Big Data

Spark Programming

Stéphane Vialle **&** **Gianluca Quercini**

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Spark Programming

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

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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

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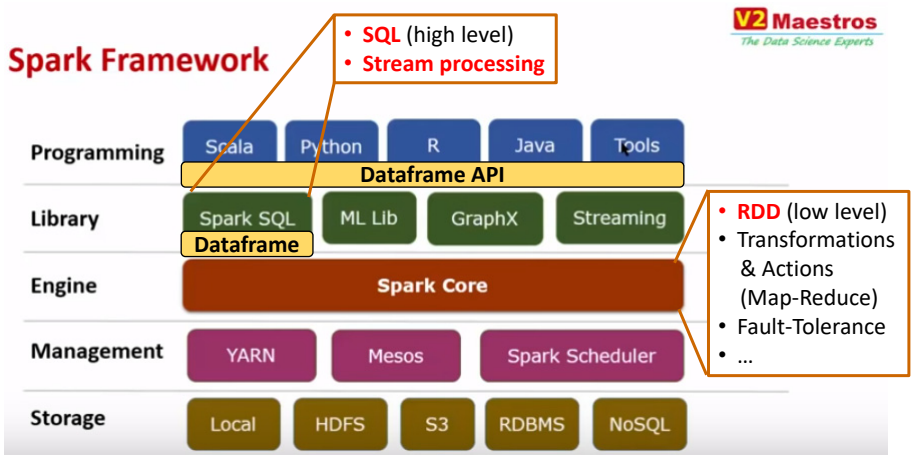
Spark main objectives



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

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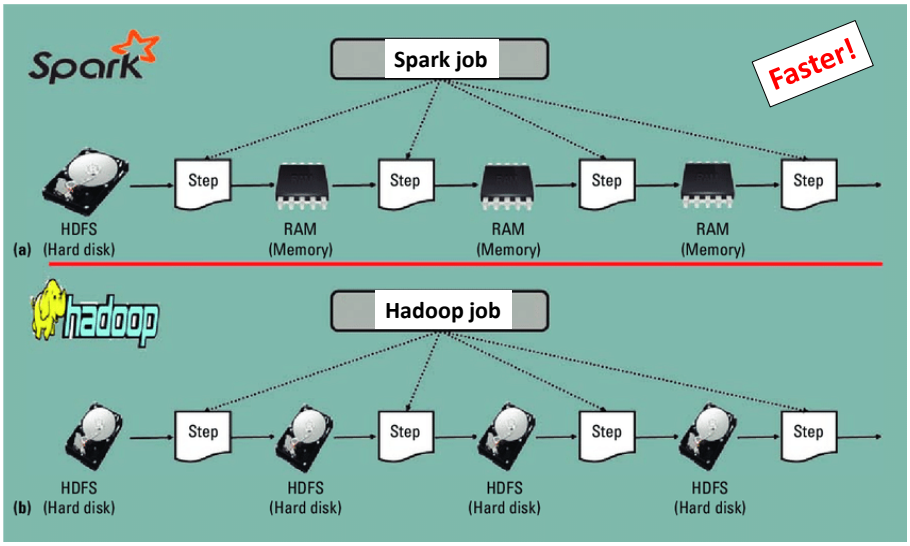
Spark main objectives

An essential difference between Spark and Hadoop: the speed!



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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

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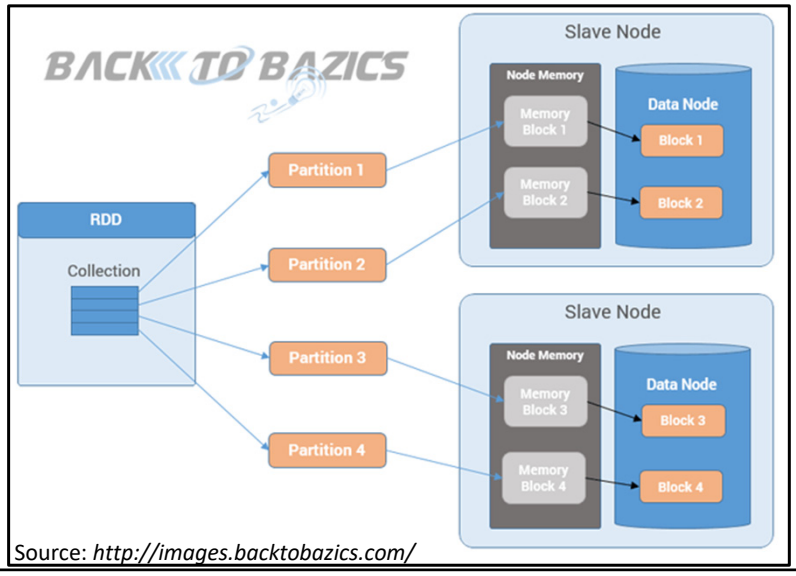
RDD concepts and operations

