

# Week 2 Tutorial

- Week 1 Review
- Accumulators
- SparkSession vs SparkContext
- Data Partitioning
- RDD vs DataFrame
- Searching in RDDs and DataFrames
- Spark SQL



- VM Setup and Jupyter Notebooks

- RDDs

- How to create RDDs?

- Transformation

- Map
- FlatMap

- Action

- Take
- Collect (take vs collect)
- Reduce

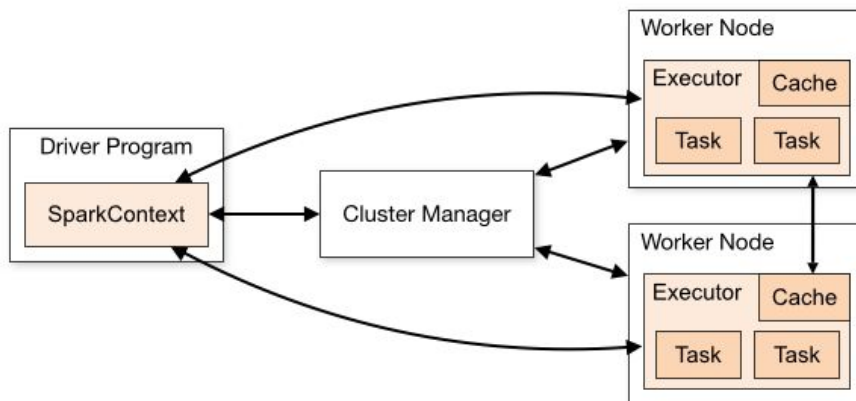


Fig : Src : [<https://spark.apache.org/docs/2.3.2/running-on-mesos.html>]

# Word Count Example Review

```
# step 1: Read the text file twitter.txt
rdd = sc.textFile("twitter.txt")

# step 2: Use a transformation to break the lines to
individual words
words = rdd.flatMap(lambda line: line.split(" "))

# step 3: Use a transformation to convert word to a
key/value pair of (word, 1)
wordCounts = words.map(lambda word: (word, 1))

# step 4: Use a transformation to reduce the value
based on the word
finalrdd = wordCounts.reduceByKey(lambda a,b:a +b)

# step 5: Collect and display the results of the count
finalrdd.collect()
```

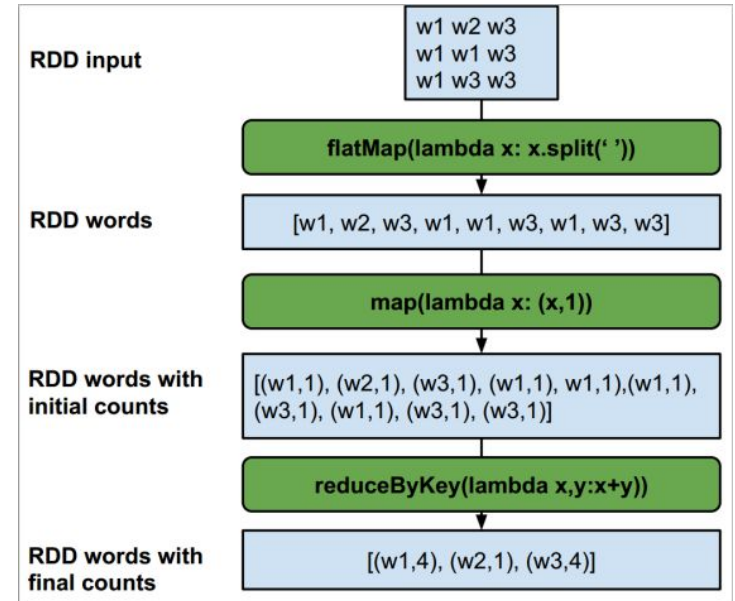


Fig : [Source]

## Accumulators

- Accumulators provides a simple syntax for aggregating values from worker nodes back to the driver program.
- They are only “added” to through an associative and commutative operation and can therefore be efficiently supported in parallel.
- They can be used to implement counters (as in MapReduce) or sums.

## Broadcast Variables

- Broadcast variables allow the program to efficiently send a large, read-only value to all the worker nodes for use in one or more Spark operations.
- Spark automatically sends all variables referenced in your closures to the worker nodes.

# Accumulators

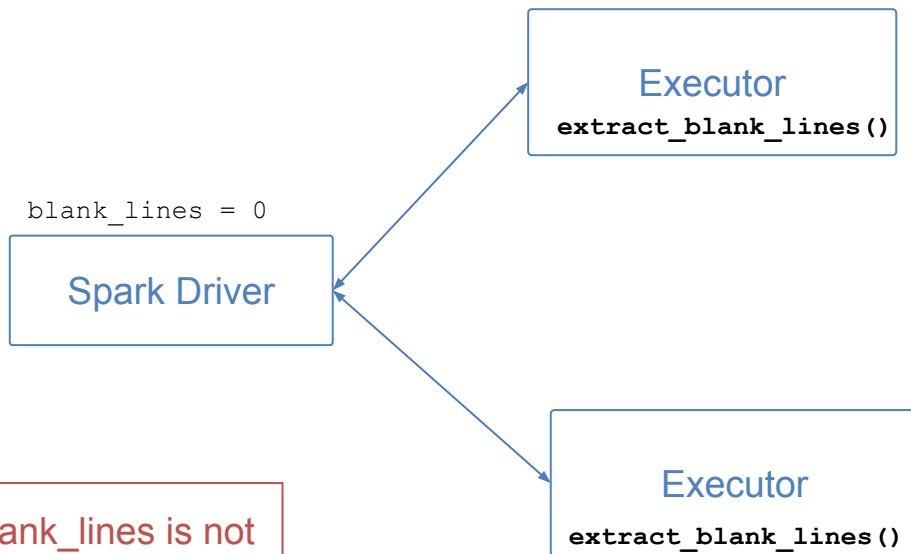
```
twitter_rdd = sc.textFile('twitter.txt', 3)
blank_lines = 0 # global variable

def extract_blank_lines(line):
    if line == "":
        blank_lines += 1
    return line.split(" ")

word_rdds = twitter_rdd.flatMap(extract_blank_lines)
word_rdds.collect()

print("Blank lines: %d" % blank_lines)
```

