The ENES Climate Analytics Service

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UNIDATA Community Equipment Award 2011



Outline

- EOSC, ECAS and EOSC-hub
- Ophidia
 - Architecture 1.0
 - Storage model
 - Primitives
 - Data and metadata operators
 - Architecture 2.0
 - Workflow support
 - Some real use cases
 - PyOphidia
 - Native I/O server for in-memory analytics
- ECASLab in the context of EOSC-hub
 - · Jupyter-Hub, Grafana, Workflow IDE
- Future work and conclusions
 - Looking forward
 - Website, github, youtube, pypi, ...material for hands-on

EOSC, ECAS & Ophidia

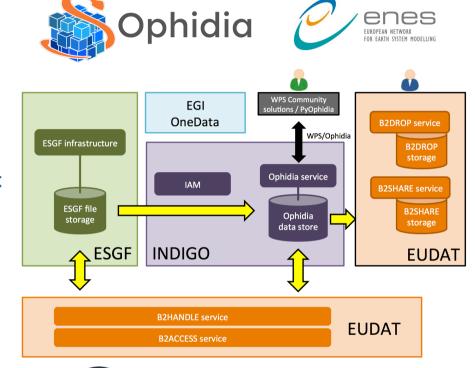
The context: European Open Science Cloud

- ✓ The European Open Science Cloud (EOSC) is an ambitious program 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.

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 and has been ranked as the 1st out of 64 Thematic Service proposals
- ✓ ECAS builds on top of the Ophidia big data analytics framework with components from INDIGO-DataCloud, EUDAT and EGI
- ✓ The Analytics-Hub is a paradigm joining data and computing able to provide a multimodel environment for CMIP-based

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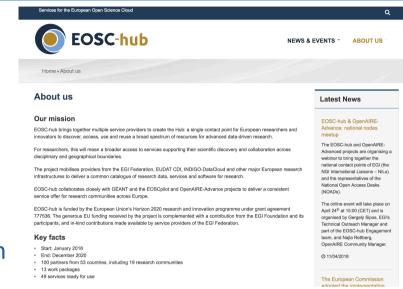
The European Commission launched the European Open ScienceCloud Initiative to capitalise on the data revolution. EOSC will provide European science, industry and public authorities with world-class digital infrastructure that bring state of the art computing and data storage capacity to the fingertips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





ECAS and the European Open Science Cloud

- ECAS: a data analytics service for EOSC
 - ENES: European Network for Earth System Modelling
 - targets the climate community at large
- Involved institutions:
 - DKRZ: German Climate Computing Center
 - CMCC: Euro-Mediterranean Center on Climate Change Foundation
- Enable server-side workflows for Earth system researchers and beyond
- Induce cultural change: No more "download and process at home"
- ECASLab is the virtual environment for ECAS
 - Integrate several UNIDATA software (NetCDF lib, THREDDS and IDV)
- ECAS is based on the Ophidia big data analytics framework

















Ophidia: a scientific big data analytics framework

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

It provides support for declarative, parallel, server-side data analysis exploiting parallel computing techniques and database approaches

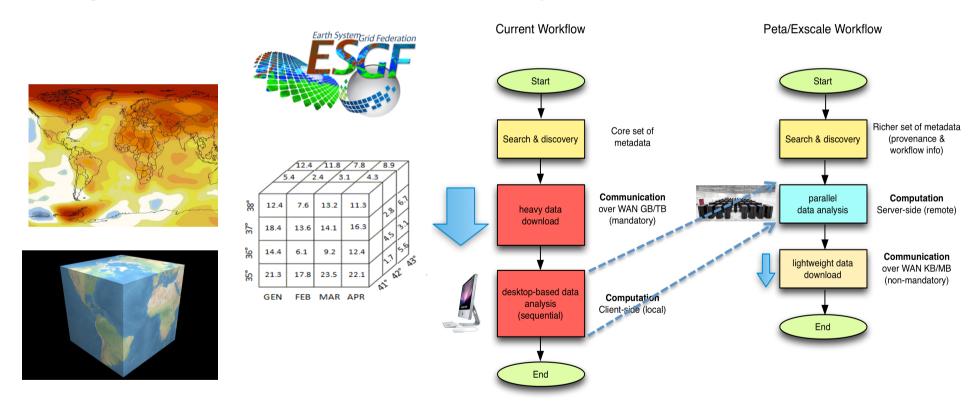
It provides end-to-end mechanisms to support complex experiments and large processing workflows on scientific datacubes





Big data challenges and the 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

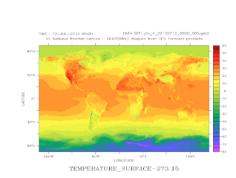
Data analytics requirements and use cases

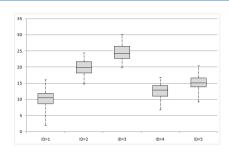
Requirements and needs focus on:

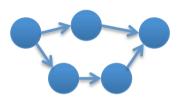
- Time series analysis
- Data subsetting
- Model intercomparison
- Multimodel means
- Massive data reduction
- Data transformation (through array-based primitives)
- ❖ Param. Sweep experiments (same task applied on a set of data)
- Climate change signal
- Maps generation
- Ensemble analysis
- Data analytics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

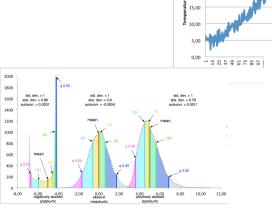
But also...

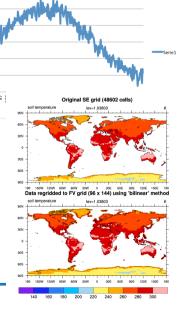
- Performance
- * re-usability
- extensibility











Ophidia in a nutshell

- ✓ Big data stack for scientific data analysis
- ✓ Features: time series analysis (array-based analysis), data subsetting (by value/index), data aggregation, model intercomparison, OLAP, etc.
- ✓ Use of parallel operators and parallel I/O
- ✓ Support for complex workflows / operational chains
- ✓ Extensible: simple API to support framework extensions like new operators and array-based primitives
 - ✓ currently 50+ operators and 100+ primitives provided
- ✓ Multiple interfaces available (WS-I, GSI/VOMS, OGC-WPS).
- ✔ Programmatic access via C and Python APIs
- ✓ Support for both batch & interactive data analysis

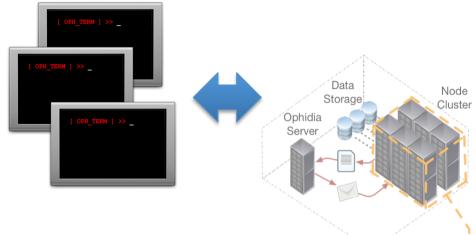
Server-side paradigm and the datacube abstraction

Svstem

metadata of the

datacube (size,

distribution, etc.)

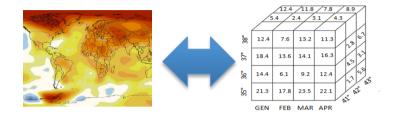


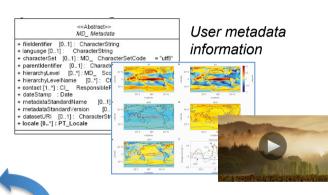
Oph Term: a terlminal-like commands interpreter serving as a client for the Ophidia framework

Ophidia framework: declarative, parallel server-side processing

Through the oph term the user can send commands to the Ophidia framework to manipulate datasets

Three interaction modes: Operators, Workflows, Python Apps





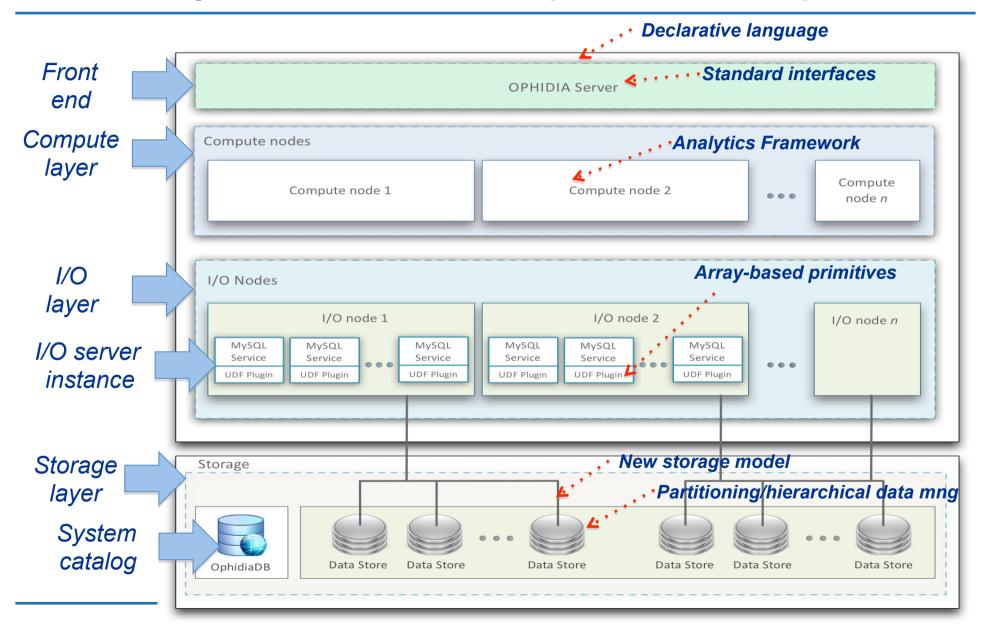
Metadata provenance

--> https://ophidia.cmcc.it:8443/162/169 (ROOT) https://ophidia.cmcc.it:8443/162/170 (oph reduce) https://ophidia.cmcc.it:8443/162/171 (oph merge) https://ophidia.cmcc.it:8443/162/172 (oph aggregate2) https://ophidia.cmcc.it:8443/162/173 (oph rollup) https://ophidia.cmcc.it:8443/162/174 (oph reduce) https://ophidia.cmcc.it:8443/162/175 (oph_reduce) https://ophidia.cmcc.it:8443/162/176 (oph aggregate) https://ophidia.cmcc.it:8443/162/177 (oph_aggregate)

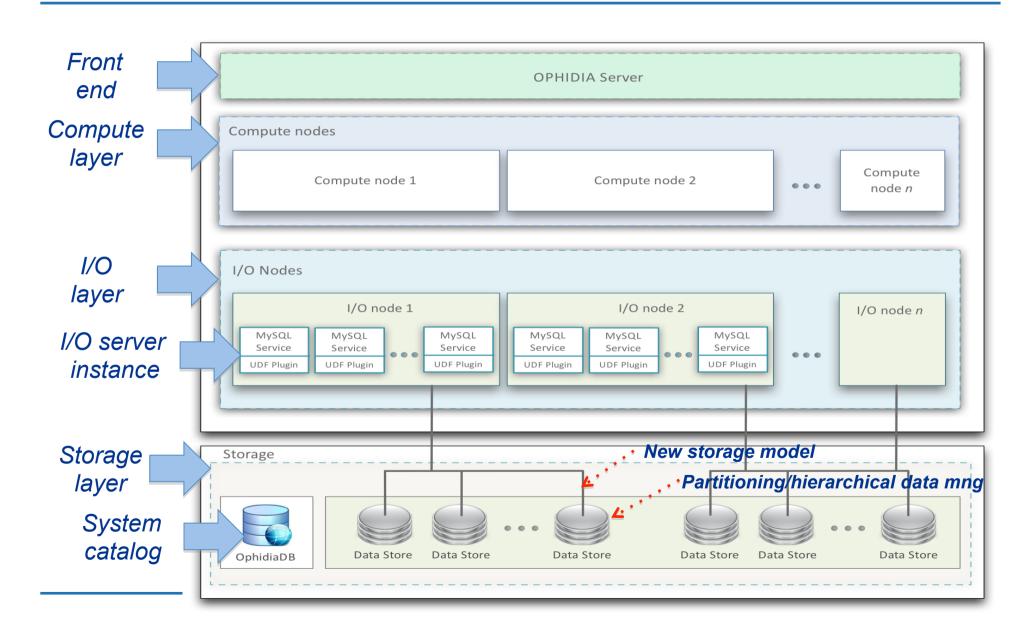
Ophidia architecture 1.0

Storage model, primitive & operators

Ophidia Architecture (sw stack view)



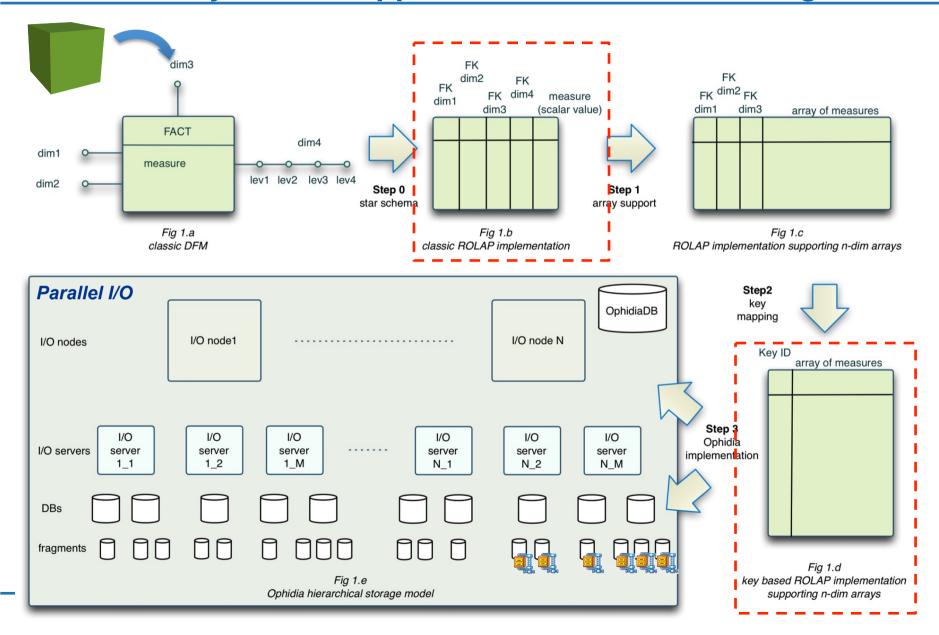
Storage model and chunks distribution



Ophidia storage model

- 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
- The second step makes the Ophidia storage model and implementation independent of the number of dimensions!

