Anemoi
Overview, Datasets and Inference

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And

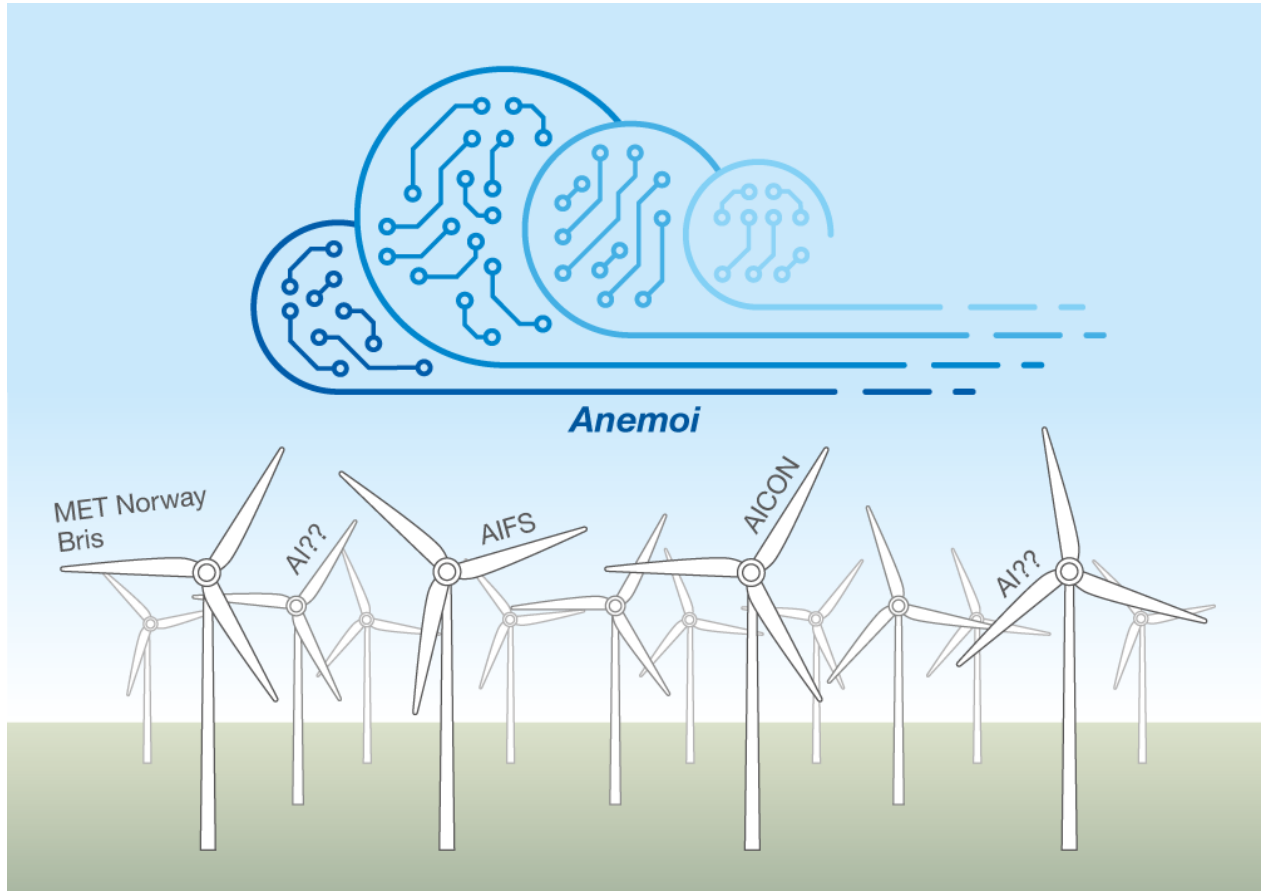
Harrison Cook

Goals

- Develop an open-source framework to facilitate:
  - the development of data-driven weather forecasts…
  - … and their running in operations

- In collaboration with the Centre's Member States and others
  - Support both global and limited area models

Anemoi



ECMWF 50 EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS

FMI

METEO FRANCE
À VOS CÔTÉS, DANS UN CLIMAT QUI CHANGE

AEMet
Agencia Estatal de Meteorología

Met Office

Koninklijk Nederlands Meteorologisch Instituut
Ministerie van Infrastructuur en Waterstaat

