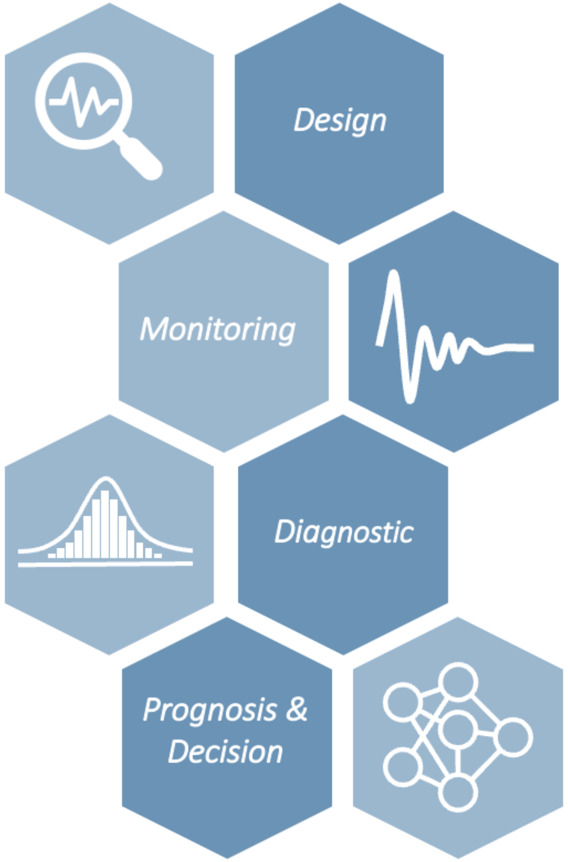
Jumeaux numériques pour la conception et l’opération hautes performances



Francisco (Paco) CHINESTA
Francisco.Chinesta@ensam.eu

Victor CHAMPANEY
Angelo PASQUALE
Daniele DI LORENZO
contact@duoverse.eu

duoverse

Bridge the gap between models & reality

Scan me :)

Who are we?

Origins

Duoverse was born from a passion for bridging the gap between simulation and reality. Originating from **CNRS@CREATE,** our expertise in **physics-based modeling** and **AI** helps tackle some of the world's most pressing challenges, accelerating disaster response, optimizing environmental sustainability, and enhancing decision-making in critical situations.

Values

At Duoverse, we believe in **precision**, **efficiency**, and **sustainability**. By merging physics with AI, we provide cutting-edge simulation tools that reduce environmental impact, improve resilience in crisis scenarios, and drive responsible innovation across key sectors such as disaster management, climate monitoring, and emergency response.

Objectives

Our mission is to revolutionize how organizations interact with simulations for a safer and more sustainable future. We aim to provide **fast, accurate, and scalable digital twin** solutions that help predict natural disasters, optimize resource allocation in emergencies, assess environmental risks, and support real-time decision-making in critical situations.

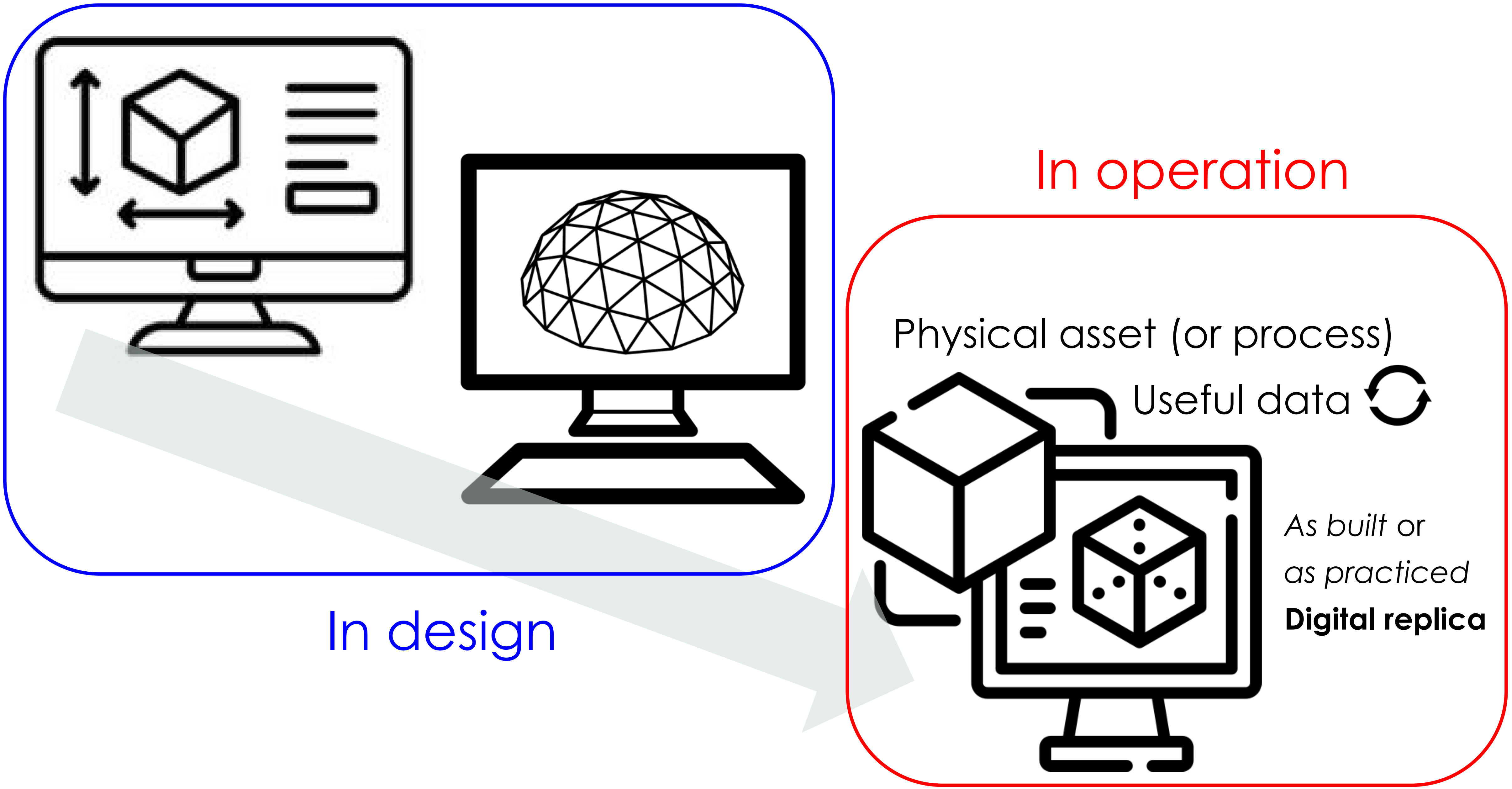
Contact Us

Agoranov
96bis Bd Raspail, 75006 Paris, France

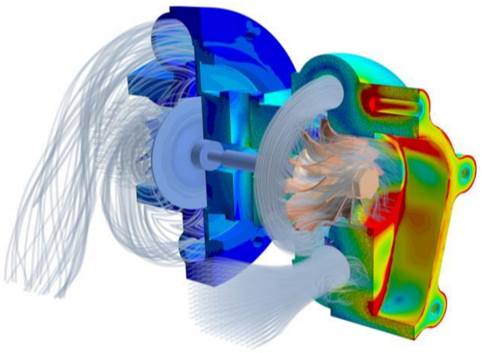
contact@duoverse.ai

www.duoverse.ai

Introduction: three levels of digitalization



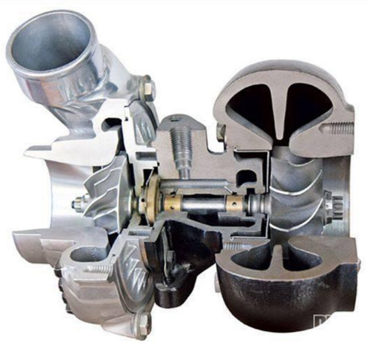
The twin continuum



21st century engineering:

- From design to operation

- From component to system of systems



The Twin Continuum

VIRTUAL

- Mostly physics
- U=U(F)
- Software

- Processing time
- Resources
- Complex systems
- Variability
- Uncertainty

INFORMED

u(x) AI-based such that L(u)=G

AUGMENTED - HYBRID

$u(x)=u^P(x)+u^D(x)$

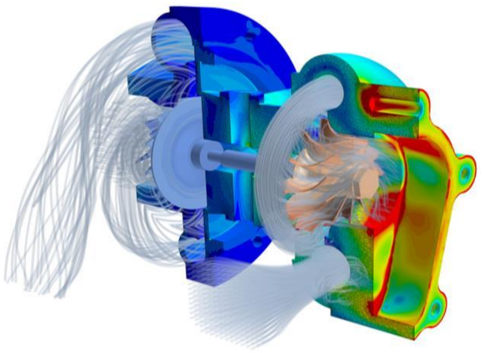
- Less data
- Faster
- Explainable

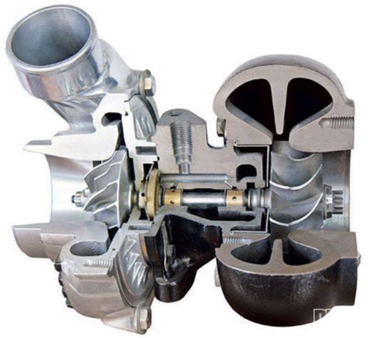
DIGITAL

- Unknown or poor model
- Ui,Fi, i=1,2, …
- Machine learning: U(F)

- Data cost
- Which data, where & when?
- Extrapolation
- Explanation

The twin continuum





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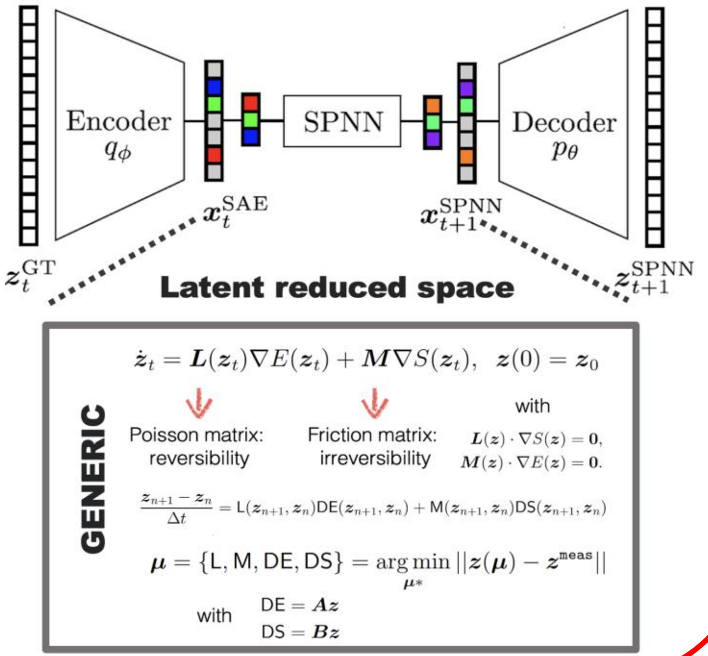
Thermodynamics Informed: TINN & PINN

