Apache Spark Lab on Docker Cloudera

Contributors:

Hareem Qazi - 5371

Tatheer Fatima -09367

Apache Spark is a fast, **in-memory** data processing engine which allows data workers to efficiently execute streaming, machine learning or SQL workloads that require fast iterative access to datasets.

Speed

- Run computations in **memory**.
- Apache Spark has an advanced **DAG** execution engine that supports acyclic data flow and **in-memory computing**.
- **100 times faster** in memory and **10 times faster** even when running on disk than MapReduce.

Generality

- A general programming model that enables developers to write an application by composing **arbitrary operators**.
- Spark makes it easy to **combine** different processing models seamlessly in the **same application**.
- Example:
  - Data classification through Spark machine learning library.
  - Streaming data through source via Spark Streaming.
  - Querying the resulting data in real time through Spark SQL.

RDD (Resilient Distributed Datasets)

What is a dataset?

A dataset is basically a **collection of data**; it can be a list of strings, a list of integers or even a number of rows in a relational database.

- RDDs can contain **any types of objects**, including user-defined classes.
- An RDD is simply a **capsulation** around a **very large dataset**. In Spark all work is expressed as either creating new RDDs, transforming existing RDDs, or calling operations on RDDs to compute a result.
- Under the hood, Spark will automatically **distribute the data** contained in RDDs across your cluster and **parallelize** the operations you perform on them.

We can do **Transformations** and **Actions** with the RDDs

Transformations

- Transformations are **operations** on RDDs which will return a **new RDD**.
- One of the most common transformations is **filter** which will return a new RDD with a subset of the data in the original RDD.

Actions

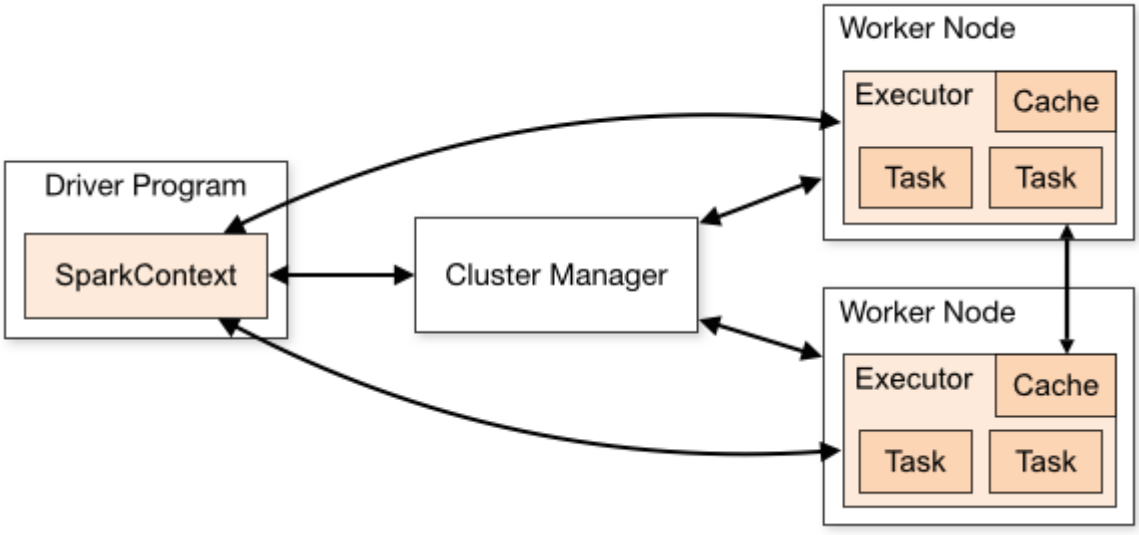
- Compute a **result** based on an RDD.
- One of the most popular Actions is **first**, which returns the first element in an RDD.

Spark RDD general workflow

- Generate **initial RDDs** from external data.
- Apply **transformations**.
- Launch **actions**.

