High-Perfomance Data Analytics in eScience

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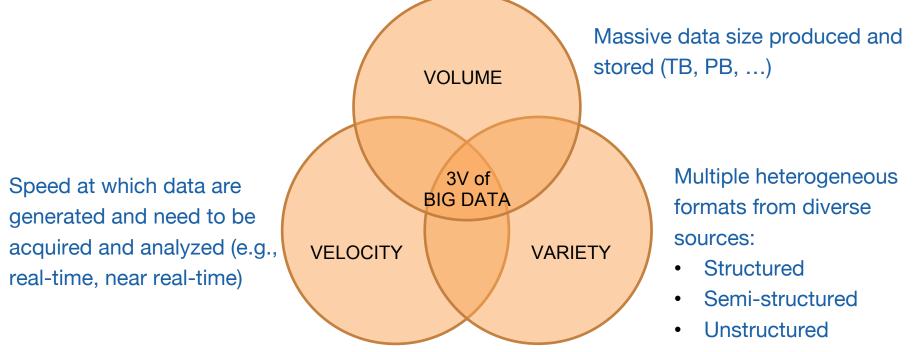


- Introduction to HPDA and data challenges in eScience
- ✓ ECAS and EOSC
- ✓ Introduction to the Ophidia HPDA Framework
- ✓ Ophidia core concepts: architecture, data model, operators and primitives
- ✓ Analytics workflows with Ophidia
 - ✓ Workflow execution demo
- ✓ Ophidia Python bindings: PyOphidia



3V's of Big Data

Back in 2001 D. Laney¹ described data management challenges according to 3 dimensions: the well-known 3V's model which has been then used to characterize big data.



Other V's have been later identified: e.g., value, veracity, ...

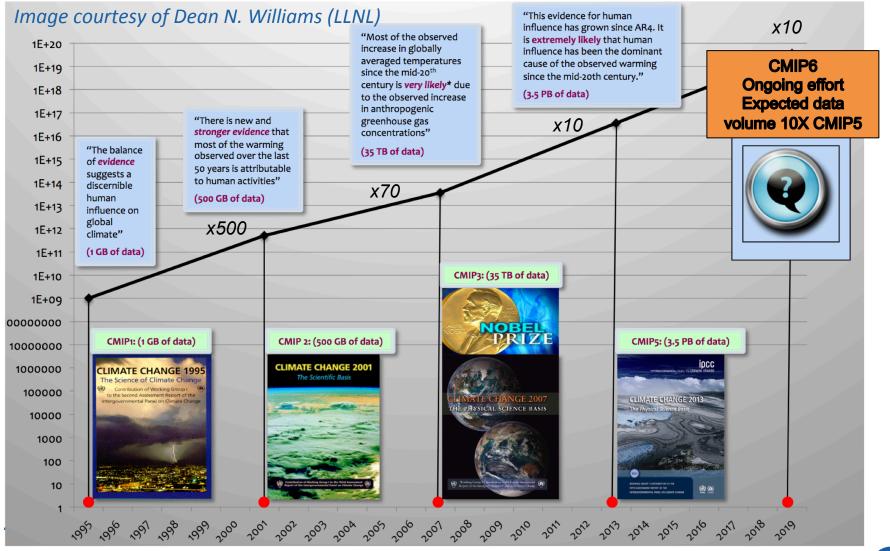
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¹Laney D (2001) 3-d data management: controlling data volume, velocity and variety. META Group Research Note, 6 February

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CMIP data evolution





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Data Analytics and HPC ecosystem

(Big) Data analytics ecosystem

- o Commodity hardware
- Shared-nothing architecture
- o Dynamic resource allocation
- Heterogeneous workloads
- MapReduce computing paradigm
- High-level programming abstractions

HPC (Scientific computing) ecosystem

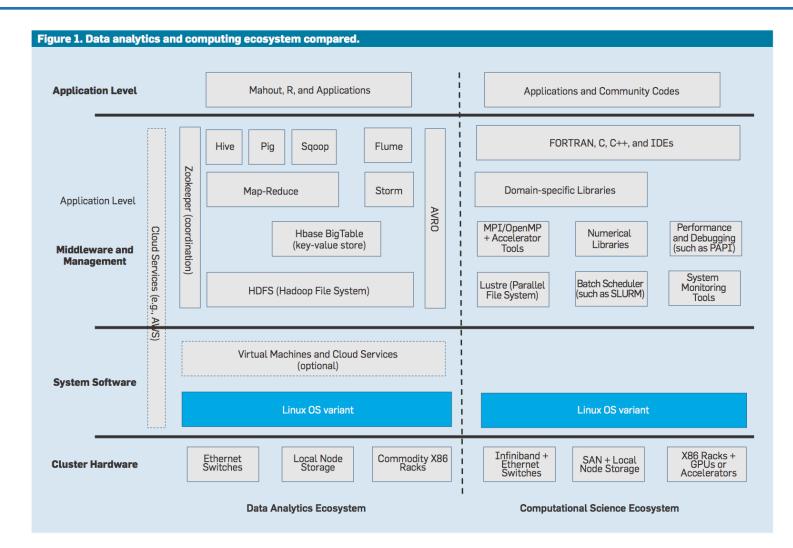
- o High-end hardware
- Shared-disk architecture
- o Fixed resource allocation
- o Large batch workloads
 - MPI+X -based computing paradigm
- o C/Fortran code

References:

-D. A. Reed and J. Dongarra. 2015. Exascale computing and big data. Commun. ACM 58, 7 (July 2015), 56–68. -Jha, S., Qiu, J., Luckow, A., Mantha, P., & Fox, G. C. (2014). A tale of two data-intensive paradigms: Applications, abstractions, and architectures. In 2014 IEEE Int. Congress on Big Data (pp. 645-652). -Asch, M., et al. (2018). Big data and extreme-scale computing: Pathways to convergence-toward a shaping strategy for a future software and data ecosystem for scientific inquiry. Int. J. High Perform. Comput. Appl., 32(4), 435-479.



Data Analytics and computing ecosystem



Source: Daniel A. Reed and Jack Dongarra. 2015. Exascale computing and big data. Commun. ACM 58, 7 (July 2015), 56–68.

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Convergenge of data analytics and HPC in eScience

Convergence of data-intensive analytics and HPC:

- (Big) Data analytics ecosystem has rapidly expanded in the last 15 years, leading to a wide spectrum of new solutions, mainly outside the scientific and engineering community
- HPC solutions have been used for several years in different scientific fields for scientific computing (simulations and modeling)
- Computational science modeling and data analytics are both crucial in scientific research
- The convergence of the solutions and technology of the two ecosystems is a key factor for accelerating scientific discovery

High-Performance Data Analytics (HPDA)

ESGF and the CMIP data archive

ESGF¹ is a coordinated multiagency, international collaboration IS-enes of institutions that continually develop, deploy, and maintain INFRASTRUCTURE FOR THE EUROPEAN NETWORK FOR EARTH SYSTEM MODELLING software needed to facilitate and empower the study of climate. Canada ! 🔶 01 ESGFOR Co 🕒 Lav Ireland Japan NSF/NCAR NOAA/GFDL IPCC/CMIP ACME Norway China DOE/NERSC Russia WCRP CMIPS OAK RIDGE 2 DOE/LLNL C-LAMP ACME ARM ACME DOE/PNNL DOE/ ORNL 之 DKRZ Argonne IPCC/CMIP5 CORDEX ACME MPI/DKRZ DOE/ANL NASA NASA/JPL IPCC/CMIP5 obs4MIPs Earth System Grid Federation NASA/NCCS PMIIP3 MERRA IPSL GMAO British Atmospi Data Centre none IPCC/CMIP5 DCMIP CORDEX NOAA/ESRL BADC CINCC Centro Euro-Mediterran IPCC/CMIP5 IPCC/CMIP5 ANU/NCI смсс

¹L. Cinquini, et al. (2014). The Earth System Grid Federation: An open infrastructure for access to distributed geospatial data. Future Gener. Comput. Syst. 36: 400-417.

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Climate analysis challenges & issues

Several key challenges and practical issues related to large-scale climate analysis

- Setup of a data analysis experiment requires the *download of input data* (also from multiple models)
 - Data download is a big barrier for climate scientists
- The complexity of the data analysis process leads to the need for *end-to-end workflow support* solutions
 - o Data analysis mainly performed using client-side approaches
 - Analysing large datasets involves *running tens/hundreds of analytics operators*
 - Installation and update of data analysis tools and libraries needed
- Large data volumes pose strong *requirements* in terms of *computational and storage* resources



New approaches for climate analysis at scale

Dedicated data intensive facilities close to the different storage hierarchies will be needed to address high-performance scientific data management & analytics

Server-side approaches will intrinsically and drastically reduce data movement

- o download will only relate to the final results of an analysis
- o they will foster re-use as well as collaborative experiments
- o need for efforts toward highly interoperable tools/envs for data analysis

Workflow supports the definition and management of *complex data-intensive analytics* applications

Higher-level programming approaches for data analytics are required to effectively exploit the resources and improve productivity

• Cultural change must be faced to encourage the adoption of novel solutions and tools

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The European Open Science Cloud (EOSC)

The European Open Science Cloud (EOSC) is an ambitious program that will offer a virtual environment with open and seamless services for storage, management, analysis and re-use of research data, across borders and scientifc disciplines by federating existing scientifc data infrastructures, currently dispersed across disciplines and Member States.

This programme will deliver an **Open Data Science Environment** that **federates existing scientific data infrastructures** to offer European science and technology researchers and practitioners seamless access to services for storage, management, analysis and re-use of research data presently restricted by geographic borders and scientific disciplines.

EOSC-hub is a key infrastructural project in the **EOSC** landscape

About EOSC: https://www.eosc-portal.eu/about/eosc



The ENES Climate Analytics Service (ECAS)



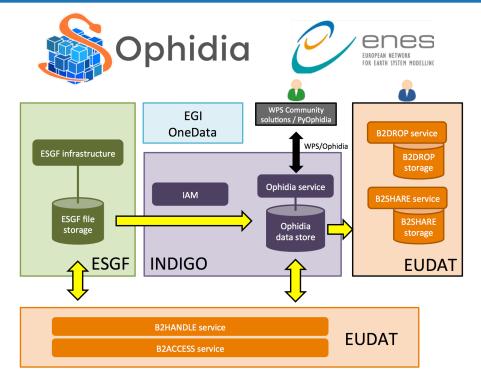
The **ENES Climate Analytics Service** (**ECAS**), proposed by CMCC & DKRZ in EOSC-hub supports climate data analysis

It is one of the EOSC-Hub Thematic Services: https://www.eosc-hub.eu/services/ENES %20Climate%20Analytics%20Service

ECAS builds on top of the *Ophidia big data analytics framework* with components from INDIGO-DataCloud, EUDAT and EGI







The European Commission launched the European Open ScienceCloud Initiative to capitalise on the data revolution. EOSC will provide European science, industry and public authorities with world-class digital infrastructure that bring state of the art computing and data storage capacity to the fingertips of any scientists and engineer in the EU.



