Big Data

Spark optimizations

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Spark optimizations

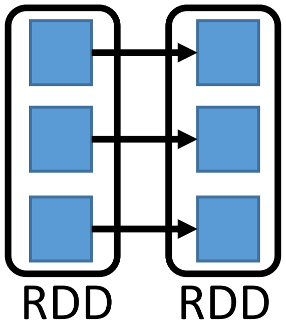
1. **Wide and Narrow transformations**
2. Optimizations
3. *Page Rank* example

Wide and Narrow transformations

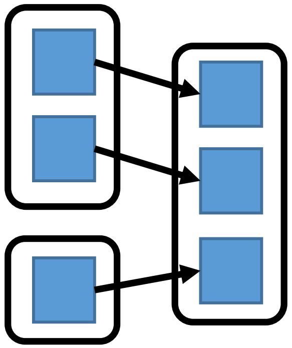
Narrow transformations

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

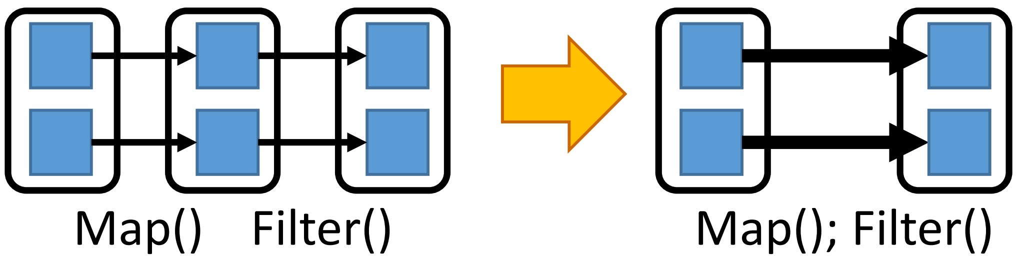
- Map()
- Filter()



- Union()



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



Wide and Narrow transformations

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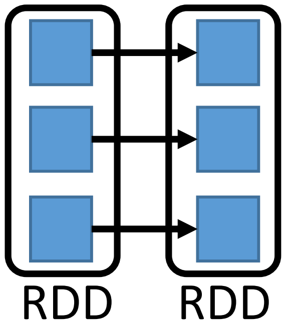

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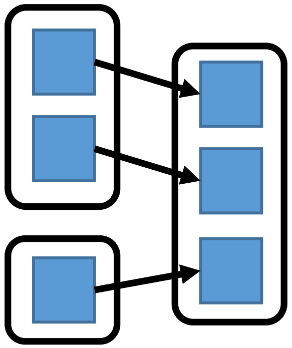
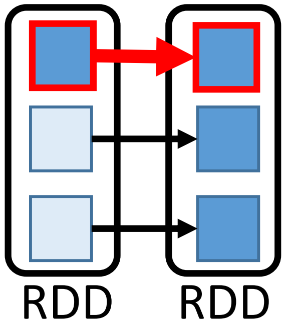
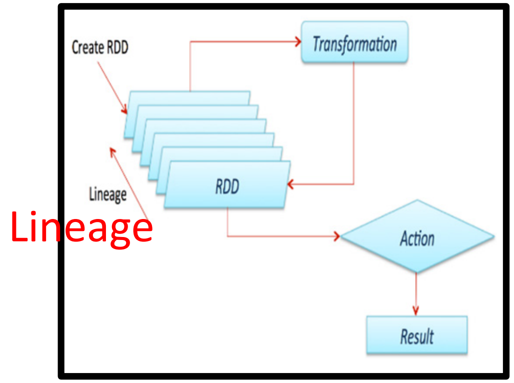


- In case of failure:
  → recompute only the damaged partition blocks
  → recompute/reload only its parent blocks





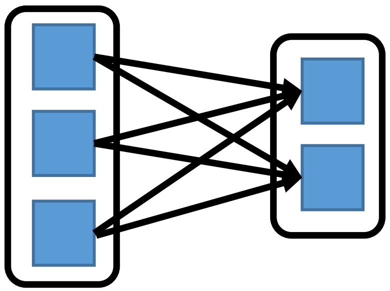
Source : *Stack Overflow*

Wide and Narrow transformations

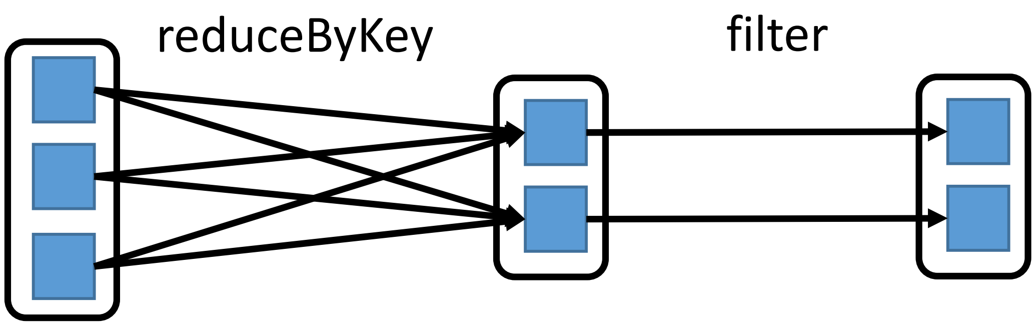
Wide transformations

- Computations requiring data from all parent RDD blocks
  → many comms between processes (and 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



