Predicting atmospheric optical properties for radiative transfer computations using neural networks

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Motivation

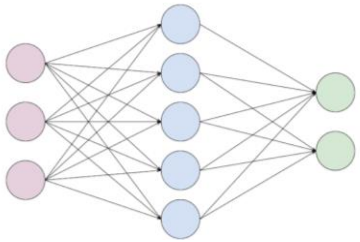
- Radiative transfer (RT) equations are well-known and can be solved with high accuracy.

- However, radiation computations in atmospheric models are computationally very expensive
  - Approximations needed to gain speed, e.g. coarser spatial/temporal resolution (e.g. Morcrette, 2000; Hogan & Bozzo, 2018) or spectral sampling (Pincus & Stevens, 2009)

- Machine learning is a promising tool to accelerate RT computations
  - Directly predicting radiative fluxes with neural networks may give speed-ups of >1 order of magnitude (e.g. Chevallier et al.,, 2018; Kransopolsky et al., 2005), but involves replacing the RT equations and therefore does not respect the well-understood underlying physics.
  - Alternative: emulating only the parts RT parametrizations that require most assumptions, not the RT equations

Goal

- Developing a machine learning-based parametrization for the gaseous optical properties to accelerate radiative transfer calculations



- Our approach:
  - Training neural networks to emulate the optical properties parametrization RRTMGP (Rapid Radiative Transfer Model for General circulation model application – Parallel; Pincus et al., 2019)
  - Using machine-specific optimised BLAS functions to significantly accelerate matrix computations when solving the neural networks
  - “case-specific” training (i.e. for a limited range of atmospheric conditions) to allow smaller and therefore faster neural networks

Three sets of “case-specific” neural networks

- One NWP-tuned set: wide range of thermodynamic variables, based on atmospheric profiles from the Radiative Forcing Model Intercomparison Project (Pincus et al, 2016)
- Two LES-tuned sets: range of thermodynamic variables in a single LES case
  - Radiative Convective Equilibrium Model Intercomparison Study (RCEMIP; Wing et al., 2018)
  - Diurnal cycle of a convective boundary layer over grassland near Cabauw, the Netherlands (Vilà-Guerau de Arellano et al., 2014, Pedruzo-Bagazgoitia et al., 2017)

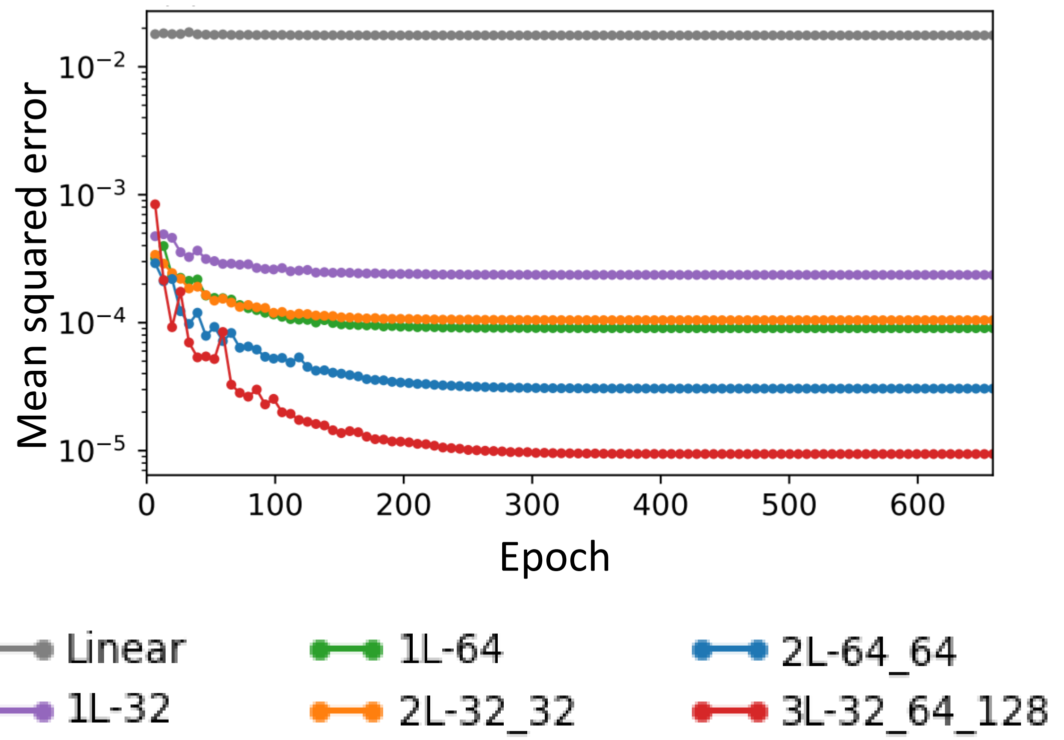
All gases except water vapour and ozone are constant (suitable for NWP/LES)

