Introduction to BigData – Spark – Processing

Concrete Examples Experience at SG

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Objectives

4 x 2 hours of lessons
4 x 2 hours of Hands-On

Objective Lesson 1 : Overview

What is BigData ?
What is Spark ?
What is Data processing ?
… concrete examples from experience in a company

Objective Lesson 2,3,4 : Deep Dive in Spark

Outline

- What is BigData ?
  - Order of Magnitudes for « Big »
  - Distributed System challenges
  - Scaling Storage Resources: Hdfs
  - Scaling Compute Resources: Yarn, Kubernetes
  - Using Storage – Compute apis
  - Evolution of Hardware – Softwares – Hadoop Ecosystem, Spark
- Description of a Datalake
  - Content
  - Usages
- Example of Data-Processing
  - RAW to LAKE, Reports
- Evolution to Cloud

About Me

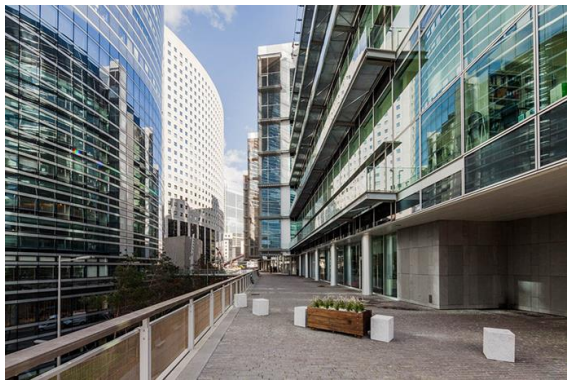
NOT using Twitter/LinkedIn/FaceBook/

Only arnaud.nauwynck@gmail.com

IT Passionate since 26 years

Working at Société Générale (La Defense)
In BigData team since 6 years

Expert Java + BigData + more



Github repos

https://github.com/Arnaud-Nauwynck

http://arnaud-nauwynck.github.io/

DISCLAIMER

I do not know everything. I am biaised with what I know.
My opinions do not represent any company

About You …
Quick Survey ?

Raise your Hands…

You are developper ?

In Java ? SQL ?

You know Hadoop / Hdfs / Spark ?

You want to be Data Engineer / Data Scientist ?

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How Big ? => Then Which Tool

1 .. 1 000

50 000

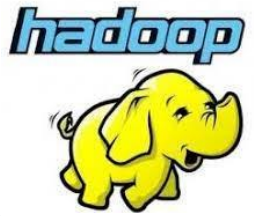
1 Million (e6)

(**Mega** Bytes)

1 Billion(e9)

(**Tera** Bytes)

>= e9 : BIG Data



(**Peta** Bytes)

Compute Resources
Vertical Scaling

Historically:

have Bigger needs => buy BIGGER Server

Very Frequent in Bank OLTP Databases

128 cores x 500Go RAM + SAN Bay of Disks

= Millions of Euros

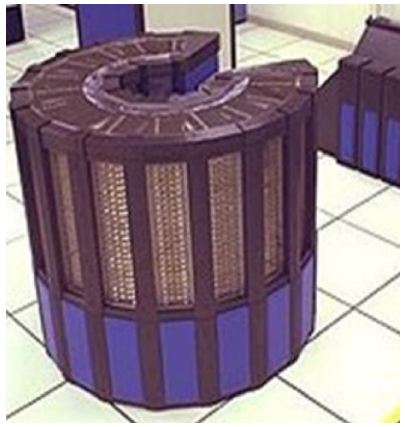
.. BUT price is exponential to performance, and limited

BigData definition

Data does not fit on 1 server … even Huge, because of

3 V = Volume / Velocity / Variety

Bigger Hardware, different Software
Vertical Scaling -> Horyzontal



1 OS, 1 process, N Threads

Distributed computing
… Sotfwares need
Network, Fault Tolerant

BigData At Scale
Google Datacenter

Not Only Gafas

Example of Smaller Companies, obviously doing BigData

Criteo (internet advertisment)
Cern (particule accelerators)
Gouvernment
Social Networks
Auchan, Carrefour, .. (E-Commerce)
MeteoFrance (Computing, Satelite Images)
Uber, Taxis, Cars (IOT)
Medical, Pharmaceutic, Genetics
Industries
Banks
..

BigData In Banks ?

Corporate Investment Bank

(for private / owned trading)

Network Bank (for everybody customers)

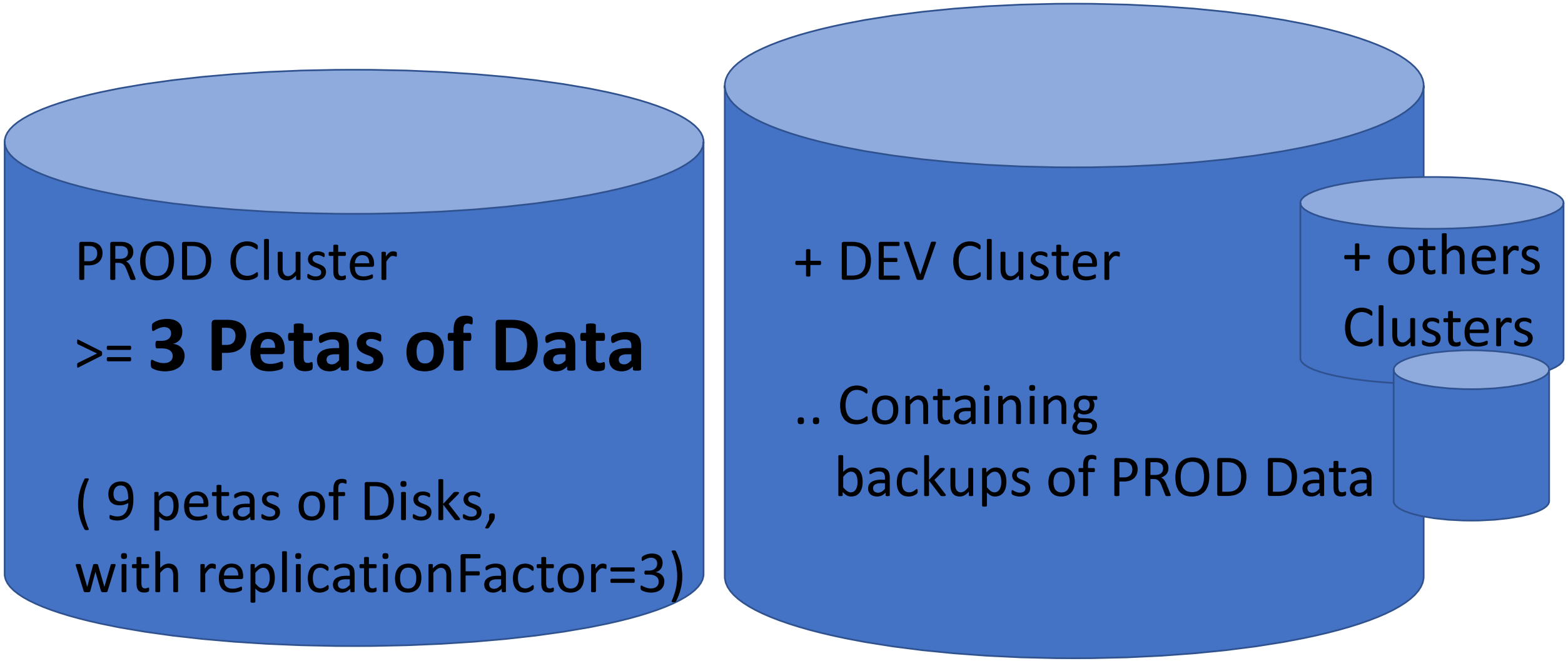
Example of Société Générale:
At La Defense

Example of Société Générale:
At Val de Fontenay

Data for
- Historical Market datas
- Risk / Var management
- Aggregation of all Trading departments
- Regulatory Reporting
- Business analysis
- ..

Data for
- RGPD… warn personnal data!
- Anti Fraud detection,
- customers-oriented
- Business analysis
- ..

BigData at SG (Investment Bank)



Typical Datacenter Hardware
= N Racks x 10 blades (1U / 2U)

1U Server for Datalake

1 server = 42 **cores** + **256** Go RAM + **network** 1Gb/s + **8** disks

« **Compute** » Resources

« **Storage** » Resources

Trend.. Splitting Compute and Storage Resources Virtualizing (VMs,Kubernetes,Cloud) for Elasticity & Costs

For Hardware historical performance
Compute = linked to Storage

1 Fixed « **Compute** » + local « **Storage** » Resource

Compute ONLY Virtual Resource

Provision **on-demand Cluster, VMs in cluster**
Choose RAM (compromise perf/cost) per VM
Dedicated for app workloads

Storage ONLY Virtual Resource

Elastic storage, pay as-you-go
Dedicated hardwares for data density

Data Density

48 * HDD disks in 2U blade

32 * SSD (E.1 EDSFF) in 1U blade

… 500 Tera / 1 Peta !! … 200 000 euros

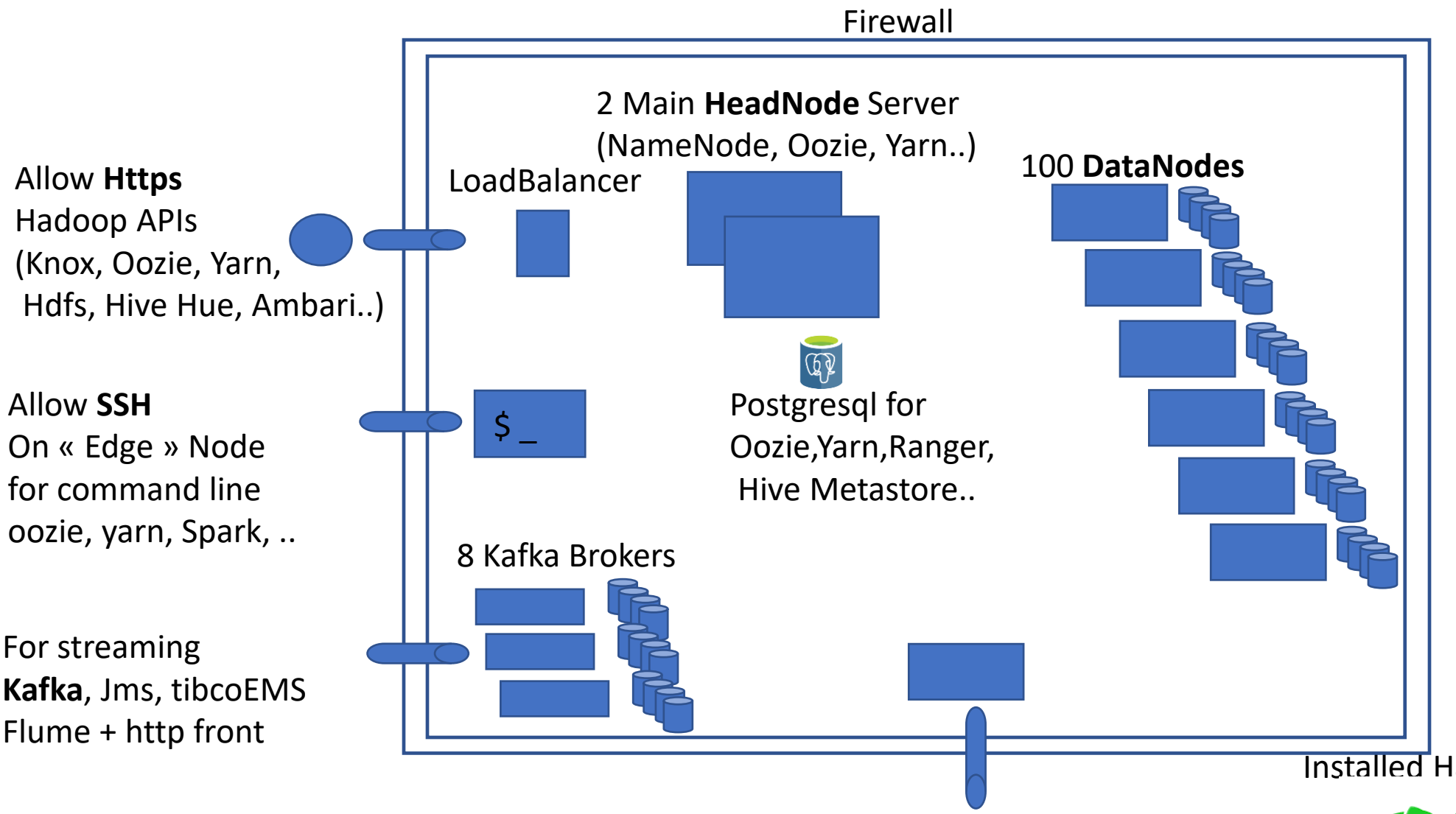
On-Premise « Small » Datalake ?

100 servers for PROD
(+ 120 servers for DEV)

= 4200 cores
+ 25600 Go RAM : 25 Tera of RAMS
+ 800 disks : 2 Petas of Data (6 peta of Disks)

… now 3 Petas on Azure

Hadoop Cluster Architecture



Installed Hadoop Distribution

HORTONWORKS®

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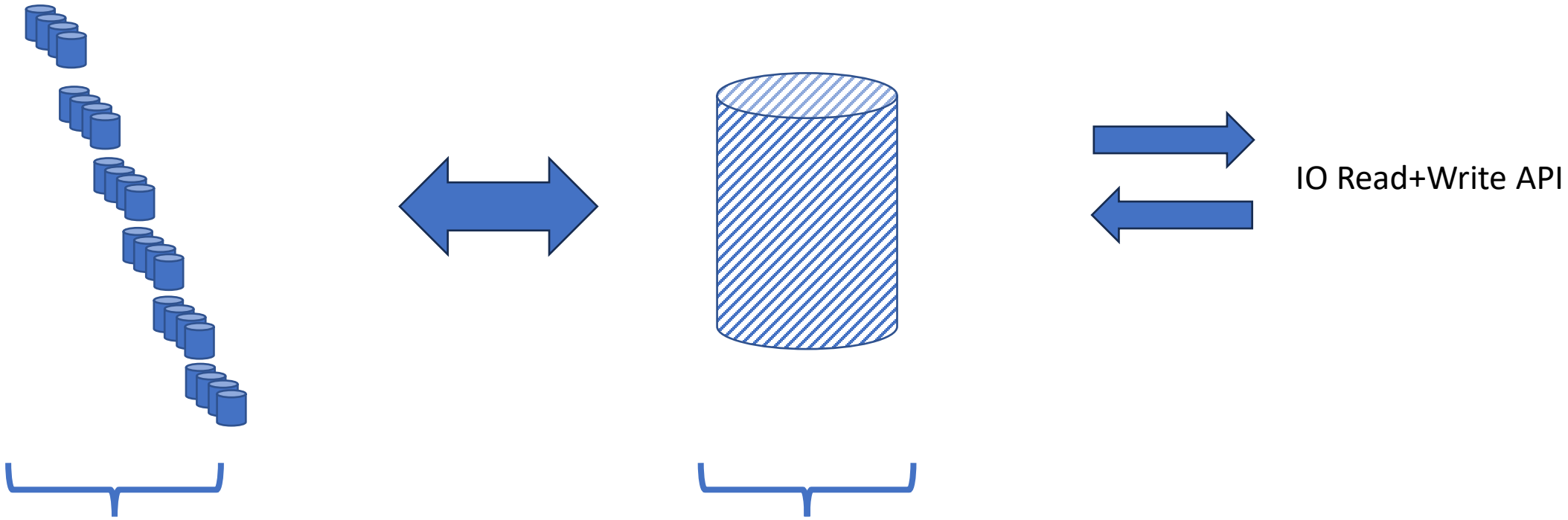
Handling 1 Server + 1 Disk
… OK with SSH,Bash,Java...

How to handle 300 Servers ?
1 Billions Files ? In 50 Millions Directories ?

… At Scale
(performance, and way of working in IT teams)

Challenge #1: Unify « Virtual » Storage Resources



Physical « **Storage** » Resources
= 800 HDD Disks
(on 100 Linux servers + network)

1 Virtual (Abstract) « **Storage** » Resource
= HDFS
Hadoop Distributed File System

Mind Shift .. Datalake FileSystem Abstractions

Instead of
Handling remote SSH / SCP
and naming server & dirs …

```
# SSH for Remote command
$ ssh  server-abc-for-dept-xyz
$ cd someDir
$ mkdir .. Ls … cp … launch java
$ scp result.file   another-server:

# SCP for Remote Copy to Local
$ scp server-abc-for-dept-xyz:result.file   local.file
```

Do this:
Servers are invisible to users
User see virtual HDFS Dirs & Files

```
# execute commands from any client
$ hdfs dfs –ls  /datalake/a/b
$ hdfs dfs mkdir /datalake/a/b/c
$ hdfs dfs rm /datalake/a/b/d

# Upload local file to Remote
$ hdfs dfs put ./local.file   /datalake/a/file

# Download Remote File to local
$ hdfs dfs get /datalake/a/file   ./local.file
```

Challenges of Distributed System

How to Handle ?
Failures,
Resilience,
Horyzontal Scalling,
Availability,
Consistance,
Replication,
…

Sh*ts Happens (Hardware Failures, Software, Electric Power, Network, Data Corruption ..)

Example for **1 Disk**

MTBF = Mean Time Between Failure = **~25 years**

… FINE ! …. Wait ! Fine ????

for a big cluster 20 000 servers x 8 Disks => ??

Big Data = Handle « Normal » (recurrent) Failures !

1 Disk: 25 Y = 25*365*24 hours = 219k hours … 1 Cluster: 20000*8=160k
=> In average : **1 failure every 1h30mn … 17 per days !!**

Failure is **NOT exceptional**, it is the « normal » way

System must (try to) **handle it TRANSPARENTLY**

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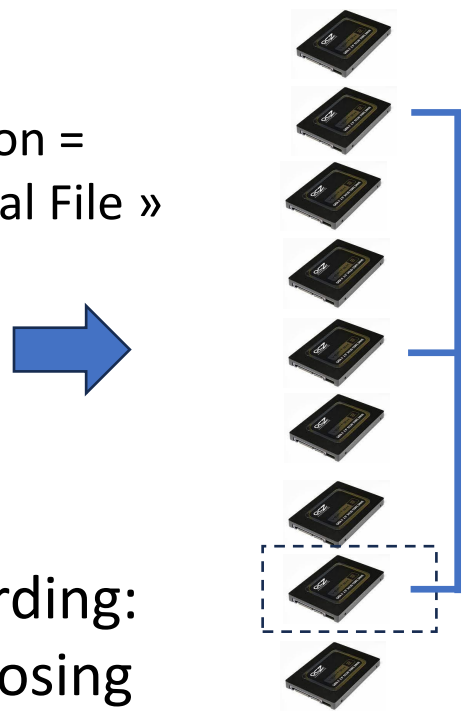
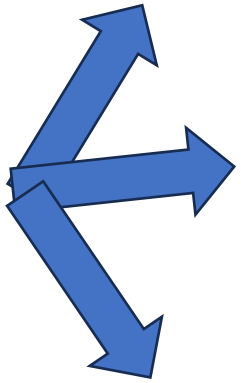
How to Handle Disk Crash:
Obviously Replication Copies, But in XA & Real-Time

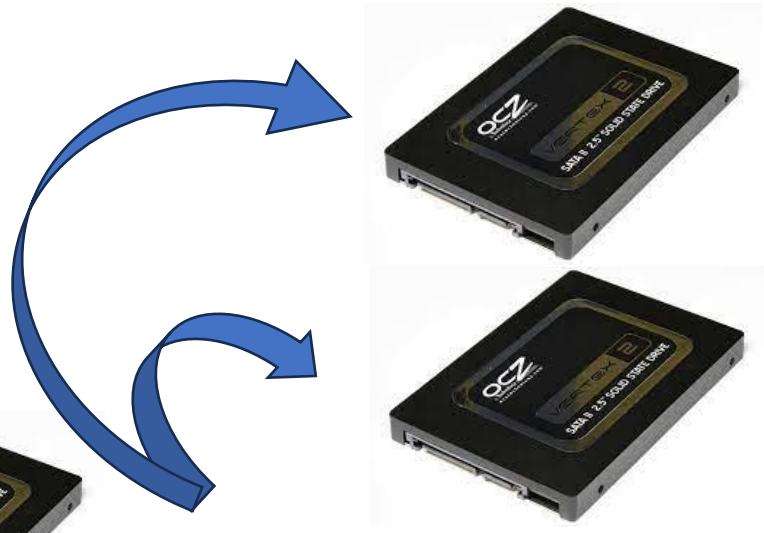
RF = Replication Factor = 3 (or more!)

