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.rtfd.io/en/latest/bigdata/

Summary

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

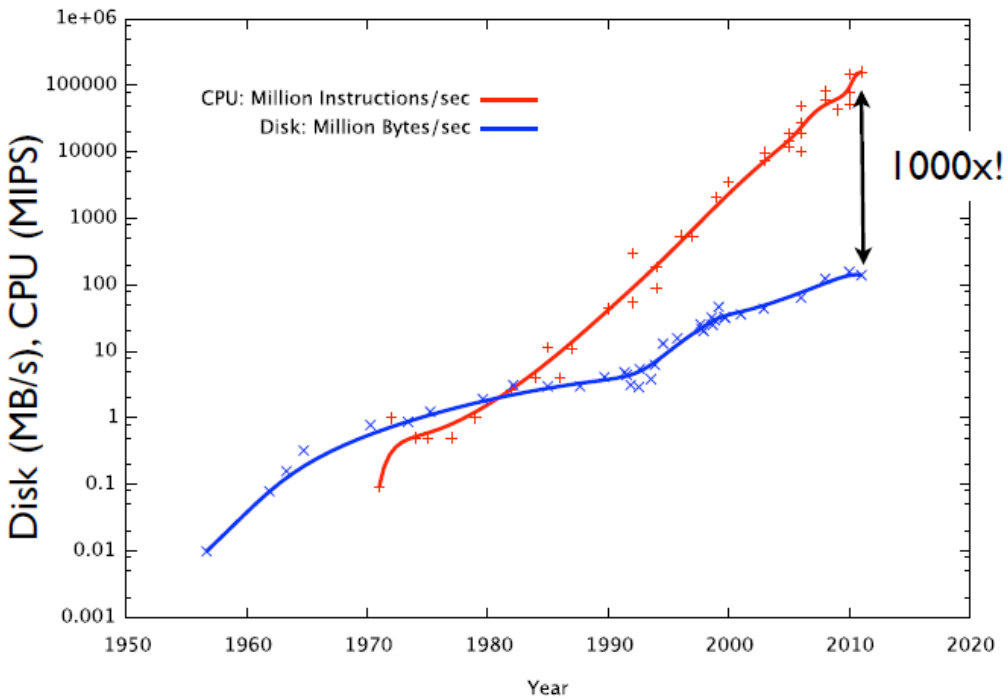
Disclaimer: Acknowledgements

- 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`

Summary

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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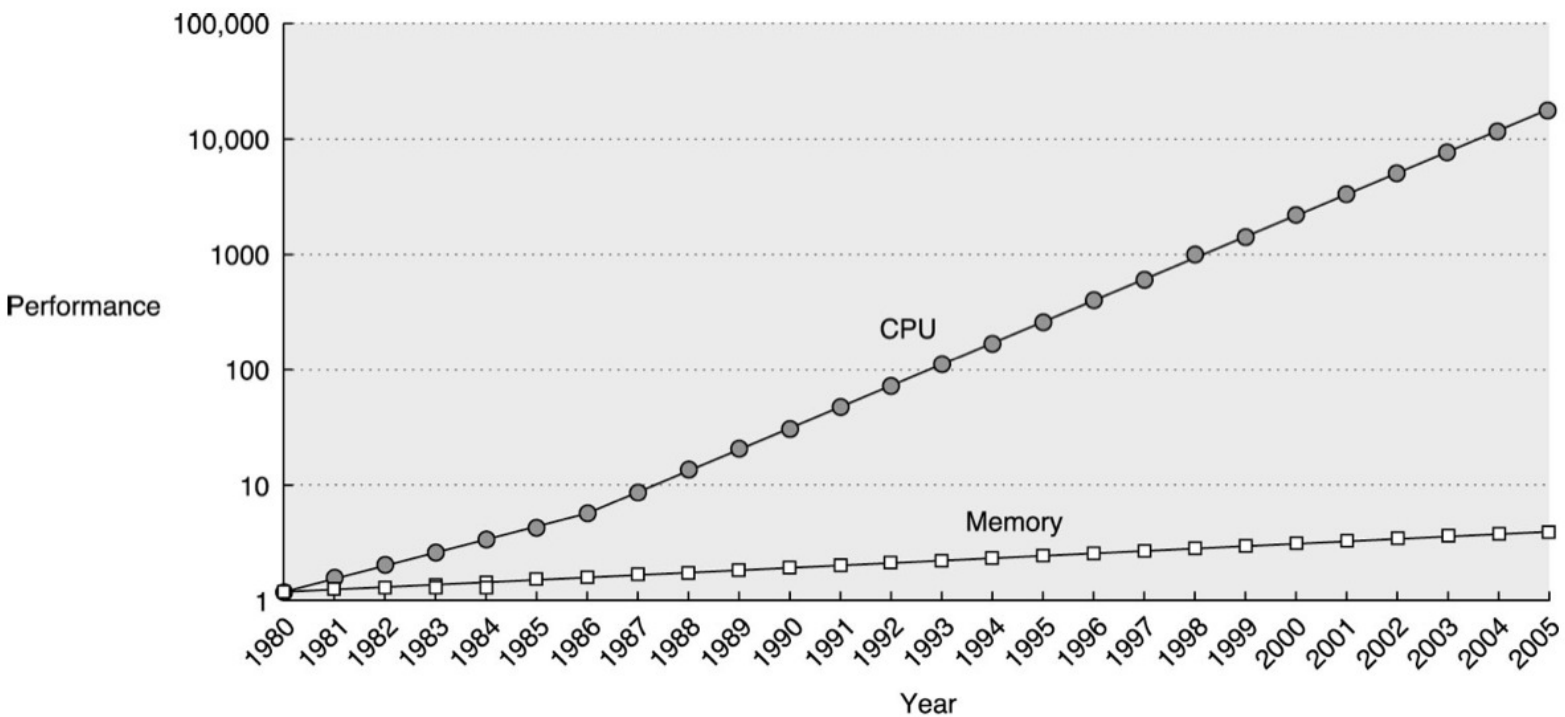


Speed Expectation on Data Transfer

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/

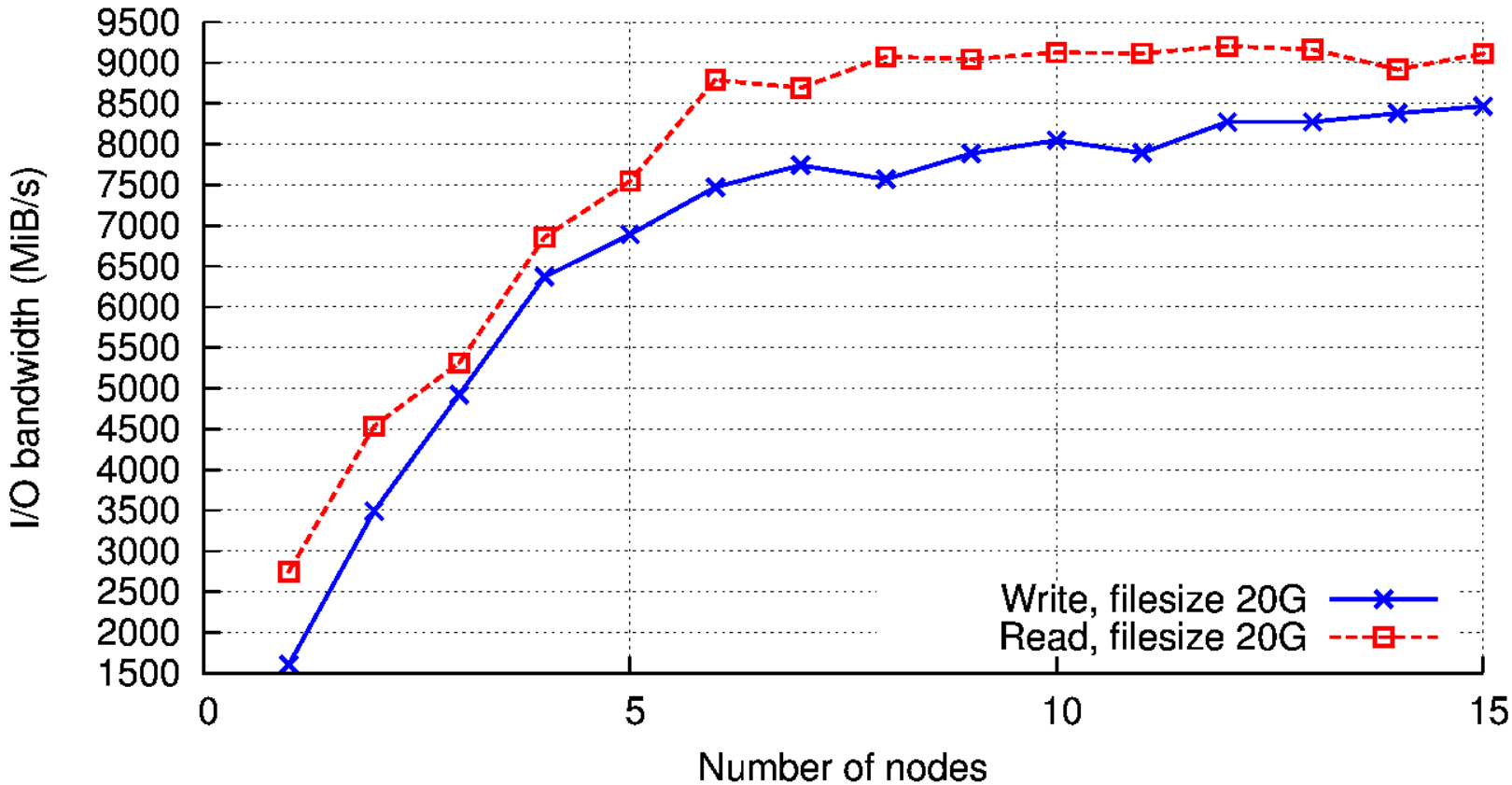
Data set size	1 Minute	5 Minutes	20 Minutes	1 Hour
	Time to transfer			
10PB	166.67 TB/sec	33.33 TB/sec	8.33 TB/sec	2.78 TB/sec
1PB	16.67 TB/sec	3.33 TB/sec	833.33 GB/sec	277.78 GB/sec
100TB	1.67 TB/sec	333.33 GB/sec	83.33 GB/sec	27.78 GB/sec
10TB	166.67 GB/sec	33.33 GB/sec	8.33 GB/sec	2.78 GB/sec
1TB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

Speed Expectation on Data Transfer

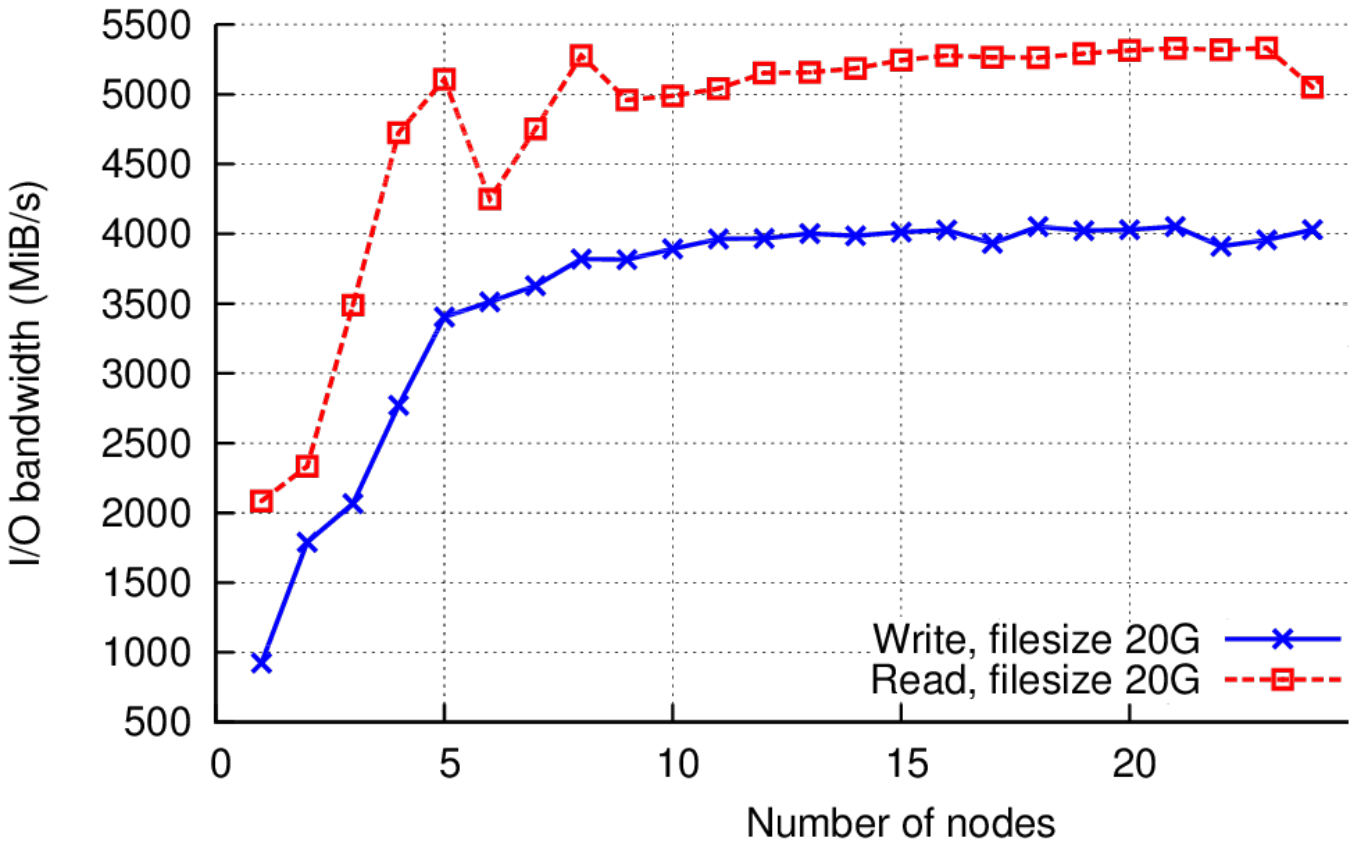
http://fasterdata.es.net/

Data set size	8 Hours	24 Hours	7 Days	30 Days
	Time to transfer			
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

Storage Performances: GPFS

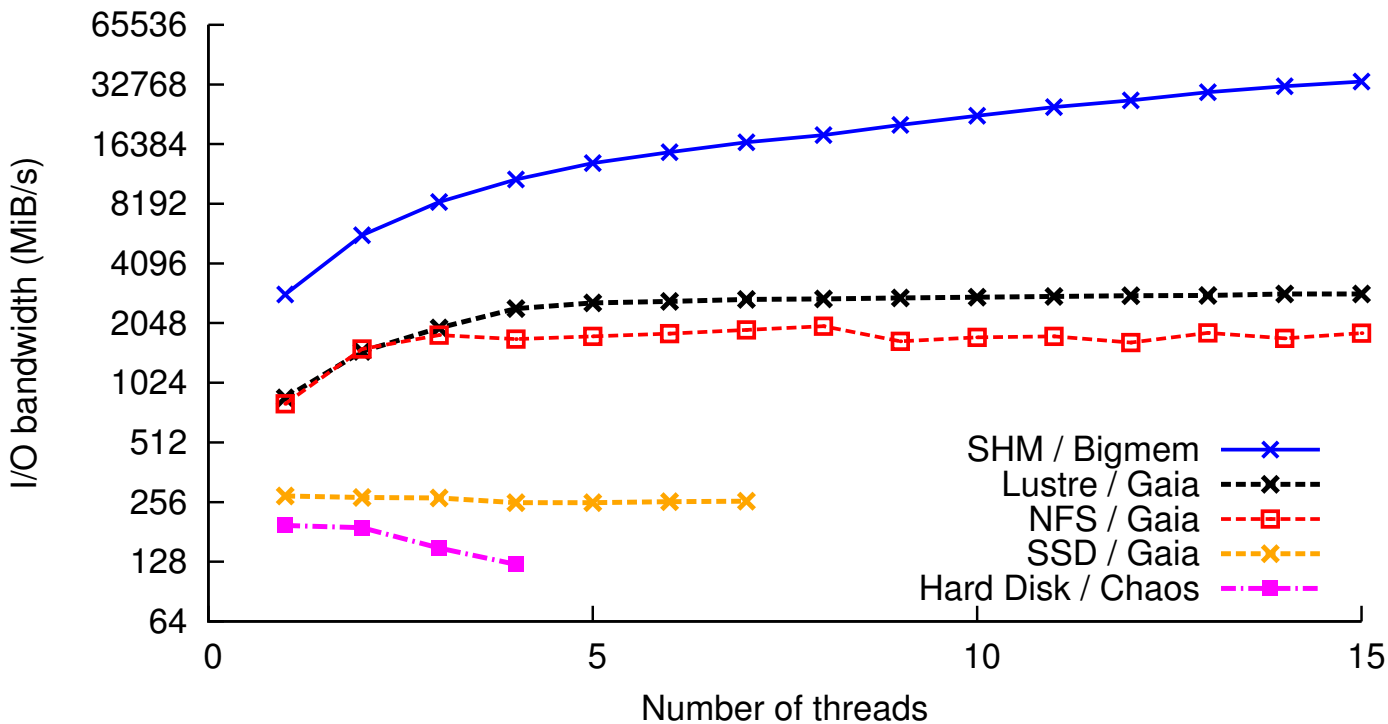


Storage Performances: Lustre



Storage Performances

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



Storage Performances

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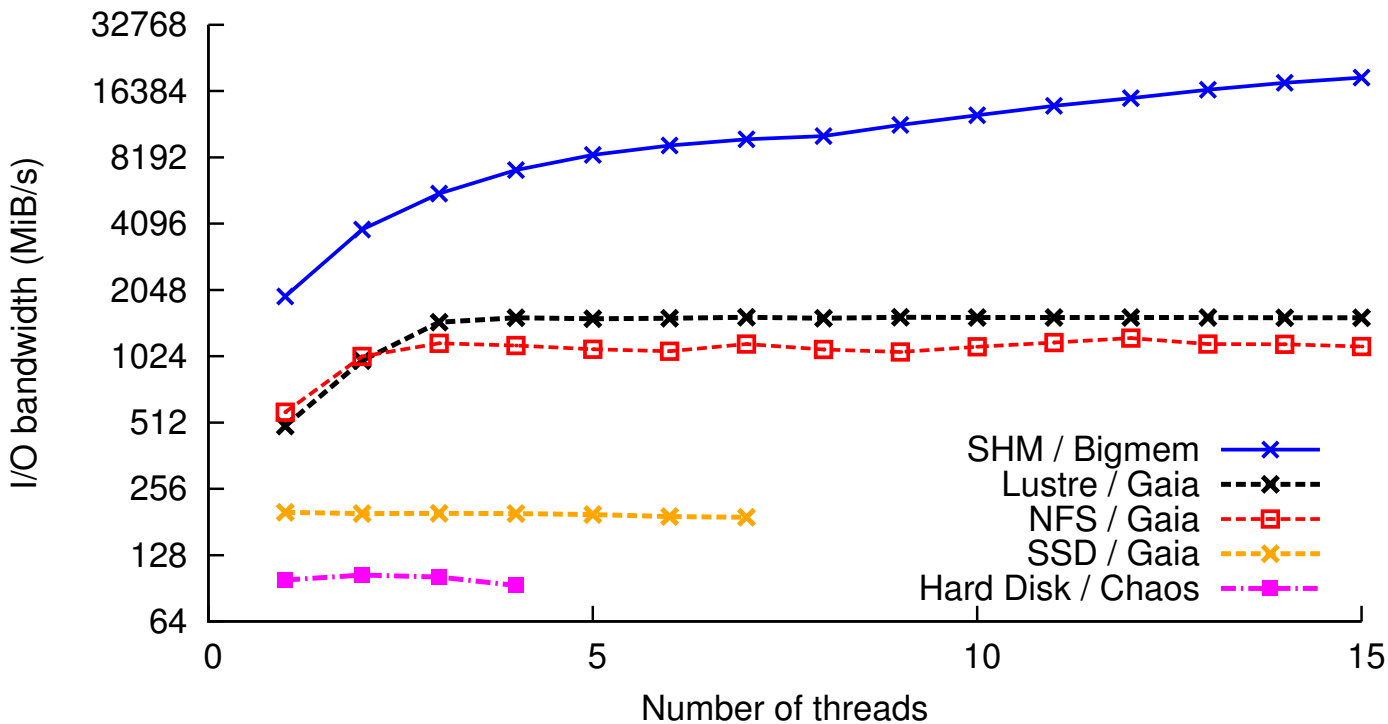

Understanding Your Storage Options

Where can I store and manipulate my data?