Fails, as blank\_lines is not accessible in the executors



# Accumulator

```
twitter_rdd = sc.textFile('twitter.txt', 3)
blank_lines = sc.accumulator(0) # Create Accumulator[int] initialized to 0

def extract_blank_lines(line):
    global blank_lines # make the global variable accessible
    lll = {'a':1}
    if line == "":
        print(type(line))
        blank_lines += 1
    return line.split(" ")

word_rdds = twitter_rdd.flatMap(extract_blank_lines)
word_rdds.collect()

print("Blank lines: %d" %blank_lines.value)
```

blank\_lines = 0

Spark Driver

Executor

extract\_blank\_lines()

Executor

extract\_blank\_lines()

# Introducing SparkSession

## SparkContext vs SparkSession

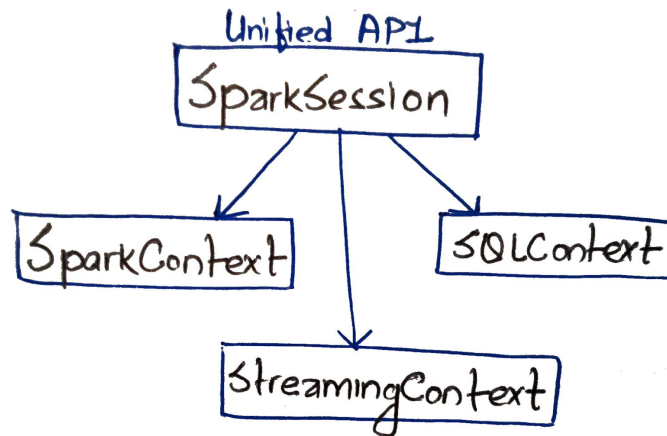
- Unified entry point of Spark application from Spark 2.0

```
# Import SparkConf class into program
from pyspark import SparkConf

# Local[*]: run Spark in local mode with as many working processors as
# If we want Spark to run locally with 'k' worker threads, we can specify
master = "local[*]"
# The `appName` field is a name to be shown on the Spark cluster UI page
app_name = "Parallel Search"
# Setup configuration parameters for Spark
spark_conf = SparkConf().setMaster(master).setAppName(app_name)
```

```
# Import SparkSession
from pyspark.sql import SparkSession # Spark SQL

# Method 1: Using SparkSession
spark = SparkSession.builder.config(conf=spark_conf).getOrCreate()
sc = spark.sparkContext
sc.setLogLevel('ERROR')
```



## Data Partitioning Strategies :

1. **Round-robin partitioning** : distribute evenly among processors
2. **Range data partitioning** : partition based on given range
3. **Hash data partitioning** : partition based on a particular attribute using a hash function



# Data Partitioning in Spark

**RDDs are partitioned by Default!**

Then why?

Reduce the overhead of the shuffle

Cost Reduction – better utilization of cluster

Avoiding Data Skew??



# Parallel Search in RDD

- Searching in RDDs using Multiple Conditions
- Finding max/min values of an attribute in RDDs

# RDD vs DataFrame in Spark

- Analogous to a table in relational database, organized into named columns
- “A Distributed in-memory table with named columns”
- Specific data types
- Significant improvement in Python performance especially PySpark

<b>Id (Int)</b>	<b>First (String)</b>	<b>Last (String)</b>	<b>Url (String)</b>	<b>Published (Date)</b>	<b>Hits (Int)</b>
1	Jules	Damji	https://tinyurl.1	1/4/2016	4535
2	Brooke	Wenig	https://tinyurl.2	5/5/2018	8908
3	Denny	Lee	https://tinyurl.3	6/7/2019	7659
4	Tathagata	Das	https://tinyurl.4	5/12/2018	10568

Ref : <https://databricks.com/p/ebook/learning-spark-from-oreilly>

# Partitioning with DataFrames

## Round-robin partitioning :

```
df_round =  
df.repartition(5)
```

repartition()

repartitionByRange()

## Range data partitioning :

```
df_range =  
df.repartitionByRange(5, "balance")
```

## Hash data partitioning :

```
column_hash = "education"  
df_hash =  
df.repartition(column_hash)
```

# Searching in Dataframe

- `Filter()`
- `Where()`
- `Select()`
- `Show()`

- To execute SQL queries.
- For further reading [link](#)
- Temporary views in Spark SQL

```
df = spark.read.csv("bank.csv", header=True)
# Register the DataFrame as a SQL temporary view
df.createOrReplaceTempView("bank")
```

```
sqlDF = spark.sql("SELECT * FROM bank")
sqlDF.show()
```

```
+---+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|age|      job| marital|education|default|balance|housing|loan|contact|day|month|duration|campaign|pdays|previous|poutcome|de
posit|
+---+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
| 59|   admin.| married|secondary|   no|  2343|   yes|  no|unknown| 5|  may|   1042|     1|   -1|     0| unknown|
yes|
| 56|   admin.| married|secondary|   no|    45|   no|  no|unknown| 5|  may|   1467|     1|   -1|     0| unknown|
yes|
| 41| technician| married|secondary|   no|  1270|   yes|  no|unknown| 5|  may|   1389|     1|   -1|     0| unknown|
```

# Thank You!

See you next week.