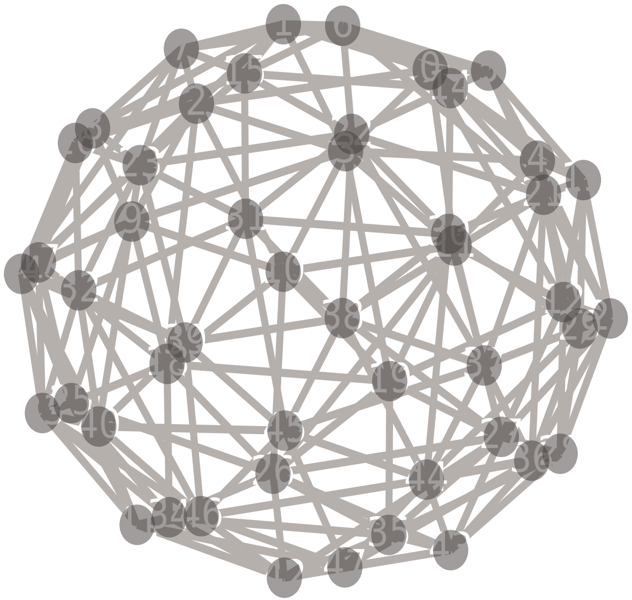

Probabilistic Deep Learning on Spheres for Weather/Climate Applications

Speakers

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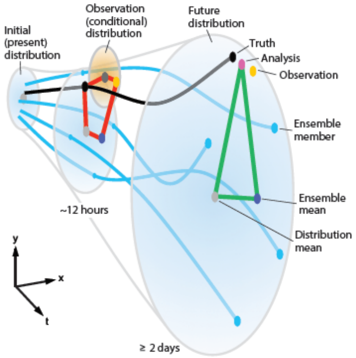
Gionata Ghiggi

16 December 2020



Introduction

Geometric projection

Spherical modeling

Accuracy and efficiency

Why go probabilistic?

Methods

Results

Conclusion and future work

Wentao Feng / Yann Yasser Haddad

Introduction

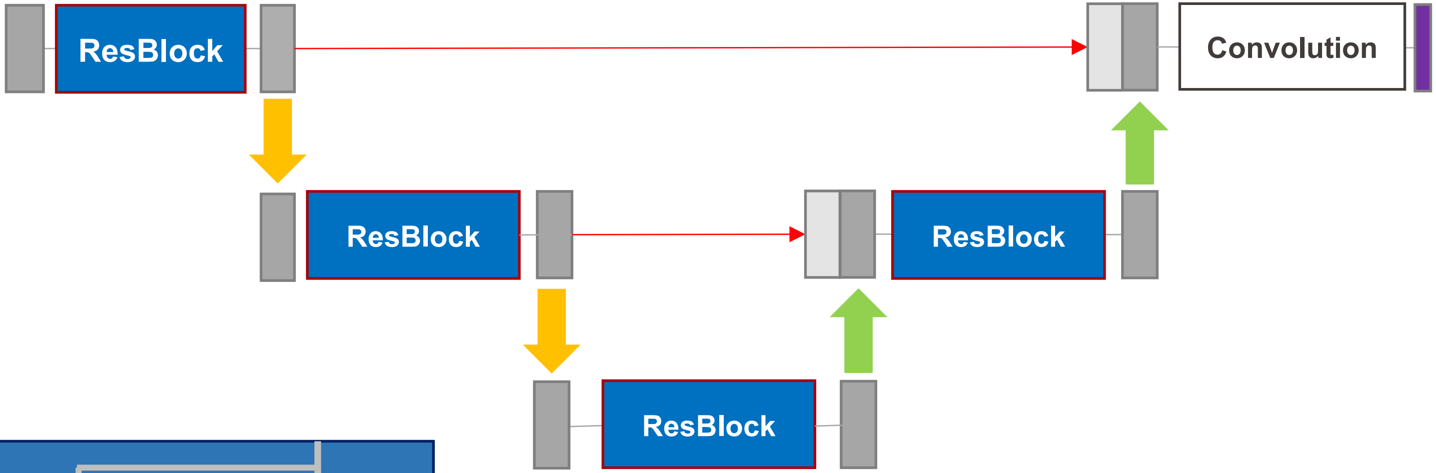
Our motivation:

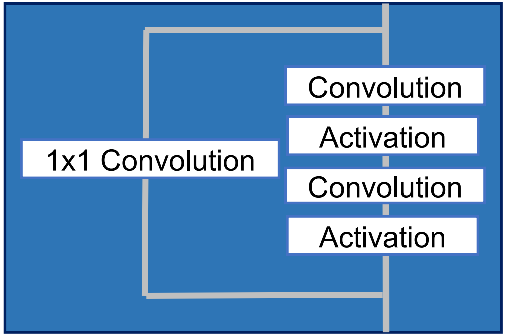
1. Deep learning method cost less computation power than NWP models
2. Can help us understand the impact of initial conditions
3. Can be used on other atmospheric problem

