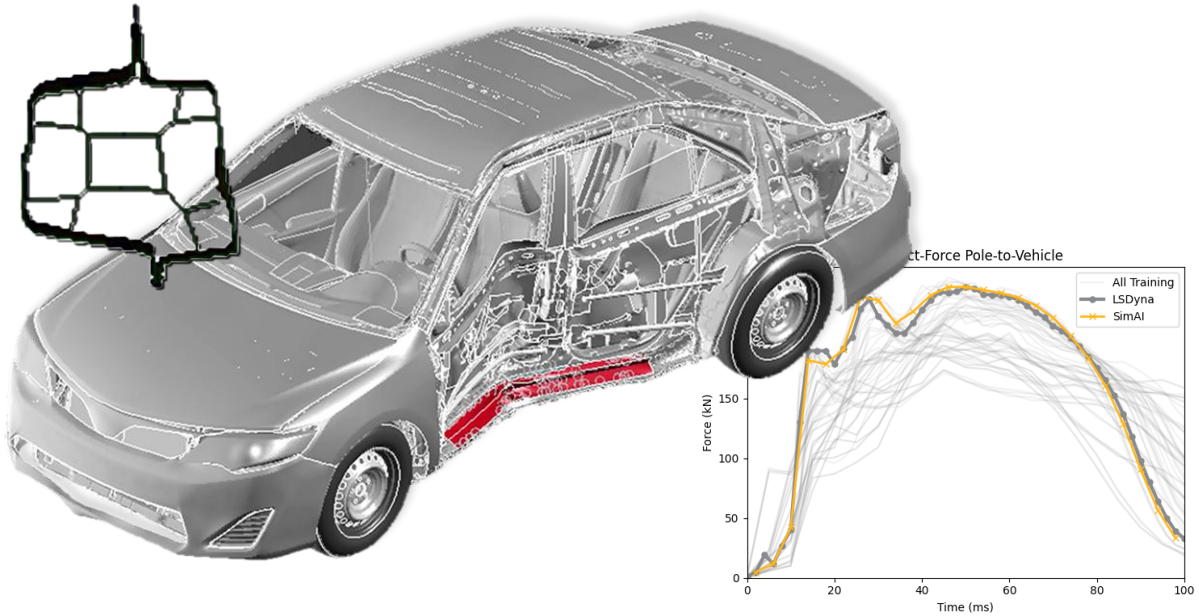




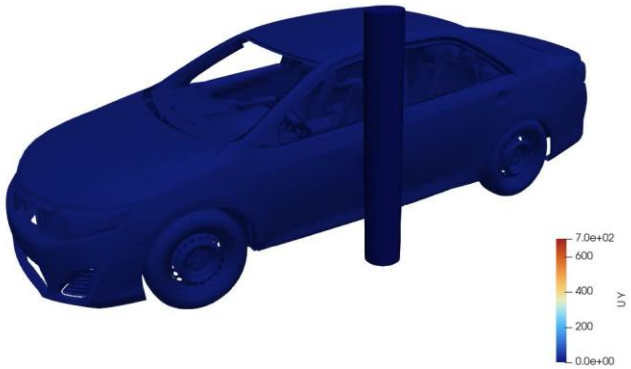


unseen data

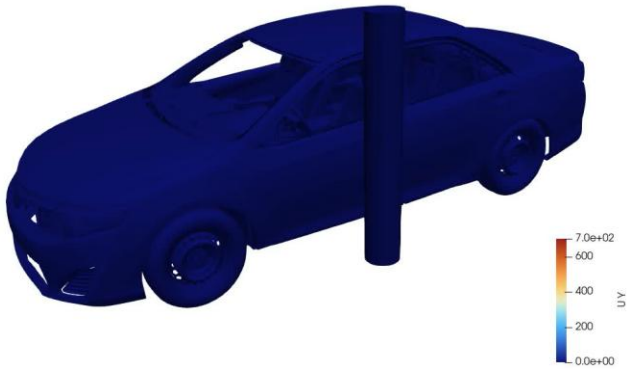
AI generated rocker inlay profile

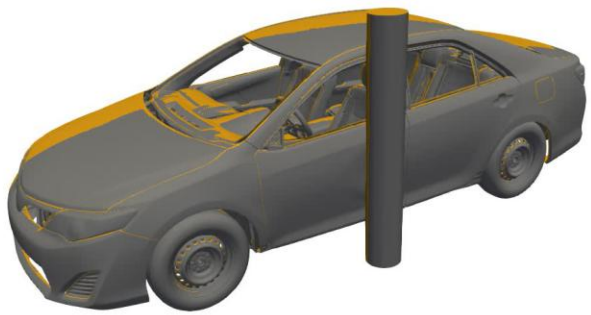


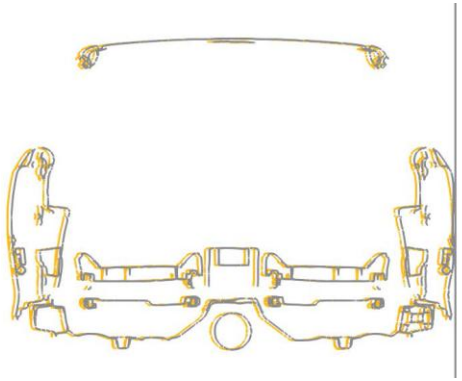
LS-DYNA

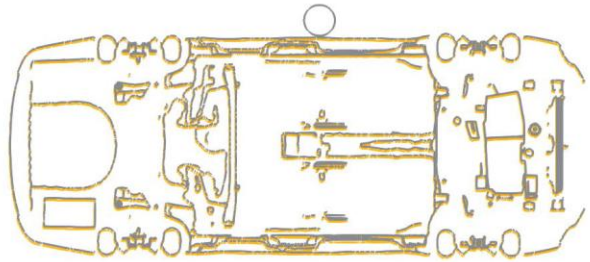


SimAI









Conclusions

Call to Action

conclusions

call to action

The study demonstrates the effectiveness of training AI models for full-vehicle crash prediction using LS-DYNA simulation data.

SimAI accurately predicts both full-field responses and time-history signals, achieving ~97% accuracy in transient crash simulations.

The results highlight the benefits of combining datasets across studies to develop domain-specific foundation models.

Together, SimAI and GeomAI transform Physics AI models into a generative AI framework, enabling rapid creation of novel design variants and expanding the design space.

Thank you for your attention

Q&A

SimAI and GeomAI Trial License