- **Shared** storage
  - ↪ `NFS` - **not scalable** $\sim\simeq$ 1.5 GB/s (R) — $\mathcal{O}$(100 TB)
  - ↪ `GPFS` - **scalable** $\sim\sim\simeq$ 10 GB/s (R) — $\mathcal{O}$(1 PB)
  - ↪ `Lustre` - **scalable** $\sim\sim\simeq$ 5 GB/s (R) — $\mathcal{O}$(0.5 PB)
- **Local** storage
  - ↪ local file system (`/tmp`) — $\mathcal{O}$(200 GB)
    - ✓ over HDD $\simeq$ 100 MB/s, over SDD $\simeq$ 400 MB/s
  - ↪ RAM (`/dev/shm`) $\simeq$ 30 GB/s (R) — $\mathcal{O}$(20 GB)
- **Distributed** storage
  - ↪ HDFS, Ceph, GlusterFS - **scalable** $\sim\sim\simeq$ 1 GB/s

$\Rightarrow$ **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

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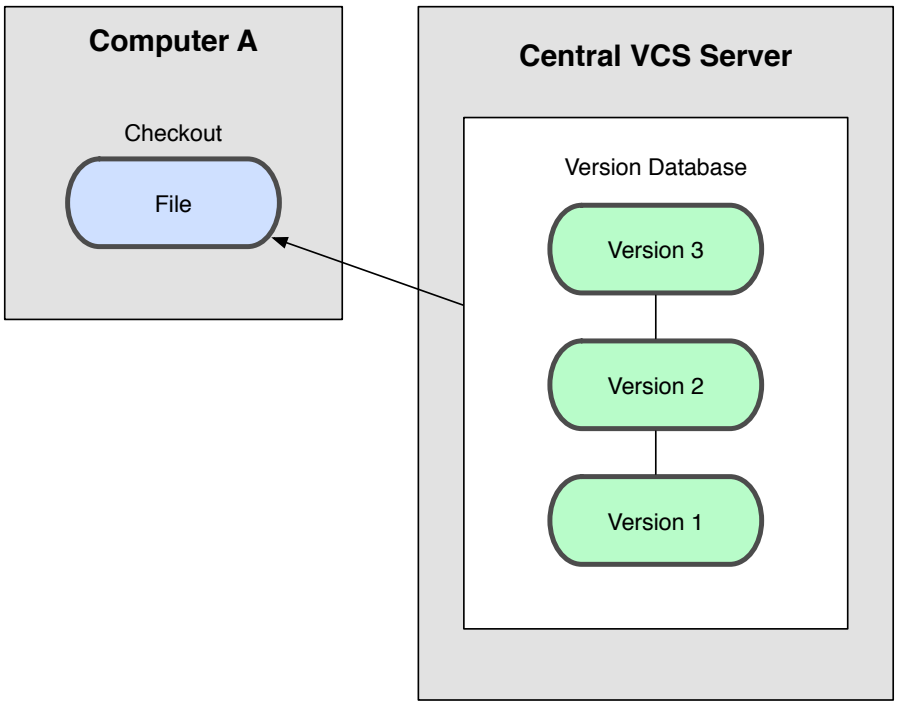
- **Which one?**
  - ↪ Depends on the level of privacy you expect
    - ✓ ... but you probably already know these tools ☺
  - ↪ **Few handle GB files...**

Centralized VCS - CVS, SVN



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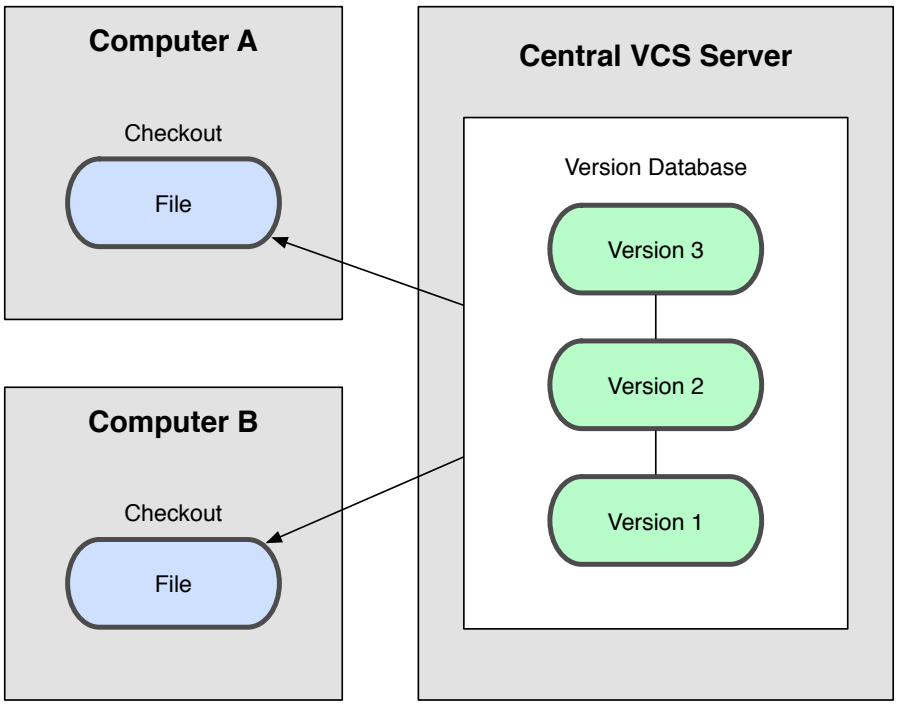
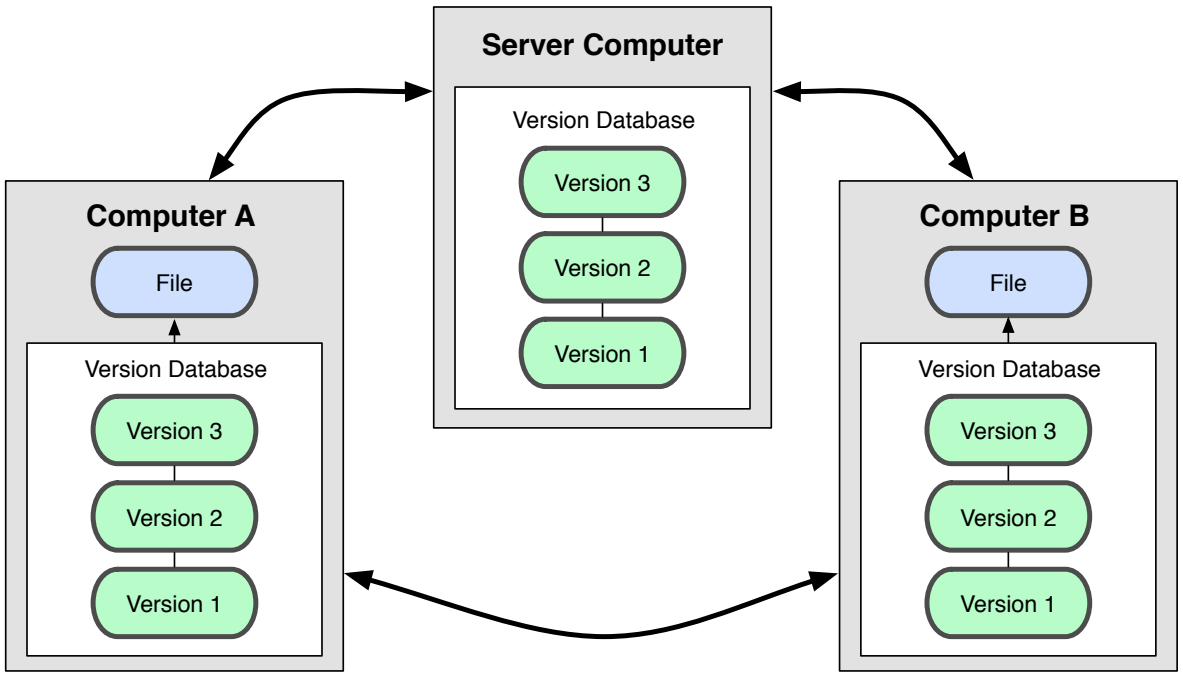
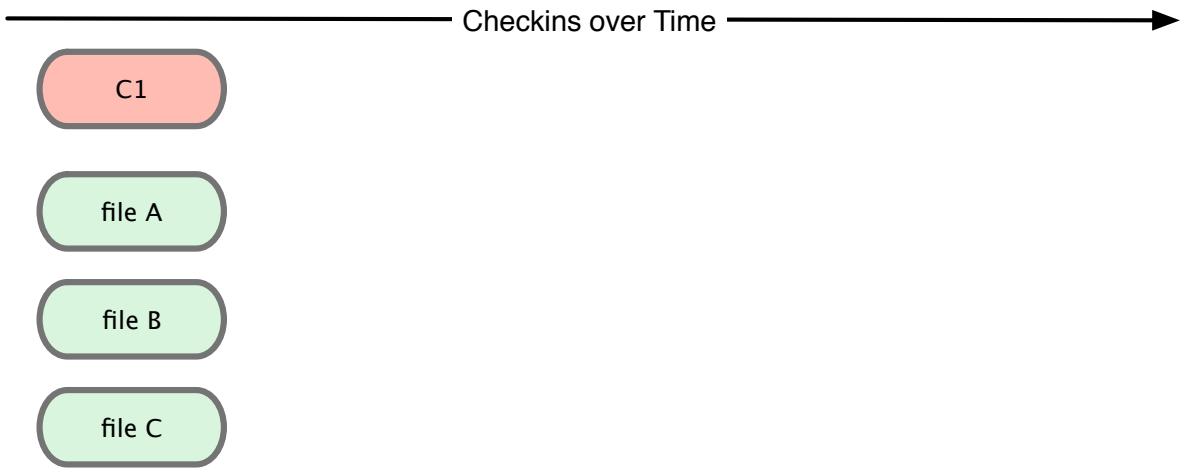


Distributed VCS - Git



Everybody has the full history of commits

Tracking changes (most VCS)



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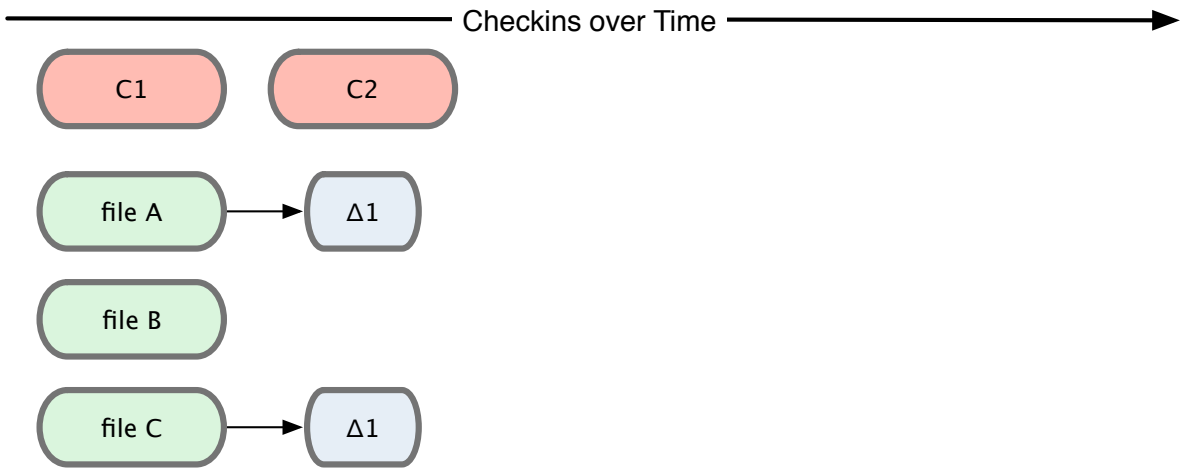

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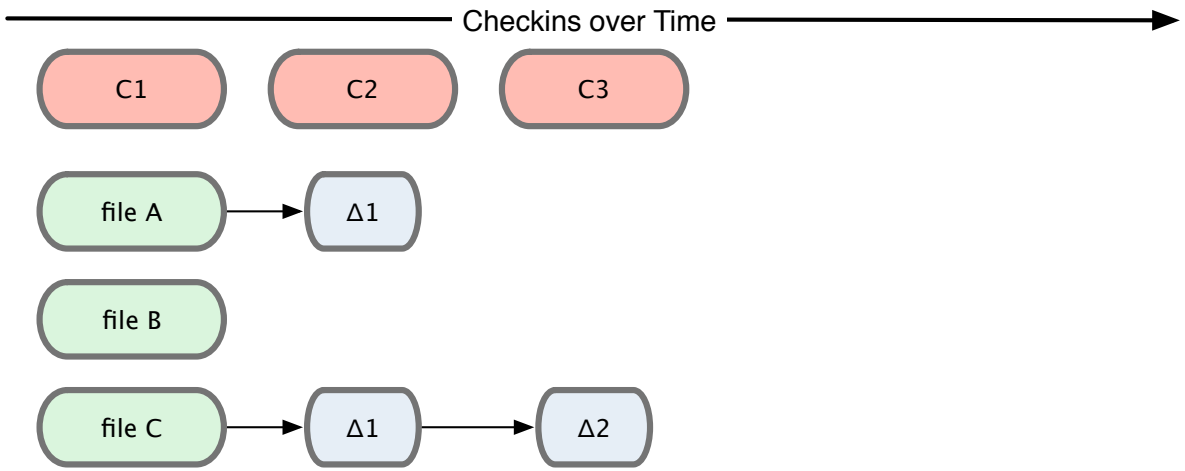

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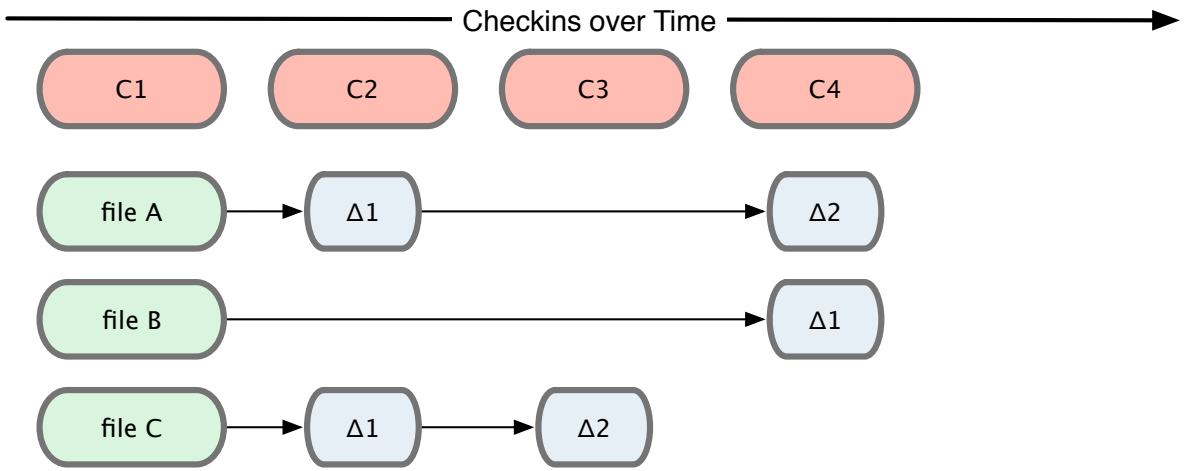

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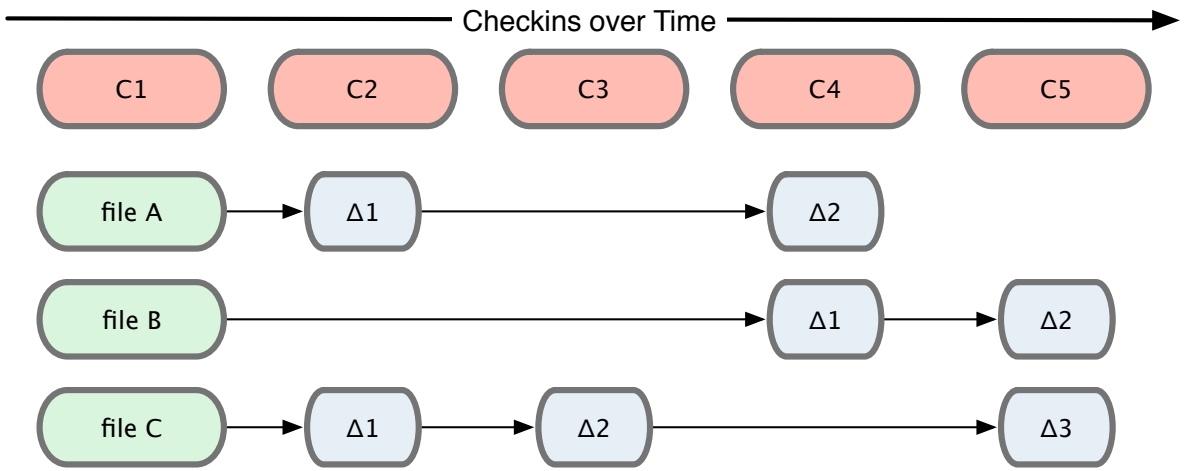

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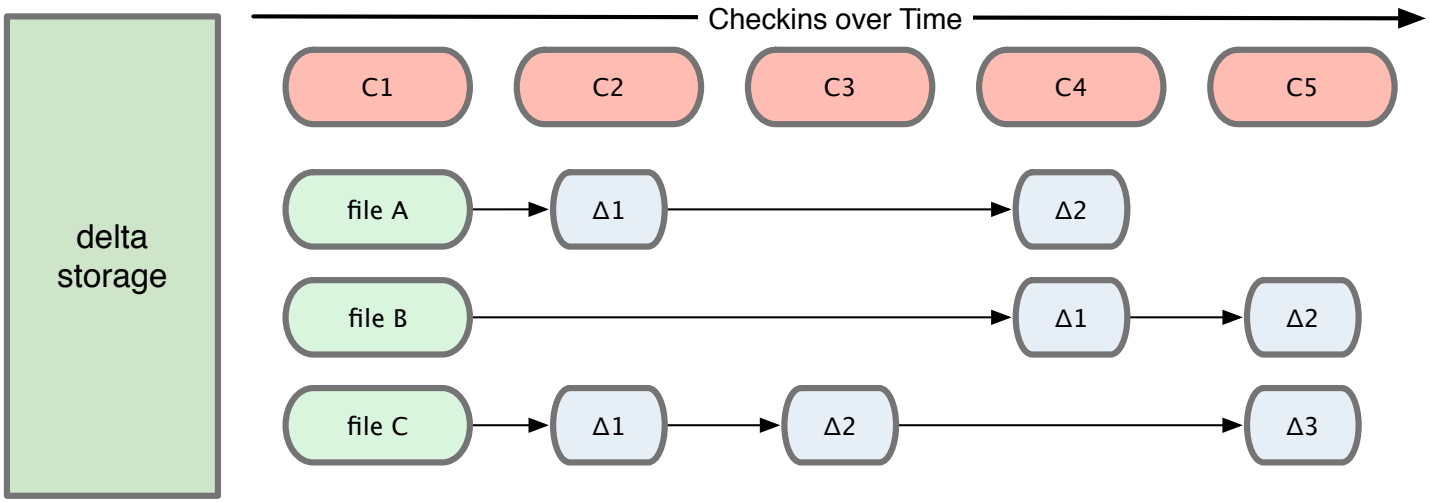

