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<tr><th>authors</th><td>Kaushik Bhattacharya
Bamdad Hosseini
Nikola B. Kovachki
Andrew M. Stuart</td></tr>
<tr><th>title</th><td>Model Reduction And Neural Networks For Parametric PDEs</td></tr>
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<tr><th>source</th><td>SupportedSources.INTERNET_ARCHIVE</td></tr>
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<tr><th>doi</th><td>10.5802/smai-jcm.74</td></tr>
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<tr><th>id</th><td>id-2338685203419385897</td></tr>
<tr><th>abstract</th><td>We develop a general framework for data-driven approximation of input-output maps between infinitedimensional spaces. The proposed approach is motivated by the recent successes of neural networks and deep learning, in combination with ideas from model reduction. This combination results in a neural network approximation which, in principle, is defined on infinite-dimensional spaces and, in practice, is robust to the dimension of finite-dimensional approximations of these spaces required for computation. For a class of input-output maps, and suitably chosen probability measures on the inputs, we prove convergence of the proposed approximation methodology. We also include numerical experiments which demonstrate the effectiveness of the method, showing convergence and robustness of the approximation scheme with respect to the size of the discretization, and compare it with existing algorithms from the literature; our examples include the mapping from coefficient to solution in a divergence form elliptic partial differential equation (PDE) problem, and the solution operator for viscous Burgers' equation. 2020 Mathematics Subject Classification. 65N75, 62M45, 68T05, 60H30, 60H15.</td></tr>
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