TINN

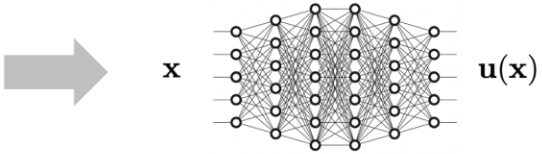


PINN

First order model $\mathcal{L}(u) = f(x)$

Unknown field $u(x)$

NN-based approximation $u = \mathcal{NN}(x)$



Collocation points where model is enforced $\{x_1^c, x_2^c, \ldots, x_C^c\}$

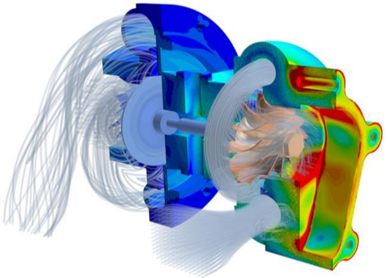
Observation points $\{x_1^o, x_2^o, \ldots, x_O^o\}$

where measures apply $\{u_1^o, u_2^o, \ldots, u_O^o\}$

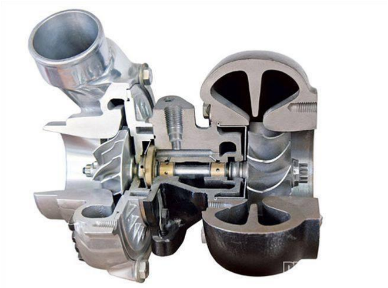
Training loss: $\text{Loss} = \sum_{i=1}^{C} \{\mathcal{L}(u)|_{x_i} - f(x_i)\}^2 + \sum_{j=1}^{O} \{u(x_j) - u_j^o\}^2 + \text{BC}$

THE TWIN CONTINUUM: AUGMENTED LEARNING

21st century engineering:
- From design to operation
- From component to system of systems



The Twin Continuum



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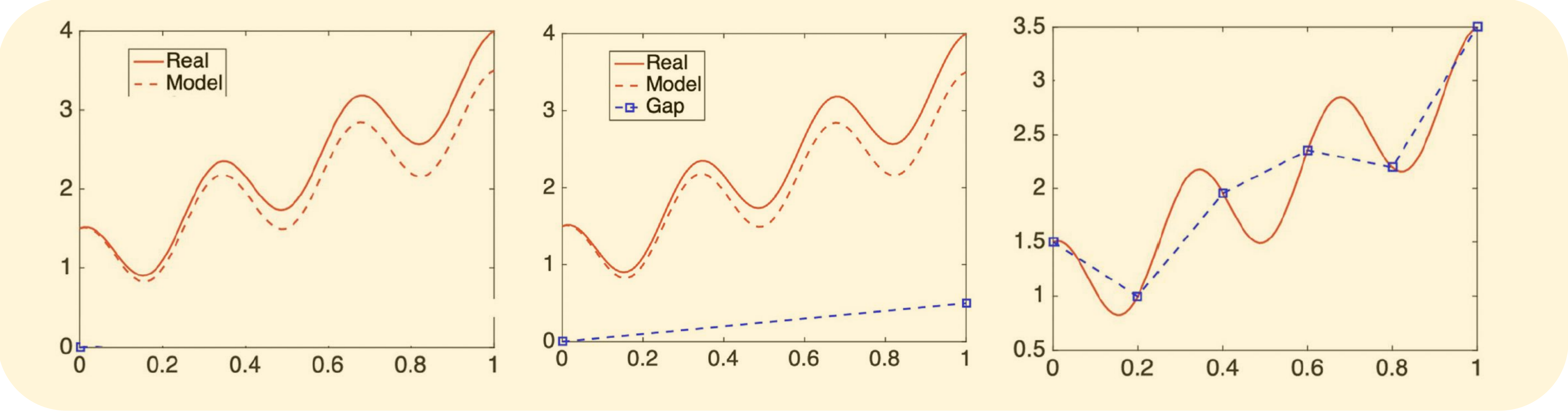
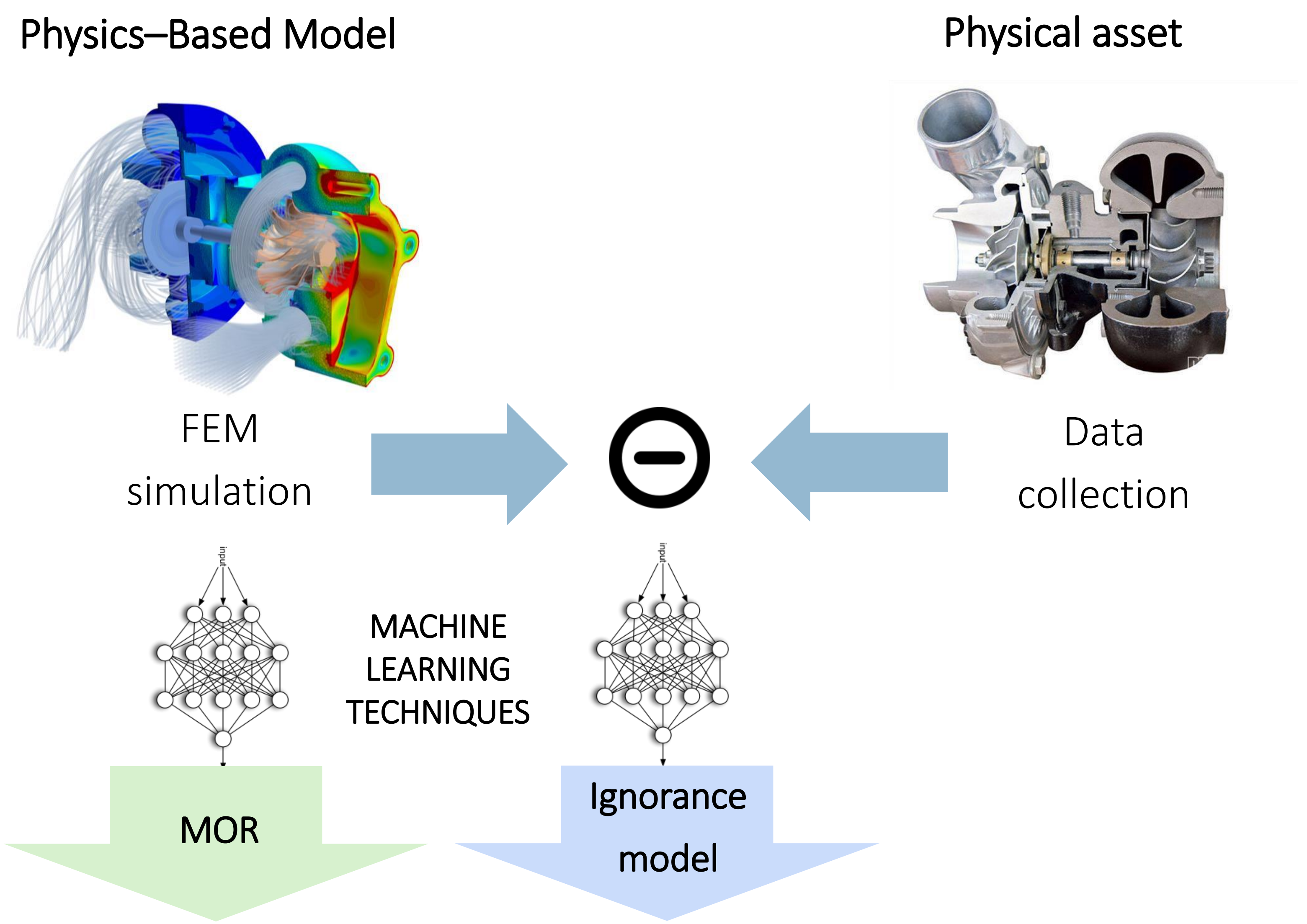
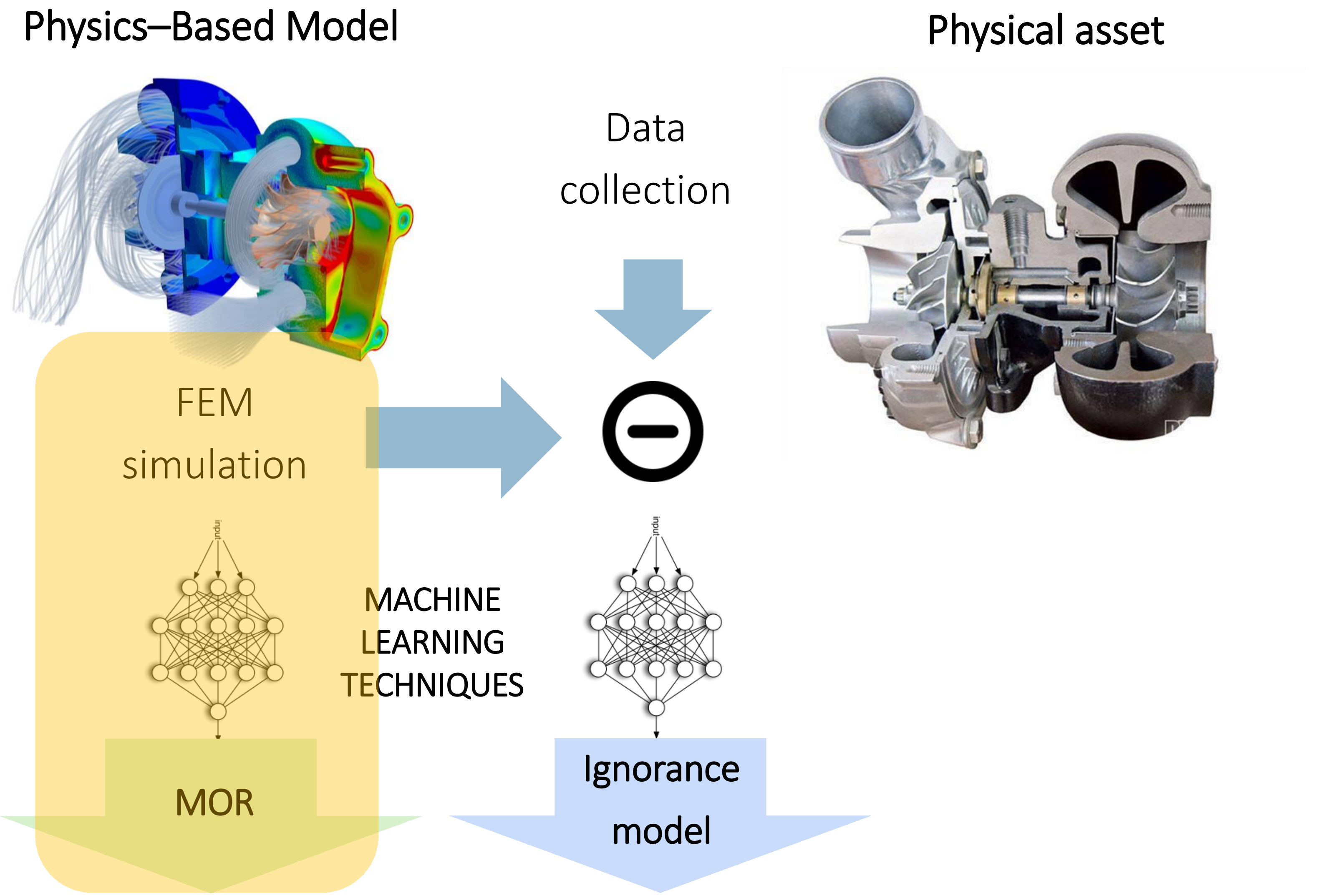


