





Programming dynamic workflows in the Exascale Era

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Workflows and Distributed Computing Group

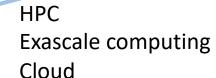
ESiWACE2 Workshop on Emerging Technologies for Weather and Climate Modelling

Challenges in highly distributed infrastructures

- Resources that appear and disappear
 - How to dynamically add/remove nodes to the infrastructure
- Heterogeneity
 - Different HW characteristics (performance, memory, etc)
 - Different architectures -> compilation issues
- Network
 - Different types of networks
 - Instability
- Trust and Security
- Power constraints from the devices in the edge

Al everywhere











Sensors Instruments **Actuators**

Edge devices

Data and storage challenge

- Sensors and instruments as sources of large amounts of heterogeneous data
 - Control of edge devices and remote access to sensor data
 - Edge devices typically have SDcards, much slower than SSD
- Compute and store close to the sensors
 - To avoid data transfers
 - For privacy/security aspects
- New data storage abstractions that enable access from the different devices
 - Object store versus file system?
 - Data reduction/lossy compression
- Task flow versus data flow: data streaming
- Metadata and traceability



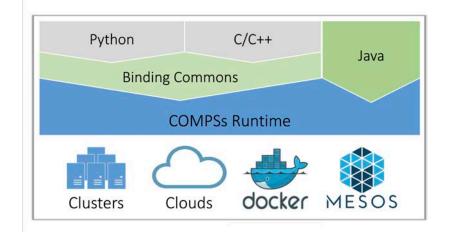


Orchestration challenges

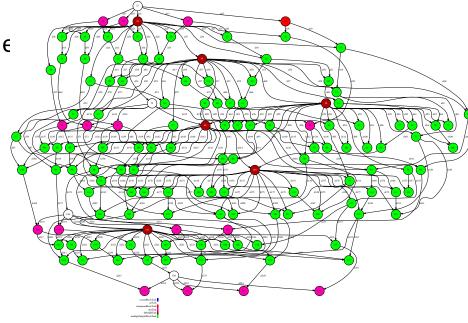
 How to describe the workflows in such environment? Which is the right interface?



- Focus:
 - Integration of computational workloads, with machine learning and data analytics
- Intelligent runtime that can make scheduling and allocation, data-transfer, and other decisions
- PyCOMPSs is a parallel task-based programming model for distributed computing platforms. Based on a sequential interface, at execution time the COMPSs runtime is able to exploit the inherent parallelism of applications at task level.

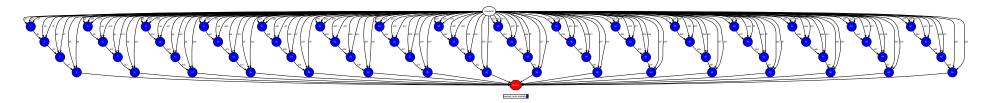






PyCOMPSs Syntax

- Use of decorators to annotate tasks and to indicate arguments directionality
- Small API for data synchronization



Tasks definition

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Supercomputing

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```
@task(c=INOUT)
def multiply(a, b, c):
    c += a*b
```

Main Program

```
initialize_variables()
startMulTime = time.time()
for i in range(MSIZE):
    for j in range(MSIZE):
        for k in range(MSIZE):
            multiply (A[i][k], B[k][j], C[i][j])
compss_barrier()
mulTime = time.time() - startMulTime
```

Other decorators: Tasks' constraints

- Constraints enable to define HW or SW features required to execute a task
 - Runtime performs the match-making between the task and the computing nodes
 - Support for multi-core tasks and for tasks with memory constraints
 - Support for heterogeneity on the devices in the platform
- Versions: Mechanism to support multiple implementations of a given behavior (polymorphism)
 - Runtime selects to execute the task in the most appropriate device in the platform

```
@constraint (MemorySize=6.0, ProcessorPerformance="5000", ComputingUnits="8")
@task (c=INOUT)
def myfunc(a, b, c):
...
```

```
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```

```
@implement (source class="myclass", method="myfunc")
@constraint (MemorySize=1.0, ProcessorType ="ARM", )
@task (c=INOUT)
def myfunc_other(a, b, c):
...
```

Failure Management

Interface than enables the programmer to give hints about failure management

```
@task(file_path=FILE_INOUT, on_failure='CANCEL_SUCCESSORS')
def task(file_path):
    ...
    if cond :
        raise Exception()
```

- Options: RETRY, CANCEL_SUCCESSORS, FAIL, IGNORE
- Implications on file management:
 - I.e, on IGNORE, output files: are generated empty
- Possibility of ignoring part of the execution of the workflow, for example if a task fails in an unstable device
- Opens the possibility of dynamic workflow behaviour depending on the actual outcome of the tasks