Norwegian Meteorological Institute

SMHI
Swedish Meteorological and Hydrological Institute

ECMWF

MeteoSwiss

anemoi

GeoSphere Austria

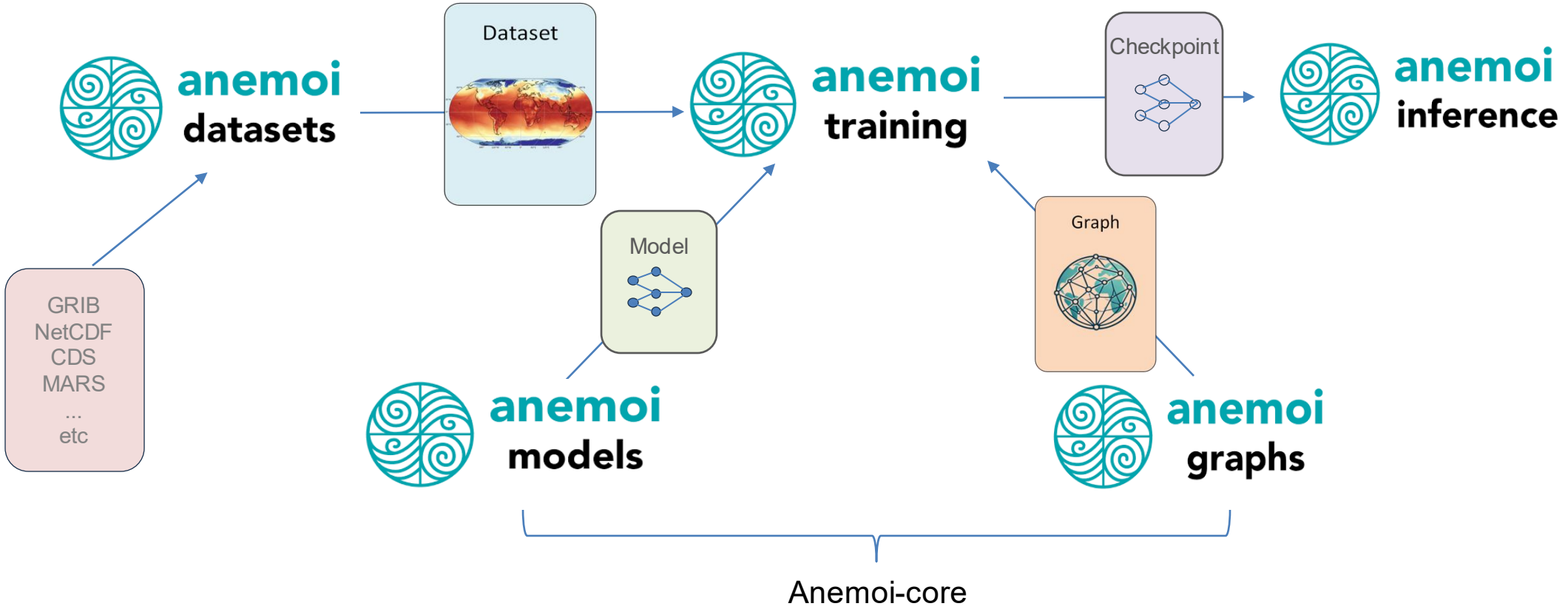
The Danish Meteorological Institute

DWD

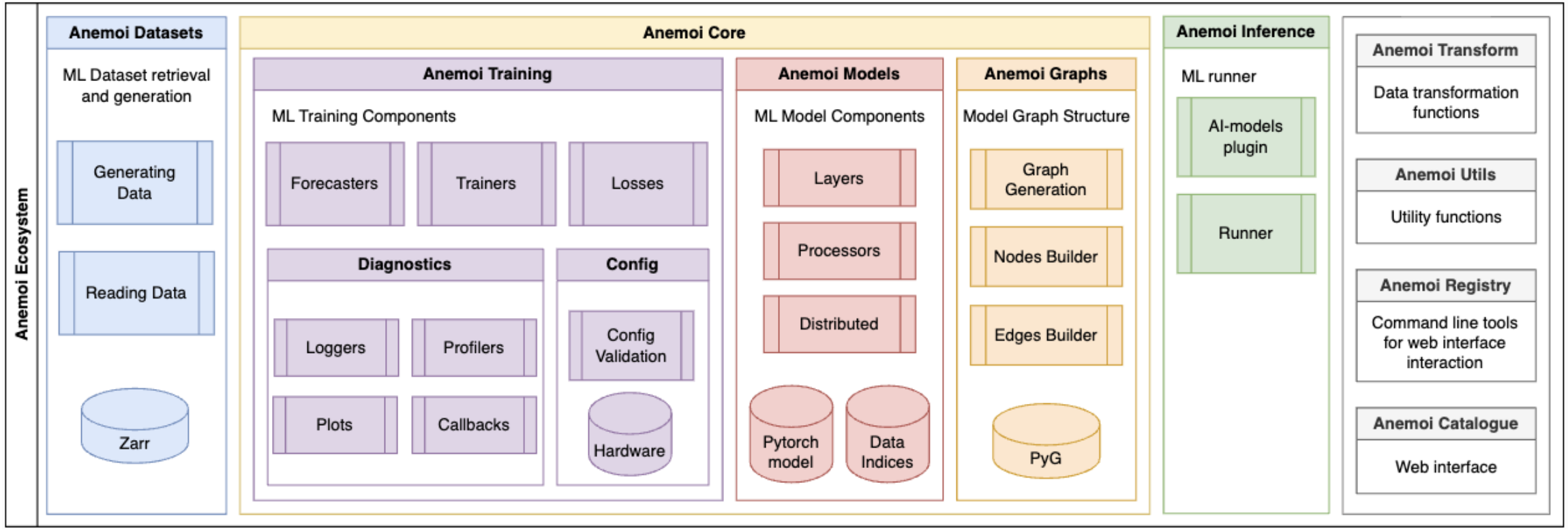
RMI

Anemoi in a Nutshell

- Anemoi is an open-source framework to develop **data-driven meteorological forecasting**.
- Anemoi is developed through a **collaborative European initiative**



Anemoi's modular structure and Python packages



Dependencies: (selection)

earthkit, Zarr, PyTorch, PyG, Numpy, Hydra, Pydantic, PyTorch Lightning, mlflow

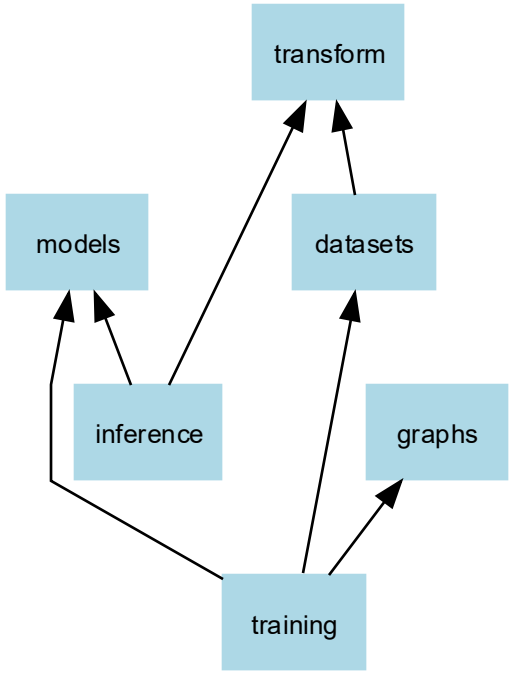
User Base

Modifies Configs for Experimentation and Implemenation of Operational Models

Modifies Codebase to implement new Features and Augment Anemoi Libraries

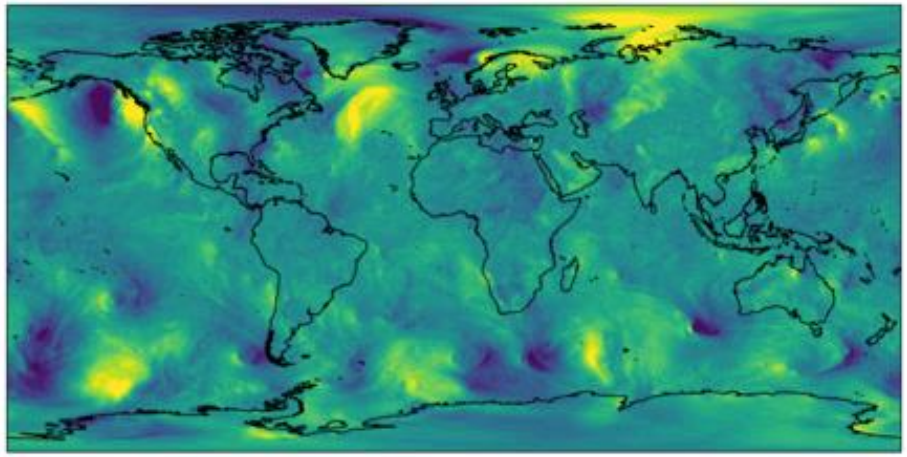
Runs the Anemoi Model in a common interface on reliable infrastructure

Main components - Design decisions



- OO design, heavy use of factories to instantiate object from configs
- Each component provides one or more command line tools
  - `anemoi-datasets create data-config.yaml out.zarr`
  - `anemoi-training train train-config.yaml`
  - `anemoi-inference run inference-config.yaml`
- Minimise software dependencies to facilitate R2O
  - Inference and training are independent
- Each component collects “metadata” that can be used by the others

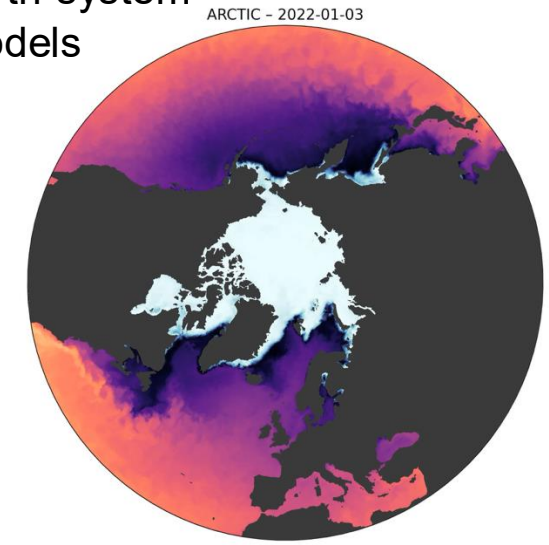
What Anemoi enables?

