

MODEL REDUCTION AND SCIENTIFIC MACHINE LEARNING FOR PARAMETRIC PDES

ANDREAS MANG[†] AND MAXIM A. OLSHANSKII[†]

[†] Department of Mathematics, University of Houston
Philip Guthrie Hoffman Hall, 3551 Cullen Blvd, Houston, Texas 77204
{amang,maolshan}@central.uh.edu

ABSTRACT

This session brings together researchers developing data- and model-driven surrogate models for parametric partial differential equations (PDEs) in high-throughput applications across computational science and engineering. Our emphasis is on many-query settings such as optimal design, statistical and deterministic inverse problems, and uncertainty quantification, where repeated evaluations of high-fidelity discretizations are computationally prohibitive and motivate the construction of accurate, low-cost surrogates that retain predictive fidelity across the parameter domain [1][2].

The session spans a broad range of methodologies that have emerged at the interface of numerical analysis, scientific computing, and machine learning. Classical projection-based approaches such as reduced basis methods continue to provide a rigorous foundation for parametric model reduction, while tensor-structured reduced-order models exploit multilinear algebra to mitigate the curse of dimensionality in problems with several parameters. Non-intrusive frameworks such as operator inference learn reduced operators directly from snapshot data, making them attractive when discretized high-fidelity operators are inaccessible or proprietary. In parallel, neural operators and physics-informed techniques offer flexible surrogates that can incorporate physical priors and exploit modern deep learning architectures.

Beyond accuracy and efficiency, the session emphasizes mathematical guarantees and structural fidelity. Topics of interest include rigorous error estimation and certification of data-driven surrogates, structure-preserving model reduction that respects conservation laws or long-time stability properties, scalability to high-dimensional parameter spaces, adaptive and online strategies that refine the surrogate as new data become available, and the seamless integration of these surrogates into outer-loop many-query workflows.

REFERENCES

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- [2] Peherstorfer, B., Willcox, K., & Gunzburger, M. (2018). Survey of multifidelity methods in uncertainty propagation, inference, and optimization. *SIAM Review*, 60(3), 550–591.