Big Data

Spark Programming

Stéphane Vialle & Gianluca Quercini

CentraleSupélec

Spark Programming

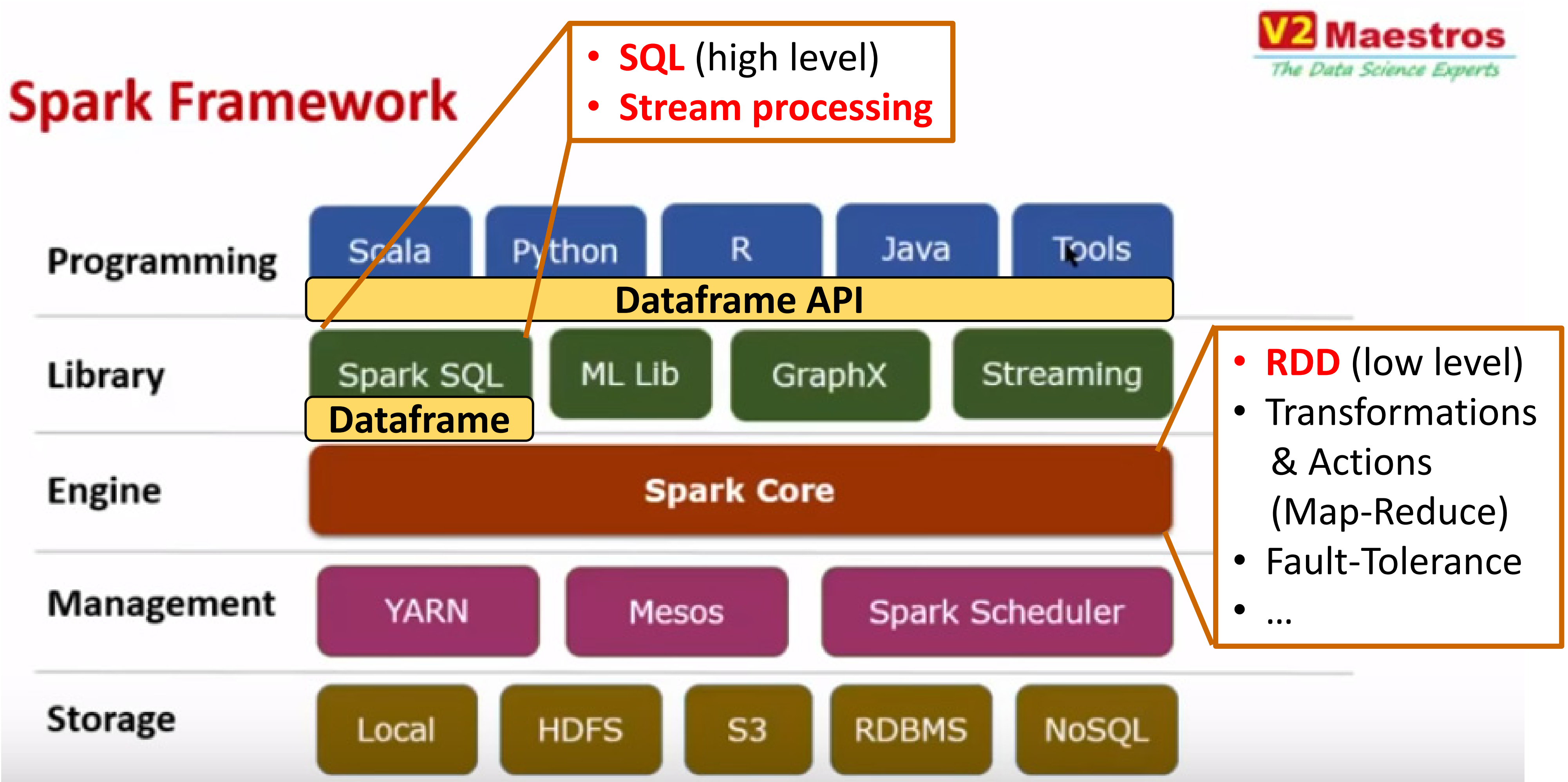
1. **Main objectives**
2. RDD concepts
3. Operations on generic RDDs
4. Operations on RDD of *key-value* pairs

Spark main objectives

Spark has been designed:

- To efficiently run iterative and interactive applications
  → keeping data in-memory between operations
- To provide a low-cost fault tolerance mechanism
  → low overhead during safe executions
  → fast recovery after failure
- To be easy and fast to use in interactive environment
  → using compact *Scala* programming language
- To be « scalable »
  → able to efficiently process bigger data on larger computing clusters