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



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

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RDD concepts and operations

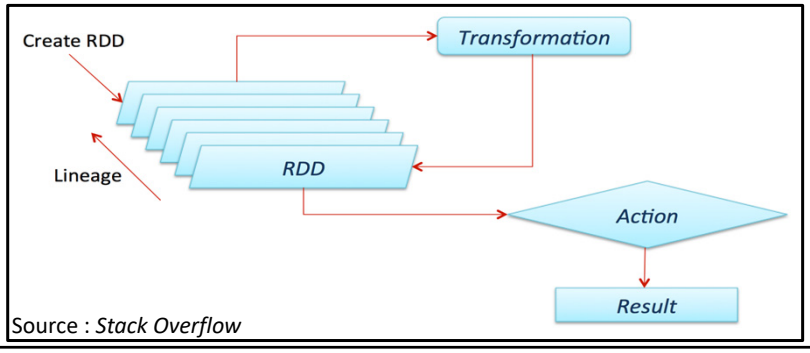
Initial input RDDs:

- 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*

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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] (Deterministic sampling)
	groupByKey()	:	RDD[(K, V)] ⇒ RDD[(K, Seq[V])]
	reduceByKey(*f* : (V, V) ⇒ V)	:	RDD[(K, V)] ⇒ RDD[(K, V)]
	union()	:	(RDD[T], RDD[T]) ⇒ RDD[T]
	join()	:	(RDD[(K, V)], RDD[(K, W)]) ⇒ RDD[(K, (V, W))]
	cogroup()	:	(RDD[(K, V)], RDD[(K, W)]) ⇒ RDD[(K, (Seq[V], Seq[W]))]
	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]
	reduce(*f* : (T, T) ⇒ T)	:	RDD[T] ⇒ T
	lookup(*k* : K)	:	RDD[(K, V)] ⇒ 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**

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RDD concepts and operations

Exemple of Transformations and Actions

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	join()	:	(RDD[(K, V)], RDD[(K, W)]) ⇒
	cogroup()	:	(RDD[(K, V)], RDD[(K, 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)]
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	lookup(*k* : K)	:	RDD[(K, V)] ⇒ Se
	save(*path* : String)	:	Outputs RDD to a st

reduceByKey returns a RDD → parallelism can continue

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

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Transformations on generic RDDs

Transformations applied on one RDD:

rdd : {1, 2, 3, 3}

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}

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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)}

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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 += _)   → does not return any value
println(sum)            → 9
```

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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

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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

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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
```

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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(…))

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4. **Operations on RDD of *key-value* pairs**

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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])}

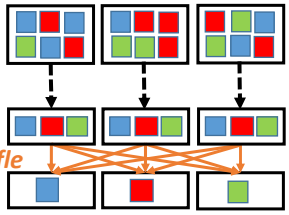
Group the values associated to the same key

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 *shuffle*

When input data type and reduced data type are identical

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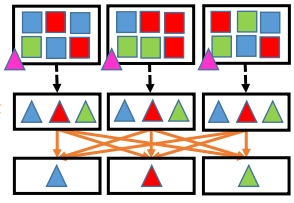
Operations on RDD of *key-value* pairs

Transformations for one pair RDD:

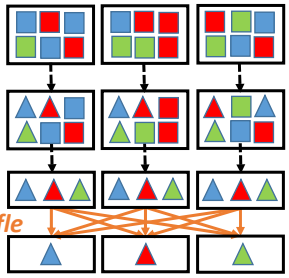
Scala :
```
rdd.aggregateByKey(init_acc)(
    …, // mergeValueAccumulator fct
    …, // mergeAccumulators fct
)
```



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)

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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

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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

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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

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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)}

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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

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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)
```

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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)
```

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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())
```

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