Using a separate neural network per optical property, the networks are trained to predict the gaseous optical properties at all quadrature points (for the spectral integration) as calculated by RRTMGP

Training performance
(NWP-tuned neural networks)

- Larger networks perform better (lower MSE)
- Performance of Linear networks is significantly worse: linear regression is not a suitable solution
- All predicted optical properties are highly accurate (R^2>0.99), except for Linear networks

Evaluation loss
(longwave optical depth)

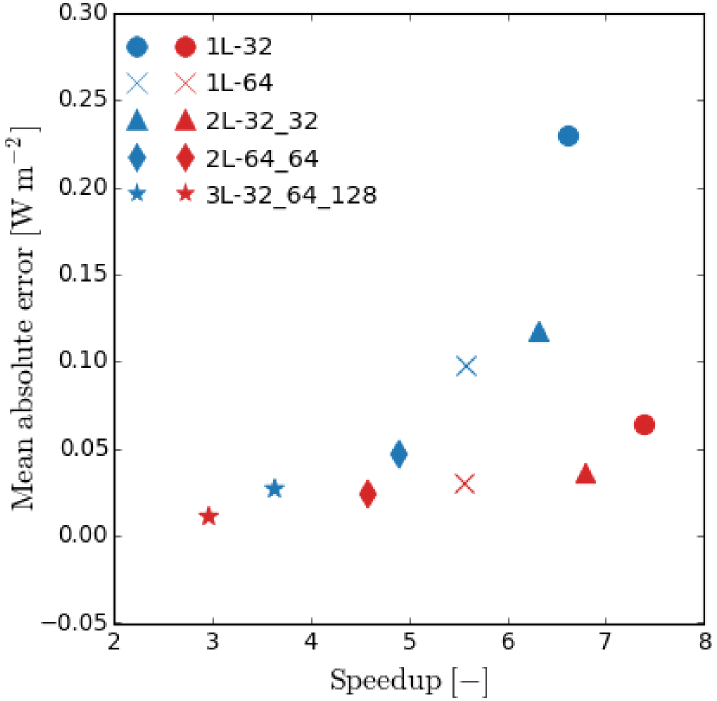


Explanation: *Linear* has no hidden layer, *1L-32 has 1 hidden layer of 32 nodes, 3L-32_64_128 has 3 hidden layers of 32, 64 and 128 nodes, respectively.*

Trade-off between accuracy and speed
(NWP-tuned networks)

