

Uni.lu HPC School 2018

PS11: Big Data Applications (batch, stream, hybrid)

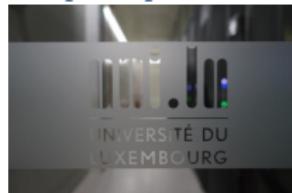


Uni.lu High Performance Computing (HPC) Team

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<http://hpc.uni.lu>



Latest versions available on Github:



UL HPC tutorials:

<https://github.com/ULHPC/tutorials>

UL HPC School:

<http://hpc.uni.lu/hpc-school/>

PS11 tutorial sources:

<ulhpc-tutorials.rtfid.io/en/latest/bigdata/>



Summary

1 Practical Session Objectives

2 [Big] Data Management in HPC Environment: Overview and Challenges

Performance Overview in Data transfer

Data transfer in practice

Sharing Data

3 Big Data Analytics with Hadoop & Spark

Apache Hadoop

Apache Spark

Main Objectives of this Session

- Brief review of [Big] Data Management
 - ↪ Data transfer in practice
 - ↪ Sharing Data through VCS/Git
- Introduction to Big Data analytics
 - ↪ Distributed File Systems (DFS)
 - ↪ Mapreduce
 - ↪ Hadoop and HDFS
 - ✓ local (Standalone) Mode
 - ✓ [pseudo-]distributed mode
- In-memory [streaming] analysis with Spark
 - ↪ Interactive runs
 - ✓ PySpark, the Spark Python API
 - ✓ Scala Spark Shell
 - ✓ R Spark Shell
 - ↪ Standalone cluster runs

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
 - ✓ © CC AttributionNonCommercial-ShareAlike 4.0
- similar hands-on material on Github for instance:
 - ↪ Jonathan Dursi: [hadoop-for-hpcers-tutorial](#)



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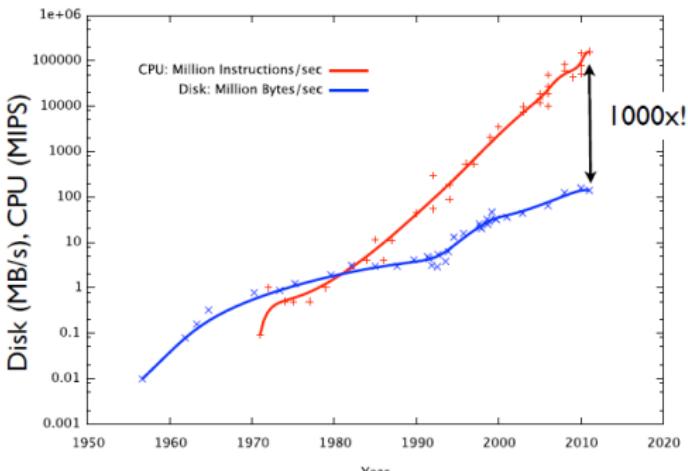
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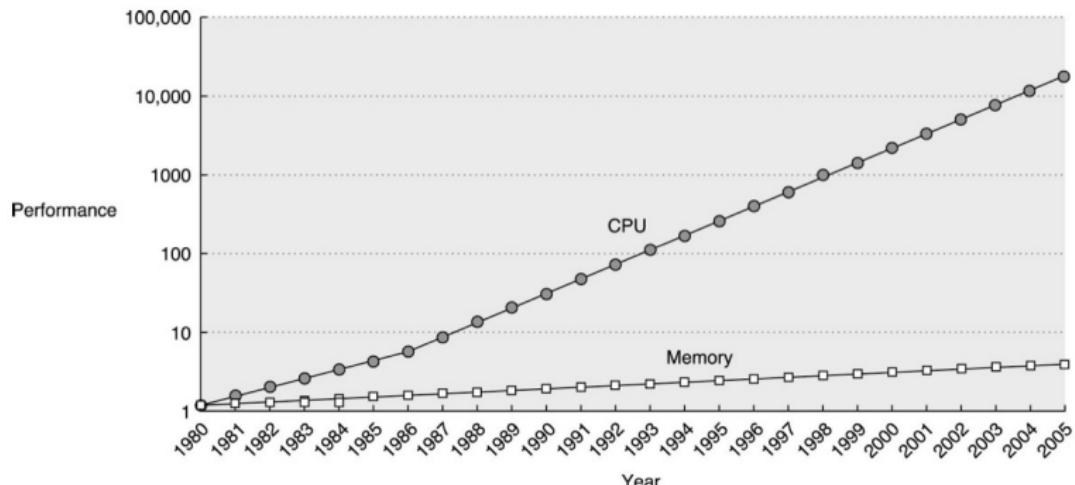
Data Intensive Computing

- Data volumes increasing massively
 - ↪ Clusters, storage capacity increasing massively
- Disk speeds are not keeping pace.
- Seek speeds even worse than read/write



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Speed Expectation on Data Transfer

<http://fasterdata.es.net/>

- How long to transfer **1 TB** of data across various speed networks?

Network	Time
10 Mbps	300 hrs (12.5 days)
100 Mbps	30 hrs
1 Gbps	3 hrs
10 Gbps	20 minutes

- (Again) small I/Os really **kill** performances
 - Ex: transferring 80 TB for the backup of `ecosystem_biology`
 - same rack, 10Gb/s. 4 weeks → 63TB transfer...

Speed Expectation on Data Transfer

<http://fasterdata.es.net/>

Data set size

	166.67 TB/sec	33.33 TB/sec	8.33 TB/sec	2.78 TB/sec
10PB	16.67 TB/sec	3.33 TB/sec	833.33 GB/sec	277.78 GB/sec
1PB	1.67 TB/sec	333.33 GB/sec	83.33 GB/sec	27.78 GB/sec
100TB	166.67 GB/sec	33.33 GB/sec	8.33 GB/sec	2.78 GB/sec
10TB	16.67 GB/sec	3.33 GB/sec	833.33 MB/sec	277.78 MB/sec
1TB	1.67 GB/sec	333.33 MB/sec	83.33 MB/sec	27.78 MB/sec
100GB	166.67 MB/sec	33.33 MB/sec	8.33 MB/sec	2.78 MB/sec
10GB	16.67 MB/sec	3.33 MB/sec	0.83 MB/sec	0.28 MB/sec
1GB	1.67 MB/sec	0.33 MB/sec	0.08 MB/sec	0.03 MB/sec
100MB	1.67 MB/sec	0.33 MB/sec	0.08 MB/sec	0.03 MB/sec
	1 Minute	5 Minutes	20 Minutes	1 Hour
Time to transfer				

Speed Expectation on Data Transfer

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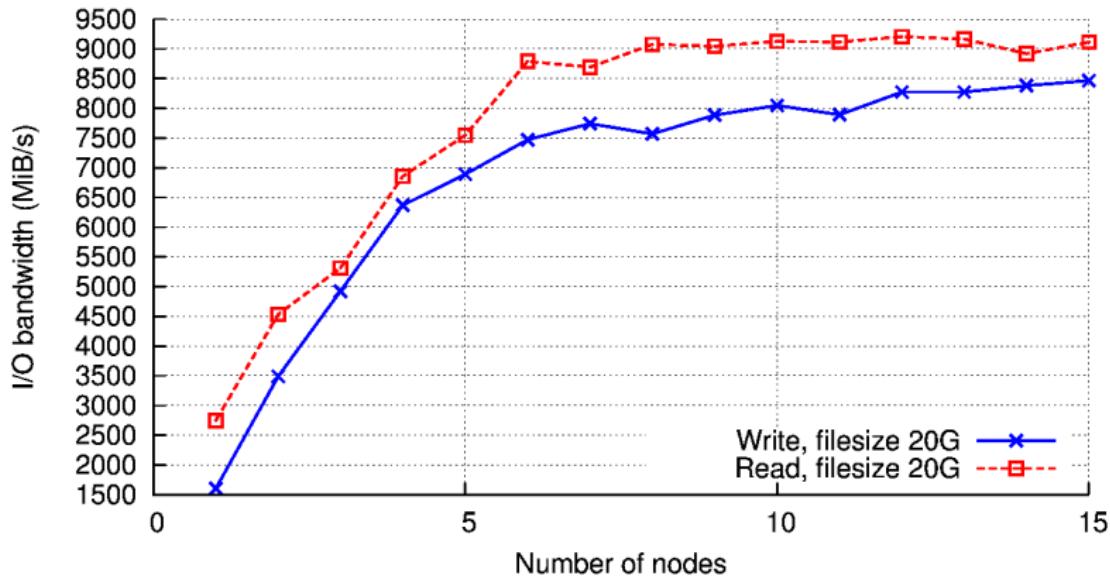
Data set size

1XB	34.72 TB/sec	11.57 TB/sec	1.65 TB/sec	385.80 GB/sec
100PB	3.47 TB/sec	1.16 TB/sec	165.34 GB/sec	38.58 GB/sec
10PB	347.22 GB/sec	115.74 GB/sec	16.53 GB/sec	3.86 GB/sec
1PB	34.72 GB/sec	11.57 GB/sec	1.65 GB/sec	385.80 MB/sec
100TB	3.47 GB/sec	1.16 GB/sec	165.34 MB/sec	38.58 MB/sec
10TB	347.22 MB/sec	115.74 MB/sec	16.53 MB/sec	3.86 MB/sec
1TB	34.72 MB/sec	11.57 MB/sec	1.65 MB/sec	0.39 MB/sec
100GB	3.47 MB/sec	1.16 MB/sec	0.17 MB/sec	0.04 MB/sec
10GB	0.35 MB/sec	0.12 MB/sec	0.02 MB/sec	0.00 MB/sec

