Big Data Algorithms, Techniques and Platforms
Course 2 : Distributed Computing with MapReduce and Hadoop

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References

- Mining of Massive Datasets - Jure Leskovec, Anand Rajaraman, Jeff Ullman.
  `http://www.mmds.org/`
- Data-Intensive Text Processing with MapReduce - Jimmy Lin and Chris Dyer
  `https://lintool.github.io/MapReduceAlgorithms/`
- MapReduce Design Patterns - Building Effective Algorithms and Analytics for Hadoop and Other Systems. Donald Miner and Adam Shook
- Hadoop : The Definitive Guide- Tom White

Processing Big Data

Solution : parallelism

- 1 server
  - 8 disks
  - Read the web : 230 days
- Cluster Hadoop Yahoo
  - 4000 servers with 8 disks each.
  - Read the web : 1h20

Processing Big Data

Some problems

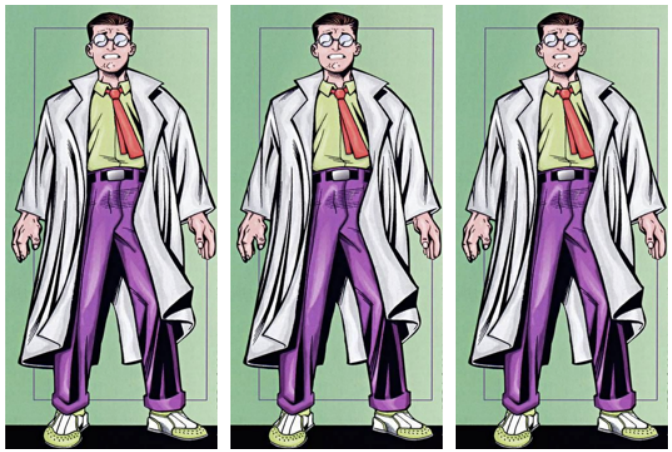
- Synchronization.
- Programming models (shared memory, message passing (MPI))
- Scalability and elasticity (arbitrary numbers of nodes)
- Fault Tolerance.

Tackling large data problems : big ideas

Scale out not up

A large number of **commodity low-end servers** (scaling out) as opposed to a small numbers of **high-end servers** (scaling up)

Scale out



Scale up

Tackling large data problems : big ideas

Assume failures as common

Assume

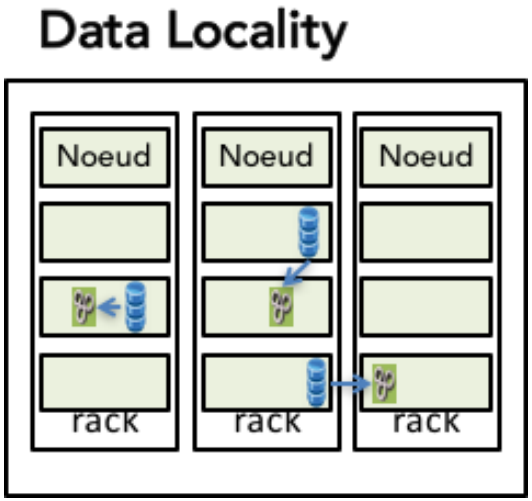
- A 10000-server cluster ;
- A mean time between failure of 1000 days

10 failures for a day

Tackling large data problems : big ideas

Move processing to the data

- Architectures where processors and storage are co-located (**data locality**)
- Distributed File Systems : GFS, HDFS...



Tackling large data problems : big ideas

Process data sequentially, avoid random access

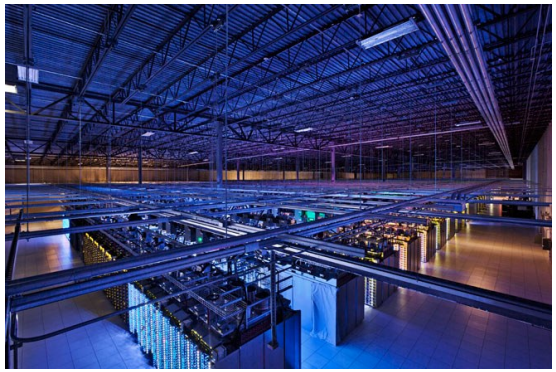
Relevant datasets are too large to fit in memory and must be held on the disk.

- Seeks are expensive, disk throughput is good.
- Organize computations so that the data is processed sequentially.

Tackling large data problems : big ideas

The data center is the computer

- Towards the right level of abstraction.
  Beyond the von Neumann architecture. What's the *instruction set* of the datacenter computer ?
- Hide system-levels details from the developers
  No need to explicitely worry about reliability, fault tolerance.
- Separating the *what* from the *how*.
  Developers specifies the computation that needs to be performed and an Execution framework handles actual execution.



Mapreduce : the first instanciation of this idea

Plan

What is MapReduce ?

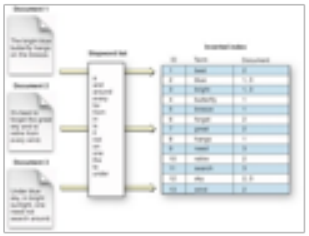
Two things

- A simple programming model for processing huge data sets in a distributed way.
- A framework that runs these programs on clusters of commodity servers, automatically handling the details of distributed computing :
  - Division of labor.
  - Distribution.
  - Synchronization.
  - Fault-tolerance.

Hadoop is one of the famous implementation of the MapReduce programming model and execution framework

MapReduce : origins

...



MAP

REDUCE

MapReduce : origins

MapReduce : Simplified Data Processing on Large Clusters [Dean and Ghemawat, OSDI 04]

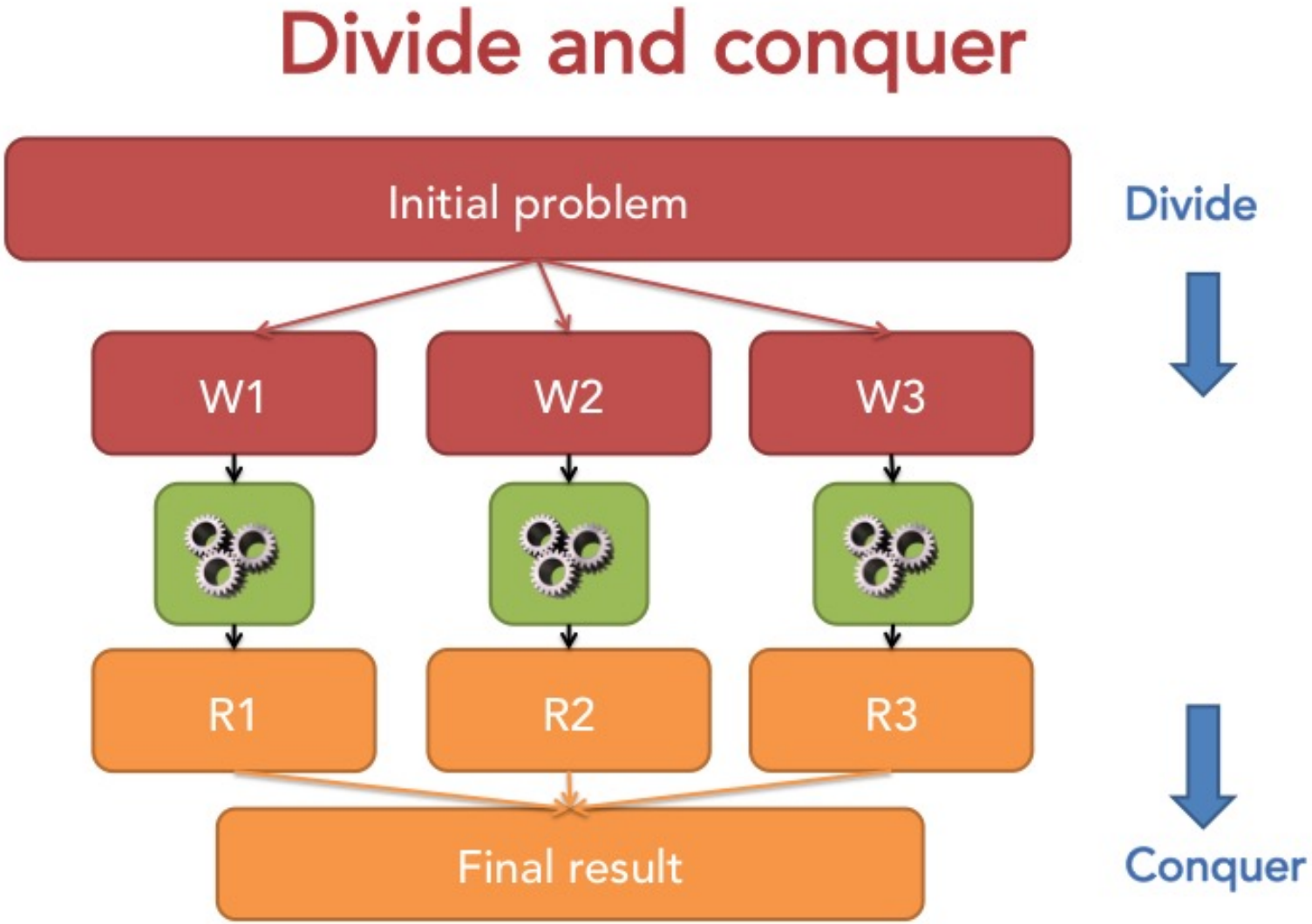
MapReduce is a programming model and an associated implementation for processing and generating large data sets. Users specify a *map* function that processes a key/value pair to generate a set of intermediate key/value pairs, and a *reduce* function that merges all intermediate values associated with the same intermediate key. Many real world tasks are expressible in this model, as shown in the paper.

MapReduce : origins

MapReduce : Simplified Data Processing on Large Clusters [Dean and Ghemawat, OSDI 04]

Programs written in this functional style are automatically parallelized and executed on a large cluster of commodity machines. The run-time system takes care of the details of partitioning the input data, scheduling the program's execution across a set of machines, handling machine failures, and managing the required inter-machine communication. This allows programmers without any experience with parallel and distributed systems to easily utilize the resources of a large distributed systems.

Divide and conquer paradigm



MapReduce : a distributed divide and conquer paradigm

Principle

- Divide a task into independent subtasks.
- Handle the sub-tasks in parallel.
- Aggregate the results of the subtasks to form the final output

Writing programs in MapReduce enables their automatic parallelization.

MapReduce : a distributed divide and conquer paradigm

A simple principle but :

- How do we break up the problem into smaller tasks that can be executed in parallel ?
- How to we assign task to workers ?
- How to we ensure that the workers get the data they need ?
- How do we coordinate synchronisation among the different workers ?
- How do we share partial resukts from one worker that is needed by another ?
- How do we accomplish all of the above in the face of software erros and hardware faults ?

Typical big-data problem

- Iterate over a large number of records.
- Extract something of interest from each record.
- Shuffle and sort intermediate results.
- Aggregate intermediate results.
- Generate final output.

The origins of MapReduce : this interesting observation made by Dean and Ghemawat. Many different problems can be processed in parallel in the same way.

Simple computations but complex issues from their parallelization.

Typical big-data problem

MAP

- Iterate over a large number of records.
- Extract something of interest from each record.

- Shuffle and sort intermediate results

REDUCE

- Aggregate intermediate results
- Generate final output.

MapReduce key idea :

- Every massive data processing can be expressed with these only two operations (outline stays the same, **map** and **reduce** change to fit the problem)
- Provide a functional abstraction of these two operations.

[Dean and Ghemawat, OSDI 2004]

MapReduce

Inspiration from functional programming

`map` and `reduce` (or `fold`) are existing list operators in functional programming (lisp, scheme, scala ...)

map

Apply a function f to each item of the list

```
map(f)[x0, ..., xn] = [f(x0), ...,f(xn)]
map(*4)[2, 3, 6] = [8, 12, 24]
```

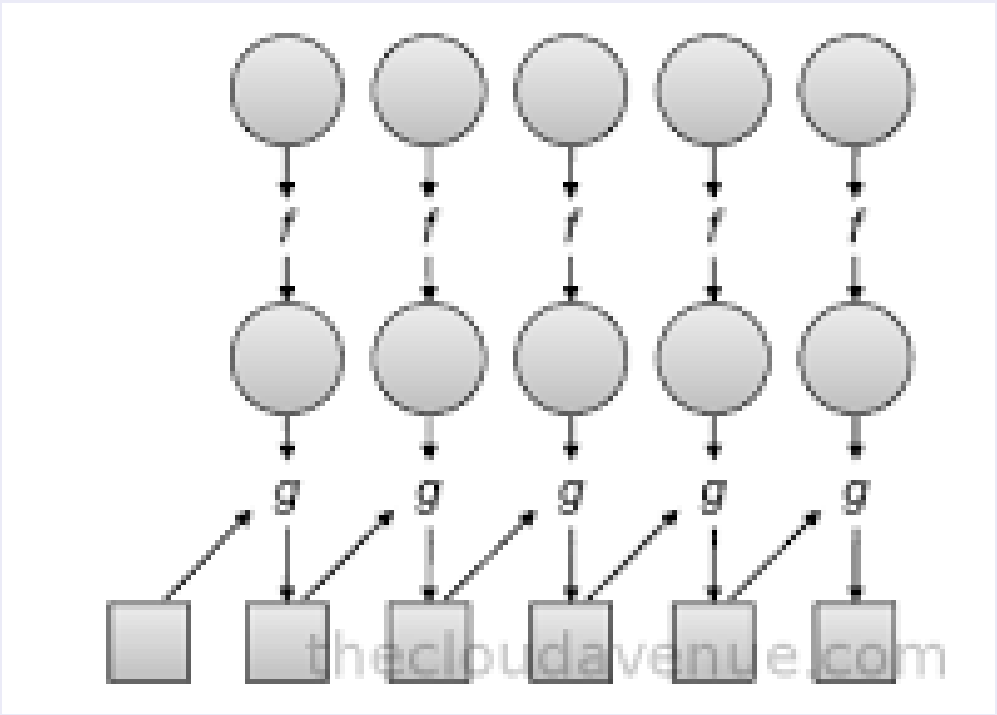
reduce

Apply a function recursively to the items of the list

```
reduce(f)[x0, ..., xn] = f(x0, f(x1, f(x2, ...)))
reduce(+)[2, 3, 6] = (2 + (3 + 6)) = 11
```

MapReduce

Inspiration from functional programming



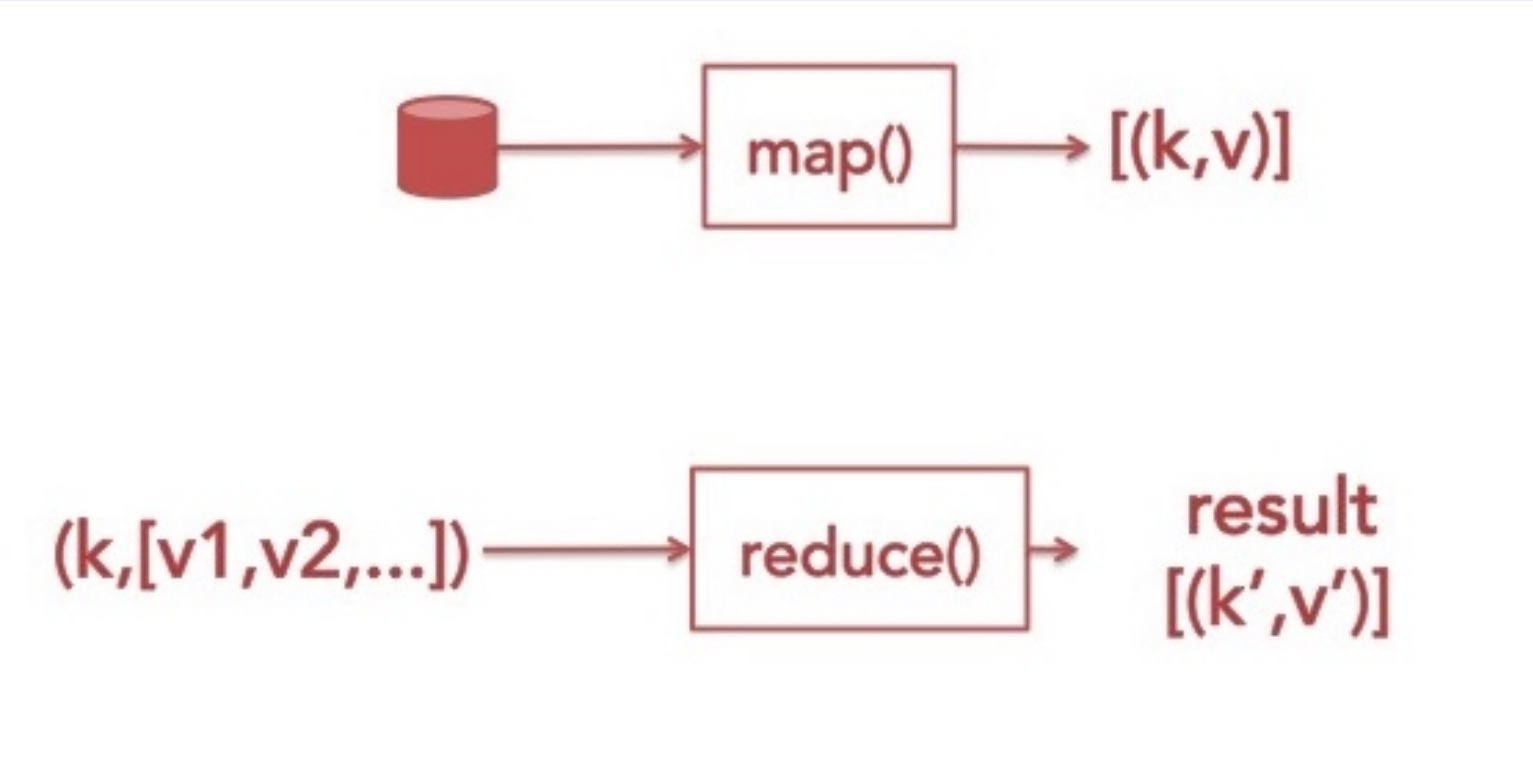
`map` : transformation of a dataset.