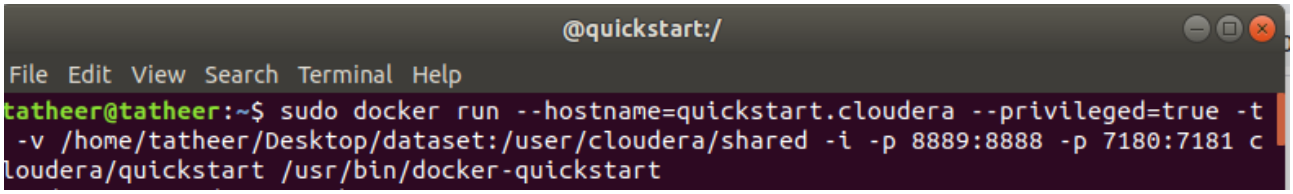
Spark Context

- SparkContext is the entry point of Spark functionality. The most important step of any Spark driver application is to generate SparkContext.
- It allows your Spark Application to access Spark Cluster with the help of Resource Manager. The resource manager can be one of these three- **Spark Standalone**, **YARN**, **Apache Mesos**.
- A SparkContext represents the connection to a Spark cluster, and can be used to create RDDs, accumulators and broadcast variables on that cluster.
- Only one SparkContext may be active per JVM. You must stop() the active SparkContext before creating a new one. This limitation may eventually be removed



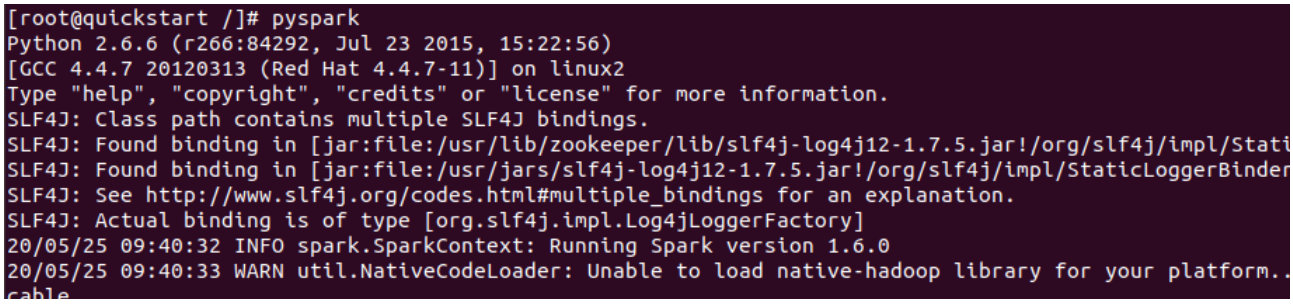
Run Quick Start Docker

```
sudo docker run --hostname=quickstart.cloudera --privileged=true -t -v
/home/tatheer/Desktop/dataset:/user/cloudera/shared -i -p 8889:8888 -p
7180:7181 cloudera/quickstart /usr/bin/docker-quickstart
```



Start Pyspark

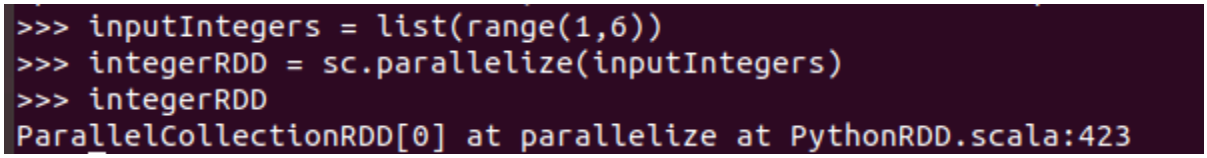
```
pyspark
```



Create RDD

- Take an existing collection in your program and pass it to SparkContext's **parallelize** method.
- All the elements in the collection will then be copied to form a **distributed dataset** that can be operated on in **parallel**.
- Very handy to create an RDD with **little effort**.

