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authors	• Kaushik Bhattacharya • Bamdad Hosseini • Nikola B. Kovachki • Andrew M. Stuart
title	Model Reduction and Neural Networks for Parametric PDEs
publication_date	2021-06-17 00:00:00
source	SupportedSources.INTERNET_ARCHIVE
journal	
volume	
doi	
urls	• https://web.archive.org/web/20210622203257/https://arxiv.org/pdf/2005.03180v2.pdf
id	id-3304648738576706200
abstract	We develop a general framework for data-driven approximation of input-output maps between infinite-dimensional 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.
versions	

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authors	• Bhattacharya, Kaushik • Hosseini, Bamdad • Kovachki, Nikola B. • Stuart, Andrew M.
title	Model Reduction and Neural Networks for Parametric PDEs
publication_date	2020-05-07 00:00:00
source	SupportedSources.CORE
journal	
volume	
doi	None
urls	• https://core.ac.uk/download/323787594.pdf
id	id-2481654370404001488
abstract	We develop a general framework for data-driven approximation of input-output maps between infinite-dimensional 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. Numerically we demonstrate the effectiveness of the method on a class of parametric elliptic PDE problems, showing convergence and robustness of the approximation scheme with respect to the size of the discretization, and compare our method with existing algorithms from the literature
versions	

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