## PAIR RDDS

# There are 2 types of RDDs

Basic RPPs Each element is a single object

Pair RDDs

Each element is a Key/Value pair

# Basic RVVs

# So far, we have only worked with Basic RDDs

ie. we treat each record in the RDD as a single object

## Basic RVVs

# All our transformations, actions act on each record as a whole

# There are 2 types of RDDs

Basic RPPs Each element is a single object

Pair RDDs

Each element is a Key/Value pair

# Each element is a Key/Value pair

Many data processing tasks can be easily expressed using Key, Value pairs

Ex: Pelays by Airline, Sales by City, Word Counts etc

# Pair RDDs are special RDDs where each record is treated as tuple

# All the basics RPP transformations and actions work for Pair RPPs too

# Special Transformations and Actions exist for Pair RDDs

#### Transformations

Keys Values mapValues groupByKey reducebykey combinebykey

# A few transformations for pair RDDs

#### Transformations

Keys Values

Return RDDs with only the keys or the values

#### Transformations

mapValues

groupByKey reduceByKey combineByKey Takes a function and applies it on the values of the key, value pairs

#### Transformations

groupbykey

Groups the values which have the same key into a list/collection

BLR, 3 MUM, 1 BLR, 2 MUM, 1

groupbykey

Transformations

# cogroup is also like groupByKey But it can group values across RDDS

#### Transformations

# reducebykey

This is like reduce on Basic RPPS

It takes a function to combine 2 values

It combines values with the same key

#### Transformations

keys
values
mapValues
groupByKey

reducebykey

Using a Pair RDD of City, Sales you can find the sum of sales for each city

combineBykey

#### Transformations

Just as for basic RDDs, we have reduce and aggregate

For Pair RPDs, we have reduceByKey and combineByKey

#### Transformations

#### combinebykey

reduce and aggregate

reducebykey and combinebykey

Note one important difference!

#### Transformations

# combinebykey

reduce and aggregate Actions on basic RPPs

reduceByKey and combineByKey Transformations on Pair RDDs

#### Transformations

One of the most common operations is to merge 2 Pair RPPs based on the keys

#### Transformations

Pair RDD1

Pair RDD2

Merge 2 Pair RPPs

BLR,3

BLR, "B"

BLR, [3, "B"]

MUM, 1

MUM, "M"

DEL, 2

DEL, "D"

MUM, [1, "M"]
DEL, [2, "D"]

Such operations are called joins

Transformations joins

left outer join right outer join

These are similar to their counter parts in SQL

left outer join

right outer join

#### Transformations

A join will return a new Pair RDD

Values from the input RDDs whose keys match are grouped together

Transformations

Only keys which exist in both RDDs are returned

left outer joil Like an inner join in SQL

right outer join

#### Transformations

Pair RDD1

BLR,3

MUM, 1

DEL, 2

Pair RDD2

BLR, "B"

MUM, "M"

BLR, [3, "B"]

MUM, [1, "M"]

#### Transformations

join

left outer join

right outer join

### All keys from the left RDD are returned

#### Pair RVS

#### lett outer join Pair RDD2 Pair RDD1

BLR,3

BLR, "B"

MUM, 1

MUM, "M"

KOL, "D"

Transformations

BLR, [3, "B"]

MUM, [1, "M"]
DEL, [2, None]

#### Transformations

lett outer join

right outer join

All keys from the right RDD are returned

#### Transformations

```
right outer join
Pair RDD1 Pair RDD2
```

```
BLR, 3 BLR, "B"
```

MUM, 1 MUM, "M"

DEL, 2 KOL, "D"

BLR, [3, "B"]

MUM, [1, "M"]

KOL, [None, "D"]

#### Actions

# countbykey collectAsMap

A few special actions are available for pair RDDs

#### Actions

countbykey count the number of values per key

returns all values for a specific key

collectAsMap returns a dict with all the key value pairs

# Exploring Airline delays data with PySpark

Part 3

# We're back to our Flight related data from USPoT

# Let's try doing a few more things with it

#### 1. Compute the average delay per airport

2. Find the top 10 airports based on delay

#### 1. Compute the average delay per airport

2. Find the top 10 airports based on delay

Average delay per airport For each airport, we need

Sum of all delays Count of number of flights

Option 1:

Compute these separately

Option 2:

Compute them in the same step

Average delay per airport
For each airport, we need
Sum of all delays
Count of number of flights

Option I: reduceByKey

Option 2: combineByKey



#### We've already created an RDD with Flights data

```
flightsParsed=flights.map(lambda x: x.split(',')).map(parse)
```

#### Each record is represented as a Flight object

Flight(date=datetime.date(2014, 4, 1), airline=u'19805', flightnum=u'1', origin=u'JFK', dest=u'LAX', dep=datetime(8, 54), dep\_delay=-6.0, arv=datetime.time(12, 17), arv\_delay=2.0, airtime=355.0, distance=2475.0)

#### Recap

```
', flightnum=u'1', origin=u'JFK', dest=u'LAX', dep=datetin
rv_delay=2.0, airtime=355.0, distance=2475.0)
```

## These represent the origin and destination airport codes

#### Option 1: reducebykey

### First let's create a Pair RDD with origin airport and delay for each flight

airportDelays = flightsParsed.map(lambda x: (x.origin,x.dep\_delay))

#### Option 1: reducebykey

```
airportDelays = flightsParsed.map(lambda x: (x.origin,x.dep_delay))
```

## To create a Pair RDD, just make sure each record is a tuple

#### Option 1: reducebykey

```
airportDelays = flightsParsed.map(lambda x: (x.origin,x.dep_delay))
```

## To see if this worked, you can try to access the keys and values of the pair RDD

### Option I: reducebykey

#### access the keys and values

```
airportDelays.keys().take(10)
```

```
[u'JFK',
u'LAX',
u'JFK',
u'LAX',
u'DFW',
u'OGG',
u'DFW',
u'HNL',
u'HNL',
```

#### keys() and values() are transformations

```
airportDelays.values().take(10)
[-6.0, 14.0, -6.0, 25.0, -5.0, 126.0, 125.0, 4.0, -7.0, 21.0]
```

#### Option 1: reducebykey

```
airportDelays = flightsParsed.map(lambda x: (x.origin,x.dep_delay))
```

## On this RDD, we can use reduceByKey twice, once for the sum and again for the count

#### Option 1: reducebykey

airportTotalDelay=airportDelays reduceByKey(lambda x,y:x+y)

#### First, let's compute the SUM

### Option I: reducebykey

airportTotalDelay=airportDelays.reduceByKey(lambda x,y:x+y)

