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RDD and DataFrame in Spark

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CN7022 – Week 8
22 November 2019

Outline

- RDD Programming using Python
- RDD Disadvantages
- RDD vs DataFrame vs DataSet
- DataFrame Programming using SQL

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Learning Outcomes

- To understand the RDD Programming using Python
- To be able to explain the differences between RDD, DataFrame, and DataSet
- To be able to read data into Spark and complete the actions using RDD Python or DataFrame SQL.

The rest of term

- **Week 8 (today, 22nd Nov.):** RDD & DataFrame Programming
- **Week 9 (29th Nov.):** Probabilistic modelling using PySpark
- **Week 10 (6th Dec., CRWK preparation, <u>no class</u>)**
- **Week 11 (13th Dec., CRWK preparation, <u>no class</u>)**

<u>Additional booked rooms on December 2019:</u>

- **KD.2.14:**
  1. Monday (2/12, 9/12, 16/12): 10:00 – 13:00
  2. Wednesday (4/12, 11/12, 18/12): 10:00 – 13:00
- **KD.2.28E:**
  1. Monday (2/12, 9/12, 16/12): 10:00 – 17:00 (all day)
  2. Wednesday (4/12, 11/12, 18/12): 10:00 – 17:00 (all day)

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The Presentation (40% weighting)

- **Week 12 (Tuesday, 17th Dec.):** CRWK presentation
  - KD.2.14 and KD.2.15 [2pm-6pm]

- **Week 12 (Wednesday, 18th Dec.):** CRWK presentation
  - KD.2.14 and KD.2.15 [9am-1pm]

	Dec 17 TUE 2:00 PM 2:20 PM	Dec 17 TUE 2:20 PM 2:40 PM	Dec 17 TUE 2:40 PM 3:00 PM	Dec 17 TUE 3:00 PM 3:20 PM	Dec 17 TUE 3:20 PM 3:40 PM	Dec 17 TUE 3:40 PM 4:00 PM	Dec 17 TUE 4:00 PM 4:20 PM	Dec 17 TUE 4:20 PM 4:40 PM	Dec 17 TUE 4:40 PM 5:00 PM	Dec 17 TUE 5:00 PM 5:20 PM	Dec 17 TUE 5:20 PM 5:40 PM	Dec 17 TUE 5:40 PM 6:00 PM
0 participants	✓0/3	✓0/3	✓0/3	✓0/3	✓0/3	✓0/3	✓0/3	✓0/3	✓0/3	✓0/3	✓0/3	✓0/3
Group 100												

Dec 18 WED 9:00 AM 9:20 AM	Dec 18 WED 9:20 AM 9:40 AM	Dec 18 WED 9:40 AM 10:00 AM	Dec 18 WED 10:00 AM 10:20 AM	Dec 18 WED 10:20 AM 10:40 AM	Dec 18 WED 10:40 AM 11:00 AM	Dec 18 WED 11:00 AM 11:20 AM	Dec 18 WED 11:20 AM 11:40 AM	Dec 18 WED 11:40 AM 12:00 PM	Dec 18 WED 12:00 PM 12:20 PM	Dec 18 WED 12:20 PM 12:40 PM	Dec 18 WED 12:40 PM 1:00 PM
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- Book your presentation(**deadline: 10th Dec.**): https://bit.ly/2NX7bJq
- The participant should be your **group ID**.

