Geometric, Interpretable Machine Learning for Streamflow Dynamics Analysis

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We introduce a framework that uses tools from differential geometry to build low-dimensional latent dynamical models that retain strong predictive skill while exposing coherent structure in the learned dynamics. In our recent work, we proposed Latent Diffeomorphic Dynamic Mode Decomposition (LDDMD), which combines Dynamic Mode Decomposition with invertible neural networks to learn oscillatory latent modes that admit a clear geometric interpretation in terms of phases, frequencies, and long-term memory. Applied to synthetic and real-world streamflow prediction, LDDMD recovers physically meaningful latent oscillations and extrapolates far beyond the training horizon, achieving competitive predictive performance alongside explicit latent trajectories and modes. Building on these results, we outline ongoing efforts to geometrically "decode" pretrained LSTM streamflow forecasters into LDDMD-style latent systems, aiming to transform state-of-the-art black-box models into geometrically structured, interpretable dynamical systems for hydrologic process analysis.

Keywords: Interpretable machine learning, Streamflow prediction, Latent dynamics, Dynamic Mode Decomposition, Data-driven modeling