

cases	doc_1		doc_2		decision	id
	authors	<ul style="list-style-type: none"><li>Aditya Balu</li><li>Sergio Botelho</li><li>Biswajit Khara</li><li>Vinay Rao</li><li>C. Hegde</li><li>S. Sarkar</li><li>Santi S. Adavani</li><li>A. Krishnamurthy</li><li>B. Ganapathysubramanian</li></ul>	authors	<ul style="list-style-type: none"><li>Aditya Balu</li><li>Sergio Botelho</li><li>Biswajit Khara</li><li>Vinay Rao</li><li>Chinmay Hegde</li><li>Soumik Sarkar</li><li>Santi Adavani</li><li>Adarsh Krishnamurthy</li><li>Baskar Ganapathysubramanian</li></ul>	DUPLICATES	246
	title	Distributed Multigrid Neural Solvers on Megavoxel Domains	title	Distributed Multigrid Neural Solvers on Megavoxel Domains		
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	doi	10.1145/3458817.3476218	doi			
	urls	<ul style="list-style-type: none"><li>https://www.semanticscholar.org/paper/7c5e6b769549a83a40d4b7174c2e86d1f3835da8</li></ul>	urls	<ul style="list-style-type: none"><li>https://web.archive.org/web/20210502084252/https://arxiv.org/pdf/2104.14538v1.pdf</li></ul>		
	id	id-6600031357365560483	id	id1440328196587944127		
	abstract	We consider the distributed training of large scale neural networks that serve as PDE (partial differential equation) solvers producing full field outputs. We specifically consider neural solvers for the generalized 3D Poisson equation over megavoxel domains. A scalable framework is presented that integrates two distinct advances. First, we accelerate training a large model via a method analogous to the multigrid technique used in numerical linear algebra. Here, the network is trained using a hierarchy of increasing resolution inputs in sequence, analogous to the $V^{\text{TM}}$ , $W^{\text{TM}}$ , $F^{\text{TM}}$ and $\text{Half-}V^{\text{TM}}$ cycles used in multigrid approaches. In conjunction with the multi-grid approach, we implement a distributed deep learning framework which significantly reduces the time to solve. We show scalability of this approach on both GPU (Azure VMs on Cloud) and CPU clusters (PSC Bridges2). This approach is deployed to train a generalized 3D Poisson solver that scales well to predict output full field solutions up to the resolution of $512 \times 512 \times 512$ for a high dimensional family of inputs. This strategy opens up the possibility of fast and scalable training of neural PDE solvers on heterogeneous clusters.	abstract	We consider the distributed training of large-scale neural networks that serve as PDE solvers producing full field outputs. We specifically consider neural solvers for the generalized 3D Poisson equation over megavoxel domains. A scalable framework is presented that integrates two distinct advances. First, we accelerate training a large model via a method analogous to the multigrid technique used in numerical linear algebra. Here, the network is trained using a hierarchy of increasing resolution inputs in sequence, analogous to the 'V', 'W', 'F', and 'Half-V' cycles used in multigrid approaches. In conjunction with the multi-grid approach, we implement a distributed deep learning framework which significantly reduces the time to solve. We show the scalability of this approach on both GPU (Azure VMs on Cloud) and CPU clusters (PSC Bridges2). This approach is deployed to train a generalized 3D Poisson solver that scales well to predict output full-field solutions up to the resolution of $512 \times 512 \times 512$ for a high dimensional family of inputs.		
	versions		versions			