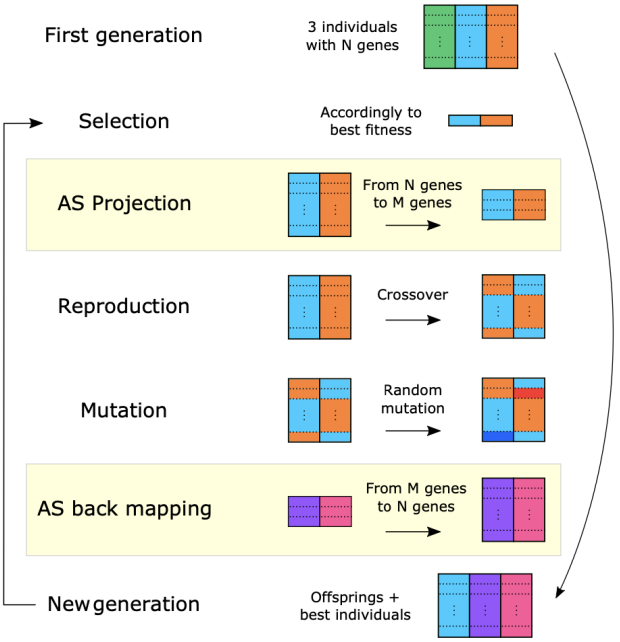
Parameter space reduction references

November 2022

N. Demo, M. Tezzele, and G. Rozza. **A supervised learning approach involving active subspaces for an efficient genetic algorithm in high-dimensional optimization problems.** *SIAM Journal on Scientific Computing*, 43(3):B831–B853, 2021. [arxiv] [doi].

Main points:

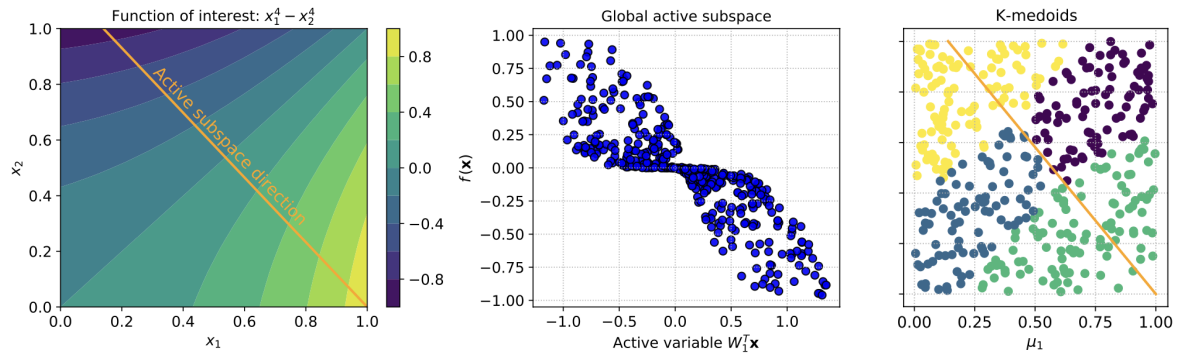
- By performing the reproduction and mutation steps in the low-dimensional subspace identified by the active subspace (AS) we are able to accelerate the mono-objective optimization of scalar functions of interest.
- Back-mapping is not unique and it allows us to explore different regions of the parameter space by sampling the inactive subspace.
- The figure on the right summarizes the concepts and the yellow boxes emphasize the differences with respect to the classical genetic algorithm.

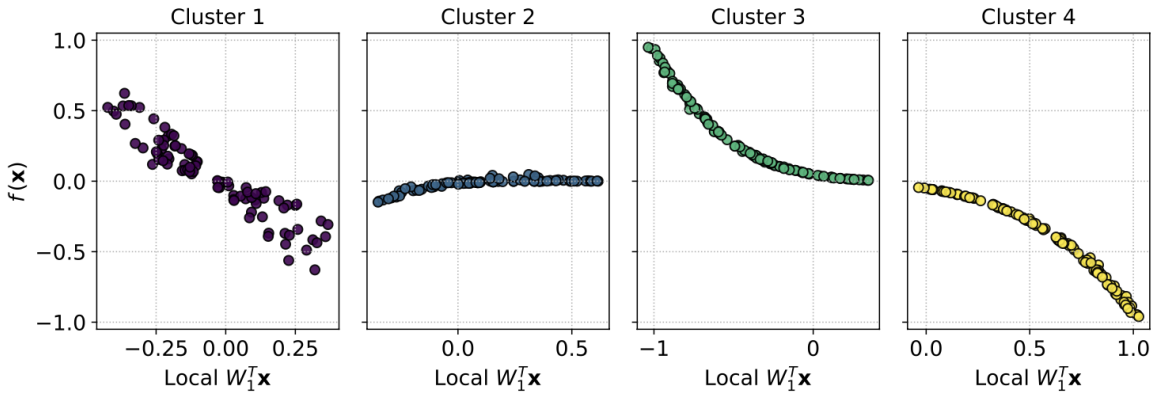


F. Romor, M. Tezzele, and G. Rozza. ***A local approach to parameter space reduction for regression and classification tasks.*** Submitted 2021.

Main points:

- We apply parameter space reduction with AS to subsets of the data.
- We identify these subsets by applying clustering techniques which account for both the inputs and outputs. This is done with a supervised distance metric defined using the global AS.
- The clusters align transversally with respect to the global AS, thus reducing the error introduced by discarding the inactive variables.
- We devise a hierarchical top-down clustering with different splitting criteria specific for parameter space reduction.
- Below a 2D example with a useless global AS and the color coded clusters the corresponding local reductions.

