Uni.lu HPC School 2021

PS12: Big Data Analytics

Batch, stream and hybrid processing Engines

Uni.lu High Performance Computing (HPC) Team

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http://hpc.uni.lu

Latest versions available on Github:

UL HPC tutorials: https://github.com/ULHPC/tutorials

UL HPC School: hpc.uni.lu/education/hpcschool

PS12 tutorial sources: ulhpc-tutorials.rtfd.io/en/latest/bigdata/

Summary

Main Objectives of this Session

- **Review Popular Python-based Data Analytics Frameworks**
  - ↪ Sandboxed Environment (**virtualenv**) for reproducible developments
  - ↪ Introduction to **Jupyter Notebooks**
    - ✓ transparent access to with SOCK 5 Proxy
- [interlude] **Install newer** version of a BDA **application with Easybuild**
- Introduction to **Big Data analytics**
  - ↪ Distributed File Systems (DFS)
  - ↪ **Mapreduce**
  - ↪ **Hadoop** and **HDFS**
- In-memory [streaming] analysis with **Spark**
  - ↪ Interactive runs
    - ✓ **PySpark**, the Spark Python API; **Scala** and **R** Spark Shell
  - ↪ Standalone cluster runs
  - ↪ Transparent access to master dashboard with SOCK 5 Proxy

Disclaimer: Acknowledgements

- Part of these slides were **courtesy** borrowed w. permission from:
  - ↪ Prof. Martin Theobald *(Big Data and Data Science Research Group)*, UL
- Part of the slides material adapted from:
  - ↪ Advanced Analytics with Spark, O Reilly
  - ↪ Data Analytics with HPC courses
    - ✓
- similar hands-on material on Github for instance:
  - ↪ Jonathan Dursi: `hadoop-for-hpcers-tutorial`

Before we start...

Hands-on Pre-requisites

▶ url ◀ | github | src

- Access to ULHPC facility and configure/create Tmux/Screen session
  - ↪ `tmux new -s <name>`, `screen -S <name>`
- Clone/Pull `ULHPC/tutorials` repository `~/git/github.com/ULHPC/tutorials`
- Prepare dedicated directory `~/tutorials/bigdata` for this session
  - ↪ set convenient symbolic links to reference material

```
(access)$> mkdir -p ~/tutorials/bigdata && cd ~/tutorials/bigdata
# create a symbolic link to the reference material
(access)$> ln -s ~/git/github.com/ULHPC/tutorials/bigdata ref.d
(access)$> ln -s ref.d/scripts .      # Don't forget trailing '.' means 'here'
(access)$> ln -s ref.d/settings .     # idem
(access)$> ln -s ref.d/src .          # idem
```

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Hands-on Firefox Extension

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- Install SOCKS 5 Proxy plugin

Summary

Software/Modules Management

easybuild.readthedocs.io

- Easybuild: open-source framework to (automatically) build scientific SW
- **Why?**: *"Could you please install this software on the cluster?"*
  - ↪ Scientific software is often **difficult** to build
    - ✓ non-standard build tools / incomplete build procedures
    - ✓ hardcoded parameters and/or poor/outdated documentation
  - ↪ EasyBuild helps to facilitate this task
    - ✓ **consistent** software **build and installation** framework,
    - ✓ **automatically generates LMod modulefiles**

```
(node)$ module spider BCFtools   # Complementaty tool to SAMTools
Lmod has detected the following error:  Unable to find: "BCFtools".
(node)$ module load tools/EasyBuild
# Search for recipes for the missing software
(node)$ eb -S BCFtools
(node)$ eb BCFtools-1.12-GCC-10.2.0.eb -Dr    # Dry-run
(node)$ eb BCFtools-1.12-GCC-10.2.0.eb -r
```

Recommended Settings for local Easybuild installs

- Easybuild is provided to you as a software module.

```
module load tools/EasyBuild
```

- Important configuration variables:
  - ↪ `EASYBUILD_PREFIX`: where to install **local** modules and software
    - ✓ **set globally for you** to `$HOME/.local/easybuild` by default
    - ✓ **YET better to make it match the cluster/software set version**
      see ULHPC technical documentation on Easybuild
  - ↪ `EASYBUILD_MODULES_TOOL`: the type of modules tool you are using, **i.e.** `LMod`
    - ✓ **set globally for you**
  - ↪ `EASYBUILD_MODULE_NAMING_SCHEME`:
    - ✓ the way the software and modules should be organized: flat view or hierarchical
    - ✓ **set globally for you to** `CategorizedModuleNamingScheme`

Building a more recent Spark with Easybuild

Hands-on: Building Spark with Easybuild

► url ◄ | github | src

- Ensure `$EASYBUILD_PREFIX` is set correctly
  ↪ `source settings/default.sh`
- Search for Spark easyconfigs
  ↪ `eb -S <pattern>`
  ↪ `./scripts/suggest-easyconfigs -v ${RESIF_VERSION_PROD} <pattern>`
- Install Spark 3.1.1 and dependencies

Building a more recent Spark with Easybuild

```
$ si -c 128  # To acceplarate the build
$ source settings/default.sh
$ echo $EASYBUILD_PREFIX      # Check the format which must be:
#    <home>/.local/easybuild/<cluster>/<version>/<arch>
# Dry-run: check the matched dependencies
$ eb src/Spark-3.1.1-foss-2020b-Python-3.8.6.eb -D -r src:   # <-- don't forget the trailing ':'
# only Arrow and Spark should noyt be checked
# Launch the build
$ eb src/Spark-3.1.1-foss-2020b-Python-3.8.6.eb -r src:
```

Summary

Python

- Effective for fast prototype coding
  - ↪ Simple (now used a reference language in schools)
  - ↪ Easy creation of reproducible and isolated environment
    - ✓ `pip`: Python package manager
    - ✓ `virtualenv`: Create virtual environment

```
$> pip install --user [-U] <package>                    # install/upgrade <package>
```

```
$> pip freeze -l > requirements.txt                     # Dump python environment
```

```
$> pip install -r requirements.txt                      # Restore saved environment
```

Python on the UL HPC Platform

- **Two different ways of using Python on the UL HPC Platform**
  1. Use the **system** Python installed on the nodes
     - ✓ version **2.7** and **3** are installed under `/usr/bin/python` and `/usr/bin/python3`
  2. Rely on Environment Modules **once** inside a job on a computing node
     - ✓ then you can search for the avaiable versions of Python with `module avail lang/python`

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```
$ module av lang/python scipy

------------------ /opt/apps/resif/aion/2020b/epyc/modules/all ----------------------
 lang/Python/2.7.18-GCCcore-10.2.0      lang/SciPy-bundle/2020.11-foss-2020b
 lang/Python/3.8.6-GCCcore-10.2.0 (D)   lang/SciPy-bundle/2020.11-intel-2020b (D)
                                        lang/SciPy-bundle/2020.11-foss-2020b-Python-2.7.18