End-user operation =
Write to a « virtual File »



Sharding:
Choosing
group of 3 disks
out of 20000





Then Dispatch to
the current « Master »
Server for this group

Then Immediate COPY
… hopefully Transactionally
To current « follower » servers

The Devil hides in the Details …

the « master » server can not reach other for copying ? Or takes too long

Files will become « Under-replicated », after a server crash (or switch Off)
… « Over-replicated » when the server rejoin cluster (switch ON)

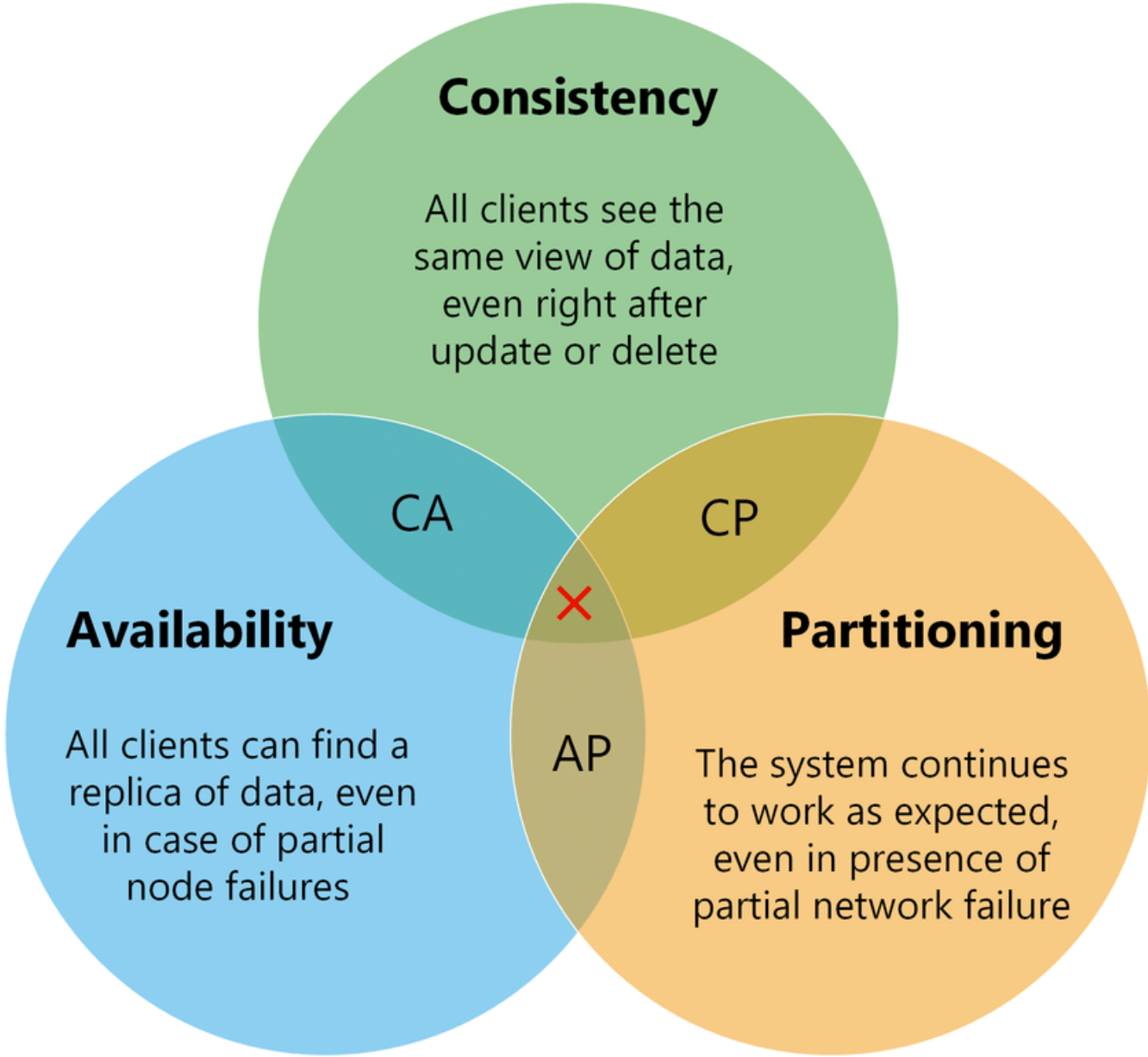
2 servers pretend to be « master » at same time (network partition) ?

Reconcile 2 conflicting (diverged) servers data ?

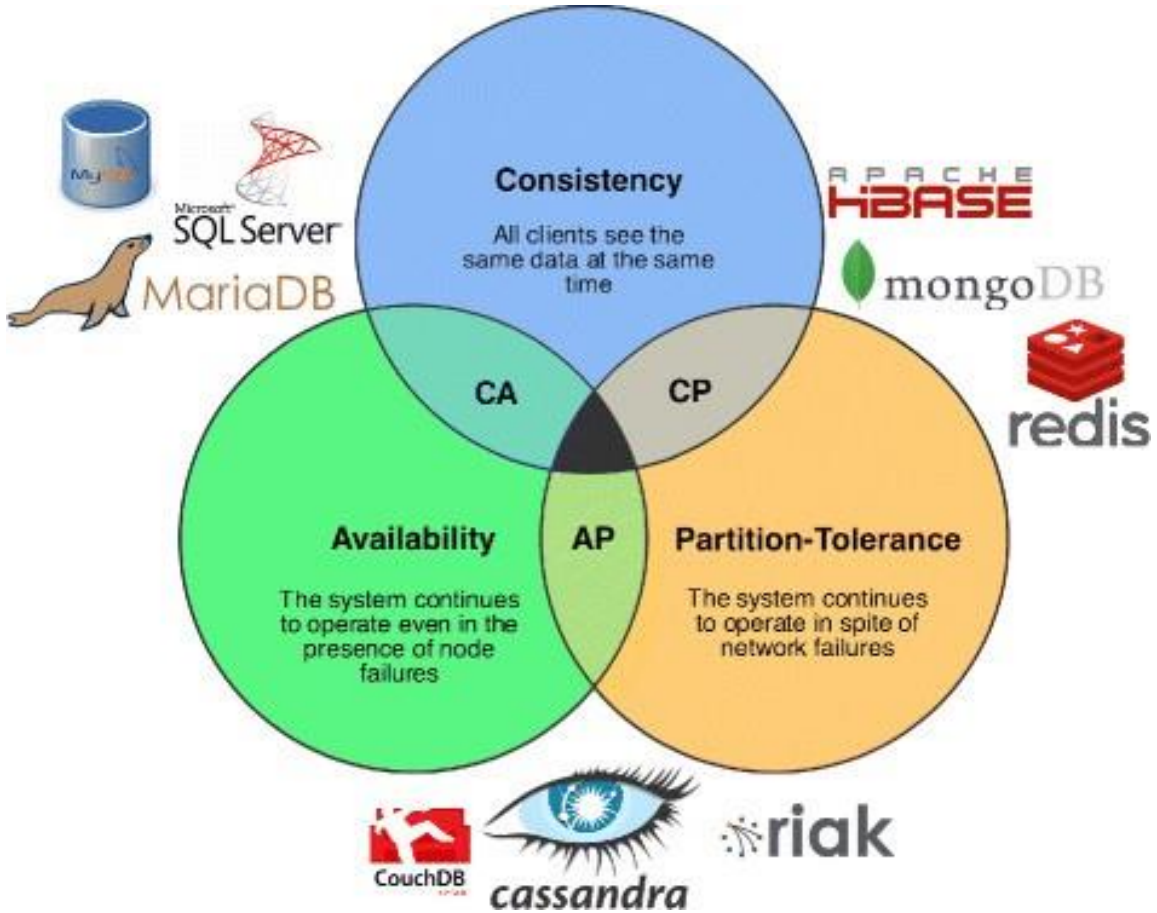
SPOF : Single Point Of Failures … all servers depends of same Electric Power supply

Etc, Etc, Etc ...

CAP Theorem .. Choose 2 out of 3



Databases choices

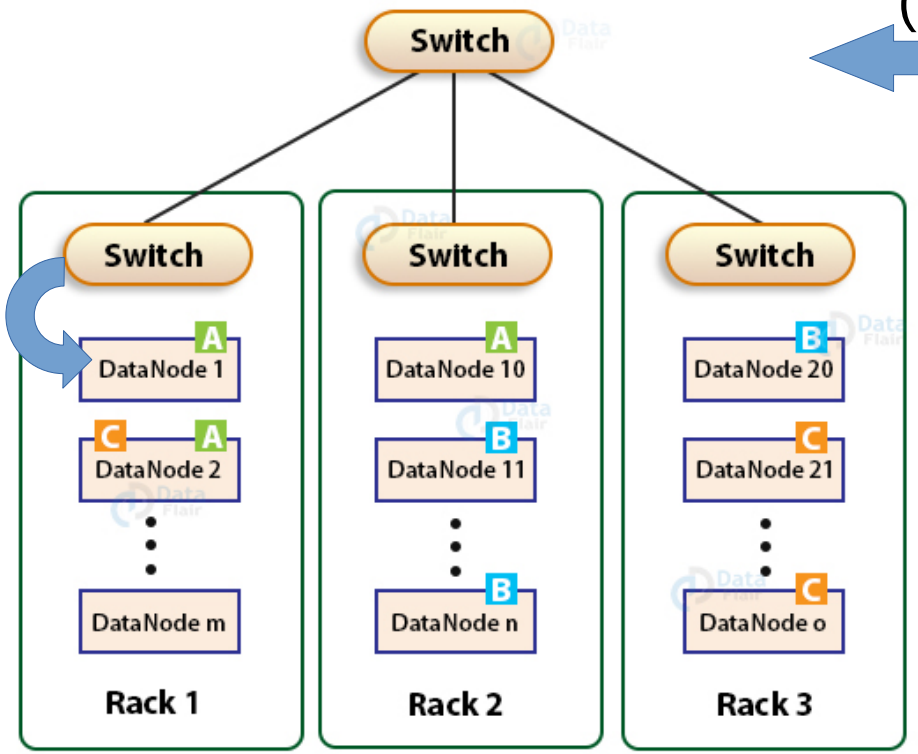


« Eventually Consistent »

.. Means « NOT » always consistent … but ends to be

Hadoop Legacy Replication Factor: Rack Aware

East-West traffic
(relatively slow / limited)



Allow replicate 1
in same Rack
(fast)

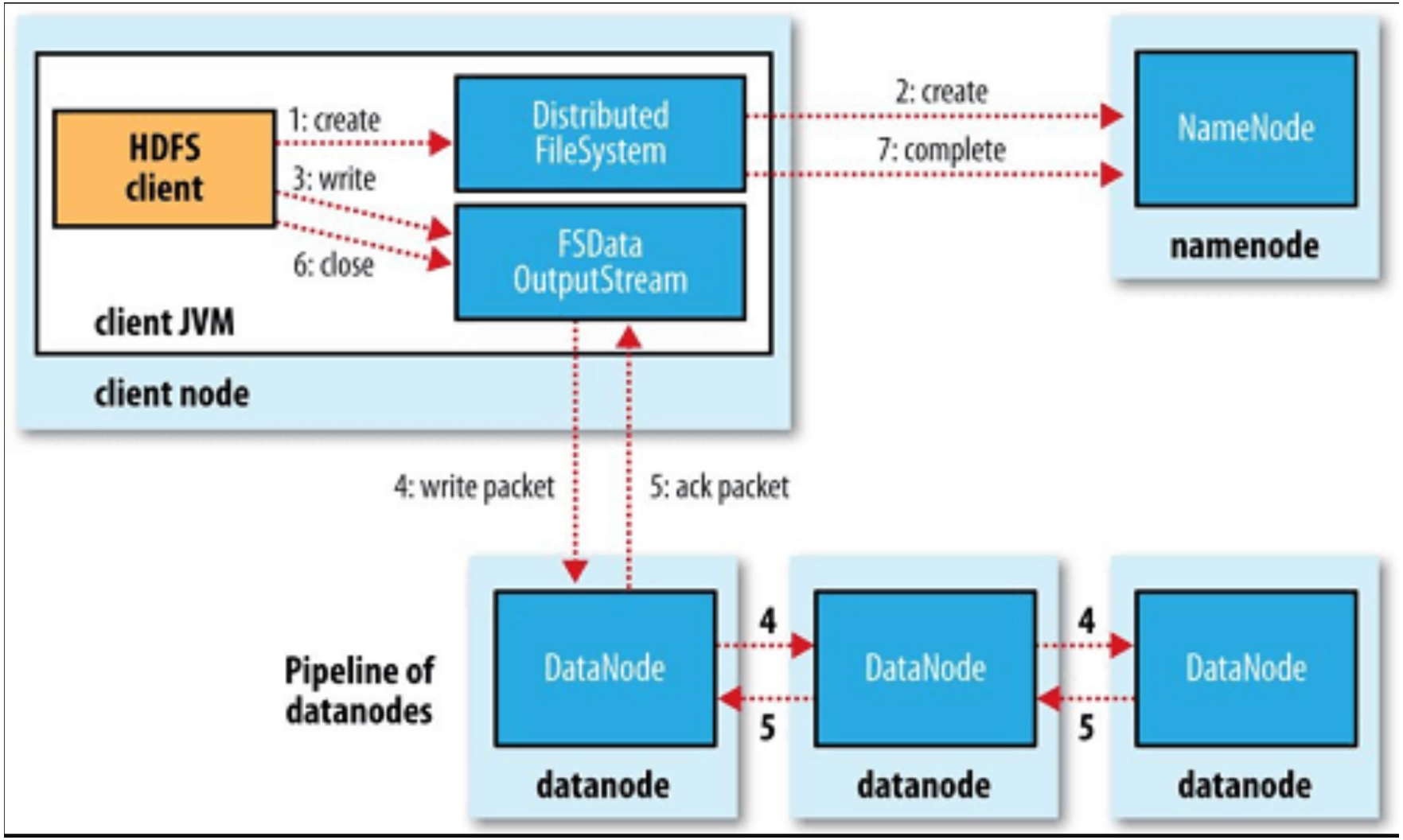
Top-Rack switch

North-South traffic
(fast)

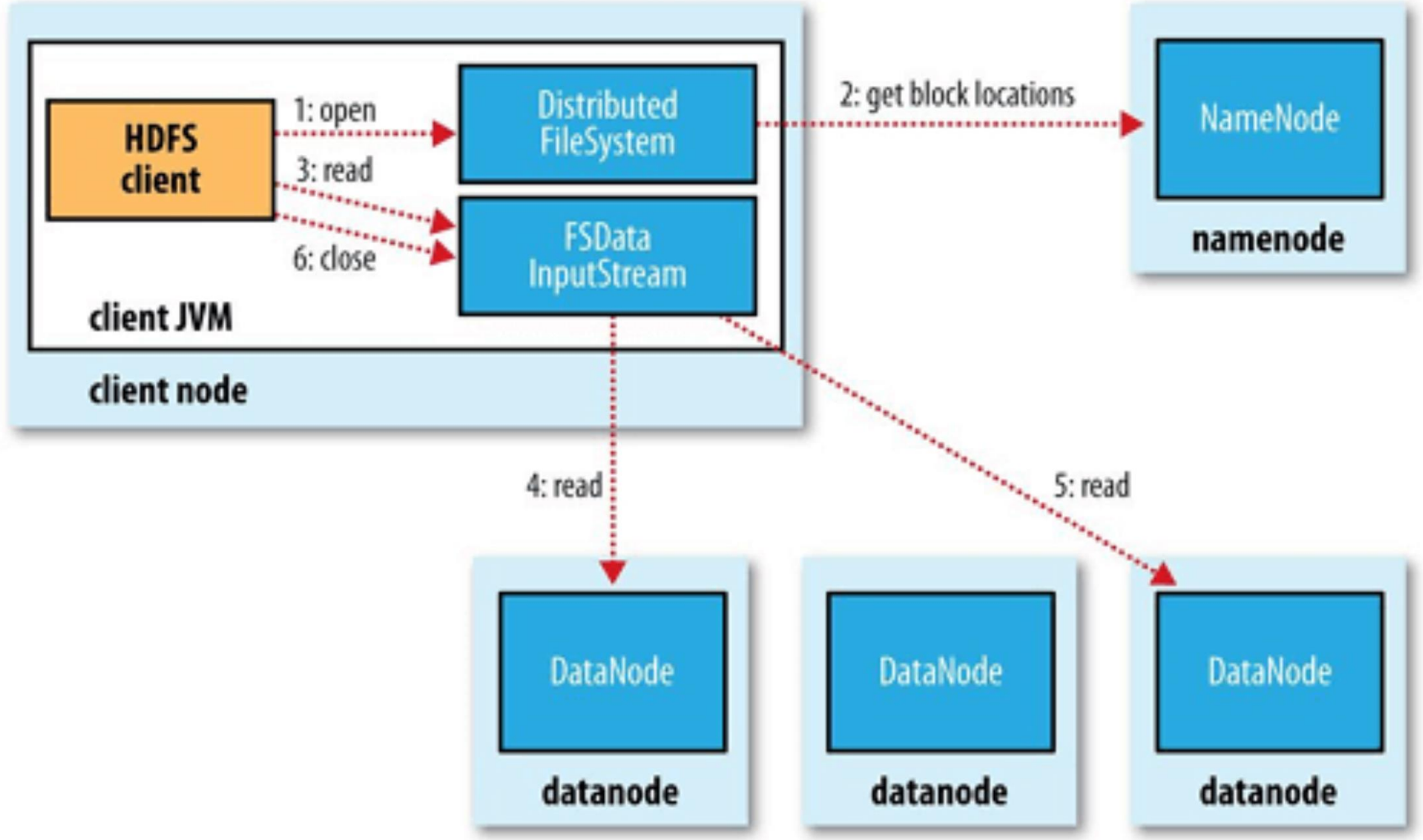
Then must replicate >= 1
in other Rack

replicate more.. In other HDFS
datacenter (distcp)

Writing a HDFS File

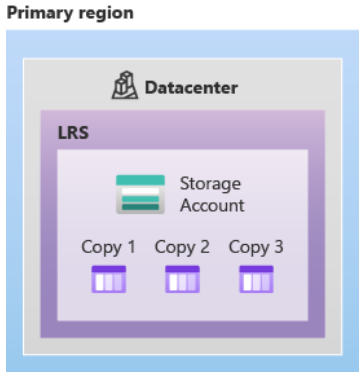


Reading a HDFS File

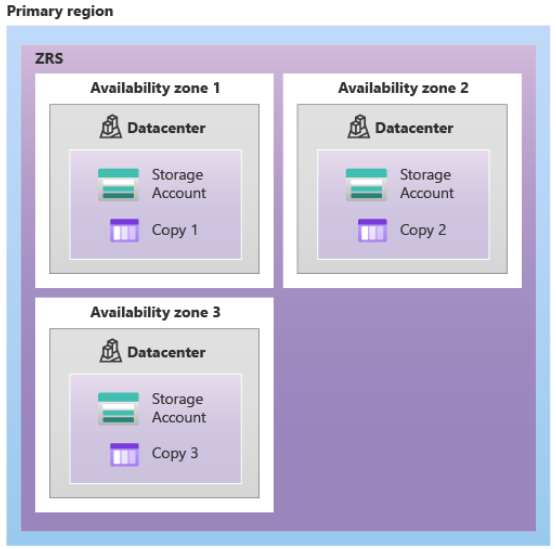


Example on Azure Storage… LRS, ZRS, GRS, GZRS
1 Region = 3 AZ (Availability Zone) .. 3 Datacenters

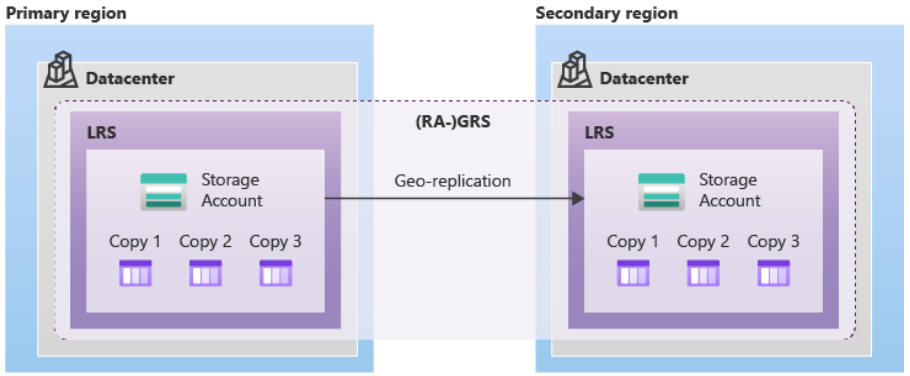
LRS (cheaper)
… 1 Datacenter



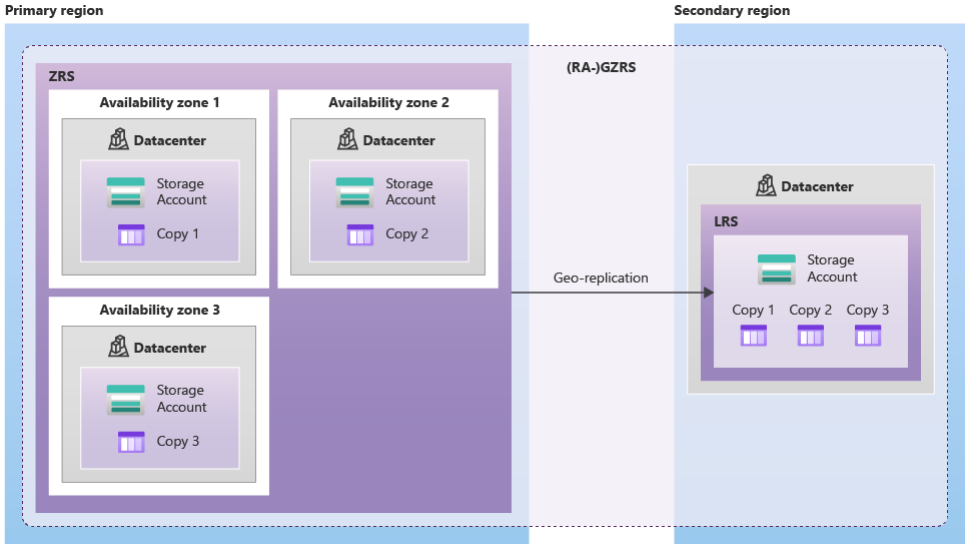
ZRS … 1 Region



(RA-) GRS … 1 LRS + async 1LRS, 2 zones



(RA-) GZRS … 1 ZRS + async 1LRS



Recap … Storage Resources

Coffe Break ?

