

MC-Toolkit
17 Nov. 2020

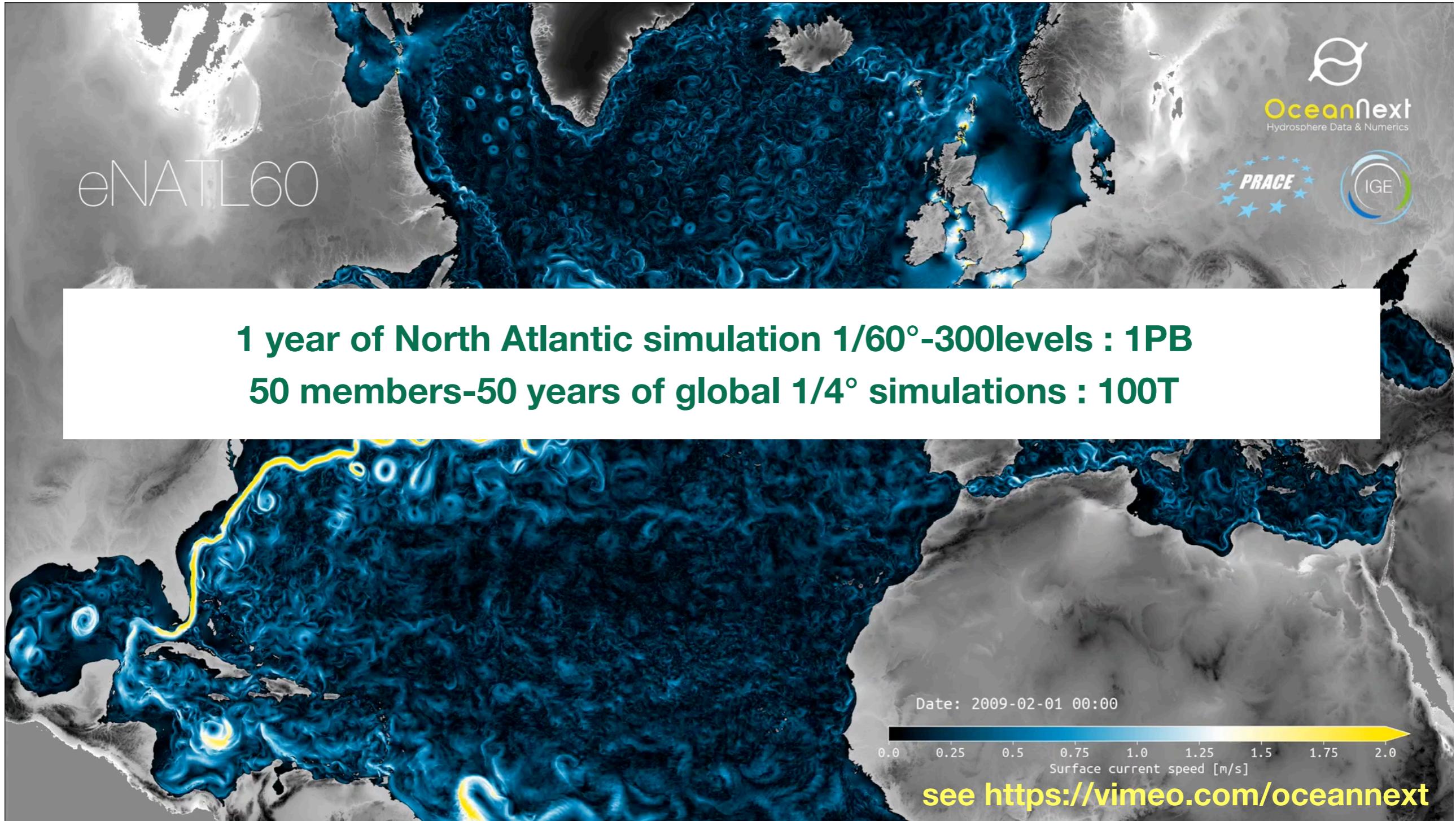


Managing “big data” in geosciences with PANGEO

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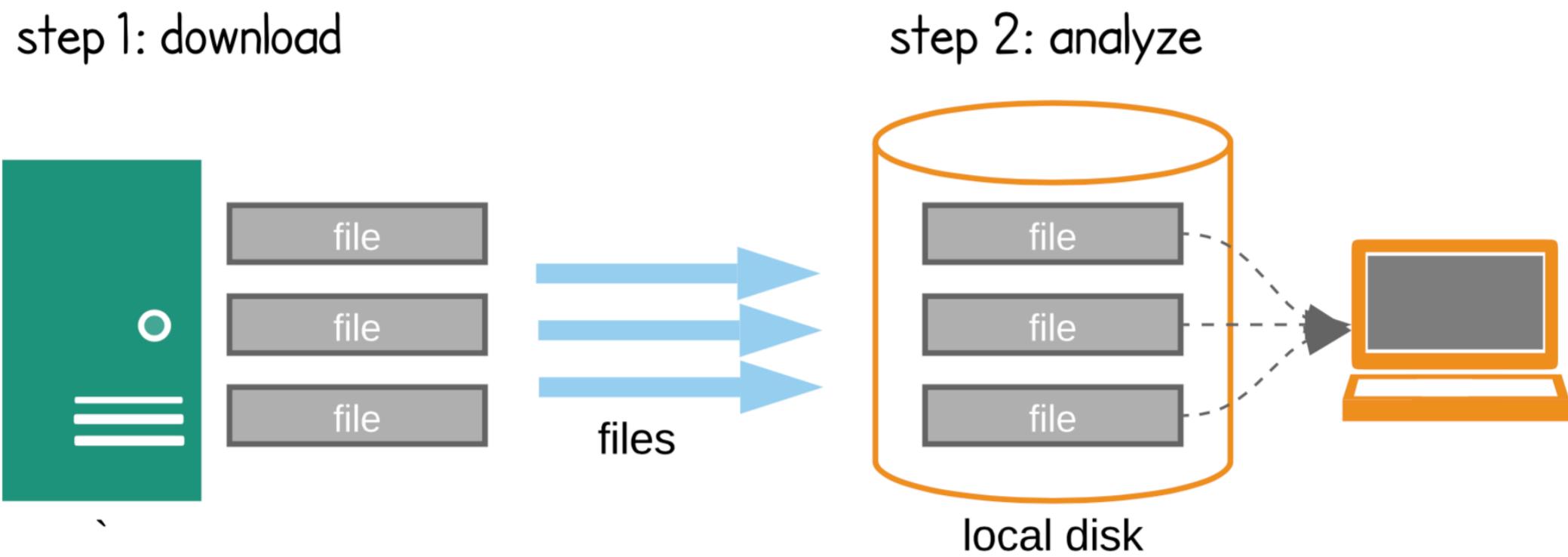
More and more data to analyse