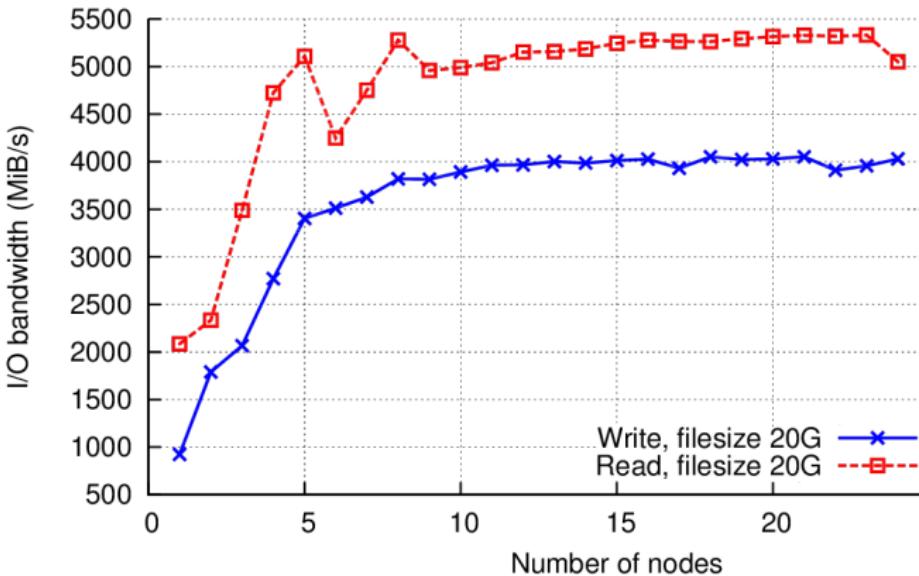
8 Hours 24 Hours 7 Days 30 Days

Time to transfer

Storage Performances: GPFS



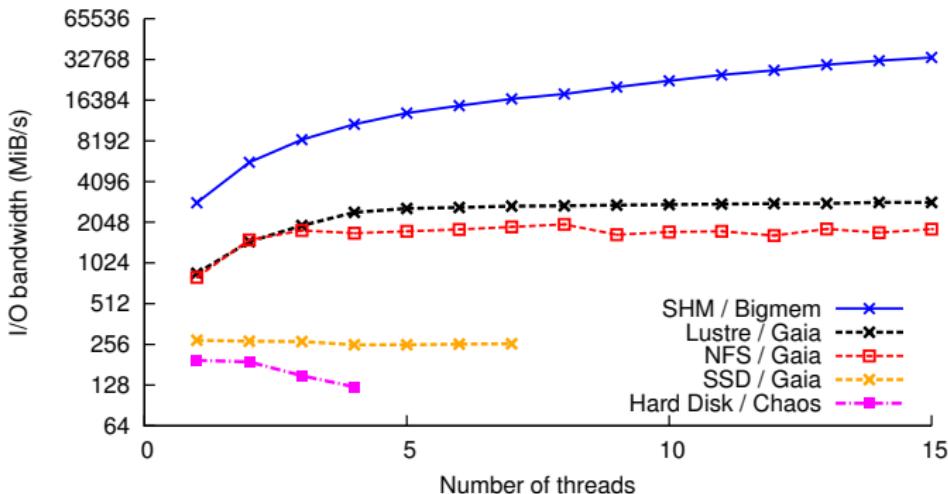
Storage Performances: Lustre



Storage Performances

- Based on IOR or IOZone, reference I/O benchmarks
 - tests performed in 2013

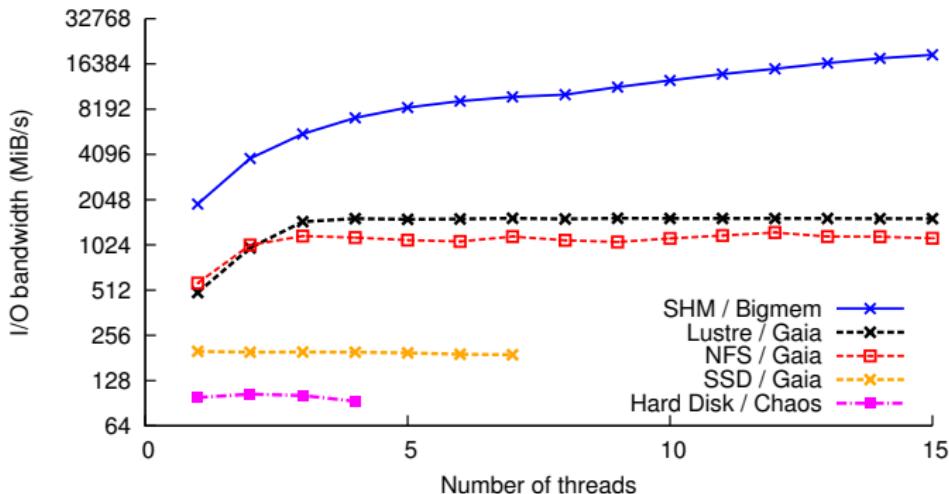
Read



Storage Performances

- Based on IOR or IOZone, reference I/O benchmarks
 - tests performed in 2013

Write



Understanding Your Storage Options

Where can I store and manipulate my data?

- **Shared storage**

- ↪ NFS - **not scalable** $\sim \simeq 1.5$ GB/s (R) $\mathcal{O}(100 \text{ TB})$
- ↪ GPFS - **scalable** $\sim \simeq 10$ GB/s (R) $\mathcal{O}(1 \text{ PB})$
- ↪ Lustre - **scalable** $\sim \simeq 5$ GB/s (R) $\mathcal{O}(0.5 \text{ PB})$

- **Local storage**

- ↪ local file system (`/tmp`) $\mathcal{O}(200 \text{ GB})$
- ✓ over HDD $\simeq 100$ MB/s, over SDD $\simeq 400$ MB/s
- ↪ RAM (`/dev/shm`) $\simeq 30$ GB/s (R) $\mathcal{O}(20 \text{ GB})$

- **Distributed storage**

- ↪ HDFS, Ceph, GlusterFS - **scalable** $\sim \simeq 1$ GB/s

⇒ In all cases: small I/Os really kill storage performances



Data Transfer in Practice

```
$> wget [-O <output>] <url>           # download file from <url>
```

```
$> curl [-o <output>] <url>           # download file from <url>
```

- Transfer **from** FTP/HTTP[S] wget or (better) curl
 - can also serve to send HTTP POST requests
 - support HTTP cookies (useful for JDK download)



Data Transfer in Practice

```
$> scp [-P <port>] <src> <user>@<host>:<path>
```

```
$> rsync -avzu [-e 'ssh -p <port>'] <src> <user>@<host>:<path>
```

- [Secure] Transfer **from/to** two remote machines over SSH
 - ↪ `scp` or (better) `rsync` (transfer **only** what is required)
- Assumes you have understood and configured appropriately SSH!

Sharing Code and Data

- Before doing **Big** Data, manage and version correctly **normal** data

What kinds of systems are available?

- Good: NAS, Cloud Dropbox, Google Drive, Figshare...
- Better - Version Control systems (VCS)
 → SVN, Git and Mercurial
- Best - Version Control Systems on the Public/Private Cloud
 → GitHub, Bitbucket, Gitlab

Sharing Code and Data

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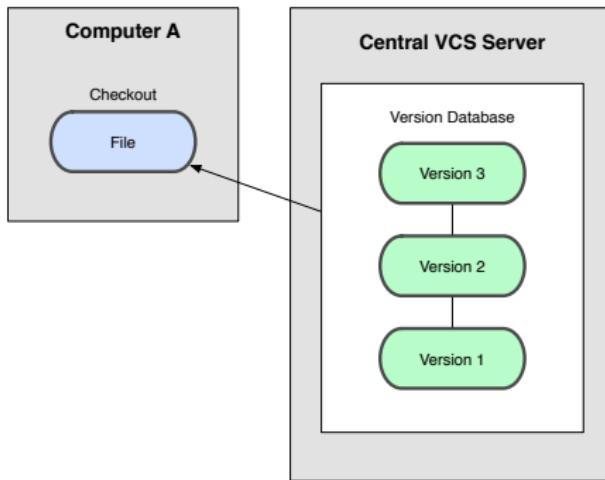
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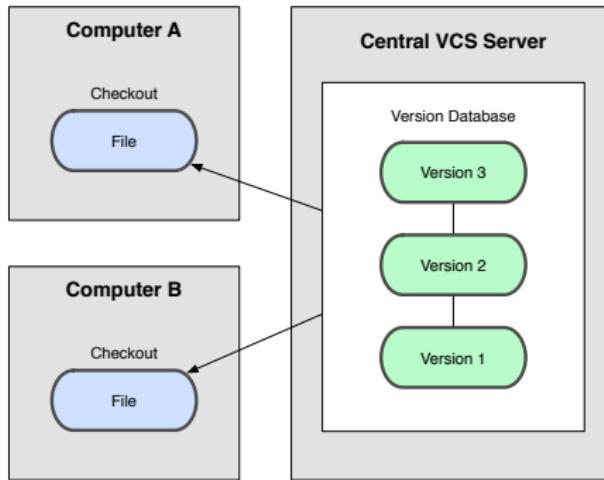
Which one?

- Depends on the level of privacy you expect
 - ✓ ... but you probably already know these tools ☺
- Few handle GB files...

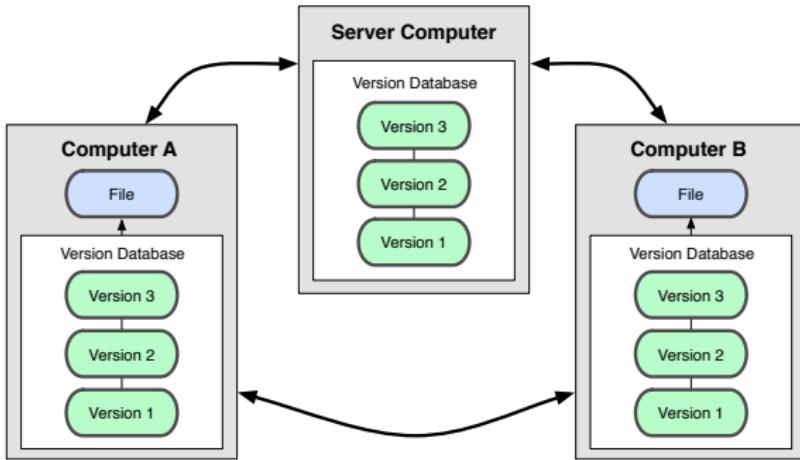
Centralized VCS - CVS, SVN



Centralized VCS - CVS, SVN

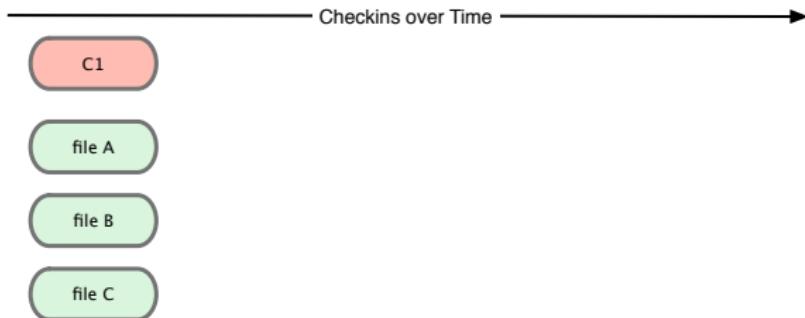


Distributed VCS - Git

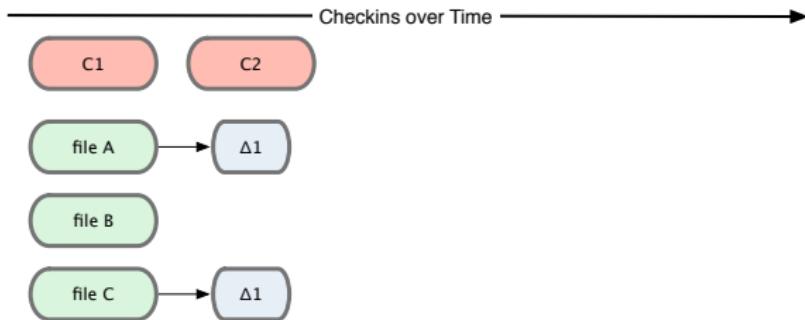


Everybody has the full history of commits

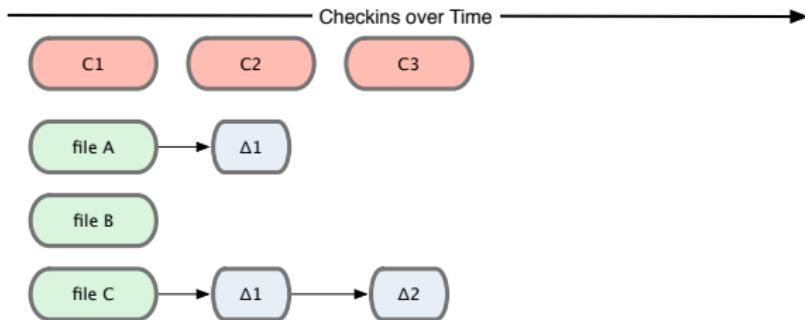
Tracking changes (most VCS)