`reduce` : aggregation operation (some locality constraints).

MapReduce

Main principles

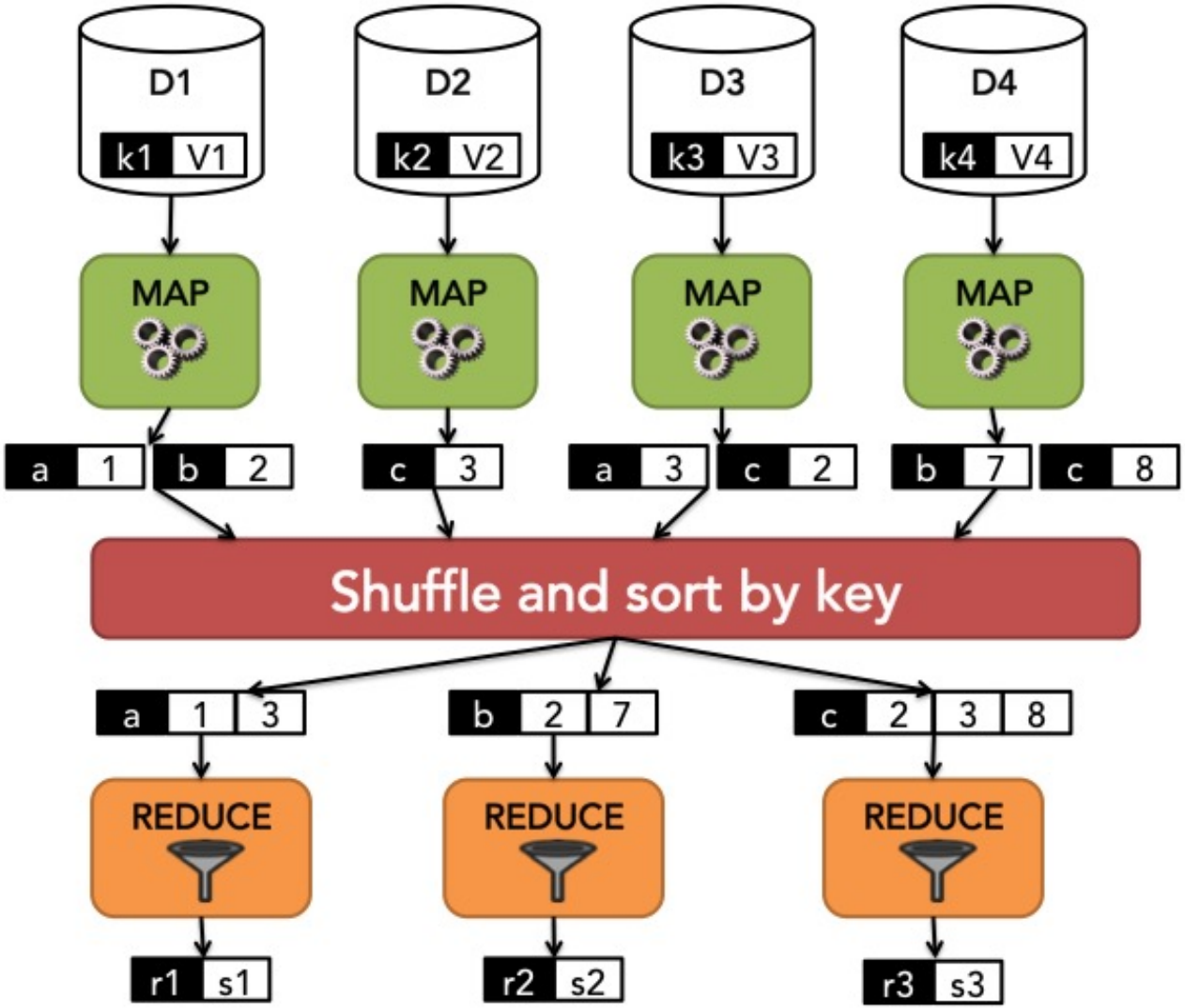
- All the data are structured in (key,value) pairs.
- Two functions :
  - MAP : Transform the input data in a list of (key,value) pairs.
  - REDUCE : Aggregate/Reduce all the values associated to the same key.



MapReduce overview

- Read a lot of data sequentially.
- MAP
  - Extract something you care about.
- SHUFFLE AND SORT
  - Group by key.
- REDUCE
  - Aggregate, summarize, filter or transform
- Write the result.

MapReduce scheme

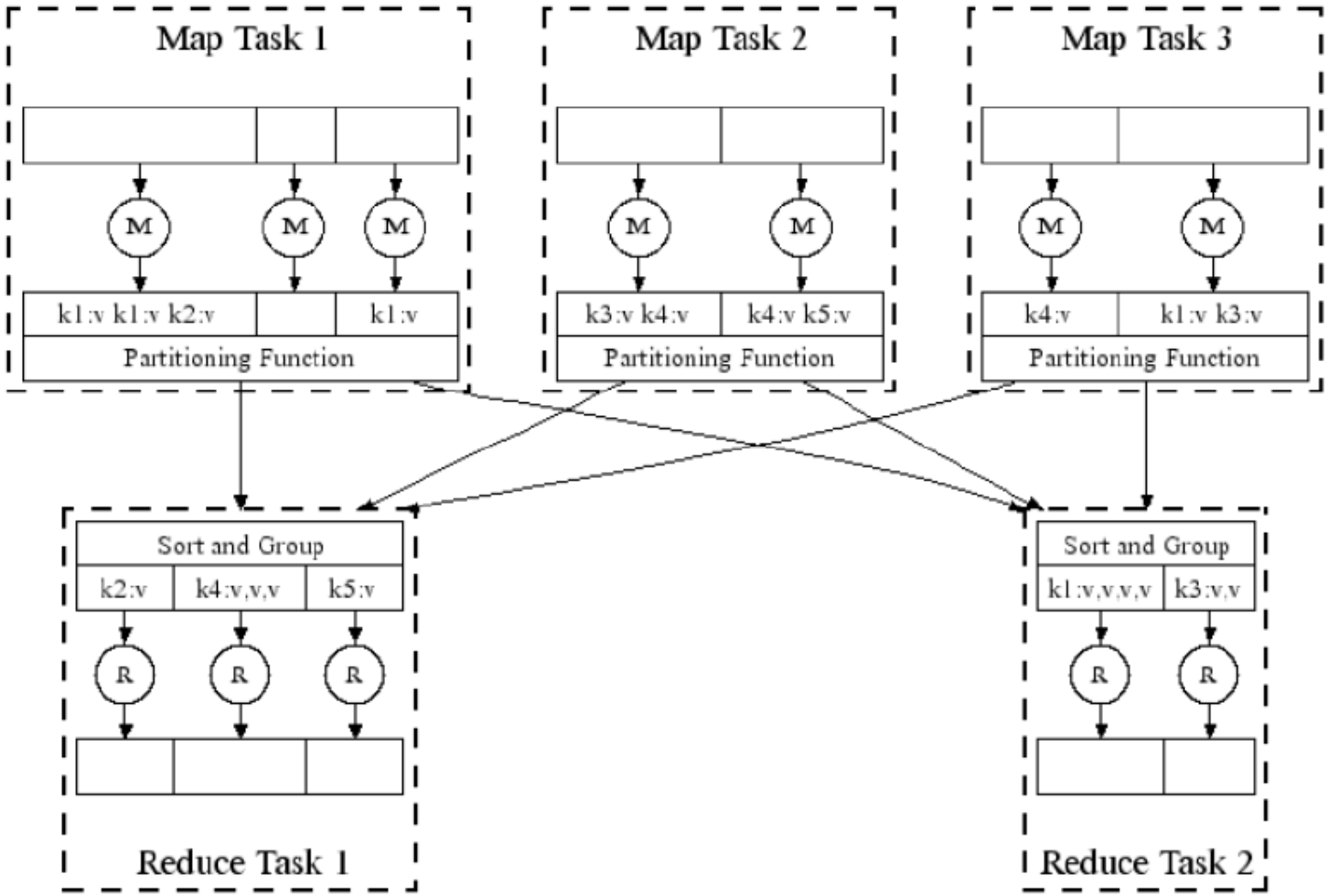


MapReduce programming model

Programmers must specify two functions :

- map $(k, v) \rightarrow [(k', v')...]$
  - Takes a key value pair and outputs a set of key value pairs (e.g. key = filename, value = the file content)
  - One Map call for every (k, v) pair.
- reduce $(k', [v'_1, ...v'_n]) \rightarrow [(k'', v'')...]$
  - All values v' with the same key k' are reduced together and processed in v' order.
  - One Reduce function call for each key k'
- The execution framework handles everything else

MapReduce : Execution in Parallel



Typical example

Task

- A huge text document.
- Count the number of times each distinct word appears in the file.

Sample applications

- Web server logs analysis to find popular URLs
- Information retrieval : document indexing
- ...

Just try (at home) !

- Write a program in python or java that achieves this task !
- Try it on files of different sizes !

Wordcount

Word Count !

Count the occurrences of each word in different documents.

Data : a set of textual documents

Le jour se lève sur notre grisaille, sur les trottoirs de nos ruelles et sur nos tours
[...]

Le jour se lève sur notre envie de vous faire comprendre à tous que c'est à notre tour
[...]

(**Grand Corps Malade,** Le Jour se lève. *Excerpt*)

Wordcount


Word Count !
SPLIT (with simplification)
jour lève notre grisaille
trottoir notre ruelle notre tour
jour lève notre envie vous
faire comprendre tous notre tour

Wordcount

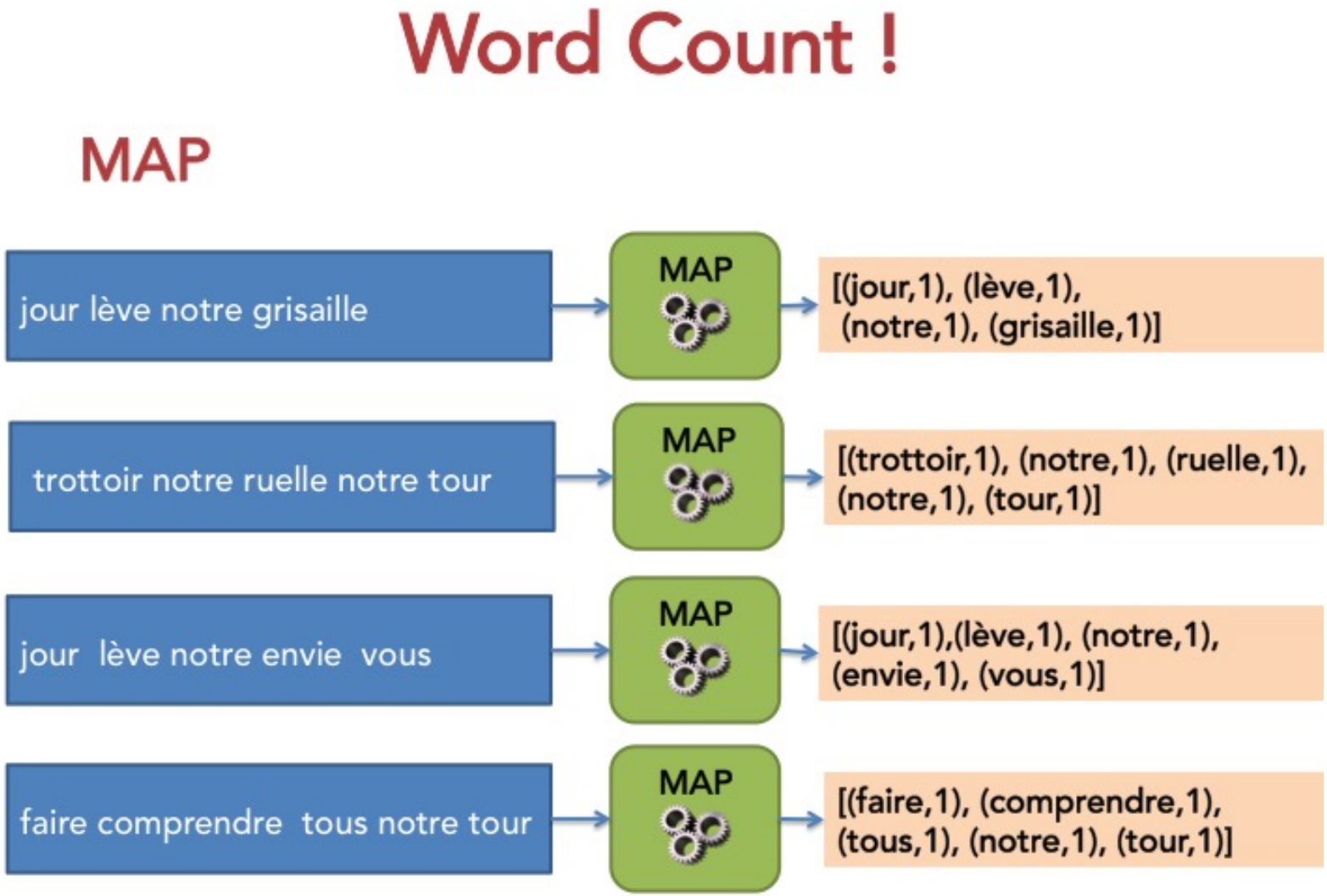
Word Count !

MAP

For each word, generate the pair (word, 1)

```
def map (key,value):     #key : nom du doc, value : contenu du doc
for word w in value:
    emitIntermediate (w,1)
```

Wordcount


Word Count !
MAP
jour lève notre grisaille
MAP
[(jour,1), (lève,1), (notre,1), (grisaille,1)]
trottoir notre ruelle notre tour
MAP
[(trottoir,1), (notre,1), (ruelle,1), (notre,1), (tour,1)]
jour lève notre envie vous
MAP
[(jour,1),(lève,1), (notre,1), (envie,1), (vous,1)]
faire comprendre tous notre tour
MAP
[(faire,1), (comprendre,1), (tous,1), (notre,1), (tour,1)]

Wordcount

Word Count !

