# TRANSFORMATIONS AND ACTIONS

http://training.databricks.com/visualapi.pdf

A Visual Guide of the API

LinkedIn

Blog: data-frack

Databricks would like to give a special thanks to Jeff Thomspon for contributing 67 visual diagrams depicting the Spark API under the MIT license to the Spark community.

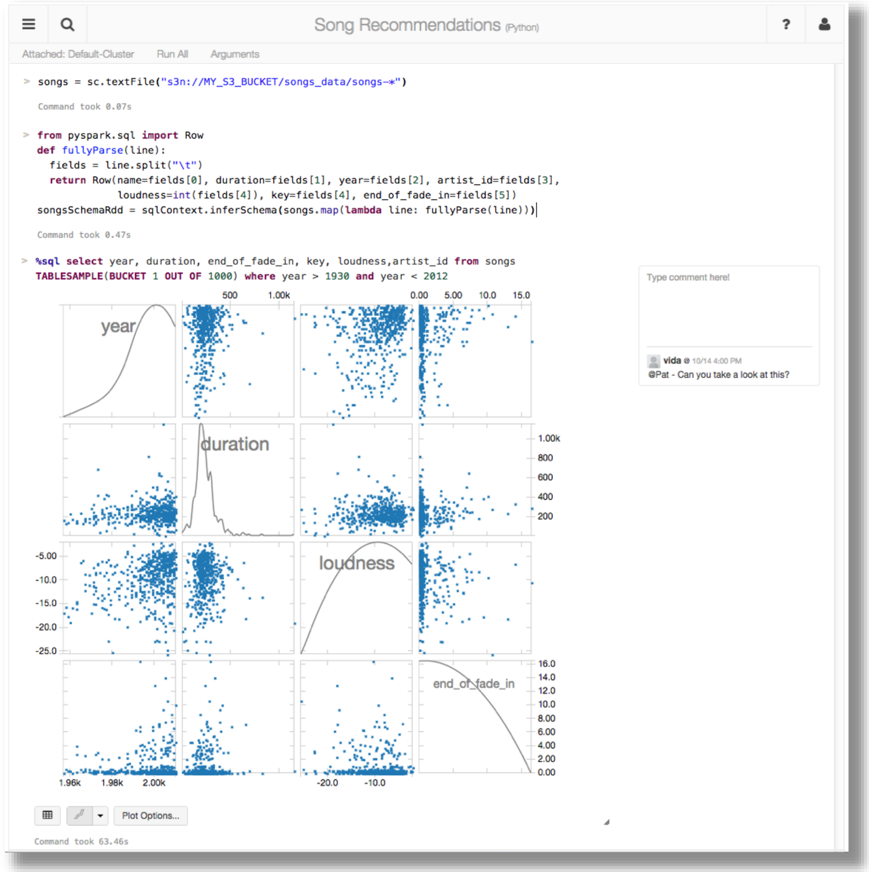
Jeff's original, creative work can be found here and you can read more about Jeff's project in his blog post.

After talking to Jeff, Databricks commissioned Adam Breindel to further evolve Jeff's work into the diagrams you see in this deck.

databricks™

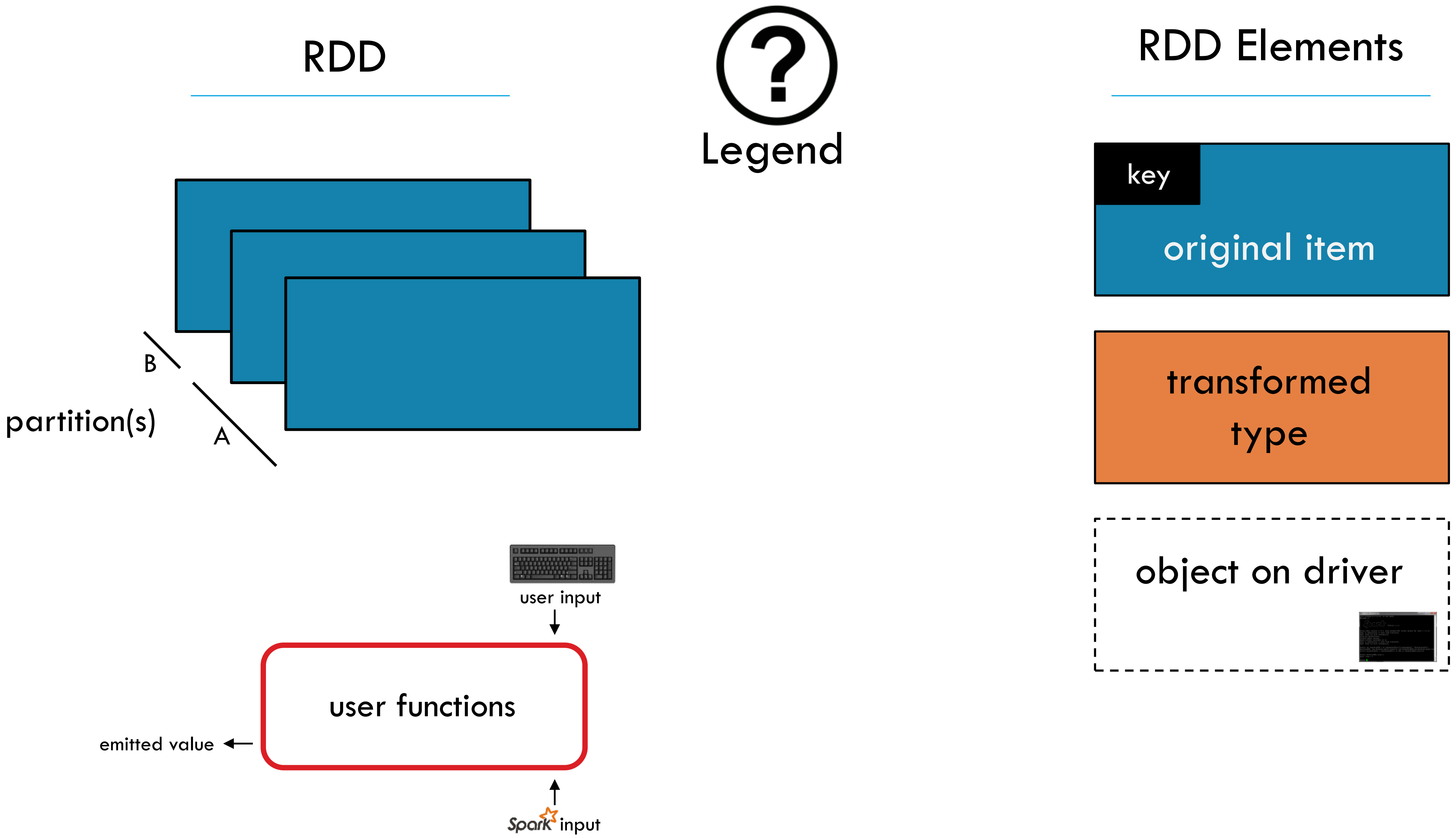
making big data simple

- Founded in late 2013
- by the creators of Apache Spark
- Original team from UC Berkeley AMPLab
- Raised $47 Million in 2 rounds
- ~55 employees
- We're hiring! (http://databricks.workable.com)
- Level 2/3 support partnerships with
  - Hortonworks
  - MapR
  - DataStax

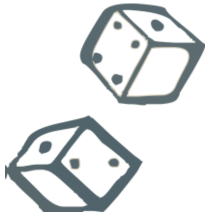



Databricks Cloud:

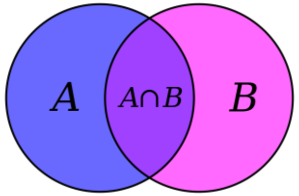
"A unified platform for building Big Data pipelines – from ETL to Exploration and Dashboards, to Advanced Analytics and Data Products."


Legend
RDD
partition(s)
B
A
user input
user functions
emitted value
Spark input
RDD Elements
key
original item
transformed type
object on driver

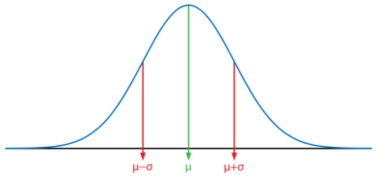
# Legend



Randomized operation

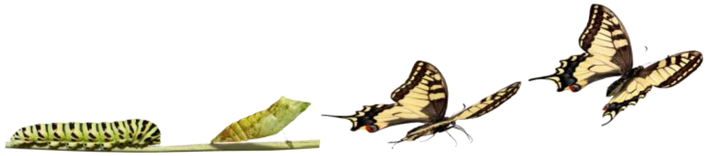



Set Theory / Relational operation




Numeric calculation

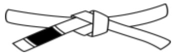
Spark Operations =



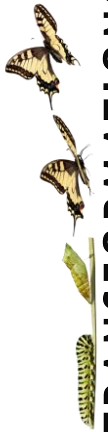
TRANSFORMATIONS

+

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

---

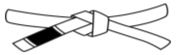
ACTIONS

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

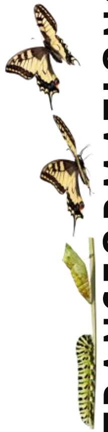
- count
- takeSample
- max
- min
- sum
- histogram
- mean
- variance
- stdev
- sampleVariance
- countApprox
- countApproxDistinct

- 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

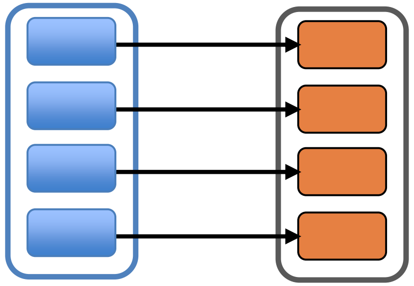
- keys
- values

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

vs

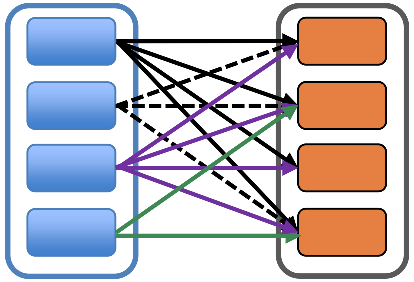
narrow

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



wide

*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.”

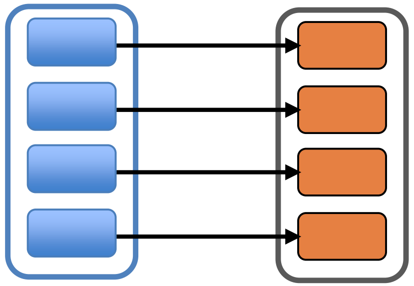
“The most interesting question in designing this interface is how to represent dependencies between RDDs.”

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

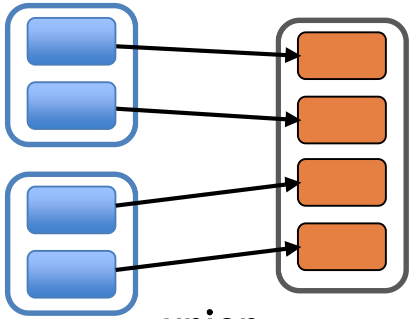
- narrow dependencies, where each partition of the parent RDD is used by at most one partition of the child RDD
- wide dependencies, where multiple child partitions may depend on it.”

## narrow

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

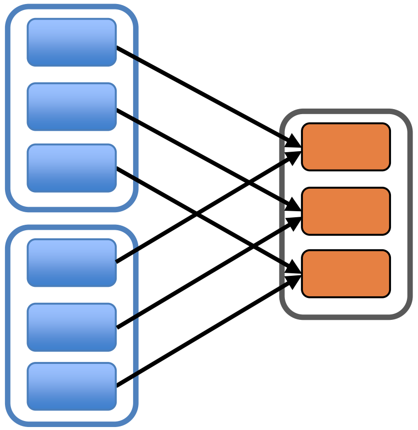


map, filter



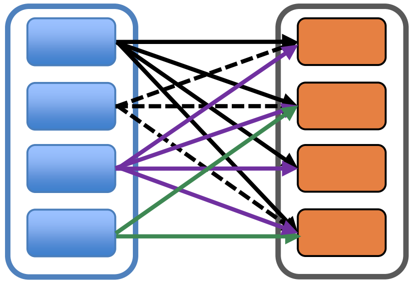
union

join w/ inputs co-partitioned

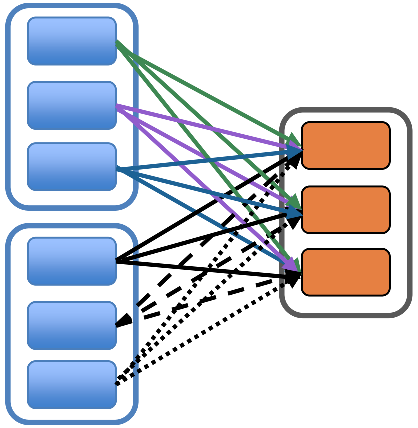


## wide

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

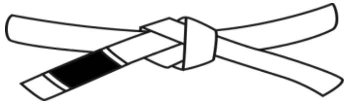


groupByKey



join w/ inputs not co-partitioned

# TRANSFORMATIONS

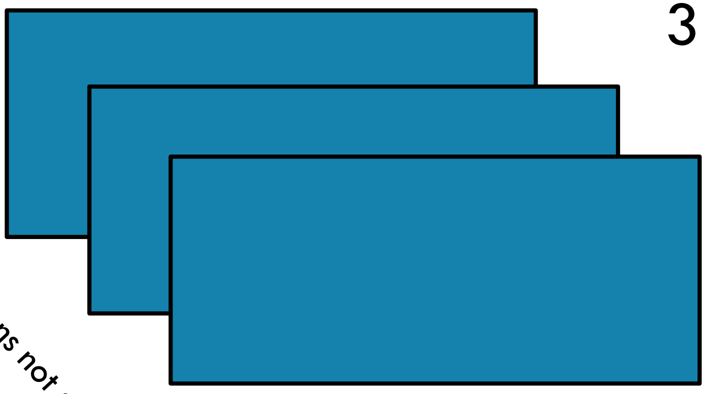


Core Operations

databricks™

# MAP

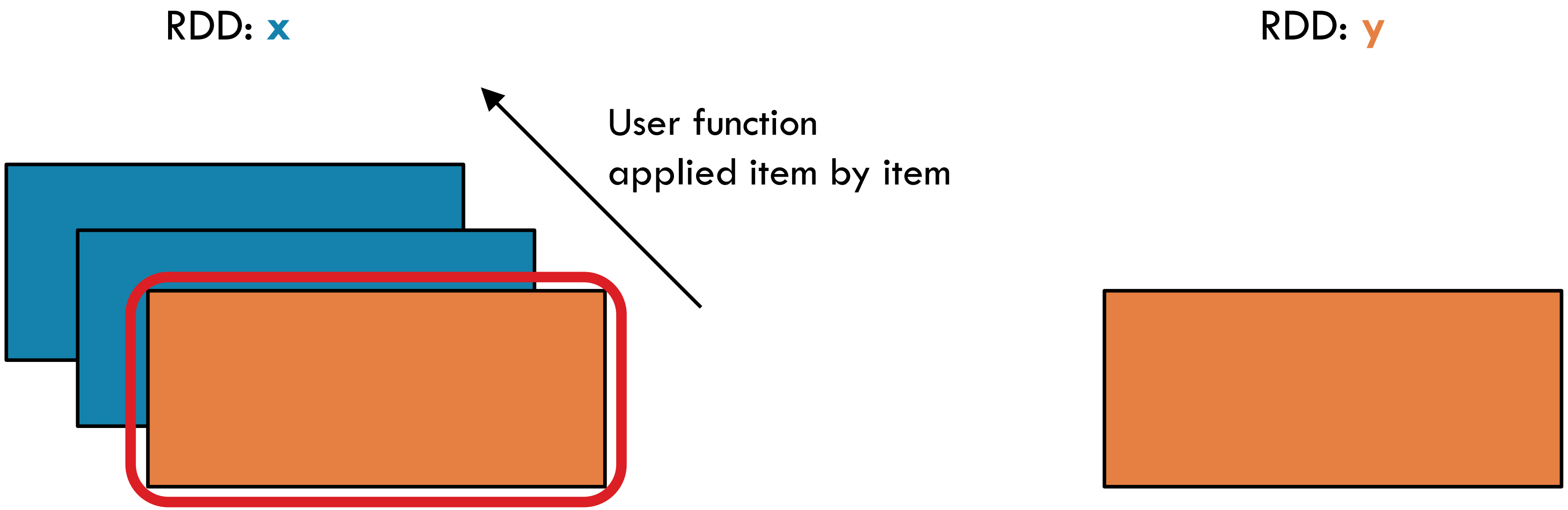
RDD: **x**



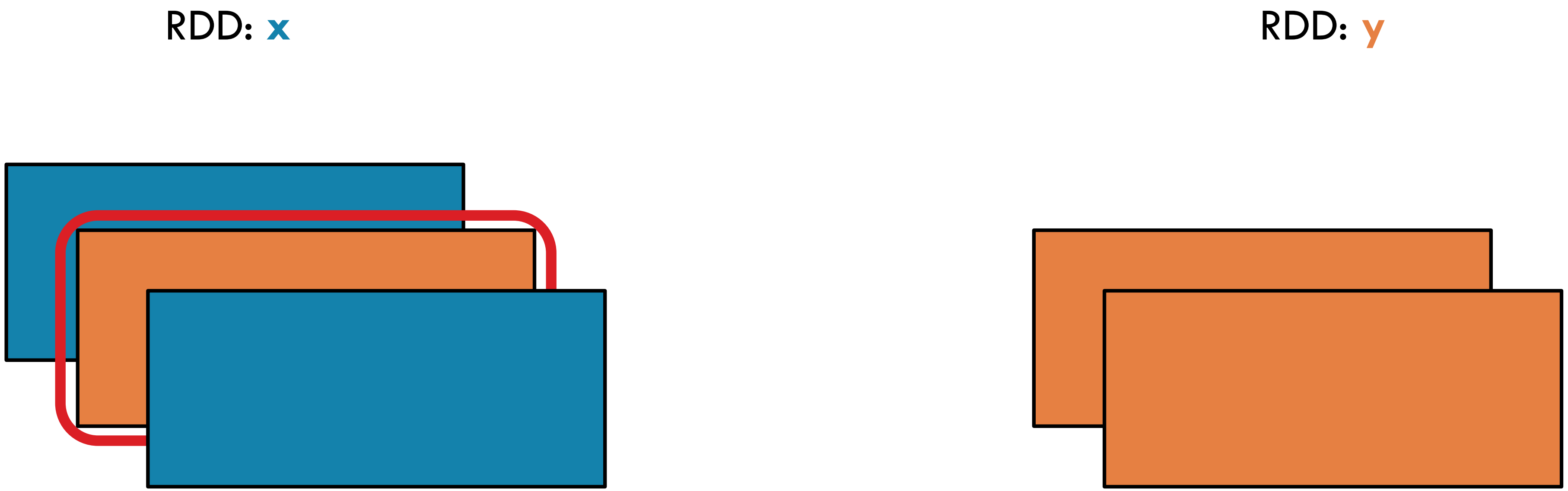
3 items in RDD

(partitions not shown)

# MAP



# MAP



# MAP

RDD: x

RDD: y

# MAP

After `map()` has been applied…

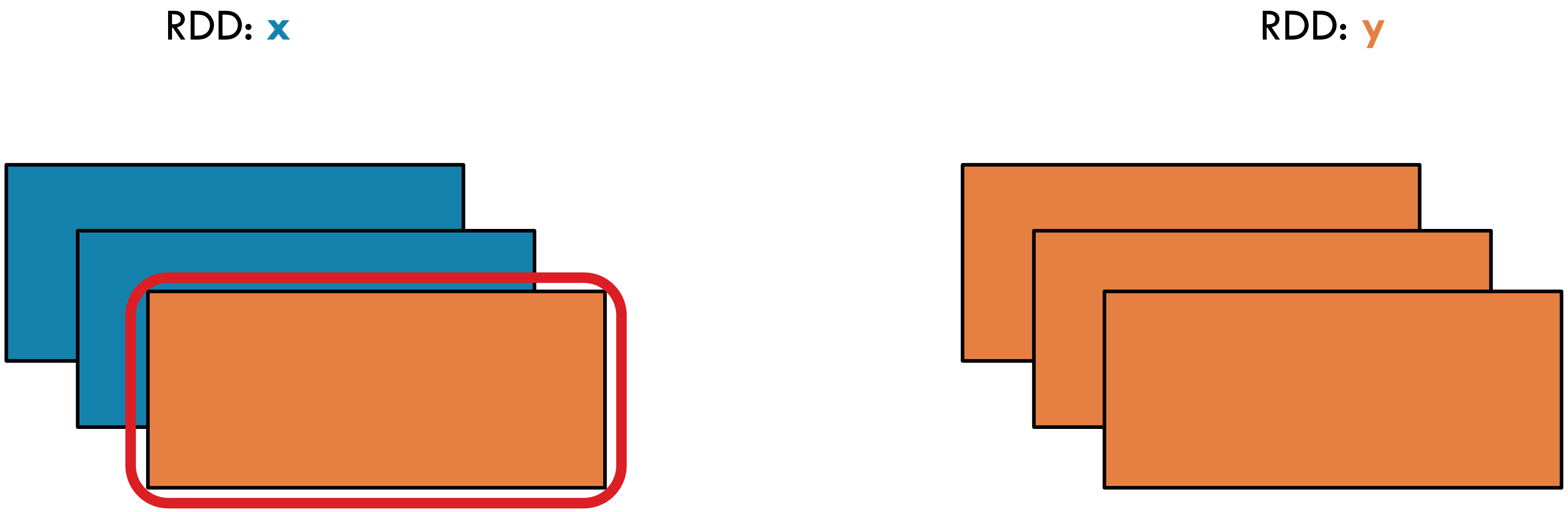
RDD: x

RDD: y

before

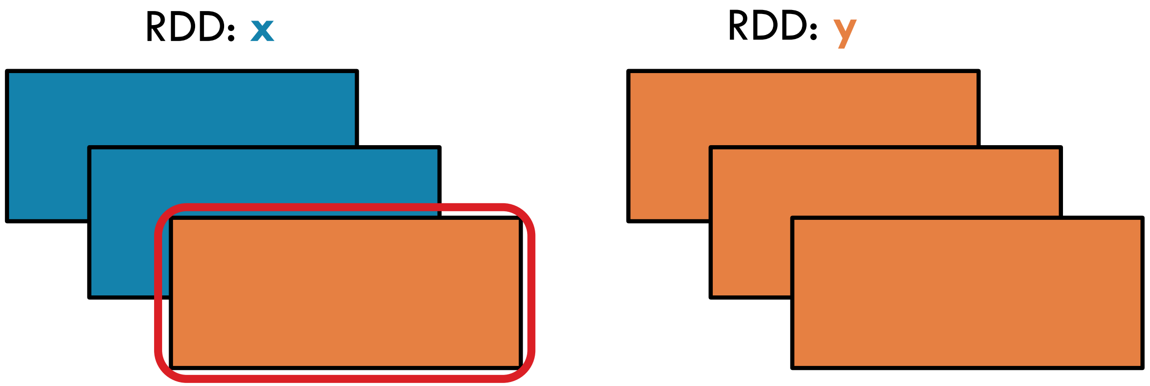
after

# MAP




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

# MAP



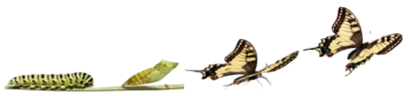

`map(f, preservesPartitioning=False)`

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())
```

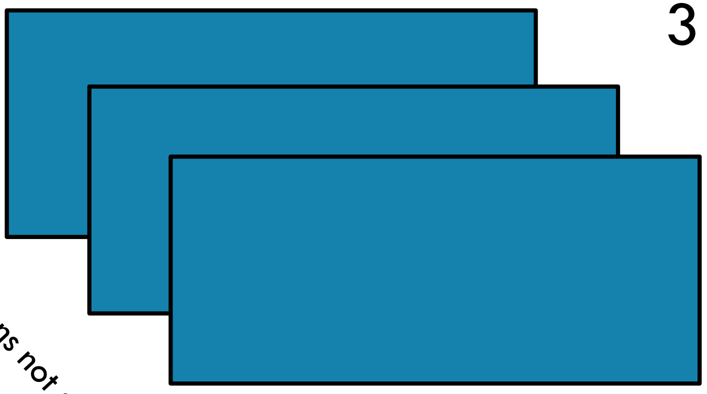
```scala
val x = sc.parallelize(Array("b", "a", "c"))
val y = x.map(z => (z,1))
println(x.collect().mkString(", "))
println(y.collect().mkString(", "))
```

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

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



# FILTER

RDD: **x**



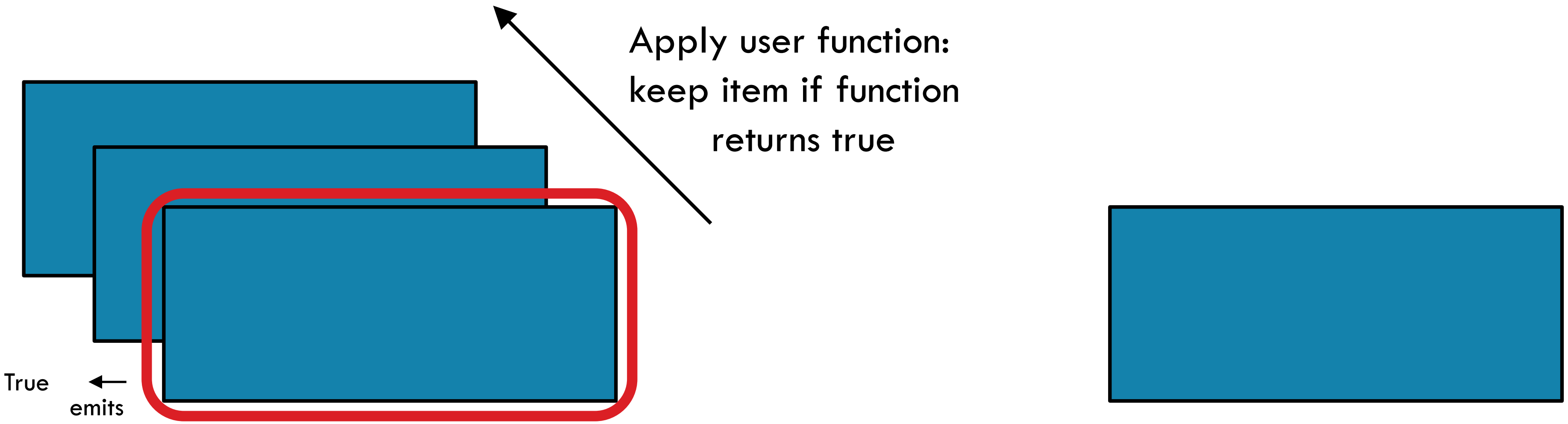
3 items in RDD

(partitions not shown)

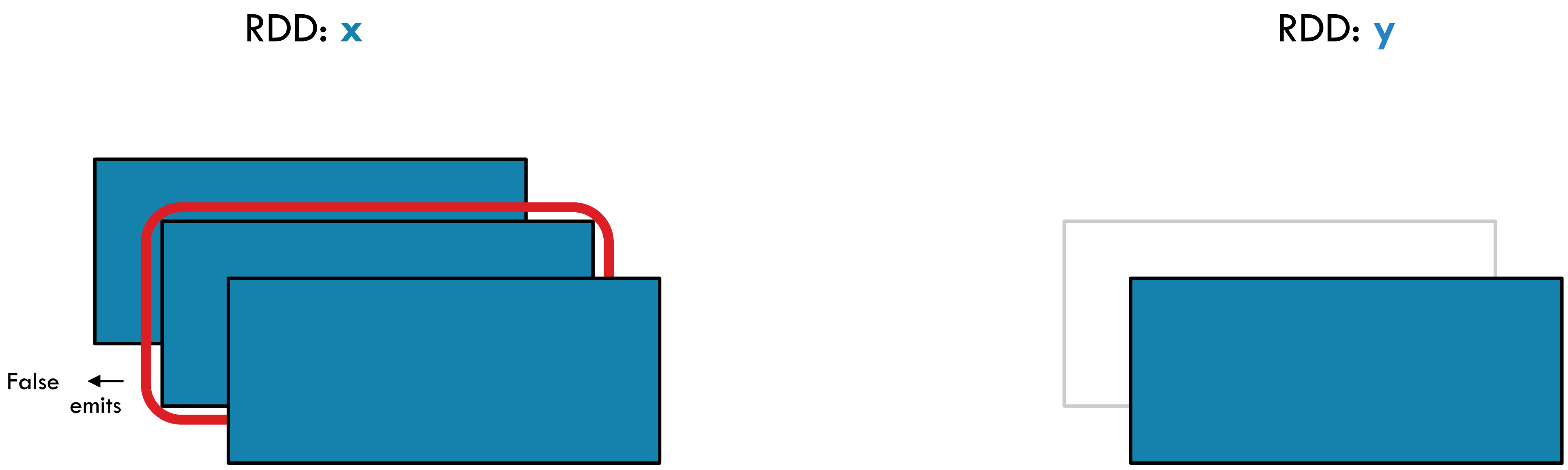
# FILTER

RDD: x

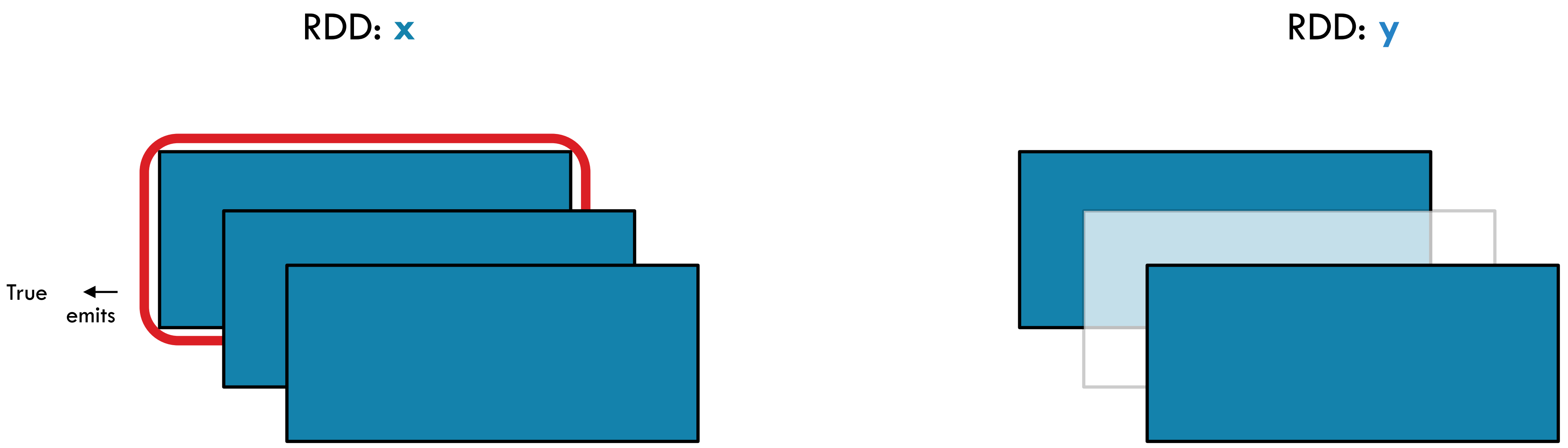
RDD: y



# FILTER



# FILTER



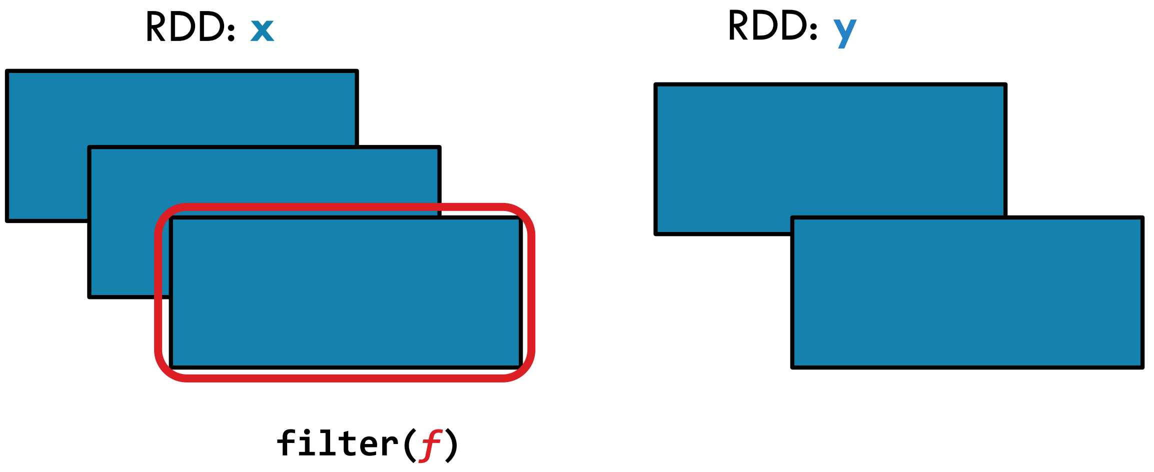
# FILTER

After `filter()` has been applied…

RDD: x          RDD: y

before          after

# FILTER




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

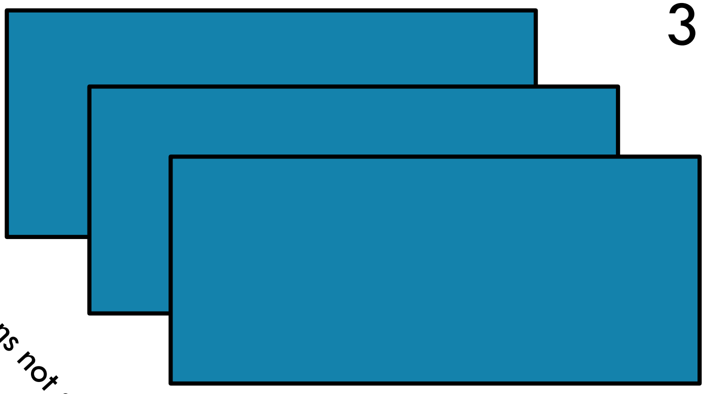
```python
x = sc.parallelize([1,2,3])
y = x.filter(lambda x: x%2 == 1) #keep odd values
print(x.collect())
print(y.collect())
```