Storage model (dimension-independent) & implementation Array-based support and hierarchical storage

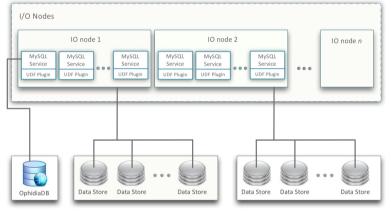


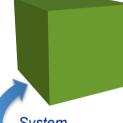
Data abstraction: cube space perspective



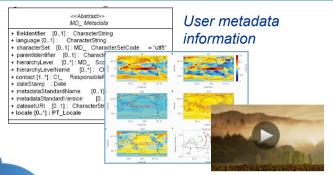
User perspective (datacube abstraction)

System perspective (internal storage representation)





System metadata of the datacube (size, distribution, etc.)



Metadata provenance

--> https://ophidia.cmcc.it:8443/162/169 (ROOT)

https://ophidia.cmcc.it:8443/162/170 (oph_reduce)

https://ophidia.cmcc.it:8443/162/172 (oph_aggregate2)

https://ophidia.cmcc.it:8443/162/173 (oph_rollup)

https://ophidia.cmcc.it:8443/162/174 (oph_reduce)

https://ophidia.cmcc.it:8443/162/175 (oph_reduce)

https://ophidia.cmcc.it:8443/162/176 (oph_aggregate)

https://ophidia.cmcc.it:8443/162/177 (oph_aggregate)

Manage the Ophidia file system

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

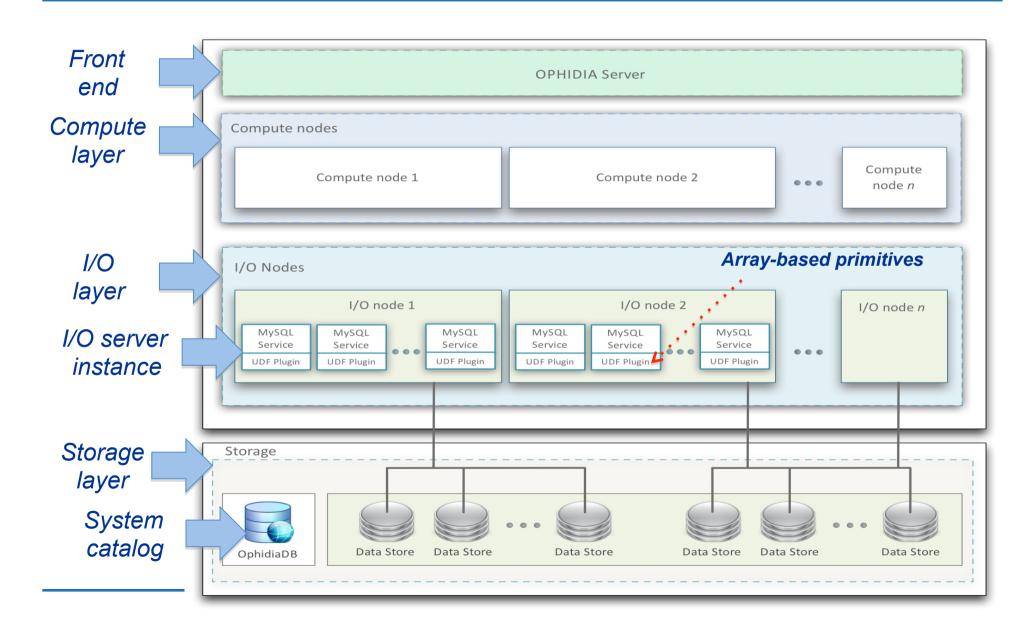
Metadata associated to the datacubes

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

Array-based primitives



Array based primitives (about 100)

- Ophidia provides a **wide set of array-based primitives** to perform data summarization, sub-setting, predicates evaluation, statistical analysis, compression, etc.
- Primitives come as plugins and are applied on a single datacube chunk (fragment)
- They are provided both for byte-oriented and bit-oriented arrays
- Primitives can be nested to get more complex functionalities
- Compression is a primitive too!
- New primitives can be easily integrated as additional plugins

Array based primitives: OPH_MATH ("SIGN")

oph_math(measure, "OPH_SIGN", "OPH_DOUBLE")



Array-based primitives: OPH_MATH support

oph_math(measure, OPH_MATH_FUNCTION, "OPH_DOUBLE")
Ophidia
Ophidia math plugin

OPH_MATH_FUNCTION MACROS

SQL

query

OPH_MATH_FUNCTION can be one of the macros in the table below

OPH_MATH_ABS	OPH_MATH_DEGREES	OPH_MATH_RAND
OPH_MATH_ACOS	OPH_MATH_EXP	OPH_MATH_ROUND
OPH_MATH_ASIN	OPH_MATH_FLOOR	OPH_MATH_SIN
OPH_MATH_ATAN	OPH_MATH_LN	OPH_MATH_SIGN
OPH_MATH_CEIL	OPH_MATH_LOG10	OPH_MATH_SQRT
OPH_MATH_COS	OPH_MATH_LOG2	OPH_MATH_TAN
OPH_MATH_COT	OPH_MATH_RADIANS	

Array based primitives: OPH_BOXPLOT

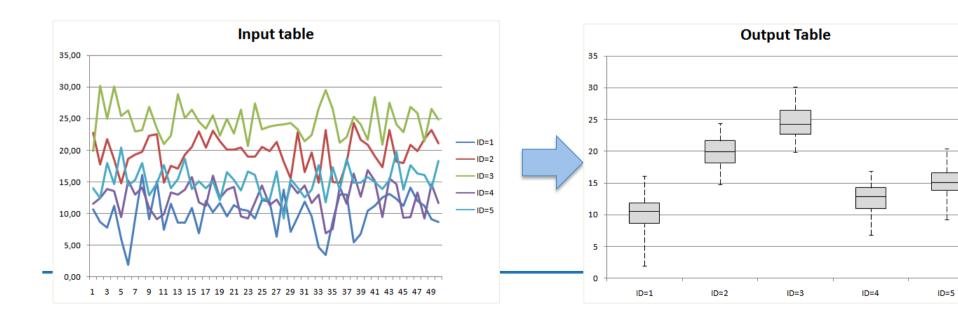
oph_boxplot(measure, "OPH_DOUBLE")

Single chunk or fragment (input)

	INPUTTABLE 5 tuples x 50 elements									
ID	MEASURE									
1	10,73	8,66	7,83	11,20	6,02	1,95	9,25	16,11		8,70
2	22,85	17,84	21,82	18,57	14,81	18,71	19,31	19,83		21,13
3	19,89	30,17	24,95	30,07	25,40	26,31	22,95	23,18		24,82
4	11,60	12,49	13,91	13,53	9,48	15,27	13,05	14,17		11,66
5	13,94	12,43	17,95	14,70	20,41	14,46	15,37	18,00		18,30

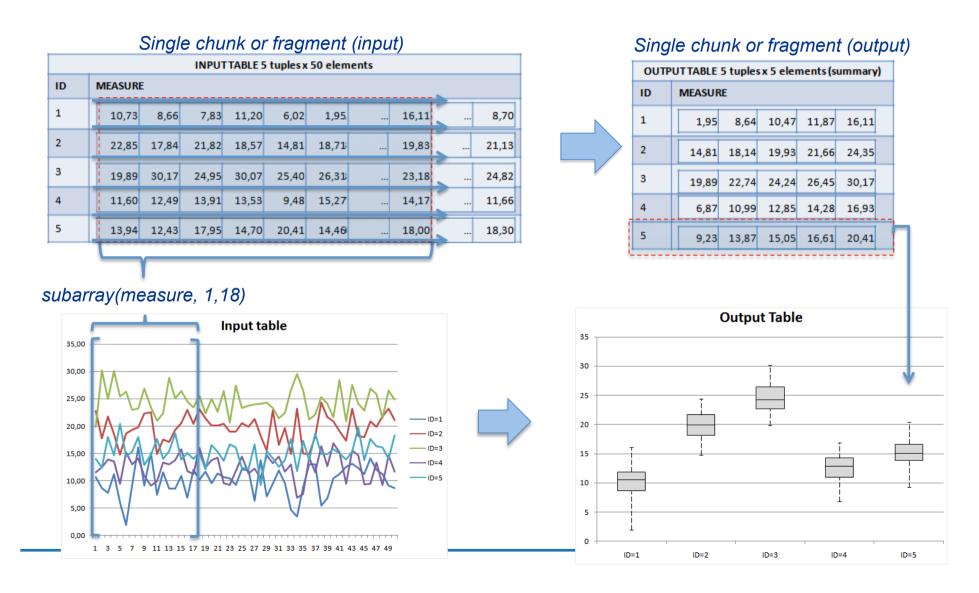
Single chunk or fragment (output)

OUTPUTTABLE 5 tuples x 5 elements (summary)								
ID	MEASUR	MEASURE						
1	1,95	8,64	10,47	11,87	16,11			
2	14,81	18,14	19,93	21,66	24,35			
3	19,89	22,74	24,24	26,45	30,17			
4	6,87	10,99	12,85	14,28	16,93			
5	9,23	13,87	15,05	16,61	20,41			



Array based primitives: nesting feature

oph boxplot(oph subarray(oph uncompress(measure), 1,18), "OPH DOUBLE")



Array based primitives: oph_aggregate

oph_aggregate(measure,"oph_avg")

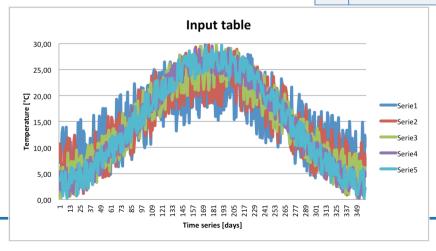
Single chunk or fragment (input)

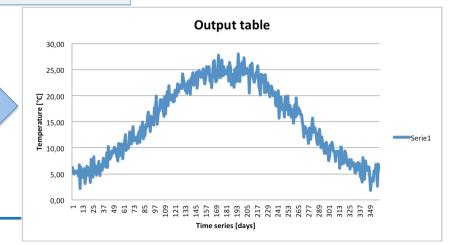
									, ,	,
INPUT TABLE 5 tuples x 360 elements										
ID MEASURE										
1	8,40	7,73	7,36	12,68	13,34	11,17	9,09	2,04		7,75
2	7,85	10,71	7,23	5,14	4,68	2,61	9,17	8,50		6,57
3	6,40	3,48	0,44	2,81	6,16	2,01	3,61	3,83		5,88
4	5,60	4,68	5,54	5,84	5,47	5,37	5,30	7,24		3,06
5	3,55	4,10	4,59	5,07	6,97	2,07	3,06	3,06		7,88

Vertical aggregation

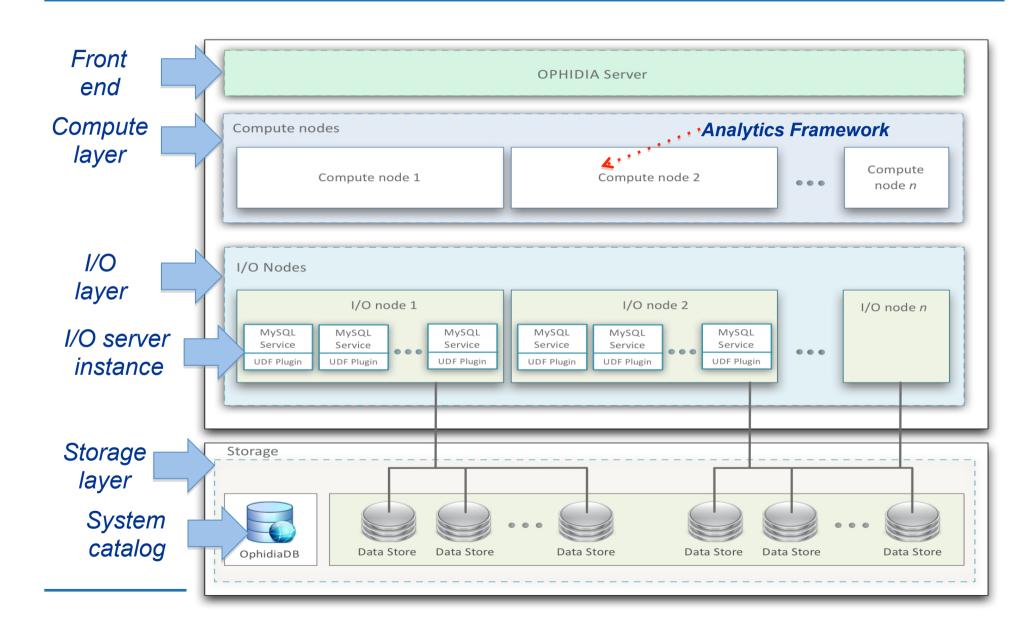
OUTPUT TABLE 1 tuple x 360 elements							
ID	MEASUR	MEASURE					
1	6,25	5,35	5,00	5,57	5,41		5,11