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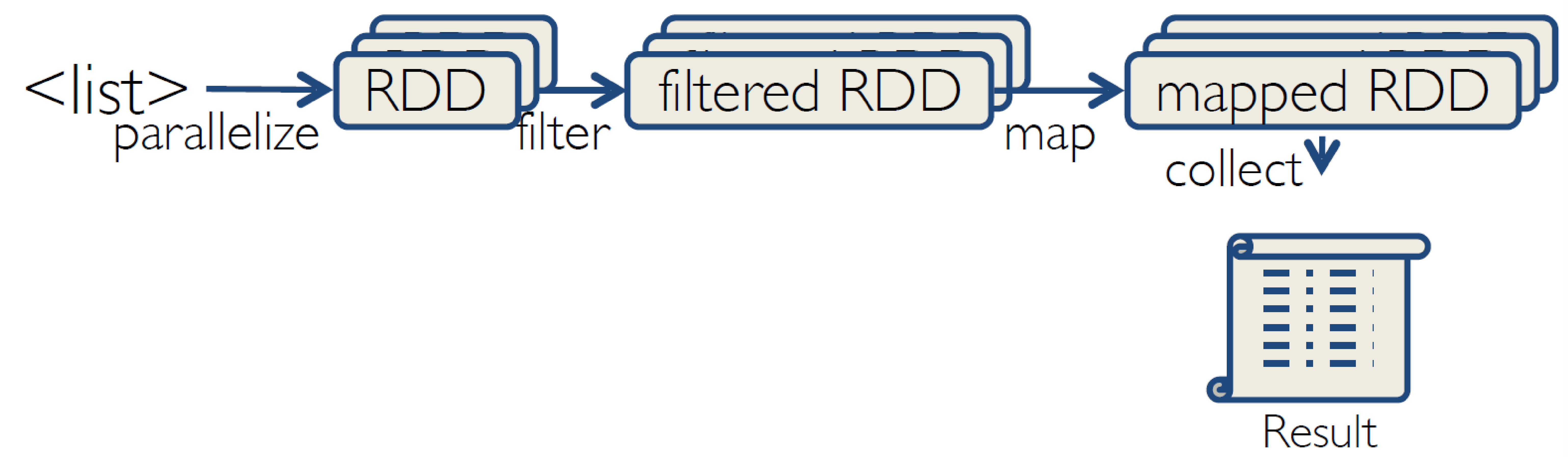
Launch PySpark

```
uel@uel-Deskop-VM: /usr/local/spark
uel@uel-Deskop-VM:~$ cd $SPARK_HOME
uel@uel-Deskop-VM:/usr/local/spark$ ./sbin/start-all.sh
starting org.apache.spark.deploy.master.Master, logging to /usr/local/spark/logs
/spark-uel-org.apache.spark.deploy.master.Master-1-uel-Deskop-VM.out
failed to launch: nice -n 0 /usr/local/spark/bin/spark-class org.apache.spark.de
ploy.master.Master --host uel-Deskop-VM --port 7077 --webui-port 8080
full log in /usr/local/spark/logs/spark-uel-org.apache.spark.deploy.master.Maste
r-1-uel-Deskop-VM.out
localhost: starting org.apache.spark.deploy.worker.Worker, logging to /usr/local
/spark/logs/spark-uel-org.apache.spark.deploy.worker.Worker-1-uel-Deskop-VM.out
localhost: failed to launch: nice -n 0 /usr/local/spark/bin/spark-class org.apac
he.spark.deploy.worker.Worker --webui-port 8081 spark://uel-Deskop-VM:7077
localhost: full log in /usr/local/spark/logs/spark-uel-org.apache.spark.deploy.w
orker.Worker-1-uel-Deskop-VM.out
uel@uel-Deskop-VM:/usr/local/spark$ pyspark
```

Tip: if you want to load/save data from/into HDFS, you need run Hadoop engine as well by `start-all.sh`

Working with Spark

1. Create a RDD from a data source (Create `<list>`)
2. Apply transformations to a RDD (e.g., `map, filter`)
3. Apply actions to a RDD: (e.g., `collect, count`)



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(step 1) data loading: Create RDD

- We start creating a data with `parallelize()` function.
- No computation occurs with `sc.parallelize()` and Spark only records how to create the RDD with **four partitions**.

```
data = [1,2,4,7,11,15,20]
```

```
data
```

```
[1, 2, 4, 7, 11, 15, 20]
```

```
rdd = sc.parallelize(data,4)
```