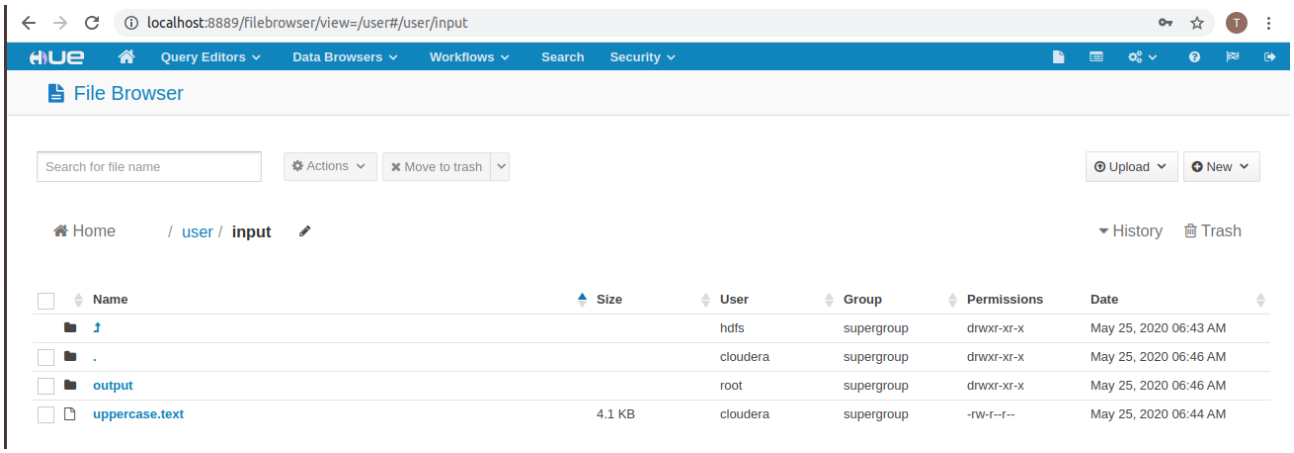
```
inputIntegers = list(range(1,6))

integerRDD = sc.parallelize(inputIntegers)
```



Load RDD

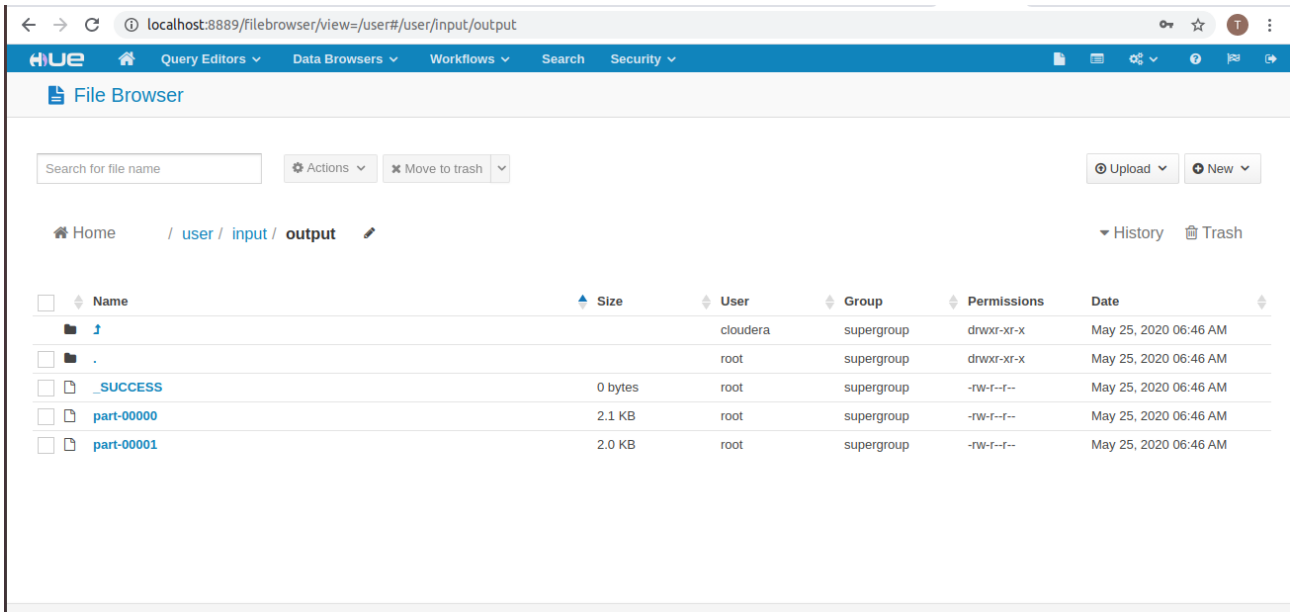
Create an input directory in hdfs user folder and upload the input file

```
lines =
sc.textFile("hdfs://quickstart.cloudera:8020/user/input/uppercase.text")
```



Save File

```
lines.saveAsTextFile("hdfs://quickstart.cloudera:8020/user/input/output")
```