```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

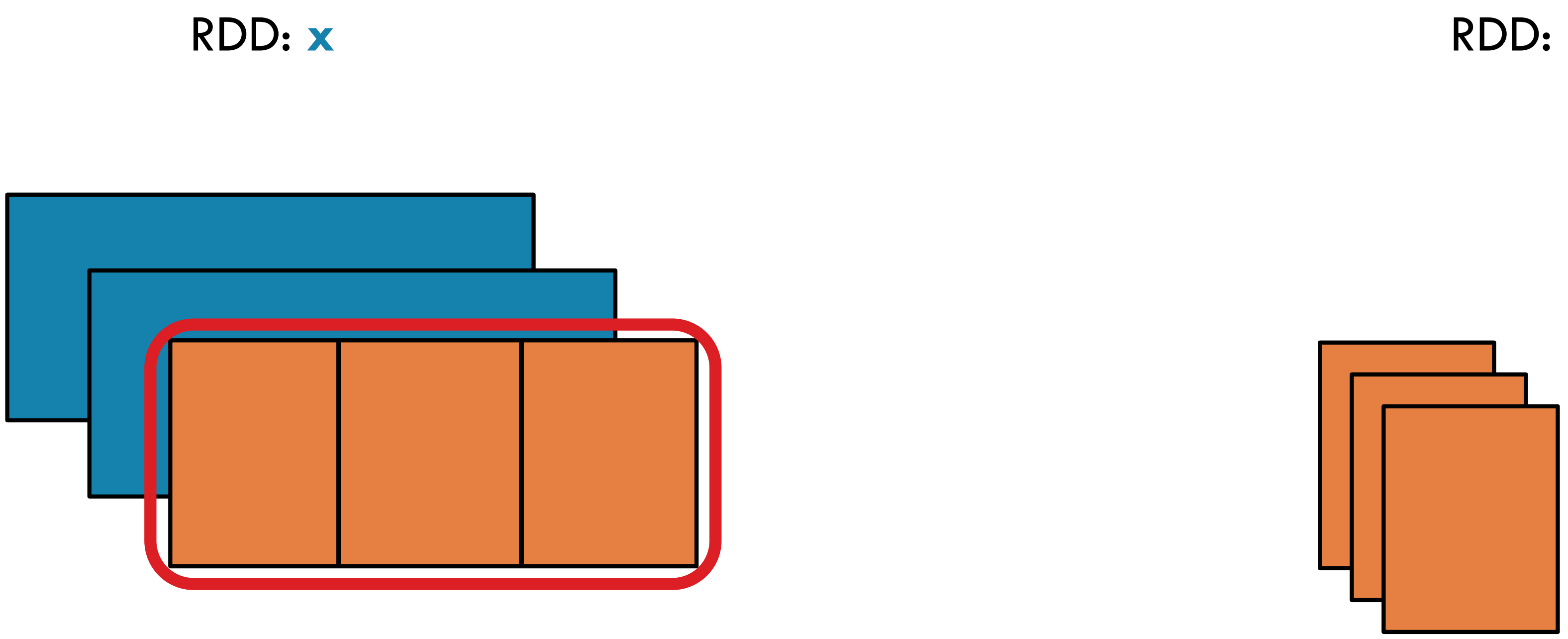
RDD: **x**



3 items in RDD

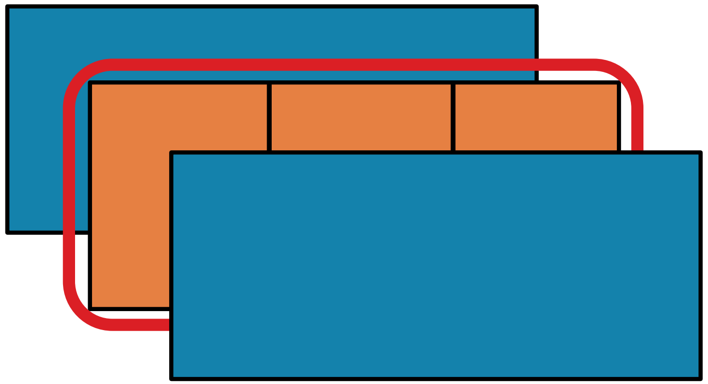
(partitions not shown)

# FLATMAP

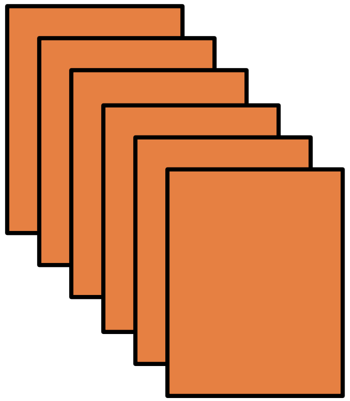


# FLATMAP

RDD: x



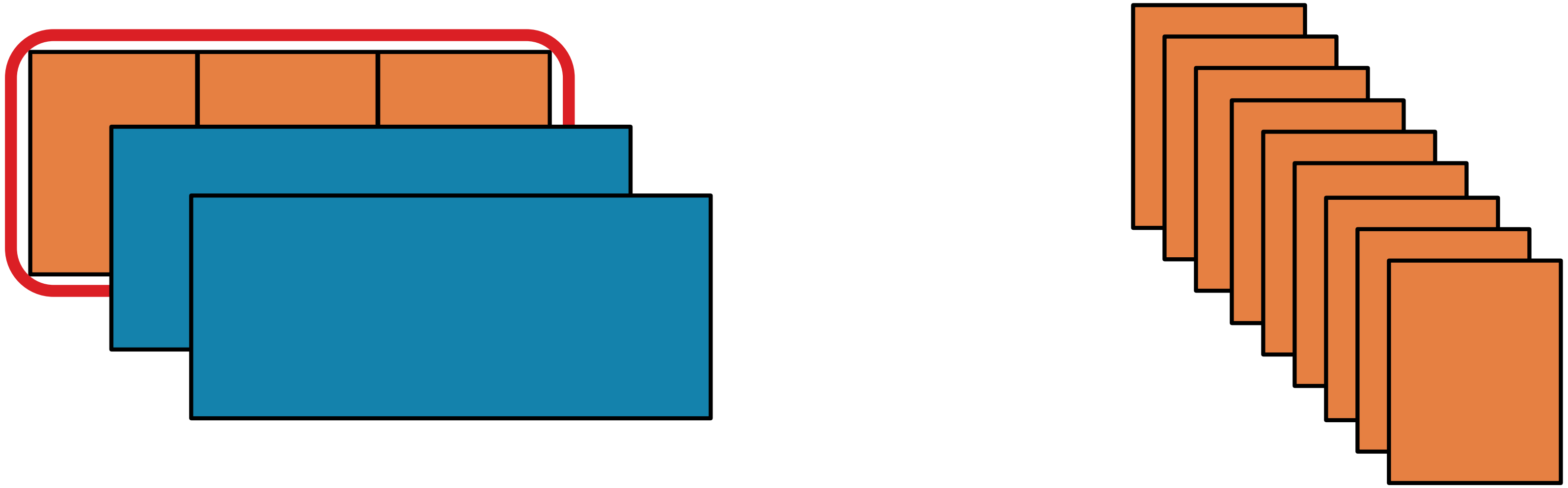
RDD: y



# FLATMAP

RDD: x

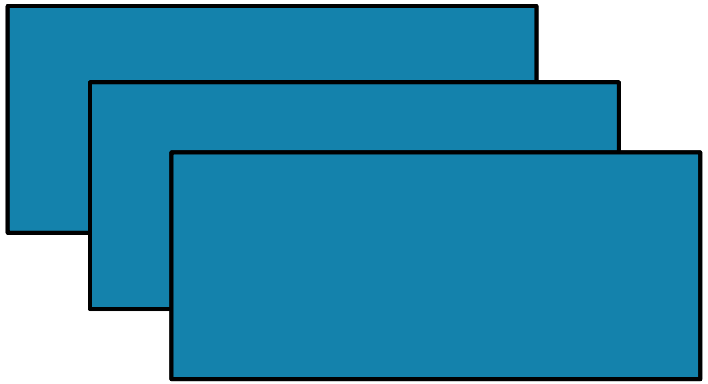
RDD: y



# FLATMAP

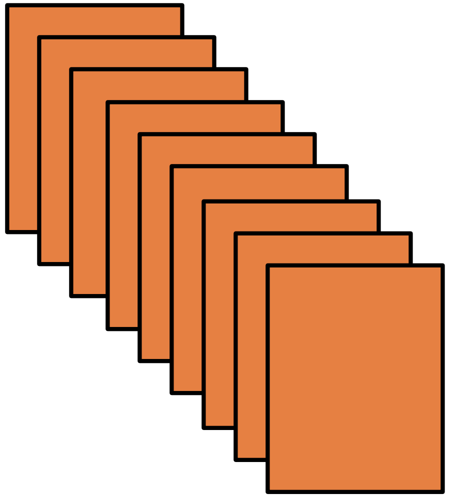
After `flatmap()` has been applied...

RDD: x



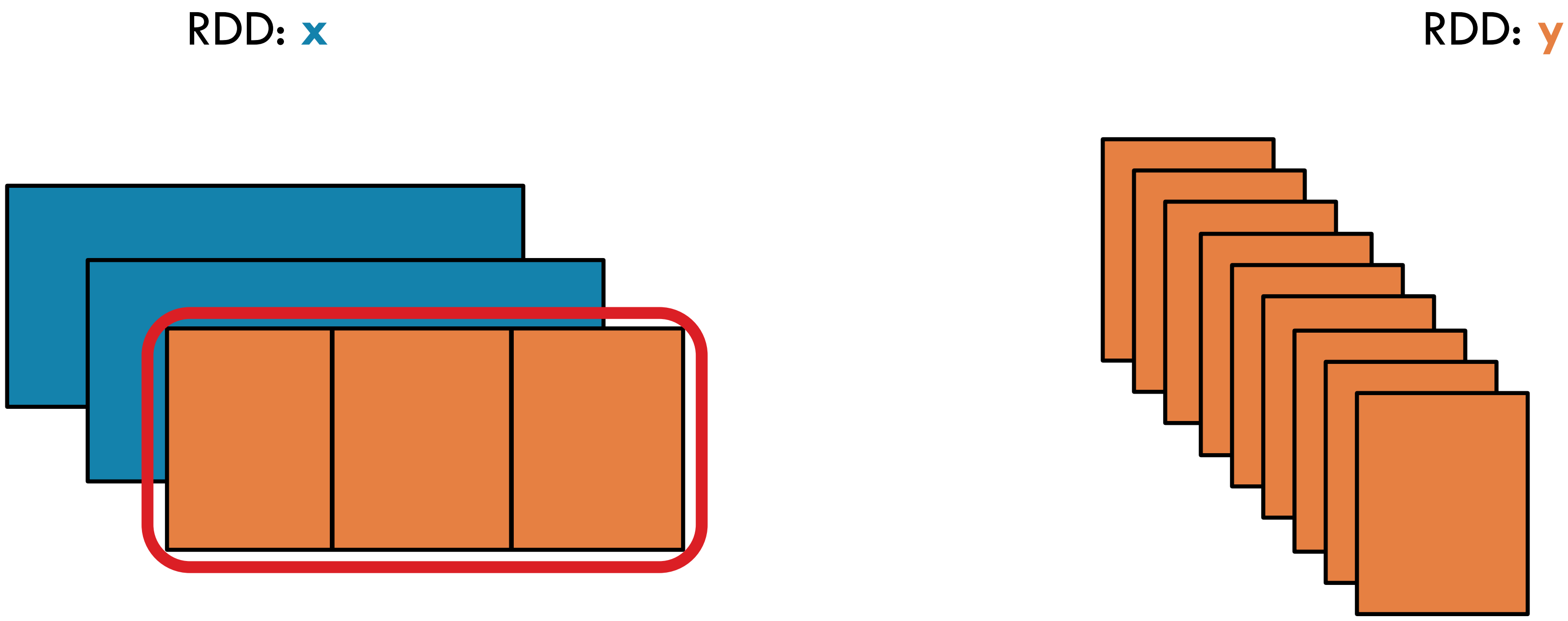
before

RDD: y



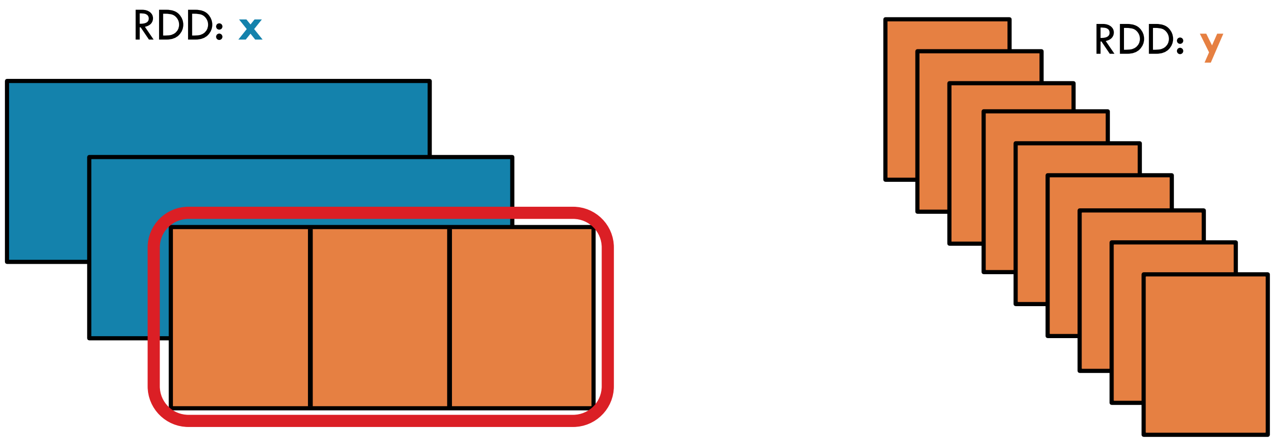
after

# 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

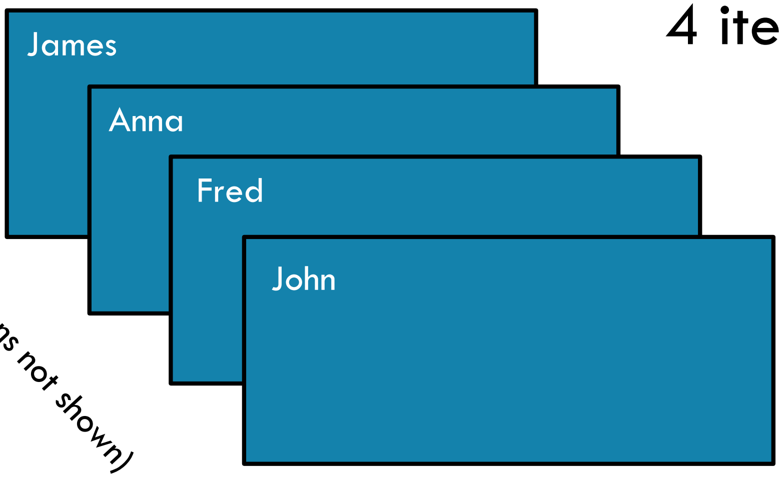
```python
x = sc.parallelize([1,2,3])
y = x.flatMap(lambda x: (x, x*100, 42))
print(x.collect())
print(y.collect())
```

```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

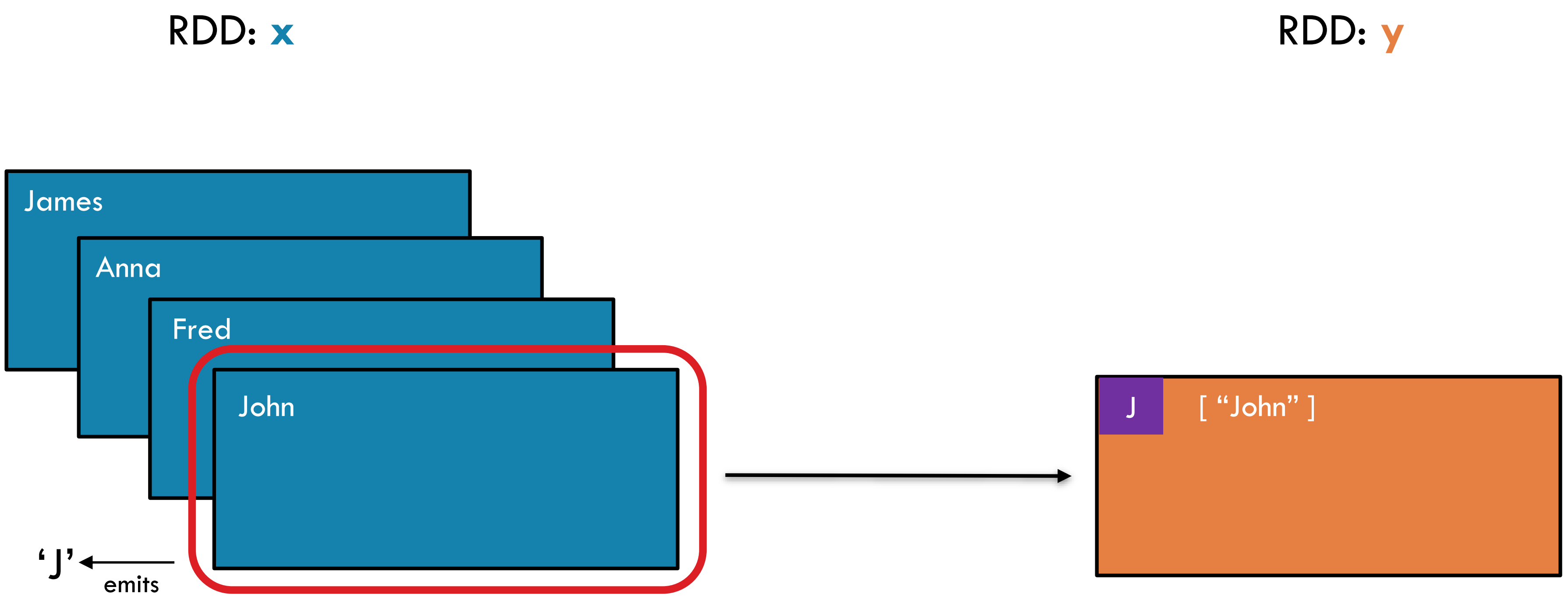
RDD: **x**



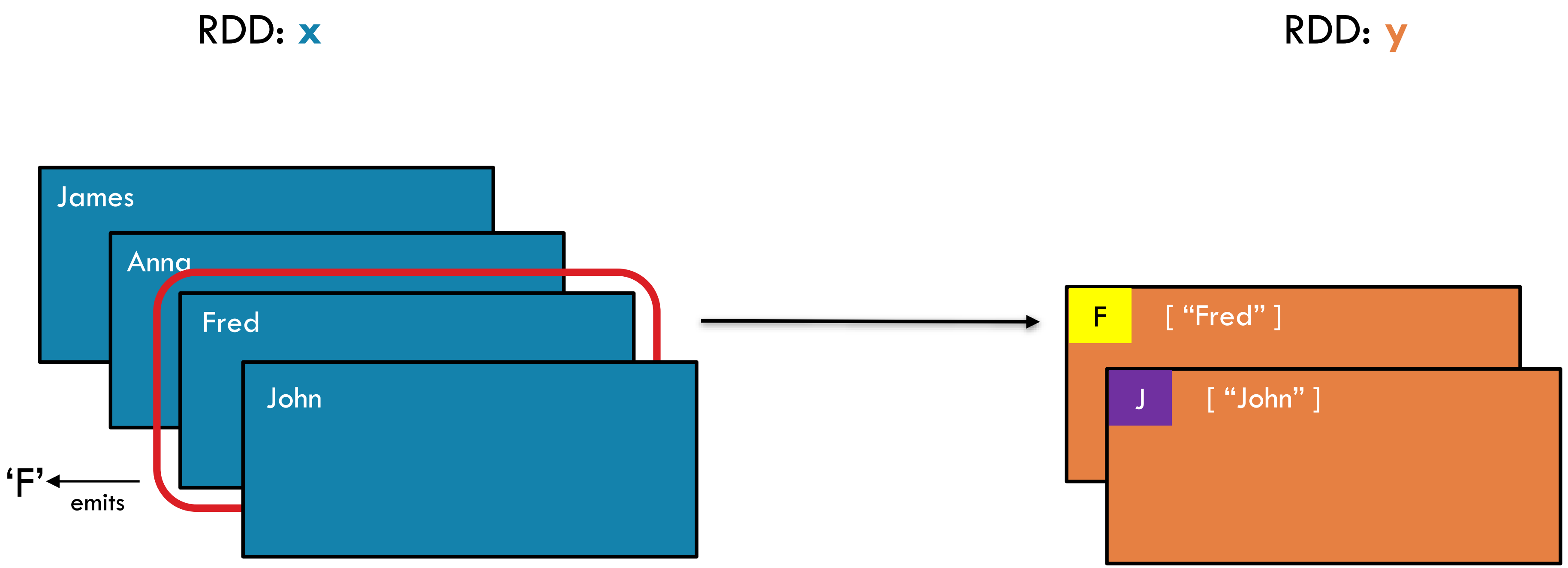

(partitions not shown)

4 items in RDD

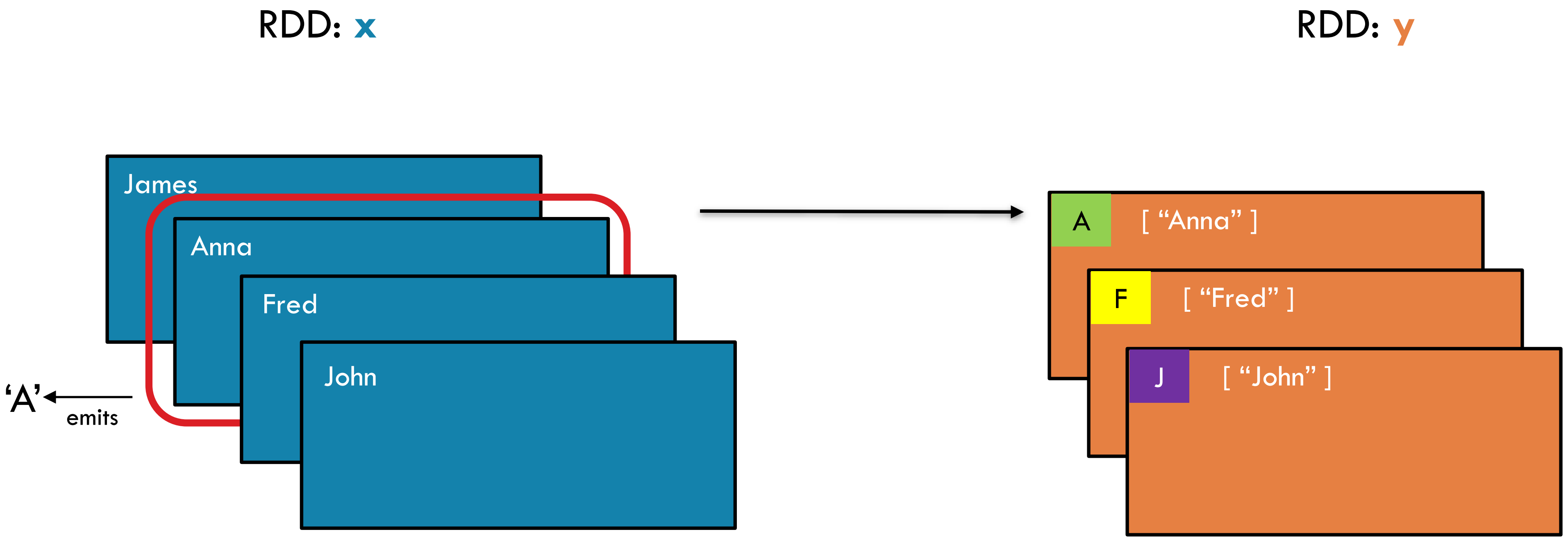
# GROUPBY



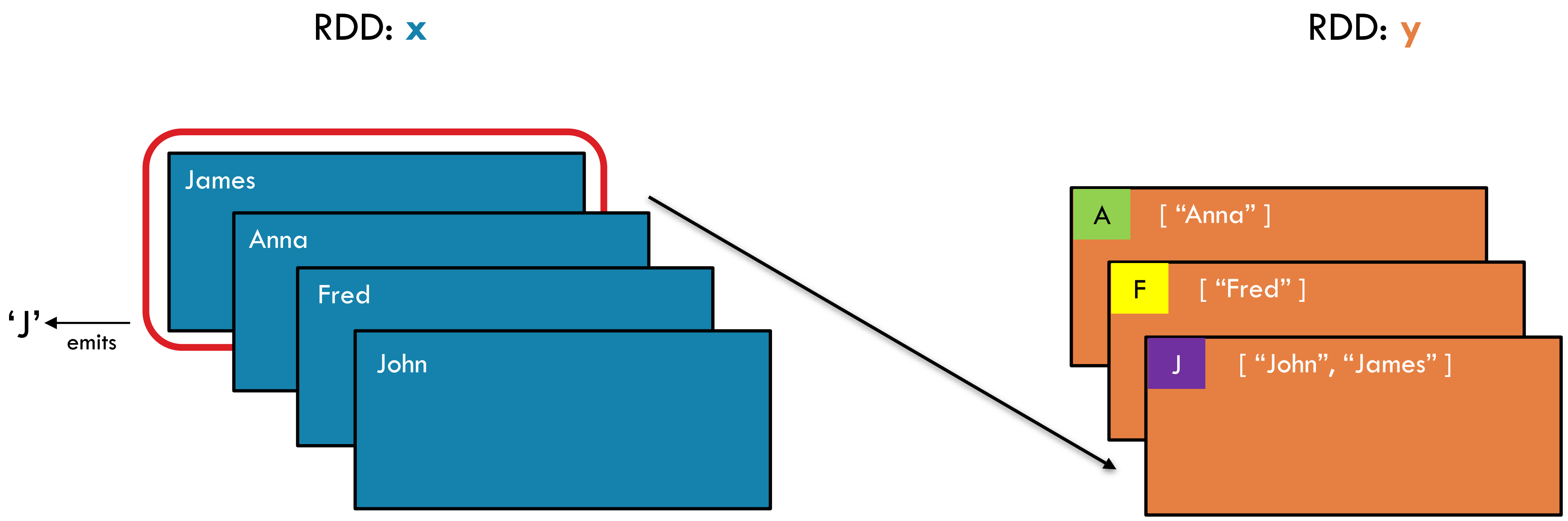
# GROUPBY



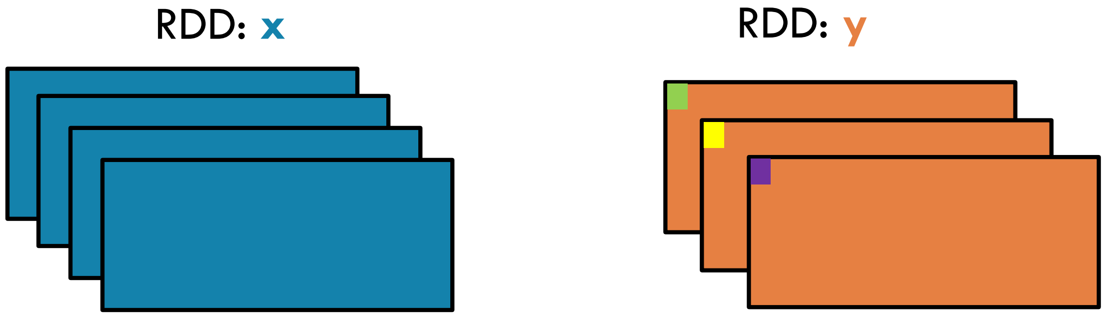
# GROUPBY



# GROUPBY


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

# GROUPBY




**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.

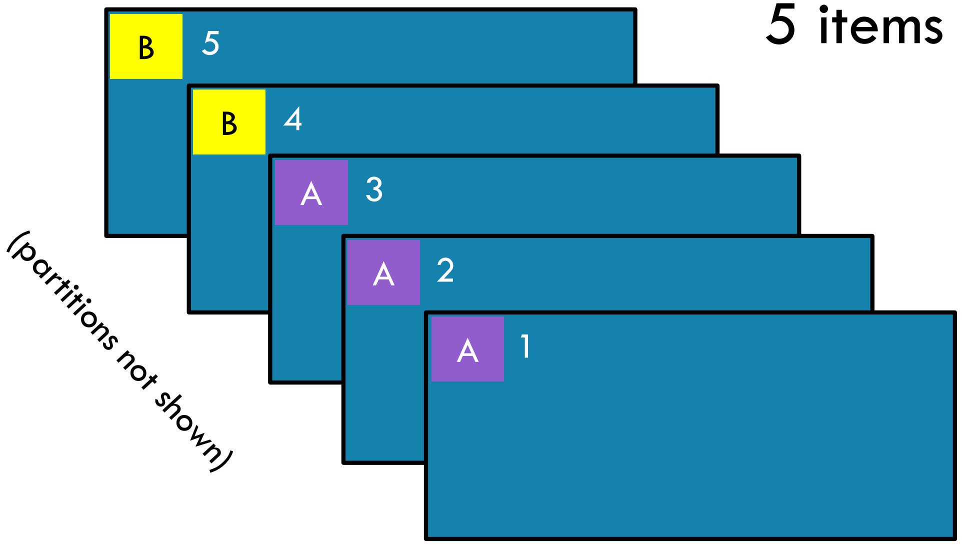
```
x = sc.parallelize(['John', 'Fred', 'Anna', 'James'])
y = x.groupBy(lambda w: w[0])
print [(k, list(v)) for (k, v) in y.collect()]
```