SHUFFLE : group and sort all the pairs by key

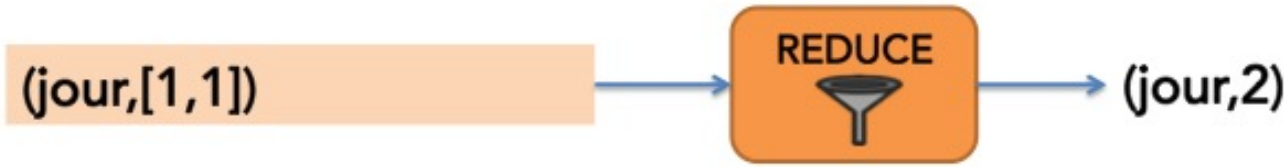
(comprendre, [1])	(notre, [1,1,1,1,1])
(envie,[1])	(ruelle,[1])
(faire,[1])	(tour,[1,1])
(grisaille,[1])	(tous,[1])
(jour,[1,1])	(trottoir,[1])
(lève, [1,1])	(vous, [1])

Wordcount

Word Count !

REDUCE : add all the values associated to a same key

```
def reduce (key,values):     #key : un mot, values : liste de valeurs
result =0
for count c in values:
    result = result +1
emit(key,result)
```

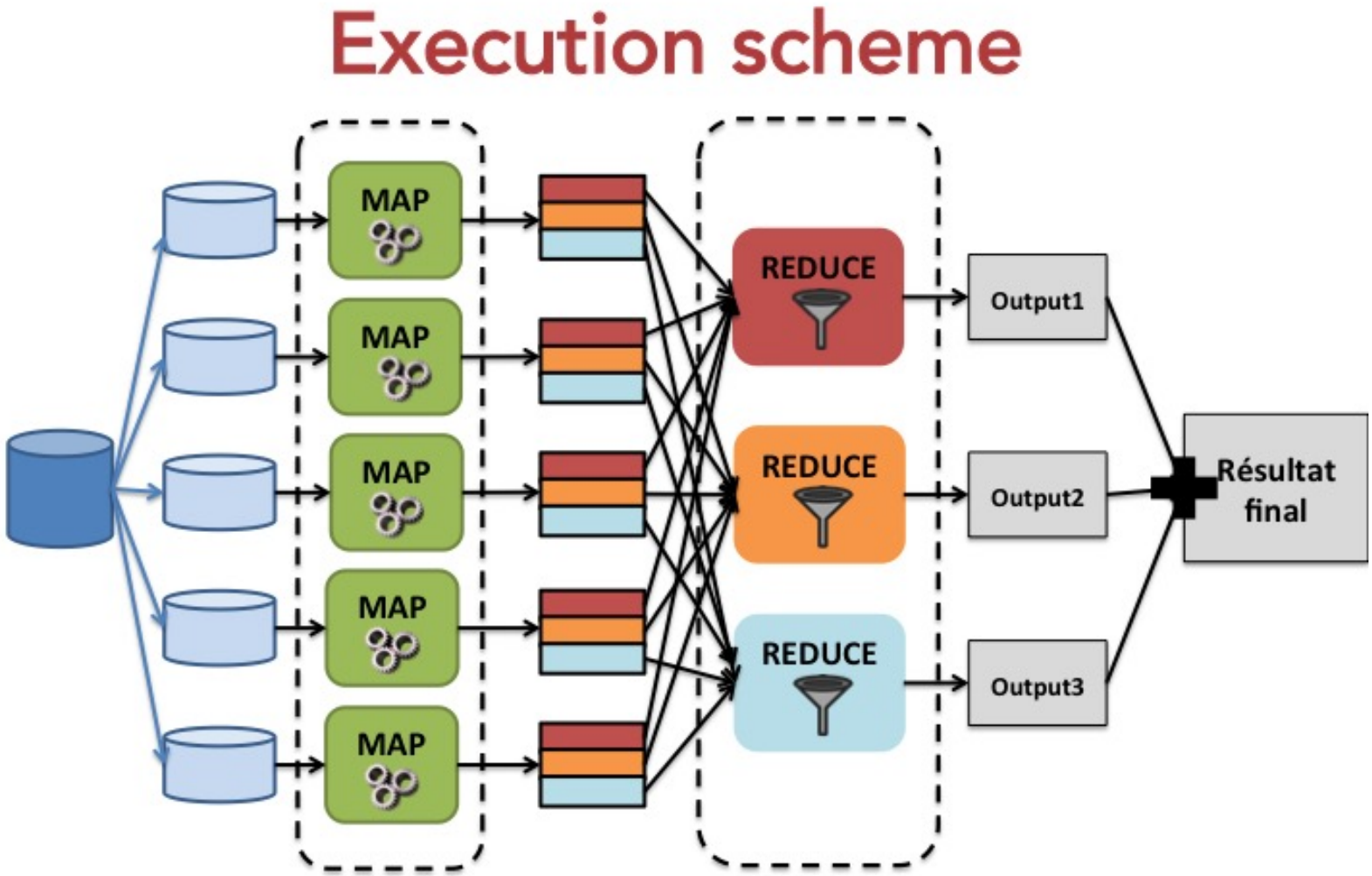


Basic WordCount algorithm in MapReduce

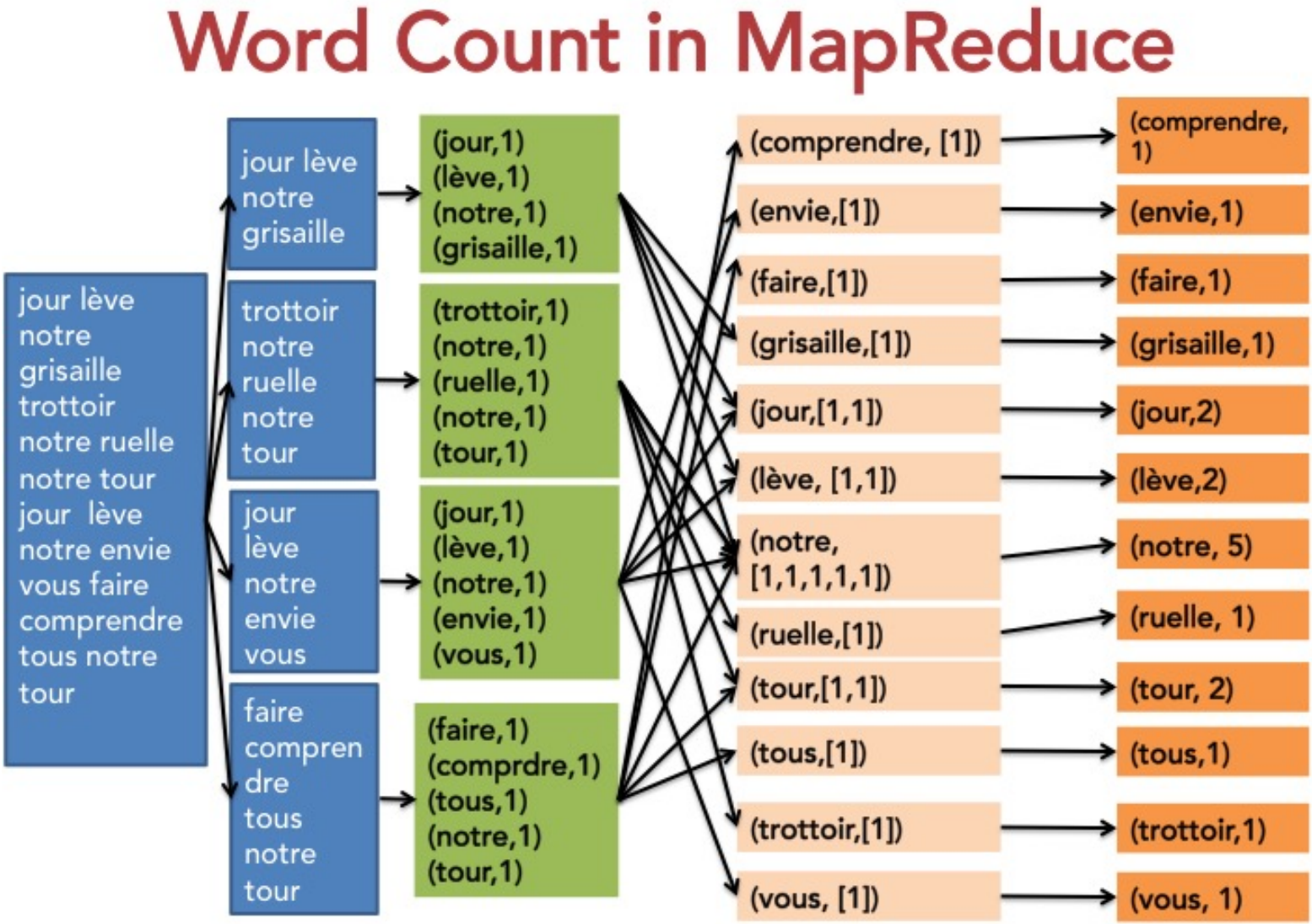
```
1: class Mapper
2:     method Map(docid a, doc d)
3:         for all term t ∈ doc d do
4:             Emit(term t, count 1)

1: class Reducer
2:     method Reduce(term t, counts [c1, c2, ...])
3:         sum ← 0
4:         for all count c ∈ counts [c1, c2, ...] do
5:             sum ← sum + c
6:         Emit(term t, count sum)
```

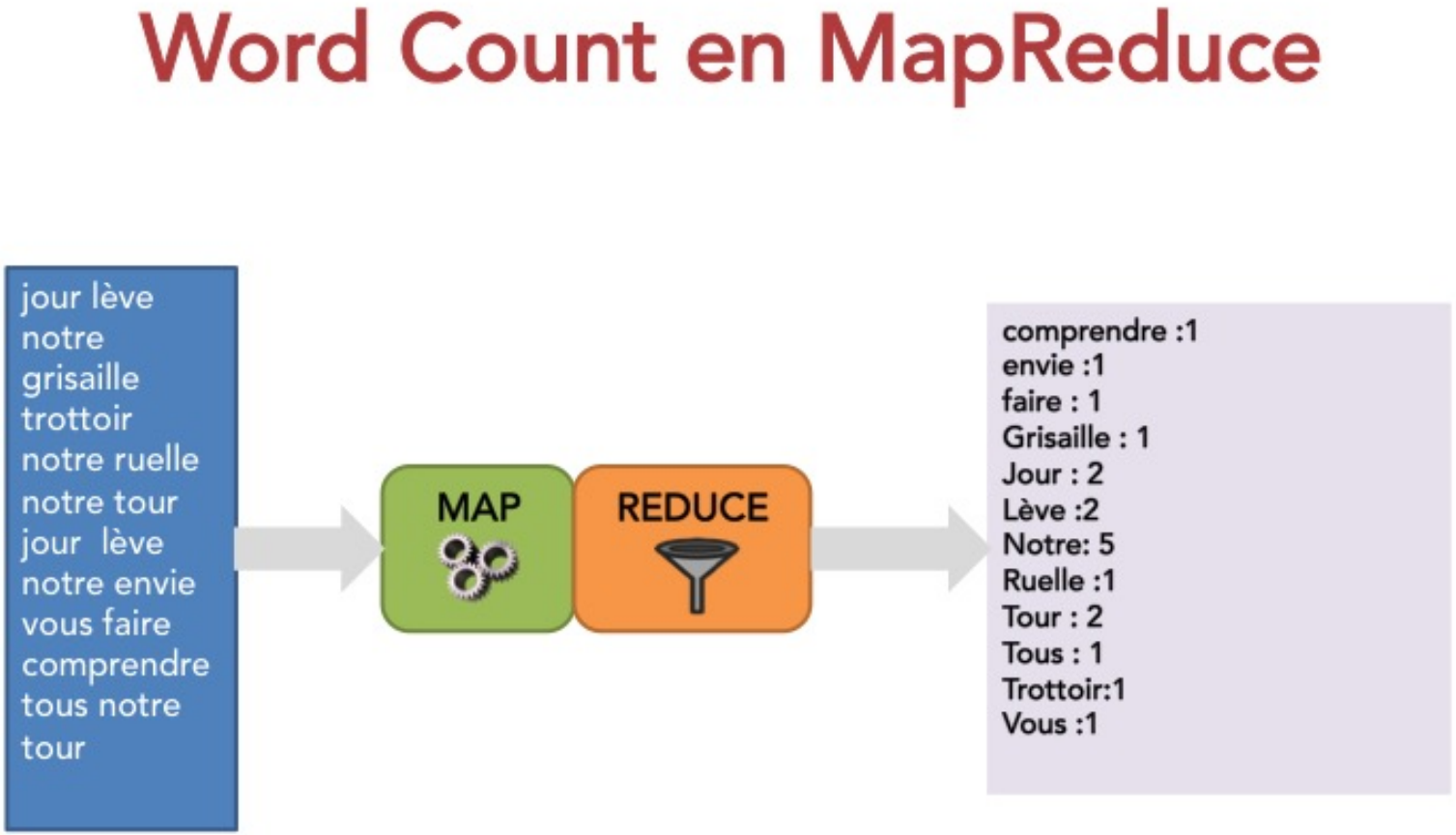
Wordcount


Execution scheme
MAP
MAP
MAP
MAP
MAP
REDUCE
REDUCE
REDUCE
Output1
Output2
Output3
Résultat final

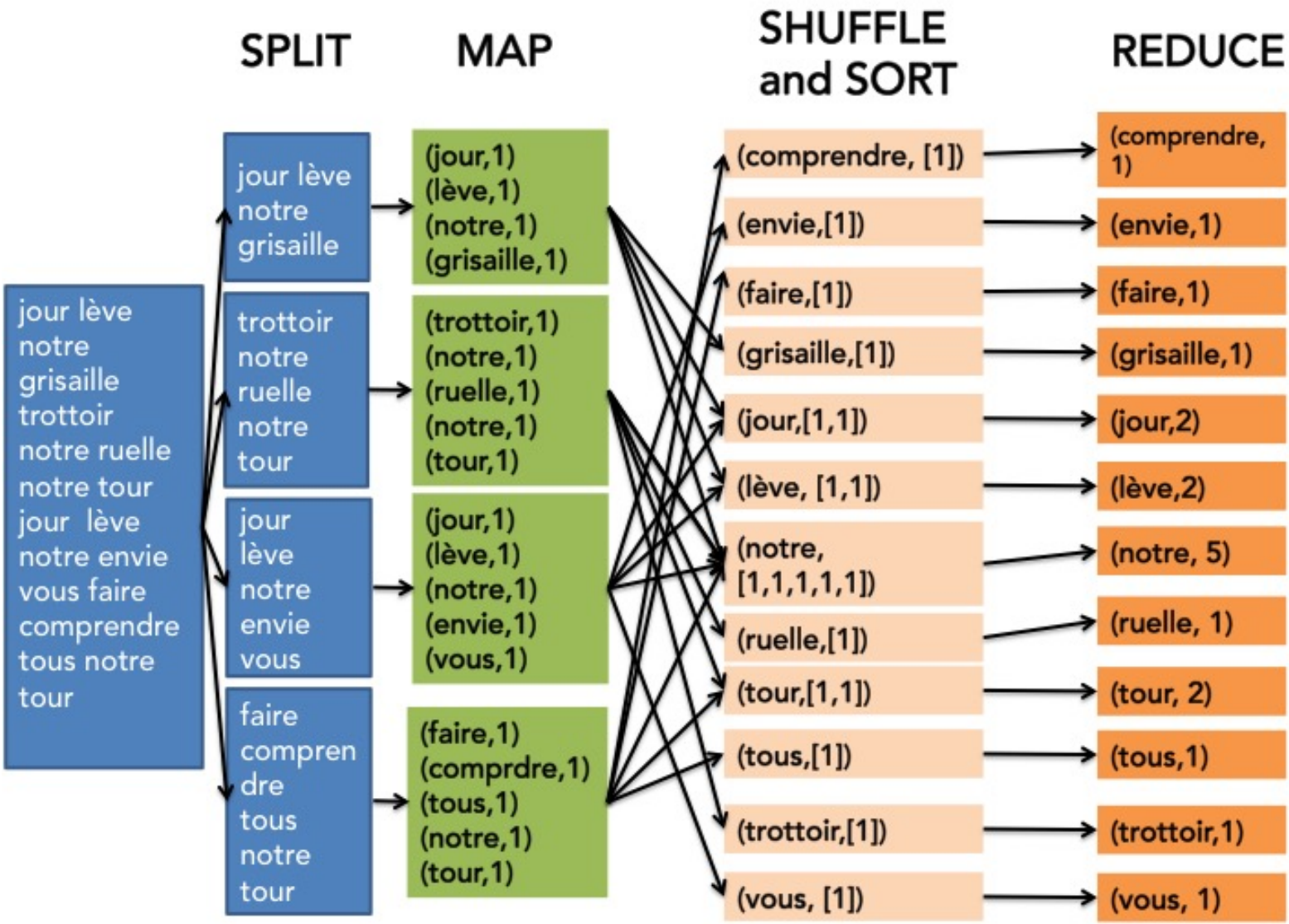
Wordcount


Word Count in MapReduce
jour lève notre grisaille trottoir notre ruelle notre tour jour lève notre envie vous faire comprendre tous notre tour
jour lève notre grisaille
trottoir notre ruelle notre tour
jour lève notre envie vous
faire compren dre tous notre tour
(jour,1) (lève,1) (notre,1) (grisaille,1)
(trottoir,1) (notre,1) (ruelle,1) (notre,1) (tour,1)
(jour,1) (lève,1) (notre,1) (envie,1) (vous,1)
(faire,1) (comprdre,1) (tous,1) (notre,1) (tour,1)
(comprendre, [1])
(envie,[1])
(faire,[1])
(grisaille,[1])
(jour,[1,1])
(lève, [1,1])
(notre, [1,1,1,1,1])
(ruelle,[1])
(tour,[1,1])
(tous,[1])
(trottoir,[1])
(vous, [1])
(comprendre, 1)
(envie,1)
(faire,1)
(grisaille,1)
(jour,2)
(lève,2)
(notre, 5)
(ruelle, 1)
(tour, 2)
(tous,1)
(trottoir,1)
(vous, 1)