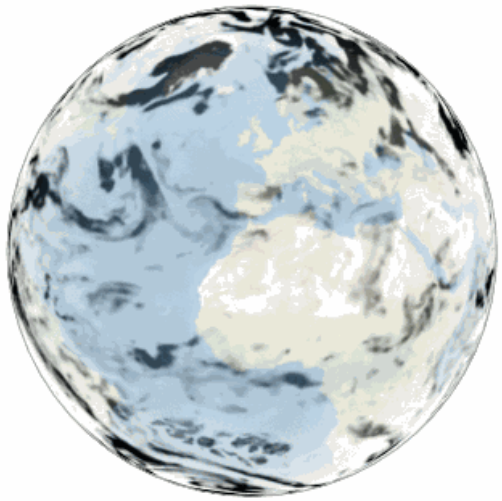


Training deterministic & ensemble models

Lang et al. 2024a & b

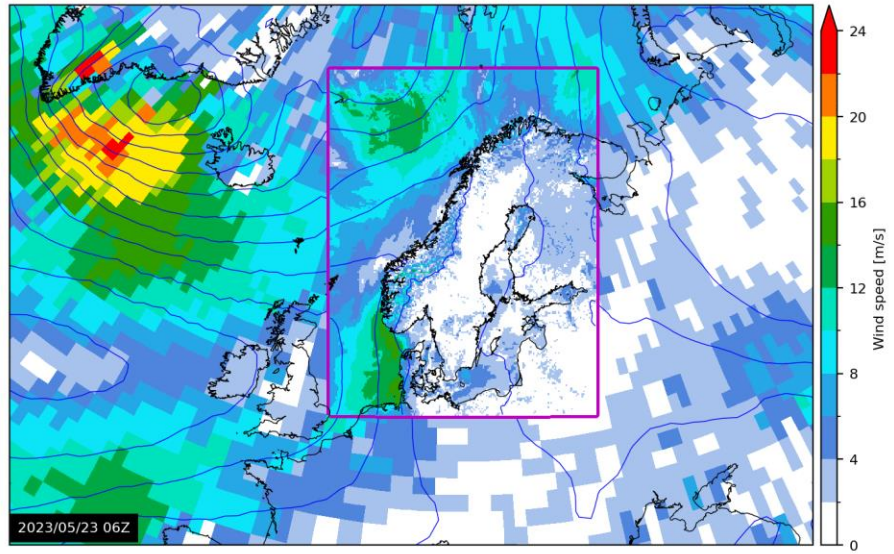
Building coupled earth-system models





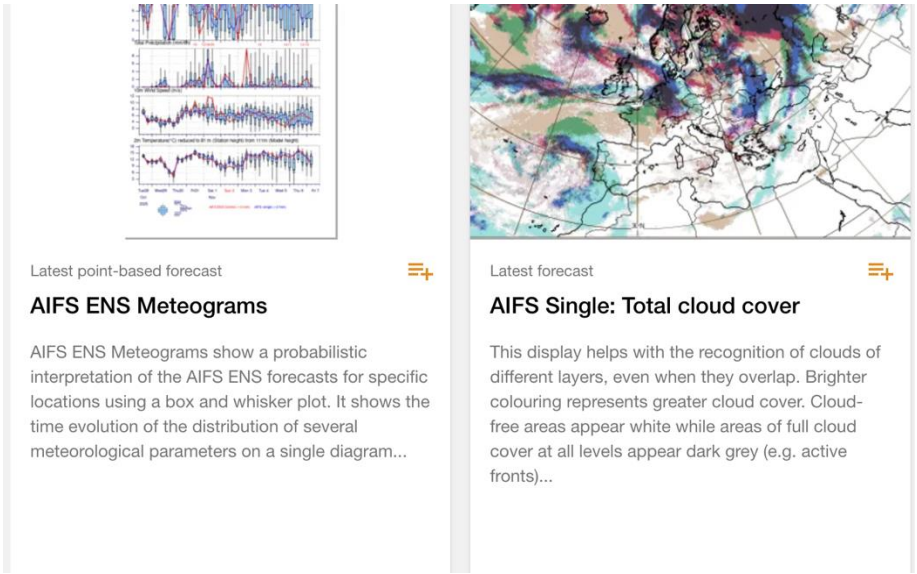
Regional high-resolution modelling:

Nipen et al. 2024



Real-time running at operation centres

Anemoi powers ECMWF's operationalisation of AIFS in 2025.



Anemoi - Datasets

Machine Learning for Weather Prediction - 2025

Matthew Chantry

On behalf of the Anemoi team and contributors

ECMWF

Datasets - Goals

- Create “machine-learning ready” datasets for training data-driven weather forecasts
- Make the loading of data samples as efficient as possible
- Provide rich metadata that can be used in training and inference

Datasets - Non-goals

- Is not a replacement for the original source of data
- Consider the datasets created by anemoi-datasets is pre-processed data that are as close as possible to the needs of training

Training data-driven forecasts

- A “sample” is the state of the atmosphere a time T
- We want to train a model that, given the state of the atmosphere a time T returns the state of the atmosphere a T+1
- The state of the atmosphere is a collections of meteorological fields (variables)
  - 2m temperature, surface pressure,…
  - geopotential, winds, temperature on 1000 hPa, 500 hPa, …

