Many ways to store data

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CERN

Thematic CERN School of Computing 2015

In the previous episode...

- We've discussed data formats
- And especially data structures
- We've talked about organising our data

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Today

Let's see how we store our data !

Outline

Storage devices

A variety of storage devices

Main differences

- Capacities from 1 GB to 10 TB per unit
- Prices from 1 to 300 for the same capacity
- Very different reliability
- Very different speeds

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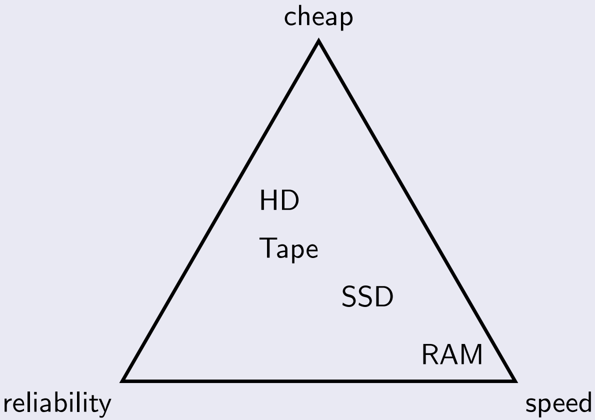
Typical numbers in 2015

	Capacity per unit	Latency	$/TB	Speed	reliability
RAM	16 GB	5 ns	7500 $	$10\,\mathrm{GB\,s^{-1}}$	volatile
SSD	500 GB	10 µs	400 $	$550\,\mathrm{MB\,s^{-1}}$	poor
HD	6 TB	3 ms	30 $	$150\,\mathrm{MB\,s^{-1}}$	average
Tape	10 TB	100 s	25 $	$300\,\mathrm{MB\,s^{-1}}$	good

A variety of storage devices

You cannot have everything



Reliability in real world (CERN)

For disks

- probability of losing a disk per year : few %, up to 10%
  - with 60K disks, it's around 10 per day
  - and all files are lost
- one unrecoverable bit error in 10^{14} bits read/written
  - for 1GB files, that's one file corrupted per 10K files written

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For tapes

- probability of losing a tape per year : 10^{-4}
  - and you recover most of the data on it
  - net result is 10^{-7} file loss per year
- one unrecoverable bit error in 10^{19} bits read/written
  - for 1GB files, that's one file corrupted per 1G files written

Practical Mass Storage - Real Big Data

when you count in 100s of PetaBytes...

The constraints

- disks or tapes are the only possible solutions
- disks are unreliable at that scale, and need redundancy
  - we'll see that extensively
- tapes are cheaper long term storage by factor 2-2.5
- tape latency imposes data access on disk

Specificities of tape storage

Key points

- 300MB/s in sequential read/write
  - 3x the speed of a disk
  - who said tape is slow ?
- latency/seek time in the order of minutes !
  - due to mount time and robot arm moving
  - due to positionning
- storage is cheap, I/O is not
  - 20$/TB for storage capacity
  - 25K$ for each drive

Tape efficiency

Computation

$$efficiency = \frac{I/O\ time}{mount\ time + I/O\ time}$$

$$mount\ size = mount\ time * drive\ speed$$

$$efficiency = \frac{1}{1 + \frac{mount\ size}{data\ size}}$$

$$mount\ size \simeq 50\,\text{GB}$$

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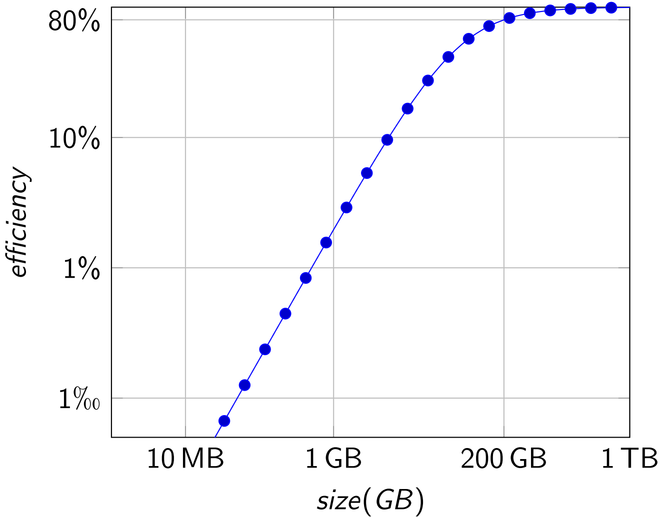
Tape efficiency



→ No mount for less than 100 GB !

Hierarchical storage

Layers

- tape as primary storage
- disks used as a cache in front of the tape system
- SSD used as cache in front of disks (or inside them)

CERN's case (2015)

- tape capacity : 200 PB
- tape usage : 120 PB
- disk raw capacity : 150 PB
- disk usable space : 80 PB

Some consequences

Disk cache management is needed

- the disk cache needs garbage collection
- different algorithm used depending on usage
  - FIFO - First In First Out
  - LRU - Least Recently Used

User need to adapt their usage

- data need to be prefetched from tape before access
- preferably in bulk

Distributed storage

Handling large distributed storage

Standard issues

- failures are very common
- data distribution is hard to balance
- congestions are frequent

Keeping balanced data distribution

sounds initially easy

- standard load balancing
- taking benefit of the numerous clients

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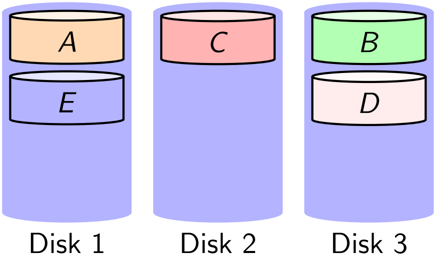

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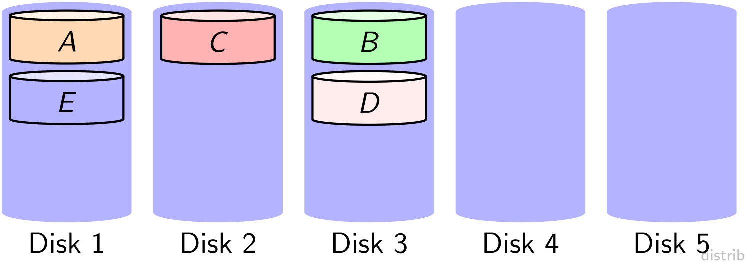
Growing the cluster

