ABSTRACT: Fluid flows often exhibit chaotic or turbulent dynamics and require a large number of degrees of freedom for accurate simulation. Nevertheless, because of the fast damping of small scales by viscous diffusion, these flows can in principle be characterized with a much smaller number of dimensions, as their long-time dynamics relax to a finite-dimensional surface in state space called a manifold. Classical data-driven methods for dimension reduction, such as Proper Orthogonal Decomposition (POD), approximate this manifold as a flat surface, but for complex flows, this linear approximation is severely limited. We describe a data-driven reduced order modeling method, which we call Data-driven Manifold Dynamics (DManD), that finds a nonlinear coordinate representation of the manifold using an autoencoder and then learns an ordinary differential equation (ODE) for the dynamics in these coordinates. Exploitation of symmetries substantially improves performance. We apply DManD to spatiotemporal chaos in the Kuramoto-Sivashinsky equation (KSE), chaotic bursting dynamics of Kolmogorov flow, and transitional turbulence in plane Couette flow, finding dramatic dimension reduction while yielding good predictions of short-time trajectories and long-time statistics. We also introduce an autoencoder architecture that provides an explicit estimate of manifold dimension as well as an orthogonal coordinate system for the manifold. DManD can be combined with a clustering algorithm to generate overlapping local representations that are particularly useful for intermittent dynamics. As an example of its utility, we apply DManD to drag reduction in wall turbulence. Deep reinforcement learning (RL) control can discover control strategies for high-dimensional systems, making it promising for flow control. However, it learns by interacting with the target system, which can be very costly. We mitigate this expense by obtaining a low-dimensional DManD model from data for the open-loop system, then learn an RL control policy using the model rather than the true system. For turbulent plane Couette flow in the transition regime, we accurately represent the turbulent dynamics with 25 degrees of freedom, as compared to the 100,000 degrees of freedom of the direct simulation. We then use the model to very rapidly train an RL control policy that is highly effective in laminarizing the flow.