Big Data Analytics

3rd NESUS Winter School on Data Science & Heterogeneous Computing

Sébastien Varrette, PhD

Parallel Computing and Optimization Group (PCOG),
University of Luxembourg (UL), Luxembourg

http://nesusws-tutorials-BD-DL.rtfd.io

Before the tutorial starts: Visit
https://goo.gl/M5ABf7
for *preliminary setup instructions*!

Jan. 23th, 2018, Zagreb, Croatia

About me

https://varrette.gforge.uni.lu

- Permanent **Research Scientist** at University of Luxembourg
  - ↪ Part of the PCOG Team led by Prof. P. Bouvry since 2007
  - ↪ **Research interests**:
    - ✓ High Performance Computing
    - ✓ Security (crash/cheating faults, obfuscation, blockchains)
    - ✓ Performance of HPC/Cloud/IoT platforms and services

- Manager of the UL HPC Facility with Prof. P. Bouvry since 2007
  - ↪ $\simeq$ 206.772 **T**Flops (2017), 7952.4 **T**B
  - ↪ expert UL HPC team *(S. Varrette, V. Plugaru, S. Peter, H. Cartiaux, C. Parisot)*
- National / EU HPC projects:
  - ↪ ETP4HPC, EU COST NESUS...
  - ↪ PRACE[2] (acting Advisor)
  - ↪ EuroHPC / IPCEI on HPC and Big Data (BD) Applications

Welcome!

- 3rd NESUS WS on Data Science & Heterogeneous Computing

In this session: Tutorial on Big Data Analytics

- Focus on **practicals tools** rather than theoretical content
- starts with **daily data management** ...
  - ↪ ... before speaking about **Big** data management
  - ↪ in particular: data transfer (over **SSH**), data versioning with **Git**
- continue with **classical tools** and their usage in HPC
  - ↪ review HPC environments and the hands-on environment
    - ✓ reviewing Environment Modules and Lmod
    - ✓ introducing Vagrant and Easybuild
  - ↪ introduction to Big Data processing engines: Hadoop, Spark
  - ↪ introduction to Tensorflow, an ML/DL processing framework

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
- the hands-on material is adapted from several resources:
  - ↪ (of course) the UL HPC School, **credits**: UL HPC team
    - ✓ S. Varrette, V. Plugaru, S. Peter, H. Cartiaux, C. Parisot
  - ↪ similar Github projects:
    - ✓ Jonathan Dursi: `hadoop-for-hpcers-tutorial`

Agenda: Jan. 23th, 2018

Lecture & hands-on:
Big Data Analytics: Overview and Practical Examples

http://nesusws-tutorials-BD-DL.rtfd.io

Time	Session
09:00 - 09:30	Discover the Hands-on tool: Vagrant
09:30 - 10:00	HPC and Big Data (BD): Architectures and Trends
10:00 - 10:30	Interlude: Software Management in HPC systems
10:30 - 11:00	[Big] Data Management in HPC Environment: Overview and Challenges
11:00 - 11:15	**Coffee Break**
11:15 - 12:30	Big Data Analytics with Hadoop & Spark
12:30 - 13:00	Deep Learning Analytics with Tensorflow
13:00	**Lunch**

Summary

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Tutorial Pre-Requisites / Setup

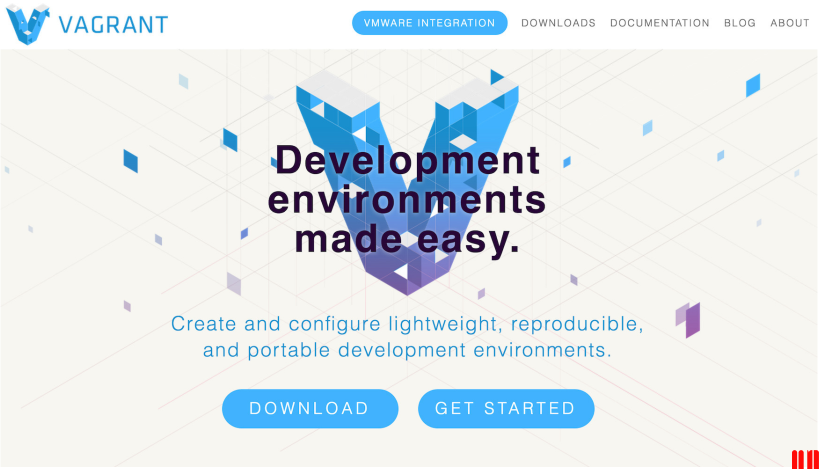
http://nesusws-tutorials-BD-DL.rtfd.io/

- Follow instructions on Getting Started / Pre-requisites
  - ↪ create (if needed) accounts: Github, Vagrant Cloud, Docker Hub
  - ↪ install **mandatory software**, *i.e.* (apart from Git):

Platform	Software	Description	Usage
Mac OS	Homebrew	The missing package manager for macOS	`brew install ...`
Mac OS	Brew Cask Plugin	Mac OS Apps install made easy	`brew cask install ...`
Mac OS	iTerm2	**(optional)** enhanced Terminal	
Windows	MobaXTERM	Terminal with tabbed SSH client	
Windows	Git for Windows	may be you guessed...	
Windows	SourceTree	**(optional)** enhanced git GUI	
Windows/Linux	Virtual Box	Free hypervisor provider for Vagrant	
Windows/Linux	Vagrant	Reproducible environments made easy.	
Linux	Docker for Ubuntu	Lightweight Reproducible Containers	
Windows	Docker for Windows	Lightweight Reproducible Containers	

Discover the Hands-on Tool: Vagrant

http://vagrantup.com/



What is Vagrant ?

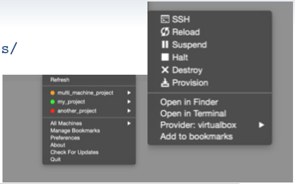
Create and configure **lightweight**, **reproducible**, and **portable** development environments

- **Command line** tool `vagrant [...]`
- Easy and Automatic per-project VM management
  - ↪ Supports many hypervisors: VirtualBox, VMWare...
  - ↪ Easy text-based configuration (Ruby syntax) `Vagrantfile`
- Supports **provisioning** through configuration management tools
  - ↪ Shell
  - ↪ Puppet https://puppet.com/
  - ↪ Salt... https://saltstack.com/

Cross-platform: runs on Linux, Windows, MacOS

Installation Notes

http://nesusws-tutorials-BD-DL.rtfd.io/en/latest/setup/preliminaries/



- **Mac OS X**:
  - ↪ best done using Homebrew and Cask

```
$> brew install caskroom/cask/brew-cask
$> brew cask install virtualbox    # install virtualbox
$> brew cask install vagrant
$> brew cask install vagrant-manager # cf http://vagrantmanager.com/
```

- **Windows / Linux**:
  - ↪ install Oracle Virtualbox and the Extension Pack
  - ↪ install Vagrant

Why use Vagrant?

- Create new VMs quickly and easily: only one command!
  - ↪ `vagrant up`
- Keep the number of VMs under control
  - ↪ All configuration in `VagrantFile`
- **Reproducibility**
  - ↪ Identical environment in development and production
- **Portability**
  - ↪ **avoid** sharing 4 GB VM disks images
  - ↪ Vagrant Cloud to share your images
- **Collaboration made easy**:

```
$> git clone ...
$> vagrant up
```

Minimal default setup

```
$> vagrant init [-m] <user>/<name> # setup vagrant cloud image
```

- A `Vagrantfile` is configured for box `<user>/<name>`
  - ↪ Find existing box: Vagrant Cloud https://vagrantcloud.com/
  - ↪ You can have multiple (named) box within the **same** Vagrantfile
    - ✓ See `ULHPC/puppet-sysadmins/Vagrantfile`
    - ✓ See `Falkor/tutorials-BD-ML/Vagrantfile`

```
Vagrant.configure(2) do |config|
   config.vm.box = '<user>/<name>'
   config.ssh.insert_key = false
end
```

Box name	Description
ubuntu/trusty64	Ubuntu Server 14.04 LTS
debian/contrib-jessie64	Vanilla Debian 8 Jessie
centos/7	CentOS Linux 7 x86_64

Pulling and Running a Vagrant Box

```
$> vagrant up          # boot the box(es) set in the Vagrantfile
```

- Base box is downloaded and stored locally `~/.vagrant.d/boxes/`
- A new VM is created and configured with the base box as template
  - ↪ The VM is booted and (eventually) provisioned
  - ↪ Once within the box: `/vagrant` = directory hosting `Vagrantfile`

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```
$> vagrant status        # State of the vagrant box(es)
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```
$> vagrant status                 # State of the vagrant box(es)
```

```
$> vagrant ssh             # connect inside it, CTRL-D to exit
```

Stopping Vagrant Box

