Improving the Efficiency and Scalability of Anemoi

5th ECMWF-ESA Machine Learning Workshop

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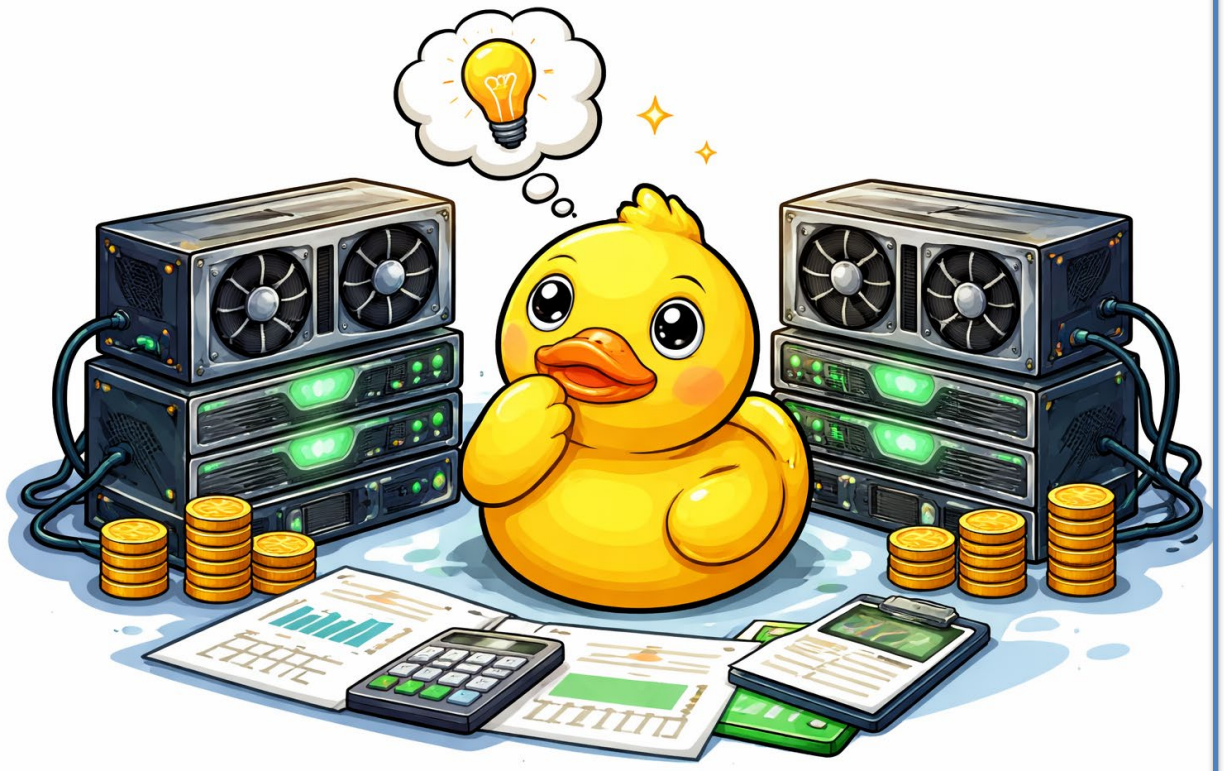
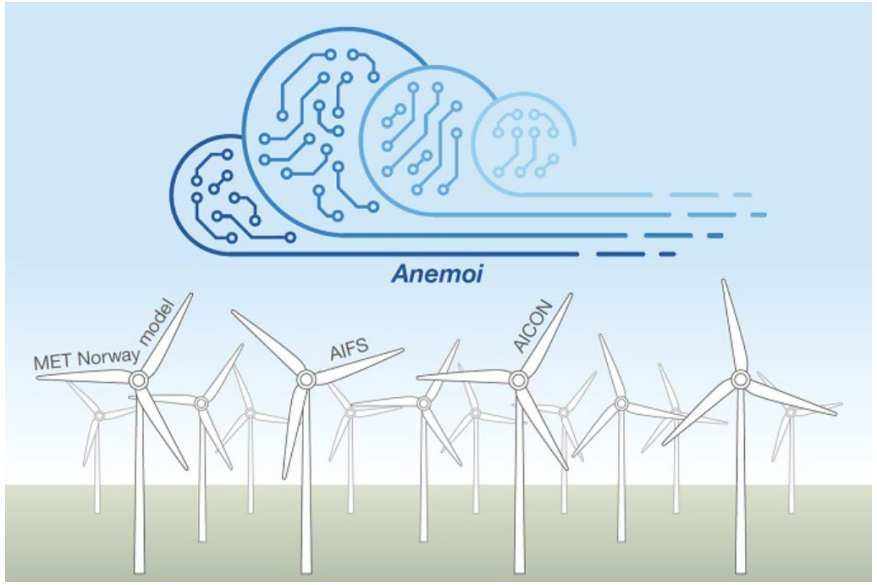
Efficiency vs Scalability