#### This is a new RDD

reduceByKey is a transformation

#### Option 1: reducebykey

```
=airportDelays.reduceByKey(<mark>lambda</mark> x,y:x+y)
```

#### Similar to the reduce action

reduceByKey takes a function that combines 2 elements into 1

#### Option 1: reducebykey

```
=airportDelays.reduceByKey(<mark>lambda</mark> x,y:x+y)
```

#### The result is a Pair RDD

```
Keys = Airports
Values = Sum of Pelays
```

#### Option 1: reducebykey

```
=airportDelays.reduceByKey(<mark>lambda</mark> x,y:x+y)
```

reduceByKey effectively flattens the Pair RDD

Let's see this visually

PI

JFK	2
JFK	14
PPG	5
PPG	10
JFK	0
PPG	4

#### This is the delays RPP

P2

JFK	3
JFK	0
LAX	6
LAX	11
JFK	0
PPG	7

Pi

JFK	2
JFK	14
PPG	5
PPG	10
JFK	0
PPG	4

P2

JFK	3
JFK	0
LAX	6
LAX	11
JFK	0
PPG	7

# First, the operation is performed on each partition

PI

JFK	2
JFK	14
PPG	5
PPG	10
JFK	0
PPG	4

# Values with the same key are grouped together

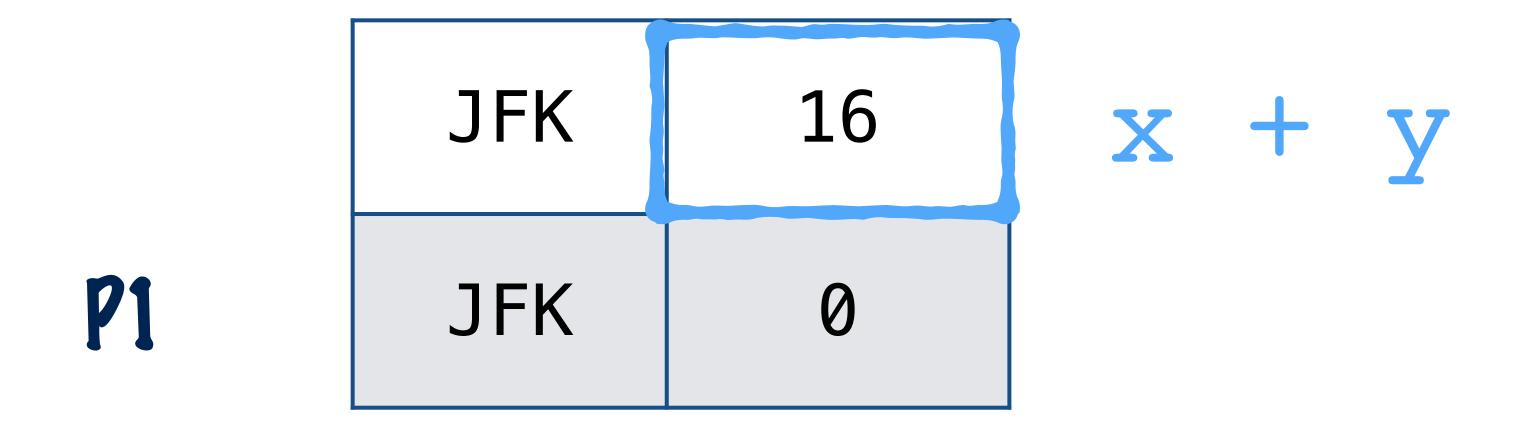
JFK	2
JFK	14
JFK	0

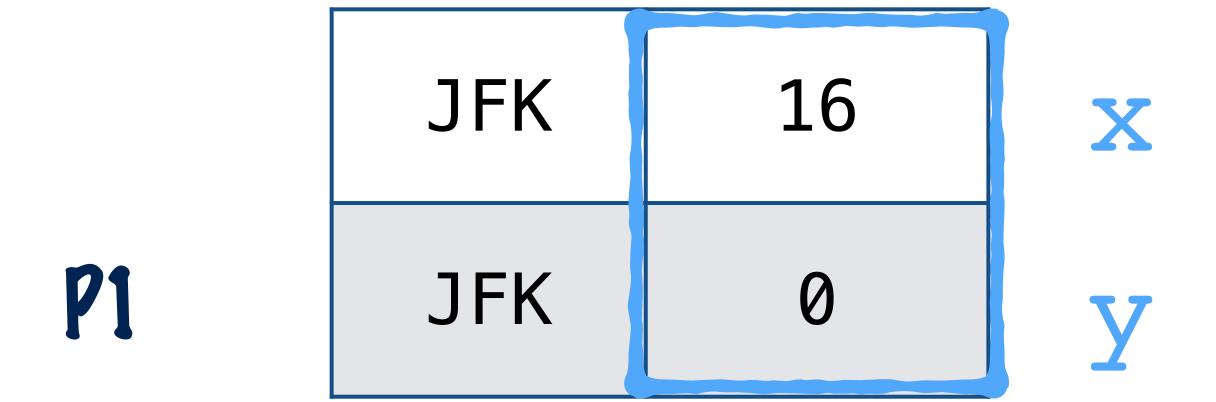
PI

PPG	5
PPG	10
PPG	4

# The given function is applied on each of these groups

	JFK	2	X
P1	JFK	14	У
	JFK	0	





**P1** JFK 16

## The same thing is done for each key

PI

JFK	16
PPG	5

## The same thing is done for each key

PI

JFK	16
PPG	5

#### We have a set of Key value pairs from each node

PI

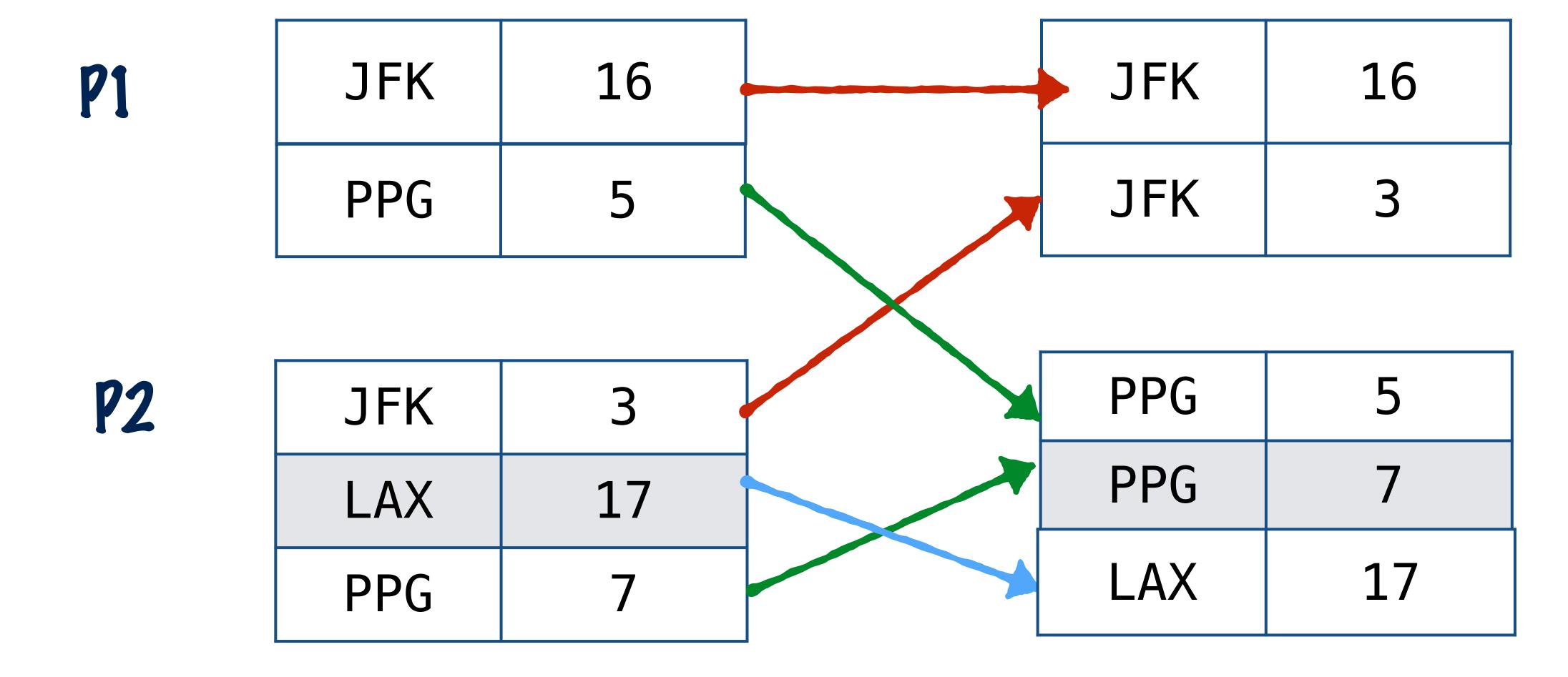
JFK	16
PPG	5

P2

JFK	3
LAX	17
PPG	7

## These are shuffled so that all the values with same key are on a single partition

#### shuffe



PI

JFK	16
JFK	3

**P2** 

PPG	5
PPG	7
LAX	17

# On each partition, again the reduceByKey operation is applied

PI

JFK 19

P2

PPG	12
LAX	17

# On each partition, again the reduceByKey operation is applied

#### Old RDD

#### New RDD

PI

JFK	2
JFK	14
PPG	5
PPG	10
JFK	0
PPG	4

71

JFK 19
--------

P2

3
0
6
11
0
7

72

PPG	12
LAX	17



airportTotalDelay=airportDelays.reduceByKey(lambda x,y:x+y)

### We can use the same idea to compute count

airportCount=airportDelays.mapValues(lambda x:1).reduceByKey(lambda x,y:x+y)

airportCount=airportDelays.mapValues(lambda x:1).reduceE

### This is our RPP with (origin airport, delay)

rtDelays.mapValues(**lambda** x:1).reduceByKey(**lambda** x,y:x+y)