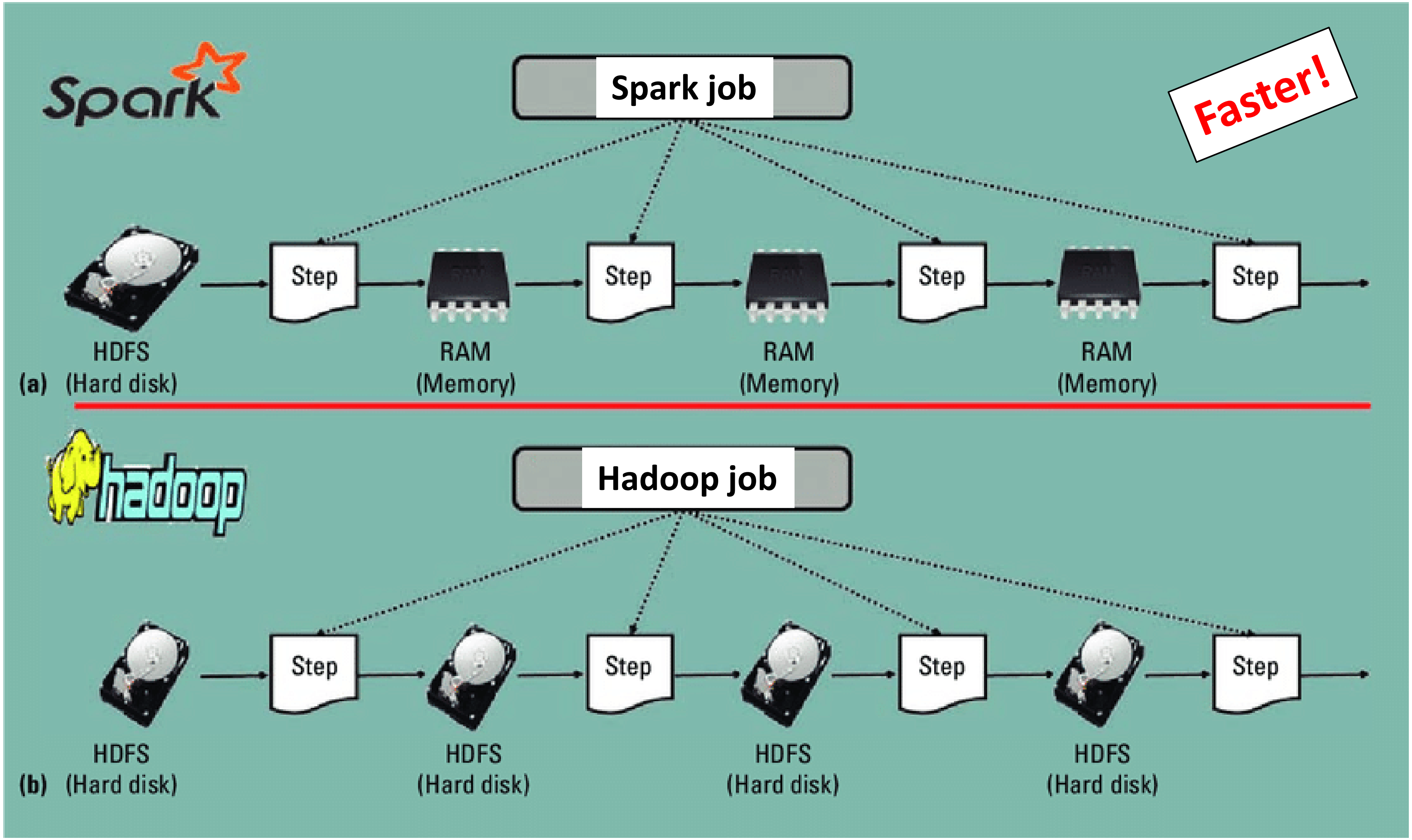
Spark main objectives



Spark design started in 2009, with the PhD thesis of Matei Zaharia at Berkeley Univ.
Matei Zaharia co-founded DataBricks in 2013.

Spark main objectives

An essential difference between Spark and Hadoop: the speed!