  Where:
   D:  Default Module
```

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     - ✓ then you can search for the avaiable versions of Python with `module avail lang/python`

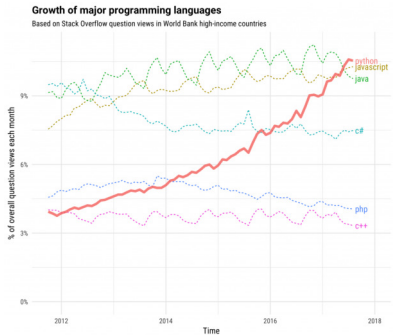
- Make sure to **always use the same Python version** (and package versions) **when running your code or workflow**.
  - ↪ The first thing you should **always** do is to **load the version of Python you need**.
    - ✓ your scripts will use the loaded module version to execute.
    - ✓ this version will be used inside your virtual environment.
- Python code is **not necessarily compatible between versions 2 and 3**.
  - ↪ For many packages recent versions are only available for Python 3.

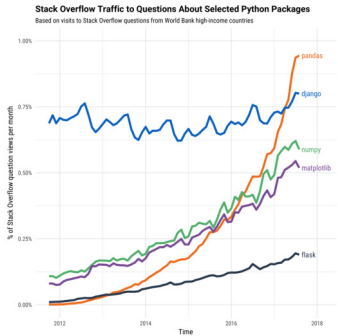
Examples of module usage

```
$(node)> module load lang/Python/3.8.6-GCCcore-10.2.0
$(node)> python --version
Python 3.8.6

$(node)> module load lang/Python/2.7.18-GCCcore-10.2.0
$(node)> python --version
Python 2.7.18

$(node)> module purge
$(node)> python --version
Python 2.7.18
```

Python's Role in Data Science

- **Dominant language** both in **data analytics** and **general programming**, fueled both by:
  - ↪ computational libraries like Numpy, Pandas, and Scikit-Learn
  - ↪ wealth of libraries for visualization, interactive notebooks, collaboration etc.





Useful Python Libraries / Data Sciences

Library	Description
numpy	Fundamental package for scientific computing
pandas	High-performance, easy-to-use data structures/data analysis tools
iPython	Interactive computing
jupyter (notebook)	Create and share documents that contain live code
Tensorflow, Pytorch	Machine learning frameworks
Scoop	Scalable COncurrent Operations in Python
RAPIDS	GPU Accelerated libraries for data science
Scikit-Learn	Machine Learning in Python
Scikit-image	Image processing in Python
pythran / Cithon	Python->C++ compilation, C bindings
Dask	Flexible library for parallel computing in Python.
...	

SciPy bundle

```
$ module show lang/SciPy-bundle
-------------------------------------------------------------------------------
   /opt/apps/resif/<cluster>/<version>/<arch>/modules/all/lang/SciPy-bundle/[...]
-------------------------------------------------------------------------------
help([[
Description
===========
Bundle of Python packages for scientific software

[...]
===================
Included extensions
===================
Bottleneck-1.3.2, deap-1.3.1, mpi4py-3.0.3, mpmath-1.1.0, numexpr-2.7.1,
numpy-1.19.4, pandas-1.1.4, scipy-1.5.4
]])
```

Python Virtualenv / venv

- Virtualenv allows you to create several environments
  - ↪ each will contain their own list of Python packages
  - ↪ Built-in support in **Python 3** for virtual environments with venv
- **Best-practice**: **create one virtual environment per project**

```
ssh [-D 1080] {aion|iris}-cluster    # assuming proper configuration
# Once on the clusters, ask for a interactive job (here for 1h)
si --time=01:00:00 # OR si-gpu --time=01:00:00 if a GPU is needed
# load your prefered **3.x** version of Python - 2.7 DEPRECACTED
module load lang/Python/3.8.6-GCCcore-10.2.0   # Load default python
# create virtual environment - distinguish between clusters
python -m venv <name>_${ULHPC_CLUSTER}
# Note: You may want to centralize your virtualenvs under '~/venv/<name>_${ULHPC_CLUSTER}'
# instead of relative to your project directory
```

Virtualenv Activation and Population

```
# source <name>/bin/activate
source venv_${ULHPC_CLUSTER}/bin/activate
pip install --upgrade pip
## Populate with your wished data science packages
pip install jupyter
# matplotlib to plot the graph inside your notebook
pip install matplotlib
# To use our virtualenv in the notebook, we need to install this module
pip install ipykernel
```

- **Save** / **Restore** your packages

```
# Save versionned configuration - git add it!
pip freeze -l > requirements.txt
```

```
# Restore full install
pip install -r requirements.txt
```

Application to Jupyter Notebook

