Emulating Aerosol Microphysics with Machine Learning

ICML 2021 Workshop Tackling Climate Change with AI

Climate Change AI

Image credit: NASA

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Motivation

Aerosol forcings remain the largest source of uncertainty in the anthropogenic effect on the current climate

Aerosol-cloud interactions: Aerosols can increase brightness and lifetime of a cloud

Aerosol-radiation interactions: Aerosols can scatter and absorb radiation

Aerosols often not modelled in detail or models are computational expensive and unable to run for longer times or higher resolution

Idea

Replace aerosol microphysics module in global climate model with a faster machine learning model

Data Generation

Using inputs from the global ECHAM-HAM run

Running the M7 aerosol microphysics module for one time step

M7: Models masses/numbers for different aerosol types and different size bins

Four days over a year, each day 2.85M data points. First two days for training, third day for validation and fourth day for testing

Methods

Predict tendencies not full variables

Changes in the variables are most of the time very small, but a few values are orders of magnitudes bigger

Special data transform needed:

$$y = \begin{cases} \log \sqrt{x} + 1 & x \geq 0 \\ -\log \sqrt{-x} + 1 & \text{else.} \end{cases}$$

Methods

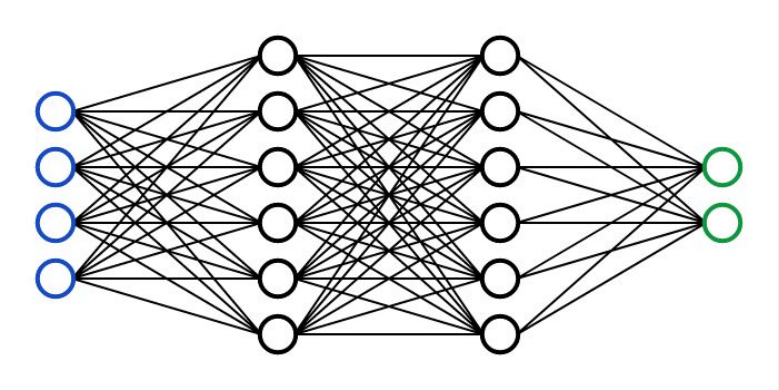
Inputs:

Temperature

RH, Pressure,...

Aerosol masses at t

Aerosol numbers at t



Outputs:

Aerosol masses at t+1

Aerosol numbers at t+1

Water content

34 dim.

2-layer MLP

28 dim.

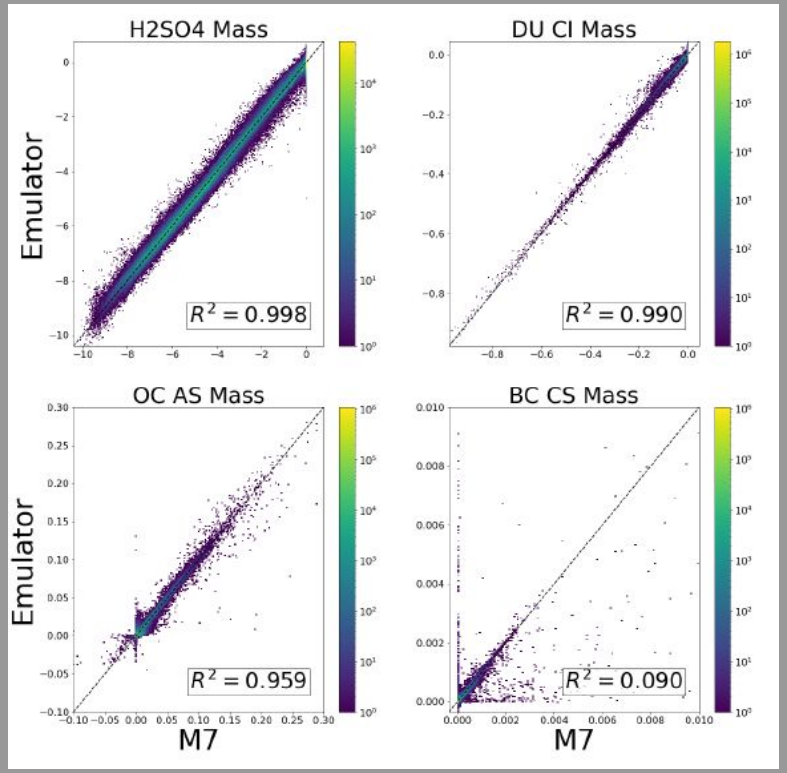
Results

Good regression performance:

Case	RMSE	R^2
train	0.230	0.933
val	0.254	0.924
test	0.249	0.892

Strong speed-up on GPU:

Model	M7	Emulator GPU	Emulator CPU
time (s)	5.781	0.048	3.716
speed-up	-	120.4	1.6



Outlook

Mass conservation important for stable climate model runs

Avoid unphysical predictions, e.g. negative masses

Leverage spatial relationships using a CNN

Include emulator model in global climate model

Thank you!

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