NEMO-eNATL60 simulations from IGE/Ocean Next : dx ~1km, 300 levels + tides



Traditional workflow

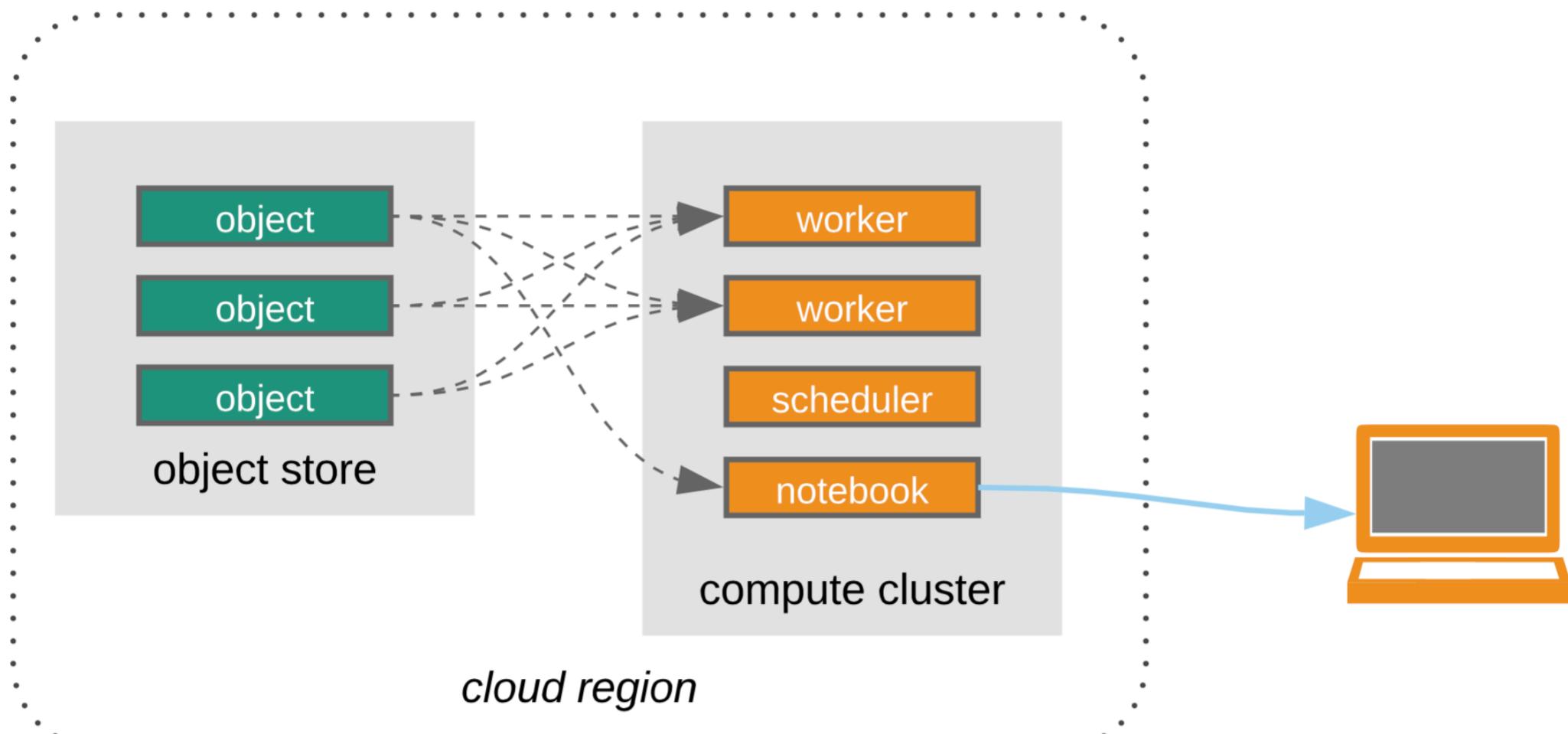


Data provider's responsibilities

End user's responsibilities



A new workflow ?