Single chunk or fragment (output)





Analytics framework and operators



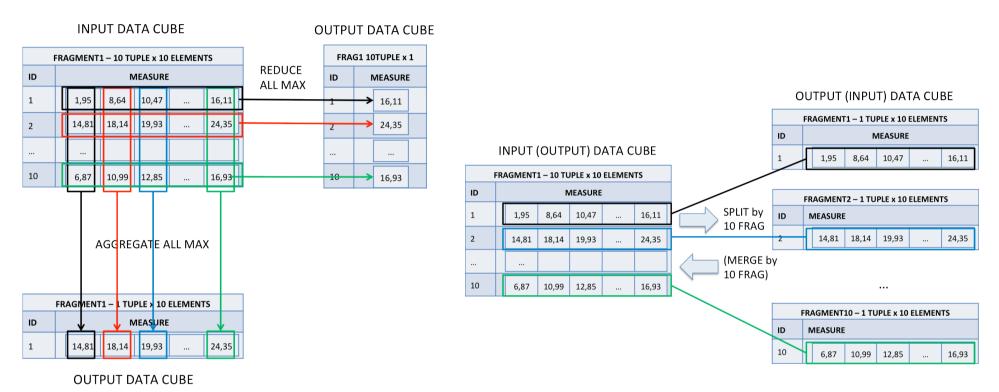
The analytics framework: datacube operators

Data Operator	Description
OPH_CONCATNC	Concatenates a NetCDF file to a data cube.
OPH_DELETE	Deletes a data cube.
OPH_DUPLICATE	Duplicates a data cube.
OPH_EXPLORECUBE	Shows the content of a data cube.
OPH_EXPORTNC	Exports a whole data cube into a single NetCDF file.
OPH_IMPORTNC	Creates new a data cube importing data from a NetCDF file.
ODLI INTERCOMPARISON	Generates the difference value-by-value between
OPH_INTERCOMPARISON	two homogeneous data cubes.
OPH_INTERCUBE	It executes an operation between two data cubes and returns a new data cube as result of the specified operation applied element by element.
OPH_MERGECUBES	Merges the measures of n input data cubes creating a new data cube with the union of the n measures.
OPH_PUBLISH	Generates web pages representing the data stored in the fragments.
OPH_RANDCUBE	Creates a new data cube with random data.
OPH_REDUCE	Applies a data reduction operation along one or more implicit dimensions.
OPH_SCRIPT	Executes a bash script.
OPH_SUBSET	Extracts a subset from a data cube using the values of the dimensions.

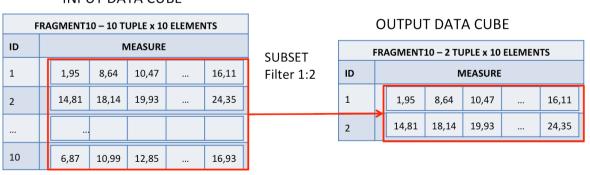
Description
omputes and displays the total number of ements contained in a data cube.
nows the provenance of a data cube.
isplays the metadata and dimension information associated to a data cube.
omputes and displays the total size (on disk) of a ata cube.
nds a data cube.
isplays the list of data cubes and containers vailable.
nows session and job information.
nows a description about an operator or rimitive.
lanages metadata information.
isplays the list of available operators.

About 50 operators for data and metadata processing

The analytics framework: "datacube" operators



INPUT DATA CUBE



The analytics framework: "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;

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]:

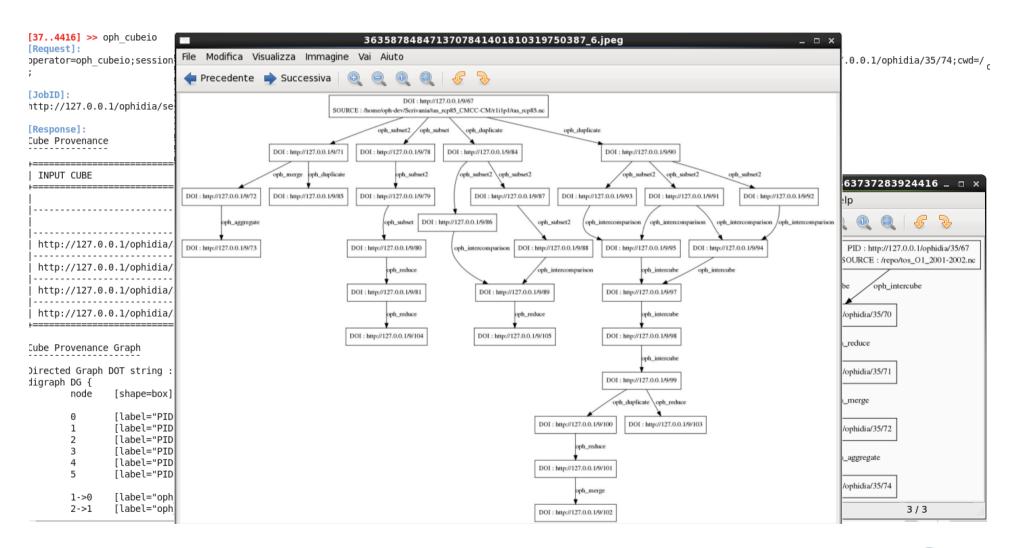
tos

lat	lon	tos
39.500000	15.000000	1.00000002e+20, 1.000000002e+20, 1.0000000002e+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	1.000000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20
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	1.000000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20, 1.00000002e+20
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

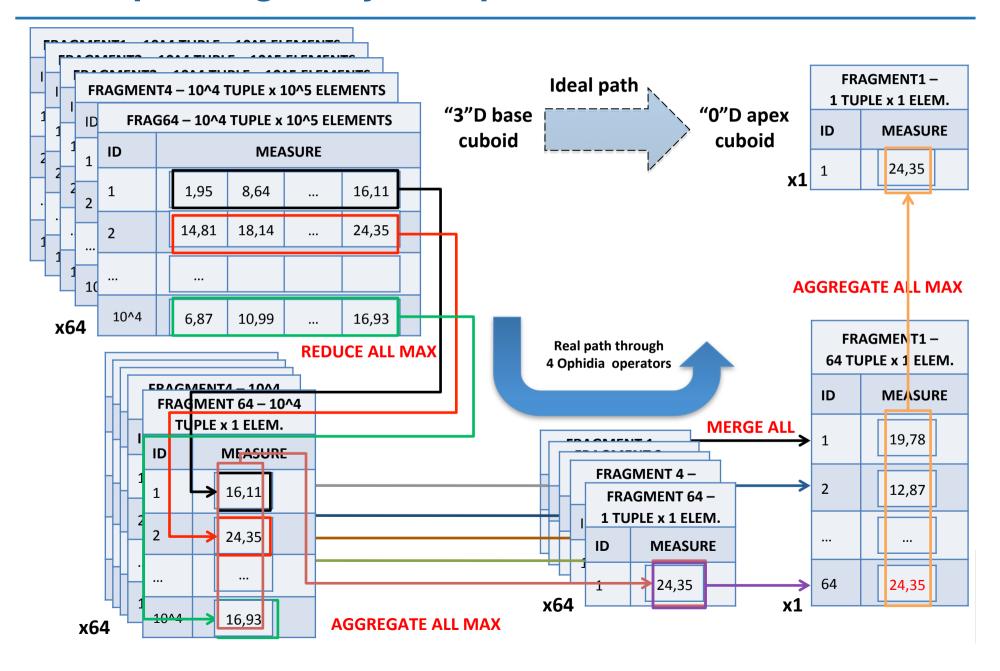
Summary

Selected 9 rows out of 9

The analytics framework: "metadata" operators



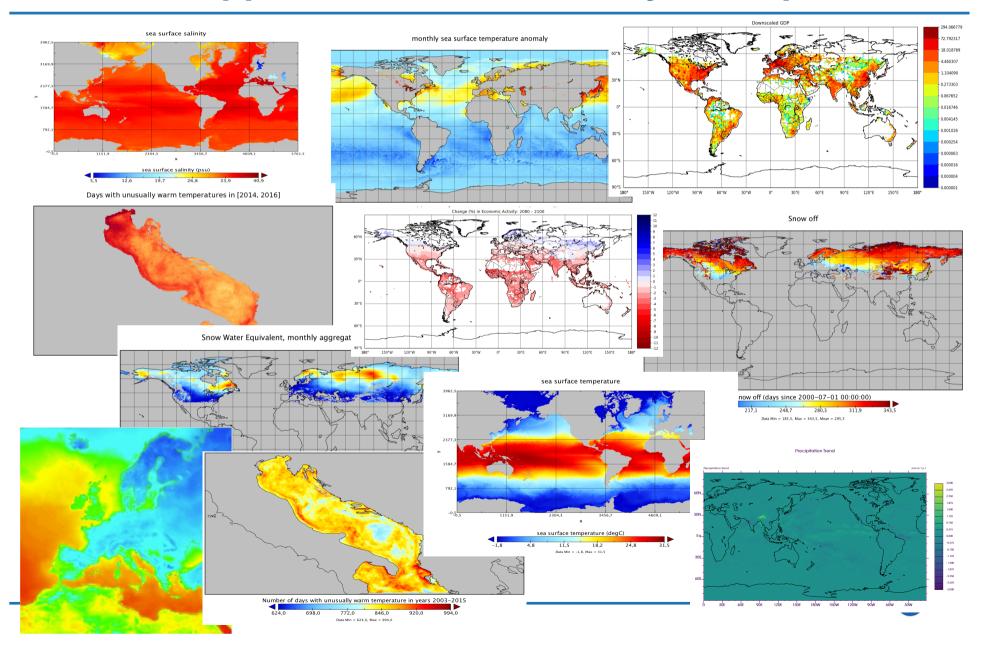
Pipelining analytics operators to reduce data



