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<tr><th>authors</th><td>Adams, Ryan P.
Beatson, Alex
McGreivy, Nick
Oktay, Deniz
Qin, Tian</td></tr>
<tr><th>title</th><td>Meta-PDE: Learning to Solve PDEs Quickly Without a Mesh</td></tr>
<tr><th>publication_date</th><td>2022-11-03 00:00:00</td></tr>
<tr><th>source</th><td>SupportedSources.CORE</td></tr>
<tr><th>journal</th><td></td></tr>
<tr><th>volume</th><td></td></tr>
<tr><th>doi</th><td>None</td></tr>
<tr><th>urls</th><td>http://arxiv.org/abs/2211.01604</td></tr>
<tr><th>id</th><td>id5804193823919256841</td></tr>
<tr><th>abstract</th><td>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</td></tr>
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