

Progress and challenges for the use of deep learning to improve weather forecasts

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Predicting weather and climate: Why is it so hard?



Earth as seen from Apollo 17

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Use cases for machine learning are all over the place...

Future perspective for machine learning in weather forecasts

▶ Use cases in quality control and automated alarm systems

weather data monitoring, model and data assimilation systems, real-time quality control for observational data, interpret anomalies and guide quality assignment and decision making

▶ Use cases in data assimilation and use of observations

derive information on the governing differential equations, non-linear bias correction, bias predictors, operational operators, define optical properties of hydrometeors and aerosols

▶ Use cases in numerical modelling

emulate model components, develop improved parametrisation schemes, provide better error models, learn the underlying equations of motion, generate tangent linear or adjoint code from machine learning emulators)

▶ Use cases in post-processing and product generation

real time adjustments of forecast products, feature detection, uncertainty quantification, error corrections for seasonal predictions, development of low-complexity models, plenty of business opportunities

▶ Use cases in HPC infrastructure and data handling

different use of data, data mining and data fusion; more/larger data requests; need for use of deep learning hardware; user products within the forecast model

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The next slides: I will show example applications and discuss challenges.

To learn the equations

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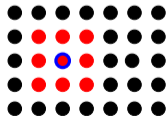
Who needs Navier Stokes?

Why would this be useful?

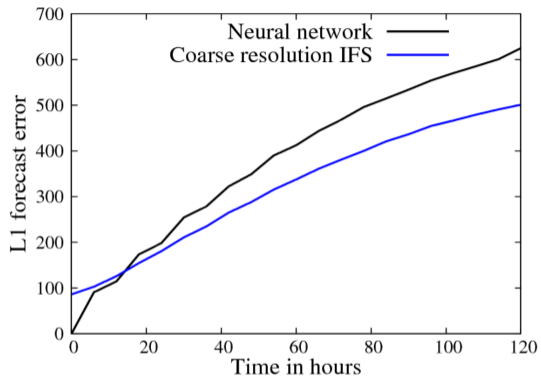
- ▶ We know the equations of motion but we cannot solve them.
- ▶ Discretisation and sub-grid-scale variability generates significant errors.
- ▶ The data handling system of ECMWF provides access to over 210 petabyte of primary data and the data archive of ECMWF grows by about 233 terabyte per day.

Global weather forecast based on Neural Networks

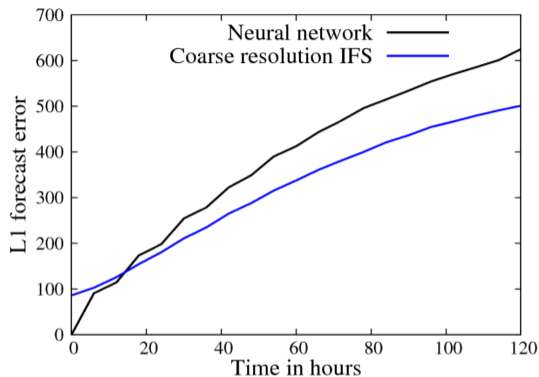
- ▶ Retrieve hourly data of geopotential height at 500 hPa from ERA5 re-analysis for training (> 65000 global data sets).
- ▶ Map the data to a coarse lon/lat grid (60x31).
- ▶ Use the state of the model at timestep i as input and the state of the model at timestep $i + 1$ as output.
- ▶ Use a 9×9 stencil around the grid point that should be predicted.
- ▶ Add time of day and year as well as the coordination of a gridpoint (lon+lat) as input variables to the network.
- ▶ The Pole needs special treatment.



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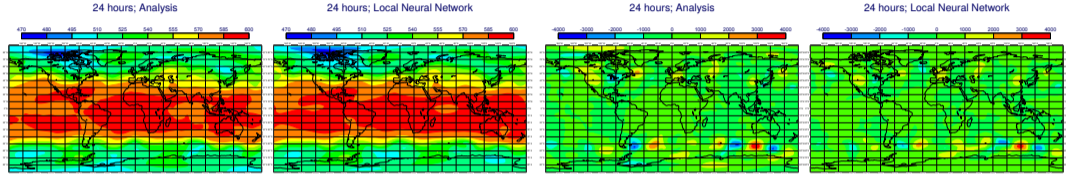
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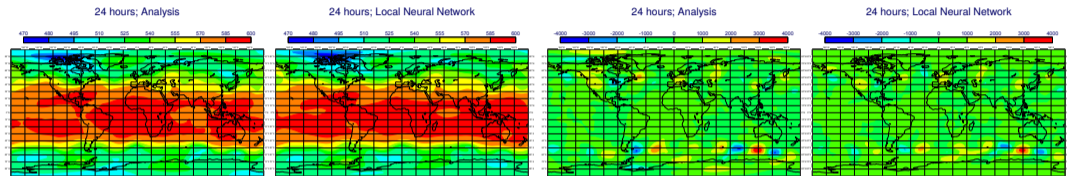
The Neural Network model can compete with a dynamical model of similar complexity.

