cases

	doc_1	doc_2
authors	• Ayano Kaneda • Osman Akar • Jingyu Chen • Victoria Kala • David Hyde • Joseph Teran	• Ayano Kaneda • Osman Akar • Jingyu Chen • Victoria Kala • David Hyde • J. Teran
title	A Deep Conjugate Direction Method for Iteratively Solving Linear Systems	A Deep Conjugate Direction Method for Iteratively Solving Linear Systems
publication_date	2022-10-01 00:00:00	2022-05-22 00:00:00
source	SupportedSources.INTERNET_ARCHIVE	SupportedSources.SEMANTIC_SCHOLAR
journal		
volume		
doi		
urls	• https://web.archive.org/web/20221005063442/https://arxiv.org/pdf/2205.10763v2.pdf	• https://www.semanticscholar.org/paper/ed9219bf3f27fecadec268844ef870cdc95e1ebd
id	id6301782577787475820	id-2417606260296319514
abstract	We present a novel deep learning approach to approximate the solution of large, sparse, symmetric, positive-definite linear systems of equations. These systems arise from many problems in applied science, e.g., in numerical methods for partial differential equations. Algorithms for approximating the solution to these systems are often the bottleneck in problems that require their solution, particularly for modern applications that require many millions of unknowns. Indeed, numerical linear algebra techniques have been investigated for many decades to alleviate this computational burden. Recently, data-driven techniques have also shown promise for these problems. Motivated by the conjugate gradients algorithm that iteratively selects search directions for minimizing the matrix norm of the approximation error, we design an approach that utilizes a deep neural network to accelerate convergence via data-driven improvement of the search directions. Our method leverages a carefully chosen convolutional network to approximate the action of the inverse of the linear operator up to an arbitrary constant. We train the network using unsupervised learning with a loss function equal to the L^2 difference between an input and the system matrix times the network evaluation, where the unspecified constant in the approximate inverse is accounted for. We demonstrate the efficacy of our approach on spatially discretized Poisson equations with millions of degrees of freedom arising in computational fluid dynamics applications. Unlike state-of-the-art learning approaches, our algorithm is capable of reducing the linear system residual to a given tolerance in a small number of iterations, independent of the problem size. Moreover, our method generalizes effectively to various systems beyond those encountered during training.	We present a novel deep learning approach to approximate the solution of large, sparse, symmetric, positive-deï¬nite linear systems of equations. These systems arise from many problems in applied science, e.g., in numerical methods for partial differential equations. Algorithms for approximating the solution to these systems are often the bottleneck in problems that require their solution, particularly for modern applications that require many millions of unknowns. Indeed, numerical linear algebra techniques have been investigated for many decades to alleviate this computational burden. Recently, data-driven techniques have also shown promise for these problems. Motivated by the conjugate gradients algorithm that iteratively selects search directions for minimizing the matrix norm of the approximation error, we design an approach that utilizes a deep neural network to accelerate convergence via data-driven improvement of the search directions. Our method leverages a carefully chosen convolutional network to approximate the action of the inverse of the linear operator up to an arbitrary constant. We train the network using unsupervised learning with a loss function equal to the L 2 difference between an input and the system matrix times the network evaluation, where the unspeciï¬ed constant in the approximate inverse is accounted for. We demonstrate the efï¬cacy of our approach on spatially discretized Poisson equations with millions of degrees of freedom arising in computational ï¬,uid dynamics applications. Unlike
versions		

decision	id
DUPLICATES	203