Data provider's responsibilities

End user's responsibilities



What is PANGEO?



pangeo.io

A community platform
for Big Data geoscience

- ◆ “big data geosciences” software ecosystem
- ◆ international community of scientists, developers
- ◆ a cloud deployment



PANGE : the community



- bringing together researchers, engineers and developers
 - members in big institutions (ECMWF, UKMO, CNES, ...)
 - inclusive and open-source approach (github, blog, tutorial, etc...)
 - annual US and Europe workshops (~30 p. in Paris, May 2019)



PANGEO : software ecosystem



Credit: Stephan Hoyer, Jake Vanderplas (SciPy 2015)



PANGEO : software ecosystem



- interactive “web-based” framework for computation
- a reproducible environment for :
 - code
 - text
 - equations (LaTeX)
 - visualisations

...back to oxygen

Set contour levels to non-uniform intervals and make the colormap centered at the hypoxic threshold using DivergingNorm.

```
In [7]: levels = [0, 10, 20, 30, 40, 50, 60, 80, 100, 125, 150, 175, 200, 225, 250, 275, 300]

norm = colors.DivergingNorm(vmin=levels[0], vmax=levels[-1], vcenter=60.)
```

Add a cyclic point to accomodate the periodic domain.

```
In [8]: from cartopy.util import add_cyclic_point
field, lon = add_cyclic_point(ds.O2, coord=ds.lon)
lat = ds.lat
```

Putting it all together...

```
In [9]: fig = plt.figure(figsize=(12, 8))
ax = fig.add_subplot(1, 1, 1, projection=ccrs.Robinson(central_longitude=305.0))

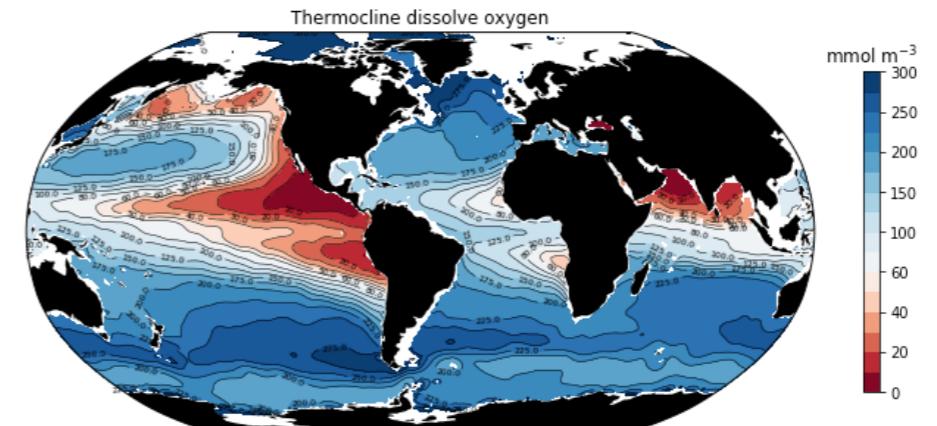
# filled contours
cf = ax.contourf(lon, lat, field, levels=levels, norm=norm, cmap='RdBu',
                  transform=ccrs.PlateCarree());

# contour lines
cs = ax.contour(lon, lat, field, colors='k', levels=levels, linewidths=0.5,
                 transform=ccrs.PlateCarree());

# add contour labels
lb = plt.clabel(cs, fontsize=6, inline=True, fmt='%r');

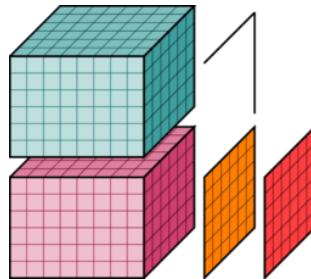
# land
land = ax.add_feature(
    cartopy.feature.NaturalEarthFeature('physical', 'land', '110m', facecolor='black'));

# colorbar and labels
cb = plt.colorbar(cf, shrink=0.5)
cb.ax.set_title('mmol m$^{-3}$')
ax.set_title('Thermocline dissolve oxygen');
```