- when you add disks, their are empty
- data need to be rebalanced



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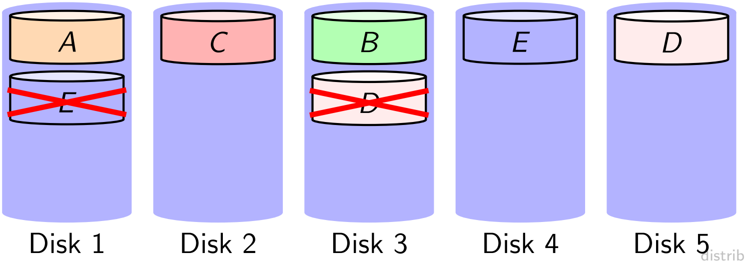

Data congestions

The problem of popular files

- on writes, you can send a piece of data where you like
- on reads, you have to send the client where the data is
- but for popular pieces of data, the device holding it may become congested

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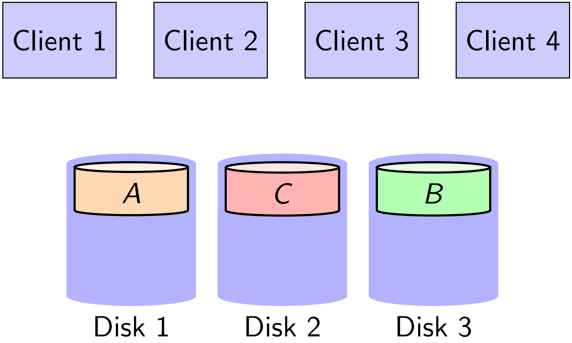

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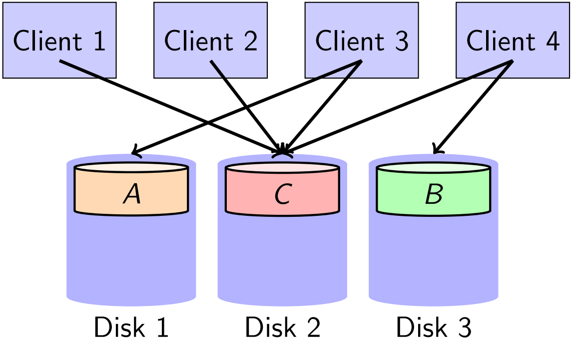

Can be solved using data temperature

Principle

- temperature is data popularity
- "hot" data is accessed more often
- data getting hotter than given threshold get replicated
- on cool down, replicas should be dropped

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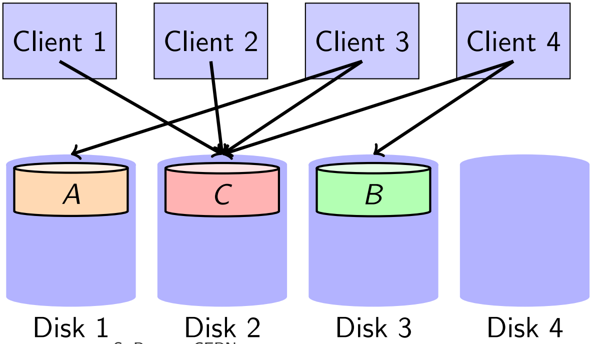

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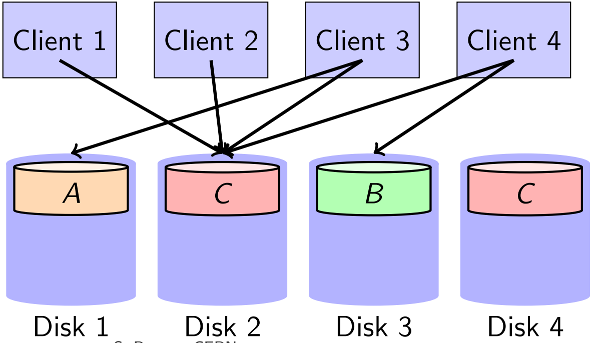

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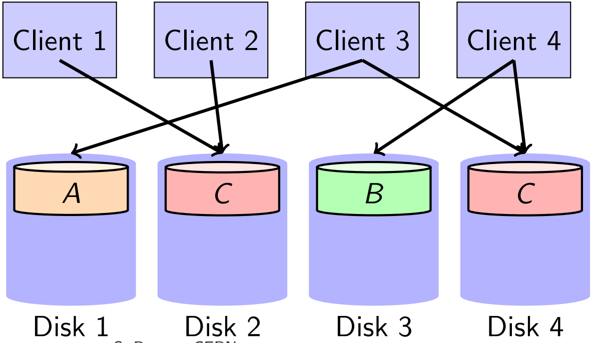

The global view

A World distributed storage

- large experiments' data are distributed around the world
- usually replicating the data at least once
- networks are now fast and you can access remote data through wide area network when local data in not available
- but you do not want to do that by default
- and you want to try the "closest" replica first

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Data geolocalization

- a global central catalog lists all available replicas
- and their "physical" location
- with information on the topology of the network to reach them

Data federation

Hiding the underlying complexity

- some interfaces that hide this world wide distribution of data
- by redirecting clients dynamically to the closest data available

Xrootd federation

- widely used by LHC experiments across the world

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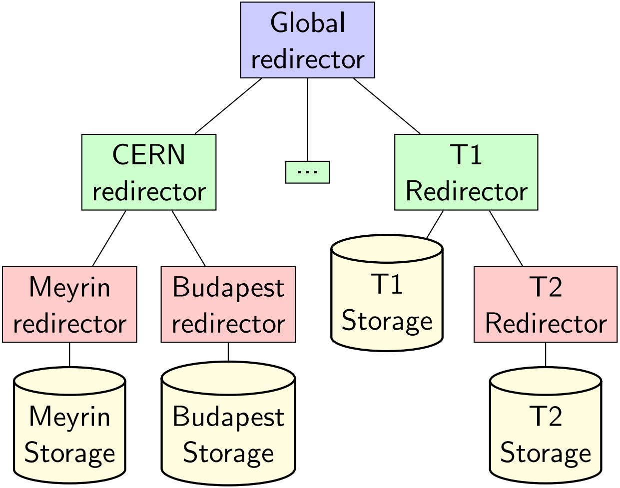
Typical federation in an LHC experiment