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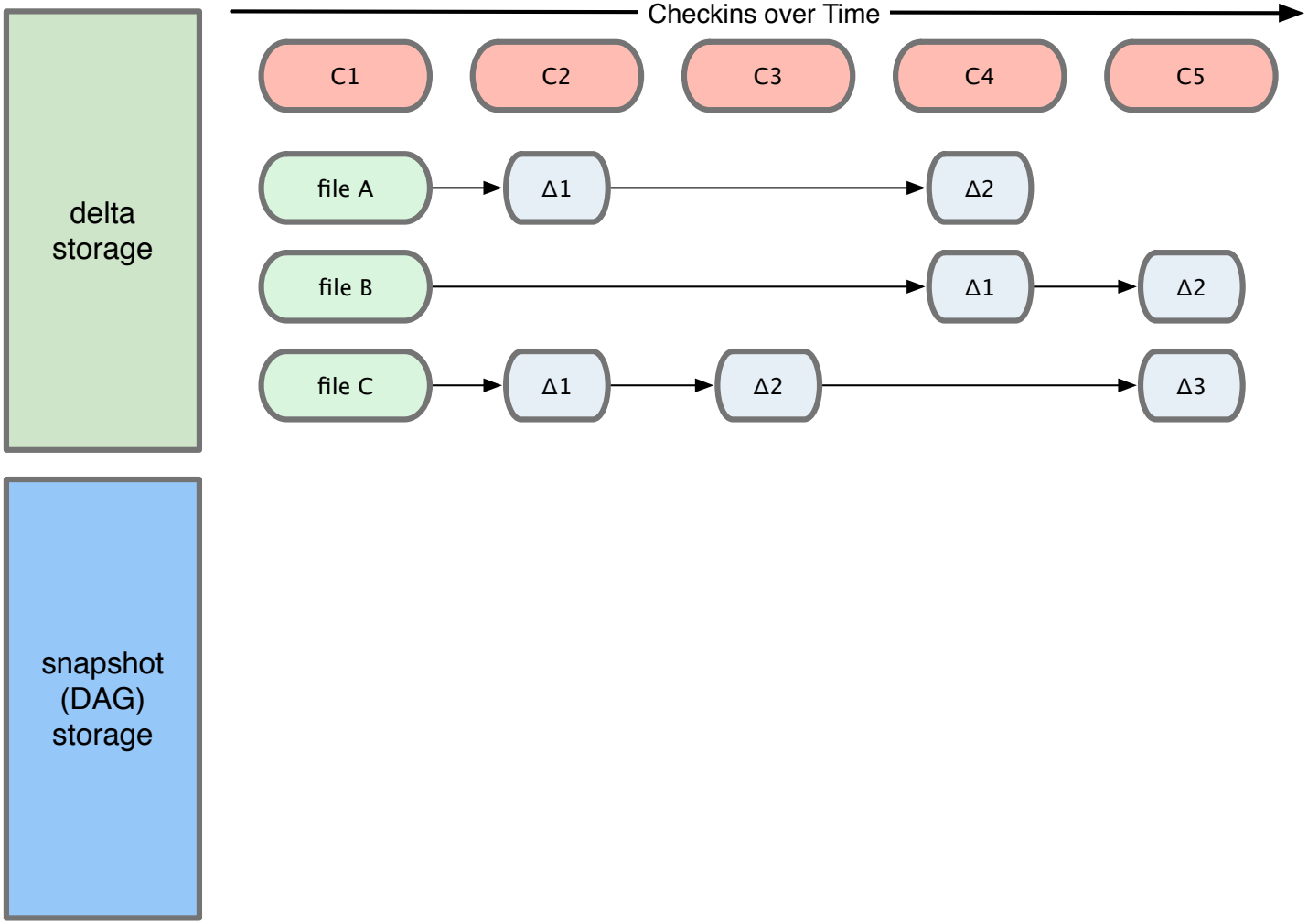

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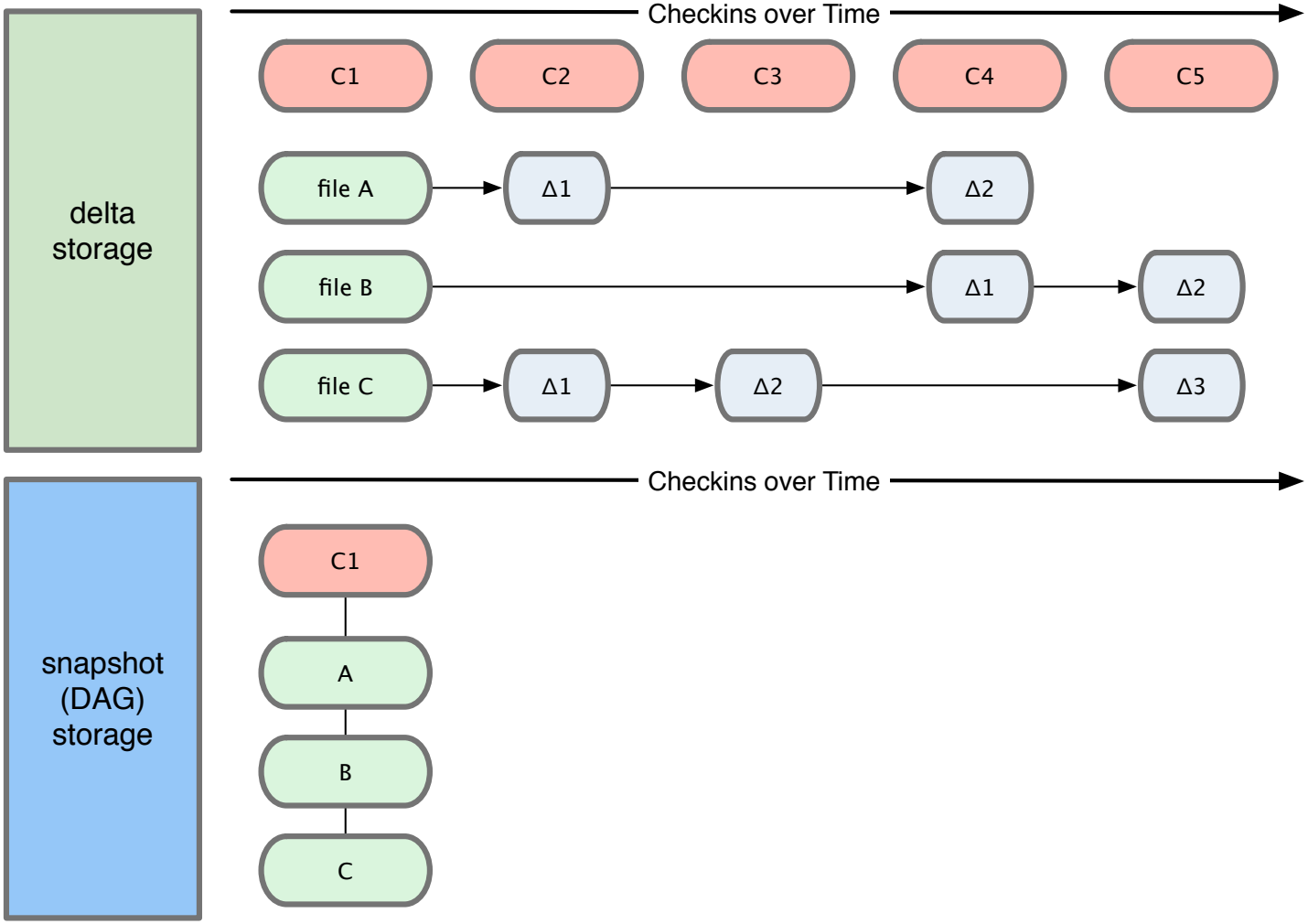

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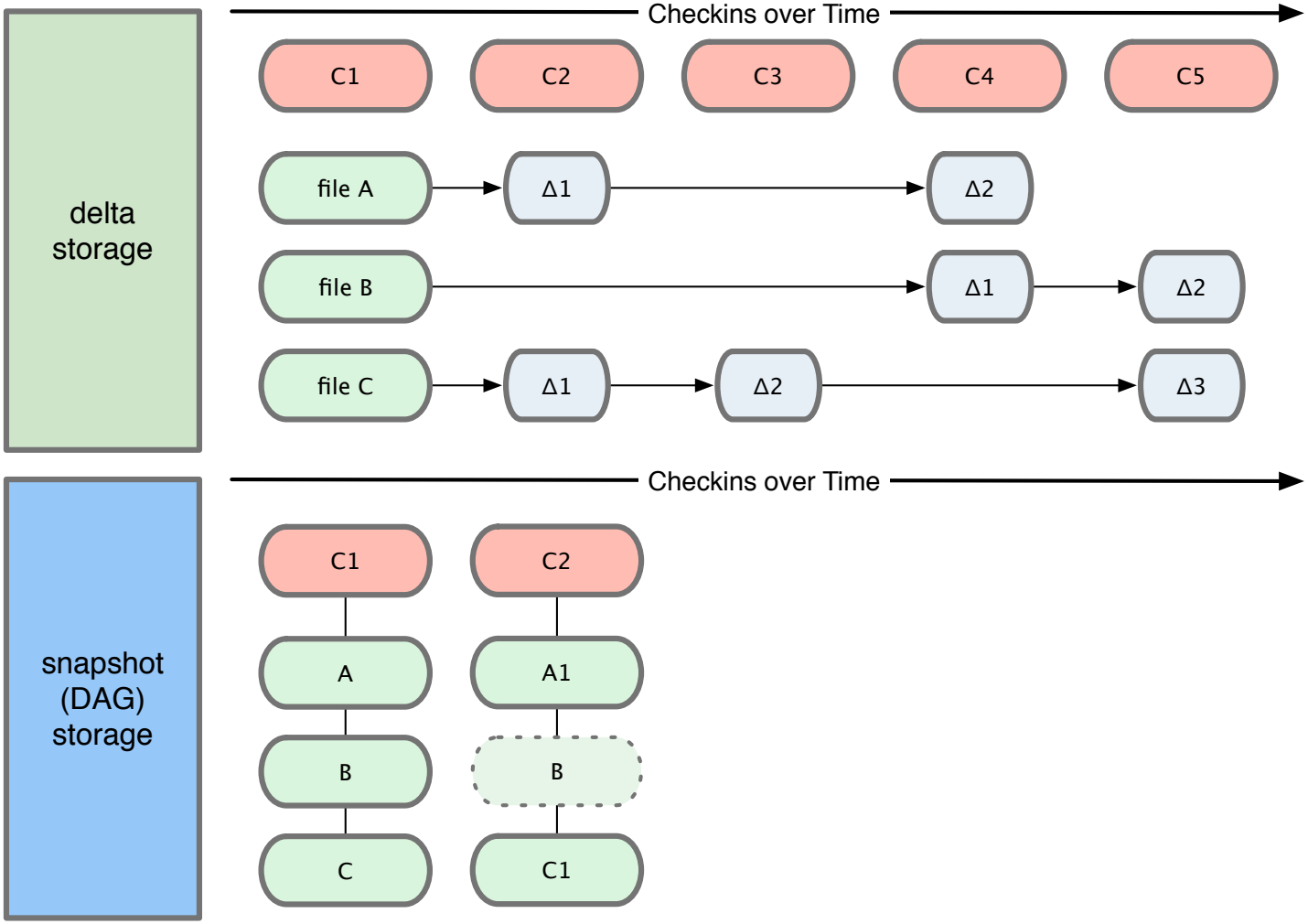

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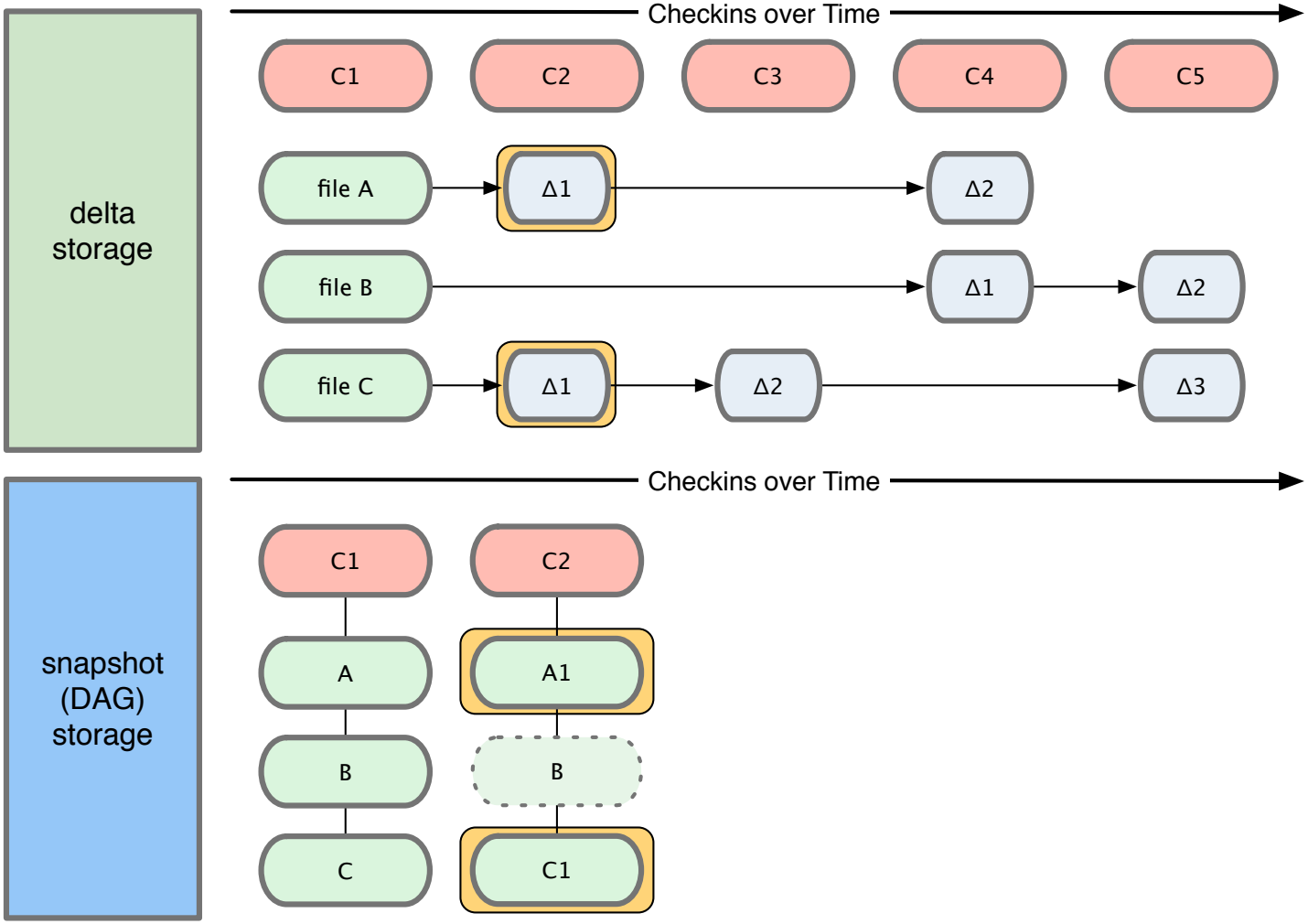

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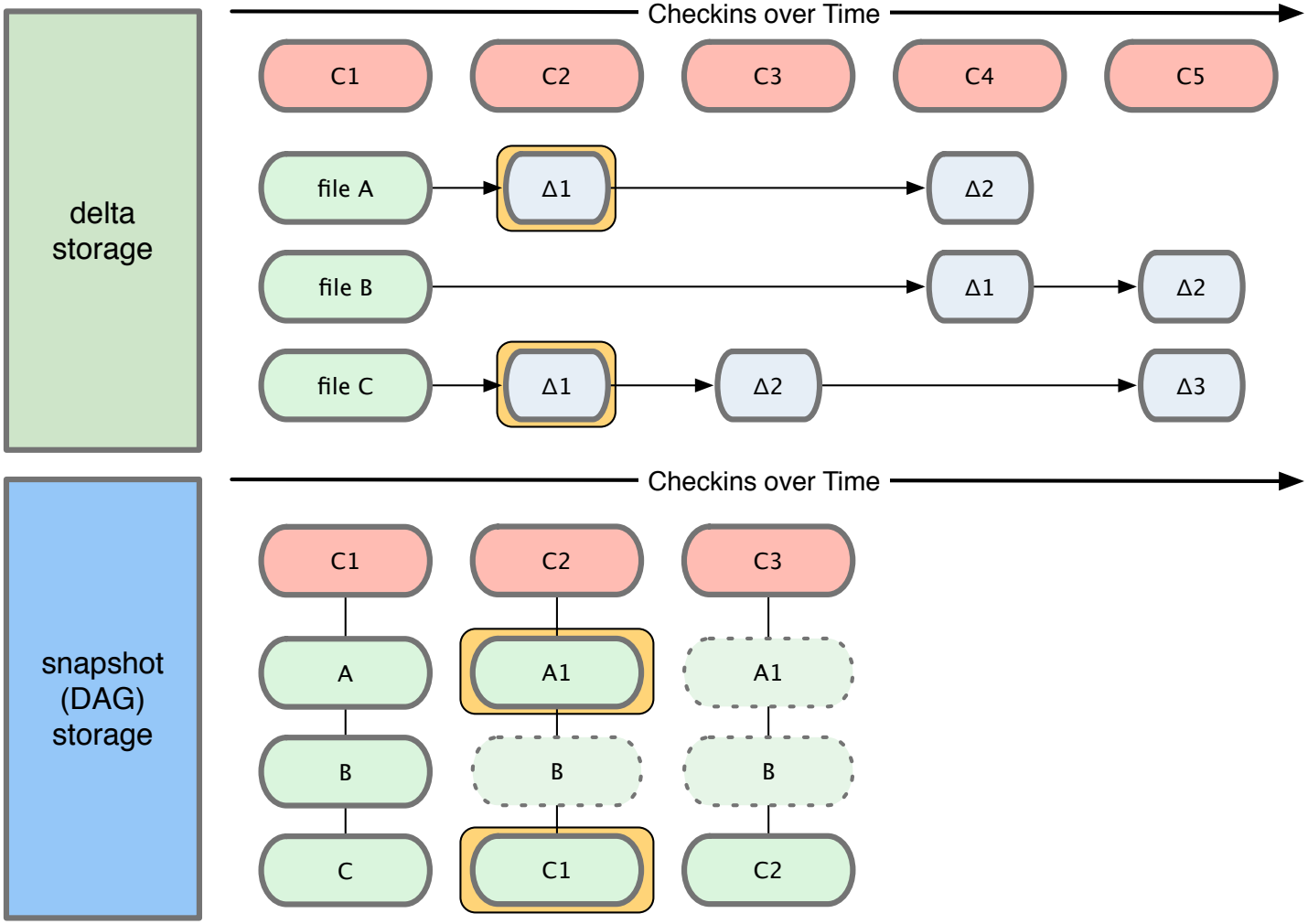

