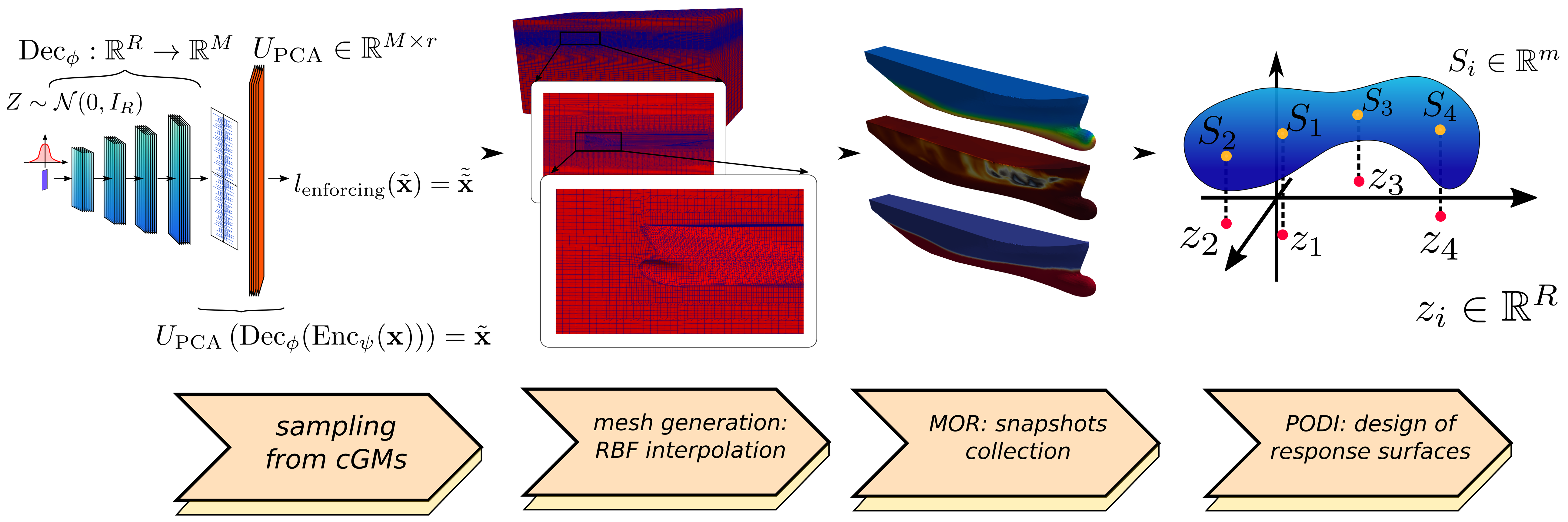
Constrained Generative Models for shape parametrisation

Guglielmo Padula, Francesco Romor, Giovanni Stabile, Gianluigi Rozza
Mathematics Area, mathLab, SISSA, International School of Advanced Studies, Trieste, Italy

Introduction

We study **generative models** for shape optimization of complex geometries with a large number of parameters; the objective is also to reduce the number of relevant geometrical parameters, for example for modeling naval hulls, and creating new artificial geometries similar to real data, as there are non-generative techniques for creating new real geometries which respect some constraints, for having fixed volume, (see the package PyGem [1] developed here at Sissa) but using them can be costly. The real geometries are parametrized by a lesser number of parameters, which in turn increases the performance of reduced order models.