Spark Programming

1. Main objectives
2. **RDD concepts**
3. Operations on generic RDDs
4. Operations on RDD of *key-value* pairs

RDD concepts and operations

A RDD (*Resilient Distributed Dataset*) is:

- an immutable (read only) dataset
- a partitioned dataset
- usually stored in a distributed file system (like HDFS)

When reading a HDFS file:

```
rdd1 = sc.parallelize(« myFile.txt »)
```

- Read each HDFS block
- Spread the blocks in memory of different *Spark Executor* processes (on ≠ nodes)

Get a RDD

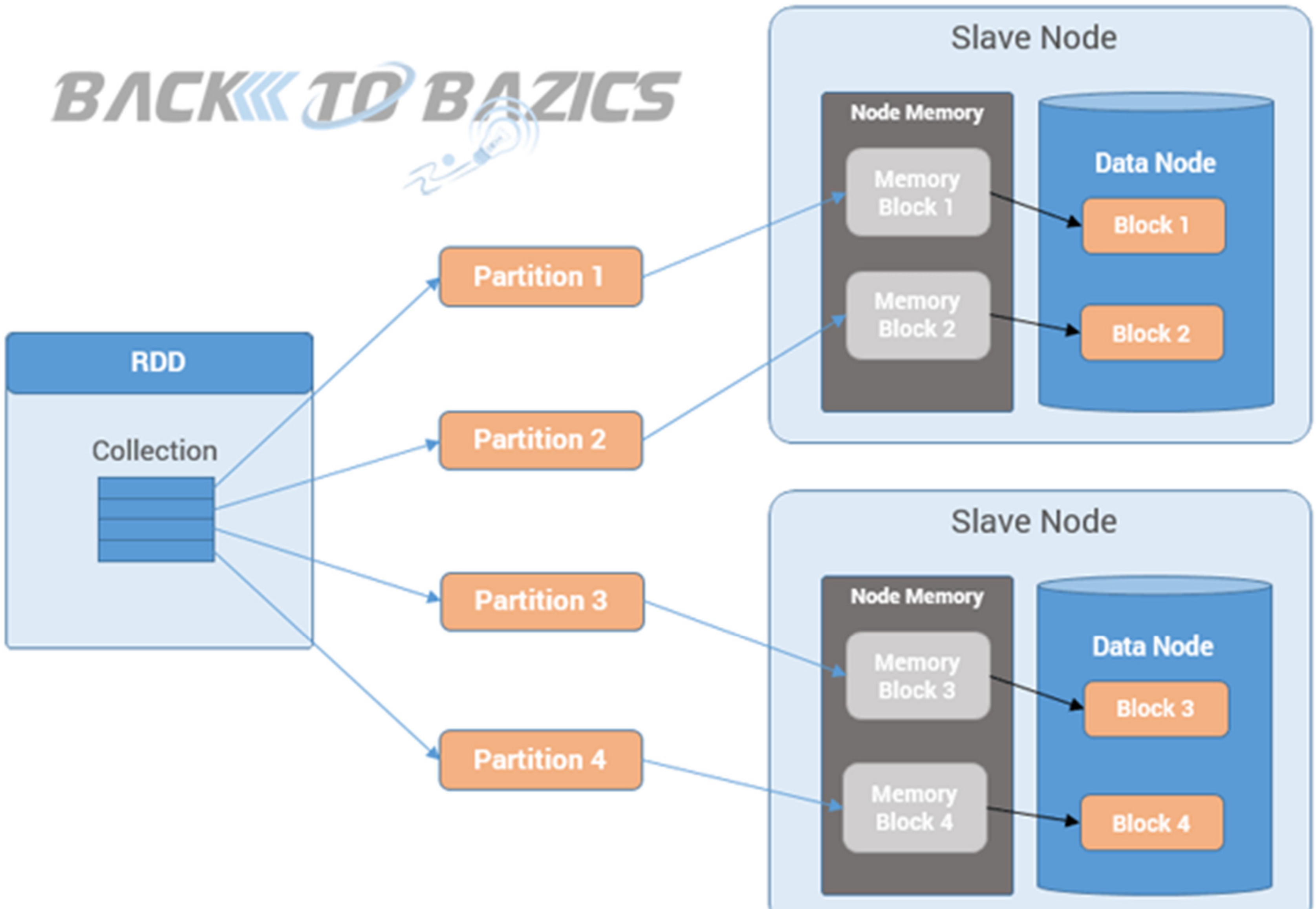
When writting a HDFS file:

- one RDD → One HDFS file
- one RDD partition block → One HDFS file block
- each RDD partition block is replicated by HDFS

CentraleSupélec

RDD concepts and operations

Example of a 4-blocks partition stored on 2 data nodes (no replication)