Wide and Narrow transformations

Wide transformations

- Computations requiring data from all parent RDD blocks
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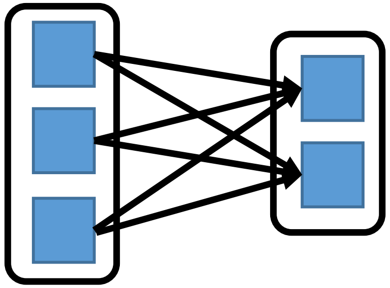
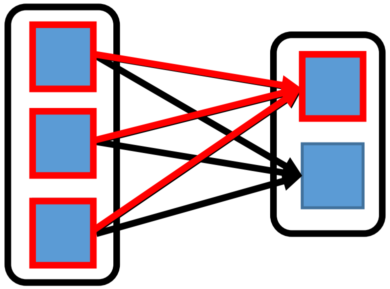
  - groupByKey()
  - reduceByKey()



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

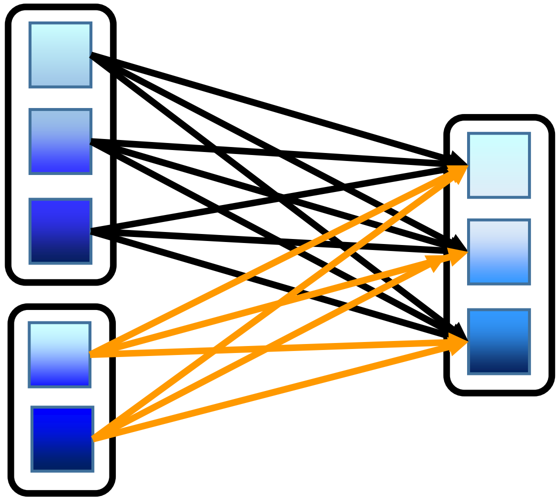


Wide and Narrow transformations

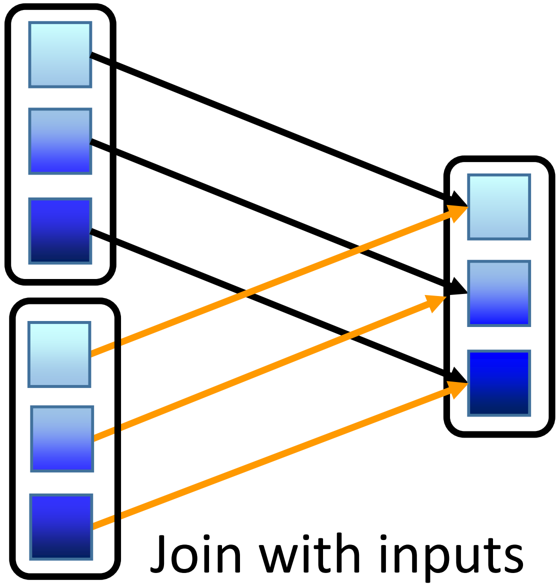
Avoiding wide transformations with co-partitioning

- 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)

Spark optimizations

1. Wide and Narrow transformations
2. **Optimizations**
   - **RDD Persistence**
   - RDD Co-partitionning
   - RDD controlled distribution
   - Traffic minimization
   - Maintaining parallelism
3. *Page Rank* example

Optimizations: persistence

Persistence of the RDD

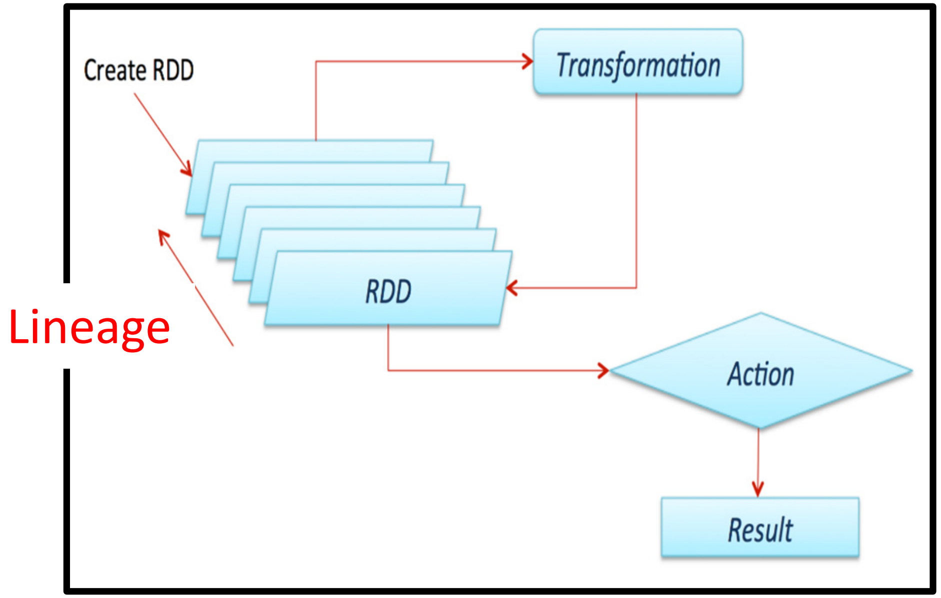
RDD are stored:

- 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



Source : *Stack Overflow*

Optimizations: persistence

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

Optimizations: persistence

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 optimizations

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    - **RDD Co-partitionning**
    - RDD controlled distribution
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Optimizations: RDD co-partitionning

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…

Optimizations: RDD co-partitionning

Specify a « partitioner »

```
val rdd2 = rdd1
        .partitionBy(new HashPartitioner(100))
        .persist()
```

Creates a new RDD (rdd2):

- Partitionned according to hash partitionner strategy
- On 100 Spark Executors

→ Redistribute the RDD (rdd1 → rdd2)
→ WIDE (expensive) transformation

- Do not keep the original partition (rdd1) in memory / on disk
- Keep the new partition (rrd2) in memory / on disk

→ to avoid to repeat a WIDE transformation when rdd2 is re-used

Optimizations: RDD co-partitionning

Specify a « partitioner »

```
val rdd2 = rdd1
          .partitionBy(new HashPartitioner(100))
          .persist()
```

Partitionners:

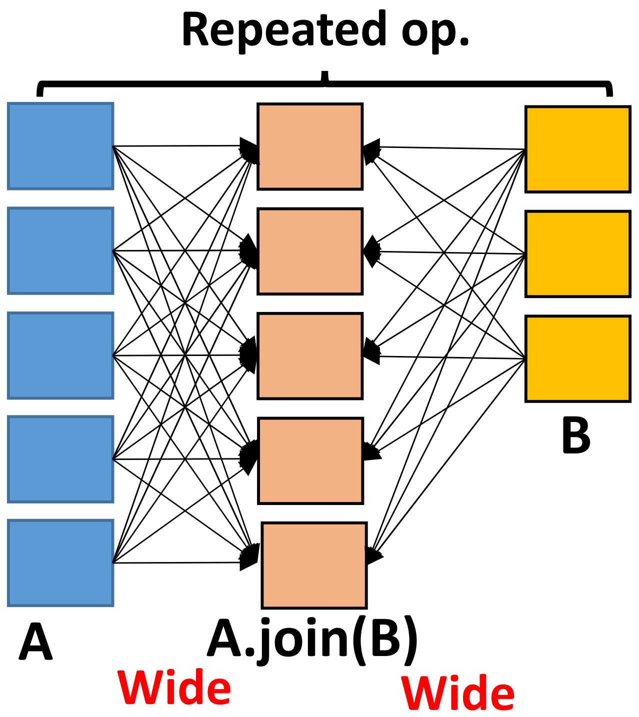
- *Hash partitioner :*
  Key0, Key0+100, Key0+200… on one Spark Executor

- *Range partitioner :*
  [Key-min ; Key-max] on one Spark Executor

- *Custom partitioner (develop your own partitioner) :*
  Ex : Key = URL, hash partitioned
  BUT : hash only the domain name of the URL
  → all pages of the same domain on the same Spark Executor because they are frequently linked