The Hybrid Twin



$$\frac{dx}{dt} = f^{\texttt{physics-based}}(x, \mathbf{z}) + f^{\texttt{data-driven}}(x, \mathbf{z})$$

Model Order Reduction: the art of surrogating !



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Surrogate construction: General workflow

Active Learning
- Goal-oriented GP
- Extended Fisher Information
  - Tensor decompositions
  - Information surrogates

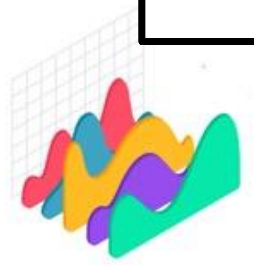
Data Reduction
- Linear (PCA)
- Nonlinear:
  - Manifold learning
  - Autoencoders

Regression (informed)
- Regularized Lineal Polynomial
  - Elastic Net, Ridge, Lasso, …
- Nonlinear:
  - NN-based
  - Optimal transport

Modelling

Design of Experiments
& Simulations

Solutions
compression



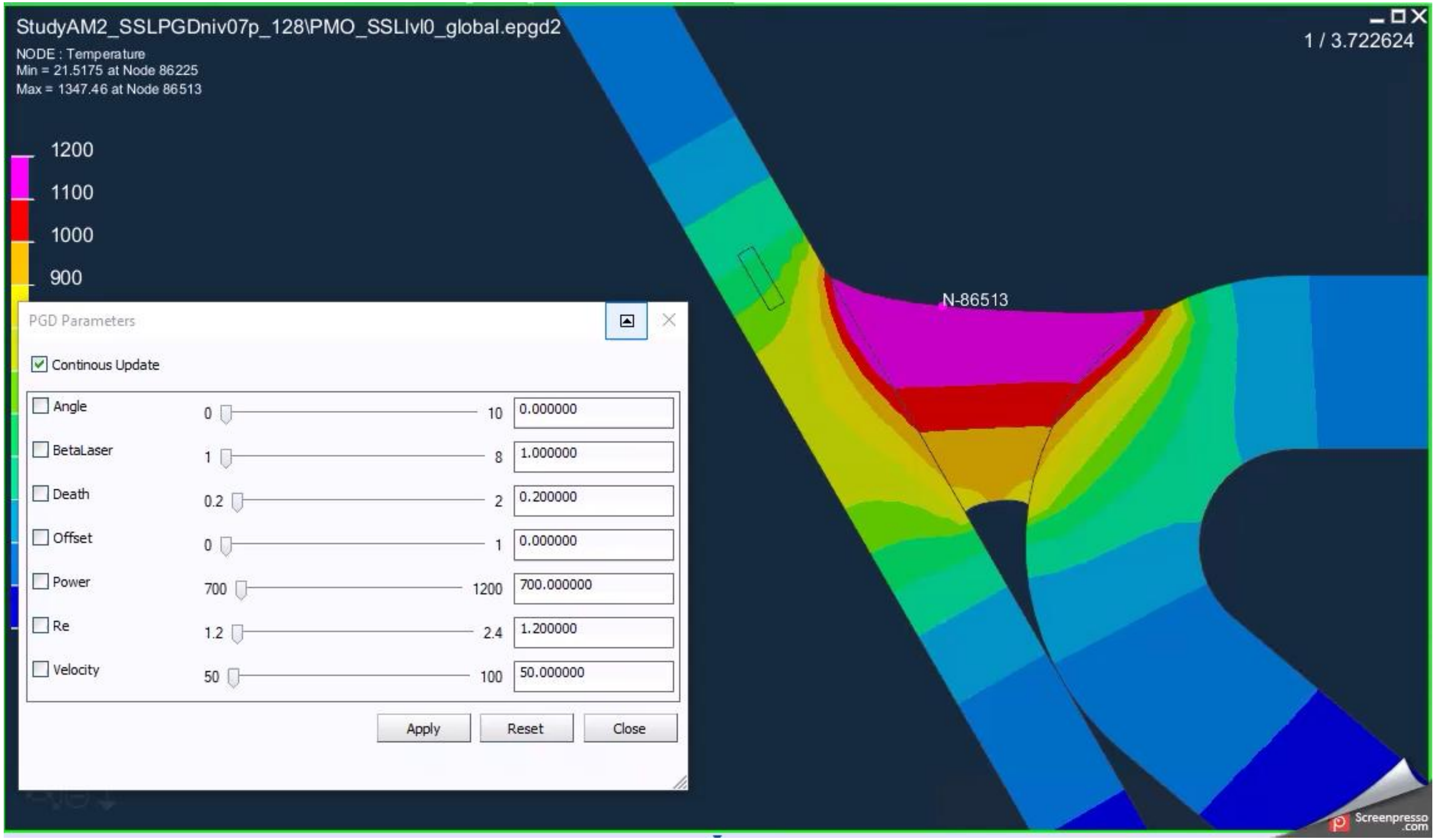
Interpolation
techniques

Parametric
Model

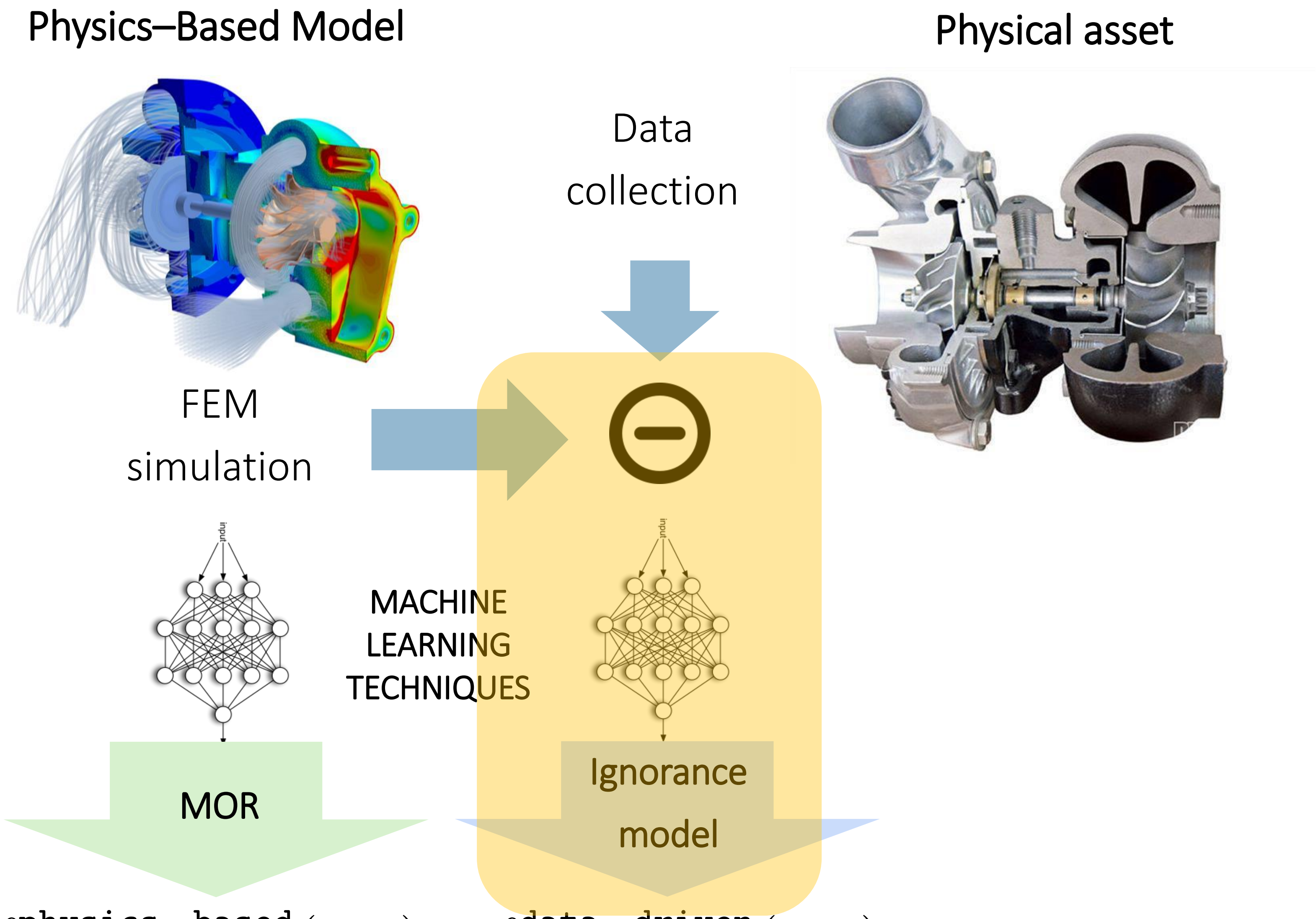
Model
Exploration

Postprocessing
- Data analytics
- Optimizers
- Uncertainty propagation
- Inversion / Data assimilation
- Control