```
$> vagrant { destroy | halt }                # destroy / halt
```

- Once you have finished your work within a *running* box
  - ↪ save the state for later with `vagrant halt`
  - ↪ reset changes / tests / errors with `vagrant destroy`
  - ↪ commit changes by generating a new version of the box

Hands-on 0: Vagrant

- This tutorial heavily relies on Vagrant
  ↪ you will need to familiarize with the tool if not yet done

Your Turn!

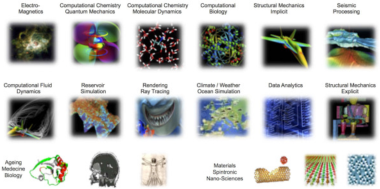
Hands-on 0

http://nesusws-tutorials-BD-DL.rtfd.io/en/latest/hands-on/vagrant/

- **Clone** the tutorial repository — Step 1
- **Basic Usage of Vagrant** — Step 2

Summary

Why HPC and BD ?



HPC: **H**igh **P**erformance **C**omputing

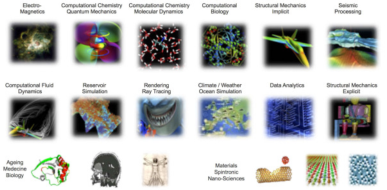
BD: **B**ig **D**ata

Andy Grant, Head of Big Data and HPC, Atos UK&I

To out-compete you must out-compute

Increasing competition, heightened customer expectations and shortening product development cycles are forcing the pace of acceleration across all industries.

Why HPC and BD ?



HPC: **H**igh **P**erformance **C**omputing
BD: **B**ig **D**ata

- Essential tools for **Science, Society and Industry**
  - ↪ All scientific disciplines are becoming computational today
    - ✓ requires very high computing power, handles **huge** volumes of data
- **Industry, SMEs** increasingly relying on HPC
  - ↪ to invent innovative solutions
  - ↪ . . . while reducing cost & decreasing time to market

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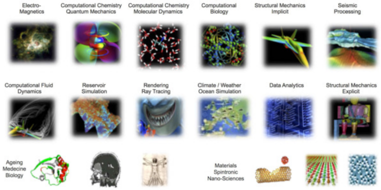

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- **Industry, SMEs** increasingly relying on HPC
  - ↪ to invent innovative solutions
  - ↪ . . . while reducing cost & decreasing time to market
- HPC = **global race** (strategic priority) - EU takes up the challenge:
  - ↪ EuroHPC / IPCEI on HPC and Big Data (BD) Applications

Andy Grant, Head of Big Data and HPC, Atos UK&I

To out-compete you must out-compute

Increasing competition, heightened customer expectations and shortening product development cycles are forcing the pace of acceleration across all industries.

New Trends in HPC

- **Continued scaling** of scientific, industrial & financial applications
  - ↪ . . . well beyond Exascale
- New trends changing the landscape for HPC
  - ↪ Emergence of **Big Data analytics**
  - ↪ Emergence of (**Hyperscale**) **Cloud Computing**
  - ↪ **Data intensive Internet of Things (IoT)** applications
  - ↪ **Deep learning & cognitive computing** paradigms

[Source : EuroLab-4-HPC]


This study was carried out for RIKEN by

IDC Analyze the Future

Special Study

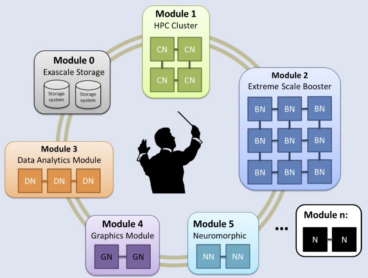
Analysis of the Characteristics and Development Trends of the Next-Generation of Supercomputers in Foreign Countries

Earl C. Joseph, Ph.D. | Robert Sorensen
Steve Conway | Kevin Monroe

[Source : IDC RIKEN report, 2016]

Toward Modular Computing

- Aiming at **scalable**, **flexible HPC infrastructures**
  - ↪ *Primary* processing on CPUs and accelerators
    - ✓ **HPC & Extreme Scale Booster** modules
  - ↪ *Specialized modules* for:
    - ✓ **HTC & I/O intensive** workloads;
    - ✓ **[Big] Data Analytics & AI**



[Source : "Towards Modular Supercomputing: The DEEP and DEEP-ER projects", 2016]

Prerequisites: Metrics

- **HPC**: **H**igh **P**erformance **C**omputing — **BD**: **B**ig **D**ata

Main HPC/BD Performance Metrics

- **Computing Capacity**: often measured in **flops** (or **flop/s**)
  - $\hookrightarrow$ **Fl**oating **p**oint **o**perations per **s**econds (often in DP)
  - $\hookrightarrow$ **GFlops** $= 10^9$ **TFlops** $= 10^{12}$ **PFlops** $= 10^{15}$ **EFlops** $= 10^{18}$

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- **Storage Capacity**: measured in multiples of **bytes** = 8 **bits**
  - ↪ **GB** $= 10^9$ bytes **TB** $= 10^{12}$ **PB** $= 10^{15}$ **EB** $= 10^{18}$
  - ↪ **GiB** $= 1024^3$ bytes **TiB** $= 1024^4$ **PiB** $= 1024^5$ **EiB** $= 1024^6$
- Transfer rate on a medium measured in **Mb/s** or **MB/s**
- Other metrics: Sequential vs Random **R/W speed**, **IOPS** ...

Summary

HPC Components: [GP]CPU

CPU

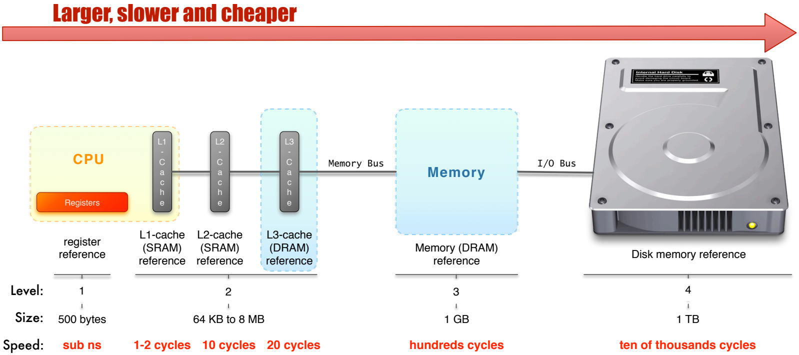
- Always multi-core
- Ex: Intel Core i7-7700K (Jan 2017) $R_{peak} \simeq 268.8$ GFlops (DP)
  - ↪ 4 cores @ 4.2GHz (14nm, 91W, 1.75 billion transistors)
  - ↪ + integrated graphics (24 EUs) $R_{peak} \simeq +441.6$ GFlops

GPU / GPGPU

- Always multi-core, optimized for vector processing
- Ex: Nvidia Tesla V100 (Jun 2017) $R_{peak} \simeq 7$ TFlops (DP)
  - ↪ 5120 cores @ 1.3GHz (12nm, 250W, 21 billion transistors)
  - ↪ focus on Deep Learning workloads $R_{peak} \simeq 112$ TFLOPS (HP)

$\simeq$ **100 Gflops** for 130$ (CPU), 214$? (GPU)

HPC Components: Local Memory

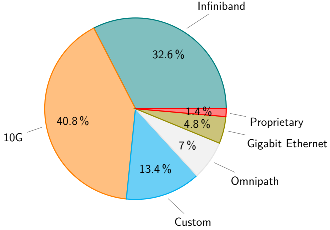


- SSD (SATA3) R/W: 550 MB/s; 100000 IOPS **450 €/TB**
- HDD (SATA3 @ 7,2 krpm) R/W: 227 MB/s; 85 IOPS **54 €/TB**

HPC Components: Interconnect

- **latency**: time to send a minimal (0 byte) message from A to B
- **bandwidth**: max amount of data communicated per unit of time

Technology	Effective Bandwidth		Latency
Gigabit Ethernet	1 Gb/s	125 MB/s	40μs to 300μs
10 Gigabit Ethernet	10 Gb/s	1.25 GB/s	4μs to 5μs
Infiniband QDR	40 Gb/s	5 GB/s	1.29μs to 2.6μs
Infiniband EDR	100 Gb/s	12.5 GB/s	0.61μs to 1.3μs
100 Gigabit Ethernet	100 Gb/s	1.25 GB/s	30μs
Intel Omnipath	100 Gb/s	12.5 GB/s	0.9μs



[Source : www.top500.org, Nov. 2017]

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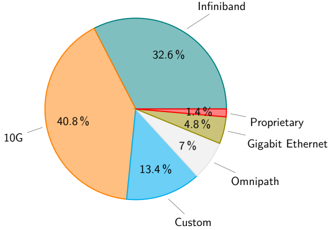

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Network Topologies

- **Direct** vs. **Indirect** interconnect
  - ↪ *direct*: each network node attaches to at least one compute node
  - ↪ *indirect*: compute nodes attached at the edge of the network only
    - ✓ many routers only connect to other routers.

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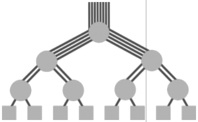
Main HPC Topologies

- **CLOS Network / Fat-Trees** [Indirect]
  - ↪ can be fully non-blocking (1:1) or blocking (x:1)
  - ↪ typically enables **best performance**
    - ✓ Non blocking bandwidth, lowest network latency



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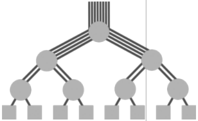

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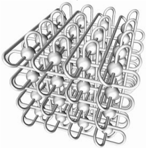
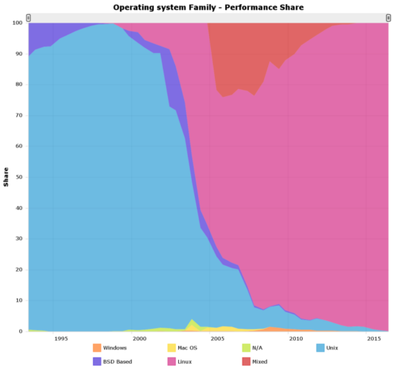


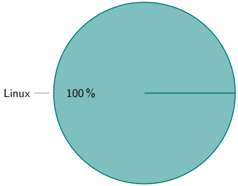
- **Mesh or 3D-torus** [Direct]
  - ↪ Blocking network, cost-effective for systems at scale
  - ↪ Great performance solutions for applications with locality
  - ↪ Simple expansion for future growth

HPC Components: Operating System



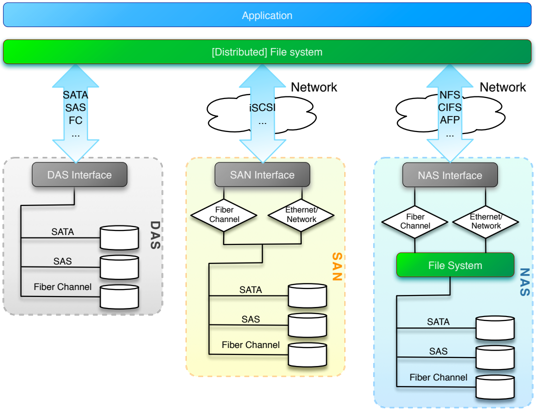
- Exclusively Linux-based (**really** 100%)
- Reasons:
  - ↪ stability
  - ↪ prone to devels

[Source : www.top500.org, Nov 2017]



[Big]Data Management

Storage architectural classes & I/O layers



[Big]Data Management: Disk Encl.

- $\simeq$ **120 K€** - enclosure - 48-60 disks (4U)
  - $\hookrightarrow$ incl. redundant (**i.e.** 2) RAID controllers (master/slave)

[Big]Data Management: File Systems

File System (FS)

- Logical manner to **store**, **organize**, **manipulate** & **access** data

[Big]Data Management: File Systems

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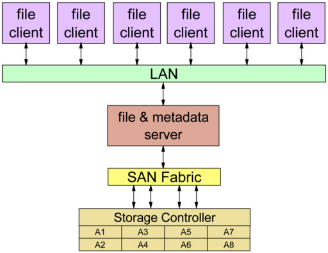
- (local) **Disk FS** : `FAT32`, `NTFS`, `HFS+`, `ext{3,4}`, `{x,z,btr}fs`...
  - ↪ manage data on permanent storage devices
  - ↪ *poor* perf. **read**: 100 → 400 MB/s | **write**: 10 → 200 MB/s

[Big]Data Management: File Systems

- **Networked FS**: NFS, CIFS/SMB, AFP
  - ↪ disk access from remote nodes via network access
  - ↪ poorer performance for HPC jobs especially parallel I/O
    - ✓ **read**: only 381 MB/s on a system capable of 740MB/s (16 tasks)
    - ✓ **write**: only 90MB/s on system capable of 400MB/s (4 tasks)



[Source : LISA'09] Ray Paden: *How to Build a Petabyte Sized Storage System*

COMMENT:
Traditionally, a single NFS/CIFS file server manages both user data and metadata operations which "gates" performance/scaling and presents a single point of failure risk. Products (e.g., CNFS) are available that provide multiple server designs to avoid this issue.

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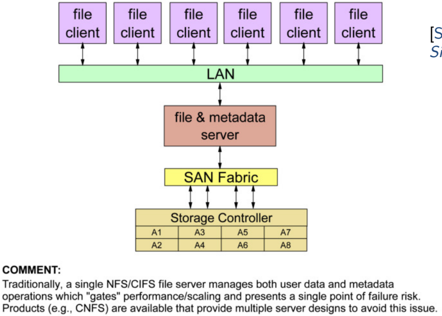

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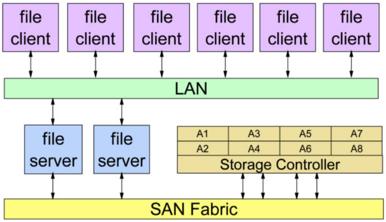
- [scale-out] **NAS**
  - ↪ aka Appliances OneFS...
  - ↪ Focus on CIFS, NFS
  - ↪ Integrated HW/SW
  - ↪ **Ex**: **EMC (Isilon)**, IBM (SONAS), **DDN**...

[Big]Data Management: File Systems

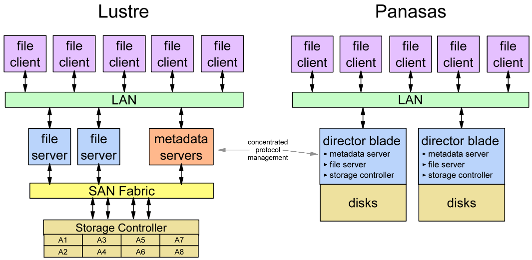
- **Basic Clustered FS** GPFS
  - ↪ File access is parallel
  - ↪ File System overhead operations is distributed and done in parallel
    - ✓ **no** metadata servers
  - ↪ File clients access file data through file servers via the LAN



File system overhead operations are *distributed* across the entire cluster and is done in parallel; it is not concentrated in any given place. There is no single server bottleneck. User data and metadata flows betweem all nodes and all disks via the file servers.

[Big]Data Management: File Systems

- **Multi-Component Clustered FS** Lustre, Panasas
  - ↪ File access is parallel
  - ↪ File System overhead operations on dedicated components
    - ✓ metadata server (Lustre) or director blades (Panasas)
  - ↪ Multi-component architecture
  - ↪ File clients access file data through file servers via the LAN



[Big]Data Management: FS Summary

- **File System (FS)**: Logical manner to *store, organize & access* data
  - ↪ (local) **Disk FS** : `FAT32`, `NTFS`, `HFS+`, `ext4`, `{x,z,btr}fs`...
  - ↪ **Networked FS**: `NFS`, `CIFS/SMB`, `AFP`
  - ↪ **Parallel/Distributed FS**: `SpectrumScale/GPFS`, `Lustre`
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Name	Type	Read* [GB/s]	Write* [GB/s]
`ext4`	Disk FS	0.426	0.212
`nfs`	Networked FS	0.381	0.090
`gpfs` (iris)	Parallel/Distributed FS	**10.14**	**8,41**
`gpfs` (gaia)	Parallel/Distributed FS	7.74	6.524
`lustre`	Parallel/Distributed FS	4.5	2.956

* maximum **random** read/write, per IOZone or IOR measures, using 15 concurrent nodes for networked FS.

HPC Components: Data Center

Definition (Data Center)

- Facility to house computer systems and associated components
  $\hookrightarrow$ Basic storage component: **rack** (height: 42 RU)

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Challenges: Power (UPS, battery), Cooling, Fire protection, Security

- Power/Heat dissipation per rack:
  - ↪ HPC **computing** racks: **30-120 kW**
  - ↪ **Storage** racks: **15 kW**
  - ↪ **Interconnect** racks: **5 kW**
- Various **Cooling** Technology
  - ↪ Airflow
  - ↪ Direct-Liquid Cooling, Immersion...

Power Usage Effectiveness

$$PUE = \frac{\textit{Total facility power}}{\textit{IT equipment power}}$$

Summary

Software/Modules Management

https://hpc.uni.lu/users/software/

- Based on Environment Modules / LMod
  - ↪ convenient way to dynamically change the users environment `$PATH`
  - ↪ permits to easily load software through `module` command
- Currently on UL HPC:
  - ↪ > **163 software packages**, in *multiple* versions, within **18 categ.**
  - ↪ reworked software set for `iris` cluster and now deployed everywhere
    - ✓ RESIF v2.0, allowing [real] semantic versioning of released builds
  - ↪ hierarchical organization **Ex**: `toolchain/{foss,intel}`