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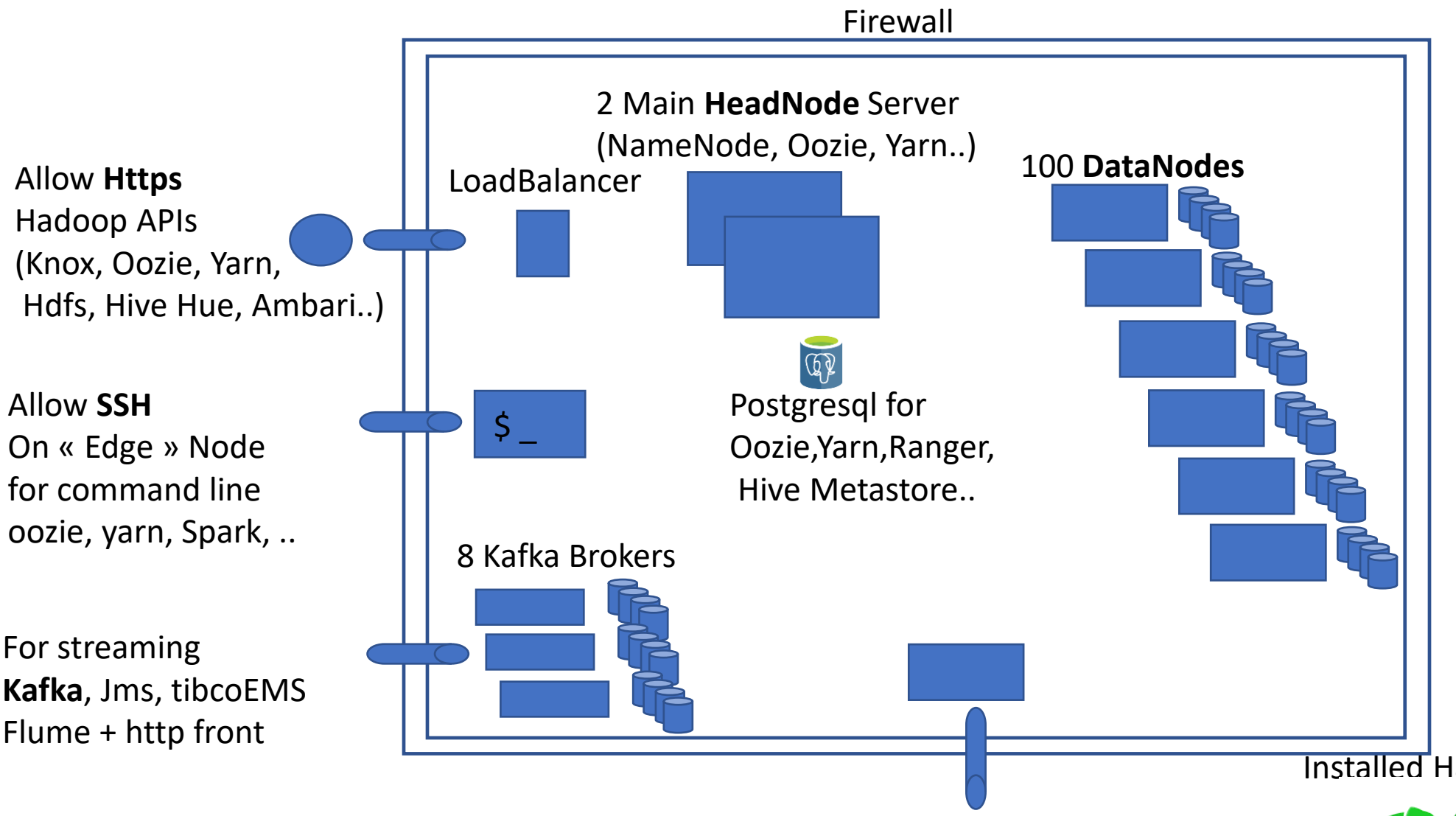
Reminder … Hadoop Cluster Architecture



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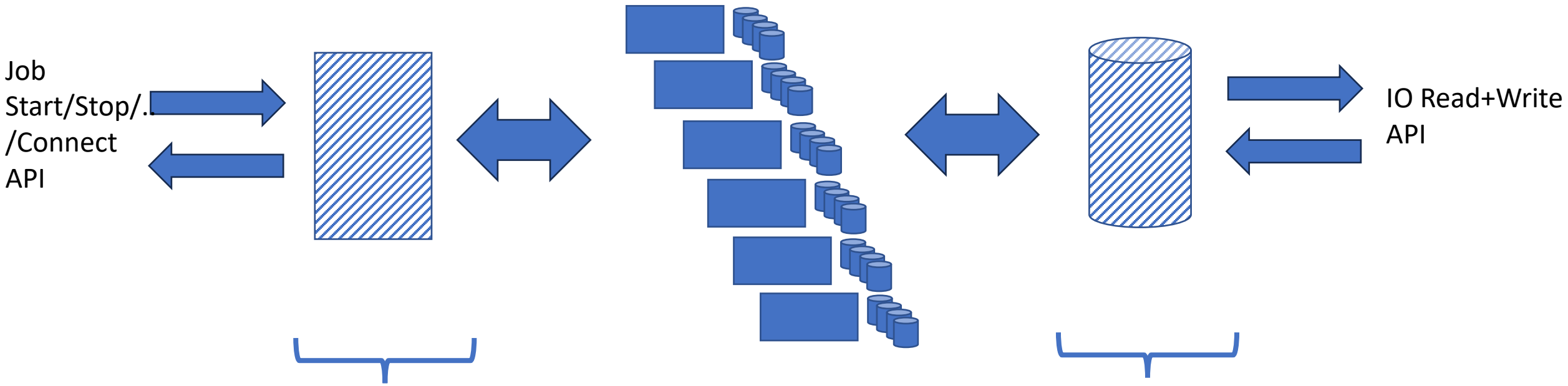
2 Distributed Challenges : 1=Storage + 1=Compute



1 Virtual « **Compute** » Resource
= Yarn (or Kubernetes)
Distributed Container(Process/Pod) API

1 Virtual « **Storage** » Resource
= HDFS
Hadoop Distributed File System

Mind Shift: SSH -> Job Compute Resource

Instead of
Handling remote SSH / exec - kill
and naming server & processes …

```
# SSH for Remote command
$ ssh  server-abc-for-dept-xyz
$ cd someDir

# long running services
$ sudo systemctl start my-service
$ do; if [ -e/proc/$pid ] ./start.sh; sleep; done

# (short running) job application
$ ./start.sh;  hdfs dfs –get yourapp.jar
$ java –jar yourapp.jar
$ ps, pid=..
$ kill -9 $pid
```

Do this:
Servers are invisible to users
User see virtual Services and Jobs scheduling

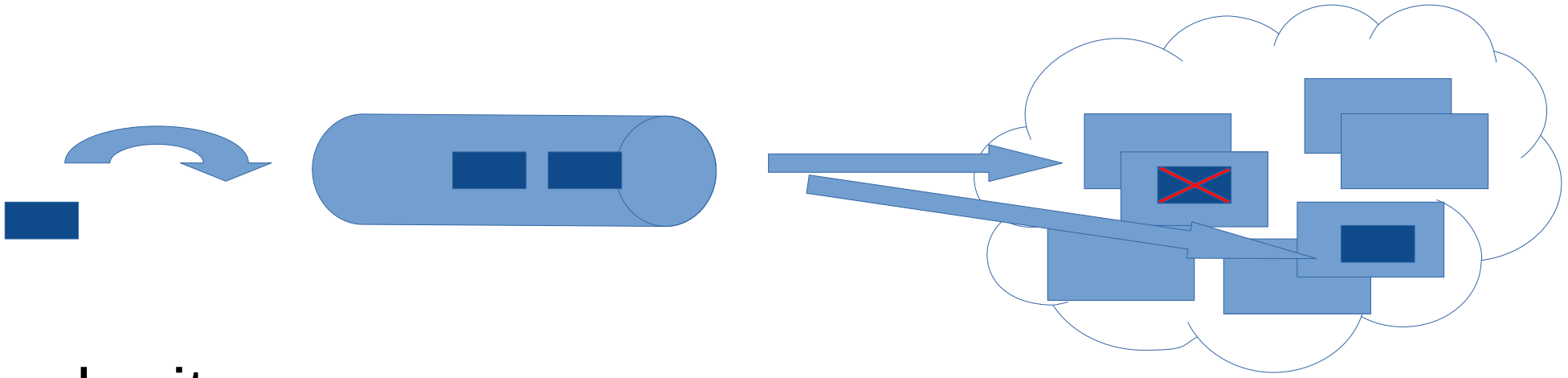
```
# execute commands from any client
$ curl http://ambari admin commands

$ oozie job start .. hdfs://…/workflow.xml
$ oozie job start .. hdfs://…/coordinator.xml
$ oozie job kill $oozieId

$ yarn app -list
$ yarn app –kill $yarnId

# OR BETTER in Kubernetes
$ kubectl apply –f myservice.yml
$ kubectl apply –f my-spark-job.yml
$ kubectl sparkApp list|get|delete
```

Pet vs Cattle

Pet have id=name
You take extra care of it

Cattle >= 1000 : anonymous
Id=Number, interchangeable

Launching => Scheduling on Allocated Resource

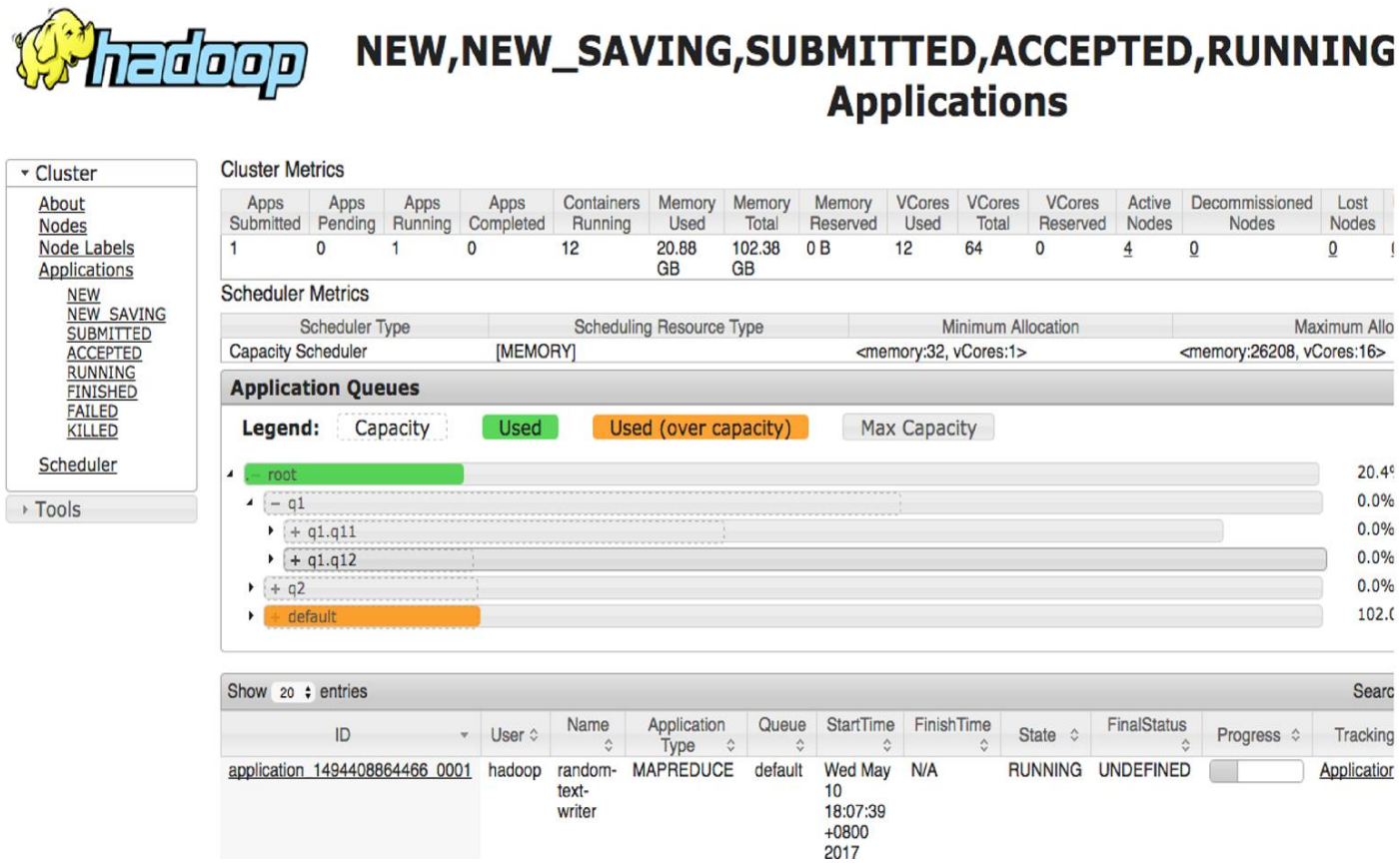


You submit
Something to run

You don’t run yourself
You don’t choose server

Then wait..
maybe allocate ++resources
(=> app retries managed)
You don’t have access to servers

Yarn Queue



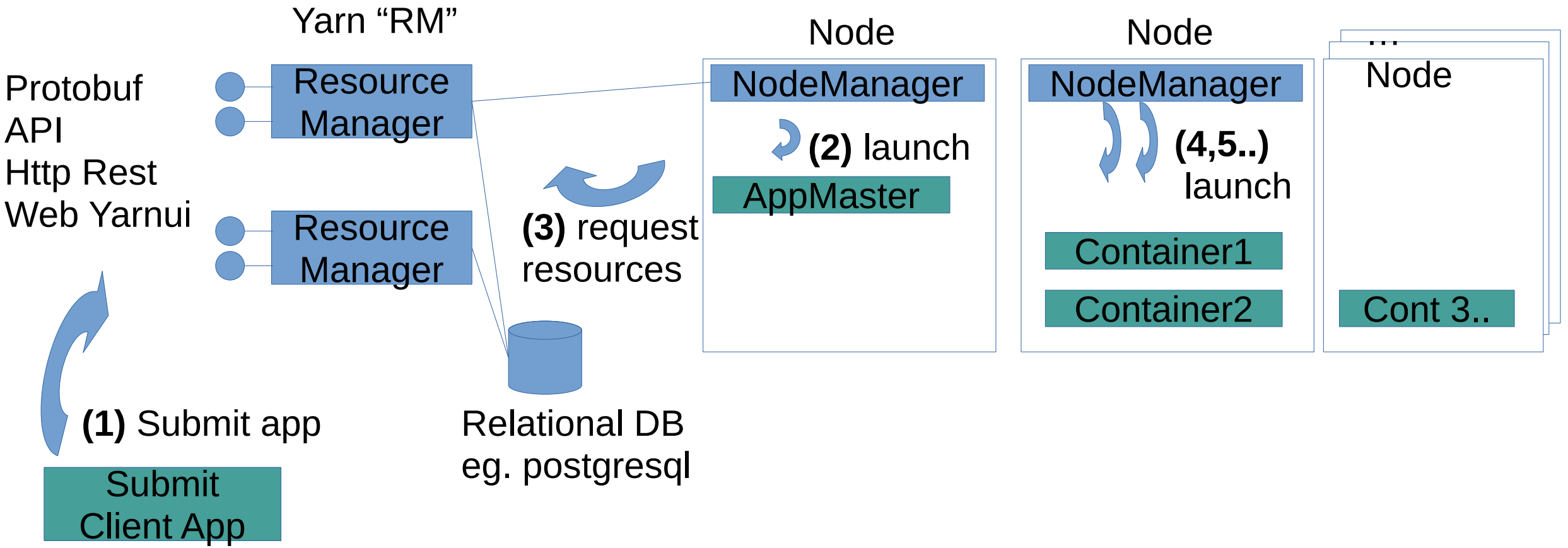
Queue Hierarchy :

Child queues => sum to 100%

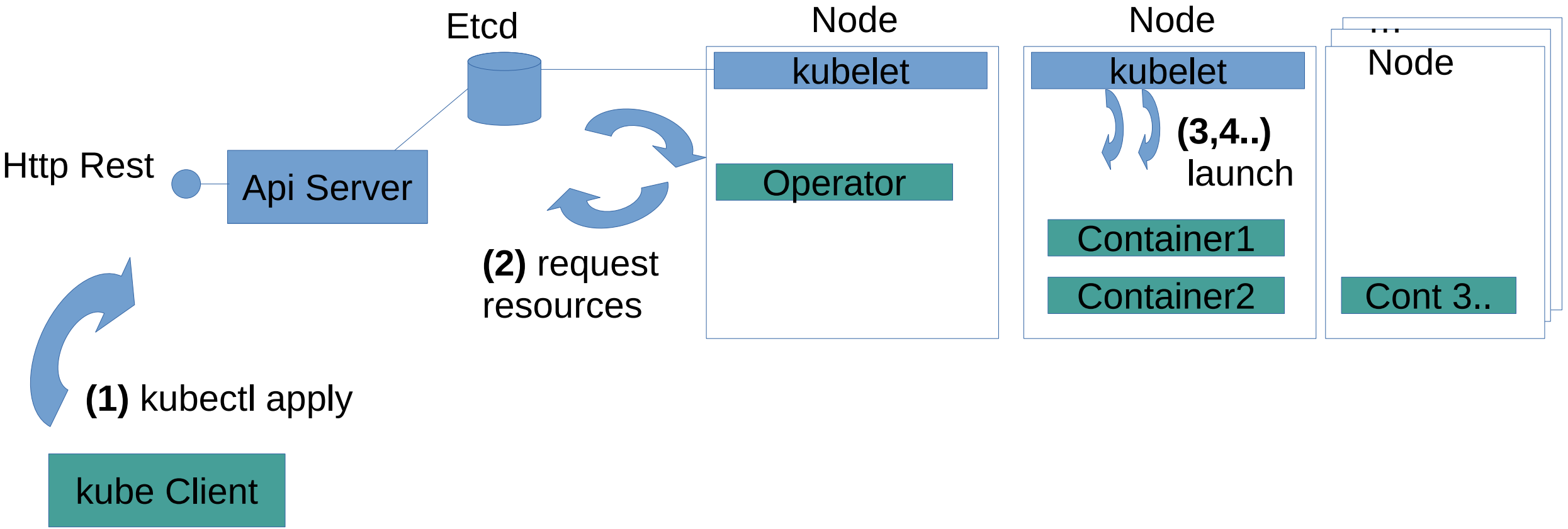
Capacity / Max Capacity
… over-quota allowed