Parametric real-time physics



Modelling from data: Machine Learning



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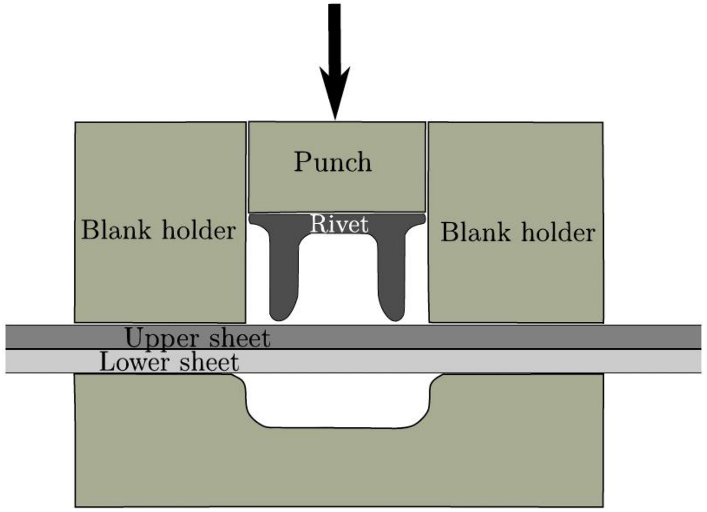
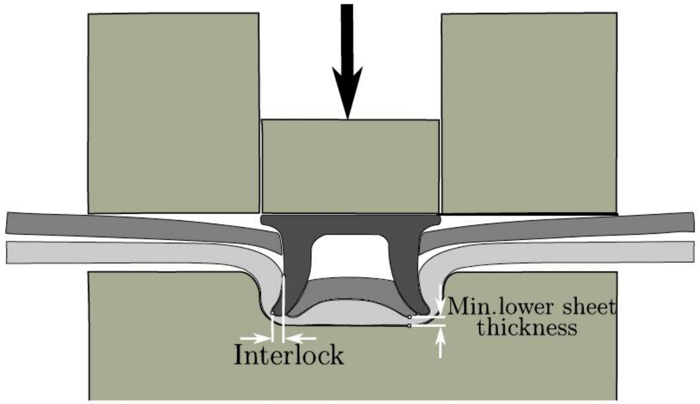
Data-Driven modelling of riveting





$$f\left(\bar{\sigma}, \bar{\varepsilon}_p\right) = \bar{\sigma} - k\left(\bar{\varepsilon}_p\right)$$

Hansel-Spittel

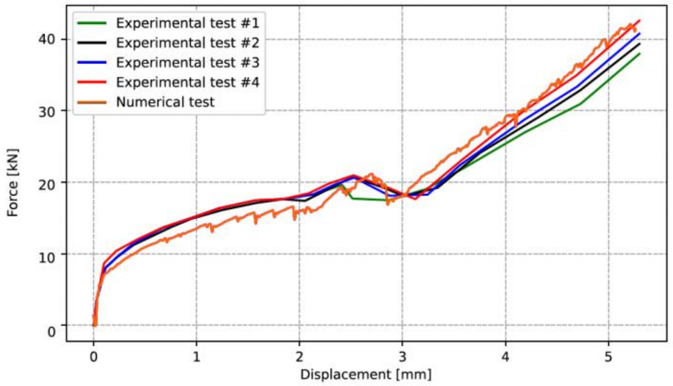
$$k\left(\bar{\varepsilon}_p\right) = A e^{m_1 \times T} \left(\bar{\varepsilon}_p\right)^{m_2} e^{\left(\frac{m_4}{\varepsilon_p}\right)} \left(\dot{\bar{\varepsilon}}_p\right)^{m_3}$$

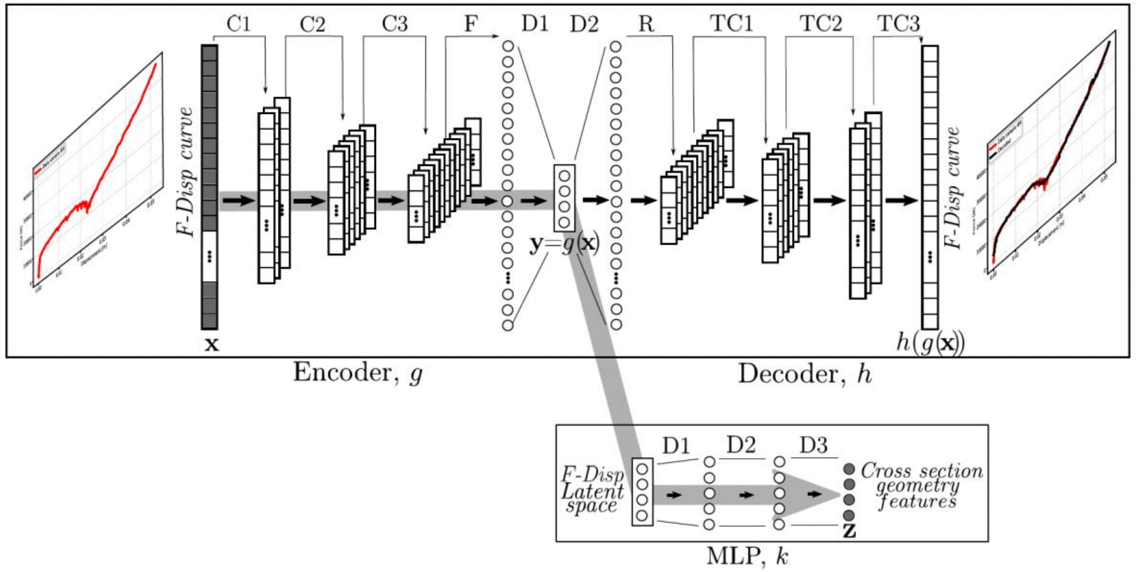
Hosford-Coulomb

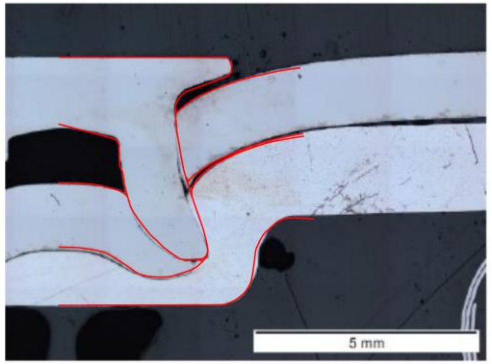
$$\varepsilon_f^{pr} = b\left(1+c\right)^{\frac{1}{p}} \left(\left\{ \frac{1}{2} \left(\left(f_1 - f_2\right)^a + \left(f_2 - f_3\right)^a + \left(f_1 - f_3\right)^a \right) \right\}^{\frac{1}{a}} + c\left(2\eta + f_1 + f_3\right) \right)^{-\frac{1}{p}}$$

Damage

$$\mathrm{d}\, D = \frac{\mathrm{d}\, \bar{\varepsilon}_p}{\varepsilon_f^{pr}\left(\eta, \bar{\theta}\right)}$$

