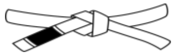
Spark Operations =

TRANSFORMATIONS

+

ACTIONS

 = easy  = medium

Essential Core & Intermediate Spark Operations

TRANSFORMATIONS

General

- map
- filter
- flatMap
- mapPartitions
- mapPartitionsWithIndex
- groupBy
- sortBy

Math / Statistical

- sample
- randomSplit

Set Theory / Relational

- union
- intersection
- subtract
- distinct
- cartesian
- zip

Data Structure / I/O

- keyBy
- zipWithIndex
- zipWithUniqueID
- zipPartitions
- coalesce
- repartition
- repartitionAndSortWithinPartitions
- pipe

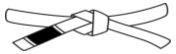
ACTIONS

- reduce
- collect
- aggregate
- fold
- first
- take
- forEach
- top
- treeAggregate
- treeReduce
- forEachPartition
- collectAsMap

- count
- takeSample
- max
- min
- sum
- histogram
- mean
- variance
- stdev
- sampleVariance
- countApprox
- countApproxDistinct

- takeOrdered

- saveAsTextFile
- saveAsSequenceFile
- saveAsObjectFile
- saveAsHadoopDataset
- saveAsHadoopFile
- saveAsNewAPIHadoopDataset
- saveAsNewAPIHadoopFile

 = easy  = medium

Essential Core & Intermediate PairRDD Operations

TRANSFORMATIONS

General

- flatMapValues
- groupByKey
- reduceByKey
- reduceByKeyLocally
- foldByKey
- aggregateByKey
- sortByKey
- combineByKey

Math / Statistical

- sampleByKey

Set Theory / Relational

- cogroup (=groupWith)
- join
- subtractByKey
- fullOuterJoin
- leftOuterJoin
- rightOuterJoin

Data Structure

- partitionBy

ACTIONS

- keys
- values

- countByKey
- countByValue
- countByValueApprox
- countApproxDistinctByKey
- countApproxDistinctByKey
- countByKeyApprox
- sampleByKeyExact

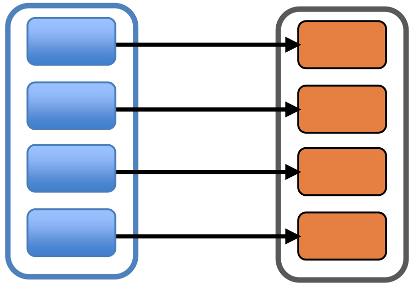
vs

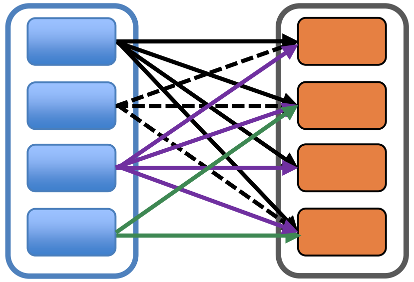
narrow

wide

each partition of the parent RDD is used by at most one partition of the child RDD

multiple child RDD partitions may depend on a single parent RDD partition





LINEAGE

Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing

Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauley, Michael J. Franklin, Scott Shenker, Ion Stoica

University of California, Berkeley

Abstract

"One of the challenges in providing RDDs as an abstraction is choosing a representation for them that can track lineage across a wide range of transformations."

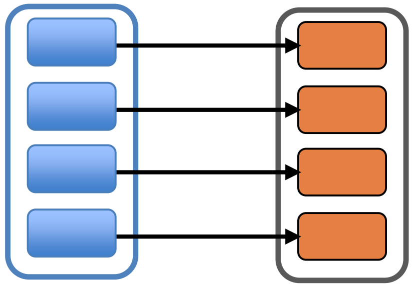
"The most interesting question in designing this interface is how to represent dependencies between RDDs."

"We found it both sufficient and useful to classify dependencies into two types:

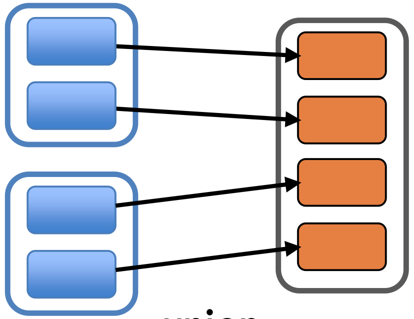
- narrow dependencies, where each partition of the parent RDD is used by at most one partition of the child RDD
- wide dependencies, where multiple child partitions may depend on it."

narrow

each partition of the parent RDD is used by at most one partition of the child RDD

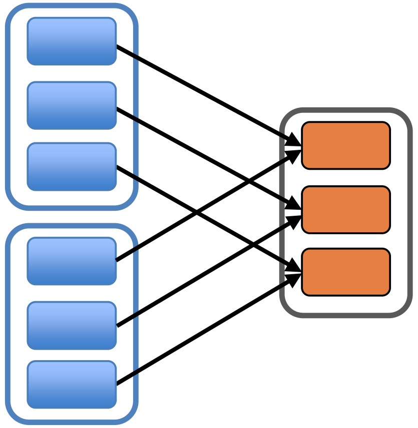


map, filter



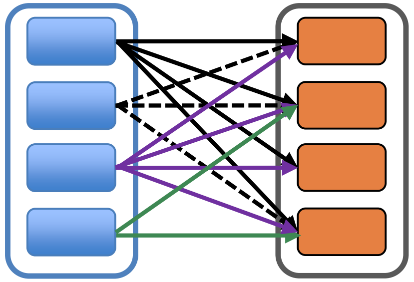
union

join w/ inputs co-partitioned

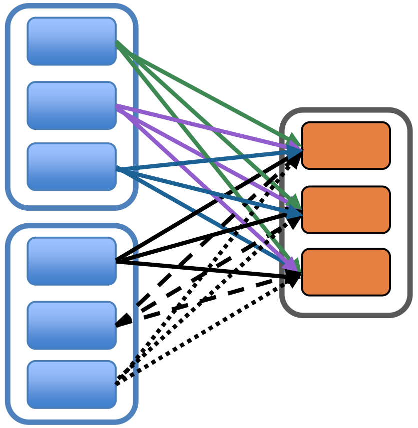


wide

multiple child RDD partitions may depend on a single parent RDD partition

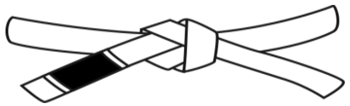


groupByKey



join w/ inputs not co-partitioned

TRANSFORMATIONS

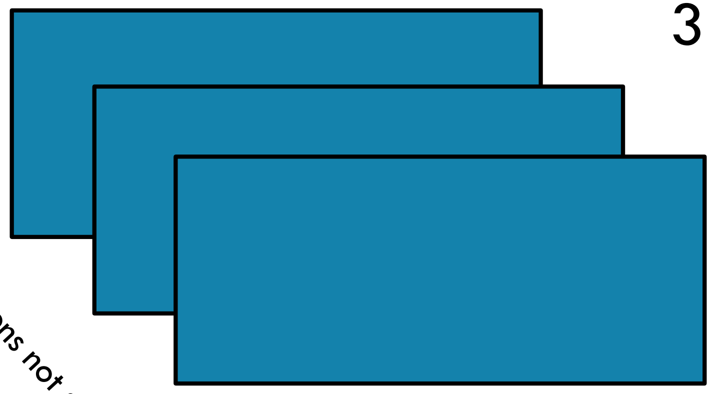


Core Operations

databricks™

MAP

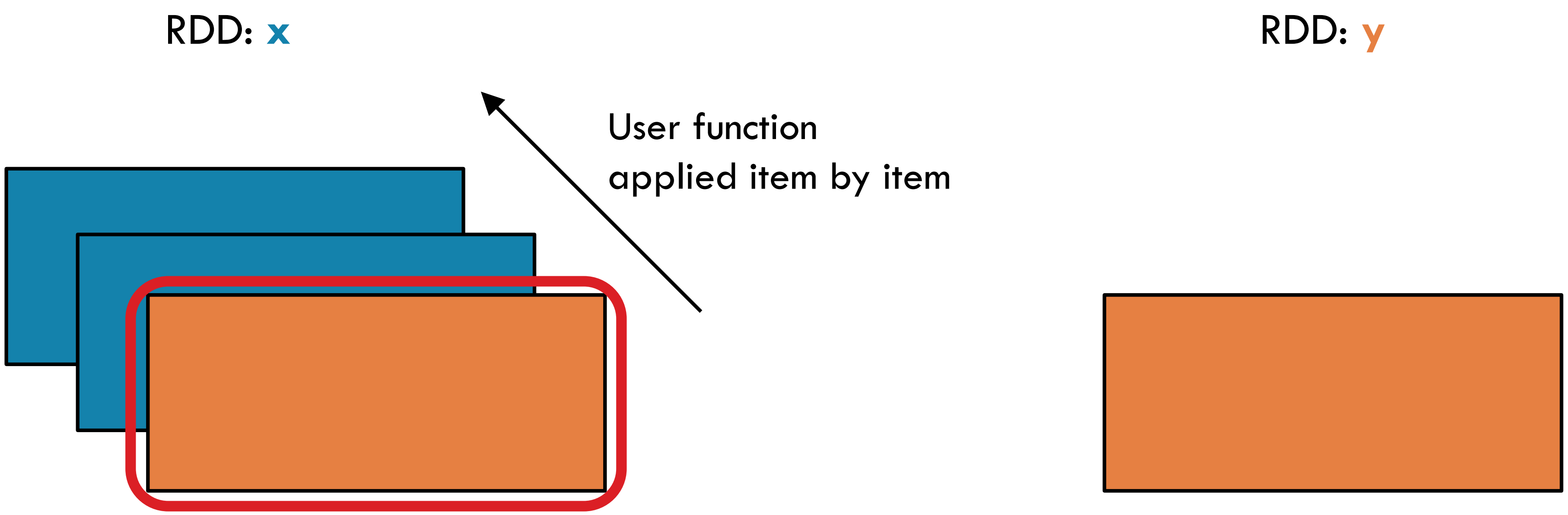
RDD: **x**



3 items in RDD

(partitions not shown)

MAP

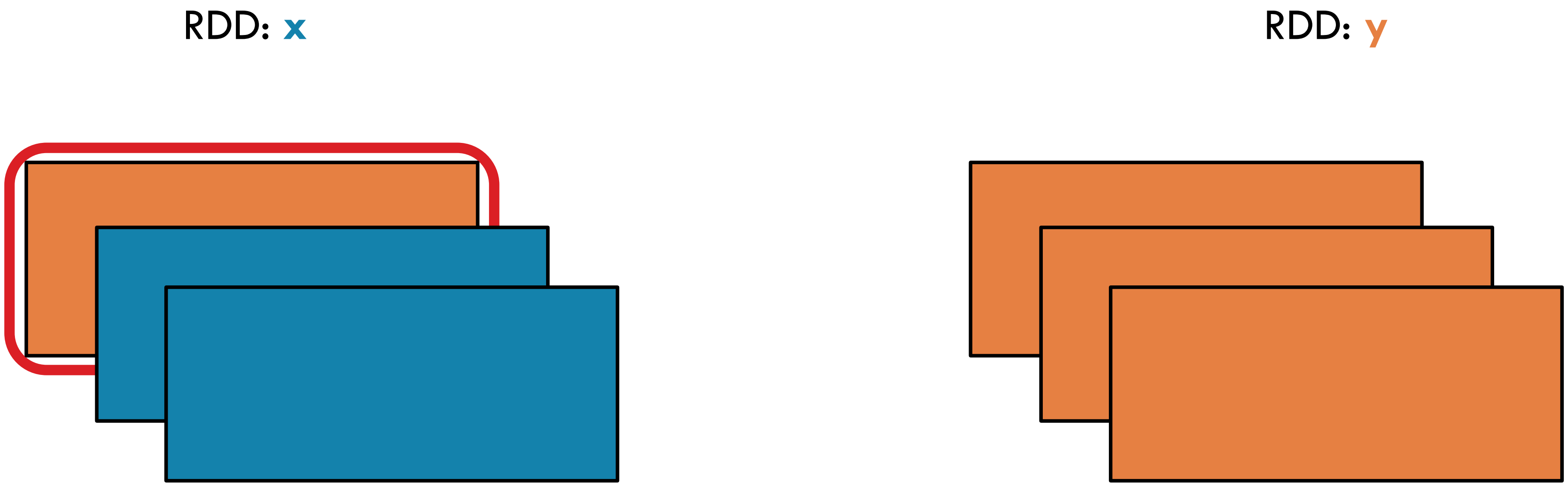


MAP

RDD: x

RDD: y

MAP

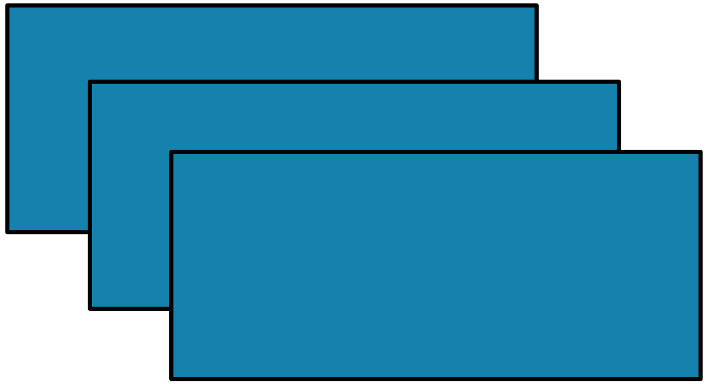


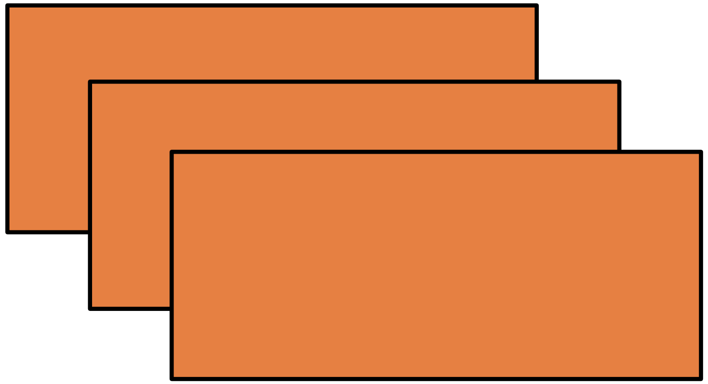
MAP

After map() has been applied…

RDD: x

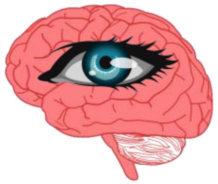
RDD: y



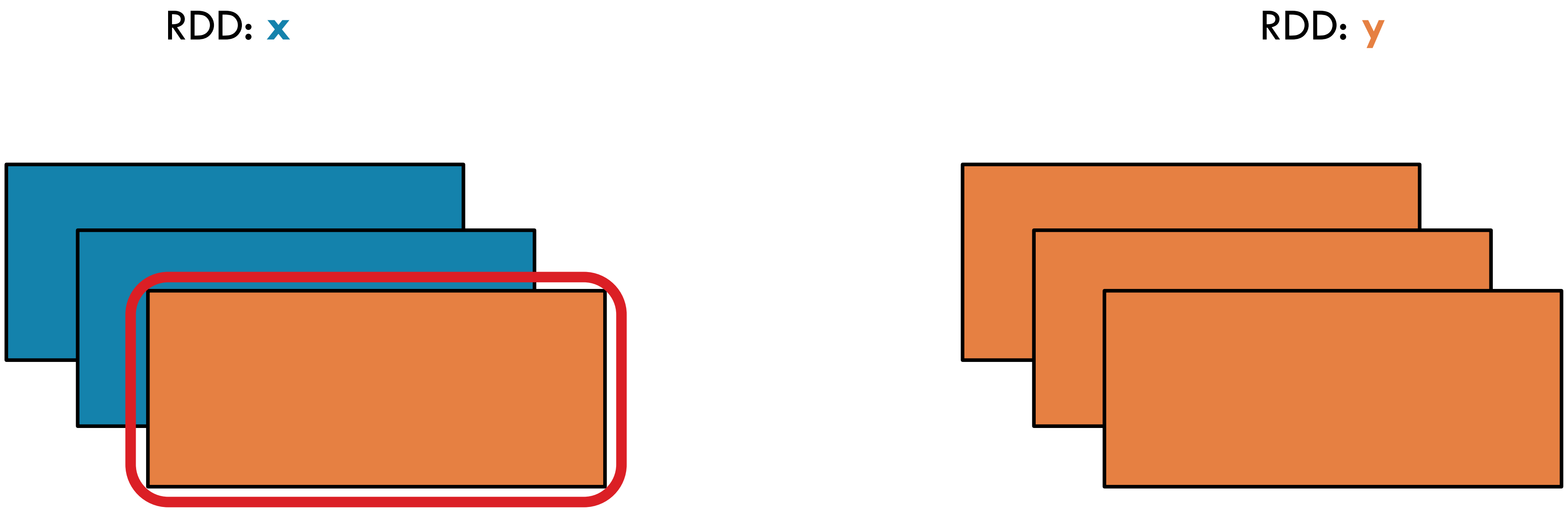


before

after

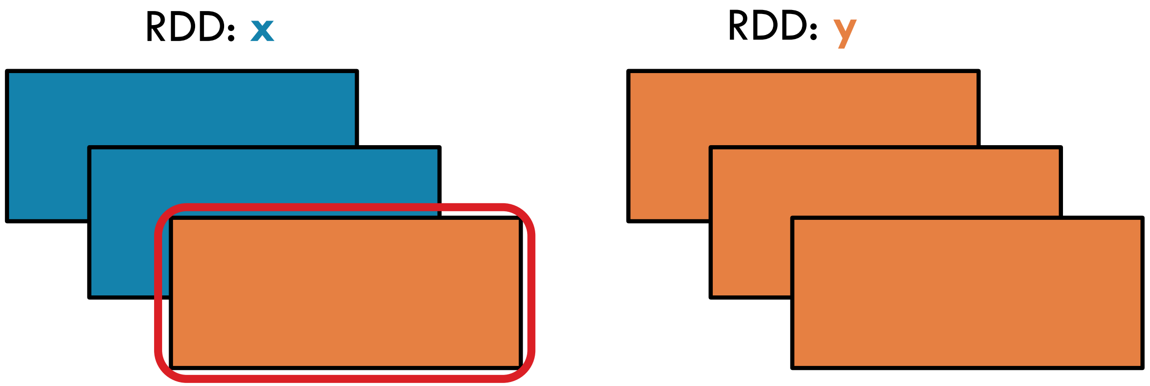


MAP



Return a new RDD by applying a function to each element of this RDD.

