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A Bias-aware Regression Model for the Development of Data-driven Reduced-order Models of Dynamical Systems

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The objective of this work is to better model the information lost during data compression in the development of data-driven reduced order models (ROMs) of dynamical systems.
Dynamical ROMs can be built by coupling dimensionality reduction, which reduces the dimensionality of the system, and non-linear regression, employed to estimate the system's trajectory in the low-dimensional space [1]. In our case, dimensionality reduction is achieved using the Proper Orthogonal Decomposition (POD) [2], while Gaussian process regression (GPR) [3] is used to learn the temporal behavior of the system from the data. The POD is a linear techniques that projects the n dimensional full-order system into the optimal q dimensional hyperplane (i.e. the hyperplane that minimizes the l_2 norm reconstruction error in the projection, with $q \ll n$). This process involves losing a (hopefully small) part of the information contained in the original system, depending on the truncation of the POD modes and the non-linearity of the full-order system.
In the regression step, the impact of the information loss on the projected manifold is generally modeled as Gaussian noise with zero mean. In this work, we test this assumption and we develop a methodology to better approximate the distribution of the noise, leading to a better estimation of the latent variables and therefore a more accurate model.
This approach is tested on a dataset which includes a series of snapshots from a 2D pulsated laminar flame.

References

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