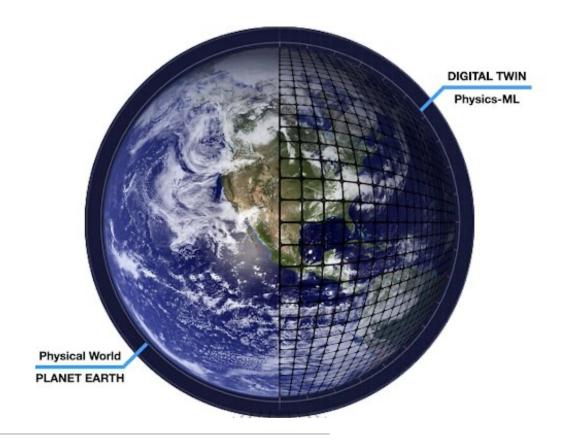
FOURCASTNET: A PRACTICAL INTRODUCTION TO A STATE-OF-THE-ART DEEP LEARNING GLOBAL WEATHER EMULATOR









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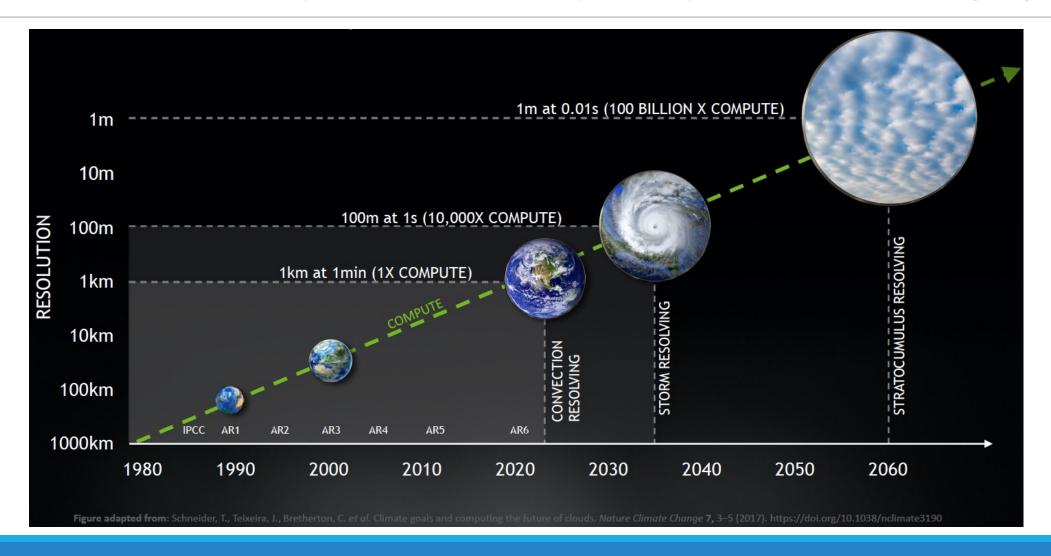
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Pathak et al. "FourCastNet: A Global Data-driven High-resolution Weather Model using Adaptive Fourier Neural Operators." arXiv:2202.11214 (2022).

Climate science requires million-x speedups and is challenging



Climate science requires million-x speedups and is challenging

Predict atmosphere dynamics and enable well-informed action

- Model complexity
 - » Multitude of physical processes: hundreds of PDEs and complex parameterizations
- Computational cost
 - » High resolution to resolve fine scales, compute scales as fourth power of resolution
 - » Large ensembles to characterize the distribution of possible outcomes
- Scalability and performance
 - » Current models not designed to exploit modern supercomputing substrates (GPUs)
 - » High energy consumption

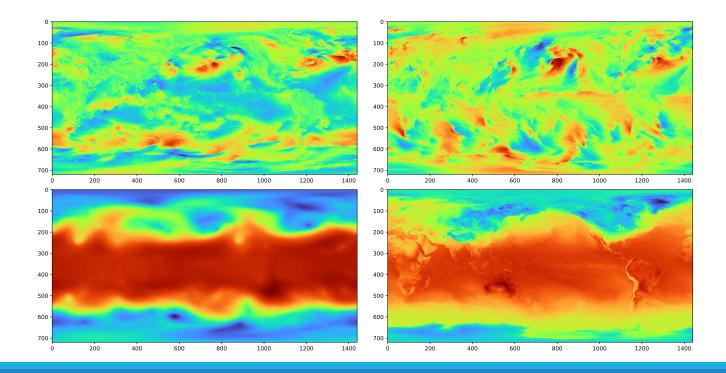
FourCastNet is a SOTA deep-learning based weather emulator