#### lorigin airport, delay)

## mapValues will leave the key as is and apply a function on the value

rtDelays.mapValues(lambda x:1).reduceByKey(lambda x,y:x+y)

rtDelays.mapValues(lambda x:1).reduceByKey(lambda x,y:x+y)

#### lorigin airport, 1) This will sum all these Is effectively giving us count of flights by airport

```
Option I:
reducebykey
```

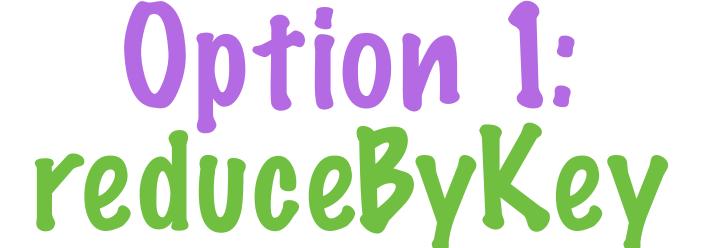
```
airportTotalDelay=airportDelays.reduceByKey(lambda x,y:x+y)
airportCount=airportDelays.mapValues(lambda x:1).reduceByKey(lambda x,y:x+y)
```

## The sum and count are in 2 separate RDDs

```
Option I:
reducebykey
```

```
airportTotalDelay=airportDelays.reduceByKey(lambda x,y:x+y)
airportCount=airportDelays.mapValues(lambda x:1).reduceByKey(lambda x,y:x+y)
```

## We can merge these using a join operation



airportSumCount=airportTotalDelay.join(airportCount)

### This will merge the 2 RDDs by matching values with the same key



airportSumCount=airportTotalDelay.join(airportCount)

#### SUM

JFK	23
LAX	14
PPG	5

### Count

JFK	4
LAX	2
PPG	1

### suncount

JFK	(23,4)
LAX	(14,2)
PPG	(5,1)



airportSumCount=airportTotalDelay.join(airportCount)

### suncount

JFK	(23,4)
LAX	(14,2)
PPG	(5,1)

### We need to divide the sum by the count



airportAvgDelay=airportSumCount.mapValues(lambda x : x[0]/float(x[1]))

#### suncount

JFK	(23,4)
LAX	(14,2)
PPG	(5,1)

### Once again, we can use map Values to do this

```
Option I:
reducebykey
```

```
airportTotalDelay=airportDelays.reduceByKey(lambda x,y:x+y)
airportCount=airportDelays.mapValues(lambda x:1).reduceByKey(lamairportSumCount=airportTotalDelay.join(airportCount)
```

```
airportAvgDelay=airportSumCount.mapValues(lambda x : x[0]/float(x[1]))
```

### With reduceByKey, it took 3 steps to compute the average delay per airport

```
Option I:
reducebykey
```

```
airportTotalDelay=airportDelays.reduceByKey(lambda x,y:x+y)
airportCount=airportDelays.mapValues(lambda x:1).reduceByKey(lambda airportSumCount=airportTotalDelay.join(airportCount)
```

- 1. Compute the sum in 1 RPP
- 2. Compute the count in another RDD
- 3. Join the 2 RPPs

```
Option I:
reducebykey
```

```
airportTotalDelay=airportDelays.reduceByKey(lambda x,y:x+y)
airportCount=airportDelays.mapValues(lambda x:1).reduceByKey(lambda airportSumCount=airportTotalDelay.join(airportCount)
```