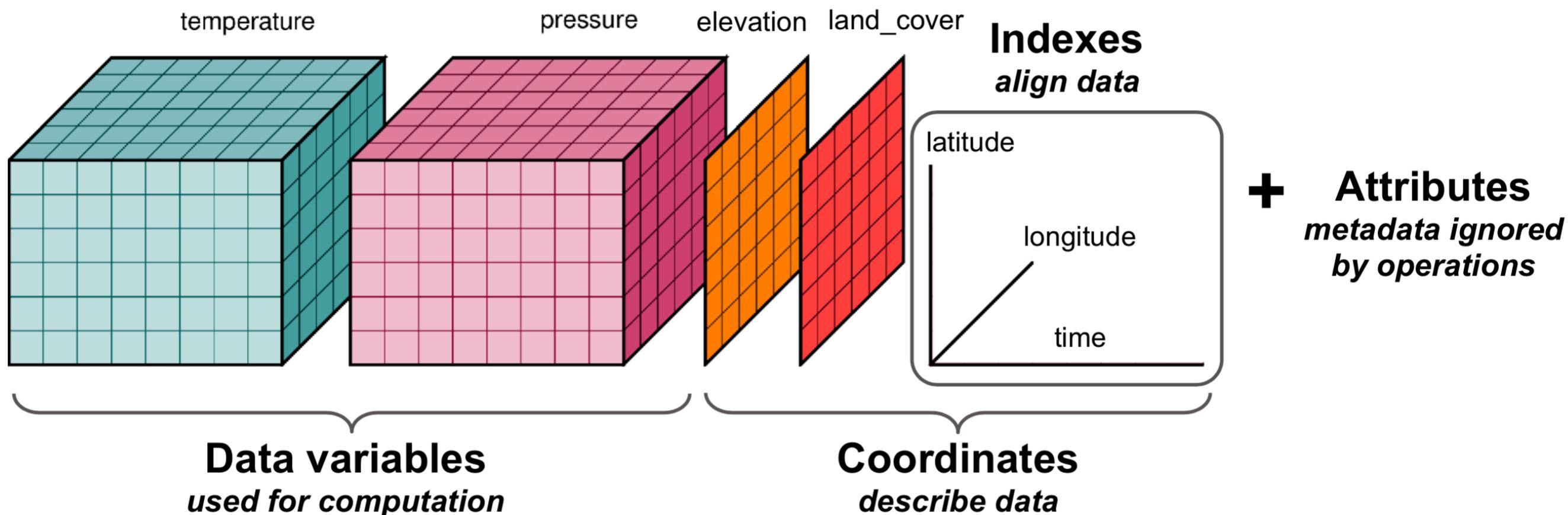


PANGEO : software ecosystem



xarray

- data structure N-D matrix
- API derived from pandas
- the base for a lot of other tools



“netCDF meets pandas.DataFrame”