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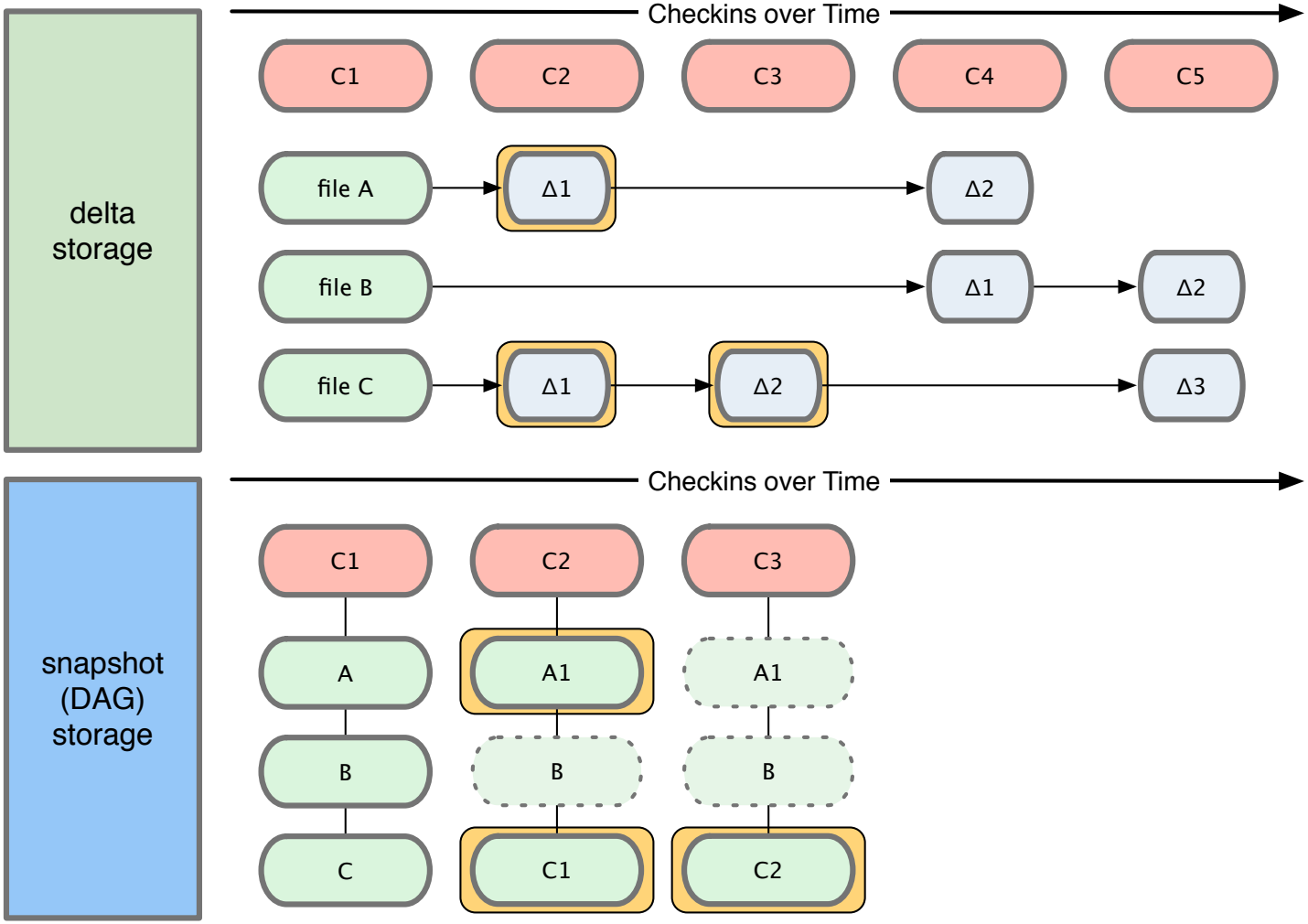

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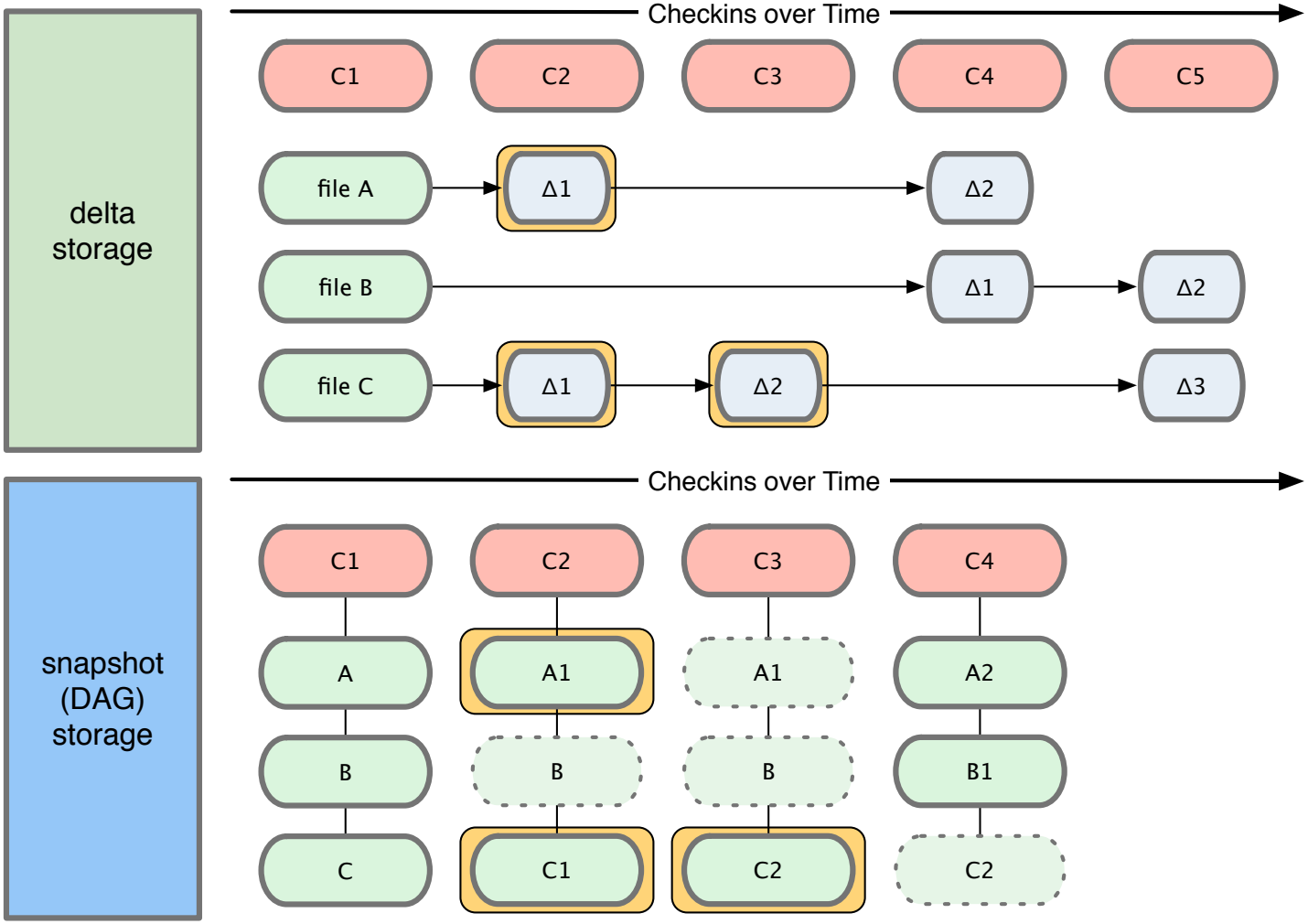

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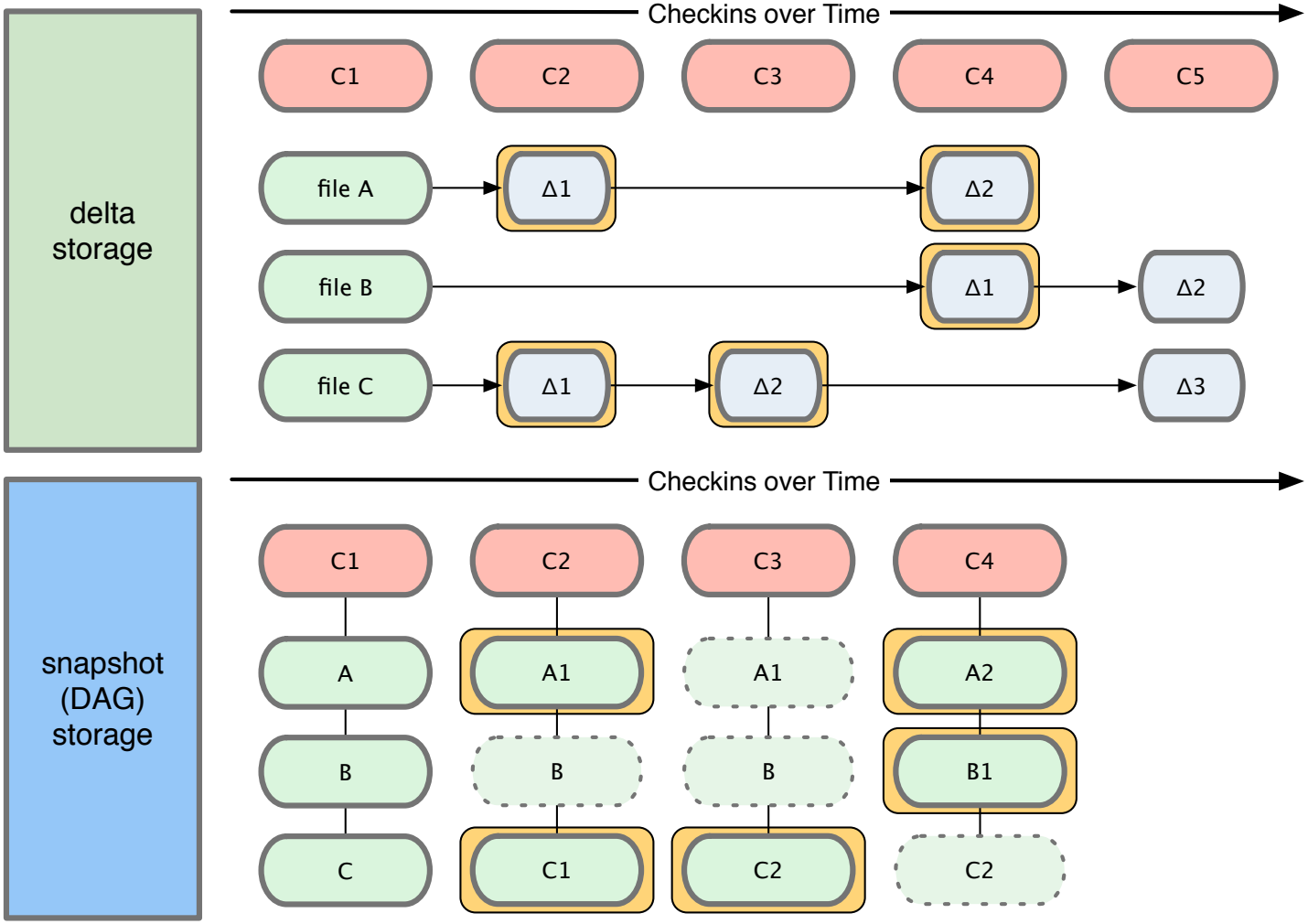

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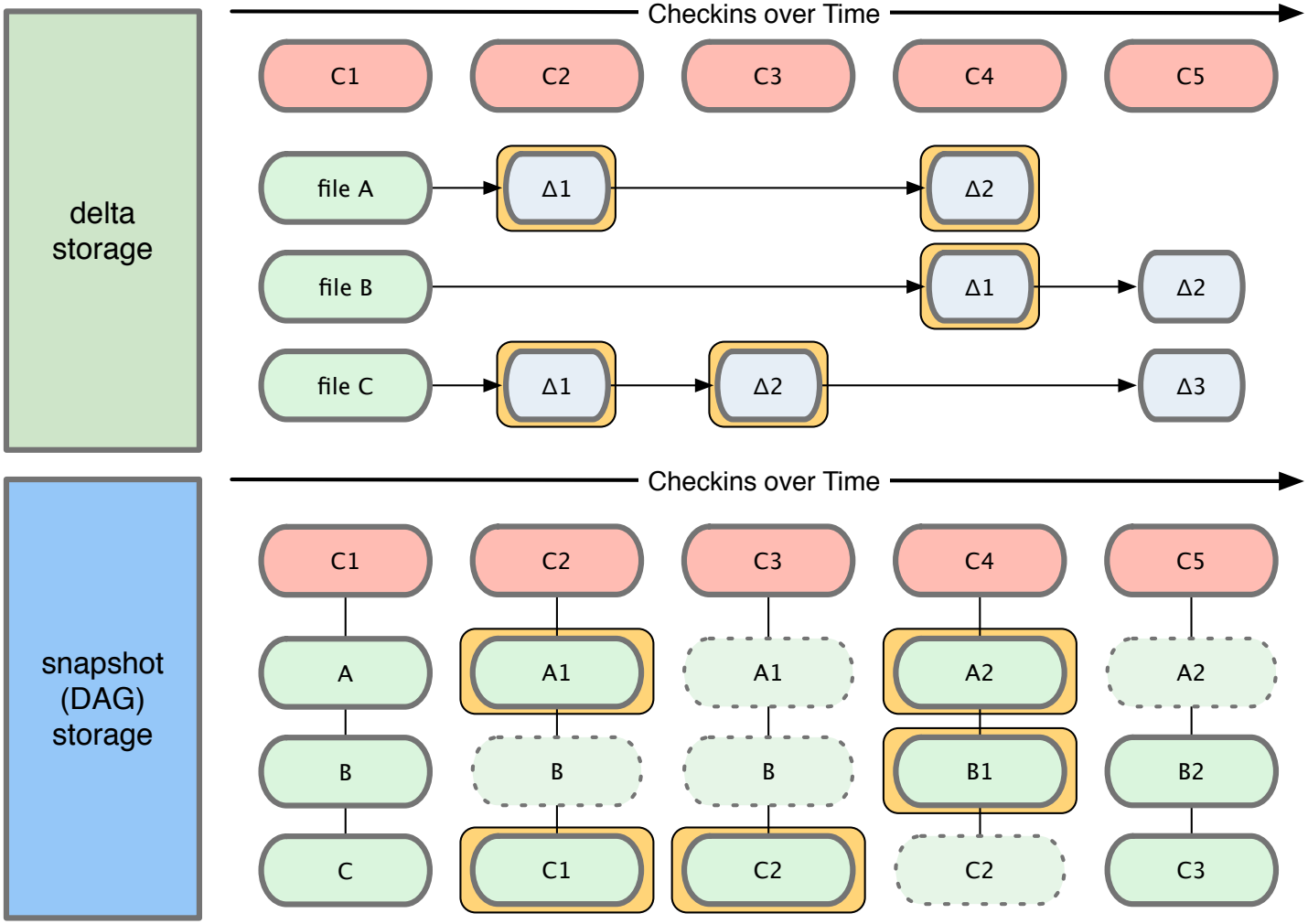

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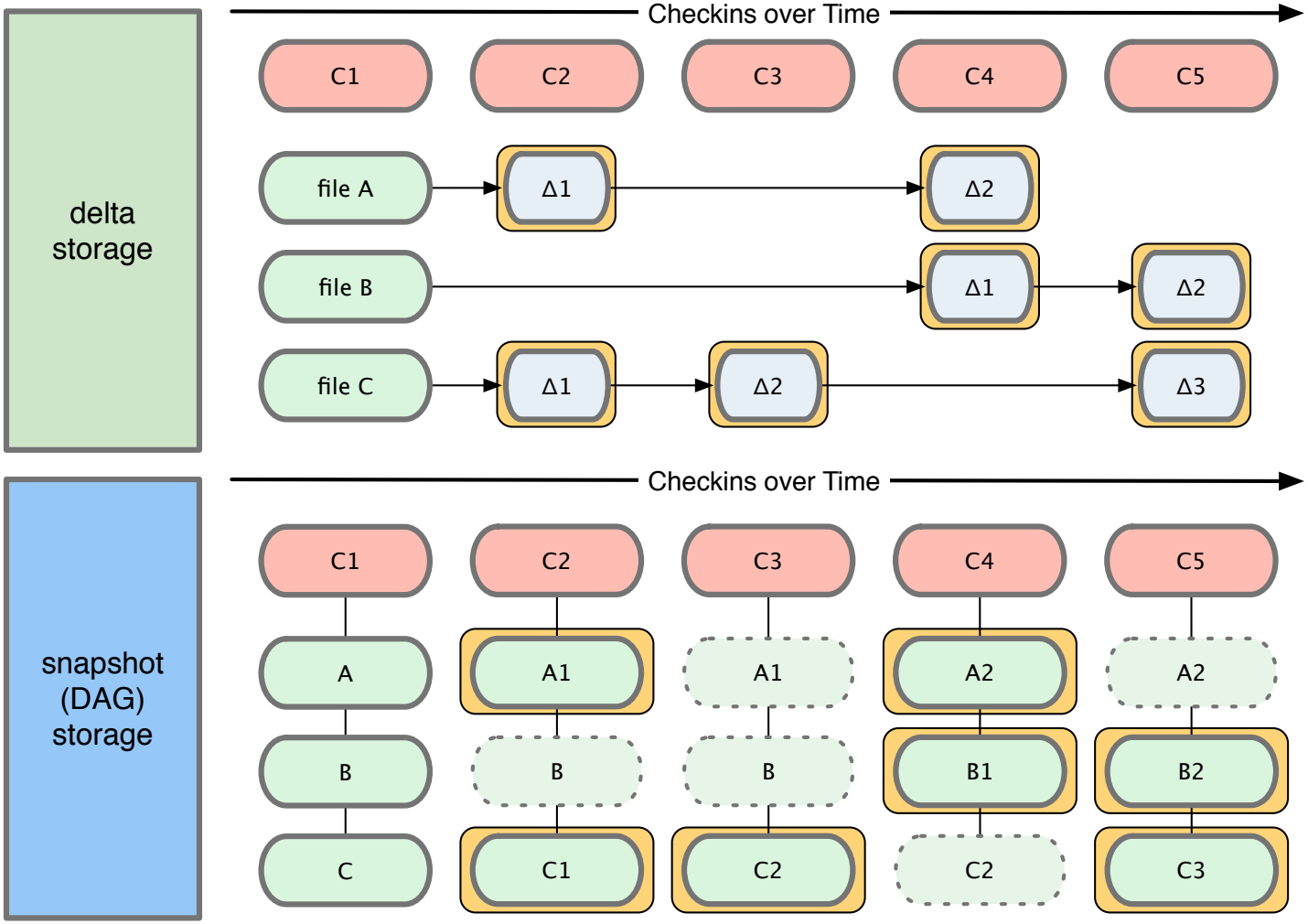
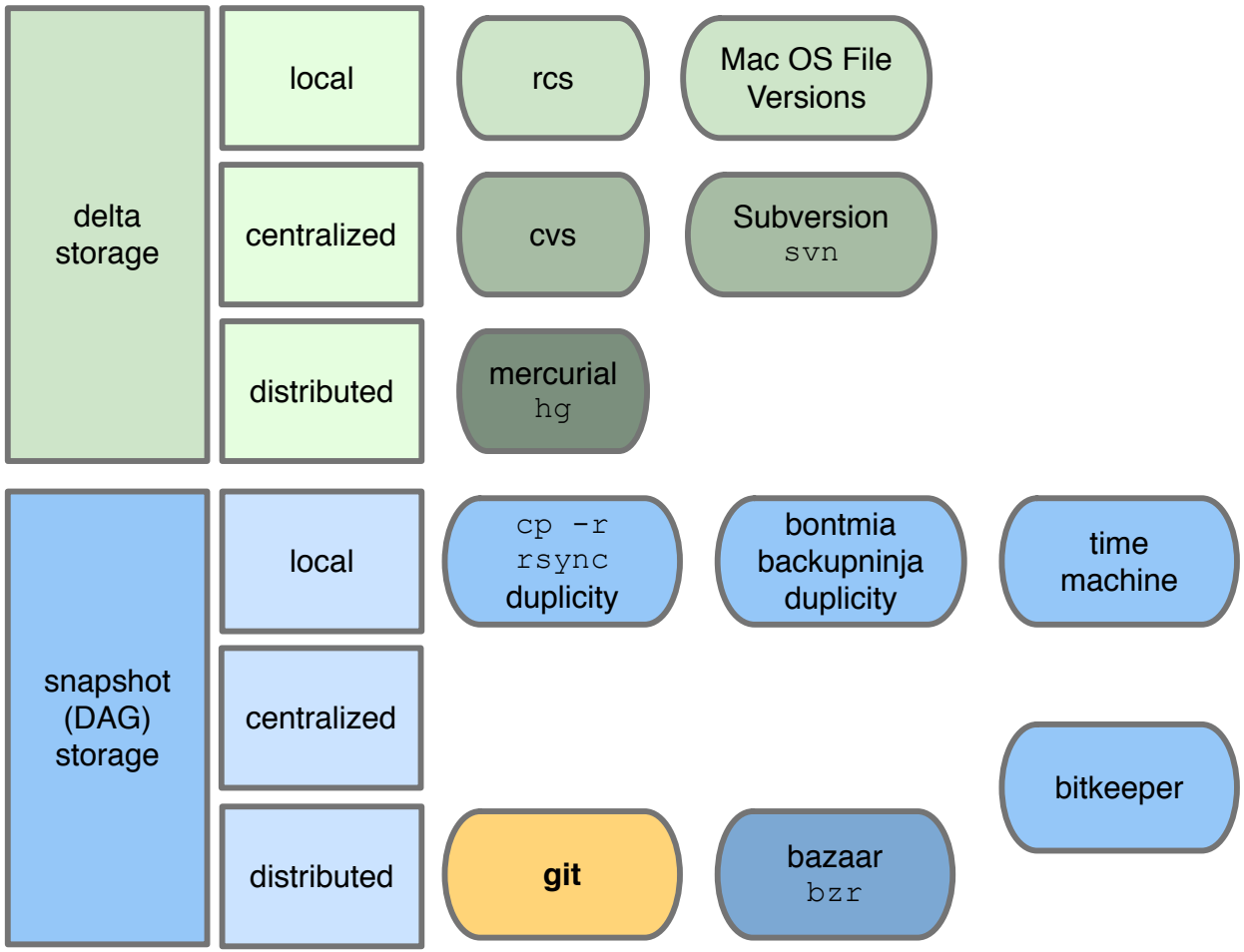