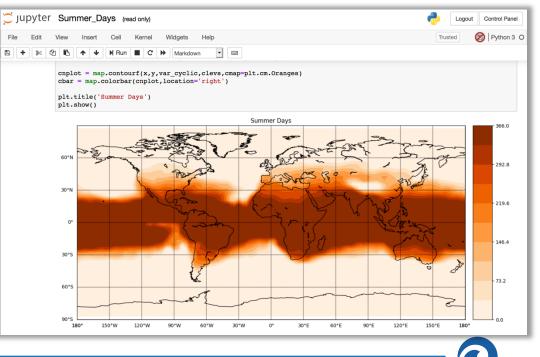
EOSC-hub receives funding from the EU's Horizon 2020 research and innovation programme under grant agreement No. 777536.



ECASLab: a Python environment for data analysis

ECASLab provides a user-friendly environment for scientific analysis based on:

- The ECAS integrated service
- A JupyterHub instance providing a graphical environment for user's experiments
- Bundled with a wide set of *Python scientific modules* for data manipulation, analysis and visualization, such as PyOphidia, NumPy, Pandas, Dask, Matplotlib, basemap, Cartopy
- o A set of ECAS usage example notebooks (https://github.com/ECAS-Lab/ecas-notebooks)



Two major instances are hosted by:

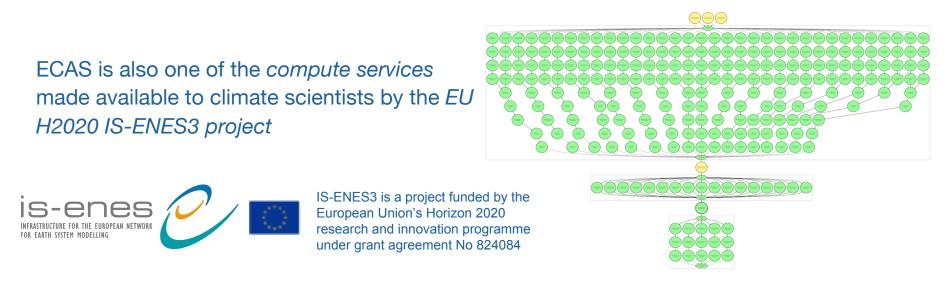
- o CMCC <u>https://ecaslab.cmcc.it</u>
- o DKRZ https://ecaslab.dkrz.de



A complete environment for climate experiments

ECASLab is a complete environment for supporting scientist in their daily research activities with a focus on those from the climate change domain

- It represents a single entrypoint to *analysis tools, scientific datasets* (e.g., from ESGF data archive) and *computing resources*
- It provides the capabilities for the implementation and execution of both interactive and complex experiments (workflows), such as *multi-model CMIP-based data analysis*¹



¹S. Fiore, D. Elia, C. Palazzo, A. D'Anca, F. Antonio, D. N. Williams, I. Foster, G. Aloisio, "Towards an Open (Data) Science Analytics-Hub for Reproducible multi-model Climate Analysis at Scale", 2018 IEEE Int. Conference on Big Data

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Ophidia High-Performance Data Analytics Framework

Ophidia (http://ophidia.cmcc.it) is a CMCC Foundation research project addressing data challenges for eScience

It provides:

- a High-Performance Data Analytics (HPDA) framework for multi-dimensional scientific data joining HPC paradigms with scientific data analytics approaches
- in-memory and server-side data analysis exploiting parallel computing techniques and database approaches
- a multi-dimensional, array-based, storage model and partitioning schema for scientific data leveraging the datacube abstraction
- end-to-end mechanisms to support complex experiments and large workflows on scientific datacubes, primarily in climate domain

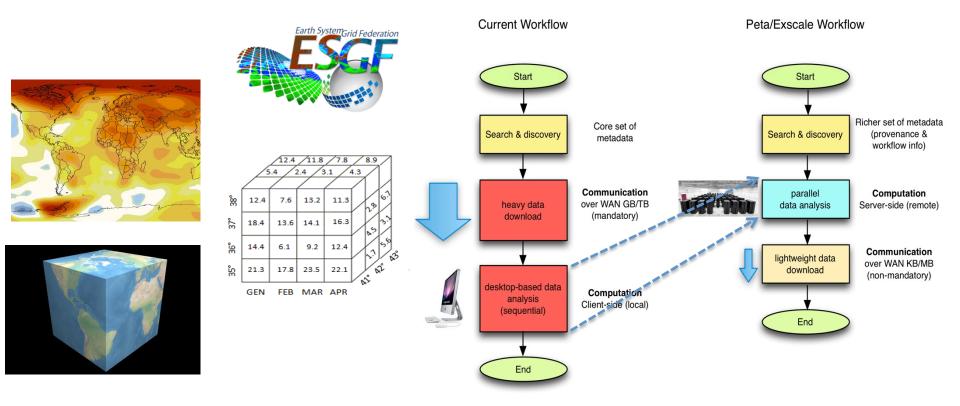






A paradigm shift

Volume, variety, velocity are key challenges for big data in general and for climate change science in particular. Client-side, sequential and disk-based workflows are three limiting factors for the current scientific data analysis tools.



S. Fiore, A. D'Anca, C. Palazzo, I. Foster, D. N. Williams, G. Aloisio, "Ophidia: toward bigdata analytics for eScience", ICCS2013 Conference, Procedia Elsevier, Barcelona, June 5-7, 2013



Data analytics requirements and use cases

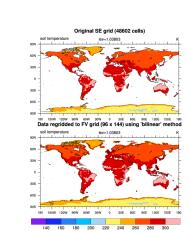
Requirements and needs focus on:

- > Time series analysis
- Data subsetting
- Model intercomparison
- Multimodel means
- Massive data reduction
- > Data transformation (through array-based primitives)
- Param. Sweep experiments (same task applied on a set of data)
- > Maps generation
- Ensemble analysis
- Data analytics workflow support

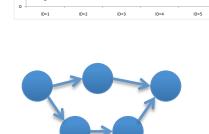
But also...

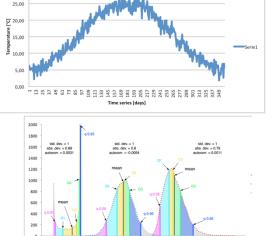
- > Performance
- ➢ re-usability
- > extensibility

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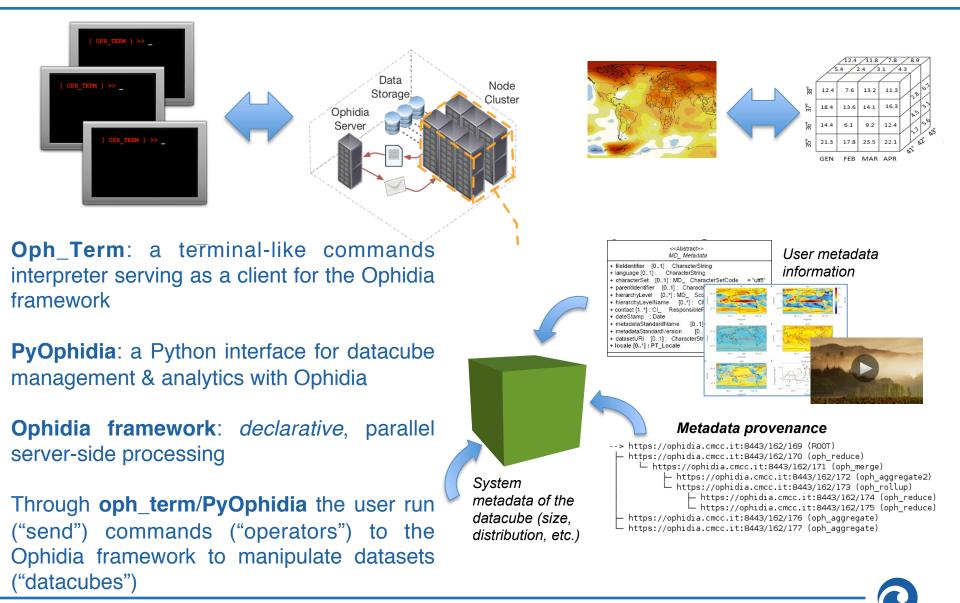
TEMPERATURE SURFACE-273.15





-4,00 -2,00

Server-side paradigm and the datacube abstraction





Some international projects exploiting Ophidia



ESIVACE CENTRE OF EXCELLENCE IN SIMULATION OF WEATHER AND CLIMATE IN EUROPE







EUROPE - BRAZIL COLLABORATION OF BIG DATA SCIENTIFIC RESEARCH THROUGH CLOUD-CENTRIC APPLICATIONS







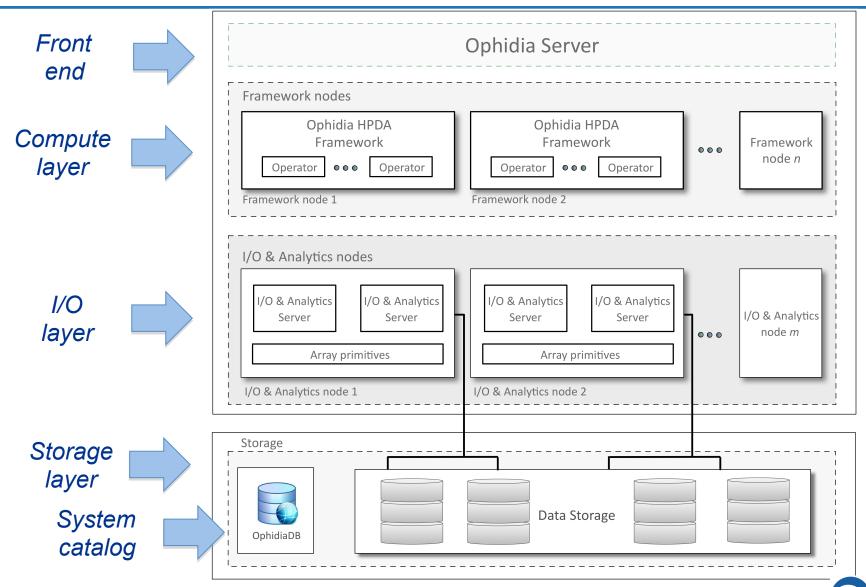




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Ophidia architecture: overview



