DERIVATIVE-INFORMED NEURAL OPERATORS (DINOS) FOR BAYESIAN INVERSE PROBLEMS GOVERNED BY PDES

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Solution of Bayesian inverse problems governed by PDEs quickly becomes prohibitive when the forward models are complex (large-scale, nonlinear, coupled) and the inference parameter is infinite dimensional. Neural network surrogates of mappings from infinite dimensional parameter spaces to observables (i.e., neural operators) have shown particular promise for making Bayesian inversion tractable. We present derivative-informed neural operators (DINOs), which exploit the geometry of the parameter-to-observable map---in particular its curvature and intrinsic low dimensionality---to learn with high accuracy not only the map, but also its Gateaux derivatives. This enables their use as surrogates to greatly accelerate geometric MCMC algorithms. Several large-scale geophysical applications will be presented.