Our aim:

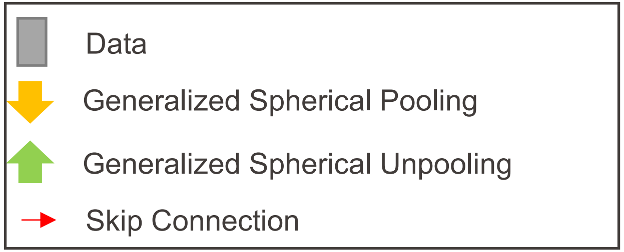
1. Design interpretable modeling method
2. Predict the weather with deep neural network

Introduction – U Net





ResBlock



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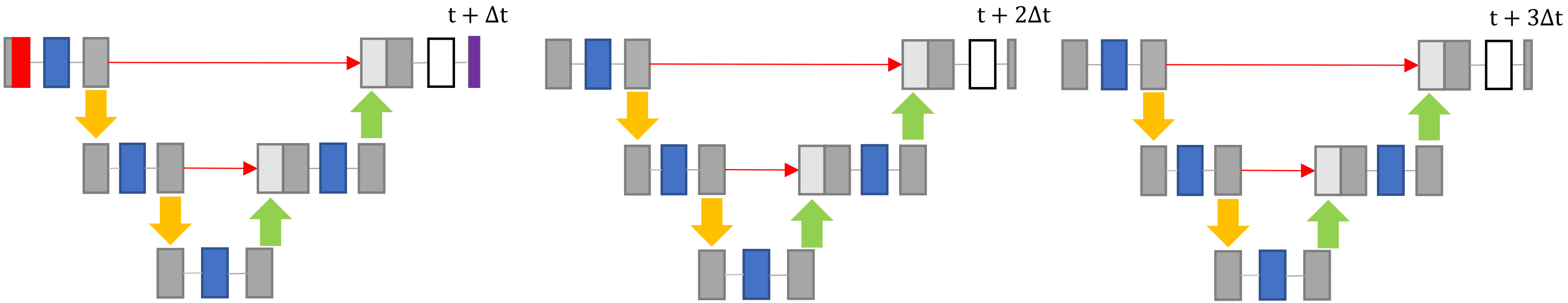
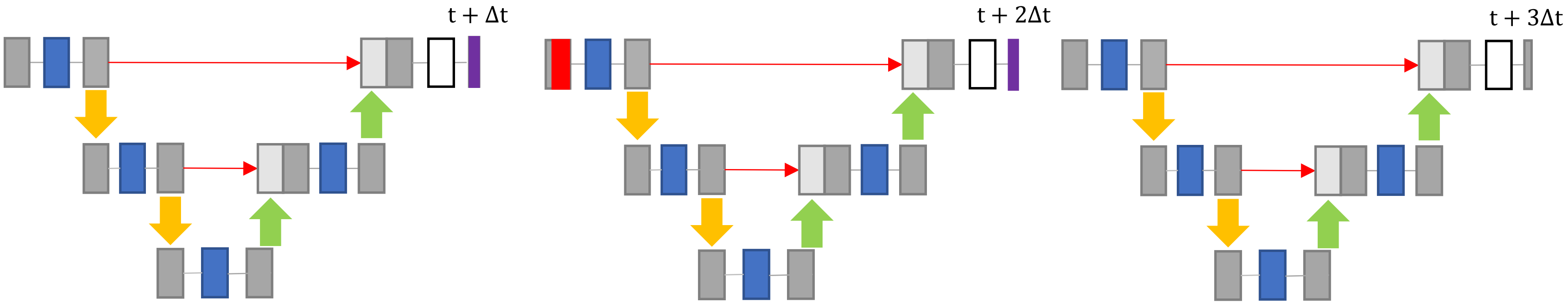
Introduction – Autoregressive model