Dueben and Bauer GMD 2018

Global weather forecast based on Neural Networks

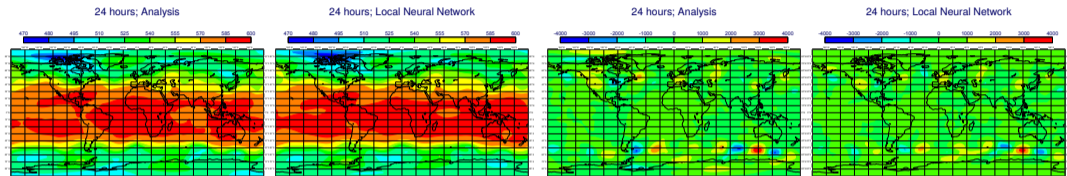


Global weather forecast based on Neural Networks



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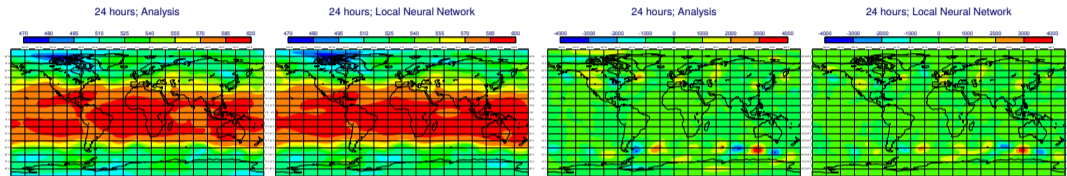
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Model runs crash after a couple of weeks.

Dueben and Bauer GMD 2018

Let's use neural networks to emulate existing parametrisation schemes

- ▶ Store input/output pairs of parametrisation schemes.
- ▶ Use this data to train a neural network to do the same job.
- ▶ Replace the parametrisation scheme by the neural network.

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Why would you do this?

- ▶ A large fraction of the computational cost is generated by parametrisation scheme.
- ▶ Parametrisation schemes cause a very large fraction of the model code.
- ▶ Optimization of this code is very difficult
(→ less than 5% peak performance).
- ▶ Neural Networks are highly optimized and can even use co-designed hardware.
→ Portability comes for free.

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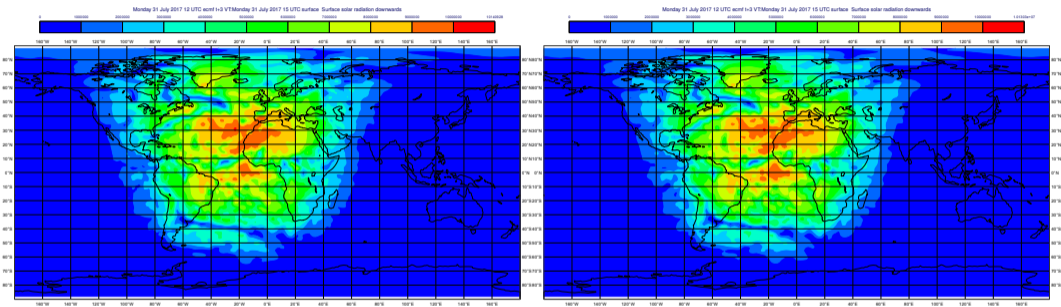
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We hope that deep Neural Networks will be almost as good as the original parametrisation schemes but much more efficient.

