Apache Spark™

Error/
Warning

Information

Flashback

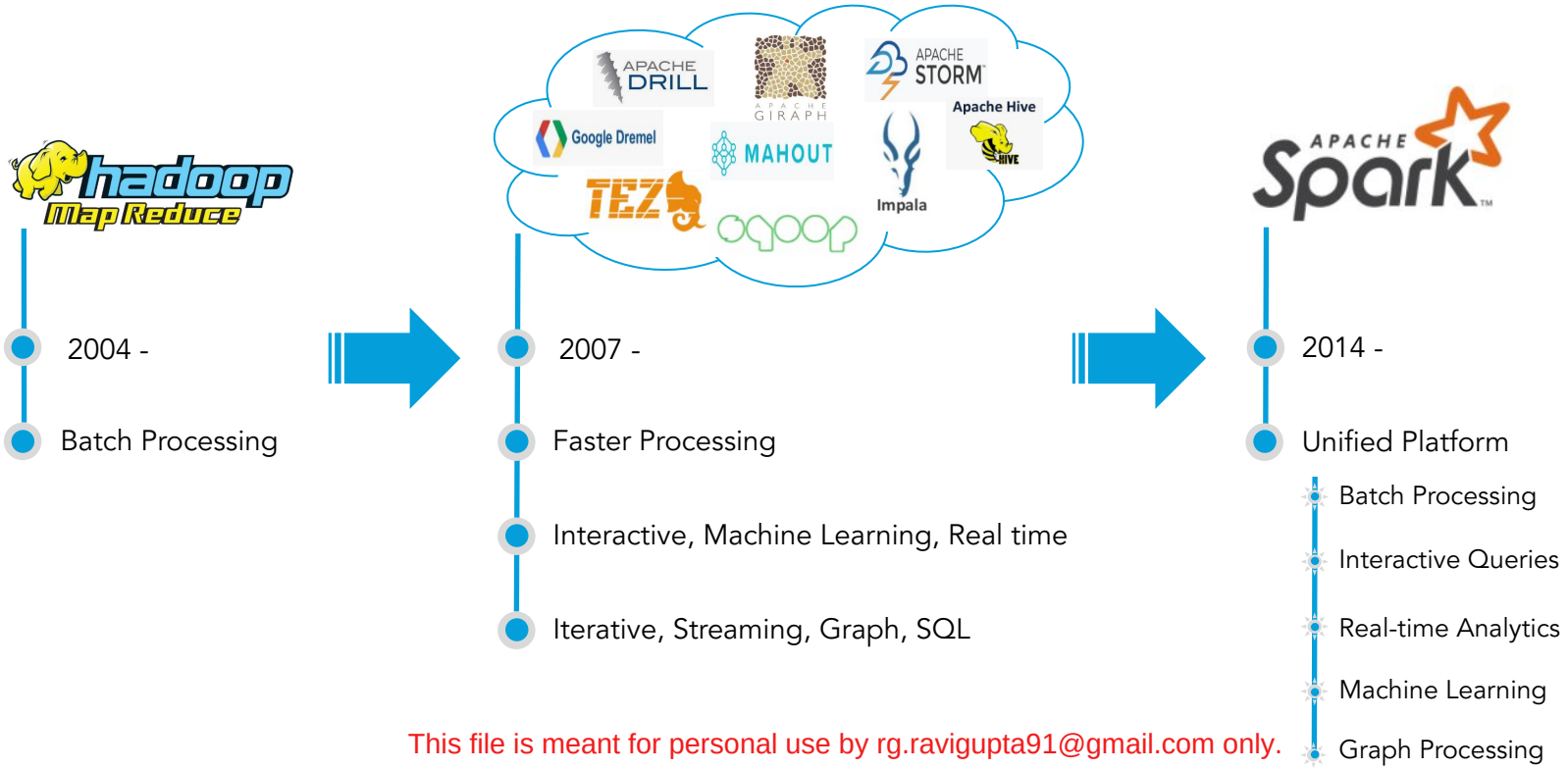
Class Exercise

Table of Content

Apache Spark is a unified analytics engine for large-scale data processing and machine learning

Unified Analytics Engine

Evolution of Unified Analytics Engine



Data Growth

- Worldwide data is expected to hit 175 zettabytes by 2025
- 90 ZB of this data will be from IoT devices in 2025
- 71% of enterprises reported that unstructured data was growing “much faster” than other business data
- 80% of data will be unstructured by 2025
- On top of business documents, video and audio are added new content such as social media, IoT, streaming and geo data
- There will be 4.8 billion internet users by 2022, up from 3.4 billion in 2017
- 90% of all data in existence today was created in the past two years
- More than 200 billion devices are projected to be generating data in the IoT trend

Source : Internet

Measurement of Data

Information

Abbreviation	Unit	Equivalent
B	Byte	8 Bits
KB	Kilobyte	1024 Bytes
MB	Megabyte	1024 Kilobytes
GB	Gigabyte	1024 Megabytes
TB	Terabyte	1024 Gigabytes
PB	Petabyte	1024 Terabytes
EB	Exabyte	1024 Petabytes
ZB	Zettabyte	1024 Exabytes
YB	Yottabyte	1024 Zettabytes
BB	Brontobyte	1024 Yottabytes

Apache Spark

- Open Source from Apache Software Foundation
- Flexibility – Scala, Python, Java, SQL and R
- In-memory, Distributed and Parallel Processing
- Batch and Streaming
- Ease of use
- Better Analytics – SQL queries, ML algorithms
- Runs on Standalone Cluster, Apache Hadoop YARN, Apache Mesos, Kubernetes
- Connects to hundreds of data sources

Building Apache Spark

Total Lines :	1,445,443	Code Lines :	918,529	Percent Code Lines :	63.5%
Number of Languages :	14	Total Comment Lines :	344,272	Percent Comment Lines :	23.8%
		Total Blank Lines :	182,642	Percent Blank Lines :	12.6%

Language	Code Lines	Comment Lines	Comment Ratio	Blank Lines	Total Lines	Total Percentage
Scala	678,509	207,413	23.4%	124,395	1,010,317	69.9%
Python	100,366	70,821	41.4%	30,735	201,922	14.0%
Java	77,881	33,546	30.1%	16,055	127,482	8.8%
SQL	25,279	12,611	33.3%	5,265	43,155	3.0%
R	16,917	14,716	46.5%	3,709	35,342	2.4%
XML	8,793	1,387	13.6%	471	10,651	0.7%
JavaScript	4,744	1,136	19.3%	604	6,484	0.4%
shell script	3,577	2,224	38.3%	983	6,784	0.5%
CSS	1,265	225	15.1%	280	1,770	0.1%
HTML	1,025	54	5.0%	55	1,134	0.1%
Ruby	201	75	27.2%	67	343	0.0%
DOS batch script	36	26	41.9%	17	79	0.0%
C	19	20	51.3%	10	49	0.0%
Make	17	21	55.3%	9	47	0.0%
Totals	918,629	344,275		182,655	1,445,559	

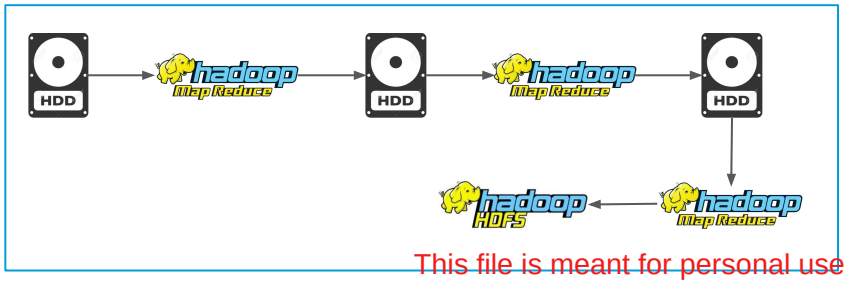
Source : https://www.openhub.net/p/apache-spark/analyses/latest/languages_summary

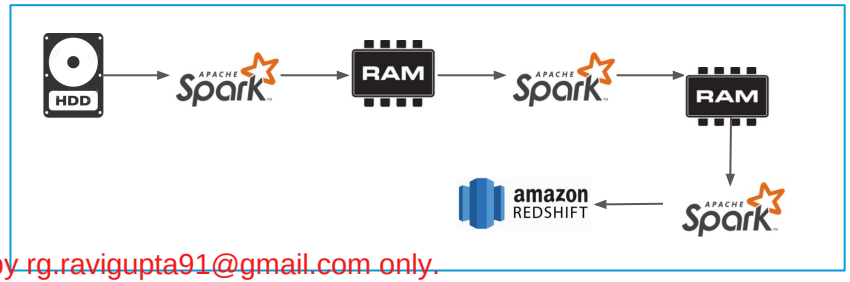
MapReduce vs Spark

Factors	Apache Spark	MapReduce
Speed	10 – 100 times faster	Faster than traditional systems
Written using	Scala (69.9%), Python (14%), Java (8.8%), SQL (3%), R (2.4%)	Java
Data Processing	Batch / Iterative / Interactive / Real-time / Graph	Batch
Complexity	Compact and Simple to use	Complex and Lengthy
Cache	In-memory/Disk Caching	More Disk IO and Minimal Caching

Beyond MapReduce

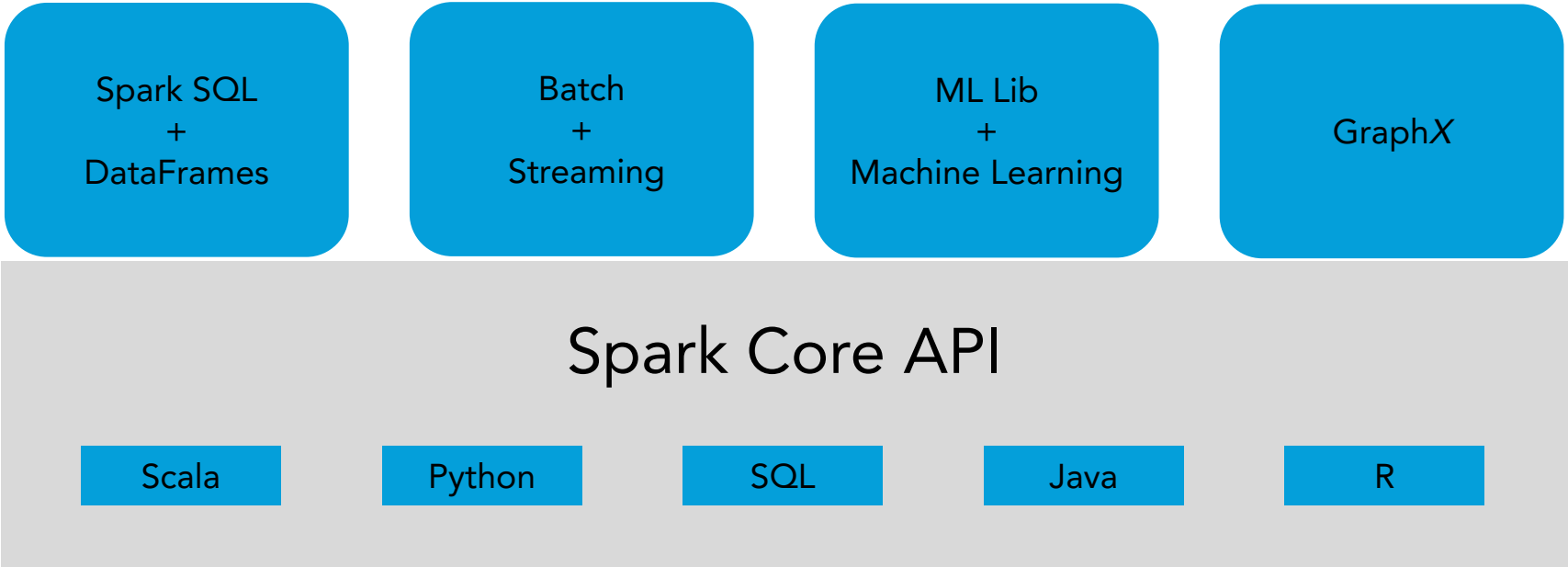
- MapReduce - Batch Processing
- MapReduce - No support for Real-time, Interactive, In-memory, Machine Learning and Graph data
- Spark - To handle all workloads. It offers
  - In-memory data caching - scan HDD only once, then all IO operations performed in RAM
  - Efficient Pipeline
  - Lazy Evaluation - Execution will not start until an action is triggered



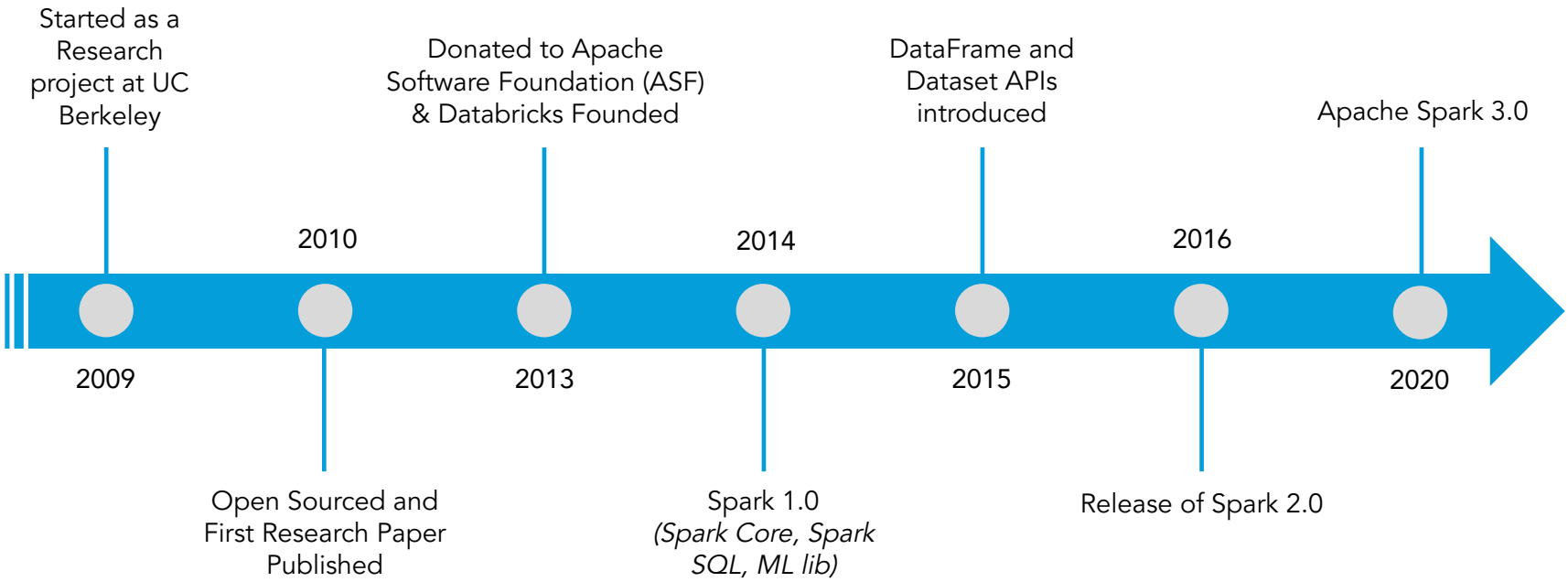


Apache Spark Ecosystem

Apache Spark Ecosystem



Apache Spark History



Spark - Pillars

- Resilient Distributed Dataset (RDD)
- Direct Acyclic Graph (DAG)

Resilient Distributed Dataset (RDD)

