Big Data

# Optimized Spark programming

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

## Spark Technology

1. **RDD concepts and operations**
2. SPARK application scheme and execution
3. Basic programming examples
4. Basic examples on pair RDDs
5. PageRank with Spark
6. Partitioning & co-partitioning

# 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 stored in HDFS:**

- One RDD → One HDFS file
- One RDD partition block → One HDFS file block

and

- Each RDD partition block is replicated by HDFS

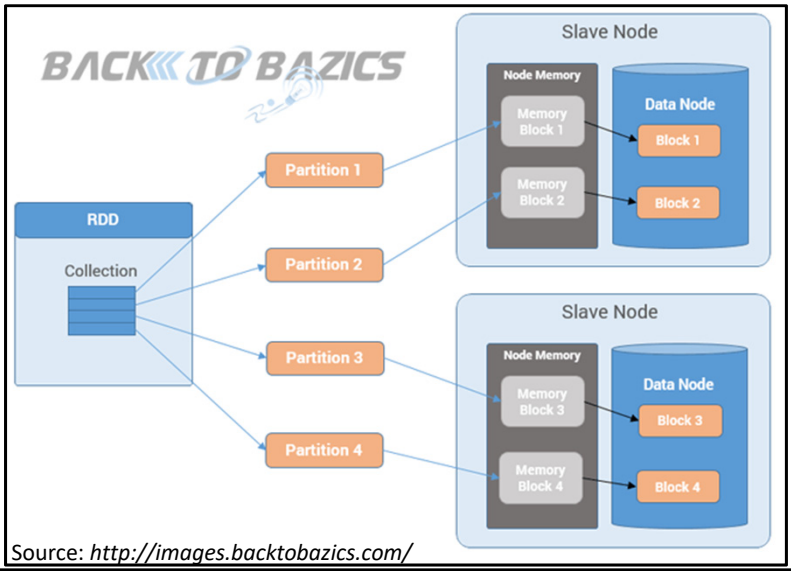
```
rdd1 = sc.parallelize(« myFile.txt »)
```

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

→ Get a RDD

# 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

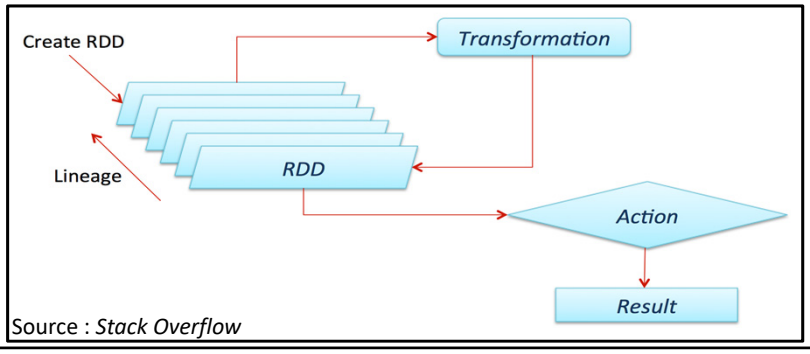
**Initial input RDDs:**

- 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 ⇒ 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**

# RDD concepts and operations

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| | *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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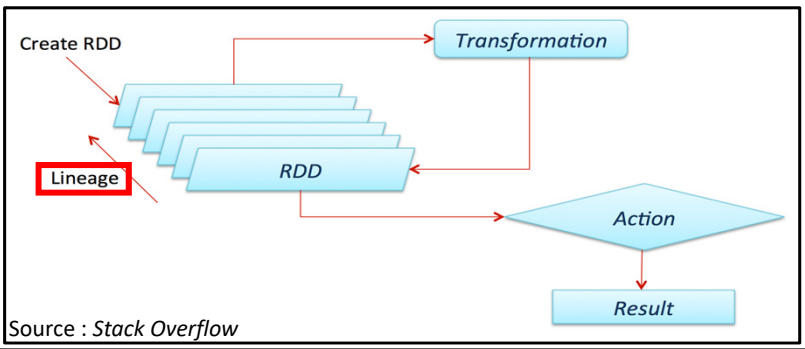
# RDD concepts and operations

**Fault tolerance:**

- Transformations are coarse grained op: they apply on all data of the source RDD
- RDD are read-only, input RDD are not modified
- A sequence of transformations (a *lineage*) can be easily stored

→ In case of failure: Spark has *just* to re-apply the lineage of the missing RDD partition blocks.