```
$> module avail                        # List available modules
```

```
$> module load <category>/<software>[/<version>]
```

Software/Modules Management

- Key `module` variable: `$MODULEPATH` / where to look for modules
  - ↪ altered with `module use <path>`. **Ex**:

```
export EASYBUILD_PREFIX=$HOME/.local/easybuild
export LOCAL_MODULES=$EASYBUILD_PREFIX/modules/all
module use $LOCAL_MODULES
```

Software/Modules Management

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export LOCAL_MODULES=$EASYBUILD_PREFIX/modules/all
module use $LOCAL_MODULES
```

Main modules commands:

Command	Description
`module avail`	Lists all the modules which are available to be loaded
`module spider <pattern>`	Search for among available modules **(Lmod only)**
`module load <mod1> [mod2...]`	Load a module
`module unload <module>`	Unload a module
`module list`	List loaded modules
`module purge`	Unload all modules (purge)
`module display <module>`	Display what a module does
`module use <path>`	Prepend the directory to the MODULEPATH environment variable
`module unuse <path>`	Remove the directory from the MODULEPATH environment variable

Software/Modules Management

http://hpcugent.github.io/easybuild/

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

```
$> module use $LOCAL_MODULES
$> module load tools/EasyBuild
$> eb -S HPL    # Search for recipes for HPL software
$> eb HPL-2.2-intel-2017a.eb # Install HPL 2.2 w. Intel toolchain
```

Hands-on 1: Modules & Easybuild

Your Turn!

Hands-on 1

http://nesusws-tutorials-BD-DL.rtfd.io/en/latest/hands-on/easybuild/

- **Discover** Environment Modules and Lmod — Part 1
- Installation of EasyBuild — Part 2 (a)
- **Local** vs. **Global** Usage — Part 2 (b)
  - ↪ local installation of zlib
  - ↪ global installation of snappy and protobuf, needed later

Hands-on 2: Building Hadoop

- We will need to install the Hadoop MapReduce by Cloudera using EasyBuild.
  - ↪ this build is quite long (∼**30 minutes on 4 cores**)
  - ↪ **Obj**: make it build while the keynote continues ;)

Hands-on 2

`http://nesusws-tutorials-BD-DL.rtfd.io/en/latest/hands-on/hadoop/install/`

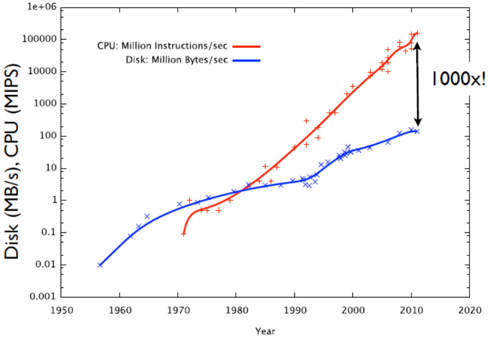
- Pre-requisites — Step 1
  - ↪ Installing **Java 1.7.0** (7u80) and **1.8.0** (8u152) — Step 1.a
  - ↪ Installing **Maven 3.5.2** — Step 1.b
- Installing **Hadoop 2.6.0-cdh5.12.0** — Step 2

Summary

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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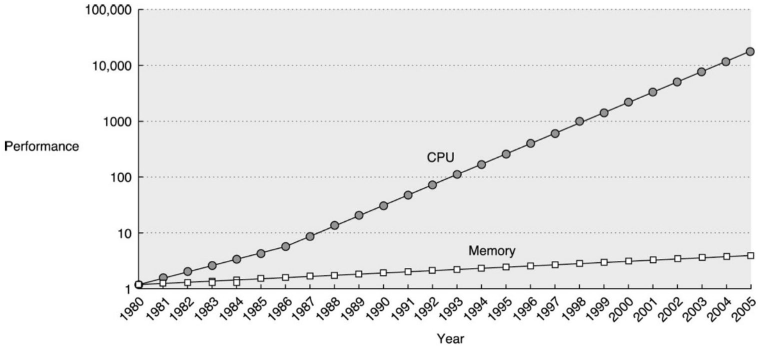


Speed Expectation on Data Transfer

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				
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
	1 Minute	5 Minutes	20 Minutes	1 Hour
	Time to transfer			

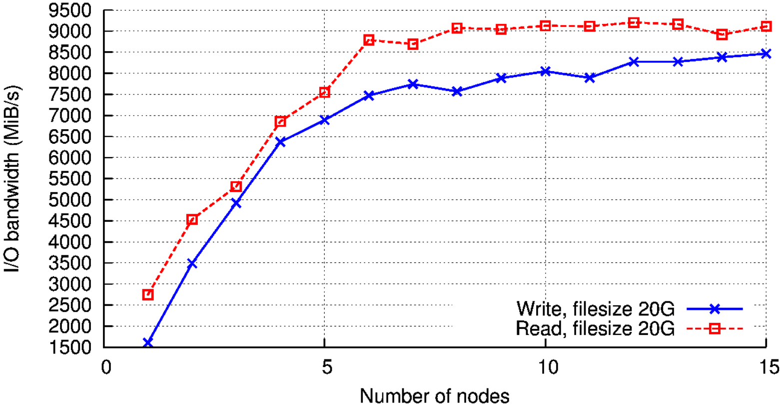
Speed Expectation on Data Transfer

http://fasterdata.es.net/

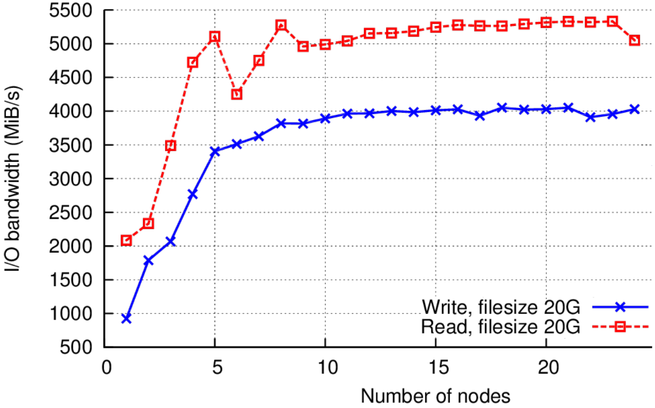
Data set size	8 Hours	24 Hours	7 Days	30 Days
1XB	34.72 TB/sec	11.57 TB/sec	1.65 TB/sec	385.80 GB/sec
100PB	3.47 TB/sec	1.16 TB/sec	165.34 GB/sec	38.58 GB/sec
10PB	347.22 GB/sec	115.74 GB/sec	16.53 GB/sec	3.86 GB/sec
1PB	34.72 GB/sec	11.57 GB/sec	1.65 GB/sec	385.80 MB/sec
100TB	3.47 GB/sec	1.16 GB/sec	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