- Data read from a file will form a single RDD

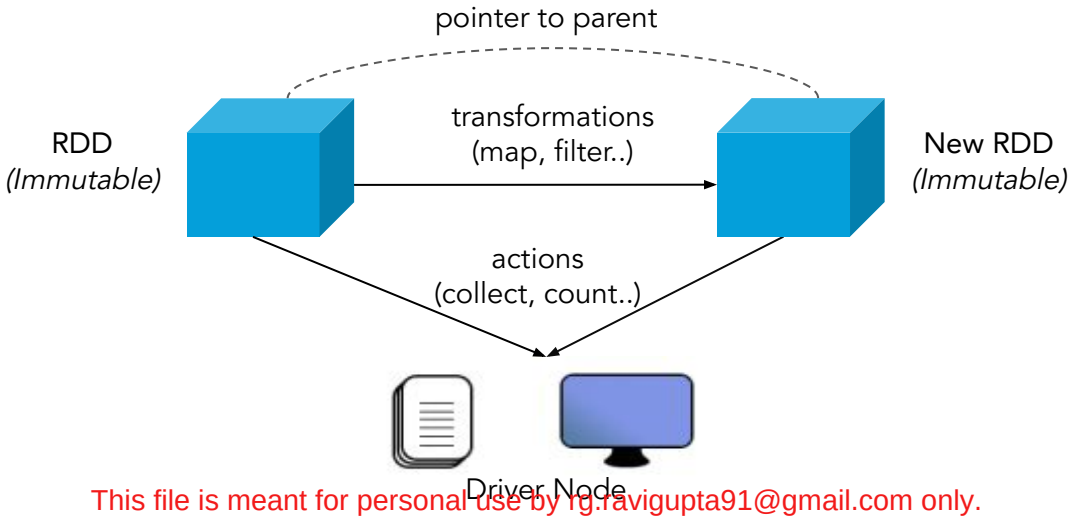
```
1  creditcardRDD = sc.textFile("/FileStore/tables/SalesTraining.csv")
2
3  print("Number of records :", creditcardRDD.count())
```

- RDDs are divided into logical partitions, which are stored on different worker machines of the cluster
- RDD is an immutable, distributed across nodes
- Fault tolerant – using DAG (Lineage)
- Partitions can be persisted in-memory or disk
- Lazily Evaluated and Executed

```
1  creditcardRDD.collect()
```

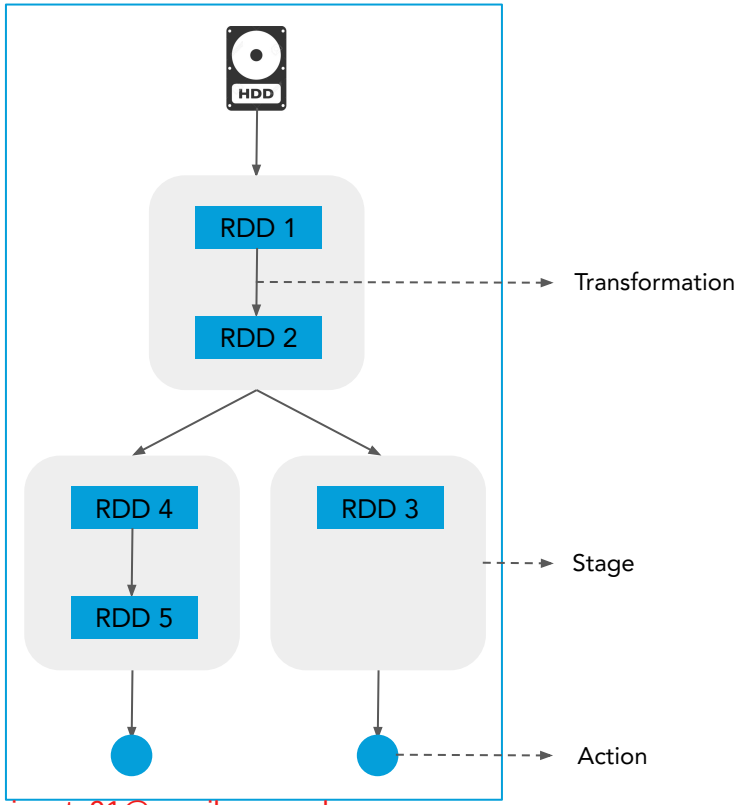
Resilient Distributed Dataset (RDD)

- Resilient (Fault Tolerant) – when the data in memory is lost, it can be recreated
- Distributed - stored in memory across the worker nodes of the cluster
- Dataset - file/created programmatically
- RDDs are the fundamental unit of data in Spark

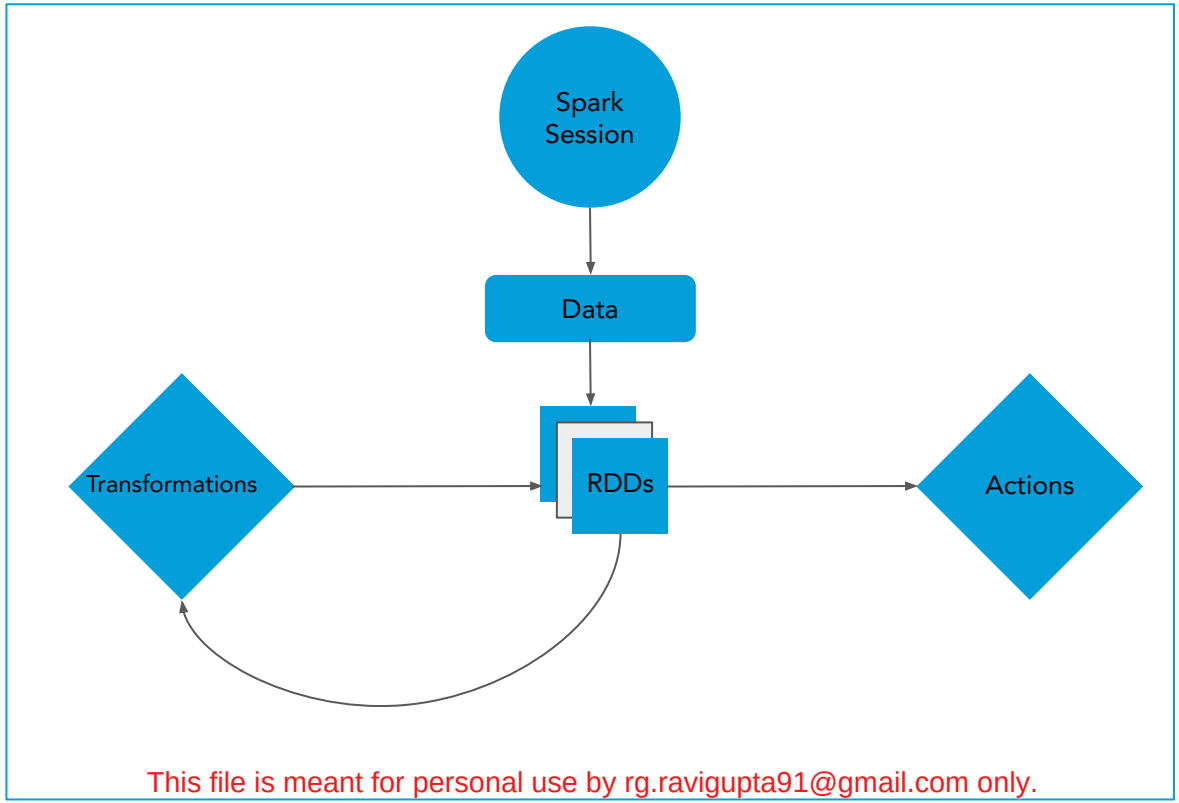


Direct Acyclic Graph (DAG)

- Sequence of computations performed on data
  - Node - Where RDD partitions resides
  - Edge - Transformation of top of data
  - Acyclic - Can't return to the old partition
  - Direct - Transformation is an action that transitions data partition state (from A to B)
- Lineage - Shows dependency between RDDs

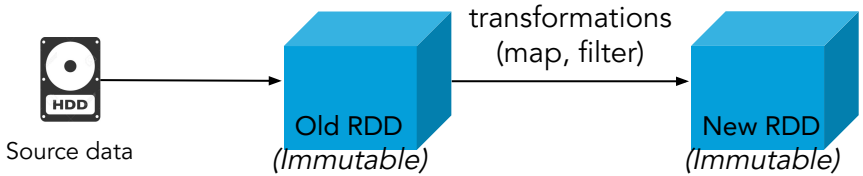


Spark Program Lifecycle



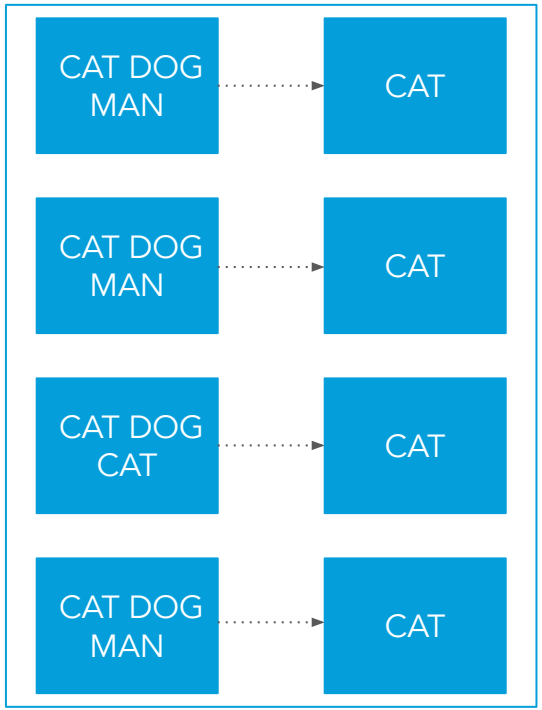
RDD Operations - Transformations

- Transformations create a new RDD from an existing RDD
- RDDs are immutable
  - Data in an RDD can't be changed
  - Transformations are performed in sequence to modify the data as needed
- Common Transformations
  - map() - creates a new RDD by performing a function on each record of the parent RDD
  - filter() - applies a boolean function on each record of the parent RDD to include/exclude records and creates a resultant RDD
- Types
  - Narrow Transformations
  - Wide Transformations

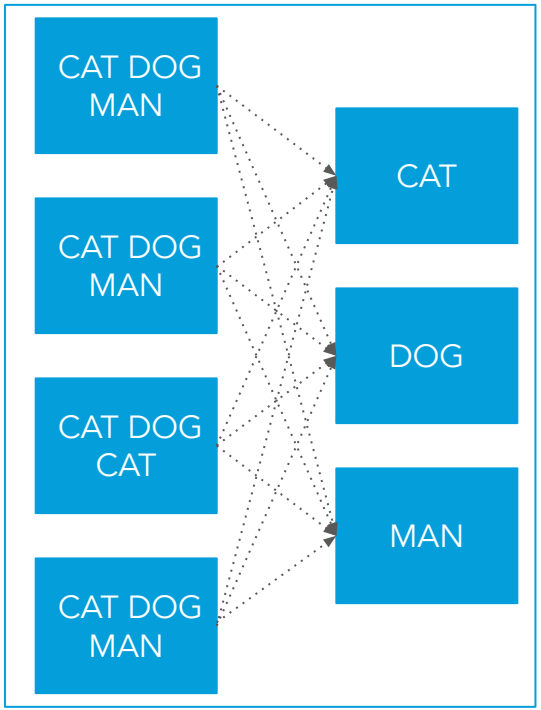


Transformations

Narrow Transformation (filter)



Wide Transformation (reduceByKey)



Transformations

- The following table lists some of the common *transformations* supported by Spark

Transformation	Meaning
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
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)
coalesce(*numPartitions*)	Decrease the number of partitions in the RDD to numPartitions. Useful for running operations more efficiently after filtering down a large dataset

Transformations

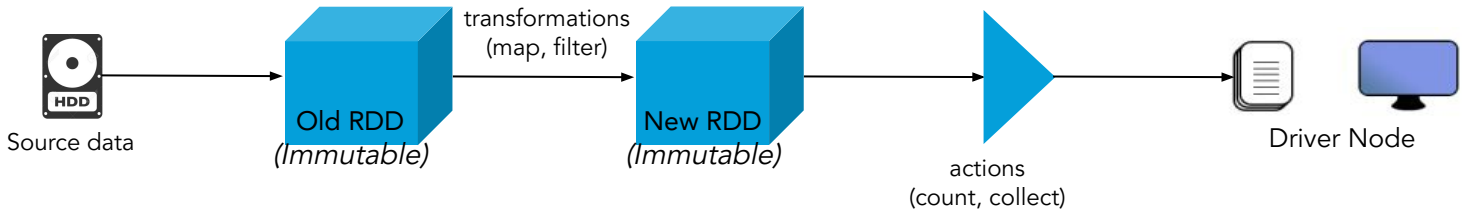
Transformation	Meaning
mapPartitions(*func*)	Similar to map, but runs separately on each partition (block) of the RDD, so *func* must be of type Iterator<T> => Iterator<U> when running on an RDD of type T
mapPartitionsWithIndex(*func*)	Similar to mapPartitions, but also provides *func* with an integer value representing the index of the partition, so *func* must be of type (Int, Iterator<T>) => Iterator<U> when running on an RDD of type T
groupByKey([*numTasks*])	When called on a dataset of (K, V) pairs, returns a dataset of (K, Iterable<V>) pairs
reduceByKey(*func*, [*numTasks*])	When called on a dataset of (K, V) pairs, returns a 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. Like in groupByKey, the number of reduce tasks is configurable through an optional second argument

Transformations

Transformation	Meaning
repartition(*numPartitions*)	Reshuffle the data in the RDD randomly to create either more or fewer partitions and balance it across them. This always shuffles all data over the network
aggregateByKey(*zeroValue*)(*seqOp*, *combOp*, [*numTasks*])	When called on a dataset of (K, V) pairs, returns a dataset of (K, U) pairs where the values for each key are aggregated using the given combine functions and a neutral "zero" value
sortByKey([*ascending*], [*numTasks*])	When called on a dataset of (K, V) pairs where K implements Ordered, returns a dataset of (K, V) pairs sorted by keys in ascending or descending order, as specified in the boolean ascending argument
distinct([*numTasks*]))	Return a new dataset that contains the distinct elements of the source dataset

RDD Operations - Actions

- Actions return a value to the Driver program after running a computation on the dataset
- Some common actions are
  - count() - returns the number of elements
  - take(n) - returns an array to the Driver program having first ‘n’ elements
  - collect() - returns an array of all the elements
  - saveAsTextFile(filename) - save the elements to text file



Actions

- The following table lists some of the common *actions* supported by Spark

Actions	Meaning
reduce(*func*)	Aggregate the elements of the dataset using a function *func* (which takes two arguments and returns one). The function should be commutative and associative so that it can be computed correctly in parallel
collect()	Return all the elements of the dataset as an array at the driver program. This is usually useful after a filter or other operation that returns a sufficiently small subset of the data
count()	Return the number of elements in the dataset
first()	Return the first element of the dataset (similar to take(1))
take(*n*)	Return an array with the first *n* elements of the dataset

Actions

Actions	Meaning
takeSample(*withReplacement*, *num*, [*seed*])	When called on a dataset of (K, V) pairs, returns a dataset of (K, Iterable<V>) pairs
takeOrdered(*n*, *[ordering]*)	Return the first *n* elements of the RDD using either their natural order or a custom comparator
saveAsTextFile(*path*)	Write the elements of the dataset as a text file (or set of text files) in a given directory in the local filesystem, HDFS or any other Hadoop-supported file system. Spark will call toString on each element to convert it to a line of text in the file
saveAsSequenceFile(*path*) (Java and Scala)	Write the elements of the dataset as a Hadoop SequenceFile in a given path in the local filesystem, HDFS or any other Hadoop-supported file system. This is available on RDDs of key-value pairs that implement Hadoop's Writable interface