VCS Taxonomy



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 — `git pull`
- **Edit** files — `vim` / `emacs` / `subl` ...
- **Stage** the changes — `git add`
- **Review** your changes — `git status`
- **Commit** the changes — `git commit`

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For cheaters: A Basicerer Workflow

- **Pull** latest changes — `git pull`
- **Edit** files — `vim` / `emacs` / `subl` ...
- Stage & commit all the changes — `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

Summary

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

ulhpc-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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- All clients R&W requests go through the global master node.
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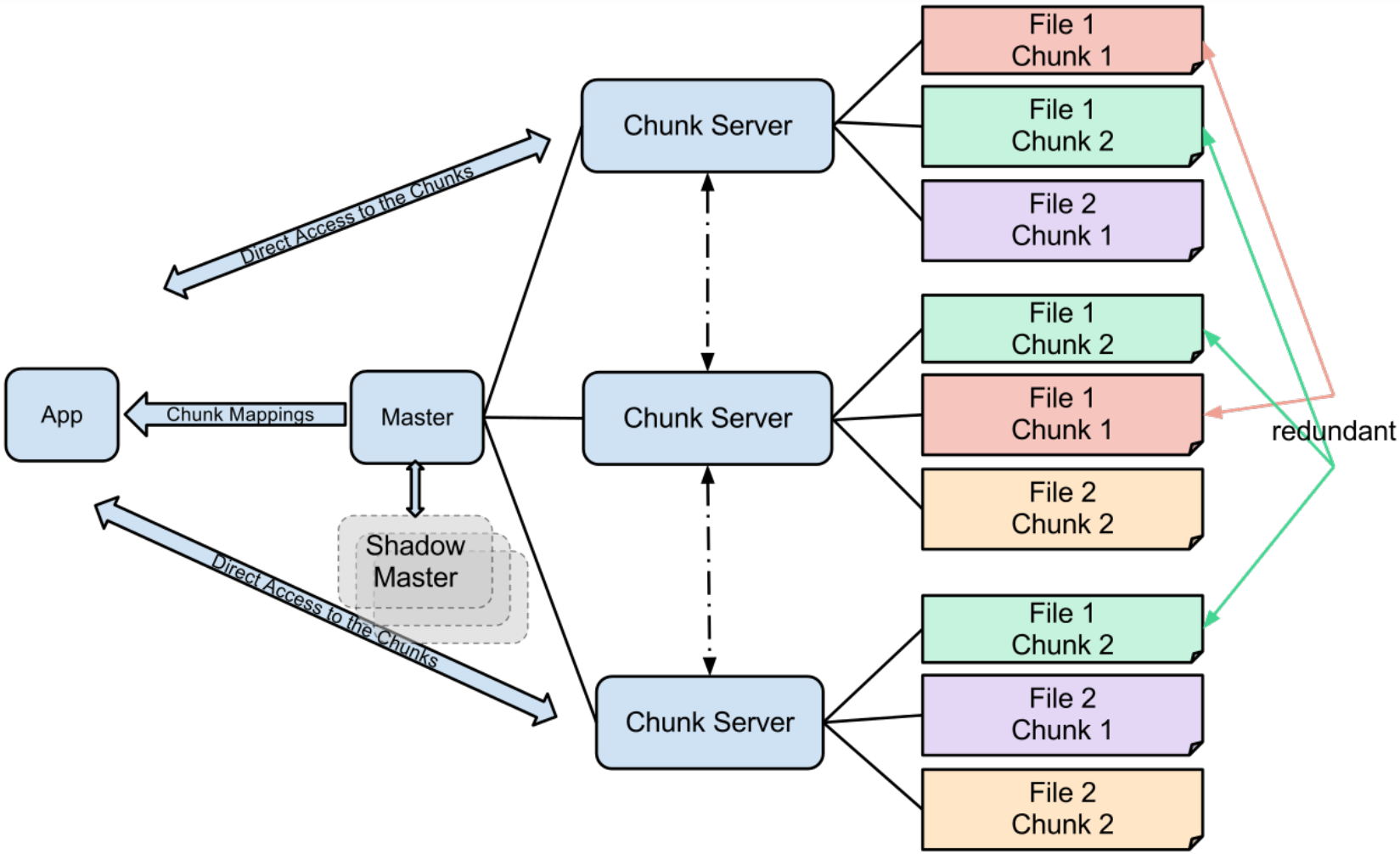
Peer-to-Peer Pattern

- 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

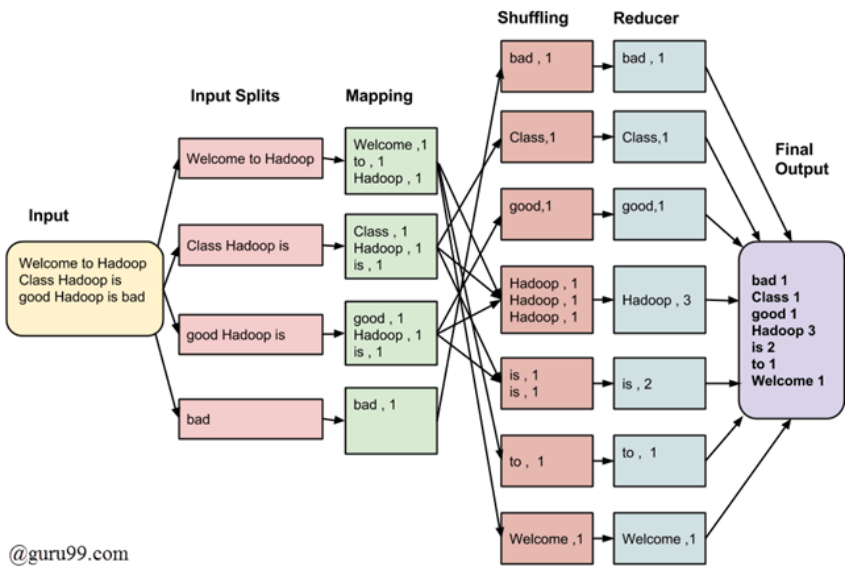
- **Atomic File Namespace Mutations**
  - ↪ File creations/deletions centrally controlled by the master node.
  - ↪ Clients typically create and write entire file,
    - ✓ then add the file name to the file namespace stored at the master.
- **Atomic Data Mutations**
  - ↪ only 1 atomic modification of 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



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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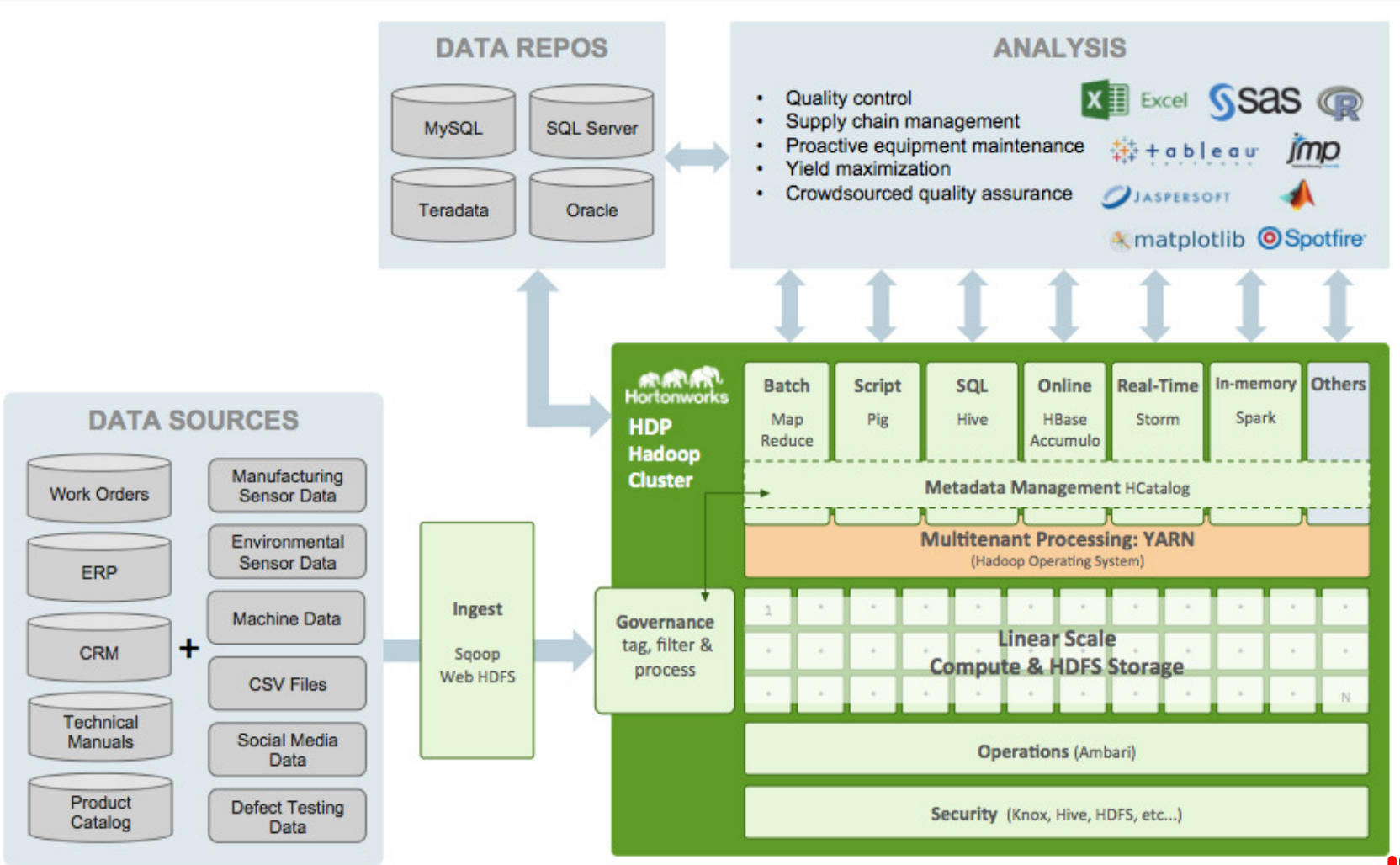
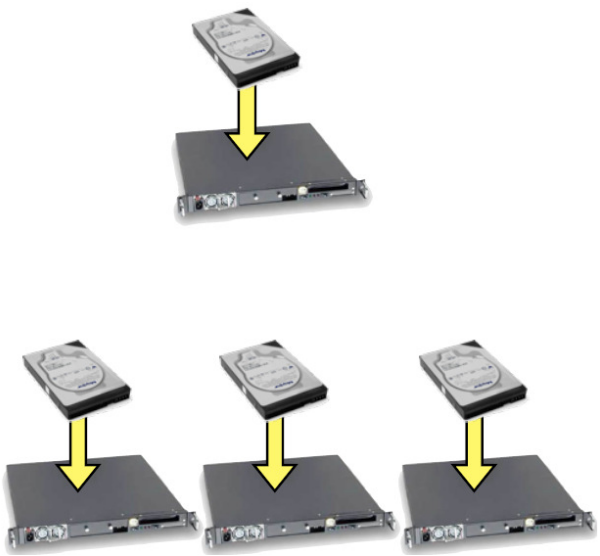
  1. **HDFS**: Hadoop distributed file system
  2. **YARN**: Hadoop job scheduling and resource allocation
  3. **MapReduce**: Hadoop adaptation of the MapReduce principle
- Basis for many other open-source Apache toolkits:
  - ↪ **PIG/PigLatin**: file-oriented data storage & script-based query language
  - ↪ **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

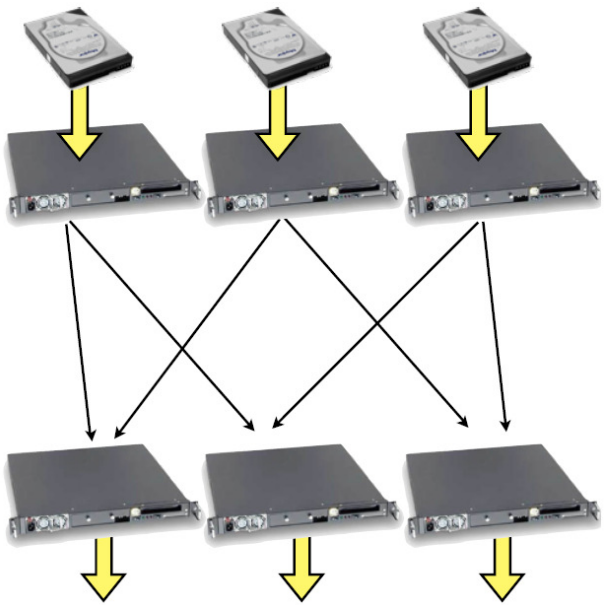


Scale-Out Design



- 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

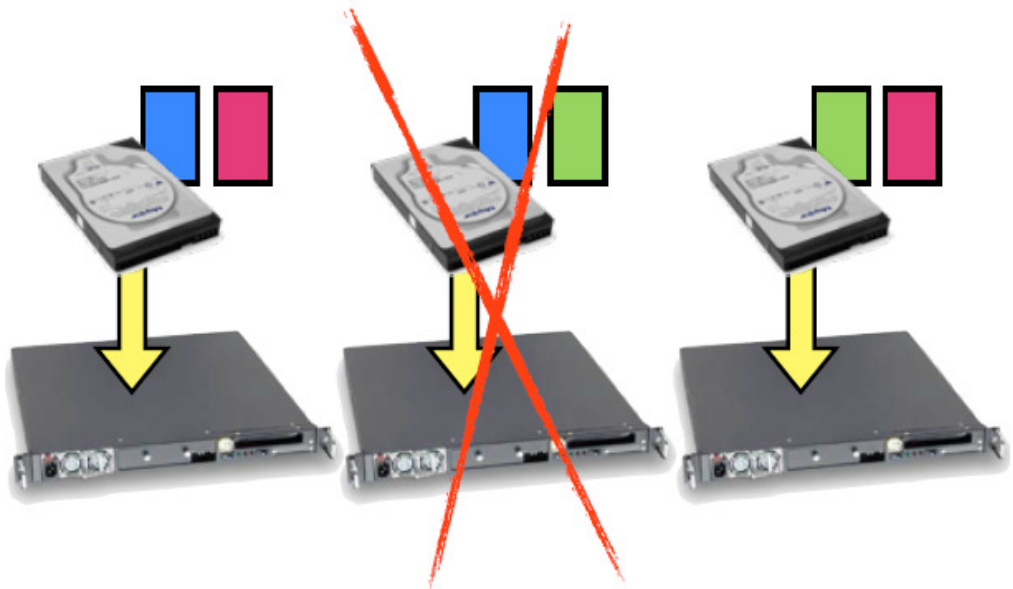
Combining Results



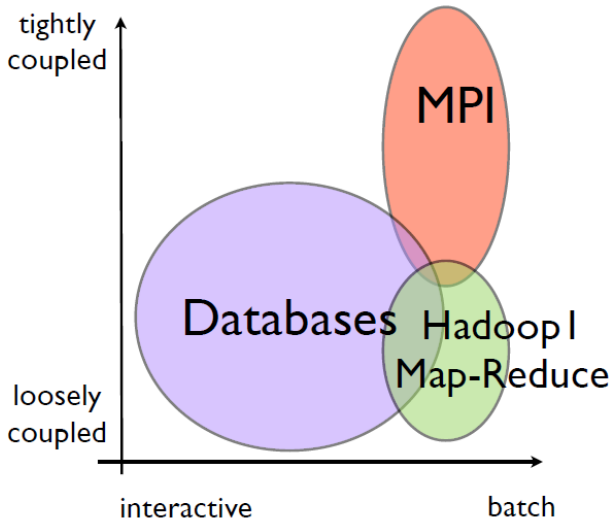
- Each node preprocesses its local data
  - ↪ Shuffles its data to a small number of other nodes
- Final processing, output is done there

Fault Tolerance

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

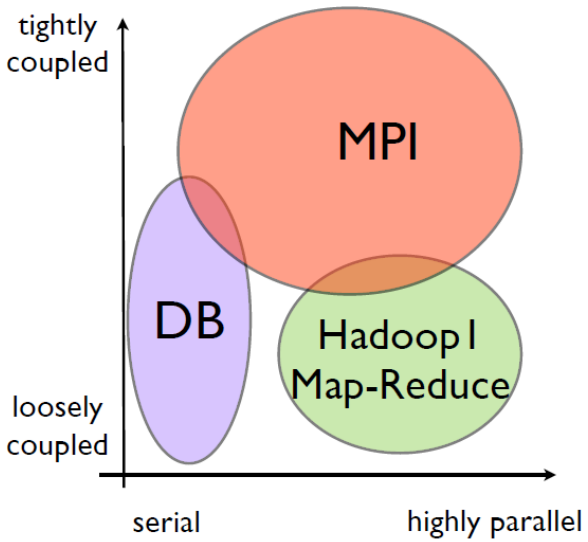


Hadoop: What is it Good At?