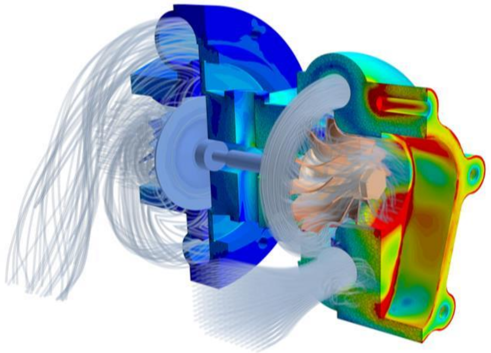






A SUCCESFULLY APPLIED HAI TECHNOLOGY FOR PREDICTING FAST & WELL

Physics–Based Model



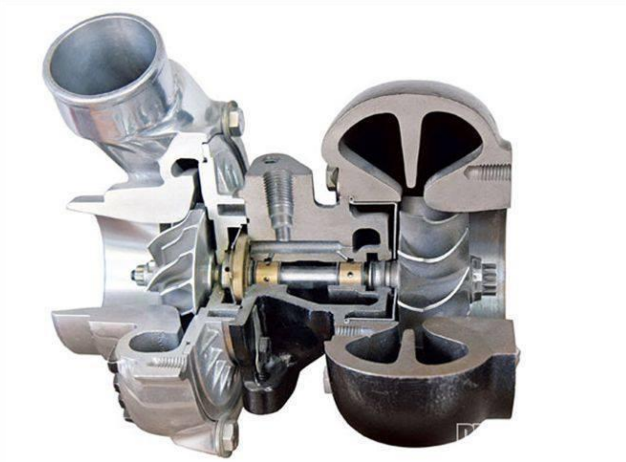
FEM

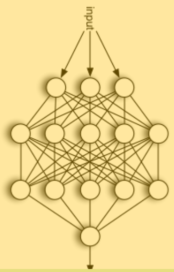
simulation

Data

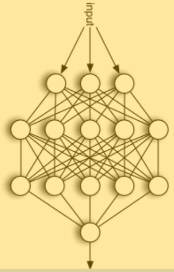
collection

Physical asset





MACHINE
LEARNING
TECHNIQUES



MOR

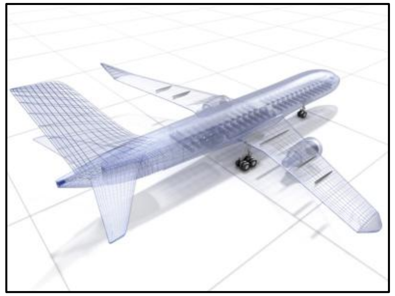
Ignorance

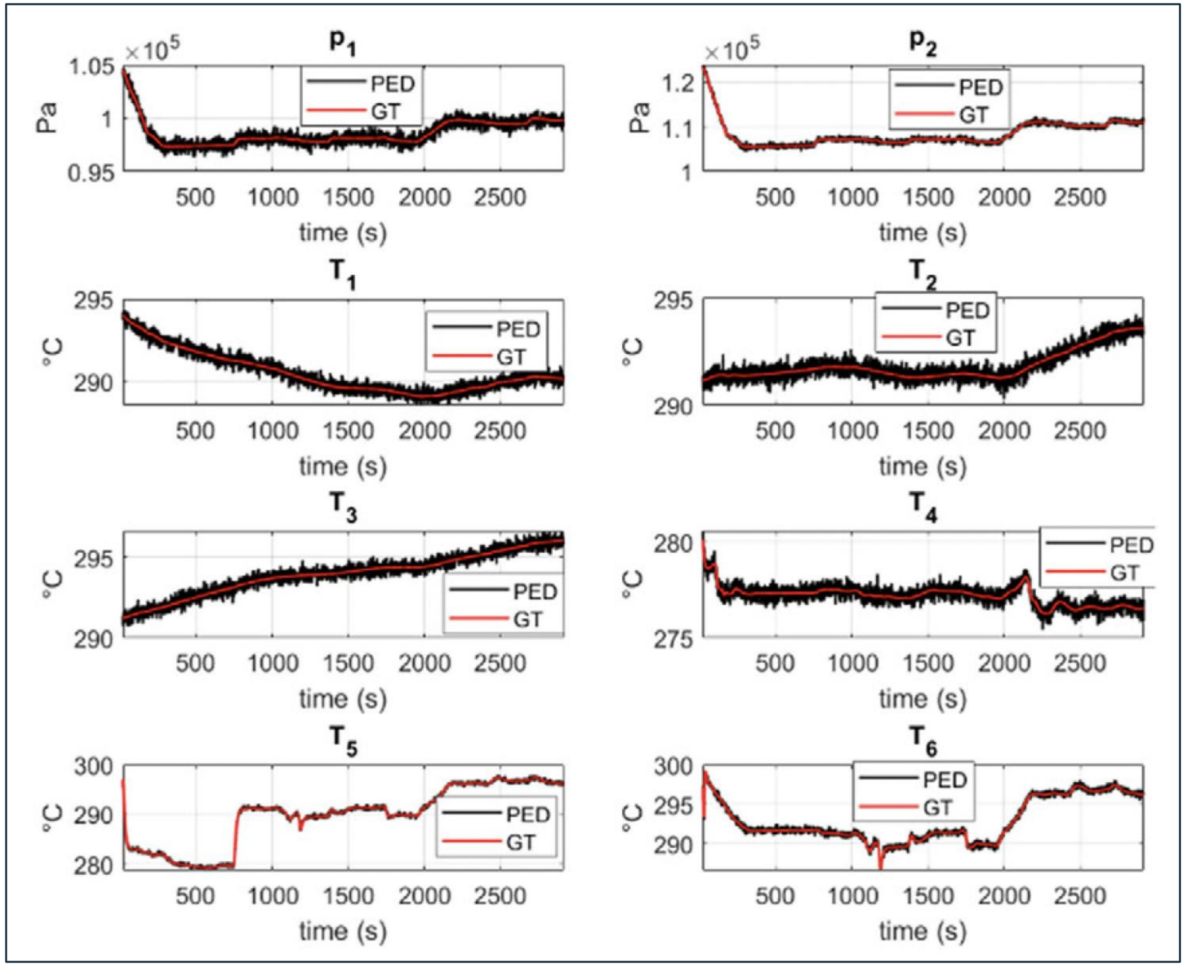
model

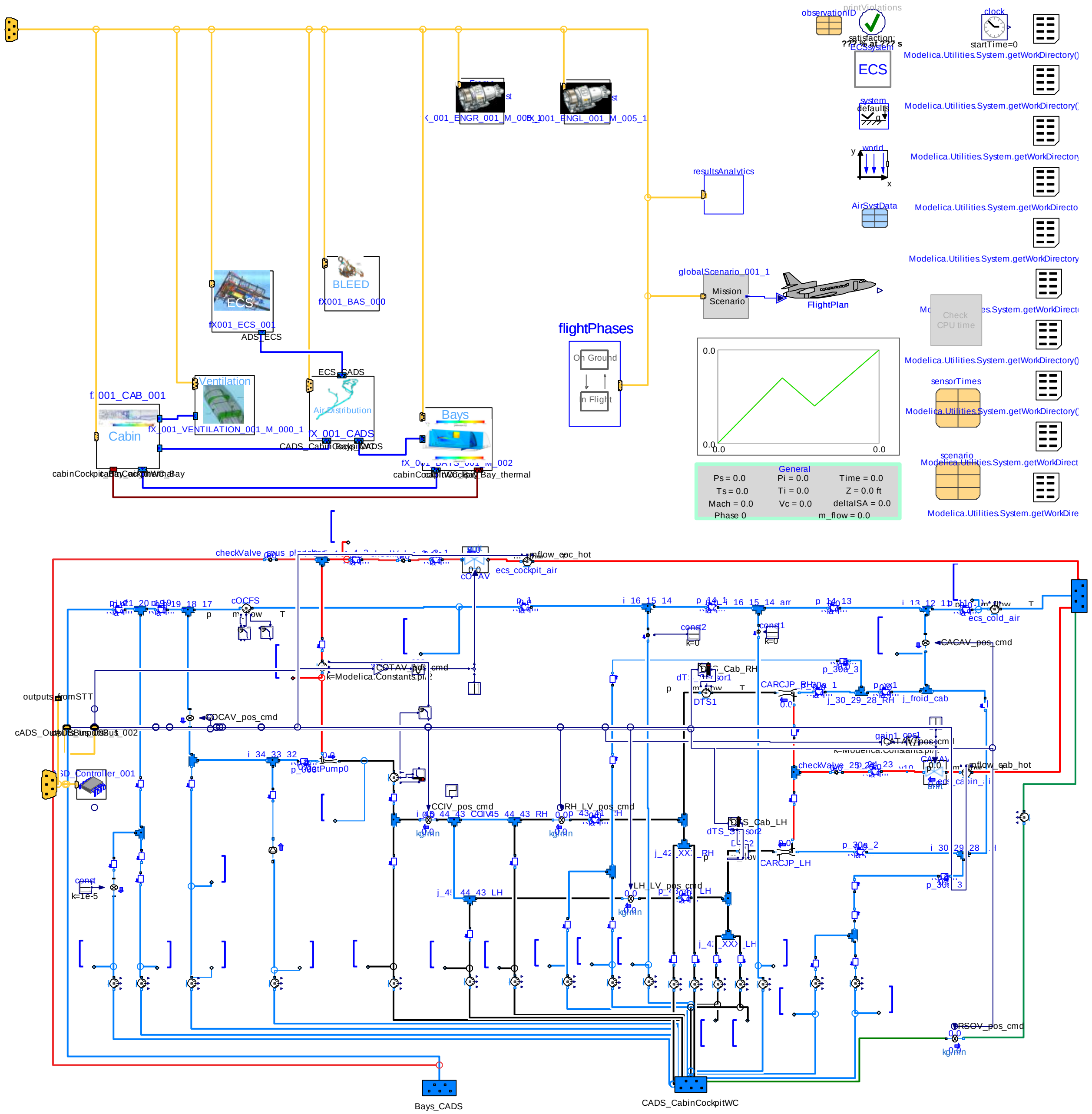
$$\frac{dx}{dt} = f^{\texttt{physics-based}}(x, \mathbf{z}) + f^{\texttt{data-driven}}(x, \mathbf{z})$$