MAP



`map(f, preservesPartitioning=False)`

Return a new RDD by applying a function to each element of this RDD

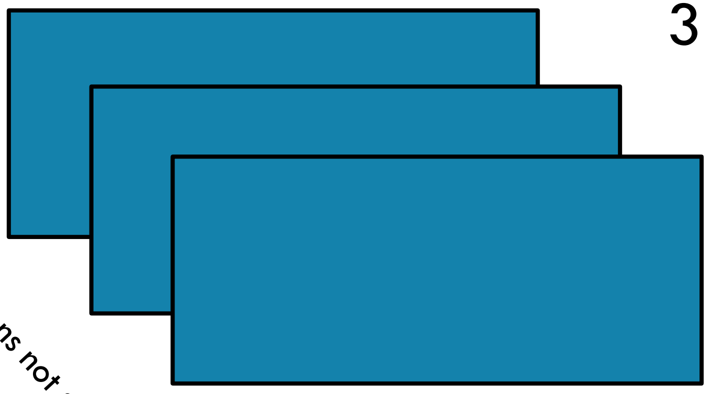
```python
x = sc.parallelize(["b", "a", "c"])
y = x.map(lambda z: (z, 1))
print(x.collect())
print(y.collect())
```

```scala
val x = sc.parallelize(Array("b", "a", "c"))
val y = x.map(z => (z,1))
println(x.collect().mkString(", "))
println(y.collect().mkString(", "))
```

```
x: ['b', 'a', 'c']

y: [('b', 1), ('a', 1), ('c', 1)]
```

FILTER

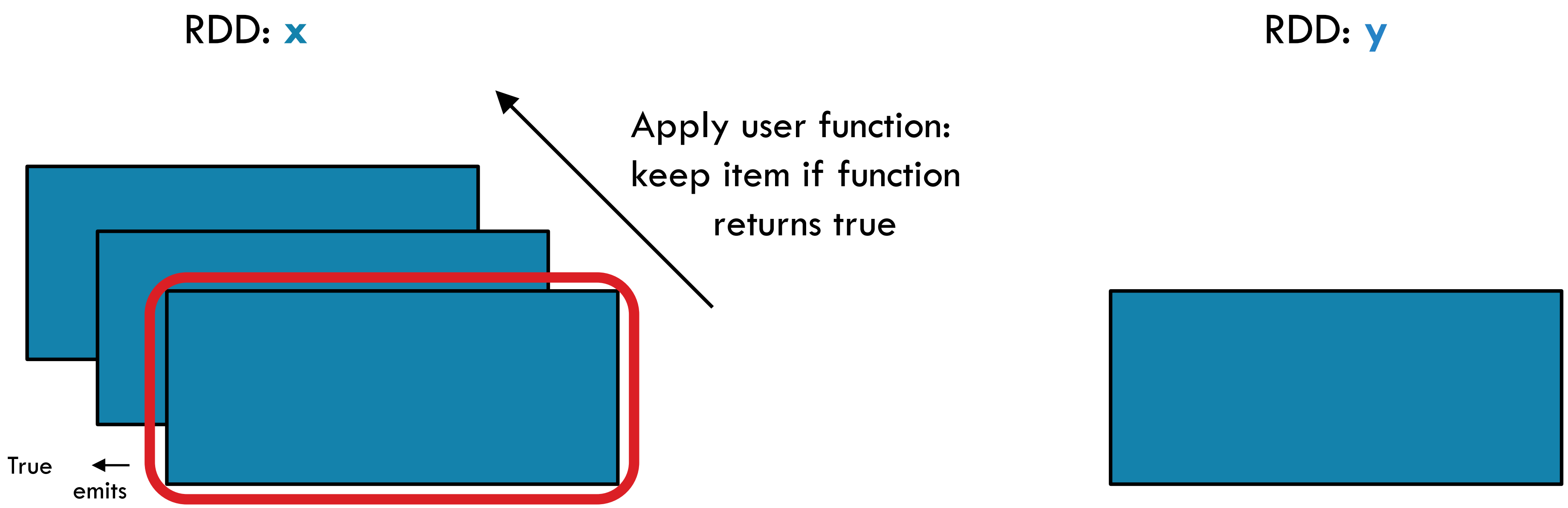
RDD: **x**



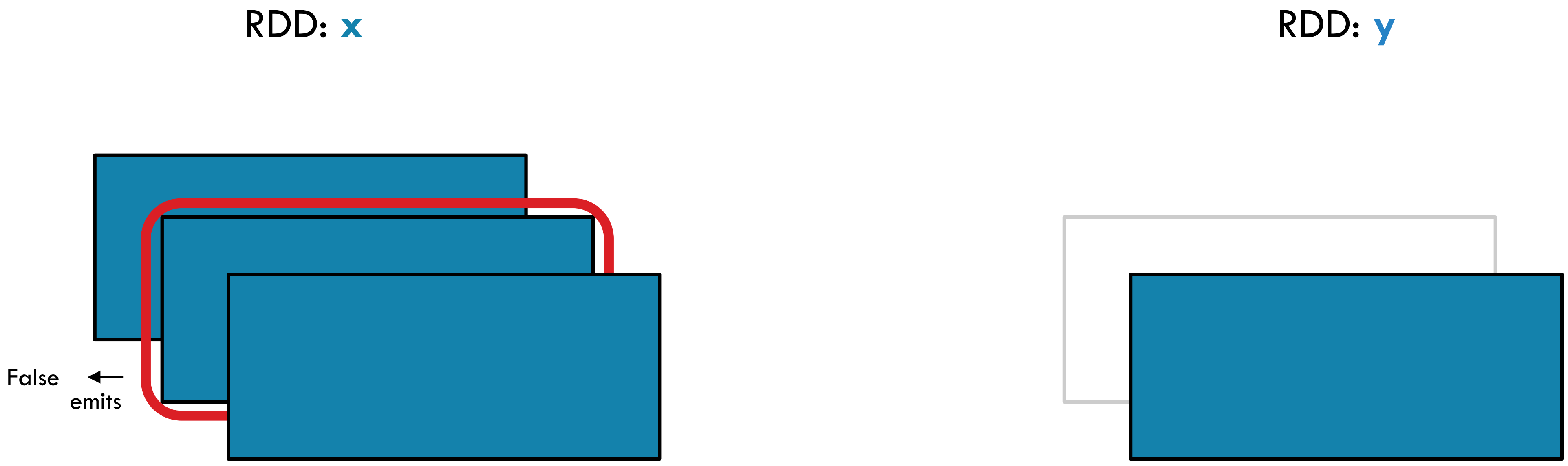
3 items in RDD

(partitions not shown)

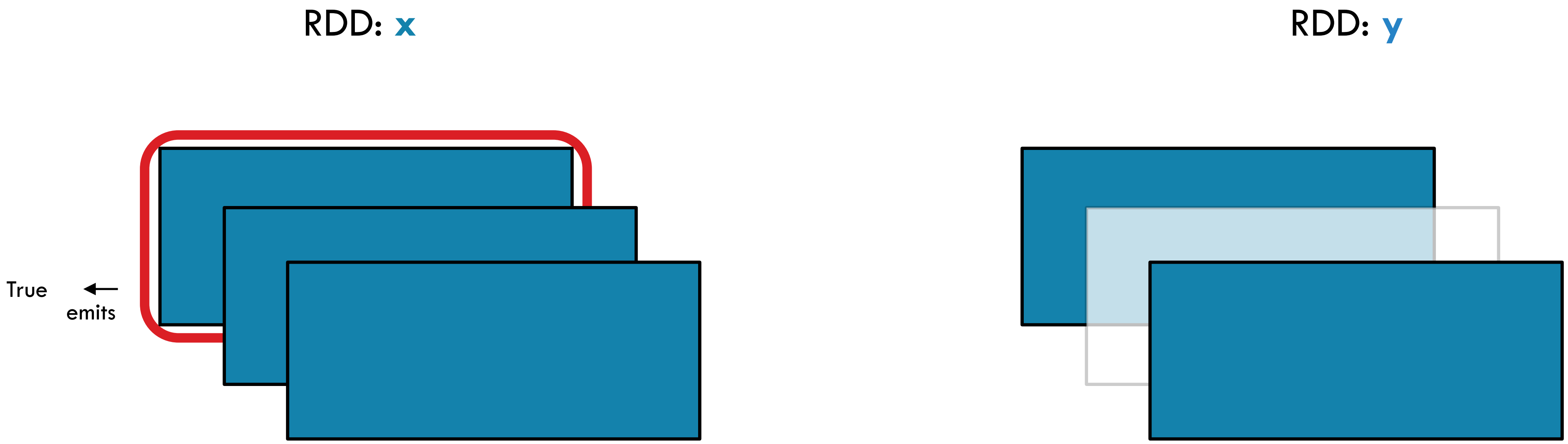
FILTER


RDD: x
RDD: y
Apply user function:
keep item if function
returns true
True
emits

FILTER



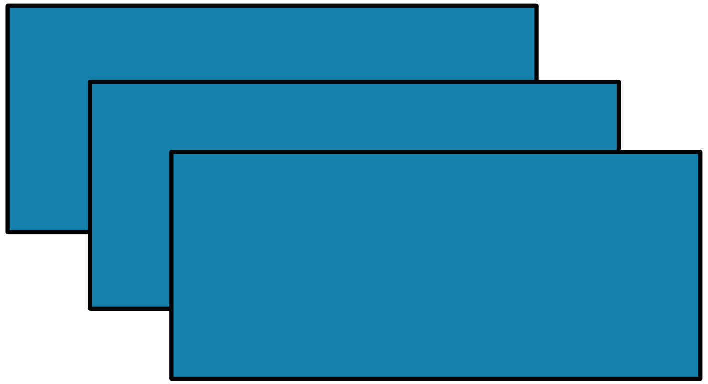
FILTER



FILTER

After `filter()` has been applied…

RDD: **x**

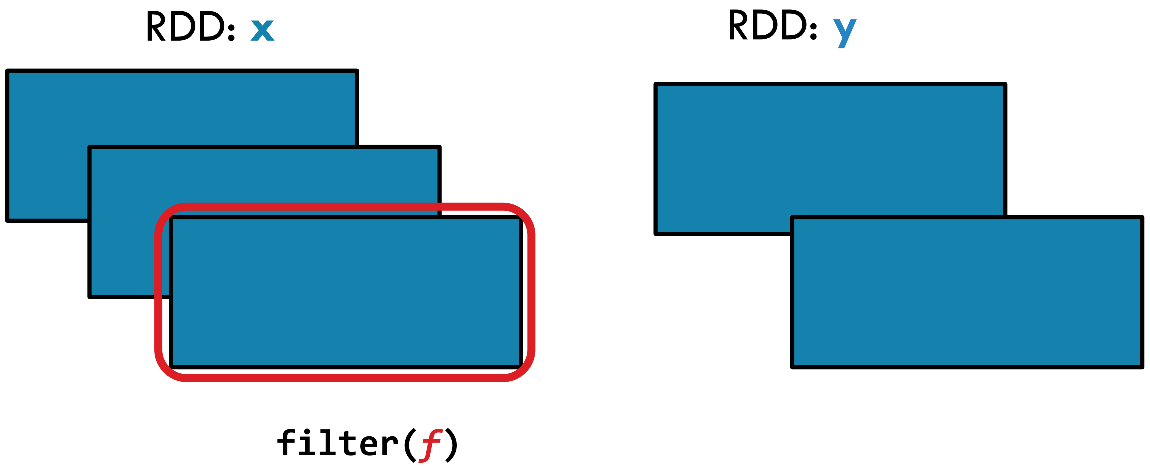


before

RDD: **y**

after

FILTER



Return a new RDD containing only the elements that satisfy a predicate

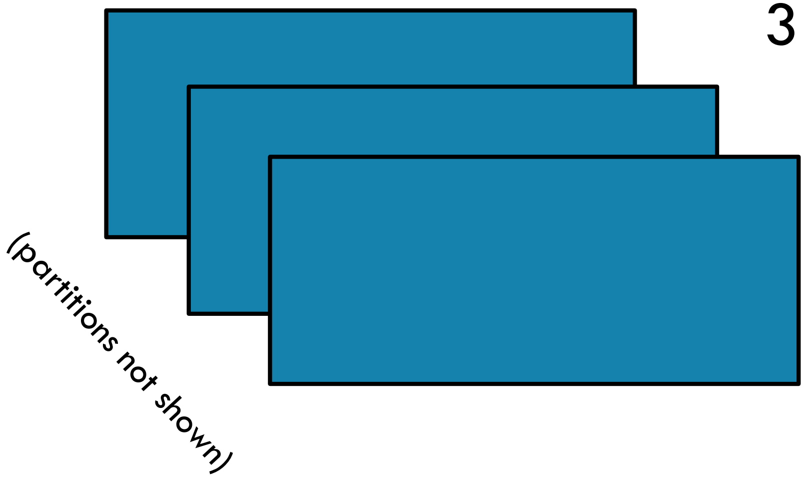
```python
x = sc.parallelize([1,2,3])
y = x.filter(lambda x: x%2 == 1) #keep odd values
print(x.collect())
print(y.collect())
```

```scala
val x = sc.parallelize(Array(1,2,3))
val y = x.filter(n => n%2 == 1)
println(x.collect().mkString(", "))
println(y.collect().mkString(", "))
```

```
x: [1, 2, 3]

y: [1, 3]
```

FLATMAP

RDD: **x**

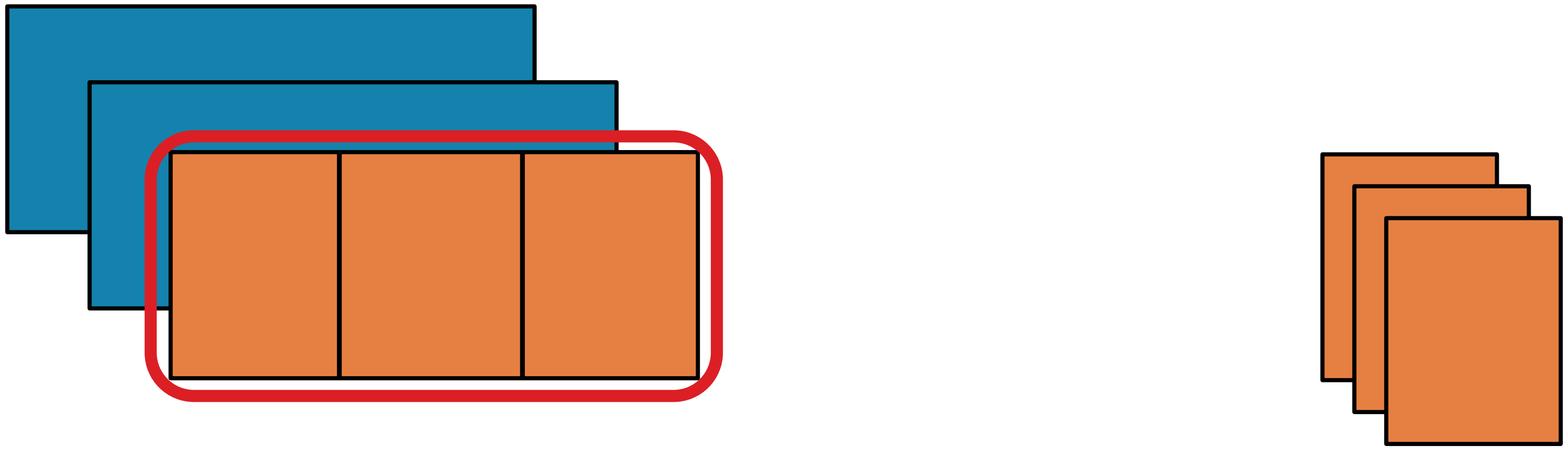


3 items in RDD

FLATMAP

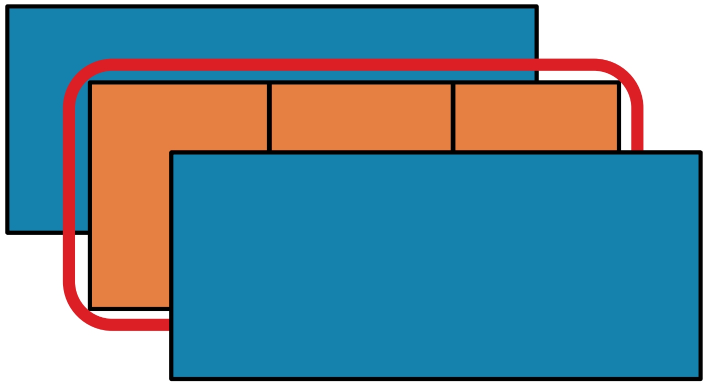
RDD: x

RDD: y

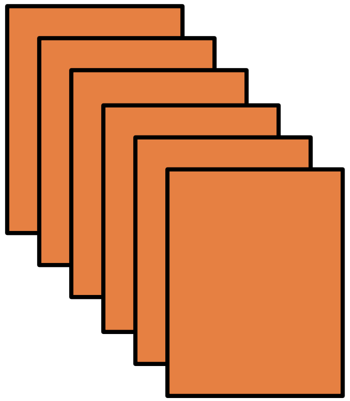


FLATMAP

RDD: x

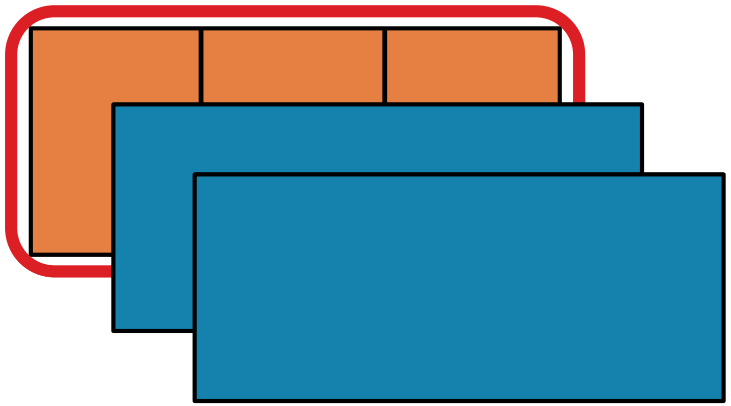


RDD: y

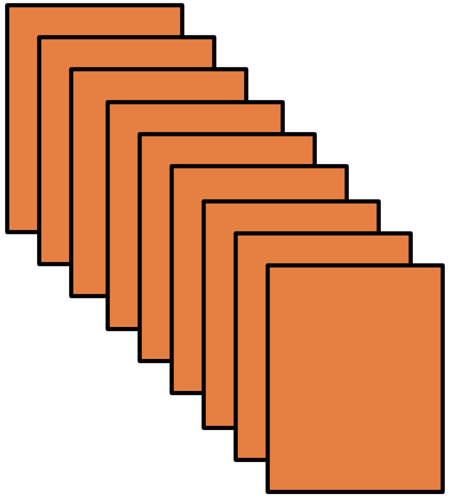


FLATMAP

RDD: x



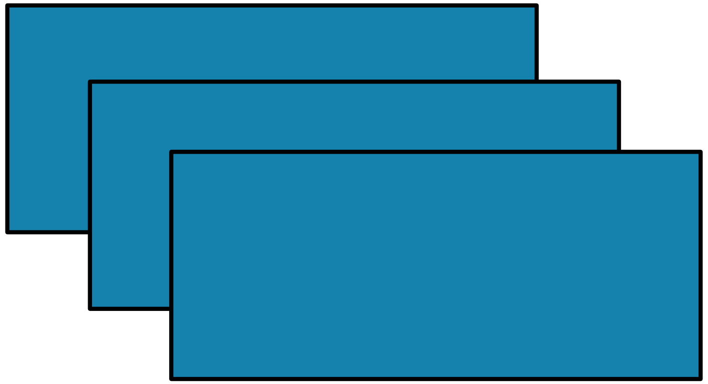
RDD: y



FLATMAP

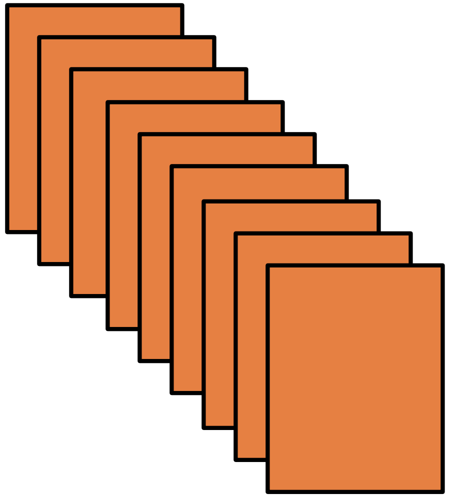
After `flatmap()` has been applied...