Source : *Stack Overflow*

# RDD concepts and operations

**5 main internal properties of a RDD:**

- A list of partition blocks
  `getPartitions()`
- A function for computing each partition block
  `compute(…)`
- A list of dependencies on other RDDs: parent RDDs and transformations to apply
  `getDependencies()`

To compute and re-compute the RDD when failure happens

**Optionally:**

- A Partitioner for key-value RDDs: metadata specifying the RDD partitioning
  `partitioner()`
- *A list of nodes where each partition block can be accessed faster due to data locality*
  `getPreferredLocations(…)`

To control the RDD partitioning, to achieve co-partitioning…

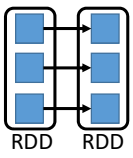
*To improve data locality with HDFS & YARN…*

# RDD concepts and operations

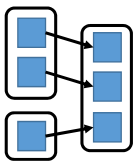
**Narrow transformations**

- Local computations applied to each partition block
  → no communication between processes/nodes
  → only local dependencies (between parent & son RDDs)

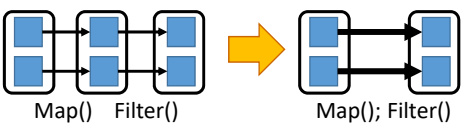
•Map()
•Filter()




•Union()



- In case of sequence of Narrow transformations:
  →possible pipelining inside one step



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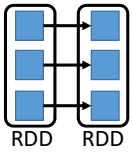


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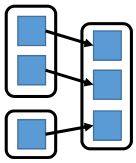
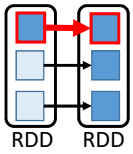


- In case of failure:
  → recompute only the damaged partition blocks
  → recompute/reload only its parent blocks

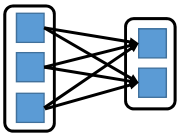



# RDD concepts and operations

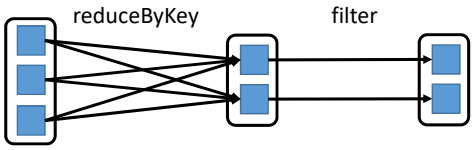
**Wide transformations**

- Computations requiring data from all parent RDD blocks
  → many communication between processes/nodes (*shuffle & sort*)
  → non-local dependencies (between parent & son RDDs)

•groupByKey()
•reduceByKey()



- In case of sequence of transformations:
  → no pipelining of transformations
  → wide transformation must be totally achieved before to enter next transformation



# RDD concepts and operations

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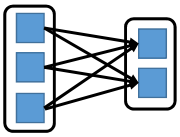
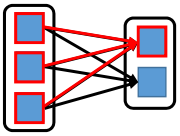


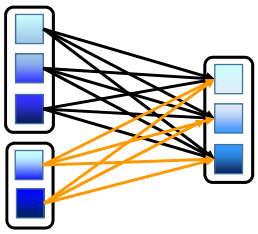
- In case of sequence of failure:
  → recompute the damaged partition blocks
  → recompute/reload all blocks of the parent RDDs



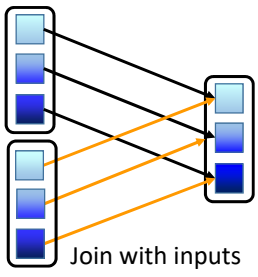
# RDD concepts and operations

**Avoiding wide transformations with co-partitioning**

- With identical partitioning of inputs:
  wide transformation → narrow transformation



Join with inputs
**not** co-partitioned



Join with inputs
**co-partitioned**

- less expensive communications
- possible pipelining
- less expensive fault tolerance

Control RDD partitioning
Force co-partitioning
(using the same partition map)

# RDD concepts and operations

**Persistence of the RDD**

RDD are stored:
- in the memory space of the Spark Executors
- or on disk (of the node) when memory space of the Executor is full

By default: an old RDD is removed when memory space is required (*Least Recently Used* policy)

→ An old RDD has to be re-computed (using its *lineage*) when needed again

→ Spark allows to make a « persistent » RDD to avoid to recompute it

# RDD concepts and operations

**Persistence of the RDD** to improve Spark application performances

Spark application developper has to add instructions to force RDD storage, and to force RDD forgetting:

```
myRDD.persist(StorageLevel)     // or myRDD.cache()
… // Transformations and Actions
myRDD.unpersist()
```