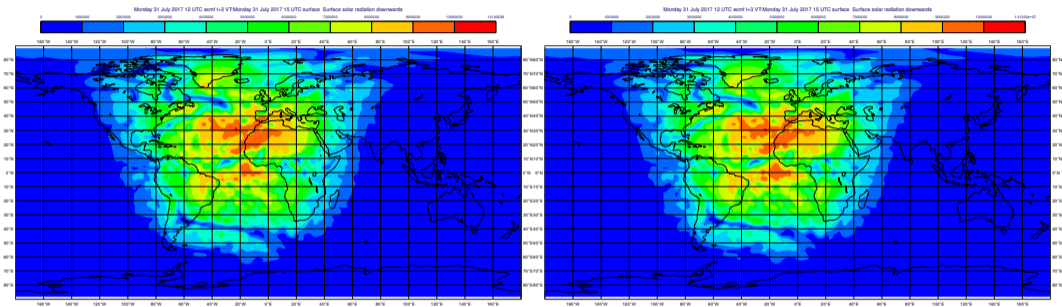
A neural network emulator for the radiation scheme of IFS with 137 vertical levels



Dueben, Hogan, Bauer @ECMWF and Progsch, Angerer @NVIDIA

Downward solar radiation at the surface for the original radiation scheme and the Neural Network emulator.

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Downward solar radiation at the surface for the original radiation scheme and the Neural Network emulator.

Free-running model simulations are stable and we get a factor of $O(10)$ speed-up for radiation.

Improve post-processing

Ensemble simulations are important but expensive.

Improve post-processing

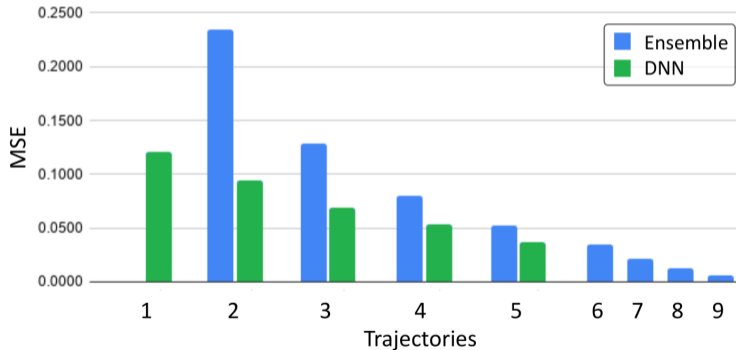
Ensemble simulations are important but expensive.

Use 3D fields of a small number of ensemble members as inputs and try to predict ensemble spread of temperature at 850 hPa for a 24h forecast of a full 10 member ensemble forecast for an area over Europe (40W-30E and 40N-60N).

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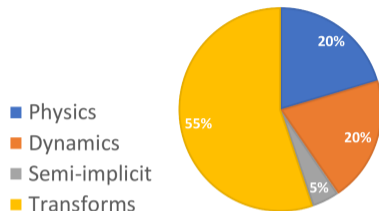
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Grönquist, Ben-Nun, Taranov, Höfler @ ETH and Dueben and Bauer @ ECMWF

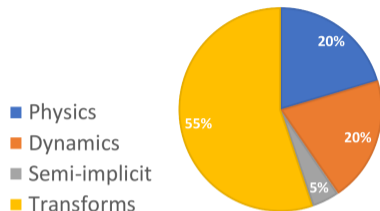
Use machine learning hardware for the Legendre transform

Relative cost for model components for a non-hydrostatic model at 1.45 km resolution:



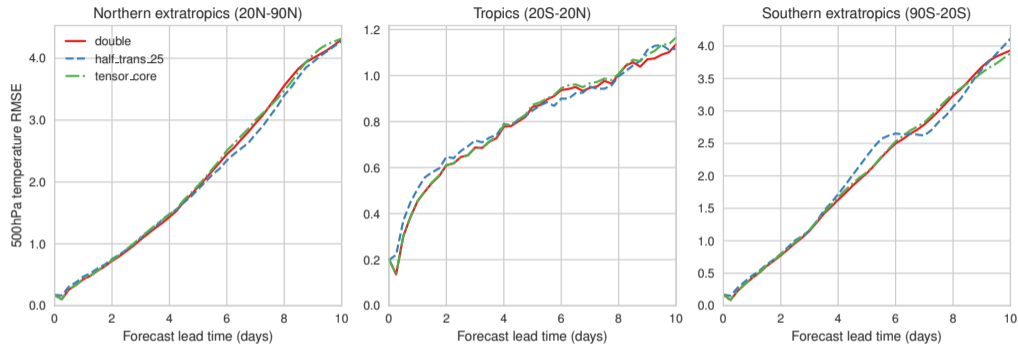
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Relative cost for model components for a non-hydrostatic model at 1.45 km resolution:



- ▶ The Legendre transform is the most expensive kernel. It consists of a large number of standard matrix-matrix multiplications.
- ▶ If we can re-scale the input and output fields, we can use half precision arithmetic.
- ▶ Tensor Cores on NVIDIA Volta GPUs are optimised for half-precision matrix-matrix calculations with single precision output. 7.8 TFlops for double precision vs. 125 TFlops for half precision on the Tensor Core.