RDD: x



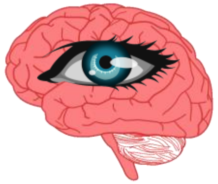
before

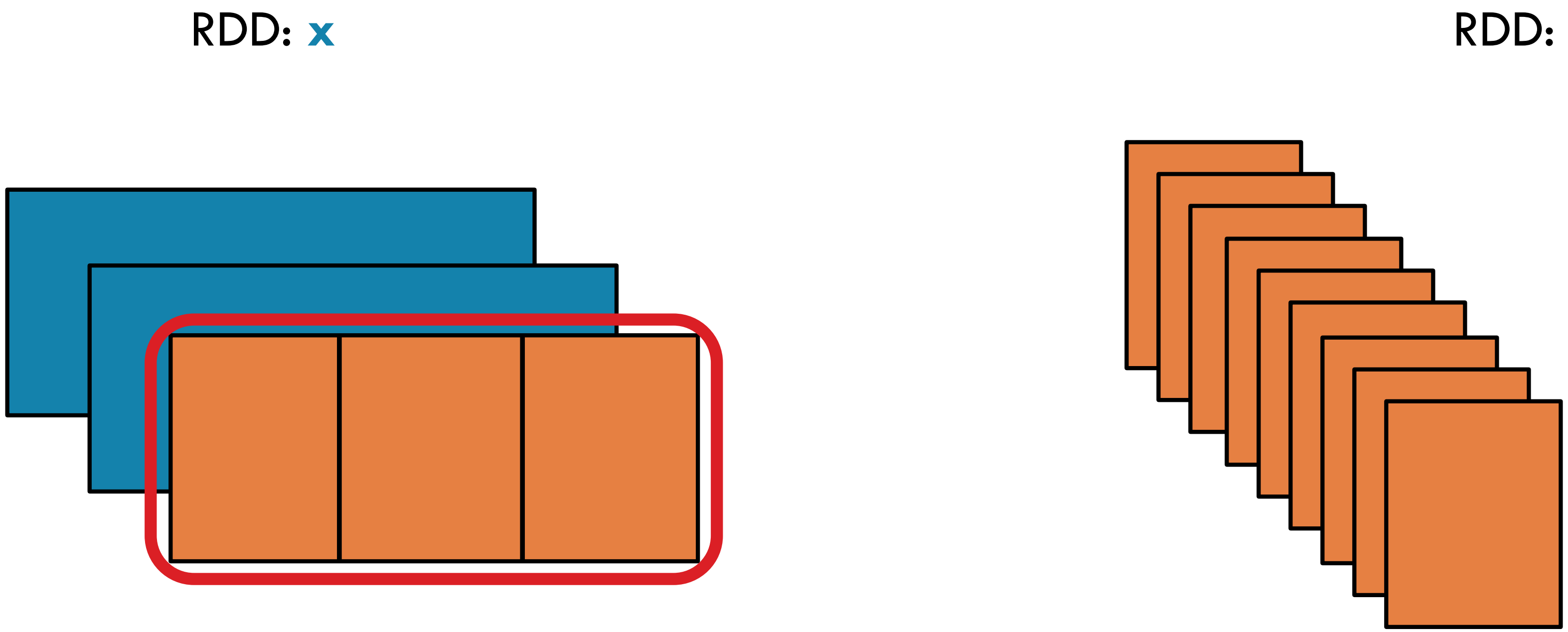
RDD: y



after

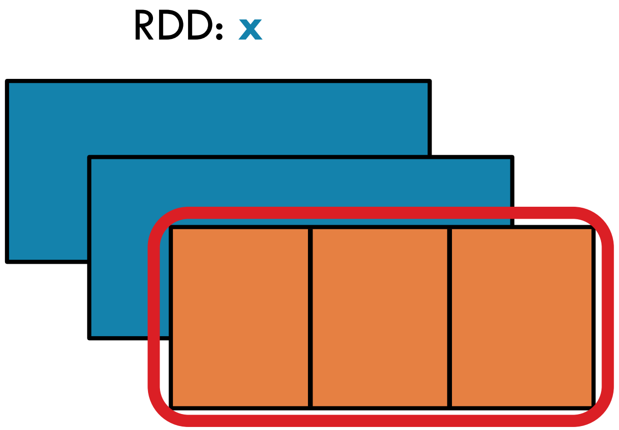
FLATMAP

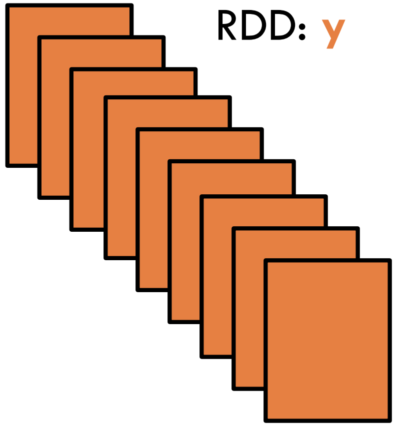




Return a new RDD by first applying a function to all elements of this RDD, and then flattening the results

FLATMAP





`flatMap(f, preservesPartitioning=False)`

Return a new RDD by first applying a function to all elements of this RDD, and then flattening the results

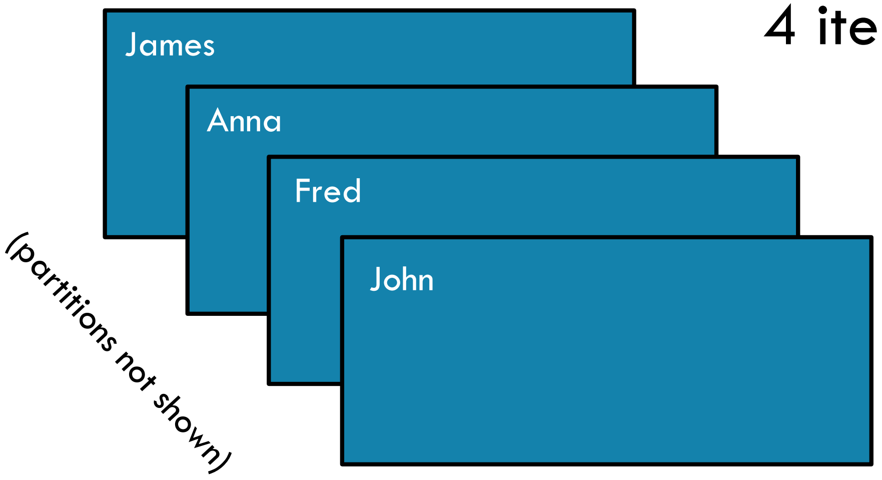
```python
x = sc.parallelize([1,2,3])
y = x.flatMap(lambda x: (x, x*100, 42))
print(x.collect())
print(y.collect())
```

```scala
val x = sc.parallelize(Array(1,2,3))
val y = x.flatMap(n => Array(n, n*100, 42))
println(x.collect().mkString(", "))
println(y.collect().mkString(", "))
```

```
x: [1, 2, 3]

y: [1, 100, 42, 2, 200, 42, 3, 300, 42]
```

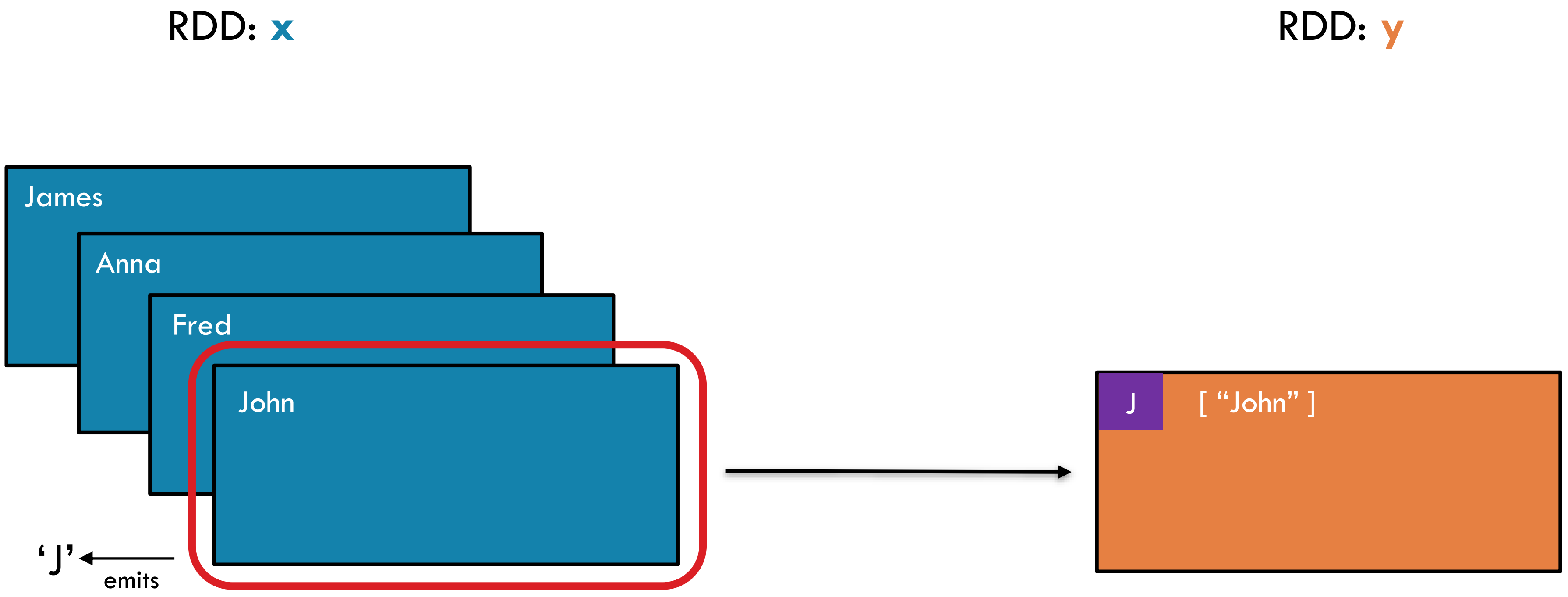
GROUPBY

RDD: x

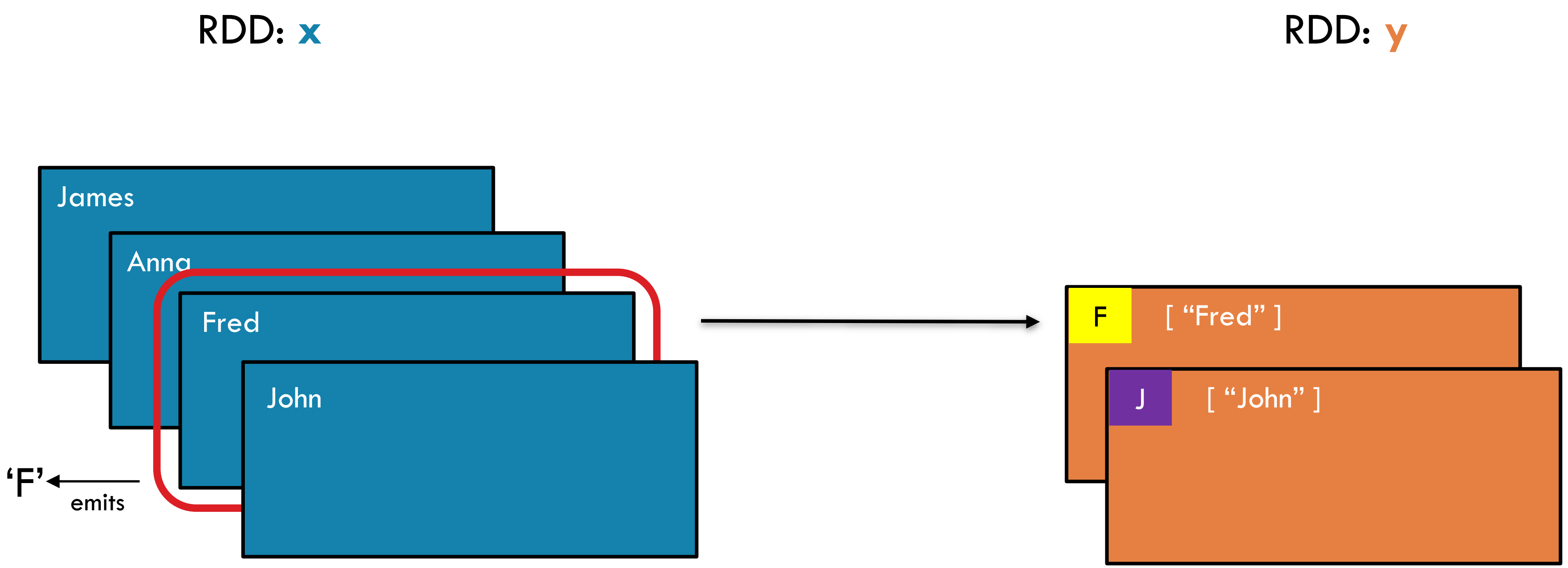


4 items in RDD

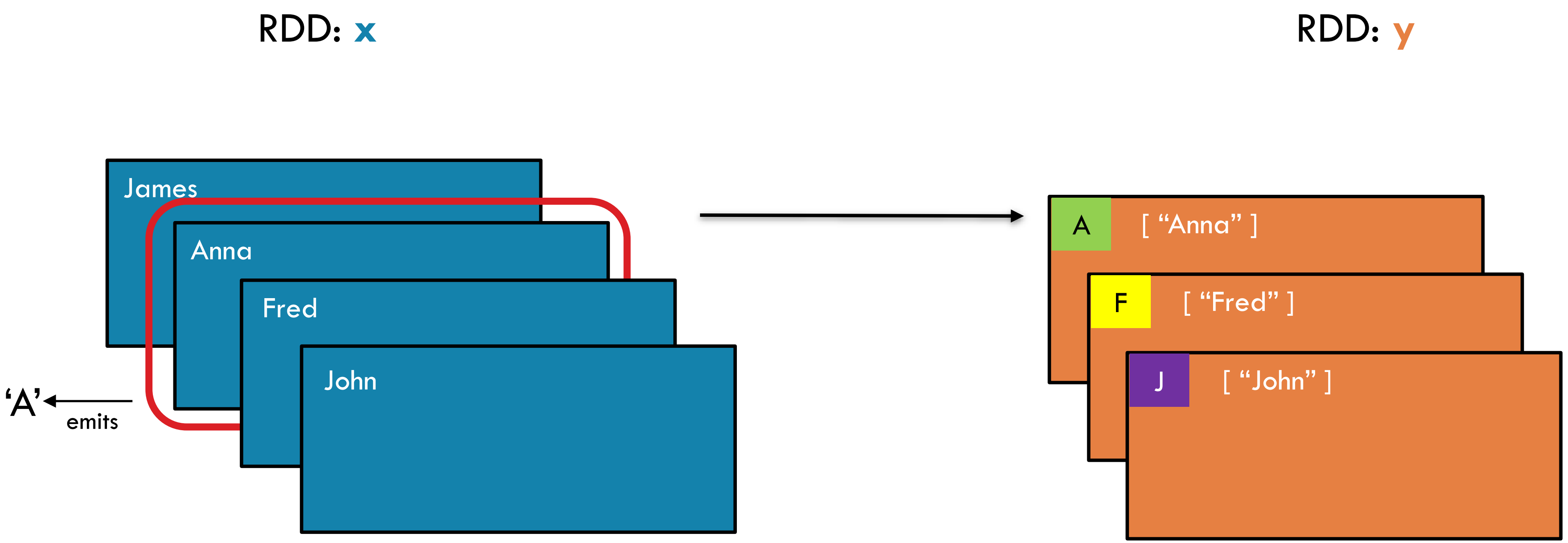
GROUPBY



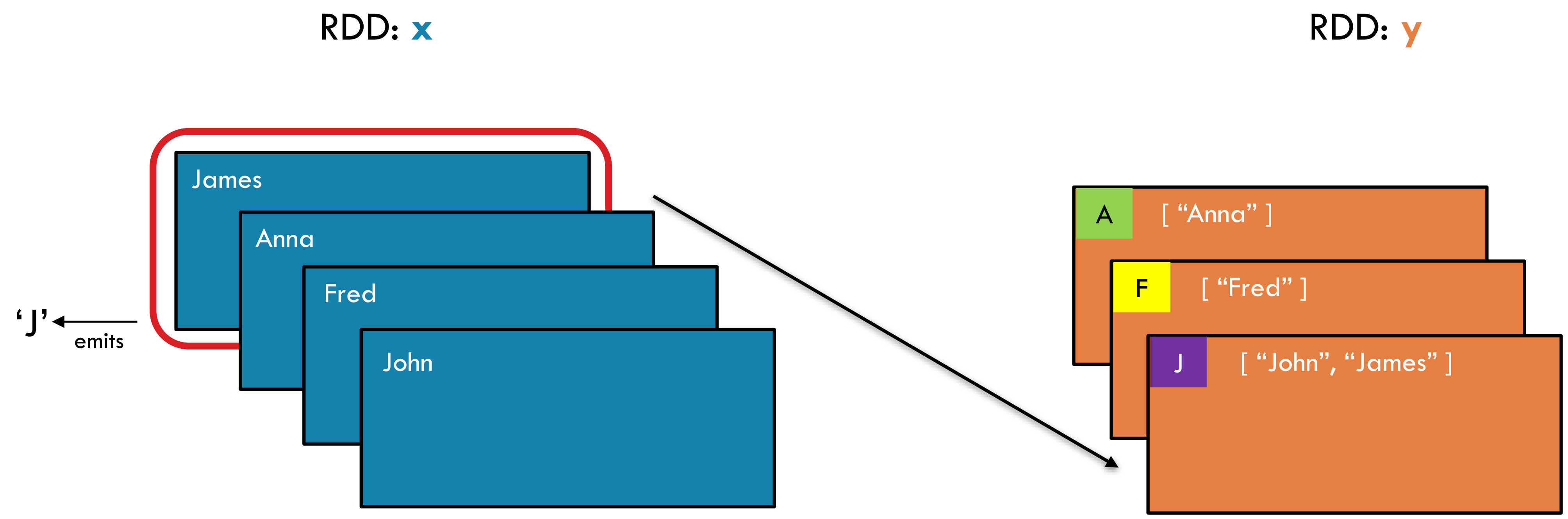
GROUPBY



GROUPBY



GROUPBY



RDD: x
RDD: y
James
Anna
Fred
John
'J'
emits
A
["Anna"]
F
["Fred"]
J
["John", "James"]

GROUPBY

RDD: x

RDD: y

groupBy(*f*, *numPartitions=None*)

Group the data in the original RDD. Create pairs where the key is the output of a user function, and the value is all items for which the function yields this key.

