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	abstract	Solving differential equations efficiently and accurately sits at the heart of progress in many areas of scientific research, from classical dynamical systems to quantum mechanics. There is a surge of interest in using Physics-Informed Neural Networks (PINNs) to tackle such problems as they provide numerous benefits over traditional numerical approaches. Despite their potential benefits for solving differential equations, transfer learning has been under explored. In this study, we present a general framework for transfer learning PINNs that results in one-shot inference for linear systems of both ordinary and partial differential equations. This means that highly accurate solutions to many unknown differential equations can be obtained instantaneously without retraining an entire network. We demonstrate the efficacy of the proposed deep learning approach by solving several real-world problems, such as first- and second-order linear ordinary equations, the Poisson equation, and the time-dependent Schrodinger complex-value partial differential equation.	**abstract**	Solving differential equations efï¬ciently and accurately sits at the heart of progress in many areas of scientiï¬c research, from classical dynamical systems to quantum mechanics. There is a surge of interest in using Physics-Informed Neural Networks (PINNs) to tackle such problems as they provide numerous beneï¬ts over traditional numerical approaches. Despite their potential beneï¬ts for solving differential equations, transfer learning has been under explored. In this study, we present a general framework for transfer learning PINNs that results in one-shot inference for linear systems of both ordinary and partial differential equations. This means that highly accurate solutions to many unknown differential equations can be obtained instantaneously without retraining an entire network. We demonstrate the efï¬cacy of the proposed deep learning approach by solving several real-world problems, such as ï¬rst- and second-order linear ordinary equations, the Poisson equation, and the time-dependent Schr Â¨ odinger complex-value partial differential equation.		
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