If Preemption enabled =>
may kill app in over-quota

Hadoop Yarn Architecture



Kubernetes Architecture

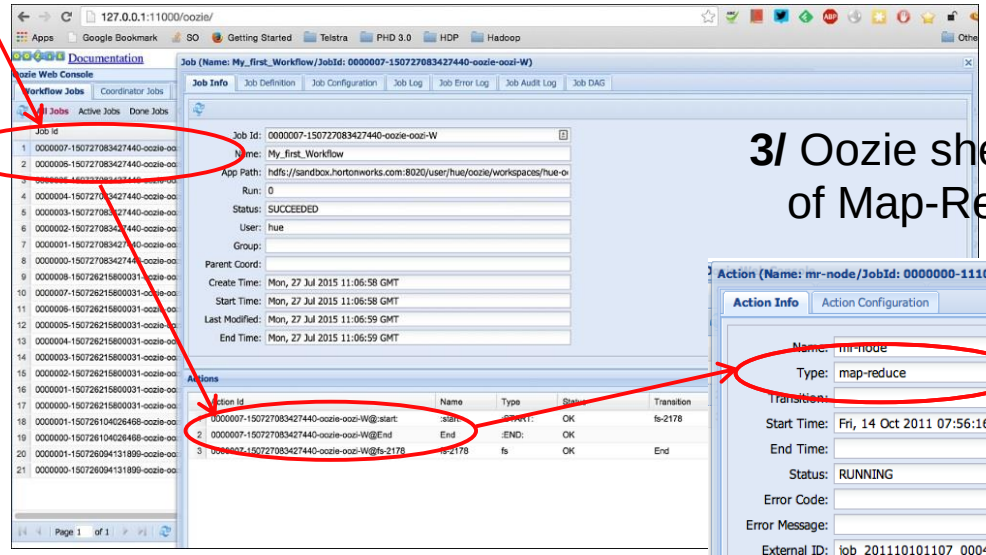


Architecture Comparison Yarn <-> Kubernetes

Resource Manager	⟷	API Server
Relational DB eg. postgresql	⟷	Etcd
NodeManager	⟷	Kubelet
Container (Jvm, Docker)	⟷	Container (Docker,..)
App Master (1 per App)	⟷	K8s Operator (1 per Type)
Yarn Quota	⟷	K8s Ns + Resource Request/Limit
Yarn Fifo Queue	⟷	Volcano / UniKorn (K8s extensions)

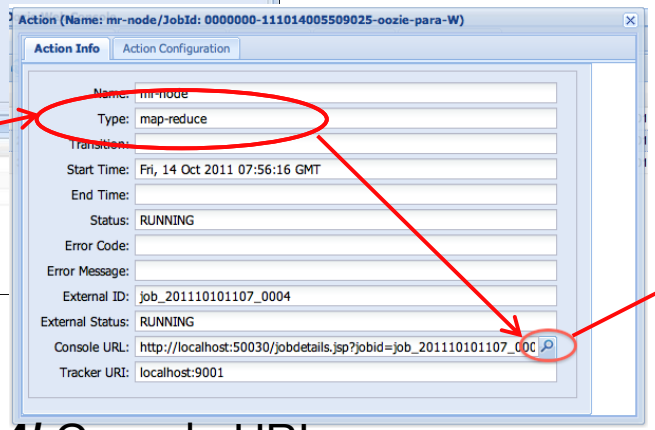
Ooozie → Yarn UI → Yarn … Nightmare, ex: Logs

1/ Find Oozie workflow Id



2/ oozie-action

3/ Oozie shell action = “Mapper” of Map-Reduce in Yarn



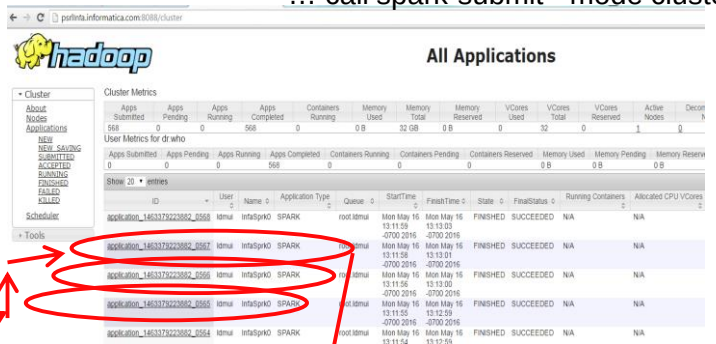
4/ Console URL = url in Yarn (Proxy or History)

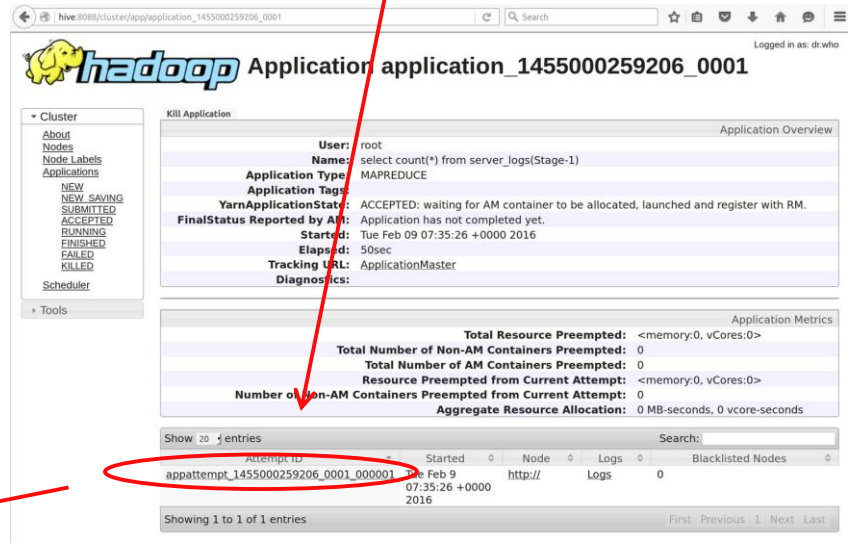
Example
Shell → spark-submit

7/ spark

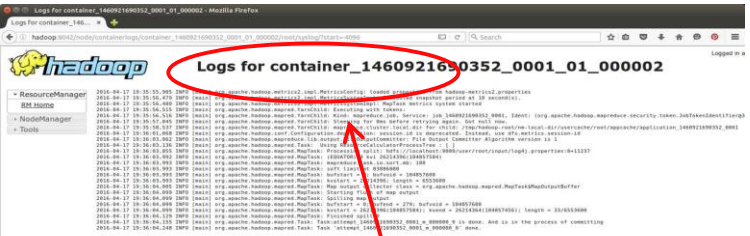
6/ Yarn (spark-submit client)

5/ Mapreduce (SHELL)
… call spark-submit --mode cluster

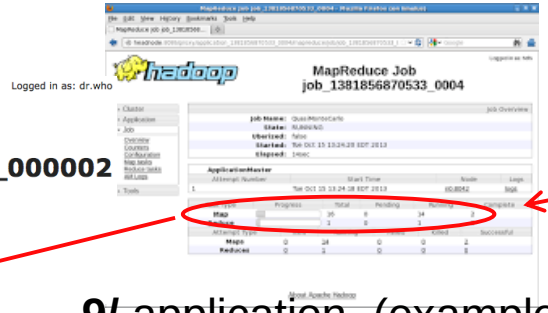




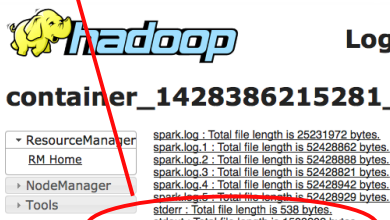
8/ appmaster application attempt 1



11/ stdout !!



9/ application (example: Reduce for shell)



10/ log files page

Outline

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  - Scaling Compute Resources: Yarn, Kubernetes
  - **Using Storage – Compute apis**
  - Evolution of Hardware – Softwares – Hadoop Ecosystem, Spark
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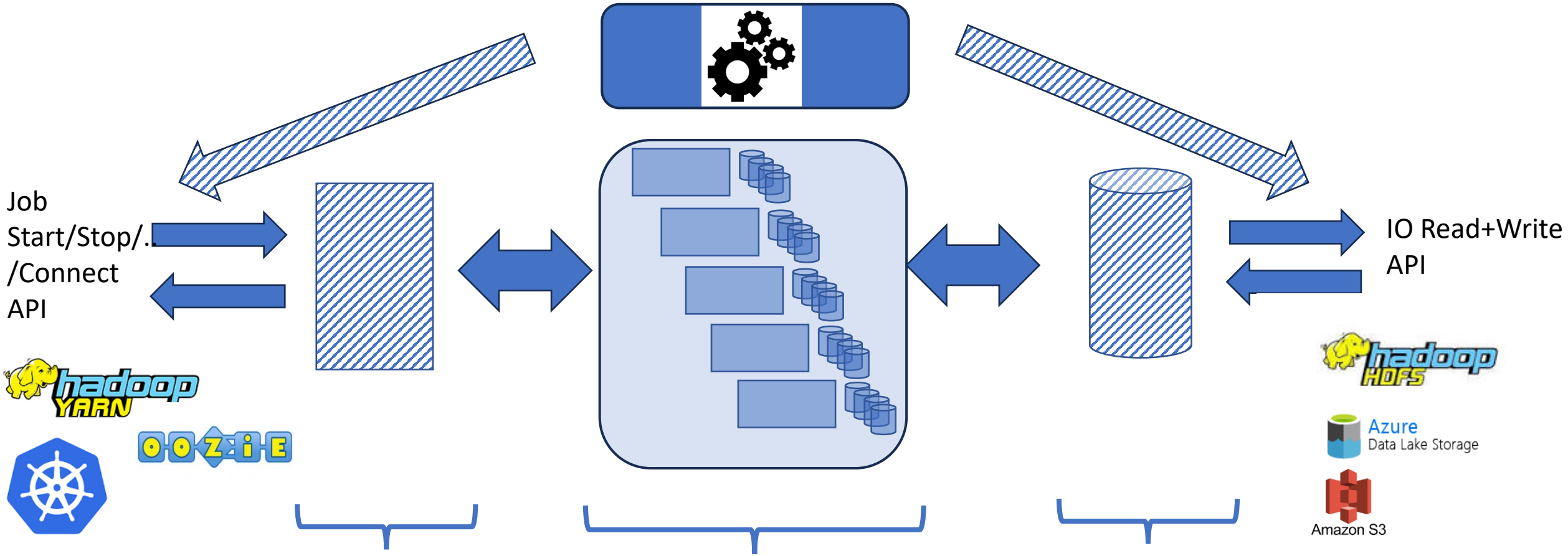
Recap .. Objective for Distributed Data Processing Solution: Use Compute + Storage APIs

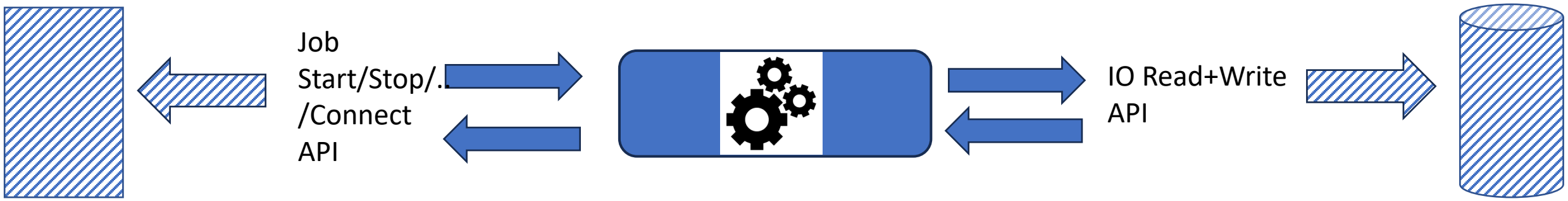


1 Virtual « **Compute** » Resource
= Yarn+Oozie (or Kubernetes)
Distributed Container(Process/Pod) API

Hidden physical
Resources

1 Virtual « **Storage** » Resource
= HDFS
Hadoop Distributed File System

Recap .. Objective for Distributed Data Processing Solution: Use Compute + Storage APIs



Use API
For **Compute** Resources

Use API
For **Storage** Resources

Compute ONLY Resources

Storage ONLY Resources

Data Processing = using Compute + Storage APIs

Compute

Cluster
>= 200 servers

Storage

>= 3 Peta bytes

Your Data Processing

hadoop YARN

OOZIE

hadoop HDFS

Azure Data Lake Storage

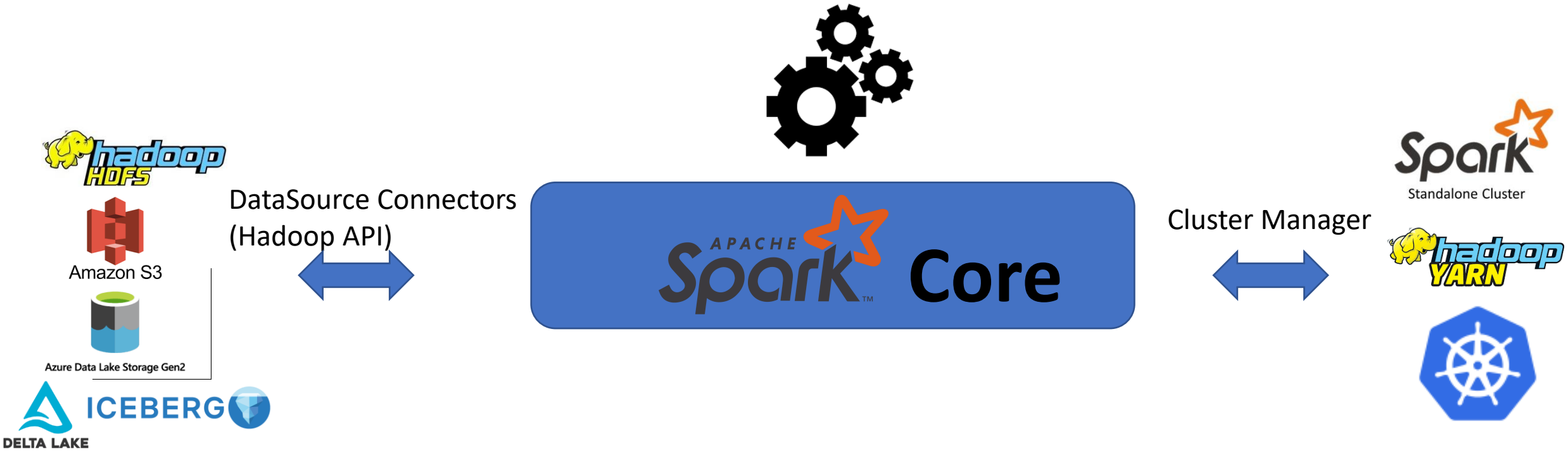
Amazon S3

https://www.youtube.com/watch?v=YVAVugfnW6Y

Spoiler Alert … Data Processing in Spark

Your Code:

Spark Core
Unified Engine… using Compute + Storage APIs



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Hardware Evolutions… => Architecture Changes

HDD = Hard Disk (magnetic + disks rotation) => slow « seek » to position
SSD => no more « seek » problem, so NO need to locally cache data in RAM
and huge read Go per second

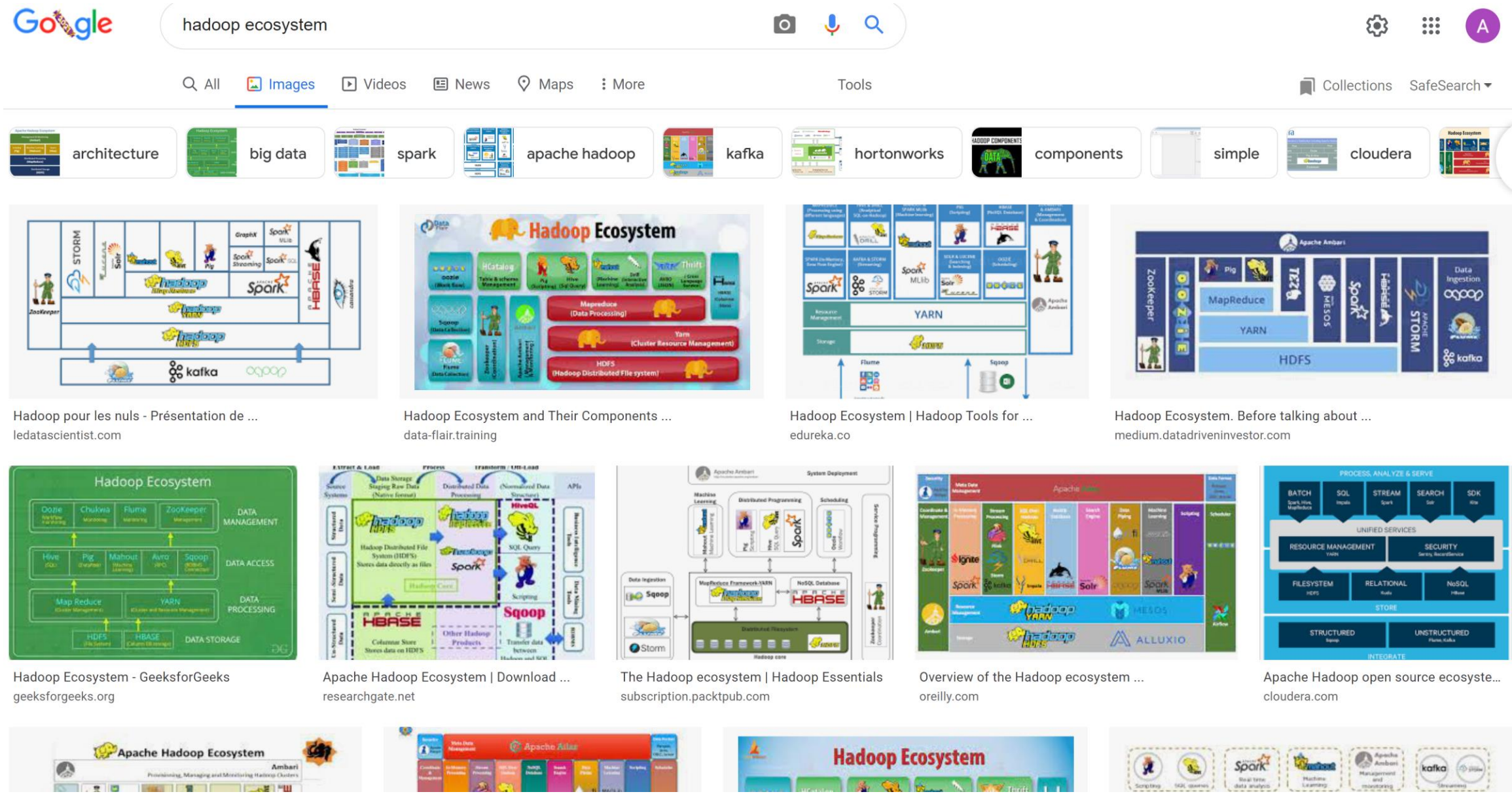
Disk connectivity to motherboard => HDI < SCSI < SATA < …PCI Nvme …
Google « nvme vs sata ssd bandwidth »
SSD + NvMe => HUGE bandwith … > 4Go per seconds
(maybe more than network card support?)

Network cards … 10Go/s … fiber channel 100Go/s
So downloading HUGE file for Full scan is now OK !!
No more need to cache in local RAM, no need to collocate program near data

How Softwares evolve to handle BigData ?

Which ones to use today?

Hadoop Ecosystem « Explosion »



Spark (Recent) History & Ancestors

MapReduce @ Google

2002 @Google

2004 Google Paper published

2014 Google No more used of MapReduce

2006 @Yahoo Hadoop implementation

2008 Apache Open-Source

2012 Yarn (v2)

2021 MapReduce bashing … HDFS & Hadoop also HortonWork bought by Cloudera HDInsight @Azure…very bad choice .. To be abandonned

MPI

1995 Message Passing Interface

2010 Spark paper

2013 Apache top-level

??

2015 Kubernetes

2020 **Spark on K8s**

Datalake History At SG

~8 years ago
2014

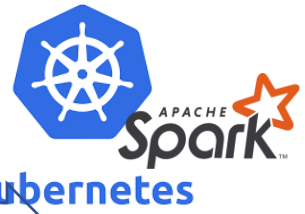
~2 years ago (2020)
Decision to migrate to Azure
+ Dismantle On-Prem

Dec 2022
OFF

Init BigData
cluster at SGCIB

2 major PROD projects:
- MiFid reports (all trades)
- Var Risk

> 150 projects



~ 1 year ago (2021)
>= 100 projects migrate to Azure

Internal Re-organizations
Another Cluster..