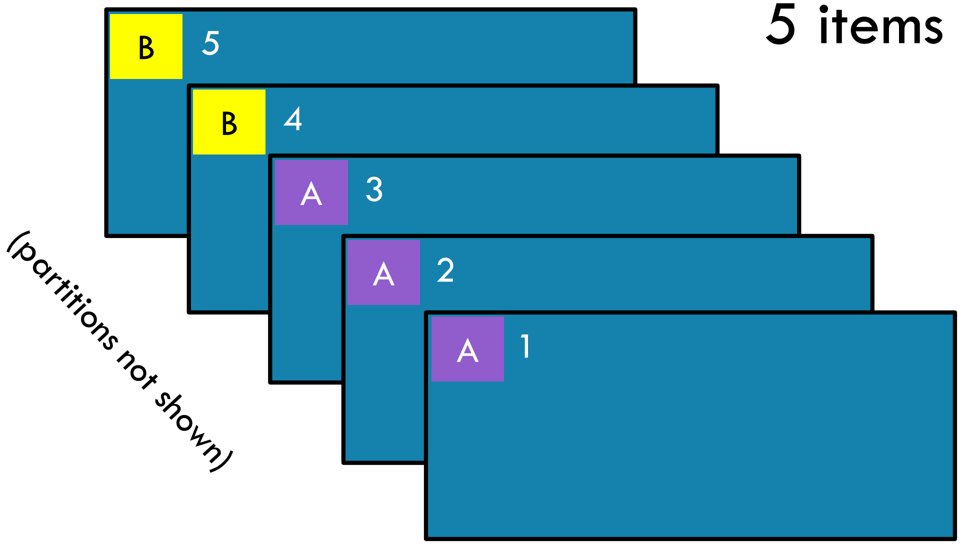
```
x = sc.parallelize(['John', 'Fred', 'Anna', 'James'])
y = x.groupBy(lambda w: w[0])
print [(k, list(v)) for (k, v) in y.collect()]
```

```
val x = sc.parallelize(
    Array("John", "Fred", "Anna", "James"))
val y = x.groupBy(w => w.charAt(0))
println(y.collect().mkString(", "))
```

```
x: ['John', 'Fred', 'Anna', 'James']

y: [('A',['Anna']),('J',['John','James']),('F',['Fred'])]
```

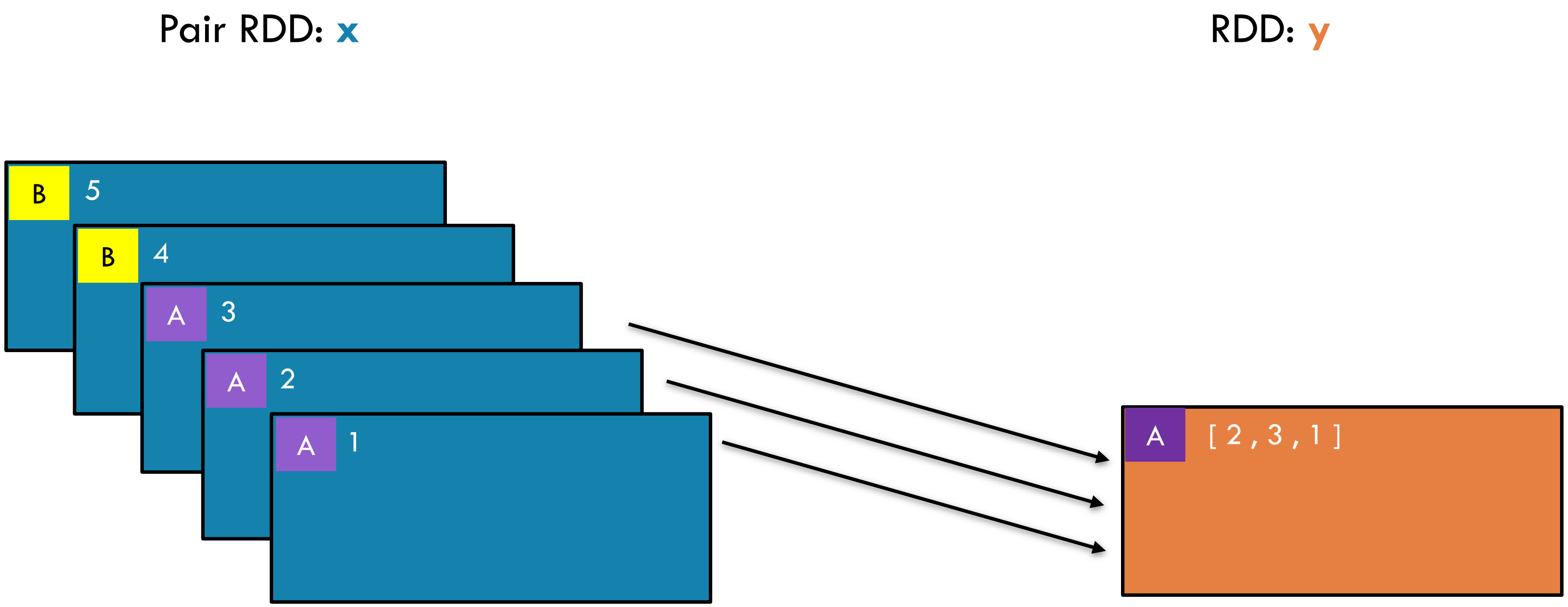
GROUPBYKEY

Pair RDD: **x**



5 items in RDD

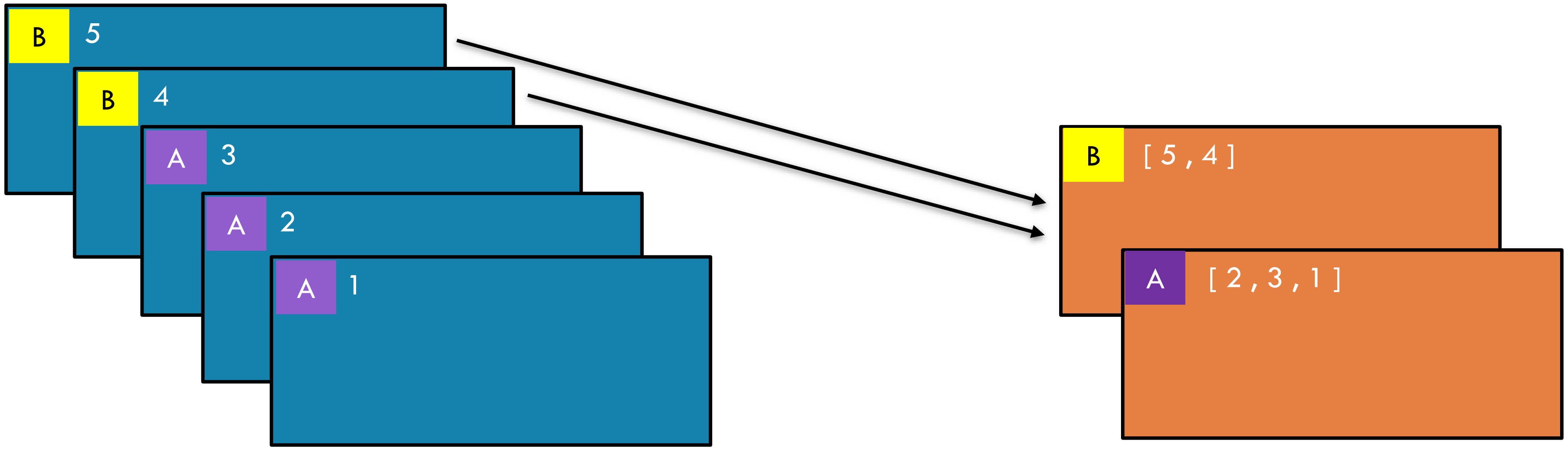
GROUPBYKEY



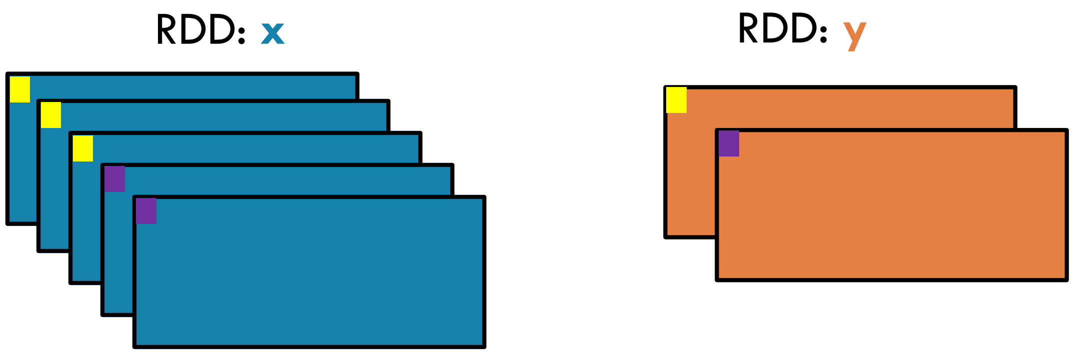
GROUPBYKEY

Pair RDD: x

RDD: y



GROUPBYKEY



groupByKey(*numPartitions=None*)

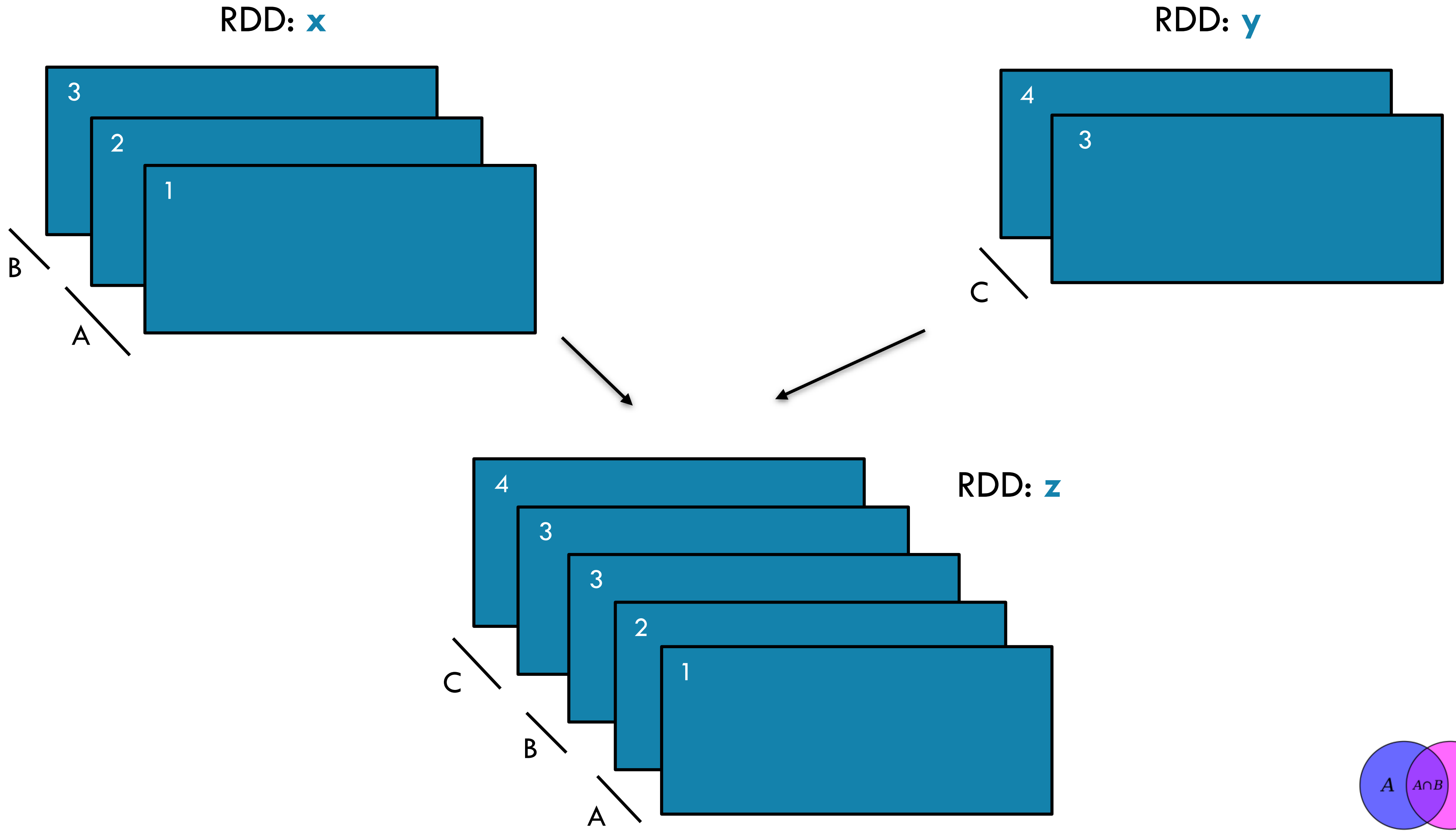
Group the values for each key in the original RDD. Create a new pair where the original key corresponds to this collected group of values.

```python
x = sc.parallelize([('B',5),('B',4),('A',3),('A',2),('A',1)])
y = x.groupByKey()
print(x.collect())
print(list((j[0], list(j[1])) for j in y.collect()))
```

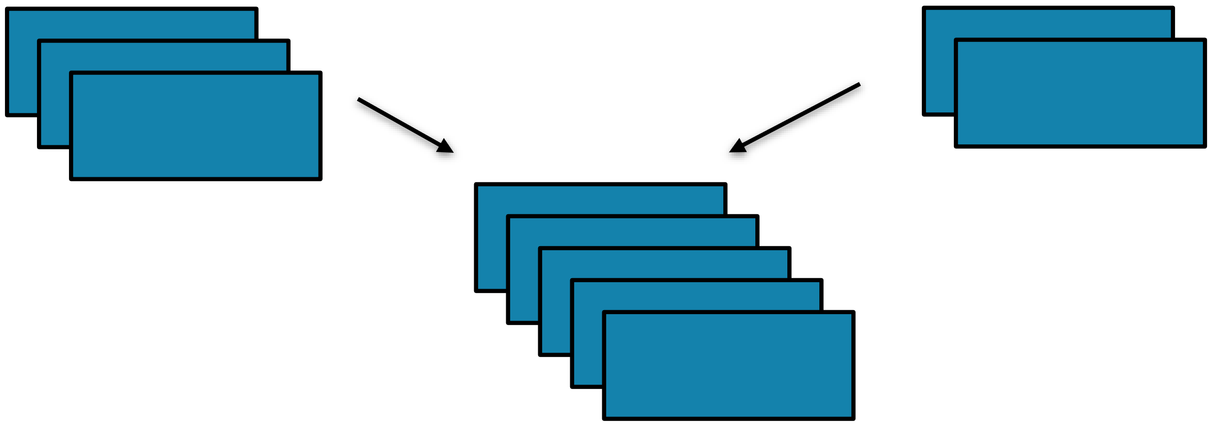
```
x: [('B', 5),('B', 4),('A', 3),('A', 2),('A', 1)]

y: [('A', [2, 3, 1]),('B',[5, 4])]
```

```scala
val x = sc.parallelize(
        Array(('B',5),('B',4),('A',3),('A',2),('A',1)))
val y = x.groupByKey()
println(x.collect().mkString(", "))
println(y.collect().mkString(", "))
```

UNION



UNION



Return a new RDD containing all items from two original RDDs. Duplicates are *not* culled.

`union(otherRDD)`

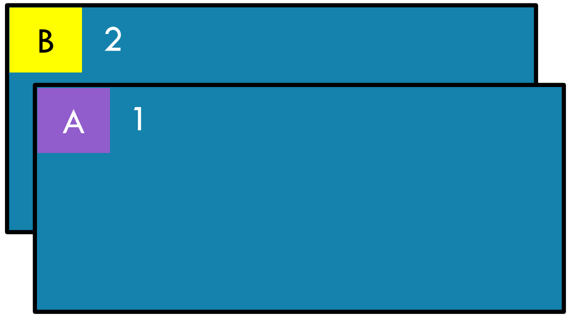
```python
x = sc.parallelize([1,2,3], 2)
y = sc.parallelize([3,4], 1)
z = x.union(y)
print(z.glom().collect())
```

```scala
val x = sc.parallelize(Array(1,2,3), 2)
val y = sc.parallelize(Array(3,4), 1)
val z = x.union(y)
val zOut = z.glom().collect()
```

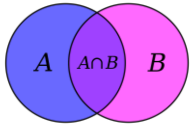
```
x: [1, 2, 3]

y: [3, 4]

z: [[1], [2, 3], [3, 4]]
```