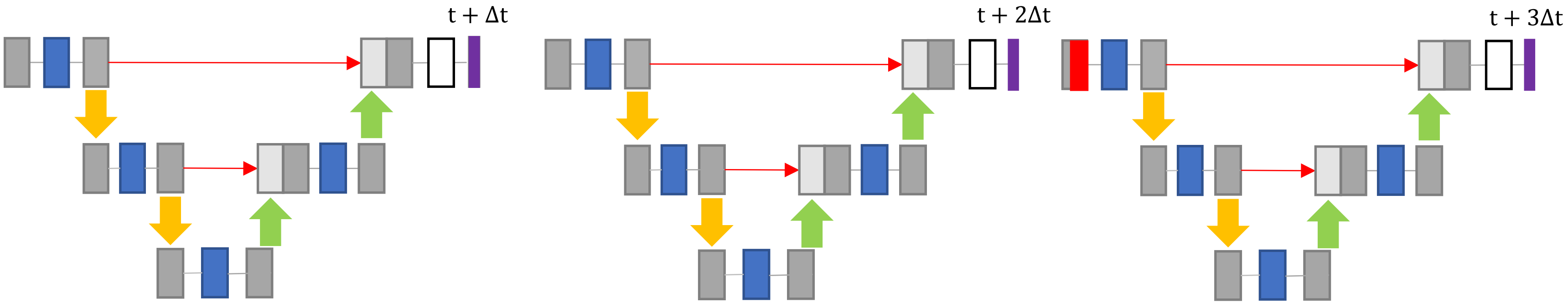
$\Delta t = 6$ hours

Introduction – Autoregressive model



$\Delta t = 6$ hours

Introduction – Autoregressive model



$\Delta t = 6$ hours

Loss function = MSE(,)

Predictions
Observations

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Introduction – Input/Output

Input at time t
1. geopotential at 500 hPa (Z500)
2. temperature at 850 hPa (T850)

Additional feature at time t:
1. top-of-atmosphere solar radiation
2. orography
3. land-sea mask
4. latitude
5. soil type

Predict at $t + \Delta t$
1. geopotential at 500 hPa (Z500)
2. temperature at 850 hPa (T850)

Introduction – Metric

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=0}^{N}(p_n - o_n)^2}$$

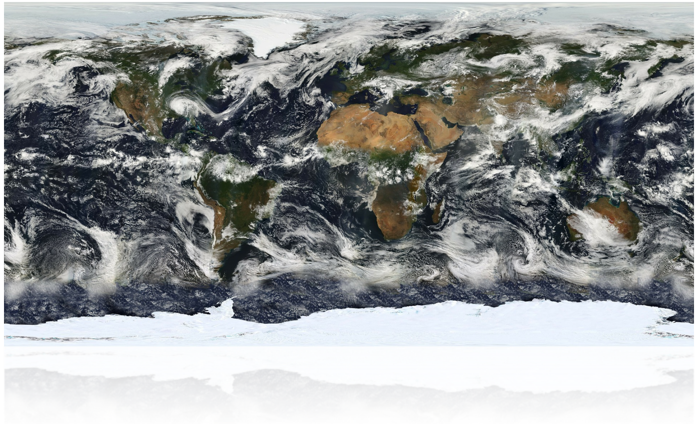
- p_n = predicted value at location n
- o_n = observed value at location n
- Measure the distance between prediction and observation
- Lower is better

Rasp et al., 2020

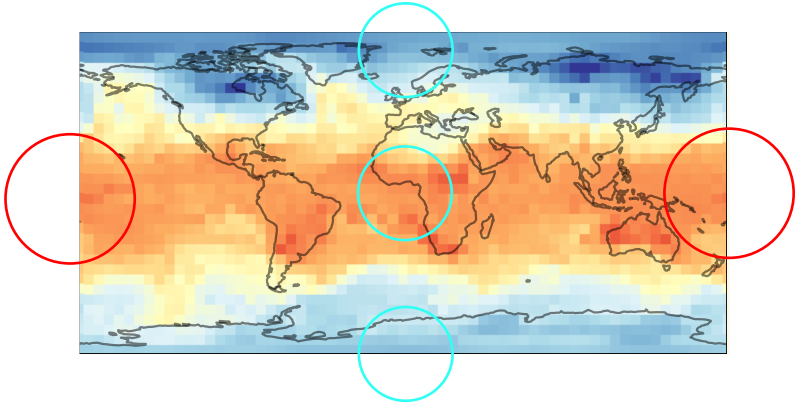
Introduction – Dataset

Results in this presentation:
- Weather Benchmark
- Region: Global
- Spatial resolution: 5.625° (approx. 600 km)
- Temporal resolution: 6h

Currently:
- ECMWF ER5



Geometric projection – Planar



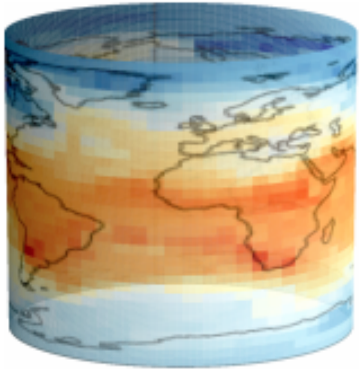
Project the sphere as planar

☹️:

1. Discontinuity on borders
2. Imbalanced projection

Figure: Rasp et al., 2020

Geometric projection – Cylinder



Project the sphere as cylinder

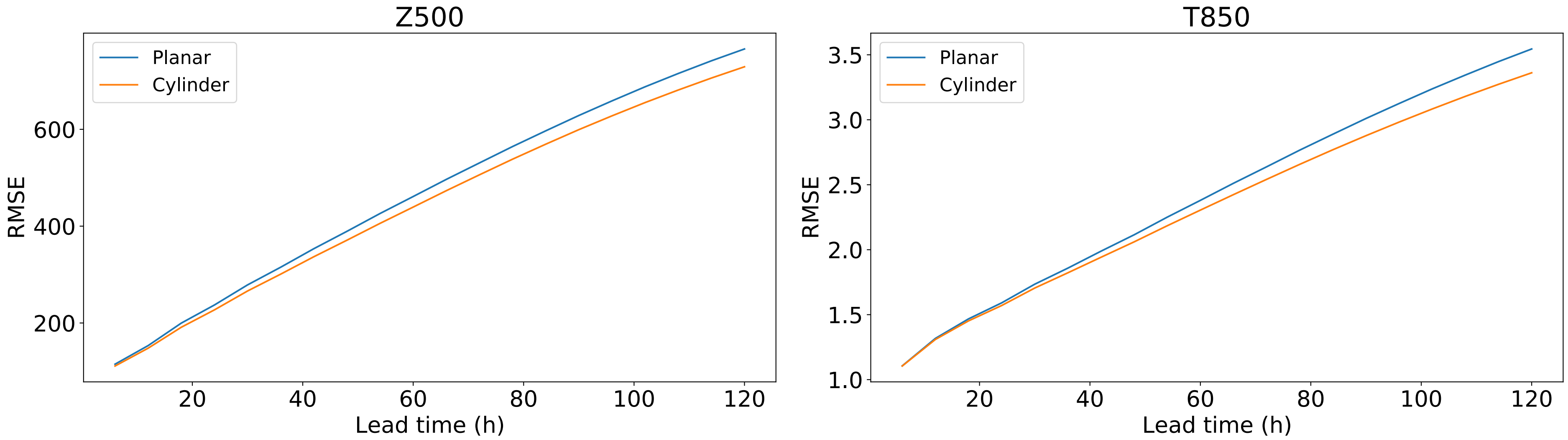
☹:

1. ~~Discontinuity on borders~~
2. Imbalanced projection

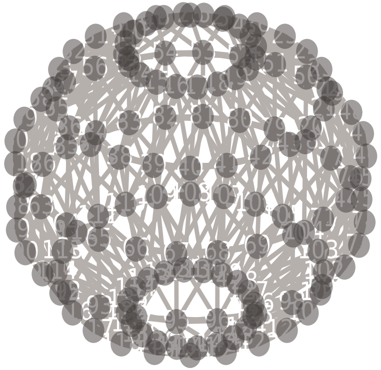
Figure: Rasp et al., 2020

Geometric projection – Cylinder

How much improvement?



How to solve imbalanced projection?