```
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'])]
```

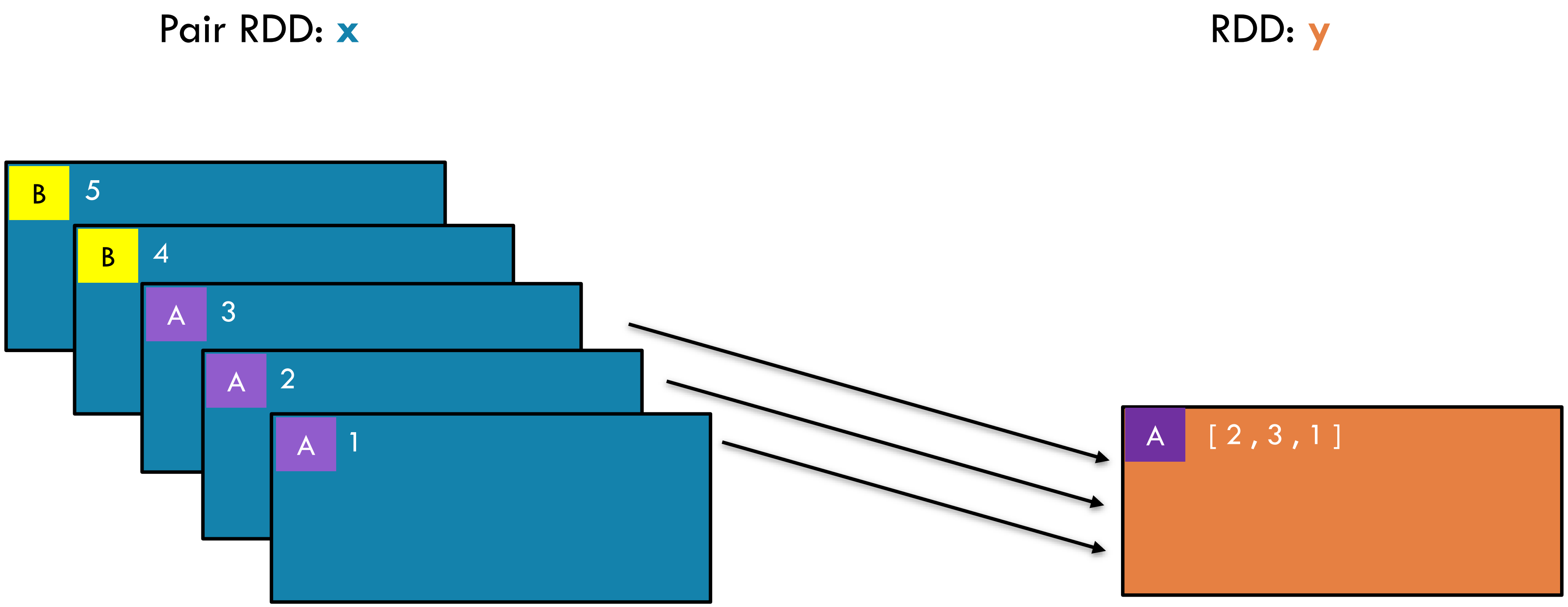
# GROUPBYKEY

Pair RDD: **x**

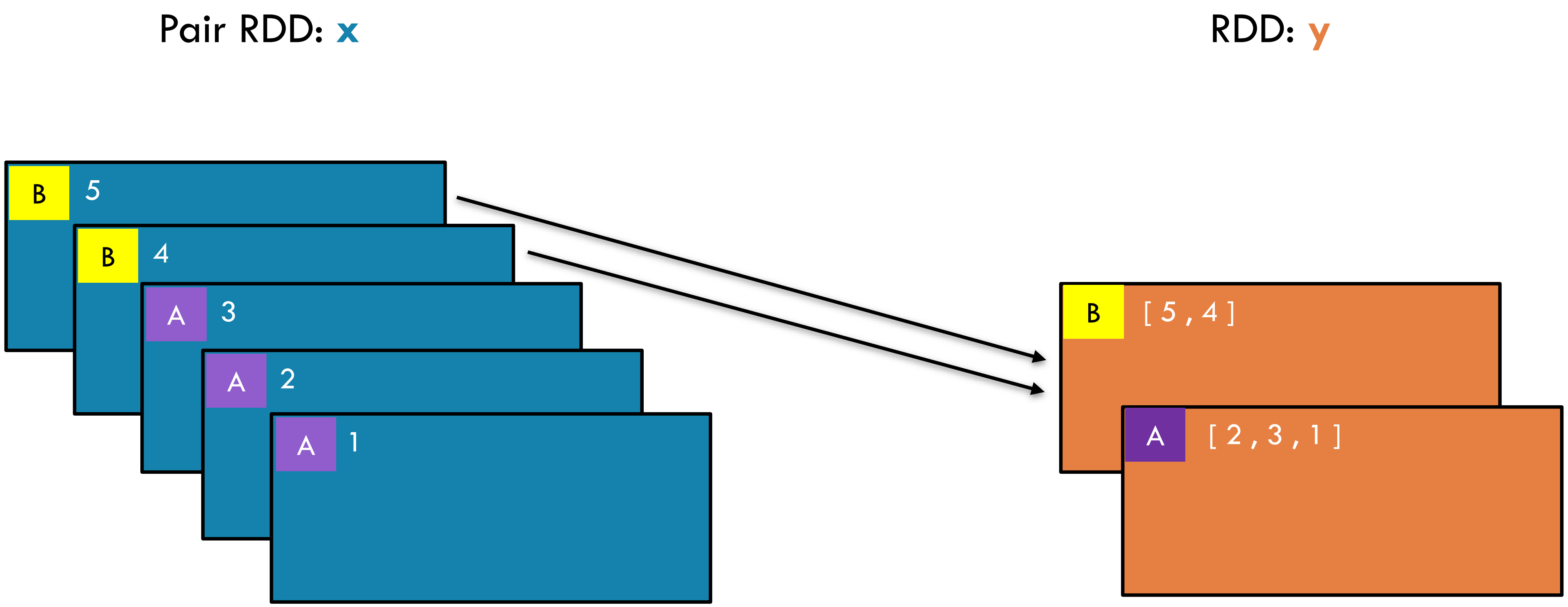



5 items in RDD

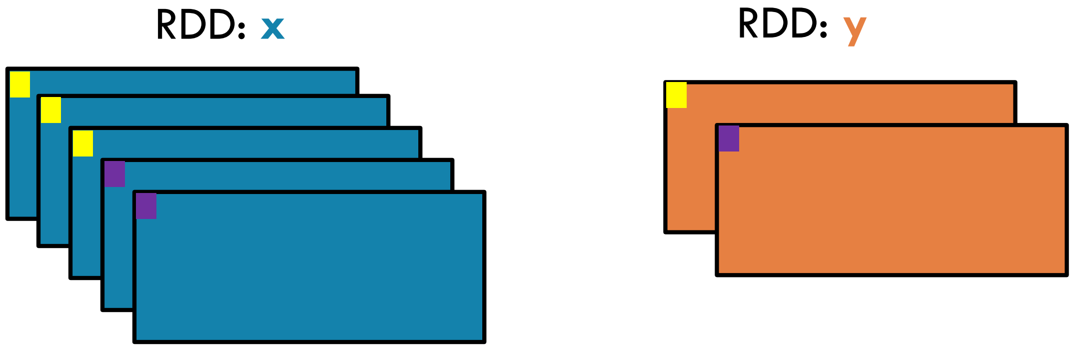
# GROUPBYKEY



# GROUPBYKEY



# GROUPBYKEY




**groupByKey(*numPartitions=None*)**

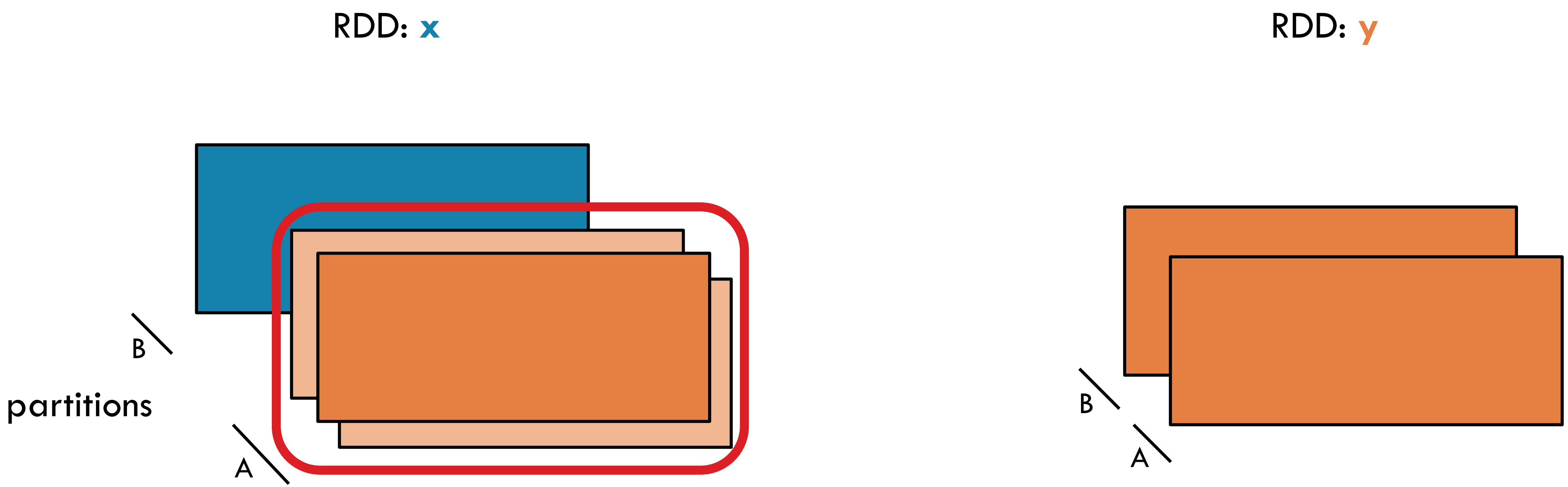
Group the values for each key in the original RDD. Create a new pair where the original key corresponds to this collected group of values.

```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()))
```

```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(", "))
```

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

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

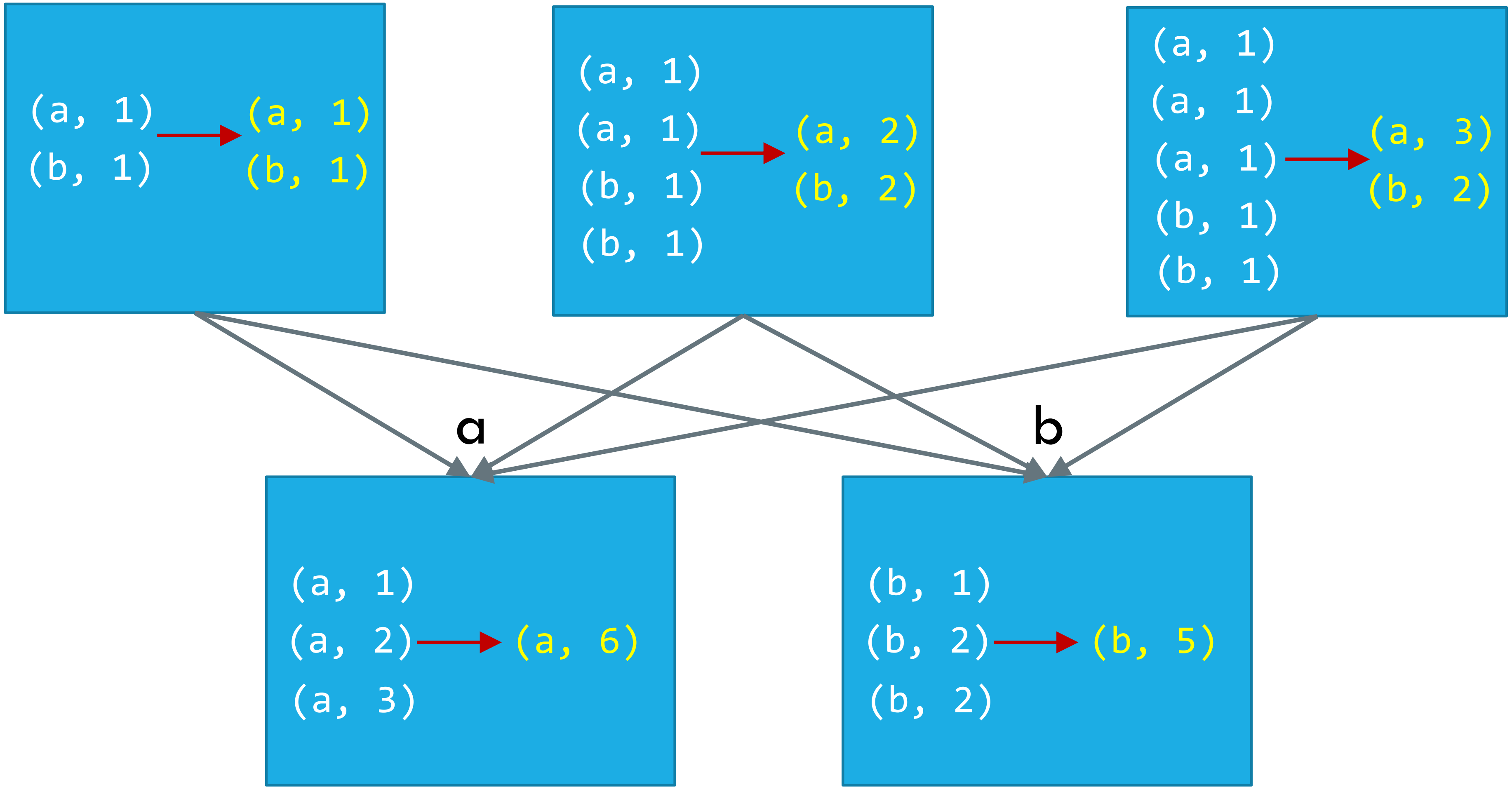
# MAPPARTITIONS



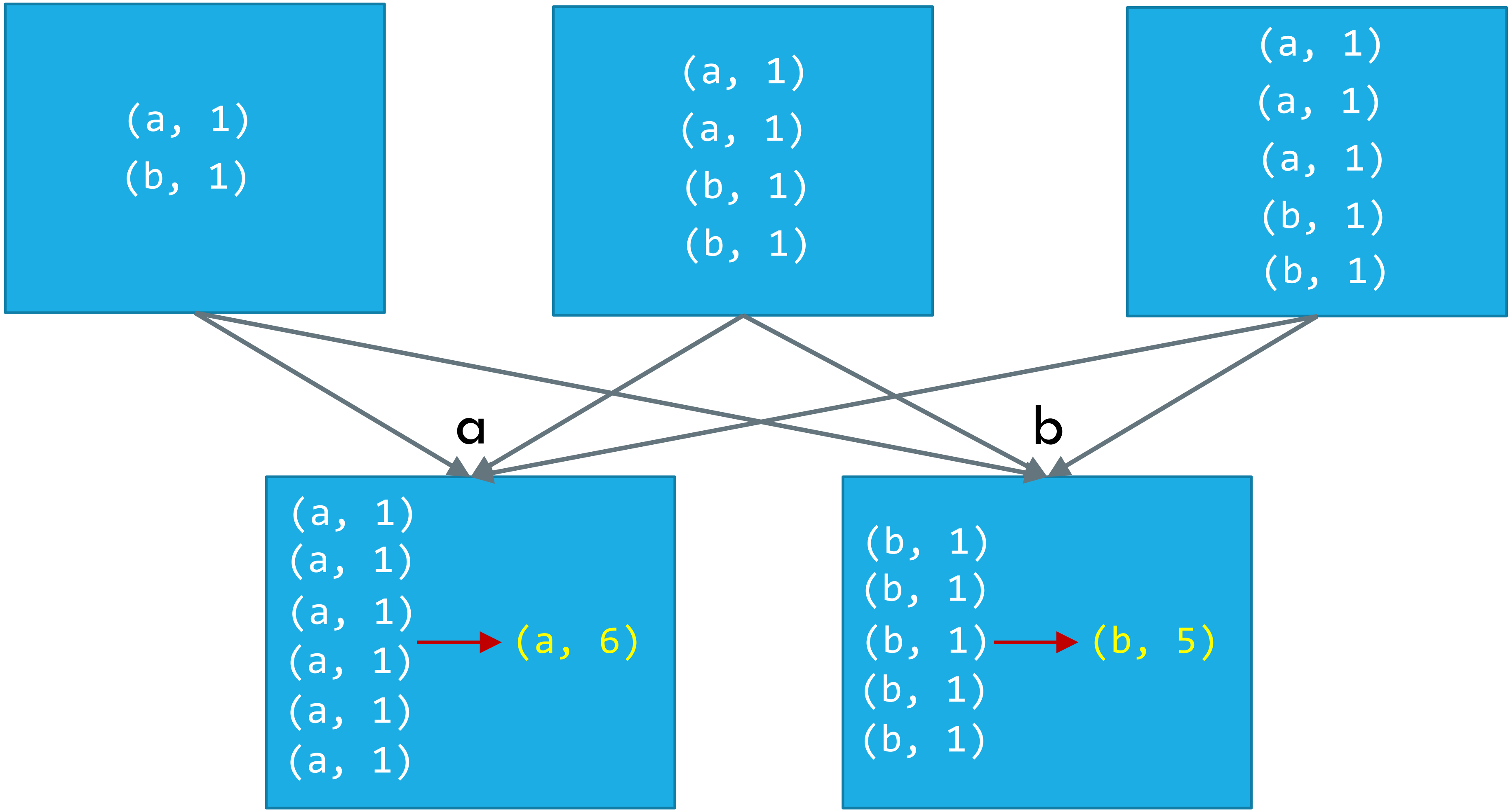
# REDUCEBYKEY vs GROUPBYKEY

```
val words = Array("one", "two", "two", "three", "three", "three")
val wordPairsRDD = sc.parallelize(words).map(word => (word, 1))

val wordCountsWithReduce = wordPairsRDD
  .reduceByKey(_ + _)
  .collect()

val wordCountsWithGroup = wordPairsRDD
  .groupByKey()
  .map(t => (t._1, t._2.sum))
  .collect()
```

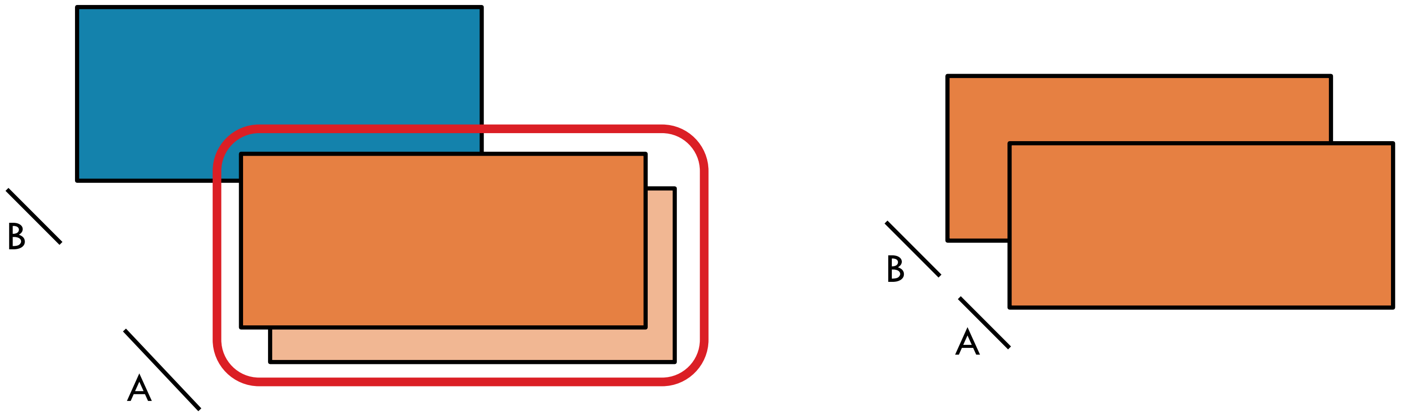
# REDUCEBYKEY



# GROUPBYKEY


(a, 1)
(b, 1)
(a, 1)
(a, 1)
(b, 1)
(b, 1)
(a, 1)
(a, 1)
(a, 1)
(b, 1)
(b, 1)
a
b
(a, 1)
(a, 1)
(a, 1)
(a, 1)
(a, 1)
(a, 1)
(a, 6)
(b, 1)
(b, 1)
(b, 1)
(b, 1)
(b, 1)
(b, 5)

# MAPPARTITIONS



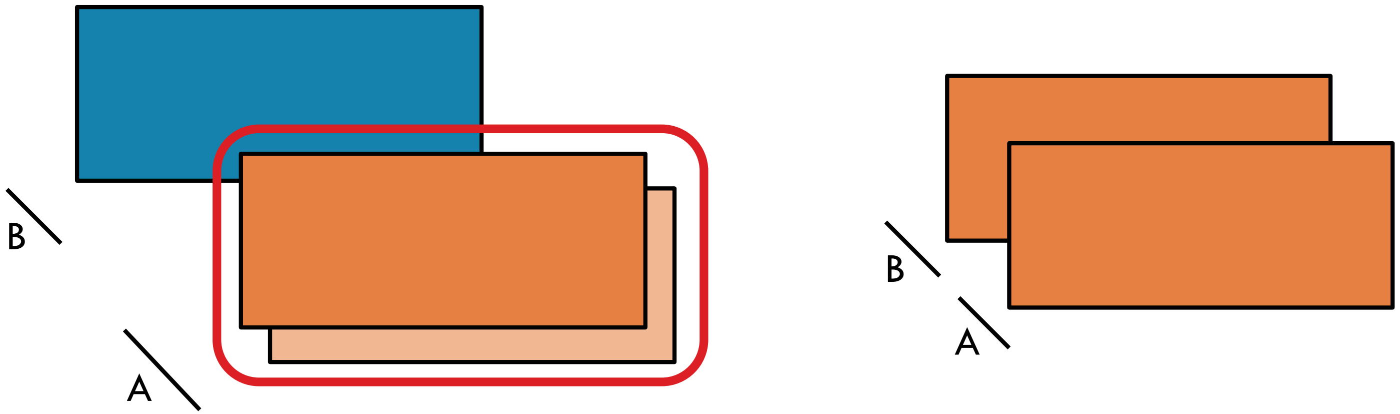

`mapPartitions(f, preservesPartitioning=False)`

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

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

def f(iterator): yield sum(iterator); yield 42

y = x.mapPartitions(f)

# glom() flattens elements on the same partition
print(x.glom().collect())
print(y.glom().collect())
```

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

y:  [[1, 42], [5, 42]]
```

# MAPPARTITIONS



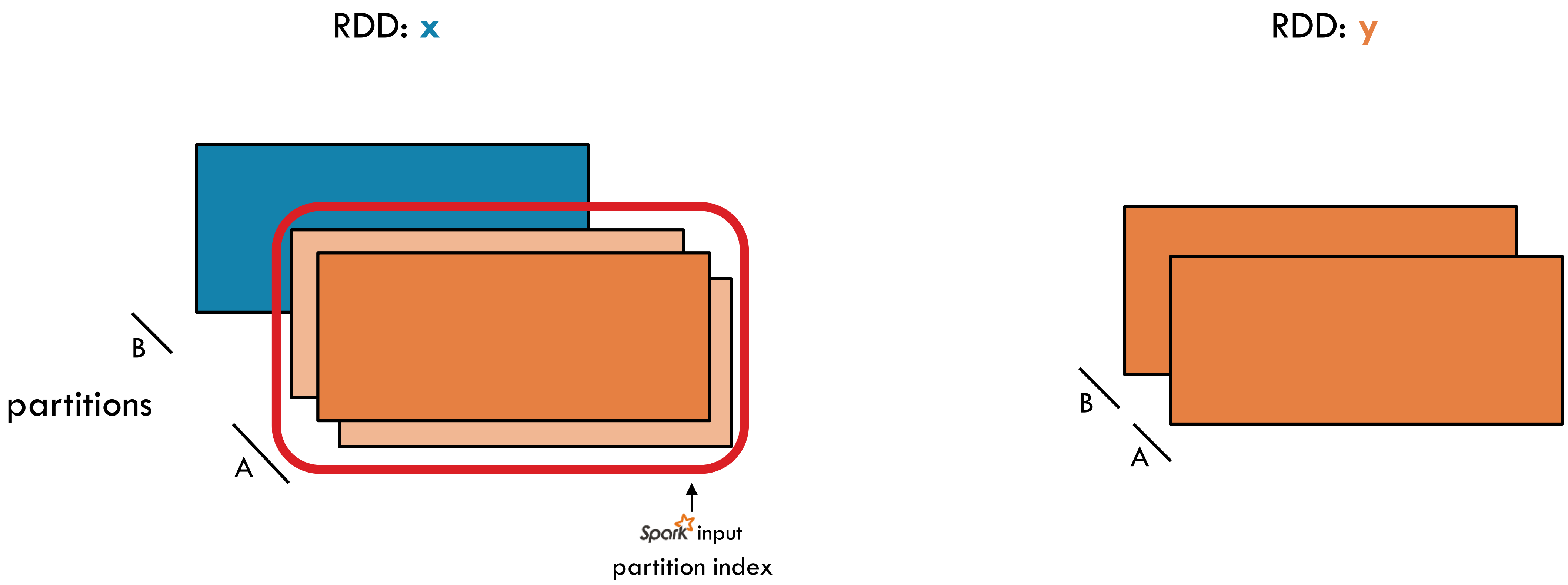

`mapPartitions(f, preservesPartitioning=False)`

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

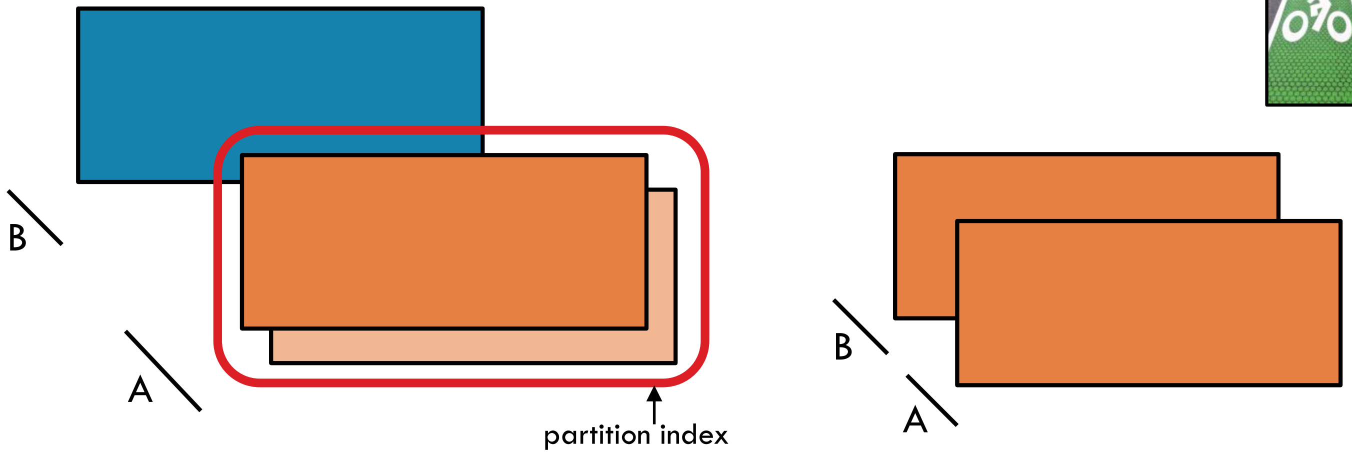
```
val x = sc.parallelize(Array(1,2,3), 2)

def f(i:Iterator[Int])={ (i.sum,42).productIterator }

val y = x.mapPartitions(f)