JOIN

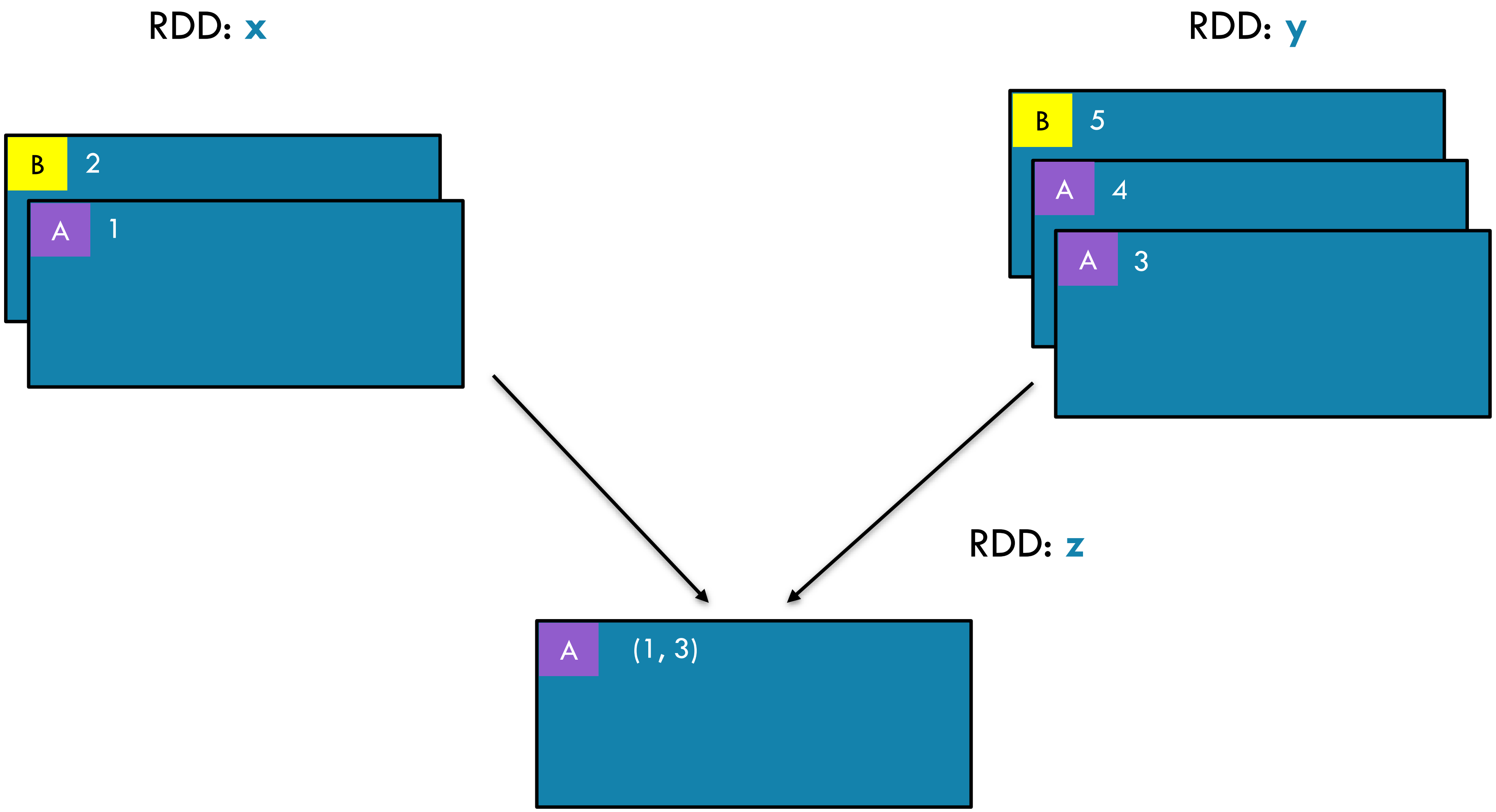
RDD: x



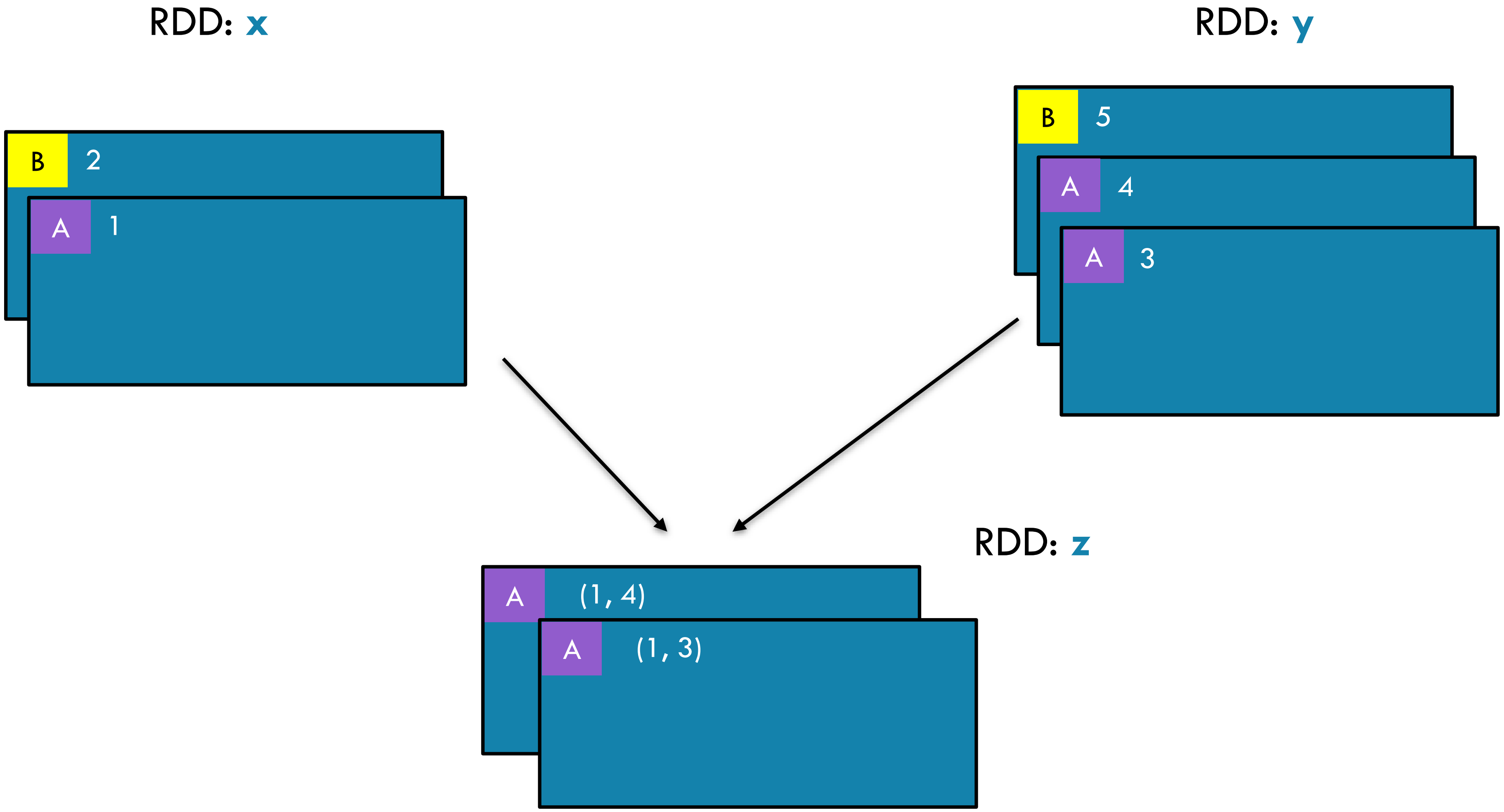
RDD: y

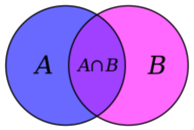


JOIN

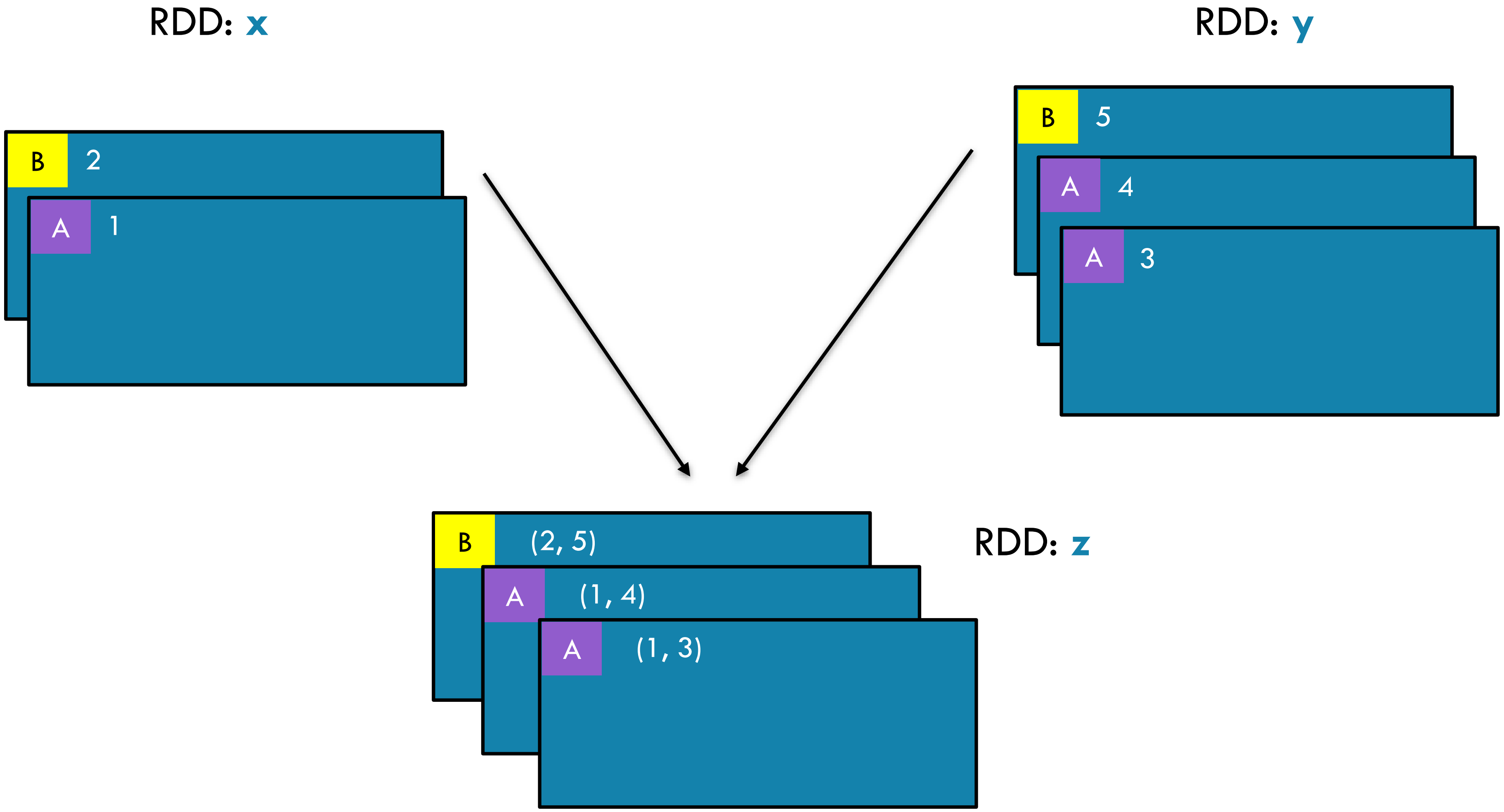


JOIN

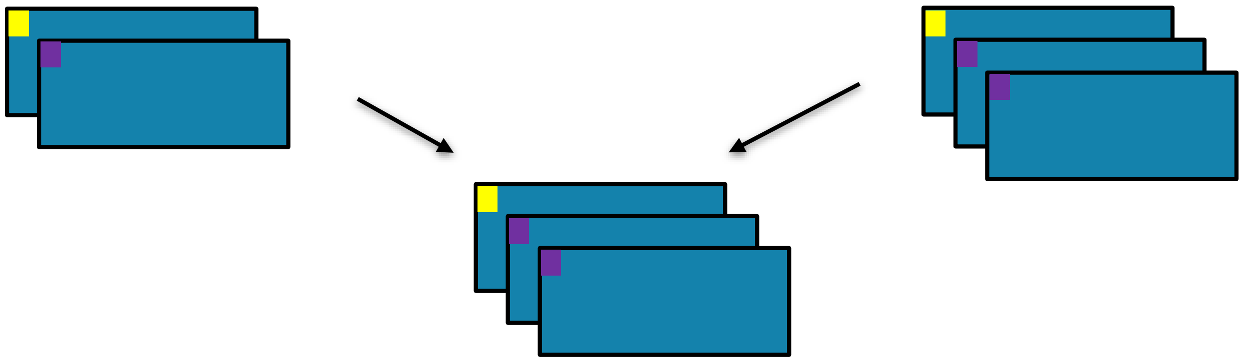




JOIN



JOIN



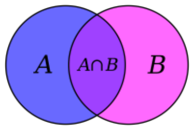
Return a new RDD containing all pairs of elements having the same key in the original RDDs

`union(otherRDD, numPartitions=None)`

```python
x = sc.parallelize([("a", 1), ("b", 2)])
y = sc.parallelize([("a", 3), ("a", 4), ("b", 5)])
z = x.join(y)
print(z.collect())
```

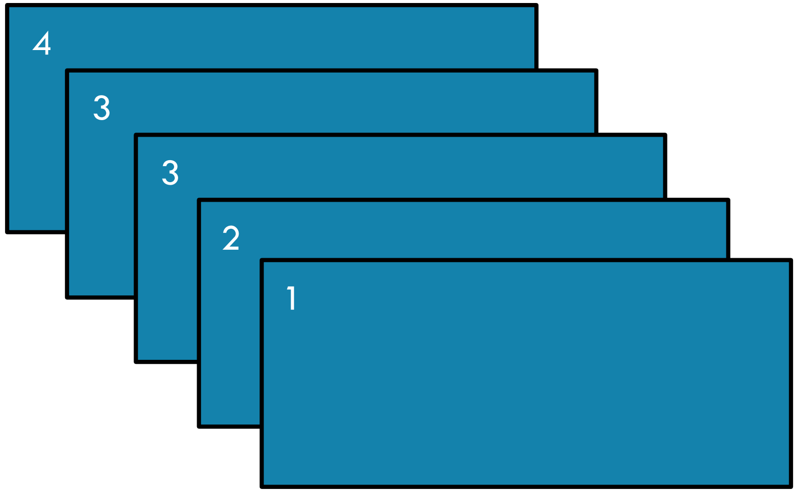
```scala
val x = sc.parallelize(Array(("a", 1), ("b", 2)))
val y = sc.parallelize(Array(("a", 3), ("a", 4), ("b", 5)))
val z = x.join(y)
println(z.collect().mkString(", "))
```

```
x: [("a", 1), ("b", 2)]

y: [("a", 3), ("a", 4), ("b", 5)]

z: [('a', (1, 3)), ('a', (1, 4)), ('b', (2, 5))]
```

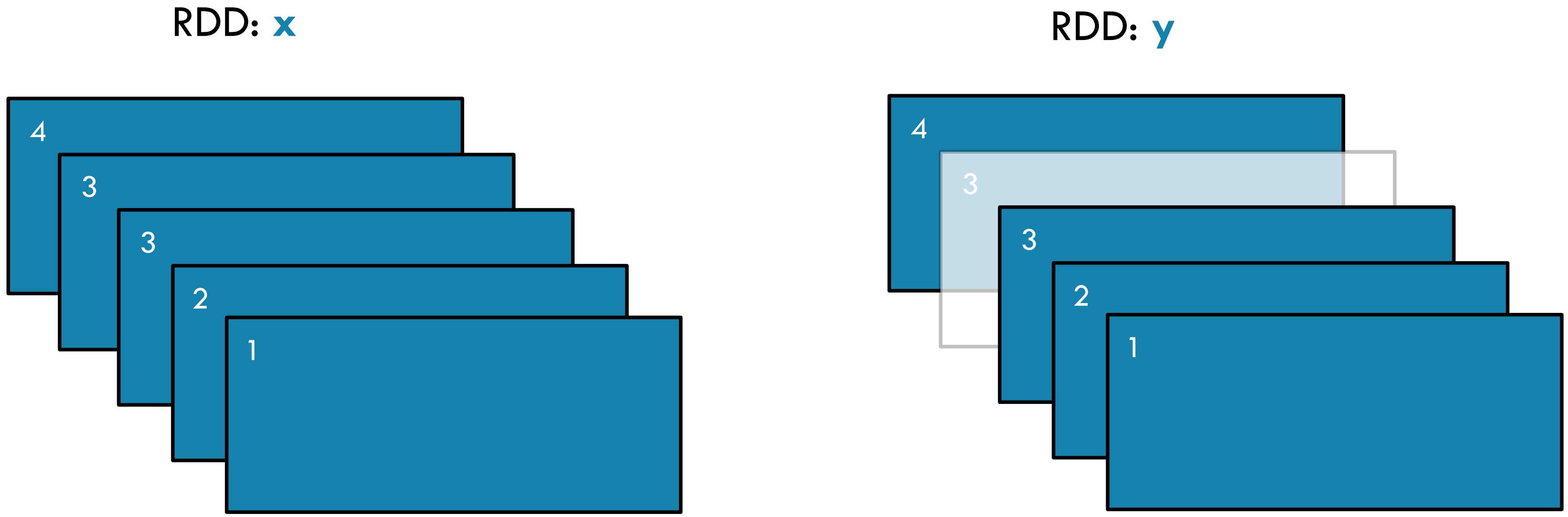


DISTINCT

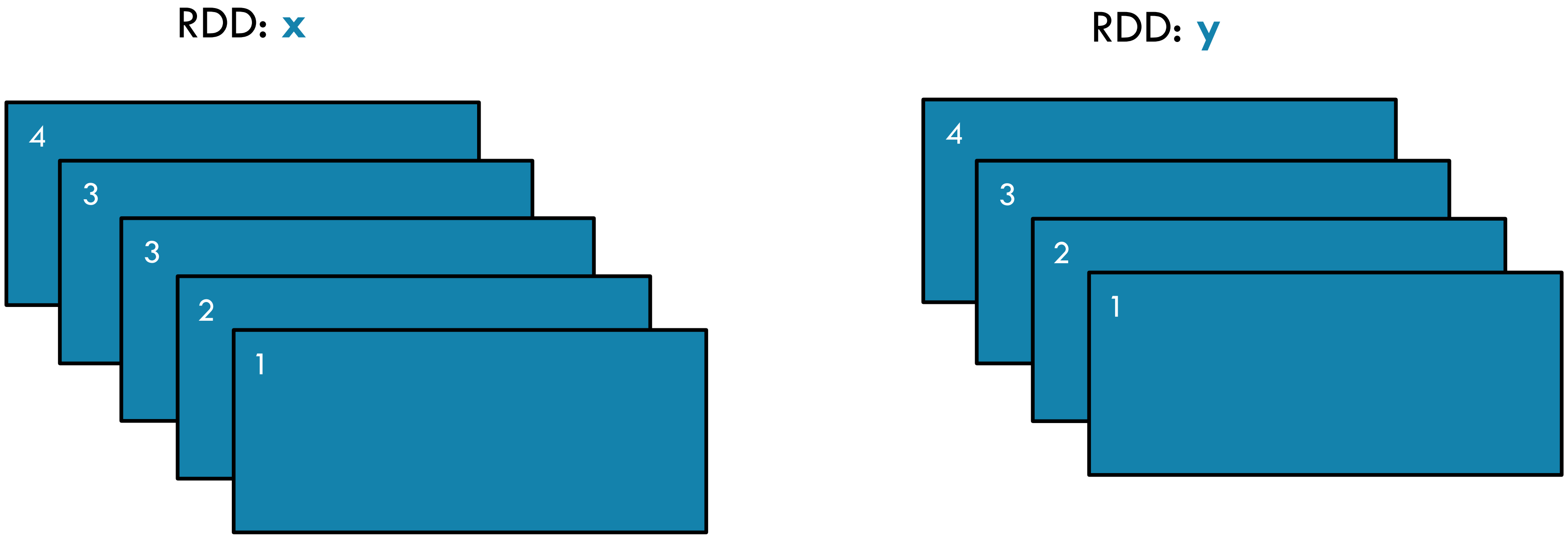
RDD: **x**



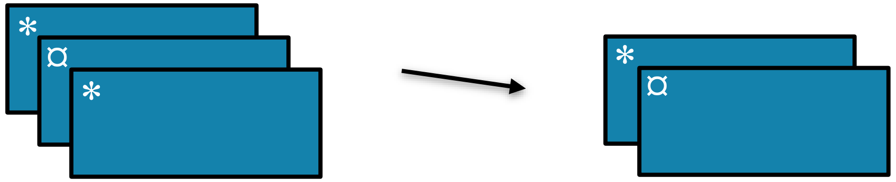
DISTINCT



DISTINCT



DISTINCT



Return a new RDD containing distinct items from the original RDD (omitting all duplicates)

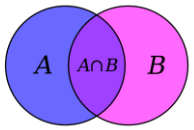
distinct(*numPartitions=None*)

```python
x = sc.parallelize([1,2,3,3,4])
y = x.distinct()

print(y.collect())
```

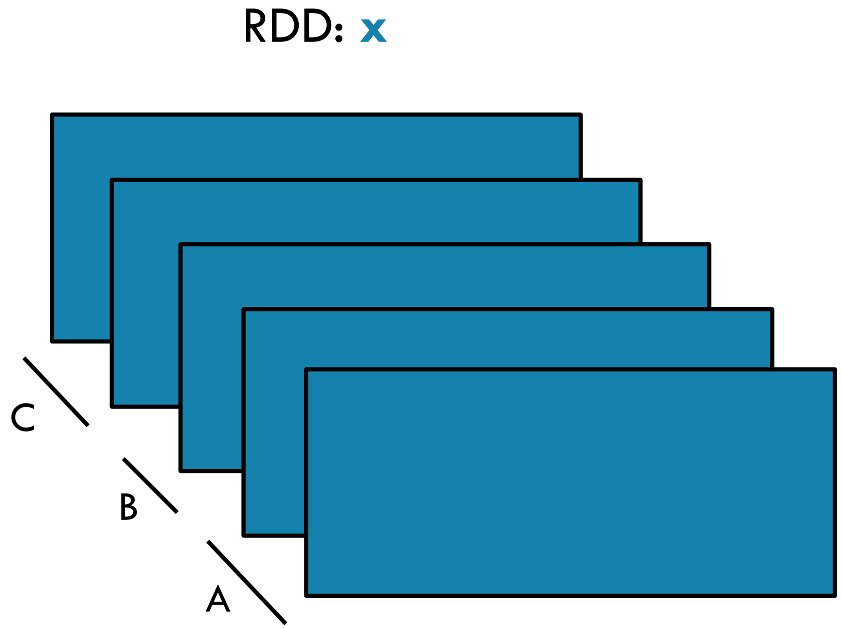
```scala
val x = sc.parallelize(Array(1,2,3,3,4))
val y = x.distinct()

println(y.collect().mkString(", "))
```

x: [1, 2, 3, 3, 4]

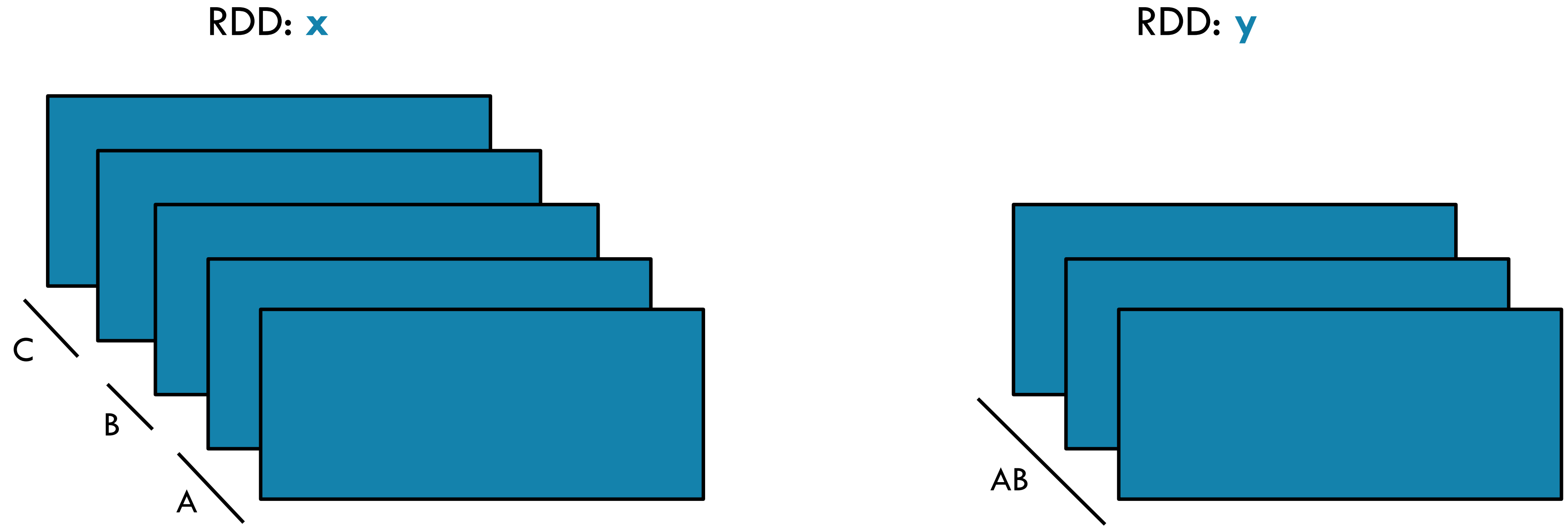
y: [1, 2, 3, 4]