Spherical modeling

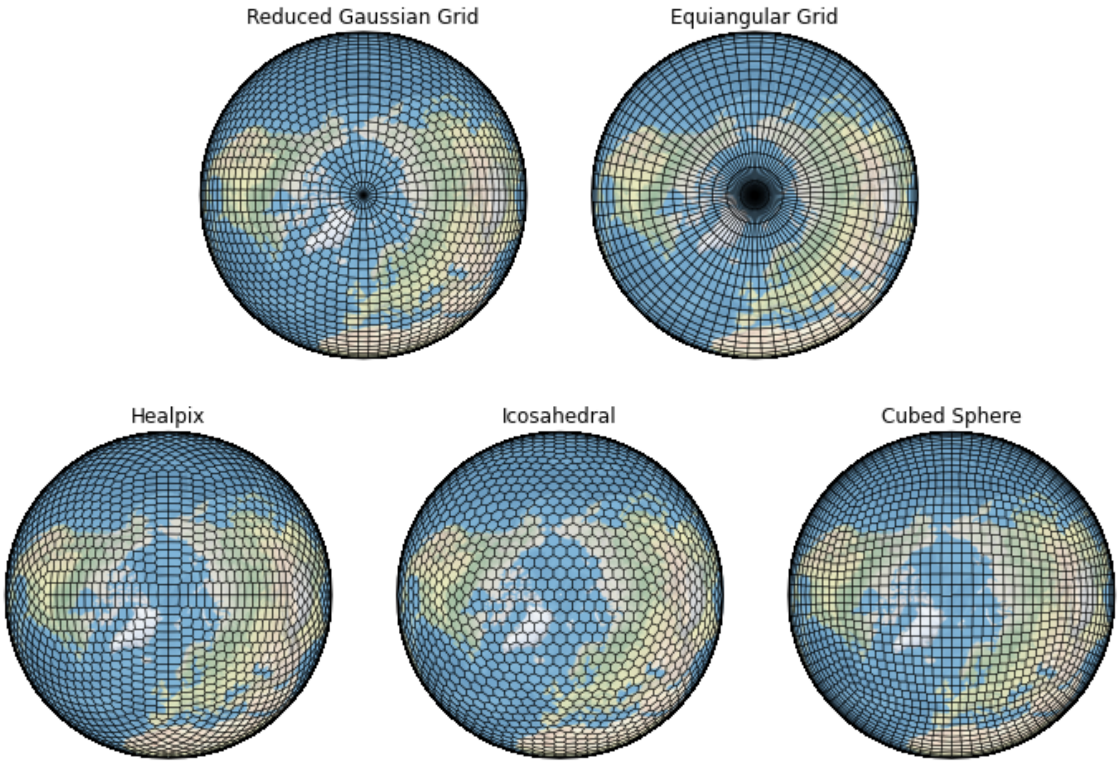
📓

- Directly modeling on spherical sampling without projection
- Using graph to represent the sphere
- Graph nodes given by sampling points

✅

- Can approximate any 3D object
- Approximation quality is proportional to number of nodes.
- Solving imbalance by using an even sampling (e.g., HEALPix)
- Adaptive to any levels of resolution

Spherical modeling – Sampling methods



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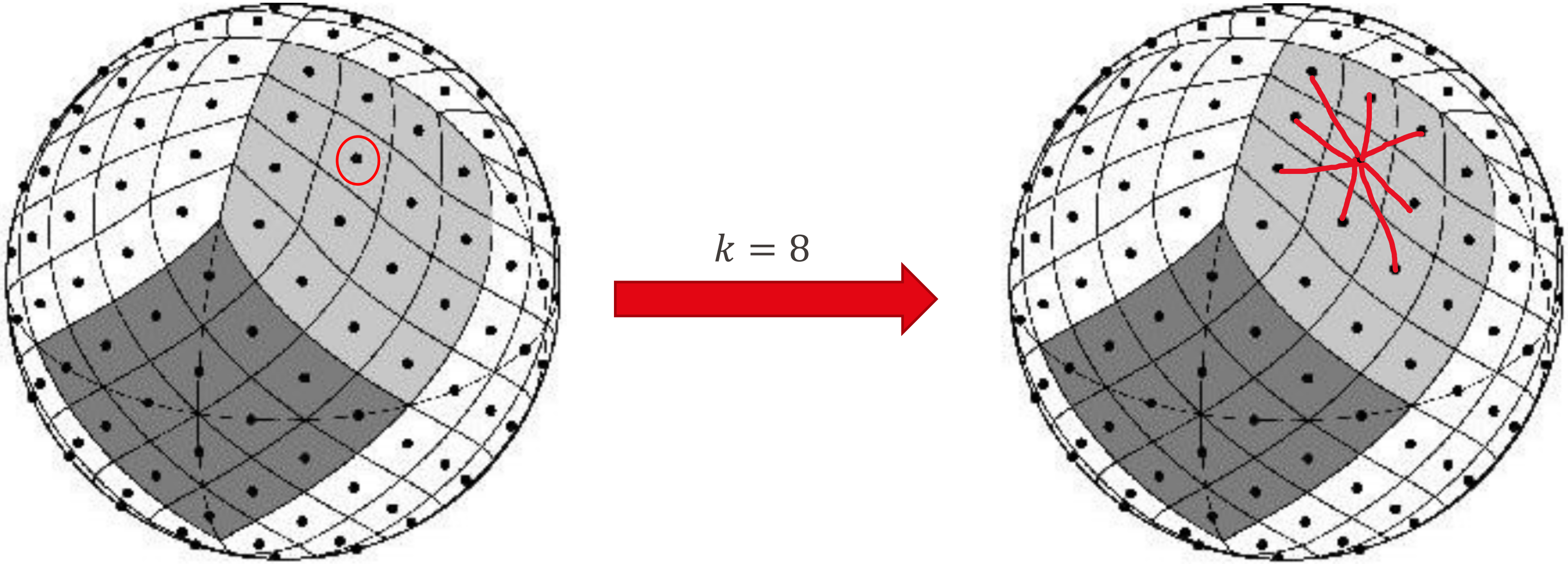
Spherical modeling – Build the graph

k Nearest Neighbors (kNN) graph

- Each nodes is connected to k nearest neighbors undirectedly.
- If we have N nodes, then we have kN edges.