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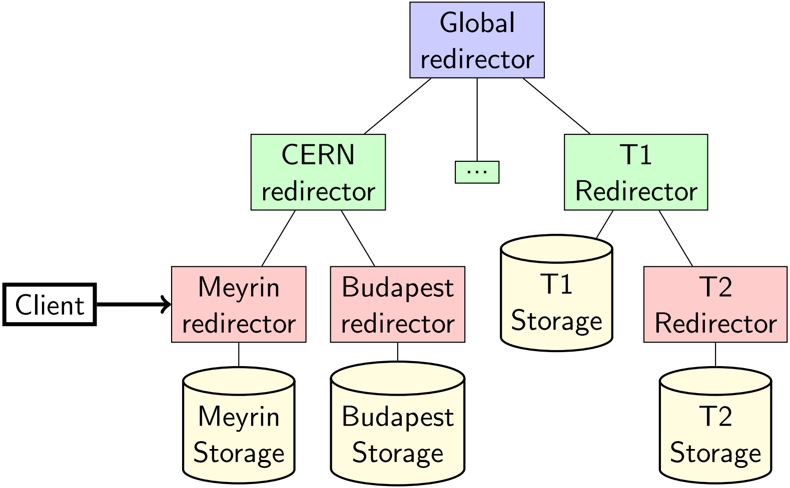

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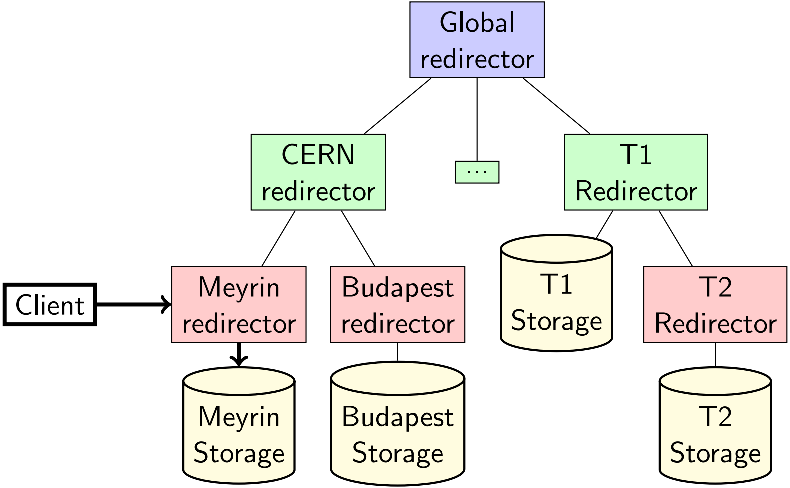

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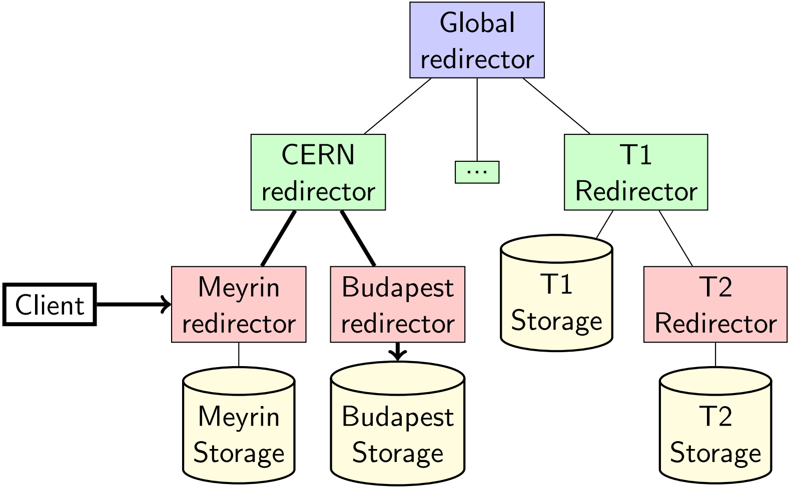

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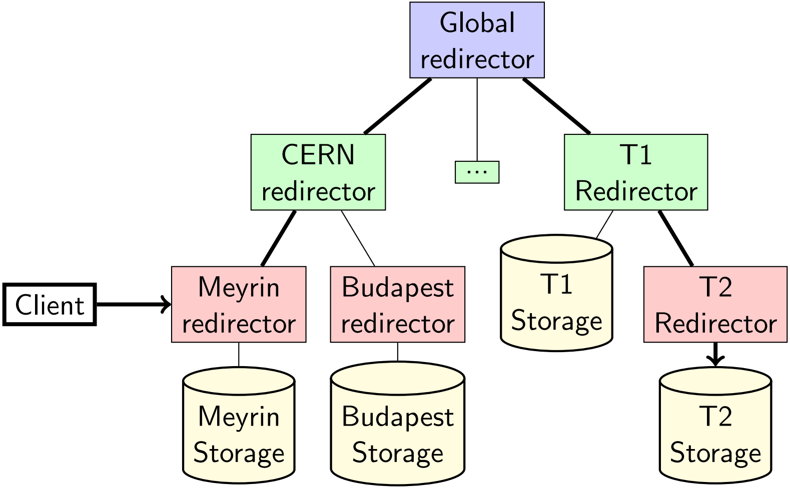

Parallelizing files' storage

Why to parallelize storage ?

to work around limitations

- individual device speed (think disk)
  - a file is typically stored on a single device
- network cards' speed
  - 1 Gbit network still present
  - network congestion on a node reduces bandwidth per stream
- core network throughput
  - switches / routers are expensive
  - machines may have less throughput than their card(s) allow(s)
- hot data congestions
  - and the black hole it can generate
  - as slower tranfers allow to accumulate more transfers

Parallelizing through striping

Main idea

- use several devices in parallel for a single stream
- moving the limitations up by summing performances

Basic striping : Divide and conquer for storage

- split data into chunks aka stripes on different devices
- access in parallel

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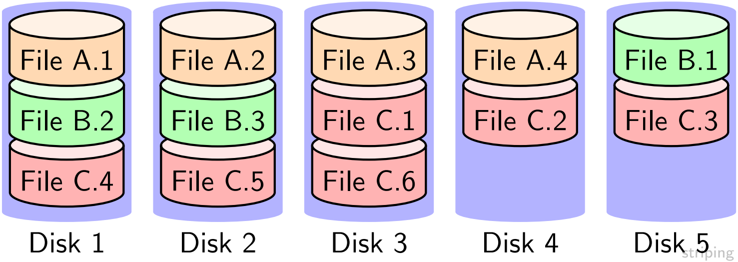