Point in common
Despite all changes

MapReduce @Yahoo = Hadoop .. 2006

Constraint
=>
Architecture
Choice

Commodity Hardwares (datacenters):
Only HDD + RAM
Data Locality : co-host Storage near Compute
use RAM to cache
avoid network

Think different?

2006

2020

MapReduce -> Spark + other changes

Constraint

=>

Architecture

Choice

Faster Disk (SSD)

Faster Network

Compute != Storage

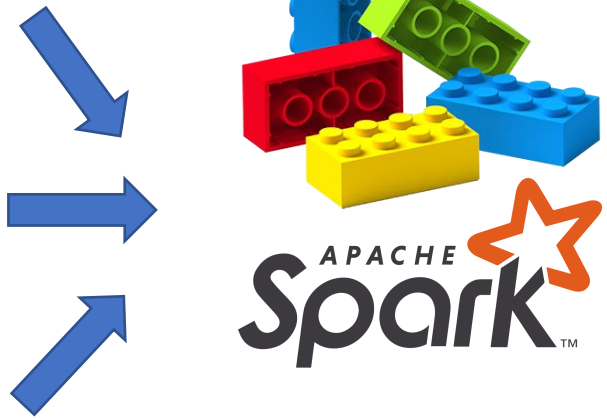
Cloud

Think different?

2006

2022

Simple => Many Specific Systems => Unified



« **Simple** » ecosystem
(verbose inneficient & complex java code)

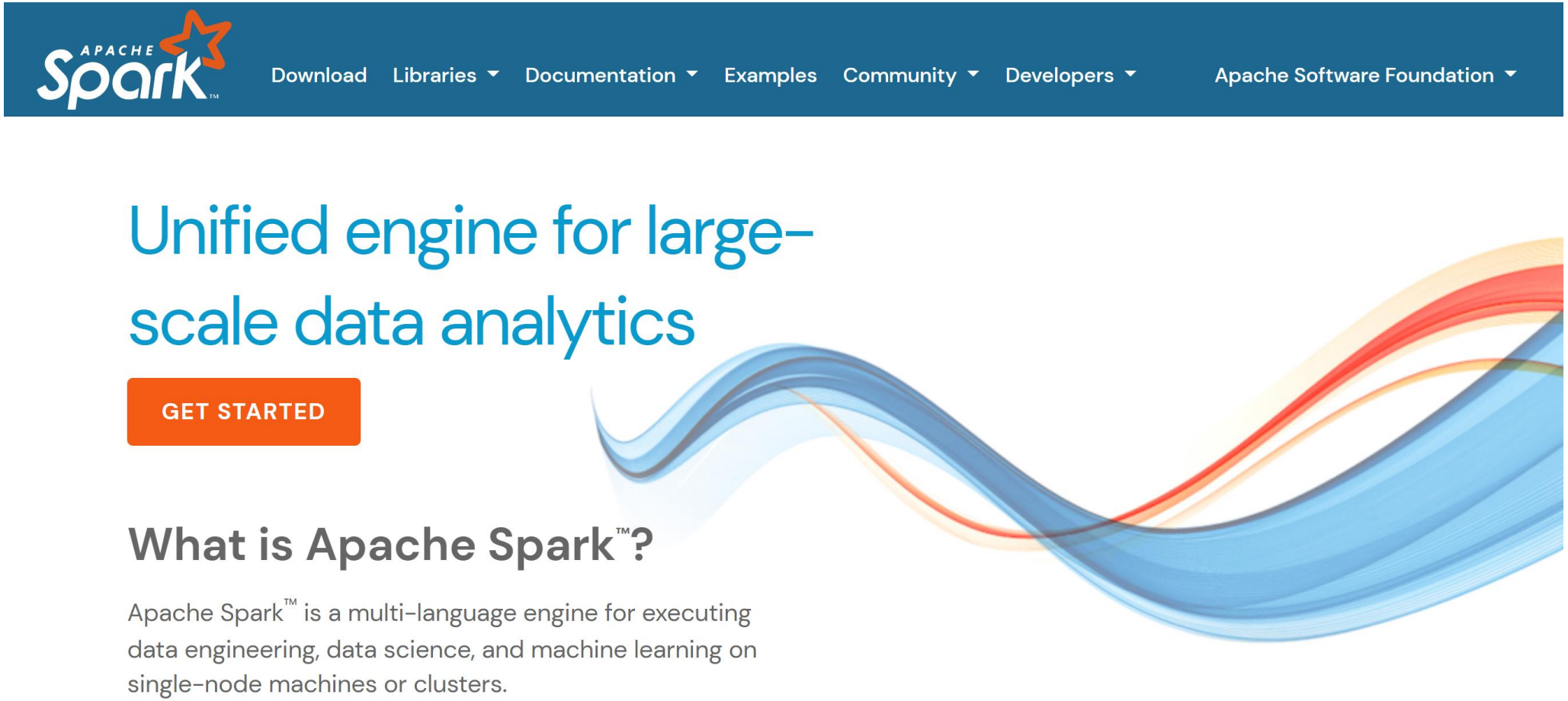
« **Bazard** » ecosystem
(**Too MANY TOO** SPECIFIC redundant, complexes)

“Unified” ecosystem
Simple
+ extensible modules

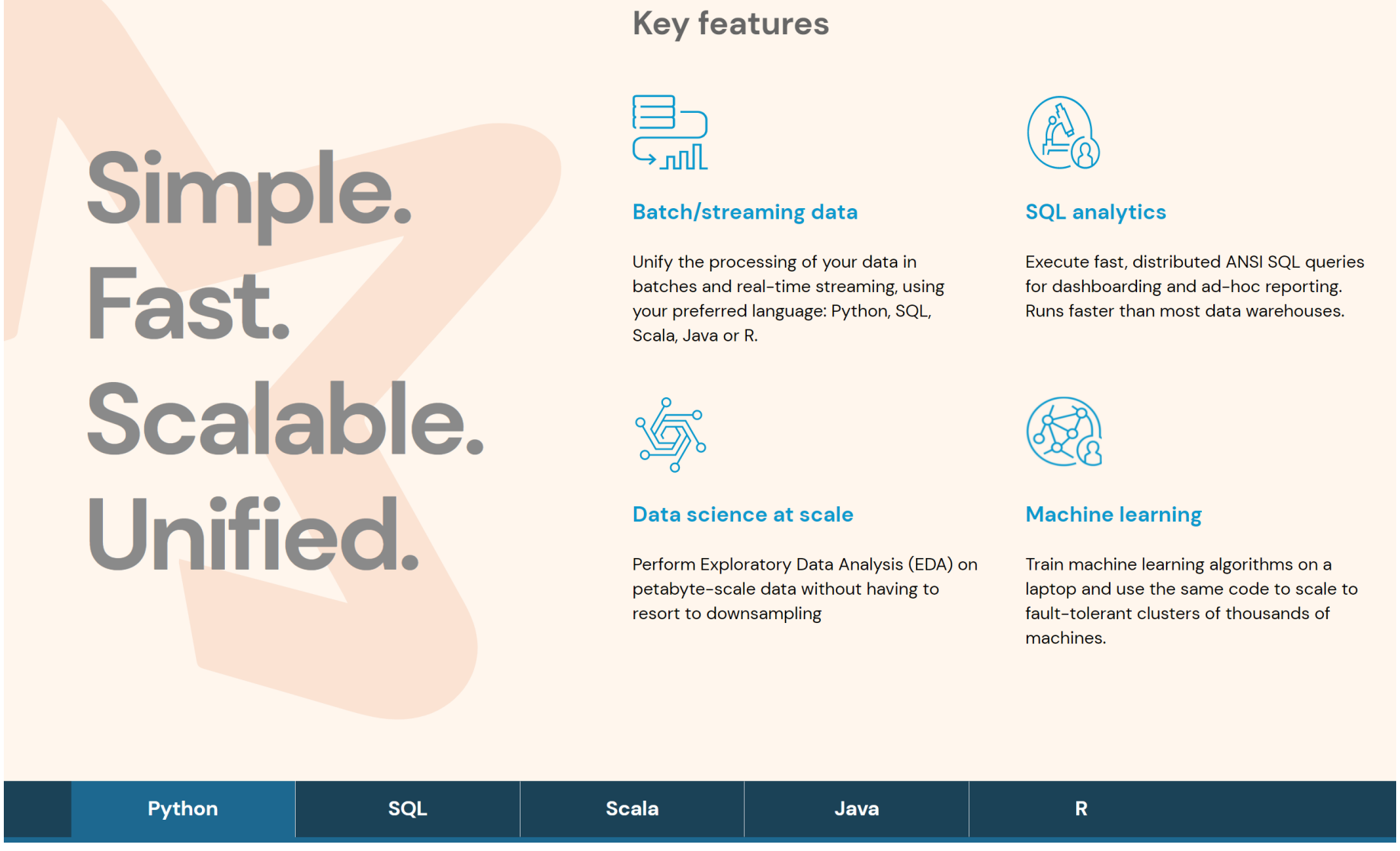
At The end, Only 1 will remain (French TV Game: Koh-Lanta)


APACHE
Spark
TM

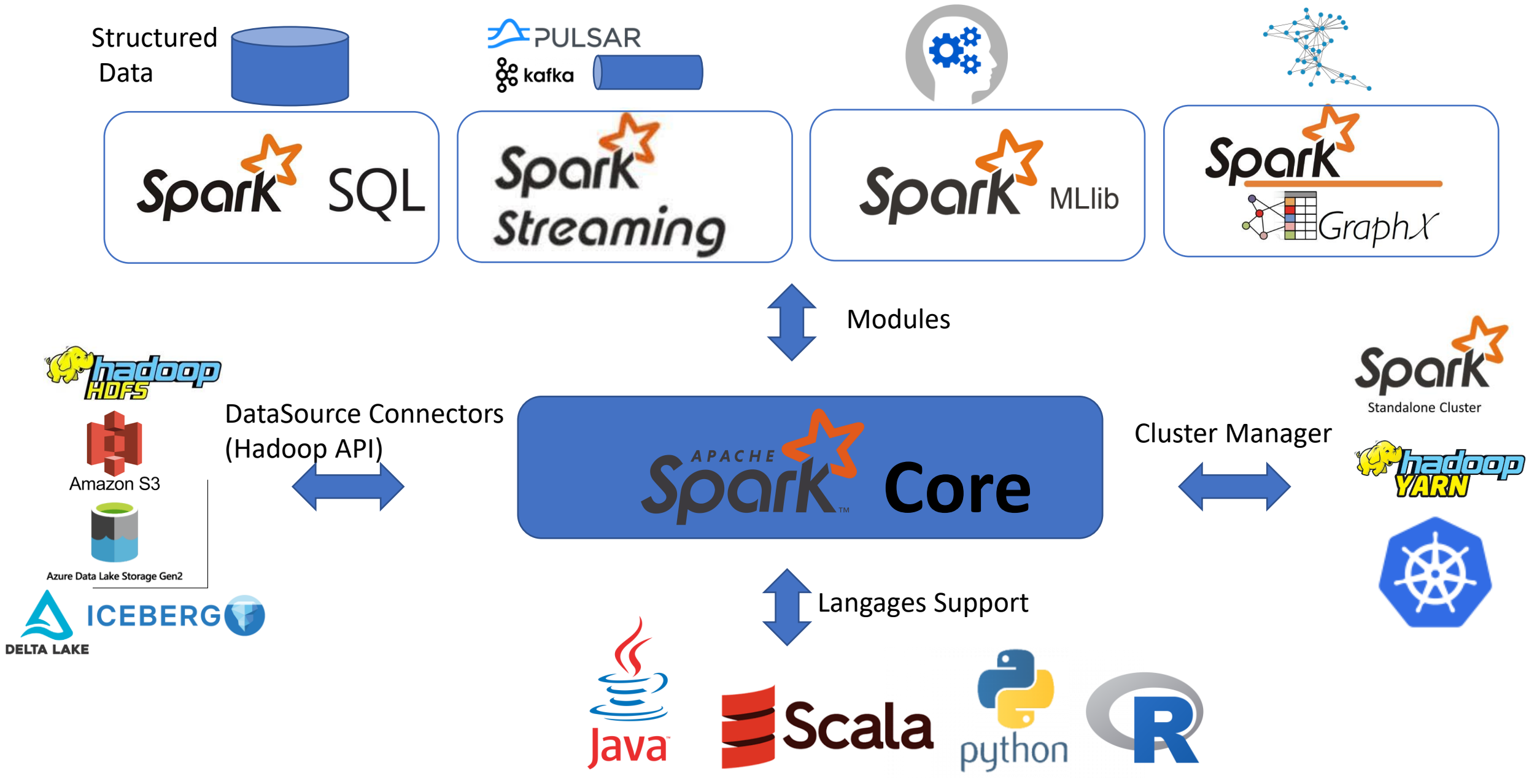
Spark = « **Unified Engine** »



Multi Purposes – Multi Langages



Spark-Core + ...


Structured Data
PULSAR
kafka
Spark SQL
Spark Streaming
Spark MLlib
Spark GraphX
Modules
hadoop HDFS
Amazon S3
Azure Data Lake Storage Gen2
ICEBERG
DELTA LAKE
DataSource Connectors (Hadoop API)
APACHE Spark Core
Cluster Manager
Spark Standalone Cluster
hadoop YARN
Langages Support
Java
Scala
python
R

Take Away

BigData = VVV …
Distributed Architectures (Horyzontal Scalling) => Challenges
Compute vs Storage Resources
Compute Api => Yarn, Kubernetes / Storage Api => Hdfs, Cloud
Hardware evolves, Hadoop Hdfs/Yarn is deprecated

Spark = Unified Engine, using both Compute Api and Storage Api

Coffee Break

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Not Only Machines

Tower of Babel

מִגְדַּל בָּבֶל

The Tower of Babel by Pieter Bruegel the Elder (1563)

General information	
Type	Tower
Location	Babylon
Height	See § Height

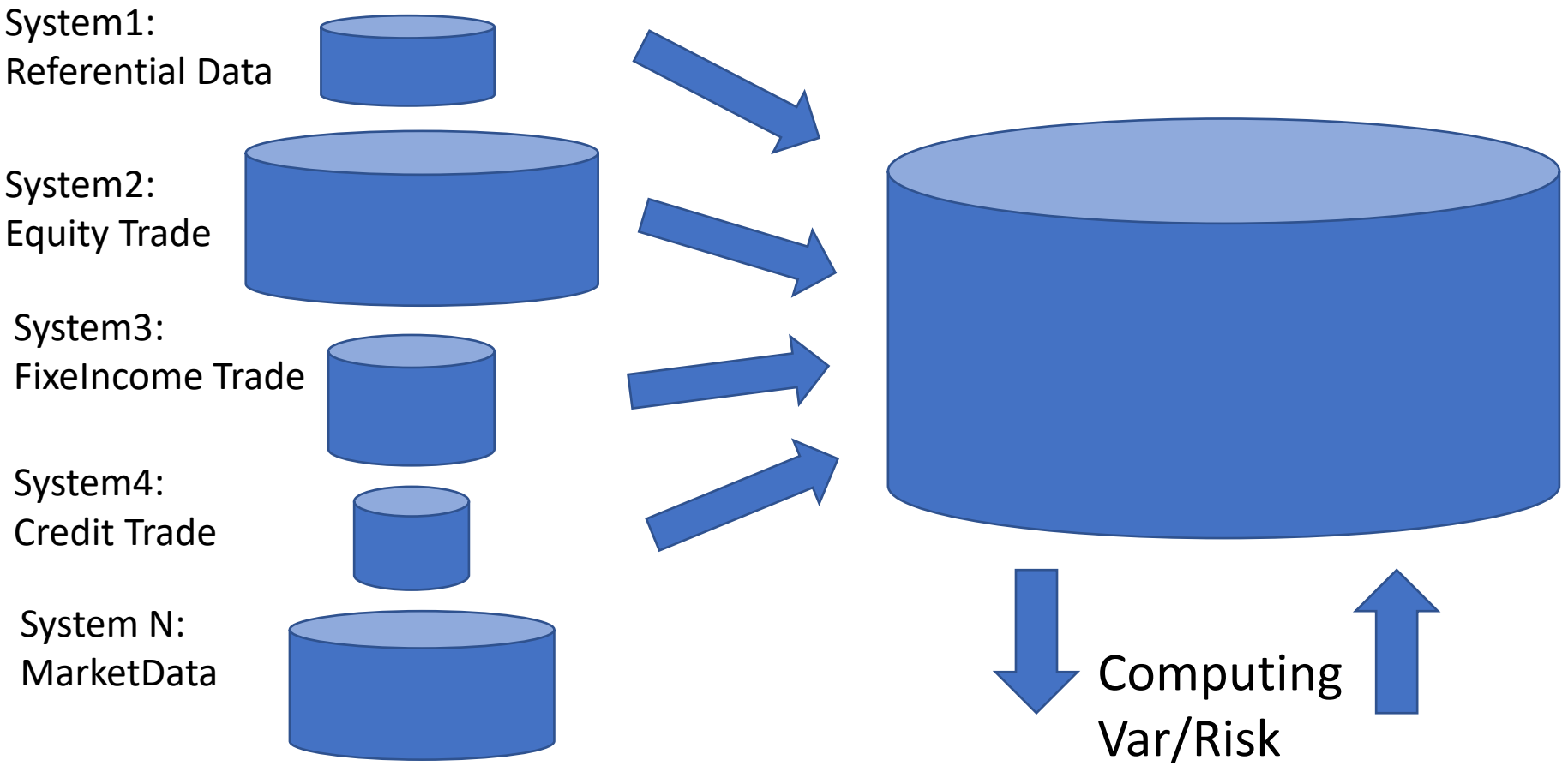
~ 200 different Teams / 10 departments
… for 1000 developpers / data engineers / users

In Paris.. But not Only (Bangalore, Montreal, London, New-York, ..)

On ~6000 tables,
described in 1500 DataSets

Lot of Financial / Functional aspects

Feeding Data Inputs to Datalake: aggregating >= 150 Systems



Feeding Data / Streaming

BigData at SG is mostly « uploading daily files »
then launching « daily batches »

Many Trade extractions are Real-Time Streaming
… but aggregated in Files per Hours / per Day

Var Computing during night … Huge streaming of events
from dedicated pricing cluster (GPUs)

Feeding Types & Volumetry

Daily batches: upload Files

Streaming then converted to Files

Teras/day
(millions of files)

Streaming to Key-Values Databases

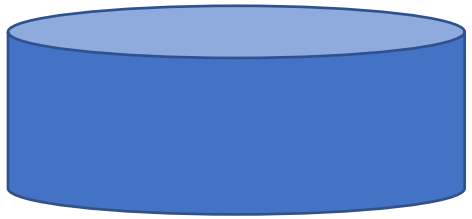
Billions events/day

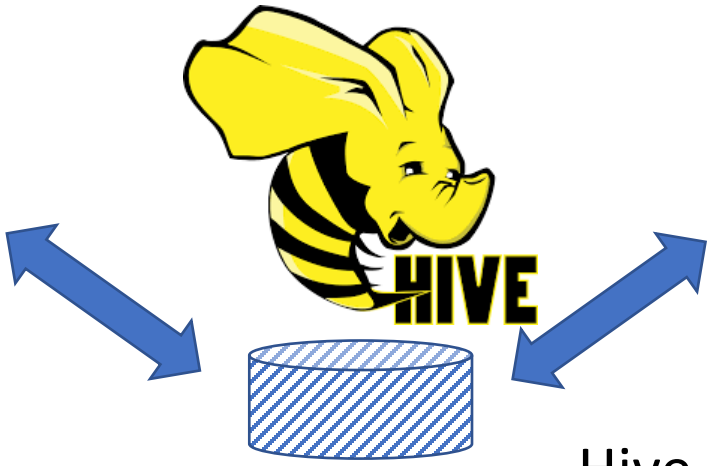
Peeks to 4000 events/seconds
on each 100 x servers
During 4hours nightly Var batches

Content of a Datalake

FileSystem
= Directories + Files

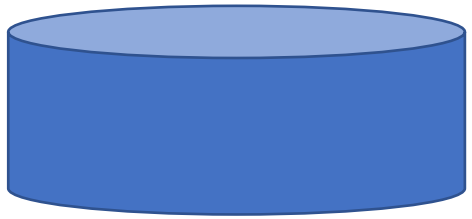
For batches





Key-Value database

FAST get/put access by single key



Hive Metastore = SQL View
« Table » abstraction for HDFS / Hbase

Storage = Files and Directories

How would you organize

1 Billions Files

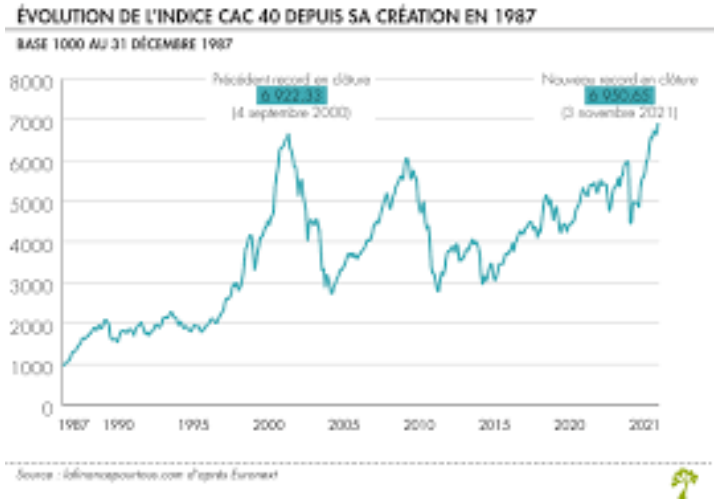
in **50 Millions Directories** ?