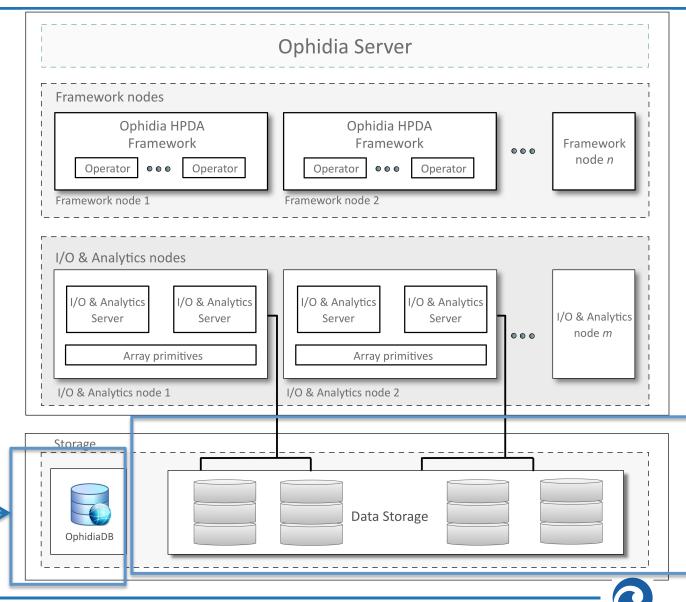


Ophidia architecture: storage layer

Distributed hardware resources to manage storage

Data partitioned in a hierarchical fashion over the storage according to the storage model & partitioning schema

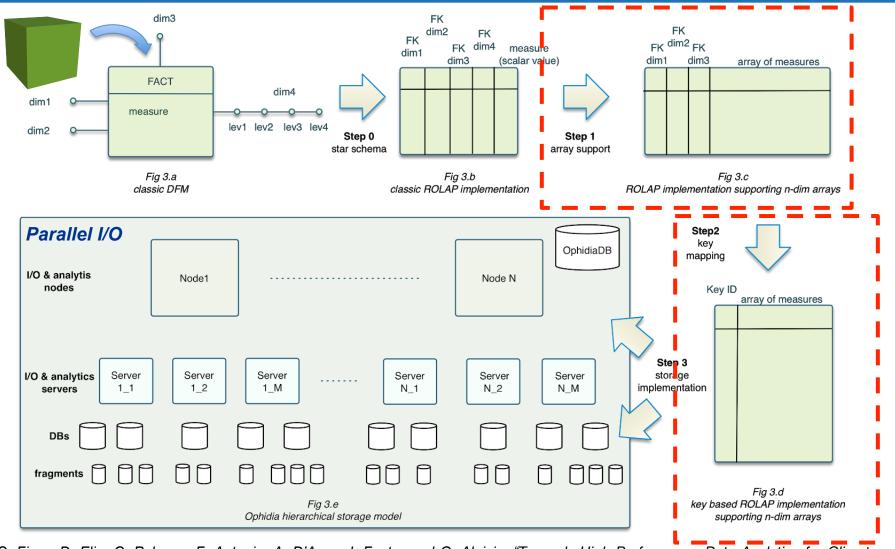
OphidiaDB is the system catalog: maps data fragmentation and tracks metadata



- o Ophidia implements the datacube abstraction from OLAP
- The Ophidia storage model is a two-step based evolution of the star schema to support scientific data management
- It relies on implicit (array-based) and explicit (tuple-based) dimensions for specific representations of data
- The first step includes the **support for array**-based data
- The second step includes a **key mapping** related to a set of foreign keys
- This second step makes the Ophidia storage model and implementation independent of the number of dimensions!



Multi-dimensional storage model implementation

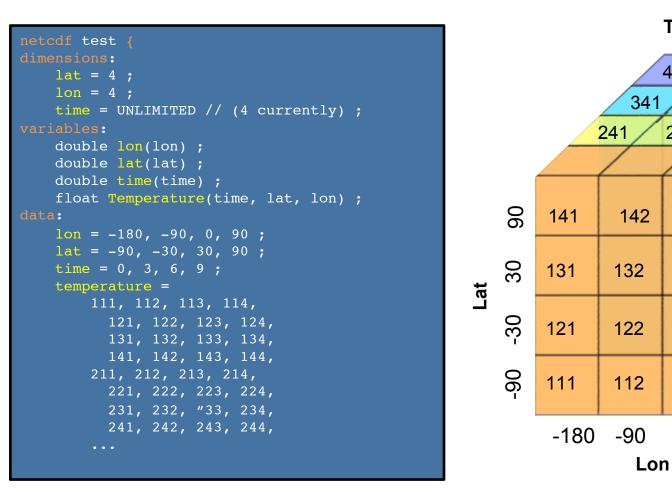


S. Fiore, D. Elia, C. Palazzo, F. Antonio, A. D'Anca, I. Foster and G. Aloisio, "Towards High Performance Data Analytics for Climate Change", ISC High Performance 2019. Lecture Notes in Computer Science, vol. 11887, pp. 240-257, 2019.



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From NetCDF to datacube





1234 334

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Time

A34

A1A

The datacube abstraction naturally fits for scientific multi-dimensional data, like climate data



<pre>netcdf test {</pre>
dimensions:
lat = 4;
lon = 4;
<pre>time = UNLIMITED // (4 currently)</pre>
variables:
<pre>double lon(lon) ;</pre>
double lat(lat);
<pre>double time(time) ;</pre>
<pre>float Temperature(time, lat, lon)</pre>
data:
lon = -180, -90, 0, 90;
<u>lat = -90, -30, 30, 90</u> ;
time = 0, 3, 6, 9 ;
temperature =
111, 112, 113, 114,
121, 122, 123, 124,
131, 132, 133, 134,
141, 142, 143, 144,
211, 212, 213, 214,
221, 222, 223, 224,
231, 232, 233, 234,
241, 242, 243, 244,
311, 312, 313, 314,
321, 322, 323, 324,
331, 332, 333, 334,
341, 342, 343, 344,
•••

		Temperature				
lat	lon	time[0]	time[1]	time[2]	time[3]	
-90	-180	111	211	311	411	
-90	-90	112	212	312	412	
-90	0	113	213	313	413	
-90	90	114	214	314	414	
-30	-180	121	221	321	421	
-30	-90	122	222	322	422	
-30	0	123	223	323	423	
-30	90	124	224	324	424	
30	-180	131	231	331	431	
30	-90	132	232	332	432	
30	0	133	233	333	433	
30	90	134	234	334	434	
90	-180	141	241	341	441	
90	-90	142	242	342	442	
90	0	143	243	343	443	
90	90	144	244	344	444	

Ophidia



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141, 142, 143, 144,
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2	7						
				Temperature			
	lat	lon	time[0]	time[1]	time[2]	time[3]	
	-90	-180	111	211	311	411	
	-90	-90	112	212	312	412	
	-90	0	113	213	313	413	
	-90	90	114	214	314	414	
	-30	-180	121	221	321	421	
	-30	-90	122	222	322	422	
	-30	0	123	223	323	423	
	-30	90	124	224	324	424	
	30	-180	131	231	331	431	
	30	-90	132	232	332	432	
	30	0	133	233	333	433	
	30	90	134	234	334	434	
	90	-180	141	241	341	441	
	90	-90	142	242	342	442	
	90	0	143	243	343	443	
	90	90	144	244	344	444	

Ophidia

NetCDF



<pre>netcdf test {</pre>						
dimensions:						
lat = 4 ;						
lon = 4;						
<pre>time = UNLIMITED // (4 currently) ;</pre>	\sim					
variables:				_		
<pre>double lon(lon) ;</pre>		D		Arı		
<pre>double lat(lat) ;</pre>		1	111	211	311	411
<pre>double time(time) ;</pre>		2	112	212	312	412
<pre>float Temperature(time, lat, lon) ;</pre>		3	113	213	313	413
data:		4	114	214	314	414
lon = -180, -90, 0, 90;		5	121	221	321	421
lat = -90, -30, 30, 90;		6	122	222	322	422
time = 0, 3, 6, 9;		7	123	223	323	423
temperature =		8	124	224	324	424
111, 112, 113, 114,						
121, 122, 123, 124,		9	131	231	331	431
131, 132, 133, 134, 141, 142, 143, 144,		10	132	232	332	432
211, 212, 213, 214,		11	133	233	333	433
221, 222, 223, 224,		12	134	234	334	434
231, 232, 233, 234,		13	141	241	341	441
241, 242, 243, 244,		14	142	242	342	442
311, 312, 313, 314,		15	143	243	343	443
321, 322, 323, 324,		16	144	244	344	444
331, 332, 333, 334,						
341, 342, 343, 344,				Ophidia		
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tem <u>peratu</u> re =
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<u> 241</u> , 242, 243, 244,
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2	-					
				Temperature		
	lat	lon	time[0]	time[1]	time[2]	time[3]
	-90	-180	111	211	311	411
	-90	-90	112	212	312	412
	-90	0	113	213	313	413
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Ophidia



```
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    temperature =
       111, 112, 113, 114,
         121, 122, 123, 124,
         131, 132, 133, 134,
         141, 142, 143, 144,
        211, 212, 213, 214,
          221, 222, 223, 224,
         231, 232, 233, 234,
          241, 242, 243, 244,
       311, 312, 313, 314,
          321, 322, 323, 324,
         331, 332, 333, 334,
          341, 342, 343, 344,
        . . .
```

			FRAG1		
			Tempe	rature	
lat	lon	time[0]	time[1]	time[2]	time[3]
-90	-180	111	211	311	411
-90	-90	112	212	312	412
-90	0	113	213	313	413
-90	90	114	214	314	414
-30	-180	121	221	321	421
-30	-90	122	222	322	422
-30	0	123	223	323	423
-30	90	124	224	324	424

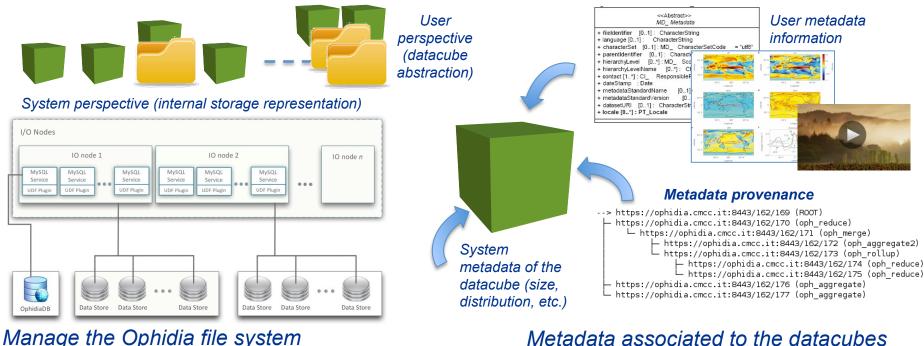
FRAG2

		Temperature			
lat	lon	time[0]	time[1]	time[2]	time[3]
30	-180	131	231	331	431
30	-90	132	232	332	432
30	0	133	233	333	433
30	90	134	234	334	434
90	-180	141	241	341	441
90	-90	142	242	342	442
90	0	143	243	343	443
90	90	144	244	344	444
	30 30 30 90 90 90	30 -180 30 -90 30 0 30 90 90 -180 90 -90 90 0	30 -180 131 30 -90 132 30 0 133 30 90 134 90 -180 141 90 -90 142 90 0 143	latlontime[0]time[1]30-18013123130-90132232300133233309013423490-18014124190-90142242900143243	latlontime[0]time[1]time[2]30-18013123133130-90132232332300133233333309013423433490-18014124134190-90142242342900143243343

