GAUSSIAN PROCESSES: FROM TOPOLOGY OPTIMIZATION TO OPERATOR LEARNING

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ABSTRACT

Topology optimization (TO) is a mathematical approach for optimizing the performance of structures by designing material distribution within a predefined domain under specific constraints. Conventional TO approaches rely on meshing the structure and have a nested nature where each design iteration requires solving a system of partial differential equations (PDEs). In contrast to existing methods, we introduce a simultaneous and mesh-free TO approach that unifies the design and analysis steps into a single optimization loop. Our method is grounded on Gaussian processes (GPs) which incorporate deep neural networks as their mean functions. Our method is inherently mesh-independent and significantly aids in (1) satisfying equality constraints in the design problem, (2) minimizing gray areas which are unfavorable in real-world applications, and (3) simplifying the inverse design by reducing the sensitivity of neural networks to factors such as random initialization, architecture type, and choice of optimizer. To show the impact of our work, we evaluate the performance of our approach against COMSOL on a few benchmark examples. The talk is concluded by sketching our recent ideas on operator learning via GPs which account for correlations not only in the input function space, but also in the support of the target function space. This unique feature allows us to incorporate the physics of the system —including PDEs, boundary conditions, and initial conditions— directly into the loss function through automatic differentiation.

REFERENCES

[1] C. Mora, A. Yousefpour, S. Hosseinmardi, R. Bostanabad, Neural Networks with Kernel-Weighted Corrective Residuals for Solving Partial Differential Equations. https://arxiv.org/abs/2401.03492