### With combineByKey, we can do all this in one step

Average delay per airport
For each airport, we need
Sum of all delays
Count of number of flights

Option 1: reducebykey

Option 2: combineByKey

```
Option 2:
combinebykey
```

### This is a new RDD

### combineByKey is a transformation

### combineByKey is similar to aggregate

### Option 2: combinebykey

### combineByKey requires 3 functions

### Option 2: combinebykey

### createCombiner Function

### This initializes a value when a key is first seen within a partition

```
Option 2:
combinebykey
```

```
airportSumCount2=airportDelays.combineByKey((lambda value (value,1)),
(lambda acc, value: (acc[0]+value,acc[1]+1)),
(lambda acc1, acc2: (acc1[0]+acc2[0],acc1[1]+acc2[1])))
```

### merge Function

This specifies how values with the same key should be combined within a partition

```
Option 2:
combinebykey
```

### mergeCombiners Function

### This specifies how the results from each partition should be combined

```
Option 2:
combineByKey
```

createCombiner merge mergeCombiners

With combineByKey we have very granular control over how the computation should happen

```
Option 2:
combine Bykey
```

### Let's see this visually

### Option 2: combinebykey

PI

JFK	2
JFK	12
PPG	5
PPG	10
JFK	0
PPG	4

### This the delays RDD

P2

JFK	3
JFK	0
LAX	6
LAX	11
JFK	0
PPG	7

### Option 2: combinebykey

**P1** 

JFK	2
JFK	12
PPG	5
PPG	10
JFK	0
PPG	4

P2

JFK	3
JFK	0
LAX	6
LAX	11
JFK	0
PPG	7

# First, the operation is performed on each partition

### Option 2: combinebykey

PI

JFK	2
JFK	12
PPG	5
PPG	10
JFK	0
PPG	4

### We start with the first record

### Option 2: combinebykey

JFK 12
PPG 5
PPG 10
JFK 0

**PPG** 

JFK

### This is first time the key "IFK" is seen

PI

### Option 2: combinebykey

```
JFK
       12
JFK
        5
PPG
       10
PPG
PPG
```

PI

JFK, (2,1)

### The createCombiner function is used to initialize a value

### Option 2: combinebykey

JFK 12 JFK PPG 5 10 **PPG JFK** 0 **PPG** 

PI

JFK, (2,1)

The next step depends on whether it's a new key or a key that's already seen

### Option 2: combinebykey

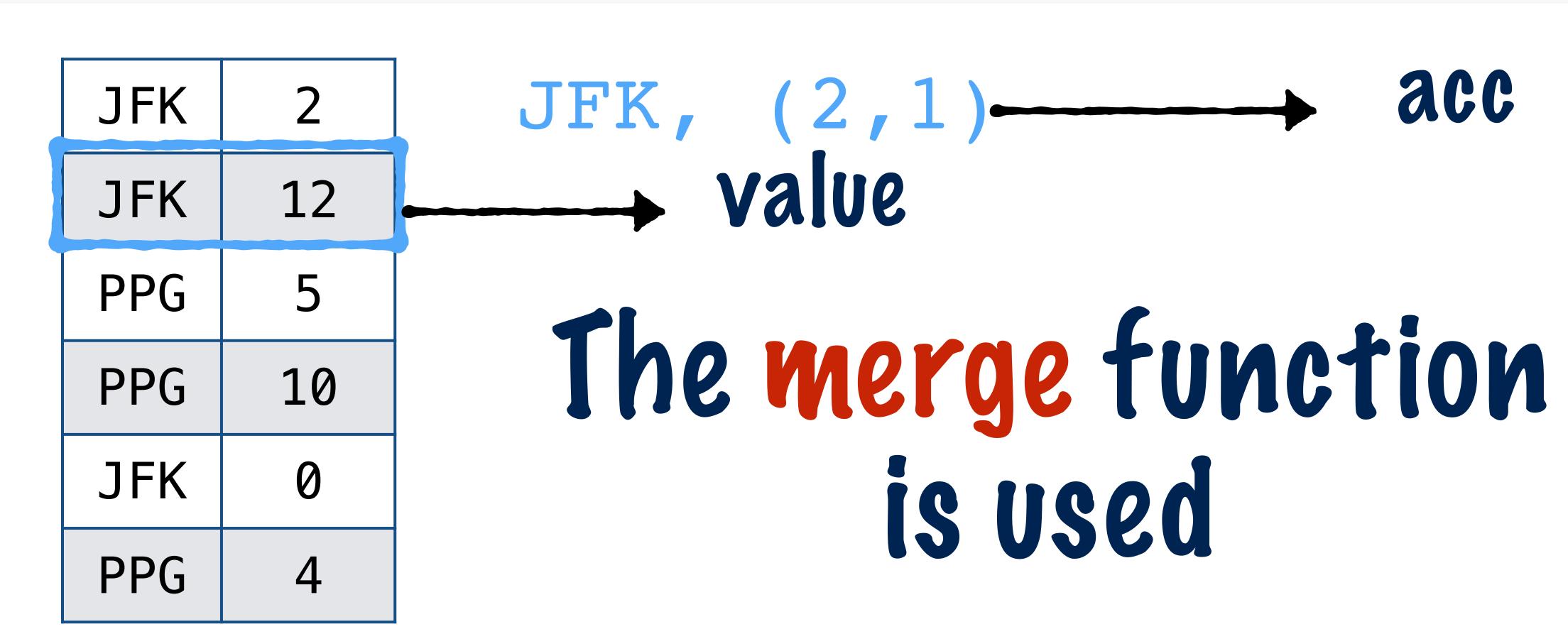
71

JFK	2
JFK	12
PPG	5
PPG	10
JFK	0
PPG	4

JFK, (2,1)

### The key "JFK" has already been seen

### Option 2: combinebykey



PI

### Option 2: combinebykey

```
JFK
JFK
       12
PPG
        5
PPG
       10
PPG
```

JFK, (14,2)