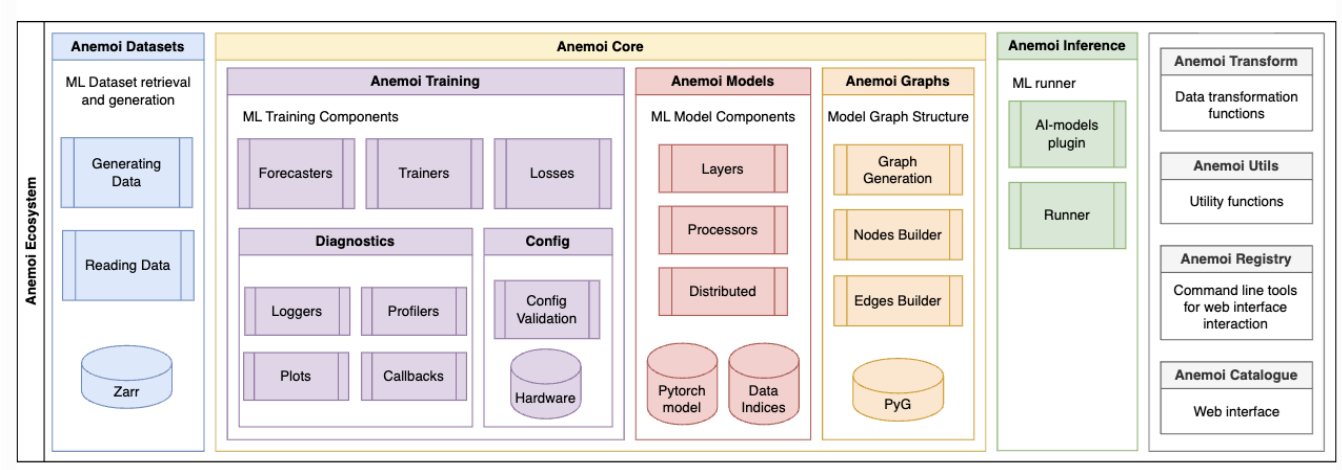


How do we achieve both across models, resolutions, and tasks?

Anemoi

- Anemoi is an open-source framework that provides a complete toolkit to develop data-driven weather models – from data preparation through to inference
- It's a highly modular framework organised into different Python packages
- The framework builds upon on established Python tool including PyTorch, Pytorch Lighting, Hydra, Pydantic, and earthkit.