Ophidia



Data abstraction: cube space perspective



CMD	BEHAVIOR
cd	change directory
mkdir	create a new folder
rm	remove an empty folder or hide (logically delete) a container
ls	list subfolders and containers in a folder
mv	move/rename a folder or a container

motua	
TYPE	CONTENT
Text	Plain text metadata
image	Binary string representation of an image
video	Binary string representation of a video
audio	Binary string representation of an audio stream
url	Text representing an URL

Search & Discovery



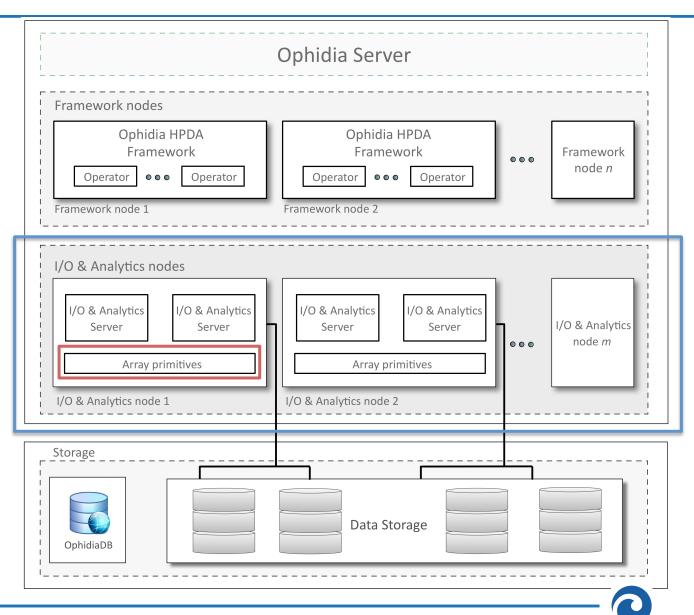
Ophidia architecture: I/O & Analytics layer

Multiple **I/O &** analytics nodes execute one or more servers

Servers run the array-based **primitives** (UDF)

Servers can transparently interface to different storage back-ends

Support for a native in-memory arraybased analytics & I/O engine





Ophidia provides a wide set of array-based primitives (around 100) to perform:

 data summarization, sub-setting, predicates evaluation, statistical analysis, array concatenation, algebraic expression, regression, etc.

Primitives come as plugins (UDF) and are applied on a single datacube chunk (fragment)

Primitives can be nested to get more complex functionalities

New primitives can be easily integrated as additional plugins

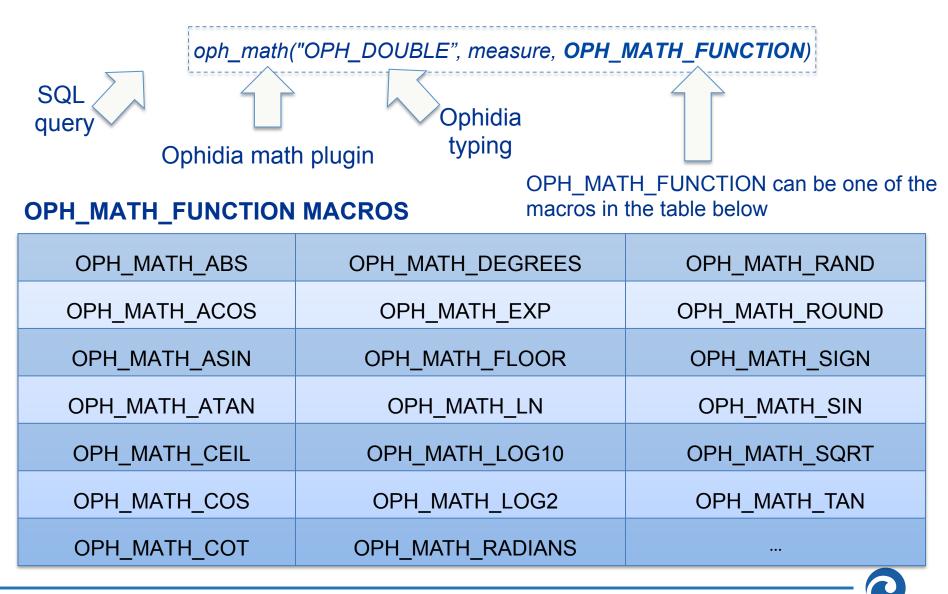
oph_apply operator to run any primitive on a datacube

oph_apply(oph_predicate(measure, 'x-298.15', '>0', '1', '0'))

Ophidia Primitives documentation: http://ophidia.cmcc.it/documentation/users/primitives/index.html



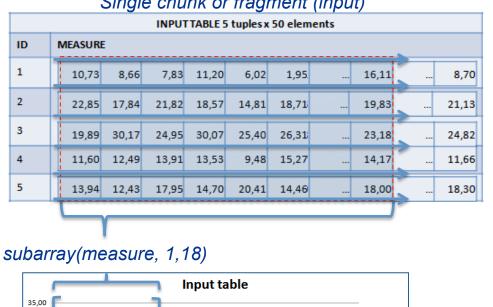
Array-based primitives: OPH_MATH





Array based primitives: nesting feature

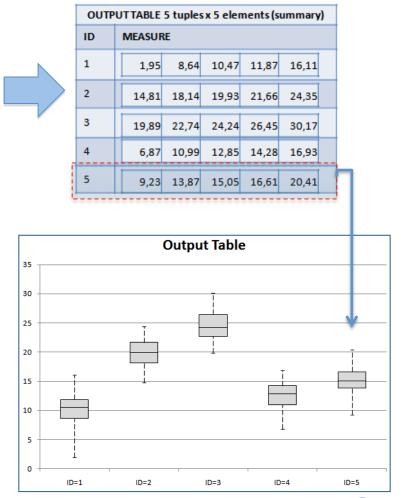
oph_boxplot(oph_subarray(oph_uncompress(measure), 1,18))



1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49

Single chunk or fragment (input)

Single chunk or fragment (output)



ID=1

ID=2

ID=3

ID=4

ID=5

30,00

25,00

20,00

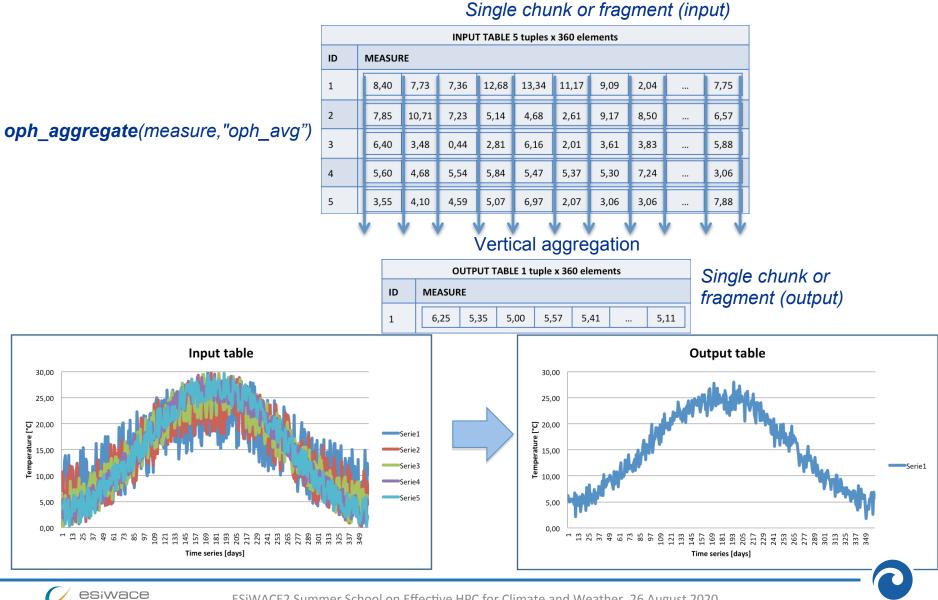
15,00

10,00

5,00

0,00

Array based primitives: oph_aggregate

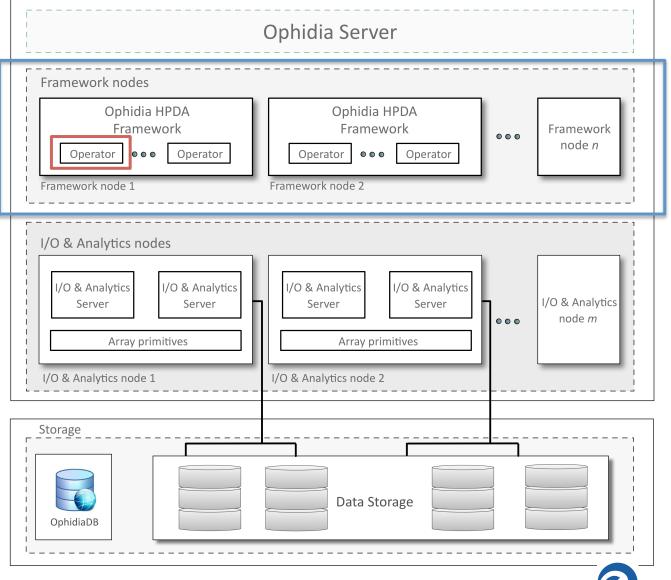


Ophidia architecture: framework layer

The Ophidia analytics framework can be executed with multiple processes/threads

Provides the environment for the execution of parallel MPI/Pthread-based operators

Operators manipulate the entire set of fragments associated to a **whole datacube**





Ophidia operators

CLASS	PROCESSING TYPE	OPERATOR(S)
I/O	Parallel	OPH_IMPORTNC, OPH_EXPORTNC, OPH_CONCATNC, OPH_RANDUCUBE
Time series processing	Parallel	OPH_APPLY
Datacube reduction	Parallel	OPH_REDUCE, OPH_REDUCE2, OPH_AGGREGATE
Datacube subsetting	Parallel	OPH_SUBSET
Datacube combination	Parallel	OPH_INTERCUBE, OPH_MERGECUBES
Datacube structure manipulation	Parallel	OPH_SPLIT, OPH_MERGE, OPH_ROLLUP, OPH_DRILLDOWN, OPH_PERMUTE
Datacube/file system management	Sequential	OPH_DELETE, OPH_FOLDER, OPH_FS
Metadata management	Sequential	OPH_METADATA, OPH_CUBEIO, OPH_CUBESCHEMA
Datacube exploration	Sequential	OPH_EXPLORECUBE, OPH_EXPLORENC