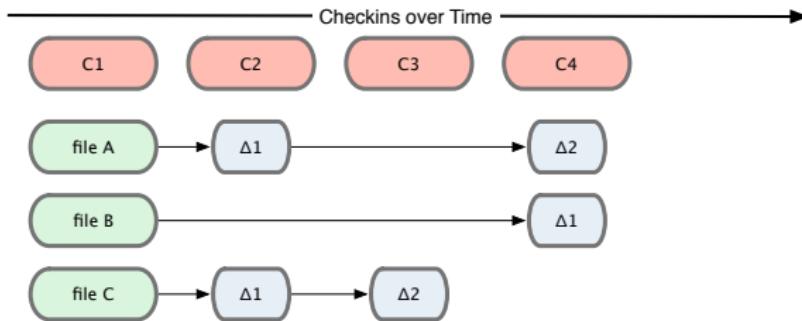
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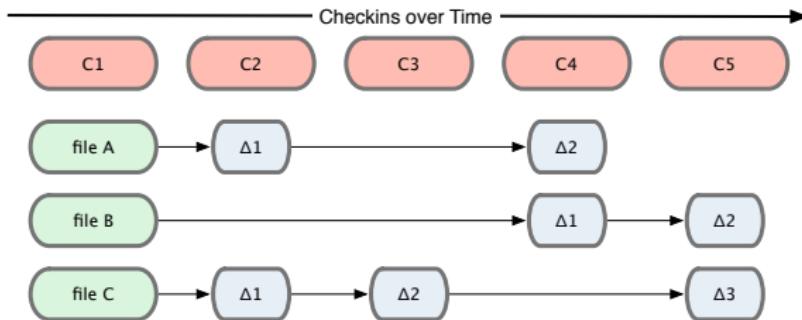
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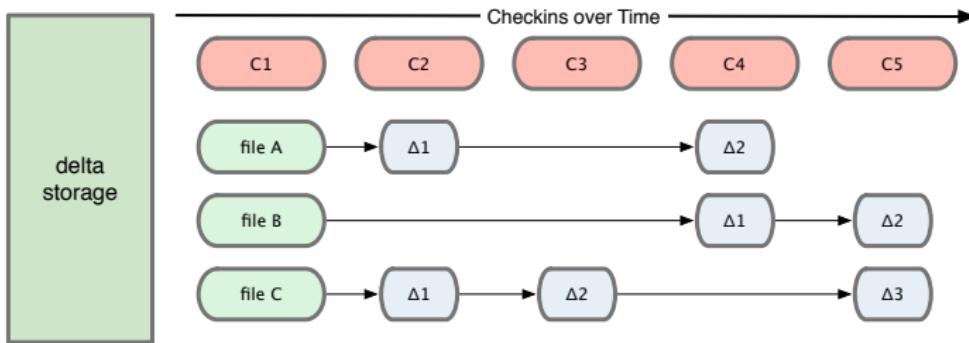
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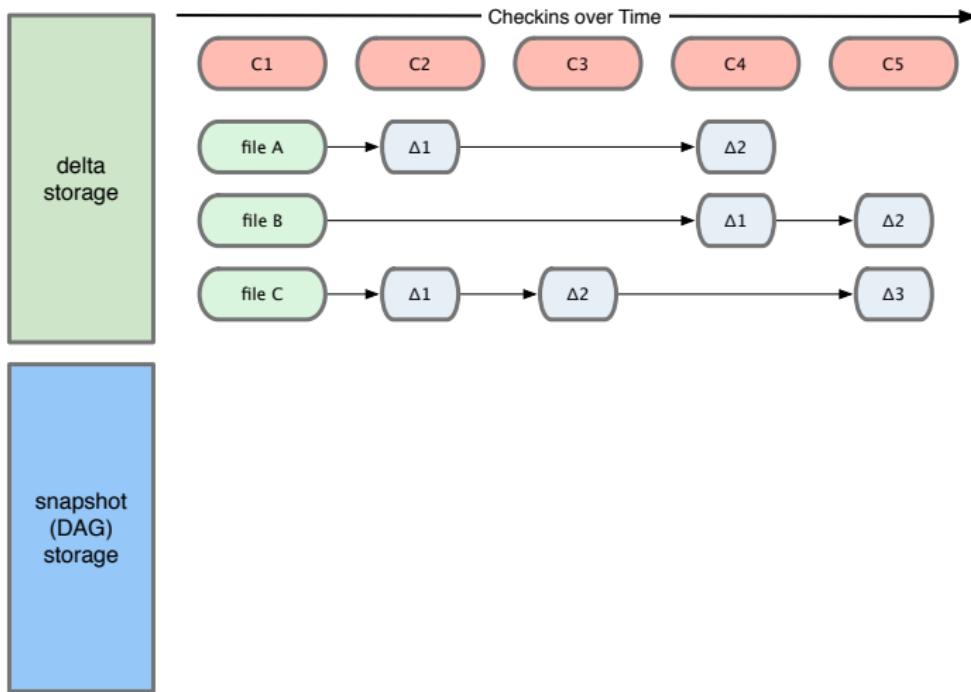
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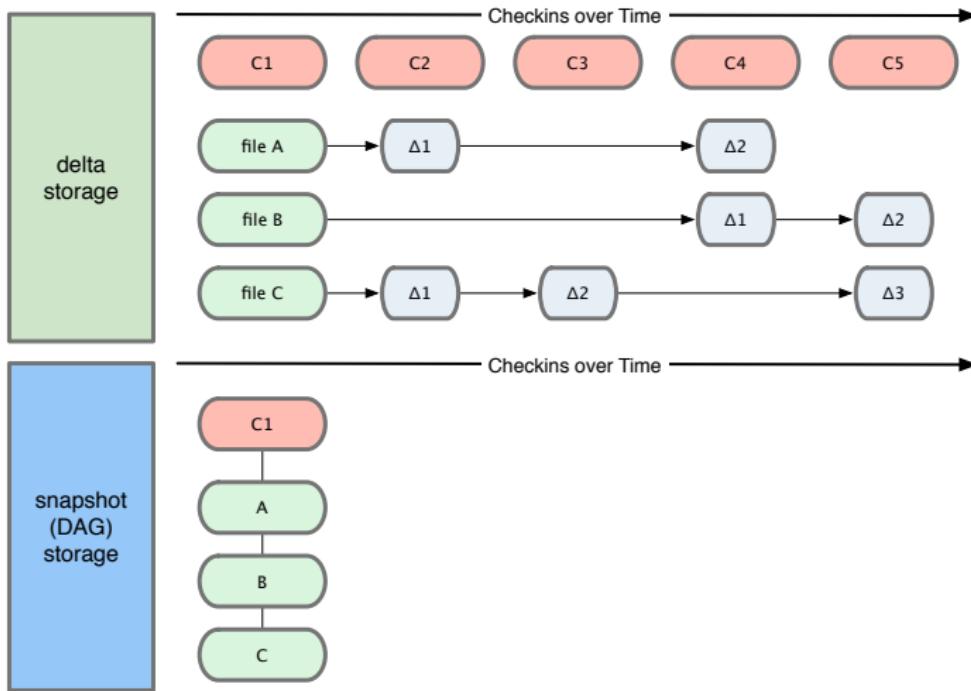
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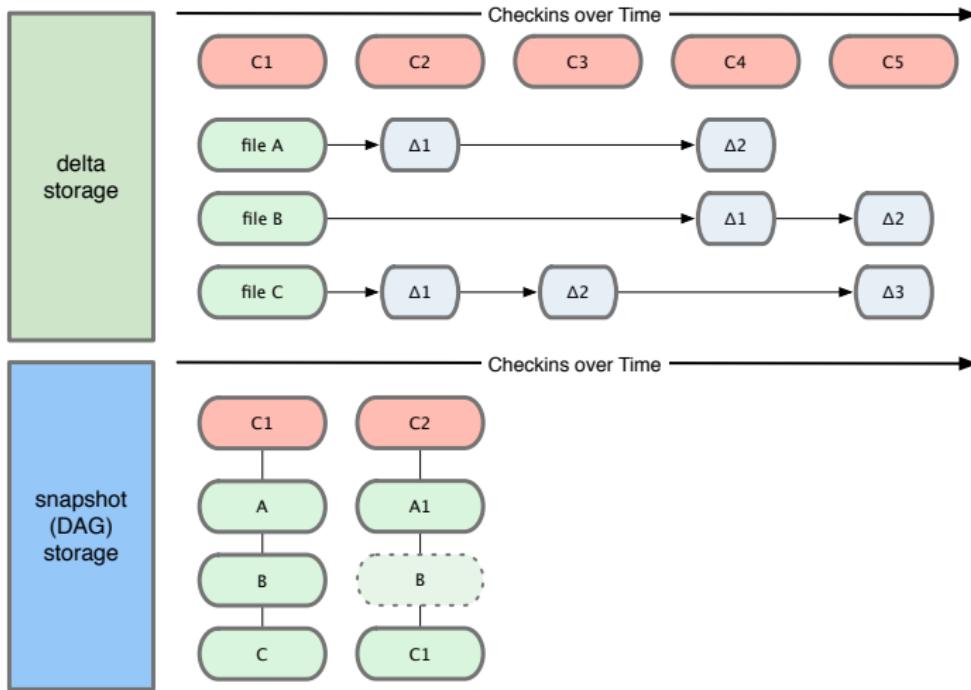
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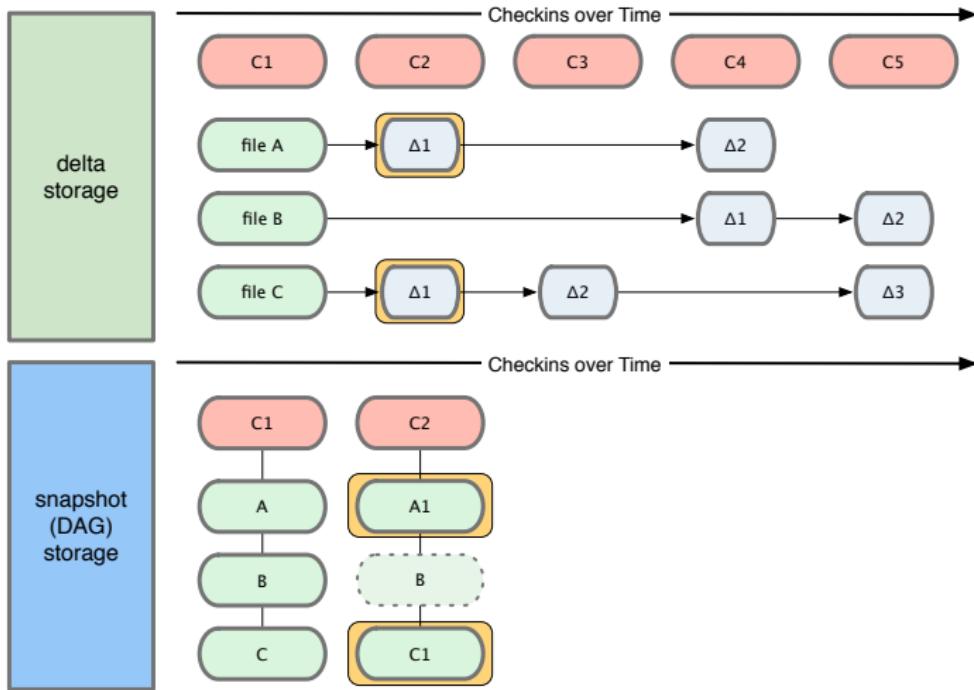