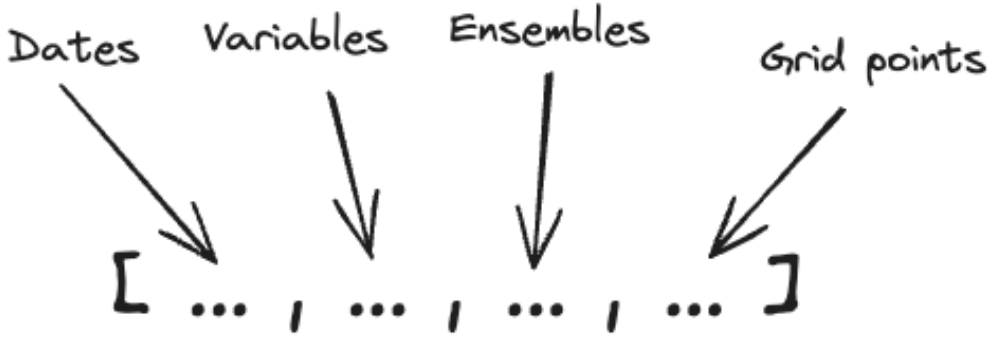
Training a weather forecast

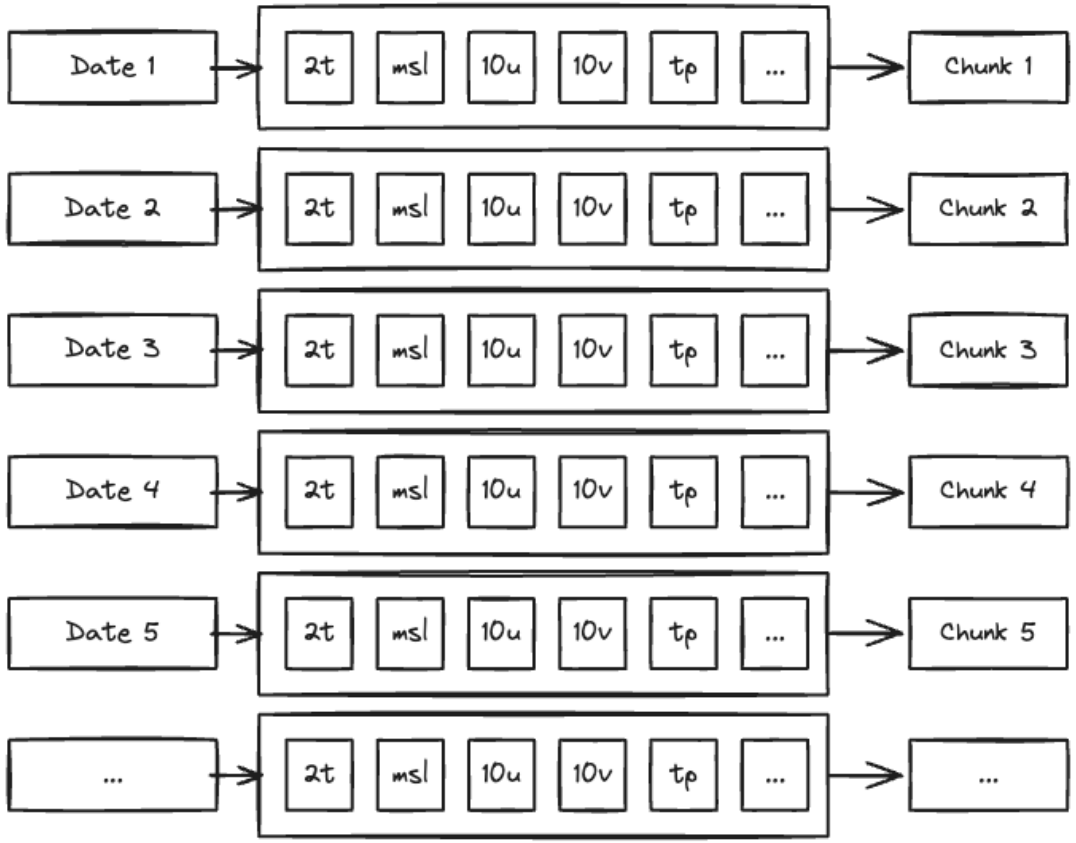
```
x, y = ds[n : n + 1]
y_hat = model.predict(x)
loss = model.loss(y, y_hat)
```

- A dataset like ERA5 is too large to fit in memory
- We need to store the data on a filesystem
- We want to create a dataset where each sample is one retrieval operation

Using Zarr

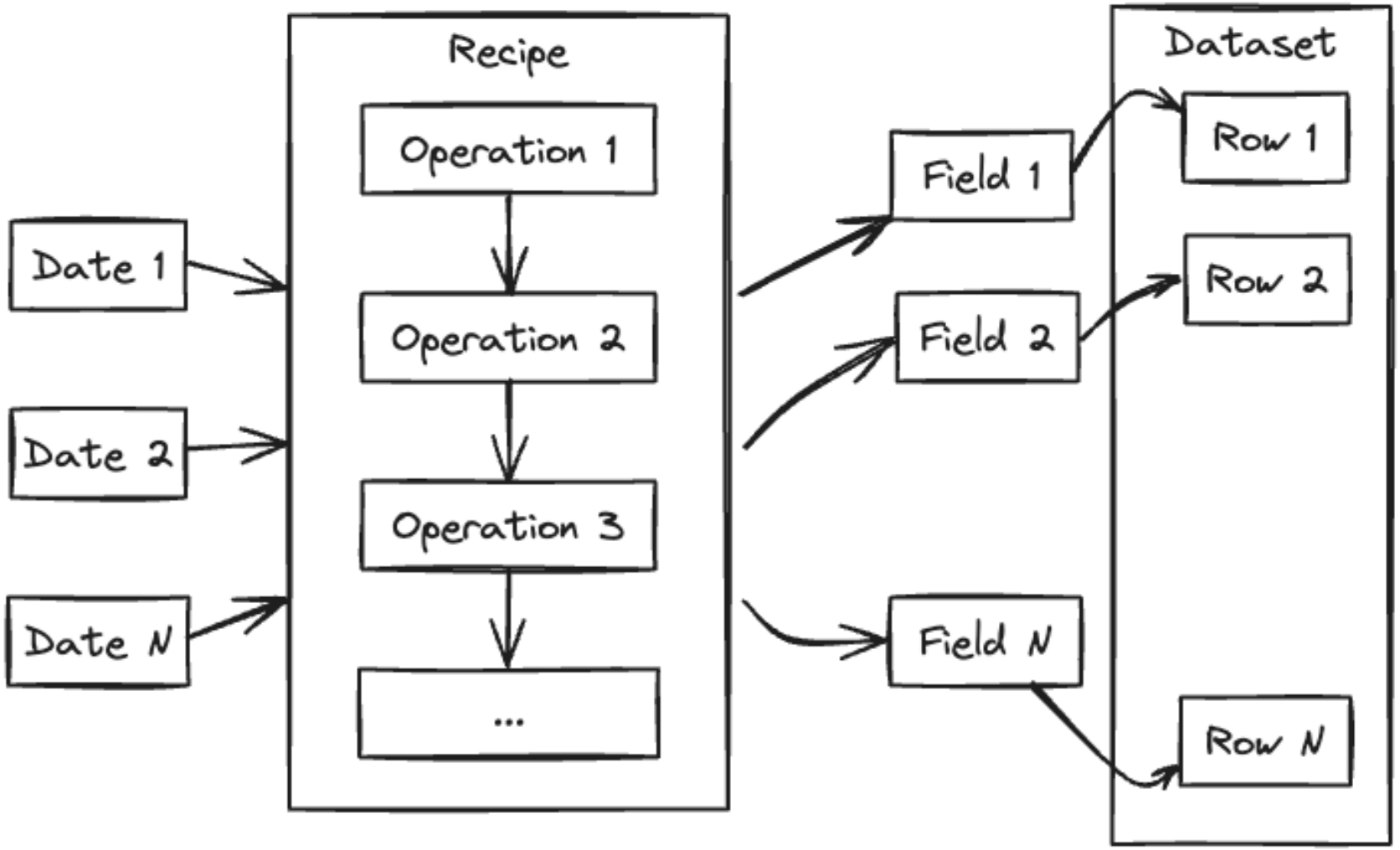
- The Zarr format is a good fit for the requirements
- It offers an array-like view on a collection of files (chunks)
- We use it to define an array that match exactly a sample
- Each file is a single date





Building datasets

Datasets are built from a recipe



Recipes are YAML files

```yaml
dates:
    start: 2024-01-01T00:00:00Z
    end: 2024-01-01T18:00:00Z
    frequency: 6h

input:
    grib:
        param: [2t, msl, 10u, 10v, lsm]
        path: /path/to/some/data.grib
```

Then:

```
% anemoi-datasets create recipe.yaml dataset.zarr
```

Join

The join is the process of combining several sources data. Each source is expected to provide different variables at the same dates.

```
input:
  join:
    - source1:
        ...
    - source2:
        ...
    - source3:
        ...
    - ...
```

Pipe

The pipe is the process of transforming fields using filters. The first step of a pipe is typically a source. The following steps are filters.

```
input:
  pipe:
    - source
        ...
    - filter1
        ...
    - filter2
        ...
    - ...
```

Concat

The concatenation is the process of combining different sets of operation that handle different dates.

```
input:
  concat:
  - dates:
      start: 2020-12-30 00:00:00
      end: 2021-01-01 12:00:00
      frequency: 12h

    source1:
      ...

  - dates:
      start: 2021-01-02 00:00:00
      end: 2021-01-03 12:00:00
      frequency: 12h

    source2:
      ...
```