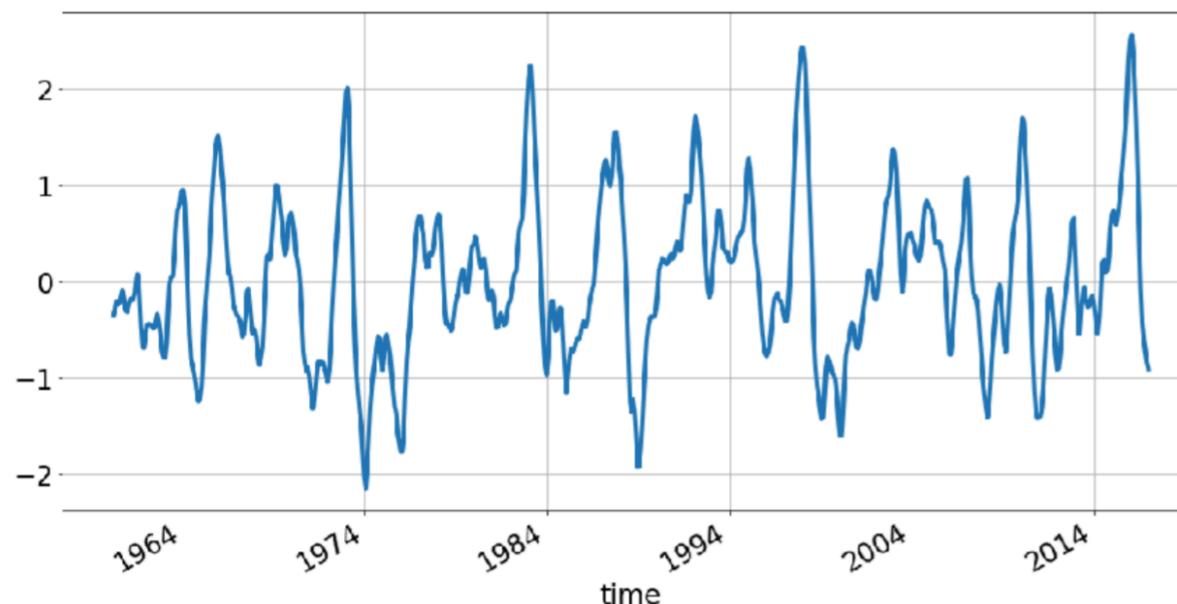


PANGEO : software ecosystem

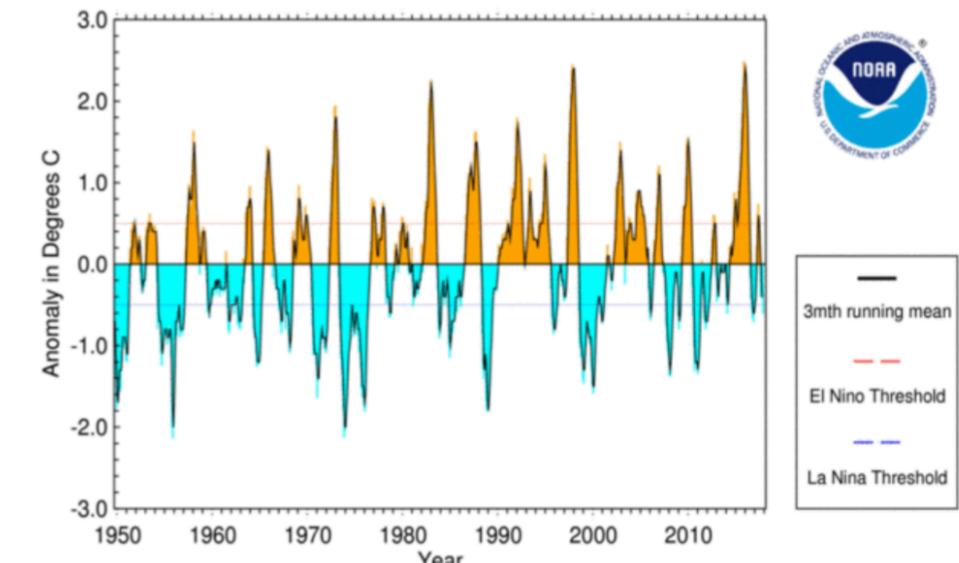


- data structure N-D matrix
- API derived from pandas
- the base for a lot of other tools

```
sst_clim = sst.groupby('time.month').mean(dim='time')
sst_anom = sst.groupby('time.month') - sst_clim
nino34_index = (sst_anom.sel(lat=slice(-5, 5), lon=slice(190, 240))
                 .mean(dim=('lon', 'lat'))
                 .rolling(time=3).mean(dim='time'))
nino34_index.plot()
```



SST Anomaly in Nino 3.4 Region (5N-5S,120-170W)

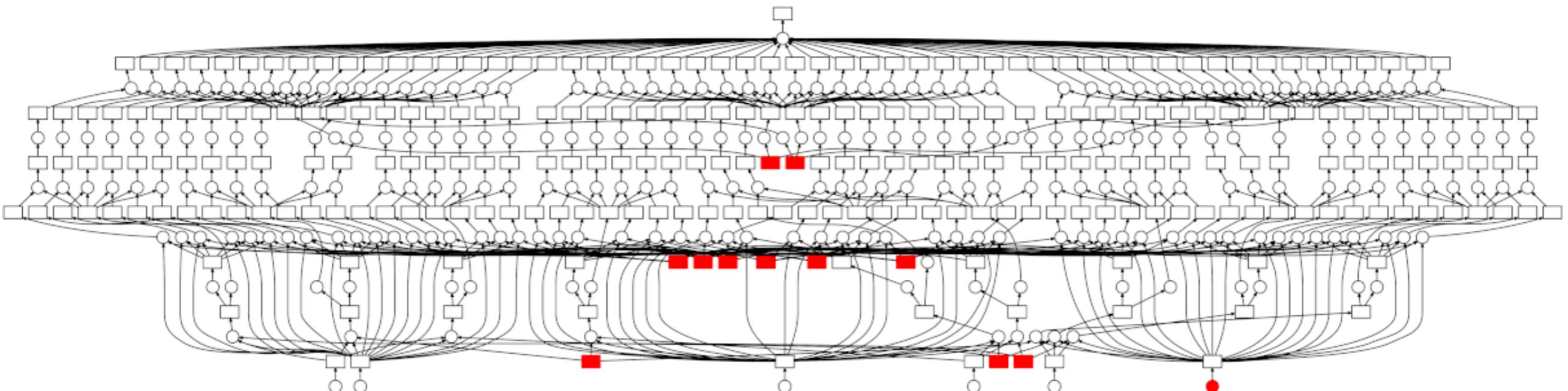




PANGEO : software ecosystem



- parallel computing library for python
- allows to scale Numpy, Pandas, Scikit-Learn, Xarray...
- can be deployed on HPC systems or on the cloud
- with a task graph and dashboard to manage the execution