Actions

Actions	Meaning
saveAsObjectFile(*path*) (Java and Scala)	Write the elements of the dataset in a simple format using Java serialization, which can then be loaded usingSparkContext.objectFile()
countByKey()	Only available on RDDs of type (K, V). Returns a hashmap of (K, Int) pairs with the count of each key

A Sample Spark Application

```
1  from operator import add
2
3  #fileRDD = sc.textFile('/FileStore/tables/input.csv')
4  fileRDD = spark.sparkContext.textFile('/FileStore/tables/input.csv')
5
6  print(type(fileRDD))
7
8  dataRDD = fileRDD.map(lambda x: x.split(','))
9  dataRDD.collect()
10
11 reduceRDD = dataRDD.map(lambda x: (x[1],1)).reduceByKey(add)
12
13 dataRDD.filter(lambda x: 'Text' in x[1]).collect()
14
15 reduceRDD.collect()
16 reduceRDD.cache()
17
18 reduceRDD.count()
```

Import library

RDDs

Transformation

Transformation

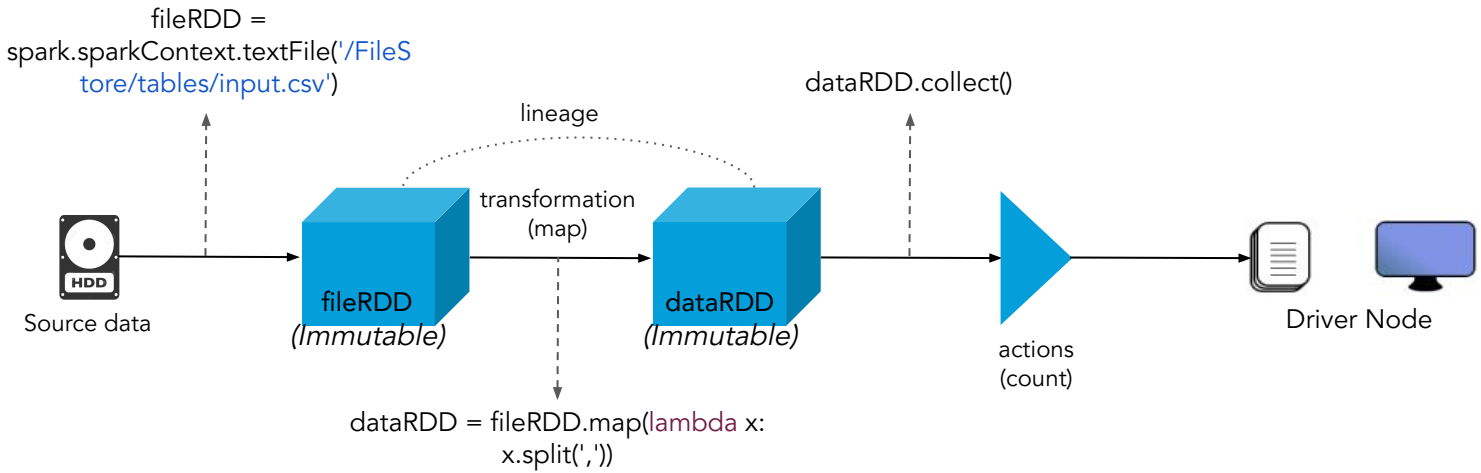
Transformation & Action

In-memory

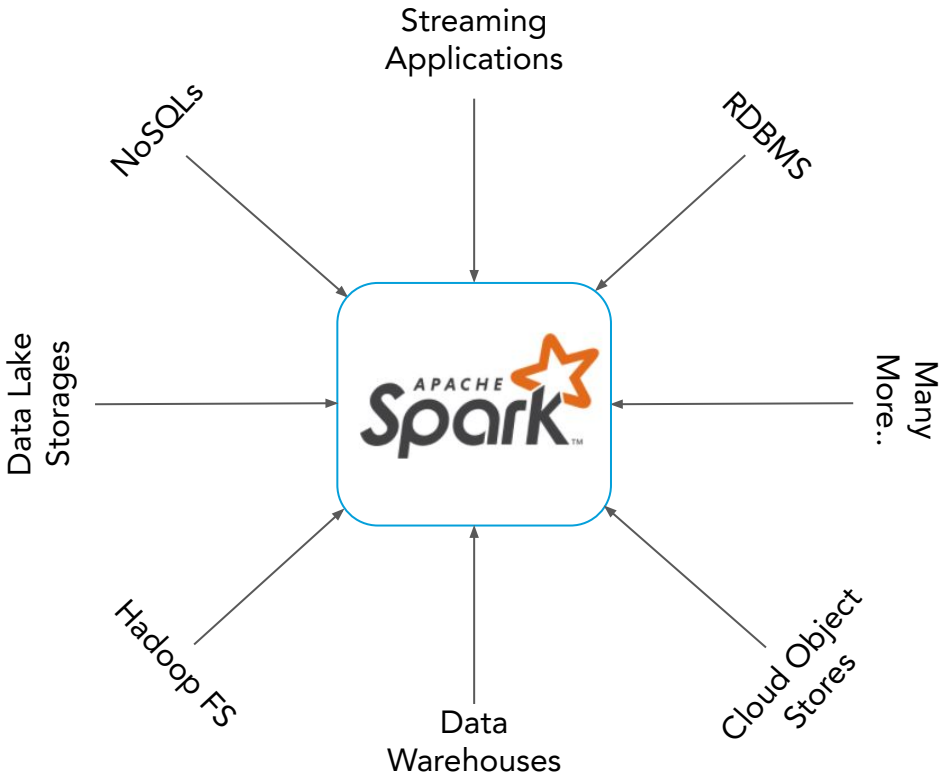
Action

RDD Lineage

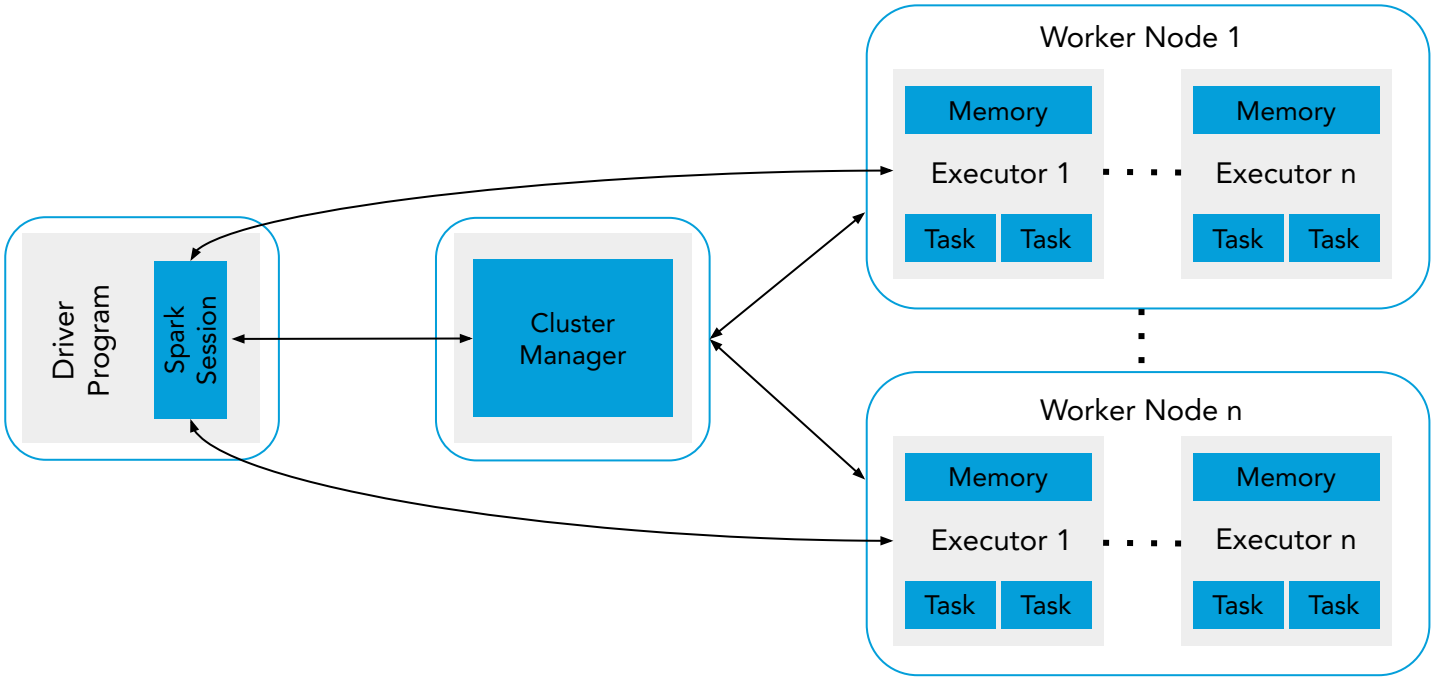
- When a transformation is called, Spark does not execute it immediately (lazy evaluation), instead it creates a lineage
- Lineages in the form of DAG, used by the Driver program to perform sequence of computations on data



Spark - Data Pipelines



Spark Cluster Architecture



Apache Spark Architecture

- Master-Slave Architecture
- One central coordinator called Spark Driver, which communicates with Workers
- Each Worker Node consists one or more Executor(s) responsible for executing the tasks (Transformations, Actions) assigned by the Driver program
- Working combination of Driver and Executors makes the Spark application
- The Spark application relies on Cluster Manager for allocating Worker Nodes. The Cluster Manager can be:
    - Apache Yarn
    - Standalone Spark Cluster
    - Apache Mesos
    - Kubernetes

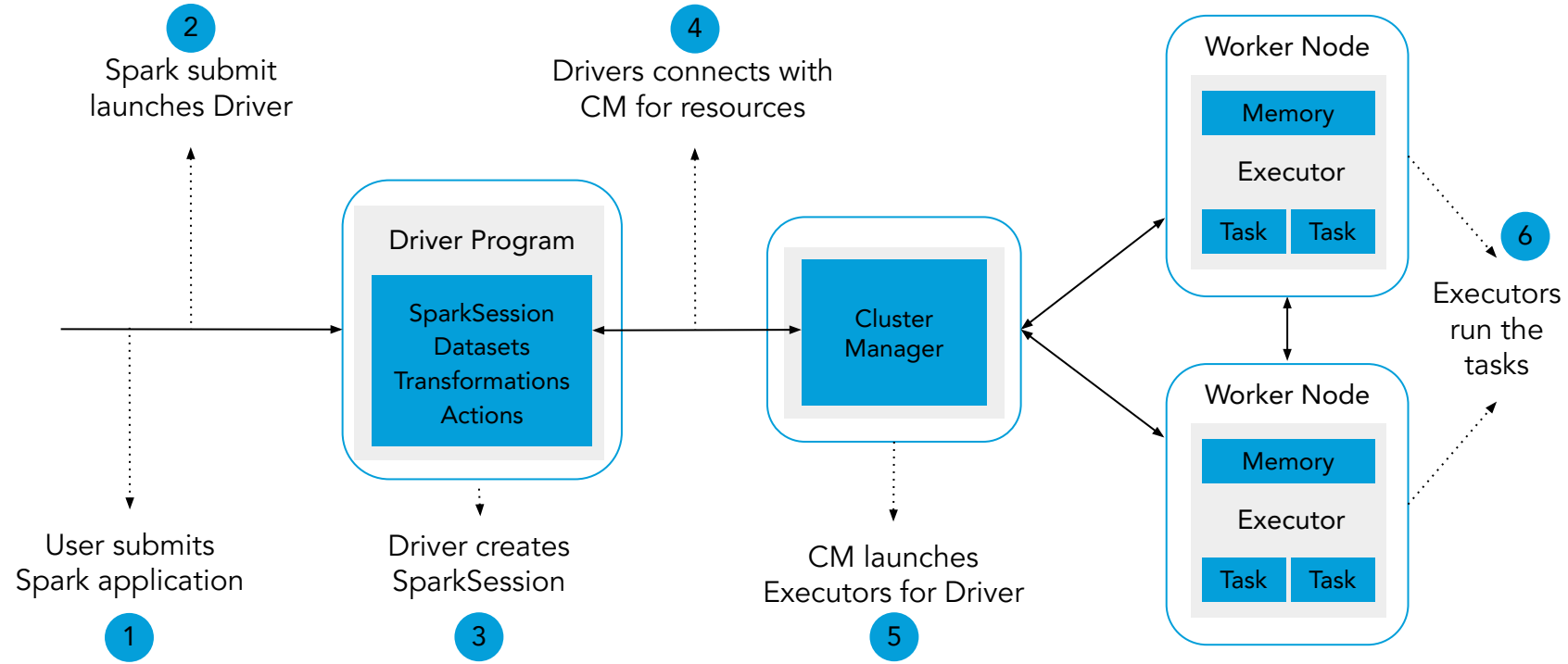
Apache Spark Architecture - Driver Program

- The Driver program creates SparkSession object, which allocates and coordinates tasks of the Spark application
- Converts the code to tasks and determines number of tasks
- Helps creating DAG, lineage, logical and physical plans
- Connects with Cluster Manager, which allocates resources (in Worker node) for the Spark application
- Acquires Executors in Worker Nodes
- Sends the Application code and tasks to the Executors to run
- Works with Executors for completing the Spark application

Apache Spark Architecture - Executors

- Executors resides in the Worker node
- Each Executor has its own computation resources for executing the tasks
- Worker node can have one or more Executors
- Responsible for executing the tasks assigned by the Driver program
- Distributed Parallel Processing - Each Executor runs the code individually and parallelly
- Sends the output to the Driver program
- Caches the data in-memory, which enables faster processing
- Upon completion of the Spark application, all the assigned Executors are released

Spark Application - Life Cycle



When Driver main() exits, all the resources are releases 7

Terminologies

- Driver Program
  - Java Virtual Machine (JVM) allocated to start the execution of main()
  - Creates SparkSession
- SparkSession
  - Tells how to access the cluster components
- Cluster Manager
  - Service to manage and allocate the resources on the cluster
- Deploy Mode
  - cluster - Driver program runs in one of the cluster Worker nodes
  - client - Driver runs outside of cluster

Terminologies

- Worker Node
  - A place, where Executor resides
- Executor
  - JVM launched by the Worker node to execute the tasks from Driver
  - Will have computation resources
  - Keeps data in memory or disk when reading from external resources
- Job
  - Collection of Stages
- Stage
  - Each Job can have one or more Stages
  - Stages are executed sequentially
  - Each Stage has tasks
- Task
  - Unit of work, which is sent to the Executor
- Partition
  - Data unit what will be handled parallelly

