Turbulence model reduction by deep learning[1] ROBIN HEINONEN, PATRICK DIAMOND, University of California San Diego — Computing turbulent fluxes is one of the central problems of turbulence modeling. In this work, we use a data-driven approach to infer a mean-field model for the fluxes. Starting from numerical solution of the 2-D Hasegawa-Wakatani system, we use deep supervised learning to train a deep neural network which outputs the local turbulent particle flux and Reynolds stress as a function of local mean gradients, flow properties, and turbulence intensity. The deep neural network detects a previously unreported, non-diffusive particle flux which is proportional to the gradient of vorticity. We recover this flux, which (in the presence of a zonal flow) tends to modulate the density profile, with a simple analytic calculation. Using the new method, we also uncover a Cahn-Hilliard-type model for the generation of zonal flow via Reynolds stress, which agrees with previous theoretical work. Together with the particle flux, we thus obtain a reduced 1-D model for the turbulent dynamics directly from numerical data. We solve this numerically and compare to direct numerical simulation of the full 2-D system. We discuss the importance of symmetry to the deep learning method, the method's portability to other applications, and its range of validity.

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