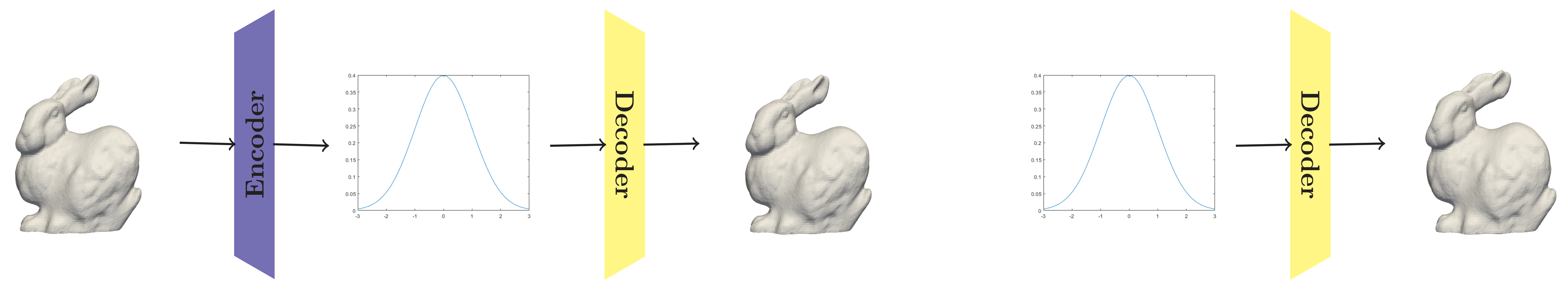
Workflow



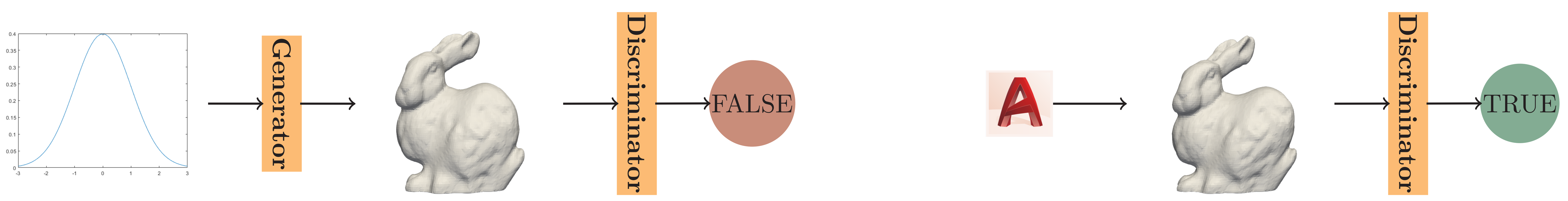
Generative models for reduction in parameter space

Two main model classes:

- Variational autoencoders(VAE): the figure describes the training using a point cloud mesh of Bulbous bow, and the right figure shows sampling of a deformed Bulbous.



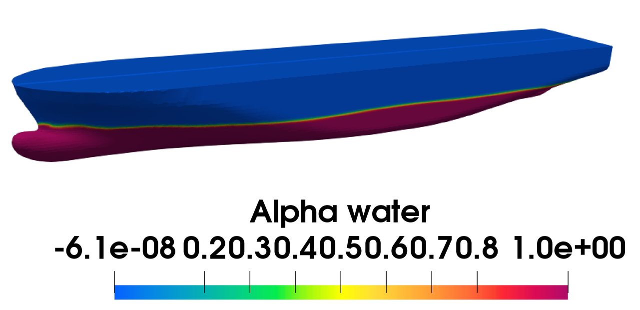
- Generative adversarial networks: it is characterized by a generator that samples point cloud mesh of rabbit and by a discriminator that accepts real rabbit (right figure)) and rejects deformed ones (left figure)).