Statistics gathering

- By defaults, the statistics are not computed on the whole dataset, but on a subset of dates.
- The dates subset used to compute the statistics is defined using the following algorithm:
  - If the dataset covers 20 years or more, the last 3 years are excluded.
  - If the dataset covers 10 years or more, the last year is excluded.
  - Otherwise, 80% of the dataset is used.
  - Using user provided dates

```
statistics:
    end: 2020
```

- By default, statistics will fail if a NaN is found. You can change that:

```
statistics:
    allow_nans: true
```

- Statistics of increments can also be computed:
  - 1h, 3h, 6h 12h and 24h increments

General purposes sources

Name	Description

grib	Access grib files on disk
	
	`input:`
	`  grib:`
	`  param:[msl, 2t]`
	`  path:/path/to/file.grib`

netcdf	Access NetCDF files on disk (xarray-based)
	
	`input:`
	`  netcdf:`
	`  path:/path/to/file.nc`

opendap	Access OpenDAP servers (xarray-based)
	
	`input:`
	`  opendap:`
	`  url: http://`

xarray-zarr	Access file-based or cloud-based Zarr (xarray-based)
	`input:`
	`  xarray-zarr:`
	`  url: http://`

xarray-kerchunk	Experimental: Access kerchunk datasets (xarray-based)
zenodo	Experimental: access a dataset given a Zenodo DOI

Filters

Name	Description
apply-mask	Apply a mask to the fields (set values to NaN according to a mask)
rotate_wind/unrotate_wind	Rotate wind vectors
rename	Rename variables
regrid	Interpolate input fields to a different grid
rescale	Apply unit conversions
orog_to_z	Convert orography (m) to z (geopotential height)
uv-2-ddff/ddff-2-uv	Convert wind components between cartesian and polar coordinates
wz_to_w	Convert geometric vertical velocity (m/s) to vertical velocity (Pa/s)

- This is only a small selection, work in progress
- Some sites implement their own filters

Using datasets

Introduction

To open a dataset, use the `open_dataset` function:

```
from anemoi.datasets import open_dataset

ds = open_dataset("/path/to/dataset.zarr")
```

You can then access the data in the dataset using the `ds` object as if it was a **NumPy** array:

```
print(ds.shape)
print(len(ds))
print(ds[0])
print(ds[10:20])
```

Introduction (cont.)

One of the main features is the ability to subset:

```
from anemoi.datasets import open_dataset

ds = open_dataset("path/to/dataset.zarr",
                  start=2000,
                  end=2020)
```

or combine datasets:

```
from anemoi.datasets import open_dataset

ds = open_dataset("path/to/dataset1.zarr",
                  "path/to/dataset2.zarr")
```

Opening a dataset

```
from anemoi.datasets import open_dataset

ds = open_dataset(dataset,
                  option1=value1,
                  option2=...)
```

or

```
ds = open_dataset({"dataset": dataset,
                   "option1"=value1,
                   "option2"=...})
```

Selecting variables

```
ds = open_dataset(dataset,
                  select=["2t", "tp"])

ds = open_dataset(dataset,
                  select={"2t", "tp"})

ds = open_dataset(dataset,
                  drop=["10u", "10v"])
```

Reordering variables

… using a list

```
ds = open_dataset(
    dataset,
    reorder=["2t", "msl", "sp", "10u", "10v"],
)
```

… or using a dictionary

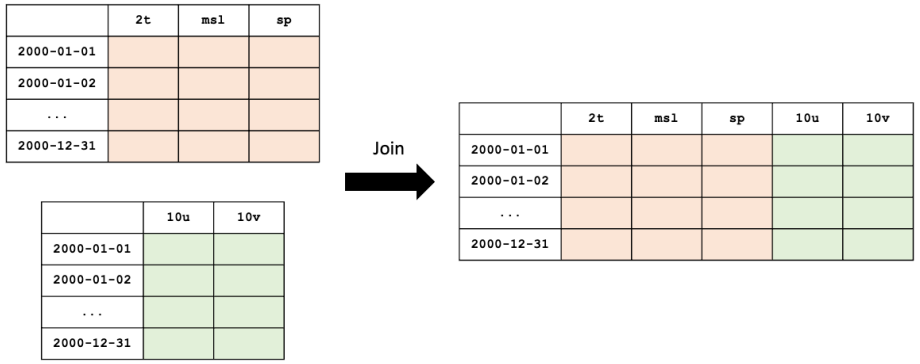
```
ds = open_dataset(
    dataset,
    reorder={
        "2t":  0,
        "msl": 1,
        "sp":  2,
        "10u": 3,
        "10v": 4,
    },
)
```

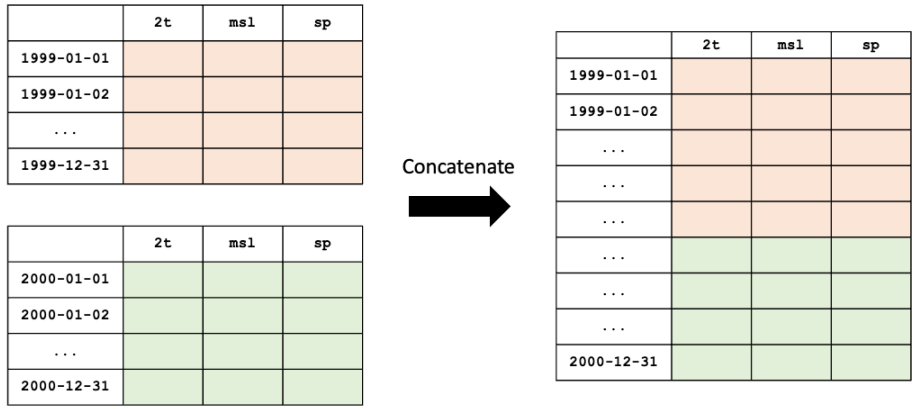
anemoi-datasets (usage)

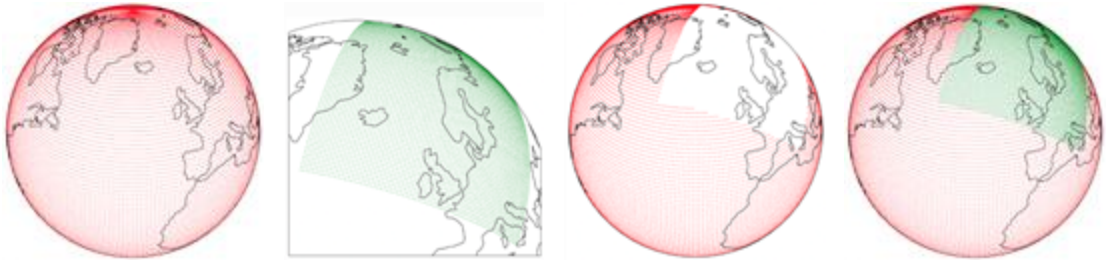
- When used, datasets can be lazily combined into “virtual” datasets
  - Allowing researchers to find the best combinations of variables for their training needs

```python
from anemoi.datasets import open_dataset

ds = open_dataset(
    [
        {
            "dataset": "aifs-od-an-oper-0001-mars-o96-2016-2023-6h-v6",
            "drop": ["sp", "2d", "skt", "tcw", "cp"],
            "end": 2023,
            "frequency": "6h",
        },
        {
            "dataset": "aifs-od-an-oper-0001-mars-o96-2016-2023-6h-v1-precipitations",
            "end": 2023,
            "frequency": "6h",
            "rename": {"tp_0h_12h": "tp"},
            "select": ["tp_0h_12h"],
        },
    ],
    end=202311,
)
```