"PPG" is a new key

### Option 2: combinebykey

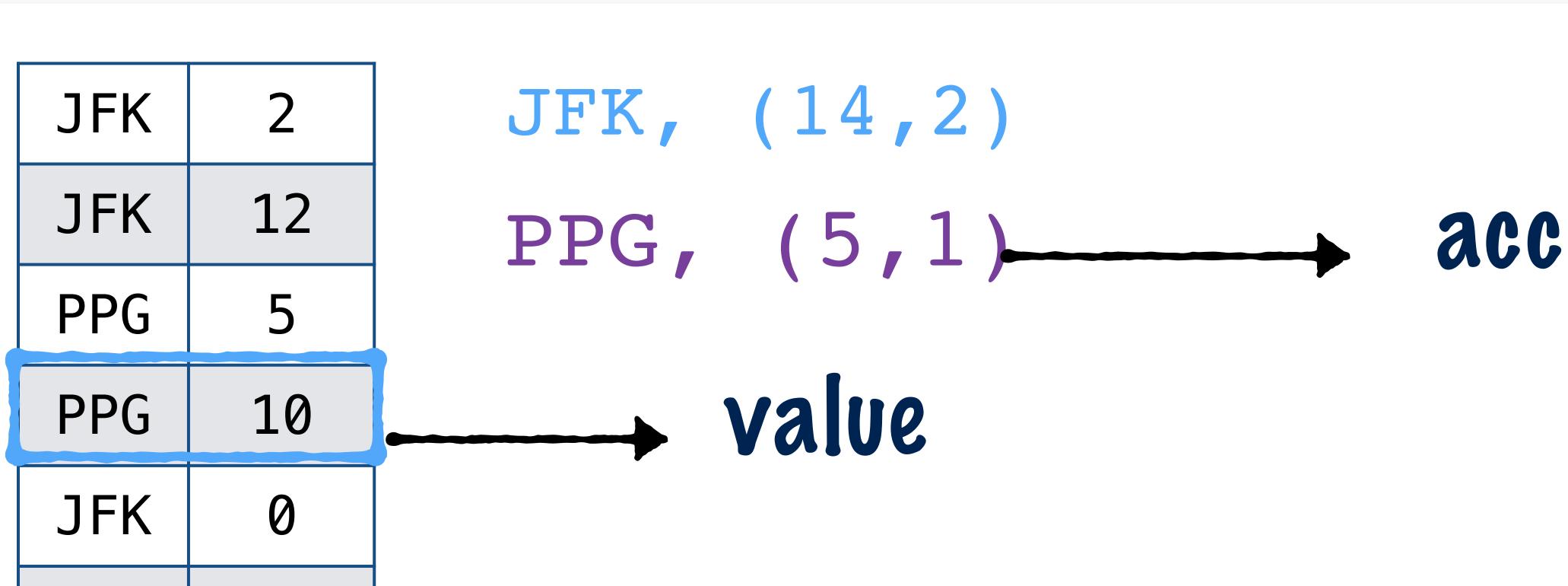
```
JFK
       12
JFK
PPG
        5
PPG
       10
JFK
PPG
```

PI

JFK, (14,2)
PPG, (5,1)

### Continue until all records are processed

```
Option 2:
combinebykey
```

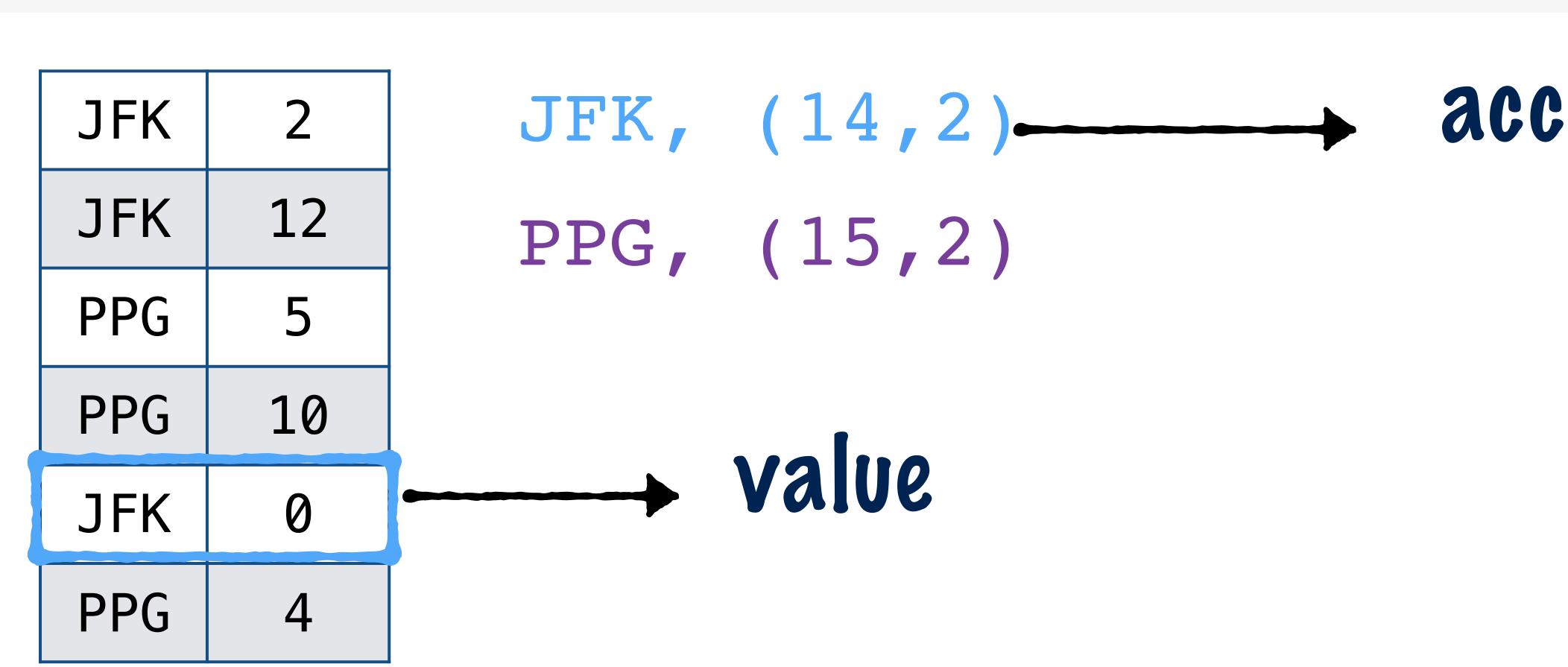


PI

**PPG** 

PI

### Option 2: combinebykey



### Option 2: combinebykey

```
JFK, (14,3)
JFK
     12
JFK
             PPG, (15,2)____
                                         acc
      5
PPG
PPG
     10
JFK
                   Value
PPG
```

PI

```
Option 2:
combinebykey
```

```
P1 JFK, (14,3)
PPG, (19,3)
```

## The same thing is done on each Partition

### Option 2: combinebykey

```
PI JFK, (14,3)
PPG, (19,3)
```

```
P2 PPG, (3,3)
LAX, (17,2)
```

The records are shuffled until all records with the same key are on the same partition

### Option 2: combinebykey

```
.combineByKey((lambda value:(value,1)),
              (lambda acc, value: (acc[0]+value,acc[1]+1)),
              (lambda acc1, acc2: (acc1[0]+acc2[0],acc1[1]+acc2[1])))
```