// glom() flattens elements on the same partition
val xOut = x.glom().collect()
val yOut = y.glom().collect()
```

```
x: Array(Array(1), Array(2, 3))

y: Array(Array(1, 42), Array(5, 42))
```

# MAPPARTITIONSWITHINDEX



# MAPPARTITIONSWITHINDEX




`mapPartitionsWithIndex(f, preservesPartitioning=False)`

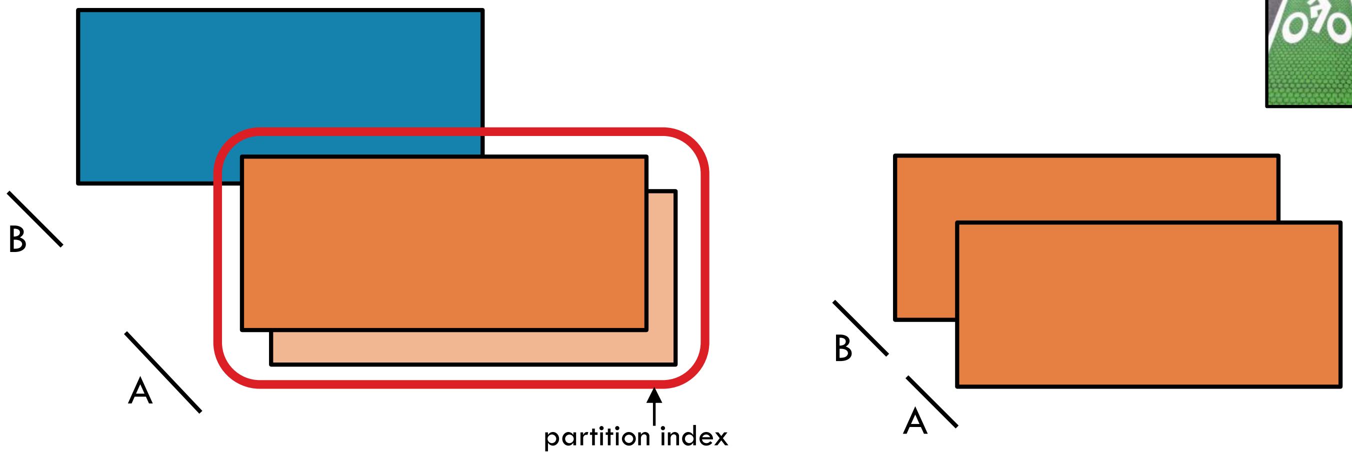
Return a new RDD by applying a function to each partition of this RDD, while tracking the index of the original partition

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

def f(partitionIndex, iterator): yield (partitionIndex, sum(iterator))

y = x.mapPartitionsWithIndex(f)

# glom() flattens elements on the same partition
print(x.glom().collect())
print(y.glom().collect())
```

B A

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

y: [[0, 1], [1, 5]]
```

# MAPPARTITIONSWITHINDEX




**mapPartitionsWithIndex(*f*, *preservesPartitioning=False*)**

Return a new RDD by applying a function to each partition of this RDD, while tracking the index of the original partition.

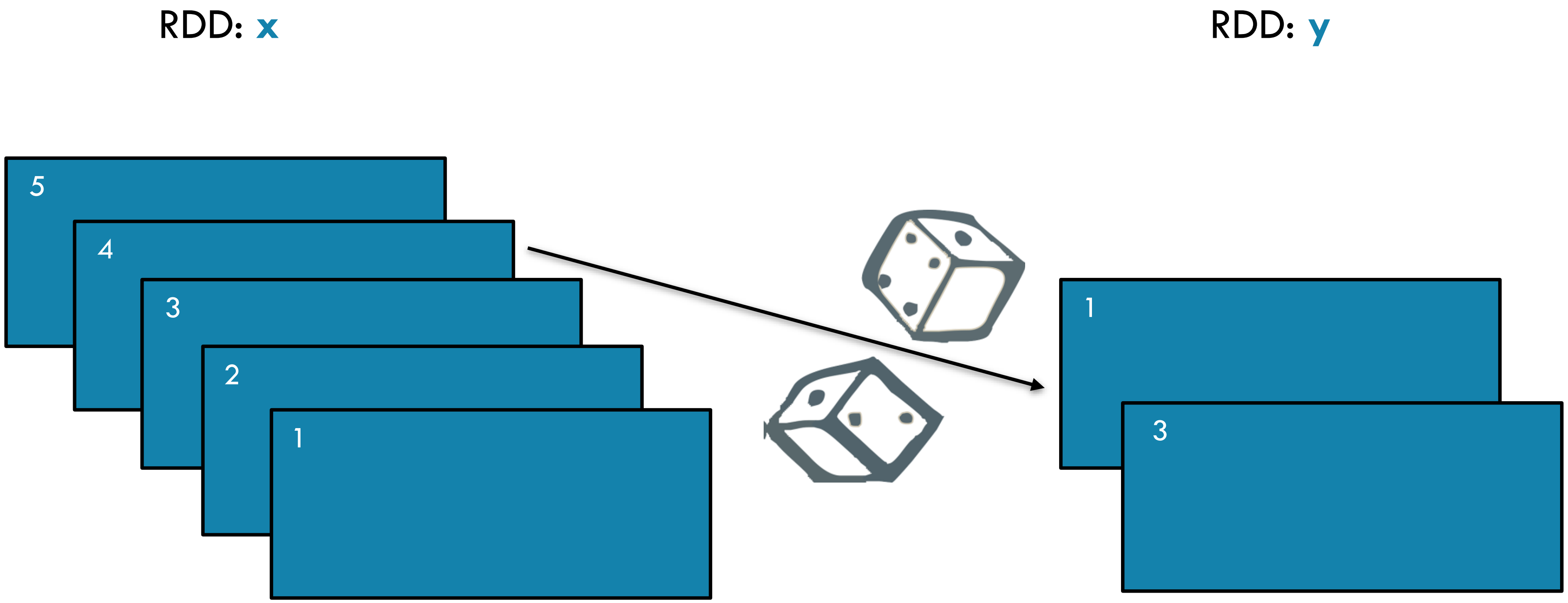
```
val x = sc.parallelize(Array(1,2,3), 2)

def f(partitionIndex:Int, i:Iterator[Int]) = {
 (partitionIndex, i.sum).productIterator
}

val y = x.mapPartitionsWithIndex(f)

// glom() flattens elements on the same partition
val xOut = x.glom().collect()
val yOut = y.glom().collect()
```

B A

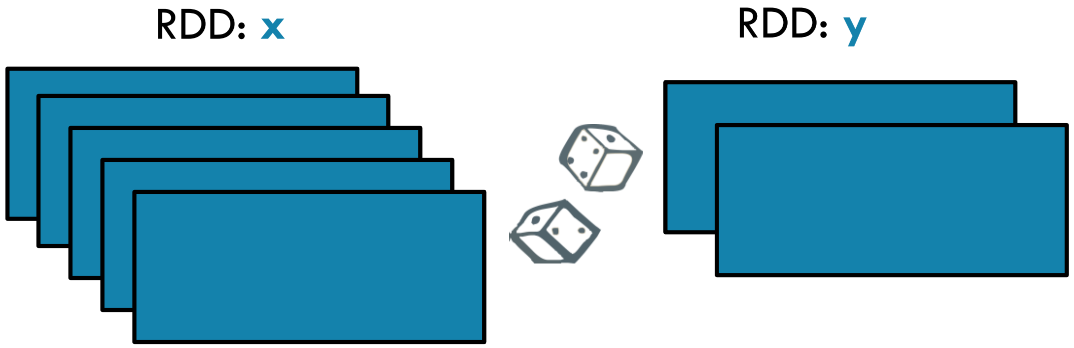
x: Array(Array(1), Array(2, 3))

y: Array(Array(0, 1), Array(1, 5))

# SAMPLE



# SAMPLE




```
sample(withReplacement, fraction, seed=None)
```

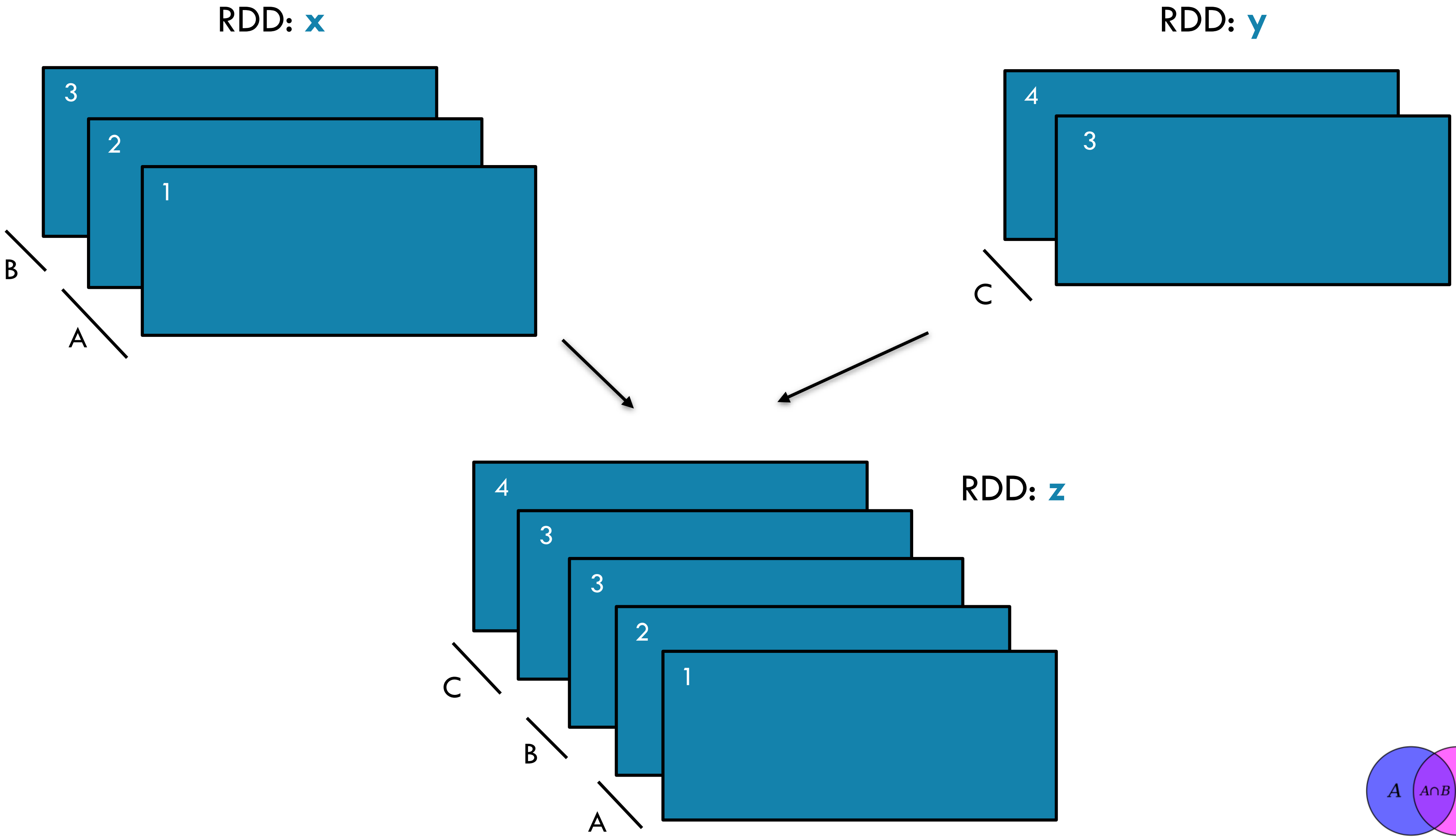
Return a new RDD containing a statistical sample of the original RDD

```python
x = sc.parallelize([1, 2, 3, 4, 5])
y = x.sample(False, 0.4, 42)
print(x.collect())
print(y.collect())
```

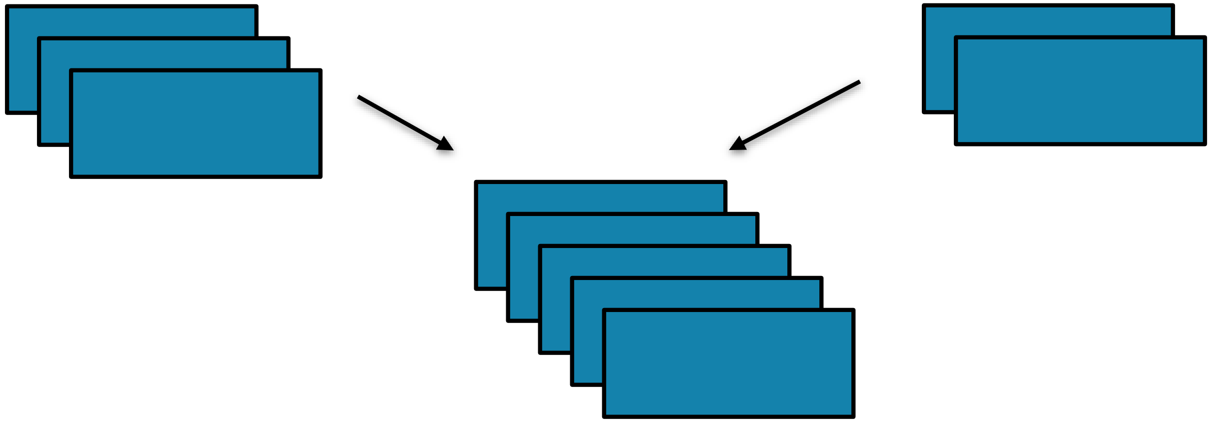
```scala
val x = sc.parallelize(Array(1, 2, 3, 4, 5))
val y = x.sample(false, 0.4)

// omitting seed will yield different output
println(y.collect().mkString(", "))
```

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

y: [1, 3]
```

# UNION



# UNION



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

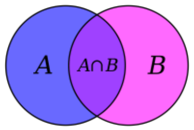
`union(otherRDD)`

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

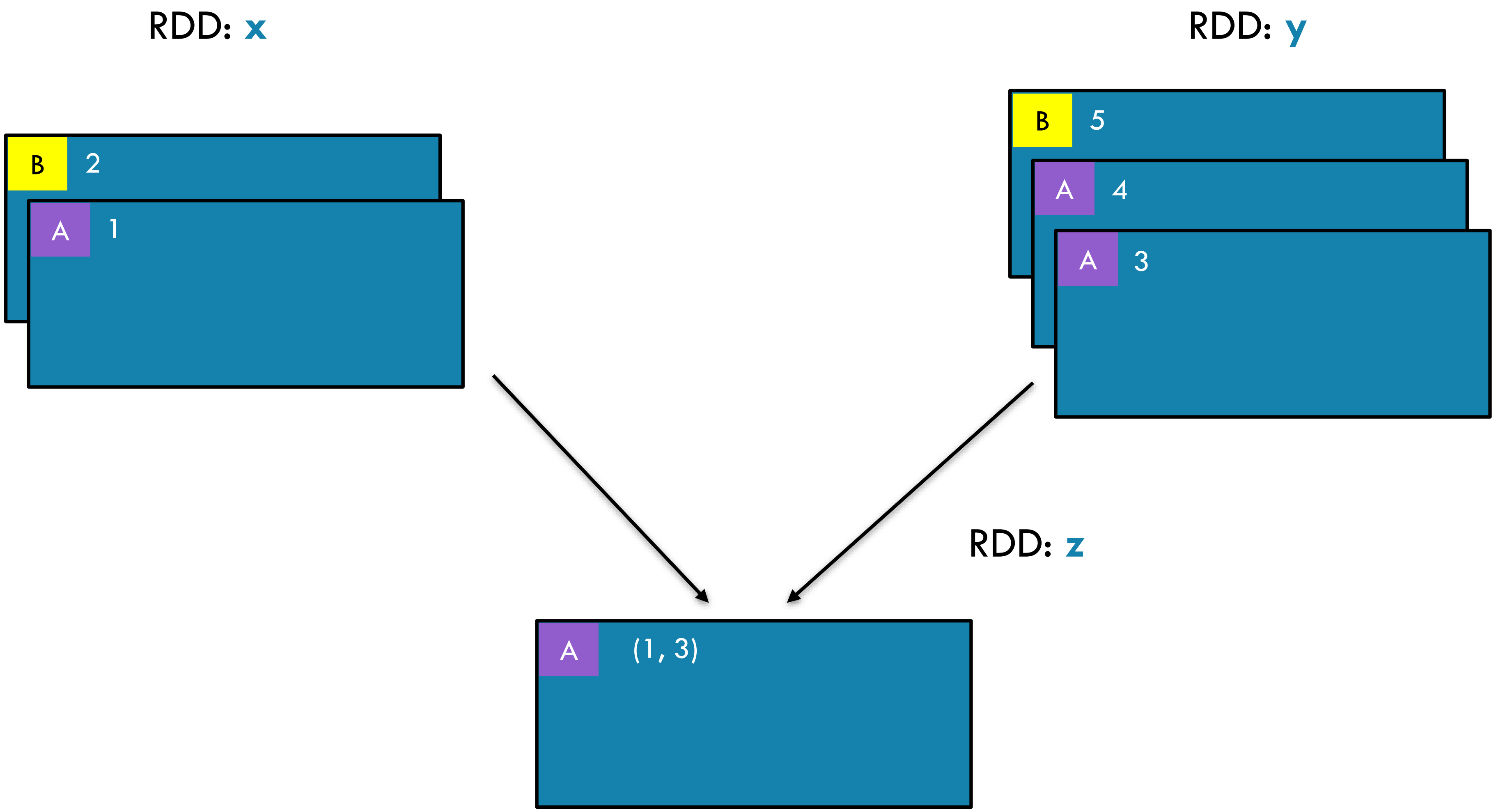
```scala
val x = sc.parallelize(Array(1,2,3), 2)
val y = sc.parallelize(Array(3,4), 1)
val z = x.union(y)
val zOut = z.glom().collect()
```

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

y: [3, 4]

