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authors	• Lulu Zhang • Tao Luo • Yaoyu Zhang • Z. Xu • Zheng Ma	• Lulu Zhang • Tao Luo • Yaoyu Zhang • Weinan E • Zhi-Qin John Xu • Zheng Ma
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abstract	. In this paper, we propose a a machine learning approach via model-operator-data network (MOD-Net) for solving PDEs. A MOD-Net is driven by a model to solve PDEs based on operator representation with regularization from data. For linear PDEs, we use a DNN to parameterize the Greenâ€™s function and obtain the neural operator to approximate the solution according to the Greenâ€™s method. To train the DNN, the empirical risk consists of the mean squared loss with the least square formulation or the variational formulation of the governing equation and boundary conditions. For complicated problems, the empirical risk also includes a few labels, which are computed on coarse grid points with cheap computation cost and signiï¬cantly improves the model accuracy. Intuitively, the labeled dataset works as a regularization in addition to the model constraints. The MOD-Net solves a family of PDEs rather than a speciï¬c one and is much more efï¬cient than original neural operator because few expensive labels are required. We numerically show MOD-Net is very efï¬cient in solving Poisson equation and one-dimensional radiative transfer equation. For nonlinear PDEs, the nonlinear MOD-Net can be similarly used as an ansatz for solving nonlinear PDEs, exempliï¬ed by solving several nonlinear PDE problems, such as the Burgers equation. subject classiï¬cations : 35C15; 35J05; 35Q20; 35Q49; 45K05	In this paper, we propose a a machine learning approach via model-operator-data network (MOD-Net) for solving PDEs. A MOD-Net is driven by a model to solve PDEs based on operator representation with regularization from data. For linear PDEs, we use a DNN to parameterize the Green's function and obtain the neural operator to approximate the solution according to the Green's method. To train the DNN, the empirical risk consists of the mean squared loss with the least square formulation or the variational formulation of the governing equation and boundary conditions. For complicated problems, the empirical risk also includes a few labels, which are computed on coarse grid points with cheap computation cost and significantly improves the model accuracy. Intuitively, the labeled dataset works as a regularization in addition to the model constraints. The MOD-Net solves a family of PDEs rather than a specific one and is much more efficient than original neural operator because few expensive labels are required. We numerically show MOD-Net is very efficient in solving Poisson equation and one-dimensional radiative transfer equation. For nonlinear PDEs, the nonlinear MOD-Net can be similarly used as an ansatz for solving nonlinear PDEs, exemplified by solving several nonlinear PDE problems, such as the Burgers equation.
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