```
# Create your own kernel matching <name> virtualenv and launch your Notebook
python -m ipykernel install --user --name=venv
# launch notebook
jupyter notebook --generate-config
jupyter notebook password
jupyter notebook \
   --ip $(ip addr | egrep '172\.17|21'| grep 'inet ' | awk '{print $2}' | cut -d/ -f1) \
   --no-browser
[...]
[I 00:40:53.547 NotebookApp] http://172.21.XX:XX:8888/
```

- Connect **transparently** to the master Web UI via the SOCK5 proxys
  - ↪ thus **using your browser on your laptop at home**
  - ↪ assumes you connected with `ssh -D 1080 [-C] {aion|iris}-cluster`

Hands-on: Jupyter Notebook

Your Turn!

Hands-on: Use Jupyter notebook on UL HPC

▶ url ◀ | github | src

- Connect with SOCKS proxy enabled `ssh -D 1080 [...]`
- **Reserve** an **interactive** job `si[-gpu]`
- Load Python and create a virtualenv `python -m venv venv_${ULHPC_CLUSTER}`
  - ↪ activate it and update `pip`
  - ↪ Install jupyter packages `jupyter matplotlib ipykernel`
  - ↪ Save installed packages
- reate your own kernel matching the virtualenv
- launch your Notebook

Summary

What is a Distributed File System?

- Straightforward idea: **separate logical from physical storage.**
  - ↪ Not all files reside on a single physical disk,
  - ↪ or the same physical server,
  - ↪ or the same physical rack,
  - ↪ or the same geographical location,...
- **Distributed file system (DFS)**:
  - ↪ virtual file system that enables clients to access files
    - ✓ ... as if they were stored locally.

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- **Major DFS distributions**:
  - ↪ **NFS**: originally developed by Sun Microsystems, started in 1984
  - ↪ **AFS/CODA**: originally prototypes at Carnegie Mellon University
  - ↪ **GFS**: Google paper published in 2003, not available outside Google
  - ↪ **HDFS**: designed after GFS, part of Apache Hadoop since 2006

Distributed File System Architecture?

Master-Slave Pattern

- Single (or few) **master** nodes maintain state info. about clients
- All clients R&W requests go through the global master node.
- **Ex**: GFS, HDFS

Distributed File System Architecture?

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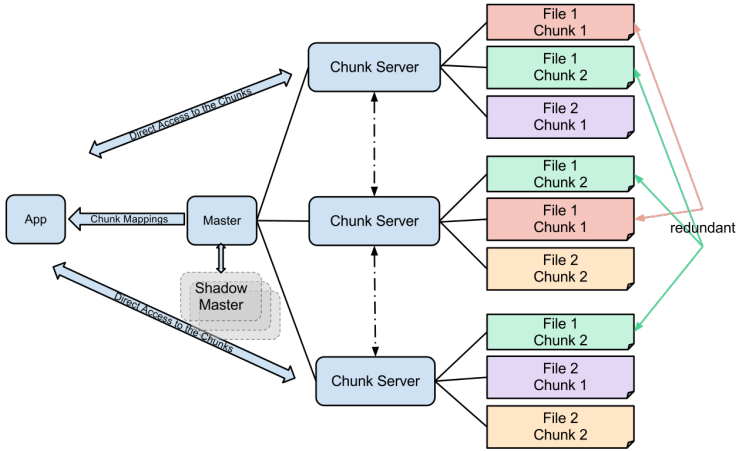
Peer-to-Peer Pattern

- No global state information.
- Each node may both serve and process data.

Google File System (GFS) (2003)

- Radically different architecture compared to NFS, AFS and CODA.
  - ↪ specifically tailored towards **large-scale** and **long-running analytical processing tasks**
  - ↪ over thousands of storage nodes.
- **Basic assumption**:
  - ↪ client nodes (aka. *chunk servers*) may fail any time!
  - ↪ Bugs or hardware failures.
  - ↪ Special tools for monitoring, periodic checks.
  - ↪ Large files (multiple GBs or even TBs) are split into 64 MB *chunks*.
  - ↪ Data modifications are mostly append operations to files.
  - ↪ Even the master node may fail any time!
    - ✓ Additional *shadow master* fallback with read-only data access.
- Two types of reads: Large sequential reads & small random reads

Google File System (GFS) (2003)



GFS Consistency Model

- **Atomic File Namespace Mutations**
  - ↪ File creations/deletions centrally controlled by the master node.
  - ↪ Clients typically create and write entire file,
    - ✓ then add the file name to the file namespace stored at the master.
- **Atomic Data Mutations**
  - ↪ only 1 atomic modification of 1 replica (!) at a time is guaranteed.
- **Stateful Master**
  - ↪ Master sends regular **heartbeat** messages to the chunk servers
  - ↪ Master keeps chunk locations of all files (+ replicas) in memory.
  - ↪ locations not stored persistently...
    - ✓ but polled from the clients at startup.
- **Session Semantics**
  - ↪ Weak consistency model for file replicas and client caches only.
  - ↪ Multiple clients may read and/or write the same file concurrently.
  - ↪ The client that last writes to a file **wins**.

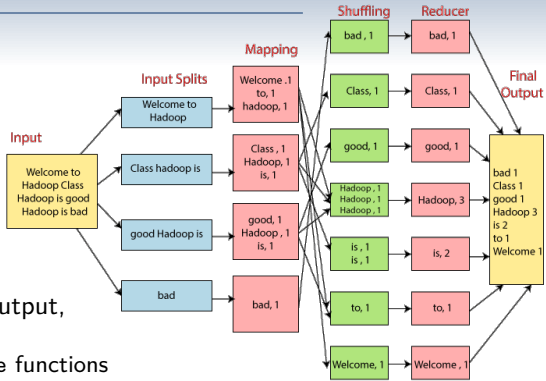
Fault Tolerance & Fault Detection

- **Fast Recovery**
  - ↪ master & chunk servers can restore their states and (re-)start in s.
    - ✓ regardless of previous termination conditions.
- **Master Replication**
  - ↪ *shadow master* provides RO access when primary master is down.
    - ✓ Switches back to read/write mode when primary master is back.
  - ↪ Master node does not keep a persistent state info. of its clients,
    - ✓ rather polls clients for their states when started.
- **Chunk Replication & Integrity Checks**
  - ↪ chunk divided into 64 KB blocks, each with its own 32-bit checksum
    - ✓ verified at read and write times.
  - ↪ Higher replication factors for more intensively requested chunks (**hotspots**) can be configured.

Map-Reduce

- **Breaks** the processing into two main phases:
  1. the **map** phase
  2. the **reduce** phase.

- Each phase has **key-value pairs** as input and output,
  - ↪ types may be chosen by the programmer.
  - ↪ the programmer also specifies `map` and `reduce` functions



Hadoop