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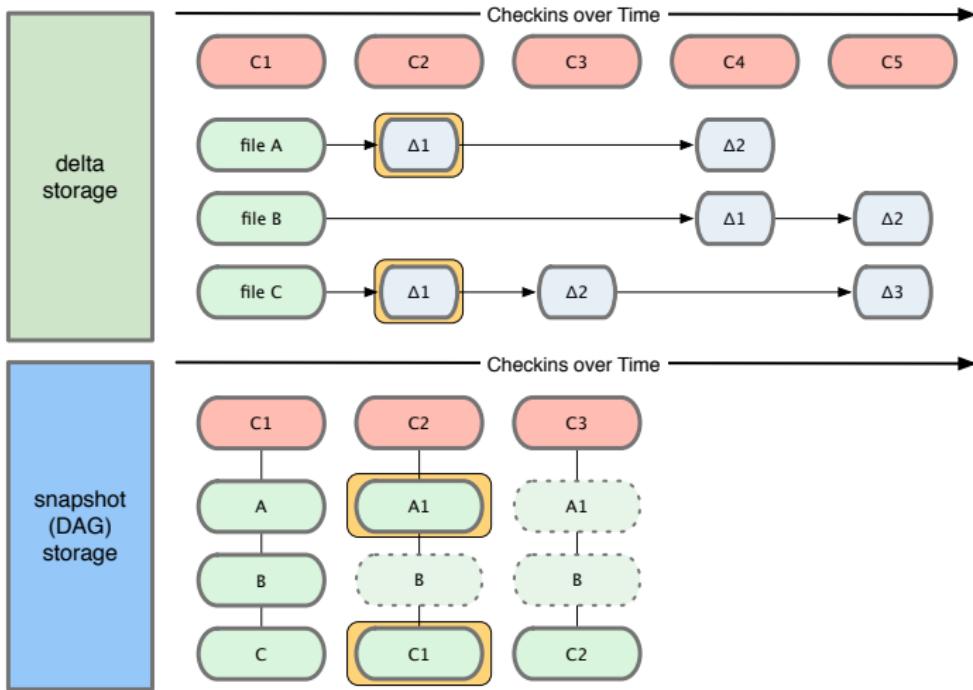
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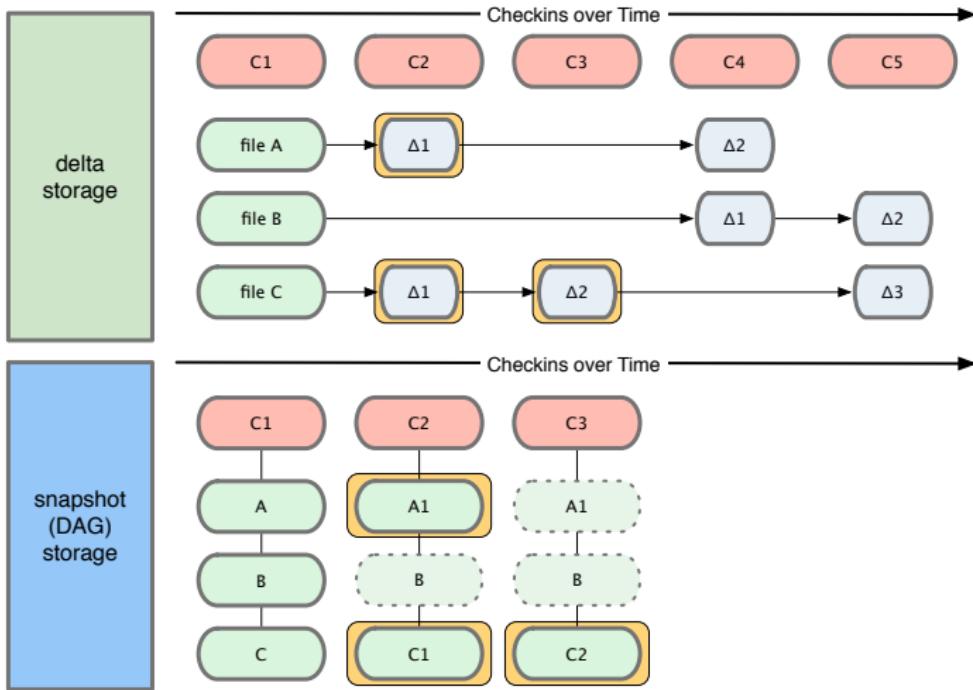
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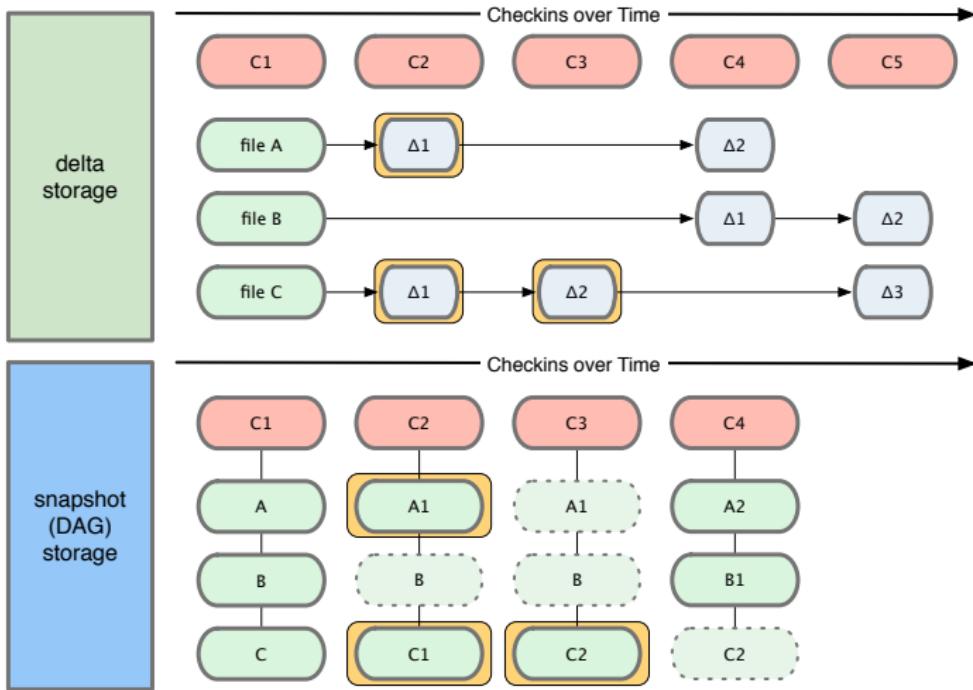
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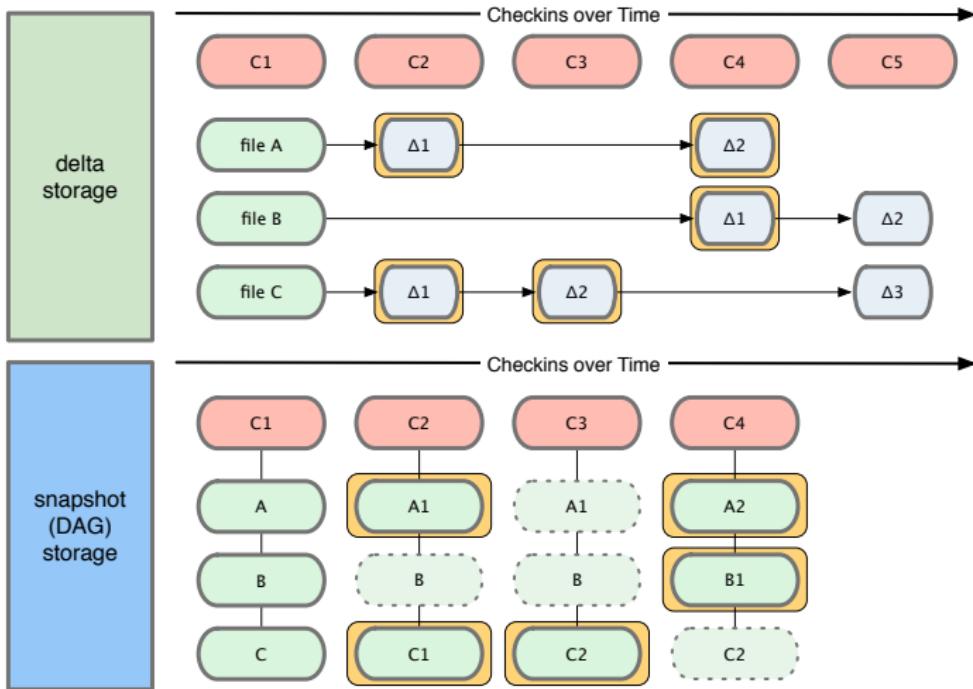
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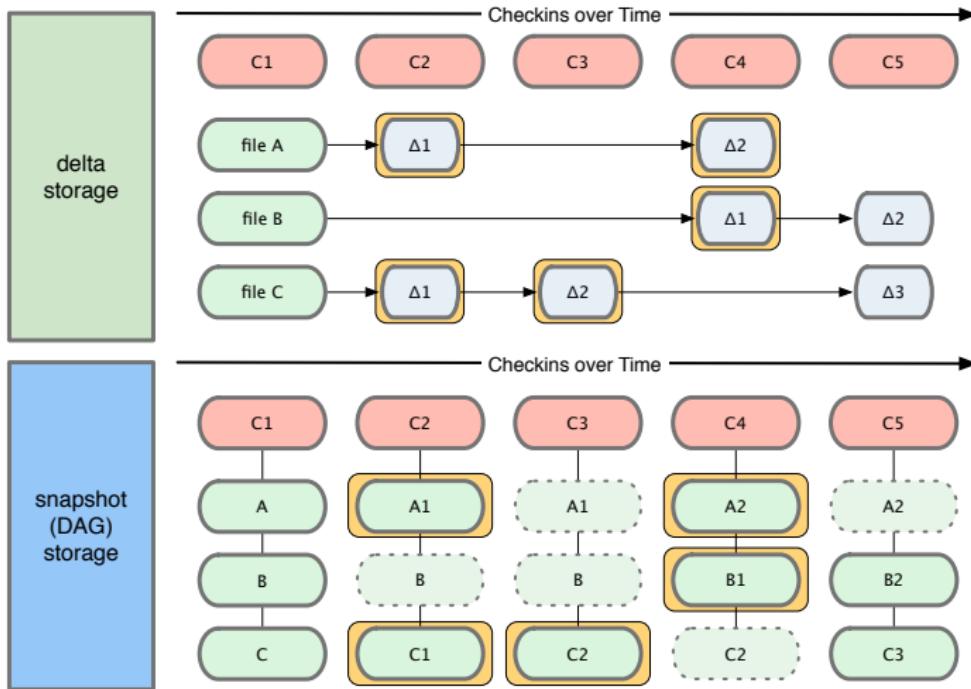
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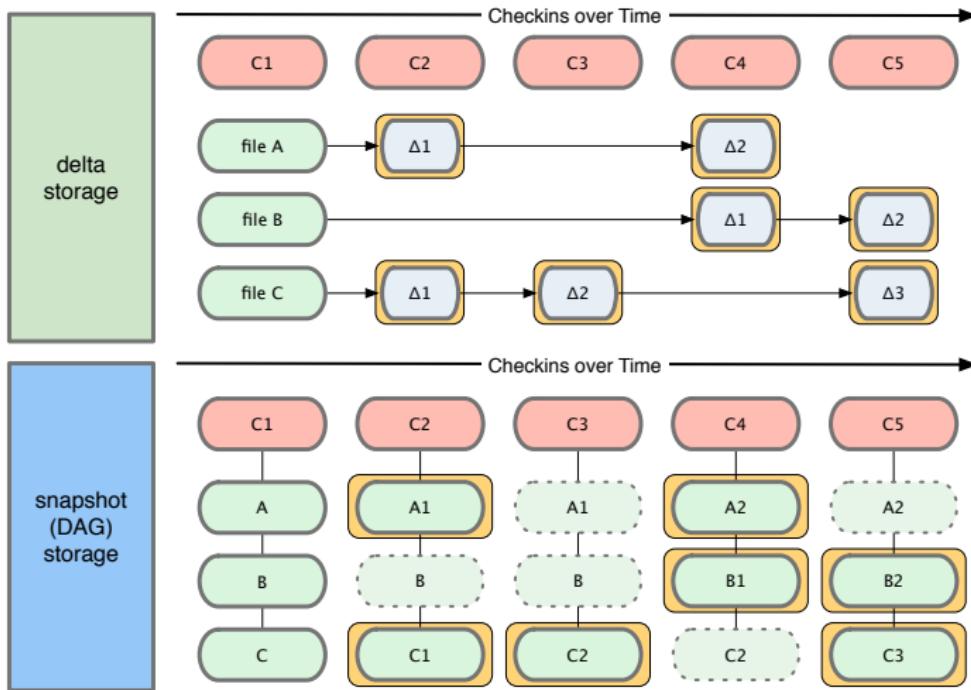
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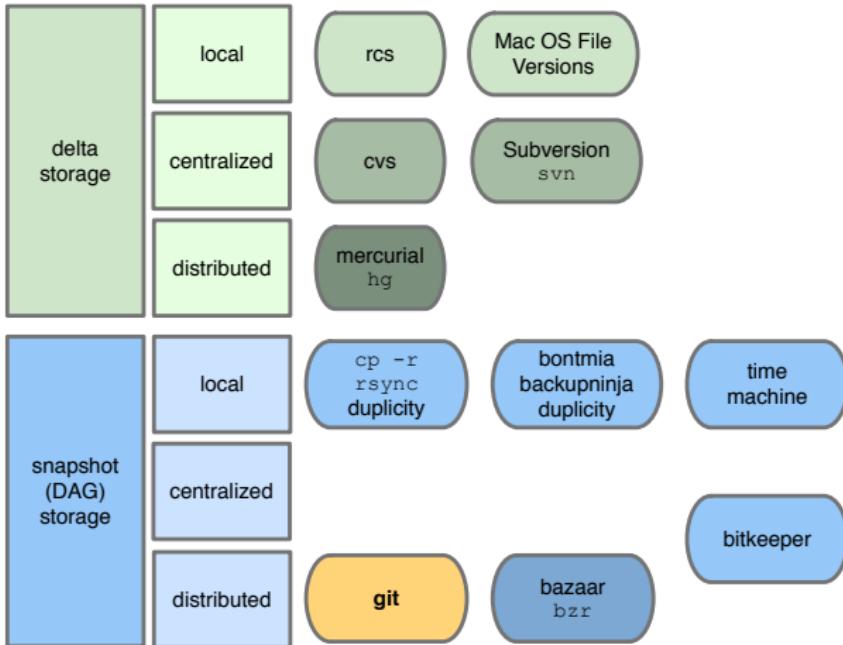
Tracking changes (Git)