Time to transfer

Storage Performances: GPFS

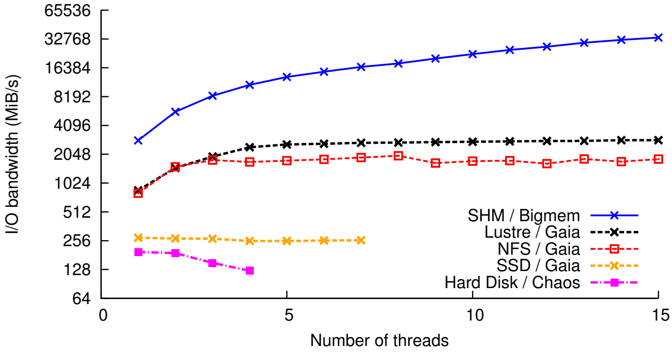


Storage Performances: Lustre



Storage Performances

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



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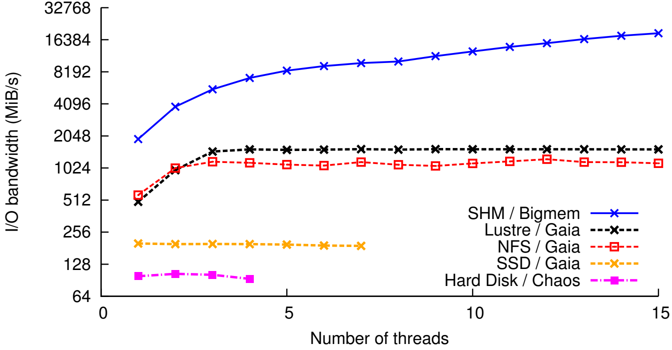

Understanding Your Storage Options

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

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

Summary

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!

SSH: Secure Shell

- Ensure **secure** connection to remote (UL) server
  - ↪ establish **encrypted** tunnel using **asymmetric keys**
    - ✓ **Public** `id_rsa.pub` **vs.** **Private** `id_rsa` (**without** `.pub`)
    - ✓ typically on a non-standard port (**Ex**: 8022) *limits kiddie script*
    - ✓ Basic rule: 1 machine = 1 key pair
  - ↪ the private key is **SECRET**: **never** send it to anybody
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- SSH is used as a secure backbone channel for **many** tools
  - ↪ Remote shell **i.e** remote command line
  - ↪ File transfer: `rsync`, `scp`, `sftp`
  - ↪ versionning synchronization (`svn`, `git`), github, gitlab etc.

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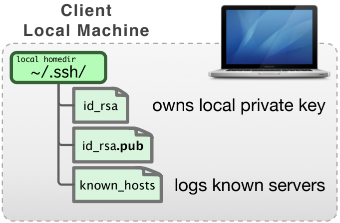
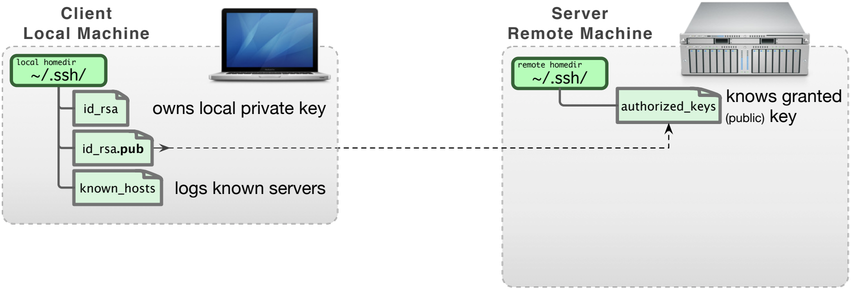
- Authentication:
  - ↪ ~~password~~ (disable if possible)
  - ↪ (*better*) **public key authentication**

SSH: Public Key Authentication



SSH: Public Key Authentication



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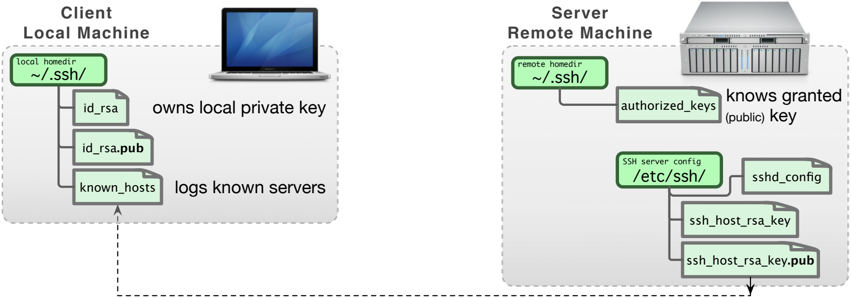

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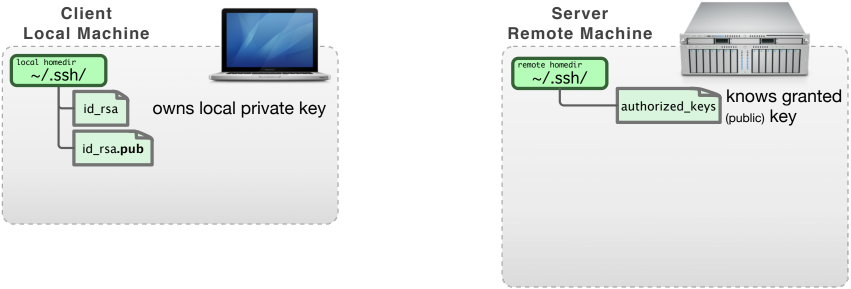

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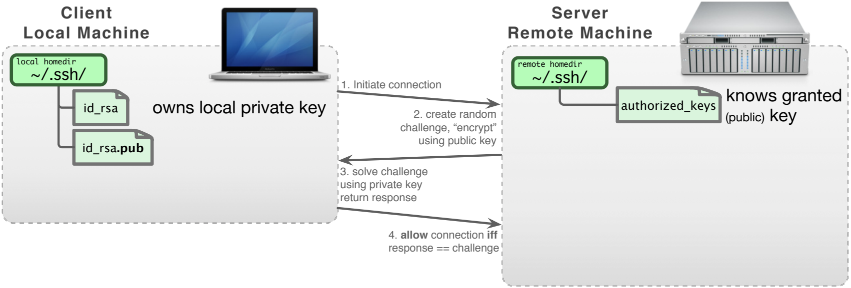

- **Restrict** to public key authentication: `/etc/ssh/sshd_config`:

```
PermitRootLogin no
# Disable Passwords
PasswordAuthentication no
ChallengeResponseAuthentication no
```

```
# Enable Public key auth.
RSAAuthentication yes
PubkeyAuthentication yes
```

Hands-on 3: Data transfer over SSH

- Before doing **Big** Data, learn how to transfer data between 2 hosts
  - ↪ do it securely over SSH

```
# Quickly generate a 10GB file
$> dd if=/dev/zero of=/tmp/bigfile.txt bs=100M count=100
# Now try to transfert it between the 2 Vagrant boxes ;)
```

Hands-on 3

http://nesusws-tutorials-BD-DL.rtfd.io/en/latest/hands-on/data-transfer/

- **Generate SSH Key Pair** and authorize the public part — Step 1
- **Data transfer** over SSH with `scp` — Step 2.a
- **Data transfer** over SSH with `rsync` — Step 2.b

Summary

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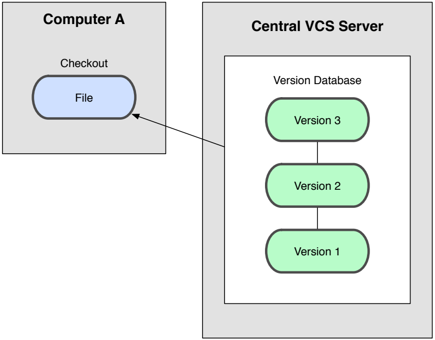
- **Which one?**
  ↪ Depends on the level of privacy you expect
  ✓ ... but you probably already know these tools ☺
  ↪ **Few handle GB files...**

Centralized VCS - CVS, SVN



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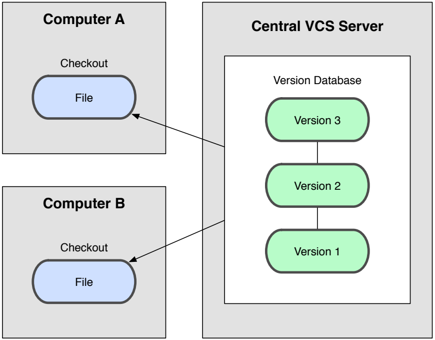
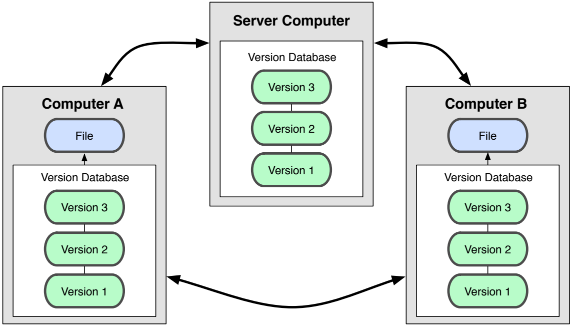
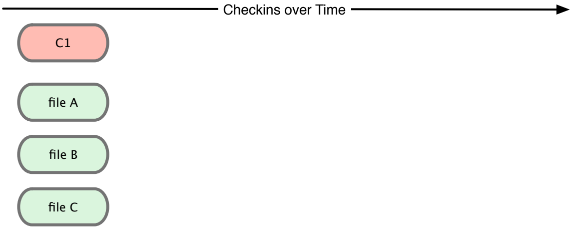


Distributed VCS - Git



Everybody has the full history of commits

Tracking changes (most VCS)



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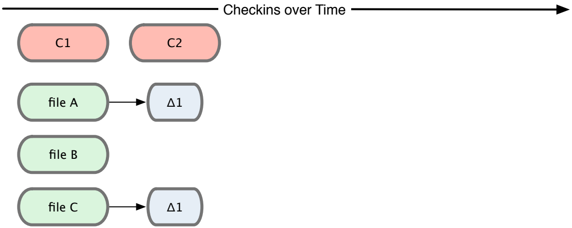