### Option 2: combinebykey

```
JFK, (14,3)
JFK, (3,3)
```

```
PPG, (19,3)
PPG, (7,1)
LAX, (17,2)
```

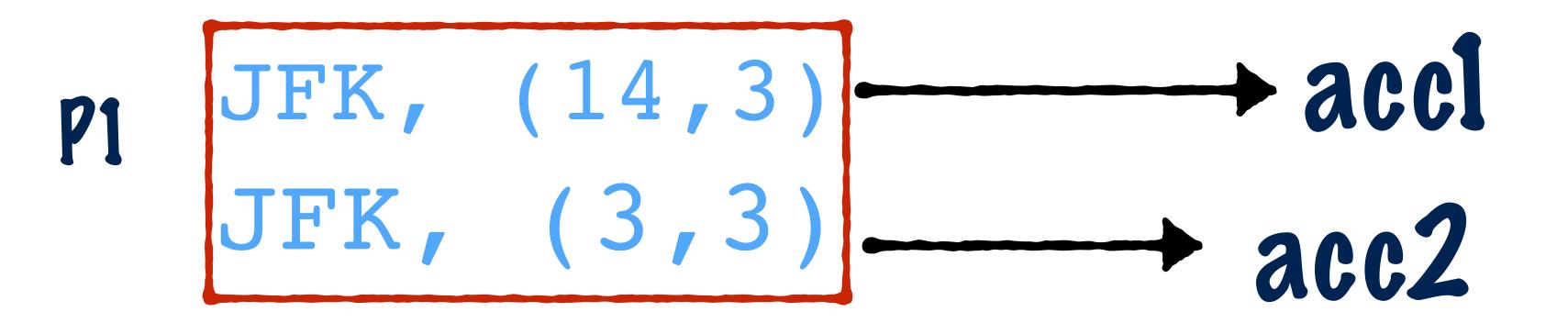
# The records in each partition are processed

### Option 2: combinebykey

```
JFK, (14,3)
JFK, (3,3)
```

# Values with the same key are combined using the mergeCombiners function

```
Option 2:
combinebykey
```



```
Option 2:
combinebykey
```

```
PI JFK, (17,6)
```

# Similarly, each partition is processed

### Option 2: combinebykey

```
airportSumCount2=airportDelays.combineByKey((lambda value
(lambda acc,
(lambda accl,
```

```
P1 JFK, (17,6)

P2 PPG, (26,4)

LAX, (17,2)
```

# Using a single transformation, we could compute the sum and the count

# 1. Compute the average delay per airport

#### 2. Find the top 10 airports based on delays

airportAvgDelay

### We already have the average delay per airport

airportAvgDelay

It's a pair RDD with

keys=Airports

Values=Avg Delay per Airport

airportAvgDelay

# We want to sort this RPP

In descending order of value

```
airportAvgDelay.sortBy(lambda x:-x[1])
```

Vescending order of value

# sortBy is a transformation It can be used with both Basic and Paired RDDS

```
airportAvgDelay.sortBy(lambda x:-x[1])
```

# This is the avg delay per airport ie. the value in the key value pair

```
airportAvgDelay.sortBy(lambda x:-x[1])
```

### By reversing the sign, we are able to sort in descending order

```
airportAvgDelay.sortBy(lambda x:-x[1]).take(10)
```

```
[(u'PPG', 56.25),
(u'EGE', 32.0),
 (u'OTH', 24.53333333333333),
 (u'LAR', 18.892857142857142),
 (u'RDD', 18.55294117647059),
 (u'MTJ', 18.3636363636363),
 (u'PUB', 17.54),
 (u'EWR', 16.478549005929544),
 (u'CIC', 15.931034482758621),
 (u'RST', 15.6993006993007)]
```

# This will give us the top 10 airports and their avg delay

```
[(u'PPG', 56.25),
 (u'EGE', 32.0),
 (u'OTH', 24.53333333333333),
 (u'LAR', 18.892857142857142),
 (u'RDD', 18.55294117647059),
 (u'MTJ', 18.3636363636363),
 (u'PUB', 17.54),
 (u'EWR', 16.478549005929544),
 (u'CIC', 15.931034482758621),
 (u'RST', 15.6993006993007)]
```

# These are the airport Codes

Which airports do these refer to?

```
[(u'PPG', 56.25),
 (u'EGE', 32.0),
 (u'OTH', 24.53333333333333),
 (u'LAR', 18.892857142857142),
 (u'RDD', 18.55294117647059),
 (u'MTJ', 18.3636363636363),
 (u'PUB', 17.54),
 (u'EWR', 16.478549005929544),
 (u'CIC', 15.931034482758621),
 (u'RST', 15.6993006993007)]
```

# We can use the airports.csv file to find out

## 1. Compute the average delay per airport

2. Find the top 10 airports based on delays

→ Looking up Airport Pescriptions

Recap

## There are 3 files

Hights.csv

Flight id, airline, airport, departure, arrival, delay

airlines.csv

airline id, airline name

airports.csv

airport id, airport name

### Let's load and parse the airports.csv file

```
import csv
from StringIO import StringIO
def split(line):
    reader = csv.reader(StringIO(line))
    return reader.next()
def notHeader(row):
    return "Description" not in row
airports=sc.textFile(airportsPath).filter(notHeader).map(split)
```

```
import csv
from StringIO import StringIO
def split(line):
    reader = csv.reader(StringIO(line))
    return reader.next()
def notHeader(row):
    return "Description" not in row
airports=sc.textFile(airportsPath).filter(not
```

# Atunction to filter out the header ruw

```
import csv
from StringIO import StringIO
def split(line):
    reader = csv.reader(StringIO(line))
    return reader.next()
def notHeader(row):
    return "Description" not in row
airports=sc.textFile(airportsPath).filter(not
```

#### We take help trom Python's csv module for a function to cleanly parse the rows

```
import csv
from StringIO impor
def split(line):

    reader = csv.re
    return reader.r

def notHeader(row):
    return "Descrip
```

# We use the functions to load the data into an RDD and parse the rows

airports=sc.textFile(airportsPath).filter(notHeader).map(split)

airports=sc.textFile(airportsPath).filter(notHeader).map(split)

### airports is also a Pair RDD

A list with 2 elements in each record, this Python treats exactly like a Pair RDD

airports=sc.textFile(airportsPath).filter(notHeader).map(split)

### airports is also a Pair RDD

Each pair has (Airport Code, Airport Pescription)

airports=sc.textFile(airportsPath).filter(notHeader).map(split)

## We have 3 options on how to use this RDD lookup action Map broadcast

airports=sc.textFile(airportsPath).filter(notHeader).map(split)