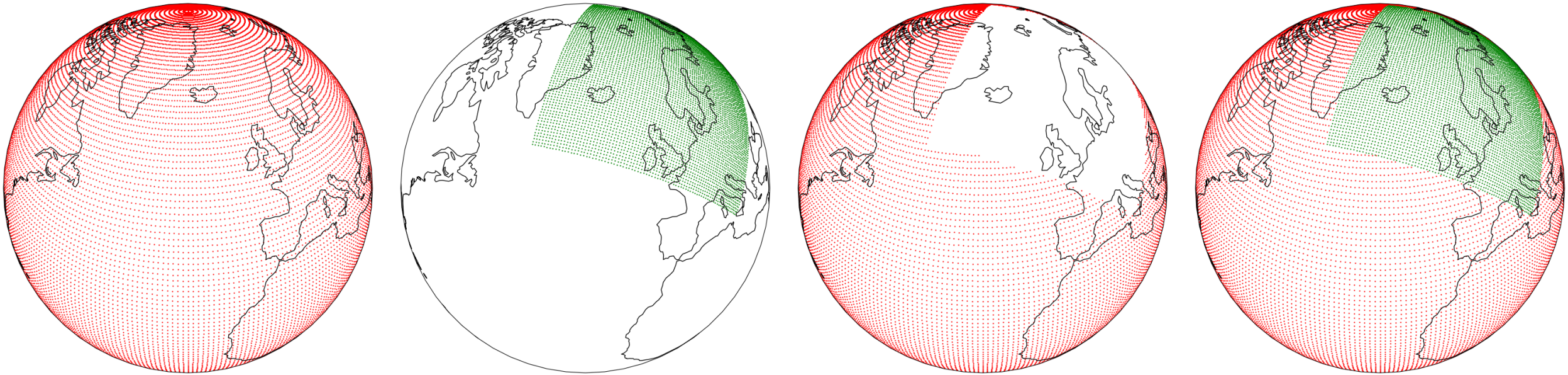




Cutout - Use to combine limited are models and global models

```
from anemoi.datasets import open_dataset

ds = open_dataset(cutout=[lam_dataset,
                          global_dataset])
```



Attributes

Attribute	Description
shape	A tuple of the dataset's dimensions.
field_shape	The original shape of a single field, either 1D or 2D. When building datasets, the fields are flattened to 1D.
dtype	The dataset's NumPy data type.
dates	The dataset's dates, as a NumPy vector of datetime64 objects.
frequency	The dataset's frequency (i.e the delta between two consecutive dates)
latitudes	The dataset's latitudes as a NumPy vector.
longitudes	The dataset's longitudes as a NumPy vector.
statistics	(Next slide)
resolution	The dataset's resolution.
name_to_index	A dictionary mapping variable names to their indices. `print(dataset.name_to_index["2t"])`
variables	A list of the dataset's variable names, in the order they appear in the dataset.
missing	The set of indices of the missing dates.

Statistics

```
ds = open_dataset(…)
stats = ds.statistics

stats["mean"]
stats["stdev"]
stats["minimum"]
stats["maximum"]


idx = ds.name_to_index("msl")

print(stats["mean"][idx], stats["stdev"][idx])
```