Ophidia architecture 2.0

Workflows management, python applications, in-memory analytics

Efficient support for advanced analytics experiments



Architecture evolution

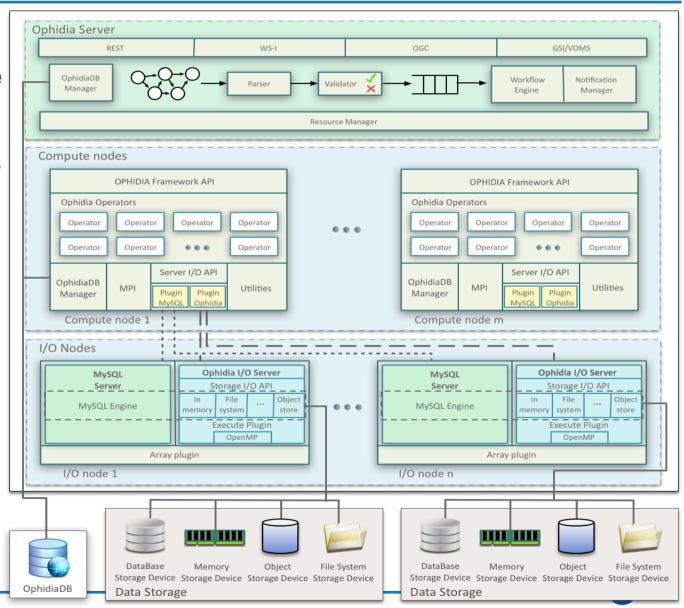
Workflow support on the server side

Separation of concerns between framework and I/O components

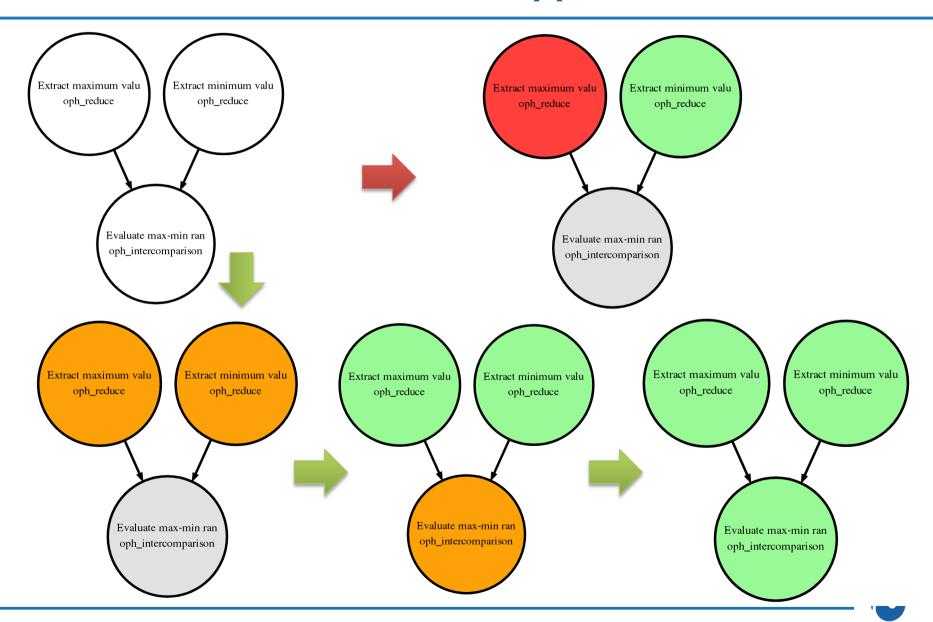
Support different I/O servers

Native I/O server with parallel execution engine

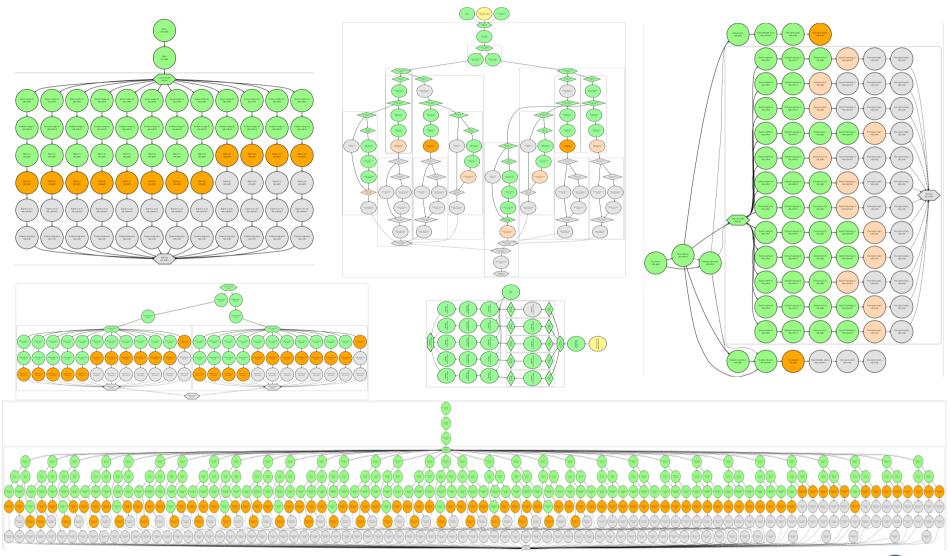
Multiple **storage systems** supported



Workflow support



Analytics workflows support and interfaces



Analytics workflows support and interfaces

Workflow Management

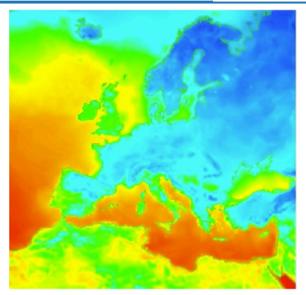
This group includes a number of flow control operators that could be used within an Ophidia workflow to implement complex data processing in batch mode. In particular, they implement several advanced features: setting of run-time variables, iterative and parallel interface, selection interface, interactive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

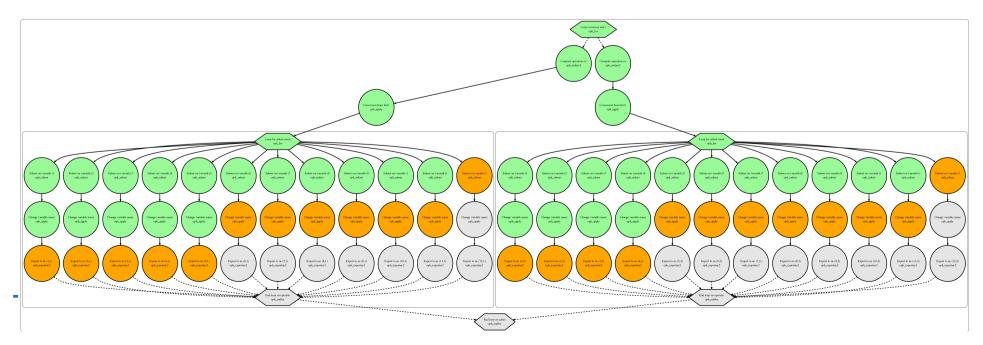
NAME	DESCRIPTION		
OPH_ELSE	Start the last sub-block of a selection block "if".		
OPH_ELSEIF	Start a new sub-block of a selection block "if".		
OPH_ENDFOR	Close a loop "for".		
OPH_ENDIF	Close a selection block "if".		
OPH_FOR	Implement a loop "for".		
OPH_IF	Open a "if" selection block.		
OPH_INPUT	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.		

Workflow I: climate indicators processing



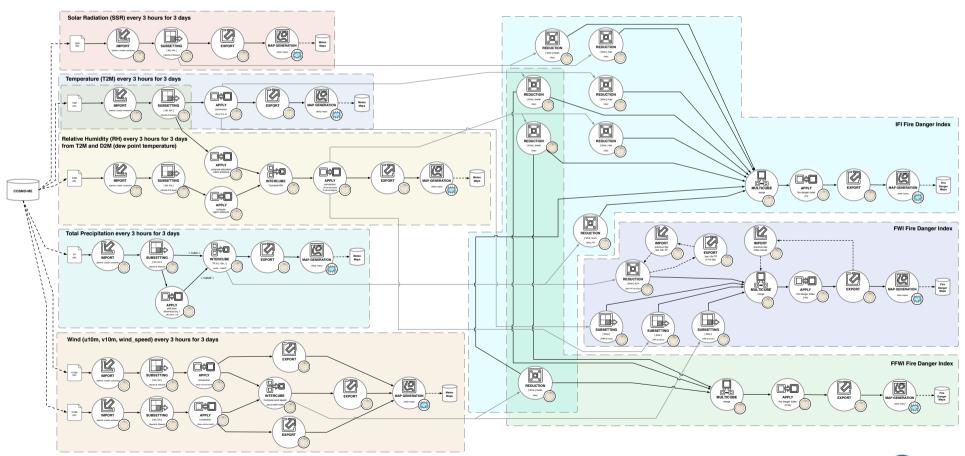
- In the CLIPC project, processing chains for data analysis are being implemented with Ophidia to compute climate indicators
- First set of indicators includes: TNn, TNx, TXn, TXx
 - Input files: 12GBs (TasMin & TasMax)
 - TNx = max of the min temperatures
 - TXx = max of the max temperatures
- Parallel approach
 - Inter-parallelism & Intra-parallelism



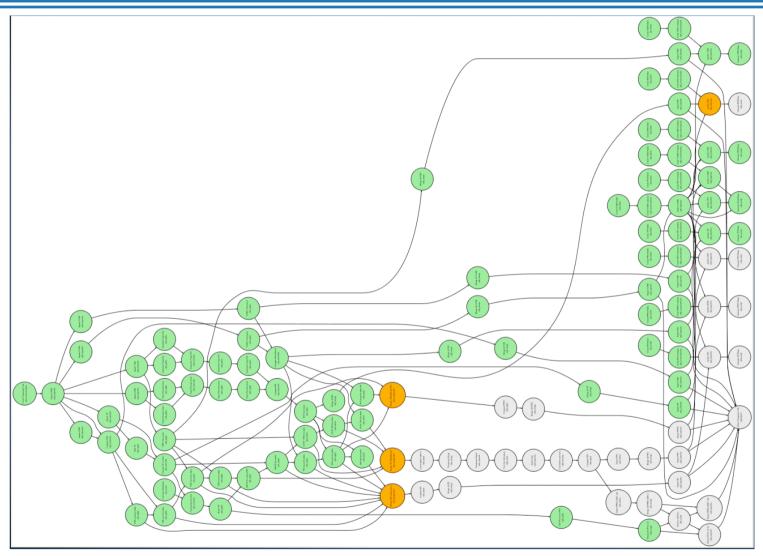




OFIDIA main objective is to build a cross-border operational fire danger prevention infrastructure that advances the ability of regional stakeholders across Apulia and Ioannina Regions to detect and fight forest wildfires



Workflow example II: fire danger analysis Runtime Execution



Workflow example III: multi-model analytics Cloud-enabled, distributed multi-model analytics experiment

2016 IEEE International Conference on Big Data (Big Data)

Distributed and cloud-based multi-model analytics experiments on large volumes of climate change data in the Earth System Grid Federation eco-system

S. Fiore¹, M. Płóciennik², C. Doutriaux³, C. Palazzo¹, J. Boutte³, T. Żok², D. Elia¹, M. Owsiak², A. D'Anca¹, Z. Shaheen³, R. Bruno⁴, M. Fargetta⁴, M. Caballer⁵, G. Moltó⁵, I. Blanquer⁵, R. Barbera^{4,6}, M. David⁷, G. Donvito⁴, D. N. Williams³, V. Anantharaj⁸, D. Salomom⁴, and G. Aloisio^{1,9}

¹Euro-Mediterraneam Center on Climate Change Foundation (CMCC), Italy
²Poznan Supercomputing and Networking Center (PSNC), Poland
¹Lawrence Livermore National Laboratory (LLNL), California, USA
⁴Italian National Institute of Nuclear Physics (INFN), Italy
⁵Universitat Politècnica de València (UPV), Spain
⁶ University of Catania, Italy
⁷Laboratório de Instrumentação e Fisica Experimental de Particulas (LIP), Portugal
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Abstract-A case study on climate models intercomparison data analysis addressing several classes of multi-model experiments is being implemented in the context of the EU H2020 INDIGO-DataCloud project. Such experiments require the availability of large amount of data (multi-terabyte order) related to the output of several climate models simulations as well as the exploitation of scientific data management tools for large-scale data analytics. More specifically, the paper discusses in detail a use case on precipitation trend analysis in terms of requirements, architectural design solution, infrastructural implementation. The experiment has been tested and validated on CMIP5 datasets, in the context of a large scale distributed testbed across EU and US involving three ESGF sites (LLNL, ORNL, and CMCC) and one central orchestrator site (PSNC).

Keywords-big analytics, workflow management, cloud computing, ESGF, INDIGO-DataCloud.

I. INTRODUCTION

The increased models resolution in the development of comprehensive Earth System Models is rapidly leading lovery large climate simulations output that pose significant scientific data management challenges in terms of data sharing, processing, analysis, visualization, preservation, curation, and archiving [1-3].

In this domain, large scale global experiments for climate model intercomparison (CMIP) have led to the development of the Earth System Grid Federation (ESGF [4-5]), a federated data infrastructure involving a large set of data providers/modelling centers around the globe, which includes the European contribution - regarding the ENES [6] community - through the IS-ENES project.

From an infrastructural standpoint, ESGF provides a production-level support for search & discovery, browsing and access to climate simulation data and observational data products. ESGF has been serving the Coupled Model Intercomparison Project Phase 5 (CMIPS) experiment, providing access to 2.5PB of data for the Intergovernmental Panel on Climate Change (IPCC) [7] Assessment Reports 5 [8], based on consistent metadata catalogues. More precisely, the Coupled Model Intercomparison Project (CMIP) has been established by the Working Group on Coupled Modelling [9] (WGCM) under the World Climate Research Programme [10] (WCRP).

It provides a community-based infrastructure in support of climate model diagnosis, validation, intercomparison documentation and data access. This framework enables a diverse community of scientists to analyse General Circulation Models (GCMs) in a systematic fashion, a process that serves to facilitate models improvement.

CMIP5 has promoted a standard set of model simulations in order to:

- evaluate how realistic the models are in simulating the recent past;
- provide projections of future climate change on two time scales, near term (out to about 2035) and long term (out to 2100 and beyond); and
- understand some of the factors responsible for differences in model projections, including quantifying some key feedbacks such as those involving clouds and the carbon cycle.

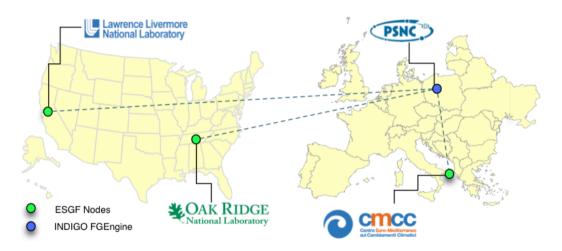
In such a context, running a multi-model data analysis experiment is very challenging, as it requires the availability of large amount of data (multi-terabyte order) related to multiple climate models simulations as well as scientific data management tools for large-scale data analytics.