Available *storage levels*:
- `MEMORY_ONLY` : in Spark Executor memory space
- `MEMORY_ONLY_SER` : + serializing the RDD data
- `MEMORY_AND_DISK` : on local disk when no memory space
- `MEMORY_AND_DISK_SER` : + serializing the RDD data in memory
- `DISK_ONLY` : always on disk (and serialized)

RDD is saved in the Spark executor memory/disk space
→ limited to the Spark session

# RDD concepts and operations

**Persistence of the RDD** to improve fault tolerance

To face *short term failures*: Spark application developper can force RDD storage with replication in the local memory/disk of several Spark Executors

```
myRDD.persist(storageLevel.MEMORY_AND_DISK_SER_2)
… // Transformations and Actions
myRDD.unpersist()
```

To face *serious failures*: Spark application developper can checkpoint the RDD outside of the Spark data space, on HDFS or S3 or…

```
myRDD.sparkContext.setCheckpointDir(directory)
myRDD.checkpoint()
… // Transformations and Actions
```

→ Longer, but secure!

# Spark Technology

1. RDD concepts and operations
2. **SPARK application scheme and execution**
3. Basic programming examples
4. Basic examples on pair RDDs
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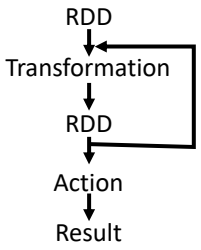
# SPARK application scheme and execution

*Transformations* are **lazy** operations: saved and executed further

*Actions* **trigger** the execution of the sequence of transformations

A *job* is a sequence of RDD transformations, ended by an action




A *Spark application* is a set of jobs to run sequentially or in parallel

# SPARK application scheme and execution

The *Spark application driver* controls the application run

- It creates the Spark context
- It analyses the Spark program

- It creates a DAG of tasks for each job
- It optimizes the DAG
  - pipelining narrow transformations
  - identifying the tasks that can be run in parallel

- It schedules the DAG of tasks on the available worker nodes (the *Spark Executors*) in order to maximize parallelism (and to reduce the execution time)

# SPARK application scheme and execution

The *Spark application driver* controls the application run

- It **attempts** to keep in-memory the intermediate RDDs

  → in order the input RDDs of a transformation are already in-memory (ready to be used)

*But developers can use persist() to obligate Spark to keep the RDD in memory (see previous section)*

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# Basic programming examples

**Ex. of transformations 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}

# Basic programming examples

**Ex. of transformations 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)}

# Basic programming examples

**Ex. of actions on a RDD:**

Examples of « aggregations »: **computing a sum**

rdd : {1, 2, 3, 3}

Computing the sum of the RDD values:

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

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

**Results are NOT RDD**

The reduce fonction is applied on 2 operands:
2 input data OR 1 input data and 1 reduce result

→ Must be an **associative** operation

→ Input and output data types must be **identical**

# Basic programming examples

**Ex. of actions on a RDD:**

Examples of « aggregations »: **computing a sum**

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Computing the sum of the RDD values:

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

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

**Results are NOT 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

# Basic programming examples

**Ex. of actions on a RDD:**

Examples of « aggregations » :

**computing an average value using** aggregate(…)(…,…)

Scala:

- Specifying the initial value of the accumulator (0 = sum, 0 = nb)
- Specifying a function to add a value to an accumulator (in 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))
```

Type inference!

- Division of the sum by the nb of values

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

# Basic programming examples

**Ex. of actions 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}

Scala : `rdd.top(2)` → {3, 3}

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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# Basic examples on pair RDDs

**Ex. of transformations on one RDD:**

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

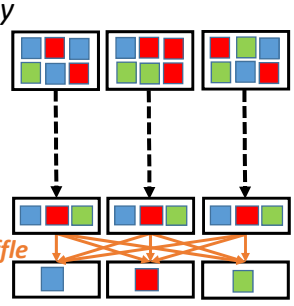
Scala : `rdd.groupByKey()` → rdd: {(1, [2]), (3, [3, 4])}

*Group values associated to the same key*

**Move almost all input data → Huge trafic in shuffle step !!**

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

*Reduce values associated to the same key*



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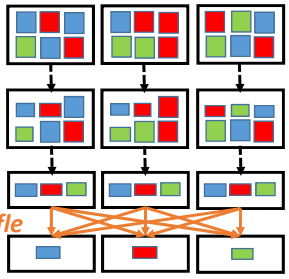
*Group values associated to the same key*

**Move almost all input data → Huge trafic in shuffle step !!**

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

*Reduce values associated to the same key*

Scala :
```
rdd.combineByKey(
  …, // createCombiner function
  …, // mergeValue function
  …, // mergeCombiners fct
)
```




**When input data type and reduced data type are different**

# Basic examples on pair RDDs

**Ex. of transformations on one 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)

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

# Basic examples on pair RDDs

**Ex. of transformations on one RDD:**

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

Scala : `rdd.keys()` → rdd: {1, 3, 3}

*Return an RDD of just the keys*

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

*Return an RDD of just the values*

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

*Return a pair RDD sorted by the keys*

# Basic examples on pair RDDs

**Ex. of transformations 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*

# Basic examples on pair RDDs

**Ex. of classic 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)}

# Basic examples on pair RDDs

**Ex. of actions on pair RDDs**

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*

# Basic examples on pair RDDs

**Ex. of transformation: Computing an average value per key**

theMarks: {(''julie'', 12), (''marc'', 10), (''albert'', 19), (''julie'', 15), (''albert'', 15),…}

- **Solution 1: mapValues + reduceByKey + collectAsMap + foreach**

```
val theSums = theMarks
  .mapValues(v => (v, 1))
  .reduceByKey((vc1, vc2) => (vc1._1 + vc2._1,
                              vc1._2 + vc2._2))
  .collectAsMap() // Return a 'Map' datastructure
```

Bad performances! Break parallelism!

```
theSums.foreach(
      kvc => println(kvc._1 +
                     " has average:" +
                     kvc._2._1/kvc._2._2.toDouble))
```

# Basic examples on pair RDDs

**Ex. of transformation: Computing an average value per key**

theMarks: {(''julie'', 12), (''marc'', 10), (''albert'', 19), (''julie'', 15), (''albert'', 15),…}

- **Solution 2: combineByKey + collectAsMap + foreach**

Type inference needs some help!

```
val theSums = theMarks
  .combineByKey(
    // createCombiner function
    (valueWithNewKey)   => (valueWithNewKey, 1),
    // mergeValue function (inside a partition block)
    (acc:(Int, Int), v) =>(acc._1 + v, acc._2 + 1),
    // mergeCombiners function (after shuffle comm.)
    (acc1:(Int, Int), acc2:(Int, Int)) =>
      (acc1._1 + acc2._1, acc1._2 + acc2._2))
  .collectAsMap()
```

Still bad performances! Break parallelism!

```
theSums.foreach(
      kvc => println(kvc._1 + " has average:" +
                     kvc._2._1/kvc._2._2.toDouble))
```

# Basic examples on pair RDDs

**Ex. of transformation: Computing an average value per key**

theMarks: {(''julie'', 12), (''marc'', 10), (''albert'', 19), (''julie'', 15), (''albert'', 15),…}

- **Solution 2: combineByKey + map + collectAsMap + foreach**

```
val theSums = theMarks
  .combineByKey(
    // createCombiner function
    (valueWithNewKey)    => (valueWithNewKey, 1),
    // mergeValue function (inside a partition block)
    (acc:(Int, Int), v) =>(acc._1 + v, acc._2 + 1),
    // mergeCombiners function (after shuffle comm.)
    (acc1:(Int, Int), acc2:(Int, Int)) =>
      (acc1._1 + acc2._1, acc1._2 + acc2._2))
  .map{case (k,vc) => (k, vc._1/vc._2.toDouble)}
```

```
theSums.collectAsMap().foreach(
      kv => println(kv._1 + " has average:" + kv._2))
```

# Basic examples on pair RDDs

**Tuning the level of parallelism**

- By default: level of paralelism set by the nb of partition blocks of the input RDD
- When the input is a in-memory collection (list, array…), it needs to be parallelized:

```
val theData = List(("a",1), ("b",2), ("c",3),……)
sc.parallelize(theData).theTransformation(…)
```

Or :