When combining datasets, the statistics of the first encountered dataset is used

Anemoi - Inference

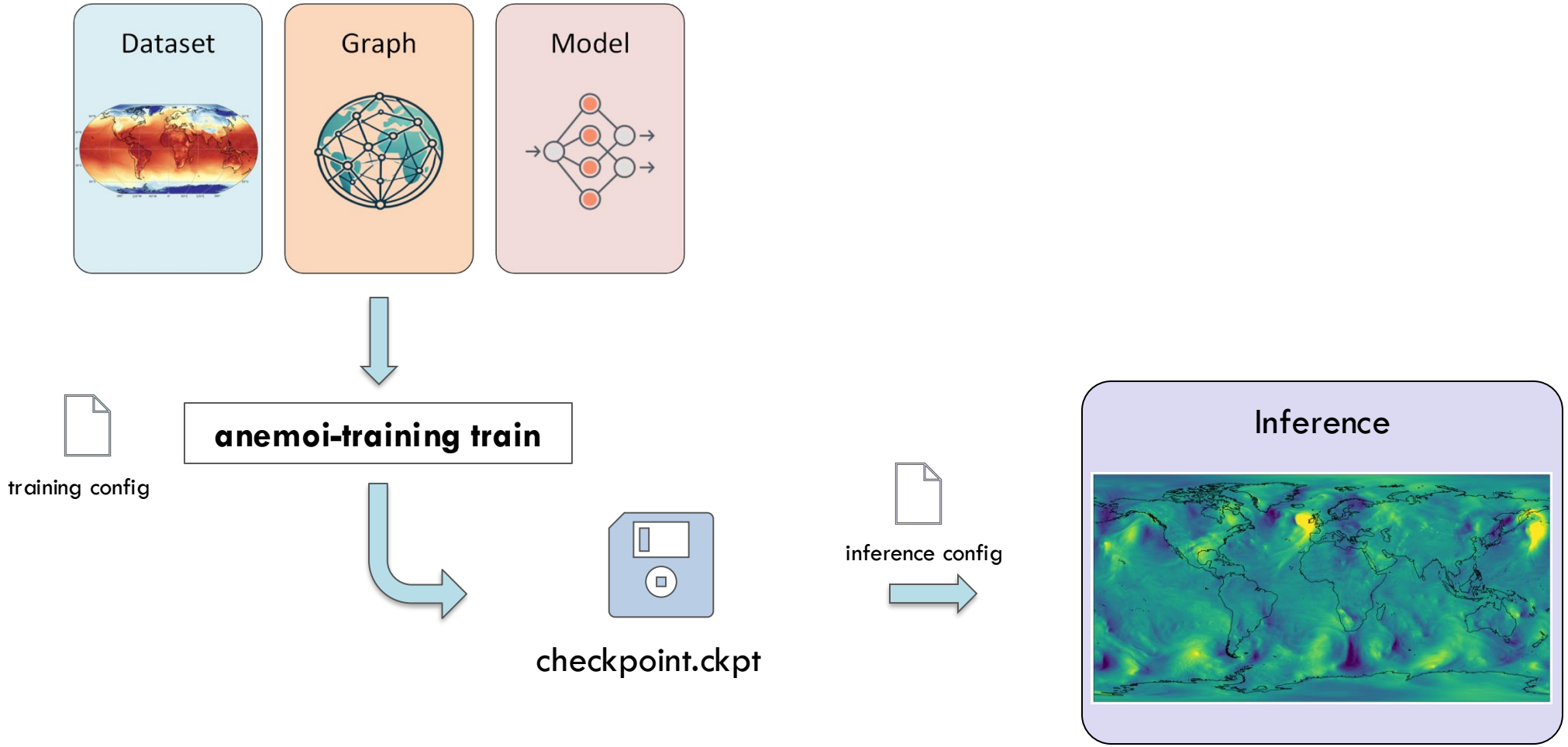
Machine Learning for Weather Prediction

Harrison Cook

On behalf of the Anemoi team and contributors

ECMWF

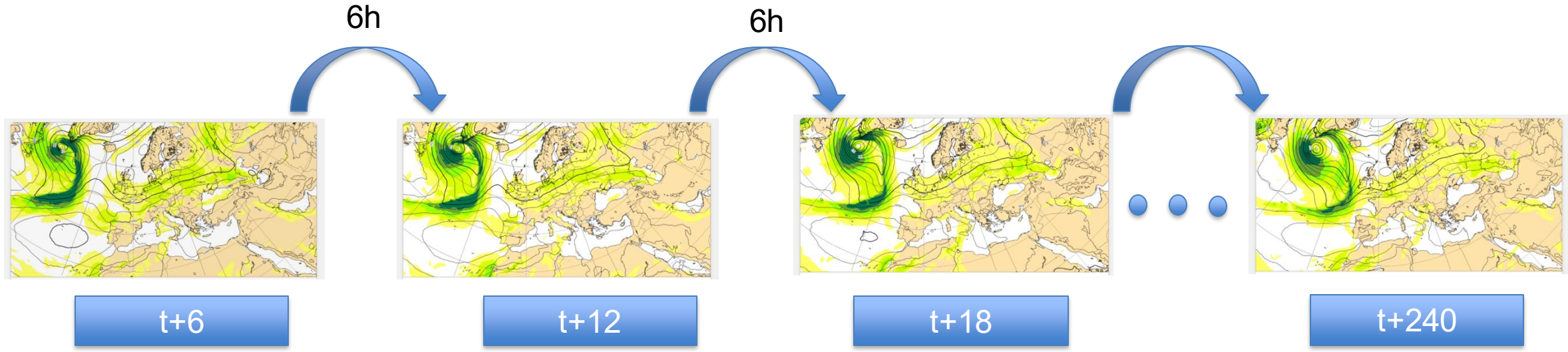
Documentation


Dataset
Graph
Model
anemoi-training train
training config
checkpoint.ckpt
inference config
Inference

Inference for the forecasting task

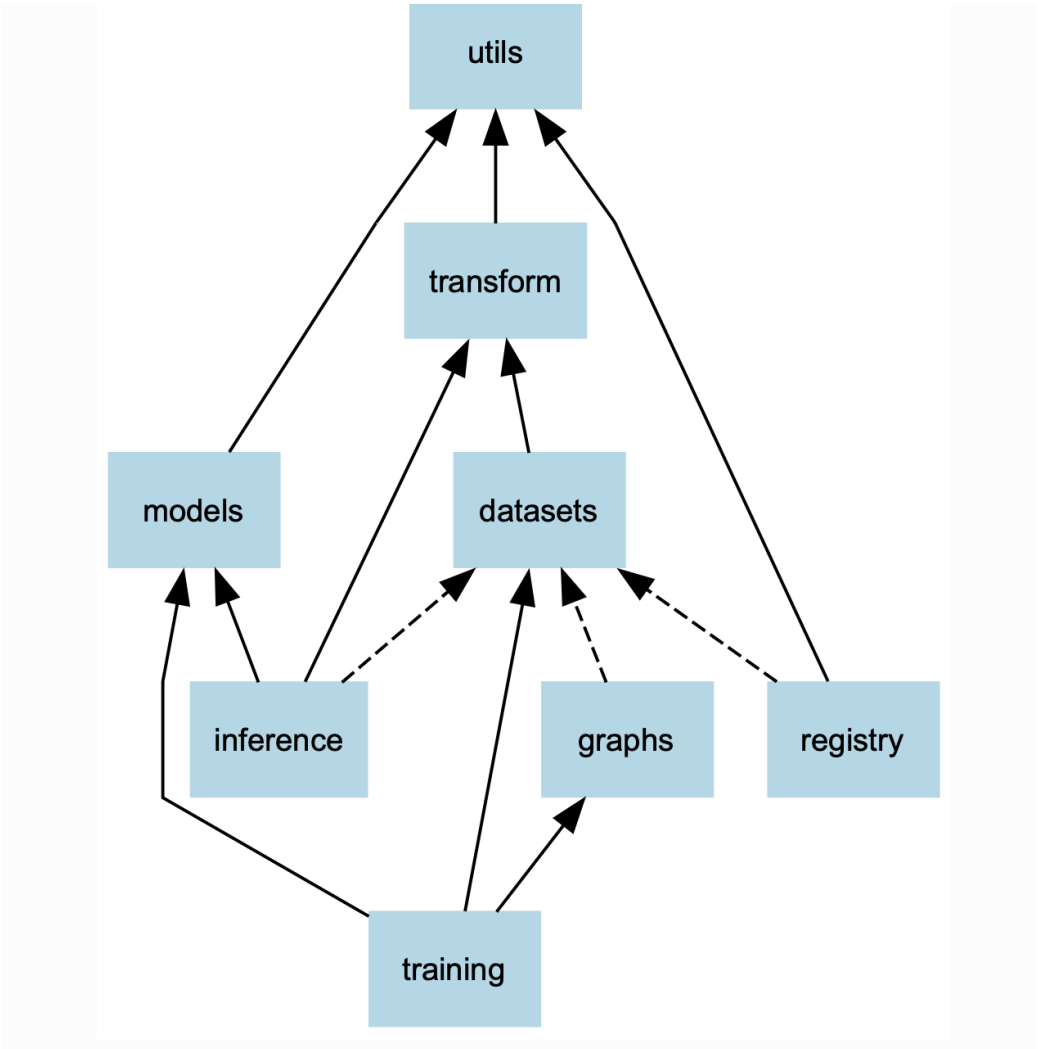
- If a model predicts t+6
  - Any time a multiple of 6 is possible

- Autoregressive rollout



Rationale

- Run trained models in inference mode
- Community project
  - ”Any” model can be run
  - But Operationalisation in mind
- Focus on the inference problem
  - Minimise unnecessary dependencies
  - Different data sources
  - Limited compute
  - Integration with external tooling



Three different API levels

- NumPy to NumPy low level API
- Object-oriented high level API
- Command-line API

Command Line Execution

Note:
Other API's for programmatic usage are also available

```
❯ anemoi-inference run --help
usage: anemoi-inference run [-h] [--defaults DEFAULTS] config [overrides ...]

Run inference from a config yaml file.

positional arguments:
  config                Path to config file. Can be omitted to pass config with overrides and defaults.
  overrides             Overrides as key=value

options:
  -h, --help            show this help message and exit
  --defaults DEFAULTS   Sources of default values
```

Command Line Configuration

```yaml
checkpoint: '/path/to/checkpoint.ckpt'

date: 20251030T00
lead_time: 240

input:
  mars:
    log: false

pre_processors:
  - no_missing_values
post_processors:
  - accumulate_from_start_of_forecast

output:
  tee:
    - grib: 'output.grib'
    - netcdf: 'output.nc'
    - plot:
        dir: plots/go/here
        variables: [2t, msl]
        method: overlay
        domain: Europe
```

Checkpoints

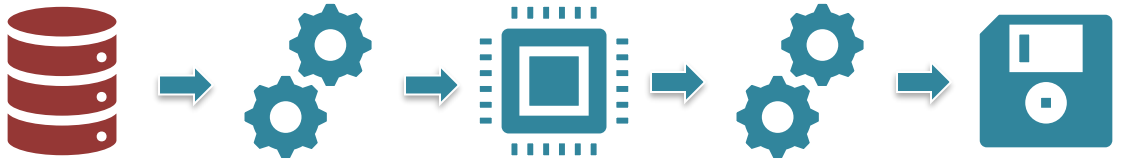
- Trained models stored in an “atomic” file with metadata

