High Performance Data Analytics and Machine Learning developments in Ophidia

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Introduction

- Research challenge: HPC & big data convergence at extreme-scale for eScience
- Goal: Scalable HPDA&ML software stack for eScience
- Research project: Ophidia (design study 2011, implementation 2012 - present)

- This talk focus: Ophidia2.0
- Ophidia is a CMCC research project addressing fast and big data challenges for eScience
- It provides a paradigm shift, from sequential & client- to parallel & server-side data analysis

Key Features in Ophidia

- eScience framework
- Server-side
- Parallel
- In-memory
- Declarative
- Datacube oriented (multi-dimensional OLAP support)
- (Shared) Sessions
- Workflows and applications
- Interactive and batch support
- HPC and HTC tasks
- Both domain-oriented (e.g. nc) and domain-agnostic support (e.g. OLAP)
Multi-dimensional data and storage model

- OLAP-based (ndim-datacube)
- Dimension-independent
- Implicit and explicit dimensions
- Partition & distribution
- Flexible and scalable
Ophidia2.0 Architecture

- Interoperable interface (e.g. OGC WPS)
- Modular and extensible
- Parallel framework runtime
- I/O & analytics runtime
- Multiple storage back-ends
- Supports ranging from single operators to complex analyses
Three levels of parallelism

- **Datacube-level parallelism**
  - HTC paradigm
  - At the front-end level
  - Based on the “massive” operator concept

- **Fragment-level parallelism**
  - HPC paradigm
  - MPI/Pthread
  - At the HPDA framework level

- **Array-level parallelism**
  - HPC paradigm
  - OpeMP based
  - At the I/O & analytics server level
Analytics Workflow support (runtime perspective)
Analytics Workflow support (end-user perspective)
Multi-model analytics workflow case study (CMIP5-based)

The ESiWACE project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 675191 http://www.esiwace.eu
Programmable framework

- **PyOphidia** provides a Python binding to Ophidia

- Consists of two classes:
  - **Client** class: connections, submissions, workflows, sessions
  - **Cube** class: datacube operators

- Available in conda-forge

https://pypi.org/project/PyOphidia/
JupyterHub front-end

- Web access/env
- Integrated into the HPC environment (e.g. GPFS)
- Access via VPN
- Multiplexed front-end
- Fat-node hosting
- Terminal features available too (embedded)
- Integrated into the EOSC-hub project (ECAS thematic service)
Analytics back-end for the NextData project (I)

- Ophidia is also exploited in the NextData project
- Computing & data capabilities integrated into the same environment
  - Several datasets published by CMCC modelling divisions
  - Catalogue browsing
  - Data download
  - Visualization capabilities
  - Computing
Analytics back-end for the NextData project (II)

- Computing & data capabilities integrated into the same environment
- Terminal-based capabilities
- Google Earth (viz)
Analytics back-end for the NextData project (III)

- Programmatic access to the back-end datasets
  - Based on Python language
  - Jupyter Notebooks
  - Through PyOphidia
Parallel Import Monitoring

- `ophclient.submit("oph_importnc2 src_path=[path=*.nc;]")`

- Three scenarios on a I/O and analytics node
  - Single import
  - Multiple imports/delete
  - Multiple imports on the same node

- Network traffic
  - Inbound burst
  - No outbound data

- Memory increase

- Cache effects
Parallel Import Benchmark (preliminary insights)

- **Importnc2 operator**
- **HTC importnc2 statements**
- **Weak scalability benchmark**
- **Metrics**
  - Execution time [s]
  - Throughput [GB/s]
- **From 1 to 64 input files**
  - 1 HPDAnode/1 input file
  - 16 fragments/node
  - 1 file 8.5GB (0.53TB)
- **Up to 64 nodes → 1024 cores**

Robustness test up to 4096 threads and 2.1TB on 1024 cores have been performed
LSTM Primitives and SANIFS use case

- Time-series predictive analytics
- The algorithm has been divided in two phases: training and test/prediction
- Implementation based on the KANN library
- After the training, 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
- For test and prediction we defined another primitive
- The primitives can run in the oph_apply operator

```python
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])
```

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

[Graphs and charts showing time-series data and model performance]
Conclusions

- **Ophidia2.0 provides a stronger integration of big data and HPC**
  - Major step forward w.r.t. Ophidia1.4 and HPDA paradigm
  - Tight integration with HPC eco-system
  - New flexible and dynamic deployment approach
  - New release of the native I/O and analytics server
  - Improved management of multi-user scenarios
  - Three levels of parallelism to address higher scalability
  - Process-level (vs thread-level) connection to the OphidiaDB

- Planned to be released by this month (January 2019 at the latest). Stay tuned!
Thanks!

Do you want to join this effort?

Please get in touch with us soon

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