

Programmatic workflows in PyCOMPSs

Tasks definition

```
@task(cc_original = INOUT, cc_surrs = INOUT)
def gather(result, cc_original, cc_surrs, start, end):
    cc_original[start:end,:] = result[0]
    cc_surrs[start:end,:,:] = result[1]

@task(returns = list)
def cc_surrogate_range(start_idx, end_idx, seed, num_neurons,
num_surrs, num_bins, maxlag):
    ...
```

Programmatic workflows

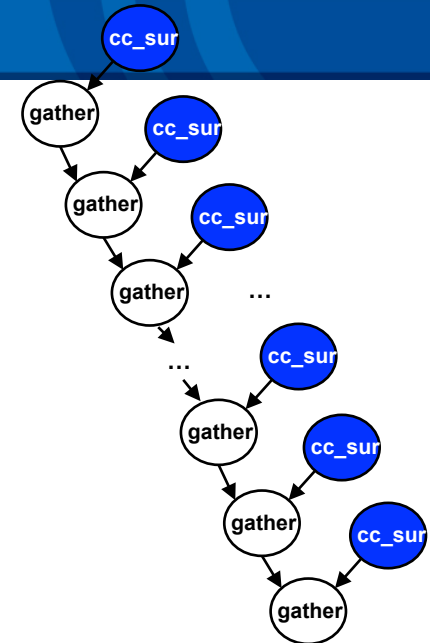
- Standard sequential coordination scripts and applications in Python
- Incremental changes: Task annotations + directionality hints

Runtime

- DAG generation based on data dependences: files and objects
- Tasks and objects offload

Platform unaware

- Clusters (also MIC)
- Clouds, distributed computing



Main program

```
from pycompss.api import compss_wait_on

cc_original = zeros((num_ccs,2*maxlag+1))
cc_surrs = zeros((num_ccs,2*maxlag+1,2))
for frag in range(num_frags):
    ...
    result = cc_surrogate_range(start_idx, end_idx, seed, ...
gather(result, cc_original, cc_surrs, start_idx, end_idx)
    seed = seed + delta

f = open('./result_cc_originals.dat','w')
cc_original = compss_wait_on(cc_original)
pickle.dump(cc_original,f)
f.close()

...

```

PyCOMPSs integrated with persistent storage

```
from pycompss.api.task import task
```

```
@task()
```

```
def cc_surrogate_range(block_i, block_j, nd, correlation,  
seed, num_surrs, num_bins, maxlag):
```

```
...
```

```
import sys
```

```
neuron_data_name = sys.argv[1]
```

```
correlation_name = sys.argv[2]
```

```
nd = NeuronData(neuron_data_name )
```

```
correlation = Correlation()
```

```
seed = 2398645
```

```
delta = 1782324
```

```
for block_i in nd.spikes.keys():
```

```
    for block_j in nd.spikes.keys():
```

```
        cc_surrogate_range(block_i, block_j, nd, ...)
```

```
        seed = seed + delta
```

PyCOMPSs integrated with persistent storage

```
from pycompss.api.task import task
```

```
@task()
```

```
def cc_surrogate_range(block_i, block_j, nd, correlation,  
seed, num_surrs, num_bins, maxlag):
```

```
...
```

☺ Data remains persistent

- Can be shared by several applications
 - Producer/Consumer
 - In-situ data-processing
- Can remain after execution
- Can be deleted by another application

☺ Implementation

- Hecuba backend can transparently map Python dictionaries into Cassandra tables
- Python iterators redefined for blocking

```
import sys
```

```
neuron_data_name = sys.argv[1]
```

```
correlation_name = sys.argv[2]
```

```
nd = NeuronData(neuron_data_name )
```

```
correlation = Correlation()
```

```
correlation.make_persistent(correlation_name)
```

```
seed = 2398645
```

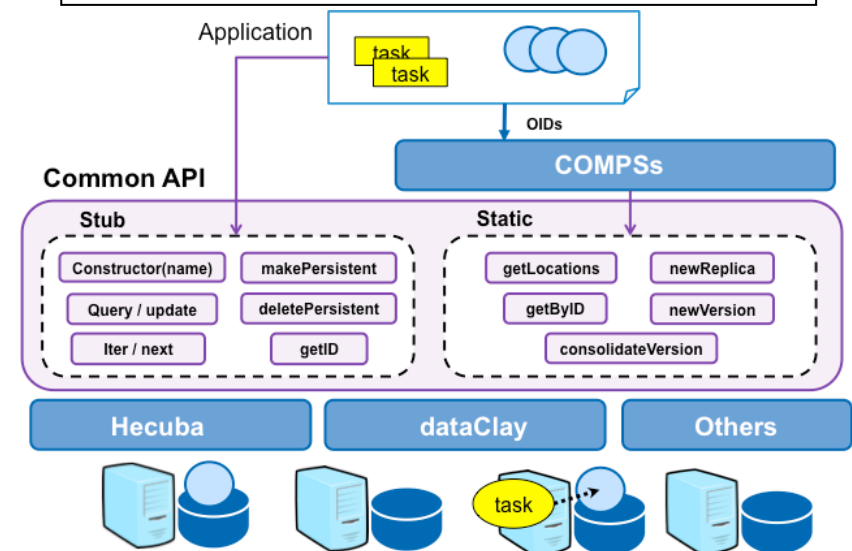
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delta = 1782324
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```
for block_i in nd.spikes.keys():
```

```
for block_j in nd.spikes.keys():
```

```
cc_surrogate_range(block_i, block_j, nd, ...)
```

```
seed = seed + delta
```



Summary: BSC vision

Applications

Regular programming languages
+ light API

Intelligent runtimes

Storage

Computing



- « Use of regular traditional programming languages
 - Python, Java, C → **COMPSs**
 - C, C++, Fortran → **OmpSs**
- « Tight, natural integration of Concurrency and data model
 - Data flow annotations
 - Persistent objects
 - Self-contained objects → **dataClay**
 - Key-value databases → **Hecuba**
 - ...

Traditional look and feel ...

... revolutionary under the covers

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Writing Efficient Computational Workflows in Python

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