# Pair RPPs have an action called lookup

```
[(u'PPG', 56.25),
 (u'EGE', 32.0),
                             We can use
 (u'OTH', 24.53333333333333),
 (u'LAR', 18.892857142857142),
 (u'RDD', 18.55294117647059),
                              lookup for
 (u'MTJ', 18.3636363636363),
 (u'PUB', 17.54),
(u'EWR', 16.478549005929544), 23Ch of the Se
 (u'CIC', 15.931034482758621),
                           airport Codes
 (u'RST', 15.6993006993007)]
```

```
[(u'PPG', 56.25),
  (u'EGE', 32.0),
  (u'OTH', 24.533333333333333333),
  (u'LAR', 18.892857142857142),
  (u'RDD', 18.55294117647059),
  (u'MTJ', 18.363636363636363),
  (u'PUB', 17.54),
  (u'EWR', 16.478549005929544),
  (u'CIC', 15.931034482758621),
  (u'RST', 15.6993006993007)]
```

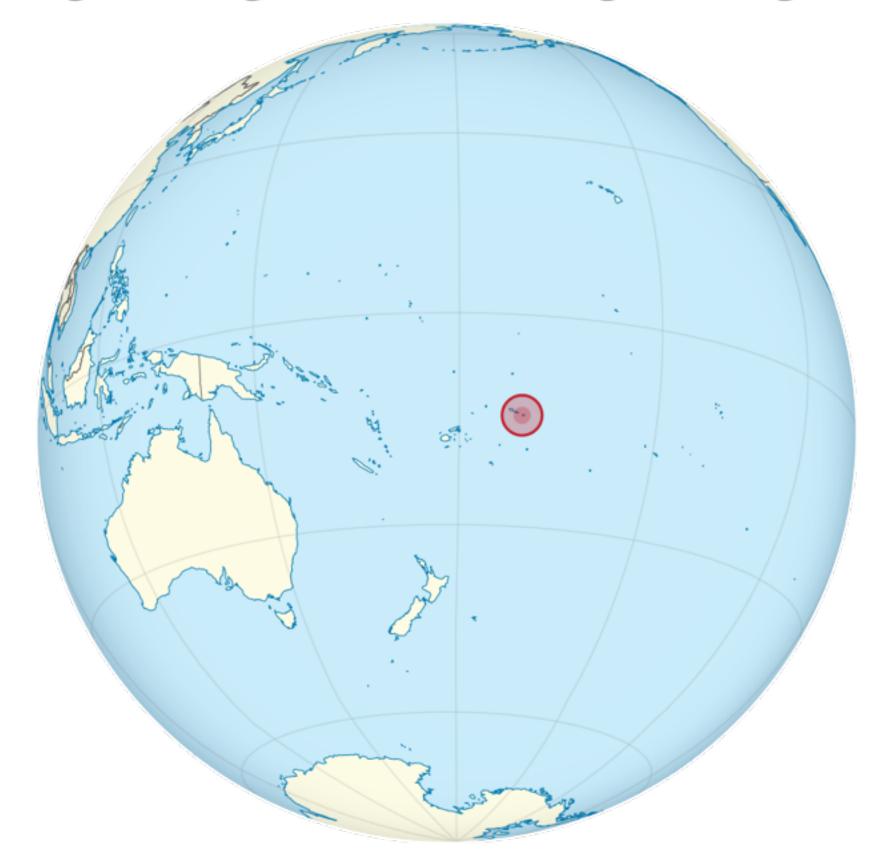
```
airports.lookup('PPG')
```

```
['Pago Pago, TT: Pago Pago International']
```

## We can use lookup for each of these airport Codes

```
airports.lookup('PPG')
```

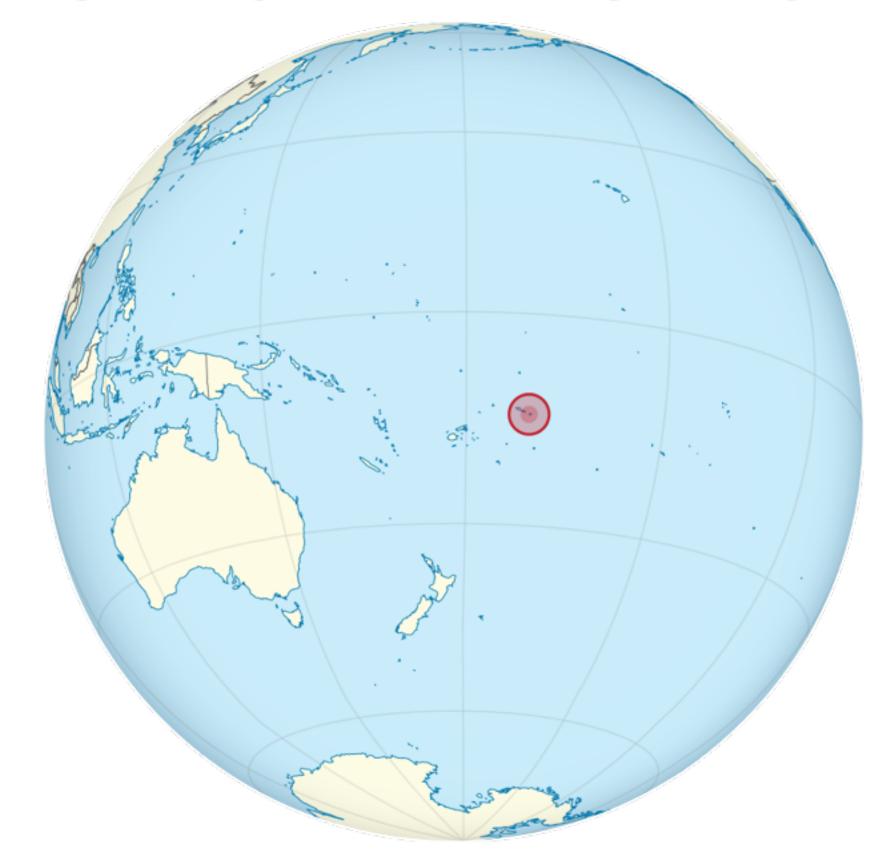
```
['Pago Pago, TT: Pago Pago International']
```



# That's an airport on a tiny little island in the South Pacific Ocean

```
airports.lookup('PPG')
```

['Pago Pago, TT: Pago Pago International']



Did you know that the US has an island territory there in a little country called Samoa?