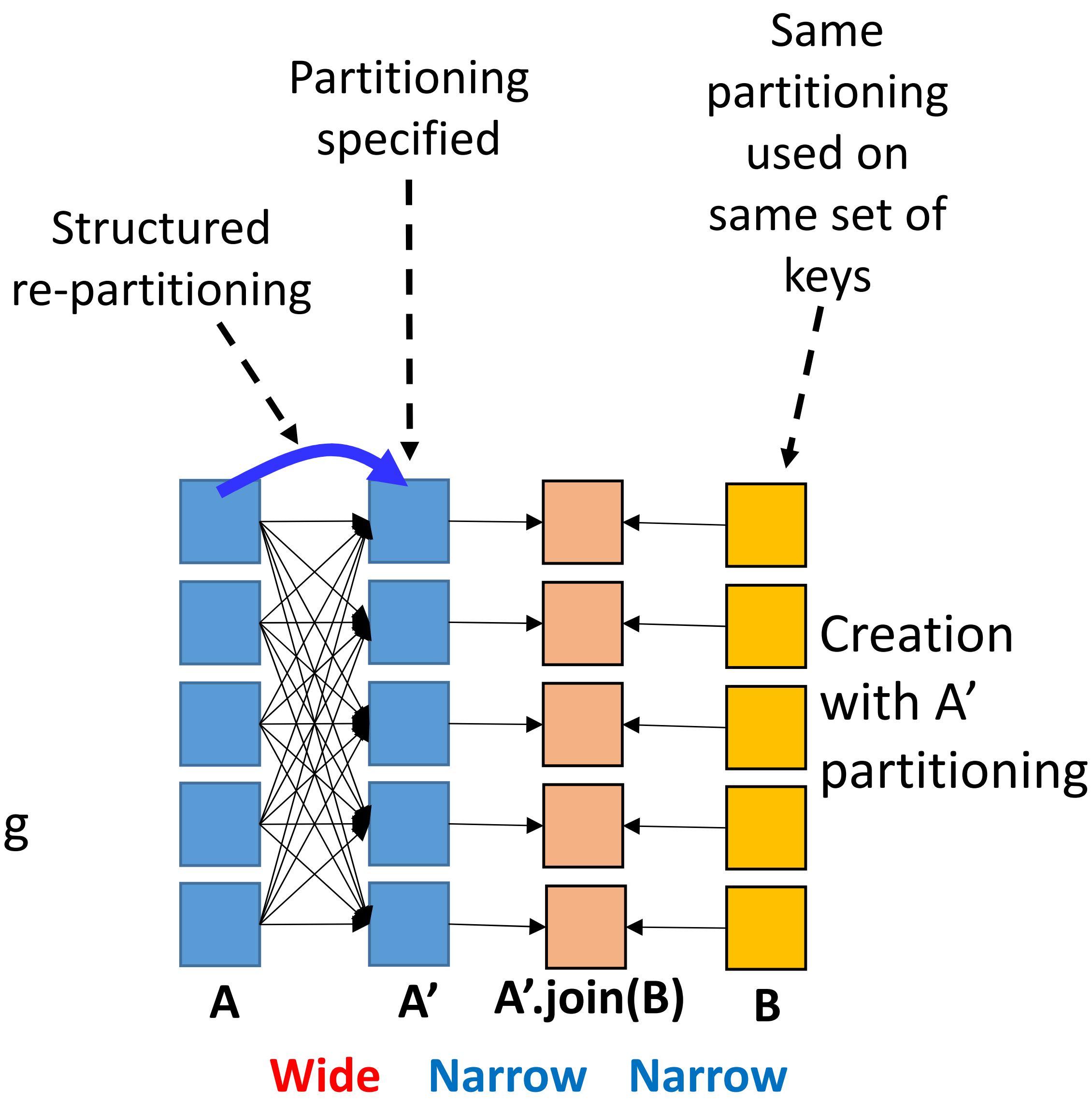
Optimizations: RDD co-partitionning

Avoid repetitive WIDE transformations on large data sets



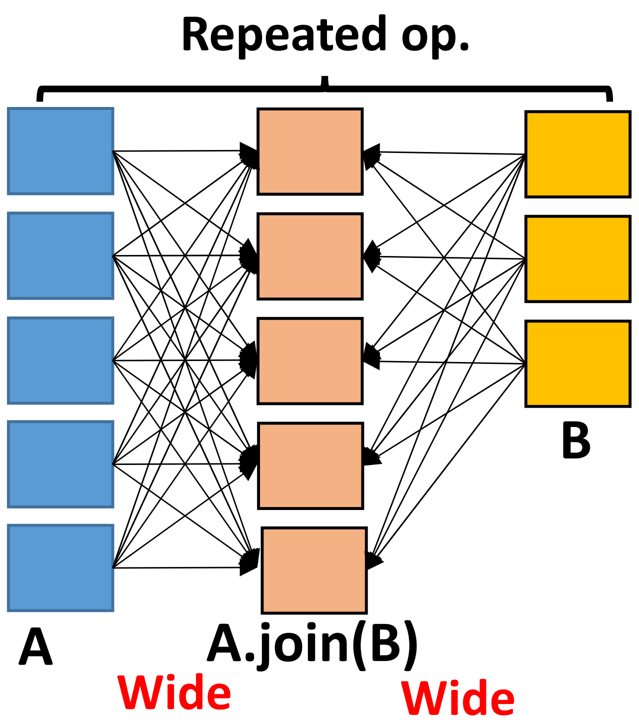
→ Control partitioning to avoid many *Wide* ops