```
val theData = List(1,2,3,……).par
theData.theTransformation(…)
```

→ Spark adopts a distribution adapted to the cluster…
… but it can be tuned

# Basic examples on pair RDDs

**Tuning the level of parallelism**

- Most of transformations support an extra parameter to control the distribution (and the parallelism)
- **Example:**

  Default parallelism:

```
val theData = List(("a",1), ("b",2), ("c",3),……)
sc.parallelize(theData).reduceByKey((x,y) => x+y)
```

  Tuned parallelism:

```
val theData = List(("a",1), ("b",2), ("c",3),……)
sc.parallelize(theData).reduceByKey((x,y) => x+y,8)
```

8 partition blocks imposed for the result of the reduceByKey

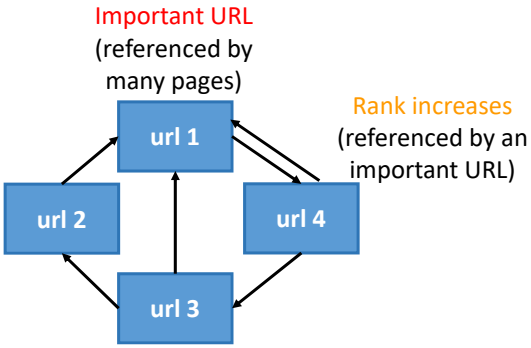
# Spark Technology

1. RDD concepts and operations
2. SPARK application scheme and execution
3. Basic programming examples
4. Basic examples on pair RDDs
5. **PageRank with Spark**
6. Partitioning & co-partitioning

# PageRank with Spark

**PageRank objectives**

Compute the probability to arrive at a web page when randomly clicking on web links…




- If a URL is referenced by many other URLs then its rank increases (because being referenced means that it is important – ex: URL 1)
- If an important URL (like URL 1) references other URLs (like URL 4) this will increase the destination's ranking

# PageRank with Spark

**PageRank principles**

- Simplified algorithm:

$$PR(u) = \sum_{v \in B(u)} \frac{PR(v)}{L(v)}$$

Contribution of page *v* to the rank of page *u*

$B(u)$: the set containing all pages linking to page *u*

$PR(x)$: PageRank of page *x*

$L(v)$: the number of outbound links of page *v*

- Initialize the PR of each page with an equi-probablity
- Iterate *k* times:
  compute PR of each page

# PageRank with Spark

**PageRank principles**

- The *damping* factor:
  the probability a user continues to click is a *damping* factor: *d*

$$PR(u) = \frac{1-d}{N_{pages}} + d. \sum_{v \in B(u)} \frac{PR(v)}{L(v)}$$

$N_{pages}$: Nb of documents in the collection

Usually : *d* = 0.85

Sum of all PR is 1

Variant:

$$PR(u) = (1-d) + d. \sum_{v \in B(u)} \frac{PR(v)}{L(v)}$$

Usually : *d* = 0.85

Sum of all PR is $N_{pages}$

# PageRank with Spark

**PageRank first step in Spark (Scala)**

```
// read text file into Dataset[String] -> RDD1
val lines = spark.read.textFile(args(0)).rdd

val pairs = lines.map{ s =>
                       // Splits a line into an array of
                       // 2 elements according space(s)
                       val parts = s.split("\\s+")
                       // create the parts<url, url>
                       // for each line in the file
                       (parts(0), parts(1))
                }
// RDD1 <string, string> -> RDD2<string, iterable>
val links = pairs.distinct().groupByKey().cache()
```

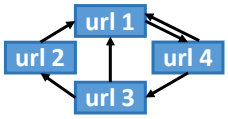
"url 4 url 3"
"url 4 url 1"
"url 2 url 1"
"url 1 url 4"
"url 3 url 2"
"url 3 utl 1"

*links RDD*

| | |
|---|---|
| url 4 | [url 3, url 1] |
| url 3 | [url 2, url 1] |
| url 2 | [url 1] |
| url 1 | [url 4] |

# PageRank with Spark

**PageRank second step in Spark (Scala)**




Initialization with 1/N equi-probability:

```
// links <key, Iter> RDD → ranks <key,1.0/N_pages> RDD
var ranks = links.mapValues(v => 1.0/4.0)
```

`links.mapValues(…)` is an immutable RDD

`var ranks` is a mutable variable