RAID 0

RAID

- stands to "Redundant Array of Inexpensive Disks"
- set of configurations that employ the techniques of striping, mirroring, or parity to create large reliable data stores from multiple general-purpose computer hard disk drives (Wikipedia)

Useful RAID levels

RAID 0 striping
RAID 1 mirroring
RAID 5 parity
RAID 6 double parity

Can be implemented in hardware or software

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RAID 1, RAID 5 and RAID 6: See data preservation talk

Can be implemented in hardware or software

RAID versus RAIN

RAIN

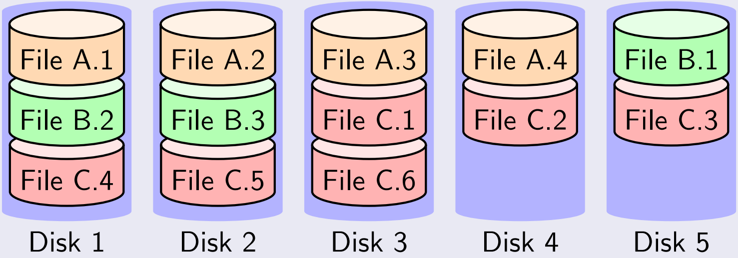
- Redundant Array of Inexpensive Nodes
- similar to RAID but across nodes

Main interest

- tackle also the network limitations
- when used for redundancy, improves reliability
- more on this in subsequent lecture

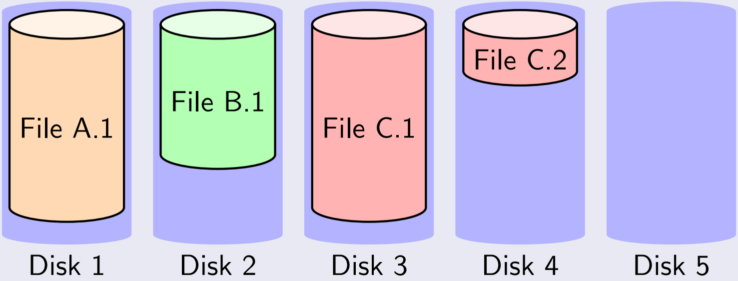
Practical striping - the stripe size

Desired picture



Practical striping - the stripe size

Stripes too big



RAID has practically not effect

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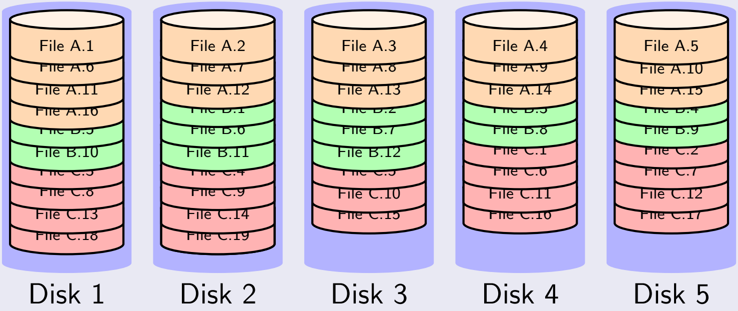
Practical striping - the stripe size

Striped too small



RAID will only kill performance by forcing disk to seek far too often

How to choose the stripe size

size of the stripe

- must be as small as possible to let small reads benefit from parallelization
- must not be too small
  - to avoid having to deal with too much metadata
  - to avoid too much disk seeking

A generic solution for the stripe size

Idea

- disentangle "stripe size" from "object size"
- "stripe size" is the size of one slice of data
- "object size" is the size of one block of data on disk
- several stripes are put together into one bigger object

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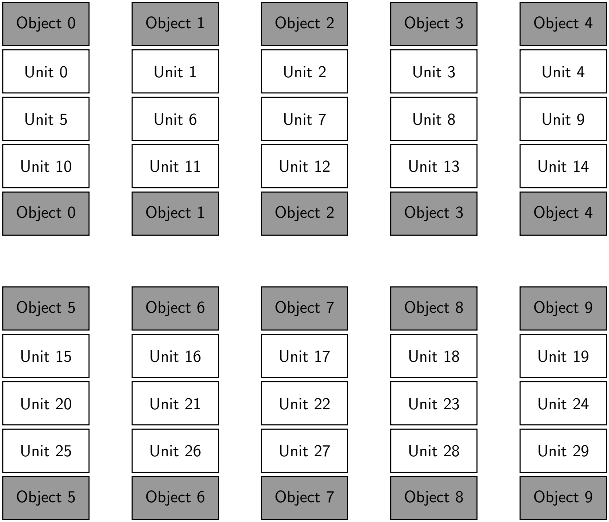
Ceph striping



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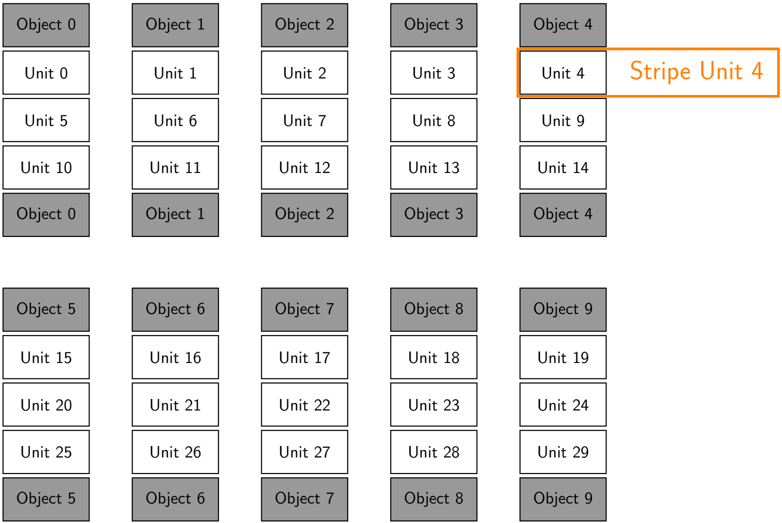