- Initially started as a student project at Yahoo! labs in 2006
  - ↪ Open-source Java implem. of GFS and MapReduce frameworks
- Switched to Apache in 2009. Now consists of three main modules:
  1. **HDFS**: Hadoop distributed file system
  2. **YARN**: Hadoop job scheduling and resource allocation
  3. **MapReduce**: Hadoop adaptation of the MapReduce principle

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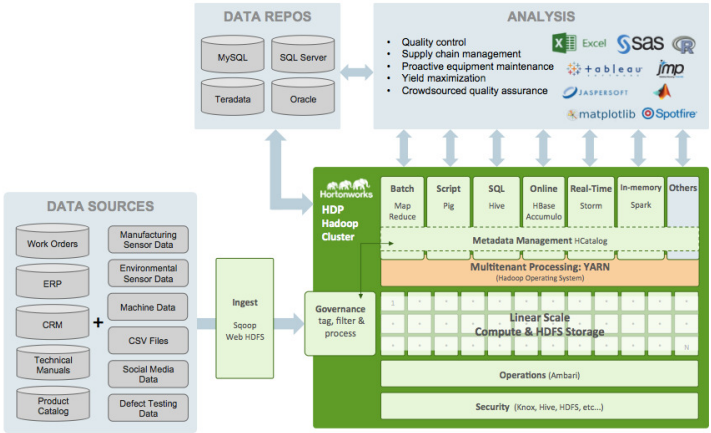
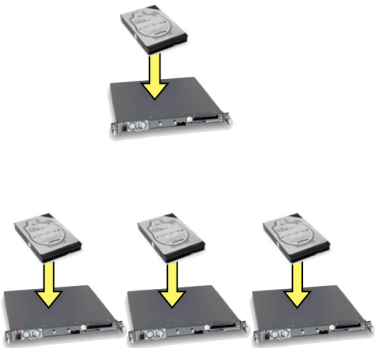
  1. **HDFS**: Hadoop distributed file system
  2. **YARN**: Hadoop job scheduling and resource allocation
  3. **MapReduce**: Hadoop adaptation of the MapReduce principle
- Basis for many other open-source Apache toolkits:
  - ↪ **PIG/PigLatin**: file-oriented data storage & script-based query language
  - ↪ **HIVE**: distributed SQL-style data warehouse
  - ↪ **HBase**: distributed key-value store
  - ↪ **Cassandra**: fault-tolerant distributed database, etc.
- HDFS still mostly follows the original GFS architecture.

Hadoop Ecosystem

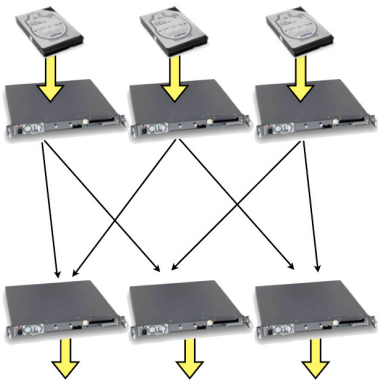


Scale-Out Design



- HDD streaming speed ~ 50MB/s
  - ↪ 3TB =17.5 hrs
  - ↪ 1PB = 8 months
- Scale-out (weak scaling)
  - ↪ **FS distributes data on ingest**
- Seeking too slow
  - ↪ ~10ms for a seek
  - ↪ Enough time to read half a megabyte
- **Batch processing**
- Go through entire data set in one (or small number) of passes

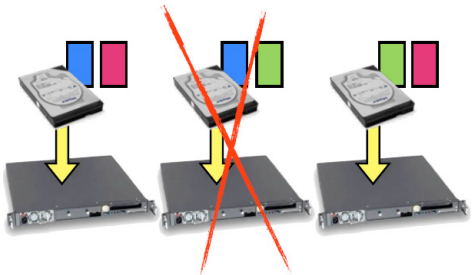
Combining Results



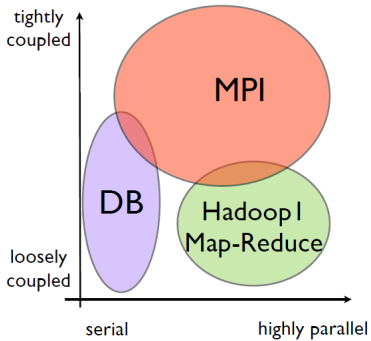
- Each node preprocesses its local data
  - ↪ Shuffles its data to a small number of other nodes
- Final processing, output is done there

Fault Tolerance

- Data also replicated upon ingest
- Runtime watches for dead tasks, restarts them on live nodes
- Re-replicates



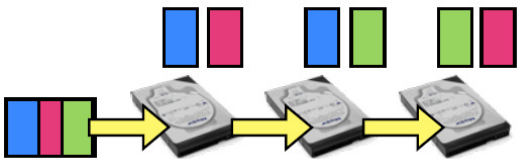
Hadoop: What is it Good At?



- **Compare with databases**
  - ↪ very good at working on small subsets of large databases
    - ✓ DBs: very interactive for many tasks
    - ✓ . . . yet have been difficult to scale
- **Compare with HPC (MPI)**
  - ↪ Also typically batch
  - ↪ Can (and does) go up to enormous scales
- Works extremely well for very tightly coupled problems:
  - ↪ zillions of iterations/timesteps/ exchanges.

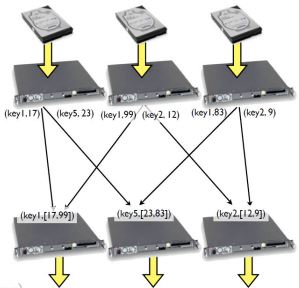
Data Distribution: Disk

- Hadoop & al. arch. handle the hardest part of parallelism for you
  - ↪ aka **data distribution**.
- **On disk**:
  - ↪ HDFS distributes, replicates data as it comes in
  - ↪ Keeps track of computations local to data



Data Distribution: Network

- **On network**: **Map Reduce** (eg) works in terms of key-value pairs.
  - ↪ Preprocessing (`map`) phase ingests data, emits (k, v) pairs
  - ↪ Shuffle phase assigns reducers,
    - ✓ gets all pairs with same key onto that reducer.
  - ↪ Programmer does not have to design communication patterns



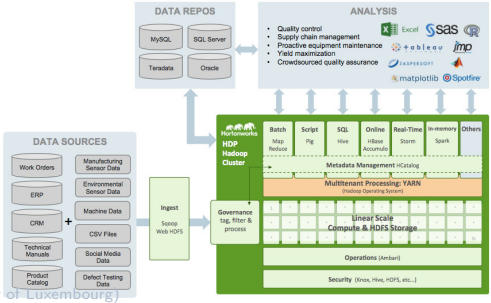
Makes the problem easier

- **Hardest parts of parallel programming with HPC tools**
  - ↪ Decomposing the problem, and,
  - ↪ Getting the intermediate data where it needs to go,

- **Hadoop does that for you**
  - ↪ automatically
  - ↪ for a wide range of problems.

Built a Reusable Substrate

- HDFS and the MapReduce layer were nicely architected.
  - ↪ Enables many higher-level tools
  - ↪ Data analysis, machine learning, NoSQL DBs,...
- Very productive environment
  - ↪ ... and Hadoop 2.x (YARN) is now much much more than just MapReduce



The Hadoop Filesystem

- **HDFS is a distributed parallel filesystem**
  - ↪ Not a general purpose file system
    - ✓ does not implement posix
    - ✓ cannot just mount it and view files
- Access via `hdfs fs` commands or programatic APIs
  - ↪ relatively complex to interact with

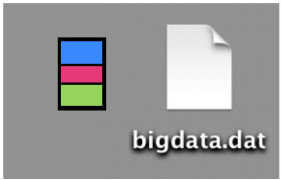
```
$> hdfs fs -[cmd]
```

cat	chgrp
chmod	chown
copyFromLocal	copyToLocal
cp	du
dus	expunge
get	getmerge
ls	lsr
mkdir	movefromLocal
mv	put
rm	rmr
setrep	stat
tail	test
text	touchz

The Hadoop Filesystem

- **Required** to be:
  - ↪ able to deal with large files, large amounts of data
  - ↪ scalable & reliable in the presence of failures
  - ↪ fast at reading contiguous streams of data
  - ↪ only need to write to new files or append to files
  - ↪ require only commodity hardware
- **As a result**:
  - ↪ Replication
  - ↪ Supports mainly high bandwidth, **not** especially low latency
  - ↪ No caching
    - ✓ what is the point if primarily for streaming reads?
    - ✓ Poor support for seeking around files
    - ✓ Poor support for zillions of files
  - ↪ Have to use separate API to see filesystem
  - ↪ Modelled after Google File System (2004 Map Reduce paper)

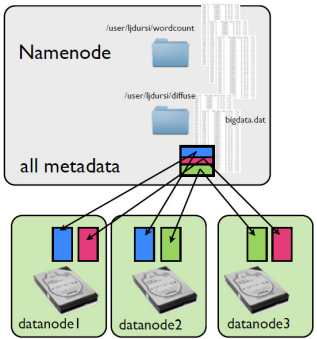
Hadoop vs [HPC] File Systems



- HDFS is a **block-based** FS
  - ↪ A file is broken into blocks,
  - ↪ these blocks are distributed across nodes
- **Blocks are large**;
  - ↪ 64MB is default,
  - ↪ many installations use 128MB or larger
- Large block size
  - ↪ time to stream a block much larger than time disk time to access the block.