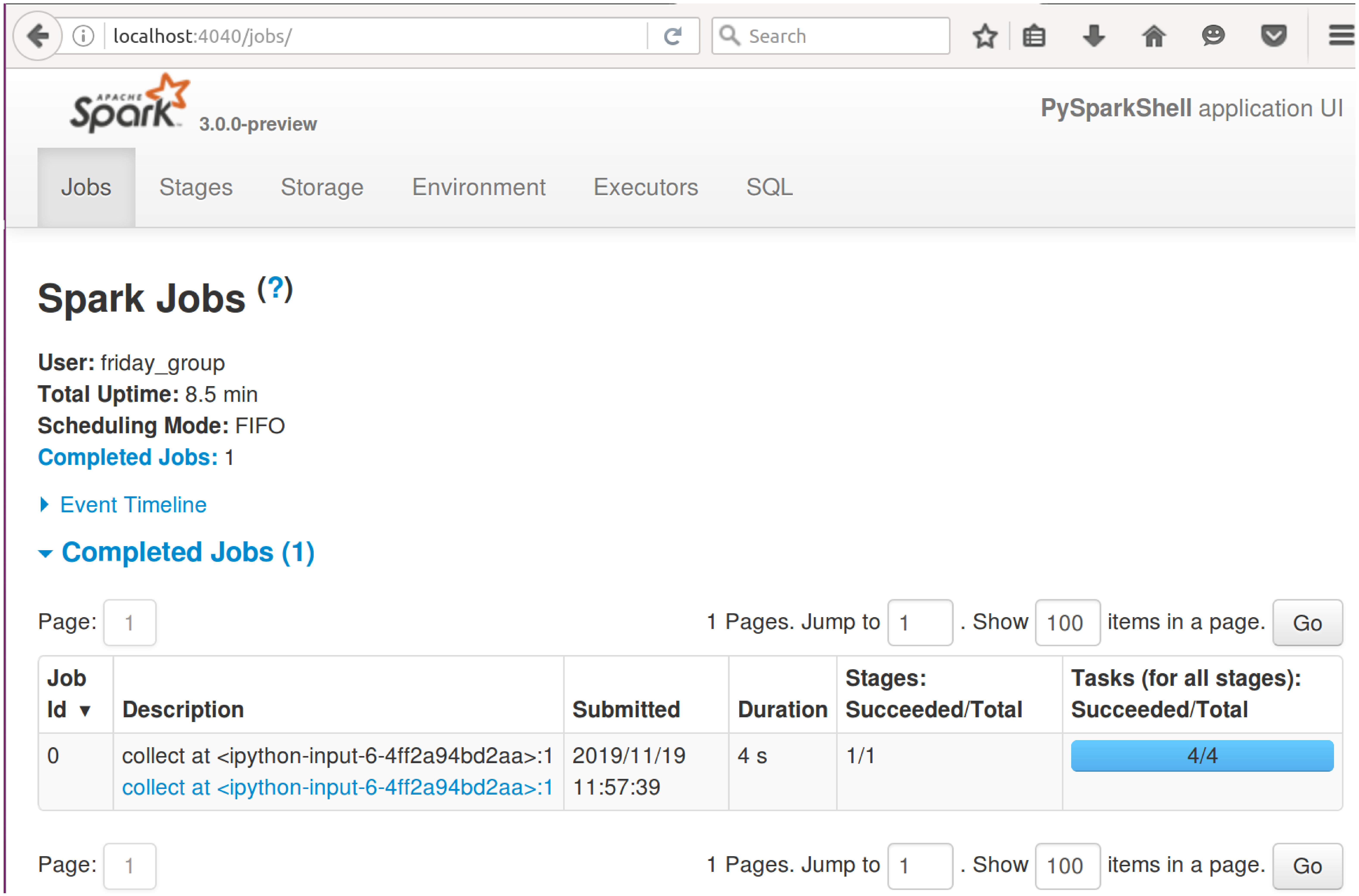
```
rdd
```

```
ParallelCollectionRDD[0] at readRDDFromFile at PythonRDD.scala:247
```

```
rdd.collect()
```

```
[1, 2, 4, 7, 11, 15, 20]
```

PySpark Shell: localhost:4040



Create RDD from a file

- We can read data from HDFS, text, Amazon S3, Apache Hbase, and many more.

```
In [3]: file1 = sc.textFile("/home/uel/textfile", 3)
        file1

Out[3]: /home/uel/textfile MapPartitionsRDD[2] at textFile at NativeMethodAccessorImpl.java:0
```