Wordcount


Word Count en MapReduce
jour lève
notre
grisaille
trottoir
notre ruelle
notre tour
jour lève
notre envie
vous faire
comprendre
tous notre
tour
MAP
REDUCE
comprendre :1
envie :1
faire : 1
Grisaille : 1
Jour : 2
Lève :2
Notre: 5
Ruelle :1
Tour : 2
Tous : 1
Trottoir:1
Vous :1

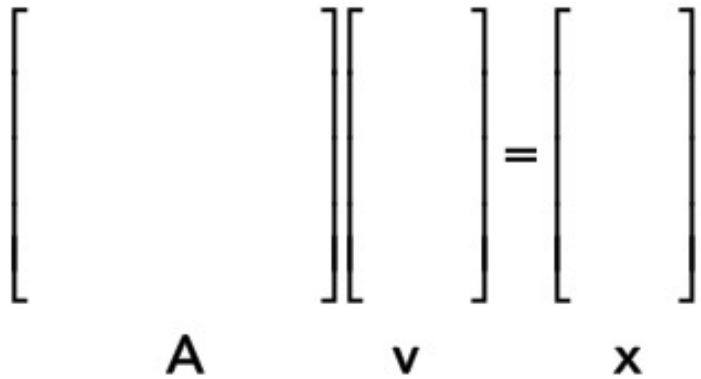
Wordcount


SPLIT
MAP
SHUFFLE and SORT
REDUCE
jour lève notre grisaille trottoir notre ruelle notre tour jour lève notre envie vous faire comprendre tous notre tour
jour lève notre grisaille
trottoir notre ruelle notre tour
jour lève notre envie vous
faire compren dre tous notre tour
(jour,1) (lève,1) (notre,1) (grisaille,1)
(trottoir,1) (notre,1) (ruelle,1) (notre,1) (tour,1)
(jour,1) (lève,1) (notre,1) (envie,1) (vous,1)
(faire,1) (comprdre,1) (tous,1) (notre,1) (tour,1)
(comprendre, [1])
(envie,[1])
(faire,[1])
(grisaille,[1])
(jour,[1,1])
(lève, [1,1])
(notre, [1,1,1,1,1])
(ruelle,[1])
(tour,[1,1])
(tous,[1])
(trottoir,[1])
(vous, [1])
(comprendre, 1)
(envie,1)
(faire,1)
(grisaille,1)
(jour,2)
(lève,2)
(notre, 5)
(ruelle, 1)
(tour, 2)
(tous,1)
(trottoir,1)
(vous, 1)

Another example

Another Example

Multiplication of a matrix by a vector



Another example

Multiplication of a matrix by a vector

	$\vec{x}$	$\vec{x}P^1$	$\vec{x}P^2$	$\vec{x}P^3$	$\vec{x}P^4$	$\vec{x}P^5$	$\vec{x}P^6$	$\vec{x}P^7$	$\vec{x}P^8$	$\vec{x}P^9$	$\vec{x}P^{10}$	$\vec{x}P^{11}$	$\vec{x}P^{12}$	$\vec{x}P^{13}$
d_0	0.14	0.06	0.09	0.07	0.07	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05
d_1	0.14	0.08	0.06	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
d_2	0.14	0.25	0.18	0.17	0.15	0.14	0.13	0.12	0.12	0.12	0.12	0.11	0.11	0.11
d_3	0.14	0.16	0.23	0.24	0.24	0.24	0.24	0.25	0.25	0.25	0.25	0.25	0.25	0.25
d_4	0.14	0.12	0.16	0.19	0.19	0.20	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
d_5	0.14	0.08	0.06	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
d_6	0.14	0.25	0.23	0.25	0.27	0.28	0.29	0.29	0.30	0.30	0.30	0.30	0.31	0.31

Use for the page rank !

Source : Wikipedia

Another example

Multiplication of a matrix by a vector

✧ How to represent the matrix?

$$A = \begin{bmatrix} 3 & 2 & 0 \\ 0 & 4 & 1 \\ 2 & 0 & 1 \end{bmatrix}$$

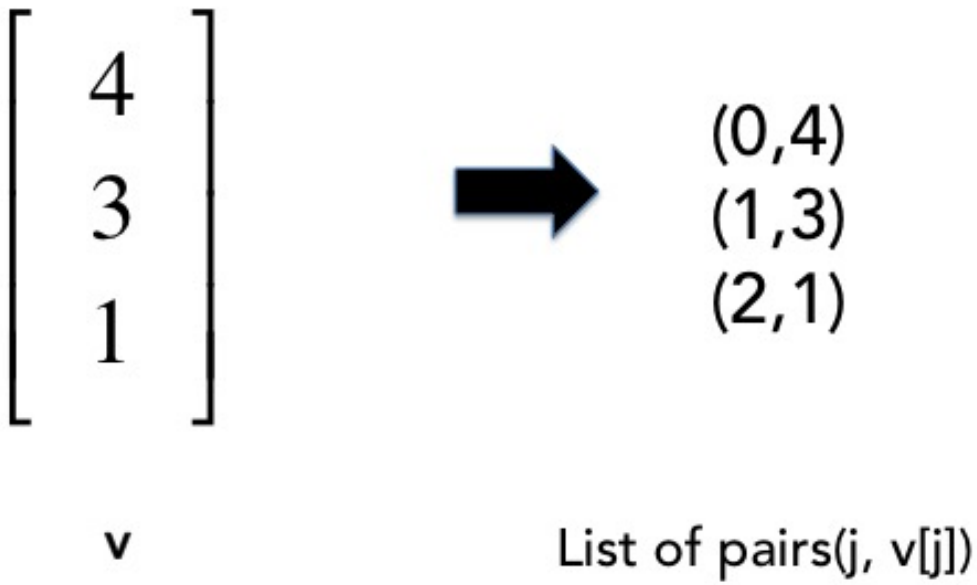
(0,0,3)
(0,1,2)
(1,1,4)
(1,2,1)
(2,0,2)
(2,2,1)

List of triples (i,j, A[i][j])

Another example

Multiplication of a matrix by a vector

✧ How to represent the vector v?



Another example

Multiplication of a matrix by a vector

Simple case : the vector v fits in memory of the MAP node

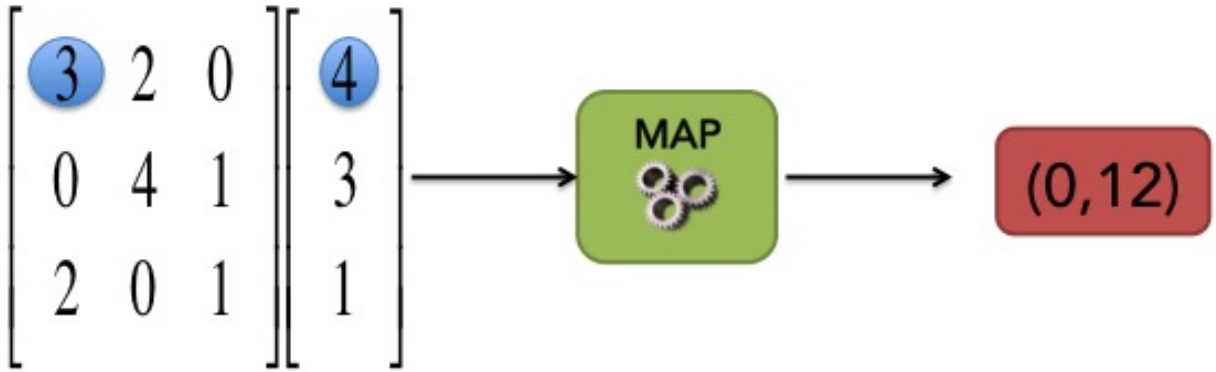
Another example

Multiplication of a matrix by a vector

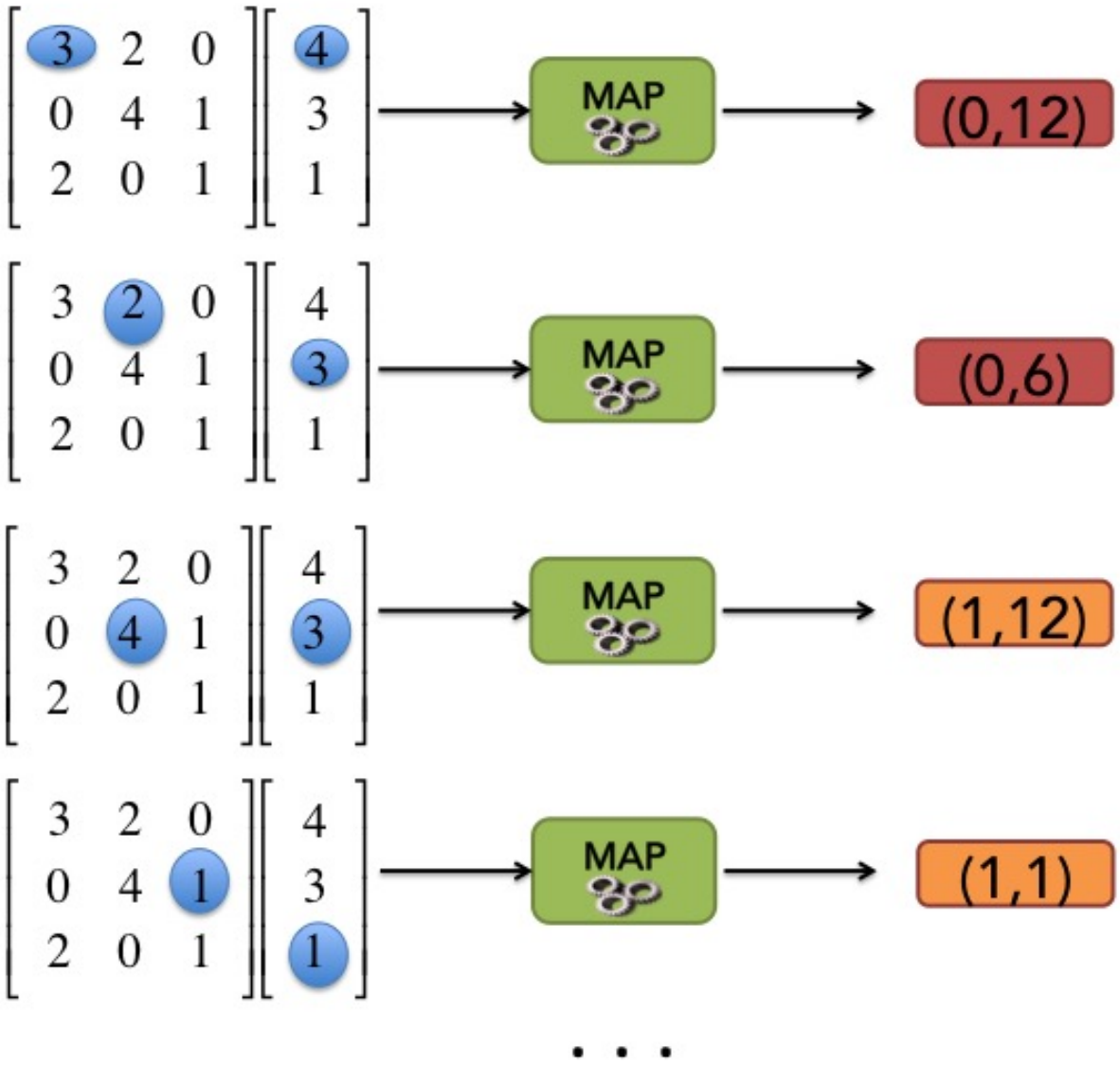
✧ MAP

Each entry (i,j,A[i][j]) of the matrix is transformed in (i, A[i][j] * v[j])

```
def map (key,value):     #key = None, value : (i,j,A[i][j])
    emitIntermediate (i,A[i][j]*v[j])
```