```
# Lists all blocks in all files:
$> hdfs fsck / -files -blocks
```

Datanodes and Namenode



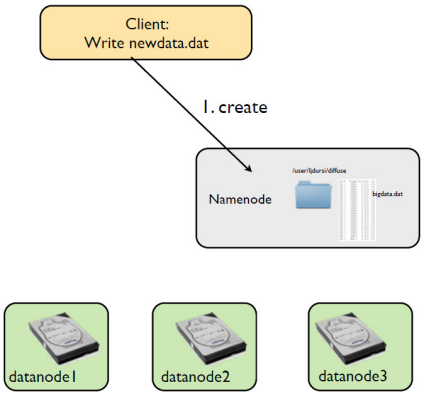
Two types of nodes in the filesystem:

1. **Namenode**
   - ↪ stores all metadata / block locations in memory
   - ↪ Metadata updates stored to persistent journal
2. **Datanodes**
   - ↪ store/retrieve blocks for client/namenode

- Newer versions of Hadoop: federation
  - ↪ $\neq$ namenodes for `/user`, `/data`...
  - ↪ High Availability namenode pairs

Writing a file

- **Writing a file** multiple stage process:
  - ↪ Create file
  - ↪ Get nodes for blocks
  - ↪ Start writing
  - ↪ Data nodes coordinate replication
  - ↪ Get ack back
  - ↪ Complete



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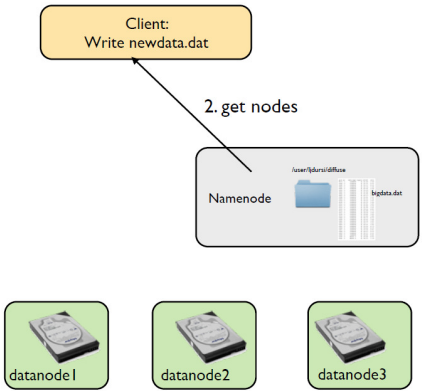

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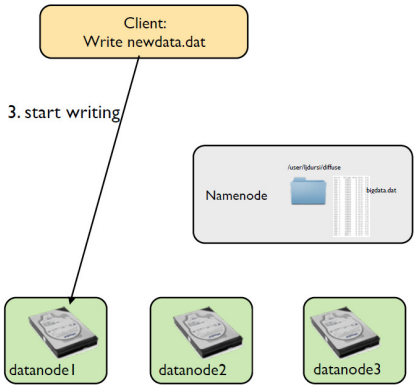

Writing a file

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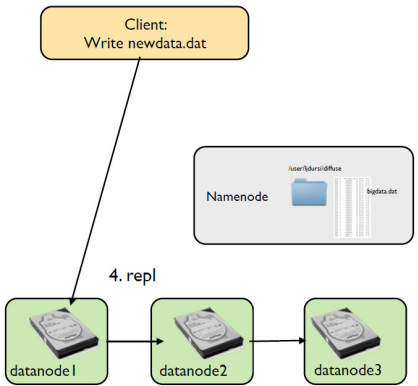

Writing a file

- **Writing a file** multiple stage process:
  - ↪ Create file
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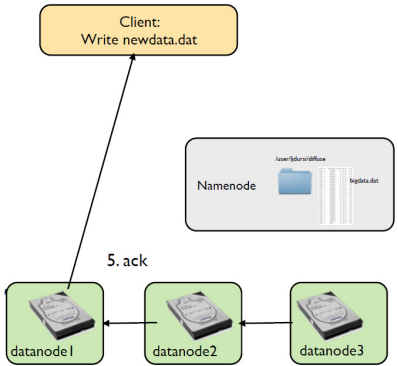
  - ↪ Get ack back **(while writing)**
  - ↪ Complete



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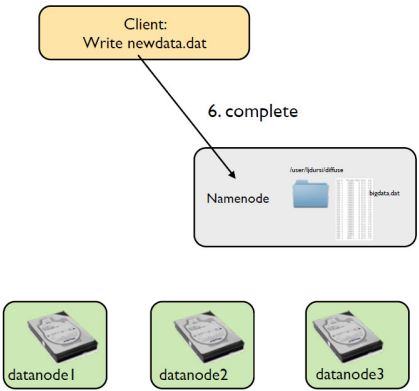
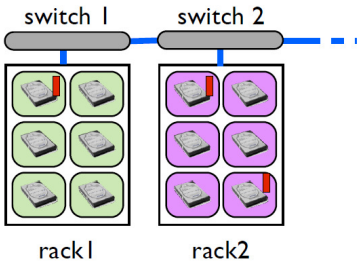


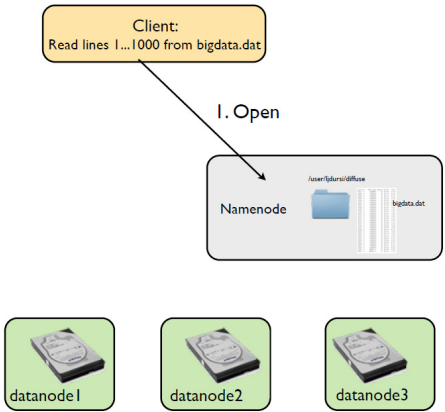
Where to Replicate?



- **Tradeoff** to choosing replication locations
  - ↪ **Close**: faster updates, less network bandwidth
  - ↪ **Further**: better failure tolerance
- **Default strategy**:
  1. copy on different location on same node
  2. second on different *rack*(switch),
  3. third on same rack location, different node.
- Strategy configurable.
  - ↪ Need to configure Hadoop file system to know location of nodes

Reading a file

- **Reading** a file
  - ↪ Open call
  - ↪ Get block locations
  - ↪ Read from a replica



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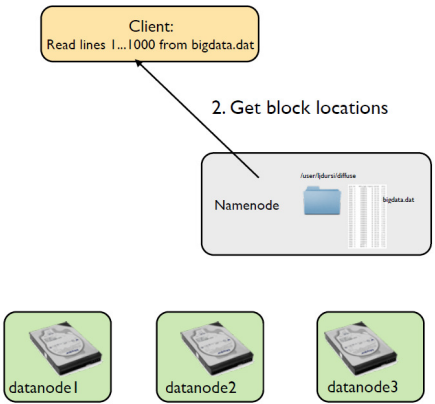

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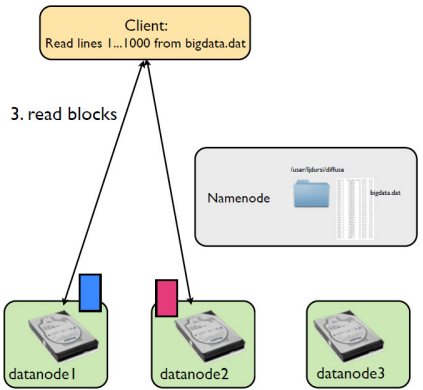

Configuring HDFS

- Need to tell HDFS how to set up filesystem
  - ↪ `data.dir`, `name.dir`
    - ✓ where on local system (eg, local disk) to write data
  - ↪ parameters like replication
    - ✓ how many copies to make
  - ↪ default name - default file system to use
  - ↪ Can specify multiple FSs

Configuring HDFS