The remainder of this work is organized as it follows. Section II provides the current workflow for the multi-model climate data analysis in the CMIP context, whereas Section III presents the paradigm shift needed to address such large-

Big Data Challenges, Research, and Technologies in the Earth and Planetary Sciences

A workshop to be held Monday December 5th at the 2016 IEEE International Big Data Conference





- A first experiment across sites was demonstrated at the 1st INDIGO Review, November 2016 in Bologna
- Strong synergy with the ESGF CWT Roadmap
- International collaboration across the Atlantic

S. Fiore, M. Plóciennik, 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. BigData 2016: 2911-2918

INDIGO-DataCloud

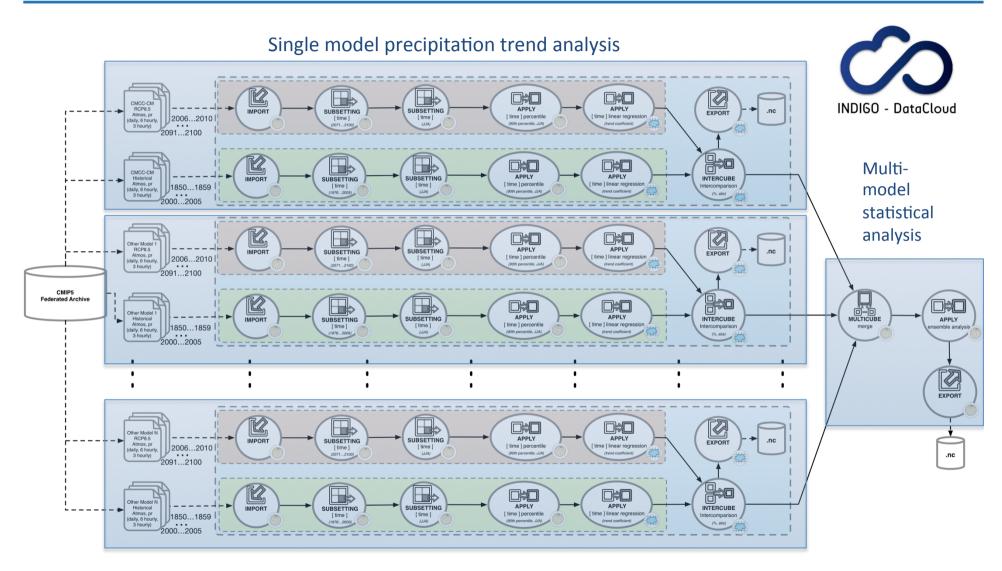
An H2020 project approved in January 2015 in the EINFRA-1-2014 call



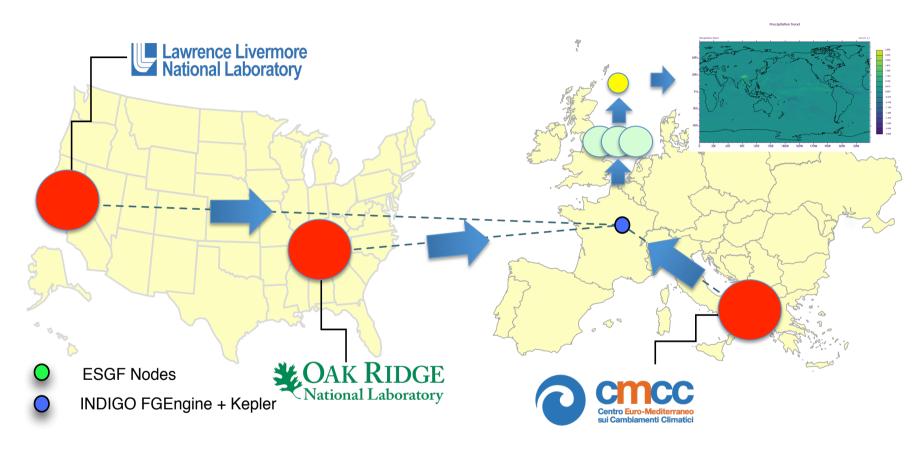
- 11.1M€, 30 months (from April 2015 to September 2017)
- Who: 26 European partners in 11 European countries
 - Coordination by the Italian National Institute for Nuclear Physics (INFN)
 - Including developers of distributed software, industrial partners, research institutes, universities, e-infrastructures
- What: develop an open source Cloud platform for computing and data ("DataCloud") tailored to science.
- For: multi-disciplinary scientific communities
 - E.g. structural biology, earth science, physics, bioinformatics, cultural heritage, astrophysics, life science, climatology
- Where: deployable on hybrid (public or private) Cloud infrastructures
 - INDIGO = INtegrating Distributed data Infrastructures for Global ExplOitation
- Why: answer to the technological needs of scientists seeking to easily exploit distributed Cloud/Grid compute and data resources.



High-level view of the multi-model "precipitation trend analysis" experiment



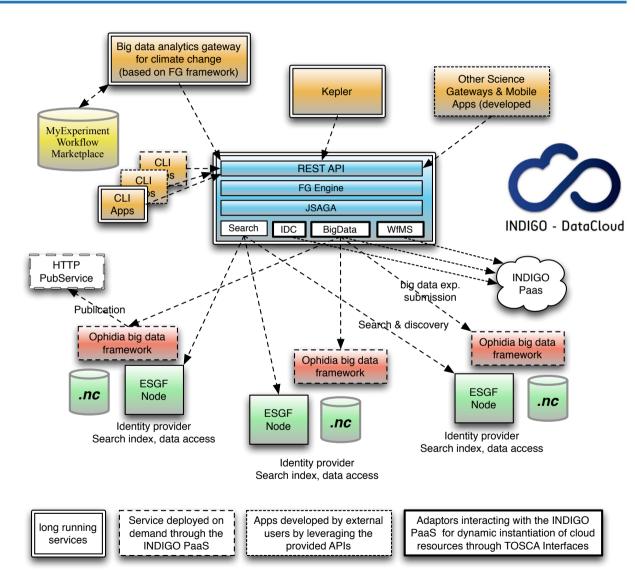
CMIP5 scientific data analysis workflow in ESGF





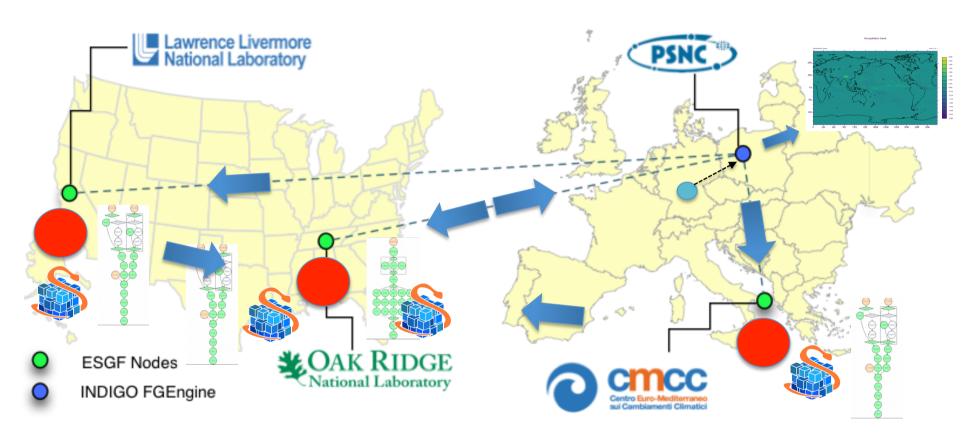
INDIGO-DataCloud architectural solution

- Distributed experiments for climate data analysis
- Server-side, parallel processing
- Two-level workflow strategy to orchestrate large scale experiments
- Interoperability with ESGF
- Access through different clients
 - Kepler
 - Science Gateway
- Interactive and batch scenarios





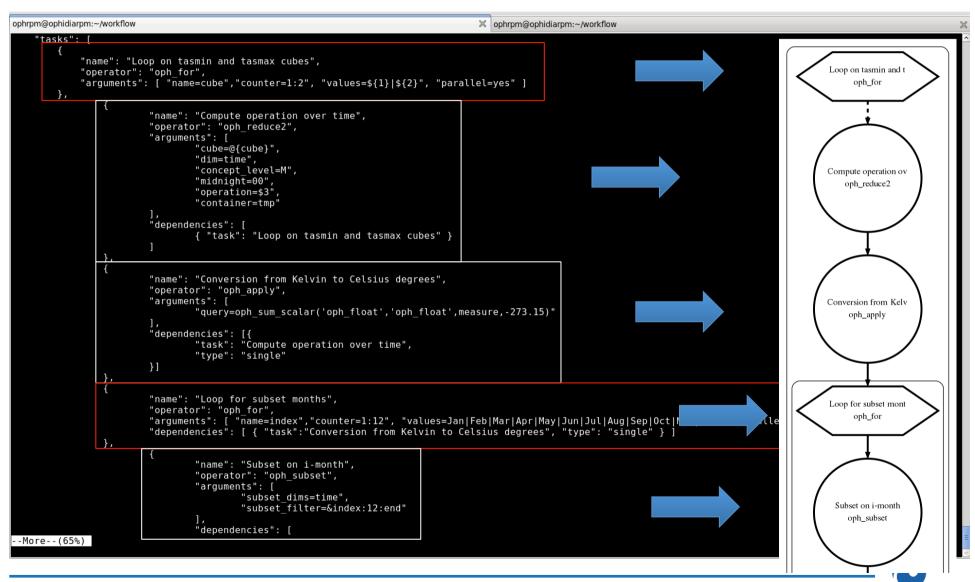
The paradigm shift proposed & exploited in INDIGO-DataCloud



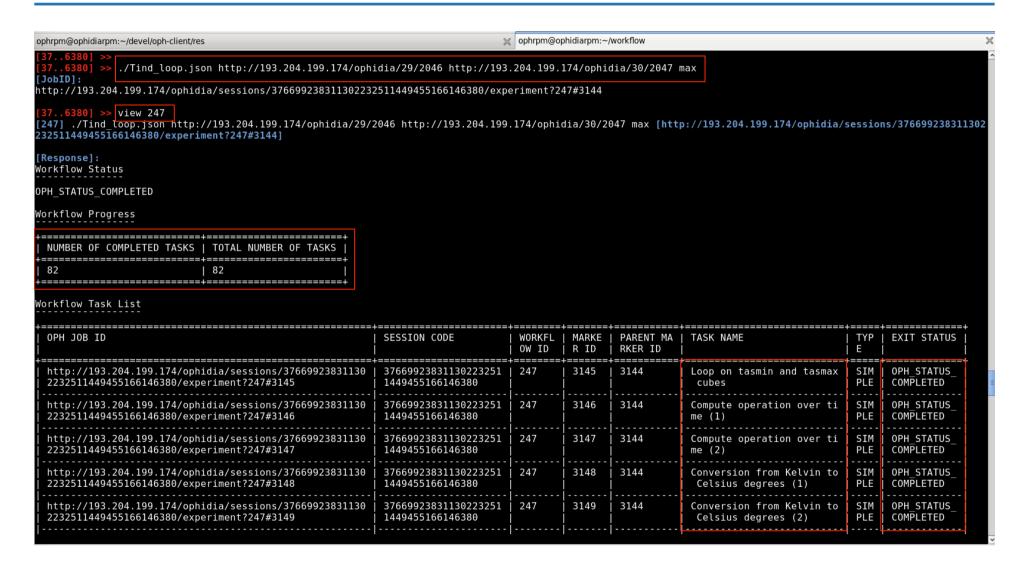




Behind the scene: workflow JSON representation



Workflow submission



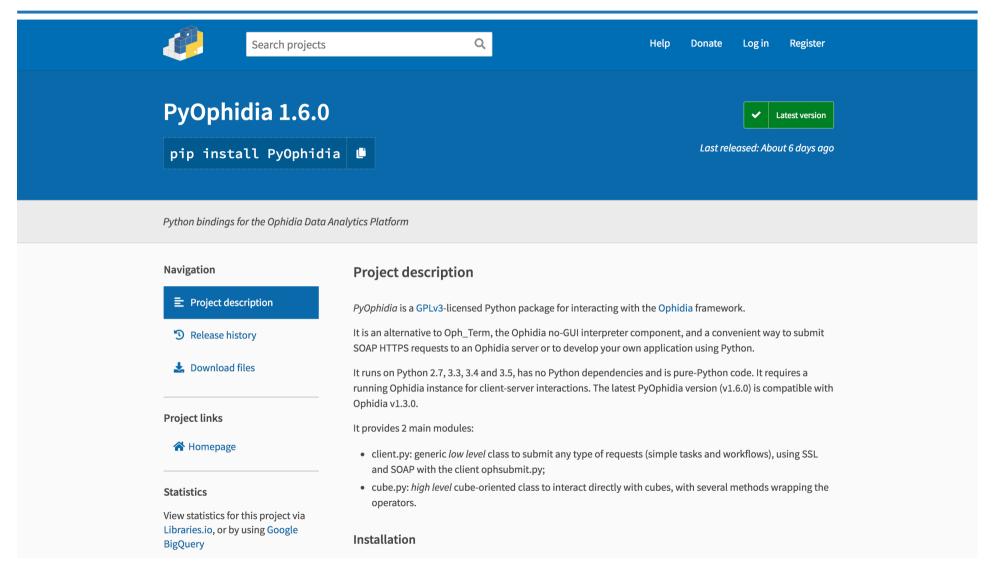


Programmatic access through the PyOphidia class

- ✓ **PyOphidia** provides a Python interface to submit commands to the Ophidia Server and to retrieve/deserialize the results
- ✓ Two classes implemented:
 - ✓ Client class: connect to the server, navigate into the ophidia file system, submit workflows, manage sessions, etc.
 - ✓ **Cube class**: manipulate cubes (reduce, subset, operations between cubes, intercomparison, etc.), get information on cubes (schema, dimensions, metadata, etc.)

```
class Cube():
    """Cube(container='-', cwd=None, exp_dim='auto', host_partition='auto', imp_dim='auto', measure=None, src_path=None, cdd=None, compressed='no',
              exp_concept_level='c', filesystem='auto', grid='-', imp_concept_level='c', import_metadata='no', check_compliance='no', offset=0,
              ioserver='mysql_table', ncores=1, ndb=1, ndbms=1, nfrag=0, nhost=0, subset_dims='none', subset_filter='all', time_filter='yes'
              subset_type='index', exec_mode='sync', base_time='1900-01-01 00:00', calendar='standard', hierarchy='oph_base', leap_month=2,
              leap_year=0, month_lengths='31,28,31,30,31,30,31,30,31,30,31', run='yes', units='d', vocabulary='-', description='-', schedule=0,
             pid=None, check_grid='no', display=False) -> obj
          or Cube(pid=None) -> obj
                                                                                                                       C # localhost:8888/notebooks/Ophidia%20Pvthon%20API%20and%20IPvthon.ipvnb
    Attributes:
                                                                                                                            Upyter Ophidia Python API and IPython Last Checkpoint: 2 minutes ago (unsaved changes)
         pid: cube PID
         creation date: creation date of the cube
         measure: name of the variable imported into the cube
         measure_type: measure data type
                                                                                                                                    var2 = [float(x) for x in res['response'][0]['objcontent'][0]['rowvalues'][1][2].split(", ")]
var3 = [float(x) for x in res['response'][0]['objcontent'][0]['rowvalues'][1][2].split(", ")]
         level: number of operations between the original imported cube and the actual cube
        nfragments: total number of fragments
                                                                                                                                    Prepare also the time/x axis:
         source_file: parent of the actual cube
        hostxcube: number of hosts associated with the cube
                                                                                                                              In [10]: time = [i+1 for i in range(len(res['response'][0]['objcontent'][0]['rowvalues'][0][2].split(", ")))]
         dbmsxhost: number of DBMS instances on each host
                                                                                                                                    Finally, plot the 3 time series inline:
         dbxdbms: number of databases for each DBMS
        fragxdb: number of fragments for each database
                                                                                                                              In [11]: plot(time, varl, 'ro-
                                                                                                                                    plot(time, var2, 'g--')
plot(time, var3, 'b+-')
show()
         rowsxfrag: number of rows for each fragment
         elementsxrow: number of elements for each row
         compressed: 'yes' for a compressed cube, 'no' otherwise
         size: size of the cube
         nelements: total number of elements
         dim_info: list of dict with information on each cube dimension
    Class Attributes:
         client: instance of class Client through which it is possible to submit all requests
                                                                                                                              In [ ]:
```