Another example

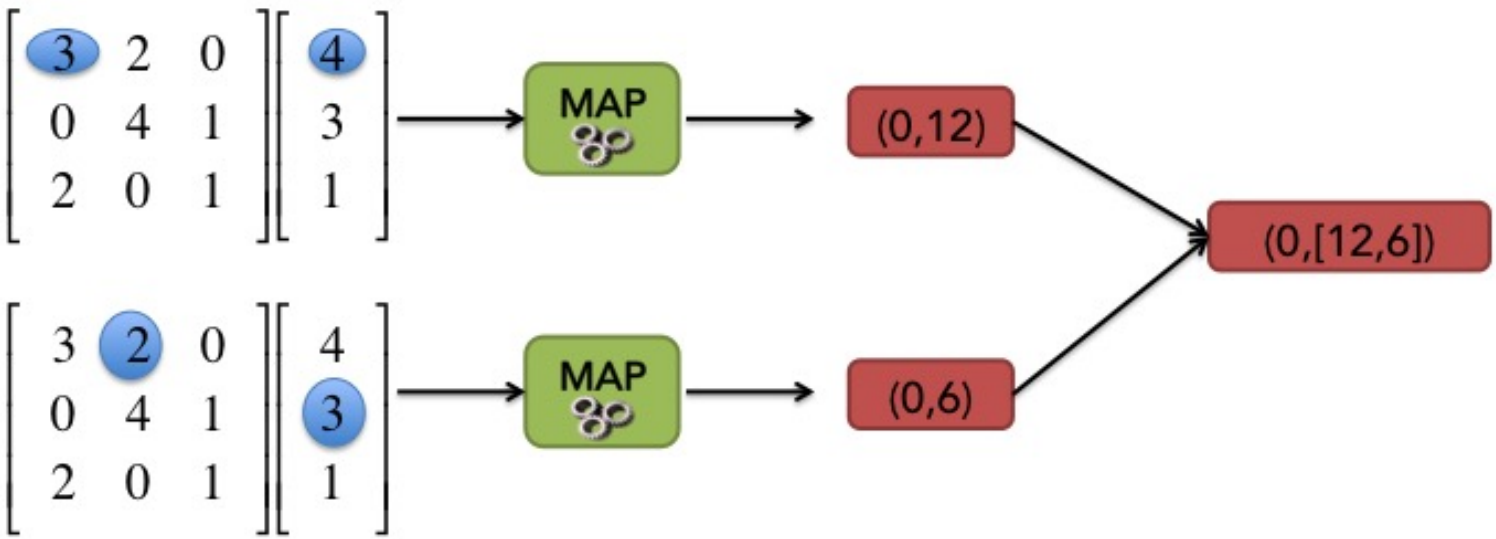


Another example

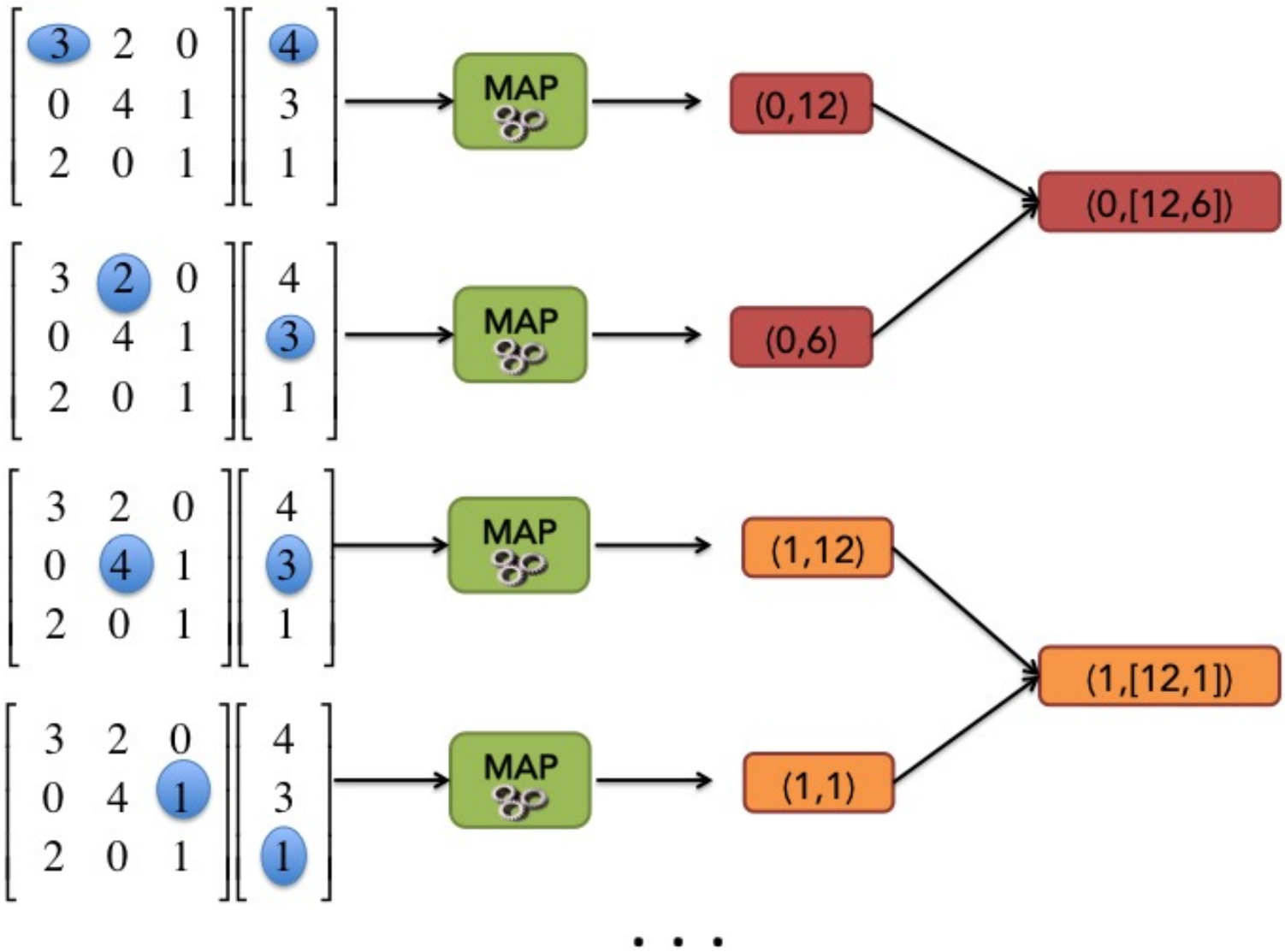
Multiplication of a matrix by a vector

✧ SHUFFLE

The pairs of the key i are grouped



Another example



Another example

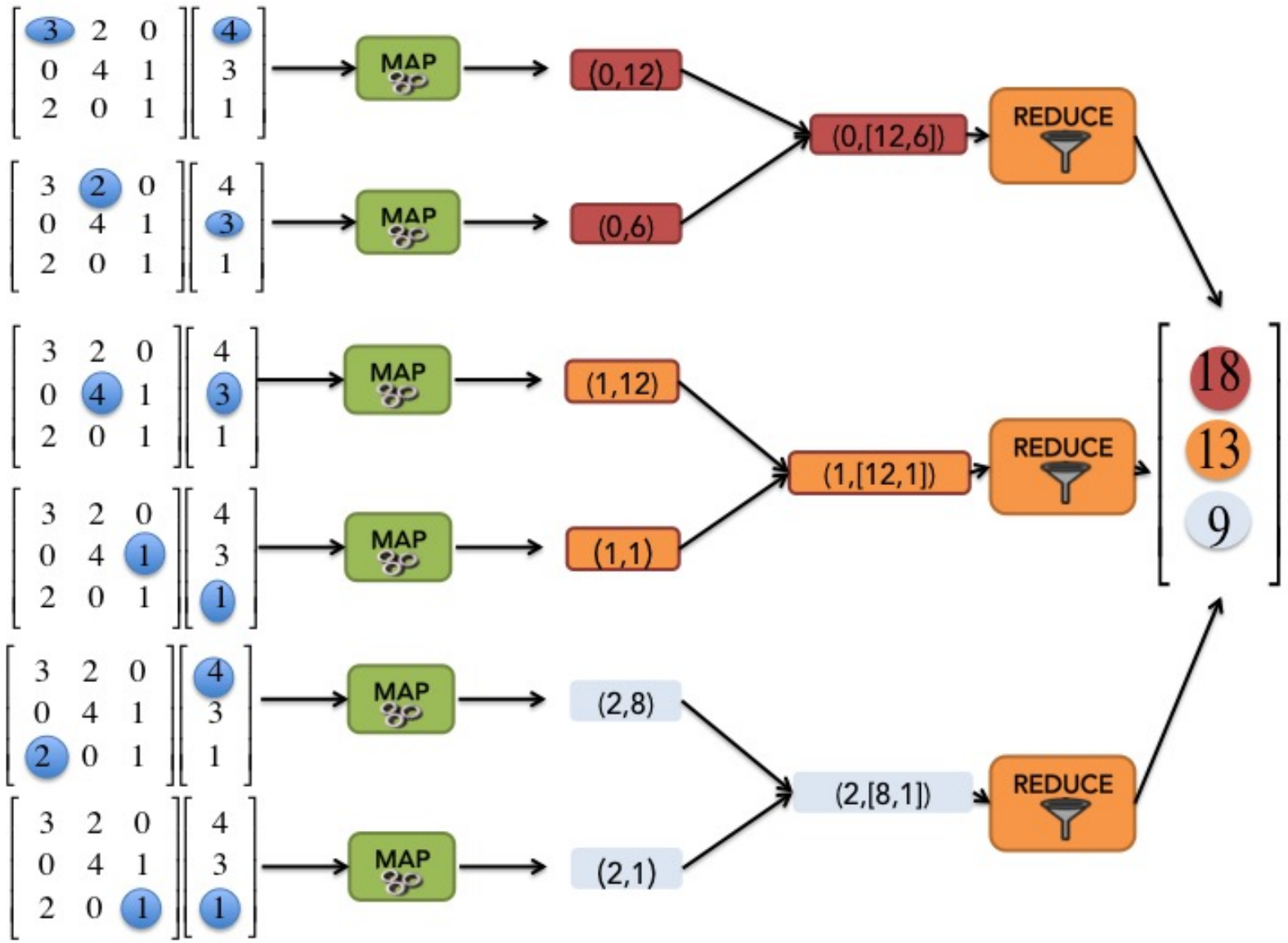
Multiplication of a matrix by a vector

✧ REDUCE

We sum the values associated to the same key

```
def reduce (key,values):     #key = row, values = liste de valeurs
    result =0
for v in values:
    result = result +v
emit(key,result)
```

Another example



MapReduce refinement : Partitioners and Combiners

Two additional elements complete the programming model : partitioners and reducers

Partitioner

Inputs to map tasks are simply created by contiguous splits of input file, but reduce tasks need to ensure that records with the same intermediate key end up at the same worker.
partition : $(k', \#partitions) \rightarrow$ partition for k'

Combiner

Combiners are an optimization in MapReduce that allow for local aggregation before the shuffle and sort phase.
combine : $(k', v') \rightarrow [(k', v'), ...]$

MapReduce : Partitioners

Partitioners are responsible for :

- Dividing up the intermediate key space.
- Assigning intermediate key-value pairs to reducers.

Hash-based partitioner

- System uses a default partition function :

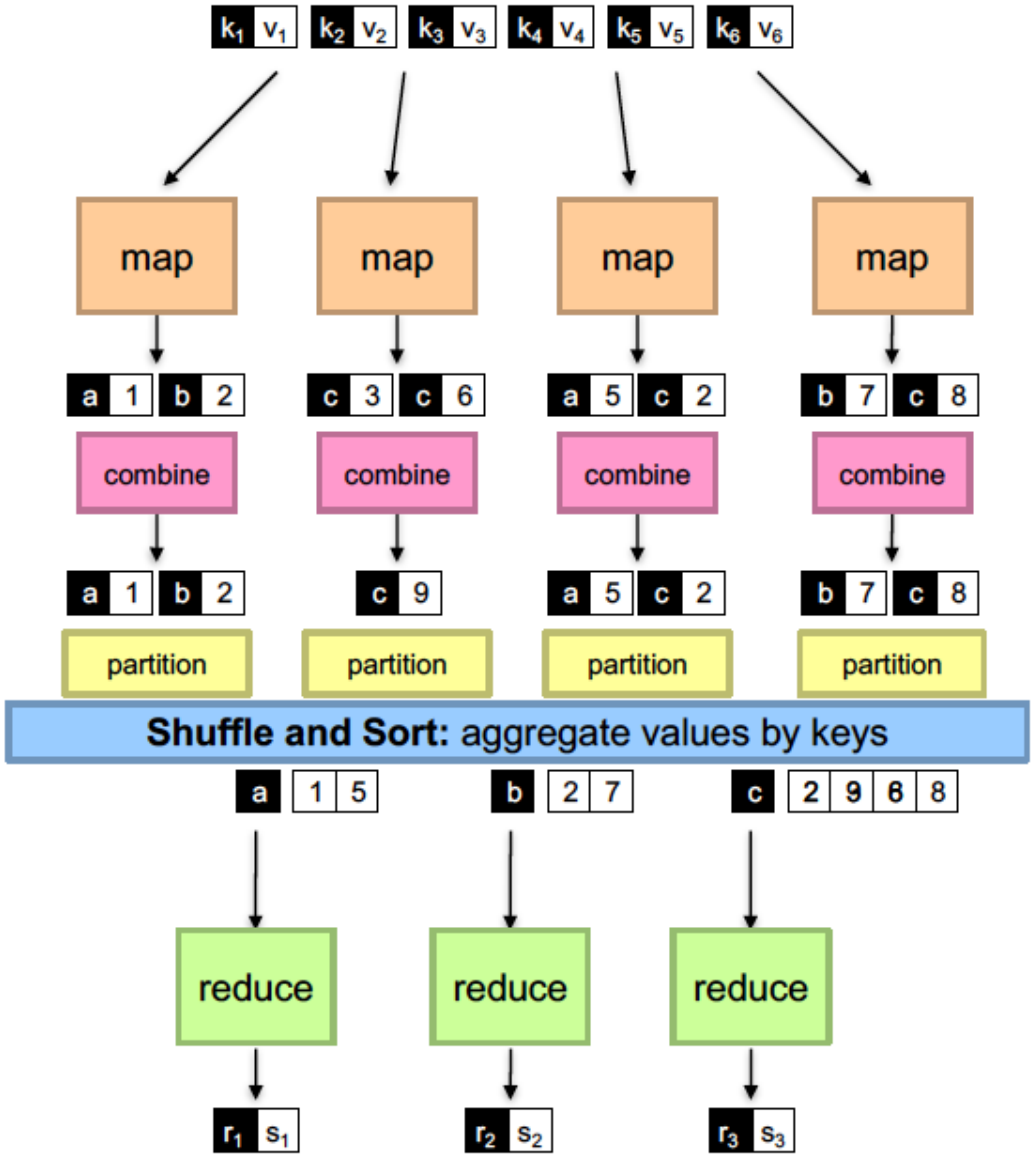
$$hash(key) mod\ R$$

  with R the number of reducers.
- When dealing with complex keys, it may be useful to override the default partition function.

MapReduce : Combiners

- A map task can produce many pairs with the same key (e.g. popular words in wordcount) : $(k, v_1), (k, v_2), ...$
- They need to be sent over the network to the reducer : costly.
- Combiner : local aggregation of these pairs into a single key-value pair at the mapper
- Decrease the size of intermediate data and save network time.
- Combiners = mini-reducers on the output of the mappers.

MapReduce scheme with combiners and partitioners



Basic WordCount algorithm in MapReduce

```
1: class Mapper
2:     method Map(docid a, doc d)
3:         for all term t ∈ doc d do
4:             Emit(term t, count 1)

1: class Reducer
2:     method Reduce(term t, counts [c1, c2, ...])
3:         sum ← 0
4:         for all count c ∈ counts [c1, c2, ...] do
5:             sum ← sum + c
6:         Emit(term t, count sum)
```

WordCount algorithm in MapReduce with combiners

```
1: class Mapper
2:     method Map(docid a, doc d)
3:         H ← new AssociativeArray
4:         for all term t ∈ doc d do
5:             H{t} ← H{t} + 1                ▷ Tally counts for entire document
6:         for all term t ∈ H do
7:             Emit(term t, count H{t})
```

A key-value pair is emitted for each unique *term* in the document.

Combiners : precautions

- The use of combiners is at the discretion of the execution framework.
- In Hadoop, they also may be invoked in the reduce phase.
- They have to be carefully written.

Plan

Algorithm Design with MapReduce

Developing algorithms involve :

- Preparing the input data.
- Writing the mapper and the reducer.
- And, optionally, writing the combiner and the partitioner.

How to recast existing algorithms in MapReduce :

- Not always obvious.
- Importance of data structures : complex data structures as keys and values.
- Difficult to optimize.

Learn by practice and examples

- MapReduce design patterns.
- Synchronization of intermediate results is difficult : the tricky task.

Algorithm Design with MapReduce

Aspects that are not under the control of the designer

- *Where* a mapper or a reducer will run.
- *When* a mapper or a reducer begins or finishes.
- *Which* input key-value pairs are processed by a specific mapper.
- *Which* intermediate key-value pairs are processed by a specific reducer.

Algorithm Design with MapReduce

Aspects that can be controlled

- Construct data structures as keys and values.
- Execution of user-specific initialisation or termination code at each Mapper or Reducer.
- State preservation in Mapper - Reducer across multiple inputs or intermediates keys.
- User-controlled partitionning of the key space.

Algorithm Design with MapReduce

Designing MapReduce algorithms can be complex

- Many algorithms cannot be easily expressed as a single MapReduce job.
- Decompose complex algorithms into a sequence of MapReduce jobs :
  - Requires orchestrating data so that the output of one job becomes the input of the next
- Often require an external driver.

