Neural SPDE solver for uncertainty quantification in high-dimensional ocean dynamics

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The challenge of reconstructing ocean dynamics from irregularly-sampled and noisy observations is often addressed by optimal interpolation (OI) or equation-driven data assimilation (DA). However, the computational complexity for large datasets led to the development of ensemble methods, sparse schemes, or iterative approaches. In this work, we introduce a neural variational scheme using UNet-based prior together with a trainable iterative gradient-based solver, which asymptotically converges to the OI solution. As illustrated for a real-world interpolation problems on SSH datasets, the proposed framework also extends to non-linear and multimodal interpolation problems and significantly outperforms state-of-the-art interpolation methods, when dealing with very high missing data rates. We also suggest here additional developments for uncertainty quantification: we leverage stochastic PDE surrogate modeling to estimate complex prior models capable of handling non-stationary covariances in both space and time. We modify our neural variational scheme to incorporate an augmented state formalism that estimates both state and SPDE parameters. The SPDE is then used as a surrogate model along the data assimilation window. Because the prior is stochastic, we can easily draw samples from the posterior distribution based on large ensemble members. We demonstrate this framework on realistic Sea Surface Height datasets. Our solution improves the OI baseline while enabling quick and interpretable online parameter estimation. Interestingly, introducing state-dependent noise in the SPDE also leads to non-Gaussian pdf with potential applications to the modeling of heavy-tailed distributions, then extremes.