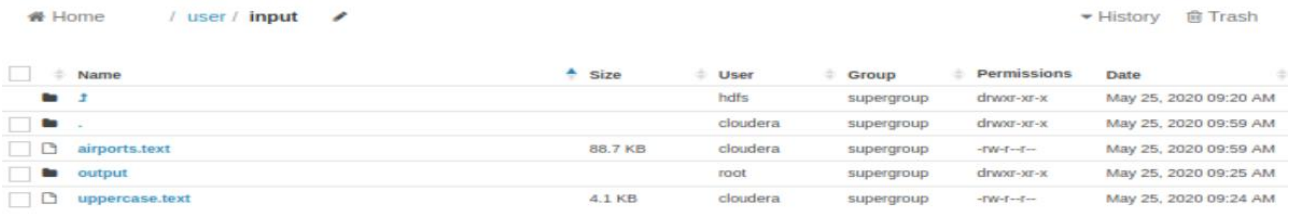
Spark Transformations

- Filter()
  - Takes **in a function** and **returns an RDD** formed by **selecting** those elements which pass the **filter function**.
  - Can be used to remove some invalid rows to **clean up** the input RDD or just **get a subset** of the input RDD based on the **filter function**.

- Map()
  - Takes **in a function** and passes each element in the **input RDD through the function**, with the result of the function being the new value of each element in the resulting RDD.
  - The **return type** of the map function is **not necessary** the same as its **input type**.

Create a spark program to read data from airport.text file and find all airports located in a country.

Upload airports.text in user/input



Create your python files i.e. AirportsInUsaSolution.py and Utils.py

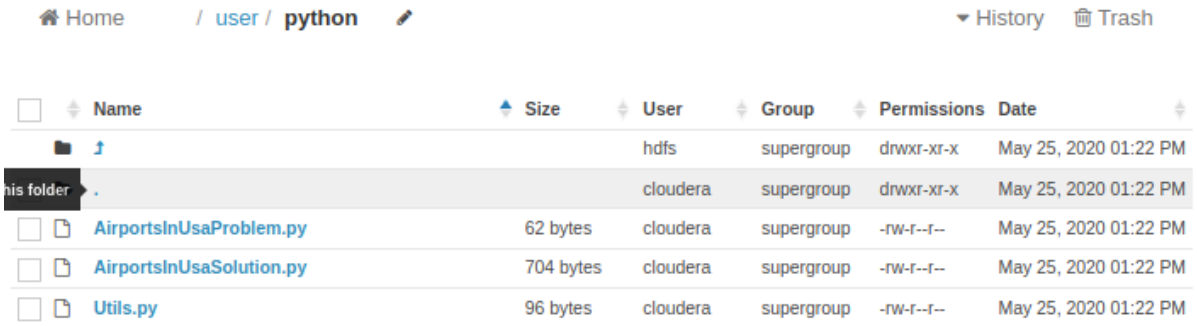
AirportsInUsaSolution.py

```
import sys

from pyspark import SparkContext, SparkConf
import Utils

def splitComma(line: str):
    splits = Utils.COMMA_DELIMITER.split(line)
    return "{}, {}".format(splits[1], splits[2])

if __name__ == "__main__":
    conf = SparkConf().setAppName("airports").setMaster("local[*]")
    sc = SparkContext(conf = conf)

    airports = sc.textFile("hdfs://quickstart.cloudera:8020/user/input/
airports.text")
    airportsInUSA = airports.filter(lambda line :
Utils.COMMA_DELIMITER.split(line)[3] == "\"United States\"")

    airportsNameAndCityNames = airportsInUSA.map(splitComma)
    airportsNameAndCityNames.saveAsTextFile("hdfs://quickstart.cloudera:8020/
user/input/output2/airports_in_usa.text")
```

Utils.py

```
import re

class Utils():

    COMMA_DELIMITER = re.compile(''',(?=(?:[^"]*"[^"]*")*[^"]*$)''')
```

Upload the two .py files in 'python' named directory



On pyspark shell

```
>>> exec('hdfs://quickstart.cloudera:8020/user/python/AirportsInUsaSolution.py'
)
```

Result:

- Union()
  - Union operation gives us back an RDD consisting of the data from **both input RDDs**
  - If there are any duplicates in the input RDDs, the resulting RDD of Spark's union operation **will contain duplicates** as well.