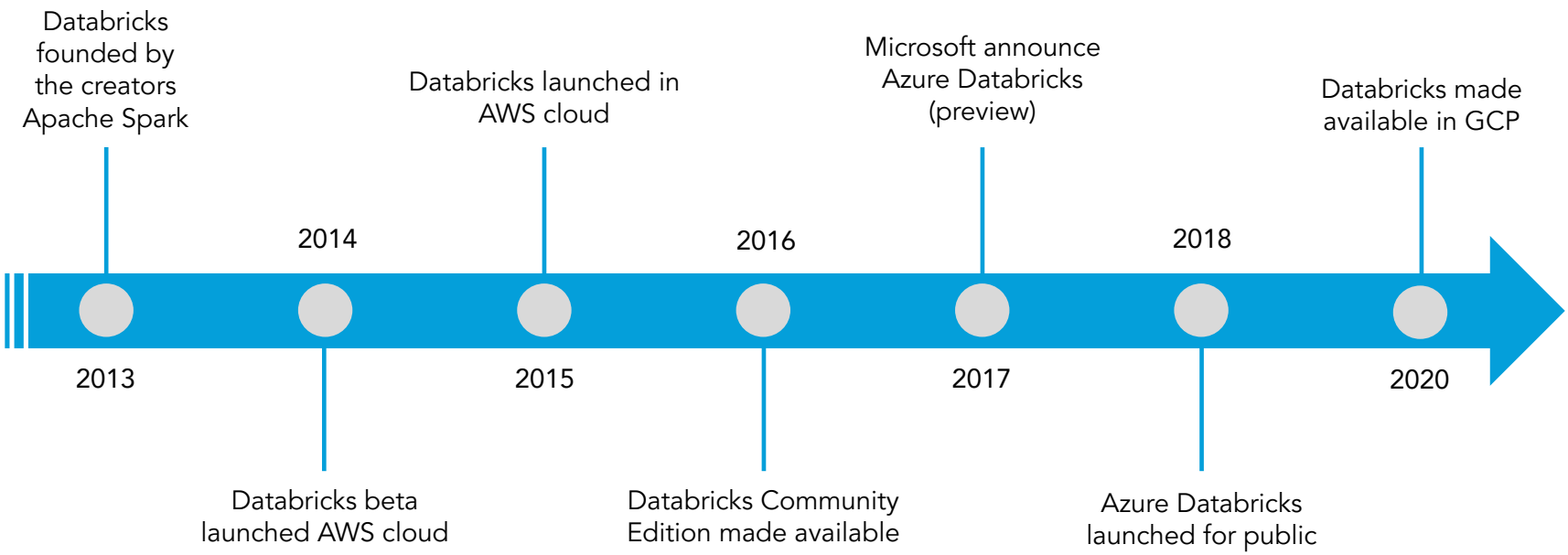
Databricks

Table of Content

Databricks

- Databricks is headquartered in San Francisco, California and was founded by the creators of open source projects, including Apache Spark, Delta Lake, MLflow and Koalas
- Cloud based Data Analytics platform for processing and transforming large quantities of data
- Apache-Spark based platform
- Runs a distributed system behind the scenes to enable distributed parallel processing for handling massive workloads
- Available in AWS, Azure and GCP
- Supports commonly used programming languages like Scala, Python, R, and SQL
- Integrates easily with other Cloud services
- Supports various file formats, connects with hundred of data sources
- Growing community, extensive documentation and support
- Thousands of global customers

Databricks History

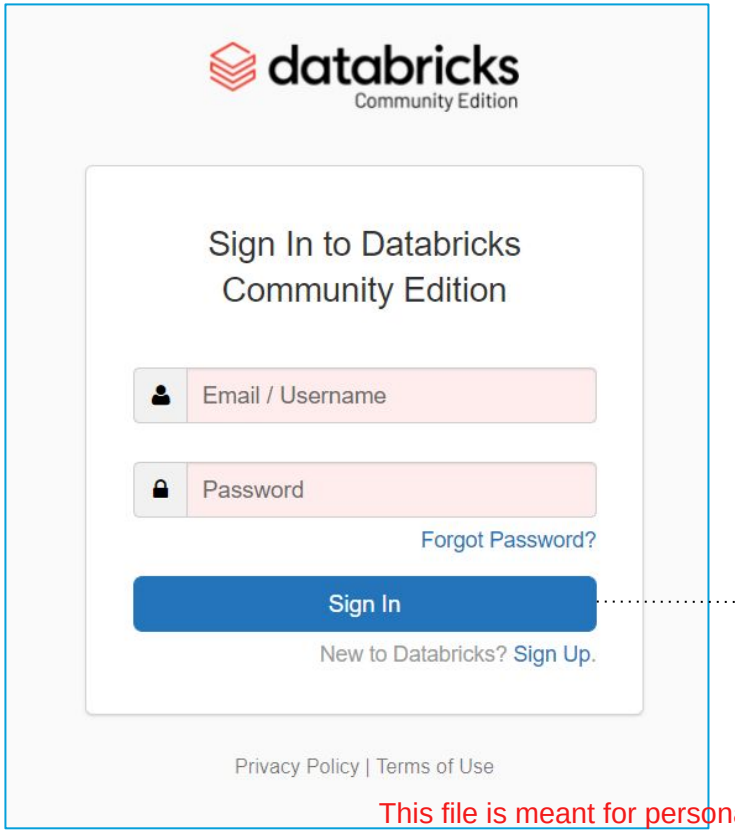


Databricks

Community Edition

Databricks - Sign Up

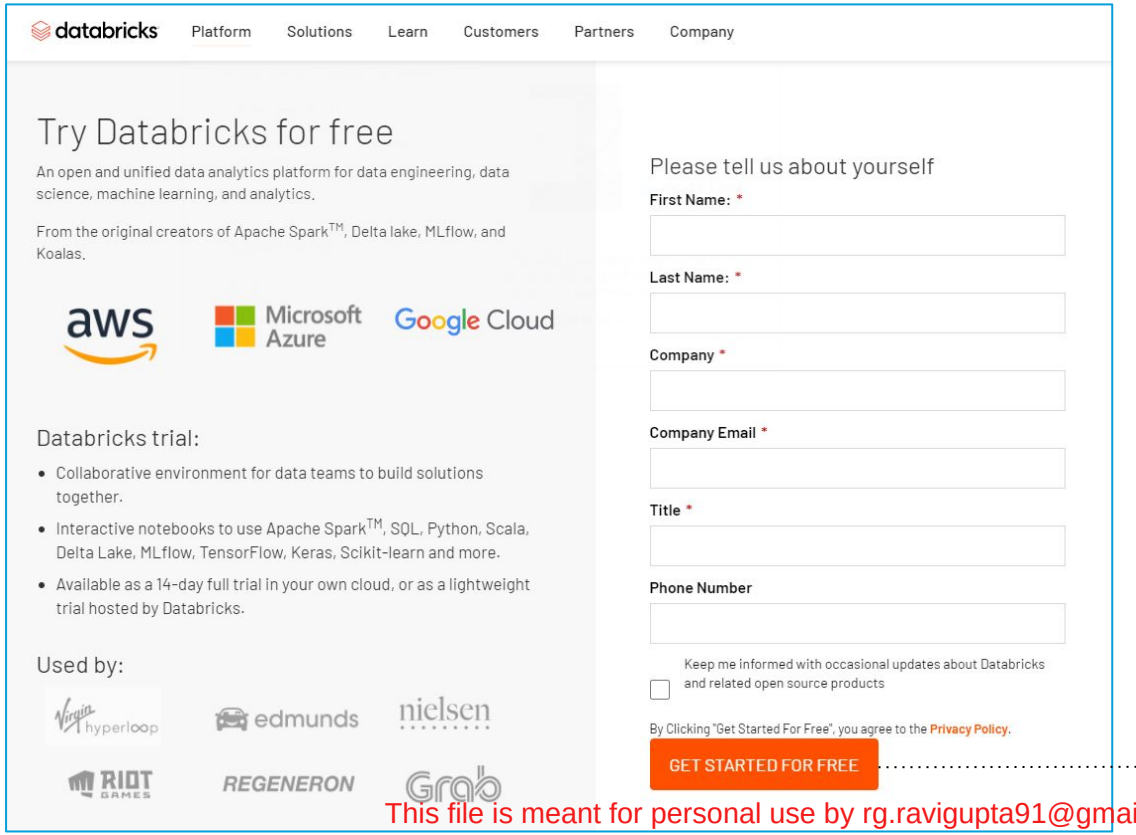
1



Click “Sign In”

Databricks - Sign Up

2



Fill all the boxes and select "GET STARTED FREE"

Databricks - Sign Up

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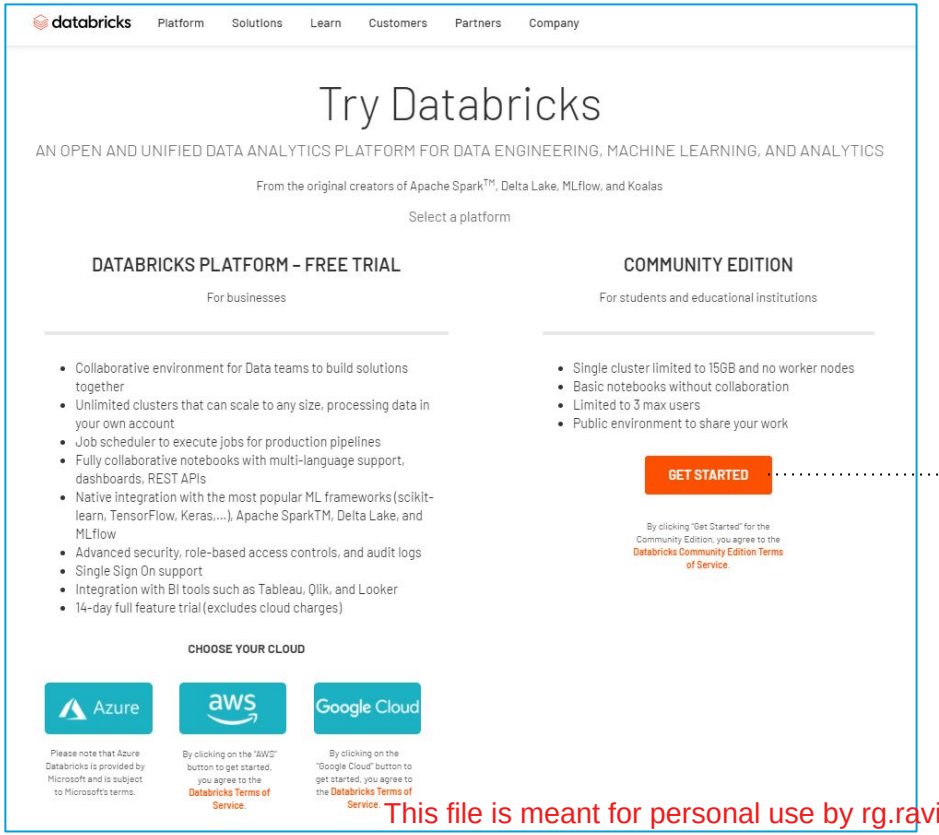

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"GET STARTED"

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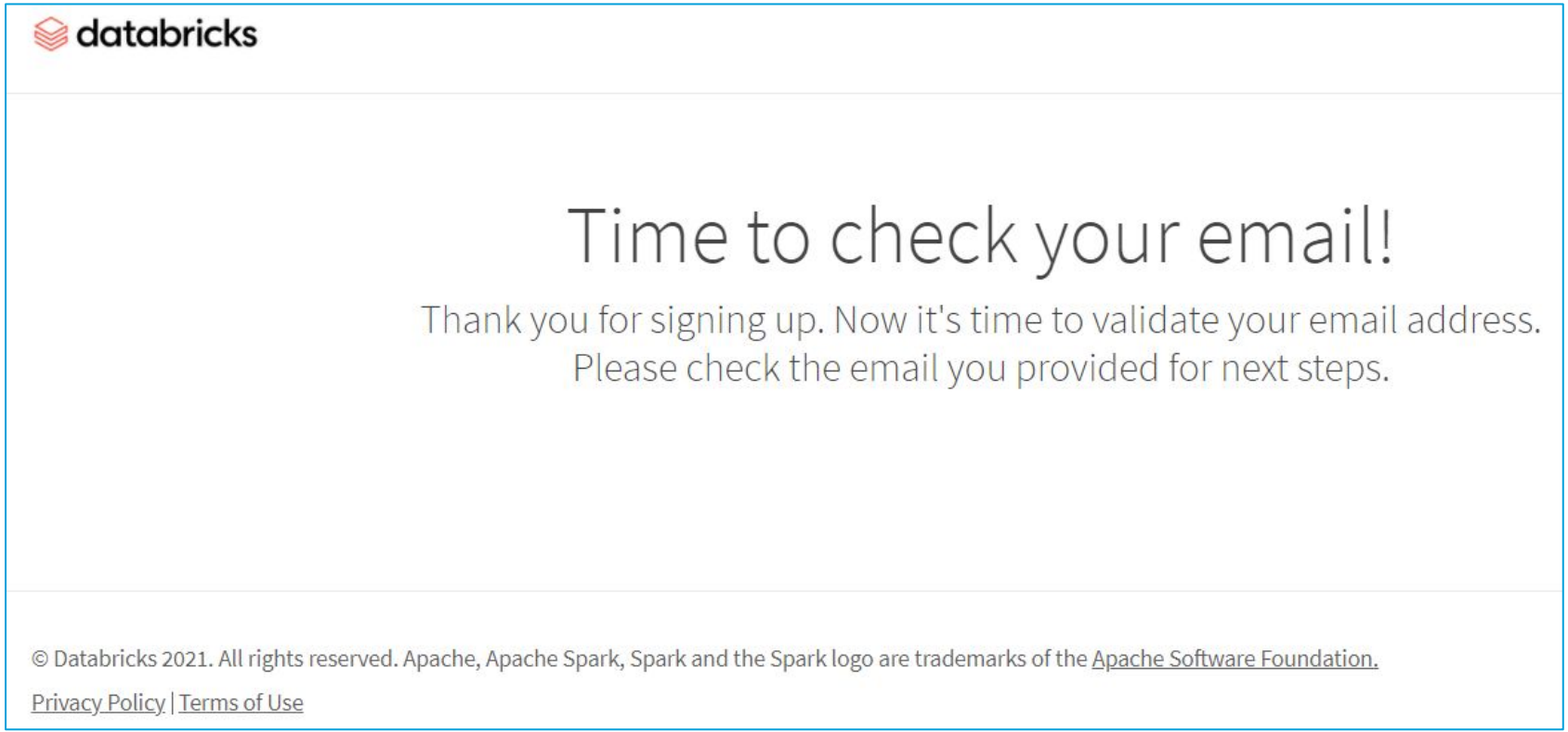

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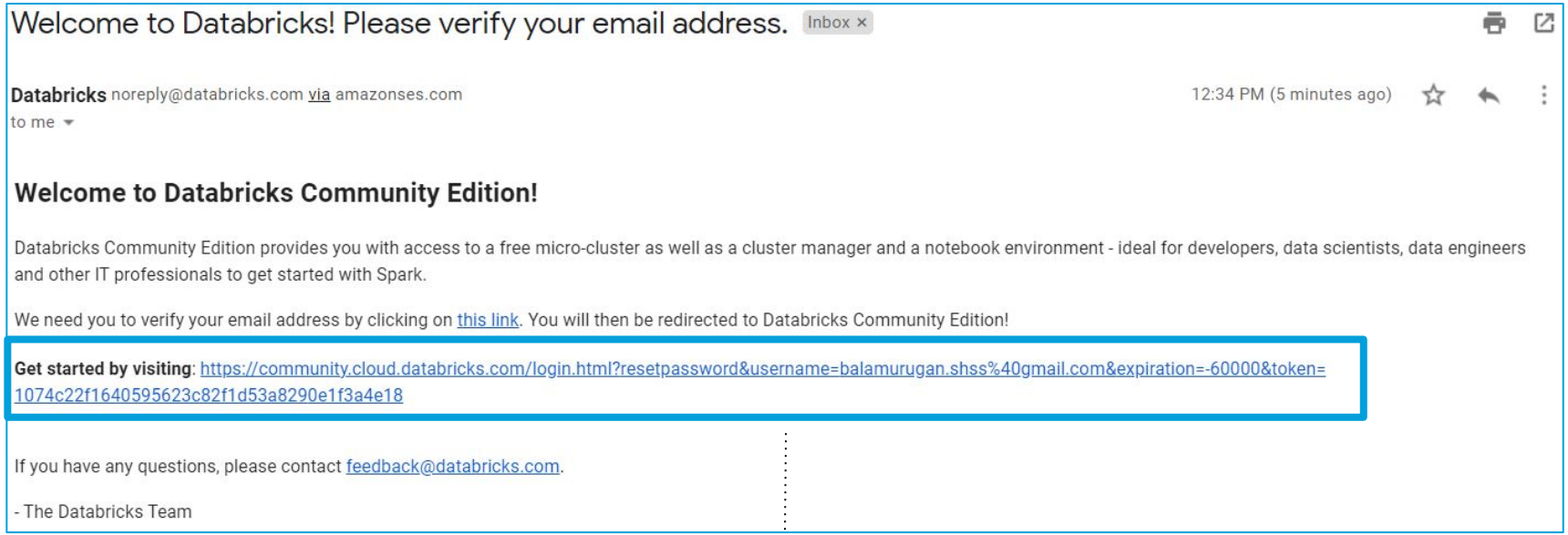

Welcome to Databricks! Please verify your email address. Inbox ×

Databricks noreply@databricks.com via amazonses.com

12:34 PM (5 minutes ago)

to me

Welcome to Databricks Community Edition!