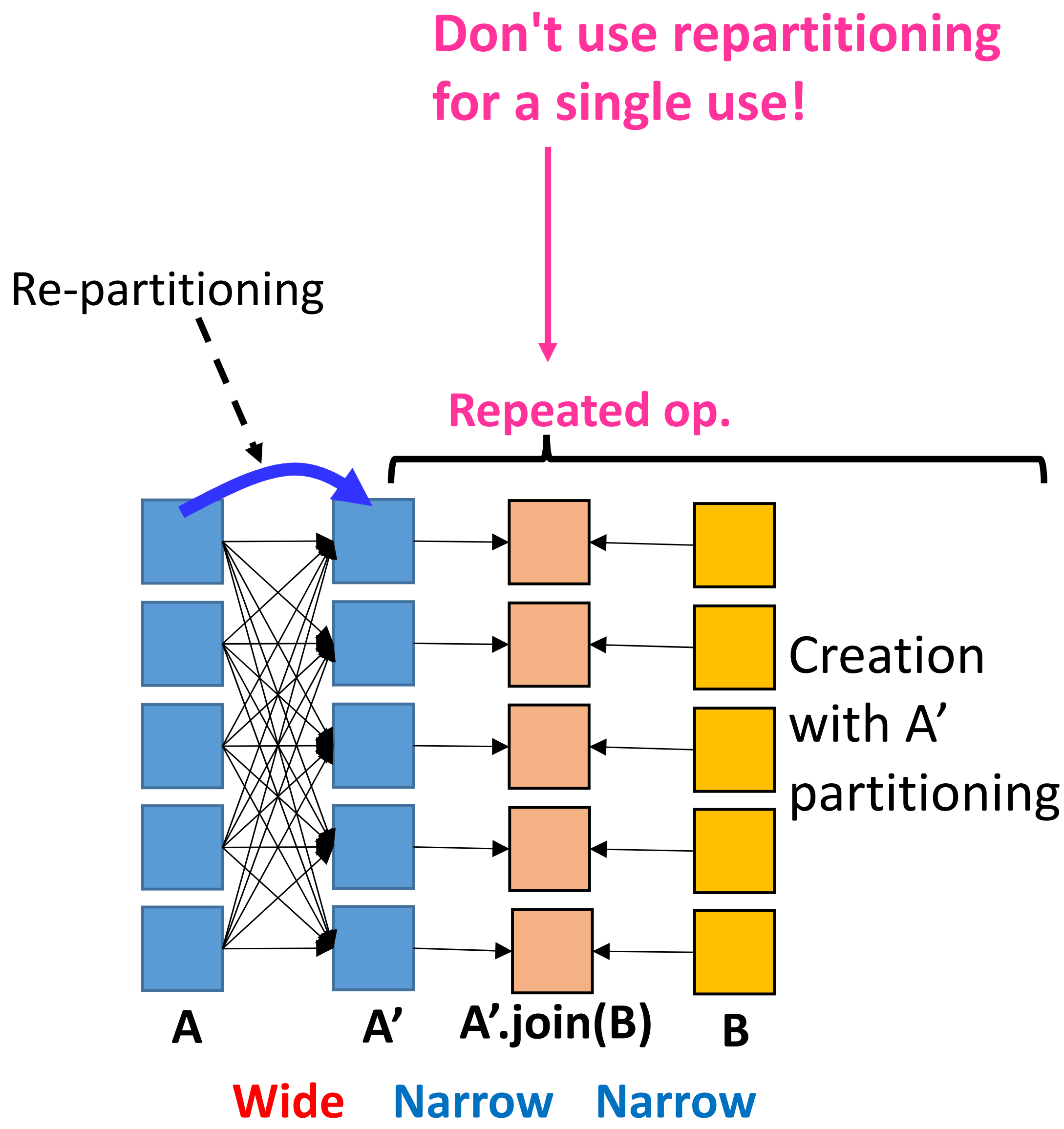
- Explicit & structured re-partitioning of A → A'
  Will *propagate* to the join result
- Create B with A' paritioning



Optimizations: RDD co-partitionning

Avoid repetitive WIDE transformations on large data sets





→ Control partitioning to avoid many *Wide* ops

- Explicit & structured re-partitioning of A → A'
  Will *propagate* to the join result
- Create B with A' paritioning

Optimizations: RDD co-partitionning

PageRank with partitioner (see further)

```
Val links = ……        // previous code
val links1 = links.partitionBy(new HashPartitioner(100)).persist()

var ranks = links1.mapValues(v => 1.0)

for (i <- 1 to iters) {
  val contribs =
       links1.join(ranks)
       .flatMap{ case (url (urlLinks, rank)) =>
                urlLinks.map(dest => (dest,rank/urlLinks.size))}
  ranks = contribs.reduceByKey(_ + _).mapValues(0.15 + 0.85 * _)
}
```

- Initial **`links`** and **`ranks`** are co-partitioned
- Repeated **`join`** is Narrow-Wide
- Repeated **`mapValues`** is Narrow: respects the **`reduceByKey`** partitioning
- Pb: flatMap{…urlinks.map(…)} can change the partitionning ?!

Spark optimizations

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   - **RDD controlled distribution**
   - Traffic minimization
   - Maintaining parallelism
3. *Page Rank* example

Optimization: RDD distribution

Create and distribute a RDD

- By default: level of parallelism 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