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

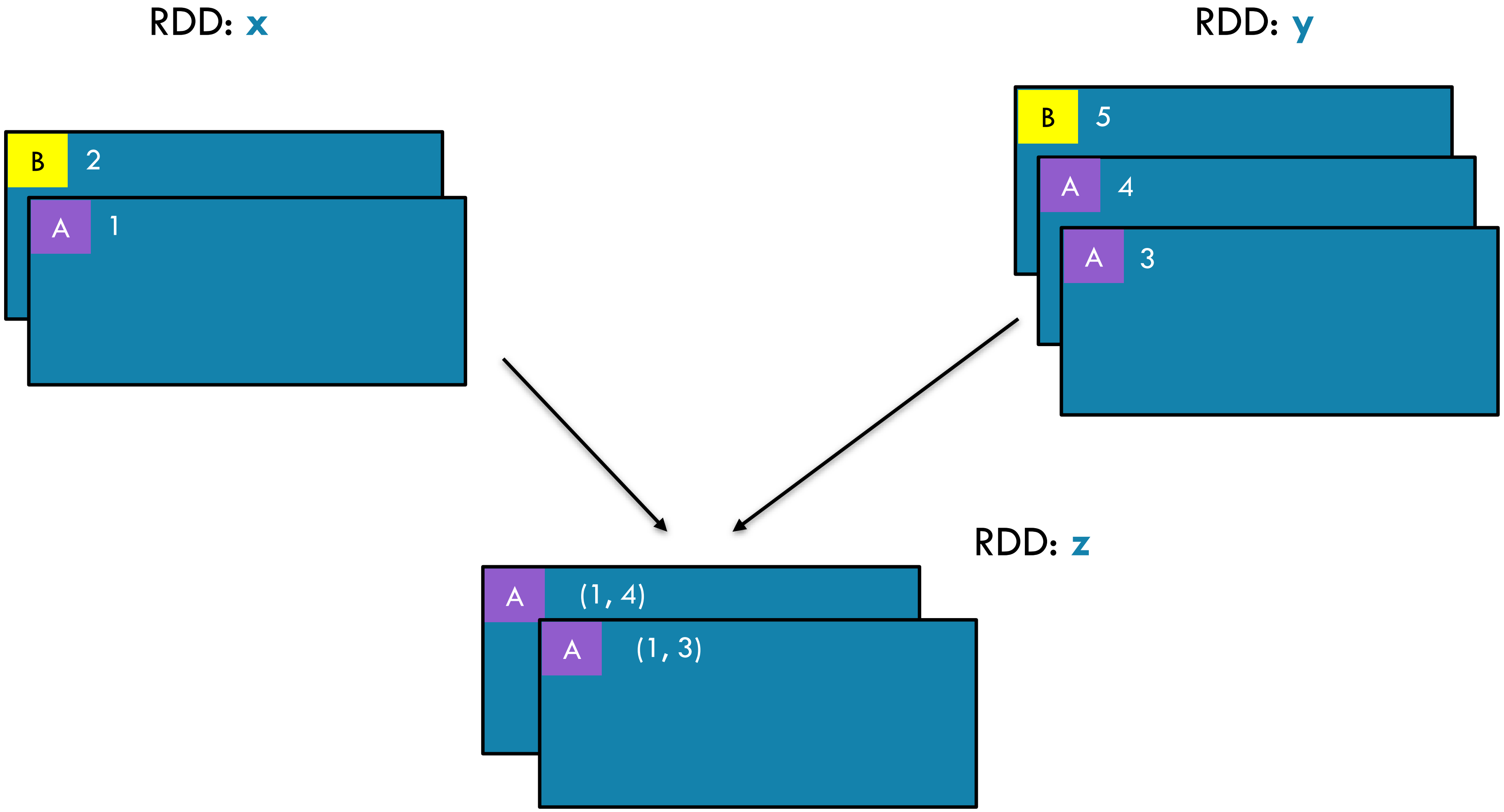
# JOIN

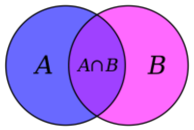



# JOIN

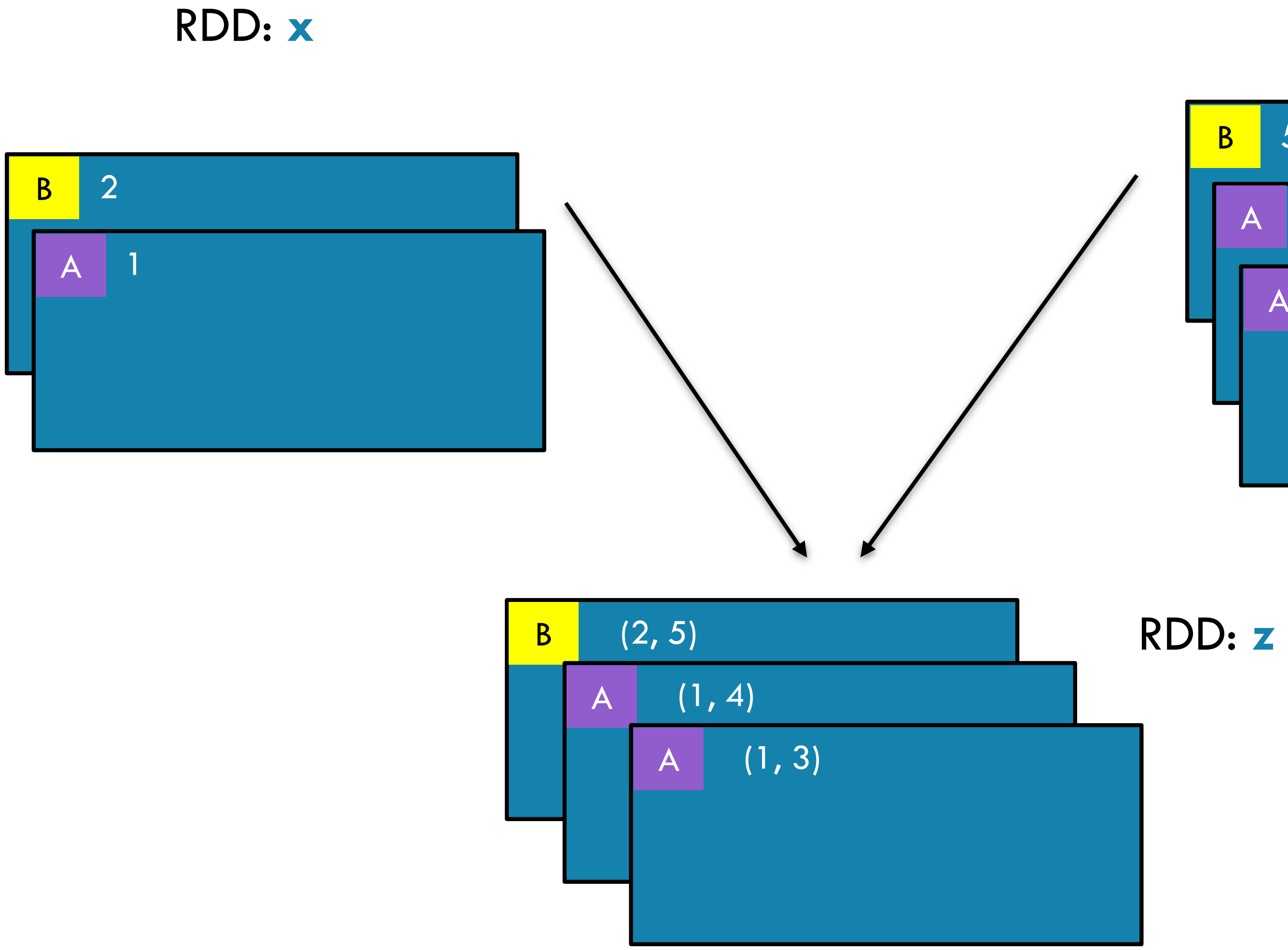


# JOIN

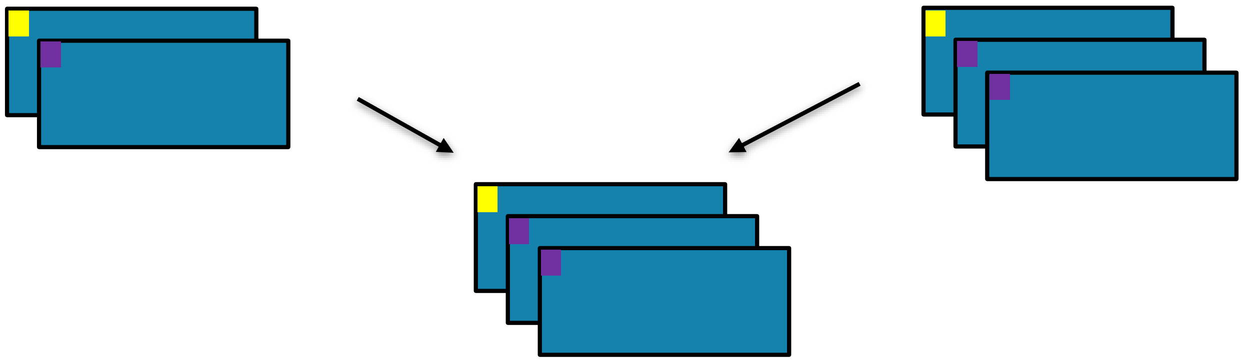


# JOIN



# JOIN



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

**union(*otherRDD, numPartitions=None*)**

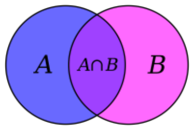
```python
x = sc.parallelize([("a", 1), ("b", 2)])
y = sc.parallelize([("a", 3), ("a", 4), ("b", 5)])
z = x.join(y)
print(z.collect())
```

```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)]

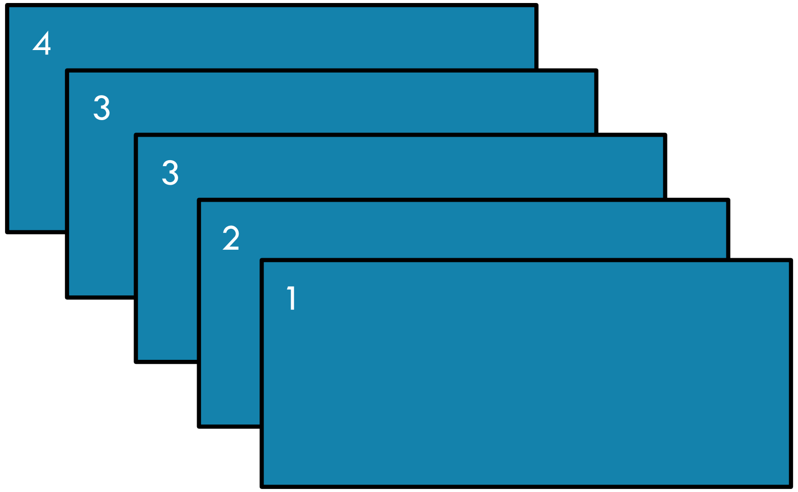
**y:** [("a", 3), ("a", 4), ("b", 5)]

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



# DISTINCT

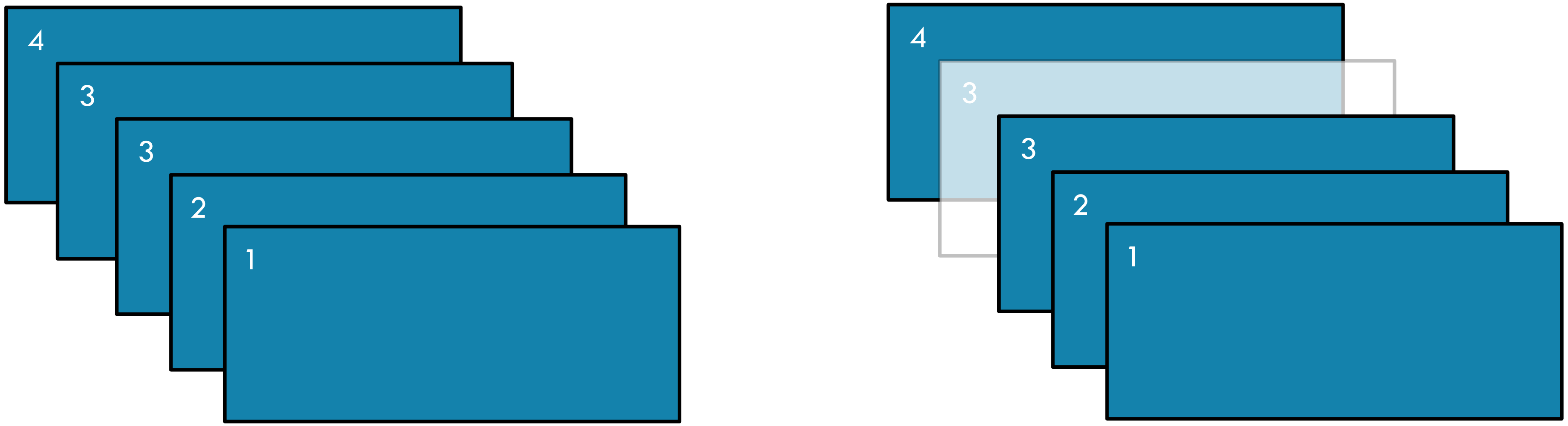
RDD: **x**



# DISTINCT

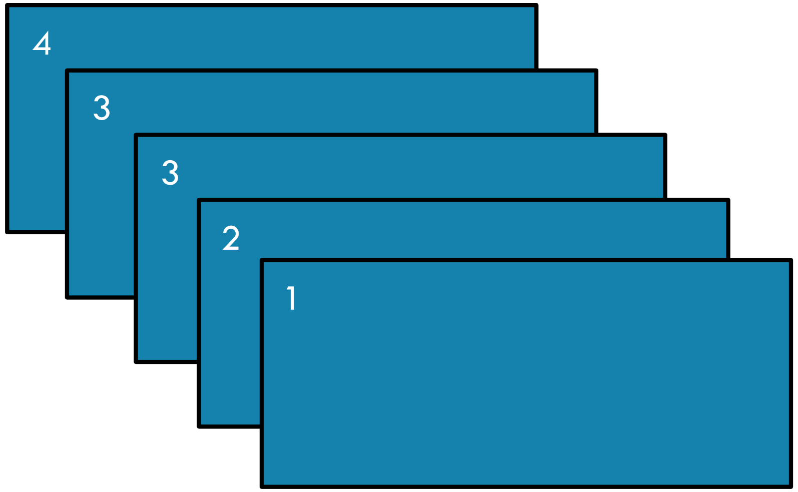
RDD: **x**

RDD: **y**

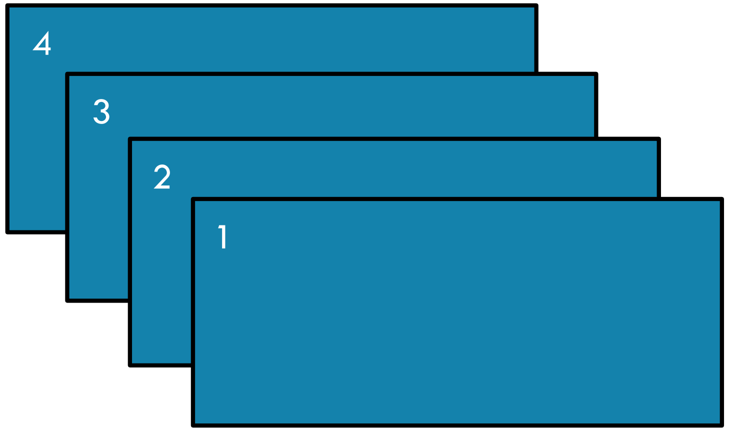


# DISTINCT

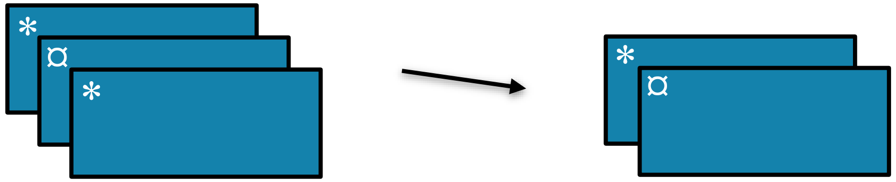
RDD: x




RDD: y



# 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())
```

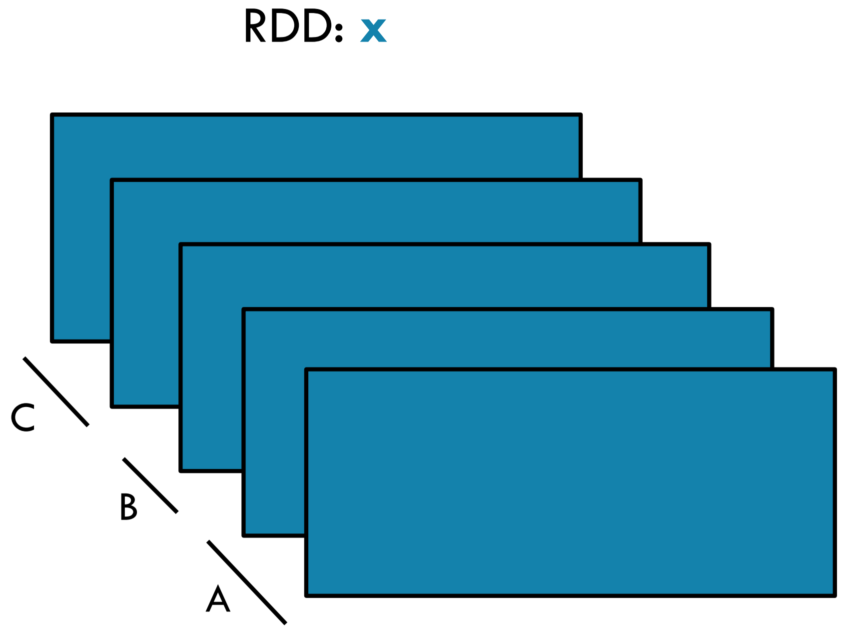
---

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

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

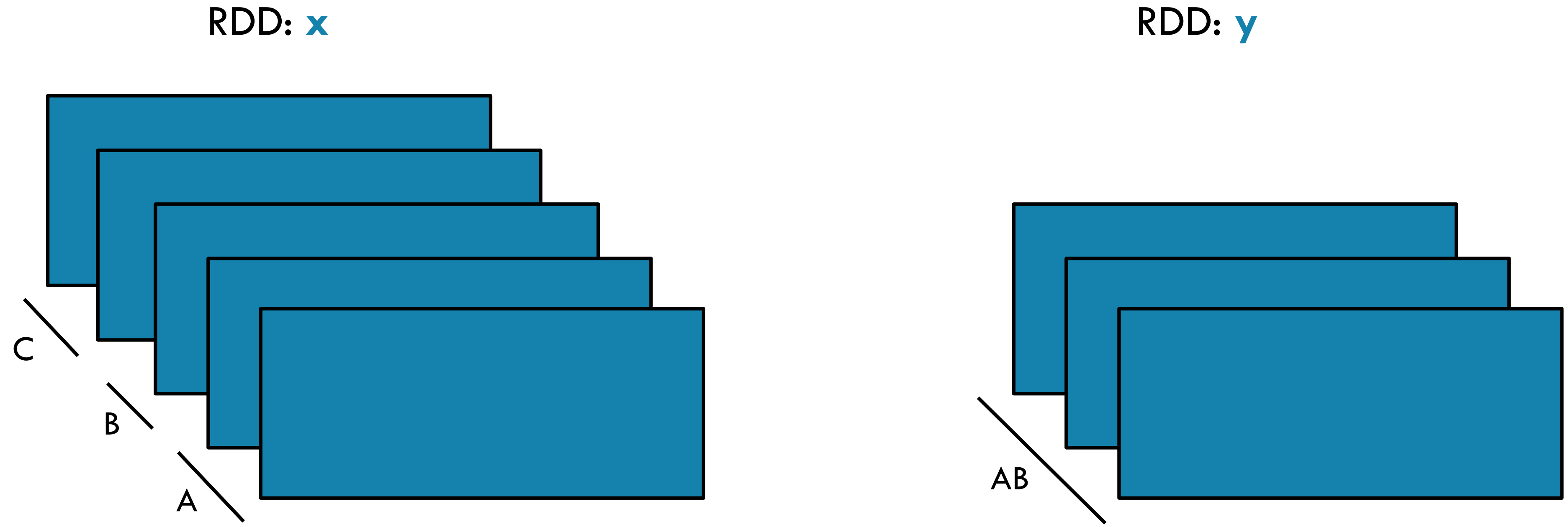
**x:** [1, 2, 3, 3, 4]

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

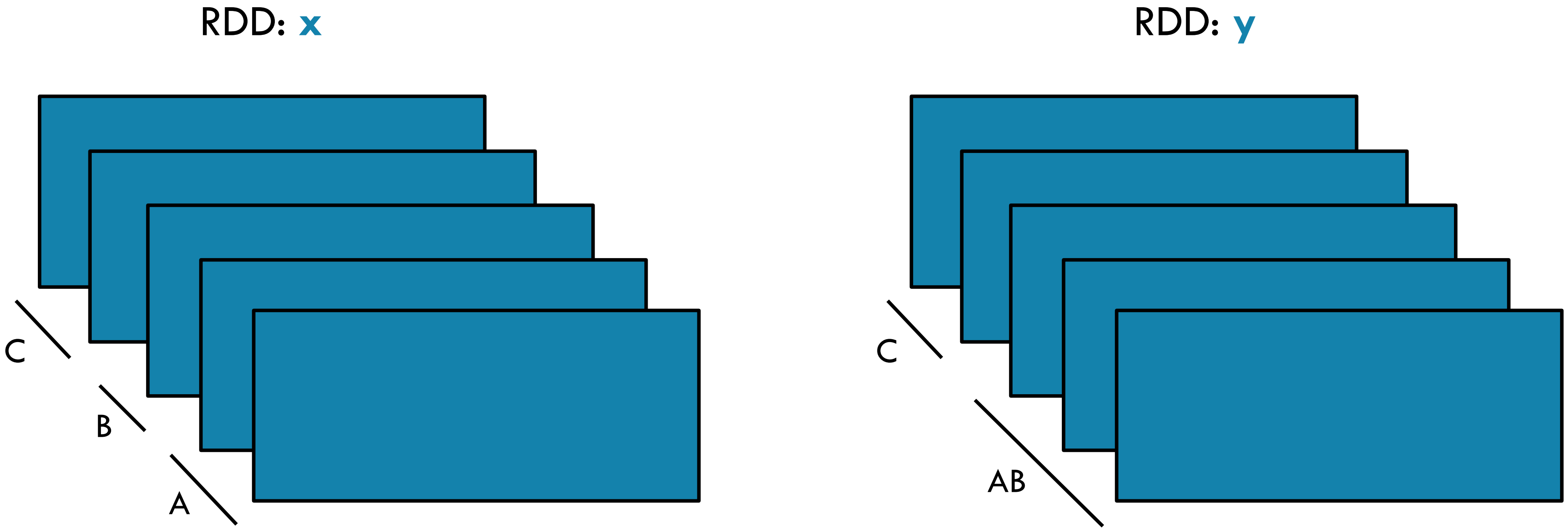
# COALESCE



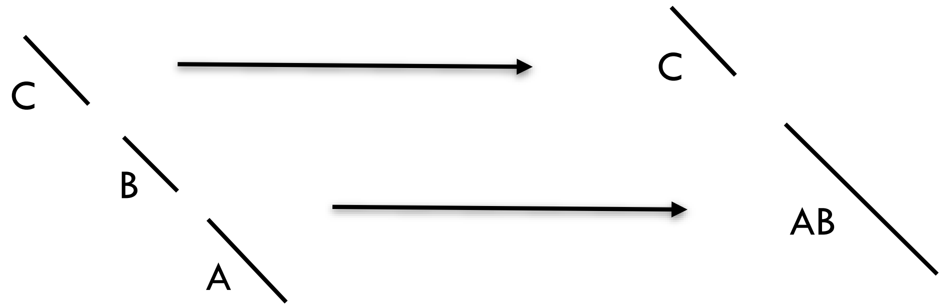
# COALESCE



# COALESCE



# COALESCE




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

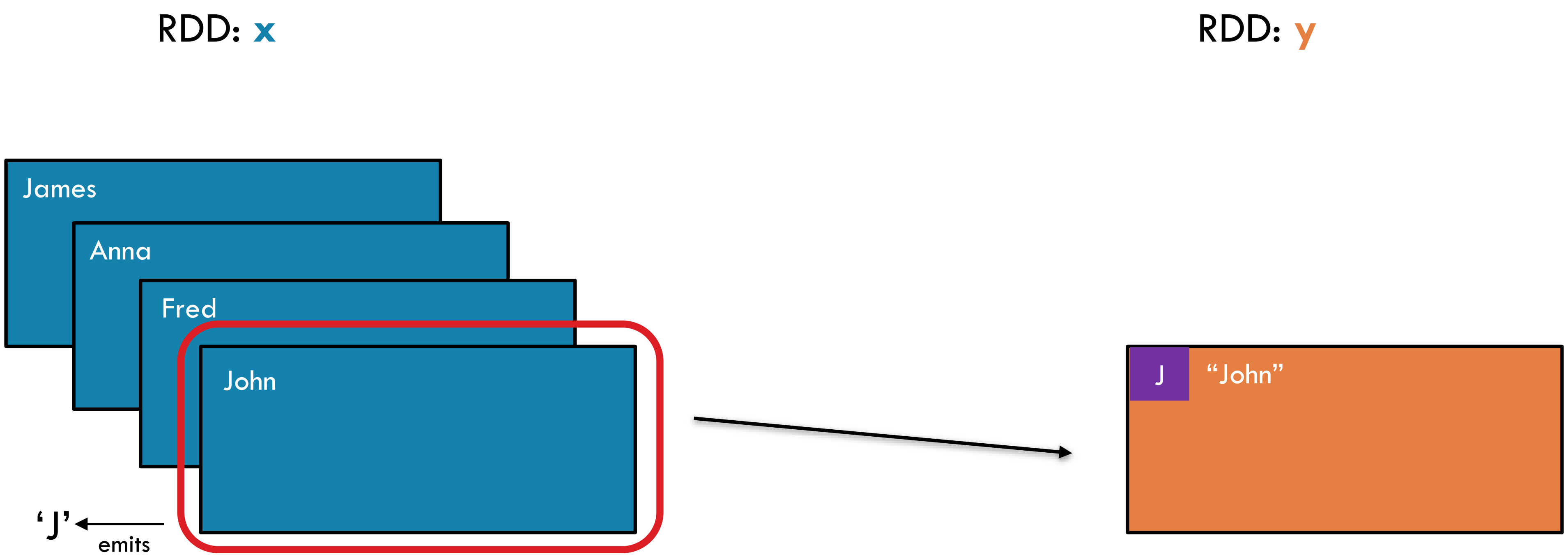
**coalesce(*numPartitions, shuffle=False*)**

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

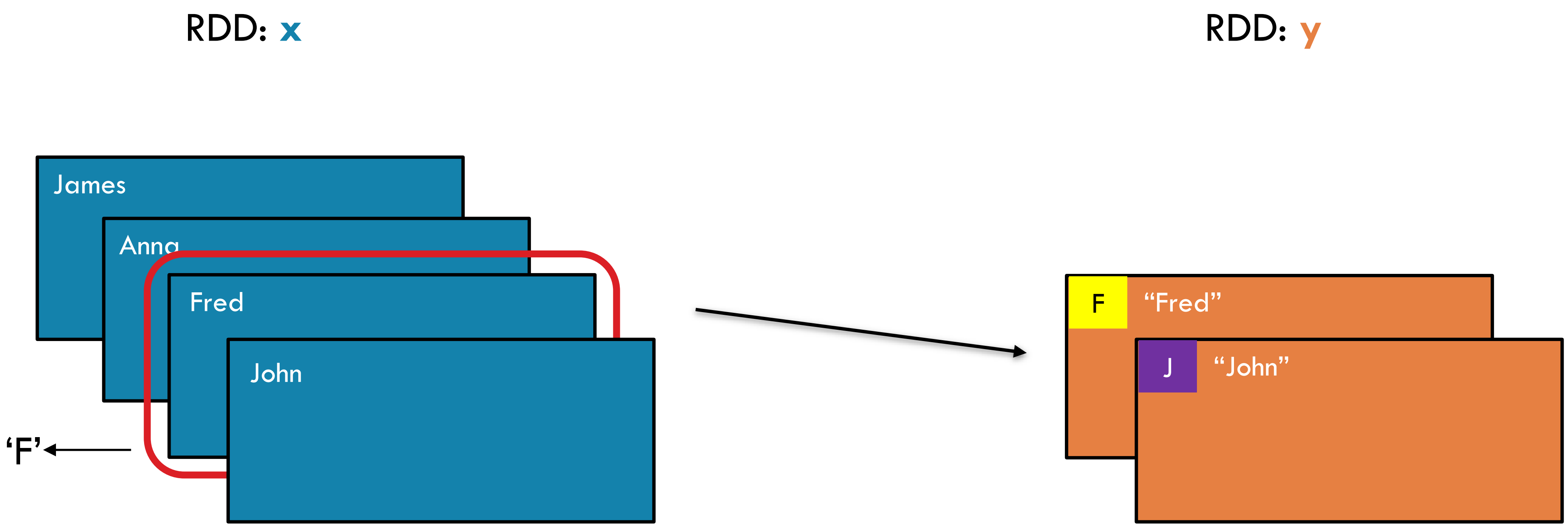
```scala
val x = sc.parallelize(Array(1, 2, 3, 4, 5), 3)
val y = x.coalesce(2)
val xOut = x.glom().collect()
val yOut = y.glom().collect()
```

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

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

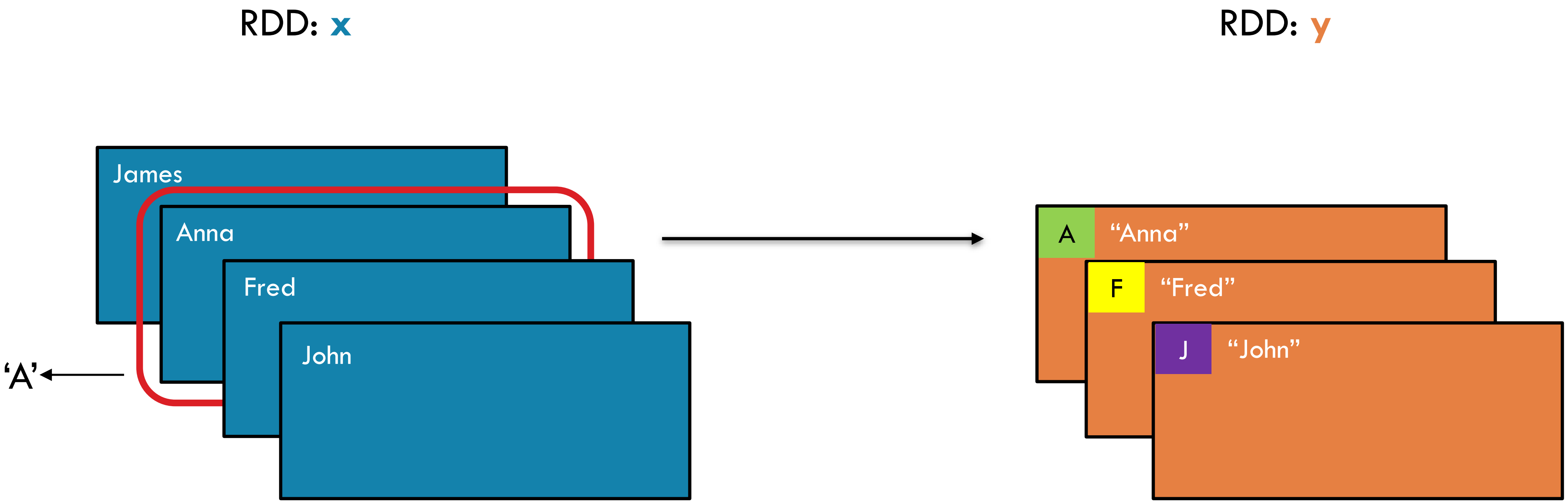
# KEYBY



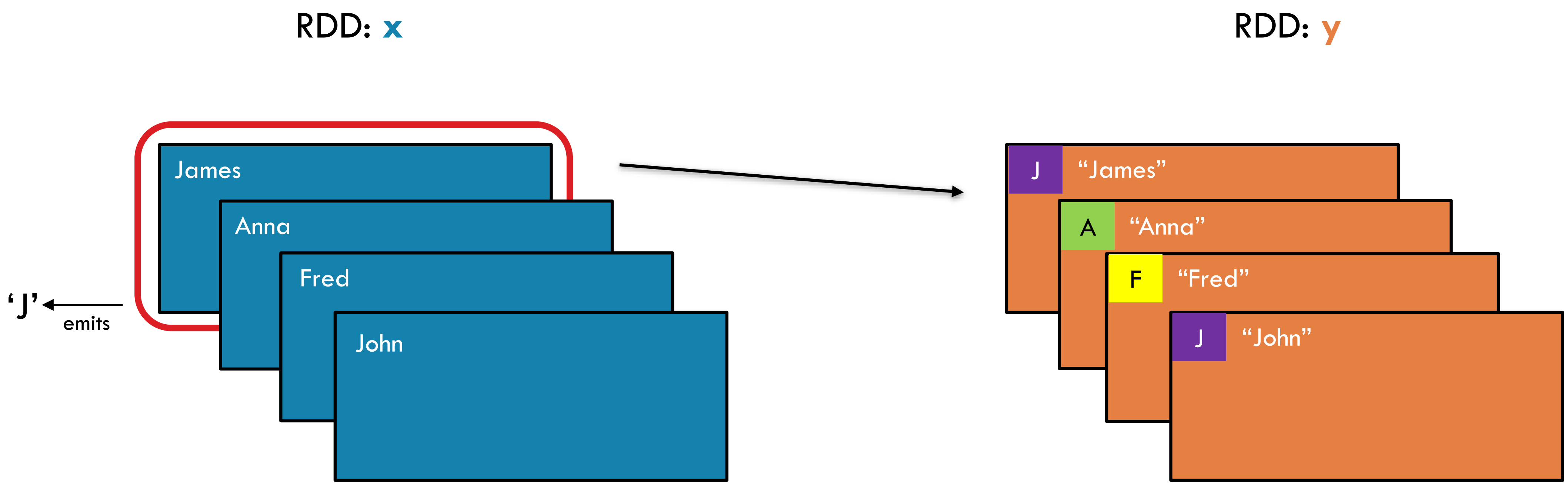

# KEYBY



# KEYBY



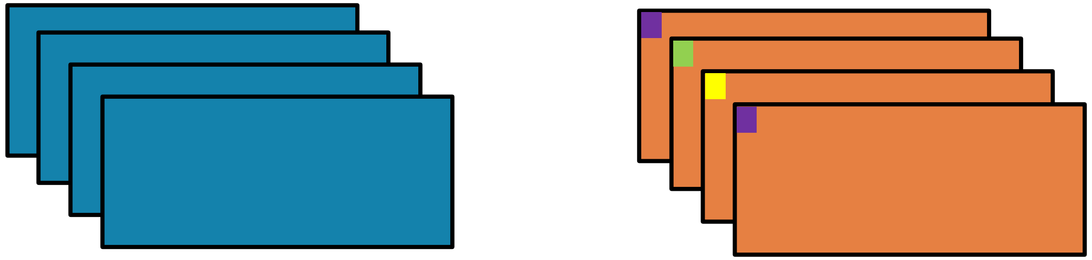
# KEYBY


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

# KEYBY

RDD: x

RDD: y



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.