Databricks Community Edition provides you with access to a free micro-cluster as well as a cluster manager and a notebook environment - ideal for developers, data scientists, data engineers and other IT professionals to get started with Spark.

We need you to verify your email address by clicking on this link. You will then be redirected to Databricks Community Edition!

Get started by visiting: https://community.cloud.databricks.com/login.html?resetpassword&username=balamurugan.shss%40gmail.com&expiration=-60000&token=1074c22f1640595623c82f1d53a8290e1f3a4e18

If you have any questions, please contact feedback@databricks.com.

- The Databricks Team

Click the link

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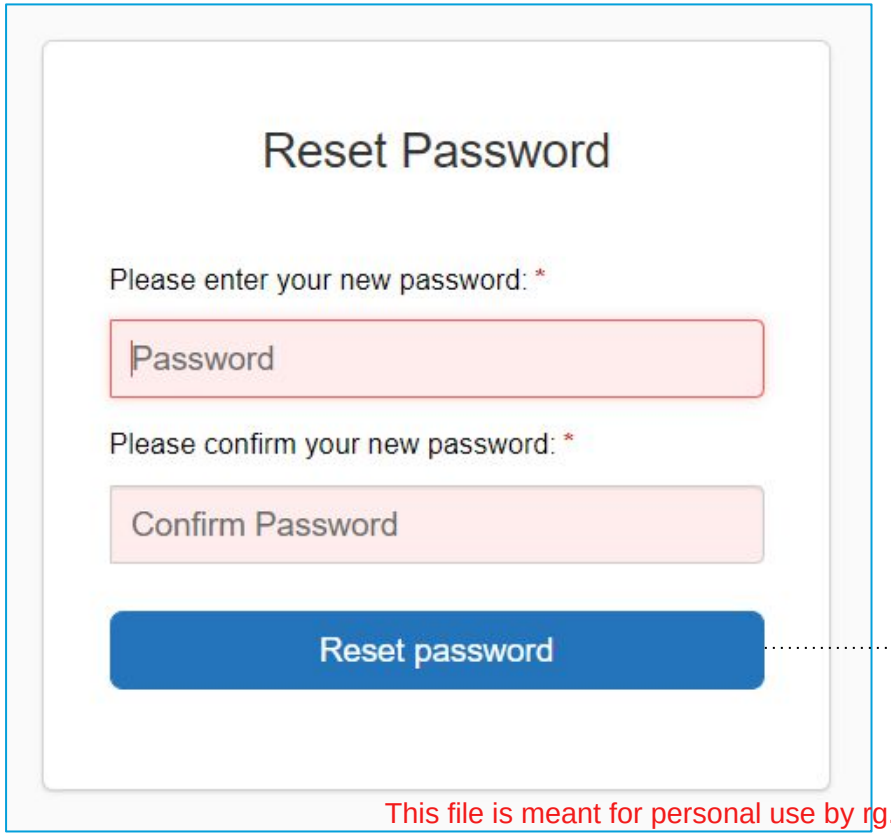
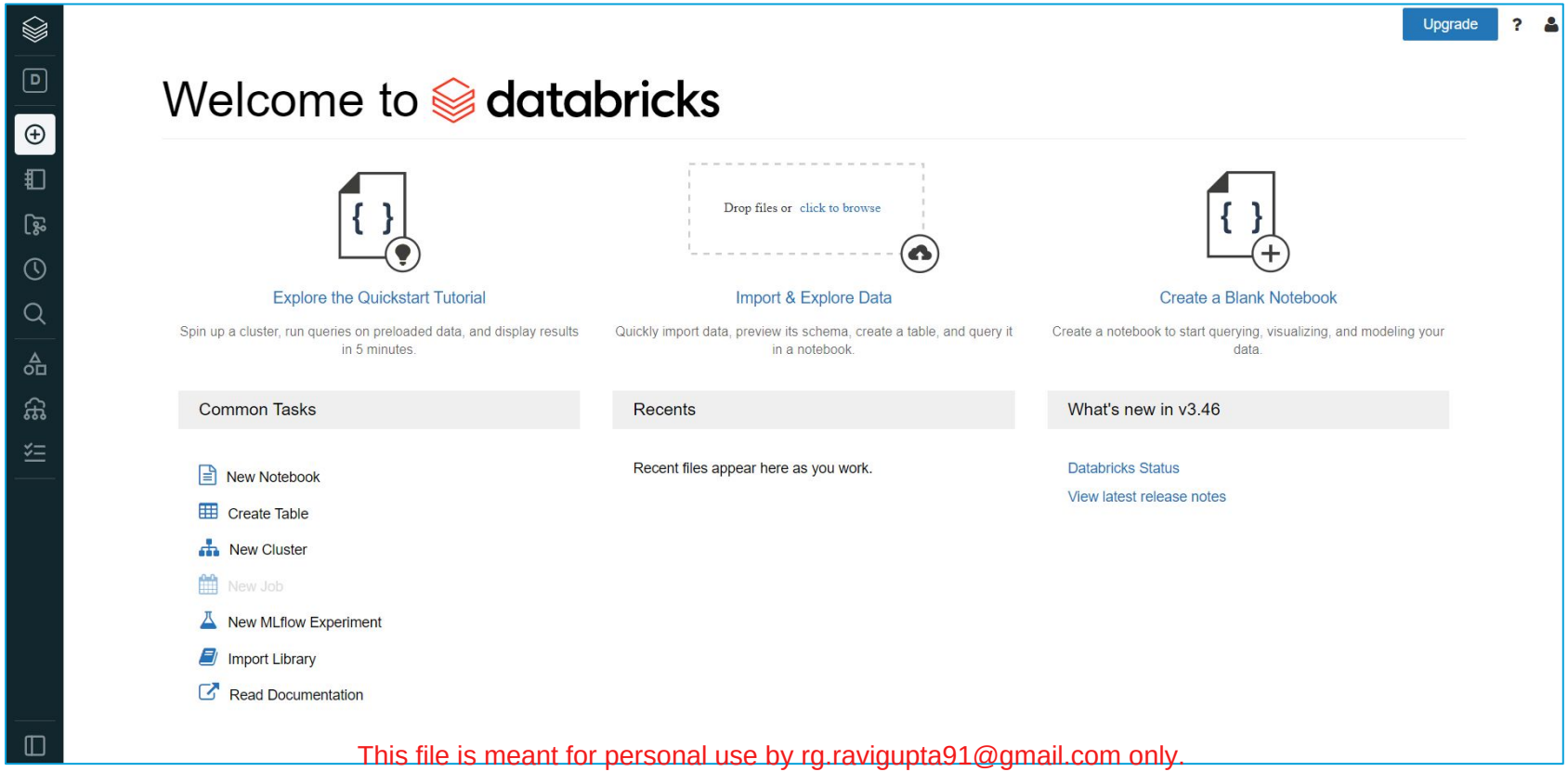


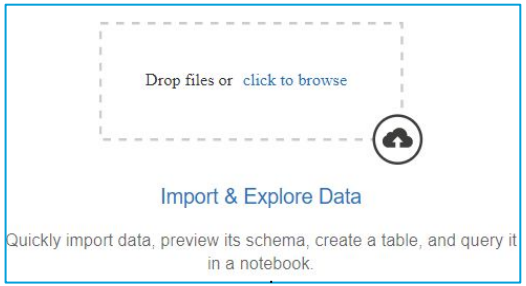
1. Enter the “Password”
2. Confirm the “Password”

Click
“Reset Password”

Welcome to Databricks



Working in Databricks



Spin up a cluster

★ Community Edition helps us to create a single node cluster. Both Driver and Executors will use the same node

Load the data

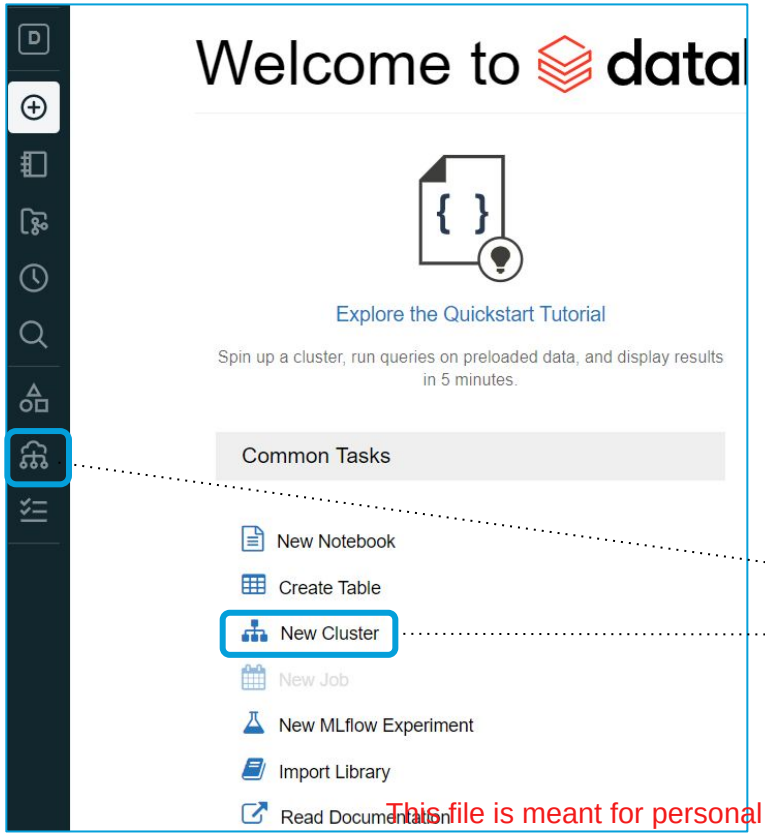
★ Databricks support various file formats like csv, json, xml, text. It can also connect to various data sources

Create a notebook

★ Databricks provide Jupyter Notebooks to write coding in Spark SQL, Python, Scala, R and Java

Spin up a cluster

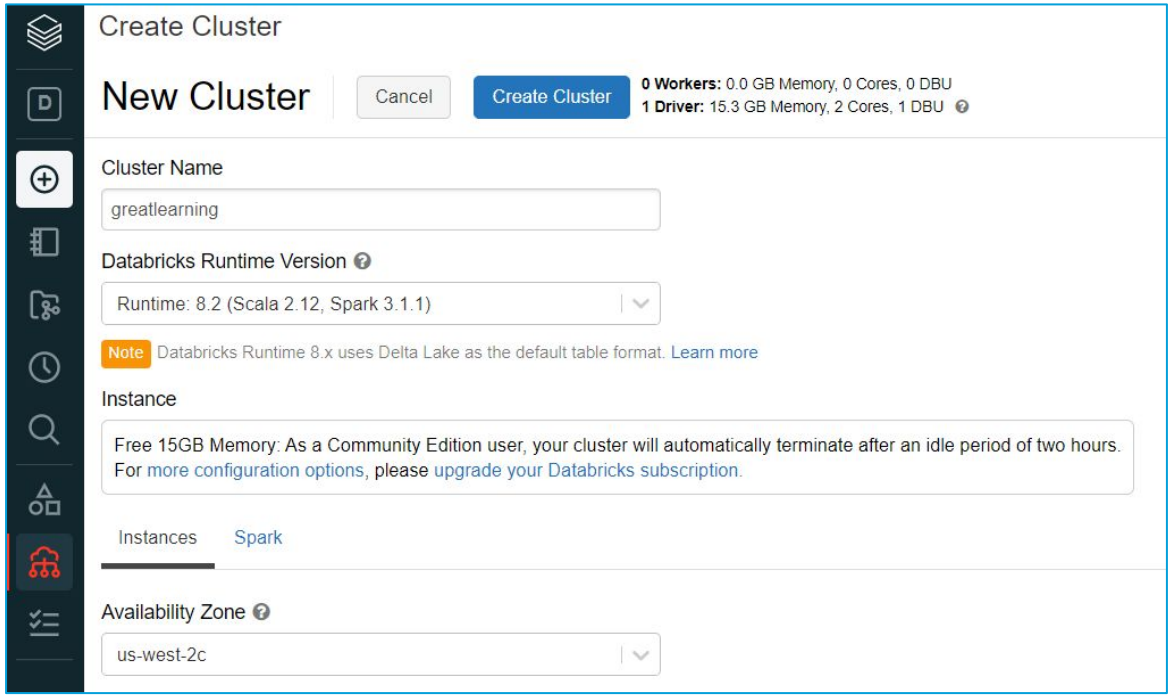
1



Create
"New Cluster"

Spin up a cluster

2



1. Enter the cluster name
2. Choose the Databricks Runtime Version
3. Choose Availability Zone
4. Click “Create Cluster”
5. It creates a single node cluster with 15.3 GB memory, 2 cores
6. It takes a few minutes to create the cluster