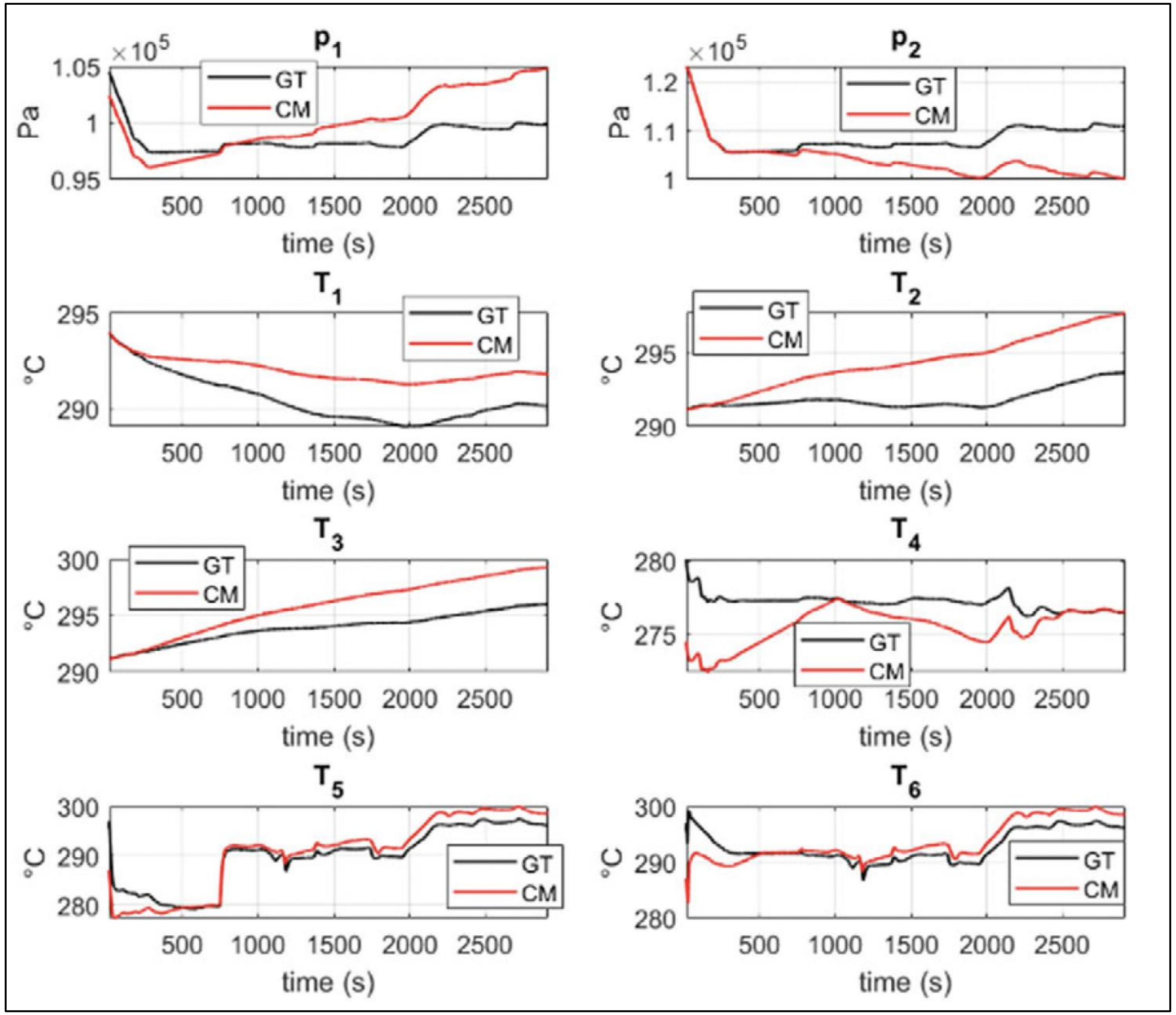
SYSTEM HYBRID TWIN

DASSAULT AVIATION









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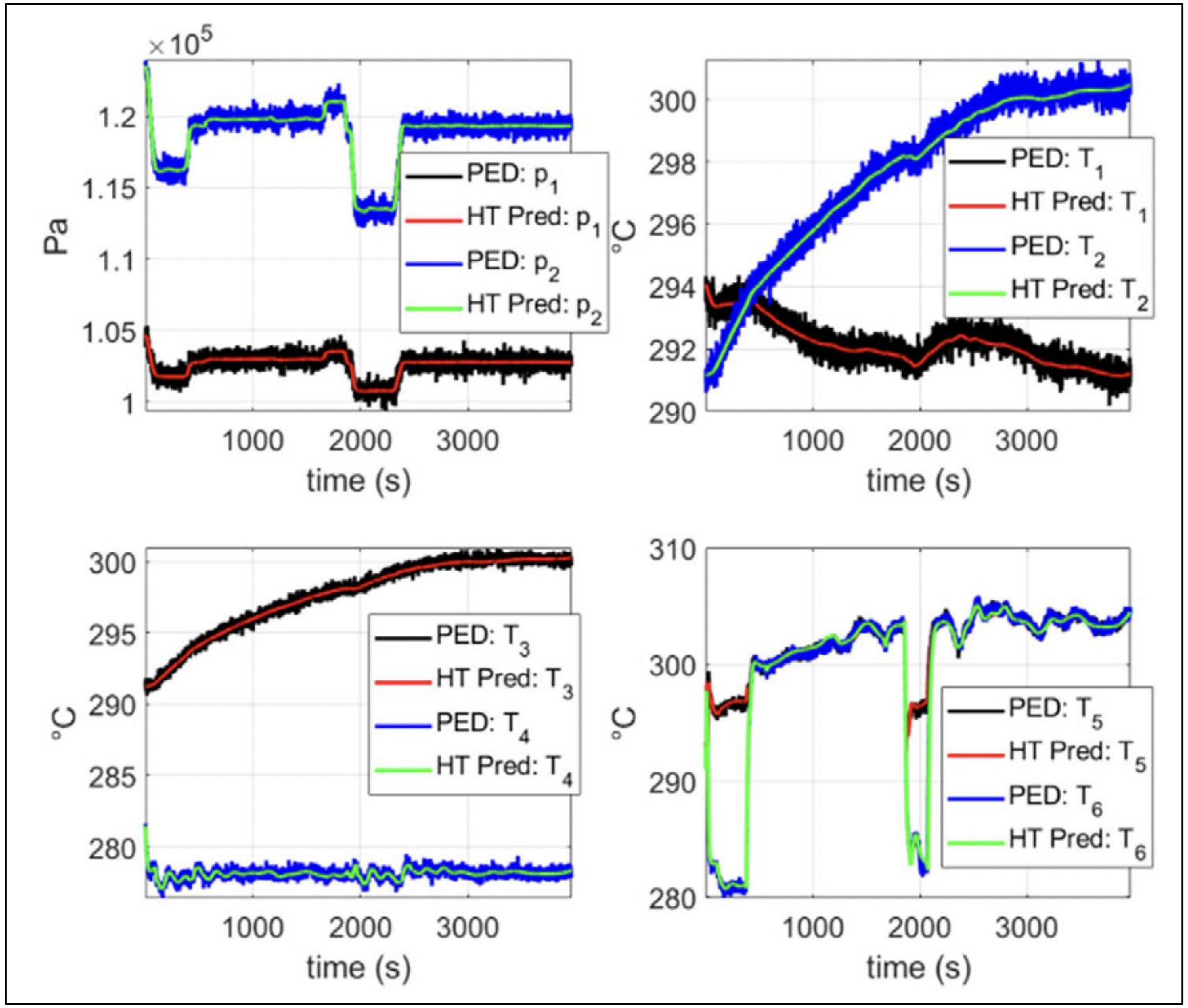
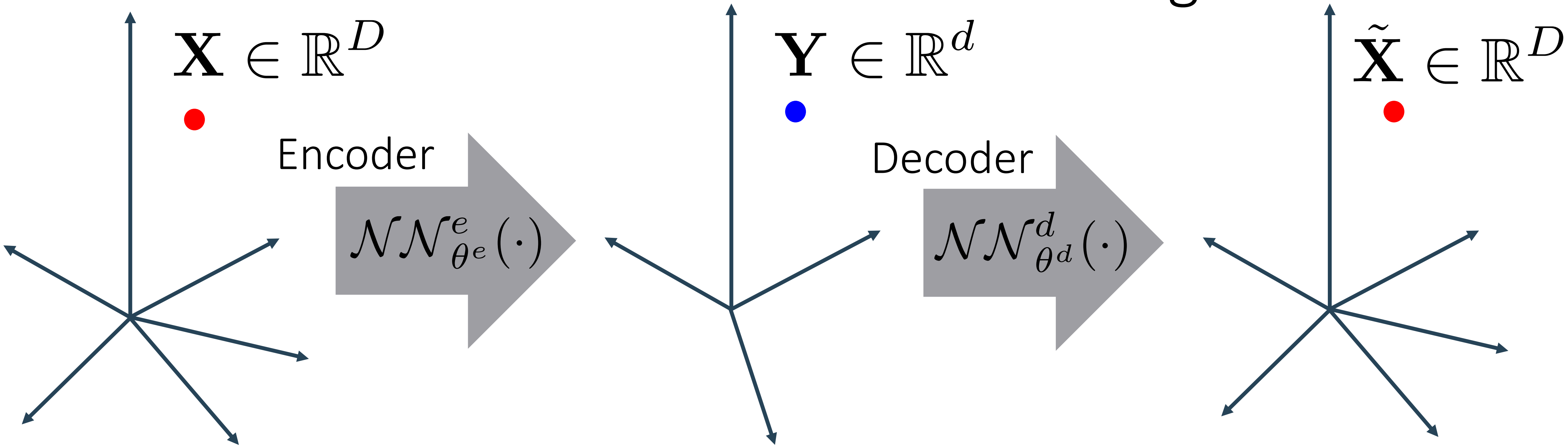


From Hybrid Twins to Generative Design

Latent space

Embedding

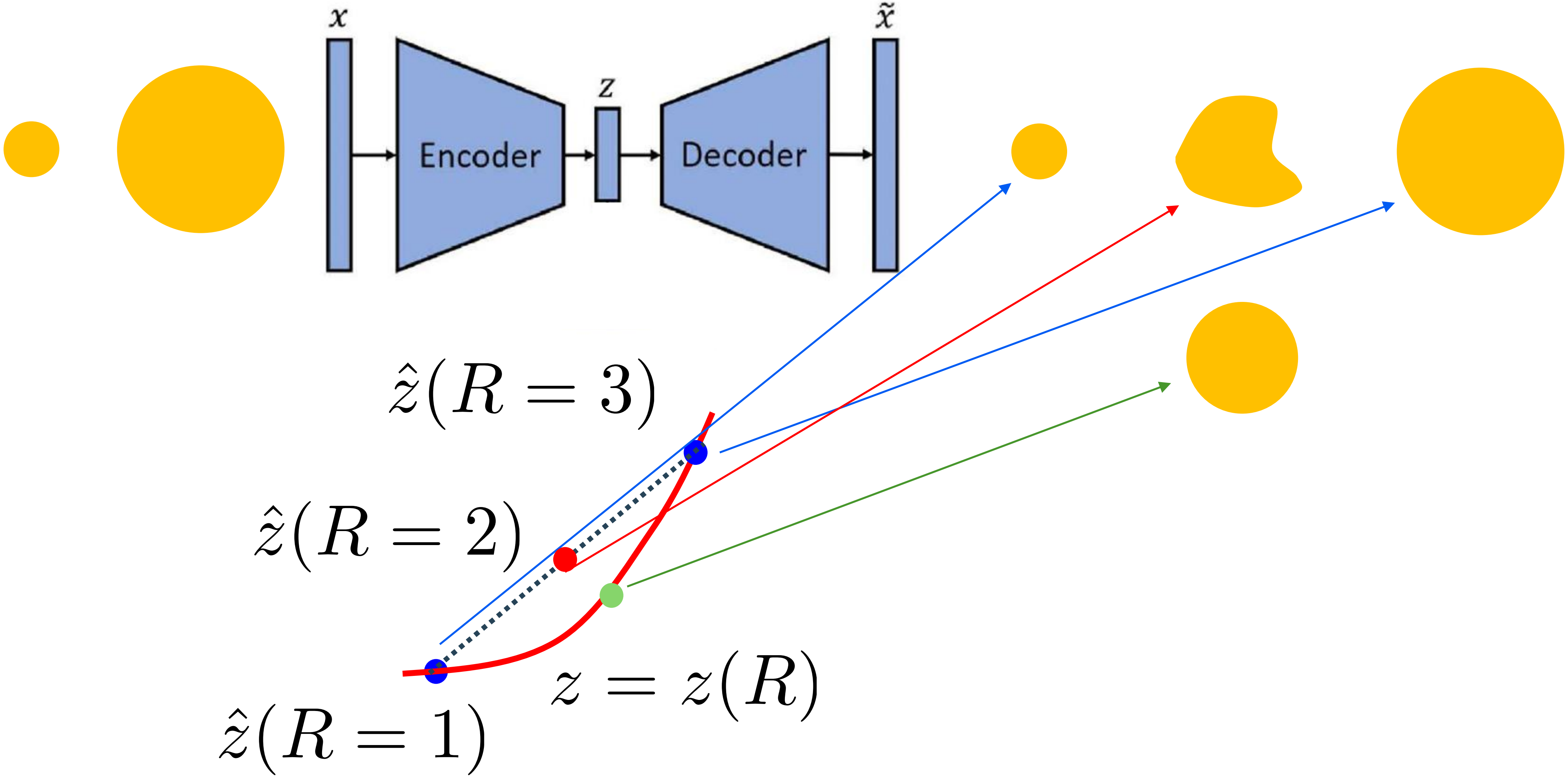


Reduction: looking for the smallest "d" such that: $\tilde{\mathbf{X}} \approx \mathbf{X}$

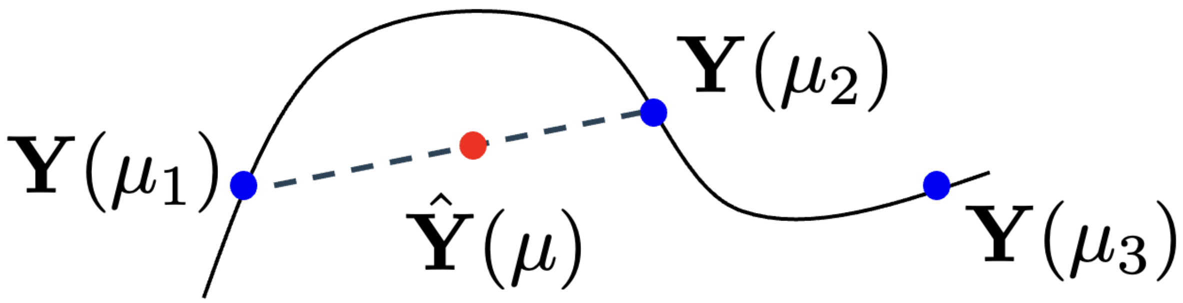
Available data: $\mathbf{X}_1, \mathbf{X}_2, \ldots$