Write the code in pyspark shell

```
>>> student1_marks = [("physics",85),("maths",75),("chemistry",95)]
>>> student2_marks = [("physics",95),("maths",55),("chemistry",45)]
>>> s1 = sc.parallelize(student1_marks)
>>> s2 = sc.parallelize(student2_marks)
>>> union=s1.union(s2).collect()
20/05/27 12:33:40 INFO spark.SparkContext: Starting job: collect at <stdin>:1
20/05/27 12:33:40 INFO scheduler.DAGScheduler: Got job 1 (collect at <stdin>:1)
 with 4 output partitions
```

Result:

```
>>> union
[('physics', 85), ('maths', 75), ('chemistry', 95), ('physics', 95), ('maths',
55), ('chemistry', 45)]
>>>
```

- Join()
  - This transformation **joins two RDDs** based on **a common key**.

```
[('physics', 85), ('maths', 75), ('chemistry', 95), ('physics', 95), ('maths',
55), ('chemistry', 45)]
>>> Subject_wise_marks = s1.join(s2)
>>> Subject_wise_marks.collect()
```

Result:

```
[('maths', (75, 55)), ('physics', (85, 95)), ('chemistry', (95, 45))]
```

- Intersection()
  - Intersection operation returns the **common elements** which appear in both input RDDs.
  - Intersection operation **removes all duplicates** including the duplicates from single RDD before returning the results.
  - Intersection operation is **quite expensive** since it requires shuffling all the data across partitions to identify common elements.

```
>>> Cricket_team = ["sachin","abhay","michael","rahane","david","ross","raj","r
ahul","hussy","steven","sourav"]
>>> Toppers = ["rahul","abhay","laxman","bill","steve"]
>>>
>>> cricketRDD = sc.parallelize(Cricket_team)
>>> toppersRDD = sc.parallelize(Toppers)
>>> toppercricketers = cricketRDD.intersection(toppersRDD)
>>> toppercricketers.collect()
```

Result:

```
tasks have all completed, from pool
['abhay', 'rahul']
>>>
```

- Distinct()
  - This transformation is used to get rid of any **ambiguities**. As the name suggest it picks out the lines from the RDD that are **unique**.
  - The distinct transformation is **expensive** because it requires shuffling all the data across partitions to ensure that we receive only one copy of each element.

```
>>> best_story = ["movie1","movie3","movie7","movie5","movie8"]
>>> best_direction = ["movie11","movie1","movie5","movie10","movie7"]
>>> best_screenplay = ["movie10","movie4","movie6","movie7","movie3"]
>>> story_rdd = sc.parallelize(best_story)
>>> direction_rdd = sc.parallelize(best_direction)
>>> screen_rdd = sc.parallelize(best_screenplay)
>>> total_nomination_rdd = story_rdd.union(direction_rdd).union(screen_rdd)
>>> total_nomination_rdd.collect()
20/05/27 12:51:30 INFO spark.SparkContext: Starting job: collect at <stdin>:1
```

Result:

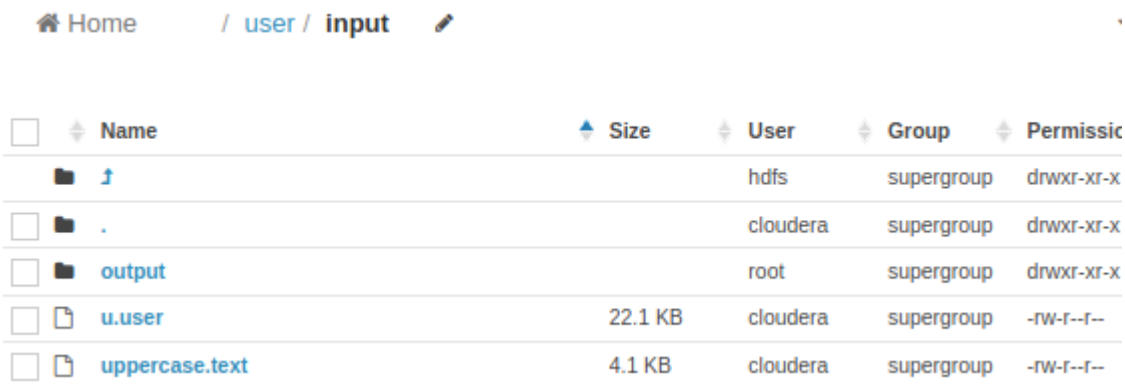
```
['movie1', 'movie3', 'movie7', 'movie5', 'movie8', 'movie11', 'movie1', 'movie5
', 'movie10', 'movie7', 'movie10', 'movie4', 'movie6', 'movie7', 'movie3']
```

UDF (User Defined Functions)

- UDF's provide a simple way to **add separate functions** into Spark that can be used during various transformation stages. UDF's are generally used to perform **multiple tasks** on Spark RDD's.