Tracking changes (Git)



VCS Taxonomy



Git at the heart of BD

<http://git-scm.org>



So what makes Git so useful?

(almost) Everything is local

- everything is fast
- every clone is a backup
- you work **mainly offline**

Ultra Fast, Efficient & Robust

- Snapshots, not patches (deltas)
- **Cheap branching and merging**
 - ↳ Strong support for thousands of parallel branches
- Cryptographic integrity everywhere

Other Git features

- **Git does not delete**

- **Immutable** objects, Git generally only adds data
- If you mess up, you can usually recover your stuff
 - ✓ Recovery can be tricky though

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Git Tools / Extension

- cf. **Git submodules** or **subtrees**

- **Introducing git-flow**

- workflow with a strict branching model
- offers the git commands to follow the workflow

```
$> git flow init  
$> git flow feature { start, publish, finish } <name>  
$> git flow release { start, publish, finish } <version>
```

Git in practice

Basic Workflow

- **Pull** latest changes
- **Edit** files
- **Stage** the changes
- **Review** your changes
- **Commit** the changes

`git pull`
`vim / emacs / subl ...`
`git add`
`git status`
`git commit`

Git in practice

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For cheaters: A Basicer Workflow

- **Pull** latest changes
- **Edit** files
- Stage & commit all the changes

`git pull`
`vim / emacs / subl ...`
`git commit -a`

Git Summary

- **Advices: Commit early, commit often!**

- ↪ commits = save points
 - ✓ use descriptive commit messages
- ↪ Do not get out of sync with your collaborators
- ↪ Commit the sources, not the derived files

- **Not covered here (by lack of time)**

- ↪ does not mean you should not dig into it!
- ↪ *Resources:*
 - ✓ <https://git-scm.com/>
 - ✓ tutorial: IT/Dev[op]s Army Knives Tools for the Researcher
 - ✓ tutorial: Reproducible Research at the Cloud Era

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 - Performance Overview in Data transfer
 - Data transfer in practice
 - Sharing Data
- 3** Big Data Analytics with Hadoop & Spark
 - Apache Hadoop
 - Apache Spark

Before we start...

- We will rely on **EasyBuild** to build Hadoop and Spark
 - ↪ assumes you have followed PS5: **Easybuild**
 - ✓ “Building [custom] software with EasyBuild”
- Building Hadoop is quite **long**
 - ↪ We're going to install the most recent **Hadoop by Cloudera**
 - ↪ **Thus** we will launch the build in parallel of this talk.
 - ↪ a few **preliminary** software are required

Hands-on 1: Preliminary installations

Your Turn!

Hands-on 1

ulhpc-tutorials.rtfd.io/en/latest/bigdata/#1-preliminary-installations

- Reserve an **interactive** job for the build
 - if possible within a screen session
- Install **Java** 7u80 and 8u152 Step 1.a
- Install **Maven** 3.5.2 Step 1.b
- Install **Cmake** 3.9.1, **snappy** 1.1.6 and **protobuf** 2.5.0 Step 1.c

Hands-on 2: Install Hadoop

Your Turn!

Hands-on 2

uhpc-tutorials.rtfd.io/en/latest/bigdata/#2-hadoop-installation

- We're going to install the most recent Hadoop by Cloudera
 - Grab the recipY/easyconfig
`Hadoop-2.6.0-cdh5.12.0-native.eb`
 - Patch it
 - run the installation
- (**reminder**) installation is quite long
 - you **want** to have that done in a **screen** session...
 - ✓ **from the start** (i.e. on the access node)

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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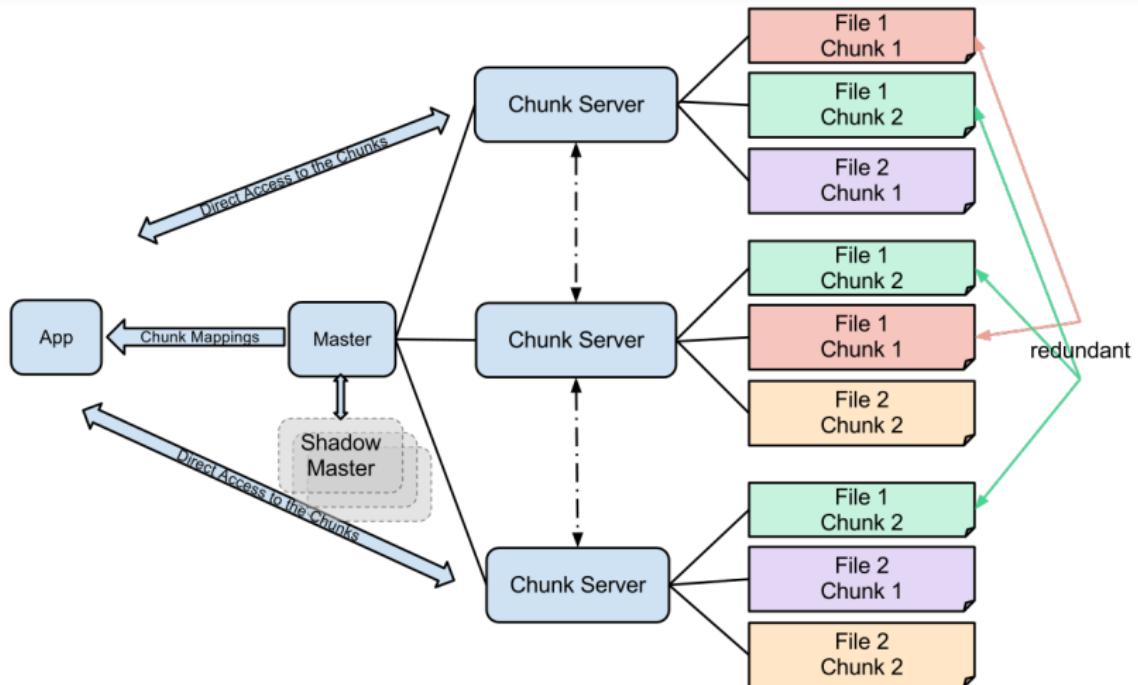
Peer-to-Peer Pattern

- 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

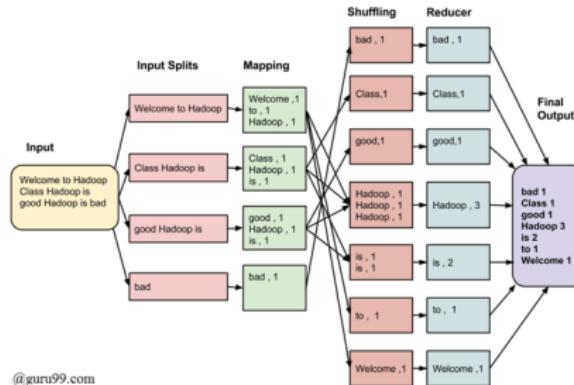
- ↪ *shadow master* provides RO access when primary master is down.
 - ✓ Switches back to read/write mode when primary master is back.
- ↪ Master node does not keep a persistent state info. of its clients,
 - ✓ rather polls clients for their states when started.

• 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,
 - ↪ the types of which may be chosen by the programmer.
 - ↪ the programmer also specifies the **map** and **reduce** functions



@guru99.com

Hadoop



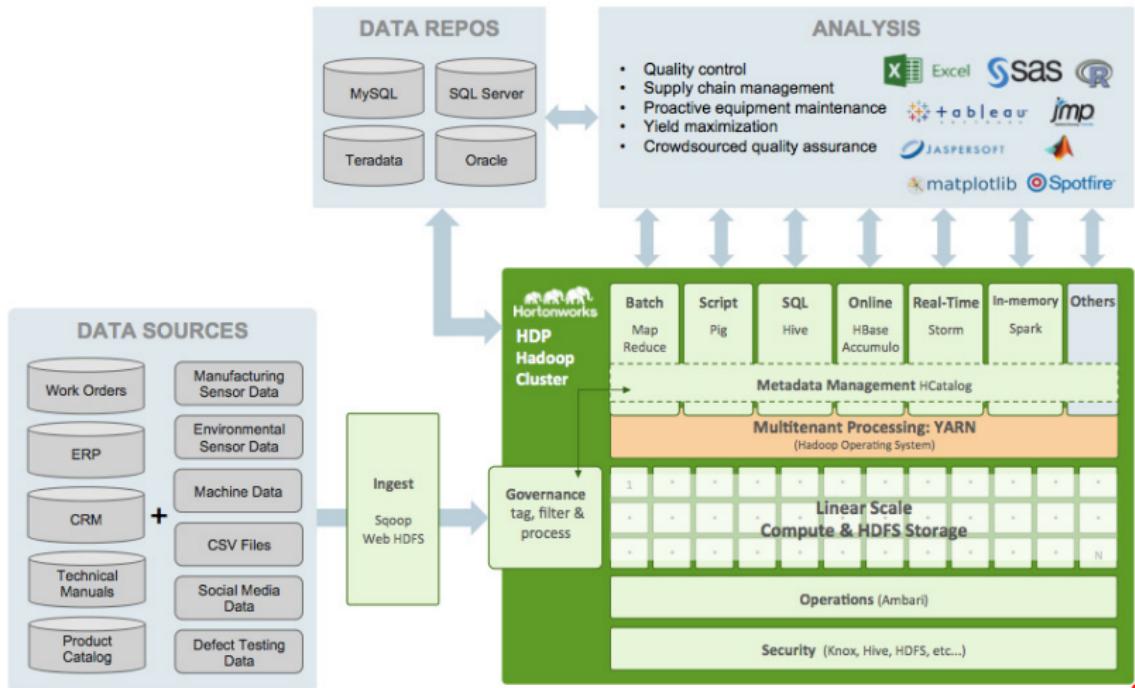
- Initially started as a student project at Yahoo! labs in 2006
 - Open-source Java implem. of GFS and MapReduce frameworks
- Switched to Apache in 2009. Now consists of three main modules:
 - ① **HDFS**: Hadoop distributed file system
 - ② **YARN**: Hadoop job scheduling and resource allocation
 - ③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

Hadoop

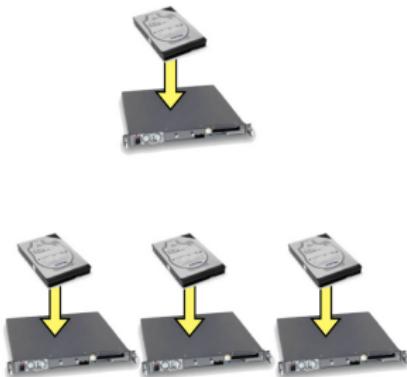


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- Basis for many other open-source Apache toolkits:
 - **PIG/PigLatin**: file-oriented data storage & script-based query language
 - **HIVE**: distributed SQL-style data warehouse
 - **HBase**: distributed key-value store
 - **Cassandra**: fault-tolerant distributed database, etc.
- HDFS still mostly follows the original GFS architecture.