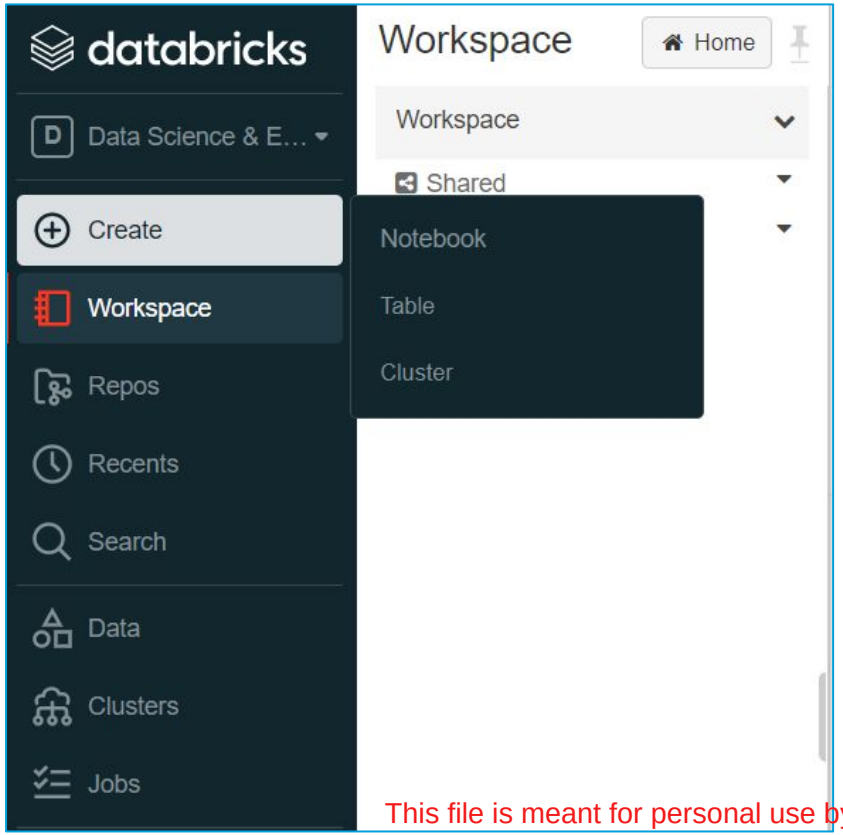
Spin up a cluster

3

Cluster is ready

Create Notebook

1



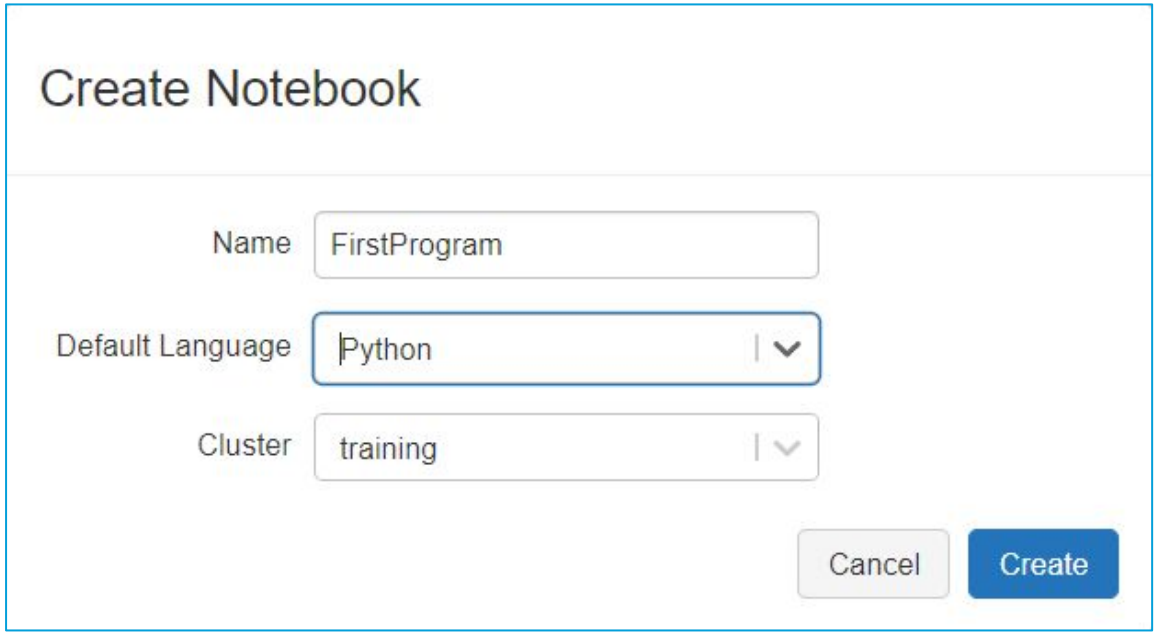
Create

↓

Click "Notebook"

Create Notebook

2



1.Enter the Notebook name

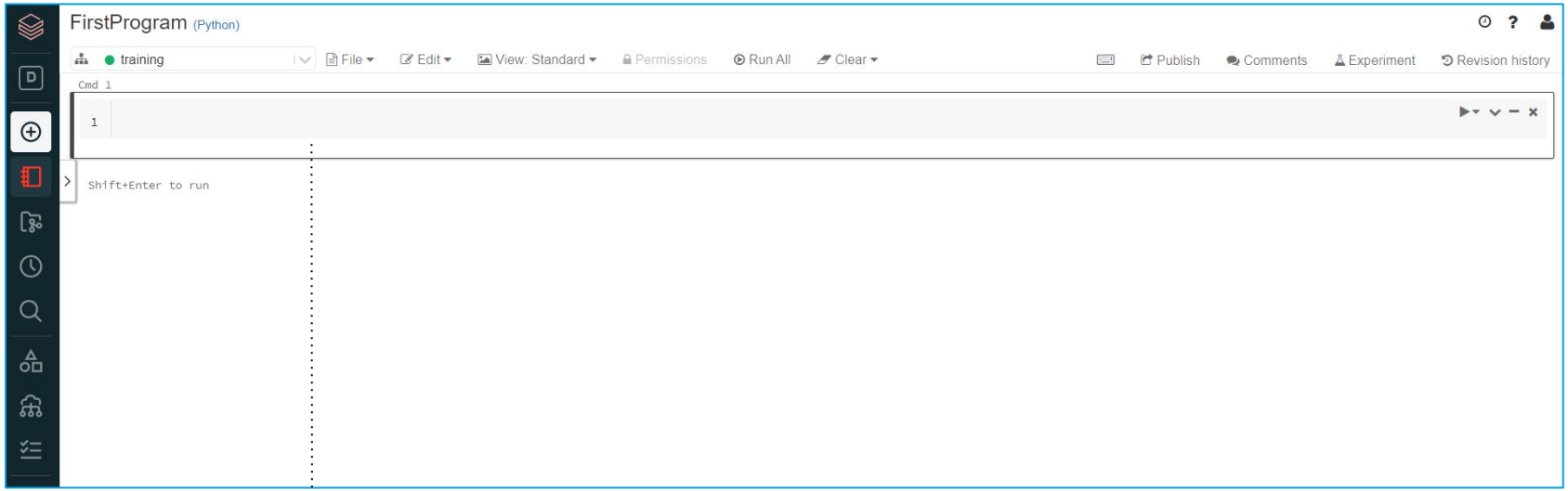
2.Choose the language. Databricks CE support Python, Scala, R and SQL

3.Choose the Cluster. In CE, you can have only one cluster

4.Click “Create”

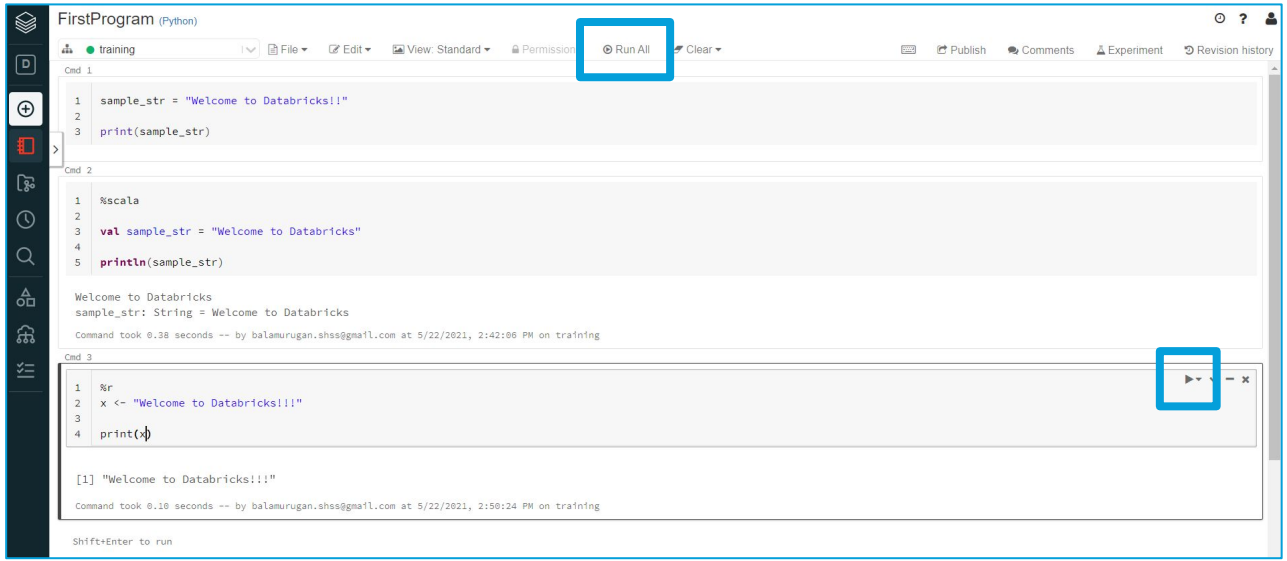
Create Notebook

3



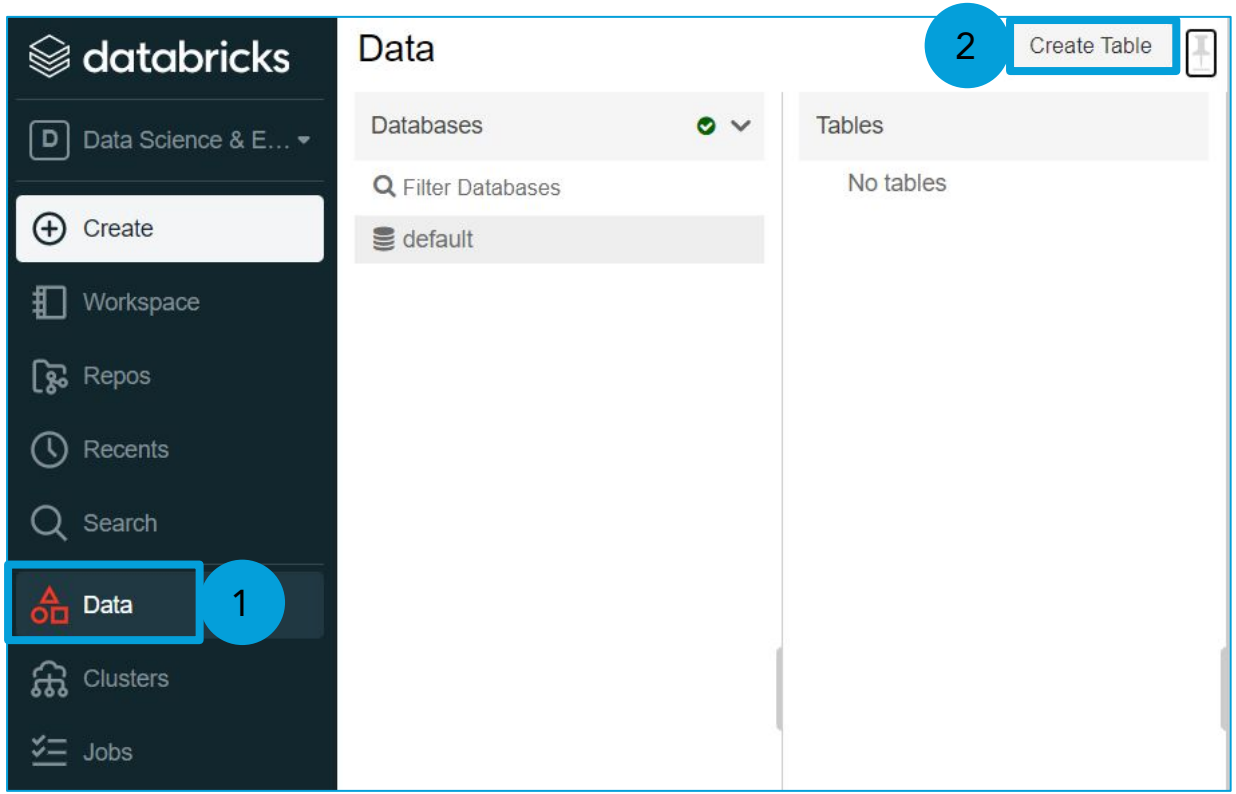
Write you code here

Write your first program



- Control + Enter => will execute a single cell
- Shift + Enter => will execute a single cell + creates a new blank cell
- "Run All" will execute all the cells (highlighted in blue)
- "Run" will execute a single cell
- %python - python, %scala - scala, %sql - Spark SQL, %r - R

Loading file(s) to DBFS

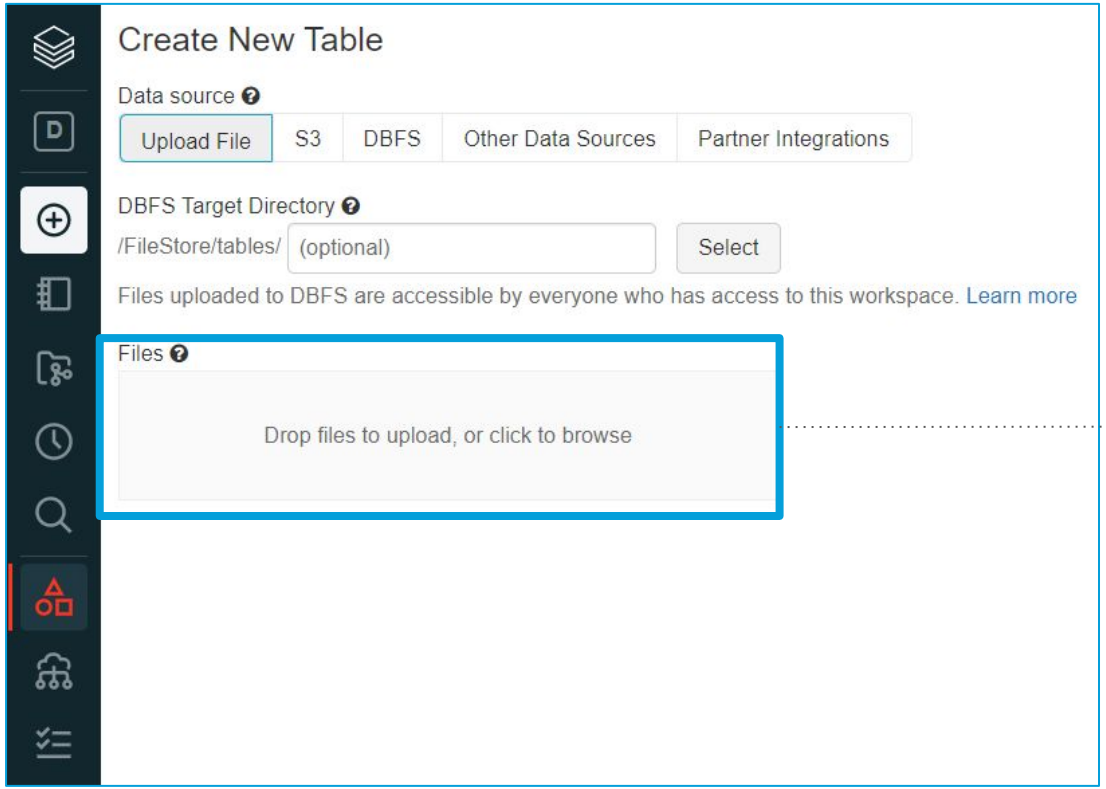


Loading files to Databricks File System (DBFS)

