

cases	doc_1		doc_2		decision	id
	authors	<ul style="list-style-type: none">Alex Bihlo			DUPLICATES	20
	title	Improving physics-informed neural networks with meta-learned optimization	authors	<ul style="list-style-type: none">A. Bihlo		
	publication_date	2023-03-13 13:58:03+00:00	title	Improving physics-informed neural networks with meta-learned optimization		
	source	SupportedSources.ARXIV	publication_date	2023-03-13 00:00:00		
	journal	None	source	SupportedSources.SEMANTIC_SCHOLAR		
	volume		journal	ArXiv		
	doi		volume	abs/2303.07127		
	urls	<ul style="list-style-type: none">http://arxiv.org/pdf/2303.07127v2http://arxiv.org/abs/2303.07127v2http://arxiv.org/pdf/2303.07127v2	doi	10.48550/arXiv.2303.07127		
	id	id4984764988597369297	urls	<ul style="list-style-type: none">https://www.semanticscholar.org/paper/4f9f96679e943f7447ac431dffa506767d3cf3f		
	abstract	We show that the error achievable using physics-informed neural networks for solving systems of differential equations can be substantially reduced when these networks are trained using meta-learned optimization methods rather than to using fixed, hand-crafted optimizers as traditionally done. We choose a learnable optimization method based on a shallow multi-layer perceptron that is meta-trained for specific classes of differential equations. We illustrate meta-trained optimizers for several equations of practical relevance in mathematical physics, including the linear advection equation, Poisson's equation, the Korteweg--de Vries equation and Burgers' equation. We also illustrate that meta-learned optimizers exhibit transfer learning abilities, in that a meta-trained optimizer on one differential equation can also be successfully deployed on another differential equation.	id	id347980468456306197		
	versions		abstract	We show that the error achievable using physics-informed neural networks for solving systems of differential equations can be substantially reduced when these networks are trained using meta-learned optimization methods rather than to using fixed, hand-crafted optimizers as traditionally done. We choose a learnable optimization method based on a shallow multi-layer perceptron that is meta-trained for specific classes of differential equations. We illustrate meta-trained optimizers for several equations of practical relevance in mathematical physics, including the linear advection equation, Poisson's equation, the Korteweg--de Vries equation and Burgers' equation. We also illustrate that meta-learned optimizers exhibit transfer learning abilities, in that a meta-trained optimizer on one differential equation can also be successfully deployed on another differential equation.		
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