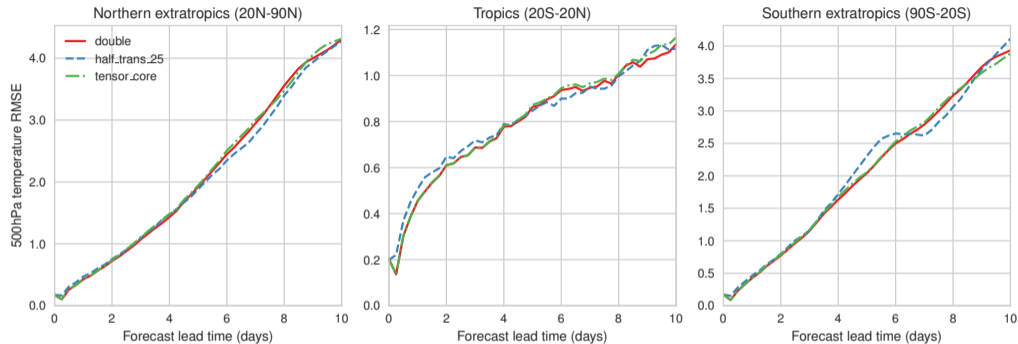
Half precision Legendre Transformations



Root-mean-square error for Z500 at 9 km resolution averaged over multiple start dates.

Hatfield, Chantry, Dueben, Palmer **Best Paper Award** PASC2019

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The simulations are using an emulator to reduce precision.

Dawson and Dueben GMD 2017

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We need to prove that machine learning tools are **better** than state-of-the-art within the next two years.

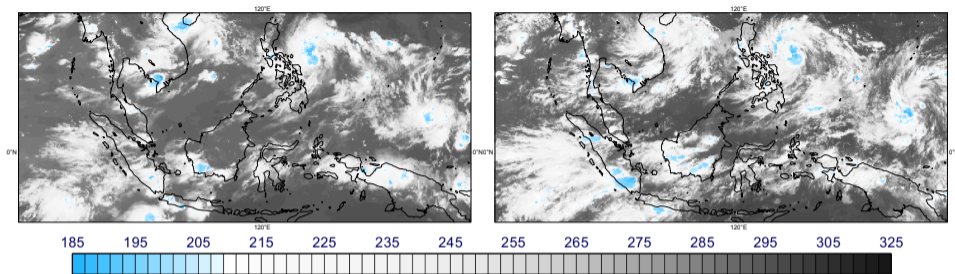
The challenge for the machine-learning community

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*We need to build **useful tools** that improve weather and climate predictions and/or help to improve our understanding of the Earth System and are able to convince the conservative weather and climate scientist.*

Why is this challenge so hard?

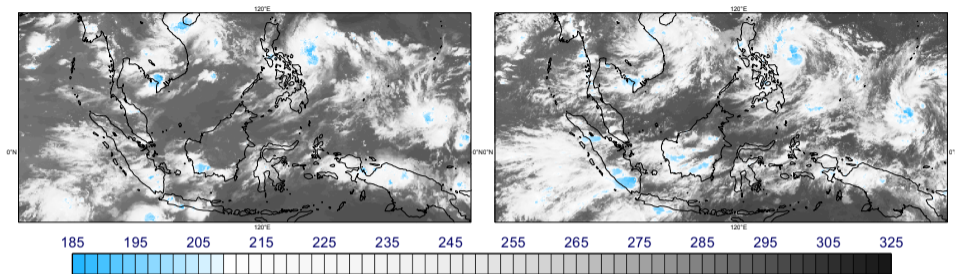


Dueben, Wedi, Saarinen and Zeman submitted

Top-of-the-atmosphere cloud brightness temperature [K] for satellite observations and a simulation of the atmosphere with 1.45 km resolution.