Source: *http://images.backtobazics.com/*

RDD concepts and operations

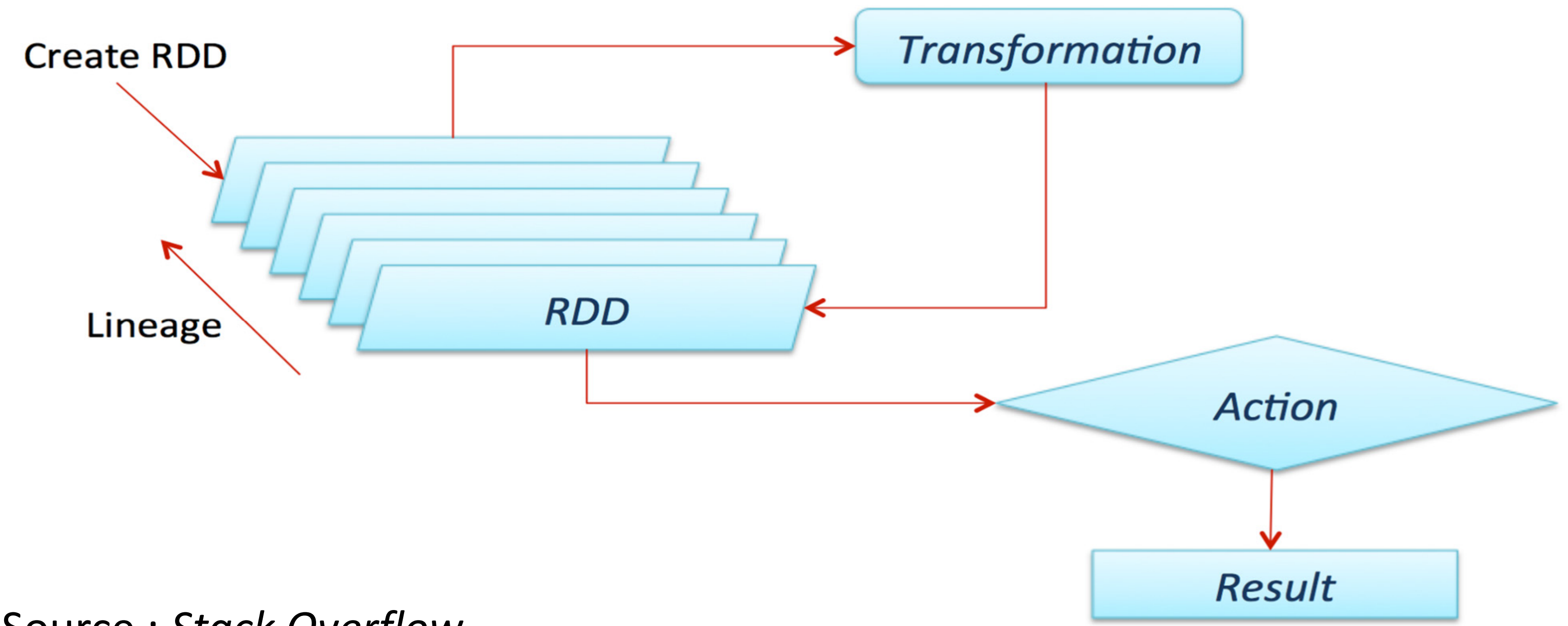
Initial input RDDs:

- are usually created from distributed files (like HDFS files),
- Spark processes read the file blocks that become in-memory RDD

Operations on RDDs:

- Transformations : read RDDs, compute, and generate a new RDD
- Actions : read RDDs and generate results out of the RDD world