Optimization: RDD distribution

Control of the RDD distribution

- 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)
```

But better to use PARTITIONERS…

8 partition blocks imposed for the result of the reduceByKey

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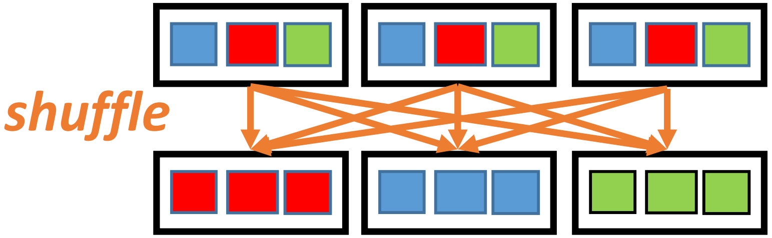
Optimization: traffic minimization

RDD redistribution:

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

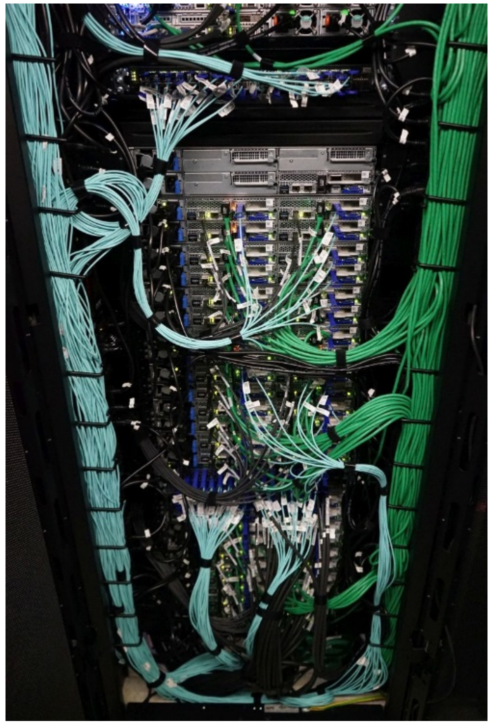
Scala : `rdd.groupByKey()` → rdd: {(1, [2]), (3, [3, 4])}

Group values associated to the same key



→ Move almost all input data

→ Huge trafic in the shuffle step !!



`groupByKey` will be time consumming:

- no computation time…
- … but huge traffic on the network of the cluster/cloud

→ Optimize computations and communications in a Spark program

Optimization: traffic minimization

RDD reduction:

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

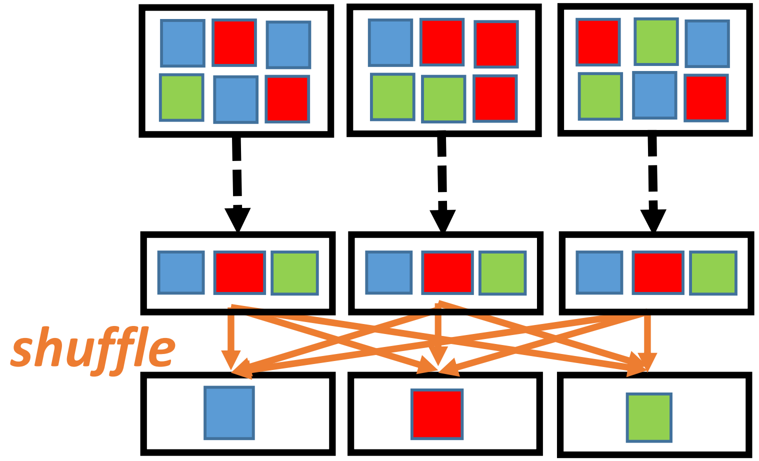
Scala : `rdd.reduceByKey((x,y) => x+y)` → rdd: {(1, 2), (3, 7)}

Reduce values associated to the same key

`((x,y) => x+y):`

`1 int + 1 int` → `1 int`

→ Limited trafic in the shuffle step



But: `((x,y) => x+y):`

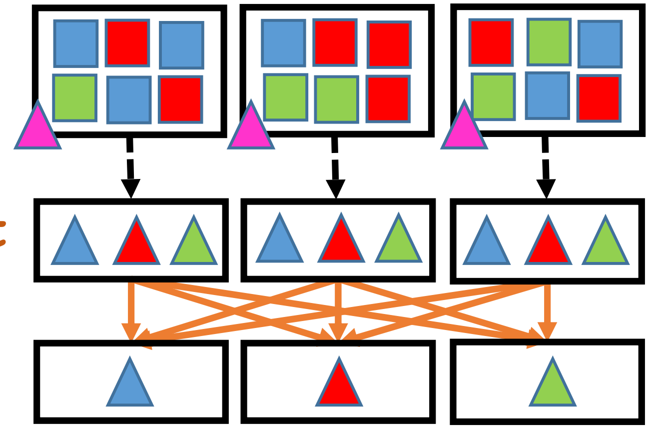
`1 list + 1 list` → `1 longer list`

→ TD-1

Optimization: traffic minimization

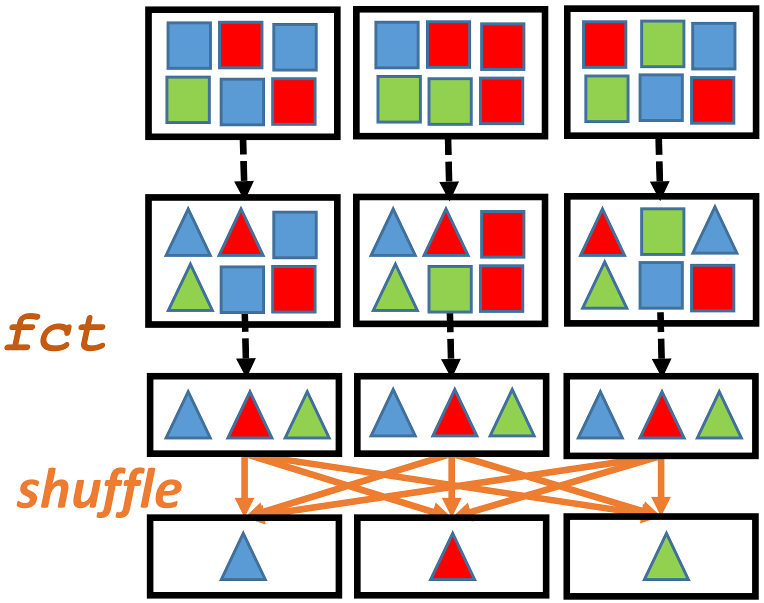
RDD reduction with different input and reduced datatypes:

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



Scala :
```
rdd.combineByKey(
    …, // createAccumulator fct
    …, // mergeValueAccumulator fct
    …, // mergeAccumulators fct
)
```

See further



Spark optimizations

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   - **Maintaining parallelism**
3. *Page Rank* example

Optimization: maintaining parallelism

Computing an average value per key in parallel

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
```

