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<tr><th>authors</th><td>Lu Lu
RaphaÃ«l Pestourie
Steven G. Johnson
Giuseppe Romano</td></tr>
<tr><th>title</th><td>Multifidelity deep neural operators for efficient learning of partial differential equations with application to fast inverse design of nanoscale heat transport</td></tr>
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<tr><th>journal</th><td>American Physical Society (APS)</td></tr>
<tr><th>volume</th><td></td></tr>
<tr><th>doi</th><td>10.1103/physrevresearch.4.023210</td></tr>
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<tr><th>abstract</th><td>Deep neural operators can learn operators mapping between infinite-dimensional function spaces via deep neural networks and have become an emerging paradigm of scientific machine learning. However, training neural operators usually requires a large amount of high-fidelity data, which is often difficult to obtain in real engineering problems. Here we address this challenge by using multifidelity learning, i.e., learning from multifidelity data sets. We develop a multifidelity neural operator based on a deep operator network (DeepONet). A multifidelity DeepONet includes two standard DeepONets coupled by residual learning and input augmentation. Multifidelity DeepONet significantly reduces the required amount of high-fidelity data and achieves one order of magnitude smaller error when using the same amount of high-fidelity data. We apply a multifidelity DeepONet to learn the phonon Boltzmann transport equation (BTE), a framework to compute nanoscale heat transport. By combining a trained multifidelity DeepONet with genetic algorithm or topology optimization, we demonstrate a fast solver for the inverse design of BTE problems.</td></tr>
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