https://healpix.sourceforge.io/

Spherical modeling – Computation on the graph

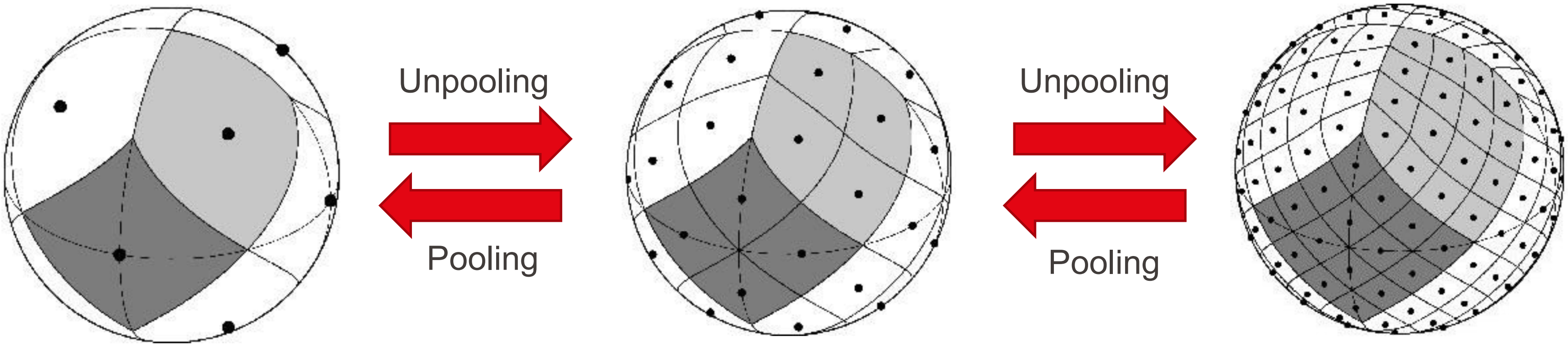
Graph convolution

1. Fourier transform to frequency domain
2. Multiply with (learnable) kernel function
3. Inverse Fourier transform

Graph pooling / unpooling

1. Max / Average aggregation
- Not applicable to all spherical sampling
- Easy to implement

2. General interpolation
- Applicable to all spherical sampling



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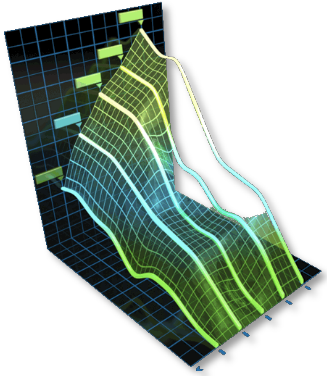

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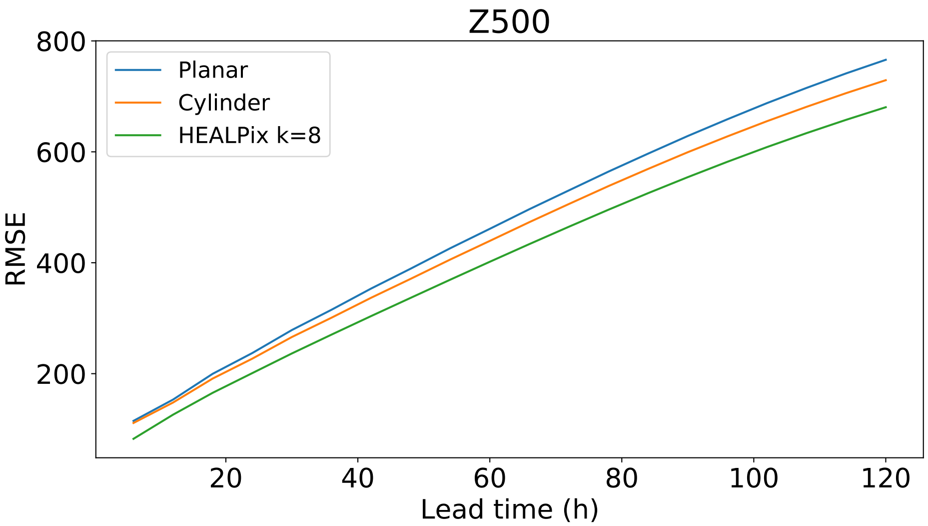
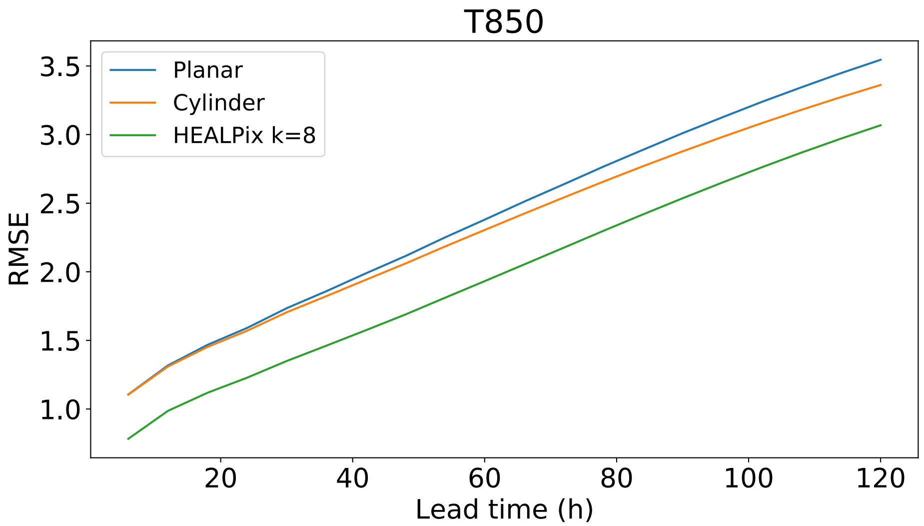
Accuracy and efficiency