ACTION → Break parallelism! Bad performances!

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

Sequential computing !

Optimization: maintaining parallelism

Computing an average value per key in parallel

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

- **Solution 2: combineByKey + 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))
   .collectAsMap()
```

Still bad performances! (Break parallelism)

Type inference needs some help!

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

Still sequential !

Optimization: maintaining parallelism

Computing an average value per key in parallel

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

- **Solution 3: 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)}
```

Transformation: compute in parallel and return a RDD

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

Action: at the end (just to print)

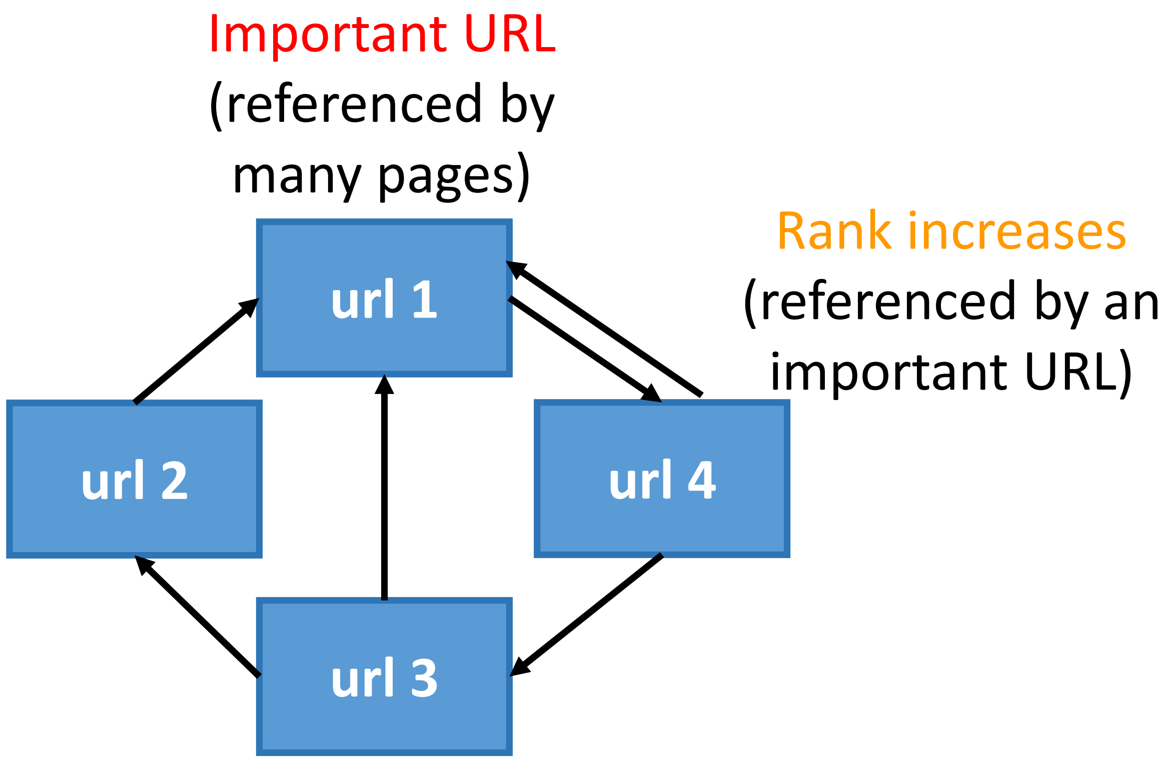
Spark optimizations

1. Wide and Narrow transformations
2. Optimizations
3. ***Page Rank* example**

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:

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

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*

  the probability a user *jumps* to a radom page is: 1-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:

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

Usually : *d* = 0.85

Sum of all PR is N_{pages}

PageRank with Spark

PageRank first step in Spark (Scala)

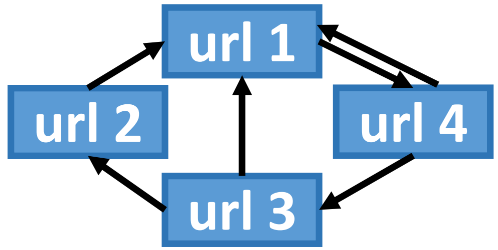
```
// read text file into Dataset[String] -> RDD1
val lines = spark.read.textFile(args(0)).rdd

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)
```