```
<configuration>            <!-- $HADOOP_PREFIX/etc/hadoop/core-site.xml -->
  <property>
   <name>fs.defaultFS</name>
   <value>hdfs://<server>:9000</value>
  </property>
  <property>
    <name>dfs.data.dir</name>
    <value>/home/username/hdfs/data</value>
  </property>
  <property>
    <name>dfs.name.dir</name>
    <value>/home/username/hdfs/name</value>
  </property>
  <property>
    <name>dfs.replication</name>
    <value>3</value>
  </property>
</configuration>
```

Configuring HDFS

- In Practice, in `single` mode
  - ↪ Only one node to be used, the VM
  - ↪ **default server**: `localhost`
  - ↪ Since only one node:
    - ✓ need to specify replication factor of 1, or will always fail

```
<property>
  <name>fs.defaultFS</name>
  <value>hdfs://localhost:9000</value>
</property>
[...]
<property>
  <name>dfs.replication</name>
  <value>1</value>
</property>
```

Configuring HDFS - General Scenario

- You will need to make sure that environment variables (path to Java/Hadoop etc.) are set
  - ↪ Easybuild does **most** of the job for you `$EBROOT<SOFTWARENAME>`
  - ↪ Still a lot to define in `{hadoop,mapred,yarn}-env.sh`
- You will need passwordless SSH access accross all nodes
- You can then start processes on various FS nodes
- Other configuration files (outside `core-site.xml`) to check:
  - ↪ `$HADOOP_PREFIX/etc/hadoop/{hdfs-site,mapred-site,yarn-site}.xml`
  - ↪ `slaves` list

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  - ↪ `$HADOOP_PREFIX/etc/hadoop/{hdfs-site,mapred-site,yarn-site}.xml`
  - ↪ `slaves` list

- Once configuration files are set up,
  - ↪ you can format the namenode like so you can start up just the file systems

```
$> hdfs namenode -format
$> start-dfs.sh
```

Using HDFS

- Once the file system is up and running,
  ↪ ... you can copy files back and forth

```
$> hadoop fs -{get|put|copyFromLocal|copyToLocal} [...]
```

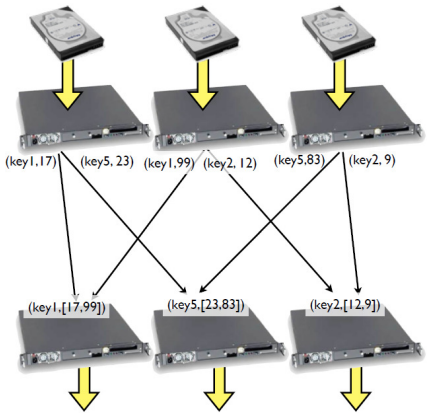
- Default directory is /user/${username}
  ↪ **Nothing like a cd**

```
$> hdfs fs -mkdir /home/vagrant/hdfs-test
$> hdfs fs -ls    /home/vagrant
$> hdfs fs -ls    /home/vagrant/hdfs-test
$> hdfs fs -put data.dat /home/vagrant/hdfs-test
$> hdfs fs -ls    /home/vagrant/hdfs-test
```

Using HDFS

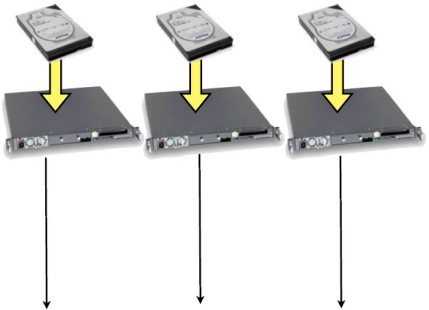
- In general, the data files you send to HDFS will be **large**
  - ↪ or else why bother with Hadoop.
- Do not want to be constantly copying back and forth
  - ↪ **view, append *in place***
- Several APIs to accessing the HDFS
  - ↪ Java, C++, Python
- Here, we use one to get a file status, and read some data from it at some given offset

Back to Map-Reduce



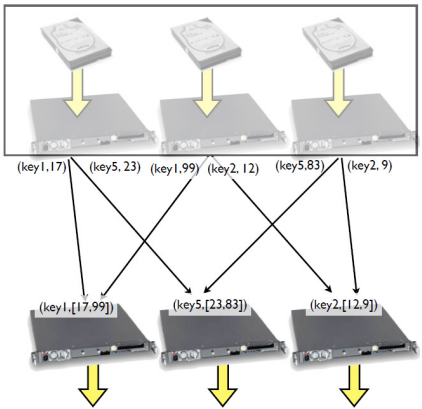
- Map processes **one element at a time**
  - ↪ emits results as (key, value) pairs.
- All results with **same key are gathered to the same reducers**
  - ↪ Reducers process list of values
  - ↪ emit results as (key, value) pairs

Map



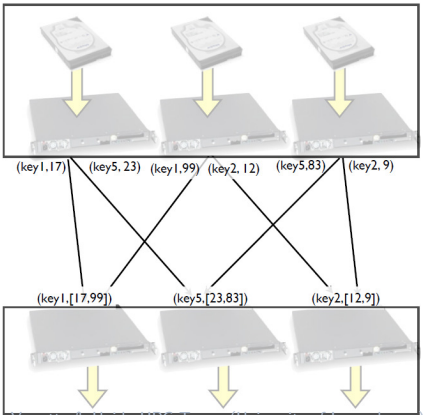
- All coupling done during **shuffle** phase
  - ↪ Embarrassingly parallel task
  - ↪ all map
- Take input, map it to output, done.
- **Famous case**
  - ↪ NYT using Hadoop to convert 11 million image files to PDFs
    - ✓ almost pure serial farm job

Reduce



- Reducing gives the coupling
- In the case of the NYT task:
  - ↪ not quite embarrassingly parallel:
    - ✓ images from multi-page articles
    - ✓ Convert a page at a time,
    - ✓ gather images with same article id onto node for conversion

Shuffle

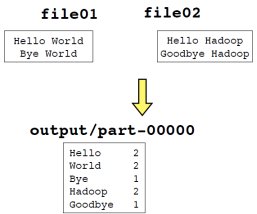


- **Shuffle is part of the Hadoop magic**
  - ↪ By default, keys are hashed
  - ↪ hash space is partitioned between reducers
- On **reducer**:
  - ↪ gathered (k,v) pairs from mappers are sorted by key,
  - ↪ then merged together by key
  - ↪ Reducer then runs on one (k,[v]) tuple at a time
- you can supply your own partitioner
  - ↪ Assign **similar** keys to same node
  - ↪ Reducer still only sees one (k, [v]) tuple at a time.

Example: Wordcount

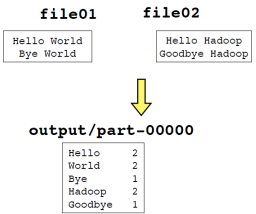
- Was used as an example in the original MapReduce paper
  ↪ Now basically the **hello world** of map reduce

- **Problem description**: Given a **set** of documents:
  ↪ **count occurences of words** within these documents



Example: Wordcount

- **How would you do this with a huge document?**
  - ↪ Each time you see a word:
    - ✓ if it is a new word, add a tick mark beside it,
    - ✓ otherwise add a new word with a tick
- **. . . But hard to parallelize**
  - ↪ pb when updating the list



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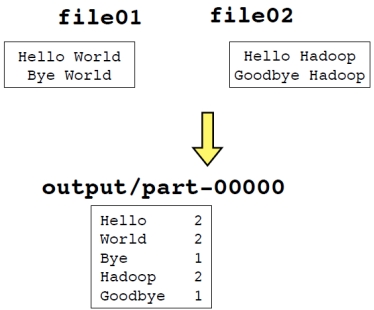

- **MapReduce way**
  - ↪ all hard work done automatically by shuffle
- **Map**:
  - ↪ just emit a 1 for each word you see
- **Shuffle**:
  - ↪ assigns keys (words) to each reducer,
  - ↪ sends (k,v) pairs to appropriate reducer
- **Reducer**
  - ↪ just has to sum up the ones

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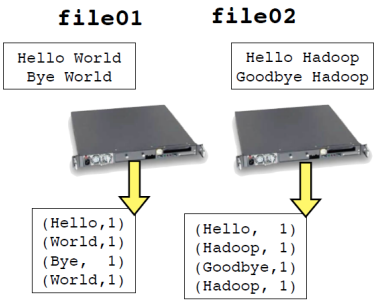

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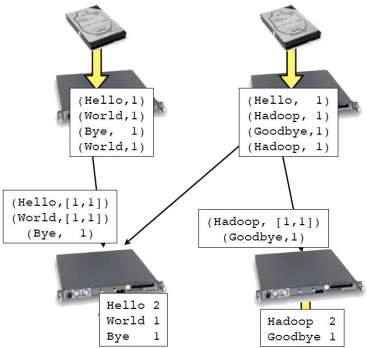

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Getting Started with Hadoop

Hands-on: Getting Started with Hadoop

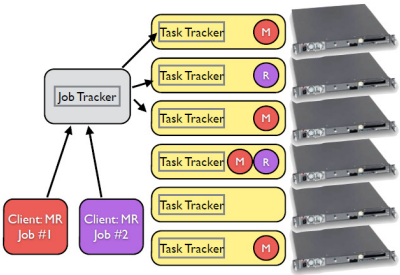
▶ url ◀ | github | src

- Load available Hadoop module (2.10.0)
- Test the `tools/Hadoop` modules in Single mode
  ↪ test on a Map-reduce `grep` application
- *(eventually)* Pseudo-Distributed Operation and Full Cluster Setup