Task Nesting

Tasks that internally invoke new tasks

- Why is task nesting relevant?
 - Support for structured programming
 - Reduces bottlenecks in scheduling and other runtime features
 - Better support for heterogeneous computing platforms



Integration of HPC, ML and data analytics



Other decorators: linking with other programming models

- A task can be more than a sequential function
 - A task in PyCOMPSs can be sequential, multicore or multi-node
 - External binary invocation: wrapper function generated automatically
 - Supports for alternative programming models: MPI and OmpSs
- Additional decorators:
 - @binary(binary="app.bin")
 - @ompss(binary="ompssApp.bin")
 - @mpi(binary="mpiApp.bin", runner="mpirun", computingNodes=8)
- Can be combined with the @constraint and @implement decorators

```
@constraint (computingUnits= "248")
@mpi (runner="mpirun", computingNodes= "16", ...)
@task (returns=int, stdOutFile=FILE_OUT_STDOUT, ...)
def nems(stdOutFile, stdErrFile):
    pass
```

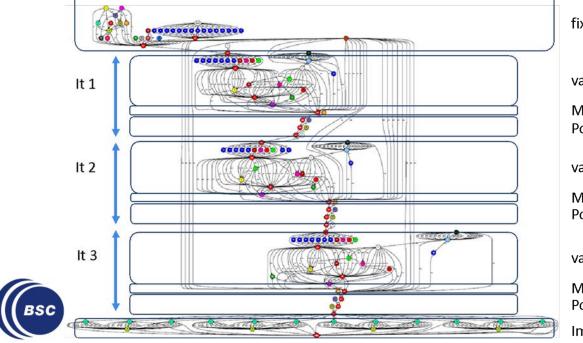


NMMB-Monarch: Weather and dust forecast

• An example of usage of this idea is the application Multiscale Online Nonhydrostatic Atmosphere Chemistry model (NMMB-Monarch) aims at providing short to medium range weather and gas-phase chemistry forecasts from regional to global scales that performs weather and dust forecast. NMMB-Monarch is used as an operational tool to provide information services at BSC.



• The application combines multiple sequential scripts and MPI simulations. PyCOMPSs enables the smooth orchestration of all them as a single workflow.



fixed step

variable step

MPI simulation Post-process

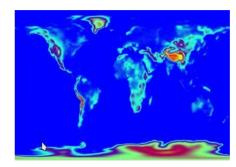
variable step

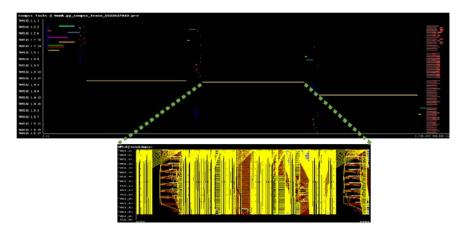
MPI simulation Post-process

variable step

MPI simulation Post-process

Image generation





Integration with persistent memory

- Programmer may decide to make persistent specific objects in its code
- Persistent objects are managed same way as regular objects
- Tasks can operate with them

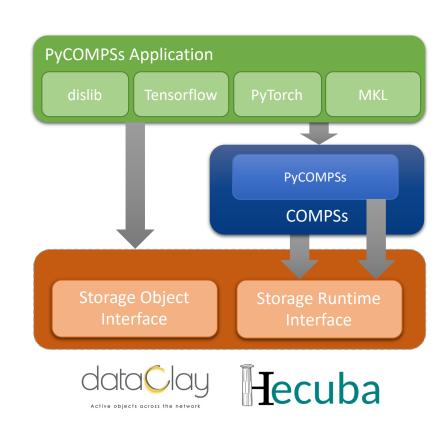
```
a = SampleClass ()
a.make_persistent()
Print a.func (3, 4)

a.mytask()
compss_barrier()

o = a.another_object
```

 Objects can be accessed/shared transparently in a distributed computing platform





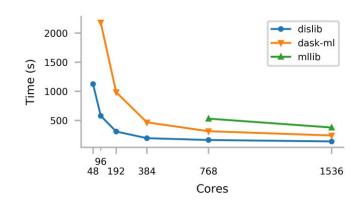
Dislib: parallel machine learning

- Dislib, a distributed machine learning library parallelized with PyCOMPSs that enables large-scale data analytics on HPC infrastructures.
- Inspired by scikit-learn, dislib provides an estimator-based interface that improves productivity by making algorithms easy to use and interchangeable. This interface also makes programming with dislib very easy to scientists already familiar with scikit-learn.