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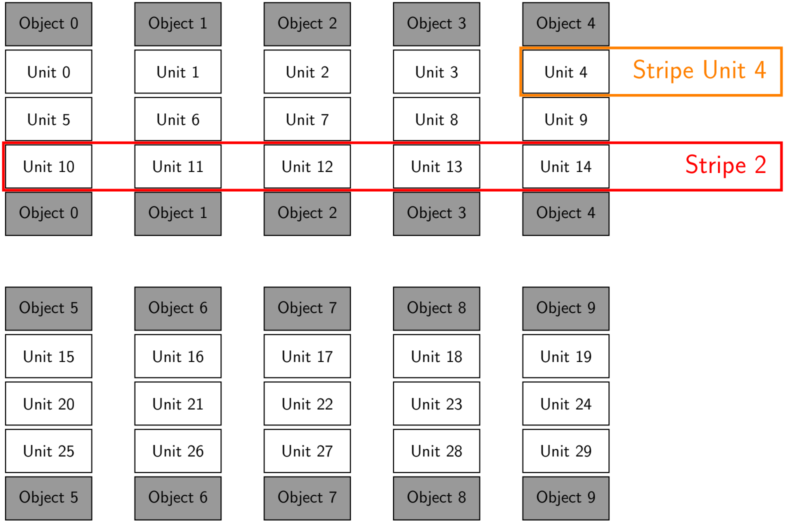

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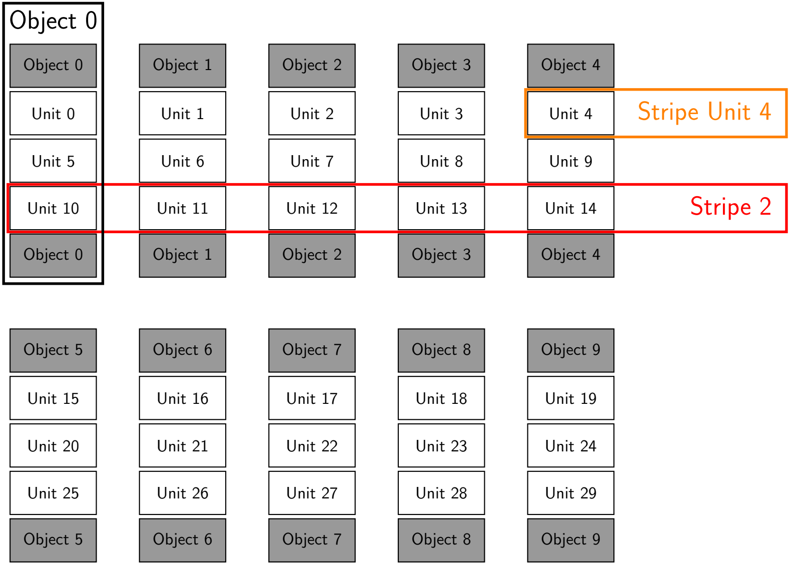

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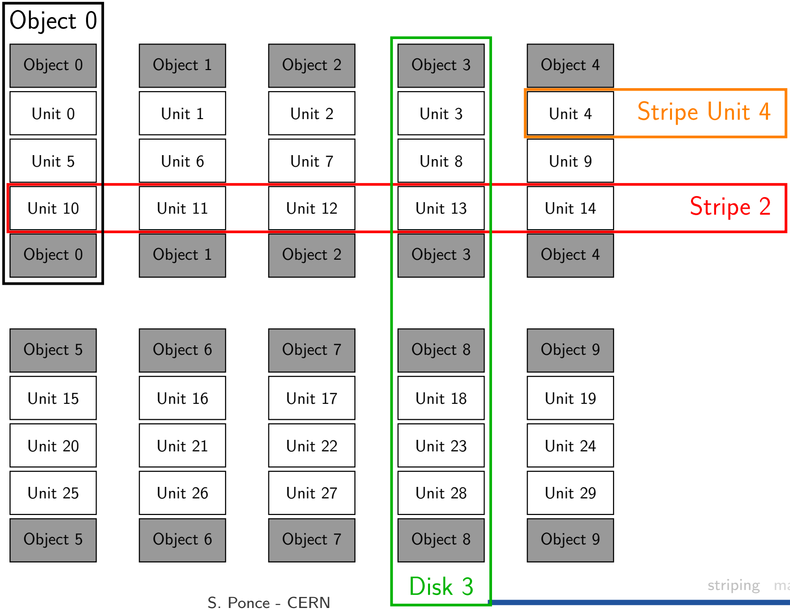

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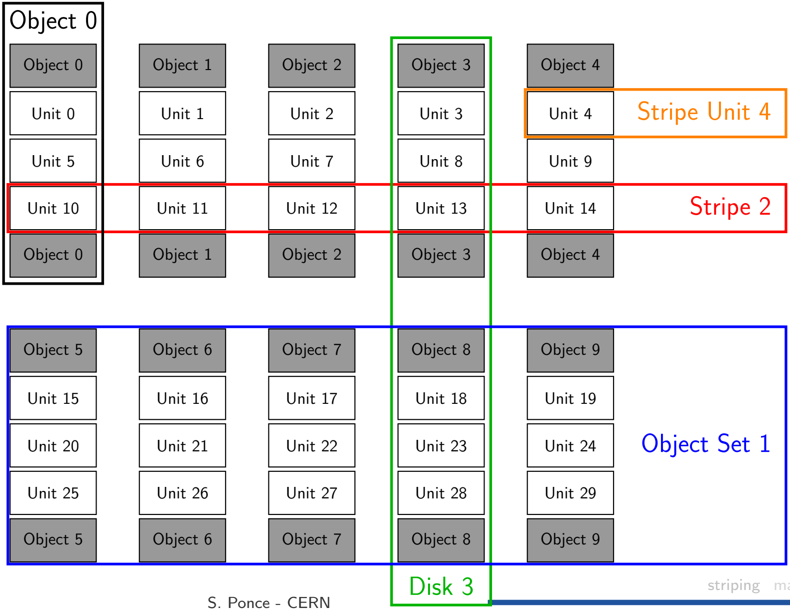

Practical striping - number of disks

Why to have many

- to increase parallelism
- to get better performances

Why to have few

- to limit the risk of losing files
- as losing a disk now means losing all files of all disks
- if p is the probability to lose a disk
  the probability to lose one in n is $p_n = np(1-p)^{n-1} \sim np$

A generic solution for the number of disks

Idea

- disentangle “nb disks” from “nb stripes”
- do not use all disks for all files
- adapt your number of disks to each file
  - more disks for high performance files
  - less disks for more safety