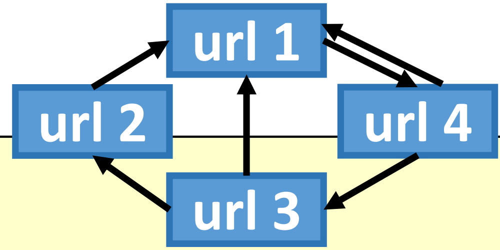
links RDD

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

ranks RDD

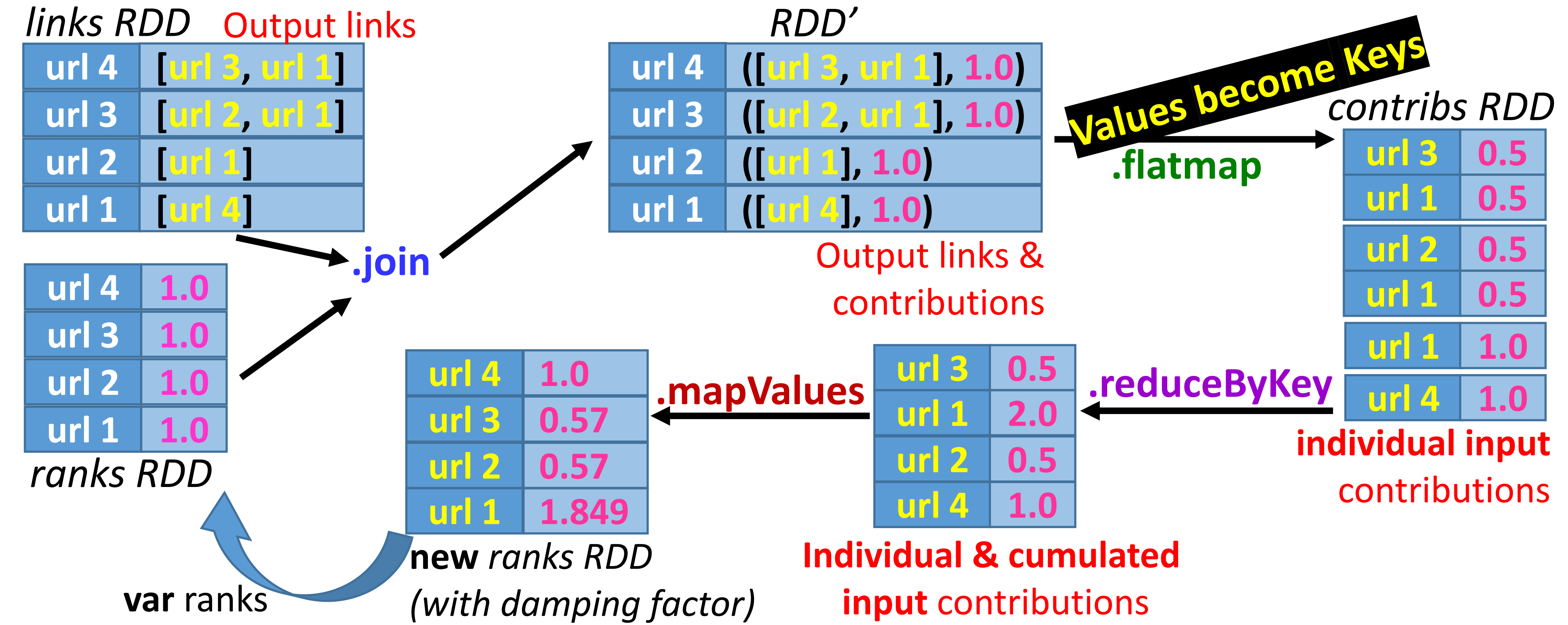
url 4	1.0
url 3	1.0
url 2	1.0
url 1	1.0

PageRank with Spark



PageRank third step in Spark (Scala)

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



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)
       .flatMap{ case (url (urlLinks, rank)) =>
                 urlLinks.map(dest => (dest,rank/urlLinks.size))}
  ranks = contribs.reduceByKey(_ + _).mapValues(0.15 + 0.85 * _)
}
```

PageRank with Spark

PageRank third step in Spark (Scala): optimized with partitioner

```
Val links = ......       // previous code
val links1 = links.partitionBy(new HashPartitioner(100)).persist()

var ranks = links1.mapValues(v => 1.0)

for (i <- 1 to iters) {
  val contribs =
       links1.join(ranks)
       .flatMap{ case (url (urlLinks, rank)) =>
                 urlLinks.map(dest => (dest,rank/urlLinks.size))}
  ranks = contribs.reduceByKey(_ + _).mapValues(0.15 + 0.85 * _)
}
```

- Initial **`links`** and **`ranks`** are co-partitioned
- Repeated **`join`** is Narrow-Wide
- Repeated **`mapValues`** is Narrow: respects the **`reduceByKey`** partitioning
- Pb: flatMap{…urlinks.map(…)} can change the partitionning ?!

Spark optimizations