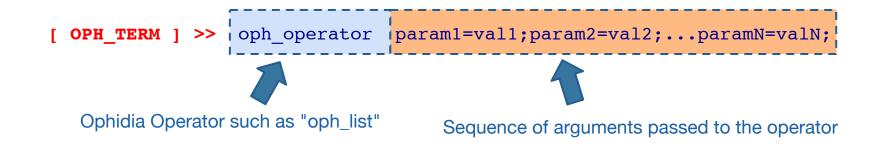
About 50 operators for data and metadata processing

Ophidia operators documentation: http://ophidia.cmcc.it/documentation/users/operators/index.html





Operators commands

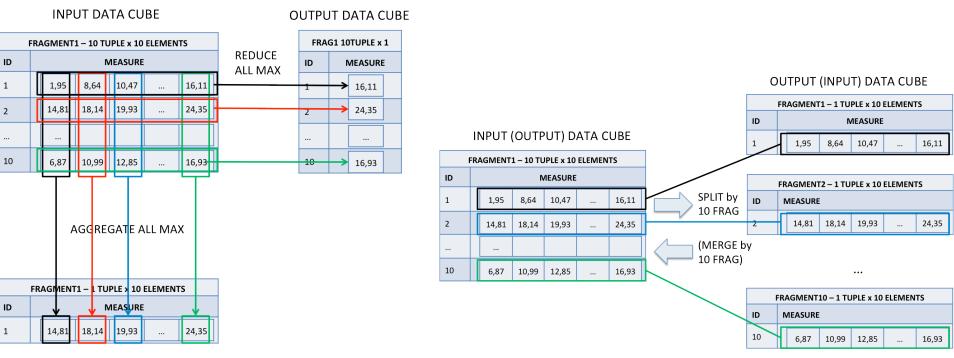


The operator strings follow a declarative style, with common arguments shared among all operators and some operator-specific arguments

Special arguments:

- "exec_mode": specifies if the command is executed in synchronous ("sync") or asynchronous mode ("async") which is the default;
- "ncores": it specifies the number of parallel processes requested for the execution of the operator (default is 1);
- "nthreads": it specifies the number of parallel threads per each processes requested for the execution of the operator (default is 1);
- "cube": it specifies the input datacube. It is automatically added by the terminal exploiting the last produced cube.

Ophidia "data" operators



OUTPUT DATA CUBE

INPUT DATA CUBE

F	FRAGMENT10 – 10 TUPLE x 10 ELEMENTS				OUTPUT DATA CUBE								
ID	ID MEASURE			SUBSET	FRAGMENT10 – 2 TUPLE x 10 ELEMENTS								
1		1,95	8,64	10,47	 16,11	Filter 1:2	ID			N	IEASURE		
2		14,81	18,14	19,93	 24,35		1		1,95	8,64	10,47		16,11
							2	1	14,81	18,14	19,93		24,35
10		6,87	10,99	12,85	 16,93								



Ophidia "data" operators

[37..4416] >> oph_explorecube cube=http://127.0.0.1/ophidia/35/67 subset_dims=lat|lon|time;subset_filter=39:42|15:19|1:275;show_time=yes;

[Request]:

operator=oph_explorecube;cube=http://127.0.0.1/ophidia/35/67;subset_dims=lat|lon|time;subset_filter=39:42|15:19|1:275;show_time=yes;sessionid=http://127.0.0.1/ophidia/sessions/374383780832141666641463737283924416/experiment;exec_mode=sync;ncores=1;cwd=/;

[JobID]:

http://127.0.0.1/ophidia/sessions/374383780832141666641463737283924416/experiment?106#224

[Response]:

tos

+======++ lat	lon	tos
39.500000	15.000000	1.00000002e+20, 1.000000002e+20, 1.00000002e+20, 1.000000002e+20, 1.0000000002e+20, 1.000000002e+20, 1.000000002e+20, 1.00000000000000000000000000000000000
39.500000	17.000000	287.3930664062, 286.8287048340, 286.5860595703, 286.9228210449, 288.5254516602, 292.3968200684, 295.8656921387, 297.2062072754, 295.7126464844
39.500000	19.000000	287.6926879883, 287.0508117676, 286.7896118164, 287.0781555176, 288.6802062988, 292.6882629395, 296.4769287109, 297.6632385254, 296.3418273926
40.500000	15.000000	1.00000002e+20, 1.000000002e+20, 1.000000002e+20, 1.00000000000000000000000000000000000
40.500000	17.000000	287.1098632812, 286.5683593750, 286.2949829102, 286.5216674805, 288.0316772461, 291.7698974609, 295.4139709473, 296.8489685059, 295.4132995605
40.500000	19.000000	287.4010009766, 286.7818298340, 286.4914245605, 286.7260742188, 288.3006286621, 292.1842346191, 296.0237731934, 297.2694702148, 295.9751892090
41.500000	15.000000	1.00000002e+20, 1.000000002e+20, 1.000000002e+20, 1.00000000000000000000000000000000000
41.500000	17.000000	286.5835876465, 286.0175781250, 285.7146911621, 285.9142761230, 287.4476623535, 291.1032104492, 294.7090454102, 296.0852355957, 294.7053222656
41.500000	19.000000	286.9717712402, 286.3946838379, 286.0617675781, 286.1446228027, 287.6101989746, 291.2955017090, 295.2700195312, 296.5146179199, 295.3194274902

Summary

Selected 9 rows out of 9



Ophidia "metadata" operators

[37..4416] >> oph_cubeio

[Request]:

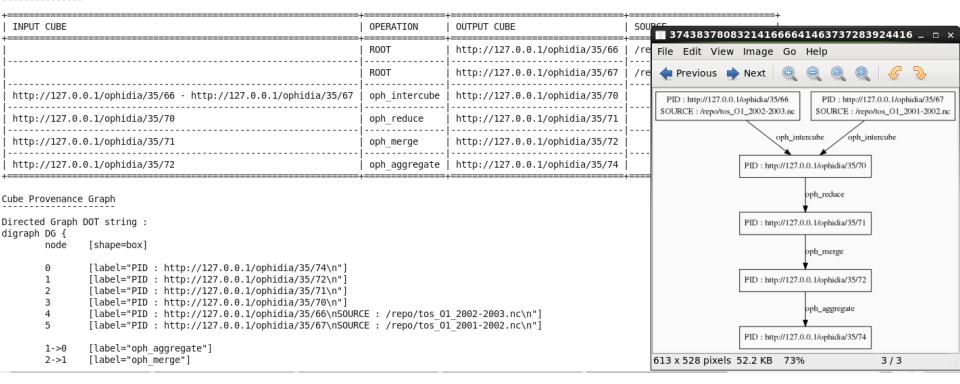
operator=oph_cubeio;sessionid=http://127.0.0.1/ophidia/sessions/374383780832141666641463737283924416/experiment;exec_mode=sync;ncores=1;cube=http://127.0.0.1/ophidia/35/74;cwd=/;

[JobID]:

http://127.0.0.1/ophidia/sessions/374383780832141666641463737283924416/experiment?82#176

[Response]:

Cube Provenance



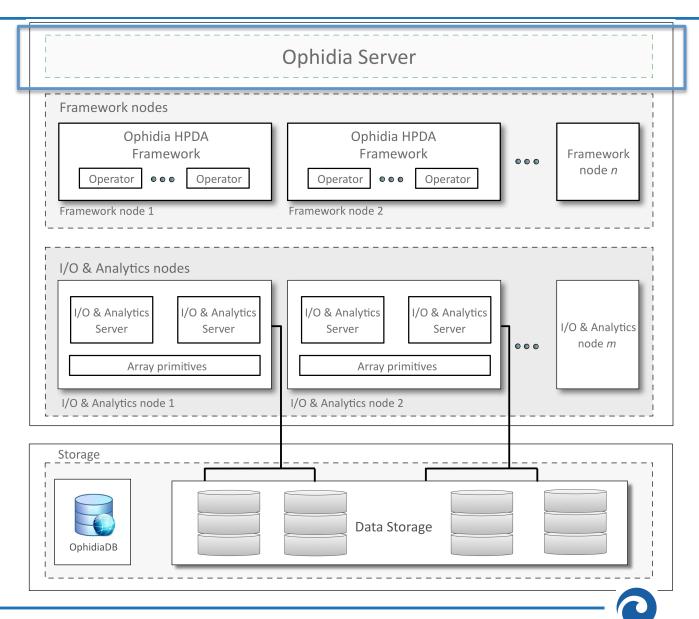
Ophidia architecture: front-end layer

Multi-interface server front-end

Manages user authN/authZ, sessions and requests

Manages task/ workflow execution

Remote interactions with a CLI, WPS clients and Python modules





Ophidia Terminal

The **Ophidia Terminal**, a CLI bash-like client for the Ophidia framework:

- o Executing interactive data analytics sessions;
- o Executing batch data analytics tasks of workflows;
- Experiment and operators debugging;
- File system exploration and environment management.

```
[11..4495] >> oph list level=2;
[Request]:
operator=oph list;path=;level=2;sessionid=http://127.0.0.1/ophidia/sessions/1112
38695229505952271558621818154495/experiment;exec mode=sync;cdd=/;
[JobID]:
http://127.0.0.1/ophidia/sessions/111238695229505952271558621818154495/experiment?2#45
[Response]:
Ophidia Filesystem:
      PATH
                            DATACUBE PID
                                                                           DESCRIPTION
      testFolder/
                            http://127.0.0.1/ophidia/2917/374976
      test
```



Three levels of parallelism

Datacube-level parallelism

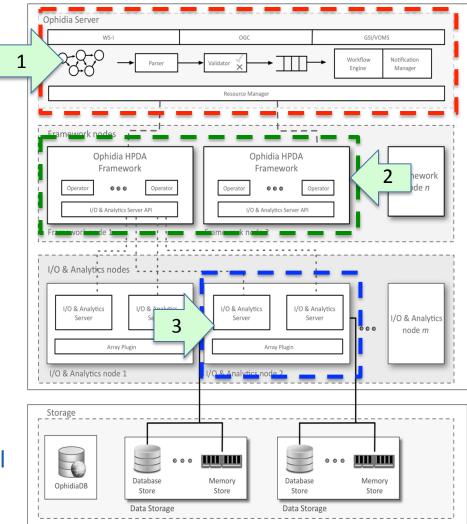
- o HTC paradigm
- o At the front-end level
- Based on the "<u>massive</u>" operator concept