PANGEONET : software ecosystem

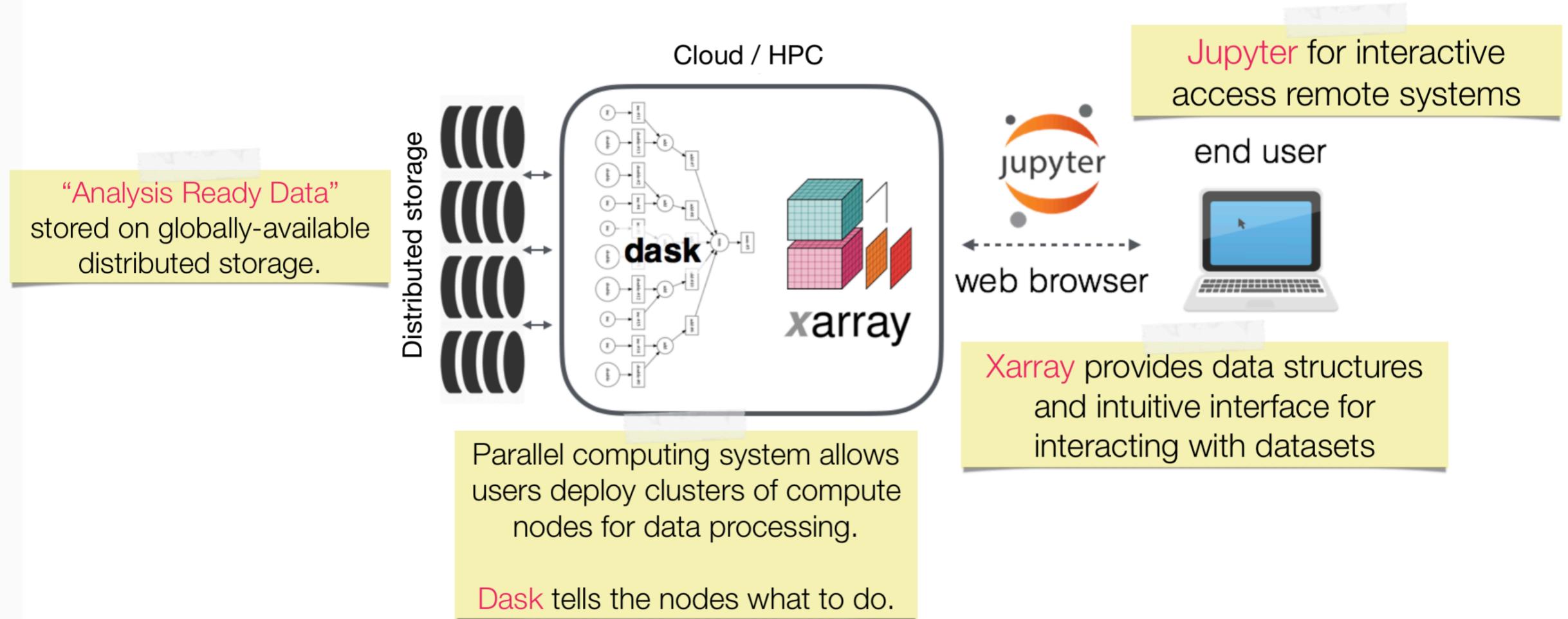
A library ecosystem based on these softwares :

- xgcm/xrft : Fourier transform for xarray data
- CNES/pangeo-pyinterp : interpolation of geo-referenced data
- willyrath/xorca : xarray with NEMO ocean model outputs
- serazing/xscale : statistics and signal computing
- the complete list : <http://xarray.pydata.org/en/stable/related-projects.html>

Open source and robust tools that allow us to scale up our analysis



PANGEO : a deployment



- a cloud deployment (Jupyterhub) pangeo.pydata.org
- other deployments on cluster/HPC : <https://pangeo.io/deployments.html>
- NCAR HPC and NASA, CNES cluster HAL.
- no jupyterhub on Occigen (personnal deployment), jupyterhub on Jean-Zay



Two more tools for our analysis

DASK-JOBQUEUE

- dask on job scheduler (PBS, Slurm, etc...)
- a french spin-off project in PANGEO
- a pythonic interface to work with dask workers/clusters

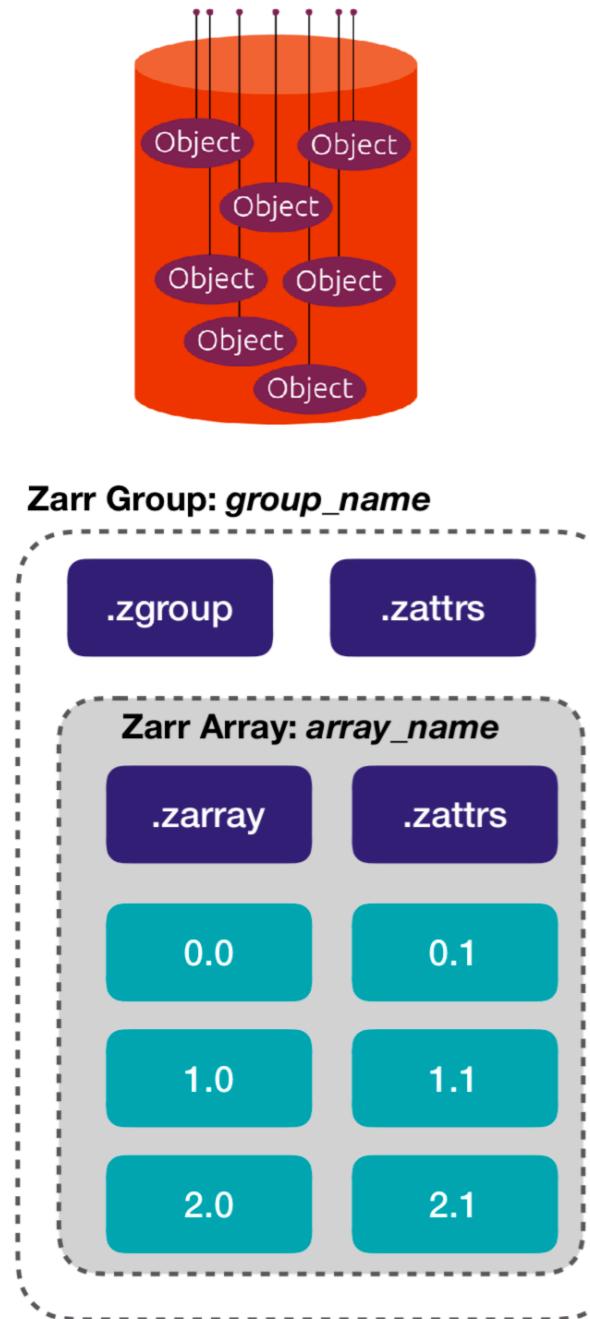
```
from dask_jobqueue import PBSCluster
from distributed import Client
cluster = PBSCluster(project=...,
    queue=..., cores=1, processes=1,
    memory="100GB", walltime=...)
# Ask for 10 nodes
cluster.scale(10)
# OR scale adaptively based on load
cluster.adapt(minimum=1, maximum=100,
               wait_count=60)
# Connect to remote workers
client = Client(cluster)
```

```
from dask_jobqueue import SLURMCluster
from distributed import Client
cluster = SLURMCluster(project=...,
    queue=..., cores=1, processes=1,
    memory="100GB", walltime=...)
# Ask for 10 nodes
cluster.scale(10)
# OR scale adaptively based on load
cluster.adapt(minimum=1, maximum=100,
               wait_count=60)
# Connect to remote workers
client = Client(cluster)
```



