

cases	doc_1		doc_2		decision	id
	authors	<ul style="list-style-type: none">Florian SchÅ¶ferSpencer H. BryngelsonYash KothariQi Zeng	authors	<ul style="list-style-type: none">Qi ZengYash KothariSpencer H. BryngelsonFlorian SchÅ¶fer	DUPLICATES	185
	title	Competitive Physics Informed Networks	title	Competitive Physics Informed Networks		
	publication_date	2022-04-23 00:00:00	publication_date	2022-10-12 00:00:00		
	source	SupportedSources.PAPERS_WITH_CODE	source	SupportedSources.INTERNET_ARCHIVE		
	journal		journal			
	volume		volume			
	doi		doi			
	urls	<ul style="list-style-type: none">https://arxiv.org/pdf/2204.11144v2.pdfhttps://github.com/comp-physics/cpinn	urls	<ul style="list-style-type: none">https://web.archive.org/web/20221013063425/https://arxiv.org/pdf/2204.11144v2.pdf		
	id	id8138487877229103170	id	id-2577085871706375610		
	abstract	Neural networks can be trained to solve partial differential equations (PDEs) by using the PDE residual as the loss function. This strategy is called "physics-informed neural networks" (PINNs), but it currently cannot produce high-accuracy solutions, typically attaining about \$0.1\%\$ relative error. We present an adversarial approach that overcomes this limitation, which we call competitive PINNs (CPINNs). CPINNs train a discriminator that is rewarded for predicting mistakes the PINN makes. The discriminator and PINN participate in a zero-sum game with the exact PDE solution as an optimal strategy. This approach avoids squaring the large condition numbers of PDE discretizations, which is the likely reason for failures of previous attempts to decrease PINN errors even on benign problems. Numerical experiments on a Poisson problem show that CPINNs achieve errors four orders of magnitude smaller than the best-performing PINN. We observe relative errors on the order of single-precision accuracy, consistently decreasing with each epoch. To the authors' knowledge, this is the first time this level of accuracy and convergence behavior has been achieved. Additional experiments on the nonlinear SchrÅ¶dinger, Burgers', and Allen-Cahn equation show that the benefits of CPINNs are not limited to linear problems.	abstract	Neural networks can be trained to solve partial differential equations (PDEs) by using the PDE residual as the loss function. This strategy is called "physics-informed neural networks" (PINNs), but it currently cannot produce high-accuracy solutions, typically attaining about 0.1% relative error. We present an adversarial approach that overcomes this limitation, which we call competitive PINNs (CPINNs). CPINNs train a discriminator that is rewarded for predicting mistakes the PINN makes. The discriminator and PINN participate in a zero-sum game with the exact PDE solution as an optimal strategy. This approach avoids squaring the large condition numbers of PDE discretizations, which is the likely reason for failures of previous attempts to decrease PINN errors even on benign problems. Numerical experiments on a Poisson problem show that CPINNs achieve errors four orders of magnitude smaller than the best-performing PINN. We observe relative errors on the order of single-precision accuracy, consistently decreasing with each epoch. To the authors' knowledge, this is the first time this level of accuracy and convergence behavior has been achieved. Additional experiments on the nonlinear SchrÅ¶dinger, Burgers', and Allen-Cahn equation show that the benefits of CPINNs are not limited to linear problems.		
	versions		versions			