Framework-level parallelism

- o HPC paradigm
- o MPI/Pthread
- o At the HPDA framework level

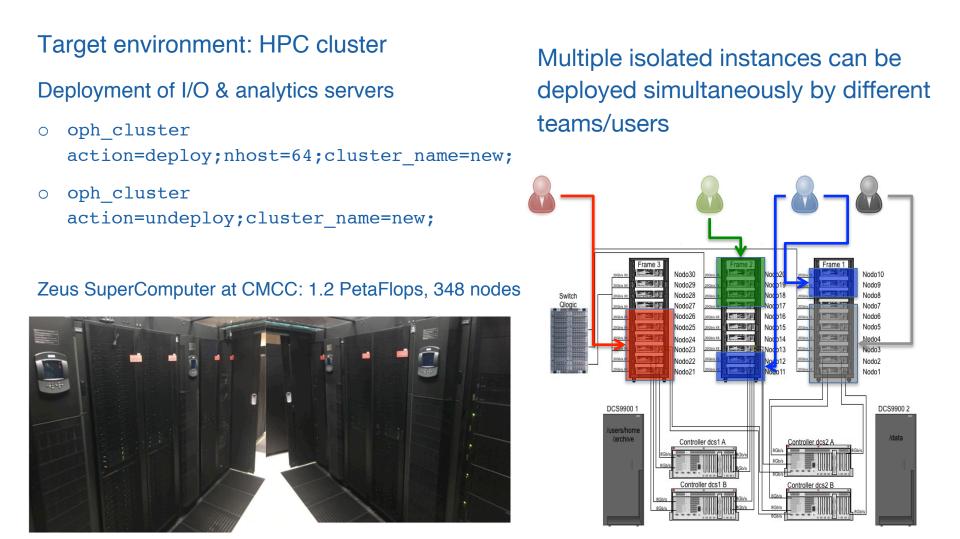
Fragment-level parallelism

- o OpenMP based
- o At the I/O & analytics server level





On-demand instantiation of an Ophidia custer





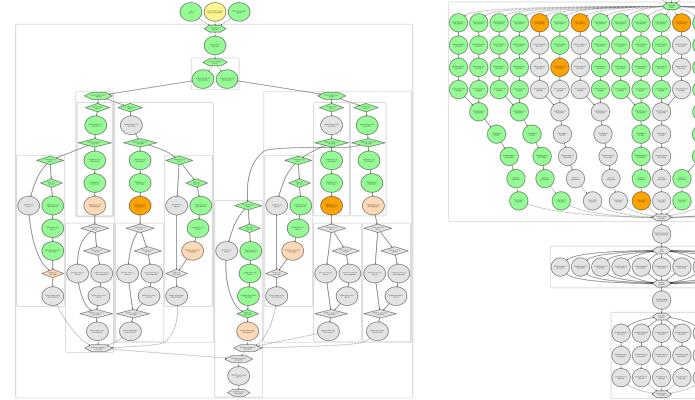
- ✓ Introduction to HPDA and data challenges in eScience
- ✓ ECAS and EOSC
- ✓ Introduction to the Ophidia HPDA Framework
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- Analytics workflows with Ophidia
 - ✓ Workflow execution demo
- ✓ Ophidia Python bindings: PyOphidia



Analytics workflows

Ophidia supports the execution of complex workflows of operators.

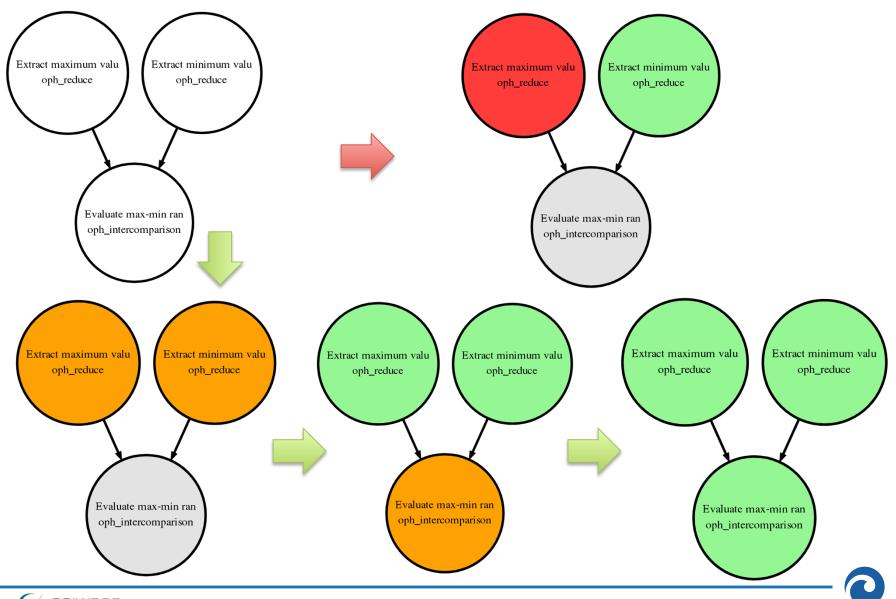
- It defines a **JSON representation** for the workflow DAG specification
- Supports different constructs: dependencies; massive tasks; iterative (group of) tasks; parallel (group of) tasks; flow and error control



C. Palazzo, A. Mariello, S. Fiore, A. D'Anca, D. Elia, D. N. Williams, G. Aloisio, "A Workflow-Enabled Big Data Analytics Software Stack for eScience", HPCS 2015, pp. 545-552



Workflow support



Workflow Management

This group includes a number of flow control operators that could be used within an Ophidia workflow to implement complex data processing in batch mode. In particular, they implement several advanced features: setting of run-time variables, iterative and parallel interface, selection interface, interactive workflows, interleaving workflows, etc.

NAME	DESCRIPTION
OPH_ELSE	Start the last sub-block of a selection block "if".
OPH_ELSEIF	Start a new sub-block of a selection block "if".
OPH_ENDFOR	Close a loop "for".
OPH_ENDIF	Close a selection block "if".
OPH_FOR	Implement a loop "for".
OPH_IF	Open a "if" selection block.
OPH_INPUT	It sends commands or data to an interactive task.
OPH_SET	Set a parameter in the workflow environment.
OPH_WAIT	Wait until an event occurs.

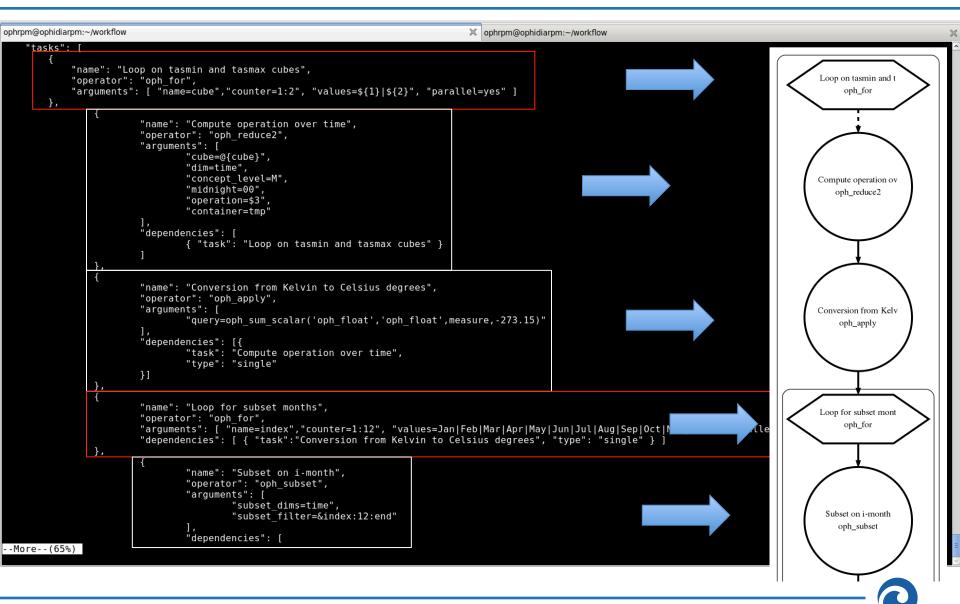
Ophidia workflow documentation: http://ophidia.cmcc.it/documentation/users/workflow/index.html

Behind the scene: workflow JSON representation

```
ophrpm@ophidiarpm:~/workflow
                                                                                    X ophrpm@ophidiarpm:~/workflow
    "tasks": [
            "name": "Loop on tasmin and tasmax cubes",
            "operator": "oph for",
            "arguments": [ "name=cube", "counter=1:2", "values=${1}|${2}", "parallel=yes" ]
        },
                         "name": "Compute operation over time",
                         "operator": "oph reduce2",
                        "arguments": [
                                 "cube=@{cube}",
                                 "dim=time",
                                 "concept level=M",
                                 "midnight=00",
                                 "operation=$3",
                                 "container=tmp"
                        "dependencies": [
                                 { "task": "Loop on tasmin and tasmax cubes" }
                         "name": "Conversion from Kelvin to Celsius degrees",
                         "operator": "oph apply",
                        "arguments": [
                                 "query=oph sum scalar('oph float','oph float',measure,-273.15)"
                         ],
                        "dependencies": [{
                                 "task": "Compute operation over time",
                                 "type": "single"
                        }]
                },
{
                        "name": "Loop for subset months",
                         "operator": "oph for",
                        "arguments": [ "name=index","counter=1:12", "values=Jan|Feb|Mar|Apr|May|Jun|Jul|Aug|Sep|Oct|Nov|Dec", "parallel=yes" ],
                         "dependencies": [ { "task":"Conversion from Kelvin to Celsius degrees", "type": "single" } ]
                },
                                 "name": "Subset on i-month",
                                 "operator": "oph subset",
                                 "arguments": [
                                         "subset dims=time",
                                         "subset filter=&index:12:end"
                                 "dependencies": [
--More--(65%)
```