- RDD distribute the data into 3 partitions
- Again, this is **Lazy evaluation**: no execution happens now

(step 2) Spark: Transformation

Transformation	Description
`map(func)`	return a new distributed dataset formed by passing each element of the source through a function *func*
`filter(func)`	return a new dataset formed by selecting those elements of the source on which *func* returns true
`distinct([numTasks]))`	return a new dataset that contains the distinct elements of the source dataset
`flatMap(func)`	similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a Seq rather than a single item)

Transformation example

```
rdd.collect()
```

```
[1, 2, 4, 7, 11, 15, 20]
```

```
rdd1=rdd.map(lambda x:(x+2)*4)
rdd1.collect()
```

```
[12, 16, 24, 36, 52, 68, 88]
```

```
rdd2=rdd.filter(lambda x:(x+2)*4)
rdd2.collect()
```

```
[1, 2, 4, 7, 11, 15, 20]
```

```
rdd3=rdd.filter(lambda x : x % 3==0)
rdd3.collect()
```

```
[15]
```

```
rdd4=rdd.map(lambda x : x % 3==0)
rdd4.collect()
```

```
[False, False, False, False, False, True, False]
```

```
rdd5 = sc.parallelize([4,2,2,6,7,7,19,40,41,40,40])
```

```
rdd5.distinct()
```

```
PythonRDD[15] at RDD at PythonRDD.scala:53
```

```
rdd5.distinct().collect()
```

```
[4, 40, 41, 2, 6, 7, 19]
```

Transformation example

```
rdd6=sc.parallelize([1,2,3,4])
```

```
rdd7=rdd6.map(lambda x : [x,x+2,x+7])
rdd7.collect()
```

```
[[1, 3, 8], [2, 4, 9], [3, 5, 10], [4, 6, 11]]
```

```
rdd8=rdd6.flatMap(lambda x : [x,x+2,x+7])
rdd8.collect()
```

```
[1, 3, 8, 2, 4, 9, 3, 5, 10, 4, 6, 11]
```

- The difference of `map` and `flatMap`.
- If you want to have map-reduce programing, you need `flatMap`. Because `map` returns list, but `flatMap` returns a sequence of values.

(step 3) Spark: Action

Action	Description
`reduce(`*func*`)`	aggregate dataset's elements using function *func*. *func* takes two arguments and returns one, and is commutative and associative so that it can be computed correctly in parallel
`take(`*n*`)`	return an array with the first *n* elements
`collect()`	return all the elements as an array WARNING: make sure will fit in driver program
`takeOrdered(`*n*`, `*key=func*`)`	return n elements ordered in ascending order or as specified by the optional key function

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Action example

```
print (rdd7.collect())
print (rdd8.collect())
```

```
[[1, 3, 8], [2, 4, 9], [3, 5, 10], [4, 6, 11]]
[1, 3, 8, 2, 4, 9, 3, 5, 10, 4, 6, 11]
```

```
rdd8.reduce(lambda a,b:a*b)
```

```
68428800
```

```
rdd8.collect()
```

```
[1, 3, 8, 2, 4, 9, 3, 5, 10, 4, 6, 11]
```

```
rdd8.take(4)
```

```
[1, 3, 8, 2]
```

```
rdd8.takeOrdered(4)
```

```
[1, 2, 3, 3]
```

Action (key-value RDDs) example

Key-Value Transformation	Description
`reduceByKey(func)`	return a new distributed dataset of (K,V) pairs where the values for each key are aggregated using the given reduce function *func*, which must be of type (V,V) ➔ V
`sortByKey()`	return a new dataset (K,V) pairs sorted by keys in ascending order
`groupByKey()`	return a new dataset of (K, Iterable<V>) pairs

```
In [35]: rdd=sc.parallelize([(1,2),(4,5),(1,7),(4,2),(5,3),(4,9)])
         rdd.collect()

Out[35]: [(1, 2), (4, 5), (1, 7), (4, 2), (5, 3), (4, 9)]

In [36]: rdd=rdd.reduceByKey(lambda a,b: a + b)
         rdd.collect()

Out[36]: [(4, 16), (1, 9), (5, 3)]

In [37]: rdd2=sc.parallelize([(1,'a'),(4,'c'),(4,'c'),(2,'b'),(1,'d')])

In [38]: rdd3=rdd2.sortByKey()
         rdd3.collect()

Out[38]: [(1, 'a'), (1, 'd'), (2, 'b'), (4, 'c'), (4, 'c')]
```