A generic solution for the number of disks

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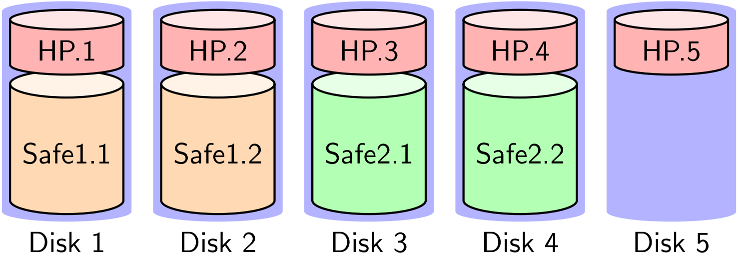


Going further : Map/Reduce

What do we have with striping

- striping allows to distribute server I/O on several devices
- but client still faces the total I/O
- and CPU is not distributed

Map/Reduce Idea

- send computation to the data nodes
- “the most efficient network I/O is the one you don’t do”

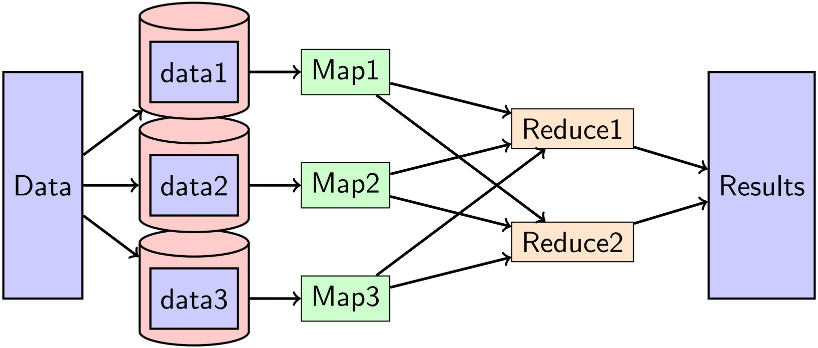
Map/Reduce Introduction

Schema

Map processes data locally and returns key/value pairs

Shuffle sends output to *Reduce* step based on output key

Reduce merges partial results to final output

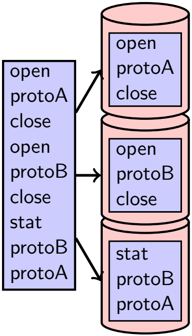


Example : usage of protocols from logs

open
protoA
close
open
protoB
close
stat
protoB
protoA

Example : usage of protocols from logs

1. split logs on different nodes



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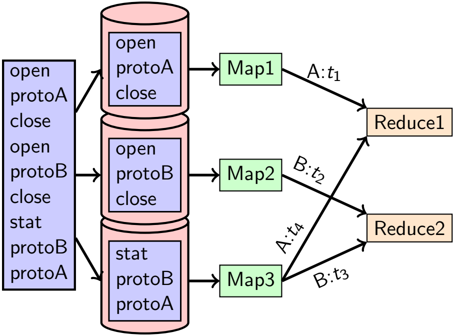
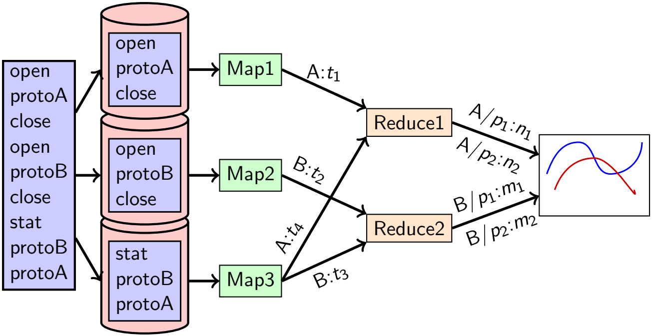


Example : usage of protocols from logs

1. split logs on different nodes
2. parse and extract key/value (*Protocol*/*Date*) in Map
3. count accesses and output *Date*/*nb accesses* in Reduce
4. build graph



The case of Hadoop, HDFS

HDFS : the Hadoop Distributed FileSystem

- Distributed
  - files split in blocks spread over the cluster
  - blocks are typically 128MB
- Redundant
  - mirroring, 3 copies by default
  - erasure coding coming in 3.0
- hardware aware

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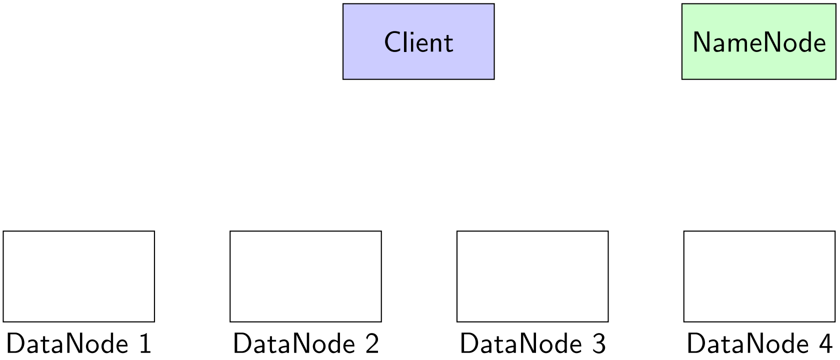
Parallel Read/Write in HDFS



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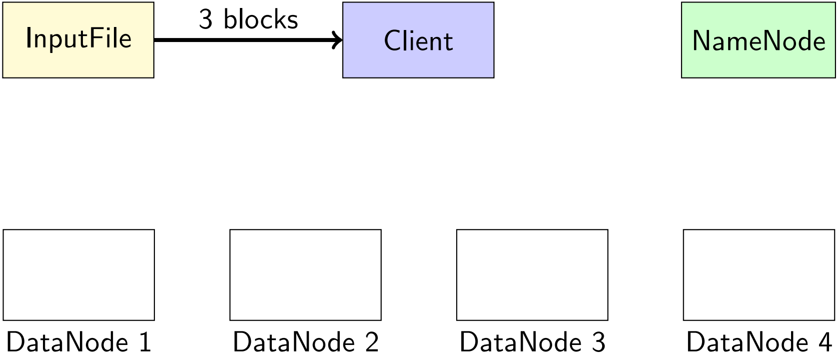