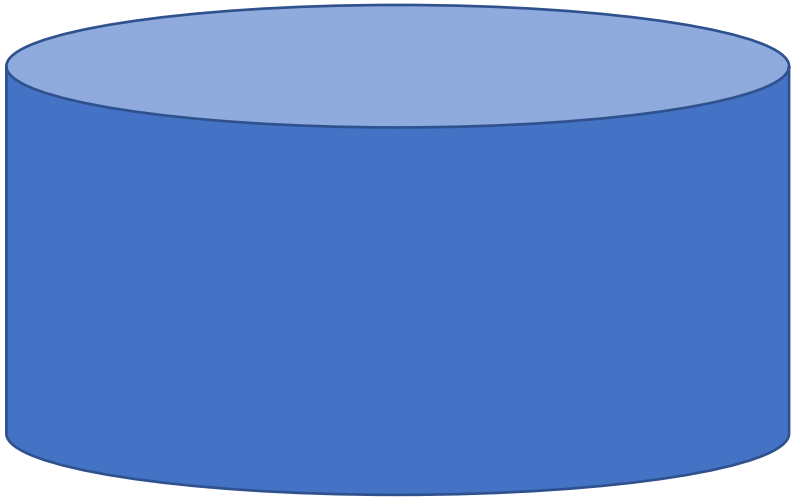
How do you ensure data respect directories organization ?

Try Scanning Directories ?

A Very « Simple » Specific Sub-System

« Tick » per seconds
From Market Exchange Places
(Bourse Paris, London Stock Exchange, …)

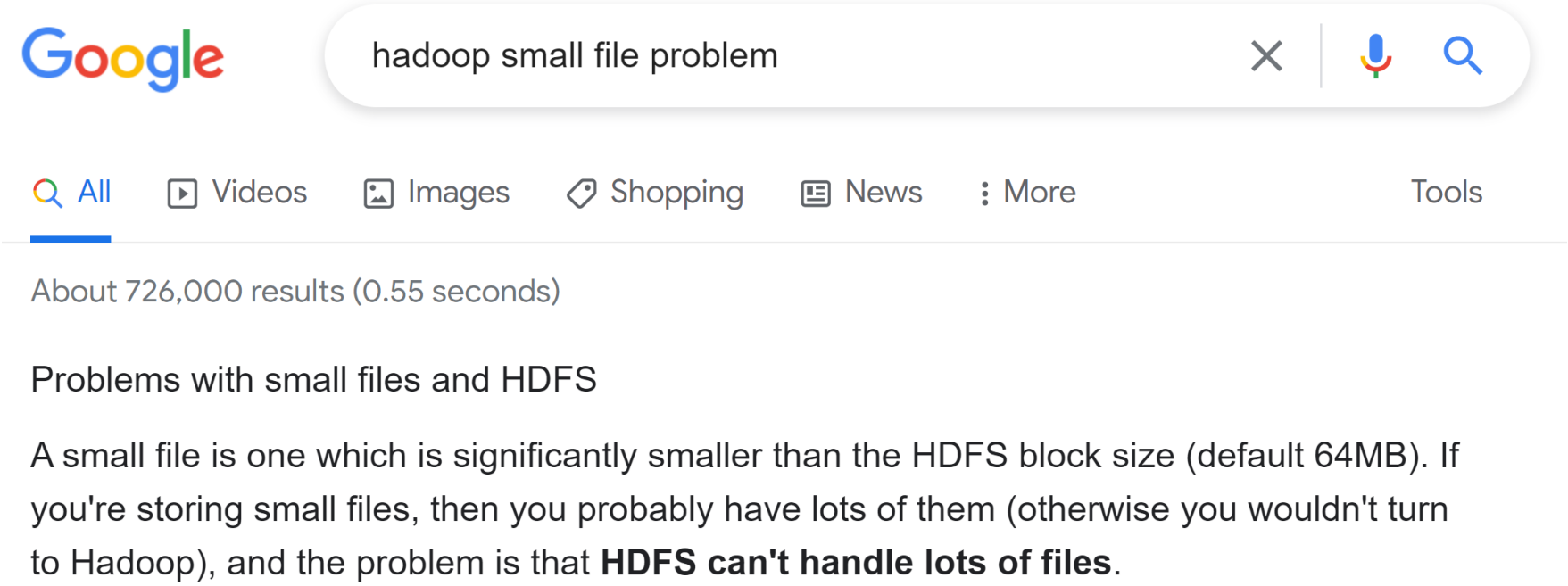




1 binary file per Day/Place/Instrument
… 2M files per day
… 40 Giga per day
… since 22 years … 25 Billions Files / Petas

Volume, Velocity … but not Variety
(NO spark, No Hadoop)

Hadoop hates too many Small Files



BIG Files ? More than Giga ?
YES … BUT PARQUET Partitioned

Doing BigData = using 

Files (correctly with 

)

End Of Story.

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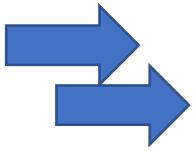
Governance
Data Directories Organization
Read-Write Permissions, Quota, RDPG …

How would you organize Read-Write Permissions on
6000 tables x 1000 jobs ?

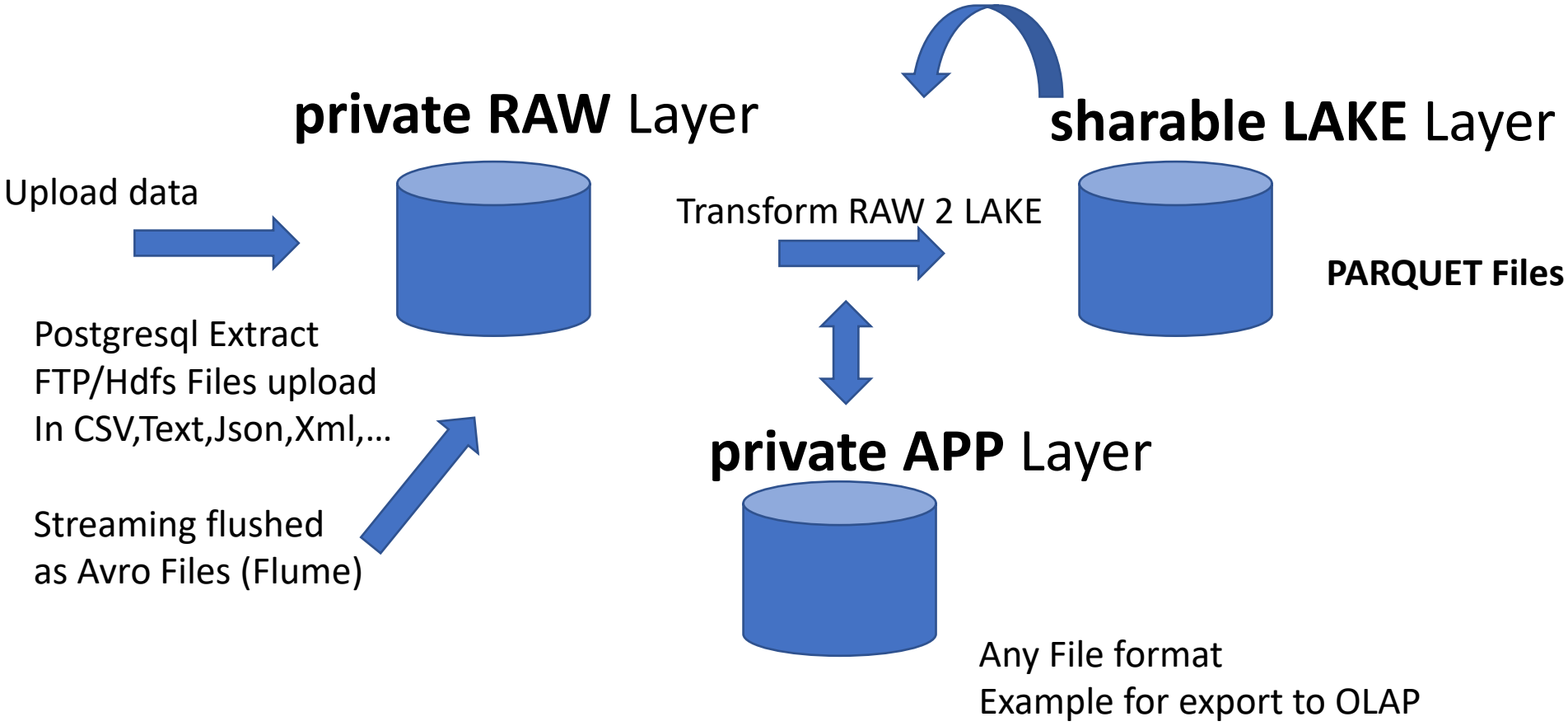
Project ask access
AND describe « Datasets »
(data owner)
=> Validation by DataOffice
=> Create domain sub-dirs
+ granted recursive
WRITE permission



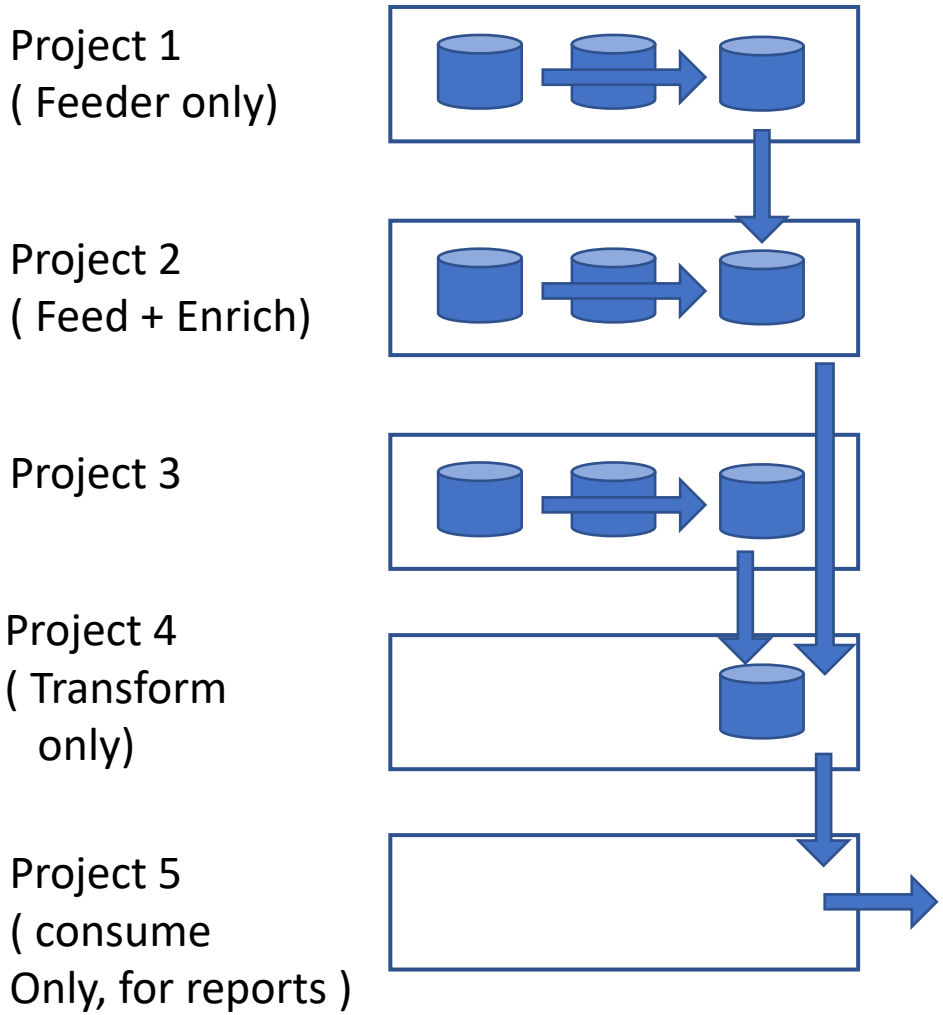
/ <root HDFS>
/env
/ {raw|lake}
/dir =by Team
/subDir =by domain
/sub-subDir=Hive table
/hive partitions
/*.parquet

Project ask for a « Usage » Job
Explain Inputs/Output
=> Validation by DataOffice
=> Grant recursive
READ permission for inputs

LAKE = Parquet
Starting from RAW: Postgresql or {CSV|Json|Avro..}
STAGING Dirs



Feeding – Transforming – Consuming Data



Every project is granted
3 Read-Write Databases: RAW, APP, LAKE

LAKE are sharable
… designed to be efficiently RE-read after (for analytical)

Every project can request Read access on others LAKE
(after validation by Data-Office)

A Dataset is writable by only 1 Project (the owner)

Big Processing

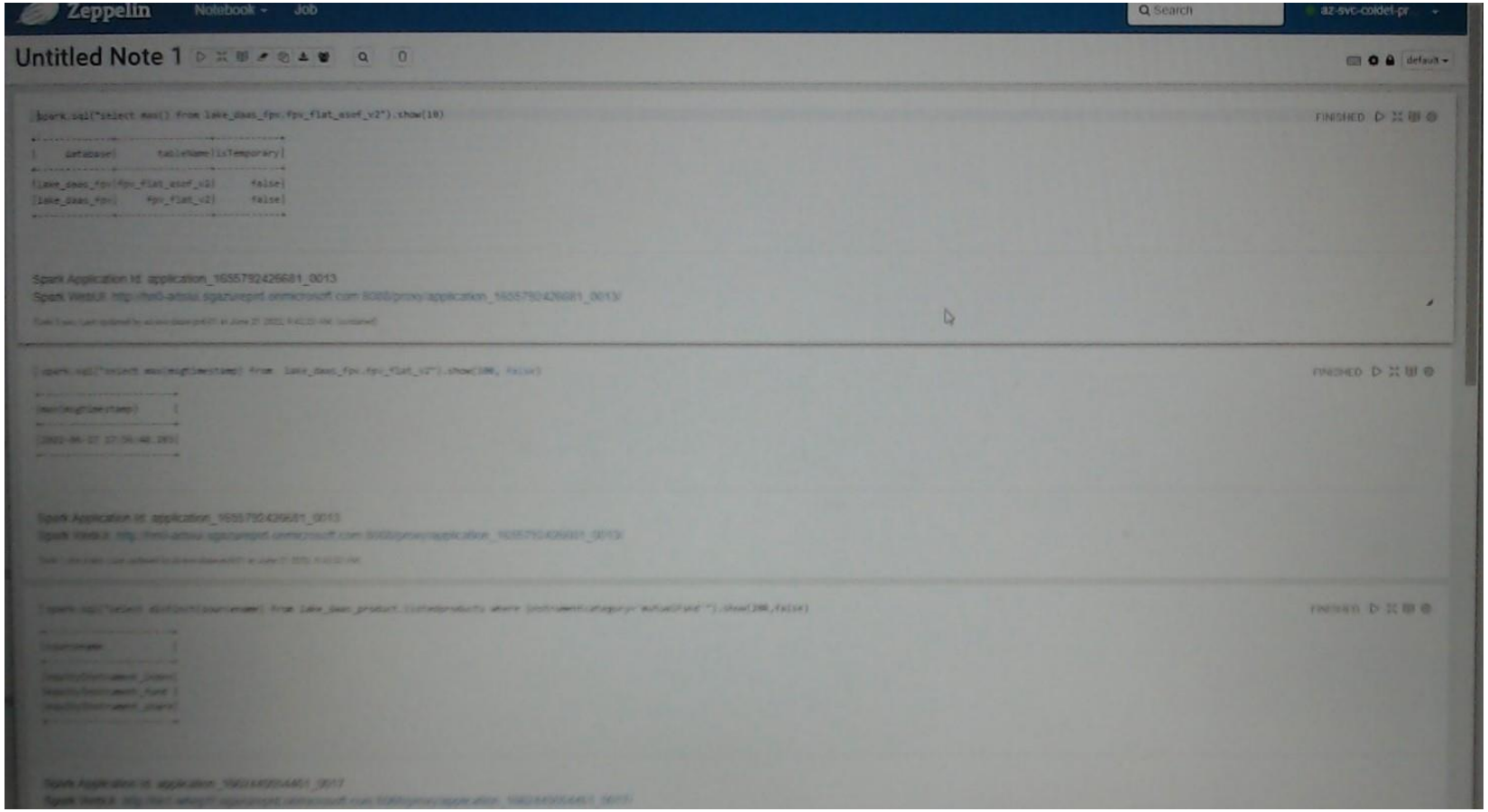
>= 1000 periodic jobs running daily / or every hours

Some processing take >= 15 Hours

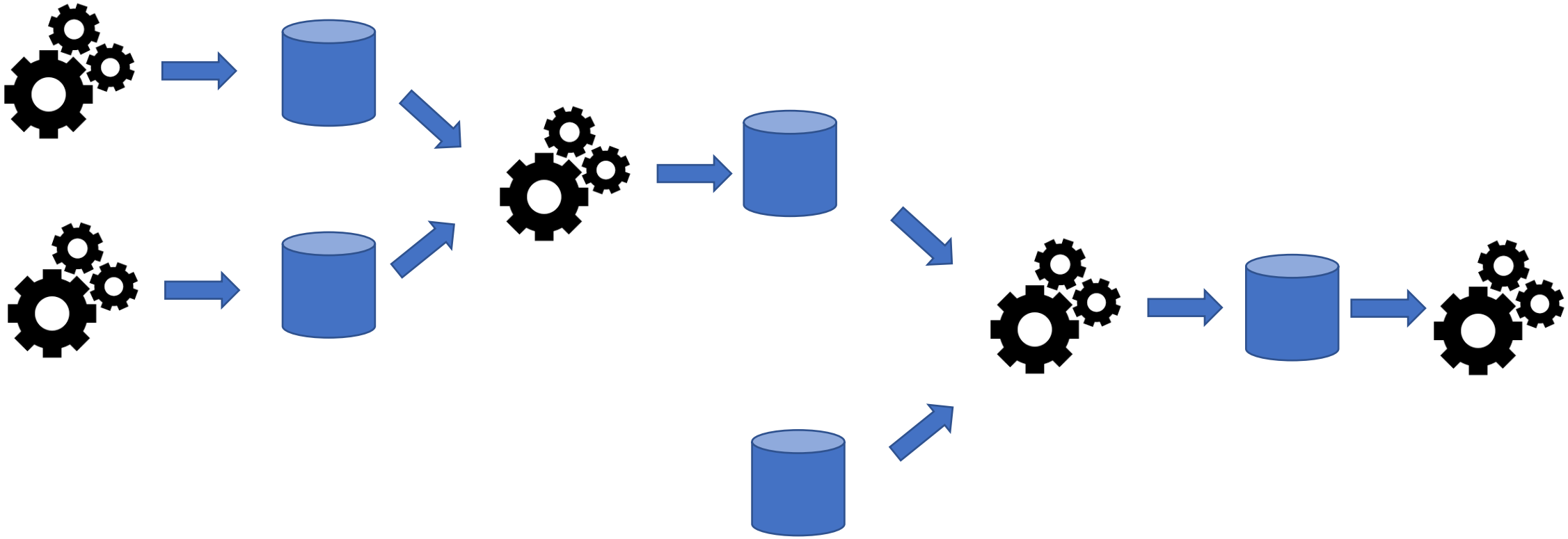
Some processing are distributed on more than 200 yarn containers