PyOphidia release



https://pypi.org/project/PyOphidia/

PyOphidia applications: Jupyter notebooks

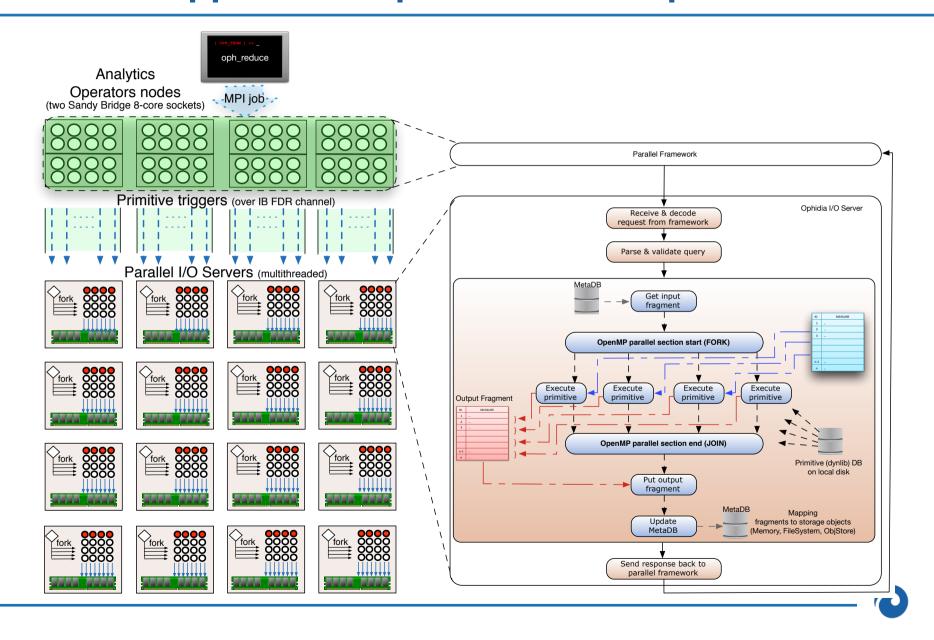
Import PyOphidia and connect to server instance In []: from PyOphidia import cube, client cube.Cube.setclient(read env=True) Import data and extract a single time series In []: mycube = cube.Cube.importnc(src path='/public/data/tos 01 2001-2002.nc', measure='tos', imp dim='time', ncores=5) mycube2 = mycube.subset2(subset dims="lat|lon", subset filter="0:1|0:1", ncores=5) data = mycube2.export array() Plot time series In []: import matplotlib.pyplot as plt y = data['measure'][0]['values'][0][:] x = data['dimension'][2]['values'][:] plt.figure(figsize=(11, 3), dpi=100) plt.plot(x, y) plt.ylabel(data['measure'][0]['name'] + " (degK)") plt.xlabel("Days since 2001/01/01") plt.title('Sea Surface Temperature (point 0.5, 1)') plt.show() Convert from Kelvin to Celsius degrees In []: mycube3 = mycube2.apply(query="oph sum scalar('OPH FLOAT', 'OPH FLOAT', measure, -273.15)", description="celsius") data = mycube3.export array() Plot time series In []: y = data['measure'][0]['values'][0][:] x = data['dimension'][2]['values'][:] plt.figure(figsize=(11, 3), dpi=100) plt.plot(x, y) plt.ylabel(data['measure'][0]['name'] + " (degC)") plt.xlabel("Days since 2001/01/01") plt.title('Sea Surface Temperature (point 0.5, 1)') plt.show()

Native Ophidia I/O server

The I/O server provides a native solution for the scientific domain applications. The requirements for the Ophidia I/O server are:

- run data analytics tasks in-memory taking advantage of the lower latency
- binary array-oriented engine to efficiently process scientific multidimensional data
- interact directly with the storage layer to exploit data locality
- exploit parallelism at the array-level
- NoSQL approach based on key-value store providing a declarative query language (SQL-like)
- guarantee extensibility and interoperability of the I/O server to support multiple storage back-ends

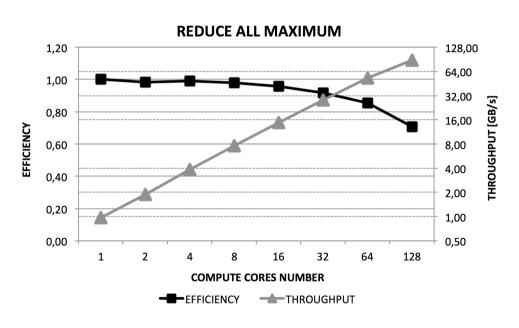
Parallel support: in-depth view of the parallel reduce



Experimental results (in-memory I/O server)

Execution time is measured by scaling up the number of parallel tasks Two metrics are evaluated:

- efficiency (speedup/computational resources)
- throughput (data processed/time unit)

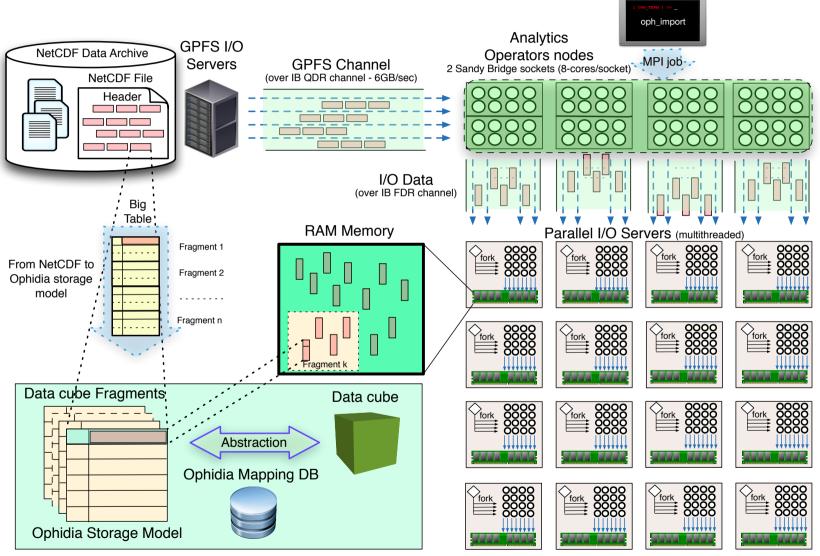


CORES NUMBER	EXECUTION TIME [s]	EFFICIENCY	THROUGHPUT [GB/s]
1	388,50	1,00	0,97
2	197,51	0,98	1,90
4	97,96	0,99	3,83
8	49,52	0,98	7,57
16	25,39	0,96	14,77
32	13,22	0,92	28,36
64	7,11	0,85	52,72
128	4,29	0,71	87,47

3D dataset, 375GB, 2.1M time series, 24K elements each (50 Billions elements) 8 nodes, 16 cores each, 128 cores in total Max computation over time dimension, 2D result (map)

With 128 cores it is around 30x faster than MySQL I/O engine! Full benchmark is ongoing on the Athena Cluster at CMCC SCC

Parallel import and the new import2 (10X speedup)

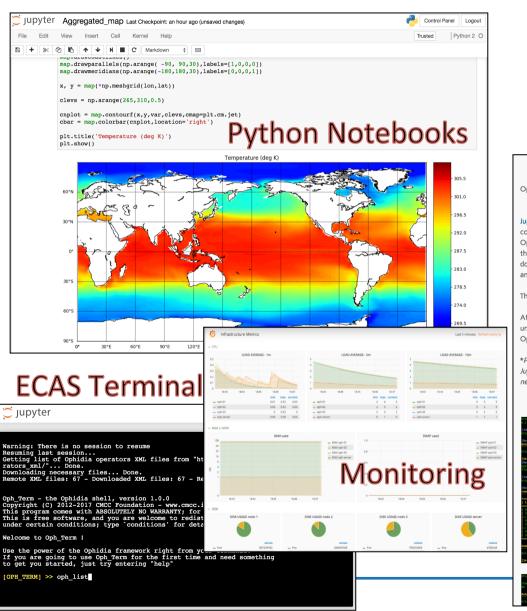


ECASLab in the EOSC-hub context

ECASLab: a user-oriented environment for data analysis and visualization

- ✓ ECASLab is an integrated scientific environment for scientific data management
- ✓ It provides a ready-to-use multi-node ECAS (ENES Climate Analytics Service) to perform data analytics on scientific datasets
- ✓ Currently setup at at CMCC (Italy) and DKRZ (Germany)
- ✓ It integrates data, analysis and visualization tools in a user-friendly environment accessible with light-weight clients (i.e. a desktop bash-like client and a web GUI)
- ✓ It exposes a JupyterHub service to create, execute and share Jupyter notebooks (Python-based) supporting live-code and visualization
- ✓ File system navigation, file editing, upload and download supported via web
- ✓ Released on May 2017, with an initial set of services:
 - ✓ Simple quick start & registration form available
 - ✓ JupyterHub, OPeNDAP/THREDDS/IDV, ECAS Terminal
 - Monitoring system based on Grafana
 - ✔ Besides PyOphidia Several Python libraries available for analysis & visualization
 - ✓ Workflow IDE (alpha release)

ECASLab in a nutshell





Ouick Start

OphidiaLab provides two different ways to get access to its scientific eco-system: JupyterHub and Ophidia client.

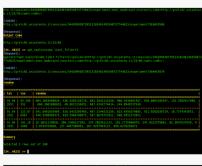
Jupyter supports interactive data science and scientific computing.

OphidiaLab includes a JupyterHub installation and, thanks to the Jupyter Notebooks, scientists can create and share documents that contain live code, equations, visualizations and explanatory text.

The JupyterHub interface is available here*.

After you login, open "Quick Start.ipynb" notebook available under the *quickstart/* folder in your home to get started with OphidiaLab environment capabilities.

*Please note that for security reasons, the access to our JupyterHub instance is restricted to authorised users only and needs an additional step after the registration process.





QuickStart

The Ophidia Terminal is a robust, comprehensive, and user-friendly Ophidia client, developed with characteristics similar to the bash shell present in almost all Unix-like environments. Please have a look at the online available documentation to learn more about the basic functionalities of the Ophidia terminal as well as some advanced features useful for more skilled users.

Two short guides (basic, advanced) in pdf format are also available.

Several examples of real-world usage of the terminal are also available on the Ophidia website tutorial section.

The latest client RPM for CentOS7 is available here.
The related DEB package can be downloaded from here.