Algorithm Design with MapReduce

Basic design patterns

- Local Aggregation.
- Pairs and Stripes.
- Order Inversion.

Local Aggregation

- In data-intensive distributed processing, the most important aspect of synchronization is the exchange of intermediate results
  - It involves the copy of intermediate results from the processes that produced them to those that consumed them.
  - It involves data transfers over the network.
  - In some MapReduce implementation (as Hadoop), disk IO is involved : intermediate results are written to disk.

Network and disk latencies are expensive.

Idea : reduce the number and size of key-values pair to be shuffle.

In-Mapper Combiners

Idea

- Use an associative array to cumulate intermediate results.
  - Wordcount : The array is used to tally up term counts within a single document.
  - The `Emit` method is called only after all `Inputrecords` have been processed.

In-Mapper Combiners

WordCount example

```
1: class Mapper
2:     method Map(docid a, doc d)
3:         for all term t ∈ doc d do
4:             Emit(term t, count 1)

1: class Reducer
2:     method Reduce(term t, counts [c1, c2, ...])
3:         sum ← 0
4:         for all count c ∈ counts [c1, c2, ...] do
5:             sum ← sum + c
6:         Emit(term t, count sum)
```

Basic WordCount algorithm : emit a key-value pair for each term in the document

In-Mapper Combiners

WordCount example

```
1: class Mapper
2:     method Map(docid a, doc d)
3:         H ← new AssociativeArray
4:         for all term t ∈ doc d do
5:             H{t} ← H{t} + 1                ▷ Tally counts for entire document
6:         for all term t ∈ H do
7:             Emit(term t, count H{t})
```

WordCount algorithm with a combiner : emit a key-value pair for each unique term in the document

In-Mapper Combiners

Combiner Across Multiple Documents

- Prior to processing any input key-value pairs, an associative array for holding term counts is initialized (`initialize` method in MapReduce implementation API, `setup` in Hadoop)
- We can continue to accumulate partial term counts in the associative array across multiple documents and emit the key-values pairs only when the mapper has processed all or part of the documents.
- It requires an API that provides an opportinuty to execute user-specified code after the Map method has been applied to all input key-value pairs of the input data split of the map task (`cleanup` in Hadoop)

In-Mapper Combiners

WordCount example

```
1: class Mapper
2:     method Initialize
3:         H ← new AssociativeArray
4:     method Map(docid a, doc d)
5:         for all term t ∈ doc d do
6:             H{t} ← H{t} + 1                ▷ Tally counts across documents
7:     method Close
8:         for all term t ∈ H do
9:             Emit(term t, count H{t})
```

WordCount algorithm with in-mapper combiner.

In-Mapper Combiners

Advantages

- Provide control over when local aggregation occurs and how it exactly takes place

Precautions

- In-mapper combining breaks the functional programming paradigm due to state preservation.
- State preservation implies that the algorithm behavior might depend on the execution order.

Scalability bottleneck

- In-mapper combining depends on having sufficient memory to store intermediate results.

In-Mapper Combiners : Another example

Computing the mean

We suppose that we have a large dataset where input keys are strings and input values are integers : we wish to compute the mean of all integers associated with the same key (e.g. logs from a populat website, keys are user ids and values some measure of activity).

1. Write MapReduce pseudo-code to solve the problem.
2. Modify the solution to use combiners.

$$mean(1, 2, 3, 4, 5) \neq mean(mean(1, 2), mean(3, 4, 5))$$

3. Modify the solution to use in-mapper combining.

Pairs and stripes

- Common approach for synchronisation in MapReduce :
  - Build complex keys and values such that data necessary for a computation are naturally brought together by the execution framework.
  - e.g. in the mean : pair of partial sums and counts.
- Two basic techniques :“
  - Pairs
  - Stripes : uses in-mapper memory data-structures.

Pairs and stripes : illustration with an example

Problem statement

Building word co-occurrence matrices for large corpora

- The co-occurence matrix of a corpus is a square $n \times n$ matrix, M.
- n : number of unique words (vocabulary size)
- A cell m_{ij} contains the number of times the word w_i co-occurs with word w_j within a specific context.
- Context : a sentence, a paragraph, a document or a window of m words

Word co-occurence : the pairs approach

- **Input to the problem**
  - Key-value pairs in the form of a `docid` and a `doc`
- **The mapper**
  - Processes each input document.
  - Emits key-value pairs with :
    - ★ Each co-occuring word pair as the key
    - ★ The integer one (the count) as the value.
  - Done with two nested loops.
- **The reducer**
  - Receives pairs relative to co-occuring words.
  - Computes an absolute count of the joint event.
  - Emits the pair and the count as the final key-value output (emits the cells of the matrix)

Word co-occurence : the pairs approach

```
1: class Mapper
2:     method Map(docid a, doc d)
3:         for all term w ∈ doc d do
4:             for all term u ∈ Neighbors(w) do
5:                 Emit(pair (w, u), count 1)        ▷ Emit count for each co-occurrence
```

```
1: class Reducer
2:     method Reduce(pair p, counts [c_1, c_2, ...])
3:         s ← 0
4:         for all count c ∈ counts [c_1, c_2, ...] do
5:             s ← s + c                              ▷ Sum co-occurrence counts
6:         Emit(pair p, count s)
```

Word co-occurence : the stripes approach

- **Input to the problem**
  - Key-value pairs in the form of a `docid` and a `doc`
- **The mapper**
  - Same two nested loops structure
  - Co-occurrence information is first stored in an associative array
  - Emit key-value pairs with words as keys and the corresponding arrays as values.
- **The reducer**
  - Receives all associative arrays related to the same word
  - Performs an element-wise sum of all associative arrays with the same key.
  - Emits key-value output in the form of a word, associative array (rows of the co-occurrence matrix).

Word co-occurence : the stripes approach

```
1: class Mapper
2:     method Map(docid a, doc d)
3:         for all term w ∈ doc d do
4:             H ← new AssociativeArray
5:             for all term u ∈ Neighbors(w) do
6:                 H{u} ← H{u} + 1                ▷ Tally words co-occurring with w
7:             Emit(Term w, Stripe H)
```

```
1: class Reducer
2:     method Reduce(term w, stripes [H_1, H_2, H_3, ...])
3:         H_f ← new AssociativeArray
4:         for all stripe H ∈ stripes [H_1, H_2, H_3, ...] do
5:             Sum(H_f, H)                        ▷ Element-wise sum
6:         Emit(term w, stripe H_f)
```

Pairs versus Stripes

- Stripes generate fewer intermediate keys than the pairs approach.
- Stripes benefit more from combiners and can be done with in-memory combiners.
- Stripes, in general faster but more complex implementation.

Order inversion : an example

Problem statement

Building relative word co-occurrence matrices for large corpora

- Similar problem as before, same matrix.
- Instead of absolute counts, we take into consideration the fact that some words appear more frequently than other.
  - Word w_i may co-occur frequently with word w_j simply because one of the two is very common.
- We need to convert absolute counts to relative frequencies $f(w_j|w_i)$

$$f(w_j|w_i) = \frac{N(w_i, w_j}{\sum_{w'} N(w_i, w')}$$

Order inversion : illustration with an example

The stripes approach

- In the reducer, the counts of all words that co-occur with the conditioning variable w_i are available in the associative array.
- Hence, the sum of all those counts gives the marginal.
- Then, we divide the joint counts by the marginal.

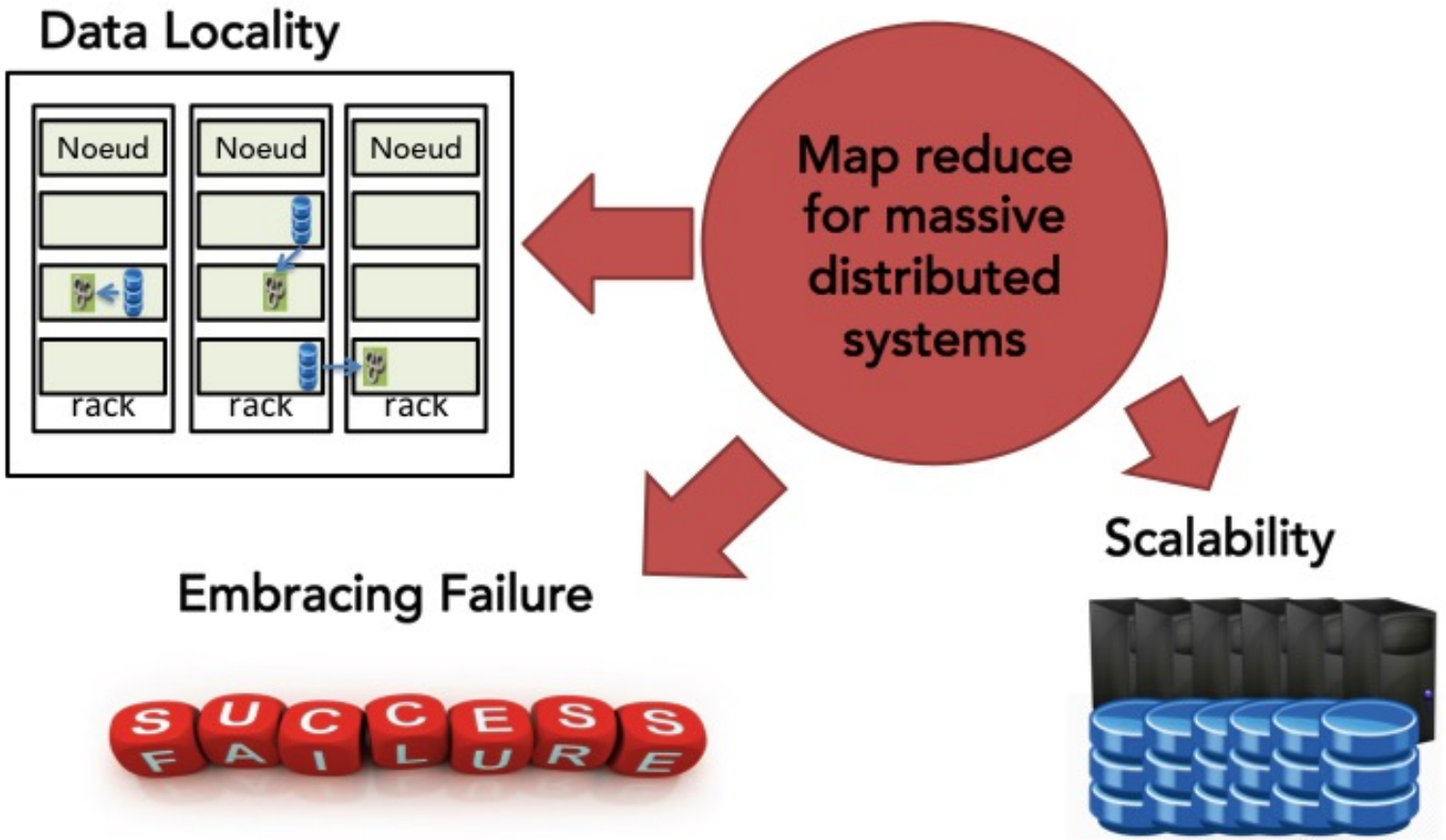
The pairs approach

- The reducer receives the pair (w_i, w_j) and the count.
- From this information alone, it is not possible to compute $f(w_i, w_j)$.
- Fortunaly, as for the mapper, the reducer can preserve state across multiple keys.
  - Buffering in memory all the words that co-occur with w_i and their counts.

Homework

Plan

MapReduce in real life



MapReduce : the execution framework

MapReduce program : a job

- Code for mappers and reducers.
- Code for combiners and partitioners.
- Configuration parameters.

A MapReduce job is submitted to the cluster

- The framework takes care of everything else.

MapReduce : runtime execution

MapReduce runtime execution environment handles :

- sheduling : assigns workers to map and reduce tasks.
- data distribution : partitions the input data and moves processes to data.
- synchronisation : manages required inter-machine communication to gather, sort and shuffle intermediate data.
- errors and faults : detects worker failures and restarts.

MapReduce : Scheduling

- **Each job is broken into tasks (smaller units).**
  - Map tasks work on fractions of the input dataset.
  - Reduce tasks work on intermediate inputs and write back to the distributed file sytem.
- **The number of tasks may exceeed the number of available machines in a cluster**
  - The scheduler takes care of maintening something similar to a queue of pending tasks to be assigned to machines with avaialble ressources.
- **Jobs to be executed in a cluster requires scheduling as well**
  - Different users may submit jobs.
  - Jobs may be of various complexity.
  - Fairness is generally a requirement.

MapReduce : data flow

- The input and final output are stored on a distributed file system
  - Scheduler tries to schedule map tasks close to physical storage location of input data.
- The intermediate results are stored on the local file system of map and reduce workers.
- The output is often the input of another MapReduce task.

MapReduce : Synchronization

- Synchronization is achieved by the *Shuffle and Sort* step.
  - Intermediate key-value pairs are group by key.
  - This requires a distributed sort involving all mappers, and taking into account all reducers.
  - If you have m mappers and r reducers, it involves $m \times r$ copying operations.
- Important : the reduce operation cannot start until all mappers have finished (to guarantee that all values associated with the same key have been gathered)

MapReduce : coordination

Master keeps an eye on each task status (Master-slave architecture)

- idle tasks get scheduled as workers become available
- When a map task completes, it sends Master the location and sizes of its R intermediate files, one for each reducer and then Master pushes this info to reducers.
- Master pings workers periodically to detect and manage failures.

MapReduce : implementations

- Google has a proprietary implementation in C++.
- Hadoop is an open-source implementation in JAVA.
  - Development led by Yahoo, used in production.
  - Apache project.
  - A big software ecosystem.
- Lot of custom research implementations.

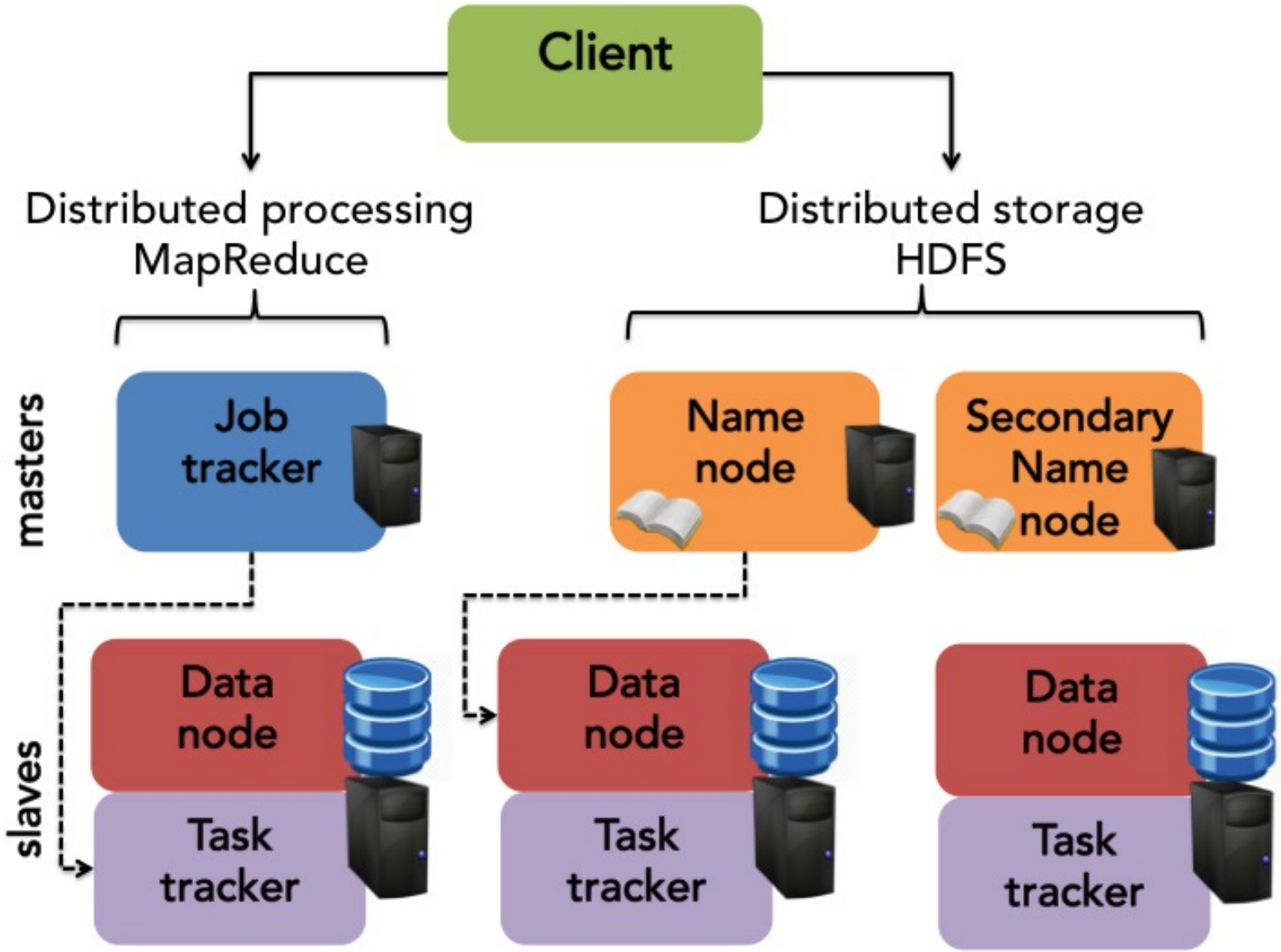
Hadoop

Hadoop

Two main components

- HDFS
- MapReduce

Hadoop : two main components



Hadoop : HDFS

- HDFS is a file system which is
  - Distributed : the files are distributed on the different nodes of the cluster.
  - Replicated : in case of failure, data is not lost.
  - Data locality : programs and data are colocated.
  - Files in HDFS are broken into block-sized chunks, which are stored as independent units.