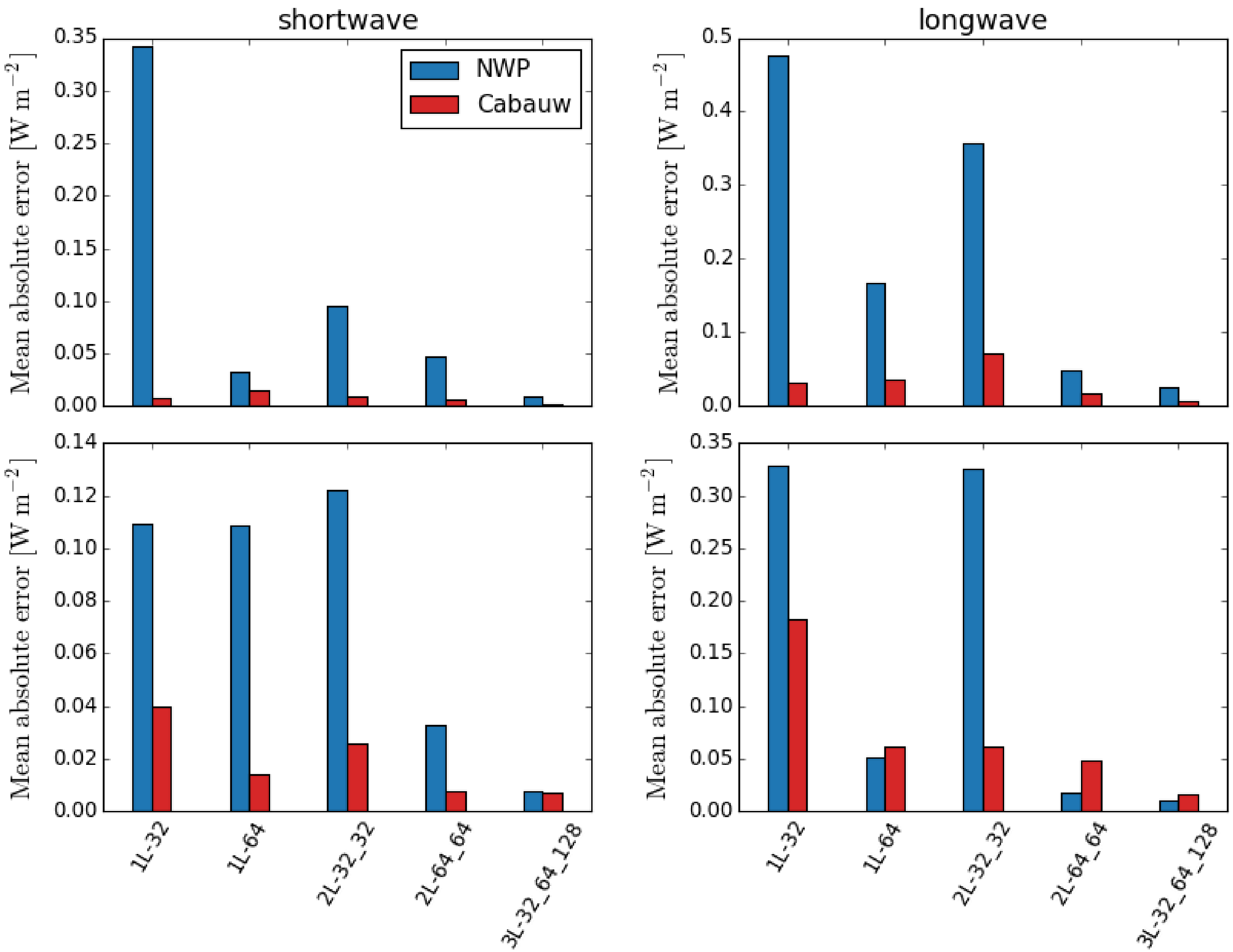
- Errors of radiative fluxes based on neural network-predicted optical properties, with respect to radiative fluxes based on optical properties of RRTMGP
  - ➢ With all network sizes, high accuracies for both longwave and shortwave radiation
- Depending on network size, our parametrization is between 3 to 7 times faster than RRTMGP
- Larger networks give more accuracy, but reduce the speed-up that can be achieved

Speedup vs mean absolute error of surface irradiance



Longwave radiation
Shortwave radiation

LES-tuning (Cabauw, RCEMIP) vs NWP-Tuning



- Mean absolute errors of the downward radiative fluxes at the surface, based on profiles of the Cabauw (top) and RCEMIP (bottom) simlations
- In general higher accuracies with LES-tuning (especially for shortwave radiation), for the LES case the networks are trained for.
- Therefore, smaller neural networks suffice
  - Higher speed-up
- Although fluxes are quite accurate, NWP networks show some signs of overfitting

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