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	authors	<ul style="list-style-type: none">A. Bihlo	authors	<ul style="list-style-type: none">Alex Bihlo	DUPLICATES	22
	title	Improving physics-informed neural networks with meta-learned optimization	title	Improving physics-informed neural networks with meta-learned optimization		
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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.	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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