```
module load tools/Hadoop
# [...]
hadoop jar ${EBROOTHADOOP}/share/hadoop/mapreduce/hadoop-mapreduce-examples-2.10.0.jar \
     grep input output 'dfs[a-z.]+'
hdfs dfs -cat output/*
```

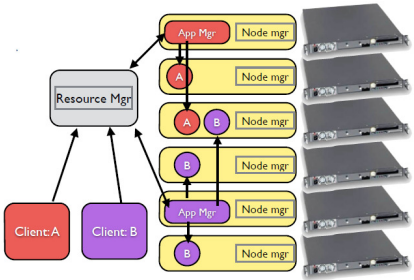
Hadoop 1x

- Original Hadoop was basically HDFS + infrastructure for MapReduce
  - ↪ Very faithful implementation of Google MapReduce paper.
  - ↪ Job tracking, orchestration all very tied to M/R model
- Made it difficult to run other sorts of jobs



YARN and Hadoop 2

- **YARN**: Yet Another Resource Negotiator
  - ↪ Looks a lot more like a cluster scheduler/resource manager
  - ↪ Allows arbitrary jobs.
- Allow for new compute/data tools. **Ex**: streaming with Spark



Apache Spark

- Spark is (yet) a(-nother) distributed, **Big Data** processing platform.
  - ↪ Everything you can do in Hadoop, you can also do in Spark.

In contrast to Hadoop

- Spark computation paradigm is not **just** MapReduce job
- Key feature - **in-memory analyses**.
  - ↪ **multi-stage, in-memory dataflow graph based on Resilient Distributed Datasets (RDDs)**.

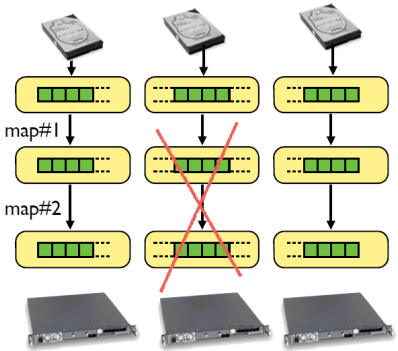
Apache Spark

- Spark is implemented in Scala, running in a Java Virtual Machine.
  - ↪ Spark supports different languages for application development:
    - ✓ Java, Scala, Python, R, and SQL.
- Originally developed in AMPLab (UC Berkeley) from 2009,
  - ↪ donated to the Apache Software Foundation in 2013,
  - ↪ top-level project as of 2014.
- **Latest release**: 3.2.0 (Oct. 2021)

RDD

- Resilient Distributed Dataset (RDD)
  - ↪ Partitioned collections (lists, maps..) across nodes
  - ↪ Set of well-defined operations (incl map, reduce) defined on these RDDs.

RDD



- Fault tolerance works three ways:
  - ↪ Storing, reconstructing lineage
  - ↪ Replication (optional)
  - ↪ Persistance to disk (optional)

RDD Lineage

- Map Reduce implemented FT by outputting everything to disk always.
  - ↪ Effective but extremely costly.
  - ↪ **How to maintain fault tolerance without sacrificing in-memory performance?**
    - ✓ for truly large-scale analyses

RDD Lineage

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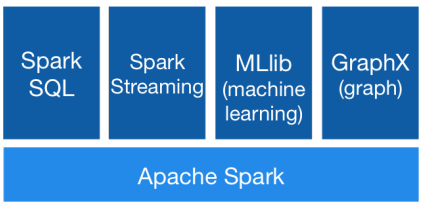
    - ✓ for truly large-scale analyses

- **Solution**:
  - ↪ Record lineage of an RDD (think version control)
  - ↪ If container, node goes down, reconstruct RDD from scratch
    - ✓ Either from beginning,
    - ✓ or from (occasional) checkpoints which user has some control over.
  - ↪ User can suggest caching current state of RDD in memory,
    - ✓ or persisting it to disk, or both.
  - ↪ You can also save RDD to disk, or replicate partitions across nodes for other forms of fault tolerance.

Main Building Blocks

- The **Spark Core API** provides the general execution layer
  ↪ on top of it, all other functionality is built upon.
- Four higher-level components (in the _Spark ecosystem):
  1. **Spark SQL** (formerly **Shark**),
  2. **Streaming**, to build scalable fault-tolerant streaming applications.
  3. **MLlib** for machine learning
  4. GraphX, the API for graphs and graph-parallel computation



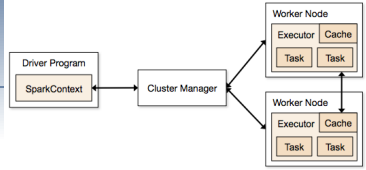
Getting Started with Spark

Hands-on: Interactive Big Data analytics with Spark

▶ url ◀ | github | src

- *(eventually)* reconnect with SOCK5 proxy enabled — `ssh -D 1080 iris-cluster`
- Get an interactive job
  - ↪ source the settings — `source settings/default.sh`
  - ↪ load Spark — `module load devel/Spark`
- Check a single **interactive run** — `pyspark,spark-shell`
  - ↪ **PySpark**, the Spark Python API; **Scala** Spark Shell
- Generate csv files
  - ↪ play with the build-in `filter()`, `map()`, and `reduce()` functions

Getting Started with Spark



Hands-on: Multi-node Spark Standalone Cluster

▶ url ◀ | github | src

- Deploy **Spark standalone cluster** `launcher.Spark.sh -i; spark-submit [...]`
  - ↪ use ULHPC launcher to deploy an (interactive) Spark cluster
    - ✓ spawn **master** and **worker** Spark processes interactively (`-i`)
  - ↪ access the **web UI** of the master
    - ✓ **Ex**: SOCKS 5 proxy approach + FoxyProxy plugin
  - ↪ submit a **sample job** (Pi estimation)
    - ✓ `spark-submit [...] $EBROOTSPARK/examples/src/main/python/pi.py 1000`
- Scale across multiple nodes

Multi-node Spark Cluster Deployment

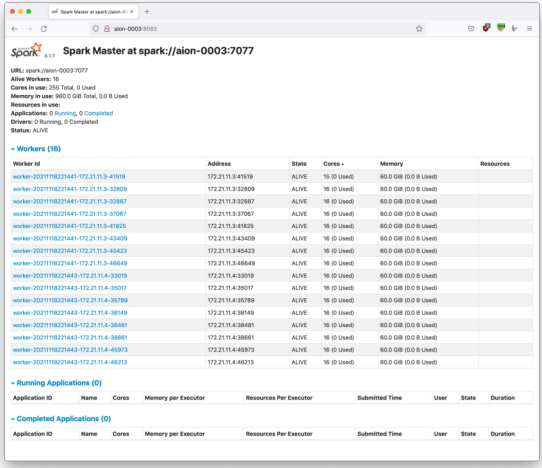
```
(laptop)$> ssh -D 1080 -C {aion|iris}-cluster
# play with -N to scale as you wish (or not)
$ salloc -N 2 --ntasks-per-node 8 -c 16 --exclusive # --reservation=hpcschool
$ source settings/default.sh
$ module load devel/Spark
```

Multi-node Spark Cluster Deployment