Scalable, data-driven global weather forecasting surrogate model

- Model complexity
- 1 » FourCastNet is a data-driven model and shows excellent skill on important variables
 - Computational cost
- 2 » FourCastNet enables 80000x faster inference and hence larger ensembles
 - Scalability and performance
- » FourCastNet is scalable up to 1000s of GPUs enabling exascale weather/climate computing

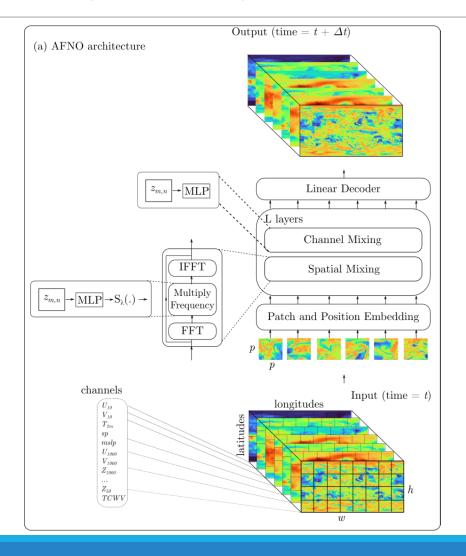
FourCastNet is trained on ERA5 reanalysis data

- Training data from ERA5 reanalysis dataset
- 40 years (at hourly intervals) for several variables at 25km grid (720 x 1440 pixels)
- Best available estimate of the earth's atmospheric state (incorporates observations)

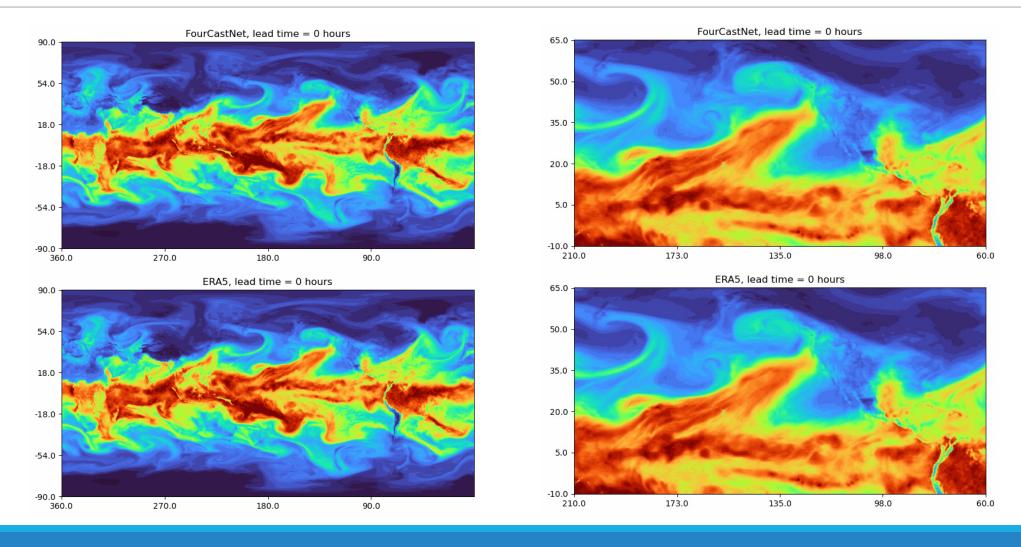


FourCastNet is based on transformers and spectral operators

- Model is based on vision transformers that performs spatial mixing in the Fourier domain
- Input vector X(t): 20 x 720 x 1440 is an input sample
 - » A few variables to characterize the atmospheric state
 - » Training: predict target X(t + dt) from X(t)
 - » Inference: autoregressive forward step in time
- Basic strategy: create forecasts by recursively stepping forward in time



Step-by-step introduction to obtaining weather forecasts



Learning objectives and resources for this tutorial

- Work with ERA5 dataset to understand different atmospheric variables
- Use a trained FourCastNet model in inference mode to generate short time-scale weather forecasts
- Visualize global weather predictions and compute key metrics to evaluate forecast skill
- Capture extreme weather phenomena like hurricanes using the model

Tutorial:

https://colab.research.google.com/drive/1Le6O2FuYmXaiIvUCW2l0zgfkbLonZHMU?authuser=2#scrollTo=QH81wjfsJsv1

Paper, code:

arxiv.org/abs/2202.11214, github.com/NVlabs/FourCastNet