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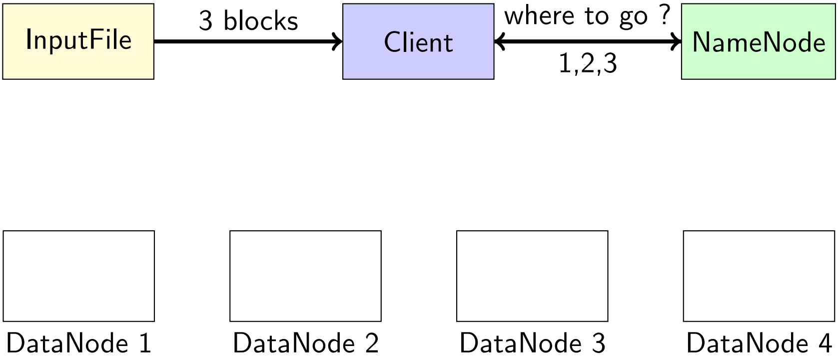

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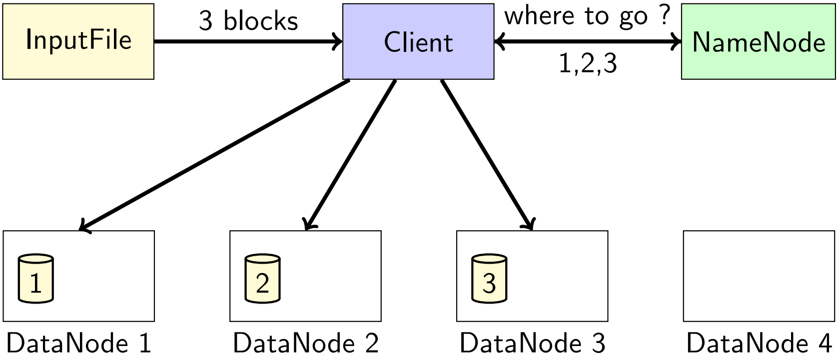

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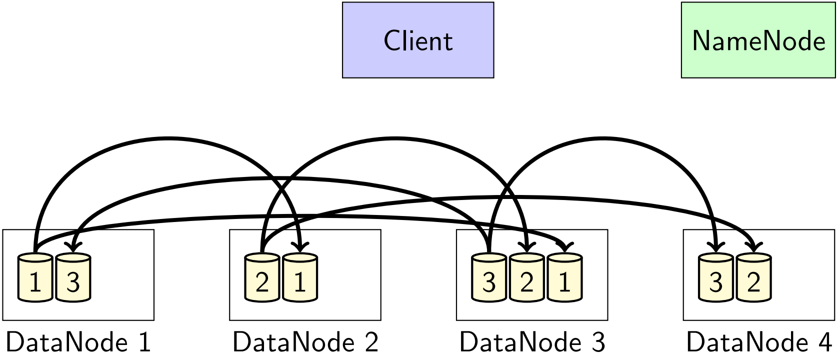

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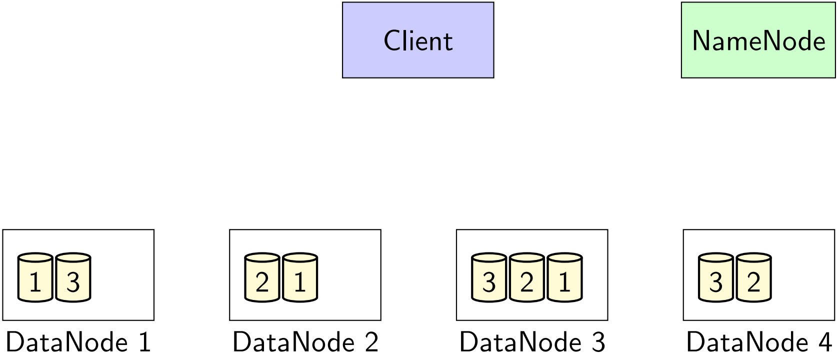

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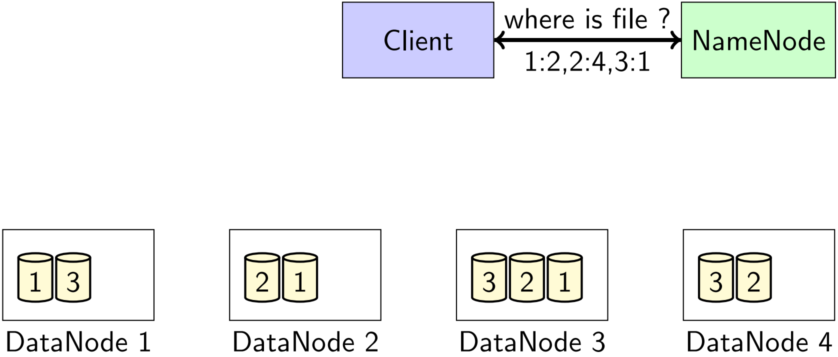

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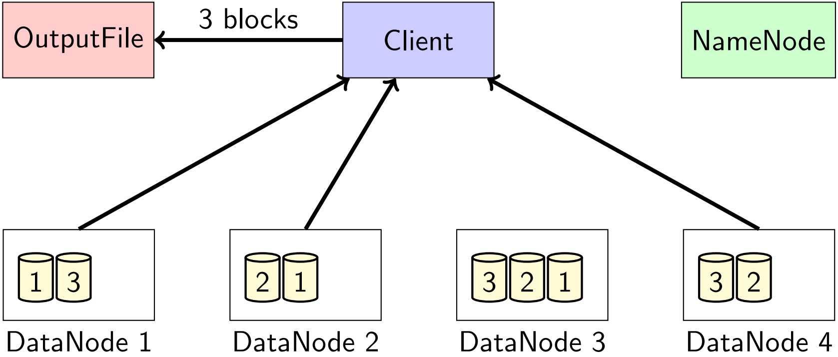

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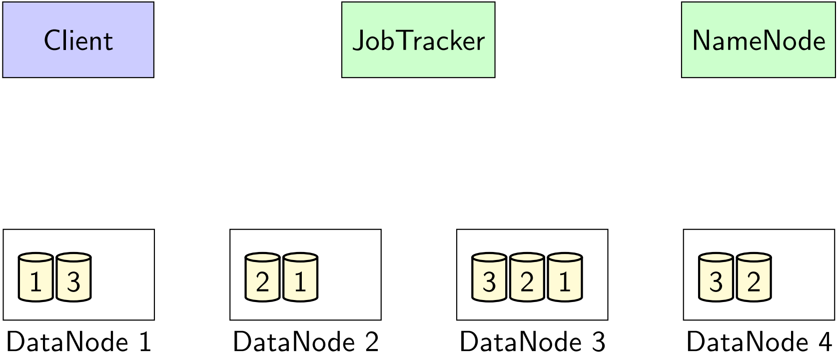

