cases

	doc_1	doc_2
authors	• Yeonjong Shin • J. Darbon • G. Karniadakis	• Yeonjong Shin • J. Darbon • G. Karniadakis
title	On the Convergence of Physics Informed Neural Networks for Linear Second-Order Elliptic and Parabolic Type PDEs	On the Convergence and generalization of Physics Informed Neural Networks
publication_date	2020-04-03 00:00:00	2020-04-03 00:00:00
source	SupportedSources.SEMANTIC_SCHOLAR	SupportedSources.SEMANTIC_SCHOLAR
journal	arXiv: Numerical Analysis	ArXiv
volume		abs/2004.01806
doi	10.4208/cicp.oa-2020-0193	
urls	• https://www.semanticscholar.org/paper/4558edee8f9212d6d7e5c9332c78273dfd5c192b	• https://www.semanticscholar.org/paper/178f63adba4fa7c4b4e0708986f4c9530983f1bf
id	id-5236458013383213450	id-1485245656428751266
abstract	Physics informed neural networks (PINNs) are deep learning based techniques for solving partial differential equations (PDEs) encountered in computational science and engineering. Guided by data and physical laws, PINNs find a neural network that approximates the solution to a system of PDEs. Such a neural network is obtained by minimizing a loss function in which any prior knowledge of PDEs and data are encoded. Despite its remarkable empirical success in one, two or three dimensional problems, there is little theoretical justification for PINNs. As the number of data grows, PINNs generate a sequence of minimizers which correspond to a sequence of neural networks. We want to answer the question: Does the sequence of minimizers converge to the solution to the PDE? We consider two classes of PDEs: linear second-order elliptic and parabolic. By adapting the Schauder approach and the maximum principle, we show that the sequence of minimizers strongly converges to the PDE solution in C^0. Furthermore, we show that if each minimizer satisfies the initial/boundary conditions, the convergence mode becomes H^1. Computational examples are provided to illustrate our theoretical findings. To the best of our knowledge, this is the first theoretical work that shows the consistency of PINNs.	Physics informed neural networks (PINNs) are deep learning based techniques for solving partial differential equations (PDEs). Guided by data and physical laws, PINNs find a neural network that approximates the solution to a system of PDEs. Such a neural network is obtained by minimizing a loss function in which any prior knowledge of PDEs and data are encoded. Despite its remarkable empirical success, there is little theoretical justification for PINNs. In this paper, we establish a mathematical foundation of the PINNs methodology. As the number of data grows, PINNs generate a sequence of minimizers which correspond to a sequence of neural networks. We want to answer the question: Does the sequence of minimizers converge to the solution to the PDE? This question is also related to the generalization of PINNs. We consider two classes of PDEs: elliptic and parabolic. By adapting the Schuader approach, we show that the sequence of minimizers strongly converges to the PDE solution in L^2. Furthermore, we show that if each minimizer satisfies the initial/boundary conditions, the convergence mode can be improved to H^1. Computational examples are provided to illustrate our theoretical findings. To the best of our knowledge, this is the first theoretical work that shows the consistency of the PINNs methodology.
versions		

decision	id
NOT DUPLICATES	368