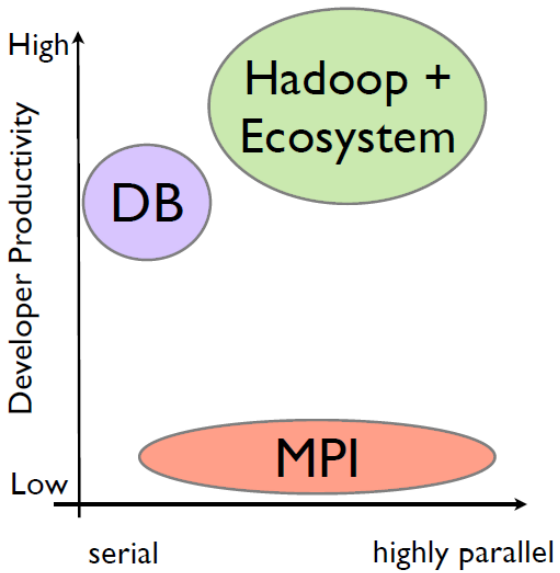
- **Classic Hadoop 1.x is all about batch processing** of massive amounts of data
  - ↪ Not much point below ~1TB
- Map-Reduce is relatively loosely coupled;
  - ↪ one **shuffle** phase.
- Very strong weak scaling in this model
  - ↪ more data, more nodes.
- **Batch**:
  - ↪ process all data in one go
    - ✓ 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:
  - ↪ zillions of iterations/timesteps/ exchanges.

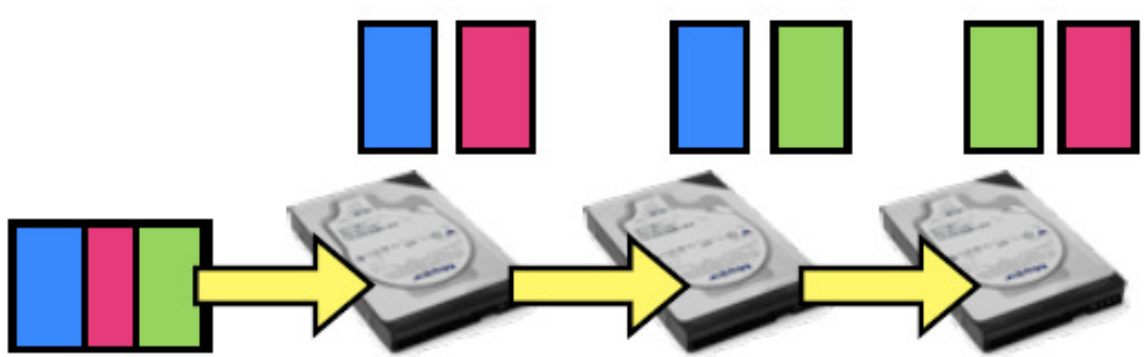
Hadoop vs HPC



- 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? Ooooooooh*
- **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...

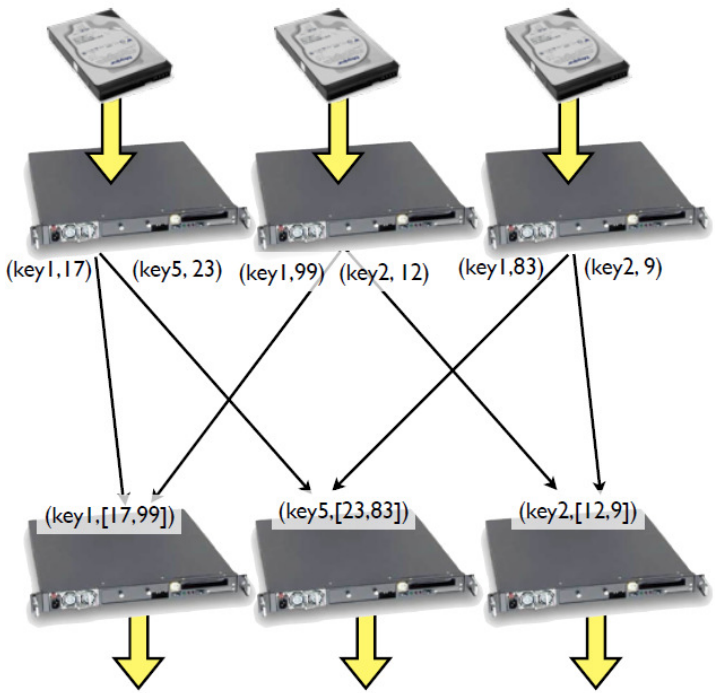
Data Distribution: Disk

- 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



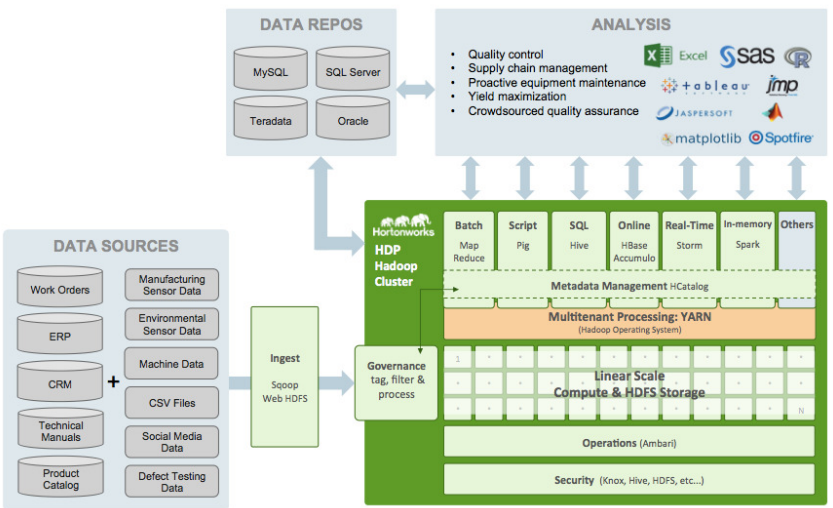
Makes the problem easier

- **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.

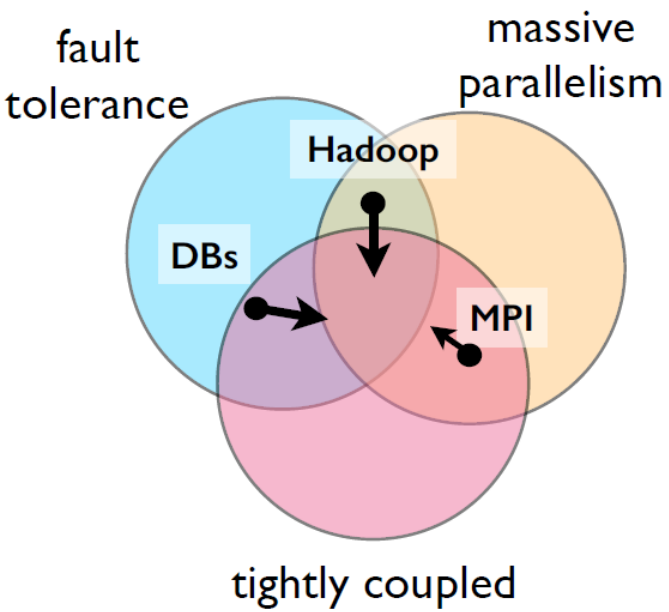
Built a reusable substrate

- 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 programatic 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

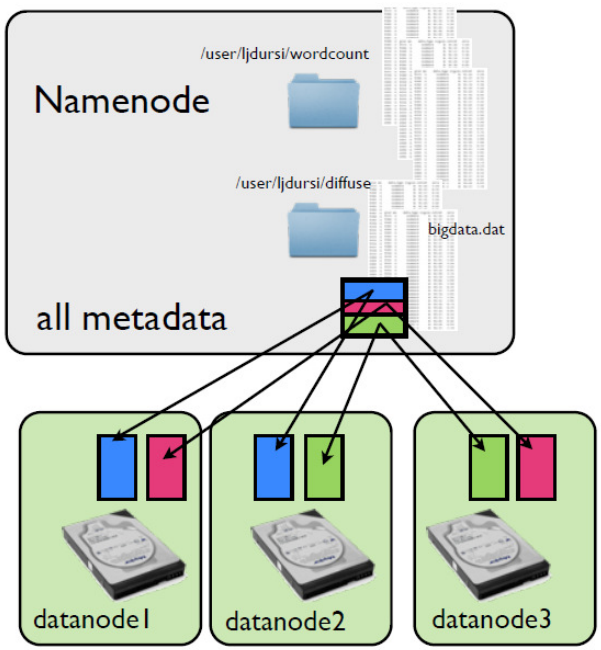
- **Required** to be:
  - ↪ able to deal with large files, large amounts of data
  - ↪ scalable & reliable in the presence of failures
  - ↪ fast at reading contiguous streams of data
  - ↪ only need to write to new files or append to files
  - ↪ require only commodity hardware
- **As a result**:
  - ↪ 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 zillions 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

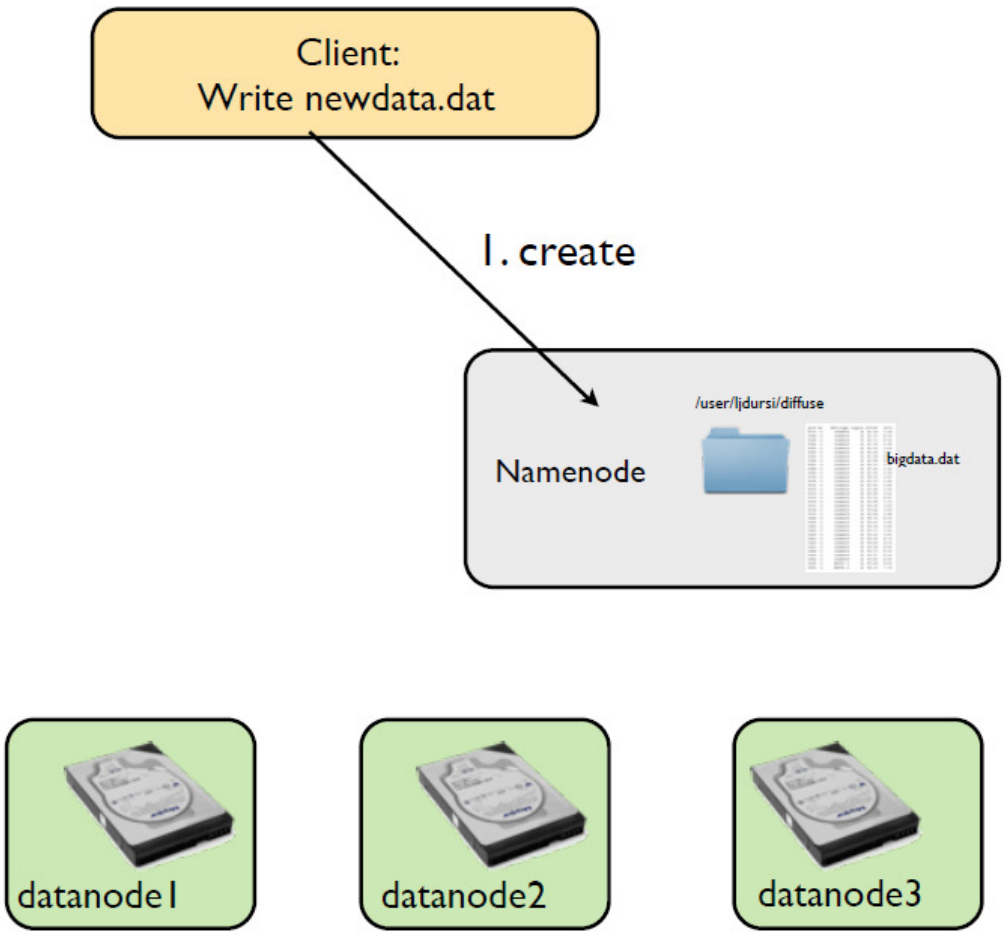


Two types of nodes in the filesystem:

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

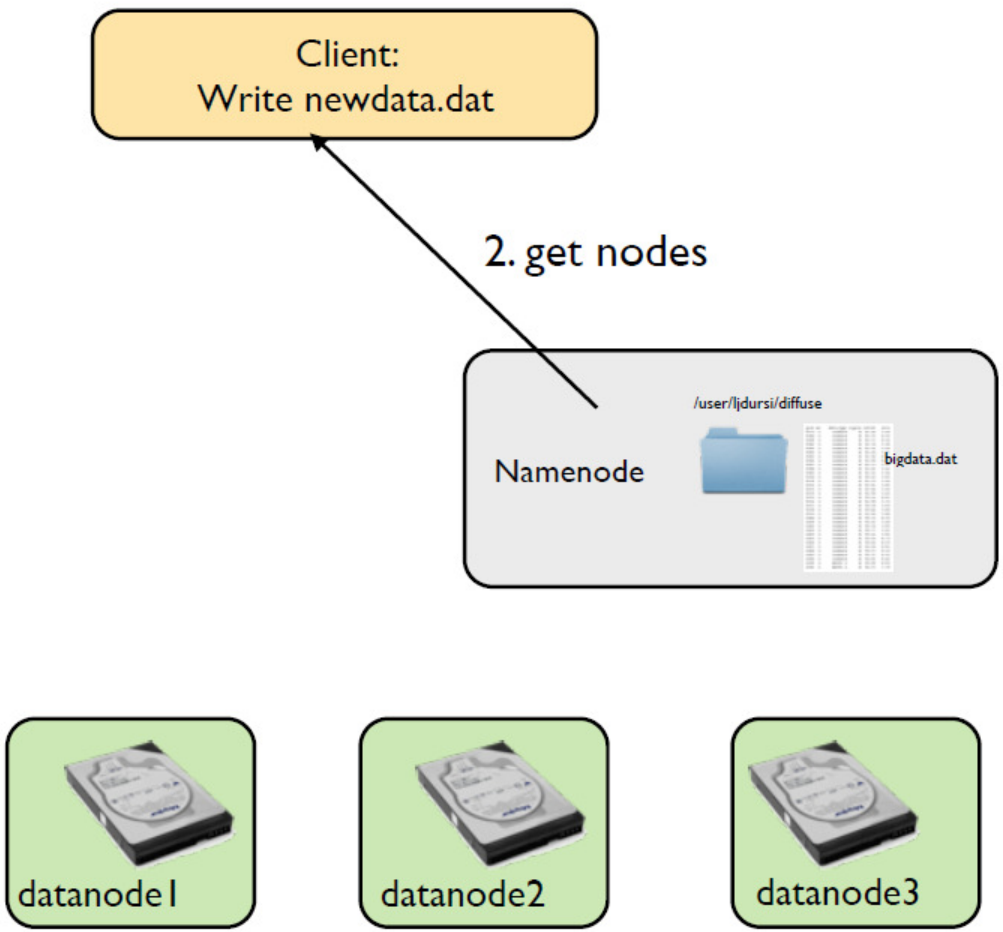
- Newer versions of Hadoop: federation
  - ↪ $\neq$ namenodes for `/user`, `/data`...
  - ↪ High Availability namenode pairs

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

Writing a file



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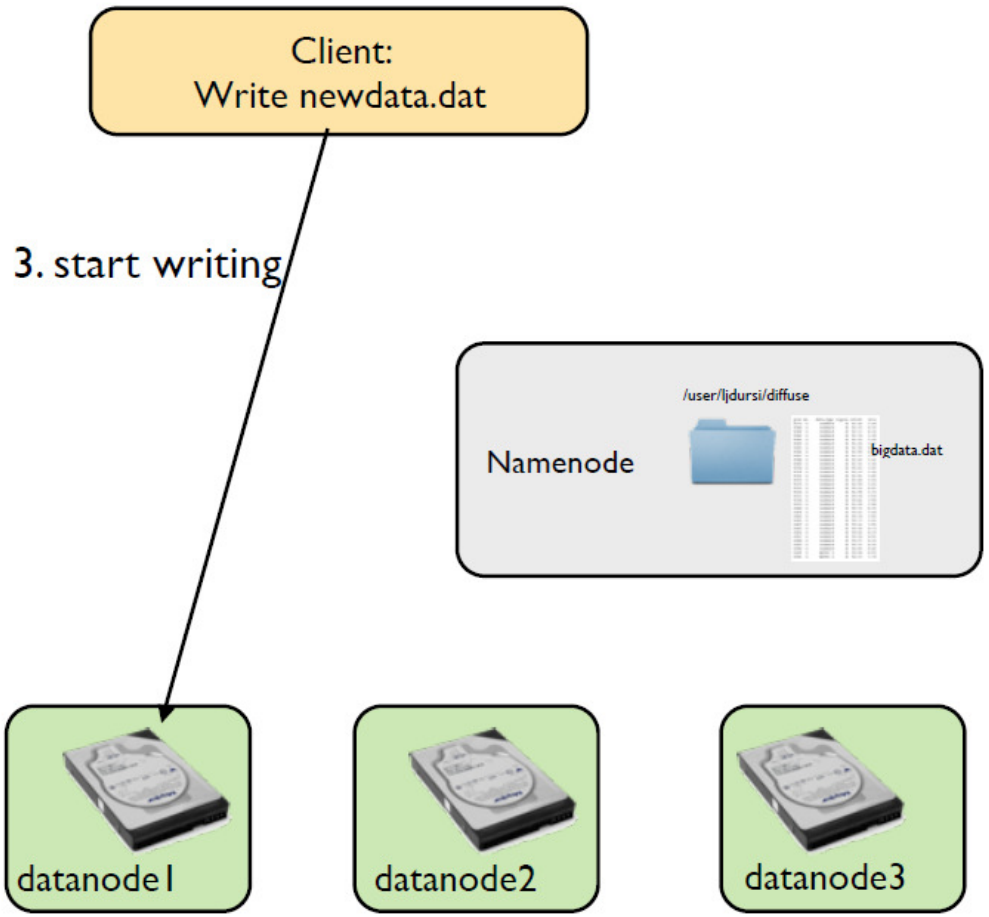

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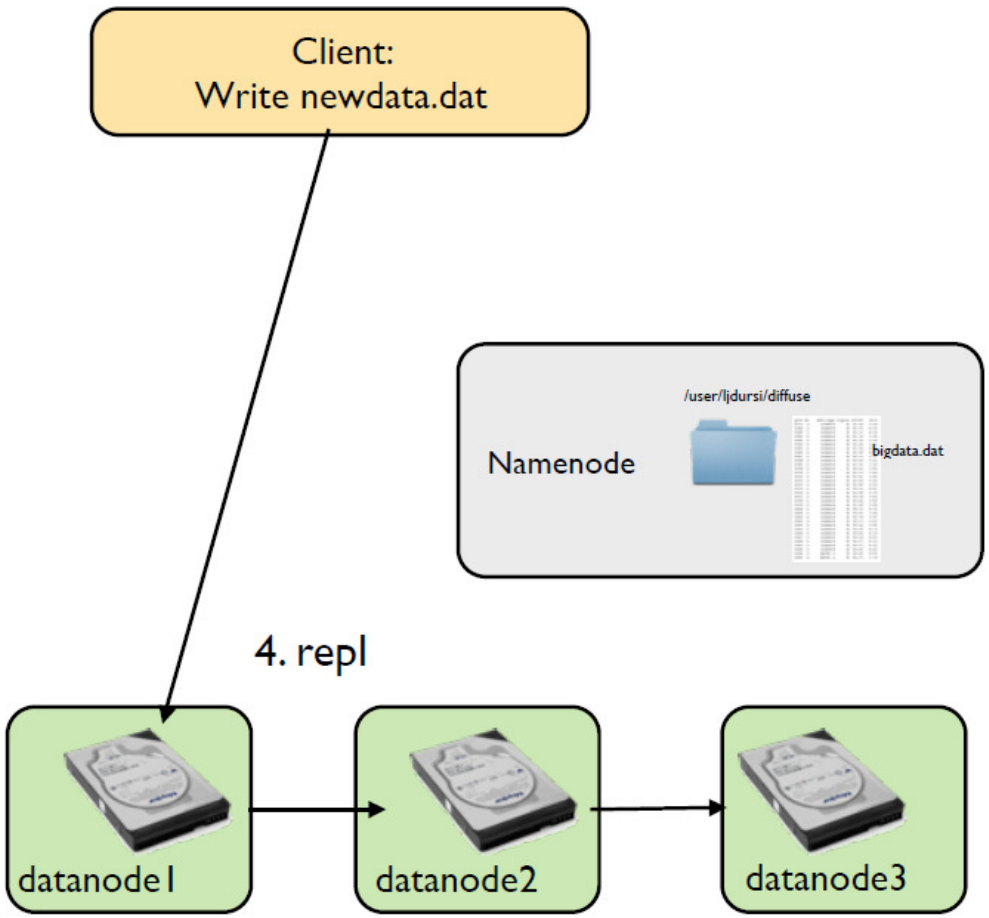