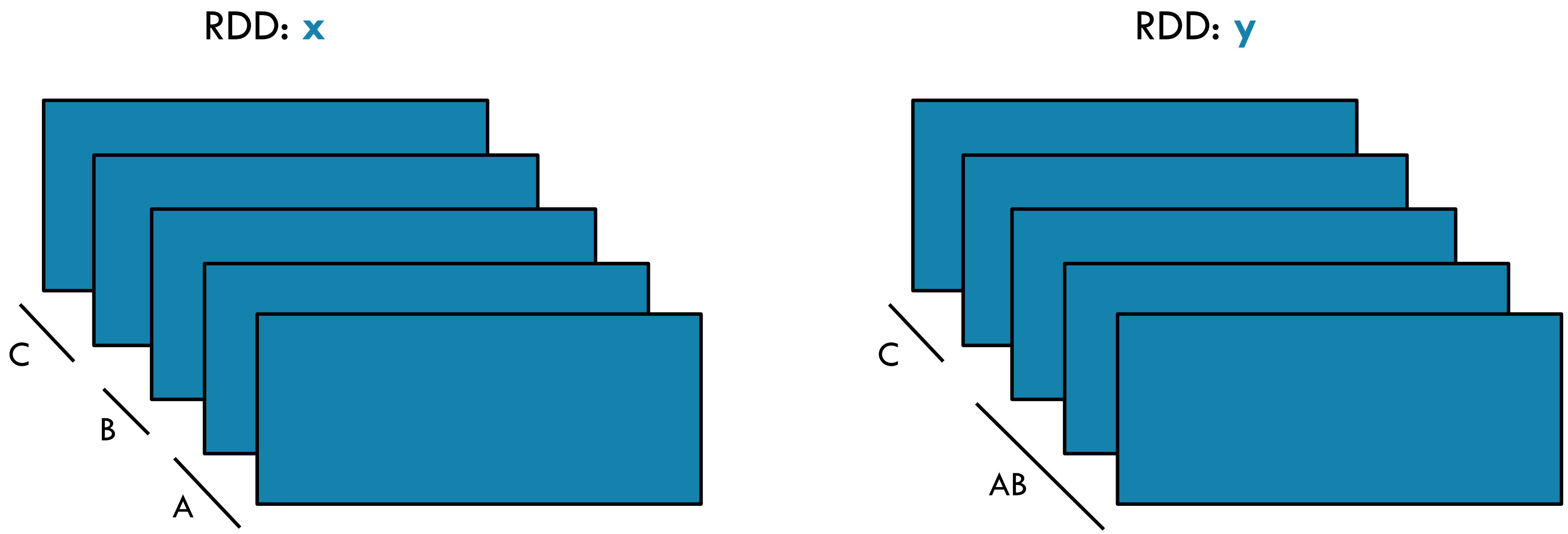
COALESCE



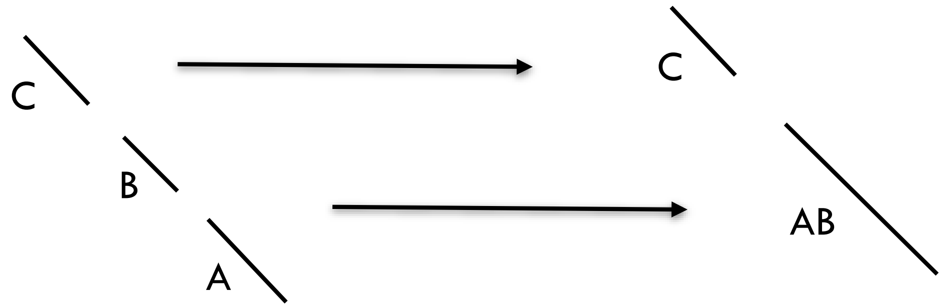
COALESCE



COALESCE



COALESCE



Return a new RDD which is reduced to a smaller number of partitions

`coalesce(numPartitions, shuffle=False)`

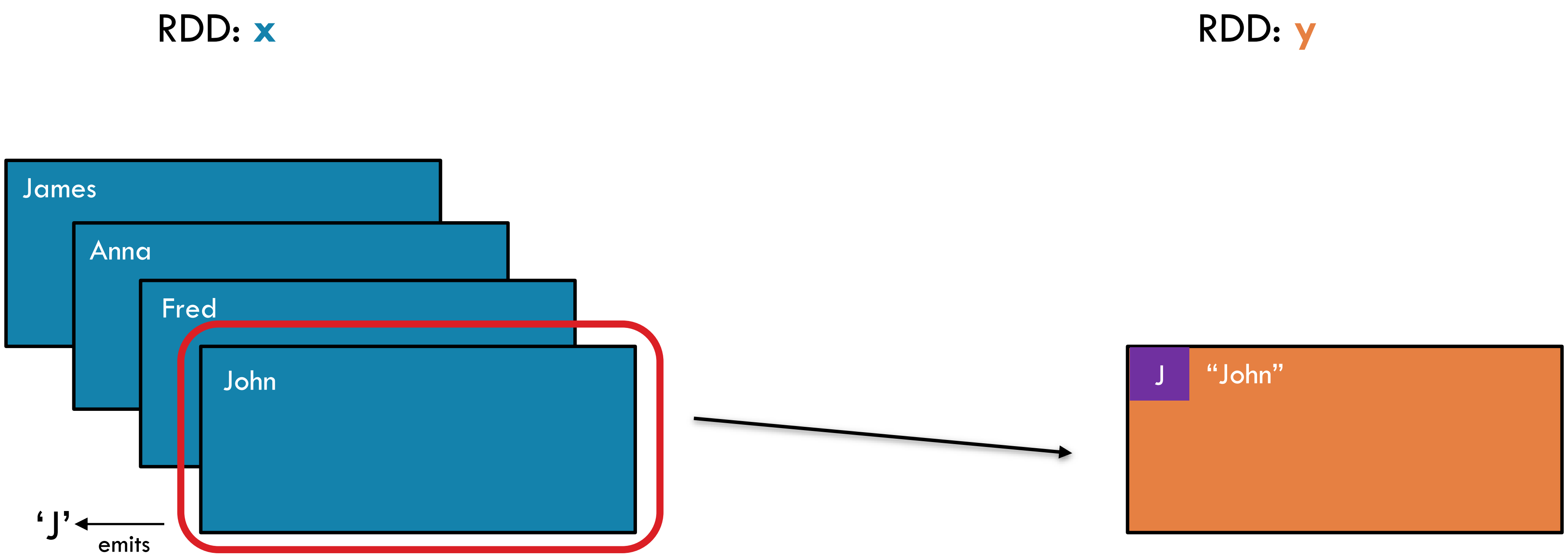
```python
x = sc.parallelize([1, 2, 3, 4, 5], 3)
y = x.coalesce(2)
print(x.glom().collect())
print(y.glom().collect())
```

```scala
val x = sc.parallelize(Array(1, 2, 3, 4, 5), 3)
val y = x.coalesce(2)
val xOut = x.glom().collect()
val yOut = y.glom().collect()
```

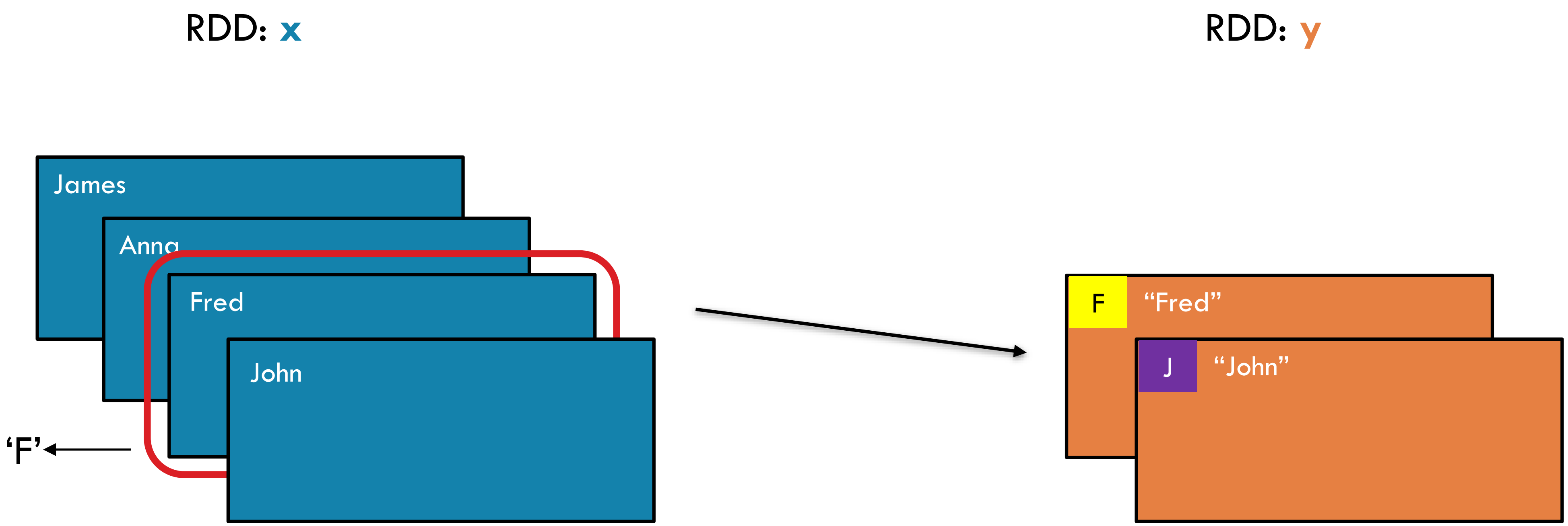
x: [[1], [2, 3], [4, 5]]

y: [[1], [2, 3, 4, 5]]

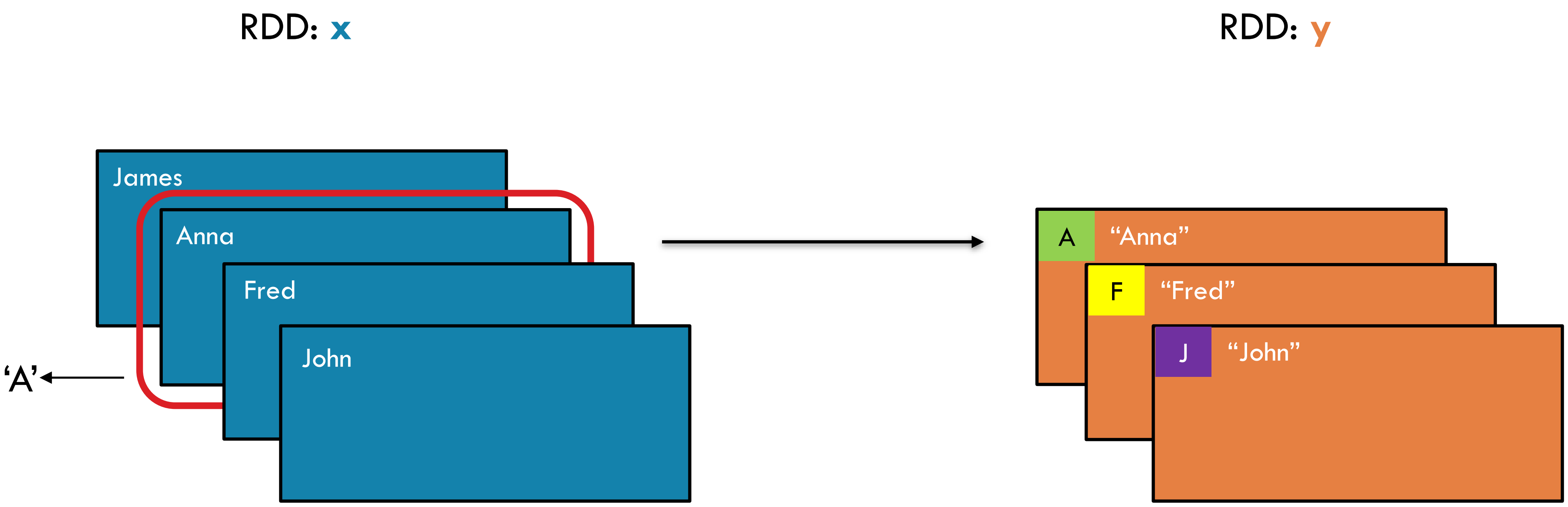
KEYBY



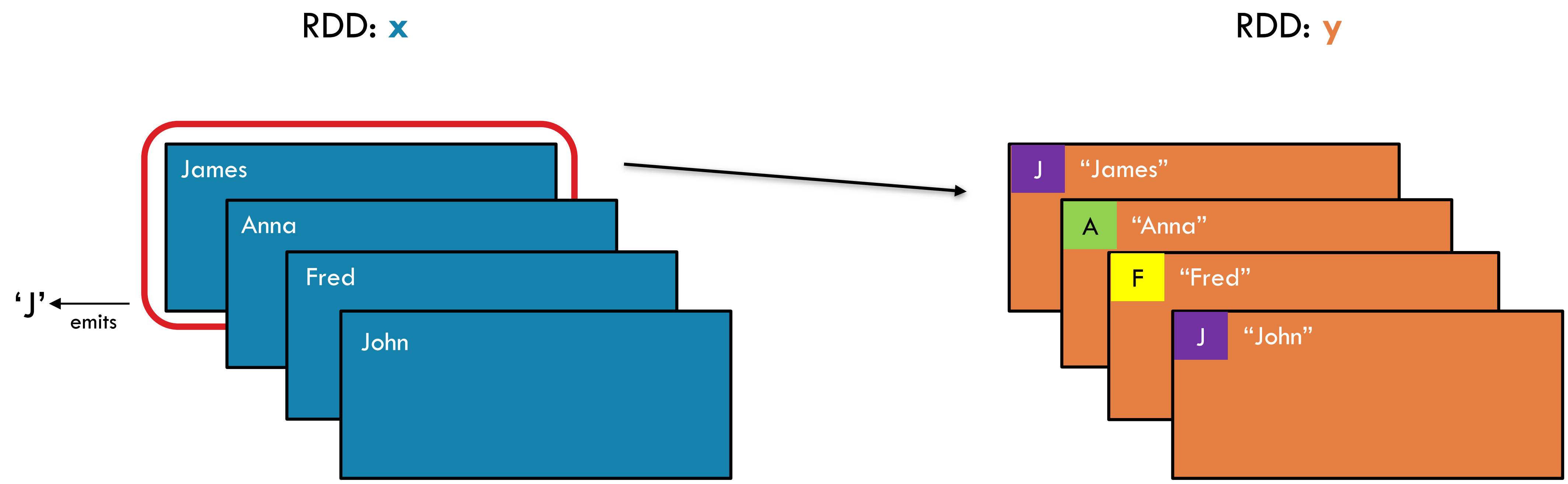
KEYBY



KEYBY

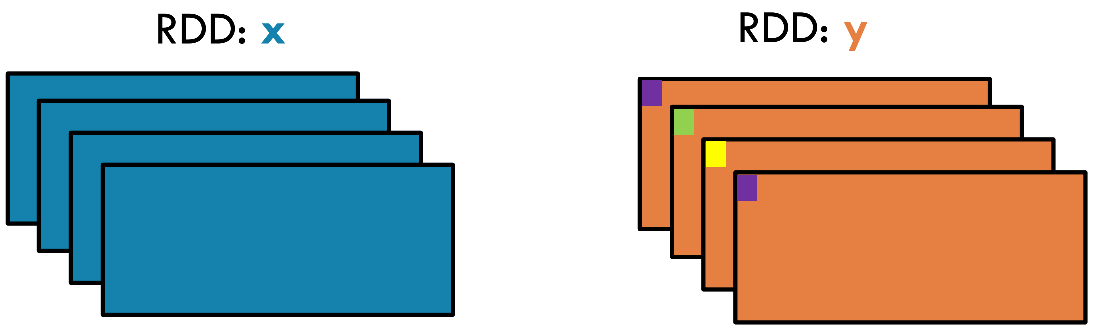


KEYBY



RDD: x
RDD: y
James
Anna
Fred
John
'J'
emits
J
"James"
A
"Anna"
F
"Fred"
J
"John"

KEYBY



keyBy(*f*)

Create a Pair RDD, forming one pair for each item in the original RDD. The pair's key is calculated from the value via a user-supplied function.

```python
x = sc.parallelize(['John', 'Fred', 'Anna', 'James'])
y = x.keyBy(lambda w: w[0])
print y.collect()
```

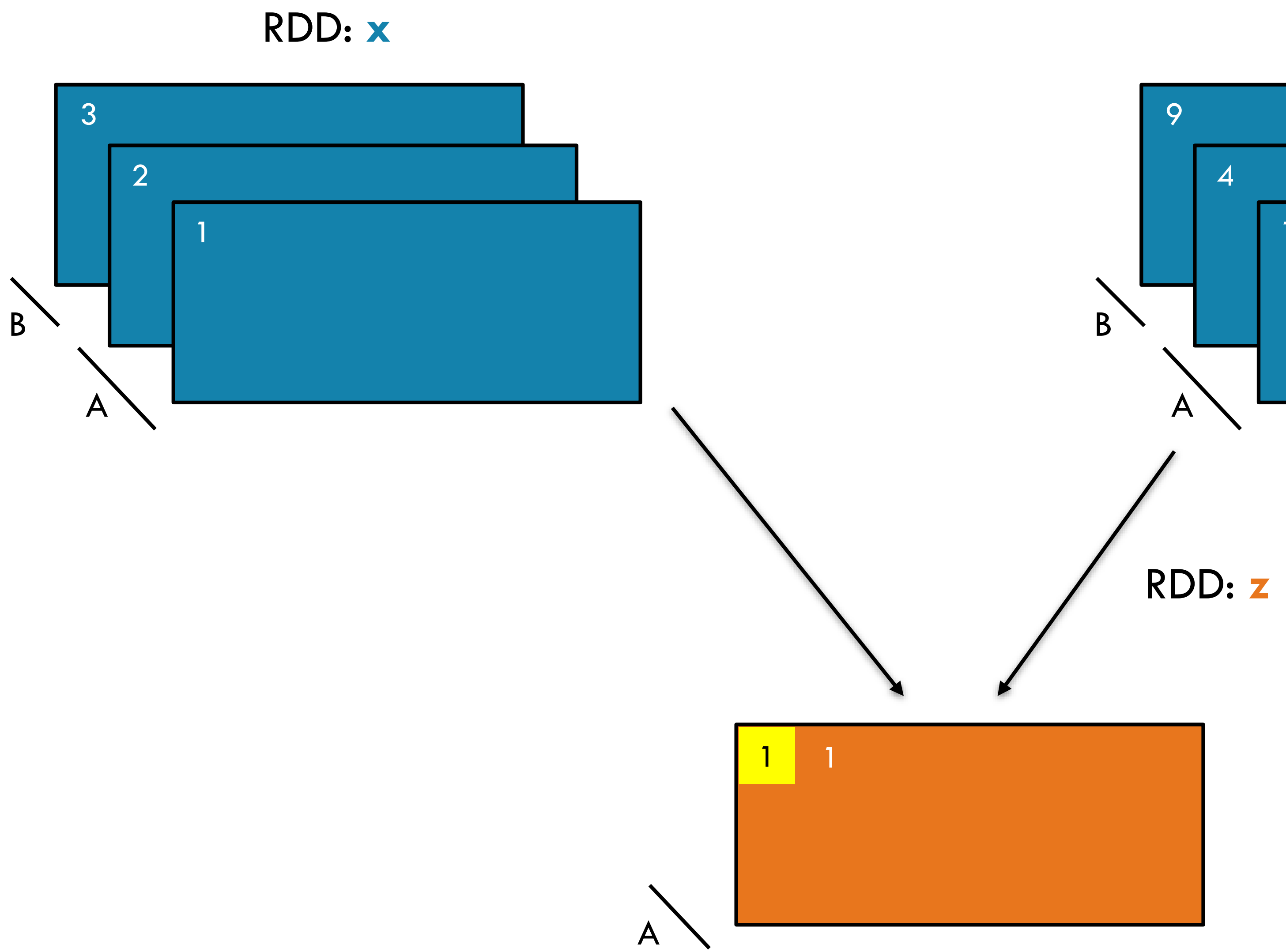
```scala
val x = sc.parallelize(
    Array("John", "Fred", "Anna", "James"))
val y = x.keyBy(w => w.charAt(0))
println(y.collect().mkString(", "))
```

x: ['John', 'Fred', 'Anna', 'James']

