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Predicting atmospheric optical properties for radiative transfer computations using neural networks

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A fast and accurate treatment of radiation in meteorological models is essential for high quality simulations of the atmosphere. Despite our good understanding of the processes governing the transfer of radiation, full radiative transfer solvers are computationally extremely expensive. In this study, we use machine learning to accelerate the optical properties calculations of the Rapid Radiative Transfer Models for General circulation model applications - Parallel (RRTMGP). These optical properties control the absorption, scattering and emission of radiation within each grid cell. We train multiple neural networks that get as input the pressure, temperature and concentrations of water vapour and ozone of each grid cell and together predict all 224 or 256 quadrature points of each optical property. All networks are multilayer perceptrons and we test various network sizes to assess the trade-off between the accuracy of a neural network and its computational costs. We train two different sets of neural networks. The first set (generic) is trained for a wide range of atmospheric conditions, based on the profiles chosen by the Radiative Forcing Model Intercomparison Project (RFMIP). The second set (case-specific) is trained only for the range in temperature, pressure and moisture found in one large-eddy simulation based on a case with shallow convection over a vegetated surface. This case-specific set is used to explore the possible performance gains of case-specific tuning.

Most neural networks are able to predict the optical properties with high accuracy. Using a network with 2 hidden layers of 64 neurons, predicted optical depths in the longwave spectrum are highly accurate ($R^2 > 0.99$). Similar accuracies are achieved for the other optical properties. Subsequently, we take a set of 100 atmospheric profiles and calculate profiles of longwave and shortwave radiative fluxes based on the optical properties predicted by the neural networks. Compared to fluxes based on the optical properties computed by RRTMGP, the downwelling longwave fluxes have errors within 0.5 W m^{-2} (<1%) and an average error of -0.011 W m^{-2} at the surface. The downwelling shortwave fluxes have an average error of -0.0013 W m^{-2} at the surface. Using Intel's Math Kernel Library's (MKL) BLAS routines to accelerate matrix multiplications, our implementation of the neural networks in RRTMGP is about 4 times faster than the original optical properties calculations. It can thus be concluded that neural networks are able to emulate the

calculation of optical properties with high accuracy and computational speed.