Training the encoder and decoder: $\{\theta^e, \theta^d\} = \texttt{argmin} \sum_i \left\| \mathcal{NN}^d_{\theta^d}(\mathcal{NN}^e_{\theta^e}(\mathbf{X}_i)) - \mathbf{X}_i \right\|^2$

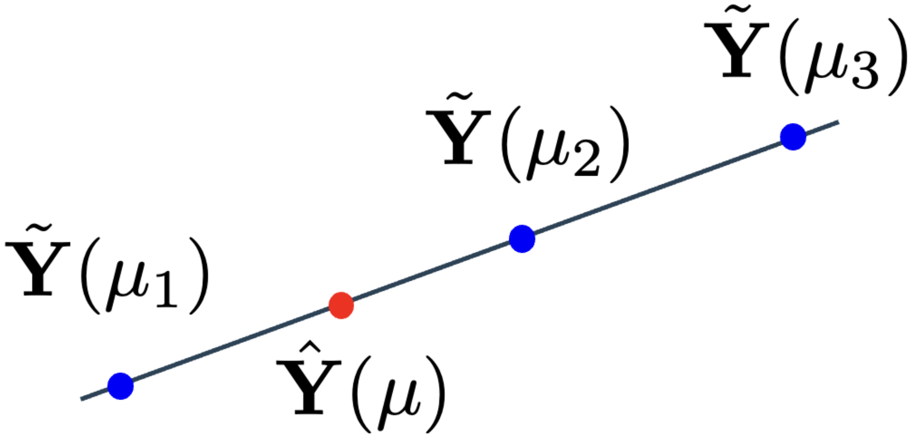
Issues

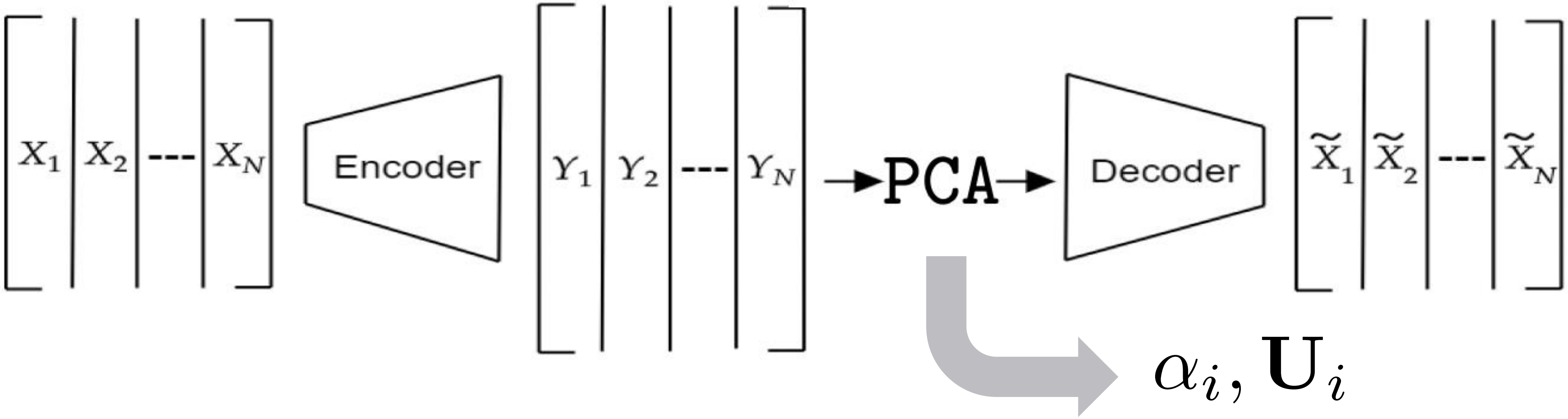


Enforcing interpolation capabilities: the rank reduction autoencoder – RRAE

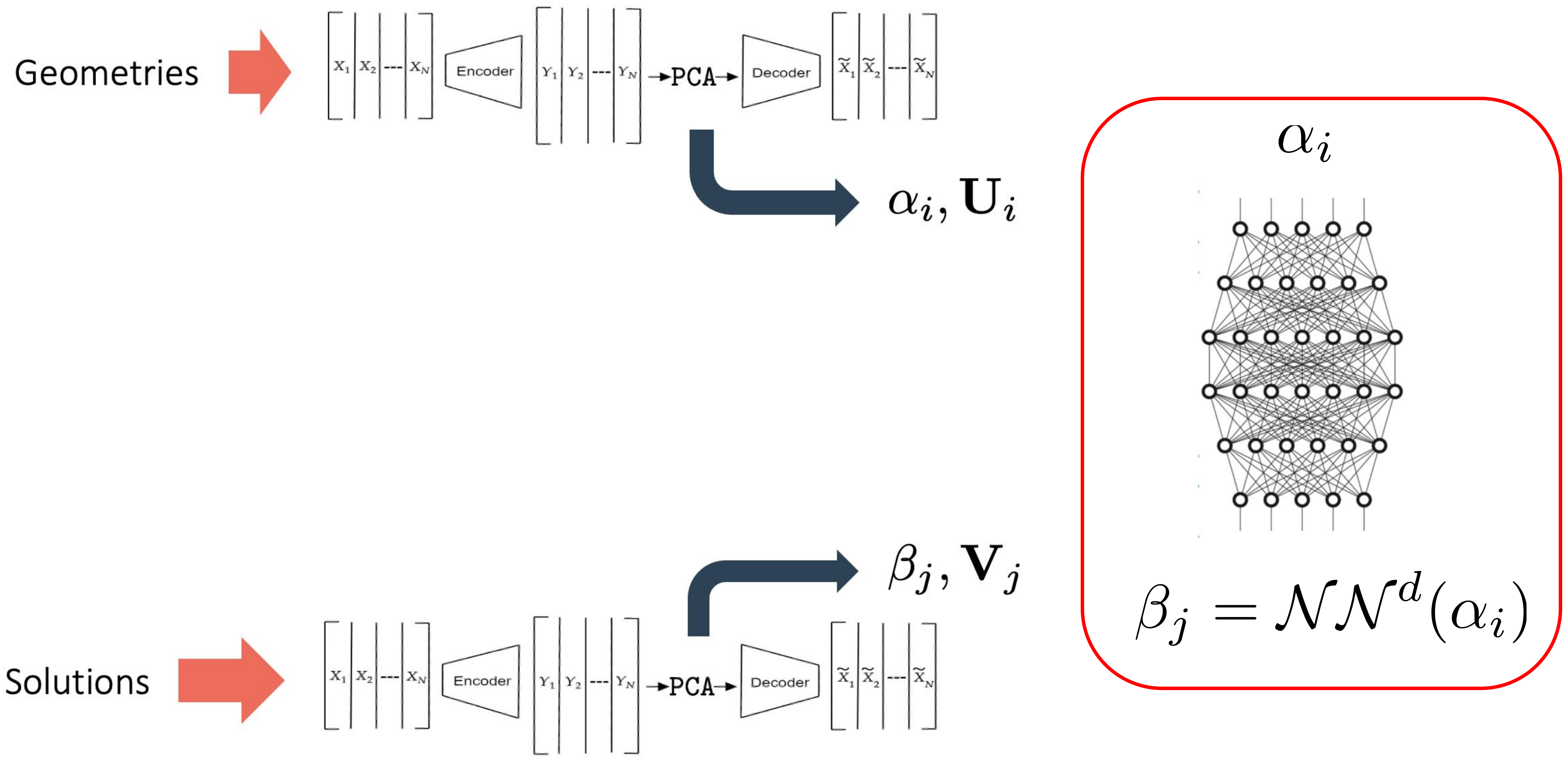


If latent space were linear

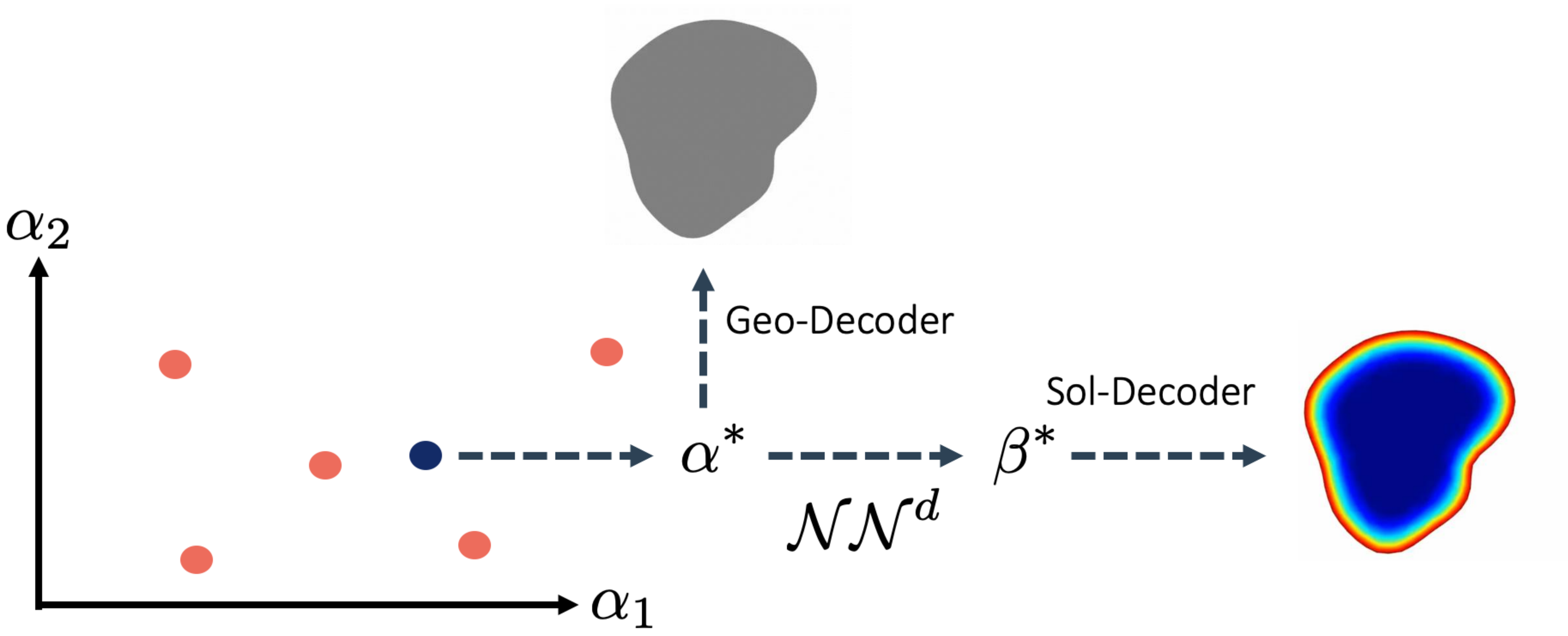




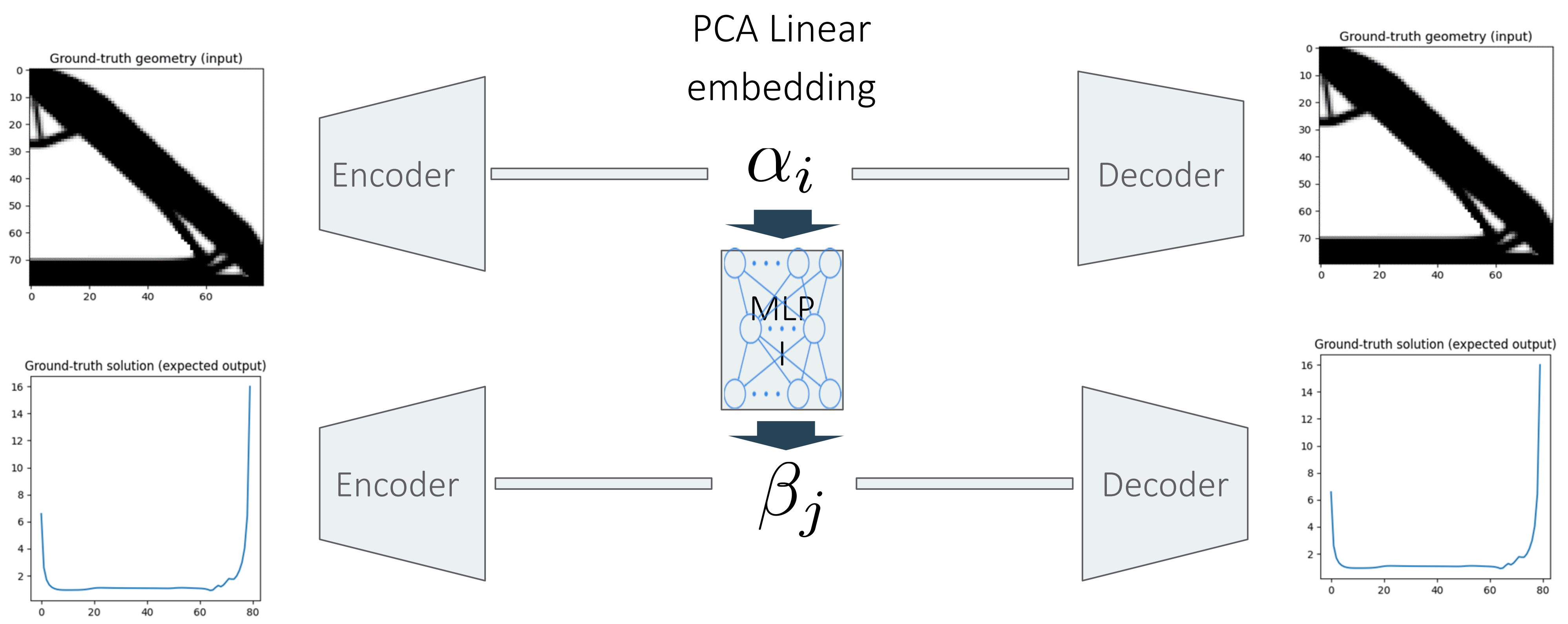