Some take more than 1000 Go of RAM

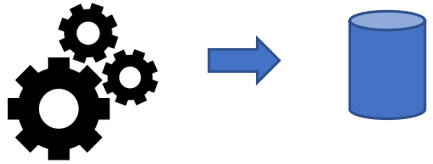
Few Interactive Queries Processing screenshot Zeppelin



Orchestration / DataLineage
Data and Workflows are linked



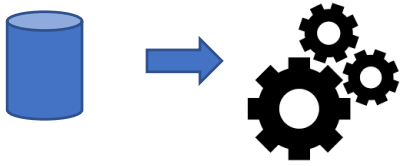
Read-Write Permissions from DataOffice



Dataset « Feeding » declaration:

= exclusive Write Permission : Project -> canWrite -> DB

For validation by DataOffice, DataSet must be described :
confidentiality, source, business owner, quality, RDPG legal

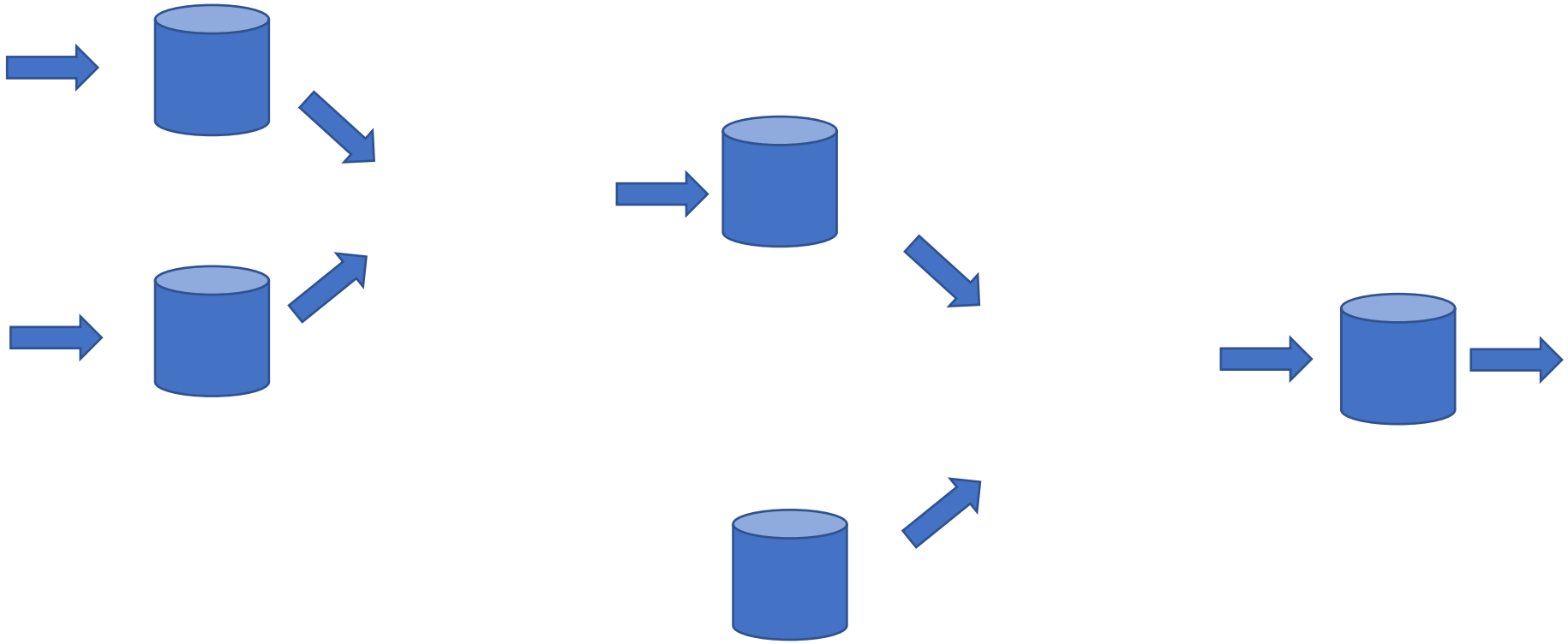


Consumer declaration:

= authorization to read : Project -> canRead -> DB
… for a specific Usage

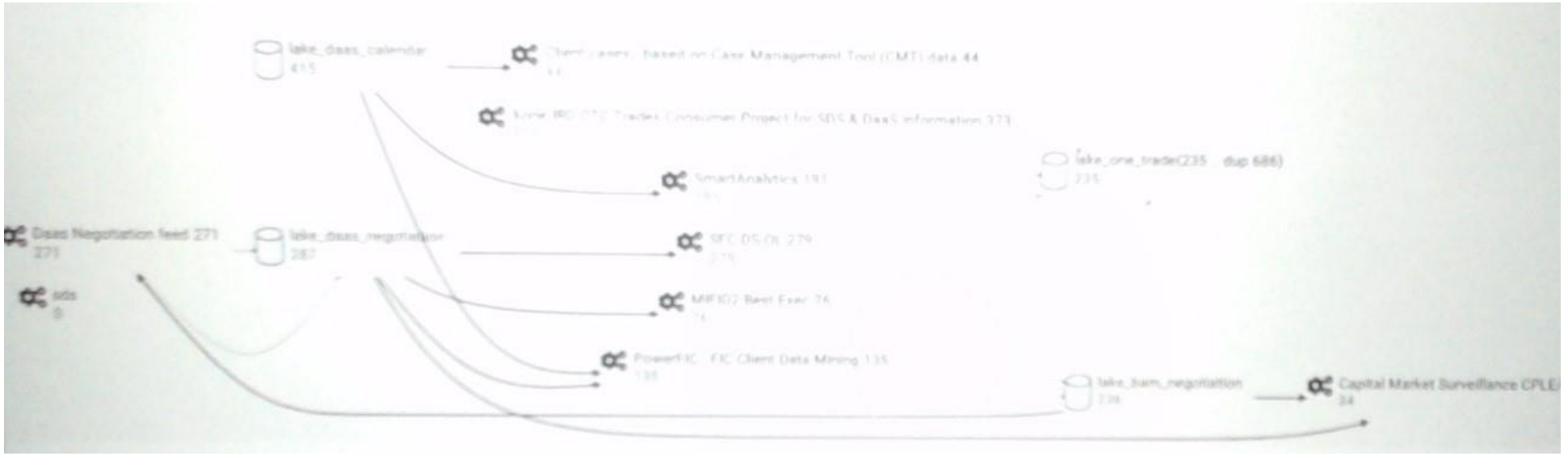
For validation by DataOffice, use-case must be described,
usage must be « legitimate » , RDI legal

DataLineage
Data depends on other Sources Data



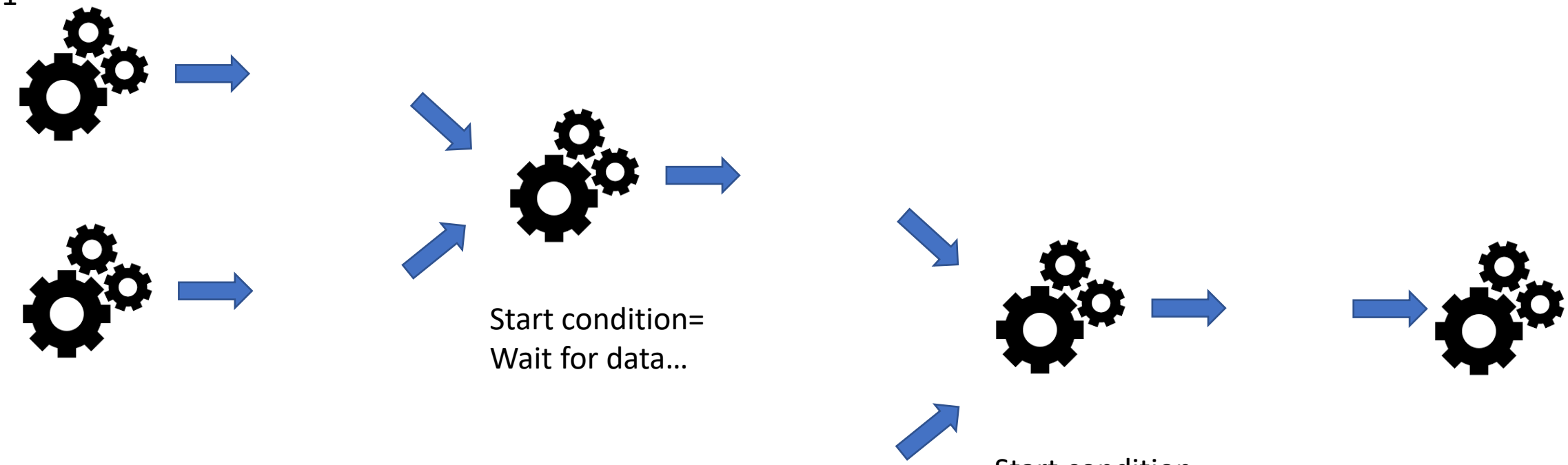
Screenshots (Fuzzy.. On purpose) Read/Write Dependencies Hive Database / Job…

Zooming on 4 out of 250 Hive databases



Orchestration
Start process2 after process1 finished

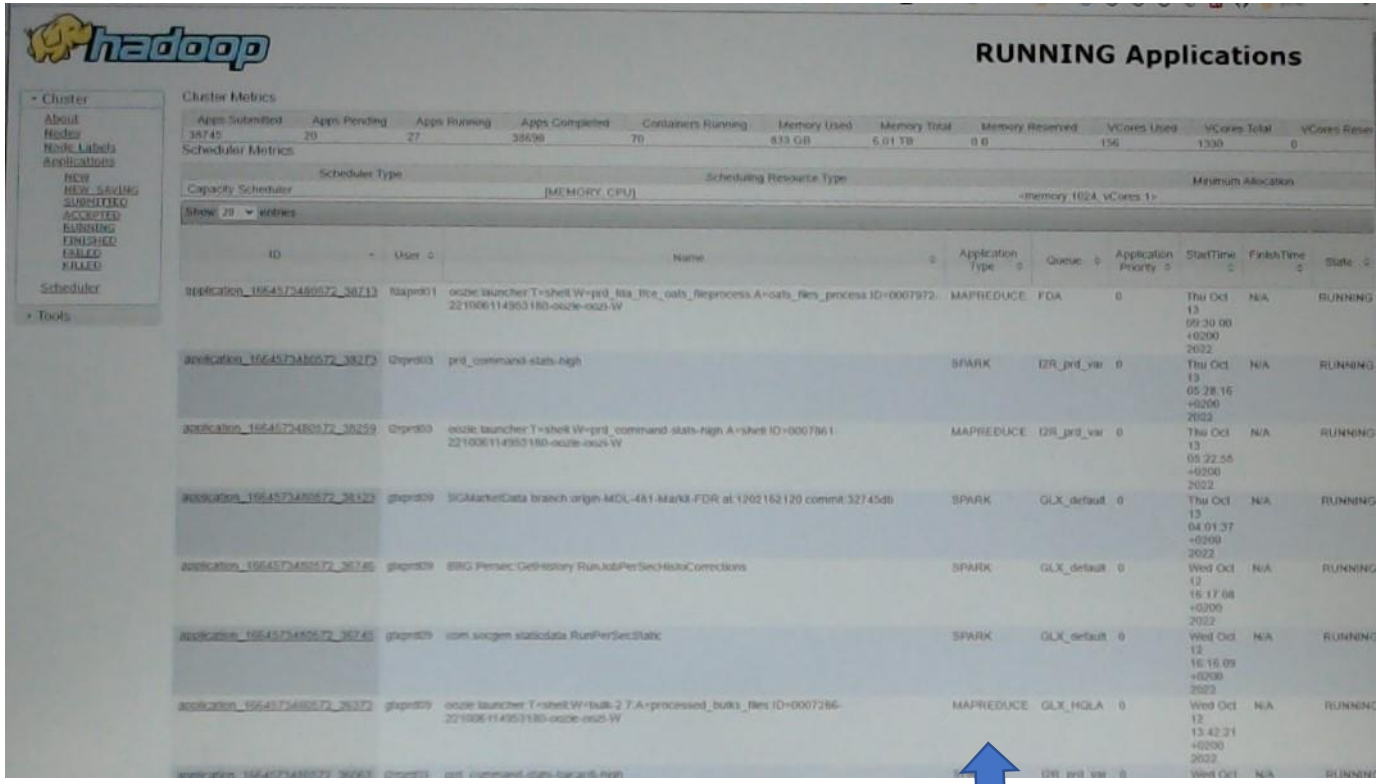
Start condition=
CRON 1 * * * * * *

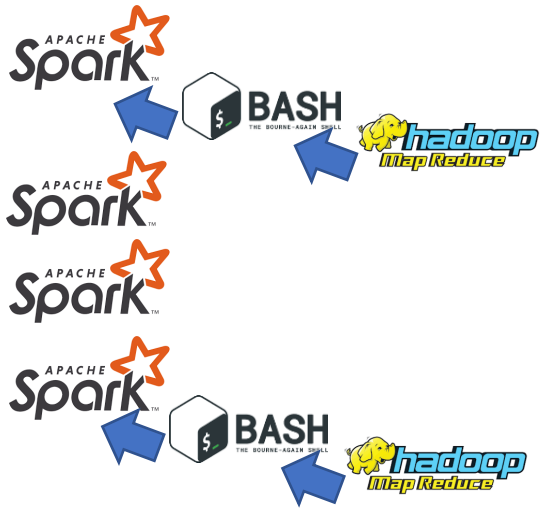


Start condition=
Wait for data…

Start condition=
CRON 10 * * * * * *

Prod Screenshot (Fuzzy.. on purpose) Running Yarn Applications



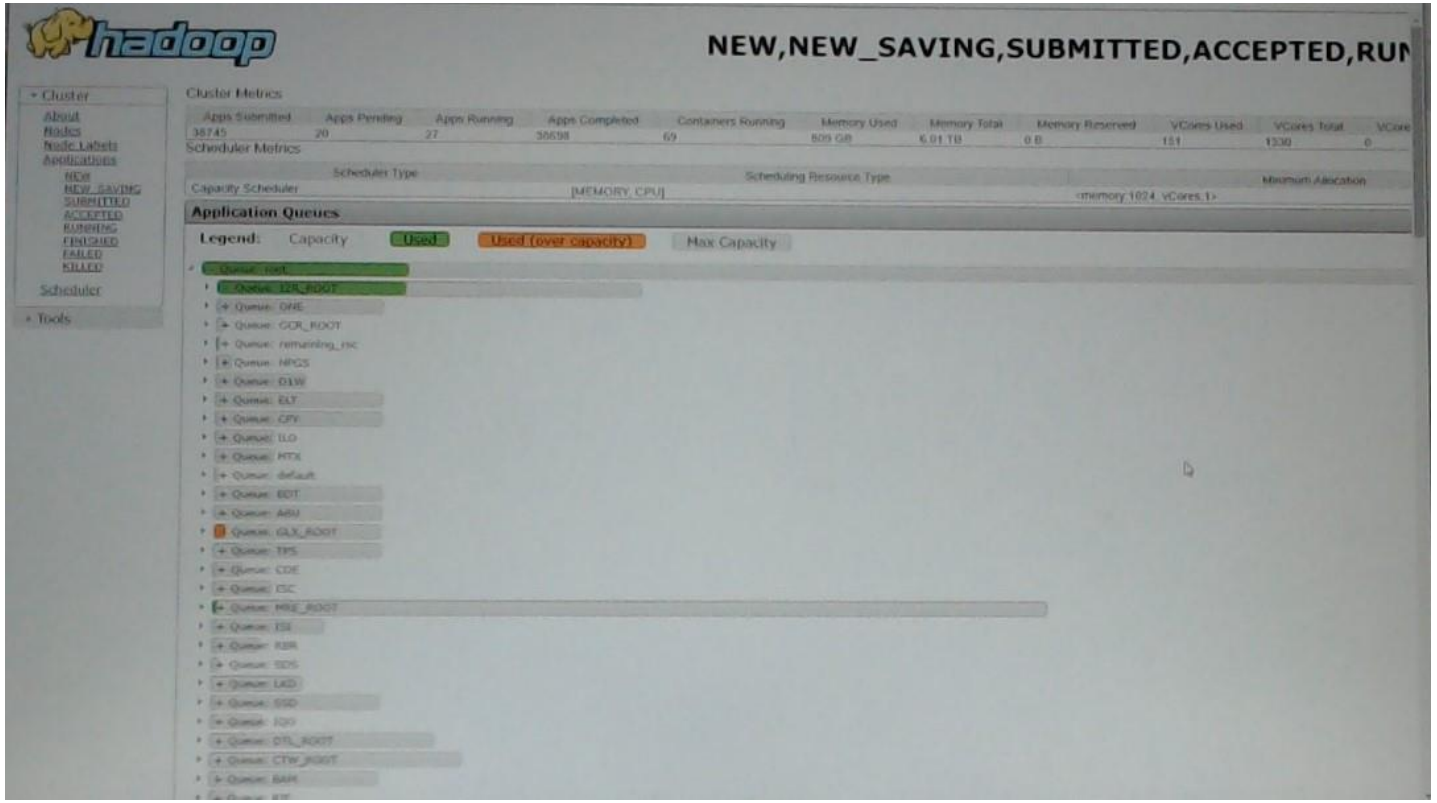


MAPREDUCE ?