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Global simulations show a breath-taking level of complexity and can represent many details of the Earth System.

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It is really difficult to compare computational speed for machine learning and conventional methods in a fair way.

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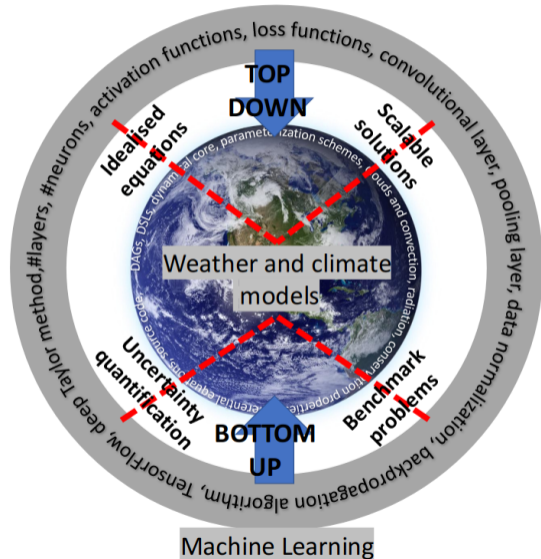
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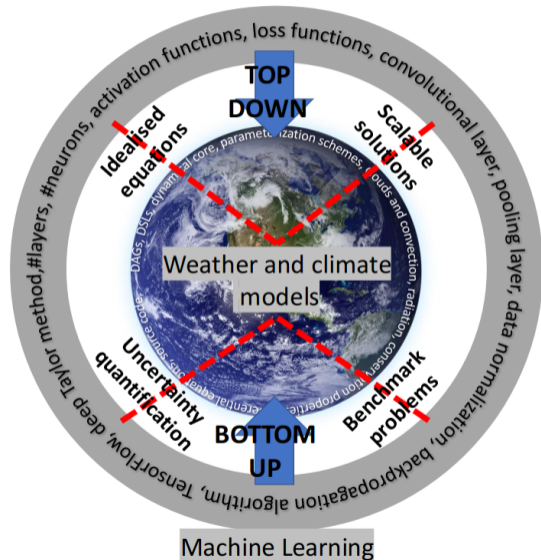
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My personal vision of the way forward...