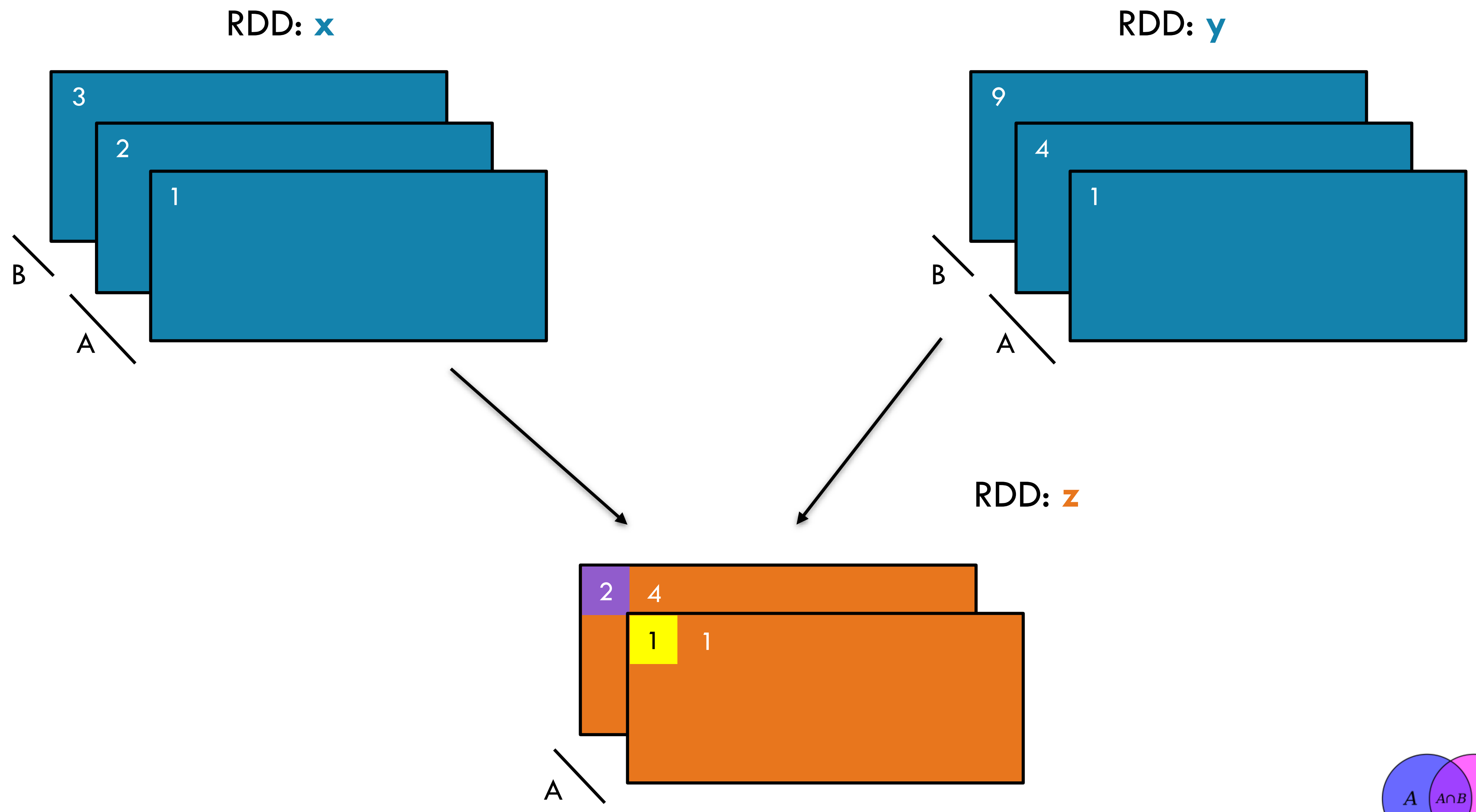
y: [('J','John'),('F','Fred'),('A','Anna'),('J','James')]

ZIP

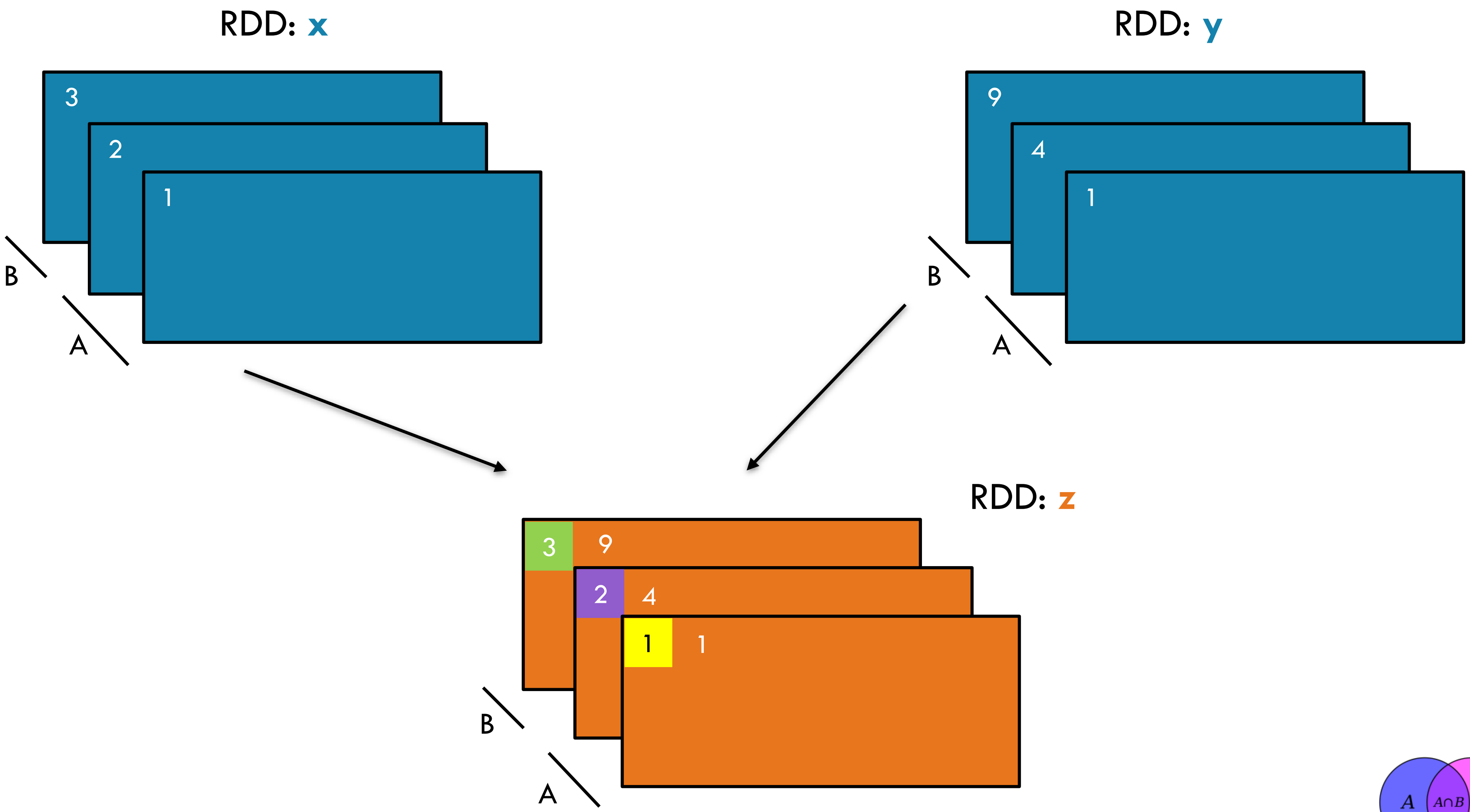
ZIP



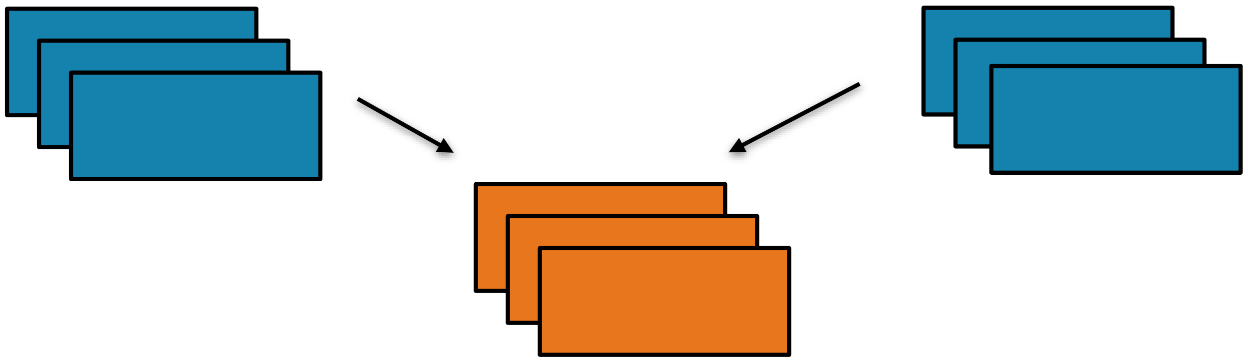
ZIP



ZIP



ZIP



Return a new RDD containing pairs whose key is the item in the original RDD, and whose value is that item's corresponding element (same partition, same index) in a second RDD

`zip(otherRDD)`

```python
x = sc.parallelize([1, 2, 3])
y = x.map(lambda n:n*n)
z = x.zip(y)

print(z.collect())
```

```scala
val x = sc.parallelize(Array(1,2,3))
val y = x.map(n=>n*n)
val z = x.zip(y)

println(z.collect().mkString(", "))
```

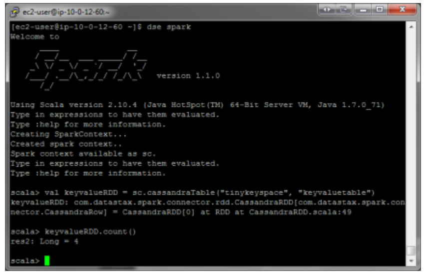
```
x: [1, 2, 3]

y: [1, 4, 9]

z: [(1, 1), (2, 4), (3, 9)]
```

ACTIONS

Core Operations

databricks™

vs



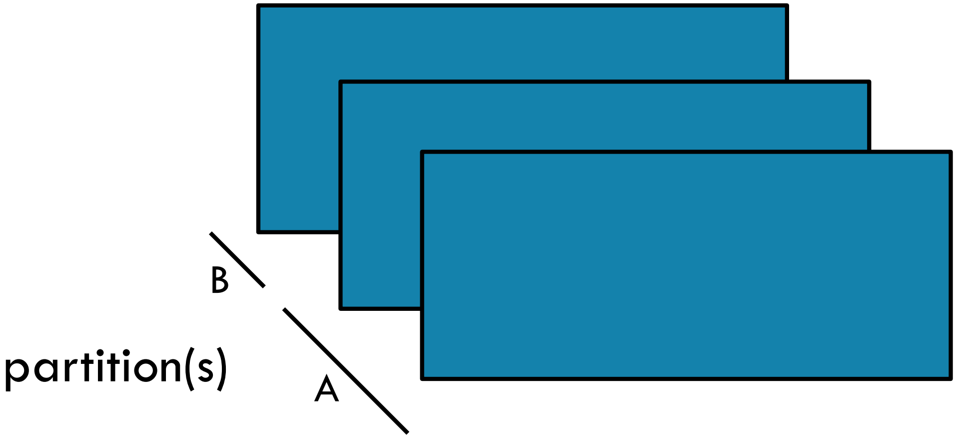
distributed

occurs across the cluster

driver

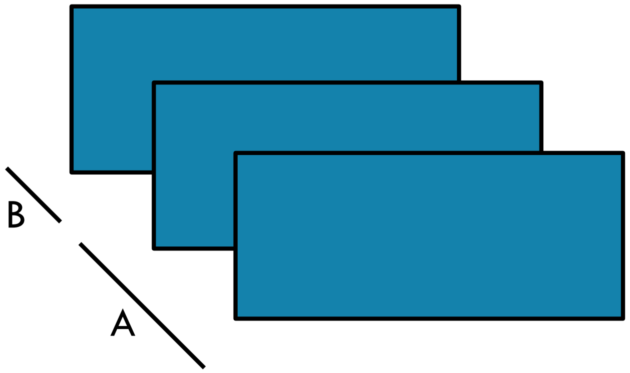
result must fit in driver JVM

GETNUMPARTITIONS



2

GETNUMPARTITIONS



2

getNumPartitions()

Return the number of partitions in RDD

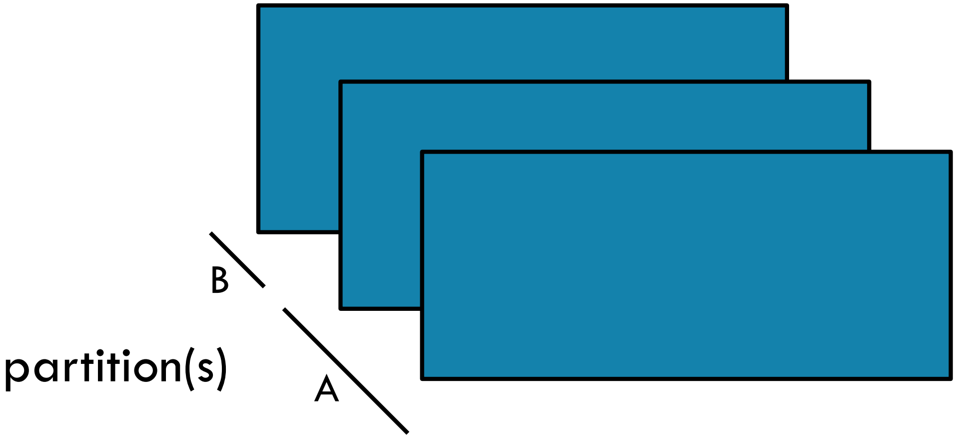
```python
x = sc.parallelize([1,2,3], 2)
y = x.getNumPartitions()

print(x.glom().collect())
print(y)
```

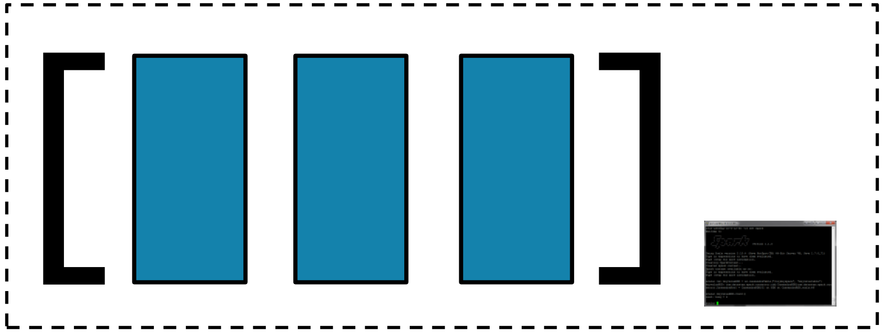
```scala
val x = sc.parallelize(Array(1,2,3), 2)
val y = x.partitions.size
val xOut = x.glom().collect()
println(y)
```

x: [[1], [2, 3]]

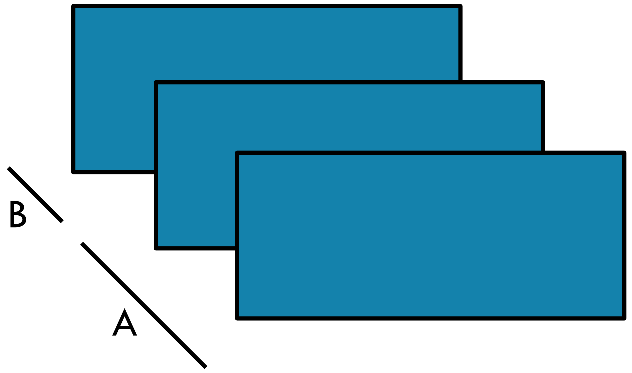
y: 2

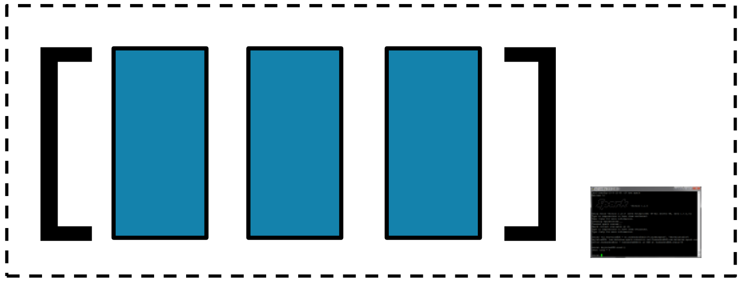
COLLECT





COLLECT





`collect()`

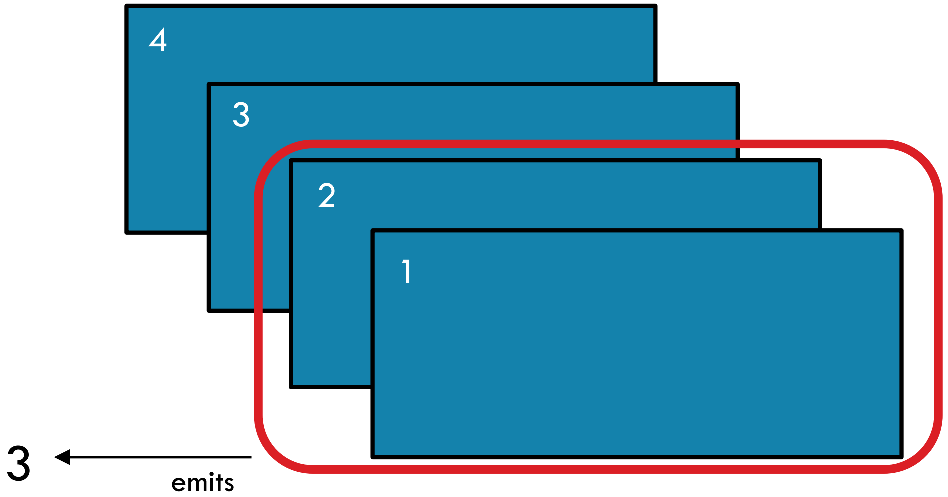
Return all items in the RDD to the driver in a single list

```python
x = sc.parallelize([1,2,3], 2)
y = x.collect()

print(x.glom().collect())
print(y)
```

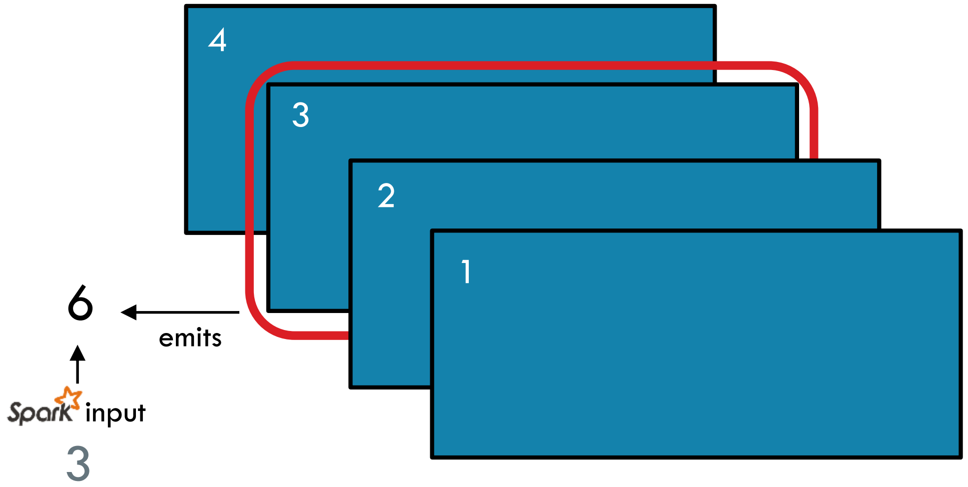
```scala
val x = sc.parallelize(Array(1,2,3), 2)
val y = x.collect()

val xOut = x.glom().collect()
println(y)
```

```
x: [[1], [2, 3]]

y: [1, 2, 3]
```