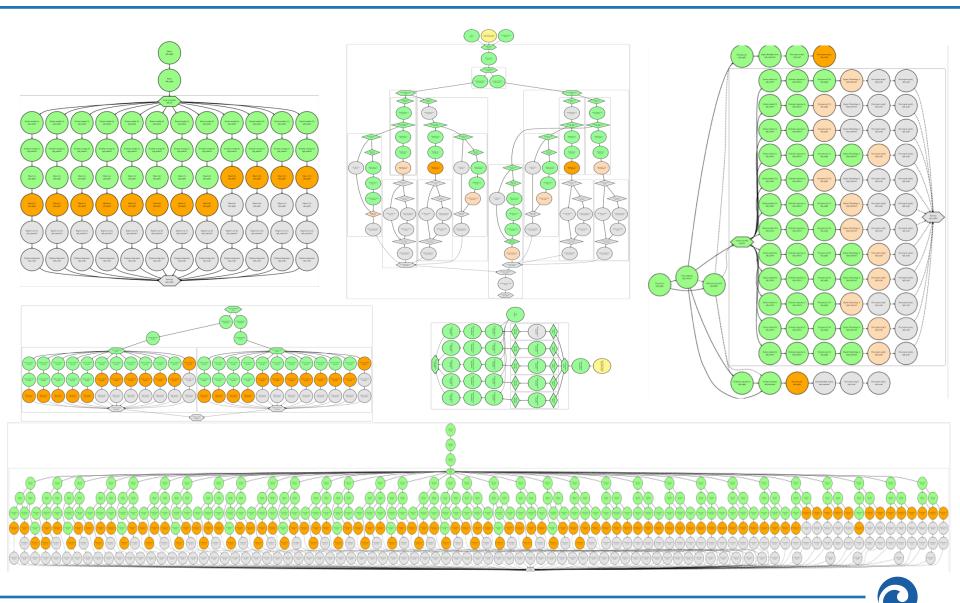


Behind the scene: workflow JSON representation





Analytics workflows support and interfaces





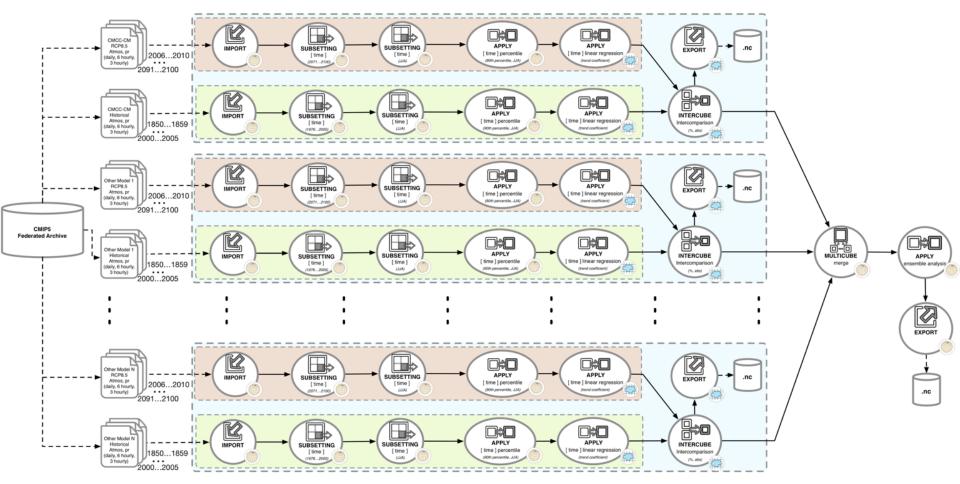
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Multi-model experiment design

Precipitation Trend Analysis use case implemented as an Ophidia workflow

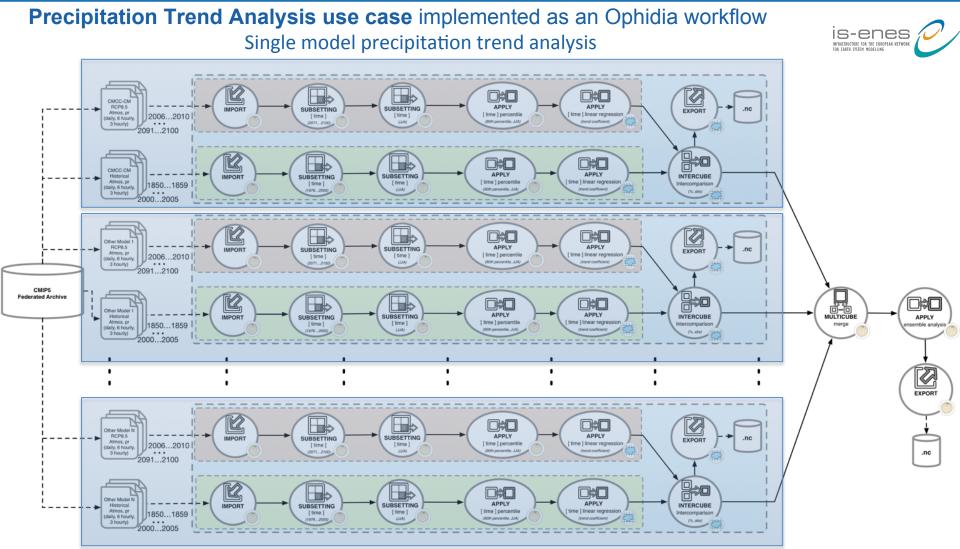




S. Fiore, et al., "Distributed and cloud-based multi-model analytics experiments on large volumes of climate change data in the earth system grid federation eco-system". In Big Data (Big Data), 2016 IEEE Int. Conference on. IEEE, 2016. pp. 2911-2918



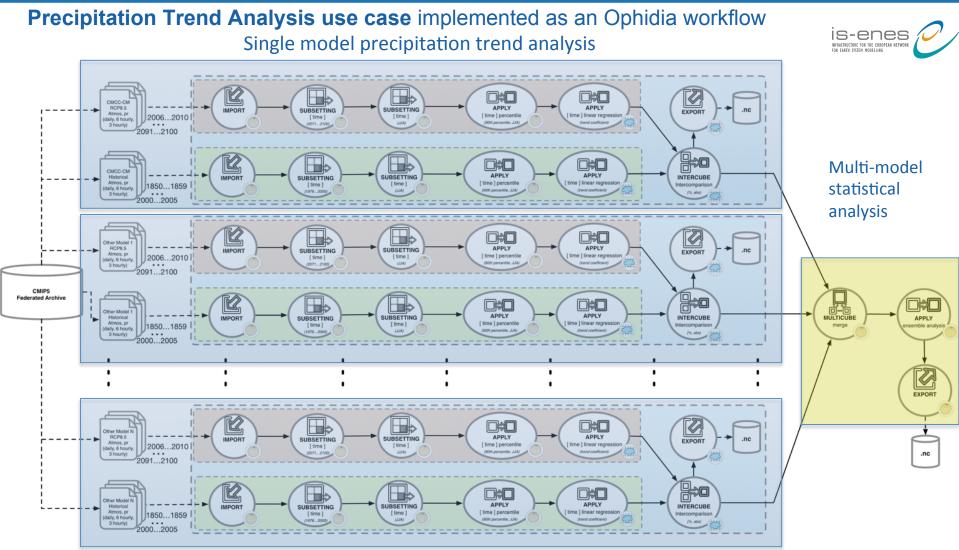
Multi-model experiment design



S. Fiore, et al., "Distributed and cloud-based multi-model analytics experiments on large volumes of climate change data in the earth system grid federation eco-system". In Big Data (Big Data), 2016 IEEE Int. Conference on. IEEE, 2016. pp. 2911-2918



Multi-model experiment design

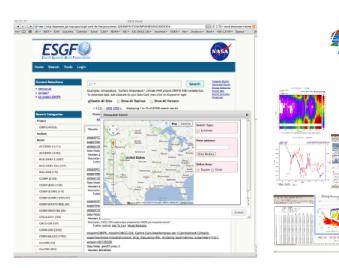


S. Fiore, et al., "Distributed and cloud-based multi-model analytics experiments on large volumes of climate change data in the earth system grid federation eco-system". In Big Data (Big Data), 2016 IEEE Int. Conference on. IEEE, 2016. pp. 2911-2918



Multi-model experiment input data

ESGF¹ is a coordinated multiagency, international collaboration of institutions that continually develop, deploy, and maintain software needed to facilitate and empower the study of climate.



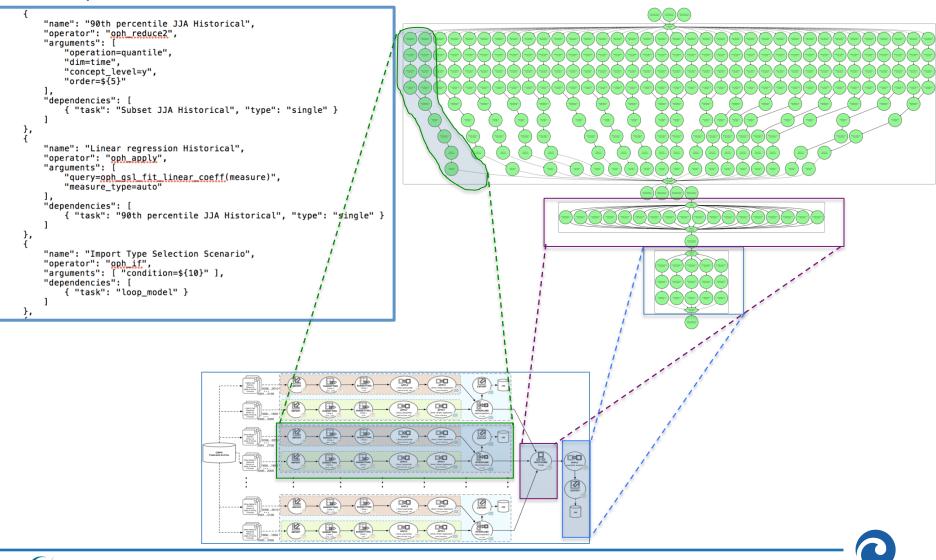


Model acronym	Model expansion	Institute				
CCSM4	Community Climate System Model, v4	National Center for Atmospheric Research (NCAR)				
CMCC-CESM	CMCC - Community Earth System Model	Euro-Mediterranean Center on Climate Change (CMCC)				
CMCC-CMS	CMCC - Coupled Modeling System	Euro-Mediterranean Center on Climate Change (CMCC)				
CMCC-CM	CMCC - Climate Model	Euro-Mediterranean Center on Climate Change (CMCC)				
CNRM-CM5 Model v5		Centre National de Recherches Météorologiques (CNRM)/Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique (CERFACS)				
CSIRO Mk3.6.0	CSIRO Mark, v3.6.0	Commonwealth Scientific and Industrial Research Organi- sation (CSIRO) in collaboration with Queensland Climate- Change Centre of Excellence (QCCCE)				
CanESM2	Second Generation Canadian Earth System Model	Canadian Centre for Climate Modelling and Analysis (CC- Cma)				
GFDL-CM3	GFDL Climate Model, v3	National Oceanic and Atmospheric Administration (NOAA)/Geophysical Fluid Dynamics Laboratory (GFDL)				
GFDL-ESM2G	GFDL Earth System Model with Generalized Ocean Layer Dynamics (GOLD) component	National Oceanic and Atmospheric Administration (NOAA)/Geophysical Fluid Dynamics Laboratory (GFDL)				
GFDL-ESM2M	GFDL Earth System Model with Modular Ocean Model 4 (MOM4) component	National Oceanic and Atmospheric Administration (NOAA)/Geophysical Fluid Dynamics Laboratory (GFDL)				
HadGEM2-CC	Hadley Centre Global Environment Model, v2 (Carbon Cycle)	Met Office (UKMO) Hadley Centre (HC)				
HadGEM2-ES	Hadley Centre Global Environment Model, v2 (Earth System)	Met Office (UKMO) Hadley Centre (HC)				
INM-CM4.0	INM Coupled Model, v4.0	Institute of Numerical Mathematics (INM)				
IPSL-CM5A-MR coupled with NEMO, mid resolution		L'Institut Pierre-Simon Laplace (IPSL)				
MIROC5	Model for Interdisciplinary Research on Climate, v5	Atmosphere and Ocean Research Institute (The Unive of Tokyo), National Institute for Environmental Studies Japan Agency for Marine-Earth Science and Technolo				
MPI-ESM-MR	MPI Earth System Model, medium resolution	Max Planck Institute for Meteorology (MPI-M)				
MRI-CGCM3	MRI Coupled Atmosphere - Ocean General Circulation Model, v3	Meteorological Research Institute (MRI)				
NorESM1-M Norwegian Earth System Model, v1 (intermediate resolution)		Norwegian Climate Centre (NCC)				



