Sensor selection using end-to-end differentiable networks with application to field reconstruction

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Abstract

Reconstucting field variables based on partially observed data is an important problem arising from a number of practical applications such as climate science, fluid dynamics, nuclear engineering Manohar et al. [2018], Erichson et al. [2020], Fukami et al. [2021]. To achieve accurate approximations, two crucial aspects need to be considered: (a) choosing the optimal location for data sensors and (b) identifying a suitable model to map the measured data to the corresponding high-dimensional fields. Existing approaches to address this challenge either adopt a linear model for reconstruction Manohar et al. [2018], leading to poor approximations or follow an ad-hoc (random) choice of sensor locations that fails to efficiently recover the true underlying field Erichson et al. [2020], Fukami et al. [2021]. In this contribution, we combine the functionalities of sensor selection and nonlinear reconstruction by proposing an end-to-end network that leads to improved reconstruction performance, while using fewer sensor measurements. Our approach leverages suitable L1-sparsity constraints to achieve this. The proposed method iteratively learns (a) good sensor locations for the field reconstruction via stochastic optimization and (b) the parameters of a neural network that will reconstruct the field from the sparsely measured data during the inference stage. We illustrate the benefits of the new approach on numerical examples from fluid dynamics and climate science.

References

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