For fair comparison, the HEALPix data are interpolated from planar/cylinder data

Accuracy and efficiency - Scalability

Scalability matters:

- In real life, spatial resolution can be less than 50 km (Large graph)
- The model need to handle real case efficiently (One of our motivation)

Accuracy and efficiency - Scalability on N

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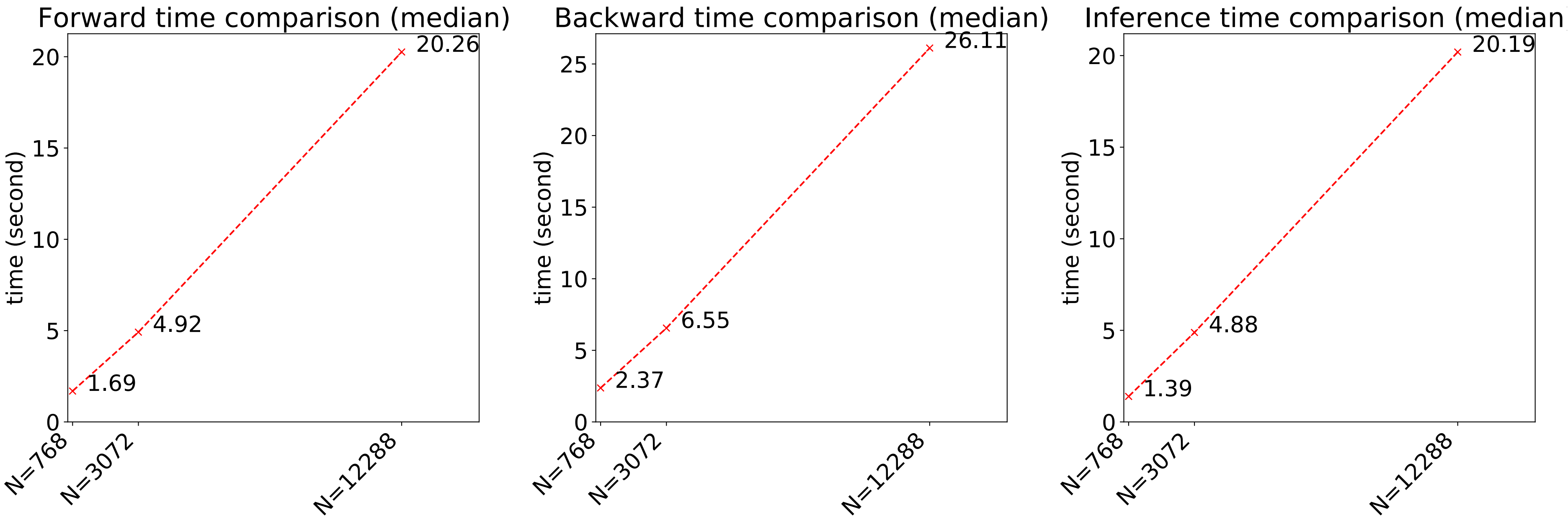