Multi-model experiment implementation & execution

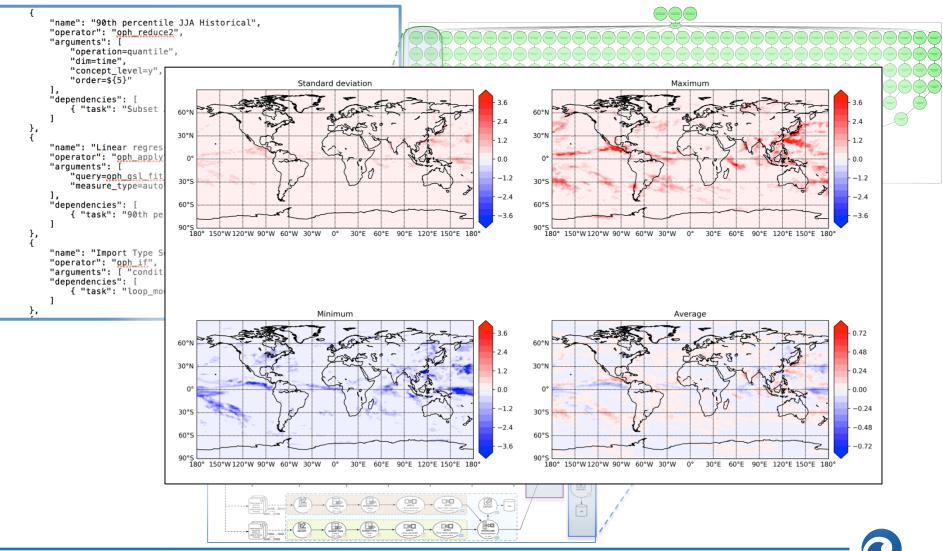
JSON implementation of the workflow





Multi-model experiment implementation & execution

JSON implementation of the workflow





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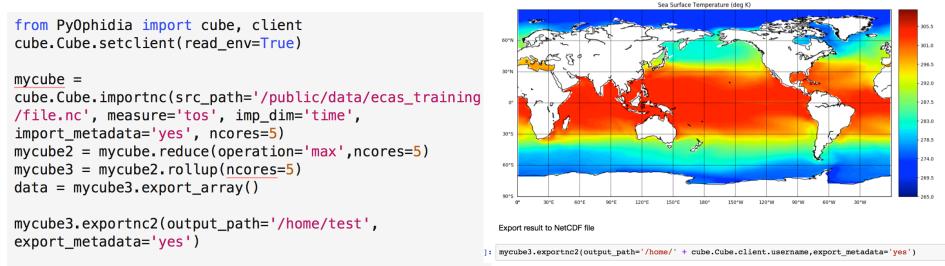


Python programmatic access to Ophidia

PyOphidia is a GPLv3-licensed Python module to interact with the Ophidia framework.

It provides a programmatic access to Ophidia features, allowing:

- o Submission of commands to the Ophidia Server and retrieval of the results
- o Management of (remote) data objects in the form of datacubes
- o Easy exploitation from Jupyter Notebooks and integration with other Python modules







esiwace

PyOphidia Repository

PyOphidia	Update interfaces in cube.py	5 months ago
conda/recipe	Adding Conda Recipe (#5)	2 years ago
Jitignore	Add .gitignore	4 years ago
AUTHORS.rst	Update author information	2 years ago
	Initial commit	4 years ago
HISTORY.rst	Update history for release	5 months ago
	Initial commit	4 years ago
MANIFEST.in	Initial commit	4 years ago
README.rst	Update readme for release	5 months ago
setup.cfg	Initial commit	4 years ago
setup.py	Update history for release	5 months ago

E README.rst

PyOphidia: Python bindings for Ophidia

PyOphidia is a GPLv3-licensed Python package for interacting with the Ophidia framework.

It is an alternative to Oph_Term, the Ophidia no-GUI interpreter component, and a convenient way to submit SOAP HTTPS requests to an Ophidia server or to develop your own application using Python.

PyOphidia on Github: https://github.com/OphidiaBigData/PyOphidia



PyOphidia Repository

	Ø	Search projects		Q Help Donate Login Register
https://pypi.org/project/PyOphidia/	PyOphid	l ia 1.8.1 ۱ PyOphidia ♥		Latest version Last released: 16 aprile 2019
pip3 install pyophidia	Python bindings fo	r the Ophidia Data Analyt	ics Platform	
	Navigation Project descri Release histor	ption Pyc	an alternative t	ription v3-licensed Python package for interacting with the Ophidia framework. to Oph_Term, the Ophidia no-GUI interpreter component, and a convenient way to submit ests to an Ophidia server or to develop your own application using Python.
O ANACONDA CLOUD Search Anaconda Cloud Q Gallery Abo	out Anaconda Hel	p Download Anacond	1a Sian in	2.7, 3.3, 3.4, 3.5 and 3.6 has no Python dependencies and is pure-Python code. It requires a stance for client-server interactions. The latest PyOphidia version (v1.8) is compatible with
conda-forge / packages / pyophidia 1.8.1		*	0	
PyOphidia is a Python package for interacting with the Ophidia framework.			_	
Conda Files Lat ■ License: GPL-3.0 ᢙ Home: http://github.com/OphidiaBigData/PyOphidia ▲ 5578 total downloads ⊞ Last upload: 4 months and 26 days ago	pels	Badges		https://anaconda.org/conda-forge/pyophidia conda install -c conda-forge pyophidia
Installers Info: This package contains files in non-standard labels.				
ESiWACE2 Summer Scho	ol on Effective	HPC for Climate	and Wea	ther, 26 August 2020

The PyOphidia library

PyOphidia implements two main classes:

- **Client class**: supports the submissions of Ophidia commands and workflows, as well as the management of session from Python code (similar to the Ophidia Terminal)
 - o It allows to run all the Ophidia operators, including massive tasks and workflows
- Cube class: provides the datacube type abstraction and the methods to manipulate, process and get information on cubes objects and it builds on the client class
 - Defines a object-oriented approach allowing a handle the datacubes more naturally

While the cube module provides a user-friendly interface, the client module allows a finer specification of the operators.



Python and HPC infrastructure transparency

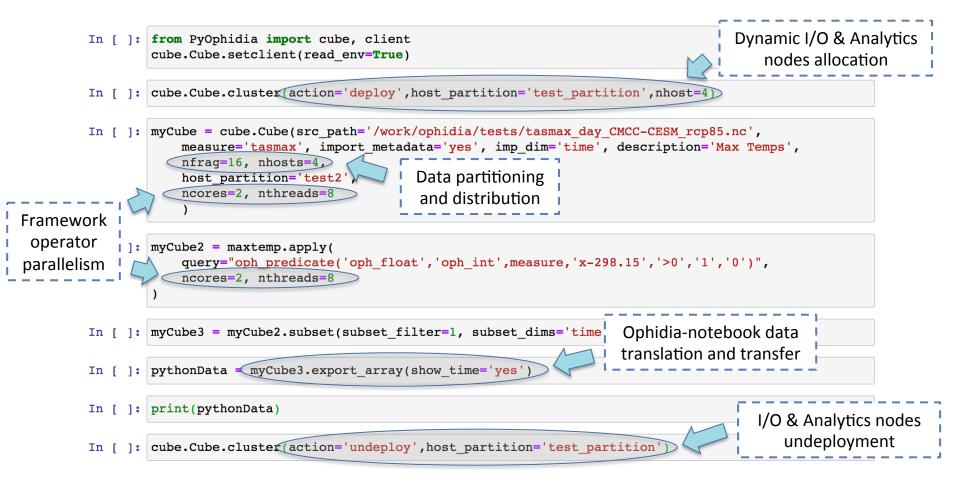
PyOphidia class hides the HPC environment complexity

```
In [ ]: from PyOphidia import cube, client
        cube.Cube.setclient(read env=True)
In [ ]: cube.Cube.cluster(action='deploy', host partition='test partition', nhost=4)
In [ ]: myCube = cube.Cube(src path='/work/ophidia/tests/tasmax day CMCC-CESM rcp85.nc',
            measure='tasmax', import metadata='yes', imp dim='time', description='Max Temps',
            nfrag=16, nhosts=4,
            host partition='test2',
            ncores=2, nthreads=8
            )
In [ ]: myCube2 = maxtemp.apply(
            guery="oph predicate('oph float','oph int',measure,'x-298.15','>0','1','0')",
            ncores=2, nthreads=8
        )
In []: myCube3 = myCube2.subset(subset filter=1, subset dims='time')
In [ ]: pythonData = myCube3.export array(show time='yes')
In [ ]: print(pythonData)
In [ ]: cube.Cube.cluster(action='undeploy', host partition='test partition')
```



Python and HPC infrastructure transparency

PyOphidia class hides the HPC environment complexity





Summary

- ✓ Joining HPC and data-intensive analytics is an enabling factor for scientific applications
- Scientific data management and analytics pose challenges requiring novel and efficient software solution
- ✓ ECAS: a solutions for server-side, parallel data analysis in the EOSC landscape
- ✓ In-depth overview of the Ophidia HPDA framework and how it addresses data analytics challenges for scientific analysis
 - Scalable architecture, data distribution, parallel operators and HPC-oriented deployment
- Real experiments can be modeled as (complex) workflows composed of hundreds of tasks
 - Multi-model climate analysis example

References and further readings (1)

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- Luca Cinquini, et al. (2014). The Earth System Grid Federation: An open infrastructure for access to distributed geospatial data. Future Gener. Comput. Syst. 36: 400-417.
- GMD topical editors (Eds.), V. Eyring (coordinator) (2012). Coupled Model Intercomparison Project Phase 6 (CMIP6) Experimental Design and Organization [Special Issue]. Geosci. Model Dev. <u>https://gmd.copernicus.org/articles/special_issue590.html</u>
- G. Aloisio, S. Fiore, I. Foster, D. Williams (2013). Scientific big data analytics challenges at large scale. Big Data and Extreme-scale Computing (BDEC), April 30 to May 01, 2013, Charleston, South Carolina, USA (position paper).
- S. Fiore, D. Elia, C. Palazzo, A. D'Anca, F. Antonio, D. N. Williams, I. Foster, G. Aloisio, "Towards an Open (Data) Science Analytics-Hub for Reproducible multi-model Climate Analysis at Scale", 2018 IEEE Int. Conference on Big Data, pp. 3226-3234.



References and further readings (2)

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