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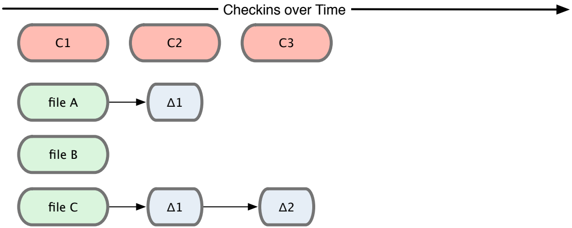

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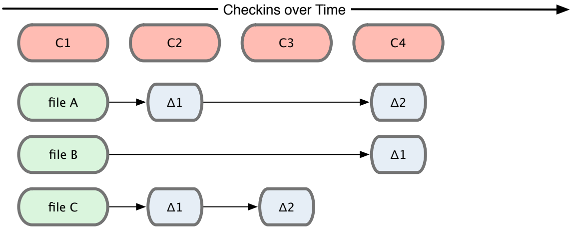

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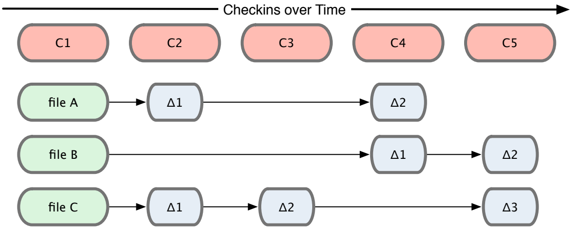

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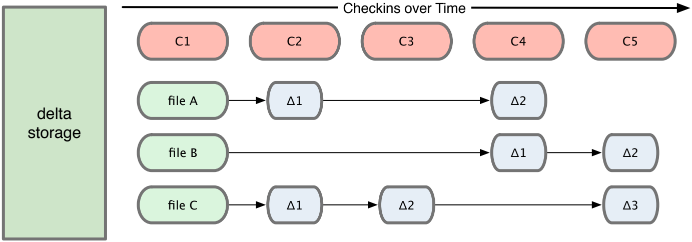

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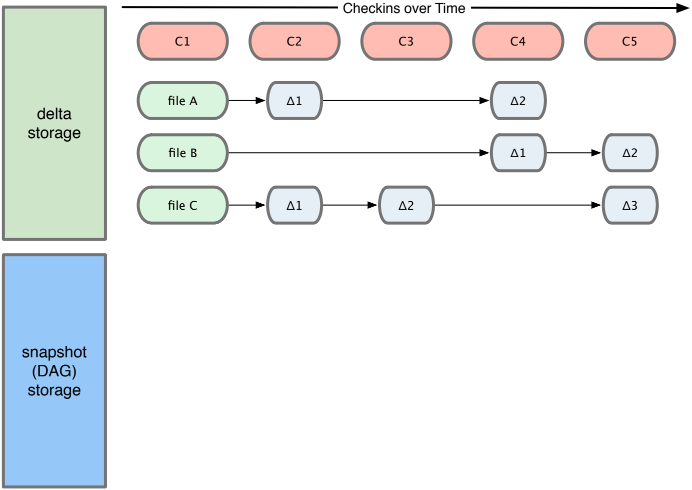

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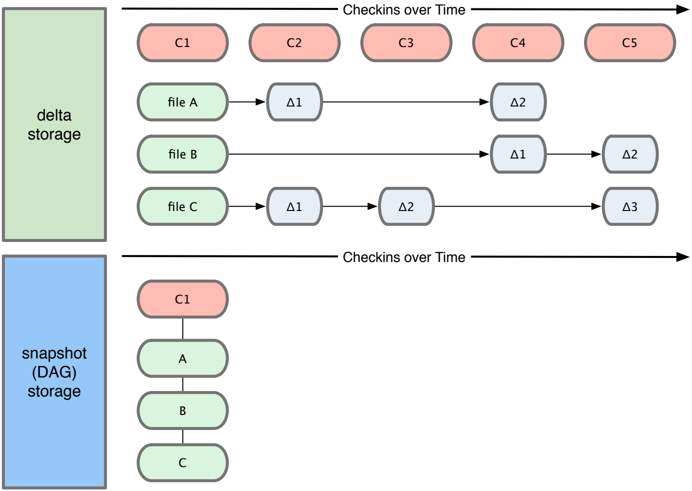

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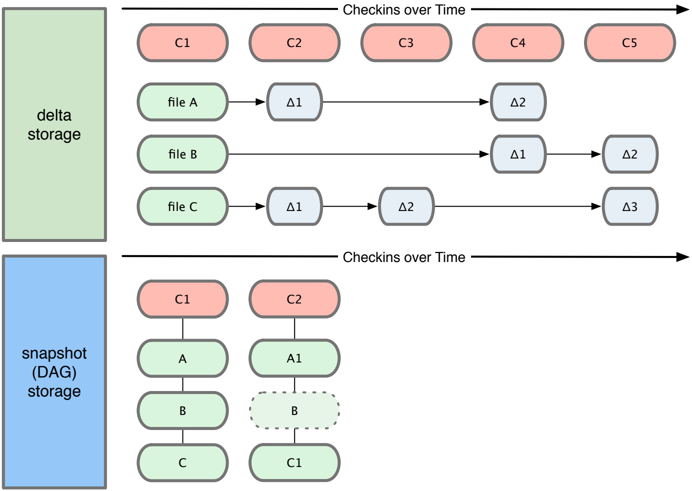

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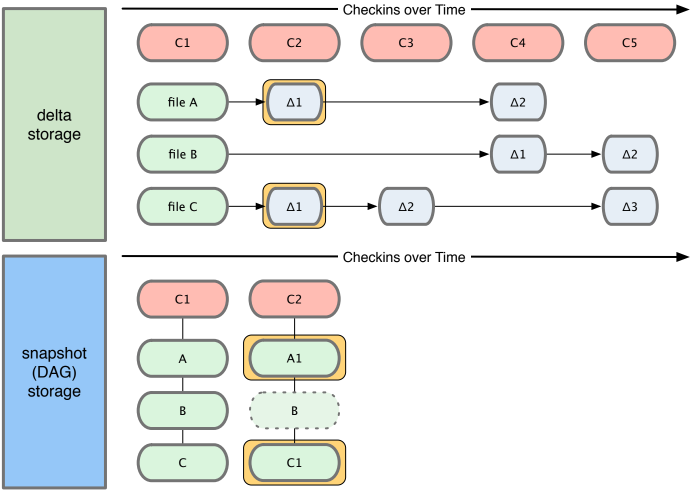

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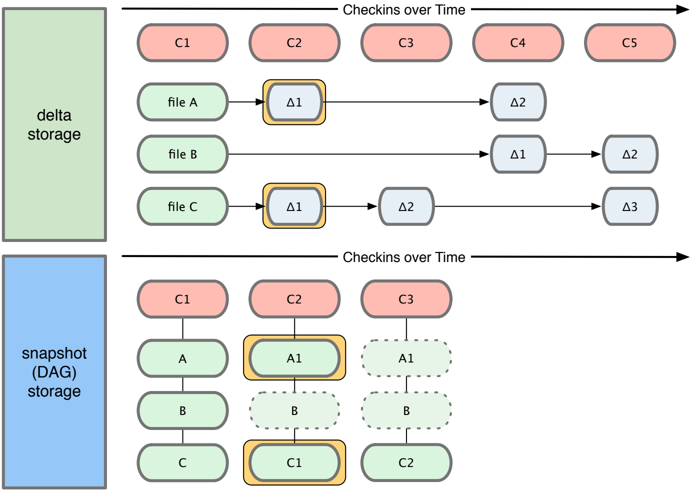

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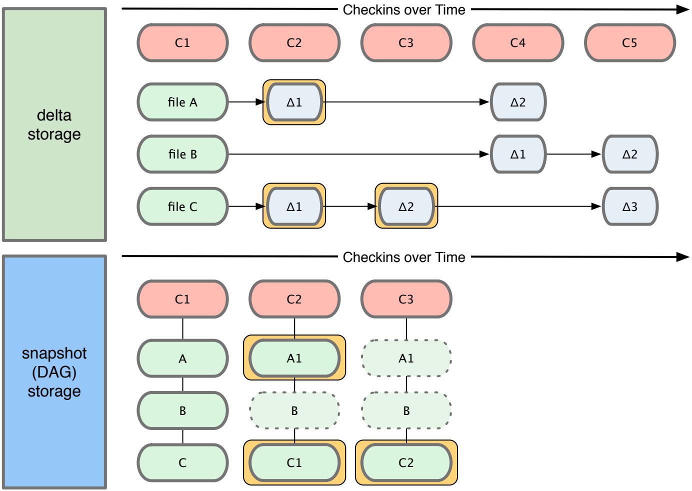

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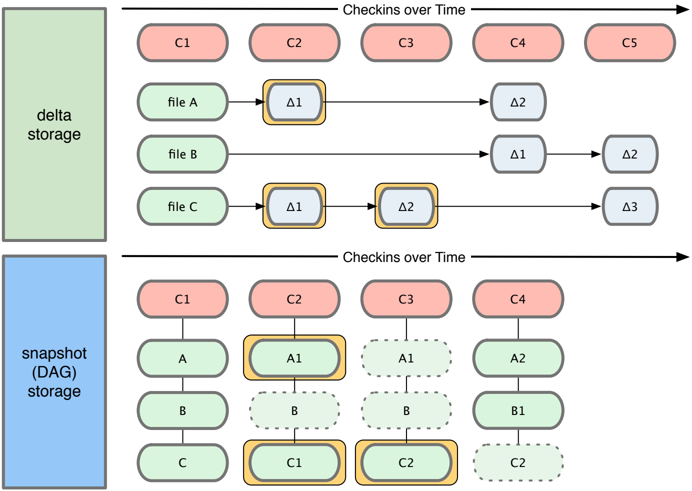

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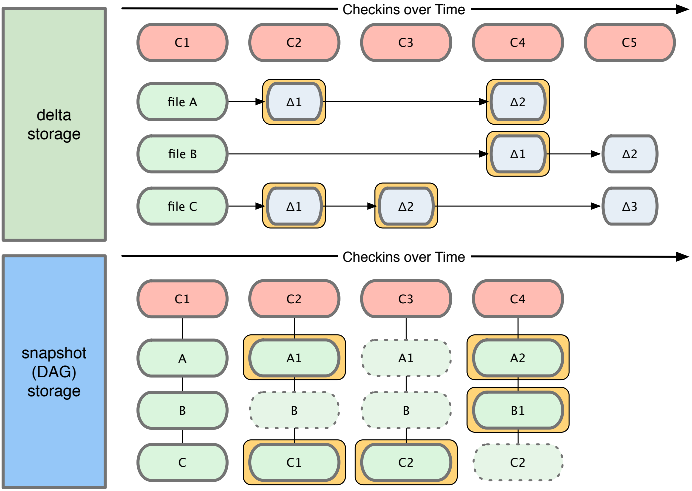