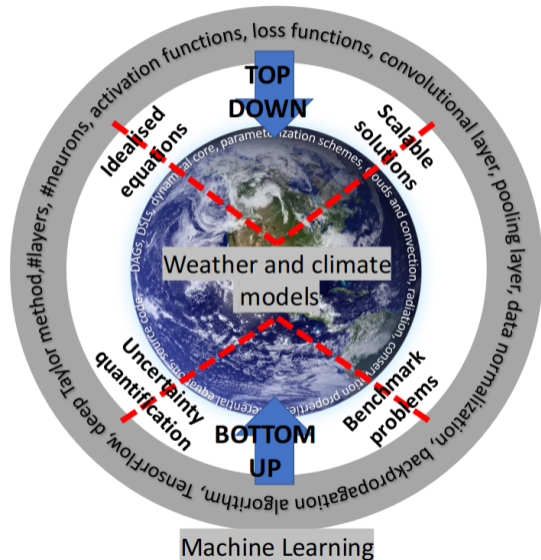


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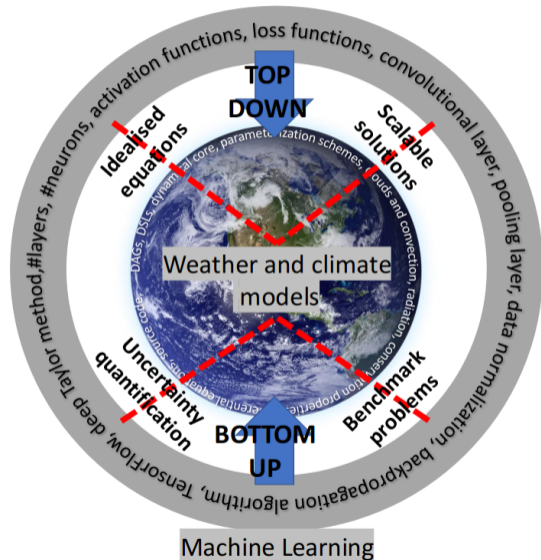
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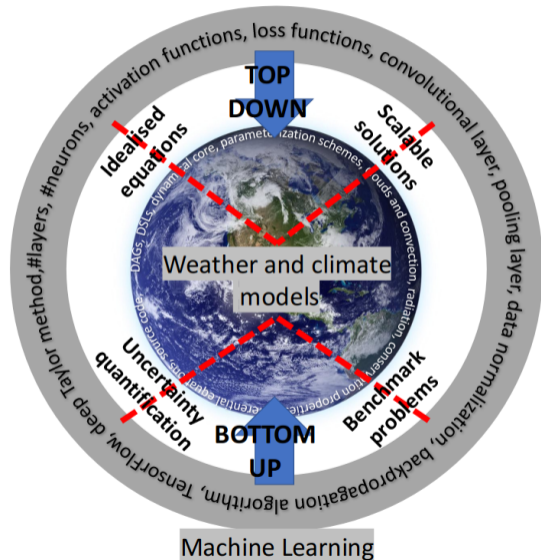
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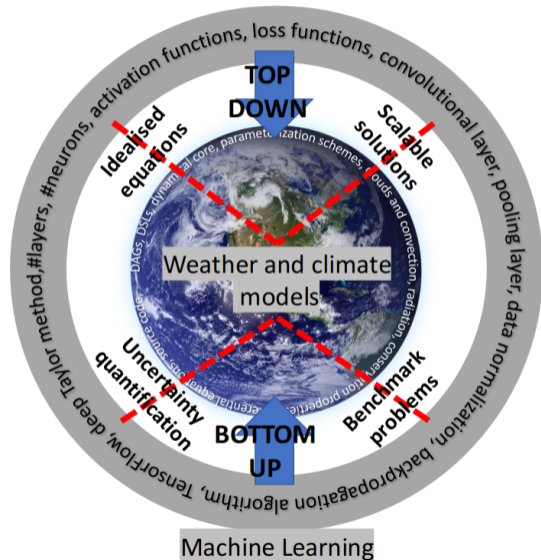
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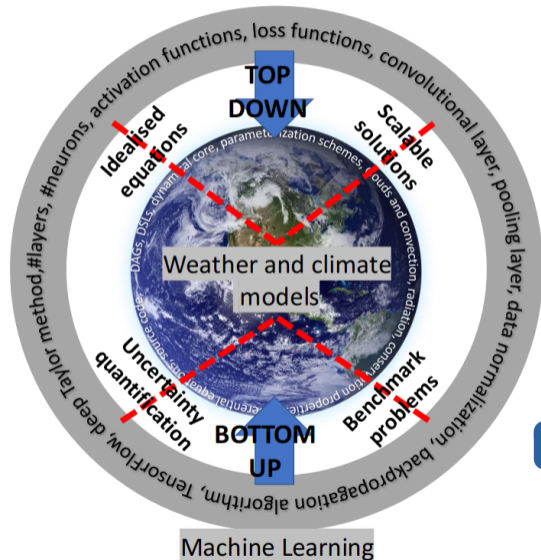
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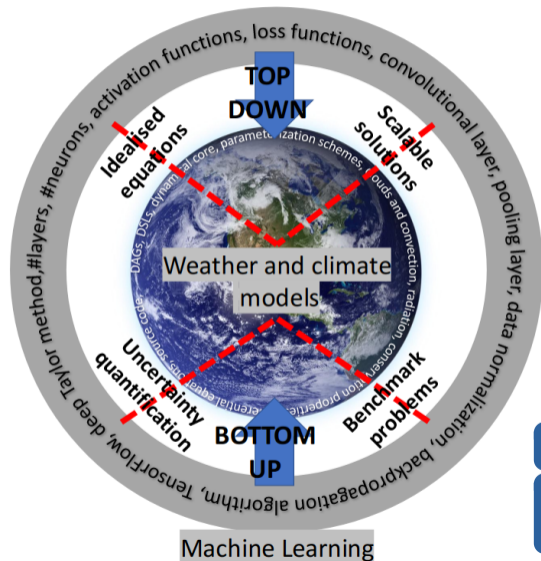
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We will require machine learning solutions that are customized to weather and climate models.

Conclusions

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- ▶ We can learn the equations of motion using deep learning and build medium-complexity models.
- ▶ We need to develop useful tools based on machine learning within the next two years.
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Many thanks for your attention.



Funded by the
European Union

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