Hadoop Ecosystem

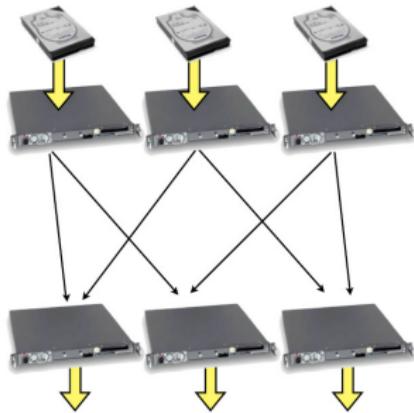


Scale-Out Design



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

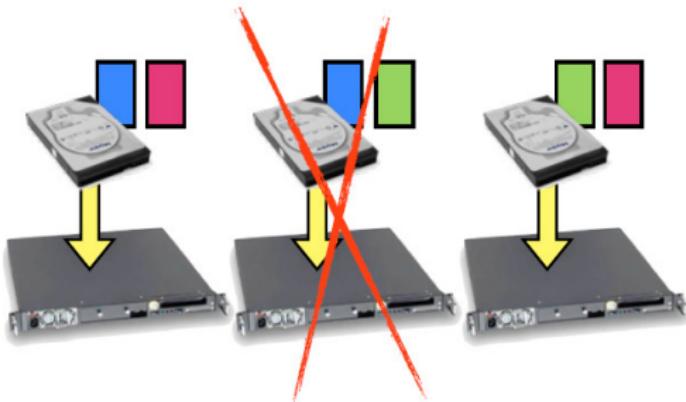
Combining Results



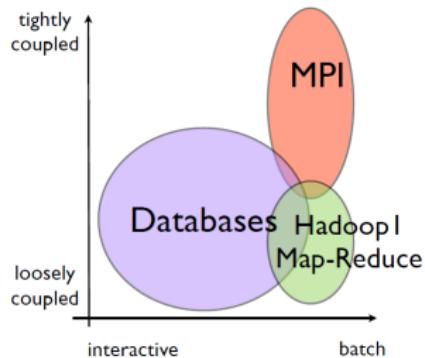
- Each node preprocesses its local data
 - ↪ Shuffles its data to a small number of other nodes
- Final processing, output is done there

Fault Tolerance

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

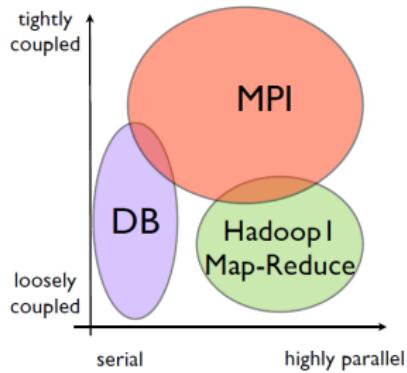


Hadoop: What is it Good At?



- **Classic Hadoop 1.x is all about batch processing** of massive amounts of data
 - ↪ Not much point below ~1TB
- Map-Reduce is relatively loosely coupled;
 - ↪ one **shuffle** phase.
- Very strong weak scaling in this model
 - ↪ more data, more nodes.
- **Batch:**
 - ↪ process all data in one go
 - ✓ w/classic Map Reduce
 - ↪ Current Hadoop has many other capabilities besides batch - **more later**

Hadoop: What is it Good At?



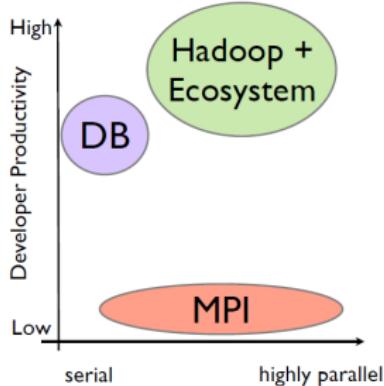
- **Compare with databases**

- ↪ 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:
 - ↪ millions of iterations/timesteps/ exchanges.

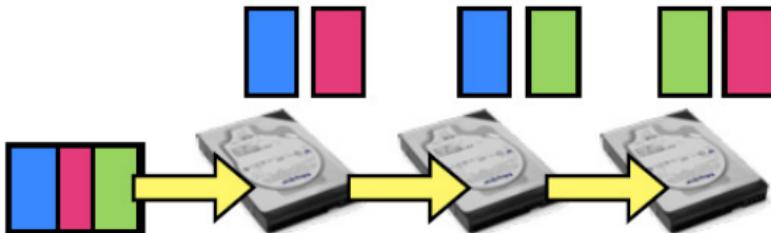
Hadoop vs HPC



- We HPC users might be tempted to an unseemly smugness
 - ↪ *They solved the problem of disk-limited, loosely-coupled, data analysis by throwing more disks at it and weak scaling? Ooooooooooh*
- **We would be wrong.**
 - ↪ A single novice developer can write:
 - ✓ real, scalable,
 - ✓ 1000+ node data-processing tasks in Hadoop-family tools in an afternoon.
 - ↪ In MPI... less likely...

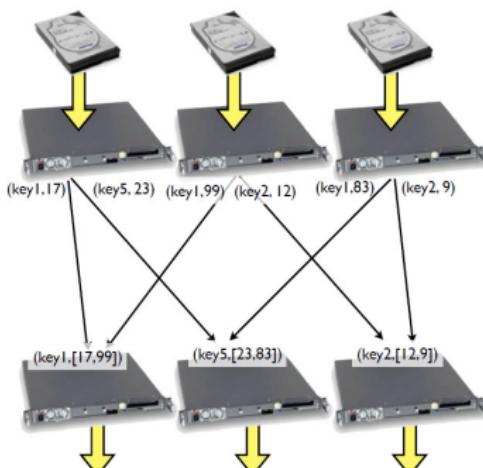
Data Distribution: Disk

- 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

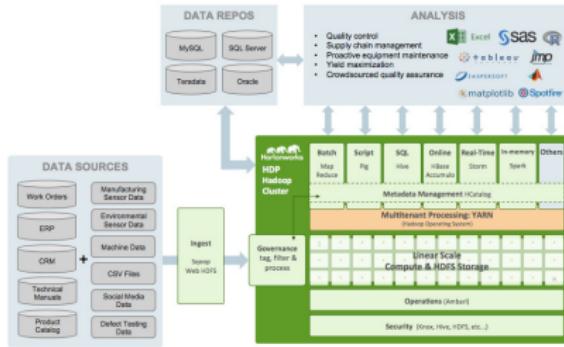
- Decomposing the problem, and,
- Getting the intermediate data where it needs to go,

- Hadoop does that for you

- automatically
- for a wide range of problems.

Built a reusable substrate

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

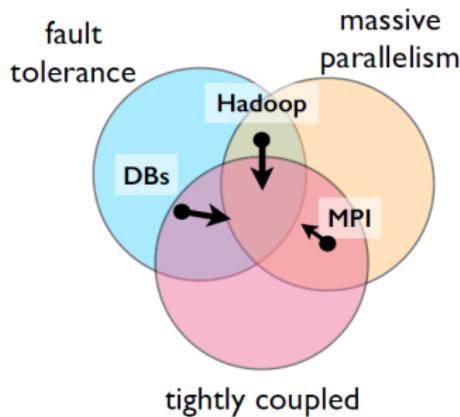


Hadoop and HPC

- Not either-or anyway

- Use HPC to generate big / many simulations,
- Use Hadoop to analyze results
 - ✓ Ex: Use Hadoop to preprocess huge input data sets (ETL),
 - ✓ ... and HPC to do the tightly coupled computation afterwards.