1.Click “Data” tab

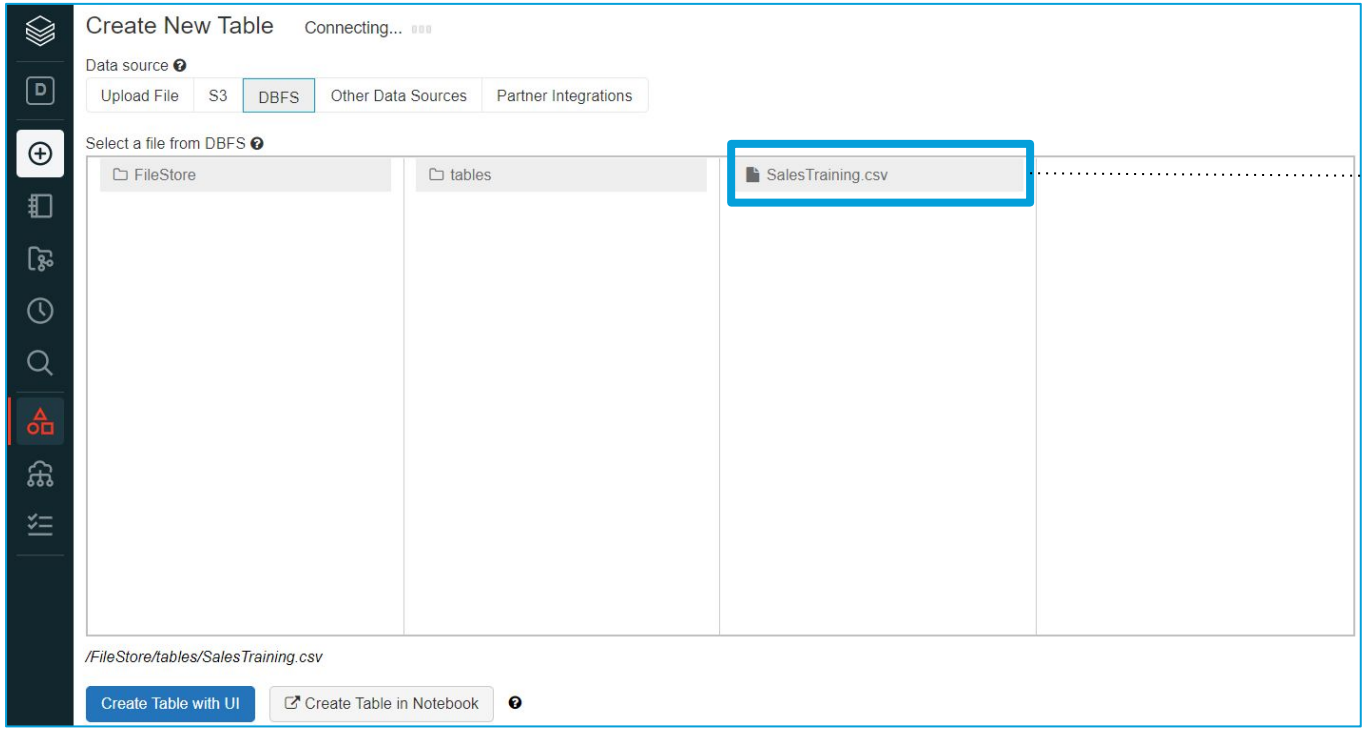
2.Click “Create Table”

Loading file(s) to DBFS



Upload your files

Loading file(s) to DBFS

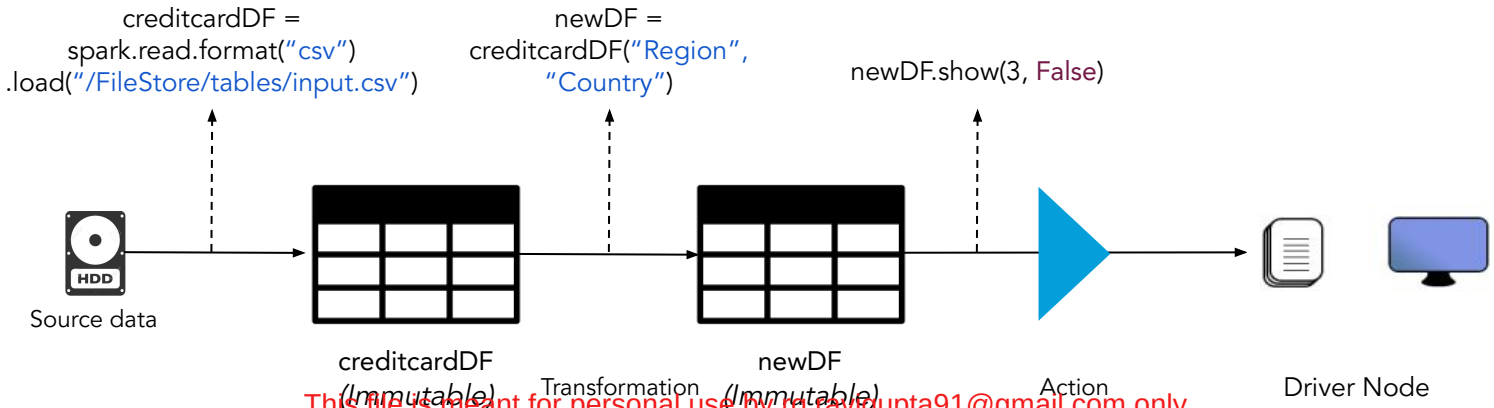


File Loaded Successfully

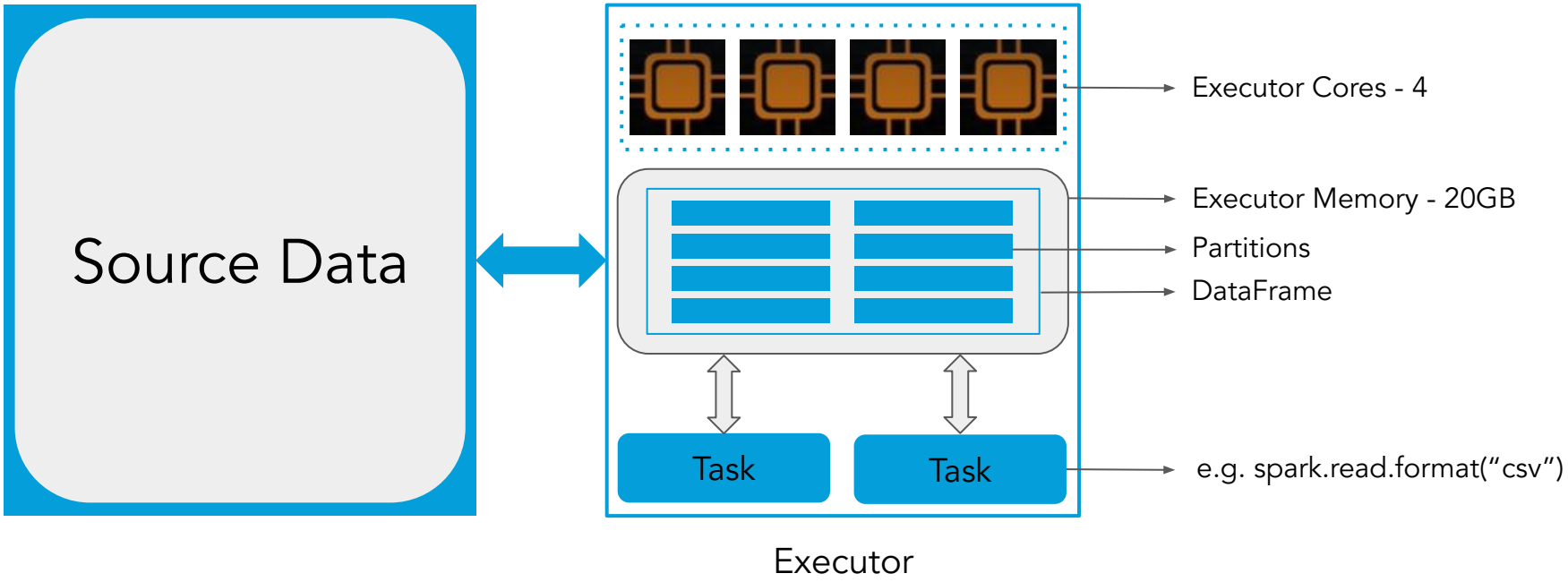
Note : File loaded to "/FileStore/tables/SalesTraining.csv" (DBFS)

Working in Databricks

```
%python


creditcardDF = spark.read.format("csv").option("header", "true").load("/FileStore/tables/SalesTraining.csv")

newDF = creditcardDF.select("Region", "Country")

print("Number of records :", creditcardDF.count())

newDF.show(3,False)
```



What happens in the background?



Class Exercise

- Create a CSV file with customer information (custID, custName, city, state, custType, balance) having a few records. Example:

```
custID,custName,city,state,custType,balance
101,John Bastin,New York,New York,savings,1000
```

- Load the file in to DBFS ("/FileStore/tables/customer.csv")
- Create the RDD by reading the file using sparkContext.textFile method
- Apply transformations like map, filter to create a new RDD having records with balance > 1000. Don't include the header record in the new RD

Spark DataFrames

Table of Content

Spark DataFrames

- Immutable, distributed collection of data that is organized into rows and columns
- Each column has a name and associated type
- Similar to a table in RDBMS
- Like RDD APIs, the DataFrame APIs are classified into 2 buckets : transformations, actions
- Transformations are lazily evaluated, and actions are eagerly evaluated
- DataFrame APIs are available in Scala, Python, Java and R
- DataFrames can be created from existing RDDs, and data sources
- Spark supports 6 built-in data formats - csv, parquet, json, jdbc, text and orc
- DataFrames can be accessed by Domain-Specific Language (DSL)

Creating DataFrames

- Creating DataFrames from RDDs
- Creating DataFrame from Data Sources/External Datasets

Creating DataFrames from RDDs

```
1  creditcardRDD = sc.textFile("/FileStore/tables/SalesTraining.csv")    # Reading the file from DBFS location
2
3  # display record count - before removing the header record
4  print("Total records including header : ", creditcardRDD.count())
5
6  header = creditcardRDD.first() # extract the header record from the RDD
7  dataRDD = creditcardRDD.filter(lambda row: row != header)   # use 'filter' (transformation) to remove the header
8
9  # display record count - after removing the header record
10 print("Total records including header : ", dataRDD.count())
11
12 # split the record by ',' and select only the first 3 columns - Region, Country and Item Type
13 tupleRDD = dataRDD.map(lambda each_row: each_row.split(',')).map(lambda each_row: (each_row[0], each_row[1], each_row[2]))
14
15 # convert the RDD to a DataFrame, display first 5 rows with no truncation of column data
16 columns = ["Region", "Country", "ItemType"]
17
18 # convert the RDD to DataFrame. Show() is as action, which shows 1st 5 records with record truncate=False
19 tupleRDD.toDF(columns).show(5, False)
```

▸ (5) Spark Jobs

```
Total records including header :  950
Total records including header :  949
+------------------+----------+----------+
|Region            |Country   |ItemType  |
+------------------+----------+----------+
|Sub-Saharan Africa|Burundi   |Vegetables|
|Europe            |Ukraine   |Cosmetics |
|Europe            |Croatia   |Beverages |
|Sub-Saharan Africa|Madagascar|Fruits    |
|Asia              |Malaysia  |Snacks    |
+------------------+----------+----------+
only showing top 5 rows
```

DataFrame Schema and Columns

```
1  # convert the tuple RDD to DataFrame with header record
2  creditcardDF = tupleRDD.toDF(columns)
3
4  # display the schema
5  creditcardDF.printSchema()
```

▸ (1) Spark Jobs

▸ creditcardDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 1 more fields]

```
root
 |-- Region: string (nullable = true)
 |-- Country: string (nullable = true)
 |-- ItemType: string (nullable = true)
```

```
1  # display the columns
2  creditcardDF.columns
3
4  # display the RDD data - top 3 records
5  creditcardDF.take(3)
```

▸ (1) Spark Jobs

```
Out[11]: [Row(Region='Sub-Saharan Africa', Country='Burundi', ItemType='Vegetables'),
 Row(Region='Europe', Country='Ukraine', ItemType='Cosmetics'),
 Row(Region='Europe', Country='Croatia', ItemType='Beverages')]
```

Creating DataFrames from Data Sources

- DataFrames can directly be created from various data sources or external datasets
- Spark supports 6 built-in data sources, where each data source is mapped to a data format
- Common formats for text data are CSV, XML and JSON
- Common formats for binary data are Avro, Parquet, and ORC
- The two main classes in Spark for reading and writing data are DataFrameReader and DataFrameWriter
- DataFrameReader and DataFrameWriter are available with SparkSession

DataFrameReader

- spark.read.format(...).option("key", value").schema(...).load()
  - format - json, parquet, jdbc, orc, csv, text
  - option - DataFrameReader has a set of default options for each data source format, which can be overridden
  - schema - Some data sources have the schema embedded inside the data files, i.e., Parquet and ORC. For other formats, provide a schema

```
# create a DF from a CSV file
creditcardDF = spark.read.format("csv") \
                         .option("header", "true") \
                         .option("inferSchema", "true") \
                         .load("/FileStore/tables/SalesTraining.csv")

# display the schema
creditcardDF.printSchema()
```

Working with CSV files

1

- One of the commonly used file formats
- Databricks can connect and read data from number of sources like Cloud Storage Services, Databricks File System, HADOOP
- Read the data using the DataFrameReader by passing all the necessary details
- Apply DataFrame APIs to transform the data, push the data on to respective sources by executing the actions

Working with CSV files


```
# create a DF from a CSV file
creditcardDF = spark.read.format("csv") \
                         .option("header", "true") \
                         .option("inferSchema", "true") \
                         .load("/FileStore/tables/SalesTraining.csv")

# display the schema
creditcardDF.printSchema()
```

```
▸ (2) Spark Jobs
▸ creditcardDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 12 more fields]
root
 |-- Region: string (nullable = true)
 |-- Country: string (nullable = true)
 |-- Item Type: string (nullable = true)
 |-- Sales Channel: string (nullable = true)
 |-- Order Priority: string (nullable = true)
 |-- Order Date: string (nullable = true)
 |-- Order ID: integer (nullable = true)
 |-- Ship Date: string (nullable = true)
 |-- Units Sold: integer (nullable = true)
 |-- Unit Price: double (nullable = true)
 |-- Unit Cost: double (nullable = true)
 |-- Total Revenue: double (nullable = true)
 |-- Total Cost: double (nullable = true)
 |-- Total Profit: double (nullable = true)
```

- spark.read.format(..) returns the DataFrame object
- Option “inferSchema” infers the schema for each column
- Option “header” treats the first record as header record

Working with CSV files


```
1  # display first 5 records with no truncation
2  creditcardDF.show(5, False)
```

▸ (1) Spark Jobs

```
+------------------+----------+----------+-------------+--------------+----------+---------+----------+----------+----------+---------+-------------+----------+-------------+
|Region            |Country   |Item Type |Sales Channel|Order Priority|Order Date|Order ID |Ship Date |Units Sold|Unit Price|Unit Cost|Total Revenue|Total Cost|Total Profit|
+------------------+----------+----------+-------------+--------------+----------+---------+----------+----------+----------+---------+-------------+----------+-------------+
|Sub-Saharan Africa|Burundi   |Vegetables|Online       |M             |11/17/2010|951380240|12/20/2010|3410      |154.06    |90.93    |525344.6     |310071.3  |215273.3     |
|Europe            |Ukraine   |Cosmetics |Online       |M             |11/13/2014|270001733|1/1/2015  |8368      |437.2     |263.33   |3658489.6    |2203545.44|1454944.16   |
|Europe            |Croatia   |Beverages |Online       |C             |6/16/2016 |681941401|7/28/2016 |470       |47.45     |31.79    |22301.5      |14941.3   |7360.2       |
|Sub-Saharan Africa|Madagascar|Fruits    |Online       |L             |5/31/2016 |566935575|6/7/2016  |7690      |9.33      |6.92     |71747.7      |53214.8   |18532.9      |
|Asia              |Malaysia  |Snacks    |Offline      |M             |10/6/2012 |175033080|11/5/2012 |5033      |152.58    |97.44    |767935.14    |490415.52 |277519.62    |
+------------------+----------+----------+-------------+--------------+----------+---------+----------+----------+----------+---------+-------------+----------+-------------+
only showing top 5 rows
```

- df.show(..) is an action, which brings the transformed data to the Driver node
- Spark executes all transformations present in the Lineage (DAG), when an action is triggered

