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abstract	Physics-informed neural networks (PINNs) are effective in solving integer-order partial differential equations (PDEs) based on scattered and noisy data. PINNs employ standard feedforward neural networks (NNs) with the PDEs explicitly encoded into the NN using automatic differentiation, while the sum of the mean-squared PDE-residuals and the mean-squared error in initial/boundary conditions is minimized with respect to the NN parameters. We extend PINNs to fractional PINNs (fPINNs) to solve space-time fractional advection-diffusion equations (fractional ADEs), and we demonstrate their accuracy and effectiveness in solving multi-dimensional forward and inverse problems with forcing terms whose values are only known at randomly scattered spatio-temporal coordinates (black-box forcing terms). A novel element of the fPINNs is the hybrid approach that we introduce for constructing the residual in the loss function using both automatic differentiation for the integer-order operators and numerical discretization for the fractional operators. We consider 1D time-dependent fractional ADEs and compare white-box (WB) and black-box (BB) forcing. We observe that for the BB forcing fPINNs outperform FDM. Subsequently, we consider multi-dimensional time-, space-, and space-time-fractional ADEs using the directional fractional Laplacian and we observe relative errors of 10^{-4}. Finally, we solve several inverse problems in 1D, 2D, and 3D to identify the fractional orders, diffusion coefficients, and transport velocities and obtain accurate results even in the presence of significant noise.	Physics-informed neural networks (PINNs) are effective in solving integer-order partial differential equations (PDEs) based on scattered and noisy data. PINNs employ standard feedforward neural networks (NNs) with the PDEs explicitly encoded into the NN using automatic differentiation, while the sum of the mean-squared PDE-residuals and the mean-squared error in initial/boundary conditions is minimized with respect to the NN parameters. We extend PINNs to fractional PINNs (fPINNs) to solve space-time fractional advection-diffusion equations (fractional ADEs), and we demonstrate their accuracy and effectiveness in solving multi-dimensional forward and inverse problems with forcing terms whose values are only known at randomly scattered spatio-temporal coordinates (black-box forcing terms). A novel element of the fPINNs is the hybrid approach that we introduce for constructing the residual in the loss function using both automatic differentiation for the integer-order operators and numerical discretization for the fractional operators. We consider 1D time-dependent fractional ADEs and compare white-box (WB) and black-box (BB) forcing. We observe that for the BB forcing fPINNs outperform FDM. Subsequently, we consider multi-dimensional time-, space-, and space-time-fractional ADEs using the directional fractional Laplacian and we observe relative errors of 10^{-4}. Finally, we solve several inverse problems in 1D, 2D, and 3D to identify the fractional orders, diffusion coefficients, and transport velocities and obtain accurate results even in the presence of significant noise.		
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