Accuracy and efficiency - Scalability on k

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Scalability matters:
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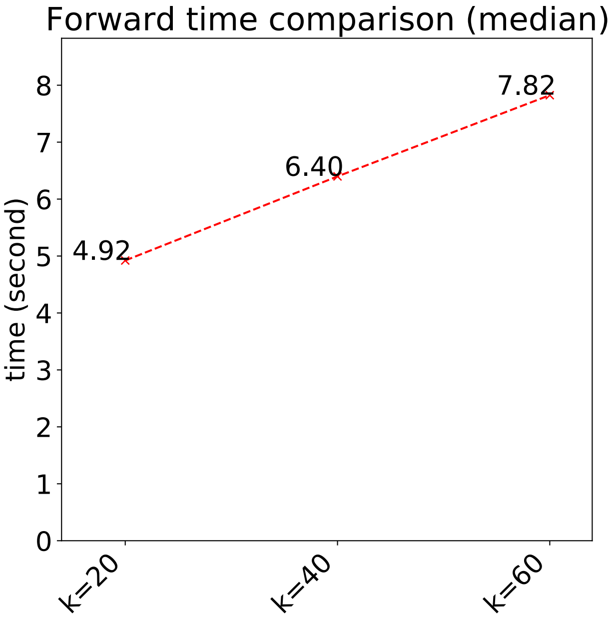

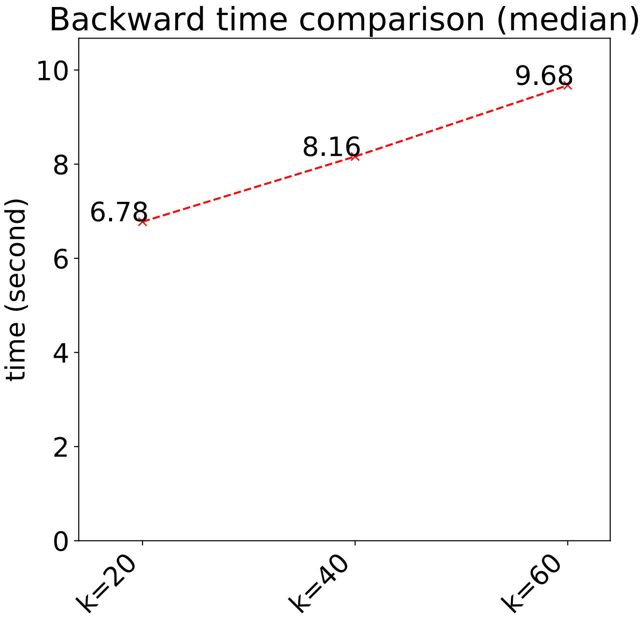

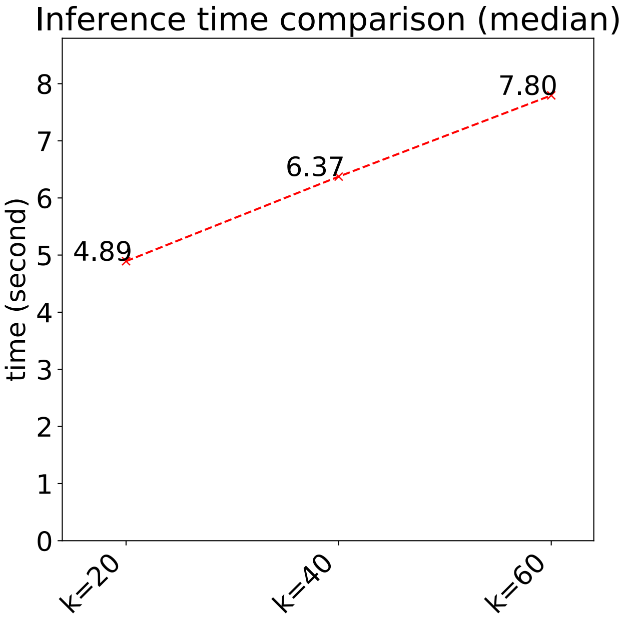

Accuracy and efficiency - Costs

What kind of infrastructure we need to run the following model?

- $N = 12288$ (approx. 200km)
- $k = 20$
- Process 15 graphs in parallel

?

or

- $N = 196608$ (approx. 50km)
- $k = 20$
- Process 1 graph

Answer: Single GTX 1080Ti with 8GB free graphical memory

😉

Multiple GPUs can

- Process larger graph
- Process larger batch
- Accelerate the learning

Conclusion until now

1. Spherical modeling better approximates the earth
   - No information lost on borders
   - Graph evenly represents balanced sampling
2. The approximation quality can be adjusted by the number of sampling points
   - More sampling points mean smaller polyhedrons to approximate sphere
3. The computation complexity increases linearly
   - The ability to handle high resolution data
4. Lower requirements for infrastructures than classical NWP.
   - Single GPU can run the experiments efficiently
   - Multiple GPUs are capable of high-resolution simulation.

Reference

1. Images sources:
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   - https://github.com/epfl-lts2/pygsp
   - https://pixabay.com/
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4. Icíar Lloréns Jover, Geometric deep learning for medium-range weather prediction

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