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RDD vs DataFrame

- **RDD**: The RDD APIs have been on Spark in 1.0 release. It is a distributed collection of data elements spread across many machines in the cluster. RDDs are a set of Java or Scala objects representing data.
- **DataFrames**: Spark introduced DataFrames in Spark 1.3 release. A DataFrame is a distributed collection of data organized into named columns, like a table in a relational database, using off-heap storage.
- **DataSet**: Spark introduced Dataset in Spark 1.6 release. It is an extension of DataFrame API that provides the benefits of the Catalyst query optimizer and off heap storage mechanism.

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RDD disadvantages

1. **Outdated:** DataFrame and Dataset are distributed collections of data with the benefits of Spark SQL's optimized execution engine.

2. **Hard to Use:** RDD needs Python/Scala/Java coding, but DataFrame and Dataset need SQL-like queries, and anyone who knows SQL will understand it in one go.
3. **Slow Speed:** the main reason to not use RDD is its performance, which can be a major issue for some applications.

DataFrame example

- We need to convert RDD/Hive to DataFrame, or find a relational dataset like csv, SQL, etc.
- Download data (FIFA 18 Player Dataset) from https://www.kaggle.com/thec03u5/fifa-18-demo-player-dataset or from here. We are going to work with *CompleteDataset.csv* file.
- Tip1: A `spark.read.csv` package converts `*.csv` files to `DF`. If your data format is different, then you need to use another package, such as `SQLContext` or `pyspark.sql` to create DF.
- Tip2: Usually we do not use lambda format in DataFrame, instead, we use SQL-like commands.

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(1) Read data from CSV

```
fifa_df = spark.read.csv("/home/friday_group/Desktop/CompleteDataset.csv",
                         inferSchema=True, header=True)
```

- Or:

```
fifa_df2 = sqlContext.read.load('/home/friday_group/Desktop/CompleteDataset.csv',
                                format = 'com.databricks.spark.csv',
                                header = 'true', inferSchema = 'true')
```

(2) The Schema of DF

To have a look at the structure of the Dataframe, we'll use the `printSchema()` method.

```
fifa_df.printSchema()
```

```
root
 |-- _c0: integer (nullable = true)
 |-- Name: string (nullable = true)
 |-- Age: integer (nullable = true)
 |-- Photo: string (nullable = true)
 |-- Nationality: string (nullable = true)
 |-- Flag: string (nullable = true)
 |-- Overall: integer (nullable = true)
 |-- Potential: integer (nullable = true)
 |-- Club: string (nullable = true)
 |-- Club Logo: string (nullable = true)
 |-- Value: string (nullable = true)
 |-- Wage: string (nullable = true)
 |-- Special: integer (nullable = true)
 |-- Acceleration: string (nullable = true)
 |-- Aggression: string (nullable = true)
 |-- Agility: string (nullable = true)
 |-- Balance: string (nullable = true)
 |-- Ball control: string (nullable = true)
 |-- Composure: string (nullable = true)
 |-- Crossing: string (nullable = true)
 |-- Curve: string (nullable = true)
 |-- Dribbling: string (nullable = true)
```

(3) Columns information in DF

```
fifa_df.columns
```

```
['_c0',
 'Name',
 'Age',
 'Photo',
 'Nationality',
 'Flag',
 'Overall',
 'Potential',
 'Club',
```

```
fifa_df.count()
```

```
17981
```

```
len(fifa_df.columns)
```

```
75
```