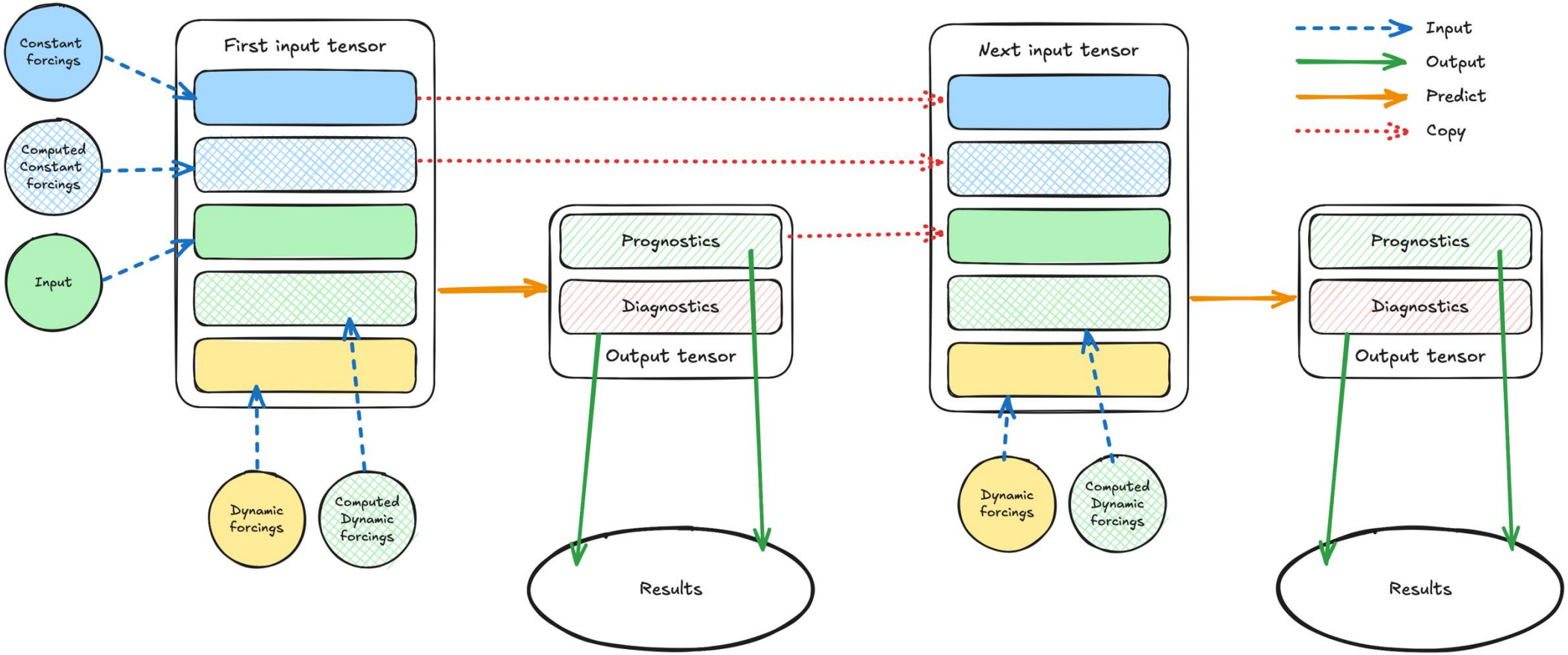
- Metadata:
  - Datasets used for training
  - Operations that took place on the data (e.g.: cutout)
  - Grid & Area
  - Mapping of variables to position in the input tensor

- Automatic setup of inference pipeline
  - List of prognostic, diagnostic and forcing variables
  - Minimal to no configuration required to retrieve initial conditions

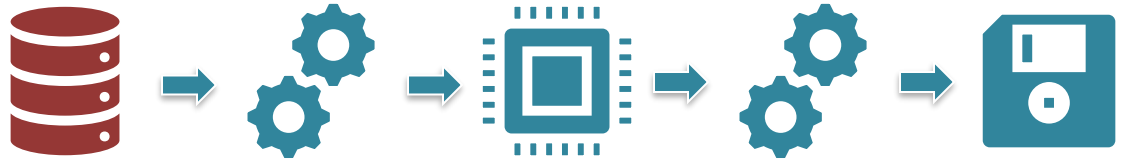
Hugging Face

Inputs




Constant forcings
Computed Constant forcings
Input
First input tensor
Dynamic forcings
Computed Dynamic forcings
Prognostics
Diagnostics
Output tensor
Results
Next input tensor
Dynamic forcings
Computed Dynamic forcings
Prognostics
Diagnostics
Output tensor
Results
Input
Output
Predict
Copy

Inputs - Available



- Direct Access to the ECMWF Archive

MARS

- Utilise publicly available ERA5

CDS

- Freely and openly available IFS analysis

Opendata *

- Regional extractions and custom collections

Polytope *

- Directly run from anemoi-datasets

Datasets

- Any local grib file

GRIB

- Merge multiple sources for LAM / Nested Grid models

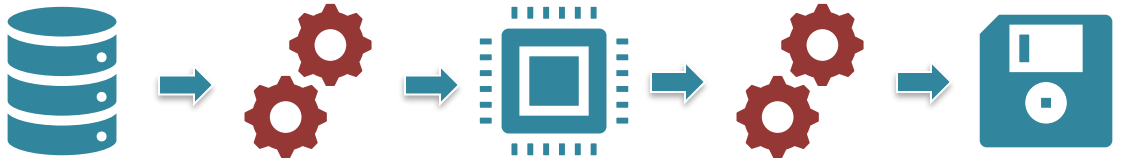
Cutout

- Quickly test your setup works with fake input

Dummy

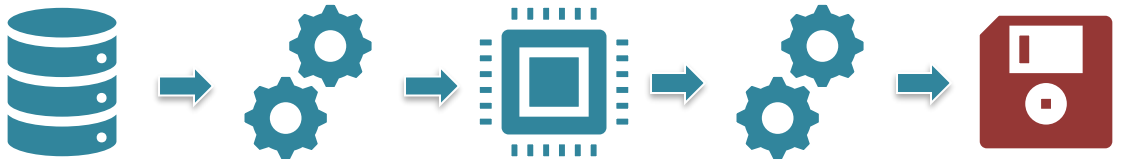
* Available as a plugin

Processors



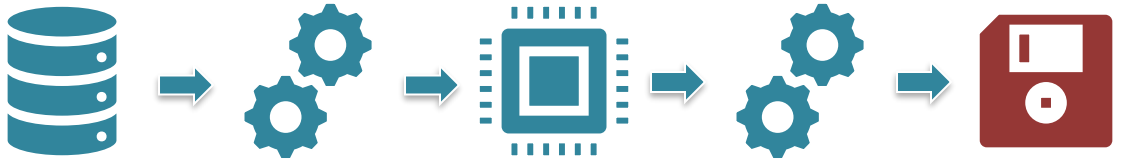
- Data is weird
  - Comes in many shapes and sizes
- For further modification of the data
  - Prepare the initial conditions
  - Finalise output state

Outputs



- Write the data to disk
- Major bottleneck in operations
- Save into various formats

Outputs - Available



- Encode to grib

GRIB

- CF Convention netcdf

Netcdf

- Plot selected fields

Plot

- Direct to numpy arrays

Raw

- Zarr 2 & 3

Zarr

Hands On Session

- Run an AIFS yourself

- Remove the training wheels, all configurable
  - Initial conditions
  - Running
  - Outputs