Using movie review data

Upload data (filename: u.user) in user/input




```
userRDD=
sc.textFile("hdfs://quickstart.cloudera:8020/user/input/u.user")

userRDD.count() //will display number of users
```

Create two functions 'parse_N_calculate_age() and age_group() in pyspark shell to divide users into age group

```
>>> def parse_N_calculate_age(data):
...     userid,age,gender,occupation,zip = data.split("|")
...     return  userid, age_group(int(age)),gender,occupation,zip,int(age)
...
```

```
...
>>> def  age_group(age):
...     if age < 10 :
...           return '0-10'
...     elif age < 20:
...           return '10-20'
...     elif age < 30:
...           return '20-30'
...         elif age < 40:
...           return '30-40'
...         elif age < 50:
...           return '40-50'
...         elif age < 60:
...           return '50-60'
...         elif age < 70:
...           return '60-70'
...         elif age < 80:
...           return '70-80'
...         else :
...           return '80+'
...
```

To perform analysis on people in age group 20-30

```
data_with_age_bucket = userRDD.map(parse_N_calculate_age)

RDD_20_30 = data_with_age_bucket.filter(lambda line : '20-30' in
line)
```

Let's count the number users by their profession in the given age_group 20-30

```
freq = RDD_20_30.map(lambda line : line[3]).countByValue()

 dict(freq)
```

Result:

```
>>> dict(freq)
{u'administrator': 19, u'lawyer': 4, u'healthcare': 4, u'marketing': 5, u'execu
tive': 7, u'doctor': 2, u'scientist': 8, u'student': 116, u'technician': 12, u'
librarian': 11, u'programmer': 30, u'salesman': 2, u'homemaker': 3, u'engineer'
: 23, u'none': 2, u'artist': 12, u'writer': 14, u'entertainment': 8, u'other':
38, u'educator': 12}
```

count the number of movie users in the same age group based on gender

```
age_wise = RDD_20_30.map (lambda line : line[2]).countByValue()

dict(age_wise)
```

Result:

```
>>> dict(age_wise)
{u'M': 247, u'F': 85}
>>>
```

Accumulators and Broadcast Variables

For **parallel processing**, Apache Spark uses **shared variables**. A copy of shared variable goes on each node of the cluster when the driver sends a task to the executor on the cluster, so that it can be used for performing tasks.

There are **two types** of shared variables supported by Apache Spark −

1.) Broadcast 2.) Accumulator

- Accumulators
  - Accumulators are variables that are used for **aggregating** information across the executors. For, example we can calculate how many records are corrupted or count events that occur during job execution for debugging purposes.
  - Using Accumulators for **outlier detection** in the above movie dataset. We are assuming that anyone who falls into age group 80+ is outlier and marked as `over_age` and anyone falling into age group 0-10 is also an outlier and marked as `under_age`.

    ```
    Under_age = sc.accumulator(0)

    Over_age = sc.accumulator(0)
    ```

Create a function `outliers()`

```
>>> def outliers(data):
...     global Over_age, Under_age
...     age_grp= data[1]
...     if(age_grp == "70-80"):
...             Over_age +=1
...     if(age_grp == "0-10"):
...             Under_age +=1
...     return data
...
```

```
df = data_with_age_bucket.map(outliers).collect()
```

Check how many users are underage and overage

```
Under_age.value
```

```
Over_age.value
```

Result:

```
>>> Under_age.value
1
>>> Over_age.value
4
>>>
```

- ## Broadcast Variables
  - Broadcast variables are **read-only** shared variables that are cached and **available on all nodes** in a cluster in-order to access or use by the tasks.
  - Spark broadcasts the **common data (reusable)** needed by tasks within each stage. The broadcasted data is cache in serialized format and deserialized before executing each task.