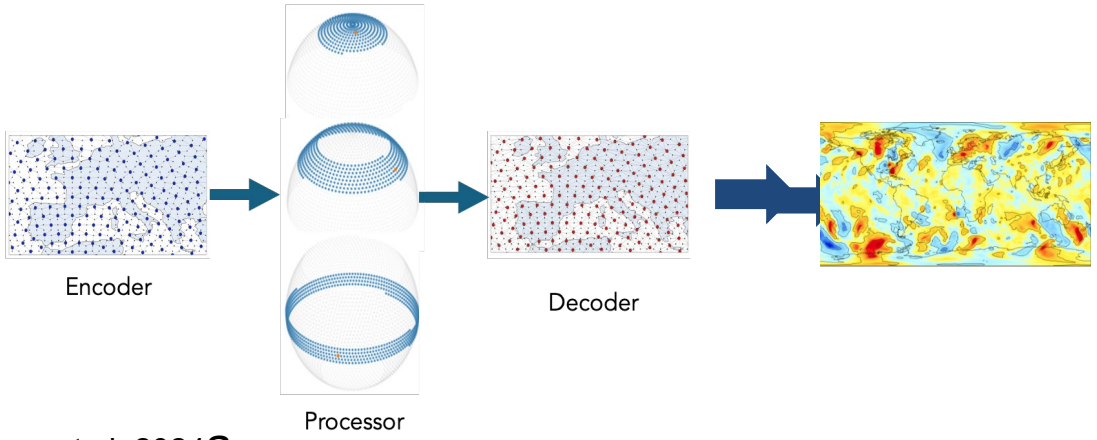




Many Models, One Framework

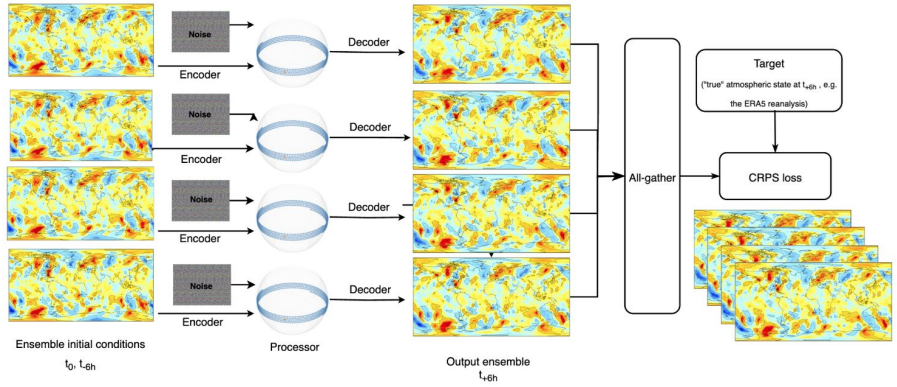
- Deterministic and Probabilistic Models

Deterministic Model



Lang et al. 2024a

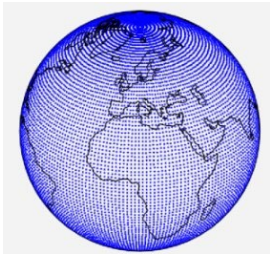
Probabilistic Model - Learn an ensemble via optimization of a probabilistic score



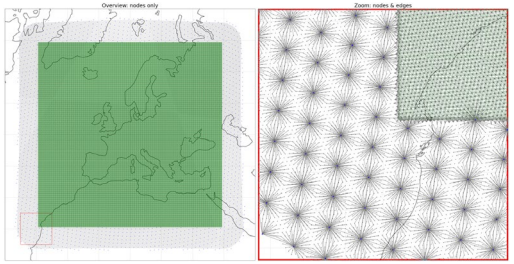
Lang et al. 2024b

https://arxiv.org/abs/2406.01465
https://arxiv.org/abs/2412.15832
https://arxiv.org/abs/2409.02891