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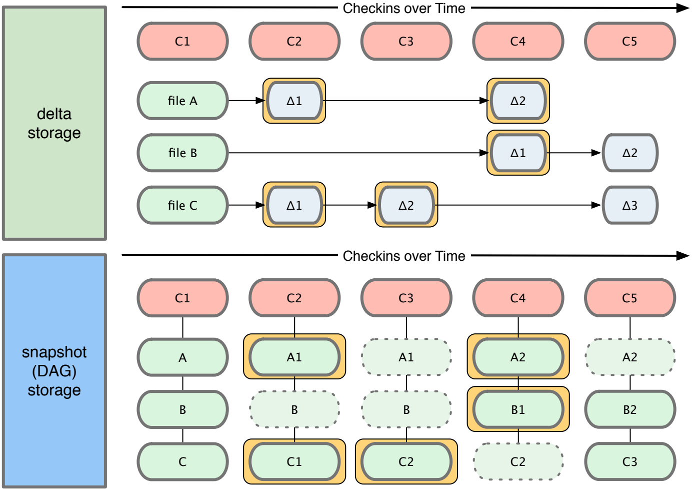

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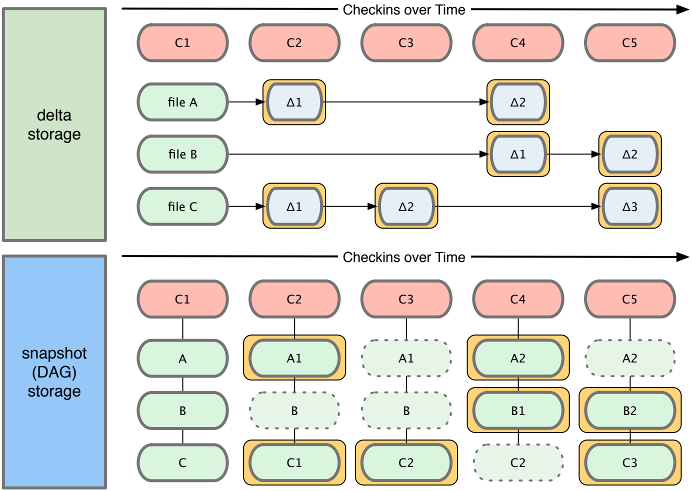
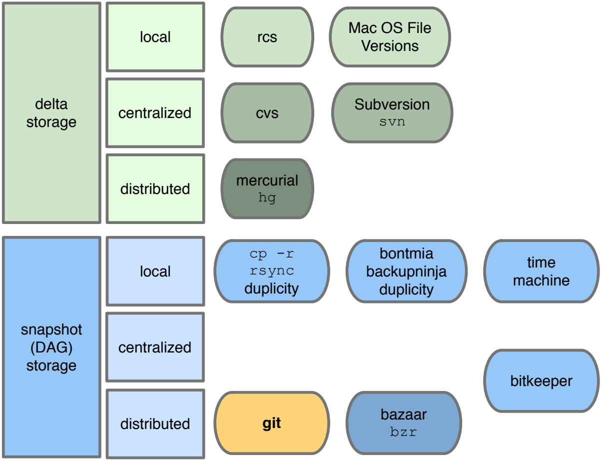


VCS Taxonomy



Git at the heart of BD

http://git-scm.org

Git on the Cloud: Github `github.com`

(Reference) web-based Git repository hosting service

Set up Git

Create Repository

Fork repository

Work together

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**
  $\hookrightarrow$ 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`

Git in practice

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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

Summary

What is a Distributed File System?

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

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

Distributed File System Architecture?

Master-Slave Pattern

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

Distributed File System Architecture?

Master-Slave Pattern

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- **Ex**: GFS, HDFS

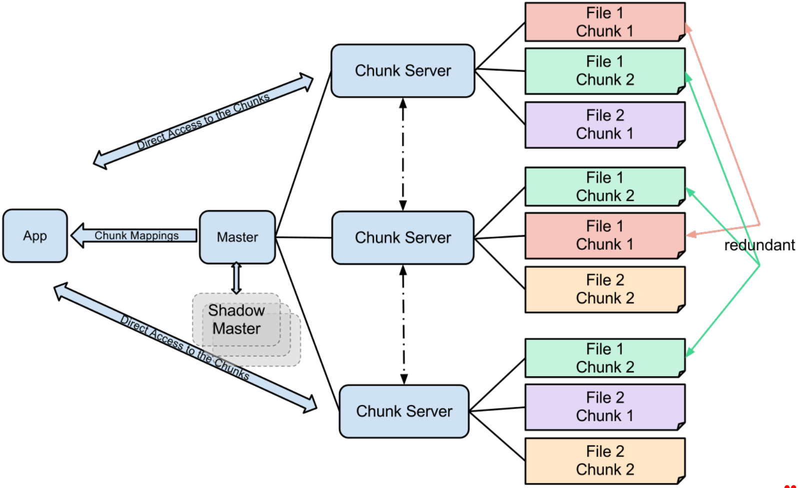
Peer-to-Peer Pattern

- 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

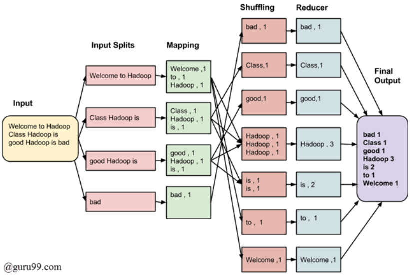
- **Atomic File Namespace Mutations**
  - ↪ File creations/deletions centrally controlled by the master node.
  - ↪ Clients typically create and write entire file,
    - ✓ then add the file name to the file namespace stored at the master.
- **Atomic Data Mutations**
  - ↪ only 1 atomic modification of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

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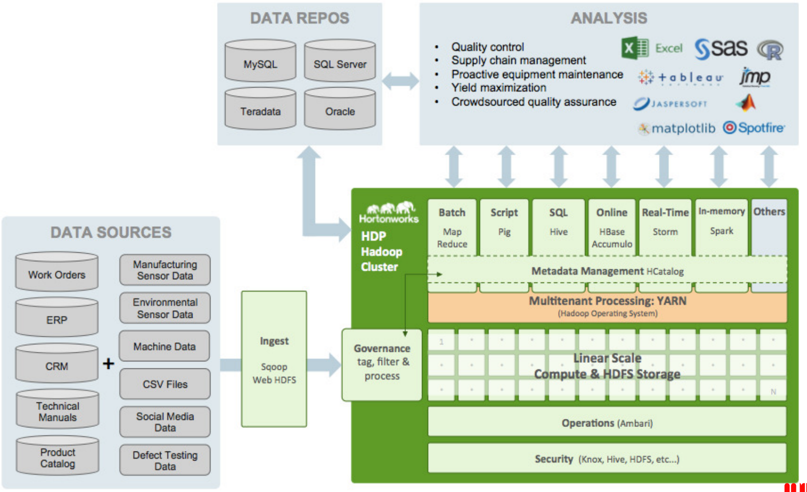
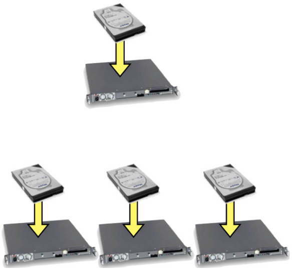
  1. **HDFS**: Hadoop distributed file system
  2. **YARN**: Hadoop job scheduling and resource allocation
  3. **MapReduce**: Hadoop adaptation of the MapReduce principle
- Basis for many other open-source Apache toolkits:
  ↪ **PIG/PigLatin**: file-oriented data storage & script-based query language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

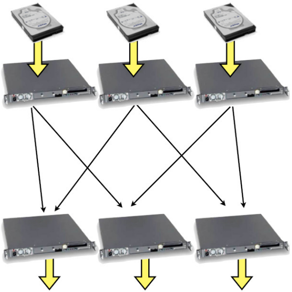


Scale-Out Design



- HDD streaming speed $\sim$ 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

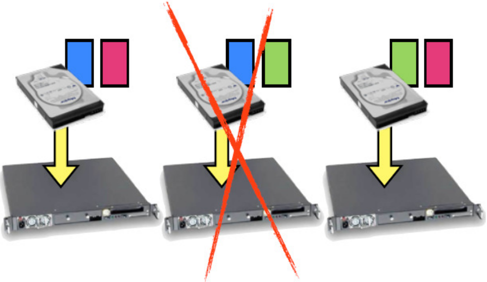
Combining Results



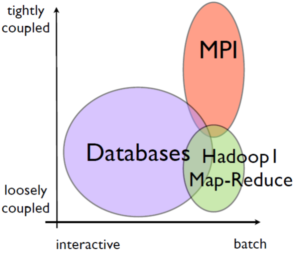
- Each node preprocesses its local data
  - ↪ Shuffles its data to a small number of other nodes
- Final processing, output is done there

Fault Tolerance

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

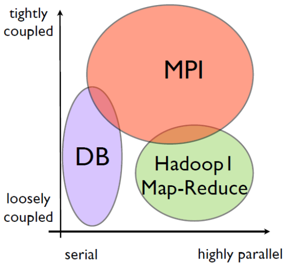


Hadoop: What is it Good At?



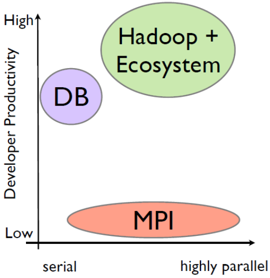
- **Classic Hadoop 1.x is all about batch processing** of massive amounts of data
  - ↪ Not much point below ~1TB
- Map-Reduce is relatively loosely coupled;
  - ↪ one **shuffle** phase.
- Very strong weak scaling in this model
  - ↪ more data, more nodes.
- **Batch**:
  - ↪ process all data in one go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

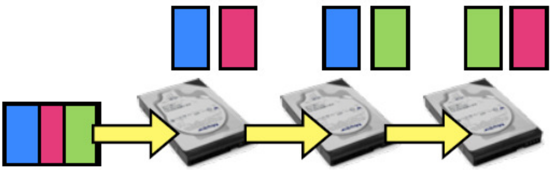
Hadoop vs HPC



- 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? Oooooooh*
- **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...