Dislib also provides a distributed data structure that can be operated as a regular Python object. The
combination of this data structure and the estimator-based interface makes dislib a distributed version of
scikit-learn, where communications, data transfers, and parallelism are automatically handled behind the

scene

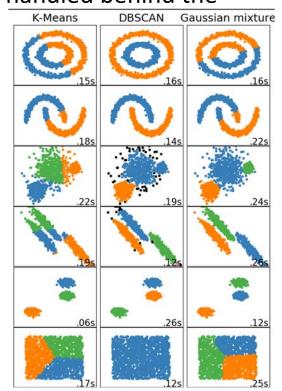
- Gaia satellite data: Sample scientific application:
 - Looking for open clusters in the sky with DBSCAN clustering
 - Subset of astrometric data from 2.5 million stars
 - Total data is 10⁹ stars
 - Execution of 6.145 DBSCANs in parallel









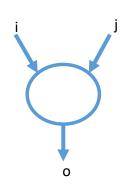


Support for data streams: Task-flow versus data-flow

- New interface to support streaming data in tasks
- Task-flow and data-flow tasks live together in PyCOMPSs/COMPSs workflows
- Data-flow tasks persist while streams are not closed
 - Parameters can be one/multiple streams and non-streamed
- Runtime implementation based on Kafka

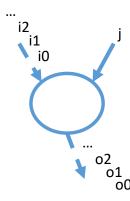
```
@task(fds=STREAM_OUT)
def sensor(fds):
    ...
    while not end():
        data = get_data_from_sensor()
        f.write(data)
    fds.close()
```

Task-flow task



- · Receives data once
- Generates data once
- Does not persist in time
- Stateless tasks

Data-flow task



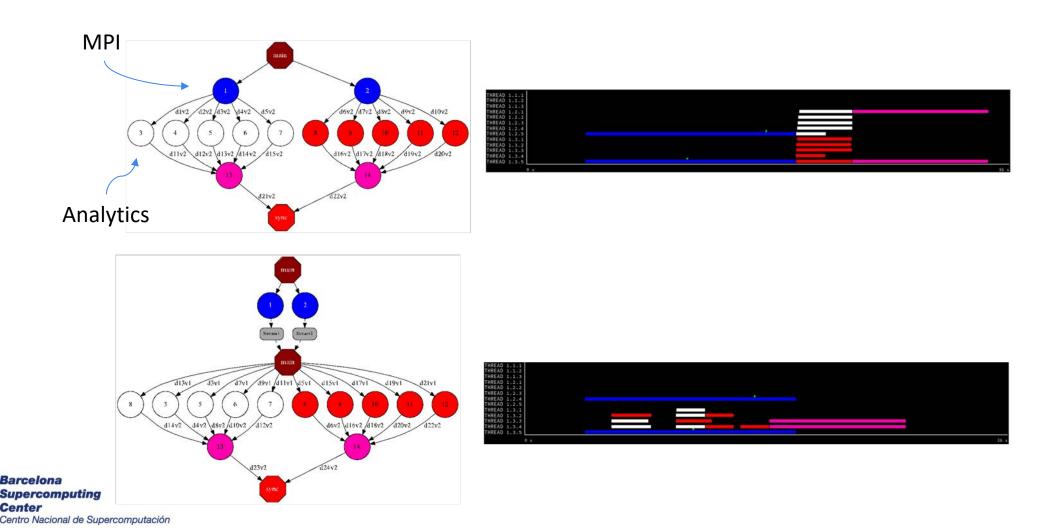
- Receives data multiple times
- Generates data multiple times
- Tasks persists in time
- Stateful tasks



```
@task(fds_sensor=STREAM_IN, filtered=OUT)
def filter(fds_sensor, filtered):
    ...
    while not fds_sensor.is_closed():
        get_and_filter(fds_sensor, filtered)
```

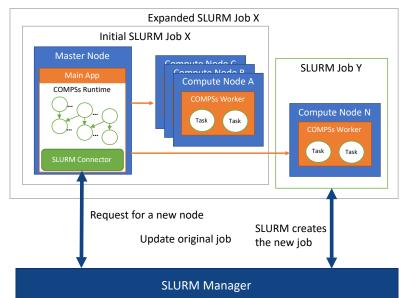
Use case: MPI simulations, analytics and streaming

• Sample case: MPI simulations generating at given steps data to be processed by some analytics