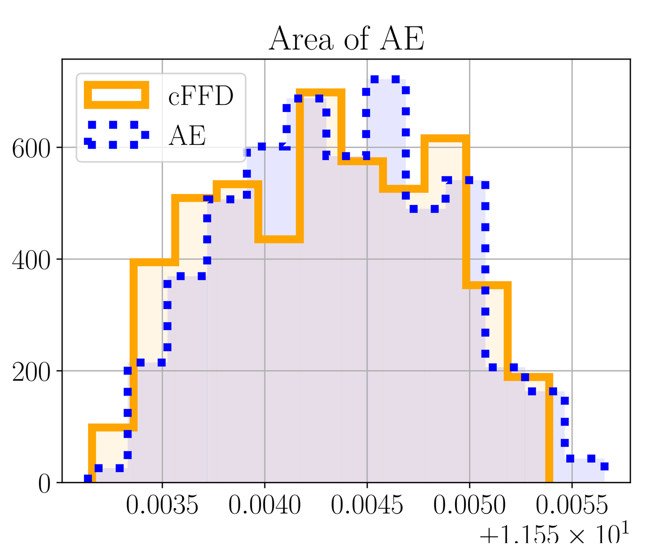


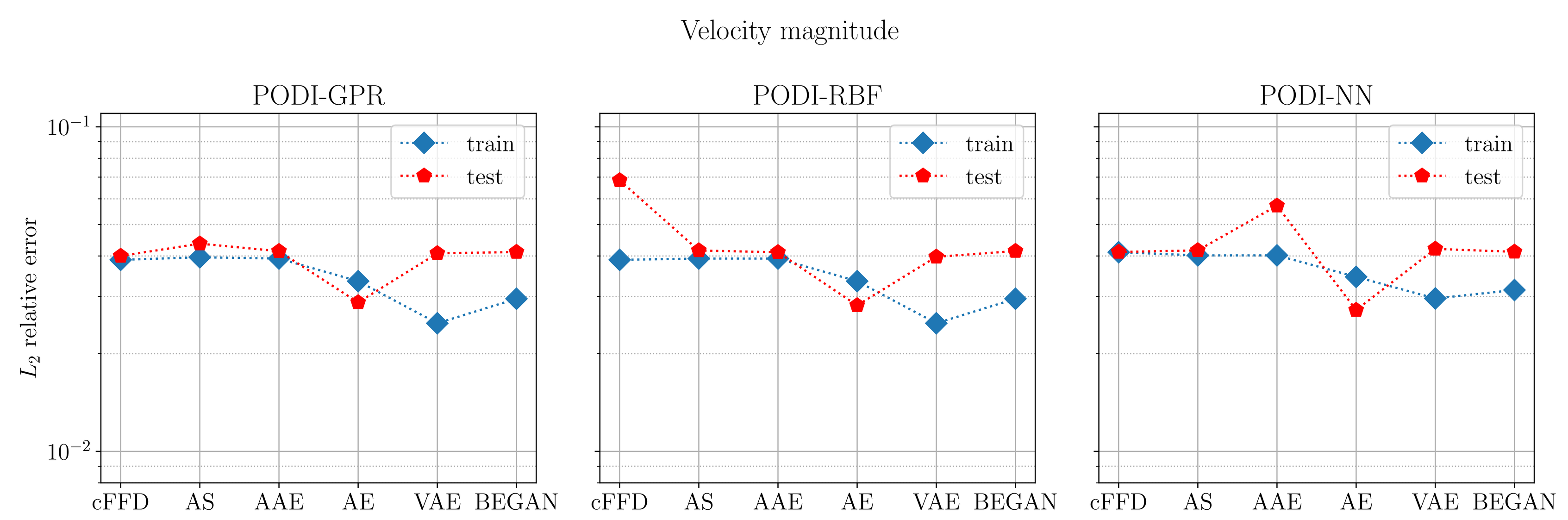
The loss for the discriminator is $\mathcal{L}_{\mathrm{D}}^{\mathrm{GAN}} = -\mathbb{E}_{x\sim p_d}[\log(D(x))] - \mathbb{E}_{\hat{x}\sim p_g}[\log(1 - D(\hat{x}))]$ and the one for the generator is $\mathcal{L}_{\mathrm{G}}^{\mathrm{GAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\log(1 - D(\hat{x}))]$.

Results and future work

We study two test case: one of them is a multifluid Interfoam simulation on the DTCHull, with the bulb deformed using Constrained Free Form Deformation with fixed volume (figure on the left). As generative models we adopt Variational Autoencoders, Adversarial Autoencoders, Classic Autoencoders and Boundary Equilibrium Generative Adversarial Networks. We validate our model by checking the distribution (on the center) and the performance of reduced order models on quantity of interest (on the right).







The other test case is the deformation of a Stanford Bunny with fixed barycenter. We refer to our paper for the details.
As future work, we could try to improve our generative models with the adoption of Graph Neural Networks.

Bibliography and Software References

[1] Pygem, `https://github.com/mathLab/PyGeM`

[2] A numerical algorithm for L_2 semi-discrete optimal transport in 3D, Bruno Levy et al, 2014

[3] Volume Preserving FFD for Programmable Graphics Hardware. Hanmann, G et al., 2012.

[4] Generative Models for the Deformation of Industrial Shapes with Linear Geometric Constraints: model order and parameter space reductions. Padula, G et al., 2023.a