Map and *Reduce* are parts of the operations



Source : *Stack Overflow*

RDD concepts and operations

Exemple of Transformations and Actions

Transformations	$map(f : T \Rightarrow U)$	:	$RDD[T] \Rightarrow RDD[U]$
	$filter(f : T \Rightarrow Bool)$	:	$RDD[T] \Rightarrow RDD[T]$
	$flatMap(f : T \Rightarrow Seq[U])$	:	$RDD[T] \Rightarrow RDD[U]$
	$sample(fraction : Float)$	:	$RDD[T] \Rightarrow RDD[T]$ (Deterministic sampling)
	$groupByKey()$	:	$RDD[(K, V)] \Rightarrow RDD[(K, Seq[V])]$
	$reduceByKey(f : (V,V) \Rightarrow V)$	:	$RDD[(K, V)] \Rightarrow RDD[(K, V)]$
	$union()$	:	$(RDD[T], RDD[T]) \Rightarrow RDD[T]$
	$join()$	:	$(RDD[(K, V)], RDD[(K, W)]) \Rightarrow RDD[(K, (V, W))]$
	$cogroup()$	:	$(RDD[(K, V)], RDD[(K, W)]) \Rightarrow RDD[(K, (Seq[V], Seq[W]))]$
	$crossProduct()$	:	$(RDD[T], RDD[U]) \Rightarrow RDD[(T, U)]$
	$mapValues(f : V \Rightarrow W)$	:	$RDD[(K, V)] \Rightarrow RDD[(K, W)]$ (Preserves partitioning)
	$sort(c : Comparator[K])$	:	$RDD[(K, V)] \Rightarrow RDD[(K, V)]$
	$partitionBy(p : Partitioner[K])$	:	$RDD[(K, V)] \Rightarrow RDD[(K, V)]$
Actions	$count()$	:	$RDD[T] \Rightarrow Long$
	$collect()$	:	$RDD[T] \Rightarrow Seq[T]$
	$reduce(f : (T,T) \Rightarrow T)$	:	$RDD[T] \Rightarrow T$
	$lookup(k : K)$	:	$RDD[(K, V)] \Rightarrow Seq[V]$ (On hash/range partitioned RDDs)
	$save(path : String)$	:	Outputs RDD to a storage system, *e.g.*, HDFS

Table 2: Transformations and actions available on RDDs in Spark. Seq[T] denotes a sequence of elements of type T.

Source : *Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing*. **Matei Zaharia** *et al.* Proceedings of the 9th USENIX conference on Networked Systems Design and Implementation. San Jose, CA, USA, **2012**

RDD concepts and operations

Exemple of Transformations and Actions

Transformations	*map*(f : T ⇒ U)	:	RDD[T] ⇒ RDD[U]
	filter(f : T ⇒ Bool)	:	RDD[T] ⇒ RDD[T]
	flatMap(f : T ⇒ Seq[U])	:	RDD[T] ⇒ RDD[U]
	sample(*fraction* : Float)	:	RDD[T] ⇒ RDD[T] (Determinis
	groupByKey()	:	RDD[(K, V)] ⇒ RDD[(K, Seq[V
	$\boxed{\textit{reduceByKey}(f : (V,V) \Rightarrow V) \quad : \quad RDD[(K, V)] \Rightarrow RDD[(K, V)]}$		
	union()	:	(RDD[T], RDD[T]) ⇒ RDD[T]
	join()	:	(RDD[(K, V)], RDD[(K, W)]) ⇒
	cogroup()	:	(RDD[(K, V)], RDD[(K, W)]) ⇒ W]))]
	cartesian~~*crossProduct*~~()	:	(RDD[T], RDD[U]) ⇒ RDD[(T, U)]
	mapValues(f : V ⇒ W)	:	RDD[(K, V)] ⇒ RDD[(K, W)] (Preserves partitioning)
	sort(c : Comparator[K])	:	RDD[(K, V)] ⇒ RDD[(K, V)]
	partitionBy(p : Partitioner[K])	:	RDD[(K, V)] ⇒ RDD[(K, V)]
Actions	*count*()	:	RDD[T] ⇒ Long
	collect()	:	RDD[T] ⇒ Seq[T]
	$\boxed{\textit{reduce}(f : (T,T) \Rightarrow T) \quad : \quad RDD[T] \Rightarrow T}$		
	lookup(k : K)	:	RDD[(K, V)] ⇒ Se
	save(*path* : String)	:	Outputs RDD to a st

Table 2: Transformations and actions available on RDDs in Spark. Seq[T] denotes a sequence of elements of type T.

reduceByKey
returns a RDD
→ parallelism
can continue

reduce(..) is an « action » :
it does **not** return a RDD
→ parallelism is stopped

Source : *Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing*. **Matei Zaharia** *et al.* Proceedings of the 9th USENIX conference on Networked Systems Design and Implementation. San Jose, CA, USA, **2012**

CentraleSupélec

Spark Programming

1. Main objectives
2. RDD concepts
3. **Operations on generic RDDs**
4. Operations on RDD of *key-value* pairs

Transformations on generic RDDs

rdd : {1, 2, 3, 3}

Transformations applied on one RDD:

Python: `rdd.map(lambda x: x+1)` → rdd: {2, 3, 4, 4}

Scala : `rdd.map(x => x+1)` → rdd: {2, 3, 4, 4}

Scala : `rdd.map(x => x.to(3))` → rdd: {(1,2,3), (2,3), (3), (3)}

Scala : `rdd.flatMap(x => x.to(3))` → rdd: {1, 2, 3, 2, 3, 3, 3}

Scala : `rdd.filter(x => x != 1)` → rdd: {2, 3, 3}

Scala : `rdd.distinct()` → rdd: {1, 2, 3}

Some sampling functions exist:

Scala : `rdd.sample(false,0.5)` → rdd: {1} or {2,3} or …

with replacement = false

Sequence of transformations:

Scala: `rdd . filter(x => x != 1) . map(x => x+1)` → rdd: {3, 4, 4}

Transformations on generic RDDs

Transformations applied on **two** RDDs:

rdd : {1, 2, 3}
rdd2: {3, 4, 5}

Scala : `rdd.union(rdd2)` → rdd: {1, 2, 3, 3, 4, 5}

Scala : `rdd.intersection(rdd2)` → rdd: {3}

Scala : `rdd.subtract(rdd2)` → rdd: {1, 2}

Scala : `rdd.cartesian(rdd2)` → rdd: {(1,3), (1,4), (1,5),
(2,3), (2,4), (2,5),
(3,3), (3,4), (3,5)}

Actions on generic RDDs

Actions applied on a RDD:

rdd : {1, 2, 3, 3}

Scala : `rdd.collect()` → (1, 2, 3, 3)

Scala : `rdd.count()` → 4

Scala : `rdd.countByValue()` → ((1,1), (2,1), (3,2))

Scala : `rdd.take(2)` → (1, 2) the first elts

Scala : `rdd.top(2)` → (3, 3) the higher elts

Scala : `rdd.takeOrdered(3,Ordering[Int].reverse)` → (3,3,2)

Scala : `rdd.takeSample(false,2)` → (?,?)

`takeSample(withReplacement, NbEltToGet, [seed])`

Scala :
```
var sum = 0
rdd.foreach(sum += _)
println(sum)
```
`rdd.foreach(sum += _)` → does not return any value

`println(sum)` → 9

Actions on generic RDDs

Actions applied on a RDD:

rdd : {1, 2, 3, 3}

Scala : `rdd.reduce(…)`

Ex: computing the sum of the RDD values

Python : `rdd.reduce(lambda x,y: x+y)` → 9

Scala : `rdd.reduce((x,y) => x+y)` → 9

Result is NOT a RDD

The **`reduce`** action is applied on 2 operands:

2 input data

or :

1 input data and 1 **`reduce`** result

It is defined by **only 1 associative function**:

because input and output data types must be **identical**

(will be different with action *aggregate*)

Computations are done in parallel but result is not a RDD

Actions on generic RDDs

Actions applied on a RDD:

rdd : {1, 2, 3, 3}

Scala : `rdd.reduce(…)`

Ex: computing the sum of the RDD values

Python : `rdd.reduce(lambda x,y: x+y)` → 9

Scala : `rdd.reduce((x,y) => x+y)` → 9

Result is NOT a RDD

Specifying the initial value of the accumulator:

Scala : `rdd.fold(0)((accu,value) => accu+value)` → 9

Specifying to start to accumulate from Left or from Right:

Scala : `rdd.foldLeft(0)((accu,value) => accu+value)` → 9

Scala : `rdd.foldRight(0)((accu,value) => accu+value)` → 9

Actions on generic RDDs

Actions applied on a RDD:

Ex. of « aggregations » to compute an average value

- Specifying the initial value of the accumulator (0 = sum, 0 = nb)
- Specifying a function to add a value to an accumulator (inside a rdd partition block)
- Specifying a function to add two accumulators (from two rdd partition blocks)

```
val SumNb = rdd.aggregate((0,0))(
                (acc,v) => (acc._1+v, acc._2+1),
                (acc1,acc2) => (acc1._1+acc2._1,
                                acc1._2+acc2._2))
```

Use type inference to select the fct to use

- Division of the sum by the nb of values

```
val avg = SumNb._1/SumNb._2.toDouble
```

Actions on generic RDDs

Actions applied on a RDD:

Ex. of « aggregations » to compute an average value

Python : `rdd.aggregate(acc0)((lambda acc,v: new_acc)`
`(lambda acc1,acc2: new_acc))`

Scala : `rdd.aggregate(acc0)((acc,v) => new_acc),`
`(acc1,acc2) => new_acc))`

The aggregate action is applied on **2 operands**:

1 input data and 1 aggregate result

or:

2 aggregate results

And is defined with **2 associative functions**

because datatypes of input and aggregated data are different (otherwise: use reduce(…))

Spark programming

1. Main objectives
2. RDD concepts
3. Operations on generic RDDs
4. **Operations on RDD of *key-value* pairs**

Operations on RDD of *key-value* pairs

Transformations for one pair RDD:

rdd : {(1, 2), (3, 3), (3, 4)}

Scala : `rdd.groupByKey()` → rdd: {(1, [2]), (3, [3, 4])}

Group the values associated to the same key

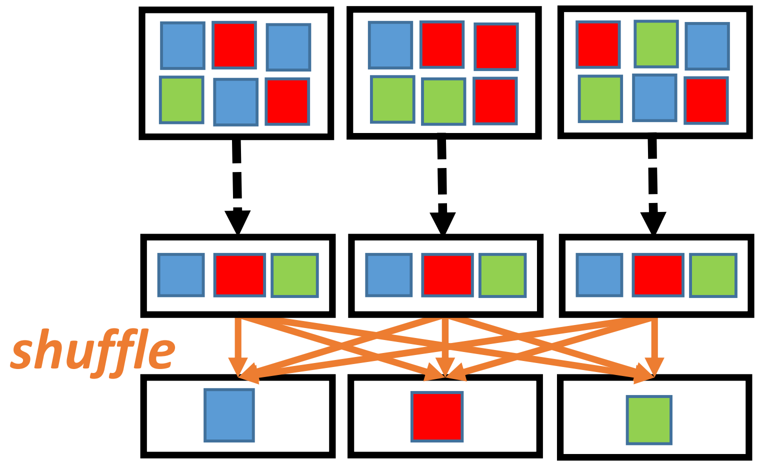
Group the values of a same key in the same Spark Executor

Move all input data → Huge network trafic in shuffle step !!

Scala : `rdd.reduceByKey((x,y) => x+y)` → rdd: {(1, 2), (3, 7)}

Reduce values associated to the same key

Limited traffic

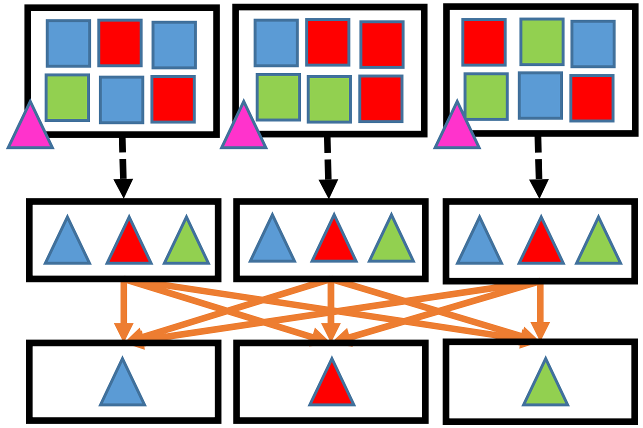


When input data type and reduced data type are identical

Operations on RDD of *key-value* pairs

Transformations for one pair RDD:

Scala : `rdd.aggregateByKey(init_acc)(`



```
    …, // mergeValueAccumulator fct
    …, // mergeAccumulators fct
)
```

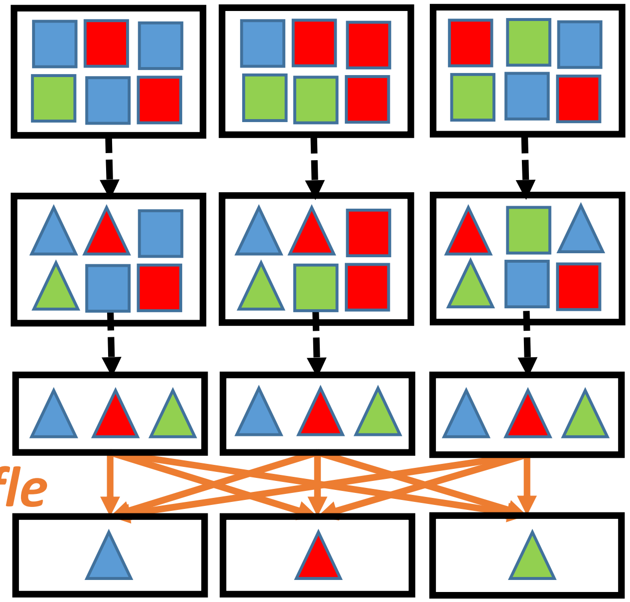
When input data type and reduced data type are different