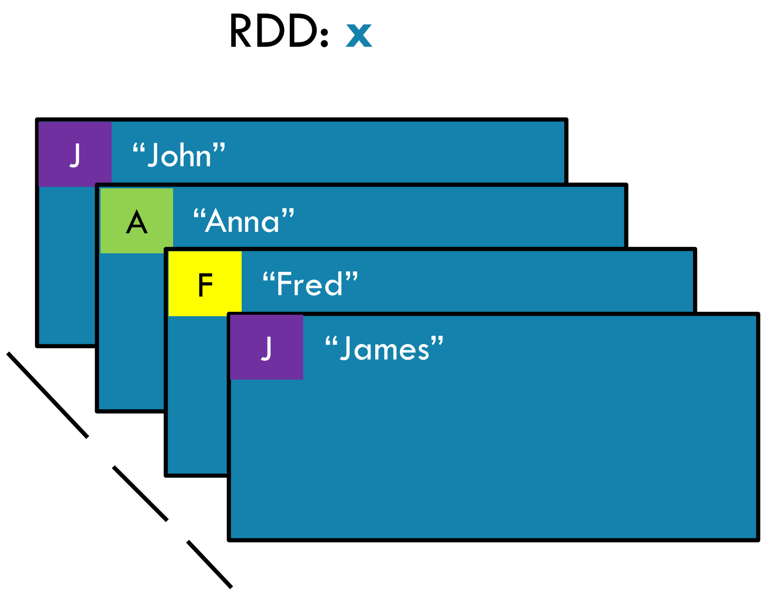
```python
x = sc.parallelize(['John', 'Fred', 'Anna', 'James'])
y = x.keyBy(lambda w: w[0])
print y.collect()
```

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

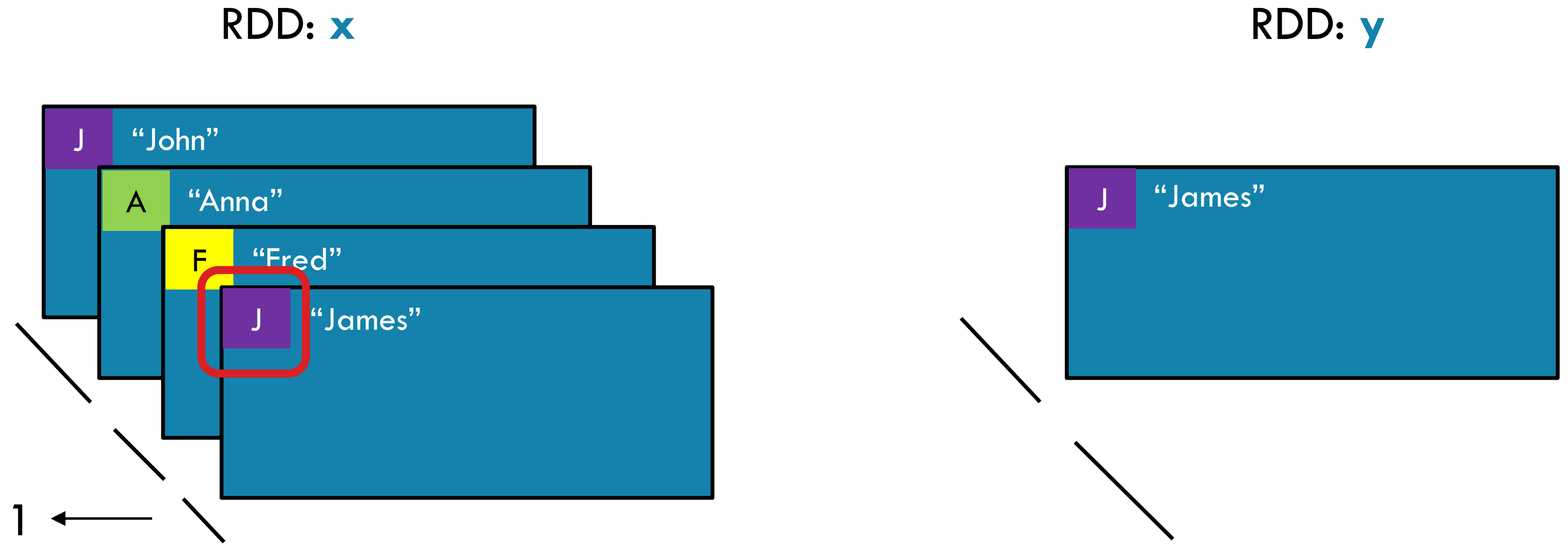
x: ['John', 'Fred', 'Anna', 'James']

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

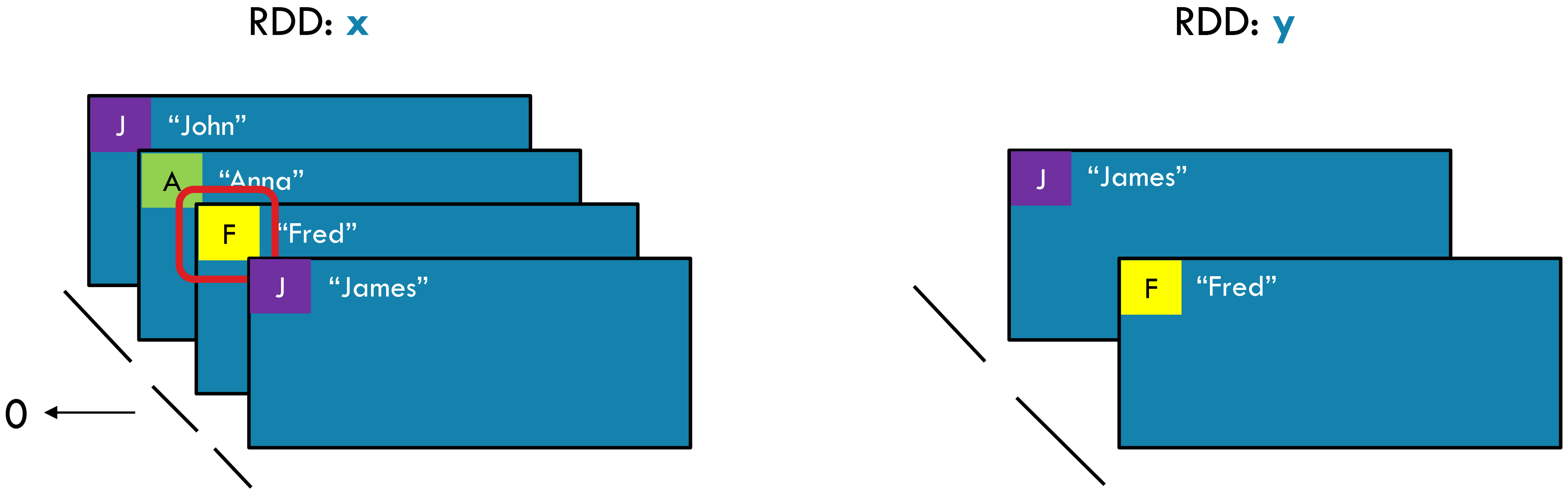
# PARTITIONBY



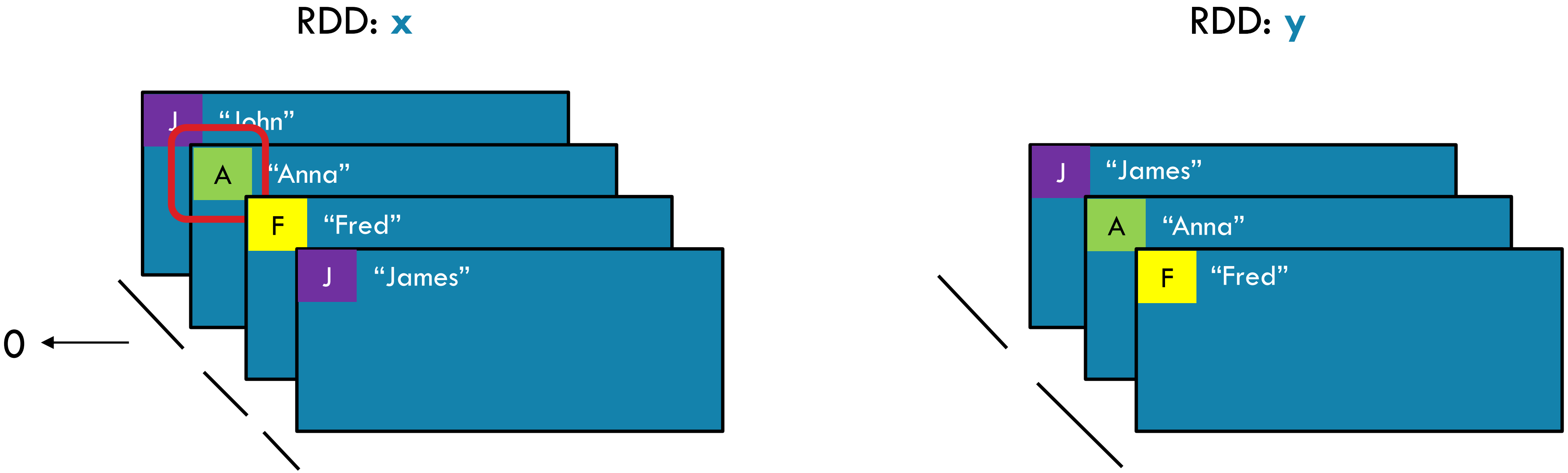
# PARTITIONBY



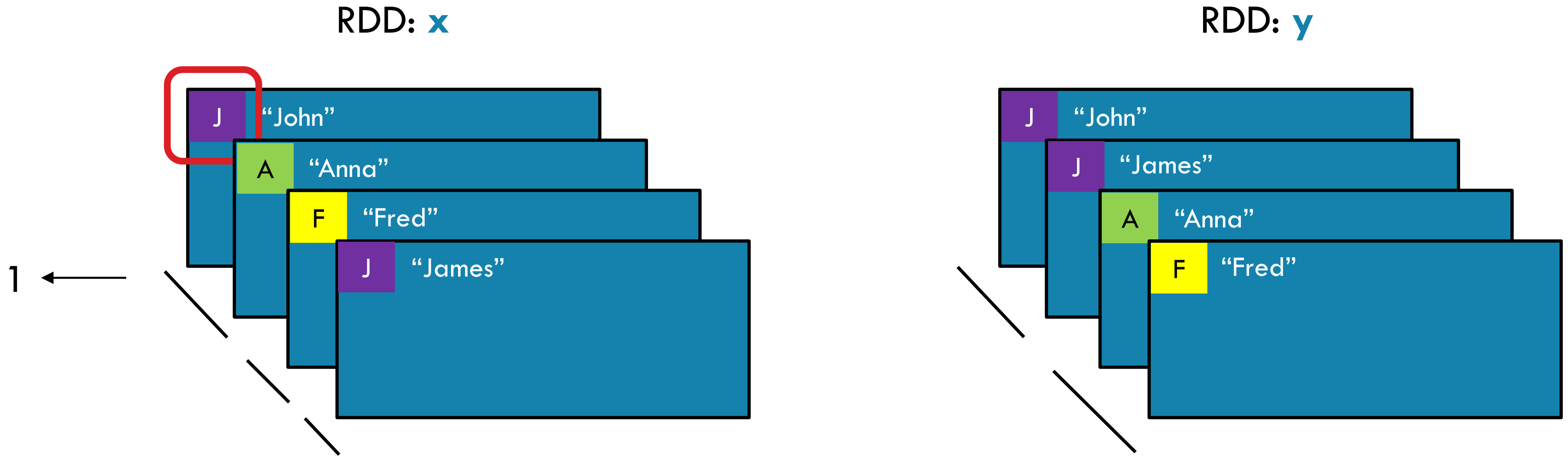
# PARTITIONBY



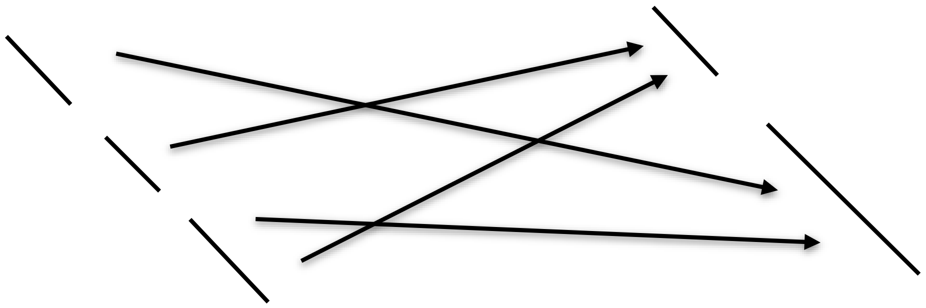
# PARTITIONBY



# PARTITIONBY



# PARTITIONBY

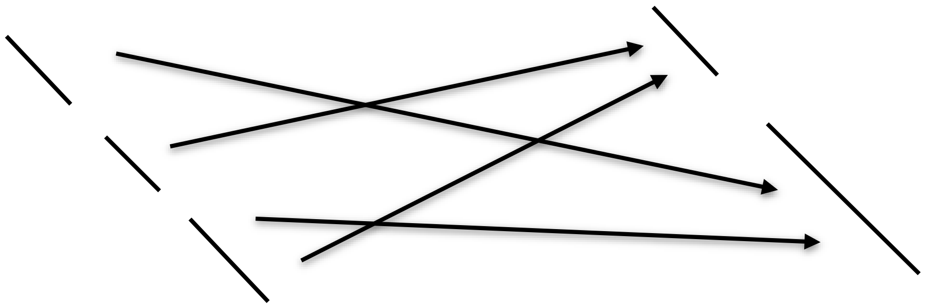


Return a new RDD with the specified number of partitions, placing original items into the partition returned by a user supplied function

```
partitionBy(numPartitions, partitioner=portable_hash)
```

```
x = sc.parallelize([('J','James'),('F','Fred'),
                    ('A','Anna'),('J','John')], 3)

y = x.partitionBy(2, lambda w: 0 if w[0] < 'H' else 1)
print x.glom().collect()
print y.glom().collect()
```

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

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



# PARTITIONBY

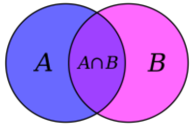
Return a new RDD with the specified number of partitions, placing original items into the partition returned by a user supplied function.

partitionBy(*numPartitions, partitioner=portable_hash*)

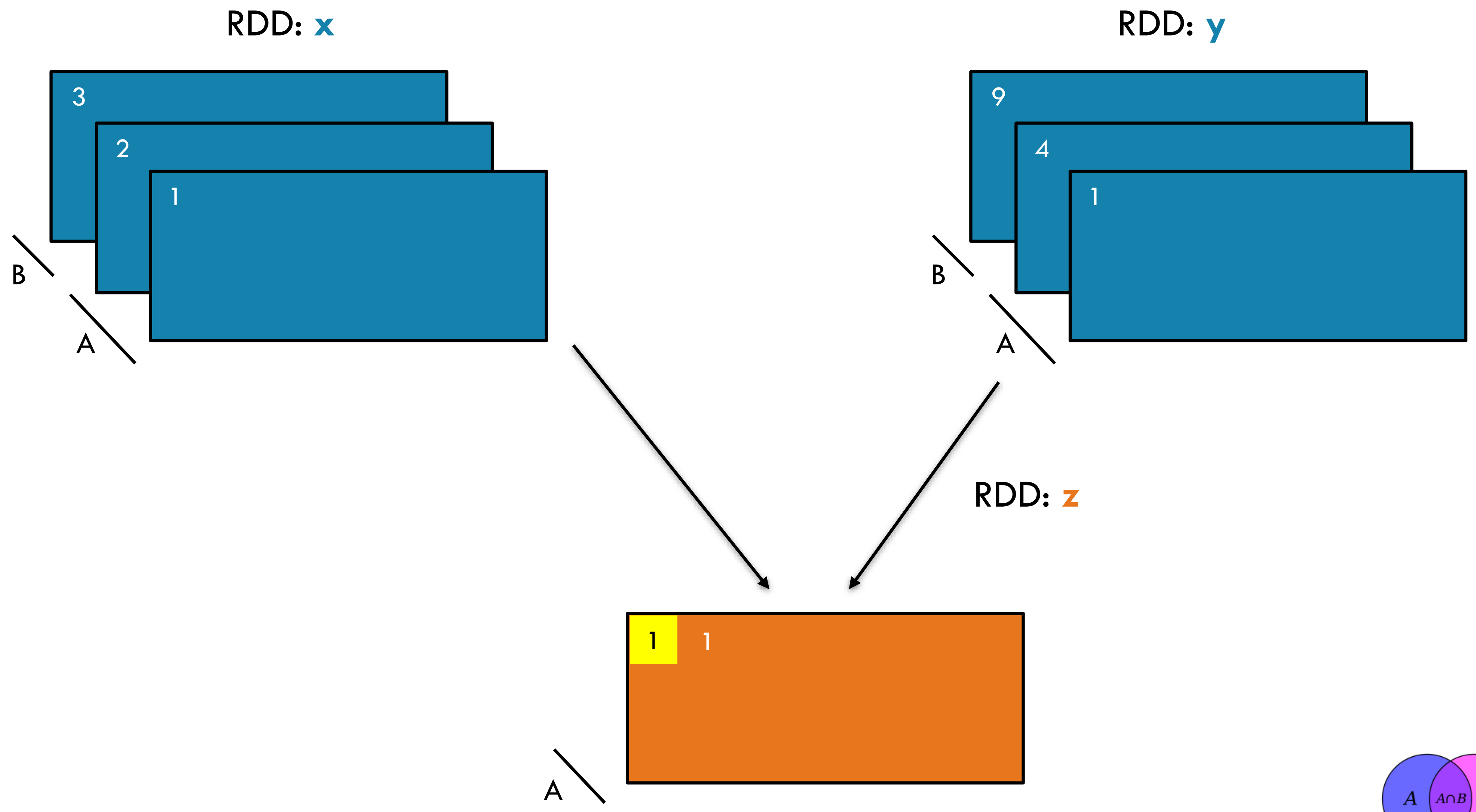
```
import org.apache.spark.Partitioner
val x = sc.parallelize(Array(('J',"James"),('F',"Fred"),
                             ('A',"Anna"),('J',"John")), 3)

val y = x.partitionBy(new Partitioner() {
  val numPartitions = 2
  def getPartition(k:Any) = {
    if (k.asInstanceOf[Char] < 'H') 0 else 1
  }
})

val yOut = y.glom().collect()
```

```
x: Array(Array((A,Anna), (F,Fred)),
         Array((J,John), (J,James)))

y: Array(Array((F,Fred), (A,Anna)),
         Array((J,John), (J,James)))
```

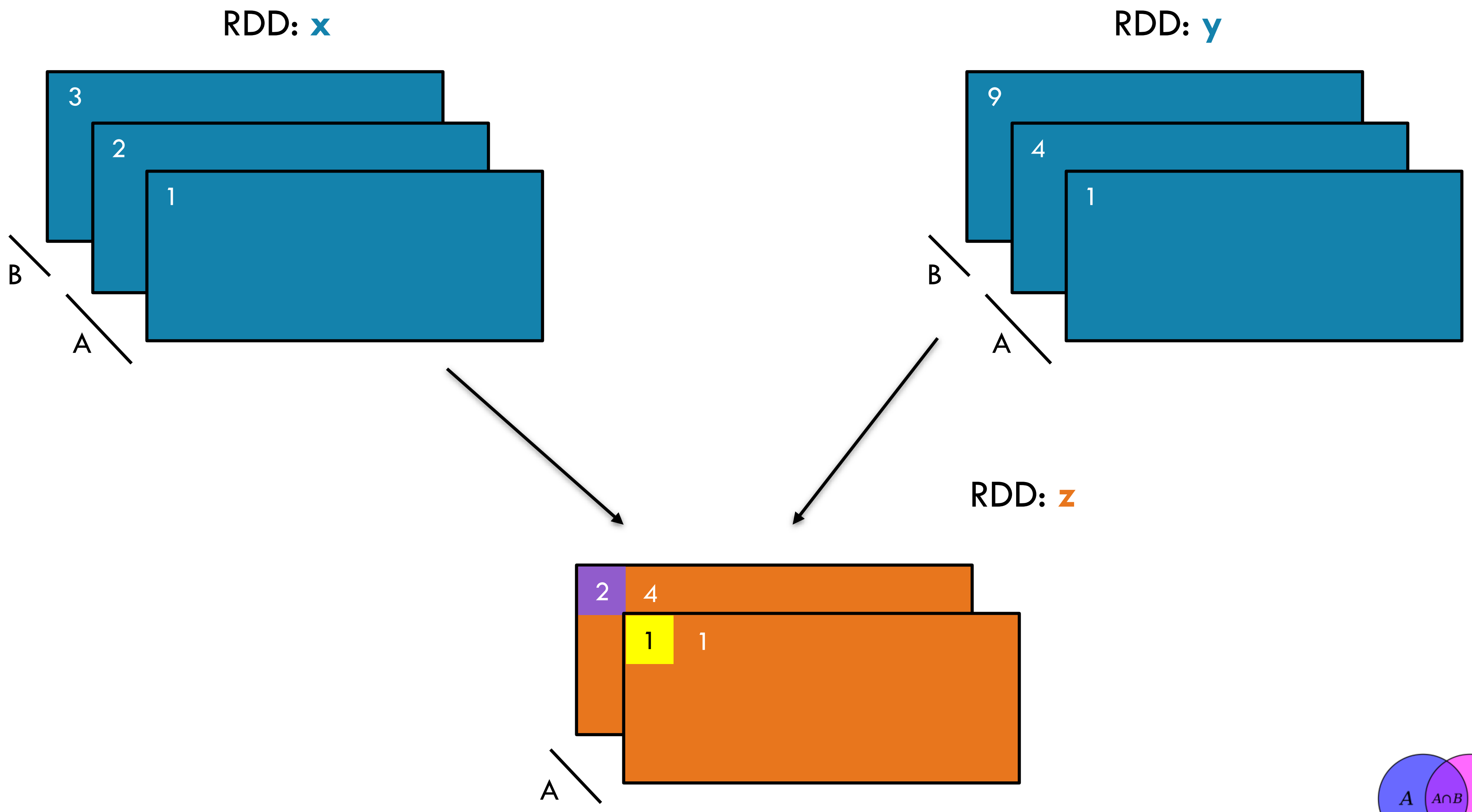
# ZIP

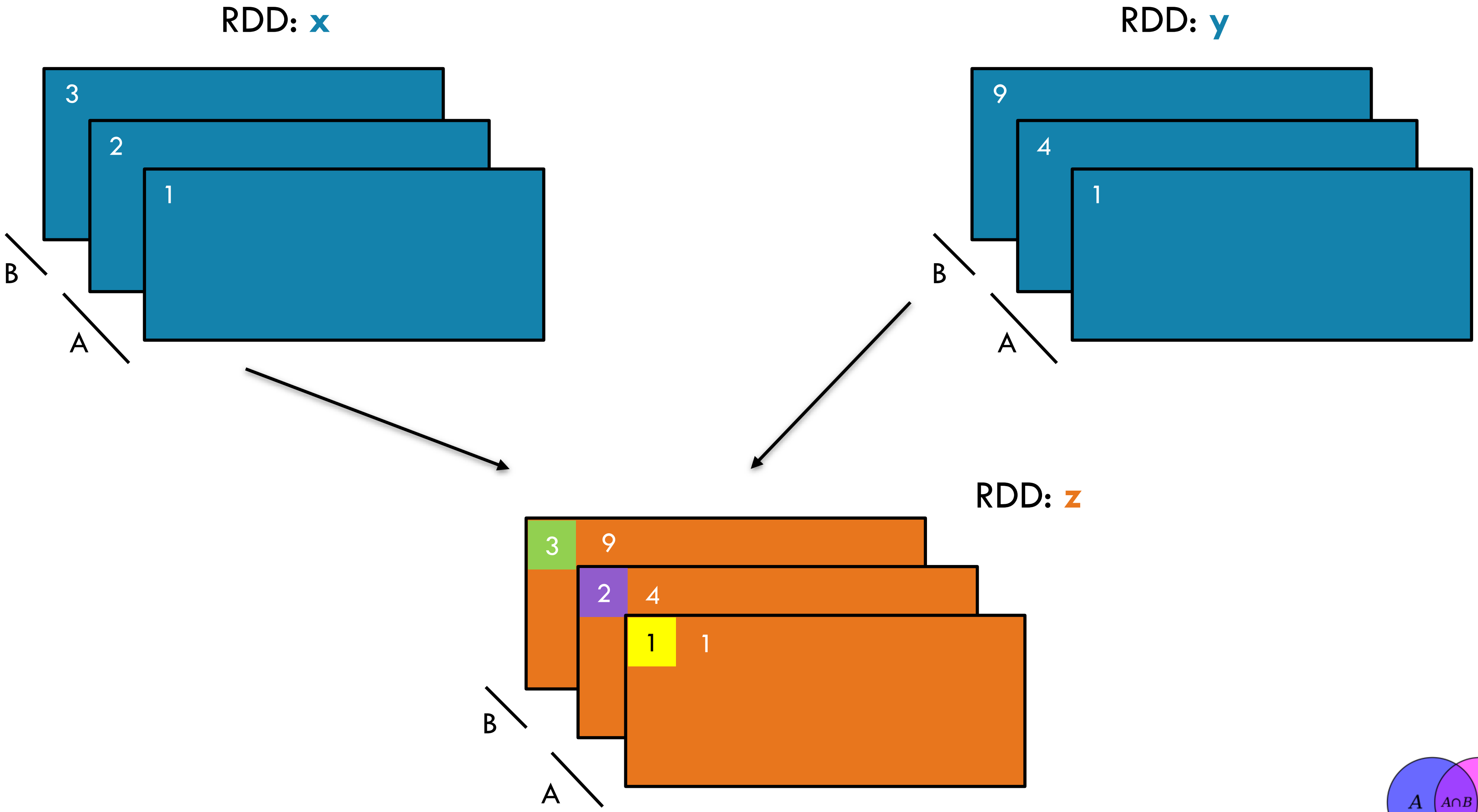
# ZIP



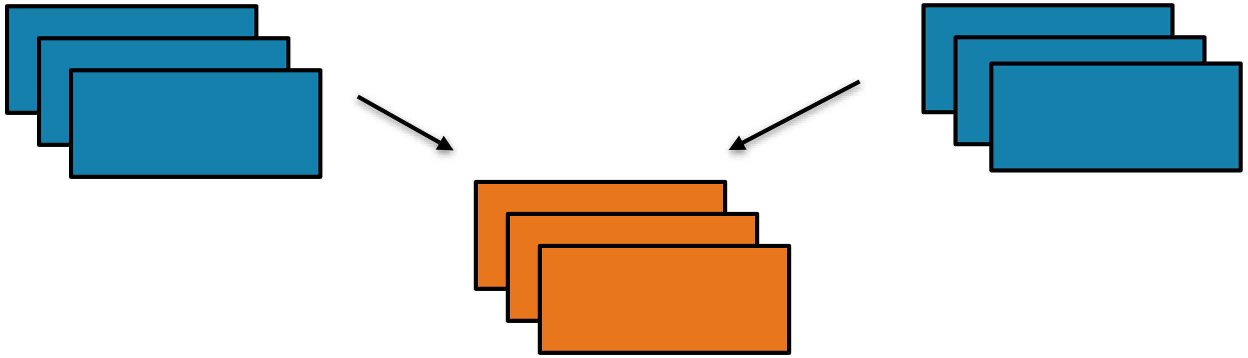
# ZIP



# 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)`

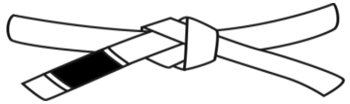
```python
x = sc.parallelize([1, 2, 3])
y = x.map(lambda n:n*n)
z = x.zip(y)

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)]
```

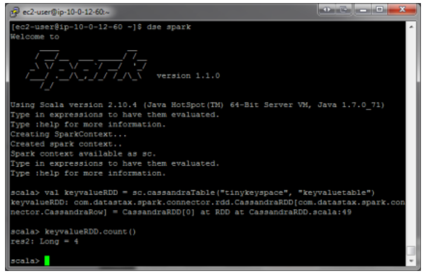
# ACTIONS



Core Operations

databricks

vs



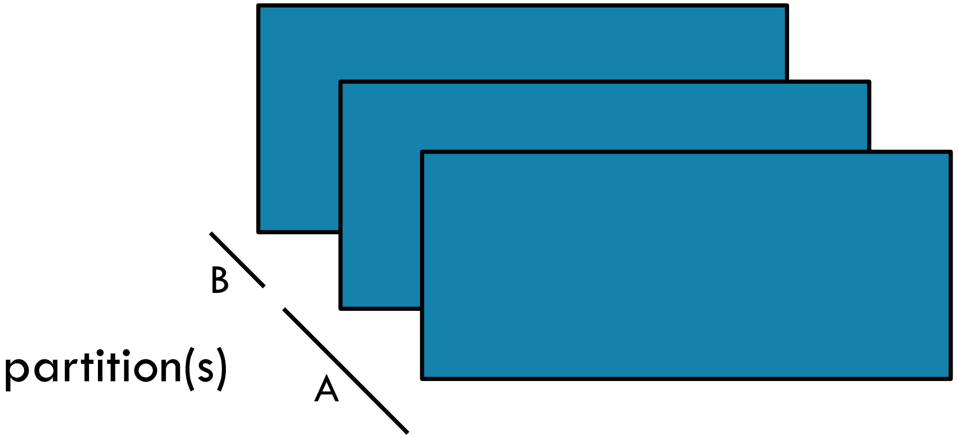

## distributed

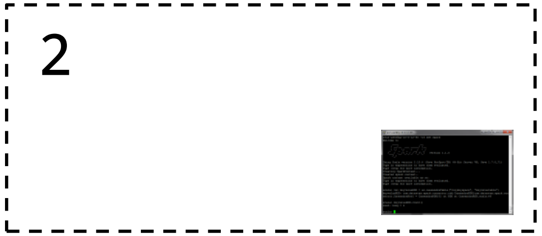
occurs across the cluster

## driver

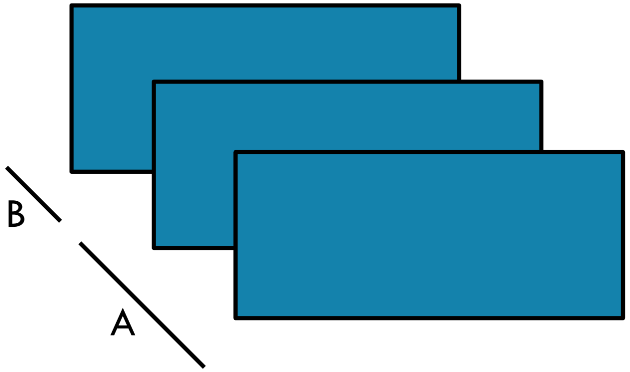
result must fit in driver JVM

# GETNUMPARTITIONS



# GETNUMPARTITIONS




2

**`getNumPartitions()`**

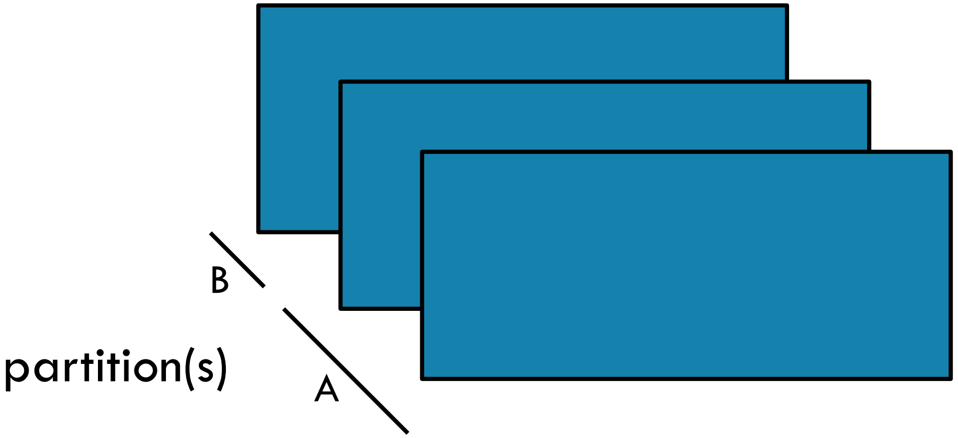
Return the number of partitions in RDD

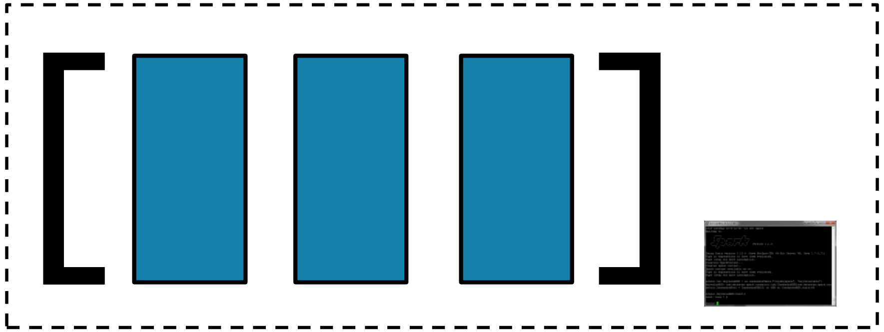
```
x = sc.parallelize([1,2,3], 2)
y = x.getNumPartitions()

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

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

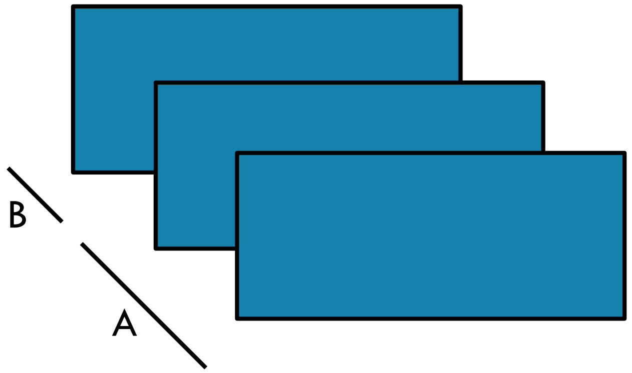
```
x: [[1], [2, 3]]