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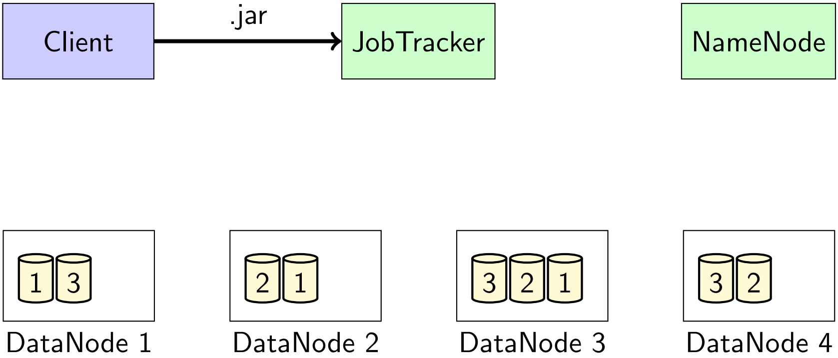

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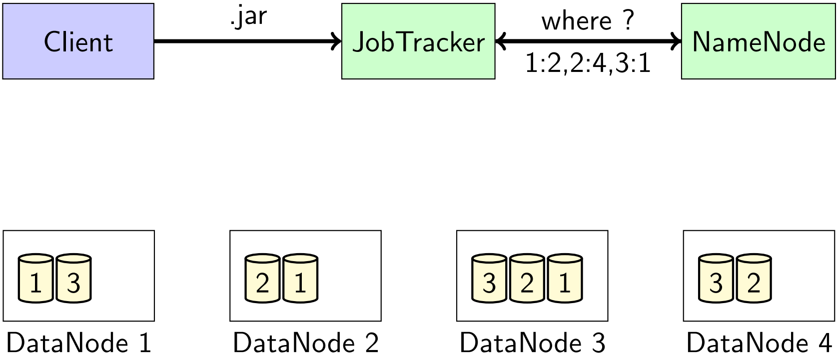

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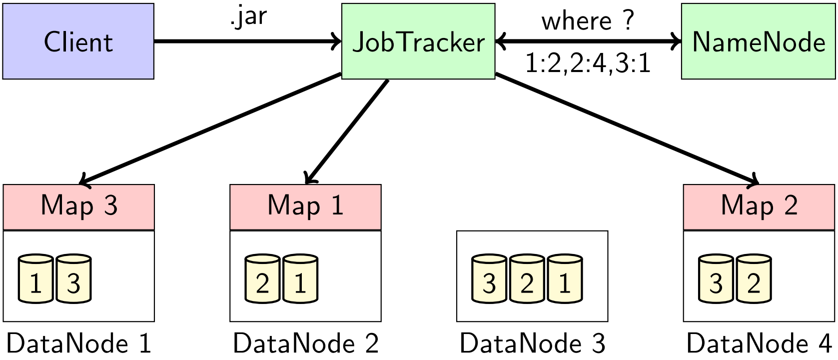

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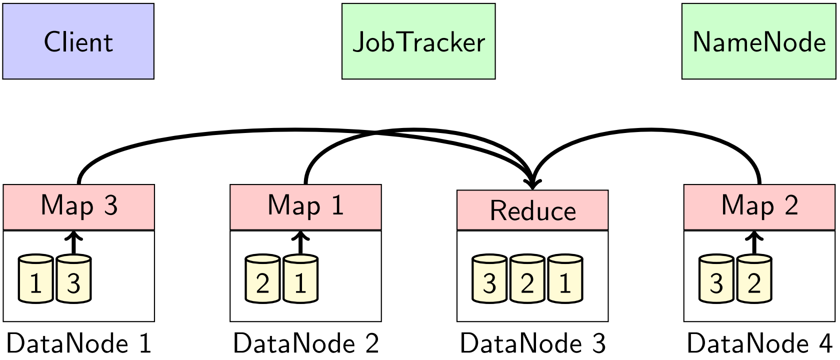

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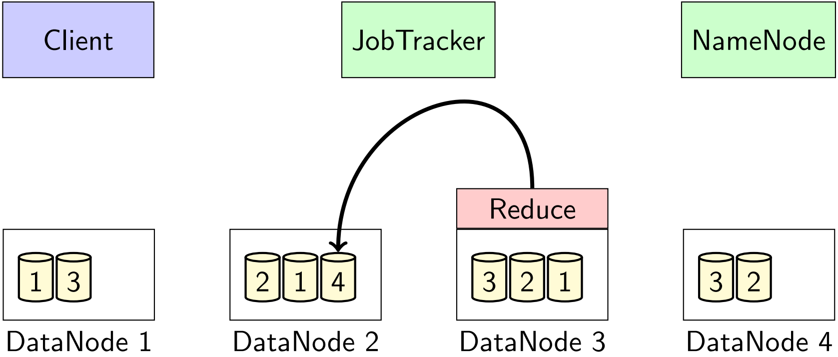
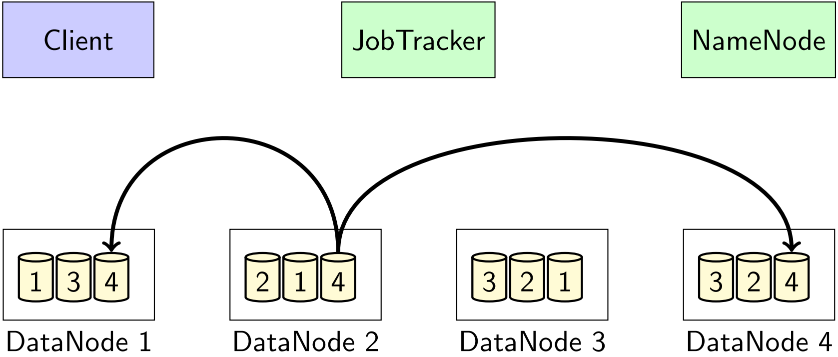


Parallel Map/Reduce



Conclusion

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Key messages of the day

- Take benefit of all existing devices to optimize your efficiency
- Do not underestimate the problem of data distribution
- Striping solves many problems. Use it but think twice
- Map/Reduce avoids a lot of I/O when results are small