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(Paper Review) PhyCRNet: Physics-informed Convolutional-Recurrent Network for Solving Spatiotemporal PDEs

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Partial differential equations (PDEs) play a fundamental role in modeling and simulating problems across a wide range of disciplines. Recent advances in deep learning have shown the great potential of physics-informed neural networks (PINNs) to solve PDEs as a basis for data-driven modeling and inverse analysis. However, the majority of existing PINN methods, based on fully-connected NNs, pose intrinsic limitations to low-dimensional spatiotemporal parameterizations. Moreover, since the initial/boundary conditions (I/BCs) are softly imposed via penalty, the solution quality heavily relies on hyperparameter tuning. To this end, we propose the novel physics-informed convolutional-recurrent learning architectures (PhyCRNet and PhyCRNet-s) for solving PDEs without any labeled data. Specifically, an encoder-decoder convolutional long short-term memory network is proposed for low-dimensional spatial feature extraction and temporal evolution learning. The loss function is defined as the aggregated discretized PDE residuals, while the I/BCs are hard-encoded in the network to ensure forcible satisfaction (e.g., periodic boundary padding). The networks are further enhanced by autoregressive and residual connections that explicitly simulate time marching. The performance of our proposed methods has been assessed by solving three nonlinear PDEs (e.g., 2D Burgers' equations, the λ-ω and FitzHugh Nagumo reaction-diffusion equations), and compared against the start-of-the-art baseline algorithms. The numerical results demonstrate the superiority of our proposed methodology in the context of solution accuracy, extrapolability and generalizability.