y: 2
```

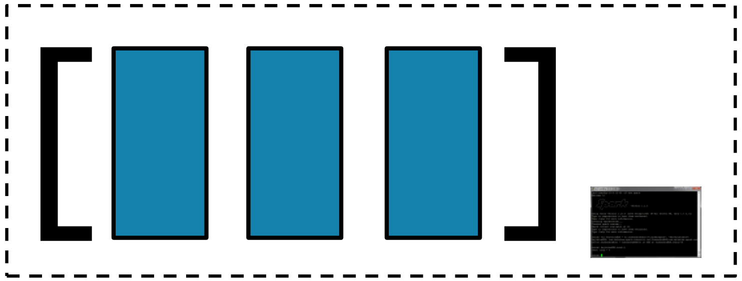
# COLLECT



# COLLECT



**`collect()`**

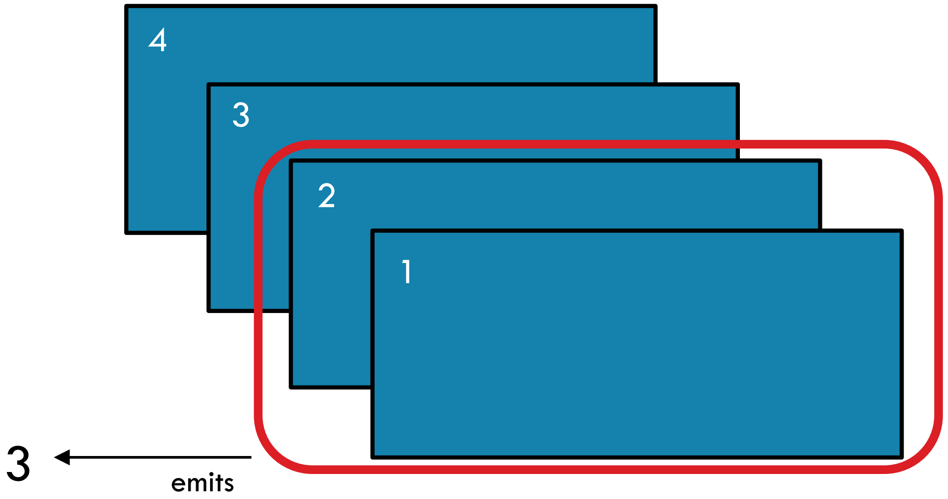
Return all items in the RDD to the driver in a single list

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

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

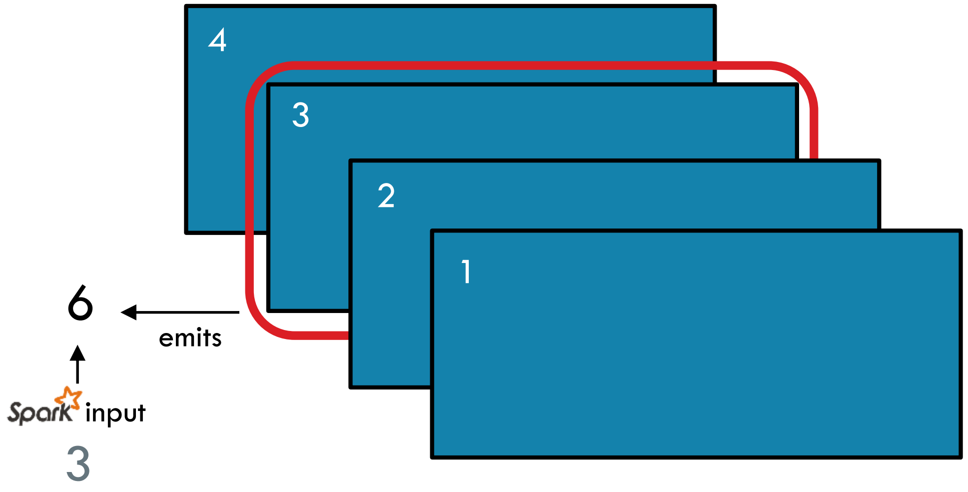
```scala
val x = sc.parallelize(Array(1,2,3), 2)
val y = x.collect()

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

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

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

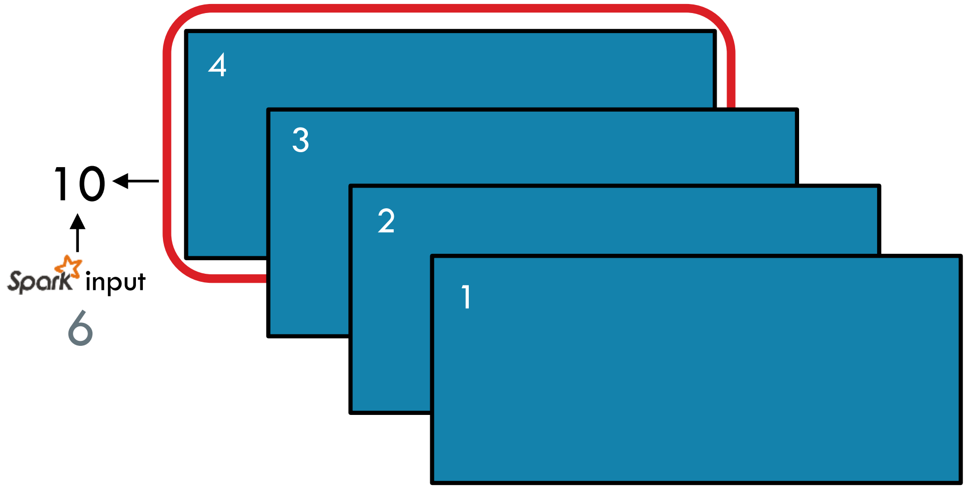
# REDUCE

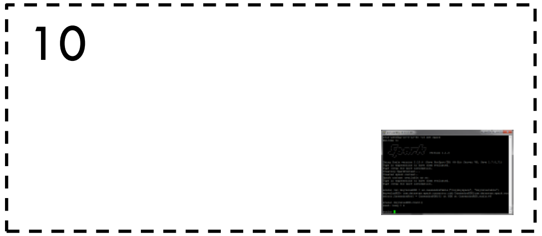



# REDUCE

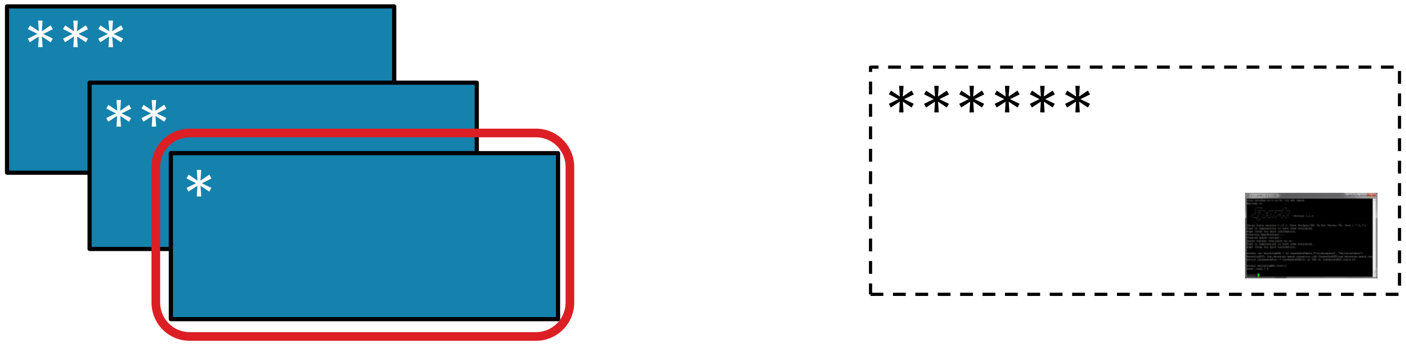



# REDUCE




# REDUCE




**reduce(*f*)**

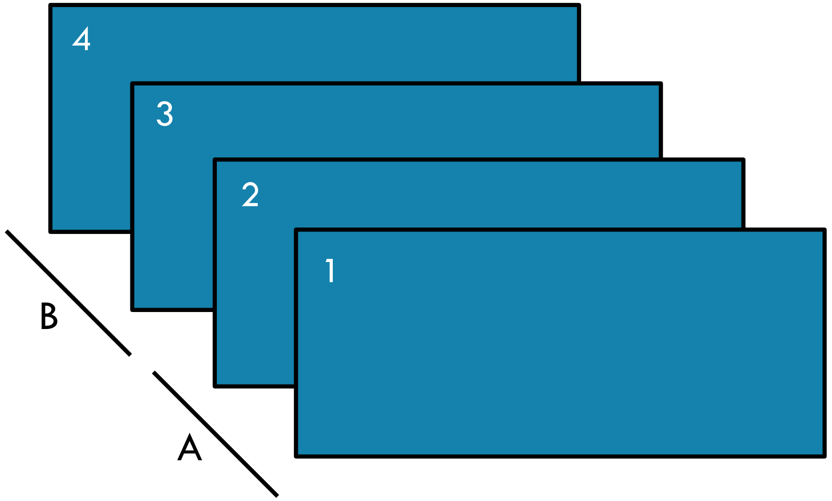
Aggregate all the elements of the RDD by applying a user function pairwise to elements and partial results, and returns a result to the driver

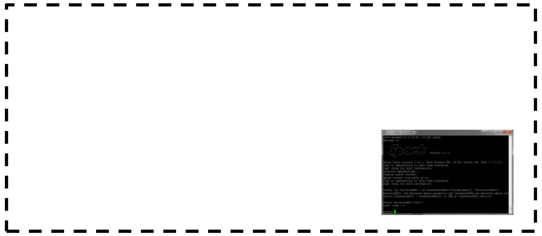
```python
x = sc.parallelize([1,2,3,4])
y = x.reduce(lambda a,b: a+b)

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)
```

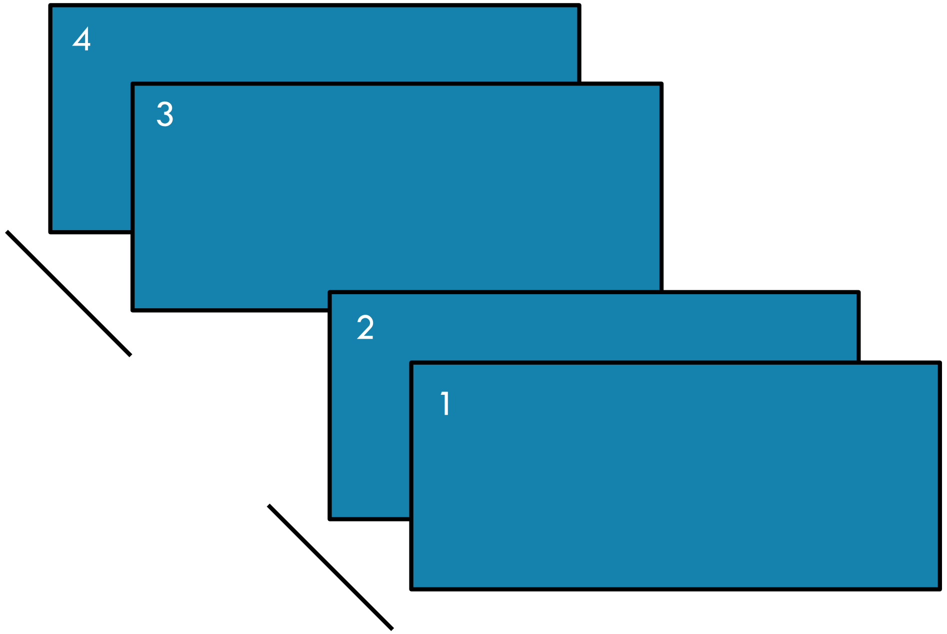
```
x:  [1, 2, 3, 4]

y:  10
```

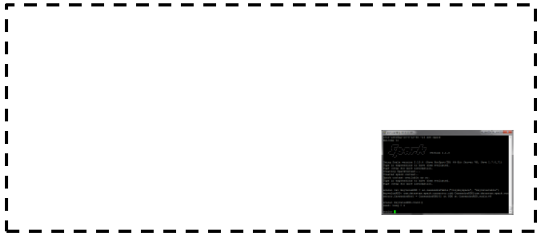
# AGGREGATE



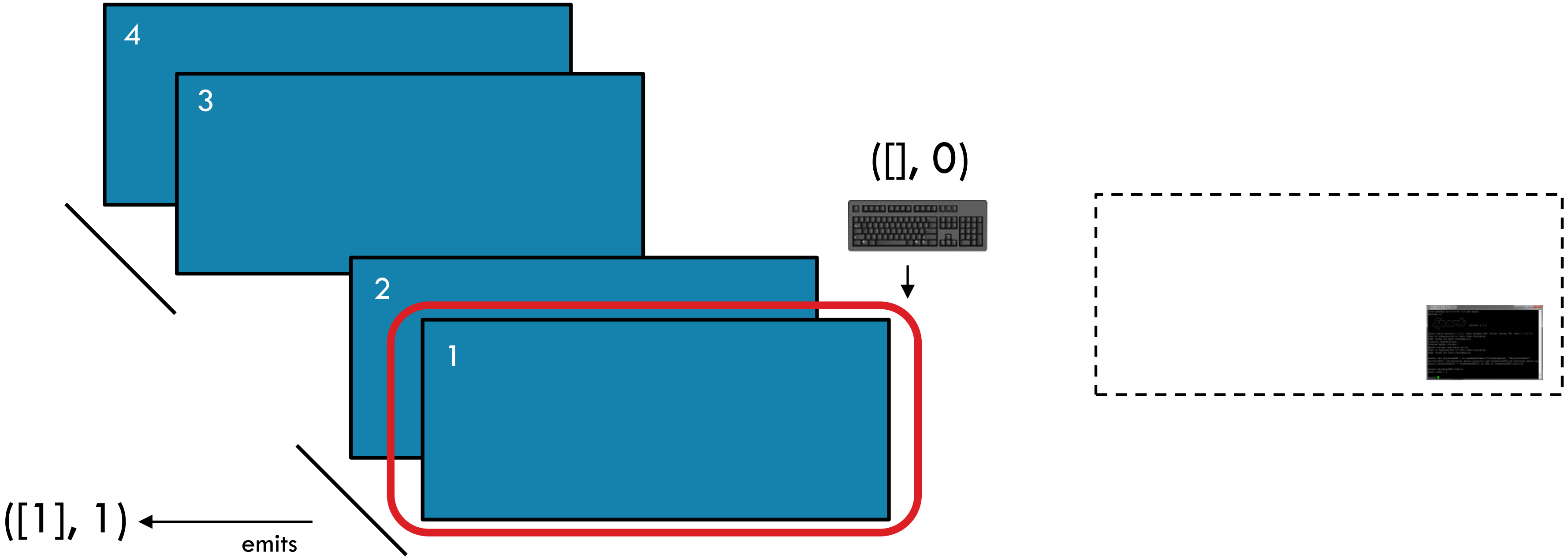



# AGGREGATE

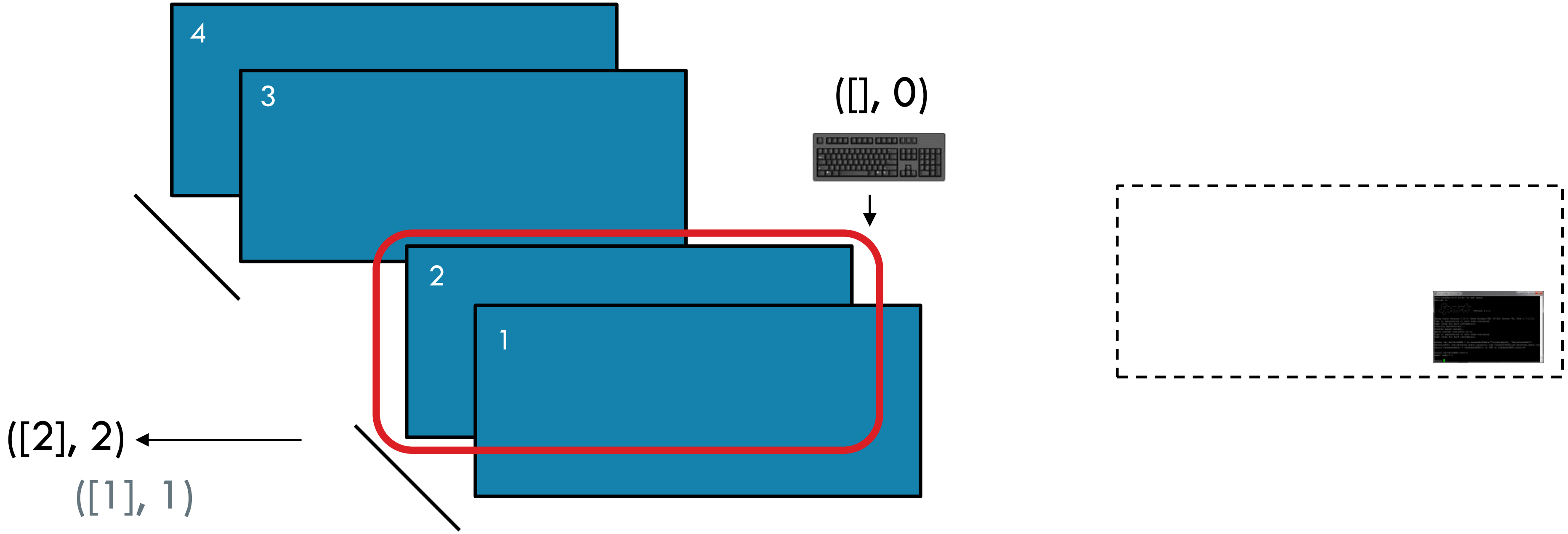


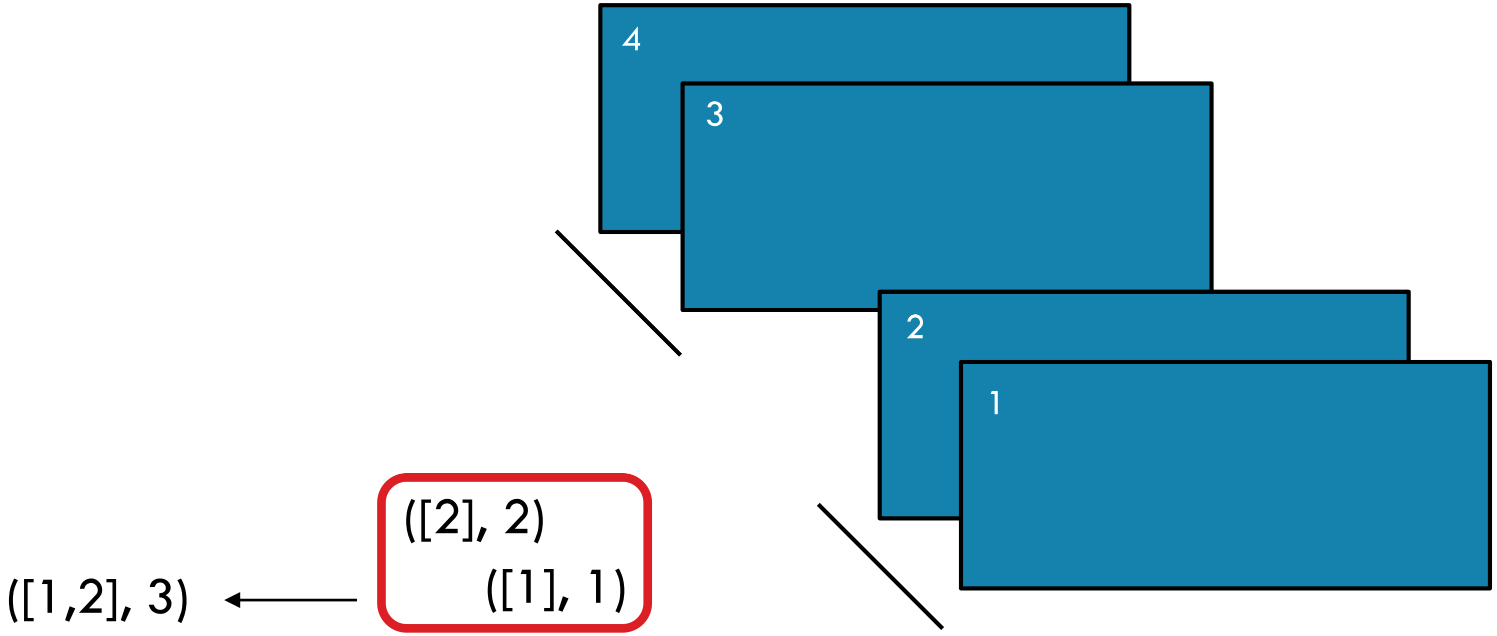
# AGGREGATE

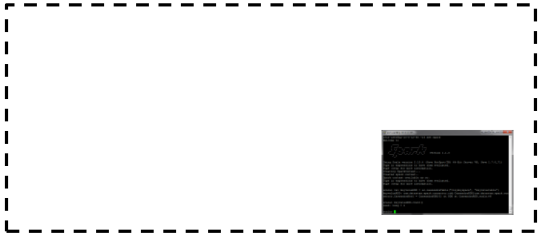


# AGGREGATE

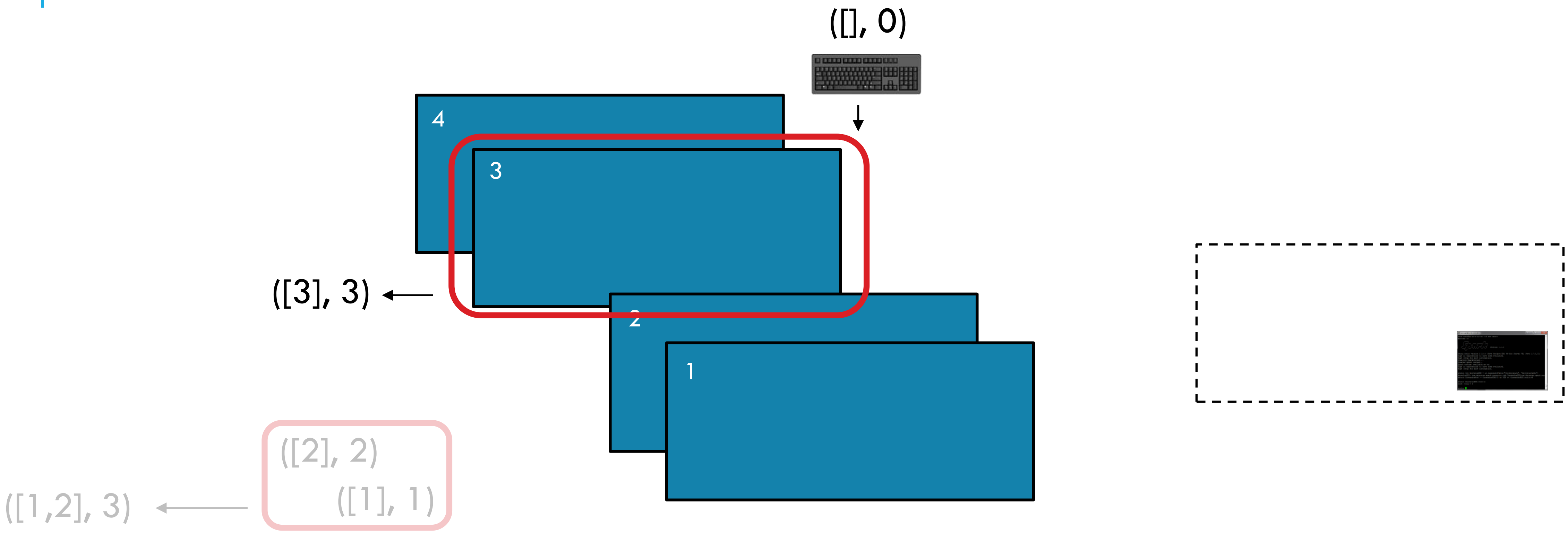



# AGGREGATE



# AGGREGATE

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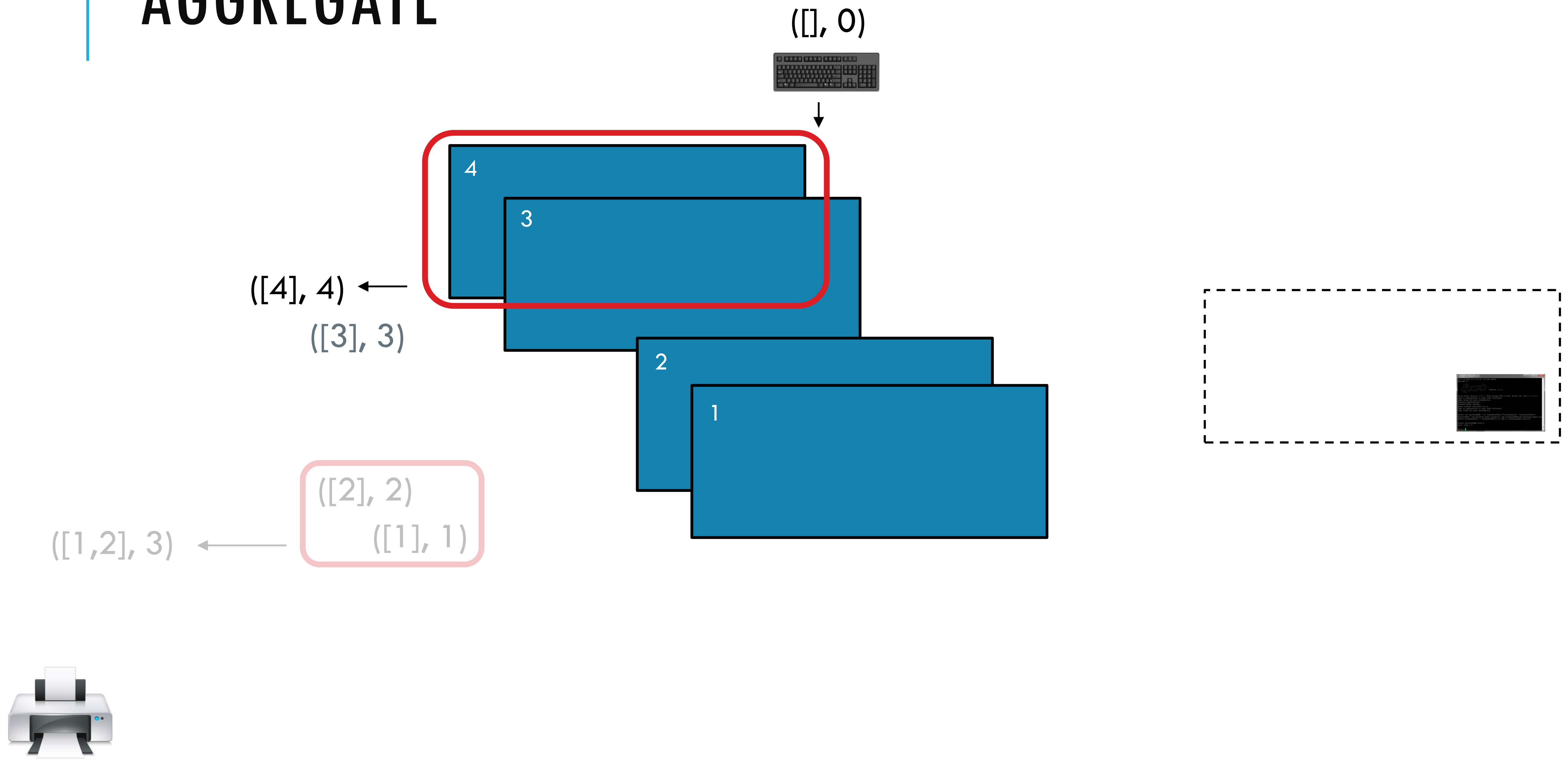
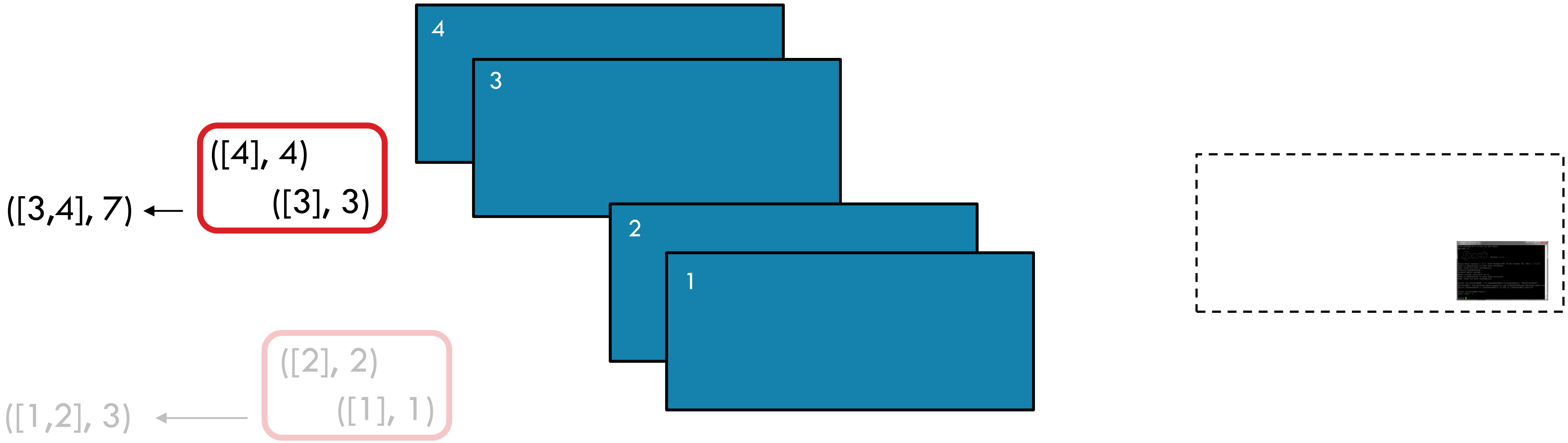