```
var ranks = RDD1
ranks = RDD2
```

« ranks » is re-associated to a new RDD

RDD1 is forgotten …

…and will be removed from memory

Other strategy:

```
// links <key, Iter> RDD → ranks <key,one> RDD
var ranks = links.mapValues(v => 1.0)
```

*links RDD*

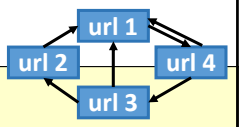
| | |
|---|---|
| url 4 | [url 3, url 1] |
| url 3 | [url 2, url 1] |
| url 2 | [url 1] |
| url 1 | [url 4] |

*ranks RDD*

| | |
|---|---|
| url 4 | 1.0 |
| url 3 | 1.0 |
| url 2 | 1.0 |
| url 1 | 1.0 |

# PageRank with Spark

**PageRank third step in Spark (Scala)**




```
for (i <- 1 to iters) {
  val contribs =
       links.join(ranks)
       .values
       .flatMap{ case (urls, rank) =>
                    urls.map(url => (url, rank/urls.size )) }
   ranks = contribs.reduceByKey(_ + _)
           .mapValues(0.15 + 0.85 * _)
}
```

*links RDD* Output links

| | |
|---|---|
| url 4 | [url 3, url 1] |
| url 3 | [url 2, url 1] |
| url 2 | [url 1] |
| url 1 | [url 4] |

*RDD'*

| | |
|---|---|
| url 4 | ([url 3, url 1], 1.0) |
| url 3 | ([url 2, url 1], 1.0) |
| url 2 | ([url 1], 1.0) |
| url 1 | ([url 4], 1.0) |

Output links & contributions

.values

*RDD''*

| |
|---|
| ([url 3, url 1], 1.0) |
| ([url 2, url 1], 1.0) |
| ([url 1], 1.0) |
| ([url 4], 1.0) |

input contributions

.flatmap

| | |
|---|---|
| url 3 | 0.5 |
| url 1 | 0.5 |
| url 2 | 0.5 |
| url 1 | 0.5 |
| url 1 | 1.0 |
| url 4 | 1.0 |

*contribs RDD*

individual input contributions

.reduceByKey

| | |
|---|---|
| url 3 | 0.5 |
| url 1 | 2.0 |
| url 2 | 0.5 |
| url 4 | 1.0 |

Individual & cumulated input contributions

.mapValues

| | |
|---|---|
| url 4 | 1.0 |
| url 3 | 0.57 |
| url 2 | 0.57 |
| url 1 | 1.849 |

**new** *ranks RDD* *(with damping factor)*

**var** ranks

| | |
|---|---|
| url 4 | 1.0 |
| url 3 | 1.0 |
| url 2 | 1.0 |
| url 1 | 1.0 |

*ranks RDD*

.join

# PageRank with Spark

**PageRank third step in Spark (Scala)**

- Spark & Scala allow a short/compact implementation of the PageRank algorithm
- Each RDD remains in-memory from one iteration to the next one

```
val lines = spark.read.textFile(args(0)).rdd
val pairs = lines.map{ s =>
                     val parts = s.split("\\s+")
                     (parts(0), parts(1)) }
val links = pairs.distinct().groupByKey().cache()

var ranks = links.mapValues(v => 1.0)

for (i <- 1 to iters) {
  val contribs =
       links.join(ranks)
       .values
       .flatMap{ case (urls, rank) =>
                    urls.map(url => (url, rank / urls.size )) }
  ranks = contribs.reduceByKey(_ + _).mapValues(0.15 + 0.85 * _)
}
```

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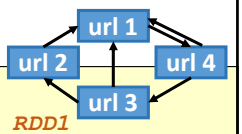
# Optimized MapReduce on Spark

# PageRank with Spark

**PageRank third step in Spark (Scala)**




```
for (i <- 1 to iters) {
  val contribs =
       links.join(ranks)                    // join -> RDD1
       .values                              // RDD1 -> RDD2
       .flatMap{ case (urls, rank) =>       // RDD2 -> contribs RDD
                   urls.map(url => (url, rank / urls.size )) }
  ranks = contribs.reduceByKey(_ + _)
          .mapValues(0.15 + 0.85 * _)
}
```