		doc_1		doc_2	decision	id
	authors	 Tian Qin Alex Beatson Deniz Oktay Nick McGreivy Ryan P. Adams 	authors	Tian Qin Alex Beatson Deniz Oktay N. McGreivy R. Adams		
	title	Meta-PDE: Learning to Solve PDEs Quickly Without a Mesh	title	Meta-PDE: Learning to Solve PDEs Quickly Without a Mesh		
cases	publication_dat	re 2022-11-03 00:00:00	publication_date	2022-11-03 00:00:00	DUPLICATES 192	
	source	SupportedSources.INTERNET_ARCHIVE	source	SupportedSources.SEMANTIC_SCHOLAR		
	journal		journal	ArXiv		
	volume		volume	abs/2211.01604		
	doi		doi	10.48550/arXiv.2211.01604		
	urls	• https://web.archive.org/web/20221107125458/https://arxiv.org/pdf/2211.01604v1.pdf	urls	https://www.semanticscholar.org/paper/bd29458e2f46280deed89b7d317cf225afb753c7		192
	id	id-6307698487433661268	id	id504442775818289046		
	abstract	Partial differential equations (PDEs) are often computationally challenging to solve, and in many settings many related PDEs must be be solved either at every timestep or for a variety of candidate boundary conditions, parameters, or geometric domains. We present a meta-learning based method which learns to rapidly solve problems from a distribution of related PDEs. We use meta-learning (MAML and LEAP) to identify initializations for a neural network representation of the PDE solution such that a residual of the PDE can be quickly minimized on a novel task. We apply our meta-solving approach to a nonlinear Poisson's equation, 1D Burgers' equation, and hyperelasticity equations with varying parameters, geometries, and boundary conditions. The resulting Meta-PDE method finds qualitatively accurate solutions to most problems within a few gradient steps; for the nonlinear Poisson and hyper-elasticity equation this results in an intermediate accuracy approximation up to an order of magnitude faster than a baseline finite element analysis (FEA) solver with equivalent accuracy. In comparison to other learned solvers and surrogate models, this meta-learning approach can be trained without supervision from expensive ground-truth data, does not require a mesh, and can even be used when the geometry and topology varies between tasks.	abstract	Partial differential equations (PDEs) are often computationally challenging to solve, and in many settings many related PDEs must be be solved either at every timestep or for a variety of candidate boundary conditions, parameters, or geometric domains. We present a meta-learning based method which learns to rapidly solve problems from a distribution of related PDEs. We use meta-learning (MAML and LEAP) to identify initializations for a neural network representation of the PDE solution such that a residual of the PDE can be quickly minimized on a novel task. We apply our meta-solving approach to a nonlinear Poisson's equation, 1D Burgers' equation, and hyperelasticity equations with varying parameters, geometries, and boundary conditions. The resulting Meta-PDE method indicated qualitatively accurate solutions to most problems within a few gradient steps; for the nonlinear Poisson and hyper-elasticity equation this results in an intermediate accuracy approximation up to an order of magnitude faster than a baseline internite element analysis (FEA) solver with equivalent accuracy. In comparison to other learned solvers and surrogate models, this meta-learning approach can be trained without supervision from expensive ground-truth data, does not require a mesh, and can even be used when the geometry and topology varies between tasks.		
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