Hadoop : HDFS

HDFS blocks

- Files are broken into block-sized chunks.
  - Blocks are big ! [64,128] MB
- Blocks are stored on independent machines.
  - Replicate across the local disks of nodes in the cluster.
  - Reliability and parallel access.
  - Replication is handled by storage node themselves.

Hadoop : HDFS

HDFS looks like an unix file system

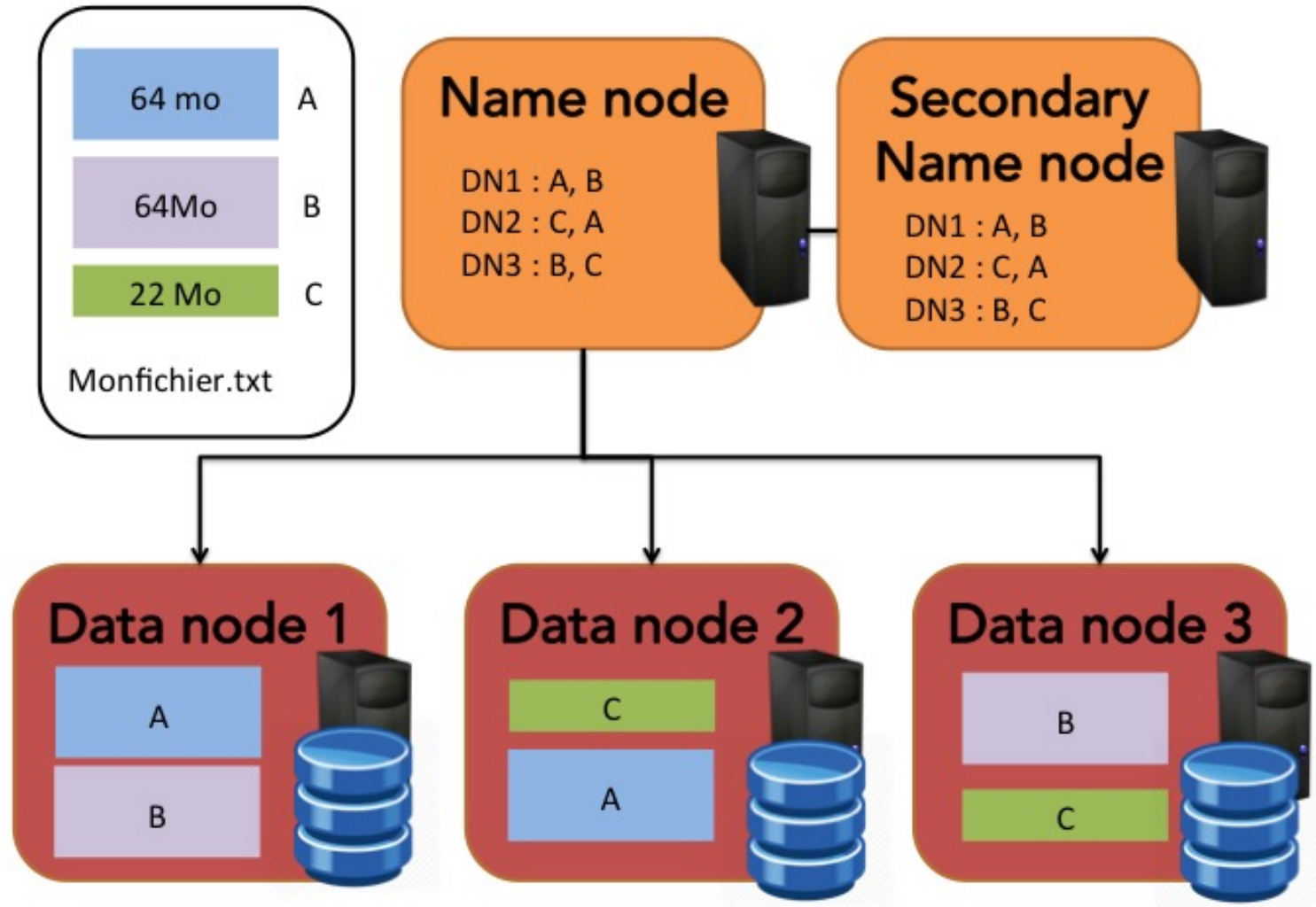
- Root : `/`
- Some directories for the Hadoop services under the root : `/hbase`, `/tmp`, `/var`
- A directory for the personal files of users : `/user`
- A directory for shared files : `/share`

Hadoop : HDFS

- Some commands : `hdfs dfs`
- An API JAVA

Hadoop : HDFS architecture

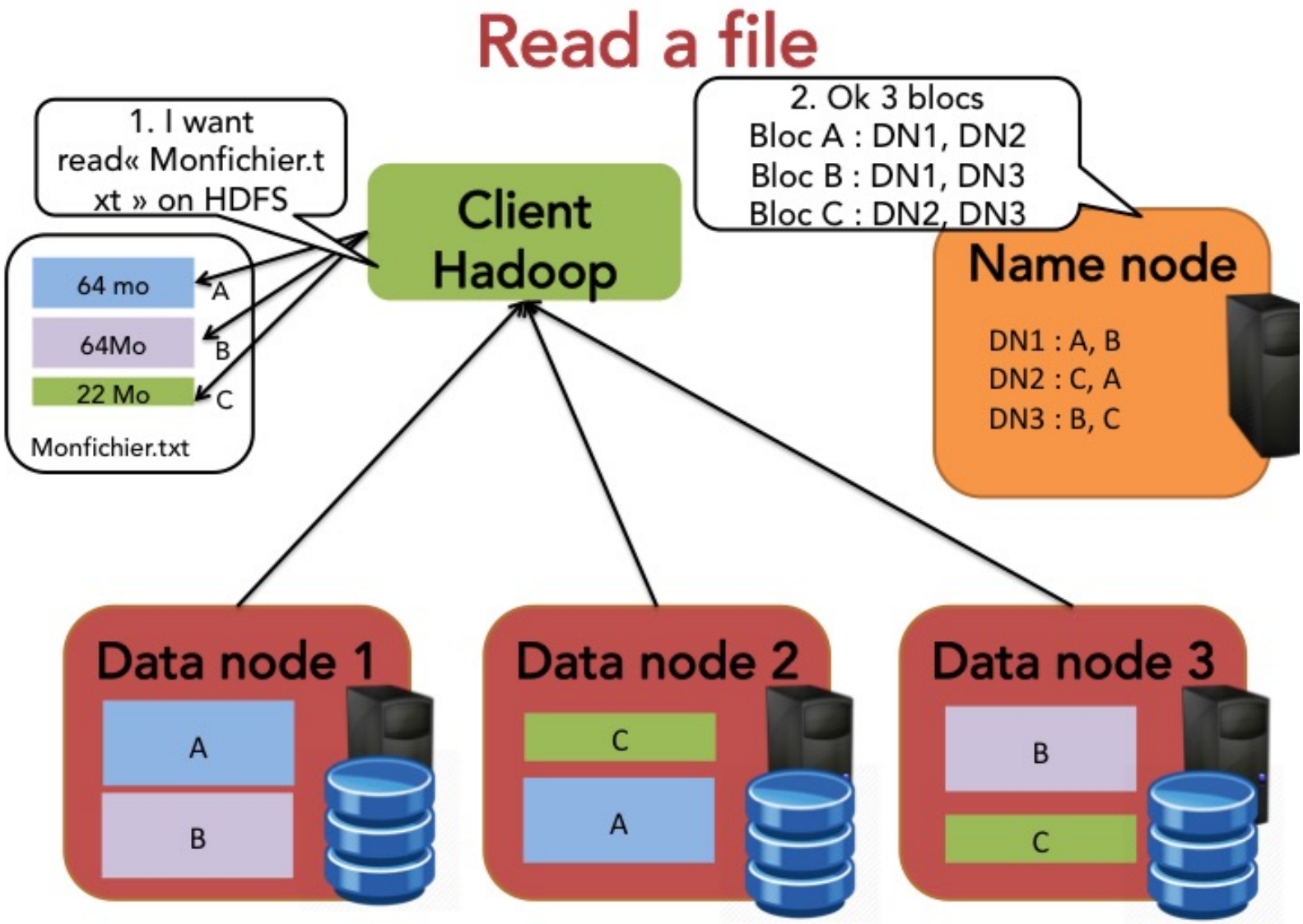
A master slave architecture



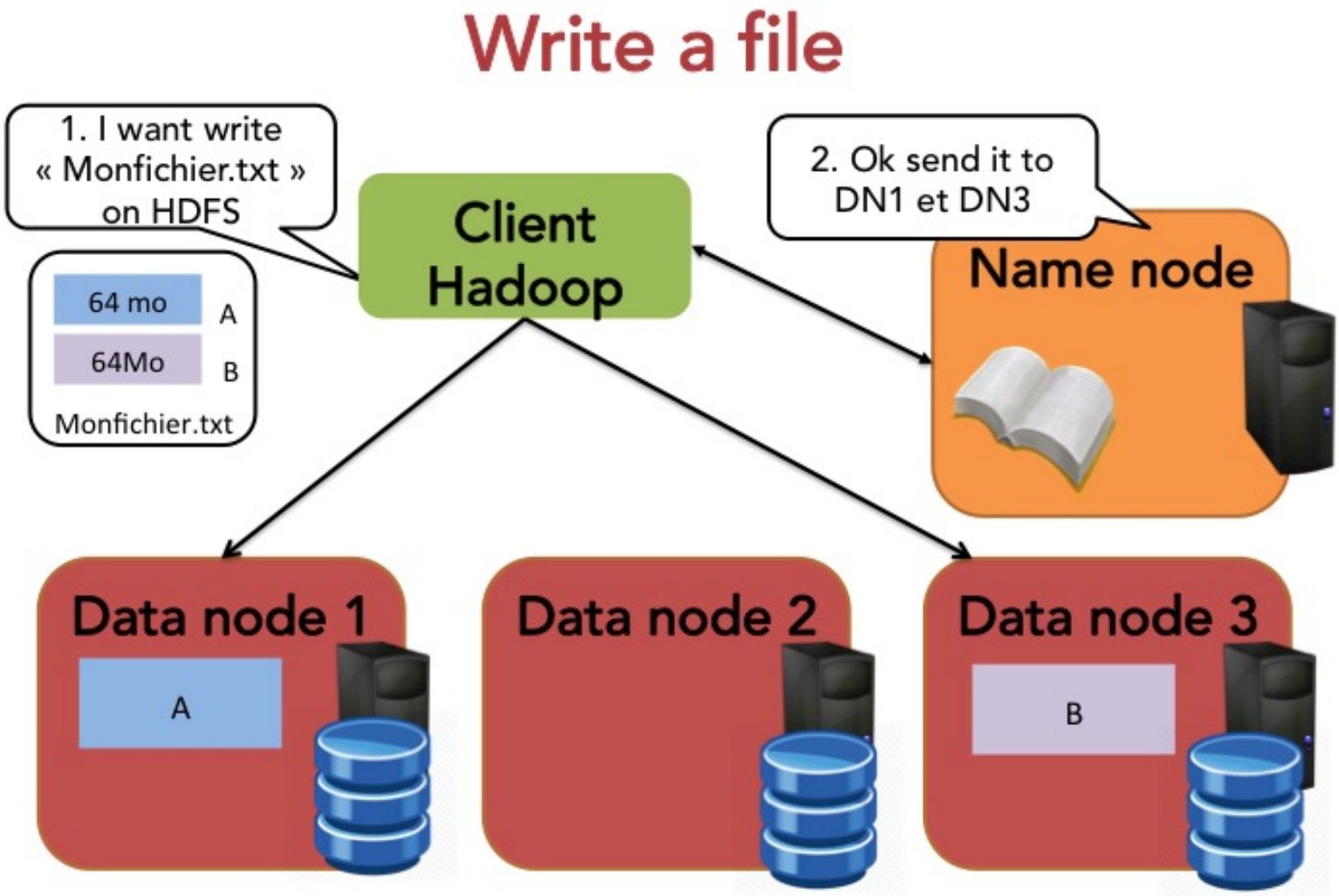
Hadoop : HDFS architecture

- **Namenode** : a kind of big directory : it stores the names and the blocks of all files as well as their location.
- **Secondary Namenode** : replication of the namenode in case of failure.
- **Datanode** : storage node that manages the local storage operations : creation, removal and duplication.