Two more tools for our analysis

ZARR OBJECT STORAGE



- Open source library for storage of chunked, compressed ND-arrays
- Created by Alistair Miles (Imperial) for genomics research (@alimanfoo); now community supported standard
- Arrays are split into user-defined chunks; each chunk is optional compressed (zlib, zstd, etc.)
- Can store arrays in memory, directories, zip files, or any python mutable mapping interface (dictionary)
- External libraries (s3fs, gcsf) provide a way to store directly into cloud object storage
- Implementations in Python, C++, Java (N5), Julia

Required for cloud computing and better performance on HPC

Exemple

```

files=sorted(glob.glob('/work/ALT/odatis/eNATL60/BLBT02/gridT-2D/eNATL60*gridT-2D*.nc'))
drop_vars = ['nav_lat', 'nav_lon', 'somx1010', 'sosaline', 'sosstsst']
extra_coord_vars = []
chunks = dict(time_counter=240, y=240, x=480)
open_kw_args = dict(drop_variables=(drop_vars + extra_coord_vars),
                    chunks=chunks, decode_cf=True, decode_times=False,
                    concat_dim="time_counter", combine='nested')

%time ds = xr.open_mfdataset(files, parallel=True, **open_kw_args)
CPU times: user 3.75 s, sys: 197 ms, total: 3.95 s
Wall time: 4.77 s

%time ds=xr.open_zarr('/work/ALT/odatis/eNATL60/zarr/eNATL60-BLBT02-SSH-1h')
CPU times: user 100 ms, sys: 29.2 ms, total: 130 ms
Wall time: 149 ms

```

```

from dask.distributed import Client
from dask_gateway import Gateway

gateway = Gateway()
cluster = gateway.new_cluster()
cluster.scale(nb_workers)
c = Client(cluster)
c

%time mean=ds.sossheig.mean(dim='time_counter')

```

CPU times: user 116 ms, sys: 7.68 ms, total: 123 ms
 Wall time: 120 ms

```

mean

xarray.DataArray 'sossheig' (y: 4729, x: 8354)

Array      Chunk
Bytes     158.02 MB   460.80 kB
Shape     (4729, 8354) (240, 480)
Count    41761 Tasks   360 Chunks
Type      float32    numpy.ndarray

```

► Coordinates: (0)
 ► Attributes: (0)

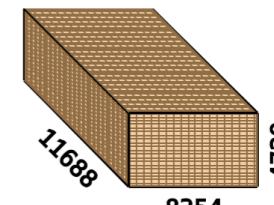
```

%time mean.load()

CPU times: user 5.38 s, sys: 561 ms, total: 5.95 s
Wall time: 4min 17s

```

sossheig	(time_counter, y, x)	float32 dask.array<chunksize=(24...
		Array
Bytes	1.85 TB	110.59 MB
Shape	(11688, 4729, 8354)	(240, 240, 480)
Count	17641 Tasks	17640 Chunks
Type	float32	numpy.ndarray

