MORE OF A GOOD(?) THING: UNCERTAINTY PROPAGATION THROUGH MULTIFIDELITY DEEP OPERATOR NETWORKS

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ABSTRACT

Training operator networks requires vast amounts of data, which can be expensive, difficult, or time consuming to produce for scientific applications. In our prior work, we have shown that multifidelity deep operator networks [1] can reduce the amount and cost of data needed to accurately train Deep Operator Networks (DeepONets) [2]. Multifidelity DeepONets can combine both low- and high-fidelity data together, along with knowledge of physics through physics-informed training. In this talk, we will discuss the use of multifidelity data to reduce uncertainty in DeepONet predictions. We will show that the addition of data, even a small amount of highly noisy data, can significantly improve training of physics-informed DeepONets, and that physics-informed DeepONets are robust to increasing noise in training data. Additionally, increasing the amount of low-fidelity data can reduce the uncertainty in high-fidelity predictions, without the need to generate additional high-fidelity data.

REFERENCES

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