HDFS architecture : read a file



HDFS architecture : write a file



Hadoop MapReduce : anatomy of a job

Job = MapReduce Task

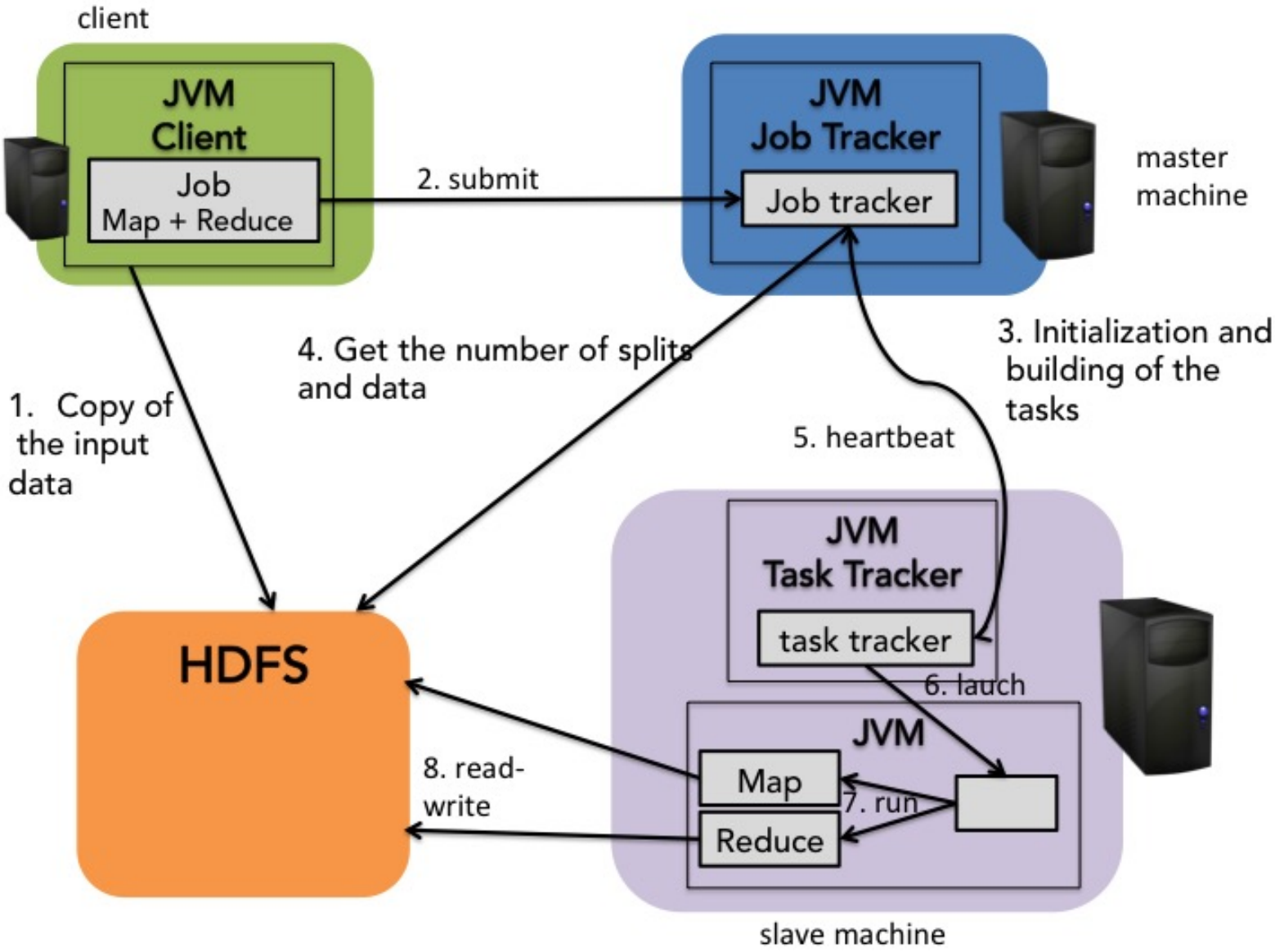
Job submission process

- Client creates a job, configures it and submits it (as a jar archive) to the job tracker.
- The job tracker asks to the namenode where are the blocks corresponding to the input data.
- The job tracker puts jobs in shared location, enqueue tasks
- Task trackers poll for tasks (and heartbeat)

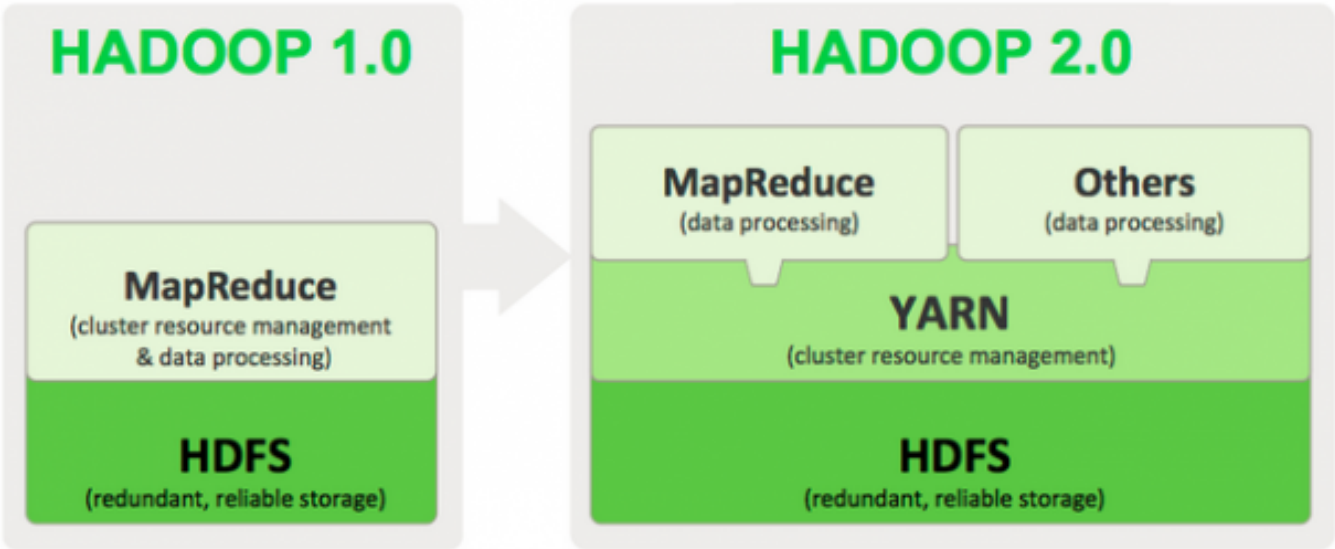
Hadoop MapReduce : anatomy of a job

- **Job tracker** : master processus that will be in charge of both processing scheduling and ressource management. It distributes the different mapreduce tasks to the task trackers by taking into account the location of the data.
- **Task tracker** : a slave computing unit. It runs the execution of map and reduce tasks (by the launch of a JVM). It communicates with the job tracker on its status.

Hadoop MapReduce : anatomy of a job



Hadoop 2.0 : YARN



Hadoop 2.0 : YARN

YARN : Yet another Ressource Negociator

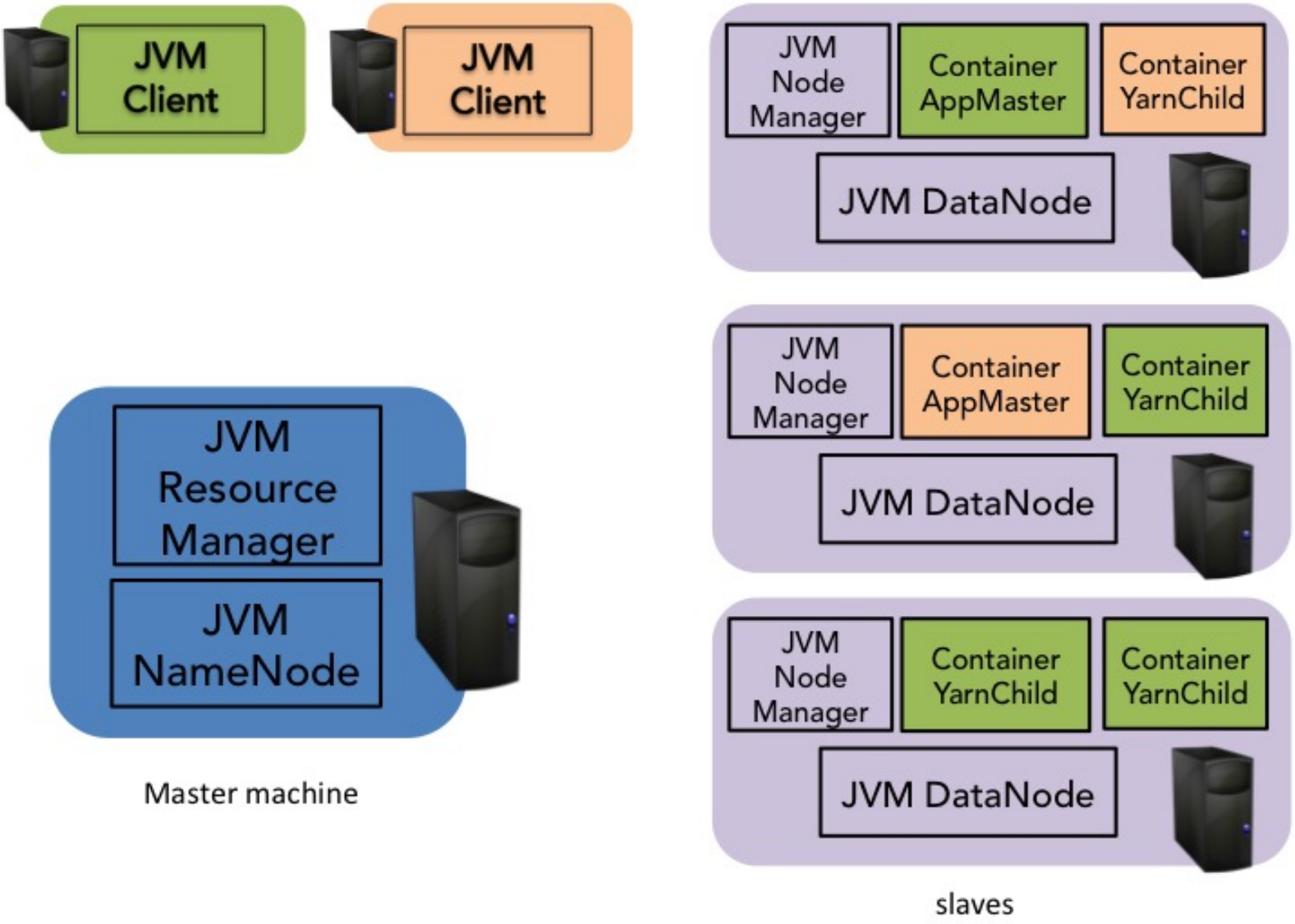
- Enable the execution on the cluster of every type of distributed application (not only MapReduce application).
- Separation of the management of the cluster and of the management of the MapReduce jobs.
- The nodes have some resources that can be allocated to the applications on demand.

Hadoop 2.0 : YARN

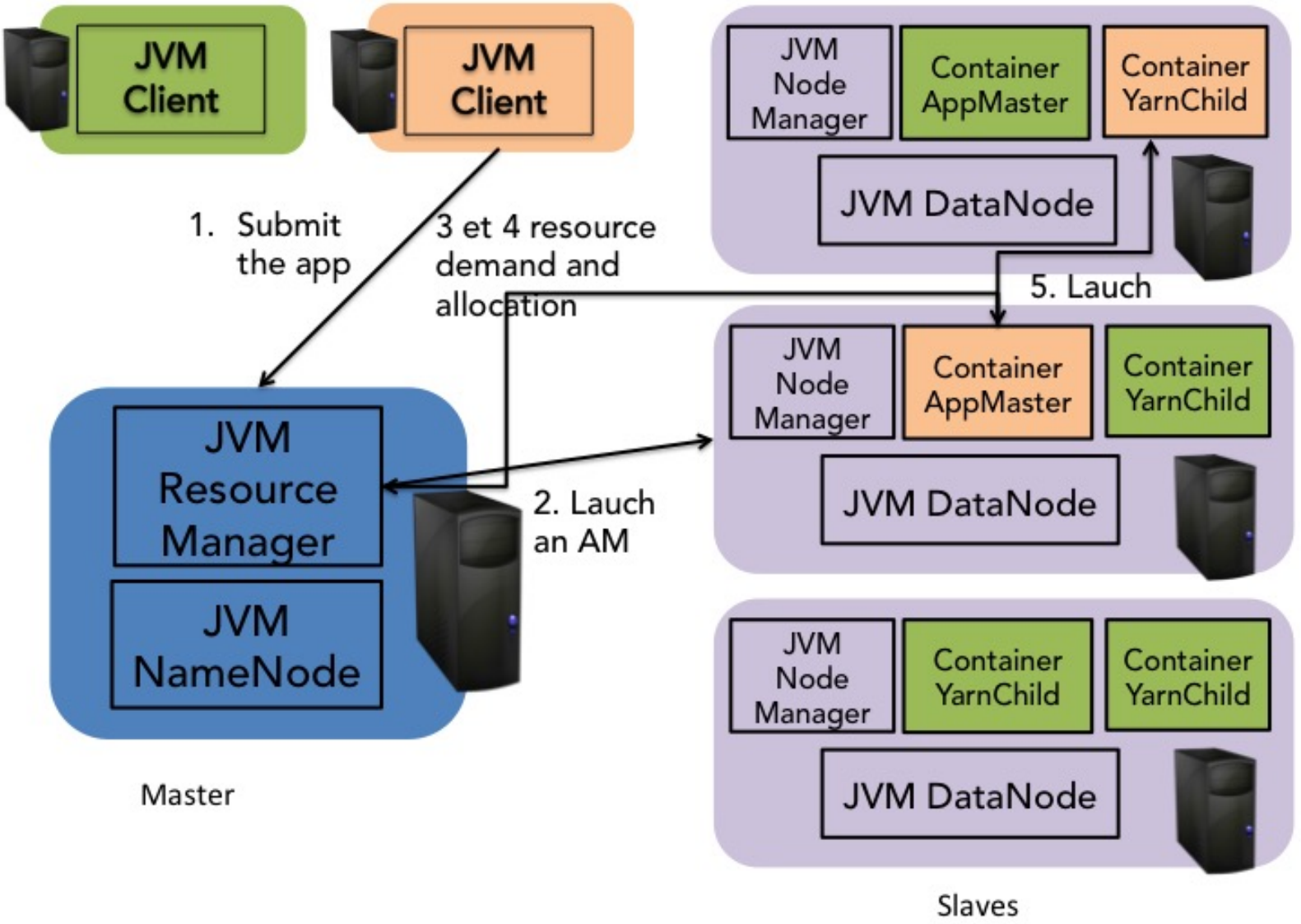
YARN : Yet another Ressource Negociator

- **Resource manager** : orchestration of the resources of the cluster. It schedules the client requests and manage the cluster with the help of **node managers** on each node of the cluster.
- **Application master** : process runned on each slave node and which manages the resources needed for the submitted job.
- **Containers** : resources abstractions that cab be used to execute a map or reduce task or to run an application master.

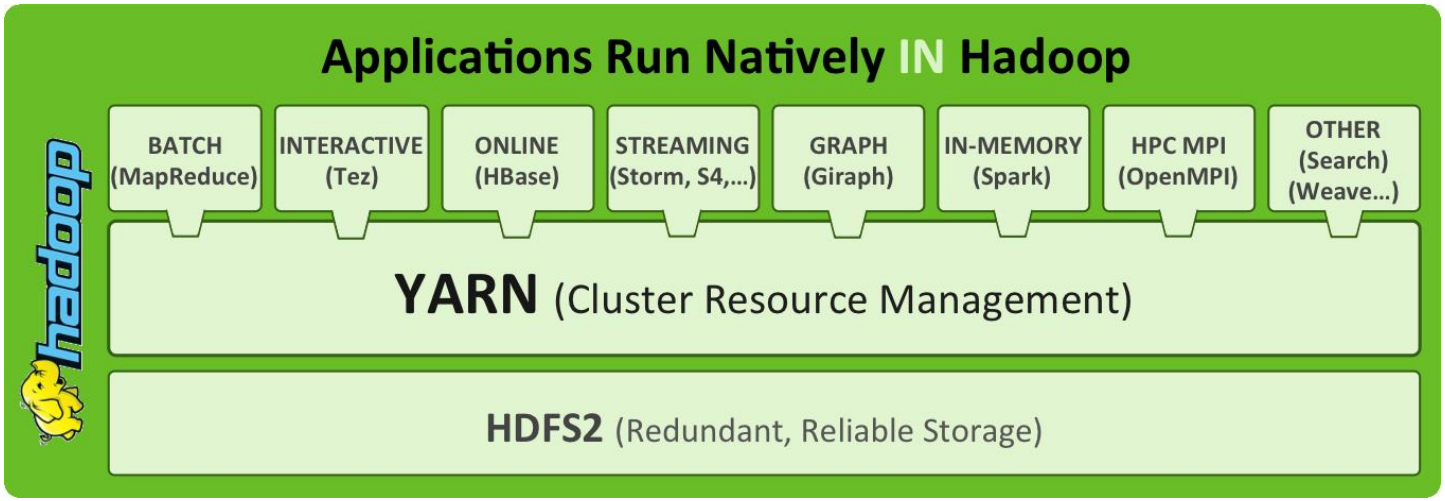
Hadoop 2.0 : YARN Architecture



Hadoop 2.0 : YARN Architecture



Hadoop 2.0 : a big ecosystem



And now

Time for practice