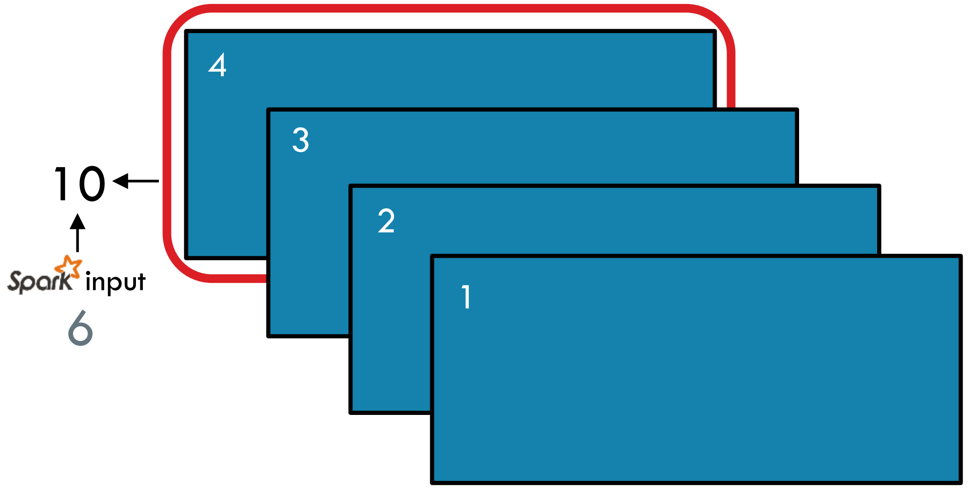
REDUCE



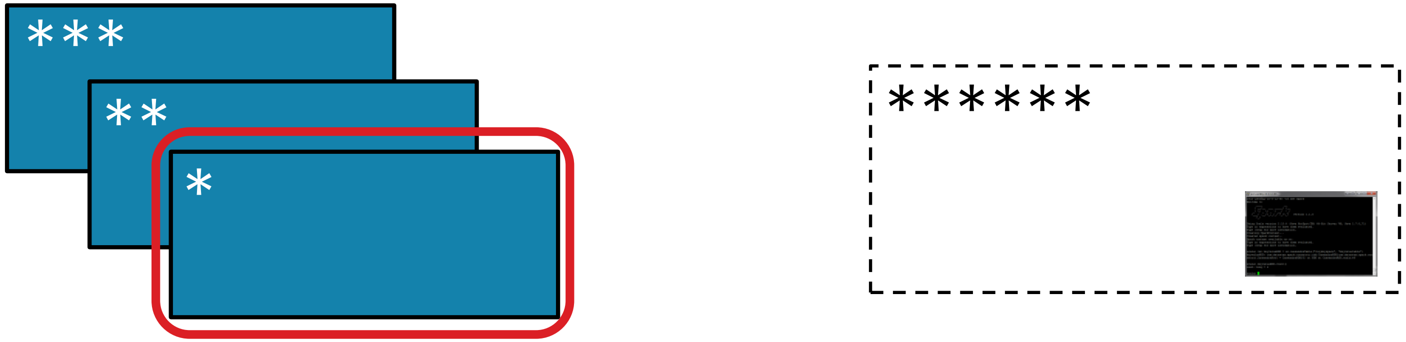
REDUCE



REDUCE



REDUCE



reduce(*f*)

Aggregate all the elements of the RDD by applying a user function pairwise to elements and partial results, and returns a result to the driver

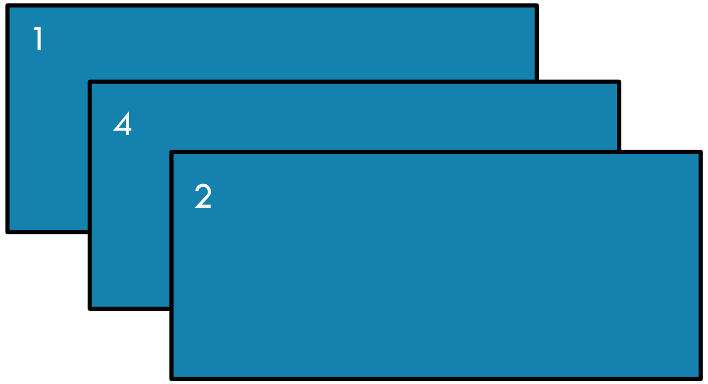
```python
x = sc.parallelize([1,2,3,4])
y = x.reduce(lambda a,b: a+b)

print(x.collect())
print(y)
```

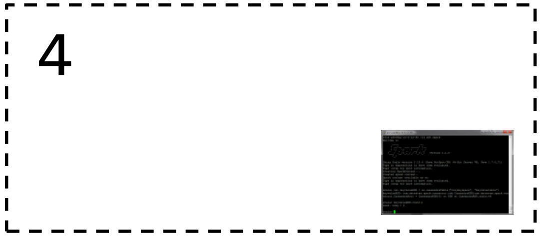
```scala
val x = sc.parallelize(Array(1,2,3,4))
val y = x.reduce((a,b) => a+b)

println(x.collect.mkString(", "))
println(y)
```

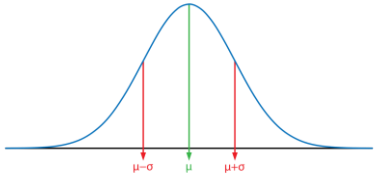
x: [1, 2, 3, 4]

y: 10

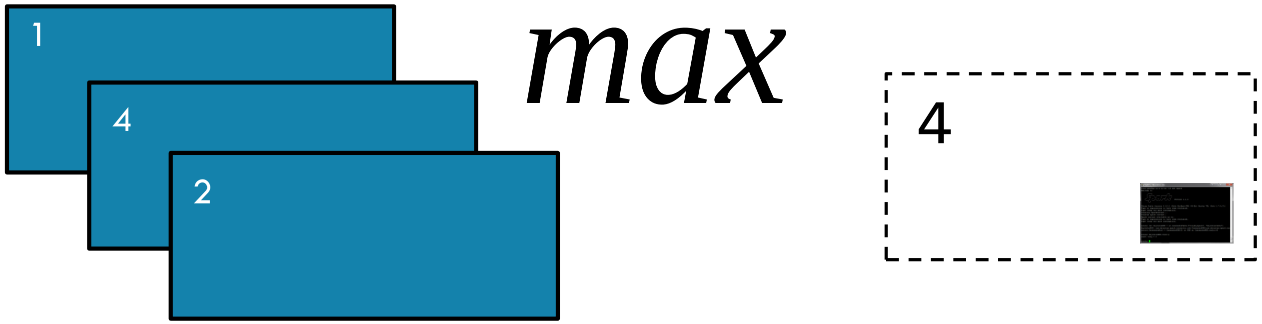
MAX







MAX



max()

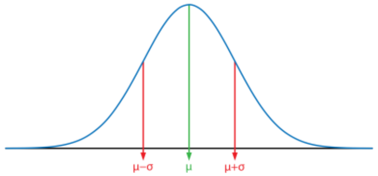
Return the maximum item in the RDD

```python
x = sc.parallelize([2,4,1])
y = x.max()

print(x.collect())
print(y)
```

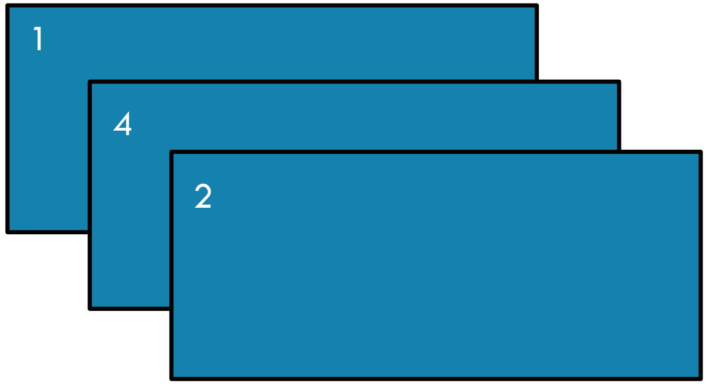
```scala
val x = sc.parallelize(Array(2,4,1))
val y = x.max

println(x.collect().mkString(", "))
println(y)
```

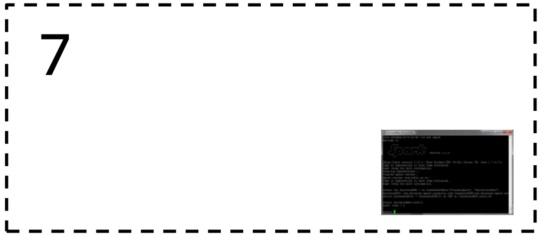
x: [2, 4, 1]

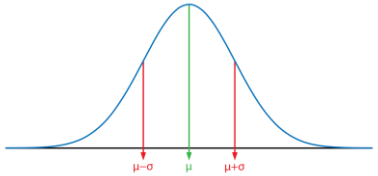
y: 4



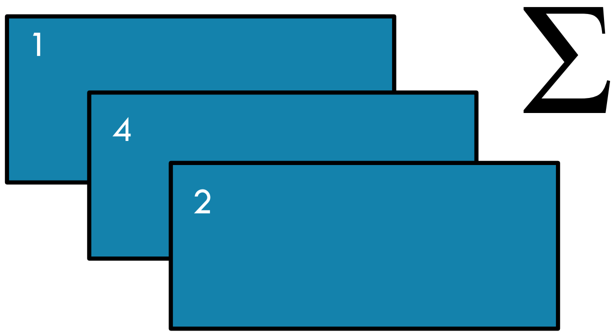
SUM







SUM



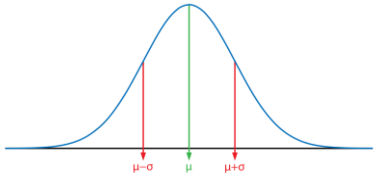
sum()

Return the sum of the items in the RDD

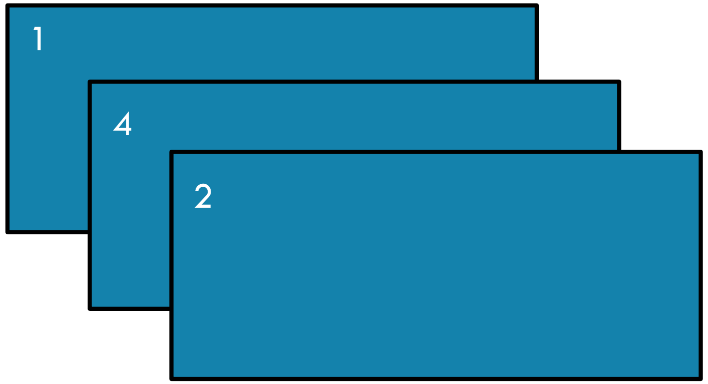
```python
x = sc.parallelize([2,4,1])
y = x.sum()

print(x.collect())
print(y)
```

```scala
val x = sc.parallelize(Array(2,4,1))
val y = x.sum

println(x.collect().mkString(", "))
println(y)
```

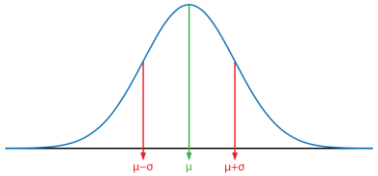
```
x: [2, 4, 1]

y: 7
```



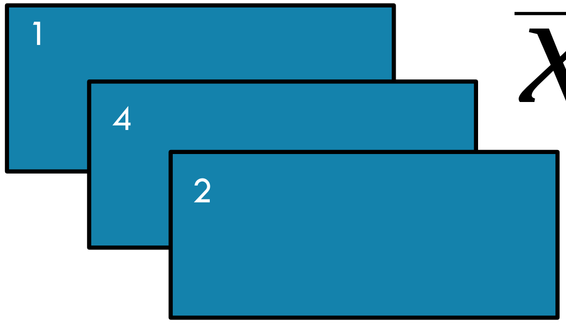
MEAN



2.33333333



MEAN



$\overline{X}$

2.3333333

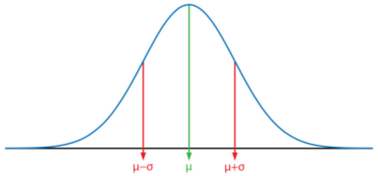
mean()

Return the mean of the items in the RDD

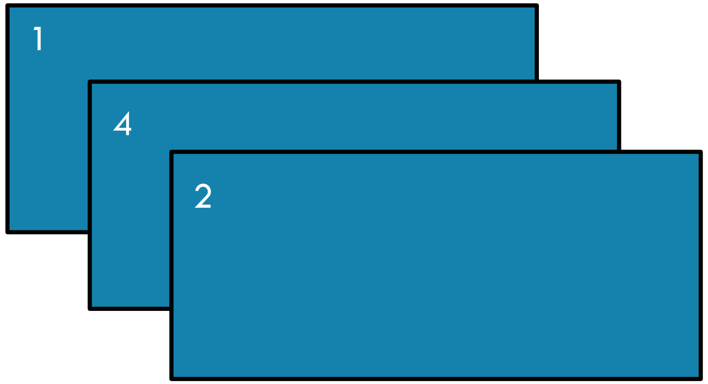
```python
x = sc.parallelize([2,4,1])
y = x.mean()

print(x.collect())
print(y)
```

```scala
val x = sc.parallelize(Array(2,4,1))
val y = x.mean

println(x.collect().mkString(", "))
println(y)
```

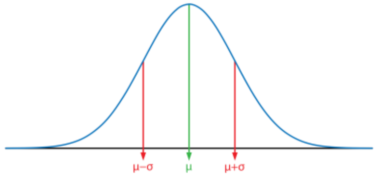
```
x: [2, 4, 1]

y: 2.3333333
```



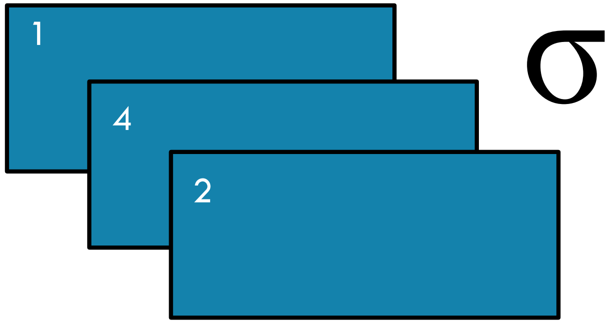
STDEV



1.2472191



STDEV



1.2472191

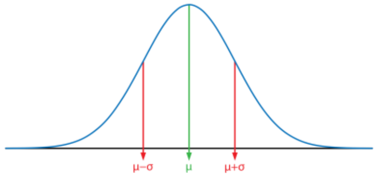
`stdev()`

Return the standard deviation of the items in the RDD

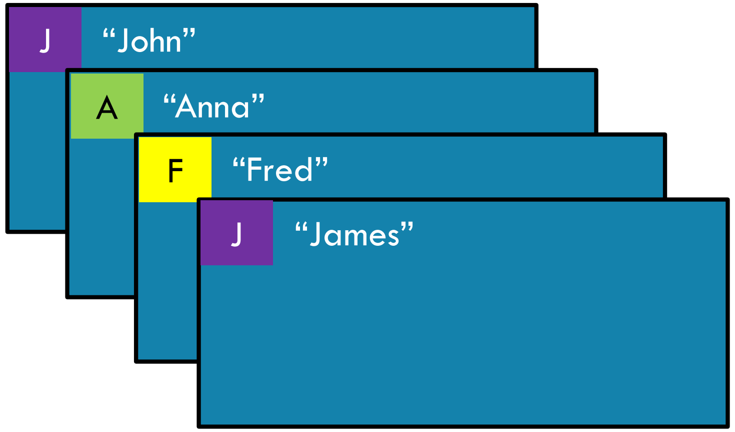
```python
x = sc.parallelize([2,4,1])
y = x.stdev()

print(x.collect())
print(y)
```

```scala
val x = sc.parallelize(Array(2,4,1))
val y = x.stdev

println(x.collect().mkString(", "))
println(y)
```

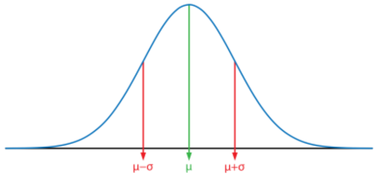
```
x: [2, 4, 1]

y: 1.2472191
```



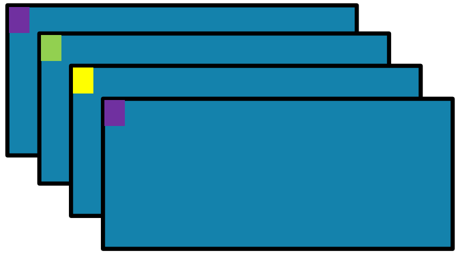
COUNTBYKEY



{'A': 1, 'J': 2, 'F': 1}



COUNTBYKEY



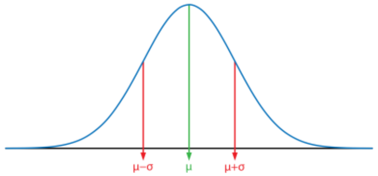
countByKey()

Return a map of keys and counts of their occurrences in the RDD

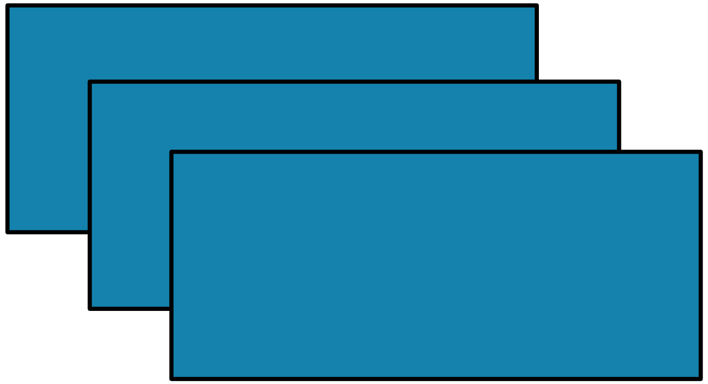
```python
x = sc.parallelize([('J', 'James'), ('F','Fred'),
                    ('A','Anna'), ('J','John')])

y = x.countByKey()
print(y)
```

```scala
val x = sc.parallelize(Array(('J',"James"),('F',"Fred"),
                             ('A',"Anna"),('J',"John")))

val y = x.countByKey()
println(y)
```

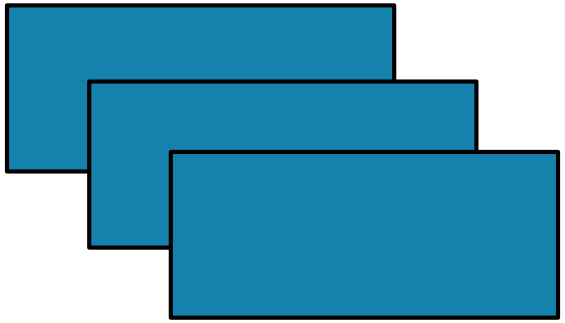
```
x: [('J', 'James'), ('F','Fred'),
    ('A','Anna'), ('J','John')]

y: {'A': 1, 'J': 2, 'F': 1}
```



SAVEASTEXTFILE



SAVEASTEXTFILE



`saveAsTextFile(path, compressionCodecClass=None)`

Save the RDD to the filesystem indicated in the path

```python
dbutils.fs.rm("/temp/demo", True)
x = sc.parallelize([2,4,1])
x.saveAsTextFile("/temp/demo")

y = sc.textFile("/temp/demo")
print(y.collect())
```

```scala
dbutils.fs.rm("/temp/demo", true)
val x = sc.parallelize(Array(2,4,1))
x.saveAsTextFile("/temp/demo")

val y = sc.textFile("/temp/demo")
println(y.collect().mkString(", "))
```

```
x: [2, 4, 1]

y: [u'2', u'4', u'1']
```

LAB

Q&A

databricks™