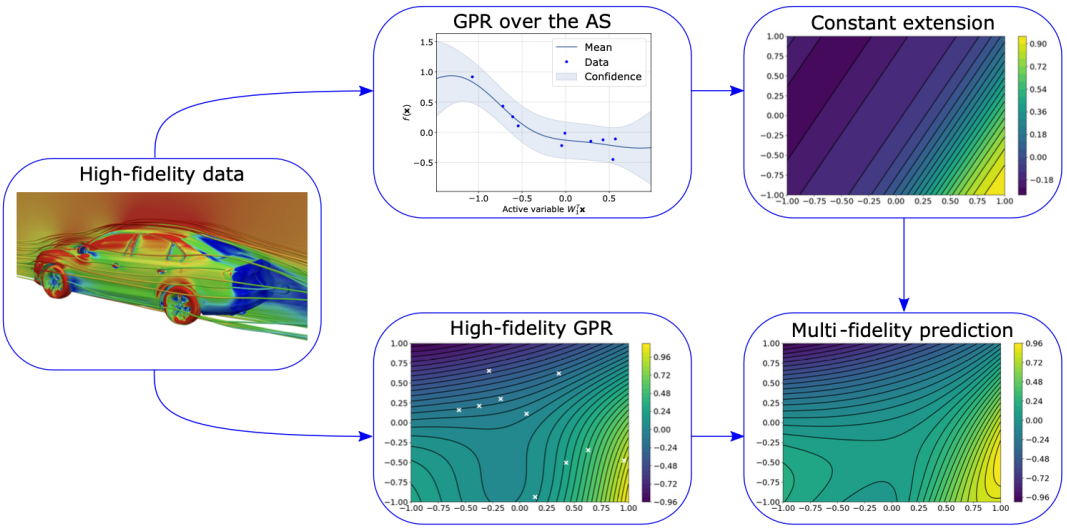




F. Romor, M. Tezzele, M. Mrosek, C. Othmer and G. Rozza. **Multi-fidelity data fusion through parameter space reduction with applications to automotive engineering.** Submitted 2021. [arxiv].

Main points:

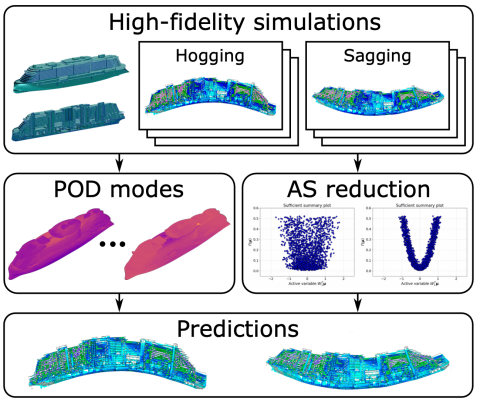
- We use the nonlinear autoregressive Gaussian process framework by Perdikaris et al. to embed a low-dimensionality bias induced by parameter space reduction.
- We use both linear AS and nonlinear level-set learning.
- We use only high-fidelity data to construct the low-fidelity model, so there is no need of corser grids of simplified physics simulations.

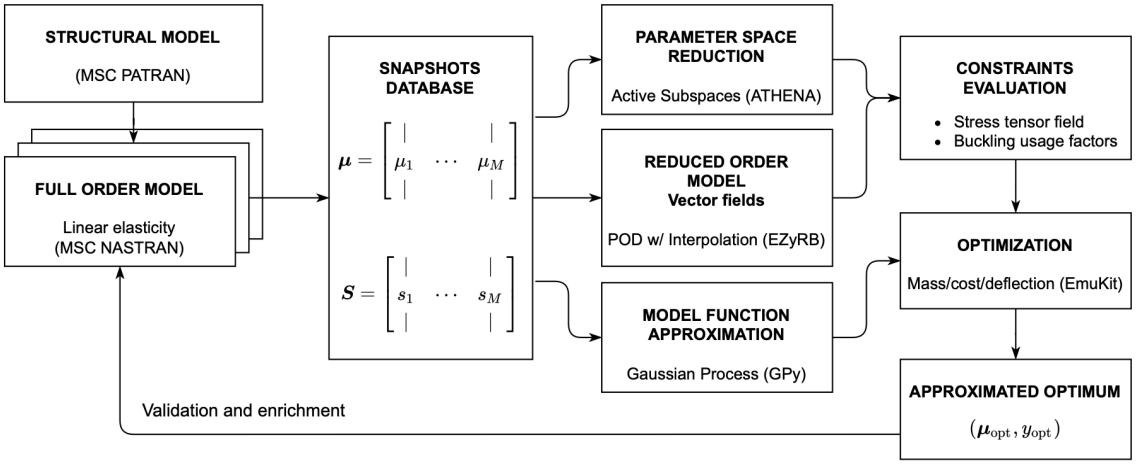


M. Tezzele, L. Fabris, M. Sidari, M. Sicchiero, and G. Rozza. **A multi-fidelity approach coupling parameter space reduction and non-intrusive POD with application to structural optimization of passenger ship hulls.** To Appear in the *International Journal for Numerical Methods in Engineering*, 2022. [arxiv].

Main points:

- We exploit the multi-fidelity model introduced above to approximate the reduced state variables obtained after the projection over the POD modes.
- We devise a complete numerical framework for the structural optimization of passenger ships, that is non-intrusive and data-driven.





Open source software

ATHENA is a Python package for reduction of high dimensional parameter spaces. It implements several dimensionality reduction techniques such as Active Subspaces (AS), Kernel-based Active Subspaces (KAS), and Nonlinear Level-set Learning (NLL). [github].

- F. Romor, M. Tezzele, and G. Rozza, ***ATHENA: Advanced Techniques for High dimensional parameter spaces to Enhance Numerical Analysis,*** Software Impacts, 10:100133, 2021. [doi].