

METAP: HOW TO TRANSFER HIDDEN PHYSICS KNOWLEDGE BETWEEN SPECIMENS

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ABSTRACT

Gradient-based meta-learning methods have primarily focused on classical machine learning tasks such as image classification and function regression, where they were found to perform well by recovering the underlying common representation among a set of given tasks. Recently, PDE-solving deep learning methods, such as neural operators, are starting to make an important impact on learning and predicting the response of a complex physical system directly from observational data. Since the data acquisition in this context is commonly challenging and costly, the call of utilization and transfer of existing knowledge to new and unseen physical systems is even more acute.

Herein, we propose a novel meta-learnt approach for transfer-learning knowledge between neural operators, which can be seen as transferring the knowledge of solution operators between governing (unknown) PDEs with varying parameter fields. With the key theoretical observation that the underlying parameter field can be captured in the first layer of the neural operator model, in contrast to typical final-layer transfer in existing meta-learning methods, our approach is a provably universal solution operator for multiple PDE solving tasks.

As new benchmark applications, we demonstrate the efficacy of our proposed approach on a PDE-based dataset with synthetic solutions and a real-world biological tissue experimental dataset, demonstrating that our method can handle complex and nonlinear physical response learning tasks while greatly improving the sampling efficiency in new and unseen material specimens.