Huhl

You learn something new all the time:)

```
airports.lookup('PPG')
```

```
['Pago Pago, TT: Pago Pago International']
```

### Back to our example, It's a little tedious to have to do this for each airport

We have 3 options on how to use this RPP

lookup action dictionary
broadcast

#### dictionary

# We can build a map with all airports from the RDD and use that

airportLookup=airports.collectAsMap()

collectAsMap is an action

#### dictionary

#### airportLookup=airports.collectAsMap()

airportLookup

```
{'SPY': "San Pedro, Cote d'Ivoire: San Pedro Airport",
 'SPZ': 'Springdale, AR: Springdale Municipal',
 'SPP': 'Menongue, Angola: Menongue Airport',
 'SPQ': 'San Pedro, CA: Catalina Air-Sea Terminal Heliport',
 'SPR': 'San Pedro, Belize: San Pedro Airport',
 'SPS': 'Wichita Falls, TX: Sheppard AFB/Wichita Falls Municipal',
 'SPU': 'Split, Croatia: Split Airport',
 'SPW': 'Spencer, IA: Spencer Municipal',
 'SPH': 'Sopu, Papua New Guinea: Sopu Airport',
 'SPI': 'Springfield, IL: Abraham Lincoln Capital',
 'SPK': 'Sapporo, Japan: Chitose AB',
 'SPM': 'Spangdahlem, Germany: Spangdahlem AB',
 'SPN': 'Saipan, TT: Francisco C. Ada Saipan International',
 'SPA': 'Spartanburg, SC: Spartanburg Downtown Memorial',
 'SPB': 'Charlotte Amalie, VI: Charlotte Amalie Harbor Seaplane Base',
 'SPC': 'Santa Cruz de la Palma, Spain: La Palma',
 'SPD': 'Saidpur, Bangladesh: Saidpur Airport',
 'SPE': 'Sepulot, Malaysia: Sepulot Airport',
 'SPF': 'Spearfish, SD: Black Hills Clyde Ice Field',
```

returns a dictionary with all the key value pairs in the RDD

#### dictionary

```
airportLookup=airports.collectAsMap()
```

```
airportAvgDelay.map lambda x: (airportLookup[x[0]],x[1]))
```

airportAvgDelay is a Pair RDD with

(Airport Code, Avg Pelay)

For each record, this function replaces the Airport Code with corresponding Pescription

```
dictionary
```

```
airportAvgDelay.map(lambda x: (airportLookup[x[0]],x[1]))
```

(Airport Code, Avg Pelay)

# It uses the airportLookup dict to do so

dictionary

```
airportAvgDelay.map(lambda x: (airportLookup[x[0]],x[1]))
```

(Airport Code, Avg Pelay)

(Airport Pesc, Avg Pelay)

#### airportLookup

```
{'SPY': "San Pedro, Cote d'Ivoire: San Pedro Airport",
 'SPZ': 'Springdale, AR: Springdale Municipal',
 'SPP': 'Menongue, Angola: Menongue Airport',
 'SPQ': 'San Pedro, CA: Catalina Air-Sea Terminal Heliport',
 'SPR': 'San Pedro, Belize: San Pedro Airport',
 'SPS': 'Wichita Falls, TX: Sheppard AFB/Wichita Falls Municipal',
 'SPU': 'Split, Croatia: Split Airport',
 'SPW': 'Spencer, IA: Spencer Municipal',
 'SPH': 'Sopu, Papua New Guinea: Sopu Airport',
 'SPI': 'Springfield, IL: Abraham Lincoln Capital',
 'SPK': 'Sapporo, Japan: Chitose AB',
 'SPM': 'Spangdahlem, Germany: Spangdahlem AB',
 'SPN': 'Saipan, TT: Francisco C. Ada Saipan International',
 'SPA': 'Spartanburg, SC: Spartanburg Downtown Memorial',
 'SPB': 'Charlotte Amalie, VI: Charlotte Amalie Harbor Seaplane Base',
 'CDC'. 'Canta Cruz do la Dalma Chain. La Dalma'
```

dictionary

```
airportAvgDelay.map(lambda x: (airportLookup[x[0]],x[1]))
```

## This is a function

Spark distributes this function to all the nodes with the partitions of the RDD

dictionary

airportAvgDelay.map lambda x: (airportLookup[x[0]],x[1]))

#### This function uses the airportLookup variable

It will carry it's own copy of this variable to each node

```
airportAvgDelay.map(lambda x: (airportLookup[x[0]],x[1]))
```

#### This is a property of closure functions

### Closure functions are pretty complicated

#### dictionary

```
airportAvgDelay.map lambda x: (airportLookup[x[0]],x[1]))
```

# Closure functions are pretty complicated

But they help Spark take complex operations defined by users and apply them on RDDs

#### dictionary

```
airportAvgDelay.map(lambda x: (airportLookup[x[0]],x[1]))
```

But they help Spark take complex operations defined by users and apply them on RDDs

while keeping the user completely abstracted from the complexities of distributed computing

```
airportAvgDelay.map(lambda x: (airportLookup[x[0]],x[1]))
```

#### We mentioned that a copy of airportLookup variable is carried over to each node in the cluster

```
airportAvgDelay.map lambda x: (airportLookup[x[0]],x[1]))
```

#### What if we had to use this lookup in multiple operations?

```
airportAvgDelay.map(lambda x: (airportLookup[x[0]],x[1]))
```

### The airportLookup variable would be copied over to the nodes every time!

#### dictionary

```
airportAvgDelay.map(lambda x: (airportLookup[x[0]],x[1]))
```

#### What if we could cache this variable on each of the nodes, so it can be reused?

```
airportAvgDelay.map lambda x: (airportLookup[x[0]],x[1]))
```

# This is exactly why Spark provides Broadcast Variables

We have 3 options on how to use this RPP

lookup action map broadcast

#### broadcast

### Spark allows you to define Broadcast Variables

#### broadcast

#### Broadcast Variables

These variables are 'broadcast' to all the nodes in the cluster

Looking up Airport Pescriptions broadcast Broadcast Variables They have 3 characteristics Immutable

Pistributed to all the nodes in the cluster

In-memory

broadcast

#### Immutable

Broadcast variables are immutable

They cannot be changed after creation

# Looking up Airport Descriptions broadcast Broadcast Variables

Distributed to all the nodes in the cluster

broadcast

Broadcast Variables

in-memory

Broadcast variables are cached in memory So, they should not be too large

#### broadcast

airportBC=sc.broadcast(airportLookup)

#### This is a broadcast variable

It has a method to lookup the value for a key

broadcast

airportBC=sc.broadcast(airportLookup)

```
airportAvgDelay.map(lambda x: (airportBC.value[x[0]],x[1]))
```

#### This is pretty similar to how we used the dictionary

```
broadcast
```

```
lay.map(lambda x: (airportBC.value[x[0]],x[1]))
```

## This is pretty similar to how we used the dictionary

But it's much more efficient because the broadcast variable is cached