Example:

```
states = [("NY" ,"New York"),("CA" ,"California"),("FL" ,"Florida")]
```

```
countries =[("USA" ,"United States of America"),("IN" ,"India")]
```

```
bstates = sc.broadcast(states)
```

```
bcountries = sc.broadcast(countries)
```

```
data = [("James","Smith","USA","CA"), ("Michael" ,"Rose"
,"USA","NY"), ("Robert","Williams","USA","CA"), ("Maria" ,"Jones"
,"USA" ,"FL")]
```

```
rdd = sc.parallelize(data)
```

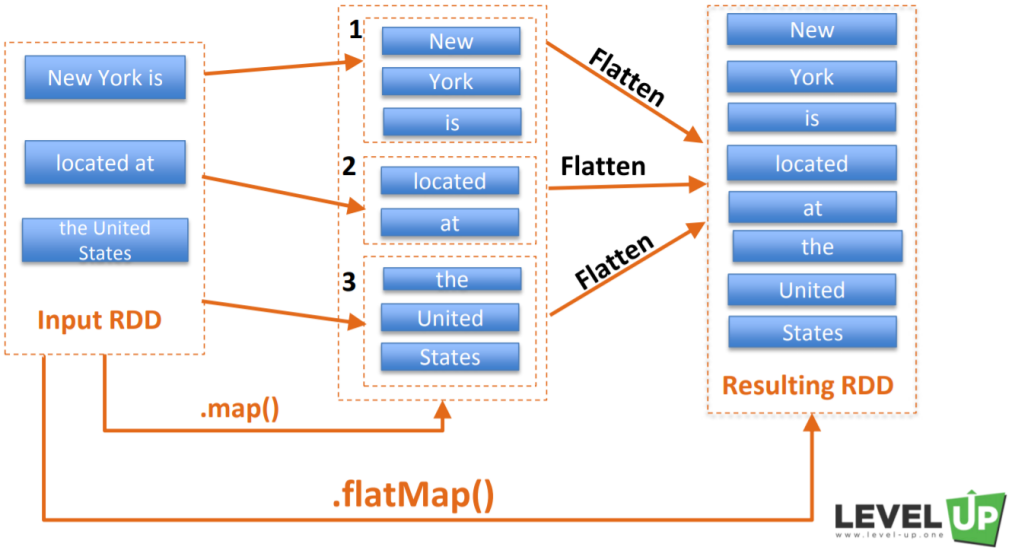
```
sc.parallelize(data[2]).collect()
```

Result:

```
n>:1, took 0.050065 s
['Robert', 'Williams', 'USA', 'CA']
```

Basic Count programming using flatMap

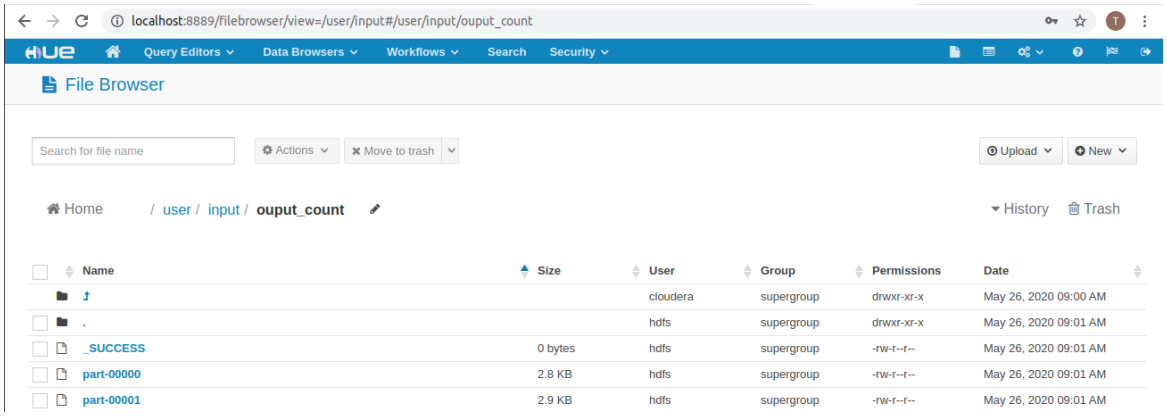
- flatMap is a transformation to **create an RDD** from an existing RDD.
- It takes **each element** from an existing RDD and it can produce **0, 1 or many outputs for each element**.



Write code in pyspark shell

```
myfile = sc.textFile("hdfs://quickstart.cloudera:8020/user/input/uppercase.text")

counts = myfile.flatMap(lambda line: line.split(" ")).map(lambda word: (word, 1)).reduceByKey(lambda v1,v2: v1 + v2)

counts.saveAsTextFile("hdfs://quickstart.cloudera:8020/user/input/ouput_count")
```

Result:




```
(u'', 7)
(u'operations', 1)
(u'all', 1)
(u'proposed', 1)
(u'Union', 1)
(u'over', 1)
(u'rest', 1)
```