# AGGREGATE

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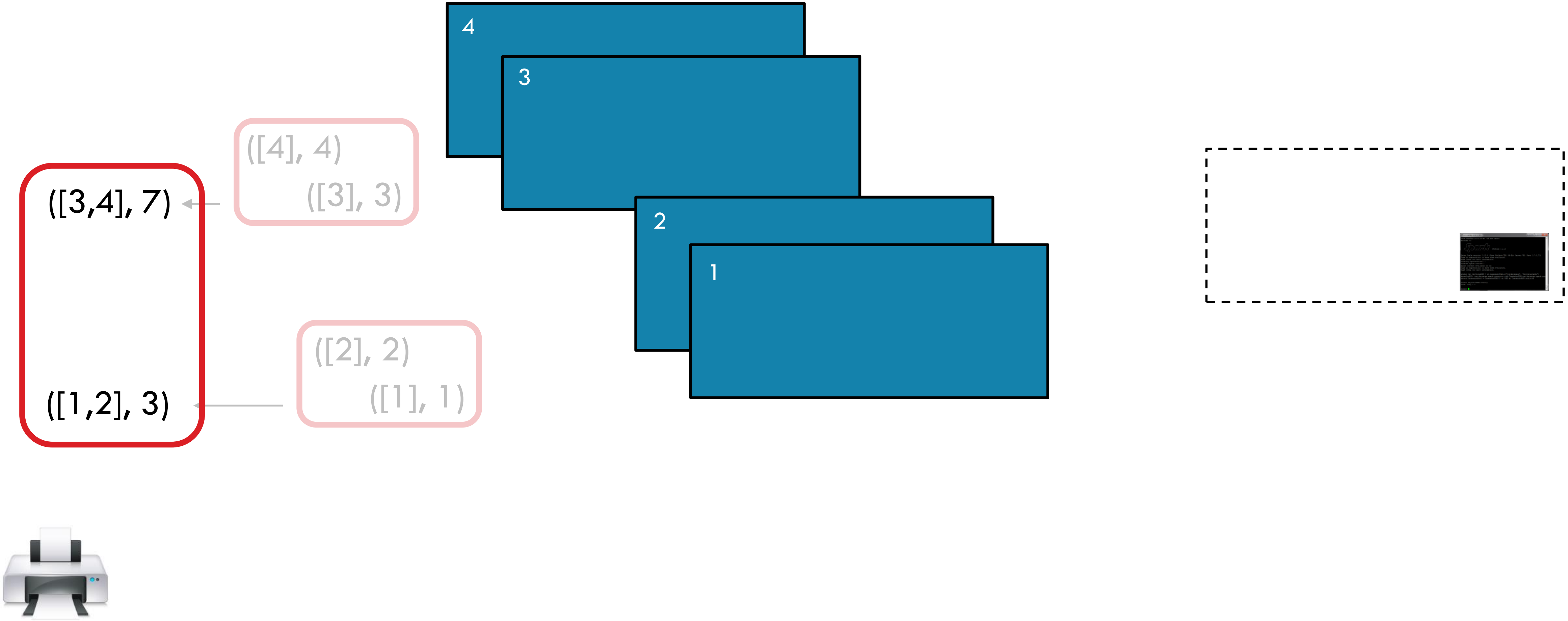

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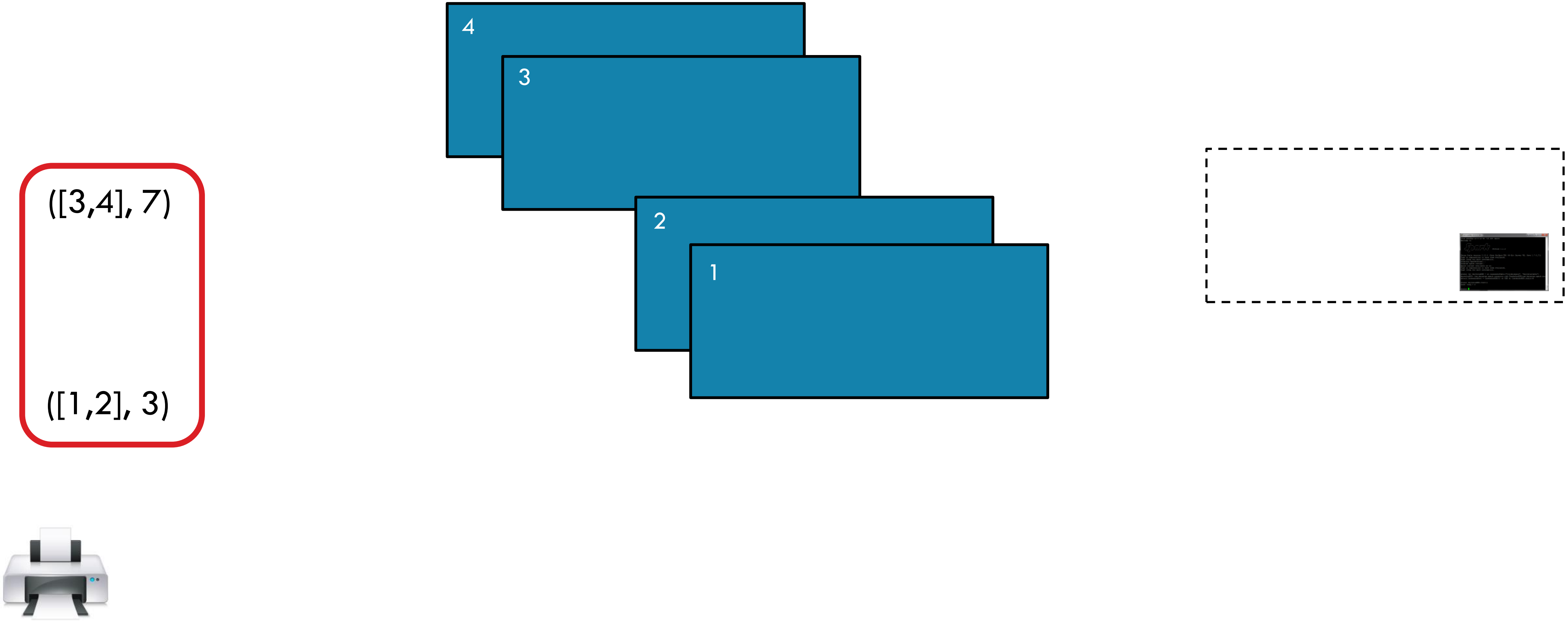

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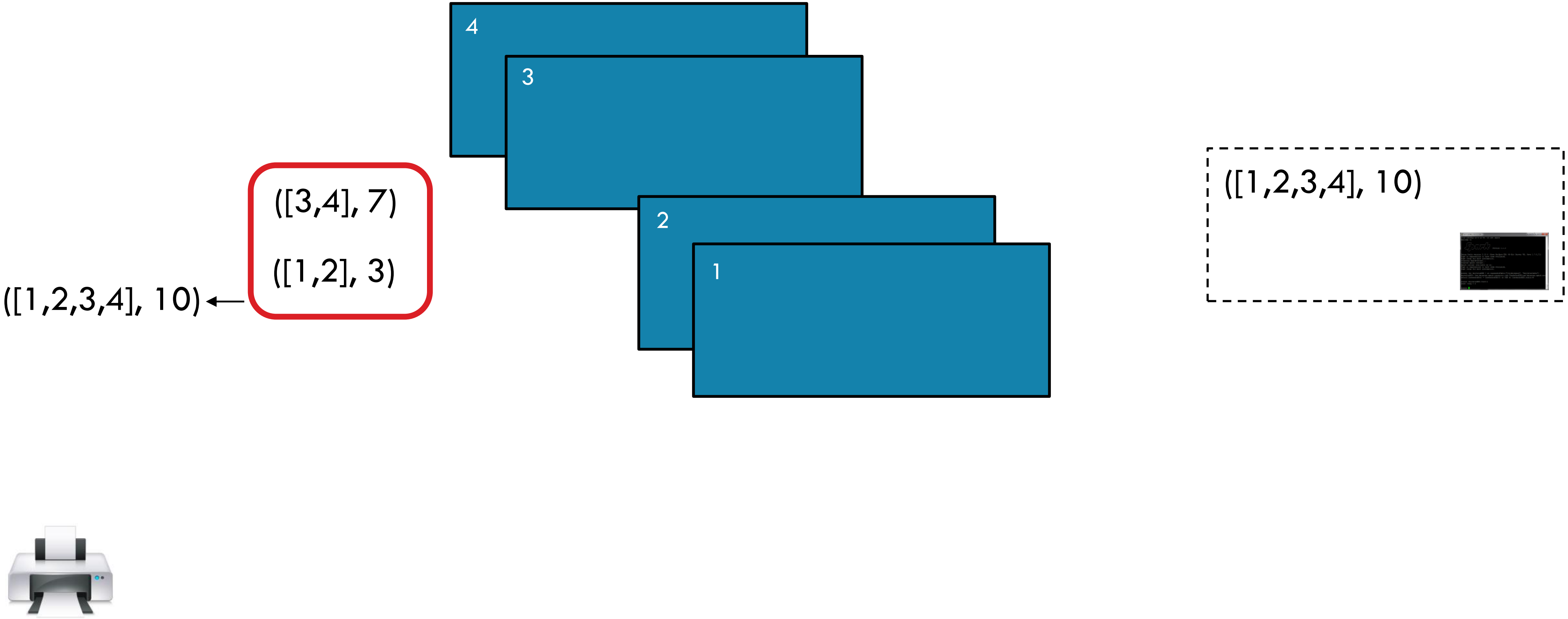
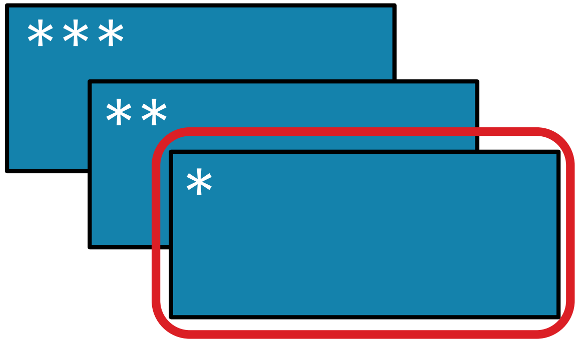
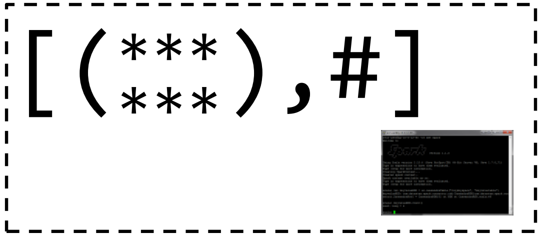


# AGGREGATE




`aggregate(identity, seqOp, combOp)`

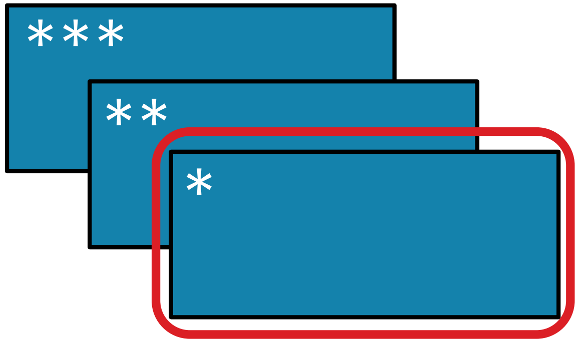
Aggregate all the elements of the RDD by:

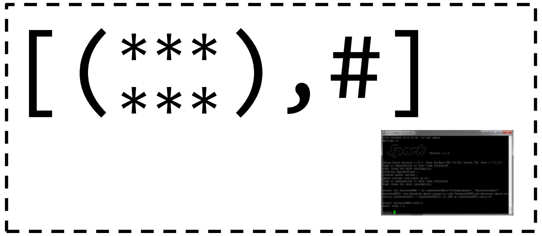
- applying a user function to combine elements with user-supplied objects,
- then combining those user-defined results via a second user function,
- and finally returning a result to the driver.

```
seqOp = lambda data, item: (data[0] + [item], data[1] + item)
combOp = lambda d1, d2: (d1[0] + d2[0], d1[1] + d2[1])

x = sc.parallelize([1,2,3,4])
y = x.aggregate(([], 0), seqOp, combOp)

print(y)
```

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

y: ([1, 2, 3, 4], 10)
```

# AGGREGATE




**aggregate(identity, *seqOp*, *combOp*)**

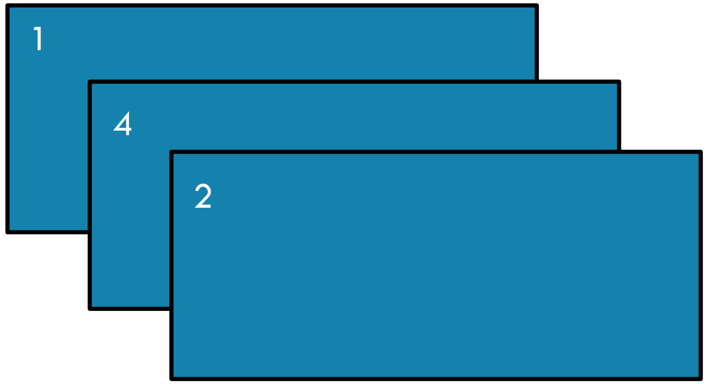
Aggregate all the elements of the RDD by:
- applying a user function to combine elements with user-supplied objects,
- then combining those user-defined results via a second user function,
- and finally returning a result to the driver.

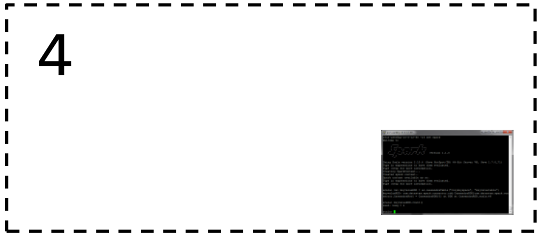
```
def seqOp = (data:(Array[Int], Int), item:Int) =>
     (data._1 :+ item, data._2 + item)

def combOp = (d1:(Array[Int], Int), d2:(Array[Int], Int)) =>
     (d1._1.union(d2._1), d1._2 + d2._2)

val x = sc.parallelize(Array(1,2,3,4))
val y = x.aggregate((Array[Int](), 0))(seqOp, combOp)

println(y)
```

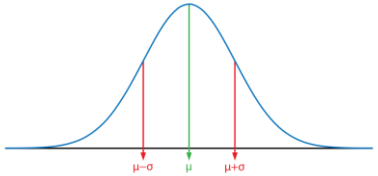
**x:** [1, 2, 3, 4]

**y:** (Array(3, 1, 2, 4),10)

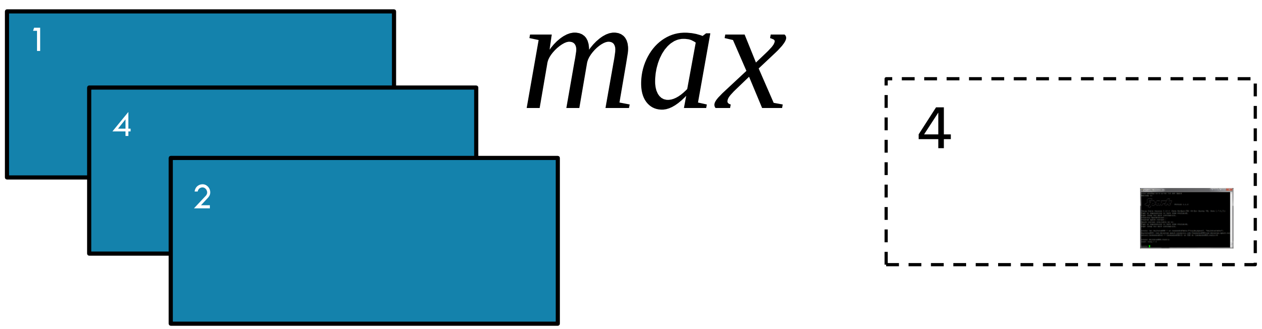
# MAX



# MAX




**max()**

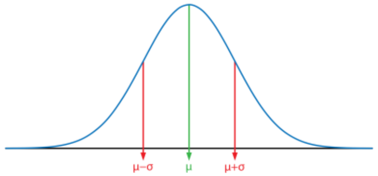
Return the maximum item in the RDD

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

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

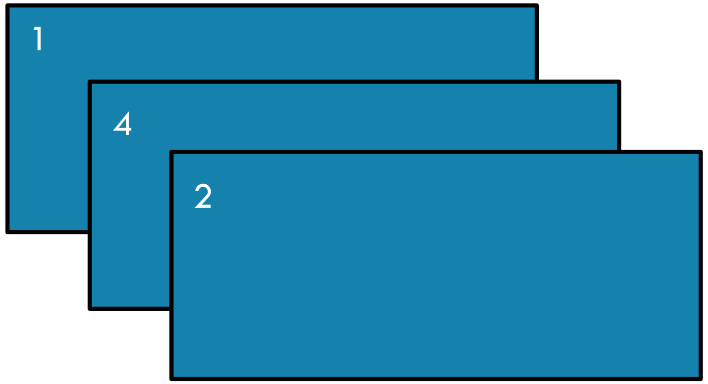
```scala
val x = sc.parallelize(Array(2,4,1))
val y = x.max

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

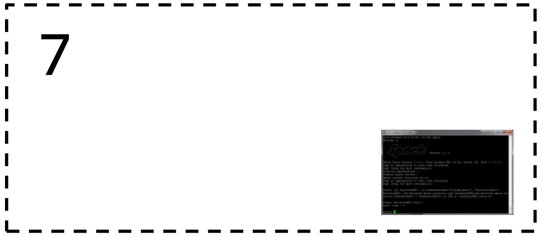
x: [2, 4, 1]

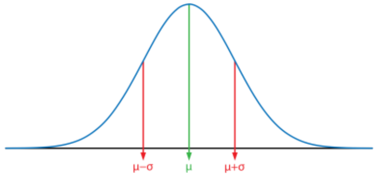
y: 4



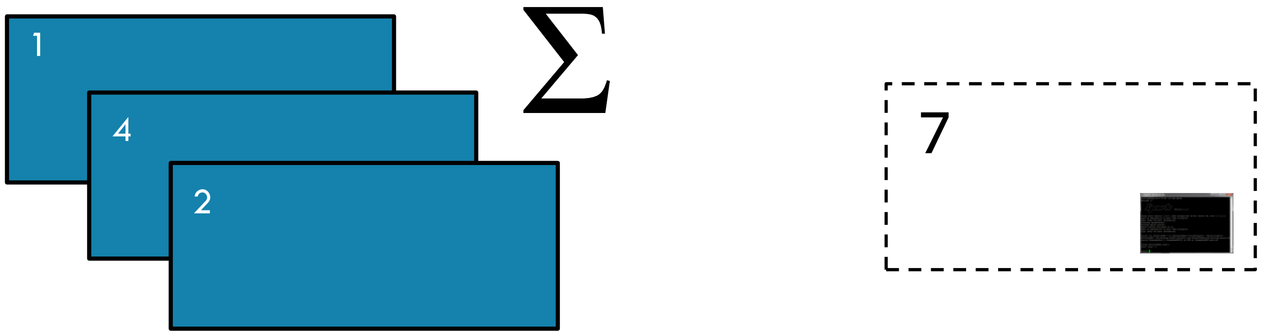
# SUM



# SUM




**sum()**

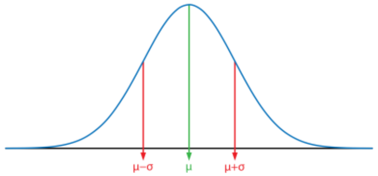
Return the sum of the items in the RDD

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

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

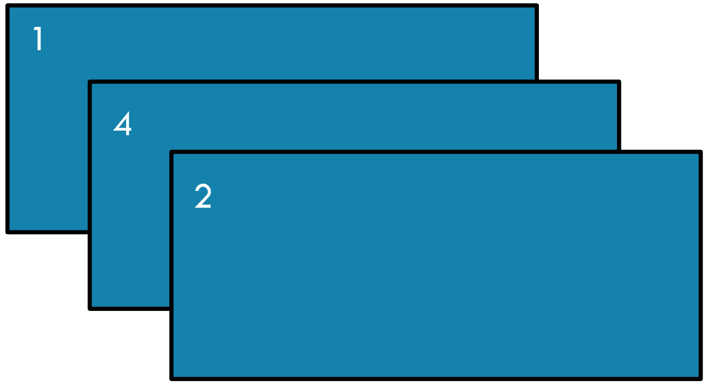
```scala
val x = sc.parallelize(Array(2,4,1))
val y = x.sum

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

x: [2, 4, 1]

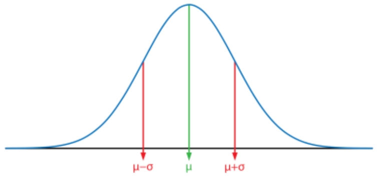
y: 7



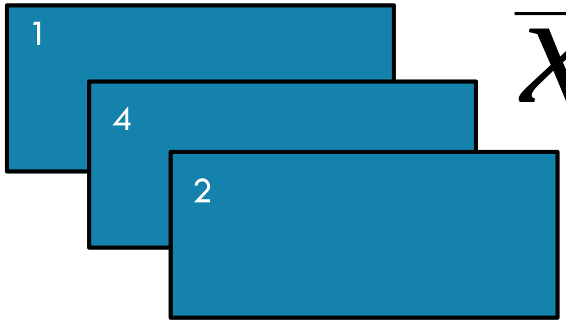
# MEAN




2.33333333



# MEAN




$\overline{X}$

2.3333333

**mean()**

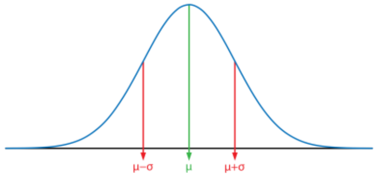
Return the mean of the items in the RDD

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

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

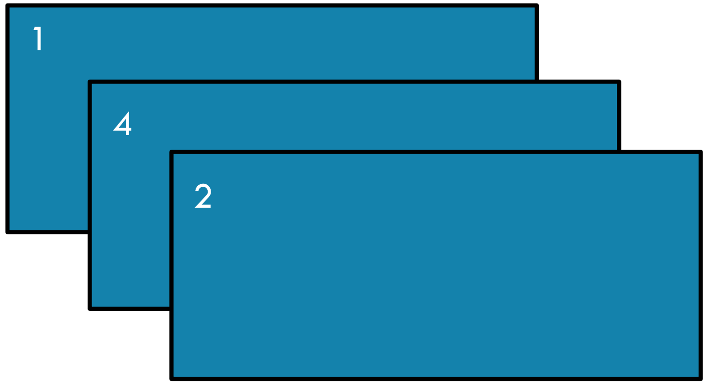
```scala
val x = sc.parallelize(Array(2,4,1))
val y = x.mean

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

x: [2, 4, 1]

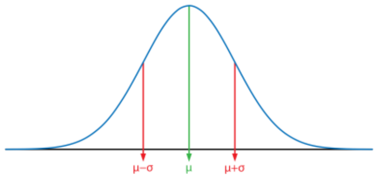
y: 2.3333333



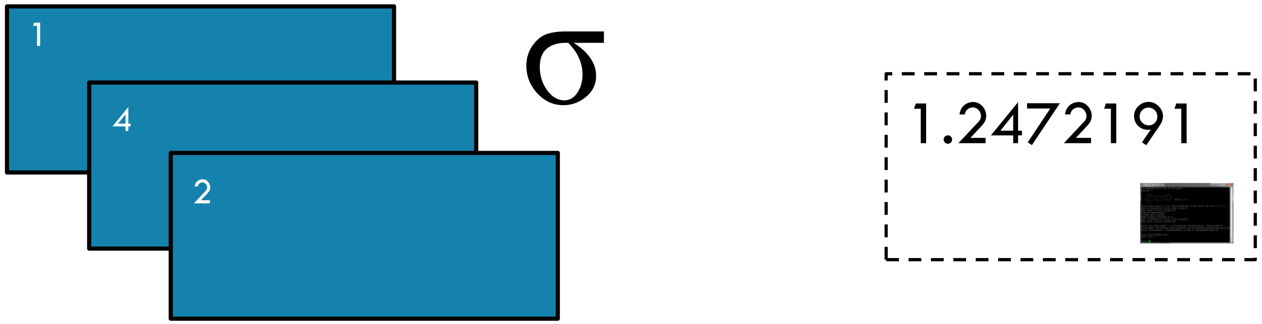
# STDEV




1.2472191



# STDEV



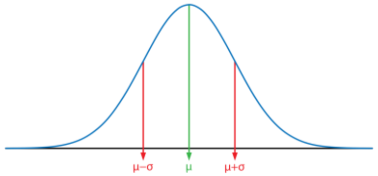

**stdev()**

Return the standard deviation of the items in the RDD

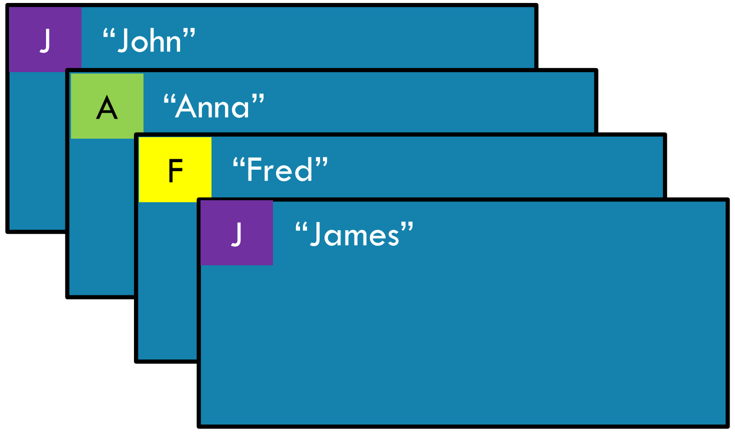
```python
x = sc.parallelize([2,4,1])
y = x.stdev()

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

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

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

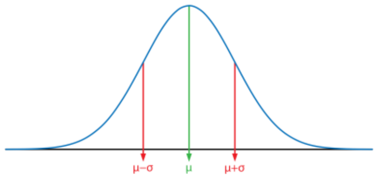
```
x: [2, 4, 1]

y: 1.2472191
```



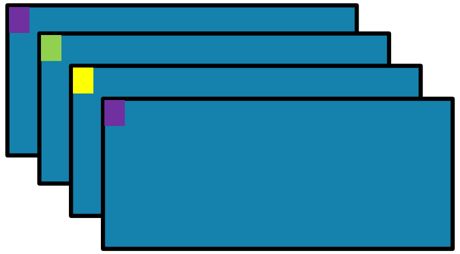
# COUNTBYKEY




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



# COUNTBYKEY




**countByKey()**

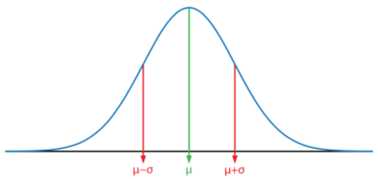
Return a map of keys and counts of their occurrences in the RDD

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

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

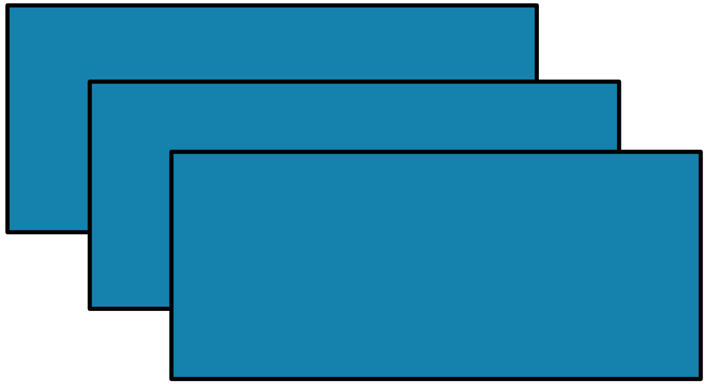
```scala
val x = sc.parallelize(Array(('J',"James"),('F',"Fred"),
                             ('A',"Anna"),('J',"John")))

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

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

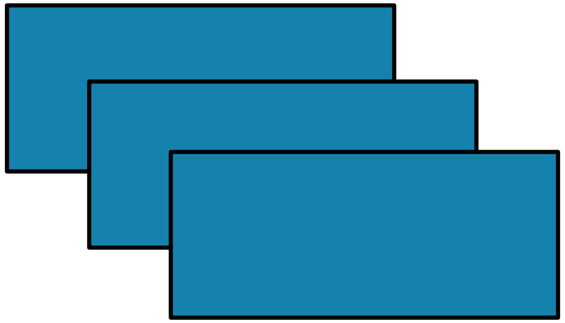
y: {'A': 1, 'J': 2, 'F': 1}



# 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™