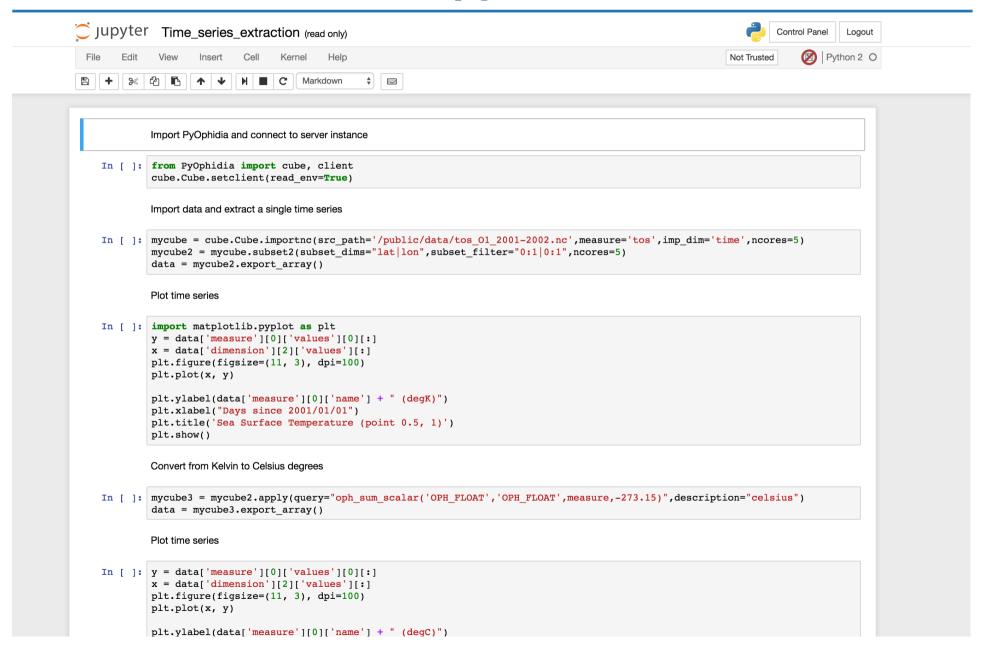
Once installed you can simply run:

/usr/local/ophidia/oph-terminal/bin/oph_term -H ophidialab.cmcc.it -u <username> -p <password> -P 11732

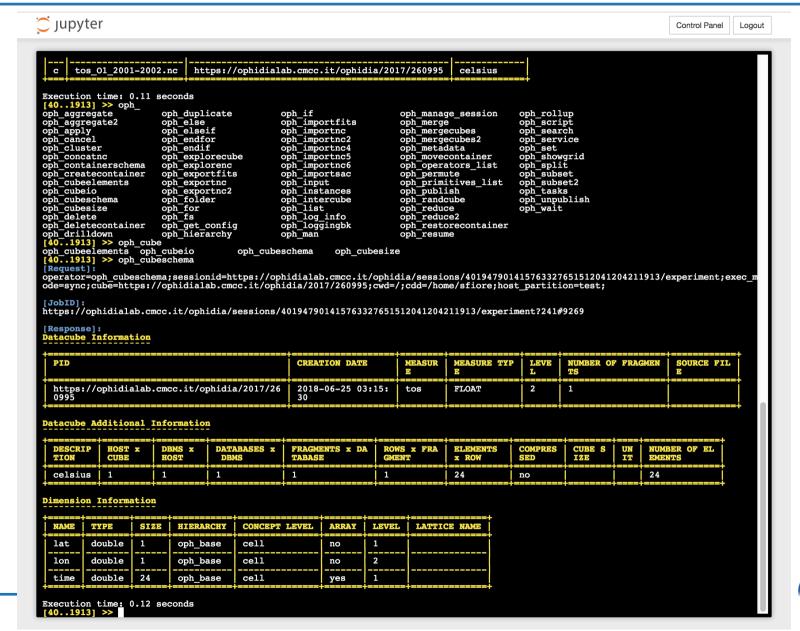
ECASLab: Jupyter user local folder



ECASLab: Jupyter notebooks



ECASLab: ECAS Terminal (from Jupyter)

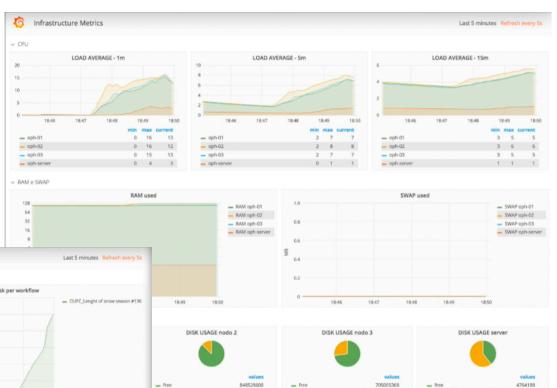




ECASLab: Grafana monitoring interface

- ✓ Based on grafana
- ✓ It provides real-time monitoring of the ECAS cluster
- ✓ Used internally by admins





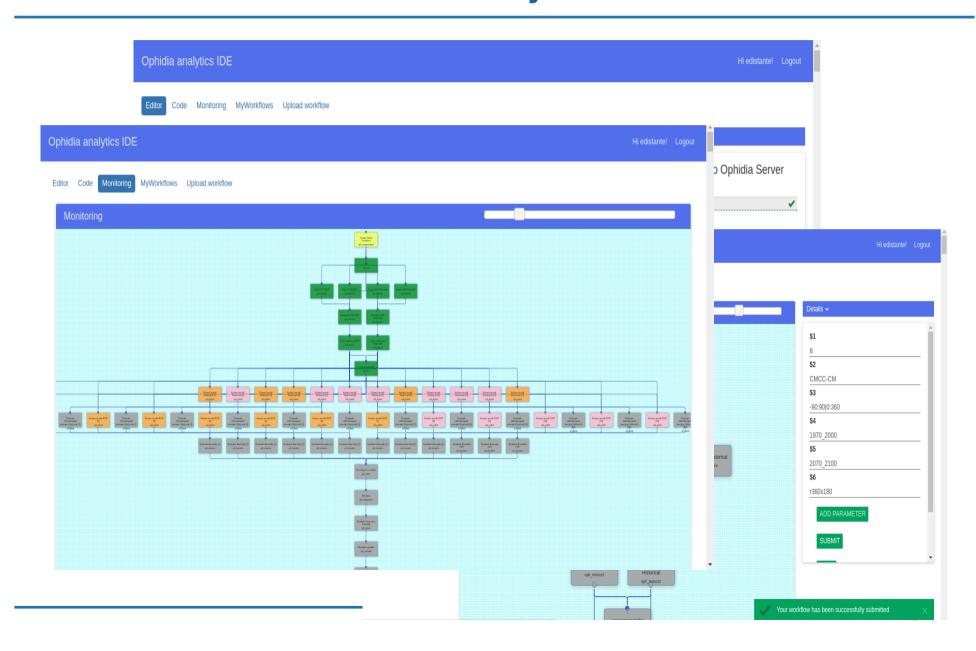
✓ It also supports applicationlevel monitoring (for wf)



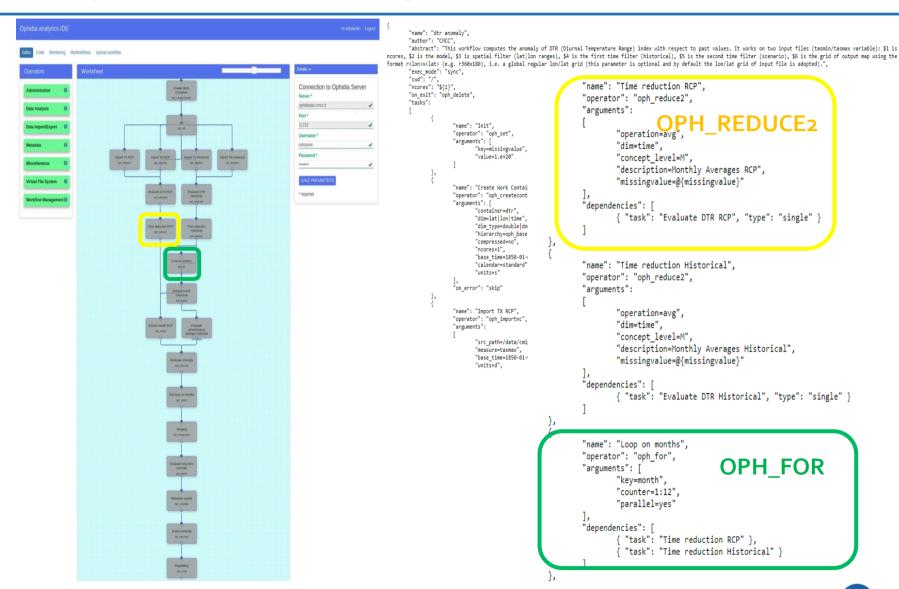
Looking forward

Workflow IDE and Server-side machine learning

ECASLab and the analytics workflow IDE

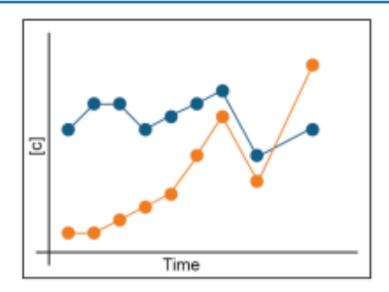


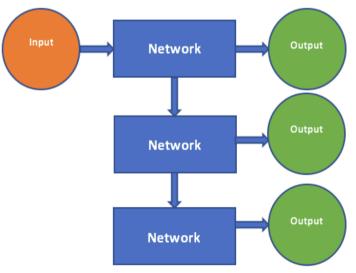
Easy and automated generation of JSON code



Long Short-Term Memory Network for Time Series Prediction

- We modeled the time series as a supervised learning problem, that is, as a sequence of inputs and outputs.
- At each stage, the network receives as input the n values in the past from a time t. The output is h nodes representing the values in the future.
- The goal of the network is to learn the mapping from the input to the output.
- Hopefully, the LSTM is able to capture some kind of temporal dependence in order to get better predictions.





Ophidia Primitives For LSTM: Training

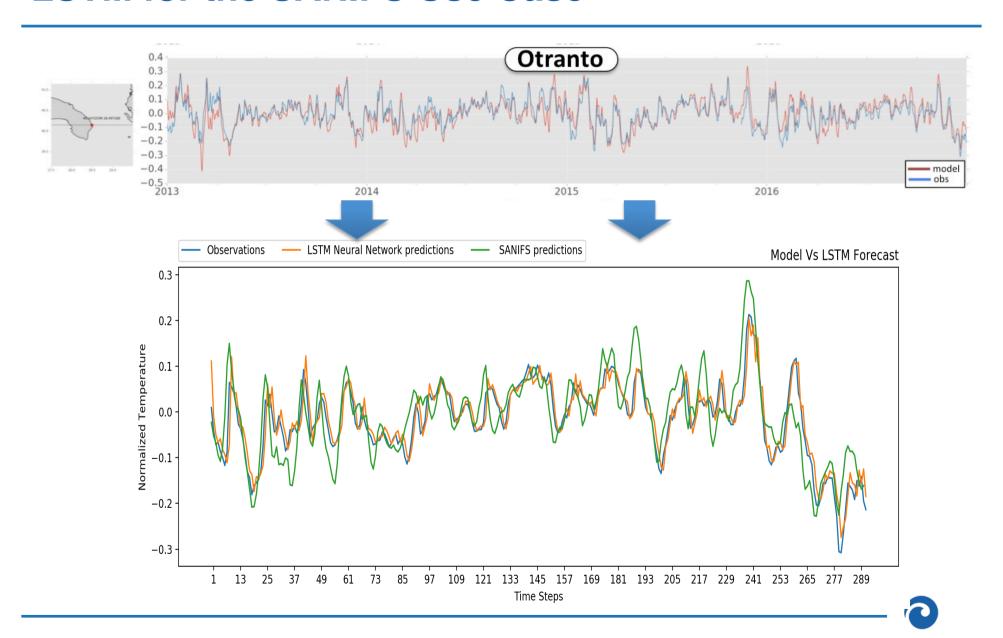
- The algorithm has been divided in two phases: one for training and one for test/prediction.
- The primitive for the **training** task:

```
oph_lstm(input_OPH_TYPE, output_OPH_TYPE, measure,
  dim_in, dim_out, n_h_layers, n_h_neurons, [dropout],
  [learning_rate], [unrolled_len], [minibatch_size],
  [max_epoch])
```

- It can be run in a SQL statement or in the OPH_APPLY operator.
- After the training phase, the resulting neural network with updated parameters is saved as a binary array in a datacube. It can then be reused in the test phase.
- The primitive for the test/prediction:

```
oph_lstm_predict(input_OPH_TYPE, output_OPH_TYPE,
measure_a, measure_b, test)
```