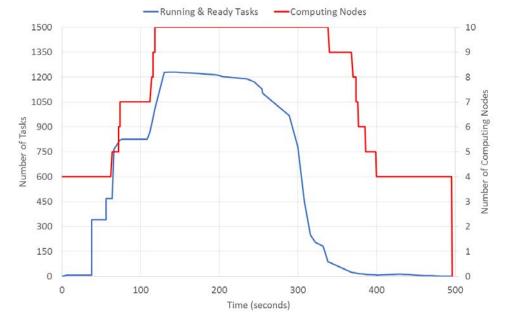


COMPSs runtime: support for elasticity

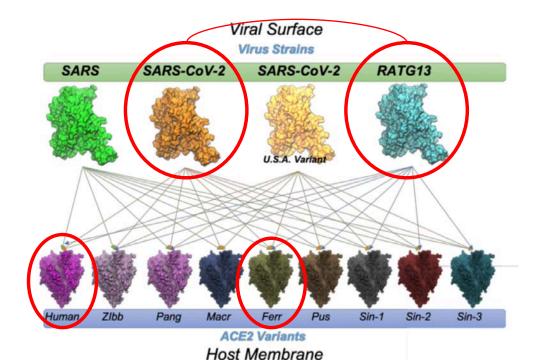
- Possibility to adapt the computing infrastructure depending on the actual workload
- Typical for cloud, now also SLURM managed systems
- Feature that contributes to a more effective use of resources
- Is **very relevant in the edge**, where power is a constraint

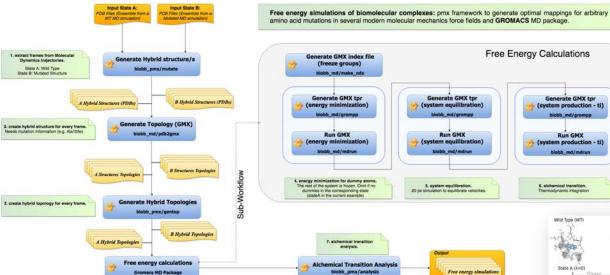






Pre-exascale workflows to explore COVID-19 Infectious Mechanisms and Host Selection Process





Impact of mutations in binding affinity

- Equilibrium MD

- Fast-growth Thermodynamic Integration
- 1000 independent short MD simulations (500 forward + 500 reverse)
- GROMACS + pmx
- Extremely parallelizable

GROMACS FAST. FLEXIBLE. FREE.

pmx: generate hybrid protein structure and topology
Computational Biomolecular Dynamics Group

Molecular Dynamics simulation data

- For each mutation:
 - MD Simulations (RBD + ACE2 + Complex)
 - Free energy calculations











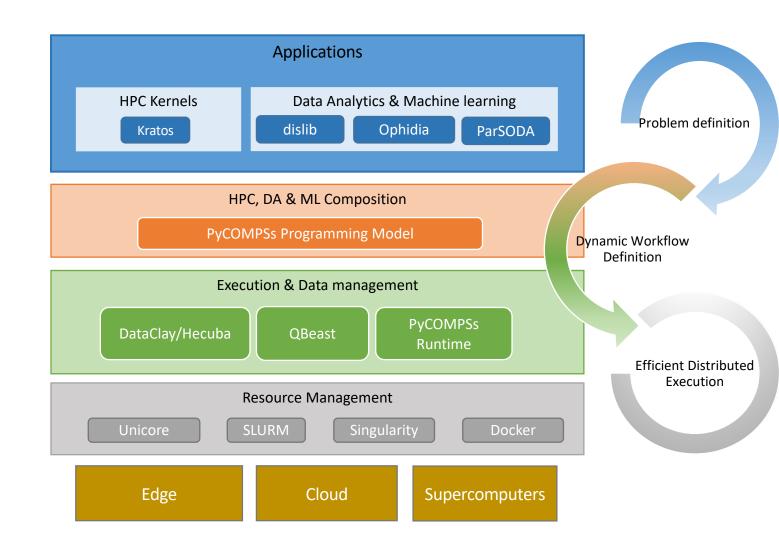




PRACE computational power
Massive amount of data

Conclusions

- PyCOMPSs provides a workflow environment that enables the integration of HPC simulation and modelling with big data analytics and machine learning
- Support for dynamic workflows that can change their behaviour during the execution
- Support for dynamic resource management depending on the actual workload needs
- Support for data-streaming enabling the combination of task-flow and data-flow in the same workflow
- Support for persistent storage beyond traditional file systems.





Projects where COMPSs is involved



















- Project page: http://www.bsc.es/compss
 - Documentation
 - Virtual Appliance for testing & sample applications
 - Tutorials
- Source Code



https://github.com/bsc-wdc/compss

Docker Image



https://hub.docker.com/r/compss/compss-ubuntu16/

Applications



https://github.com/bsc-wdc/apps



https://github.com/bsc-wdc/dislib