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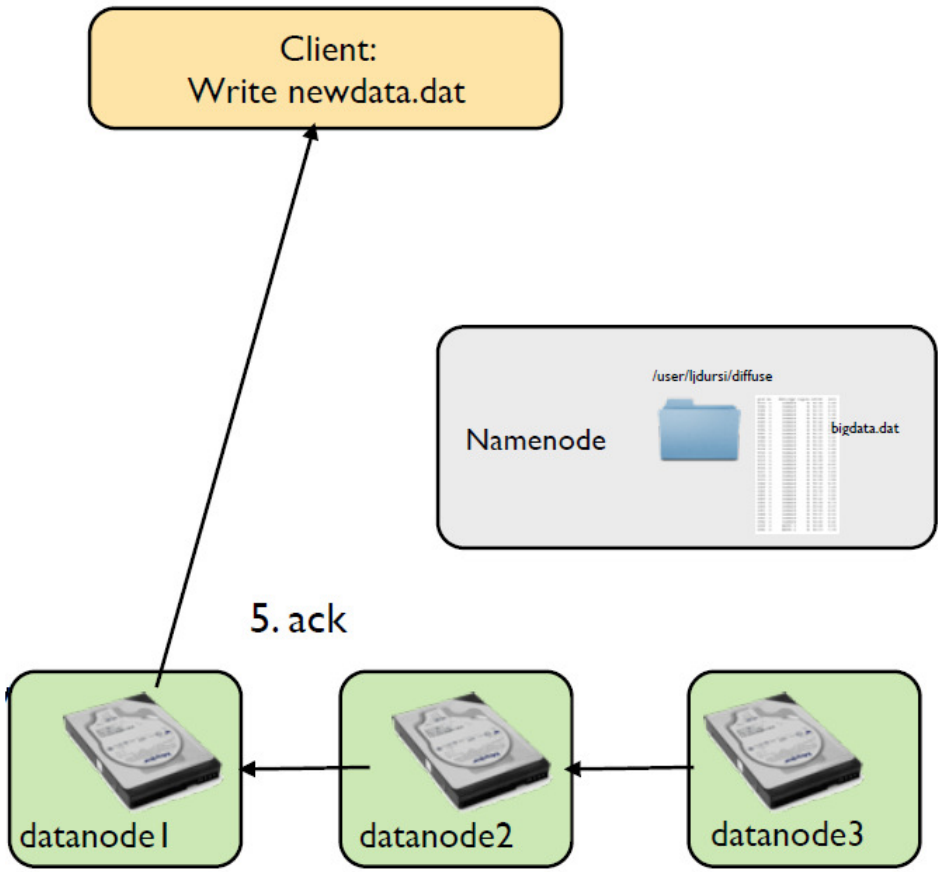

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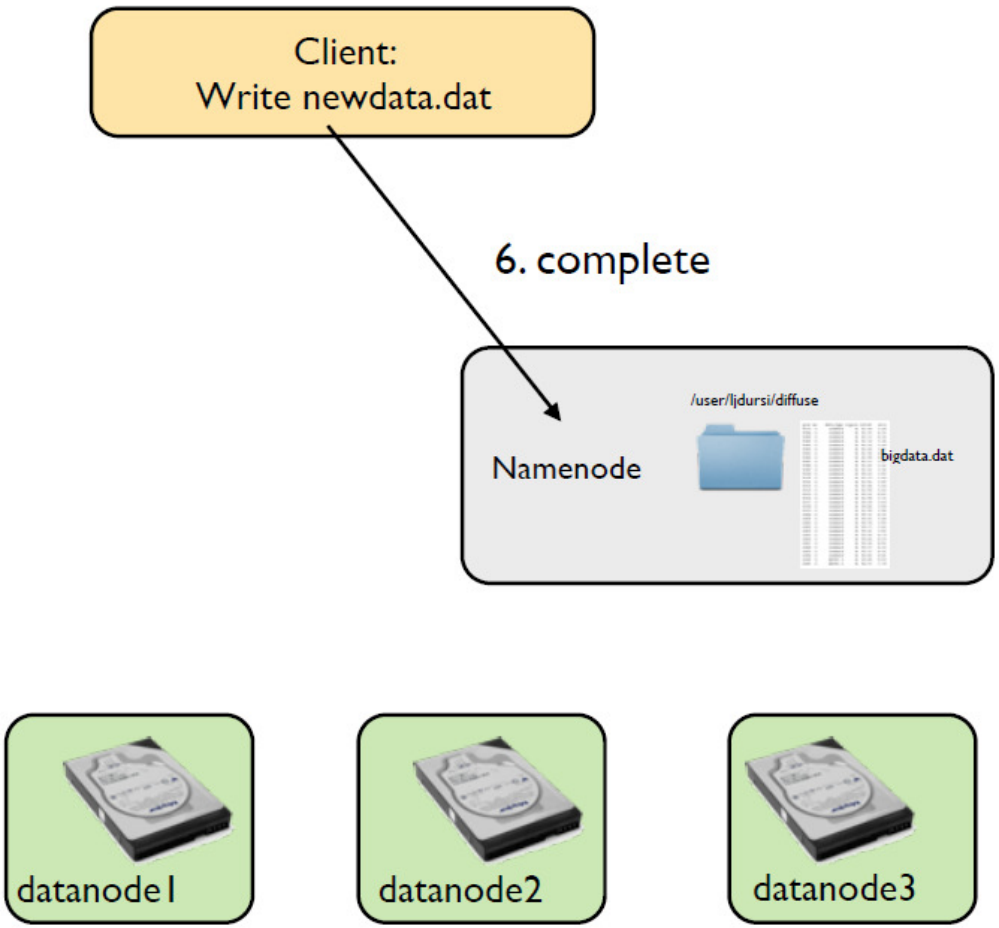

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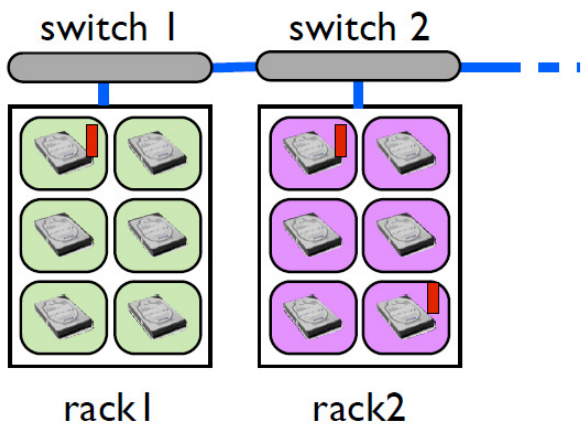
  - ↪ Complete

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



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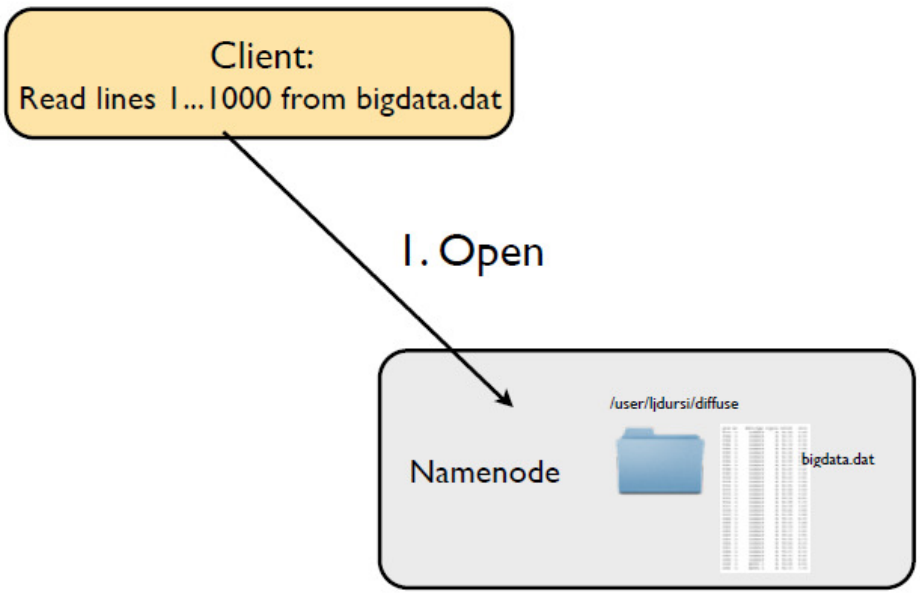

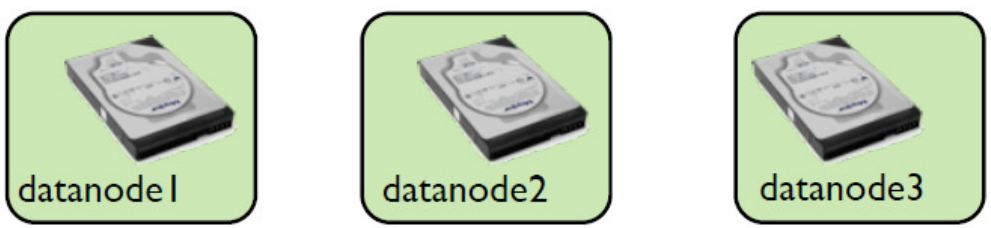

- **Reading** a file
  - ↪ Open call
  - ↪ Get block locations
  - ↪ Read from a replica

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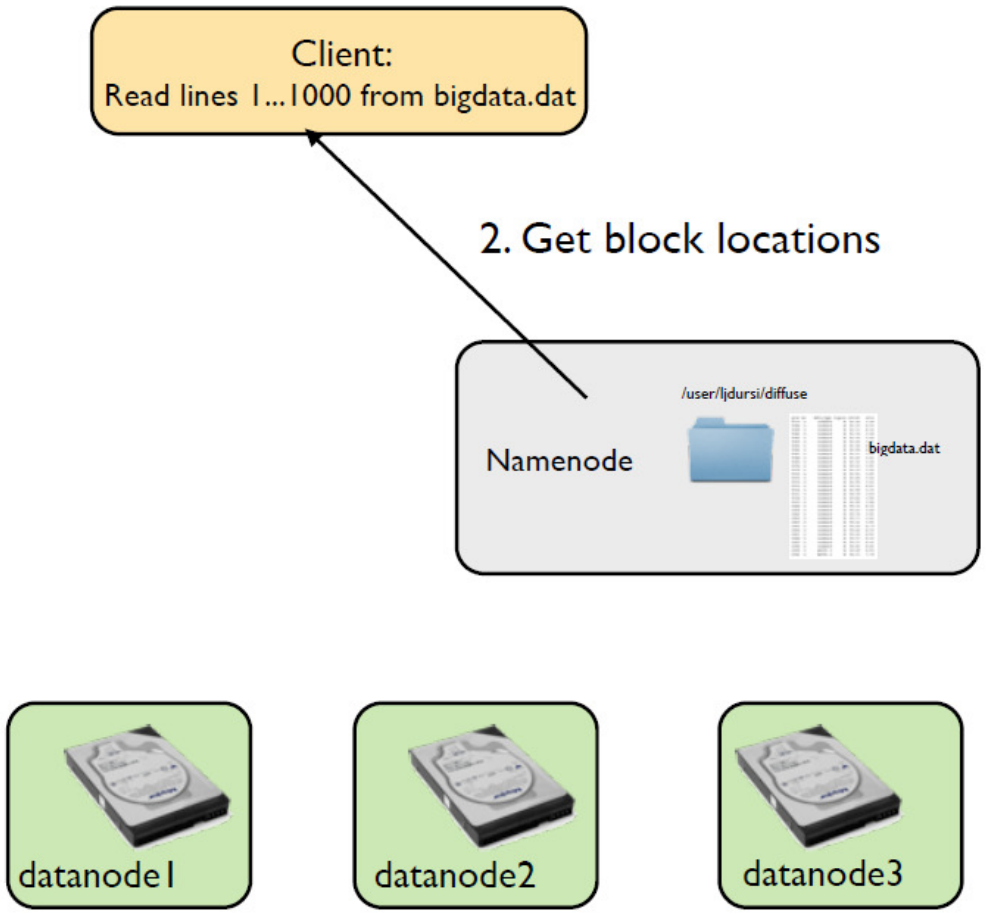

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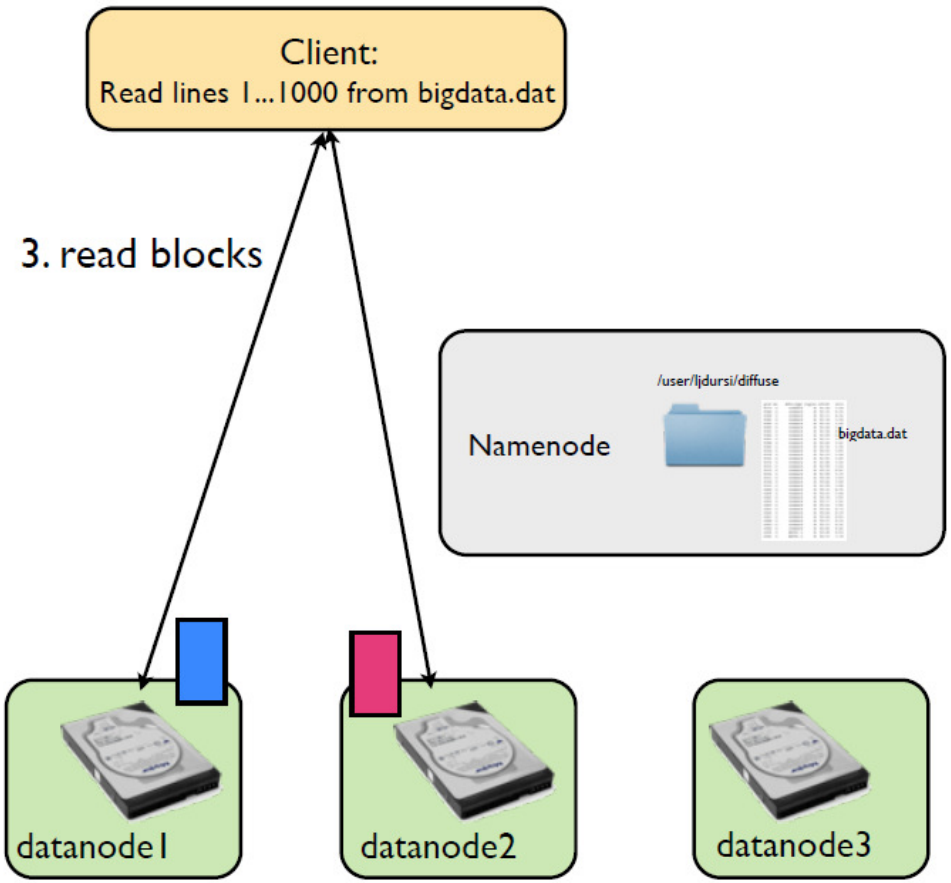

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Configuring HDFS

- 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

```
<!-- $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 accross all nodes
- You can then start processes on various FS nodes

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  - ↪ path to Java, path to Hadoop...
  - ↪ Easybuild does **most** of the job for you
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- 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} [...]
```