- Global and Regional Area Models



Global Model

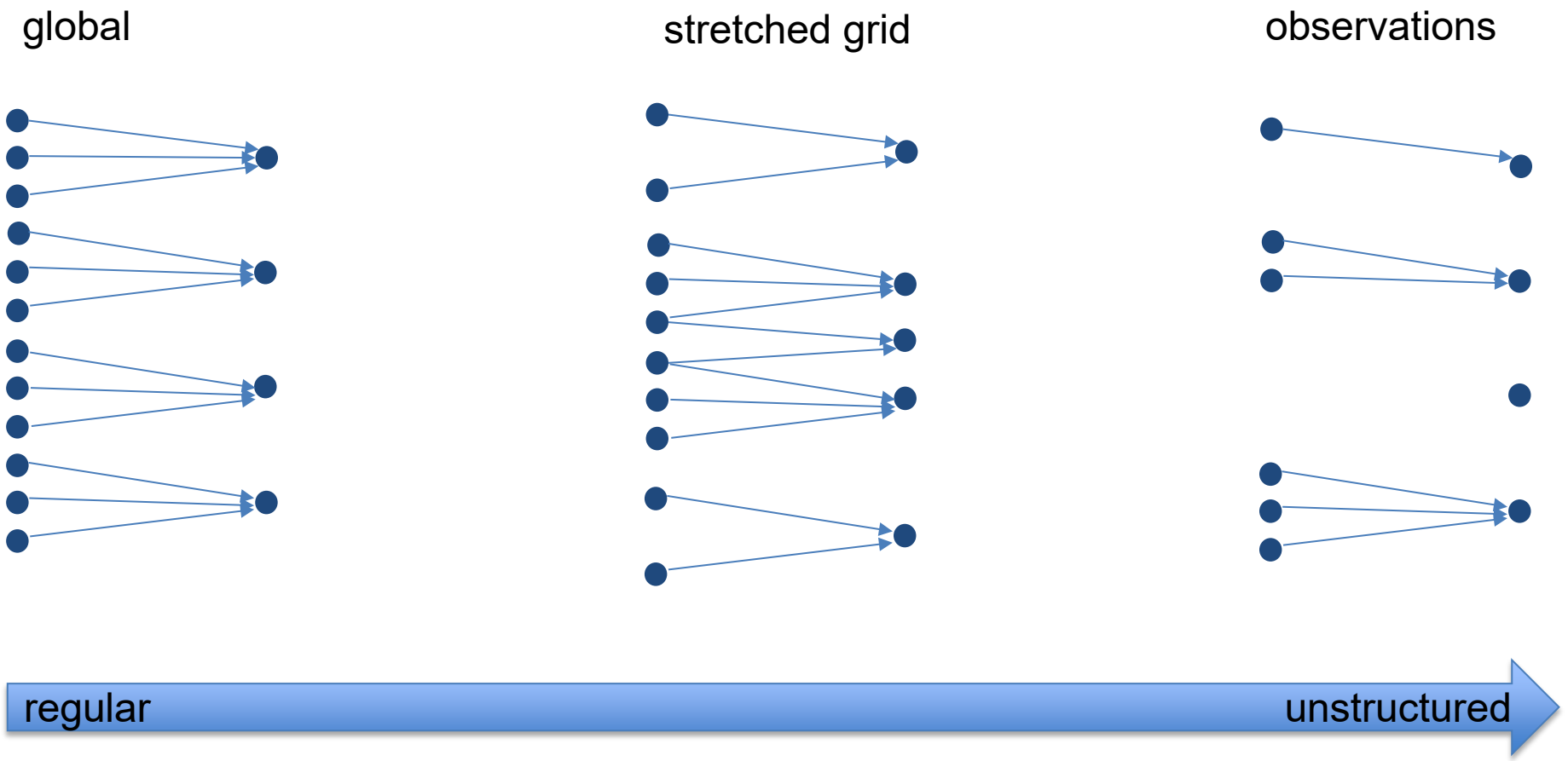


LAM

Nipen et al. 2024

Stretched Grid Model