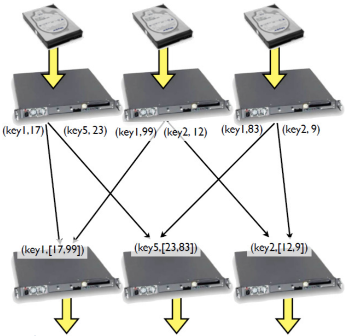
Data Distribution: Disk

- 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



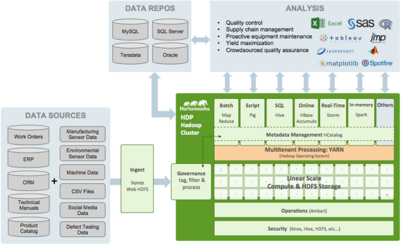
Makes the problem easier

- **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.

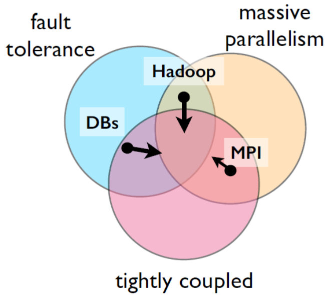
Built a reusable substrate

- 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

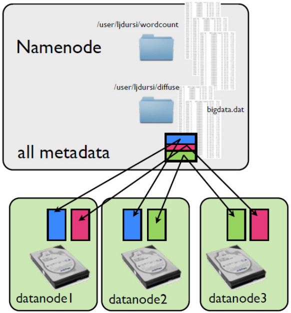
- **Required** to be:
  - ↪ able to deal with large files, large amounts of data
  - ↪ scalable & reliable in the presence of failures
  - ↪ fast at reading contiguous streams of data
  - ↪ only need to write to new files or append to files
  - ↪ require only commodity hardware
- **As a result**:
  -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

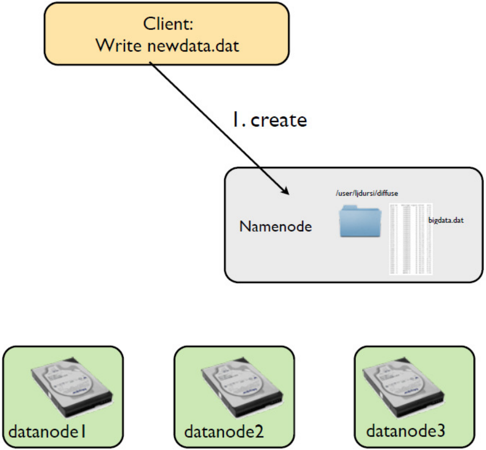


Two types of nodes in the filesystem:

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

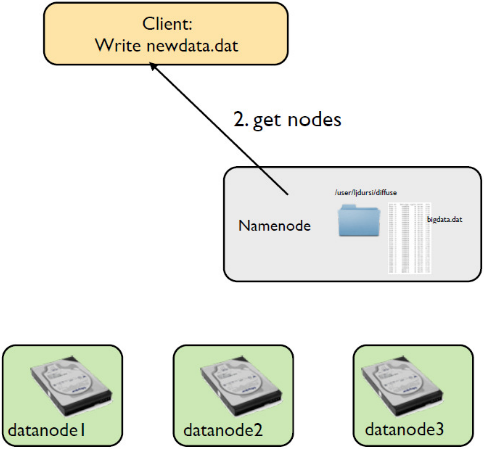
- Newer versions of Hadoop: federation
  - ↪ $\neq$ namenodes for `/user`, `/data`...
  - ↪ High Availability namenode pairs

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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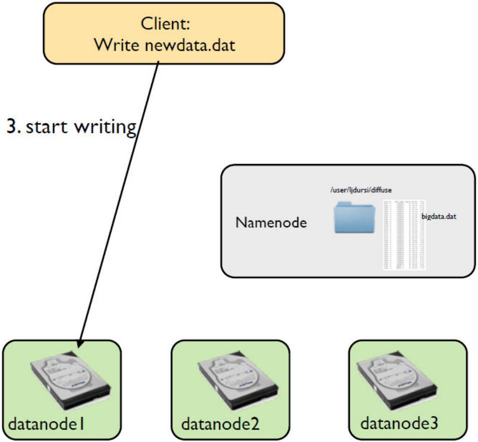

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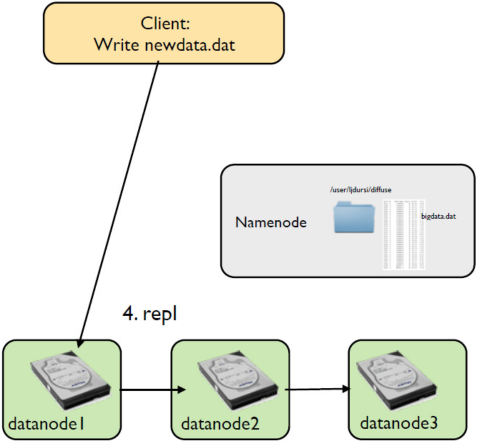

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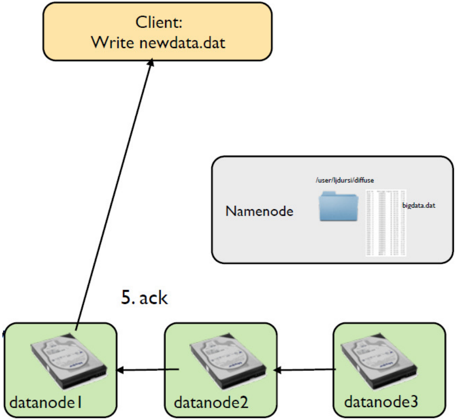

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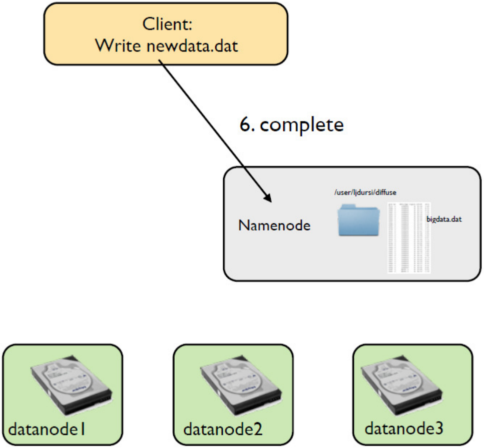

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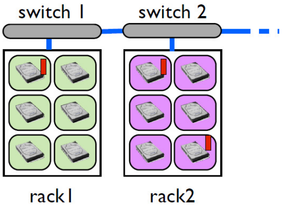
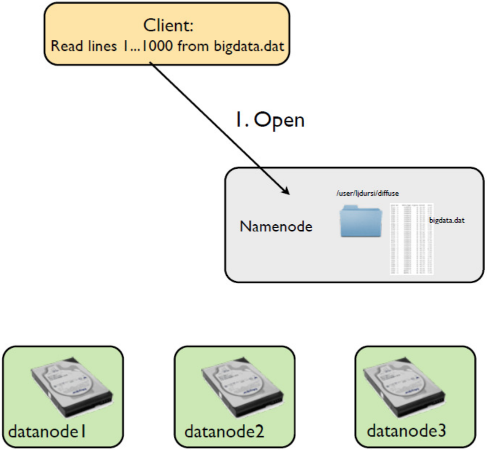
  - ↪ Complete

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



Reading a file



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

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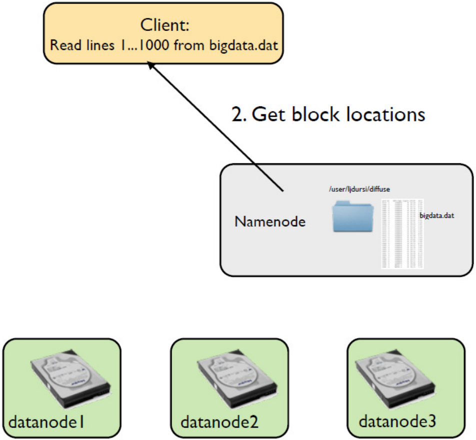

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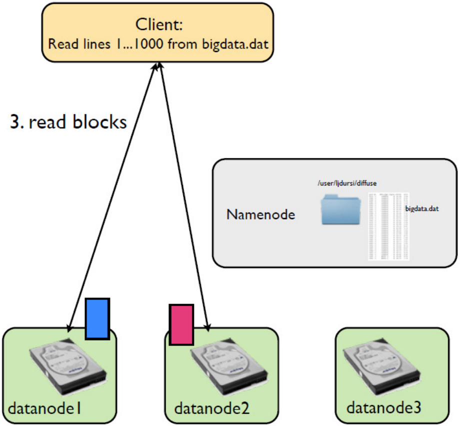

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Configuring HDFS

- 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

Configuring HDFS

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- 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} [...]
```

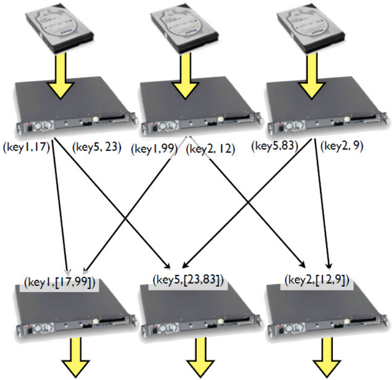
- Default directory is /user/${username}
  - ↪ **Nothing like a cd**

```
$> 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

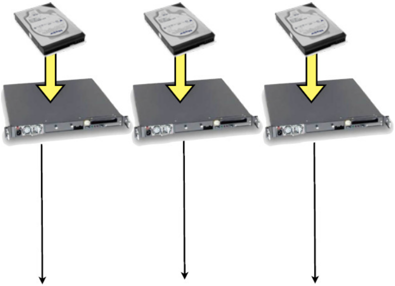
- In general, the data files you send to HDFS will be **large**
  ↪ or else why bother with Hadoop.
- Do not want to be constantly copying back and forth
  ↪ **view, append *in place***
- Several APIs to accessing the HDFS
  ↪ Java, C++, Python
- Here, we use one to get a file status, and read some data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

Back to Map-Reduce



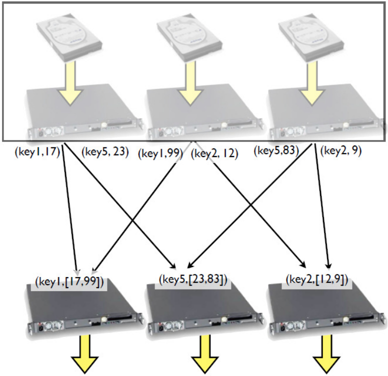
- Map processes **one element at a time**
  - ↪ emits results as (key, value) pairs.
- All results with **same key are gathered to the same reducers**
  - ↪ Reducers process list of values
  - ↪ emit results as (key, value) pairs