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(4) Select in DF

```
fifa_df.select('Name','Nationality','club').show()
```

```
+-----------------+-----------+-------------------+
|             Name|Nationality|               club|
+-----------------+-----------+-------------------+
|Cristiano Ronaldo|   Portugal|     Real Madrid CF|
|         L. Messi|  Argentina|       FC Barcelona|
|           Neymar|     Brazil|Paris Saint-Germain|
|        L. Suárez|    Uruguay|       FC Barcelona|
|         M. Neuer|    Germany|   FC Bayern Munich|
|   R. Lewandowski|     Poland|   FC Bayern Munich|
|           De Gea|      Spain|  Manchester United|
|        E. Hazard|    Belgium|            Chelsea|
|         T. Kroos|    Germany|     Real Madrid CF|
|       G. Higuaín|  Argentina|           Juventus|
|     Sergio Ramos|      Spain|     Real Madrid CF|
|     K. De Bruyne|    Belgium|    Manchester City|
|      T. Courtois|    Belgium|            Chelsea|
|       A. Sánchez|      Chile|            Arsenal|
|        L. Modrić|    Croatia|     Real Madrid CF|
|          G. Bale|      Wales|     Real Madrid CF|
|        S. Agüero|  Argentina|    Manchester City|
|     G. Chiellini|      Italy|           Juventus|
|        G. Buffon|      Italy|           Juventus|
|        P. Dybala|  Argentina|           Juventus|
+-----------------+-----------+-------------------+
only showing top 20 rows
```

```
fifa_df.select('Name','Long shots').distinct().show()
```

```
+-----------------+----------+
|             Name|Long shots|
+-----------------+----------+
|Cristiano Ronaldo|        92|
|      J. Cuadrado|        80|
|      M. Brozović|        79|
|          A. Rami|        58|
|       D. Abraham|        65|
|     Borja Bastón|        73|
|       J. Montero|        68|
|      T. Barnetta|        74|
|          Wallace|        26|
|       A. Barreca|        42|
|     Y. Benalouane|       39|
|          Juankar|        64|
|        D. Appiah|        38|
|   Rafael Martins|        69|
|          Granell|        77|
|     A. Cornelius|        68|
|         J. Henry|        75|
|        M. Ozdoev|        69|
|            Fábio|        58|
|       T. Dingomé|        60|
+-----------------+----------+
only showing top 20 rows
```

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(4) GroupBy in DF

```
fifa_df.groupBy("age").count().show()
```

```
+---+-----+
|age|count|
+---+-----+
| 29| 1121|
| 30|  804|
| 34|  272|
| 28| 1051|
| 22| 1324|
| 35|  191|
| 16|   13|
| 47|    1|
| 43|    2|
| 31|  671|
| 18|  672|
| 27| 1152|
| 17|  258|
| 26| 1202|
| 19| 1069|
| 23| 1394|
| 41|    3|
| 38|   36|
| 40|    8|
| 25| 1522|
+---+-----+
only showing top 20 rows
```

(5) SQL on DF

```
fifa_df_sql = sqlContext.read.csv("/home/friday_group/Desktop/CompleteDataset.csv", header= True)
```

```
# Register the DataFrame as a SQL temporary view
fifa_df_sql.createOrReplaceGlobalTempView("fifa")
```

```
sqlDF = spark.sql("SELECT age, count(*) as count FROM global_temp.fifa GROUP BY age")
```

```
sqlDF.show()
```

```
+---+-----+
|age|count|
+---+-----+
| 29| 1121|
| 30|  804|
| 34|  272|
| 28| 1051|
| 22| 1324|
| 35|  191|
| 16|   13|
| 47|    1|
| 43|    2|
| 31|  671|
| 18|  672|
| 27| 1152|
| 17|  258|
| 26| 1202|
| 19| 1069|
| 23| 1394|
| 41|    3|
| 38|   36|
| 40|    8|
| 25| 1522|
+---+-----+
only showing top 20 rows
```

Spark SQL and DataFrames:
https://spark.apache.org/docs/2.3.0/sql-programming-guide.html

Summary

- Introduced RDD Programming
- Discussed RDD and DataFrame
- Exercised RDD programming using Python
- Exercised DataFrame programming using SQL