- In all cases: Everything is Converging



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 programmatic APIs
- Security slowly improving

```
$> 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

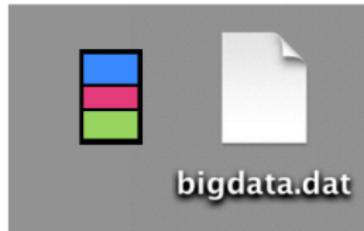
- **Required** to be:

- 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 millions of files
- Have to use separate API to see filesystem
- Modelled after Google File System (2004 Map Reduce paper)

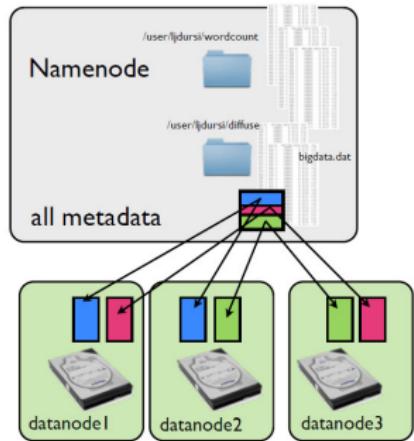
Hadoop vs HPC



- 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

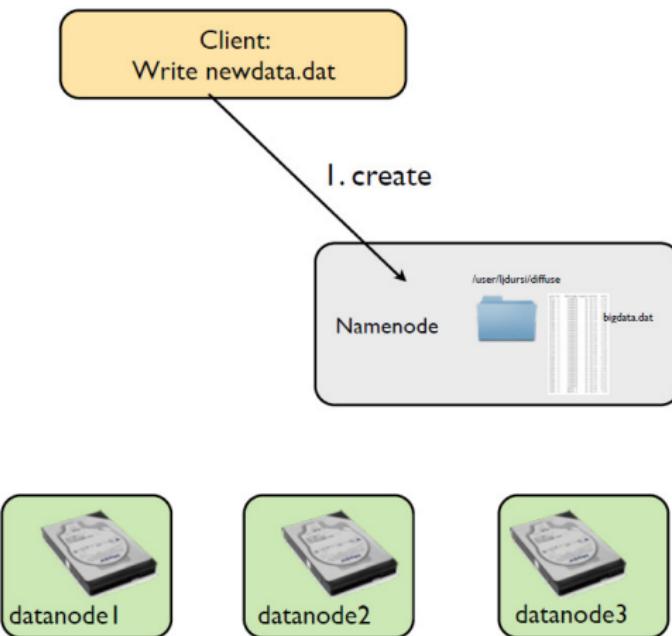
2 Datanodes

- store/retrieve blocks for client/namenode

- Newer versions of Hadoop: federation

- ≠ namenodes for /user, /data...
- High Availability namenode pairs

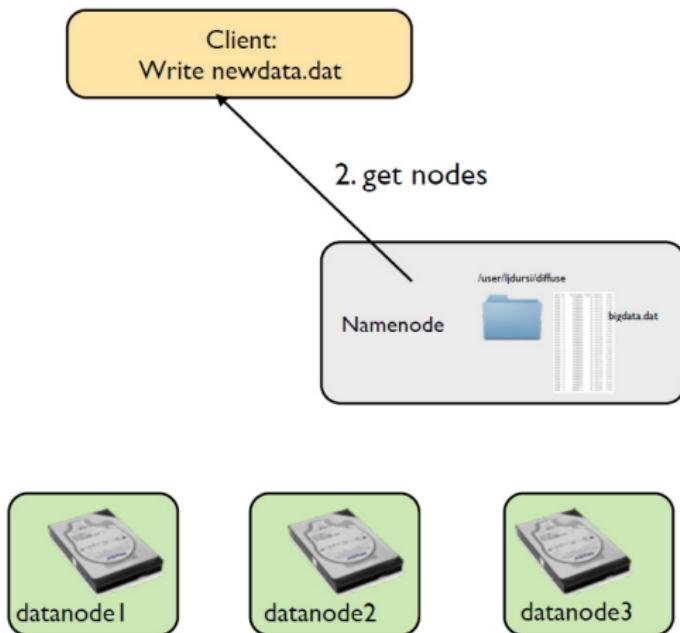
Writing a file



- **Writing a file** multiple stage process:

- ↪ Create file
- ↪ Get nodes for blocks
- ↪ Start writing
- ↪ Data nodes coordinate replication
- ↪ Get ack back
- ↪ Complete

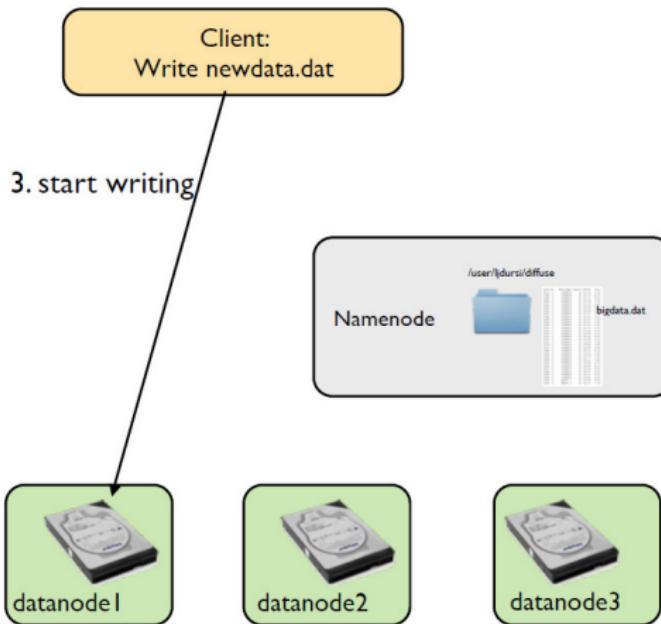
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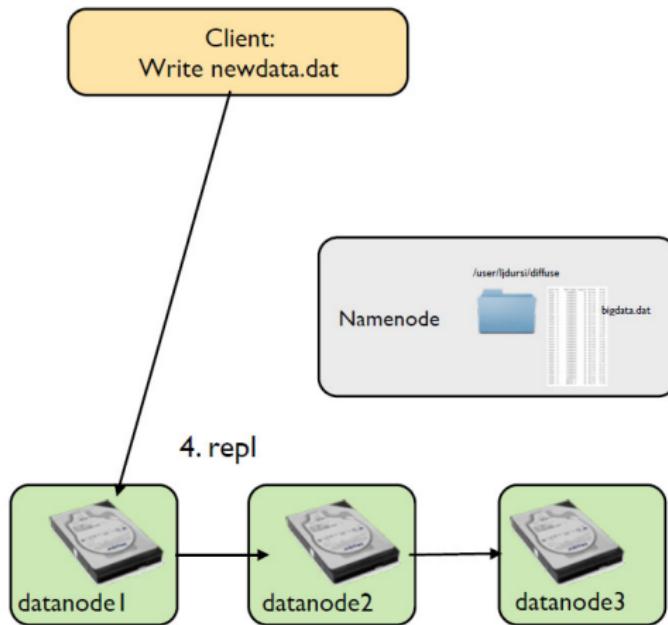
Writing a file



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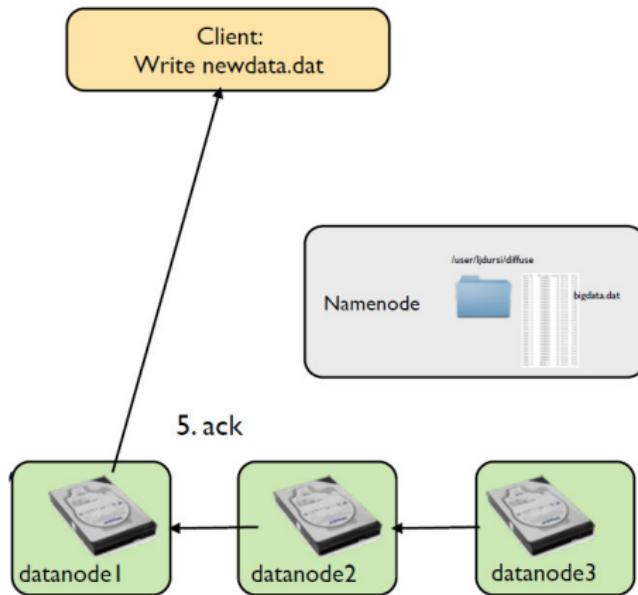
Writing a file



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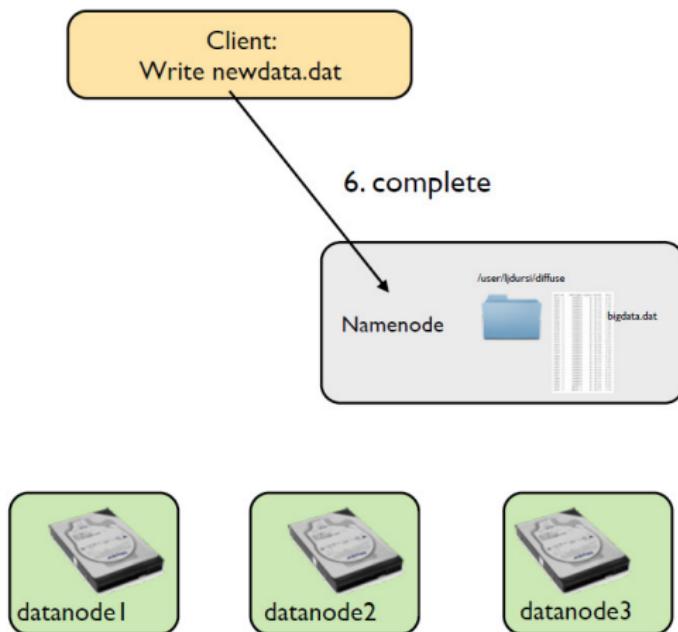
Writing a file



- **Writing a file** multiple stage process:

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- ↪ Complete

Writing a file

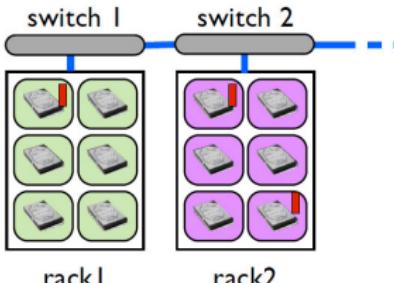


- **Writing a file** multiple stage process:

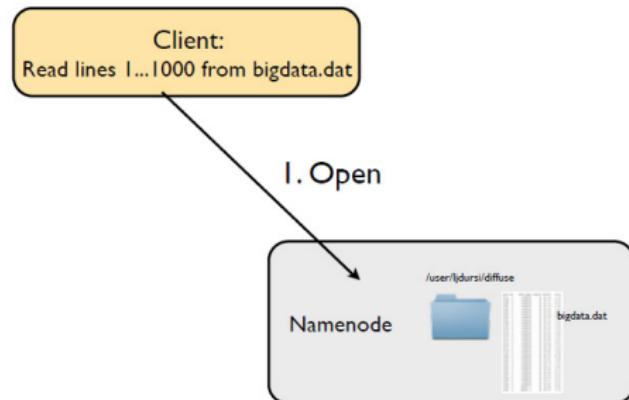
- ↪ Create file
- ↪ Get nodes for blocks
- ↪ Start writing
- ↪ Data nodes coordinate replication
- ↪ Get ack back (**while writing**)
- ↪ Complete

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

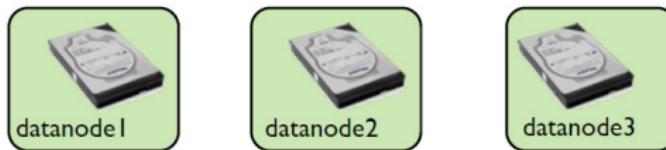


Reading a file

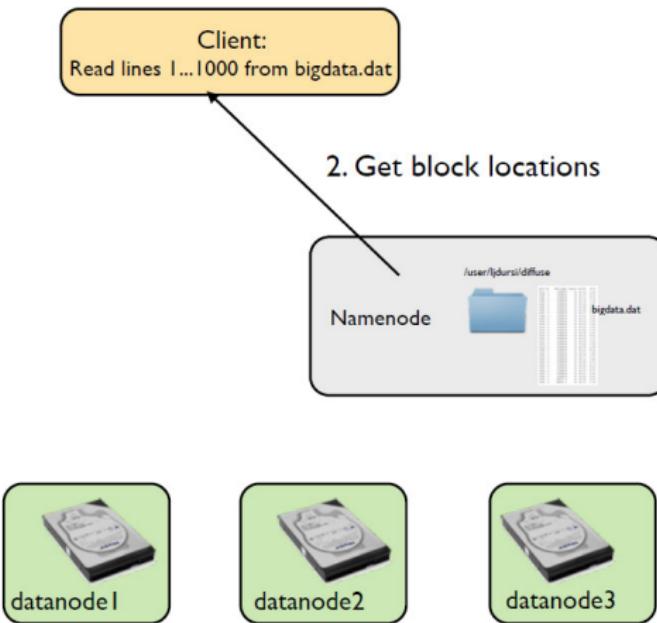


- **Reading** a file

- ↪ Open call
- ↪ Get block locations
- ↪ Read from a replica



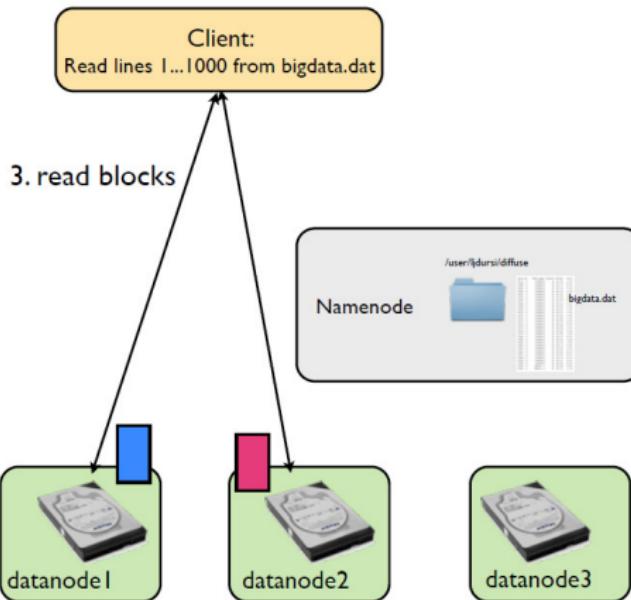
Reading a file



• Reading a file

- ↪ Open call
- ↪ Get block locations
- ↪ Read from a replica

Reading a file



- **Reading** a file

- ↪ Open call
- ↪ Get block locations
- ↪ Read from a replica

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

```
<!-- $HADOOP_PREFIX/etc/hadoop/core-site.xml -->
<configuration>
  <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

- You will need to make sure that environment variables are set
 - ↪ path to Java, path to Hadoop...
 - ↪ Easybuild does **most** of the job for you
- You will need passwordless SSH access across all nodes
- You can then start processes on various FS nodes

Configuring HDFS

- You will need to make sure that environment variables are set
 - ↪ path to Java, path to Hadoop...
 - ↪ Easybuild does **most** of the job for you
- You will need passwordless SSH access across all nodes
- You can then start processes on various FS nodes

- 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} [...]
```

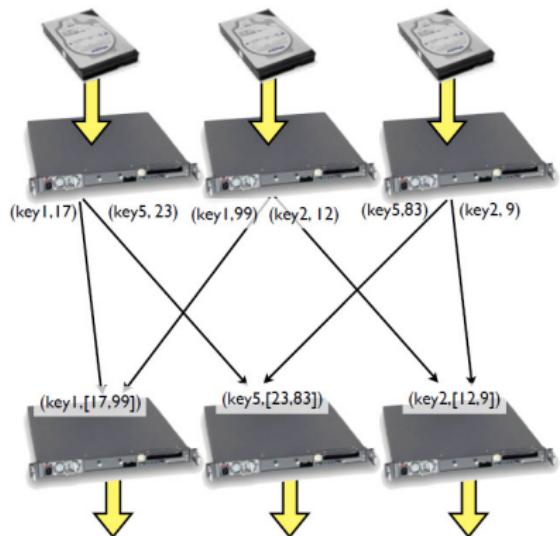
- Default directory is /user/\${username}
 - ↪ Nothing like a cd

```
$> 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

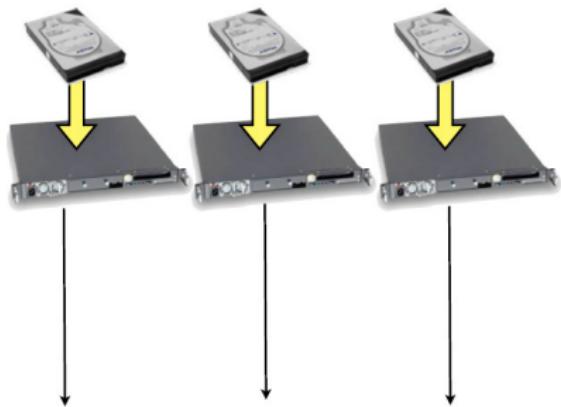
- In general, the data files you send to HDFS will be **large**
 - ↪ or else why bother with Hadoop.
- Do not want to be constantly copying back and forth
 - ↪ **view, append *in place***
- Several APIs to accessing the HDFS
 - ↪ Java, C++, Python
- Here, we use one to get a file status, and read some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

Back to Map-Reduce



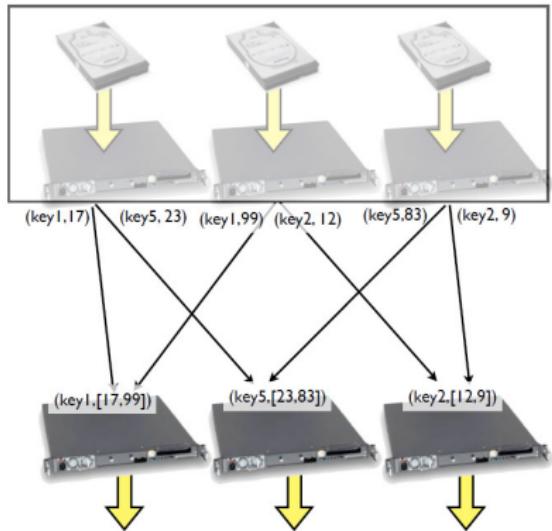
- Map processes **one element at a time**
 - ↪ emits results as (key, value) pairs.
- All results with **same key are gathered to the same reducers**
 - ↪ Reducers process list of values
 - ↪ emit results as (key, value) pairs