LSTM for the SANIFS Use Case

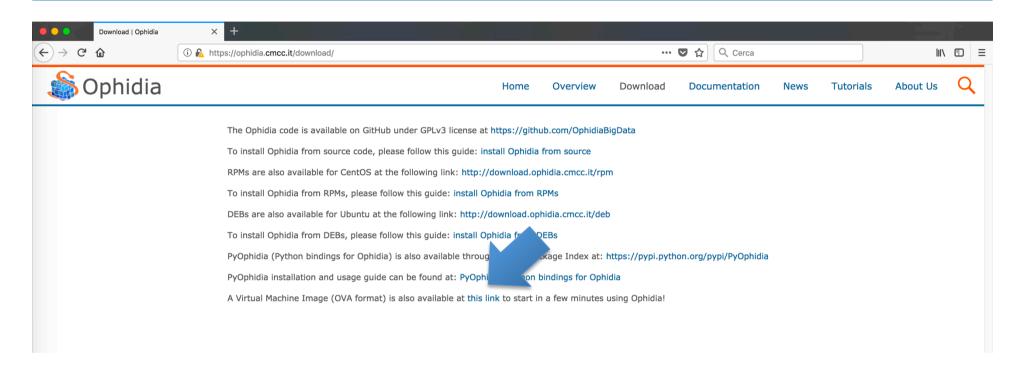


Useful resources and final remarks

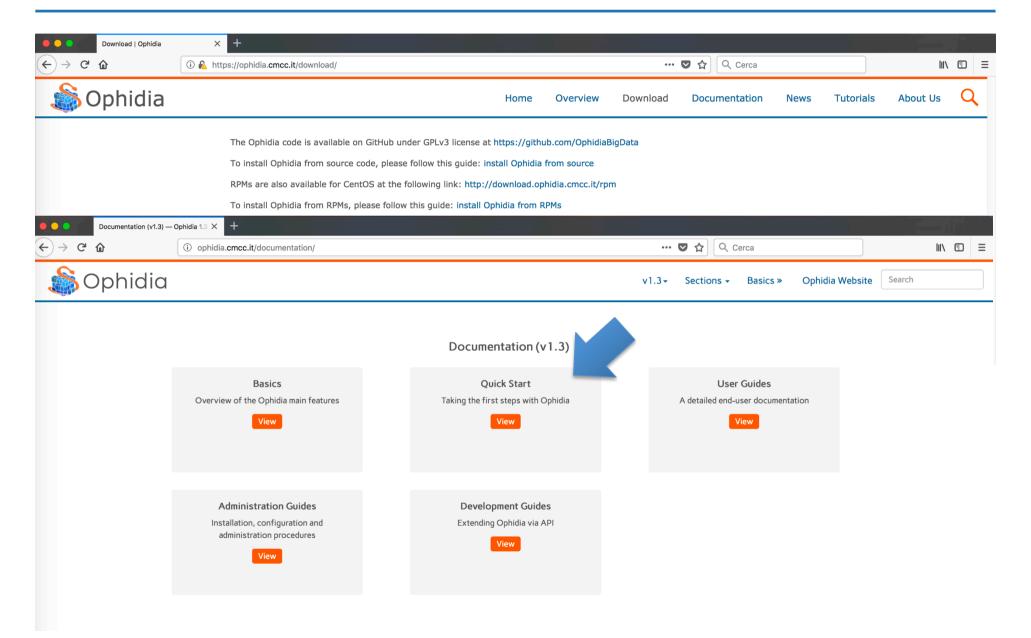
Hands-on session - Quick Start



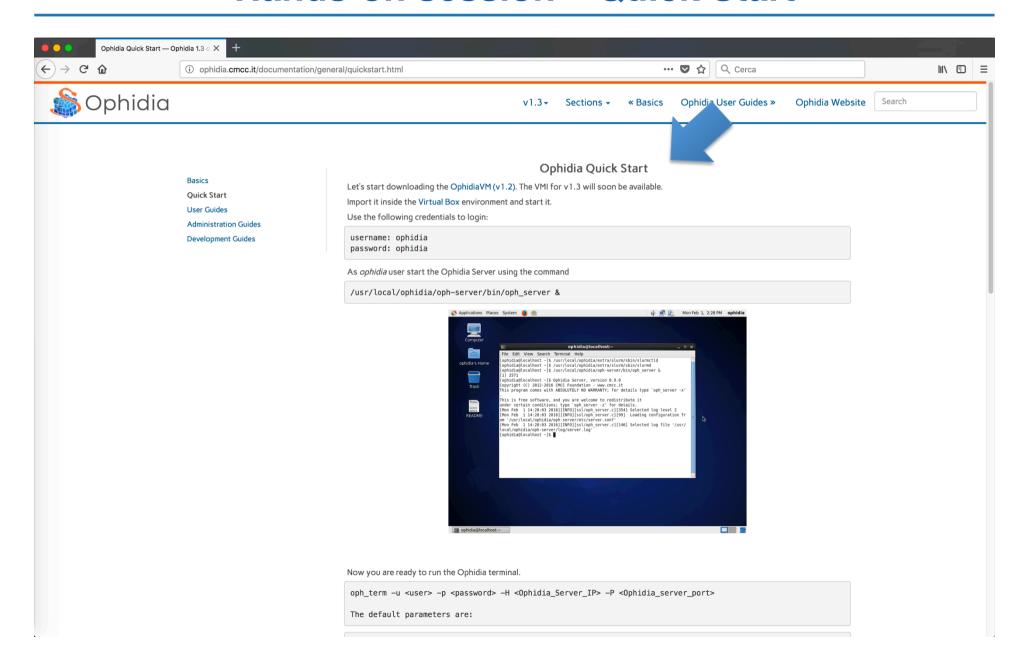
Hands-on session - Quick Start



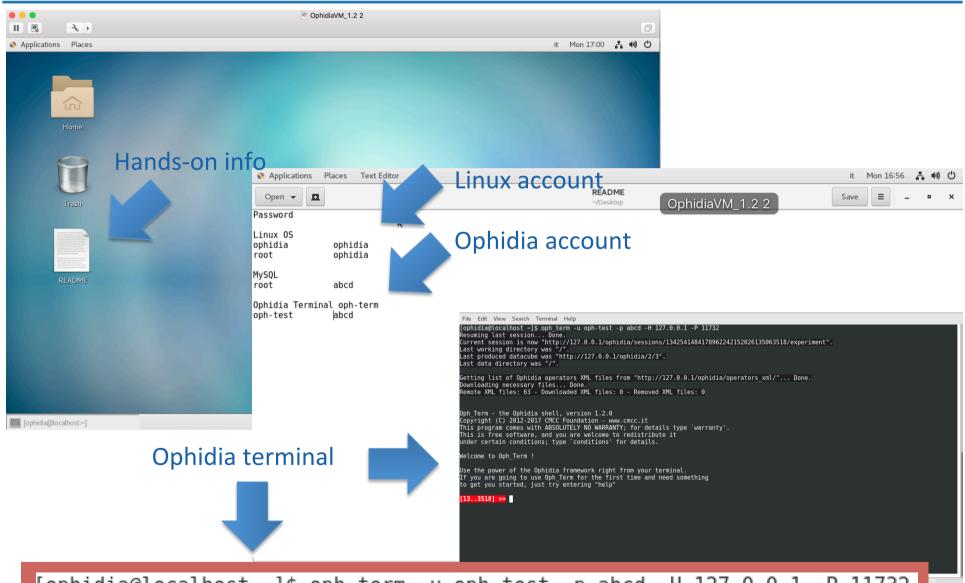
Hands-on session - Quick Start



Hands-on session - Quick Start



Hands-on session – Accounts on the VM



Website: http://ophidialab.cmcc.it



Quick Start JupyterHub

Experiments

Monitoring

Support

Register

ECASLab

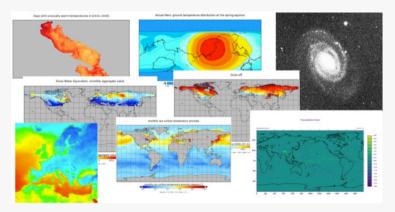
ECASLab is a scientific data analytics environment. It builds on top of ECAS (the ENES Climate Analytics Service), one of the thematic services included in the EOSC-hub service portfolio.

ECASLab starts from a previous effort (OphidiaLab, developed at CMCC Foundation) with the main aim of providing a virtualized research environment for researchers. It represents the entry point for users that want to test, train, exploit the ECAS Thematic Service.

ECASLab provides a scientific environment exploiting a server-side approach and integrating both data and analysis tools to support data scientists in their daily research activities.

It consists of several components like an ECAS cluster, a JupyterHub instance jointly with a large set of pre-installed Python libraries for running data manipulation, analysis, and visualization, a data publication service and a tool for the infrastructure monitoring (mainly intended for the administrators).

In order to get started with ECASLab please have a look at the Quick Start guide and register here to get an account.

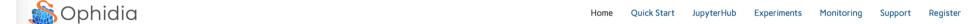


A few examples of output related to different analytics experiments implemented in the ECASLab environment.

Website: http://ophidialab.cmcc.it

Ophidia		Home	Quick Start	JupyterHub	Experiments	Monitoring	Support	Register
	ECASLab Registration Form							
	Sign up!							
	First Name *							
	Last Name *							
	E-mail *							
	Affiliation *							
	Country*							
	Motivation * (Research, Training, etc.)							
	Captcha *							
	QODFgs6							
	Can't read the above security code? Refresh Security Code *							
		Lab.						
	Your request has been submitted. You'll receive an email registration.	to confi	irm the					
	Register						7.0	

Website: http://ophidialab.cmcc.it



ECASLab

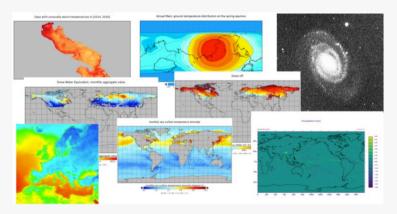


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A few examples of output related to different analytics experiments implemented in the ECASLab environment.

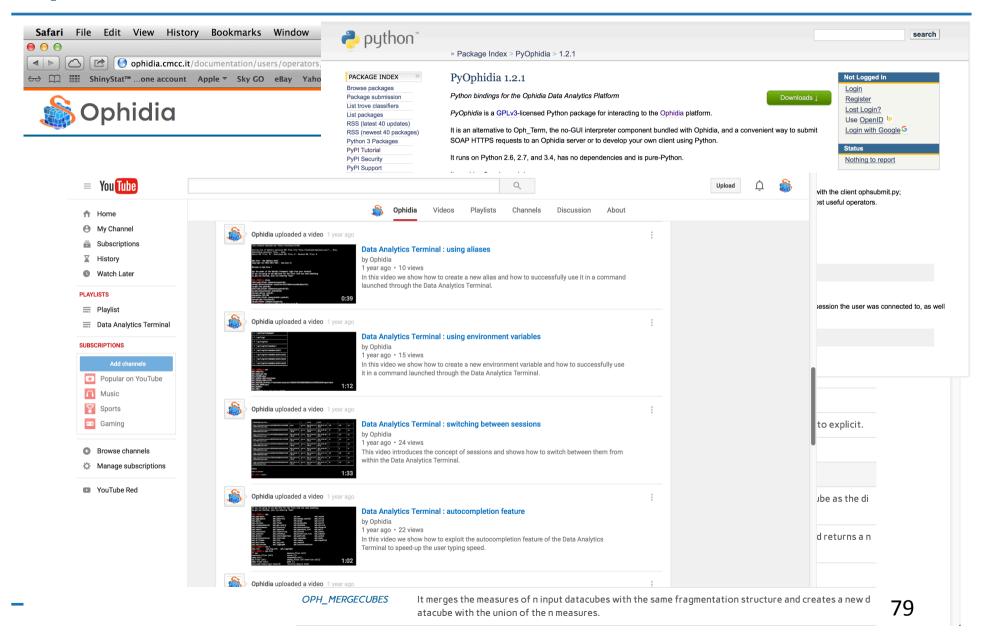
Th

Th



```
Import PyOnhidia and connect to server instance
In [14]: from PyOphidia import cube, client cube.Cube.setclient(read env=True)
             Current session is https://ophidialab.cmcc.it/ophidia/sessions/401947901415763327651512041204211913/experiment
             Current cwd is /
The last produced cube is https://ophidialab.cmcc.it/ophidia/2017/260991
              Import data and extract a single time series
In [15]: mycube = cube.Cube.importnc(src_path='/public/data/tos_01_2001-2002.nc', measure='tos', imp_dim='time', ncores=5) mycube2 = mycube2.subset2(subset_dims="lat|lon", subset_filter="0:1|0:1", ncores=5)
             data = mycube2.export_array()
              Plot time series
In [16]: import matplotlib.pyplot as plt
y = data('measure'|[0]('values')[0][:)
x = data('dimension'|[2]('values')[:]
plt.figure(figsize=(11, 3), dpi=100)
plt.plot(x, y)
             plt.ylabel(data['measure'][0]['name'] + " (degK)")
plt.xlabel("Days since 2001/01/01")
             plt.title('Sea Surface Temperature (point 0.5, 1)')
plt.show()
                                                                      Sea Surface Temperature (point 0.5, 1)
                  304.0
                  303.5
                  303.0
                   302.5
                  302.0
                  301.5
                                              100
                                                                200
                                                                                                                        500
                                                                                                                                           600
                                                                                   Days since 2001/01/01
In [17]: mycube3 = mycube2.apply(query="oph_sum_scalar('OPH_FLOAT','OPH_FLOAT',measure,-273.15)",description="celsius")
             Plot time series
In [18]: y = data['measure'][0]['values'][0][:]
x = data['dimension'][2]['values'][:]
             plt.figure(figsize=(11, 3), dpi=100)
plt.plot(x, y)
             plt.ylabel(data['measure'][0]['name'] + " (degC)")
plt.xlabel("Days since 2001/01/01")
             plt.title('Sea Surface Temperature (point 0.5, 1)')
                                                                    Sea Surface Temperature (point 0.5, 1)
                  30.5
                  30.0
                  29.5
               ₽ 29.0
                  28.5
                                                                                 Days since 2001/01/01
```

Ophidia documentation and social/multimedia content



Useful Resources

- Website: <u>https://ophidia.cmcc.it</u>
- Doc: http://ophidia.cmcc.it/documentation
- The Ophidia code is available on GitHub under GPLv3 license at https://github.com/OphidiaBigData
- RPMs are also available for CentOS6 at the following repo: <u>http://download.ophidia.cmcc.it/rpm</u>
- Youtube Channel <u>https://www.youtube.com/user/OphidiaBigData/</u>
- A Virtual Machine Image (OVA format) is also available at https://download.ophidia.cmcc.it/vmi_desktop/ to get started in a few minutes with Ophidia

Publications

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Conclusions

- ✓ ECAS represents the community evolution of Ophidia and is a key thematic service in the context of the EOSC-hub
- ✓ OLAP approach for big data multidimensional data model
- ✓ Multiple use cases for data analysis in different domains have been implemented.
- ✓ It provides access via CLI (end-users) and API (devel users)
- ✔ Programmatic access via C and Python APIs
- ✓ Several deployment scenarios tested in cloud and HPC environments
- ✓ Strong workflow support and in-memory analytics
- ✓ ECASLab integrates several UNIDATA software (NetCDF lib, THREDDS, IDV)
- ✔ Official Release available from February 1st 2016 on github
 - ✓ Latest Release v1.3 released in June (last week)

Do you want to join?

That's an **open source** effort aiming at becoming a **community effort**

I'll be very happy to know what aspects of this project you are more interested in

Feel free to get in touch with us sandro.fiore@cmcc.it