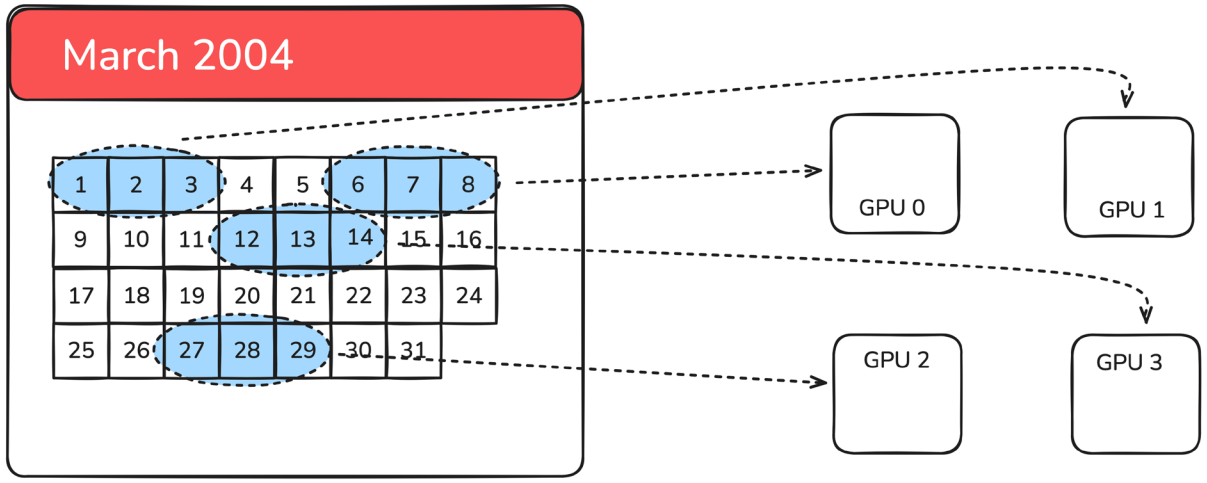
Everything is a Graph



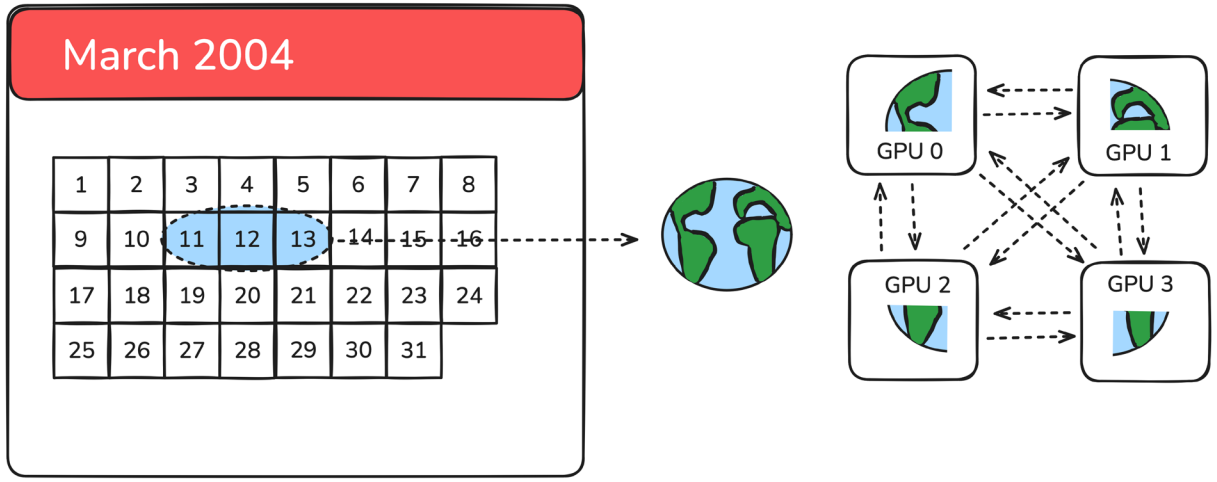
optimise the graph operations -> improvements across models