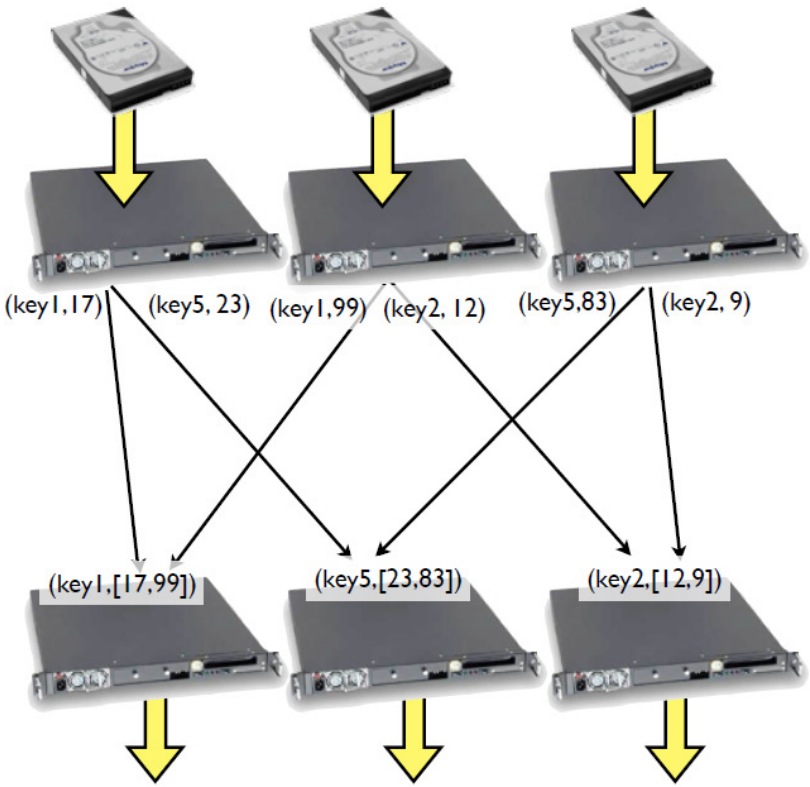
- Default directory is /user/${username}
  - ↪ **Nothing like a cd**

```
$> 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

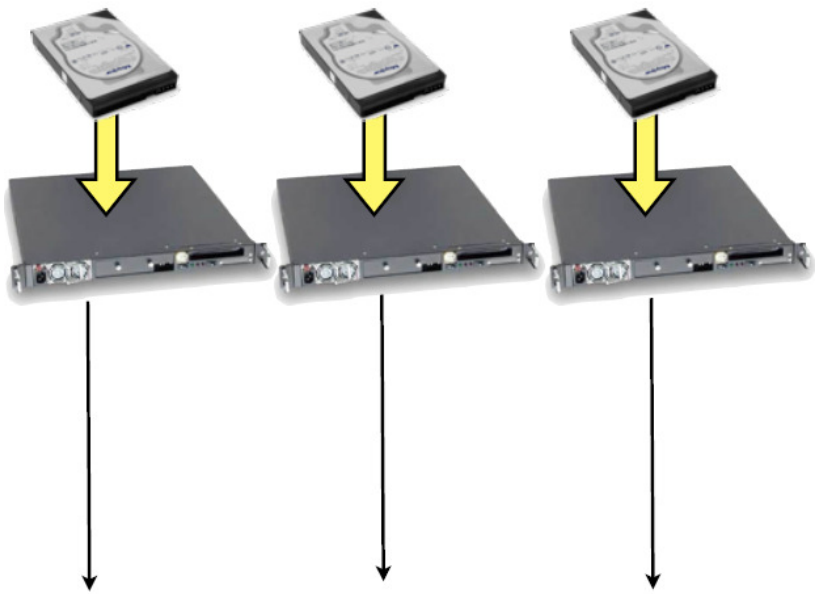
- In general, the data files you send to HDFS will be **large**
  - ↪ or else why bother with Hadoop.
- Do not want to be constantly copying back and forth
  - ↪ **view, append *in place***
- Several APIs to accessing the HDFS
  - ↪ Java, C++, Python
- Here, we use one to get a file status, and read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

Back to Map-Reduce



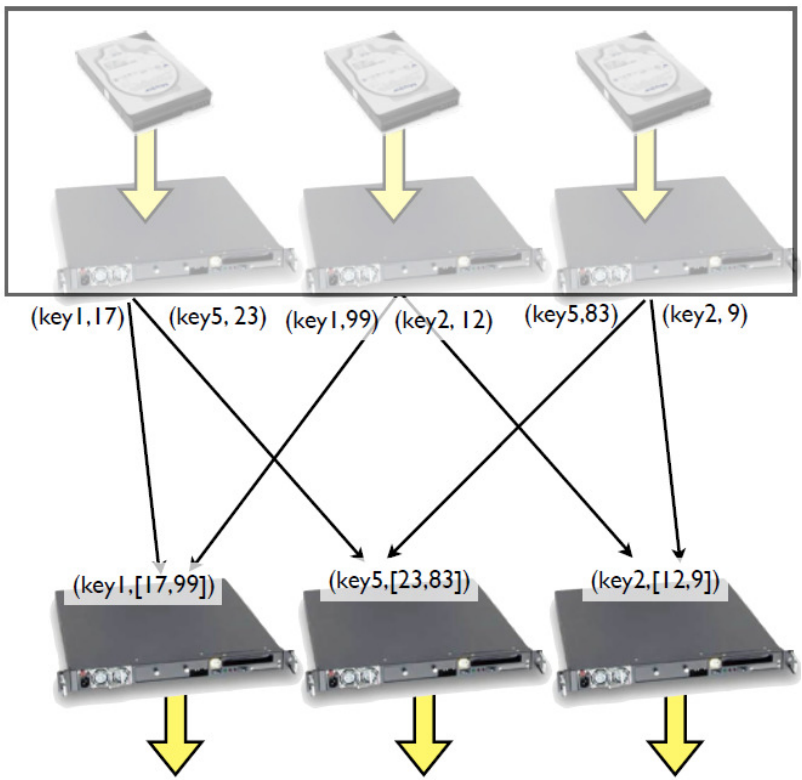
- Map processes **one element at a time**
  - ↪ emits results as (key, value) pairs.
- All results with **same key are gathered to the same reducers**
  - ↪ Reducers process list of values
  - ↪ emit results as (key, value) pairs

Map



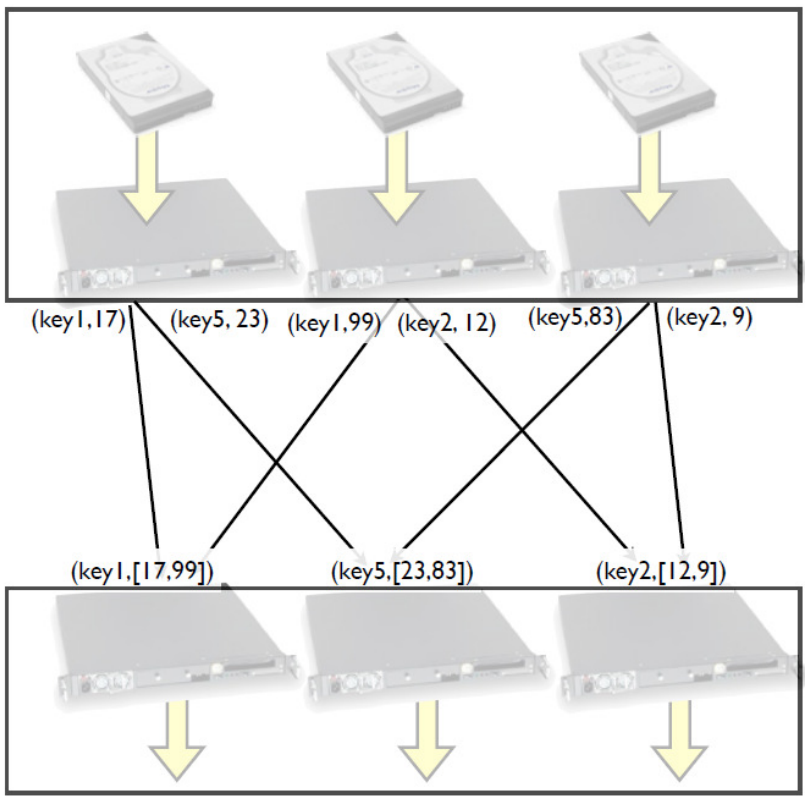
- All coupling done during **shuffle** phase
  - ↪ Embarrassingly parallel task
  - ↪ all map
- Take input, map it to output, done.
- **Famous case**
  - ↪ NYT using Hadoop to convert 11 million image files to PDFs
    - ✓ almost pure serial farm job

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

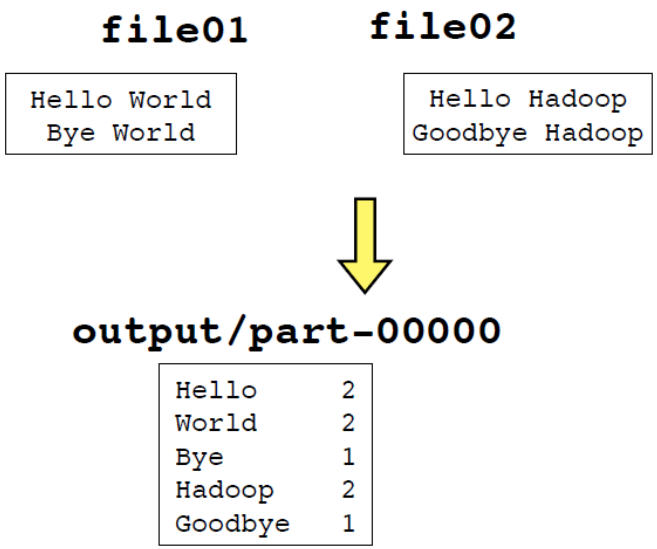


- **shuffle is part of the Hadoop magic**
  - ↪ By default, keys are hashed
  - ↪ hash space is partitioned between reducers
- On **reducer**:
  - ↪ gathered (k,v) pairs from mappers are sorted by key,
  - ↪ then merged together by key
  - ↪ Reducer then runs on one (k,[v]) tuple at a time
- you can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

Example: Wordcount

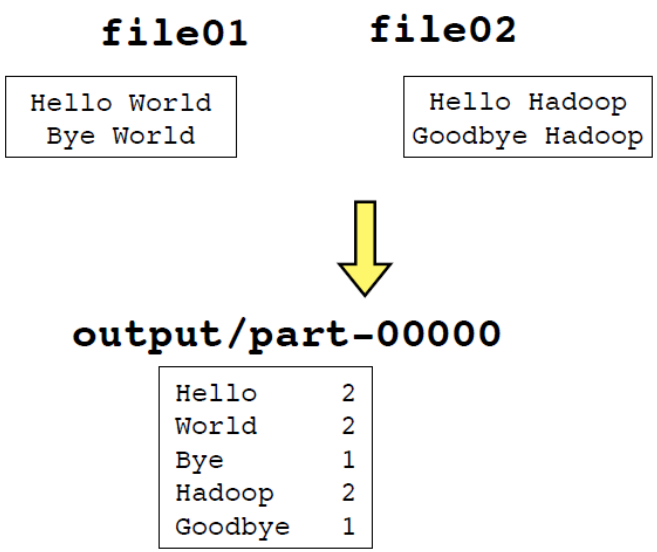
- Was used as an example in the original MapReduce paper
  - ↪ Now basically the **hello world** of map reduce

- **Problem description**: Given a **set** of documents:
  - ↪ **count 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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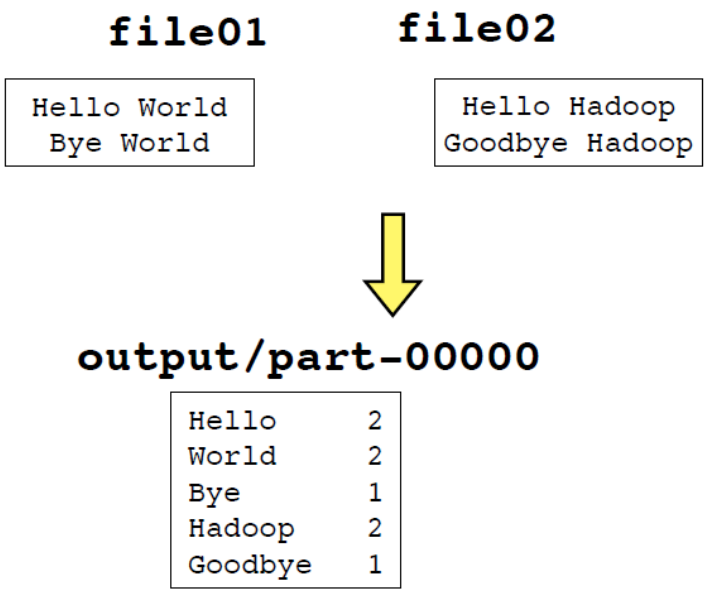

- **MapReduce way**
  - ↪ all hard work done automatically by shuffle
- **Map**:
  - ↪ just emit a 1 for each word you see
- **Shuffle**:
  - ↪ assigns keys (words) to each reducer,
  - ↪ sends (k,v) pairs to appropriate reducer
- **Reducer**
  - ↪ just has to sum up the ones

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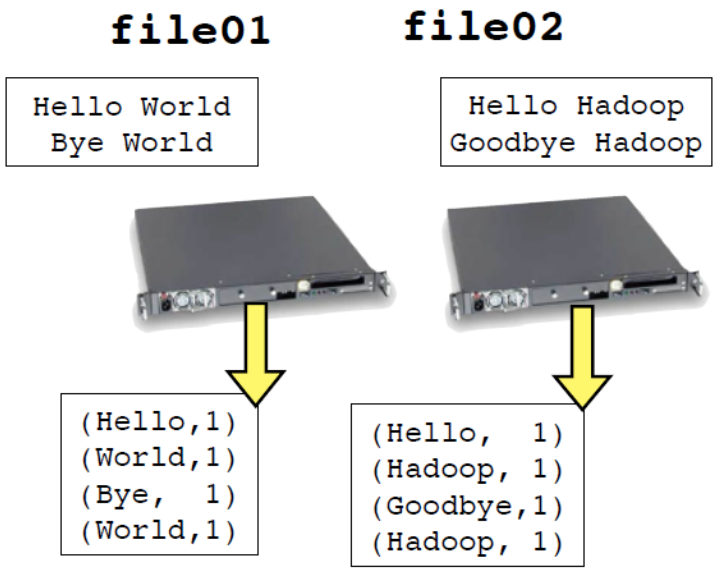

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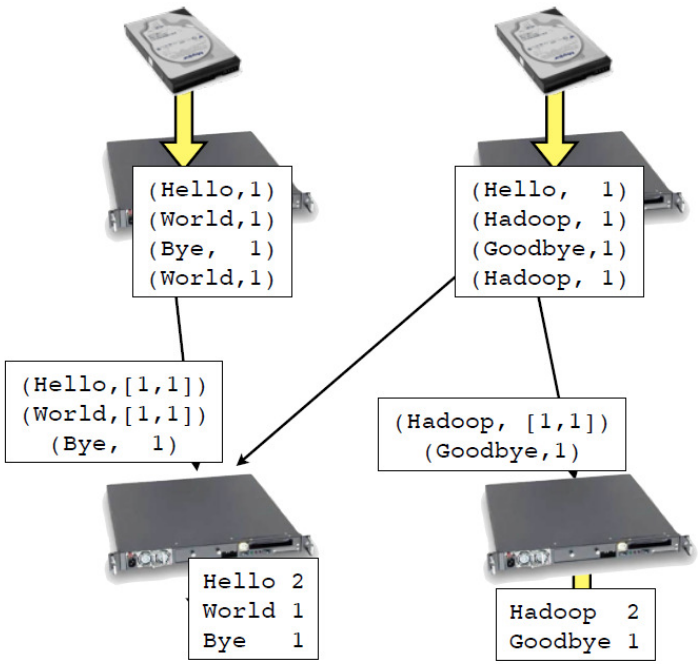

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Hands-on 3: Playing with Hadoop

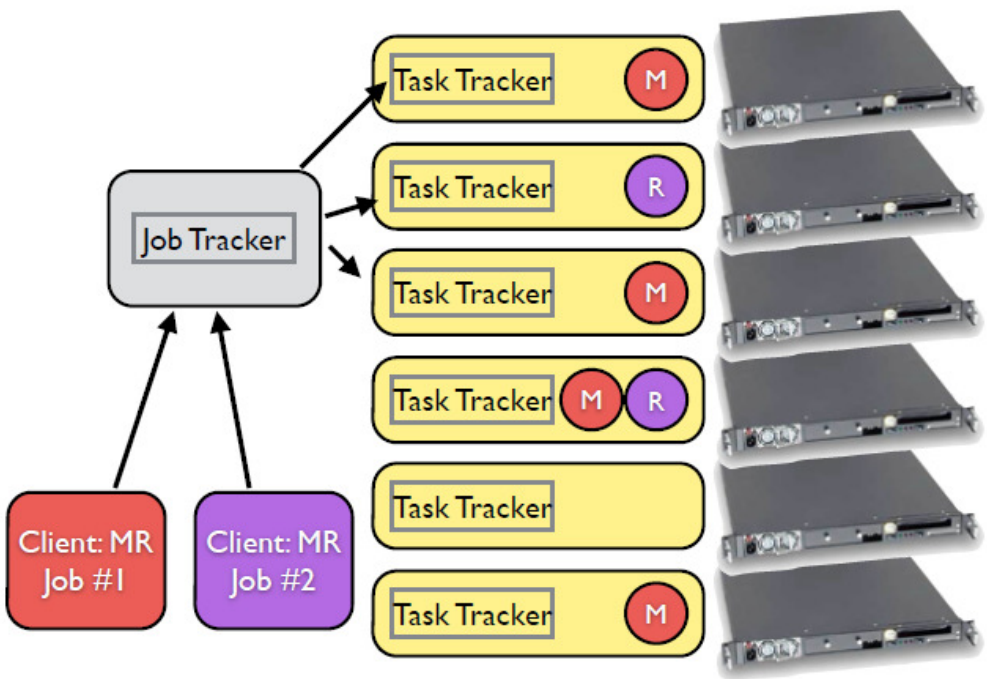
Hands-on 3

ulhpc-tutorials.rtfd.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

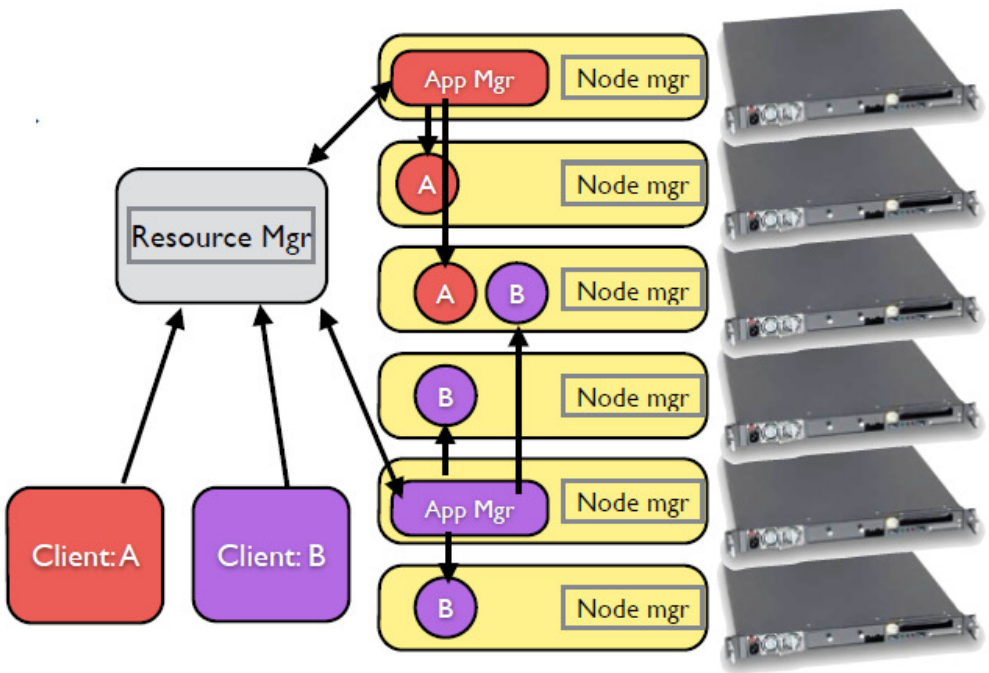
Hadoop 0.1x

- 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)**.

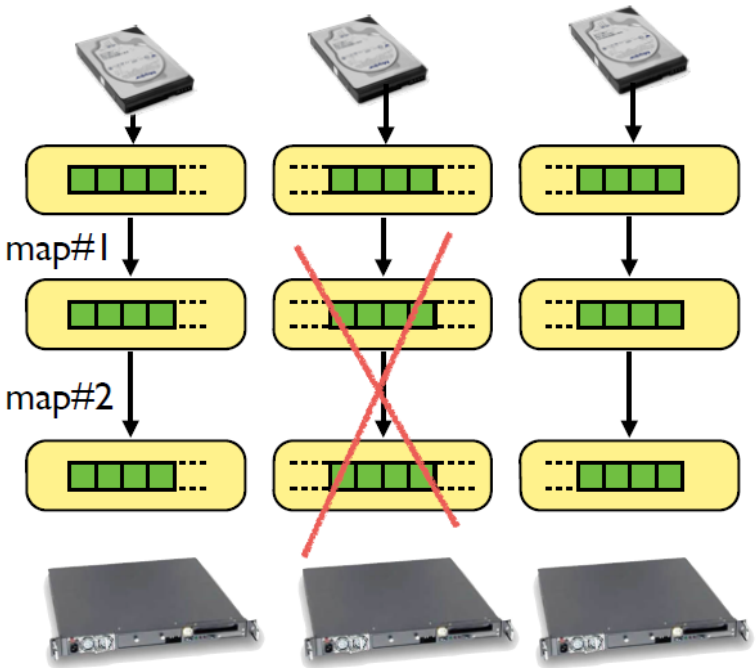
Apache Spark

- 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)
  - ↪ 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

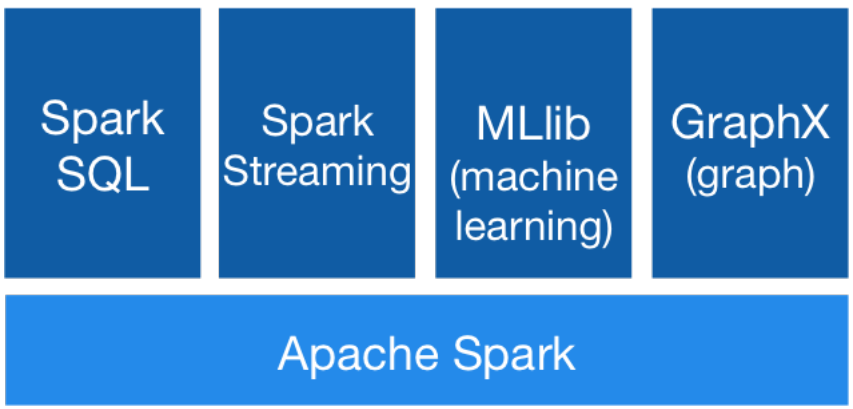
RDD Lineage

- 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

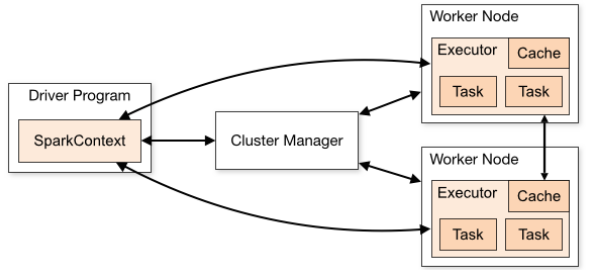
- **Solution**:
  - ↪ Record lineage of an RDD (think version control)
  - ↪ If container, node goes down, reconstruct RDD from scratch
    - ✓ Either from beginning,
    - ✓ or from (occasional) checkpoints which user has some control over.
  - ↪ User can suggest caching current state of RDD in memory,
    - ✓ 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** — Step 4.2
  - ↪ **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)
  - ↪ prepare a **launcher script**

Questions?

http://hpc.uni.lu

High Performance Computing @ uni.lu

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