Map



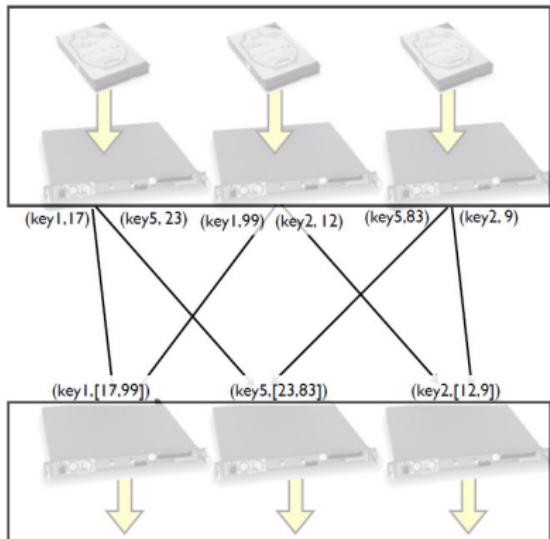
- All coupling done during **shuffle** phase
 - ↪ Embarrassingly parallel task
 - ↪ all map
- Take input, map it to output, done.
- **Famous case**
 - ↪ NYT using Hadoop to convert 11 million image files to PDFs
 - ✓ almost pure serial farm job

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

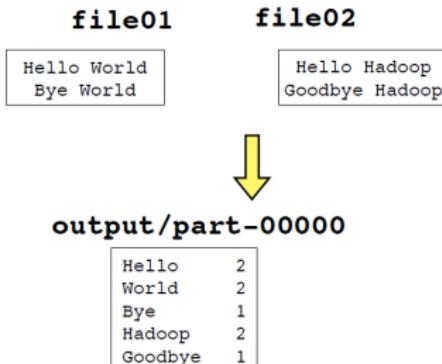


- **shuffle is part of the Hadoop magic**
 - ↪ By default, keys are hashed
 - ↪ hash space is partitioned between reducers
- On **reducer**:
 - ↪ gathered (k,v) pairs from mappers are sorted by key,
 - ↪ then merged together by key
 - ↪ Reducer then runs on one (k,[v]) tuple at a time
- you can supply 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 occurrences of words within these documents



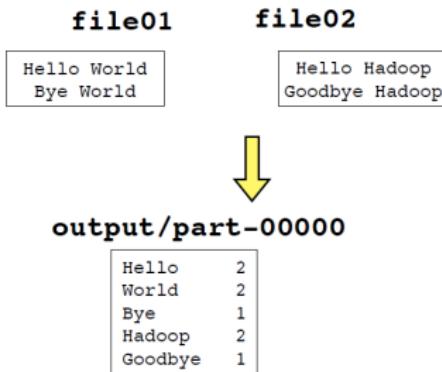
Example: Wordcount

- How would you do this with a huge document?

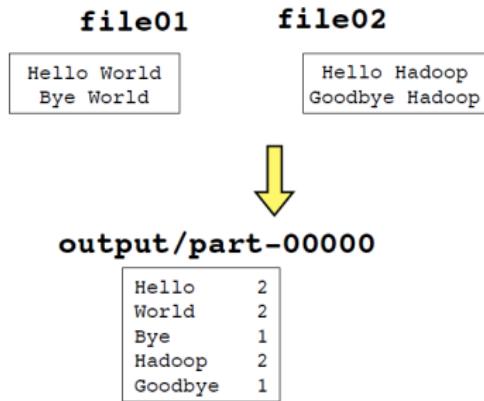
- ↪ Each time you see a word:
 - ✓ if it is a new word, add a tick mark beside it,
 - ✓ otherwise add a new word with a tick

- ... But hard to parallelize

- ↪ pb when updating the list



Example: Wordcount



- **MapReduce way**

- ↪ all hard work done automatically by shuffle

- **Map:**

- ↪ just emit a 1 for each word you see

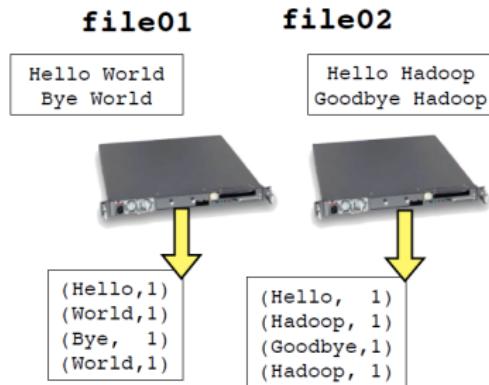
- **Shuffle:**

- ↪ assigns keys (words) to each reducer,
 - ↪ sends (k,v) pairs to appropriate reducer

- **Reducer**

- ↪ just has to sum up the ones

Example: Wordcount



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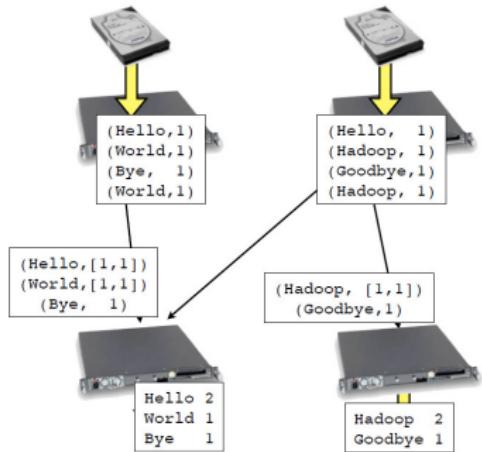
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Hands-on 3: Playing with Hadoop

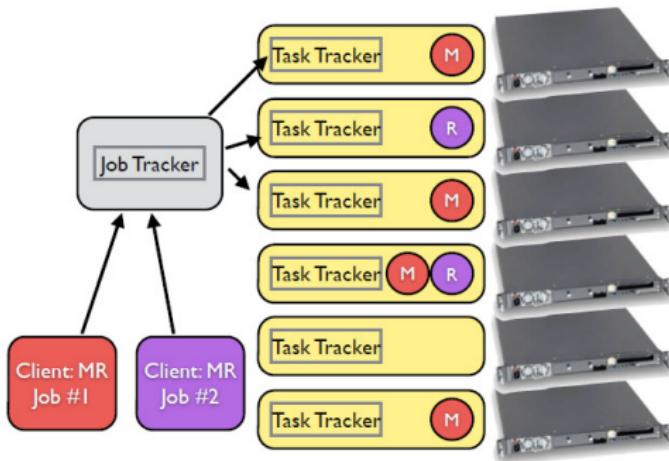
Hands-on 3

ulhpc-tutorials.rtfid.io/en/latest/bigdata/#3-running-hadoop

- Test the tools/Hadoop modules in Single mode Step 3.a
 ↳ test on a Map-reduce grep application
- Pseudo-Distributed Operation Step 3.b
 ↳ application on the official Wordcount instructions
- Enable a Full Cluster Setup Step 3.c

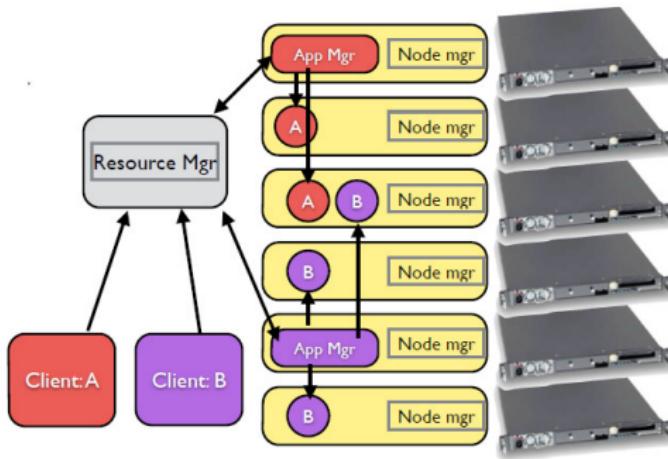
Hadoop 0.1x

- Original Hadoop was basically HDFS + infra. 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

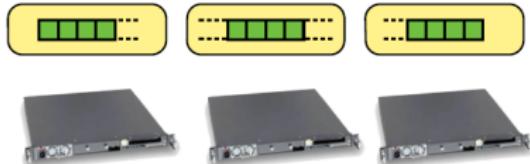
- Spark computation paradigm is not **just** MapReduce job
- Key feature - **in-memory analyses**.
 - ↪ **multi-stage, in-memory dataflow graph based on Resilient Distributed Datasets (RDDs)**.

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:** 2.2.1 (Dec. 2017)

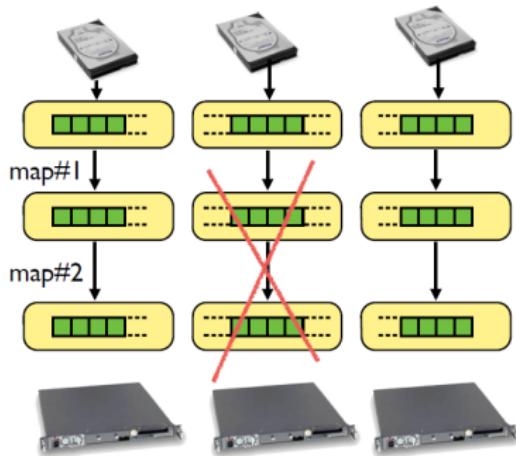
RDD



- 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)
 - ↳ Persistence to disk (optional)

RDD Lineage

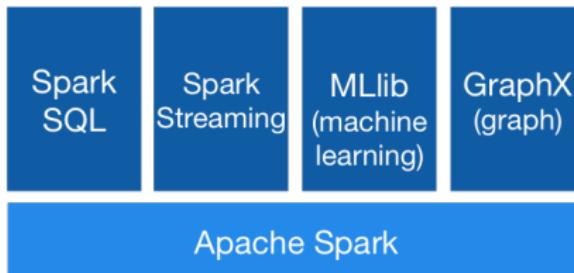
- Map Reduce implemented FT by outputting everything to disk always.
 - ↪ Effective but extremely costly.
 - ↪ **How to maintain fault tolerance without sacrificing in-memory performance?**
 - ✓ for truly large-scale analyses

RDD Lineage

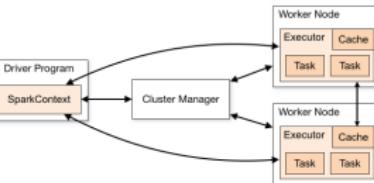
- Map Reduce implemented FT by outputting everything to disk always.
 - ↪ Effective but extremely costly.
 - ↪ **How to maintain fault tolerance without sacrificing in-memory performance?**
 - ✓ for truly large-scale analyses
- **Solution:**
 - ↪ Record lineage of an RDD (think version control)
 - ↪ 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 which 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



Hands-on 4: Spark



Hands-on 4

ulhpc-tutorials.rtfd.io/en/latest/bigdata/#4-interactive-big-data-analytics-with-spark

- Build Spark 2.2.0 Step 4.1
- Check a single **interactive run**
 - PySpark, the Spark Python API
 - Scala Spark Shell
 - R Spark Shell **will not be reviewed** here
- Running **Spark standalone cluster** Step 4.3
 - launch **master** and **worker** Spark processes
 - access the **web UI** of the master
 - ✓ Ex: SOCKS 5 proxy approach + FoxyProxy plugin
 - submit a **sample job** (Pi estimation)
 - ✓ \$EBROOTSPARK/examples/src/main/python/pi.py 1000
 - prepare a **launcher script** runs/launcher.Spark.sh

Questions?

<http://hpc.uni.lu>

High Performance Computing @ uni.lu

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1 Practical Session Objectives

2 [Big] Data Management in HPC Environment: Overview and Challenges

Performance Overview in Data transfer

Data transfer in practice
Sharing Data

3 Big Data Analytics with Hadoop & Spark

Apache Hadoop
Apache Spark