Parallelism in Anemoi

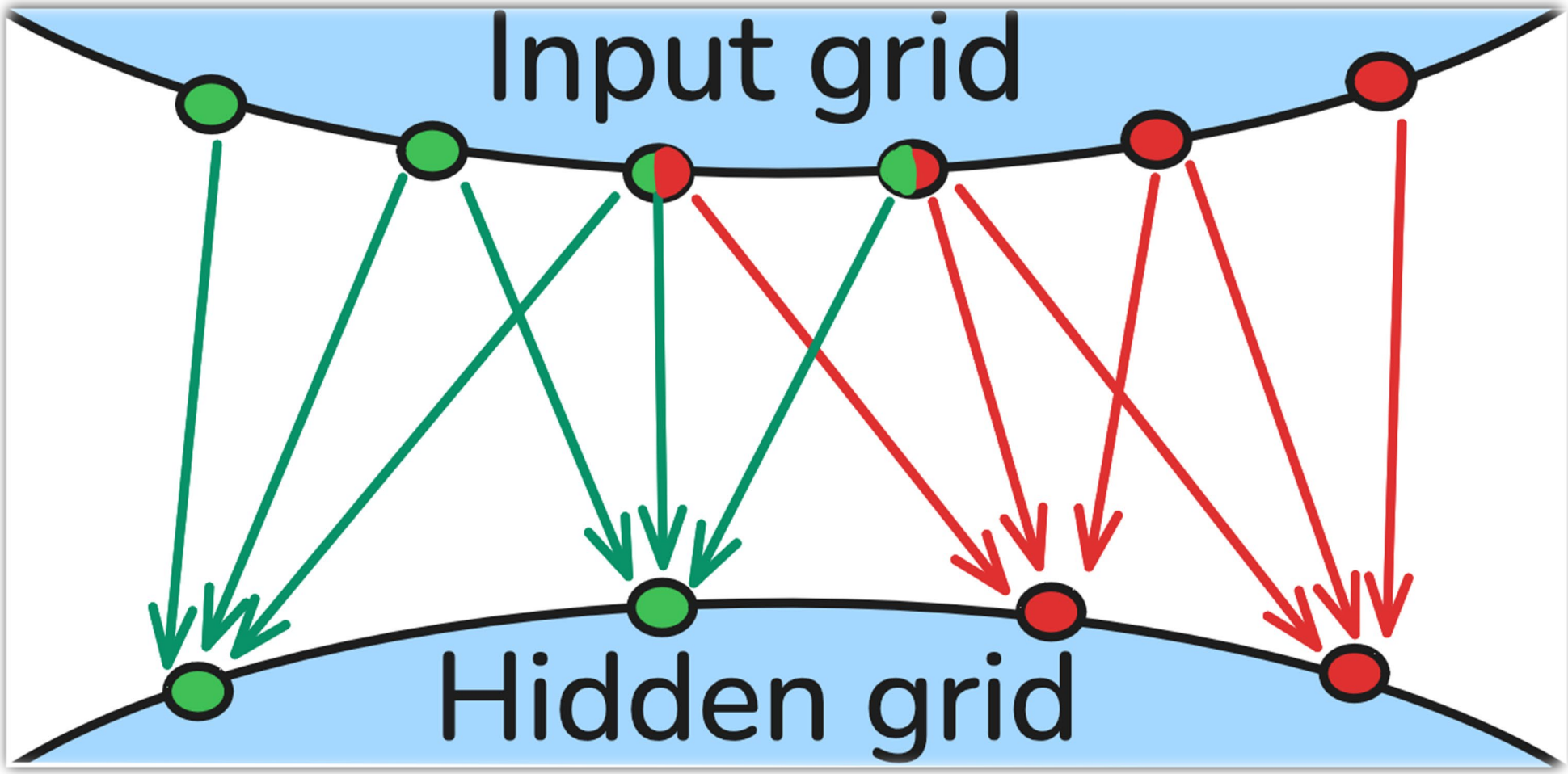
- Data Parallelism: DistributedDataParallel (PyTorch)
  - Distribute training batch across model replicas
  - Aggregate gradients via all-reduce, good scaling :)
  - Limited by batch size :(



- Model parallelism: domain-specific sharding
  - Distribute input data and activations across GPUs
  - Collective communication to handle synchronisation
  - Limited by communication overheads