Scala : `rdd.combineByKey(`

```
    …, // createAccumulator fct
    …, // mergeValueAccumulator fct
    …, // mergeAccumulators fct
)
```

See further

shuffle



The real function (used to implement the previous ones)

Operations on RDD of *key-value* pairs

Transformations for one pair RDD:

rdd : {(1, 2), (3, 3), (3, 4)}

Scala : `rdd.mapValues(x => x+1)` → rdd: {(1, 3), (3, 4), (3, 5)}

Apply to each value (keys do not change)

Scala : `rdd.flatMapValues(x => x to 3)` → rdd: {(1,2), (1,3), (3,3)}

key: 1, 2 to 3 → (2, 3) → (1, 2), (1, 3),
key: 3, 3 to 3 → (3) → (3, 3)
key: 3, 4 to 3 → () → nothing

~~((1,2), (1,3)), (3,3)~~
(1,2), (1,3), (3,3)

Apply to each value (keys do not change) and flatten

Operations on RDD of *key-value* pairs

Transformations applying to one *pair RDD*:

rdd : {(1, 2), (3, 3), (3, 4)}

Scala : `rdd.keys()` → rdd: {1, 3, 3}

Return an RDD containing only the keys

Scala : `rdd.values()` → rdd: {2, 3, 4}

Return an RDD containing only the values

Scala : `rdd.sortByKeys()` → rdd: {(1, 2), (3, 3), (3, 4)}

Return a pair RDD sorted by the keys

Operations on RDD of *key-value* pairs

Transformations applying on two *pair RDDs*

rdd : {(1, 2), (3, 4), (3, 6)}
rdd2: {(3, 9)}

Scala : `rdd.subtractByKey(rdd2)` → rdd: {(1, 2)}

Remove pairs with key present in the 2nd pairRDD

Scala : `rdd.join(rdd2)` → rdd: {(3, (4, 9)), (3, (6, 9))}

Inner Join between the two pair RDDs

Scala : `rdd.cogroup(rdd2)` → rdd: {(1, ([2], [])),
(3, ([4, 6], [9]))}

Group data from both RDDs sharing the same key

Operations on RDD of *key-value* pairs

Standard transformations applied on a *pair RDD*

rdd : {(1, 2), (3, 4), (3, 6)}

A pair RDD remains a RDD of tuples (key, values)

→ Classic transformations can be applied

Scala : `rdd.filter{case (k,v) => v < 5}` → rdd: {(1, 2), (3, 4)}

Scala : `rdd.map{case (k,v) => (k,v*10)}` → rdd: {(1, 20),
(3, 40),
(3, 60)}

Operations on RDD of *key-value* pairs

Actions applying on a *pair RDD*

rdd : {(1, 2), (3, 4), (3, 6)}

Scala : `rdd.countByKey()` → ((1, 1), (3, 2))

Return a tuple of couple, counting the number of pairs per key

Scala : `rdd.collectAsMap()` → Map{(1, 2), (3, 4), (3, 6)}

Return a 'Map' datastructure containing the RDD

Scala : `rdd.lookup(3)` → [4, 6]

Return an array containing all values associated with the provided key

Quiz

Q1: What does the RDD "r" at the end of the following code contain?

```
words = 'Technology is best when it brings people together'\
        .split(' ')
r = sc.parallelize(words)\
      .filter(lambda x: len(x) >= 3)\
      .map(lambda x: (x[0].lower(), x.lower()))\
      .reduceByKey(lambda w,v: w if len(w)>len(v) else v)
```

Quiz

Q2: One or more Spark-Workers work on each step of this code?

```
def f(x):
  if x > 0:
    print(x)

r = sc.parallelize(data)\
      .filter(lambda t: t[0] == 10)\
      .mapValues(lambda v: v*10)\
      .reduceByKey(lambda w,v: w+v)\
      .values()\
      .collect()\
      .foreach(f)
```

Quiz

Q3: What is the output ?

data : {(‘a’,(12,1)), (‘b’,(13,1)), (‘a’,(9,2)),
(‘c’,(18,4)), (‘b’,(13,1)), (‘b’,(15,2))}

```
res = sc.parallelize(data)\
        .filter(lambda t: t[0] <= ‘z’ and t[0] >= ‘a’) \
        .reduceByKey(lambda w,v: (w[0]+v[0],w[1]+v[1]))\
        .mapValues(lambda v: float(v[0])/float(v[1]))
print(res.collect())
```

Spark Programming