Geometry to Solution



Generative Design

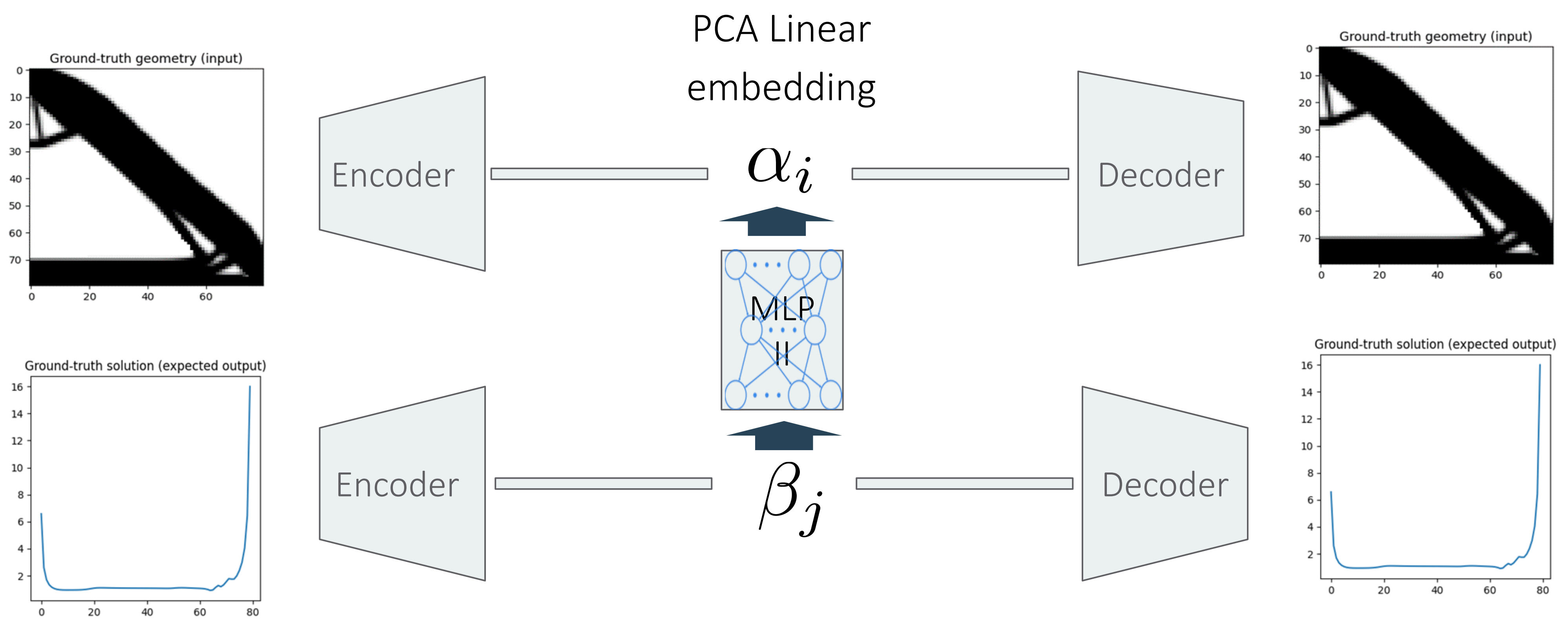


USE CASE



PCA Linear embedding
Ground-truth geometry (input)
Encoder
α_i
Decoder
Ground-truth geometry (input)
MLP
Ground-truth solution (expected output)
Encoder
β_j
Decoder
Ground-truth solution (expected output)

USE CASE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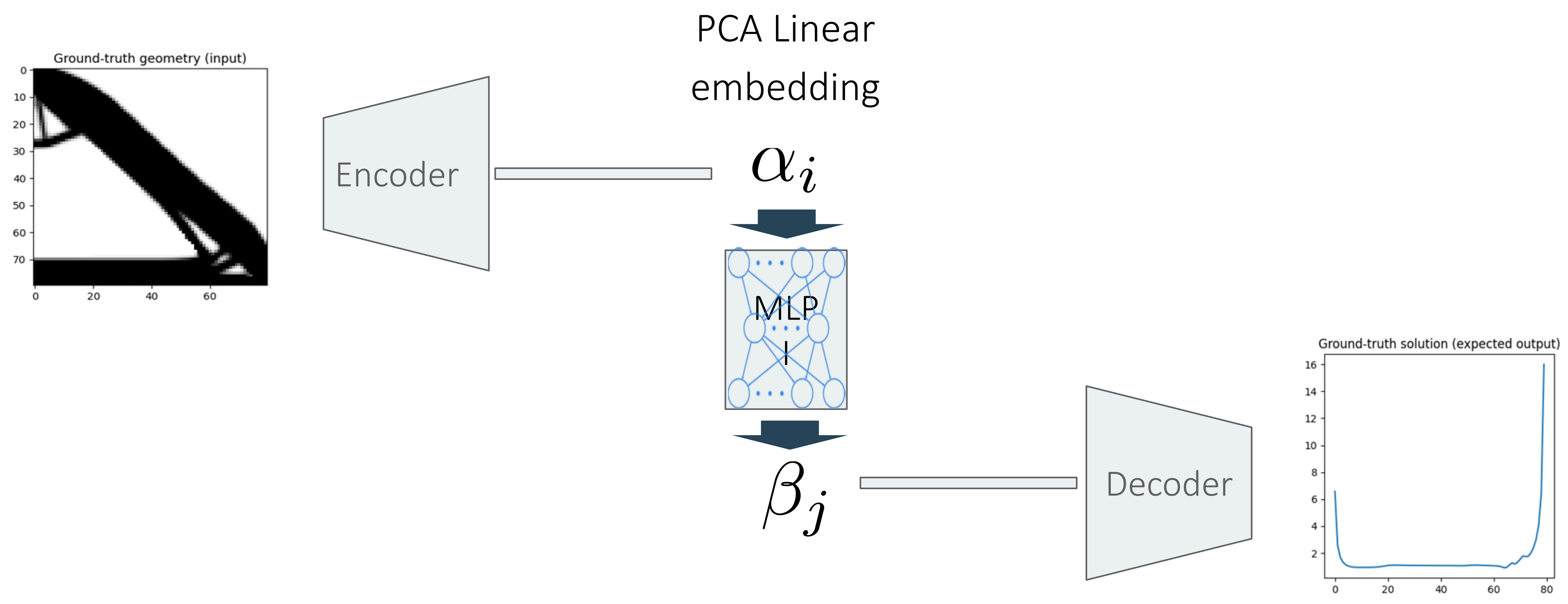
USE CASE: topology to performances



USE CASE: performances to topology