```
# Deploy an interactive Spark cluster **ACROSS** all reserved nodes
$>./scripts/launcher.Spark.sh -i
============== Spark Master ==============
url: spark://aion-0003:7077
Web UI: http://aion-0003:8082
============ 16 Spark Workers ==============
export SPARK_HOME=$EBROOTSPARK
export MASTER_URL=spark://aion-0003:7077
export SPARK_DAEMON_MEMORY=4096m
export SPARK_WORKER_CORES=16
export SPARK_WORKER_MEMORY=61440m
export SPARK_EXECUTOR_MEMORY=61440m
# [...] *** Interactive mode ***
```

- Connect **transparently** to the master Web UI via the SOCK5 proxys
  - ↪ thus **using your browser on your laptop at home**

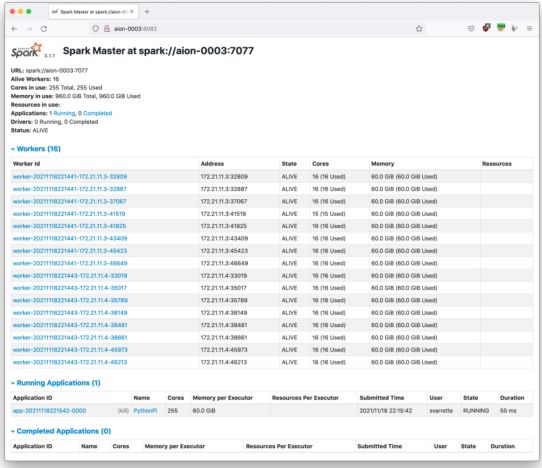
Multi-node Spark Cluster Deployment



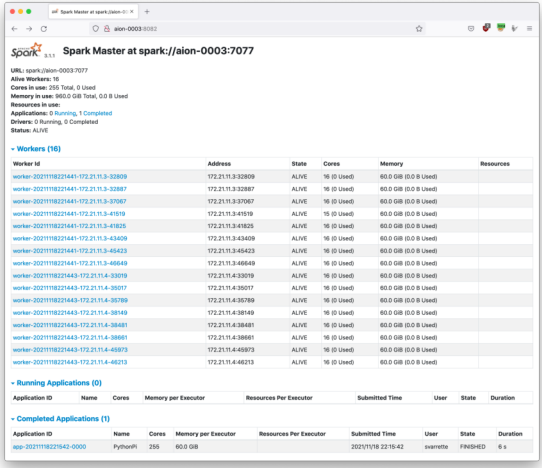
Multi-node Spark Cluster Deployment

```
# Submit your Spark job
spark-submit \
        --master spark://$(scontrol show hostname $SLURM_NODELIST | head -n 1):7077 \
        --conf spark.driver.memory=${SPARK_DAEMON_MEMORY} \
        --conf spark.executor.memory=${SPARK_EXECUTOR_MEMORY} \
        --conf spark.python.worker.memory=${SPARK_WORKER_MEMORY} \
        $SPARK_HOME/examples/src/main/python/pi.py 1000
```

Multi-node Spark Cluster Deployment



Multi-node Spark Cluster Deployment



Thank you for your attention...

Questions?

ulhpc-tutorials.rtfd.io/en/latest/bigdata/

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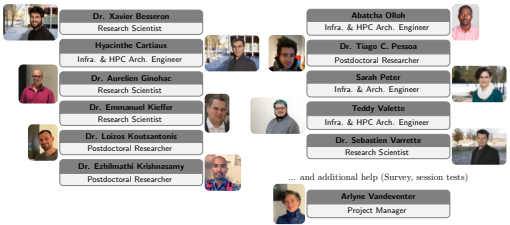
1. **Practical Session Objectives**
2. **Interlude: Installing [missing] software with Easybuild**
3. **Python and Data Science**
4. **Big Data Analytics with Hadoop & Spark**
   - Apache Hadoop
   - Apache Spark

Uni.lu HPC School 2021 Contributors



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