… only internally to launch shell commands.. To spark

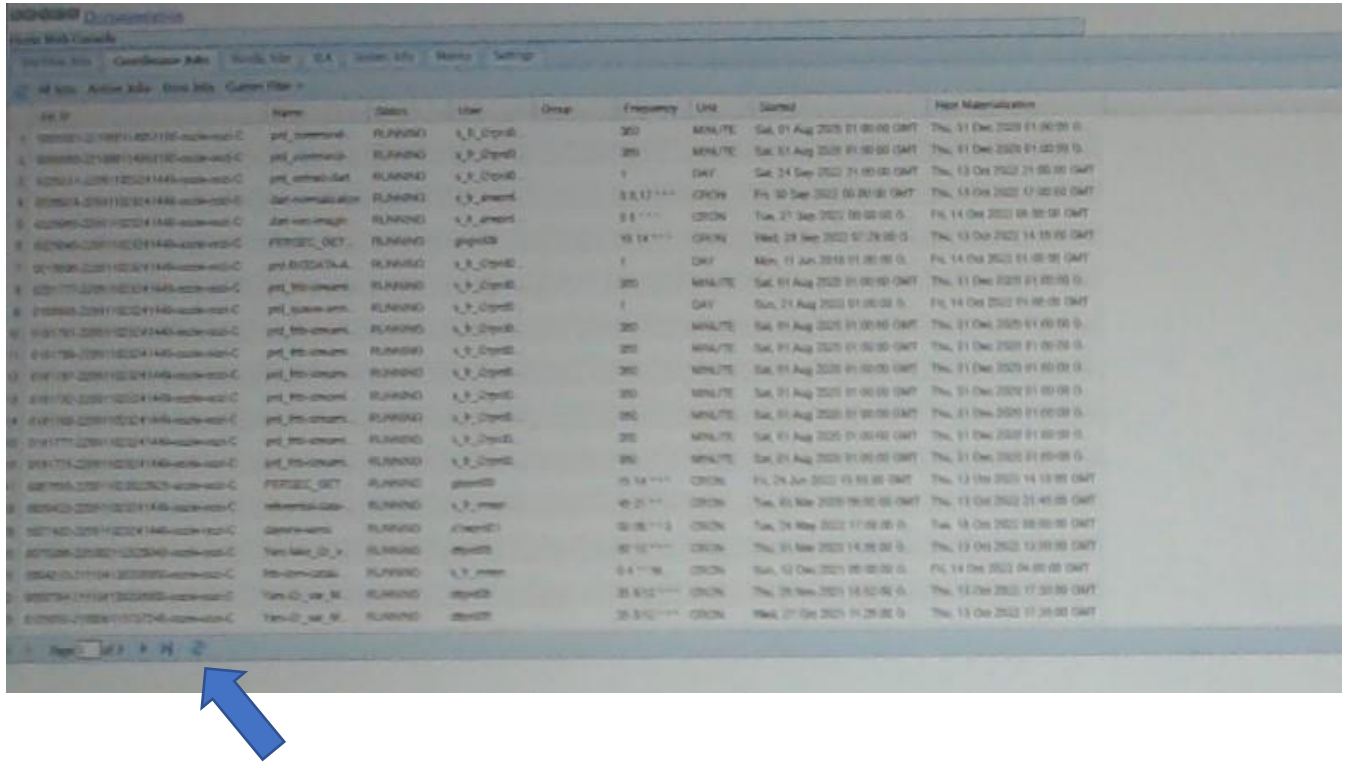
ALL others = SPARK

Prod Screenshot : Yarn Queues (Scheduler, CPU+Mem usages)



You see scrollbar?...
Hundreds or Yarn Queues
+ dozen of sub-queues

Screenshot
Oozie (Coordinators / Workflows)



You see pagination?...
Thousands of CRON jobs

Oozie display only last 50 000 workflows
… so only 2 days of history

Orchestration « By CRON: 10 * * * * * * » Example of Possible Failures

batch1 started at 1 *** … but takes today (anormally) 15h instead of 10h

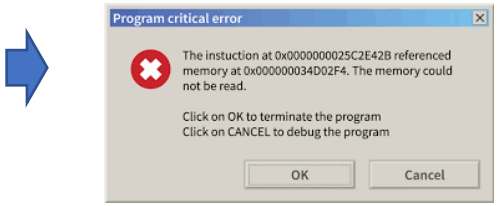
expected

actual

batch2 started at 12 *** …. data not yet present

=> NO « today » data (only yesterday)
Finished FAST, with NO data

batch2 started, during critical section of batch1 … table dropped/recreated after



Outline

- What is BigData ?
  - Order of Magnitudes for « Big »
  - Distributed System challenges
  - Scaling Storage Resources: Hdfs
  - Scaling Compute Resources: Yarn, Kubernetes
  - Using Storage – Compute apis
  - Evolution of Hardware – Softwares – Hadoop Ecosystem, Spark
- Description of a Datalake
  - Content
  - Usage
- Example of Data-Processing
  - **RAW to LAKE, Reports**
- Evolution to Cloud

Typical Example of adding 1 daily partition

```
$ hdfs dfs –mkdir hdfs://raw/team/domain/table/date=2022-10-12

$ hdfs dfs –put localFile hdfs://raw/team/domain/table/date=2022-10-12/

$ spark-sql –master local[1] \
        –e « ALTER TABLE raw_lake_domain.table
              ADD PARTITION ( date='2022-10-12' ) »
```

Typical RAW to LAKE processing with Spark as Java code

read

```
spark.read
    .format(« csv »)
    .option(«schema », « col1 type1, … colN typeN »)
    .load(« hdfs://raw/team/domain/table/date=2022-10-12 »)
```

transform

```
    .map(row ->  transformData(row) )
```

write

```
    .repartition(3, « col1 »)
    .sortWithinPartition(« col1, col2, col3 »)
    .write
    .format(« parquet »)
    .save(« hdfs://lake/team/domain/table/date=2022-10-22 »)
    ;
```

Typical RAW to LAKE processing with Spark as SQL code

write

```
INSERT OVERWRITE
      lake_team_domain.table
```

transform

```
SELECT /* +REPARTITION(col1, 3) */
   col1, col2,
   udf_func1(col3, col4)  as col3,
   udf_func2(col4, col5)  as col4,
   ..
```

read

```
FROM
      raw_team_domain.table
```

transform

```
JOIN
      lake_anotherTeam_domain.anotherTable x ON x.ID=id
```

read

```
WHERE date='2022-10-22' AND ..
```

write

```
SORT BY col1, col2, col3     -- idem sortWithinPartition
```

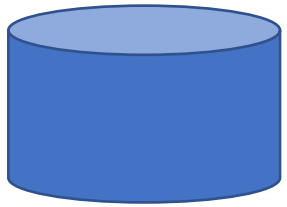
Example of LAKE Aggregation

```
INSERT OVERWRITE
      lake_team_domain.table
SELECT * FROM (
    SELECT * FROM table1 WHERE ..
  UNION
    SELECT * FROM table2 WHERE ..
  UNION
    SELECT * FROM table3 WHERE ..
  UNION
    SELECT * FROM table4 WHERE ..
)
SORT BY col1, col2, col3     -- idem sortWithinPartition
```

Example of « latest value » cristalisation analytical query « over(partition by) »

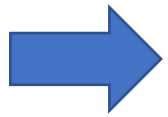
```
INSERT OVERWRITE
      lake_team_domain.table
SELECT
  col1,col2,…. colN    -- idem * EXCEPT rank   (cf issue SPARK-33164)
FROM (
  SELECT *,
    RANK() OVER (PARTITION BY id ORDER BY update_time DESC) as rank
  FROM lake_team_domain.event_table
)
WHERE rank=1
SORT BY col1, col2, col3     -- idem sortWithinPartition
```

Example of a « Small » Data Processing resource needed = RAM

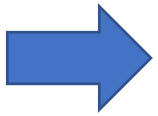


Extract all the Trades on perimeter « X »
Since <= 3 Years

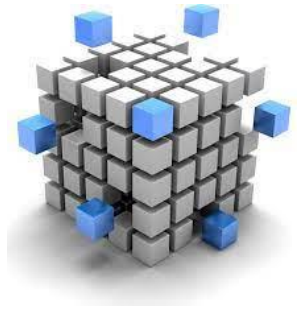
Enrich « JOIN »
With other tables



Basic Compute
SQL
Select .. where ..

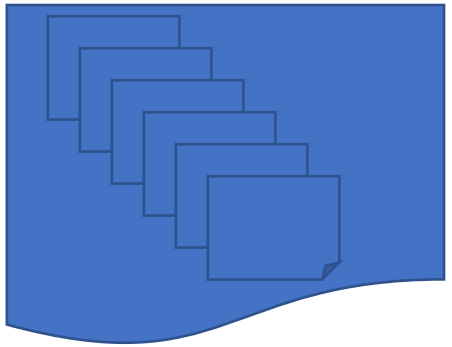


Save Result
Export to OLAP Cube



Processing on Azure
using cluster 10 x D14 (100 000 euros/year)
ONLY 600 Giga of RAM data …
NOT Enough => Swapping => take 4 Hours

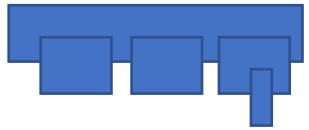
Example of a Slow « Un-parallelized » Processing resource needed = CPU x Time x ..



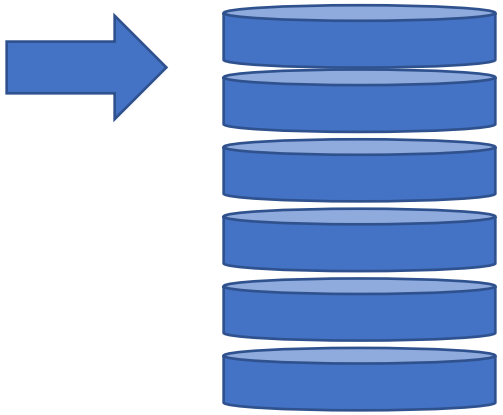
Appending every day
~1 Avro file, containing
~50 Millions of <XML>..</XML>
~70 Mega bytes

<XML>

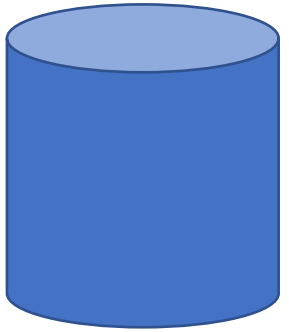
For each XML, extract
xpath(« a/b/c/d/e ») as column1,
xpath(« a/b/f/g/h ») as column2,
…. as column150,



Append to History
(Audit Events)



Synthesised Latest View



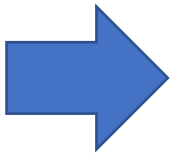
(updates on EquityOption trade description)

A Slow Processing ?

Legacy « On-Prem »

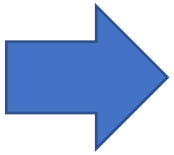
Daily Batch takes >= 15 Hours
But is mostly SINGLE-THREADED !!!

Some Parallelized intermediate parts take
>= 200 yarn containers … 10% of Cluster
… Result = ULTRA FAST !!



Backported code « as-is » to Azure HDInsight
Used Cluster of 10 x D14 cluster (40 000 euros/month)

Run NEVER Finished
… stopped in « echo count lines before insert $(…) »



Fully re-implemented in Spark + Java
instead of Hive SQL + UDF xpath
+ Optimized …

Now run in 40 minutes on 2 x D13 cluster

Take Away

At SG, most workflows are uploading daily files + processing by daily batches
Except 1 Huge stream feeding
Almost all use Spark

Spark Supports

- Interactive queries
- Batch mode
- Streaming mode

Coffee Break

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Appendix:
Cloud

… More Detailed on

« From OnPrem to Azure Cloud »

see Document « -cloud.pdf »

Appendix: Cloud

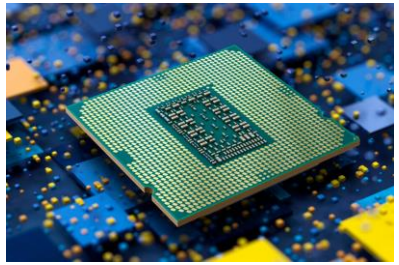
Fundamental Resources TradeOffs

Network (Bandwith, Latency)

Horyzontal Scale

X

CPU (HOT, Watts)

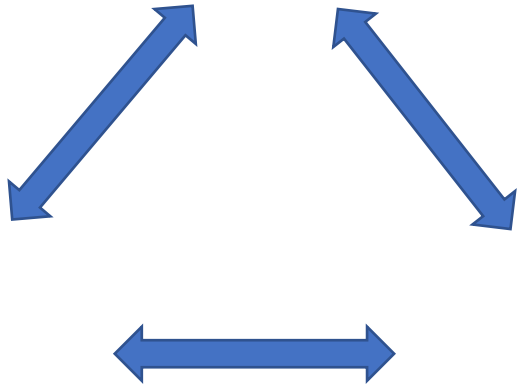


Development price / Run cost

€€€€€€$$$$$

Cold Storage (SLOW)

Storage (~Small)



RAM (FAST .. Expensive)

\+ + + + + +

\- - - - - -

Appendix: Cloud

Performance Changes -> Architecture Changes

Historically:
SLOW Disks
Disk Collocated with RAM+CPU

MapReduce « send program » collocated to data

Now:
FAST(ER) SSD Disks + Networks

Can « send» data to distributed programs

Storage and Compute can be SPLIT … OK !

Higher Density for Huge Storage, lower prices

48 * disks in 2U blade

1 Peta SSD … 200 000 €

Cloud Provider : AWS, Azure, Google
offer Storage solutions (S3, Azure Storage, ..)

+ Managed Services
+ Serverless
+ Kubernetes

Appendix: Cloud

Migration to Cloud
Azure - AWS - Google

Goals:

- Elasticity of Storage
  (No more fear of HDFS FileSystem Full)
- Elasticity of Compute
  (adapt CPU to workload… Pay only what you use)

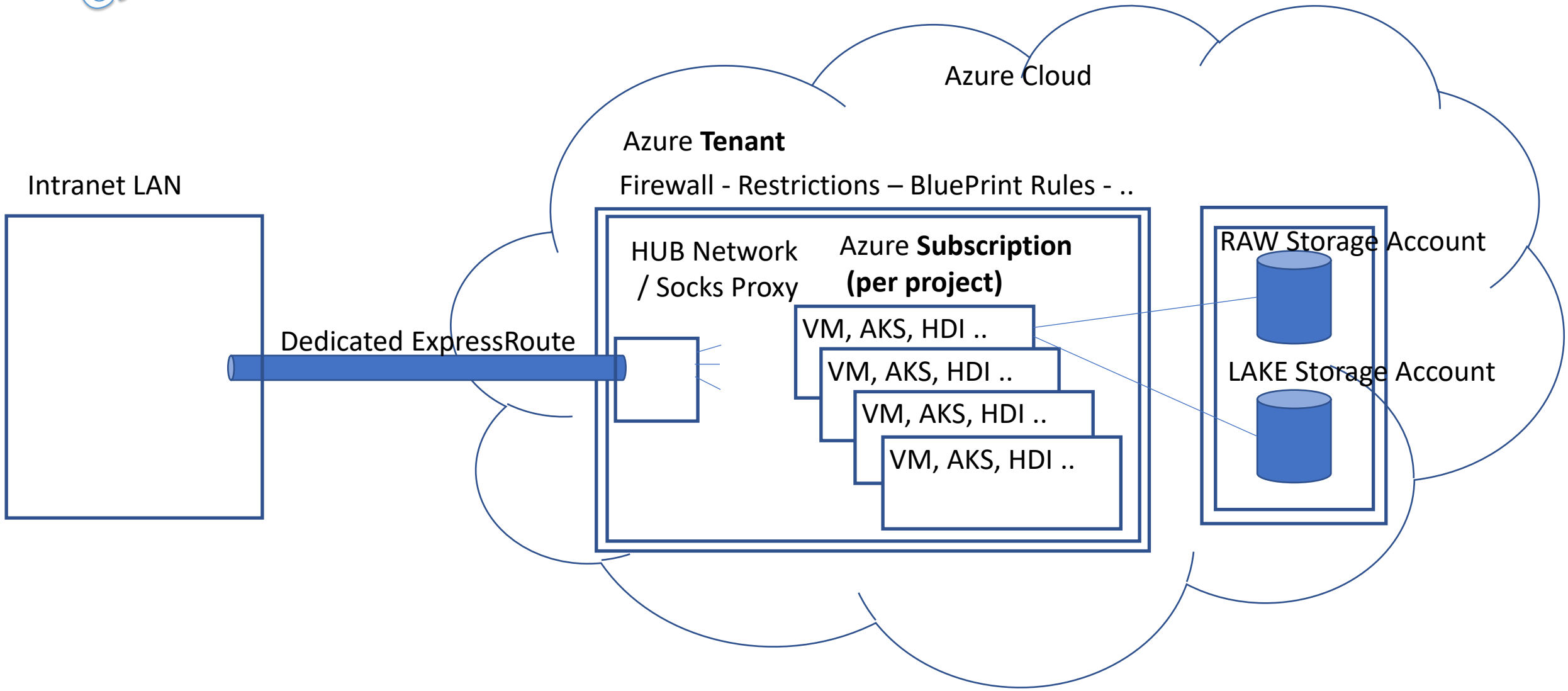
- Clear visibility of cost per Projects / internal refacturation
- By-Pass internal IT department

- Easier (?) Self-Service API for Provisionning
- No More Multi-tenant (no risk of 1 project crashing/consuming whole cluster)

Since 2020 SGCIB is moving its Datalake to Azure

Appendix: Cloud

Architecture of Datalake on Clouds



Appendix: Cloud

BigData Engineering from OnPrem to Azure

Development of custom Yarn/Oozie/Ranger tools

1 Huge cluster, used as Multi-tenant (several users)

Used at 100%

Almost Disk-Full
Many report on disk usage / data purges

Clear view of all Running workloads
(1 Ambari screen)

Lot of Network & Security
Development of Provisionning « sudo » tools

NO more multi-tenant system… but LOT of small clusters

Hundred of clusters, each used at 5% !!!
COST COST COST
Necessity to Optimize Performance
(batches too long… 100x slower / too expensive)

No more Disk worry
… data is growing (no more purges?)

NO admin central view
NO Orchestration of workloads

Appendix: Cloud

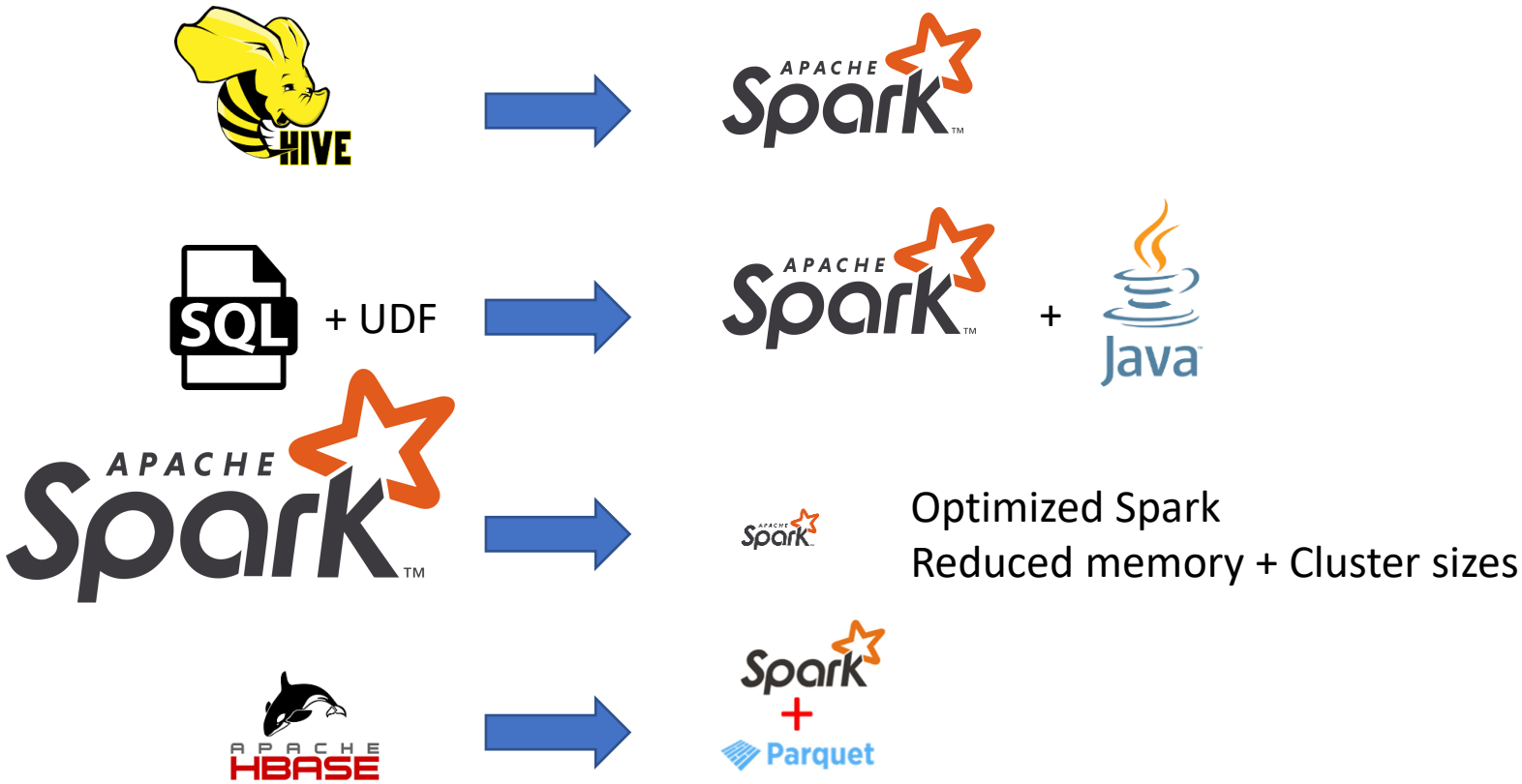
What About Spark in Azure Migration?

COST COST COST

Necessity to Optimize Performance

(batches too long… 100x slower / too expensive)

=> Many projects have migrated + optimized



Appendix: Cloud

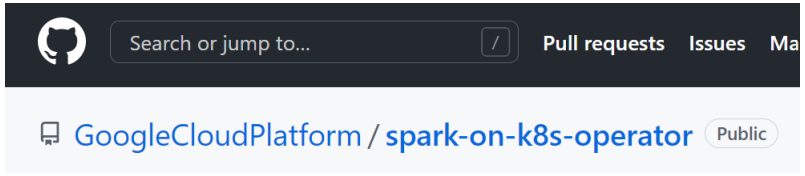
Managed Spark ?
Goals: Autoscaling / « serverless »

Managed by Azure :

Azure Synapse Analytics

=

Managed via Kubernetes



=

kubernetes

databricks

=

databricks

AWS : EMR

GCP : BigQuery

Questions?

Take Away

What is BigData ? Horyzontal Scaling
- compute: cluster with Tera of RAM used by Spark apps
- storage: Petas of Files, in parquet

What is Spark ?
- Simple unified Sql/Java engine
- for distributed compute (Yarn/Kubernetes)
  - distributed storage (HDFS/cloud)

What is Processing ?
- mostly spark batches
- Feeding RAW
- Transforming RAW to LAKE
- Consuming SQL analytics

Hadoop ecosystem is complex, Spark brings simplicity
Ecosystem is evolving (Cloud, Kubernetes)