Map



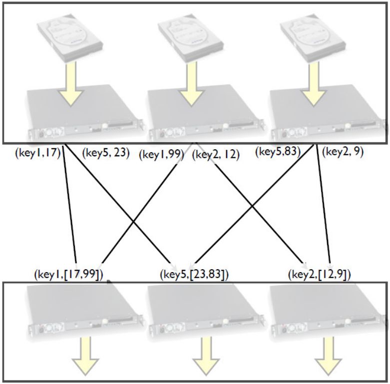
- All coupling done during **shuffle** phase
  - ↪ Embarrassingly parallel task
  - ↪ all map
- Take input, map it to output, done.
- **Famous case**
  - ↪ NYT using Hadoop to convert 11 million image files to PDFs
    - ✓ almost pure serial farm job

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

file01

```
Hello World
Bye World
```

file02

```
Hello Hadoop
Goodbye Hadoop
```

output/part-00000

```
Hello    2
World    2
Bye      1
Hadoop   2
Goodbye  1
```

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

file01

```
Hello World
Bye World
```

file02

```
Hello Hadoop
Goodbye Hadoop
```

⇓

output/part-00000

```
Hello     2
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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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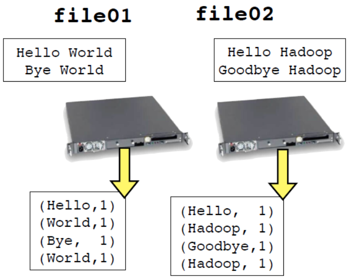

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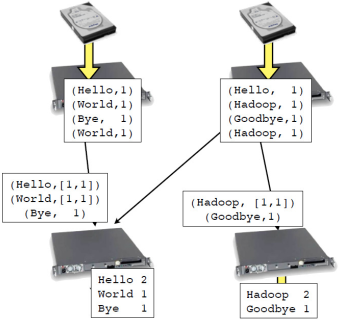

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Hands-on 4: Playing with Hadoop

Your Turn!

- Now you are ready to play with the installed Hadoop

Hands-on 4

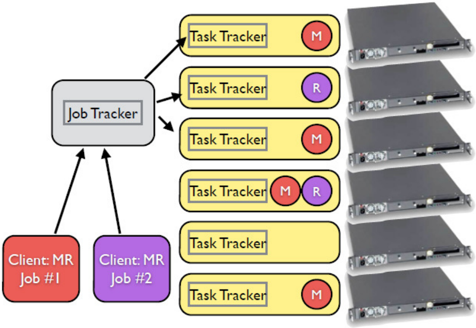
http://nesusws-tutorials-BD-DL.rtfd.io/en/latest/hands-on/hadoop/wordcount

- Test the `tools/Hadoop` modules in Single mode — Step 1
  - ↪ setup the wordcount example
- Enable a Cluster Setup — Step 2

Summary

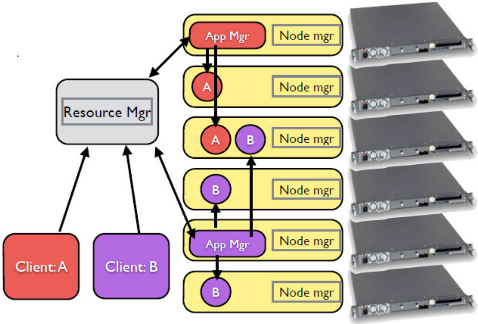
Hadoop 0.1x

- 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)**.

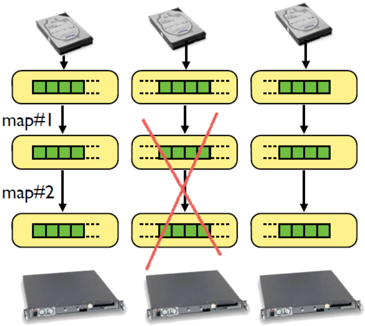
Apache Spark

- 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

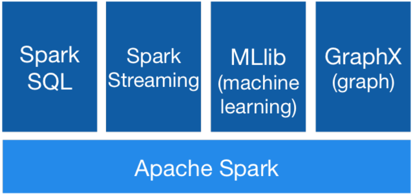
RDD Lineage

- 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 5: Spark installation

Your Turn!

Hands-on 5

http://nesusws-tutorials-BD-DL.rtfd.io/en/latest/hands-on/spark/install/

- Use EasyBuild to search for a ReciPY for Apache Spark
- Install it and check the installed software

Hands-on 6: Spark Usage

Your Turn!

Hands-on 6

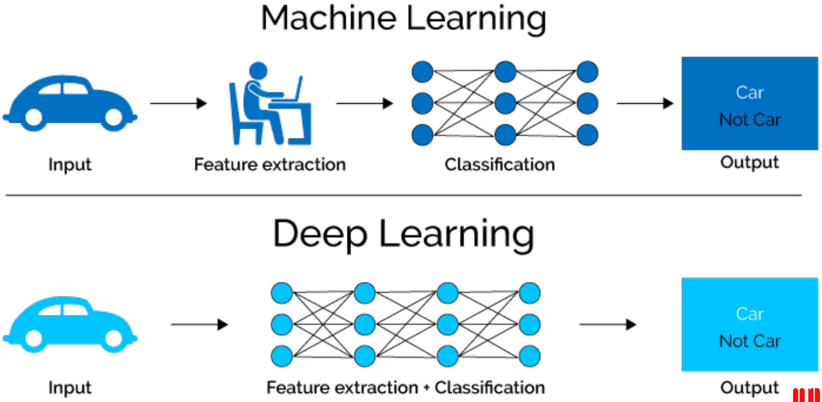
http://nesusws-tutorials-BD-DL.rtfd.io/en/latest/hands-on/spark/usage/

- Check a single interactive run — Step 1
  - ↪ PySpark, the Spark Python API — Step 1.a.
  - ↪ Scala Spark Shell — Step 1.b.
  - ↪ R Spark Shell **will not be reviewed** here.
- Running Spark standalone cluster — Step 2
  - ↪ In particular, illustrated on Pi estimation.

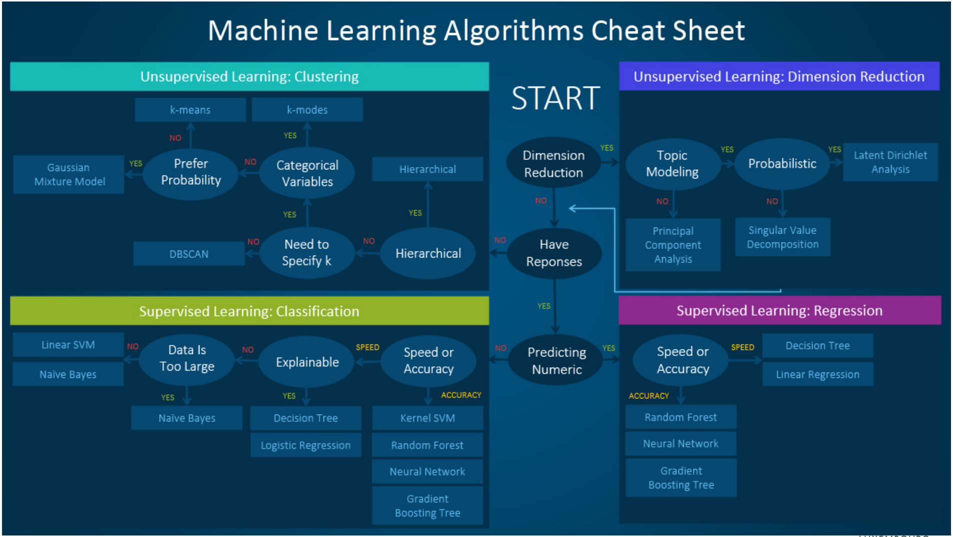
Summary

Big data and Machine/Deep Learning

- **Out-of-scope of this tutorial**:
  ↪ Machine Learning (ML) / Deep Learning theoretical basis



Machine Learning Cheat sheet



Machine/Deep-Learning Frameworks

- Pytorch
  - ↪ Python version of Torch open-sourced by Facebook in 2017.
  - ↪ Torch is a computational framework with an API written in Lua that supports machine-learning algorithms.
  - ↪ PyTorch offers dynamic computation graphs, which let you process variable-length inputs and outputs.
- TensorFlow
  - ↪ open source software library from Google for numerical computation using data flow graphs,
  - ↪ thus close to the Deep Learning book way of thinking about neural networks.
- Keras,
  - ↪ high-level neural networks API,
  - ↪ written in Python and capable of running on top of TensorFlow.
- Caffee
  - ↪ a well-known and widely used machine-vision library that ported Matlabs implementation of fast convolutional nets to C and C++
  - ↪ YouâĂŹll also have to consider its successor, Caffee 2,

Machine/Deep-Learning Frameworks

- Offer various **Package Design Choices**
  - ↪ **Model specification**:
    - ✓ Configuration file (Caffe, DistBelief, CNTK) vs. programmatic generation (Torch, Theano, Tensorflow)
  - ↪ For programmatic models, choice of high-level language:
    - ✓ Lua (Torch)
    - ✓ vs. Python (Theano, Tensorflow)
    - ✓ vs others (Go etc.)

In this talk

- We chose to work with python because of rich community and library infrastructure.

TensorFlow vs. Theano

- Theano is another deep-learning library with pythonwrapper
  - ↪ was inspiration for Tensorflow
- Theano and TensorFlow are very similar systems.
  - ↪ TensorFlow has better support for distributed systems though,
  - ↪ development funded by Google, while Theano is an academic project.

What is TensorFlow ?

- TensorFlow is a deep learning library recently open-sourced by Google.
  - ↪ library for numerical computation using **data flow graphs**.
    - ✓ **Nodes** represent mathematical operations,
    - ✓ **edges** represent the multidimensional data arrays (**tensors**) communicated between them.
- Flexible architecture allowing to deploy computation anywhere:
  - ↪ to one or more CPUs or GPUs in a desktop, server,
  - ↪ or mobile device with a single API.
- TensorFlow was originally developed within the Google Brain Team

Hands-on 7: Installing Tensorflow

- **Without further development**
  - ↪ you are ready to play with tensorflow
  - ↪ provided tutorial is self-explicit and make use of Jupyter Notebook

Hands-on 7

http://nesusws-tutorials-BD-DL.rtfd.io/en/latest/hands-on/tensorflow/install/

- Preparation of a Python sand-boxed environment — Step 1
  - ↪ using pyenv and virtualenv
- Tensorflow installation using `pip` — Step 2
- Installation of jupyter Jupyter Notebook — Step 3

Hands-on 8: Playing with Tensorflow

Your Turn!

Hands-on 8

http://nesusws-tutorials-BD-DL.rtfd.io/en/latest/hands-on/tensorflow/mnist/

- Run a very simple MNIST classifier — Step 1
  ↪ MNIST: computer vision dataset (images of handwritten digits)
- Run a deep MNIST classifier using convolutional layers — Step 2
  ↪ compare results with best models

Questions?

http://hpc.uni.lu

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