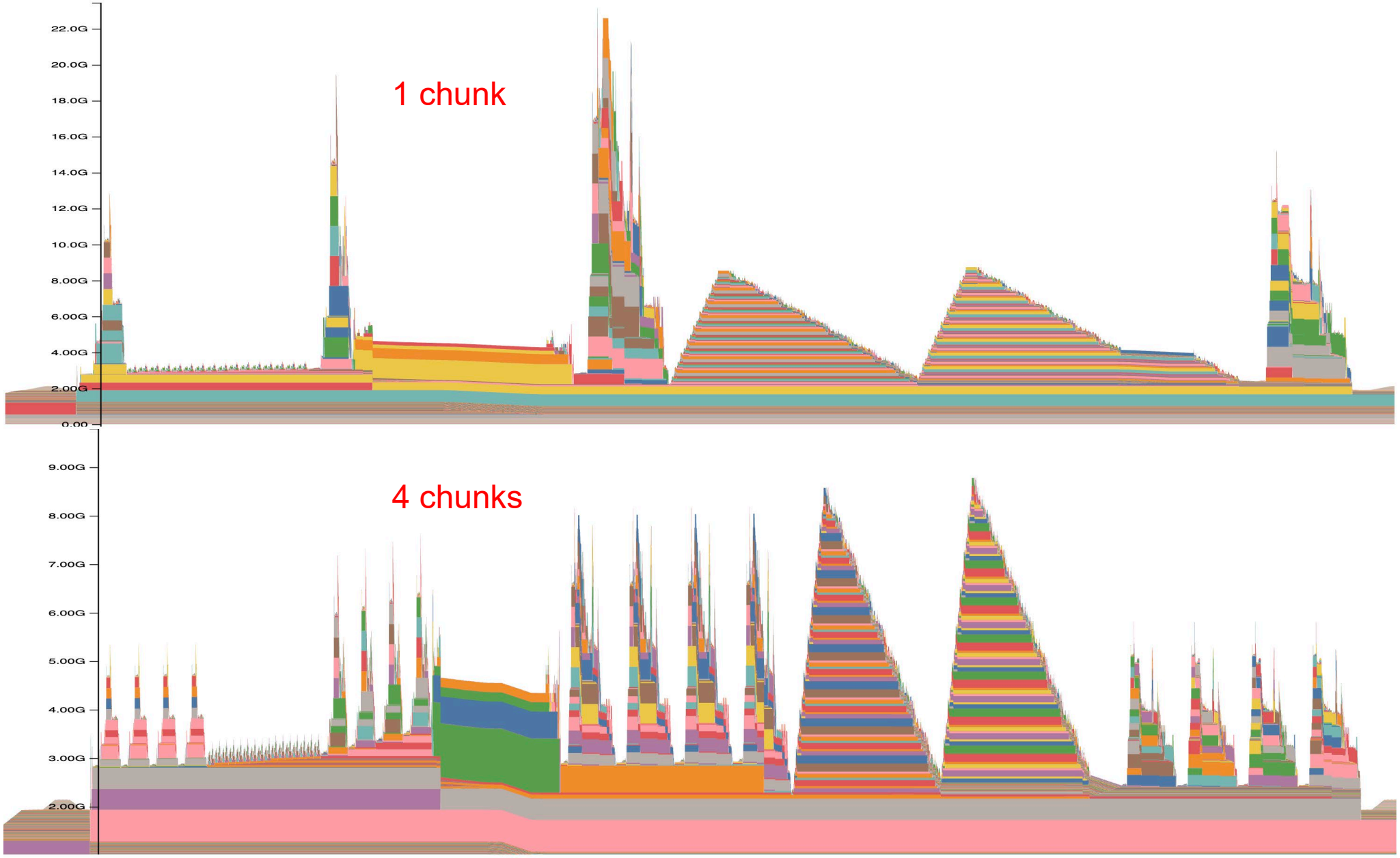


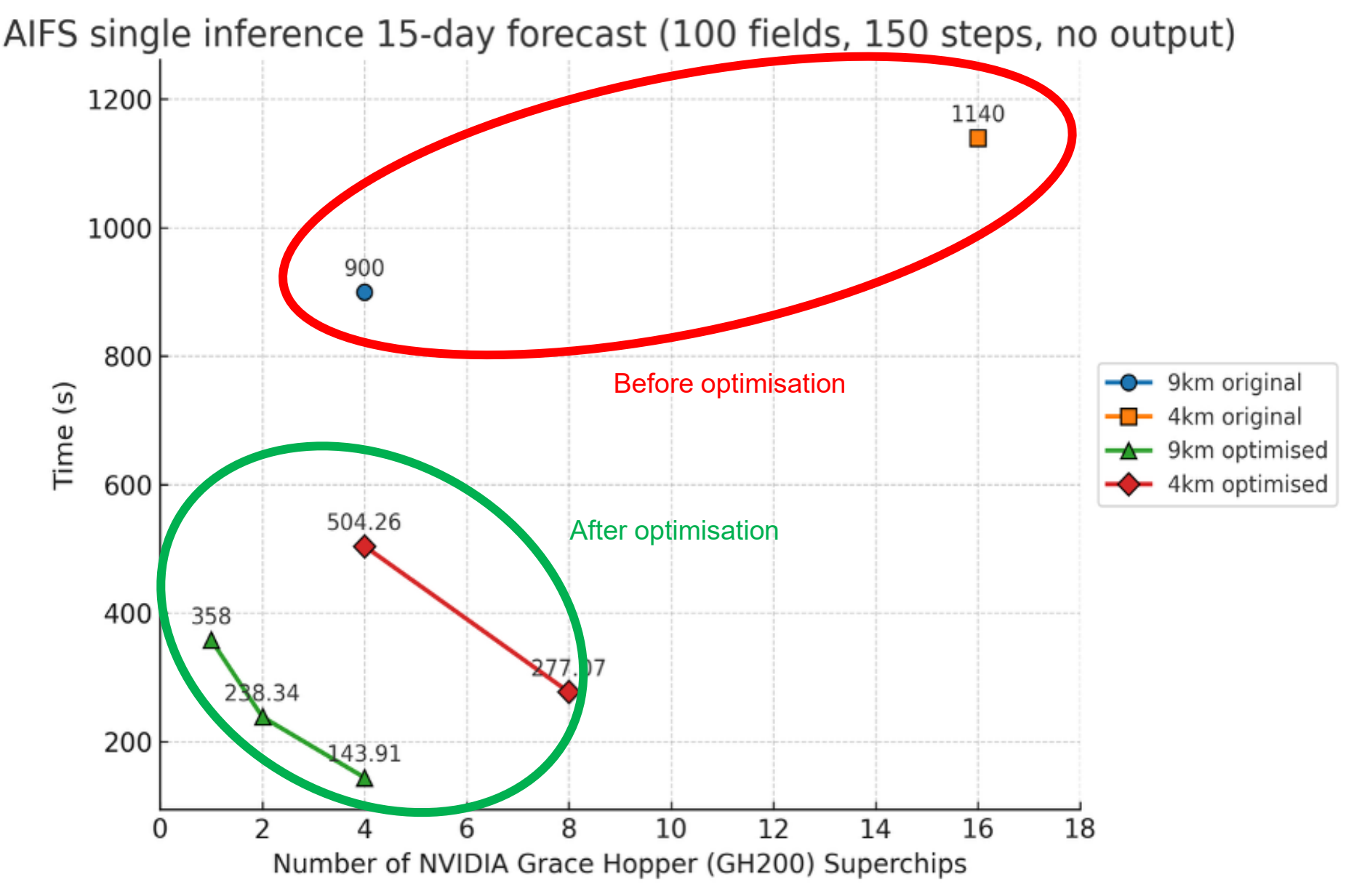
Partitioning the Graph



Same idea enables both multi-GPU parallelism and sequential processing

Reducing Activation Memory




AIFS single inference 15-day forecast (100 fields, 150 steps, no output)
Time (s)
Number of NVIDIA Grace Hopper (GH200) Superchips
1200
1000
800
600
400
200
0
2
4
6
8
10
12
14
16
18
1140
900
Before optimisation
After optimisation
504.26
358
238.34
143.91
277.07
9km original
4km original
9km optimised
4km optimised

Efficient Graph Kernels in Triton

- GraphTransformer kernel
  - flash-attn style online softmax
  - no atomics, aggregate per-node
  - CSC edge layout for optimized memory access patterns
- Fast KNN on regular grids (WIP)
  - fast dynamic graph construction for obs
  - ~10x vs torchcluster

GraphTransformer Triton Kernel

H200

Graph type	PyG	PyG (compiled)	Triton
era_to_h	23.97	6.02	**2.77**
h_to_h	9.64	1.69	**0.83**
h_to_era	46.99	8.16	**4.87**
dop_enc	26.62	6.85	**3.86**

Exemplary impact on training for an o800 lvl7 GraphTransformer model in bf16 on H200s:
pyg compiled: 3.90 s/it → Triton: 2.62 s/it (×1.5 faster)

2x speedup across different graphs

Summary:

Optimising graph operations enables efficiency and scalability across models and tasks.

Next Steps

- fully local communication via halo exchange
- support for observations (dynamic, unstructured)
- explore parameter sharding