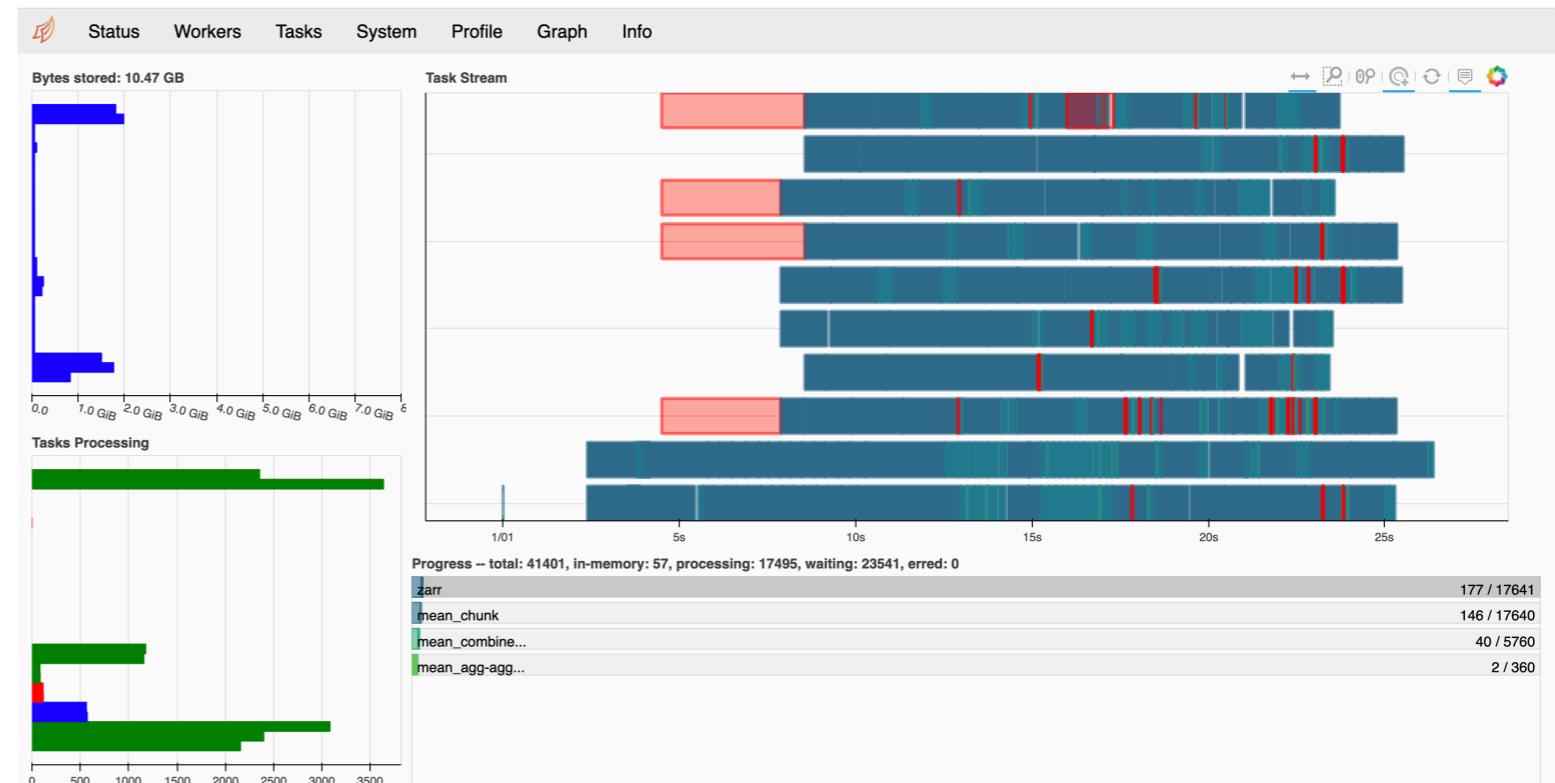


Client

Scheduler: gateway://traefik-gcp-uscentral1b-prod-dask-gateway.prod:80/prod.3a7a52cc26364e0198c7e52896bc0d60
 Dashboard: /services/dask-gateway/clusters/prod.3a7a52cc26364e0198c7e52896bc0d60/status

Cluster

Workers: 5
 Cores: 10
 Memory: 42.95 GB





Demonstration on binder

on github : <https://tinyurl.com/MCToolkit>

The screenshot shows a Jupyter notebook environment on a binder instance. The left sidebar lists notebooks: 'completed-compute-and...' (4 days ago) and 'compute-and-plot-mean...' (4 minutes ago). The main area displays three code cells:

- [16]:
xarray.DataArray 'adt' (latitude: 60, longitude: 120)
dask.array<chunksize=(60, 120), meta=np.ndarray>
Coordinates:
 - crs () int32 ...
 - latitude (latitude) float32 30.125 30.375 ... 44.625 44.875
 - longitude (longitude) float32 270.125 270.375 ... 299.625 299.8...
- [17]:
mean_ssh_AVISO_GS
xarray.DataArray 'adt' (latitude: 60, longitude: 120)
dask.array<chunksize=(60, 120), meta=np.ndarray>
Coordinates:
 - crs () int32 -2147483647
 - latitude (latitude) float32 30.125 30.375 ... 44.625 44.875
 - longitude (longitude) float32 270.125 270.375 ... 299.625 299.8...
- [18]:
std_ssh_eNATL60_GS
xarray.DataArray 'sossheig' (y: 1290, x: 1825)
dask.array<chunksize=(100, 100), meta=np.ndarray>

To the right of the notebook are three panels:

- Dask Task Stream**: A timeline visualization showing task execution from 27s to 32s. Tasks are represented by colored bars (blue, yellow, red) indicating their status.
- Dask Workers**: Monitors CPU and memory usage across multiple workers. CPU use is shown as a bar chart, and memory use is shown as a table of names, addresses, nthreads, cpu, and mem.

name	address	nthreads	cpu	mem
Total (50)		100	101.3 %	32 C
dask-gateway-tls://10.51.7.15	2		97.9 %	517

- Dask Progress**: Displays the progress of various operations. Total operations: 33214, in-memory: 4446, processing: 1. Operations include: getitem 14614 / 14911, mean_combine... 34 / 98, concatenate@4346 / 14610, mean_agg-agg... 0 / 1, zarr 1456 / 1471, rechunk-split 561 / 828, mean_chunk 249 / 494, rechunk-merge 172 / 307, sub 0 / 247, and mean_agg-agg.120 247.