Defining Own Schema

1

```
# defining your own schema
from pyspark.sql.types import StructType, StructField, StringType, DoubleType, FloatType, LongType, IntegerType, DateType

# define the structure
schema = StructType([
    StructField("Region", StringType()),
    StructField("Country", StringType()),
    StructField("Item", StringType()),
    StructField("SalesChannel", StringType()),
    StructField("OrderPriority", StringType()),
    StructField("OrderDate", StringType()),
    StructField("OrderID", LongType()),
    StructField("ShipDate", StringType()),
    StructField("UnitsSold", IntegerType()),
    StructField("UnitPrice", FloatType()),
    StructField("UnitCost", FloatType()),
    StructField("TotalRevenue", DoubleType()),
    StructField("TotalCost", DoubleType()),
    StructField("TotalProfit", DoubleType())
])

# read the file by using the defined schema
creditcardDF1 = spark.read.format("csv").option("header", "true").schema(schema).load("/FileStore/tables/SalesTraining.csv")

# display the schema
creditcardDF1.printSchema()
```

Defining Own Schema

2

```
23  creditcardDF1.printSchema()
```

```
▸ creditcardDF1:  pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 12 more fields]
root
 |-- Region: string (nullable = true)
 |-- Country: string (nullable = true)
 |-- Item: string (nullable = true)
 |-- SalesChannel: string (nullable = true)
 |-- OrderPriority: string (nullable = true)
 |-- OrderDate: string (nullable = true)
 |-- OrderID: long (nullable = true)
 |-- ShipDate: string (nullable = true)
 |-- UnitsSold: integer (nullable = true)
 |-- UnitPrice: float (nullable = true)
 |-- UnitCost: float (nullable = true)
 |-- TotalRevenue: double (nullable = true)
 |-- TotalCost: double (nullable = true)
 |-- TotalProfit: double (nullable = true)
```

Defining Own Schema

3

```
1  # display the records
2  creditcardDF1.show(3, False)
```

▸ (1) Spark Jobs

```
+------------------+-------+----------+------------+-------------+----------+---------+----------+---------+---------+--------+------------+----------+-----------+
|Region            |Country|Item      |SalesChannel|OrderPriority|OrderDate |OrderID  |ShipDate  |UnitsSold|UnitPrice|UnitCost|TotalRevenue|TotalCost |TotalProfit|
+------------------+-------+----------+------------+-------------+----------+---------+----------+---------+---------+--------+------------+----------+-----------+
|Sub-Saharan Africa|Burundi|Vegetables|Online      |M            |11/17/2010|951380240|12/20/2010|3410     |154.06   |90.93   |525344.6    |310071.3  |215273.3   |
|Europe            |Ukraine|Cosmetics |Online      |M            |11/13/2014|270001733|1/1/2015  |8368     |437.2    |263.33  |3658489.6   |2203545.44|1454944.16 |
|Europe            |Croatia|Beverages |Online      |C            |6/16/2016 |681941401|7/28/2016 |470      |47.45    |31.79   |22301.5     |14941.3   |7360.2     |
+------------------+-------+----------+------------+-------------+----------+---------+----------+---------+---------+--------+------------+----------+-----------+
only showing top 3 rows
```

Selecting DataFrame Columns

```
1  # selecting all the columns
2  creditcardDF.select("*").show(4, False)
```

▸ (1) Spark Jobs

```
+------------------+----------+----------+-------------+--------------+----------+---------+----------+----------+----------+---------+-------------+----------+-------------+
|Region            |Country   |Item Type |Sales Channel|Order Priority|Order Date|Order ID |Ship Date |Units Sold|Unit Price|Unit Cost|Total Revenue|Total Cost|Total Profit|
+------------------+----------+----------+-------------+--------------+----------+---------+----------+----------+----------+---------+-------------+----------+-------------+
|Sub-Saharan Africa|Burundi   |Vegetables|Online       |M             |11/17/2010|951380240|12/20/2010|3410      |154.06    |90.93    |525344.6     |310071.3  |215273.3    |
|Europe            |Ukraine   |Cosmetics |Online       |M             |11/13/2014|270001733|1/1/2015  |8368      |437.2     |263.33   |3658489.6    |2203545.44|1454944.16  |
|Europe            |Croatia   |Beverages |Online       |C             |6/16/2016 |681941401|7/28/2016 |470       |47.45     |31.79    |22301.5      |14941.3   |7360.2      |
|Sub-Saharan Africa|Madagascar|Fruits    |Online       |L             |5/31/2016 |566935575|6/7/2016  |7690      |9.33      |6.92     |71747.7      |53214.8   |18532.9     |
+------------------+----------+----------+-------------+--------------+----------+---------+----------+----------+----------+---------+-------------+----------+-------------+
only showing top 4 rows
```

```
1  # selecting only a few columns
2  from pyspark.sql.functions import col, column
3  import pyspark.sql.functions as F
4
5  # select a few columns
6  creditcardDF.select("Region", "Country", F.col("Item Type"), "Order Date", "Units Sold", "Total Revenue", F.lit('DefaultValue')).show(4, False)
```

▸ (1) Spark Jobs

```
+------------------+----------+----------+----------+----------+-------------+------------+
|Region            |Country   |Item Type |Order Date|Units Sold|Total Revenue|DefaultValue|
+------------------+----------+----------+----------+----------+-------------+------------+
|Sub-Saharan Africa|Burundi   |Vegetables|11/17/2010|3410      |525344.6     |DefaultValue|
|Europe            |Ukraine   |Cosmetics |11/13/2014|8368      |3658489.6    |DefaultValue|
|Europe            |Croatia   |Beverages |6/16/2016 |470       |22301.5      |DefaultValue|
|Sub-Saharan Africa|Madagascar|Fruits    |5/31/2016 |7690      |71747.7      |DefaultValue|
+------------------+----------+----------+----------+----------+-------------+------------+
only showing top 4 rows
```

Renaming Columns

1

```
# renaming a column
creditcardDF.columns
```

```
Out[41]: ['Region',
 'Country',
 'Item Type',
 'Sales Channel',
 'Order Priority',
 'Order Date',
 'Order ID',
 'Ship Date',
 'Units Sold',
 'Unit Price',
 'Unit Cost',
 'Total Revenue',
 'Total Cost',
 'Total Profit']
```

Renaming Columns

2

```
# renaming the columns - "Sales Channel" to "SalesChannel" and "Item Type" to "Item"
creditcardDF2 = creditcardDF.withColumnRenamed("Sales Channel", "SalesChannel").withColumnRenamed('Item Type','Item')
```

creditcardDF2: pyspark.sql.dataframe.DataFrame

```
Region: string
Country: string
Item: string
SalesChannel: string
Order Priority: string
Order Date: string
Order ID: integer
Ship Date: string
Units Sold: integer
Unit Price: double
Unit Cost: double
Total Revenue: double
Total Cost: double
Total Profit: double
```

Command took 0.04 seconds -- by balamurugan.shss@gmail.com at 5/24/2021, 11:16:38 AM on training

md 10

```
# display records
creditcardDF2.show(3, False)
```

(1) Spark Jobs

Region	Country	Item	SalesChannel	Order Priority	Order Date	Order ID	Ship Date	Units Sold	Unit Price	Unit Cost	Total Revenue	Total Cost	Total Profit
Sub-Saharan Africa	Burundi	Vegetables	Online	M	11/17/2010	951380240	12/20/2010	3410	154.06	90.93	525344.6	310071.3	215273.3
Europe	Ukraine	Cosmetics	Online	M	11/13/2014	270001733	1/1/2015	8368	437.2	263.33	3658489.6	2203545.44	1454944.16
Europe	Croatia	Beverages	Online	C	6/16/2016	681941401	7/28/2016	470	47.45	31.79	22301.5	14941.3	7360.2

only showing top 3 rows

Changing Columns Data Type

```
1  # change column data type
2  from pyspark.sql.functions import col
3
4  # change the data type from integer to long
5  df = creditcardDF.withColumn("Order ID", col("Order ID").cast("long"))
6  df.printSchema() # display the schema
```

```
▸ df:  pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 12 more fields]
root
 |-- Region: string (nullable = true)
 |-- Country: string (nullable = true)
 |-- Item Type: string (nullable = true)
 |-- Sales Channel: string (nullable = true)
 |-- Order Priority: string (nullable = true)
 |-- Order Date: string (nullable = true)
 |-- Order ID: long (nullable = true)
 |-- Ship Date: string (nullable = true)
 |-- Units Sold: integer (nullable = true)
 |-- Unit Price: double (nullable = true)
 |-- Unit Cost: double (nullable = true)
 |-- Total Revenue: double (nullable = true)
 |-- Total Cost: double (nullable = true)
 |-- Total Profit: double (nullable = true)
```

Adding Columns to a DataFrame

```
1  # adding columns to a dataframe
2  import pyspark.sql.functions as F
3
4  # add a new column "Register_Site" with default value "www.google.com"
5  dataDF = creditcardDF.withColumn("Register_Site", F.lit("www.google.com"))
6
7  # display only a few columns
8  dataDF.select("Region","Country", "Item Type", "Register_Site").show(3, False)
```

▸ (1) Spark Jobs

▸ dataDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 13 more fields]

```
+------------------+-------+----------+--------------+
|Region            |Country|Item Type |Register_Site |
+------------------+-------+----------+--------------+
|Sub-Saharan Africa|Burundi|Vegetables|www.google.com|
|Europe            |Ukraine|Cosmetics |www.google.com|
|Europe            |Croatia|Beverages |www.google.com|
+------------------+-------+----------+--------------+
only showing top 3 rows
```

Removing Columns from a DataFrame

```
# removing columns from a DataFrame

# number of columns in a dataframe - before removing columns
print("Number of columns : ", len(dataDF.columns))

# columns - before dropping
print(list(dataDF.columns))

# drop columns - "Country", "Item Type"
datanewDF = dataDF.drop("Country", "Item Type")

# number of columns in a dataframe - after removing columns
print("Number of columns : ", len(datanewDF.columns))

# columns - after dropping
print(list(datanewDF.columns))
```

```
▸ datanewDF:  pyspark.sql.dataframe.DataFrame = [Region: string, Sales Channel: string ... 11 more fields]
Number of columns :  15
['Region', 'Country', 'Item Type', 'Sales Channel', 'Order Priority', 'Order Date', 'Order ID', 'Ship Date', 'Units Sold', 'Unit Price', 'Unit Cost', 'Total Revenue', 'Total Cost',
'Total Profit', 'Register_Site']
Number of columns :  13
['Region', 'Sales Channel', 'Order Priority', 'Order Date', 'Order ID', 'Ship Date', 'Units Sold', 'Unit Price', 'Unit Cost', 'Total Revenue', 'Total Cost', 'Total Profit', 'Regist
er_Site']
```

Arithmetic with DataFrames

```
1  # arithmetic with dataframes
2  # number of columns in a dataframe - before a adding a column
3  print("Number of columns : ", len(creditcardDF.columns))
4
5  # perform arithmetic operations on a dataframe column
6  creditnewDF = creditcardDF.withColumn("TotalSale", col("Units Sold") * col("Unit Price"))
7
8  # number of columns in a dataframe - after adding columns
9  print("Number of columns : ", len(creditnewDF.columns))
10
11 # display records
12 creditnewDF.show(3)
```

▸ (1) Spark Jobs

▸ creditnewDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 13 more fields]

```
Number of columns :  14
Number of columns :  15
+------------------+-------+----------+-------------+--------------+----------+--------+----------+----------+----------+----------+-------------+----------+-----------+----------+
|            Region|Country| Item Type|Sales Channel|Order Priority|Order Date| Order ID| Ship Date|Units Sold|Unit Price|Unit Cost|Total Revenue|Total Cost|Total Profit| TotalSale|
+------------------+-------+----------+-------------+--------------+----------+--------+----------+----------+----------+----------+-------------+----------+-----------+----------+
|Sub-Saharan Africa|Burundi|Vegetables|       Online|             M|11/17/2010|951380240|12/20/2010|      3410|    154.06|     90.93|     525344.6|  310071.3|    215273.3|  525344.6|
|            Europe|Ukraine| Cosmetics|       Online|             M|11/13/2014|270001733|  1/1/2015|      8368|     437.2|    263.33|    3658489.6|2203545.44|  1454944.16| 3658489.6|
|            Europe|Croatia| Beverages|       Online|             C| 6/16/2016|681941401| 7/28/2016|       470|     47.45|     31.79|      22301.5|   14941.3|     7360.2|   22301.5|
+------------------+-------+----------+-------------+--------------+----------+--------+----------+----------+----------+----------+-------------+----------+-----------+----------+
only showing top 3 rows
```

How to Filter a DataFrame

```
1  # filter a dataframe
2
3  creditcardDF.where(col("Region") == "Asia").show(5)
```

▸ (1) Spark Jobs

```
+------+-----------+---------------+-------------+--------------+----------+---------+---------+----------+----------+---------+-------------+----------+------------+
|Region|    Country|      Item Type|Sales Channel|Order Priority|Order Date| Order ID|Ship Date|Units Sold|Unit Price|Unit Cost|Total Revenue|Total Cost|Total Profit|
+------+-----------+---------------+-------------+--------------+----------+---------+---------+----------+----------+---------+-------------+----------+------------+
|  Asia|   Malaysia|         Snacks|      Offline|             M| 10/6/2012|175033080|11/5/2012|      5033|    152.58|    97.44|    767935.14| 490415.52|   277519.62|
|  Asia| Uzbekistan|Office Supplies|      Offline|             L| 3/10/2012|276595246|3/15/2012|      9535|    651.21|   524.96|   6209287.35|5005493.6|  1203793.75|
|  Asia|      Nepal|     Vegetables|      Offline|             C|  6/2/2014|443121373|6/19/2014|      8316|    154.06|    90.93|   1281162.96| 756173.88|   524989.08|
|  Asia|      India|         Fruits|       Online|             H| 7/29/2010|658348691|8/22/2010|      8862|      9.33|     6.92|     82682.46|  61325.04|    21357.42|
|  Asia|South Korea|         Fruits|      Offline|             L|  3/7/2010|769205892|3/17/2010|      3972|      9.33|     6.92|     37058.76|  27486.24|     9572.52|
+------+-----------+---------------+-------------+--------------+----------+---------+---------+----------+----------+---------+-------------+----------+------------+
only showing top 5 rows
```

```
1  # filter a dataframe - multiple columns
2
3  creditcardDF.where((col("Region") == "Asia") & (col("Sales Channel") == "Online")).show(5)
```

▸ (1) Spark Jobs

```
+------+-----------+---------+-------------+--------------+----------+---------+---------+----------+----------+---------+-------------+----------+------------+
|Region|    Country|Item Type|Sales Channel|Order Priority|Order Date| Order ID|Ship Date|Units Sold|Unit Price|Unit Cost|Total Revenue|Total Cost|Total Profit|
+------+-----------+---------+-------------+--------------+----------+---------+---------+----------+----------+---------+-------------+----------+------------+
|  Asia|      India|   Fruits|       Online|             H| 7/29/2010|658348691|8/22/2010|      8862|      9.33|     6.92|     82682.46|  61325.04|    21357.42|
|  Asia|Philippines|Baby Food|       Online|             L| 2/23/2014|160127294|3/23/2014|      4079|    255.28|   159.42|   1041287.12| 650274.18|   391012.94|
|  Asia| Bangladesh|Baby Food|       Online|             H| 8/17/2011|254927718| 9/7/2011|      7632|    255.28|   159.42|  1948296.96|1216693.44|   731603.52|
|  Asia|    Vietnam|Baby Food|       Online|             C| 6/20/2011|881974112|7/11/2011|      4594|    255.28|   159.42|   1172756.32| 732375.48|   440380.84|
|  Asia|     Taiwan|Household|       Online|             C| 1/23/2017|607261836|2/22/2017|      1127|    668.27|   502.54|    753140.29| 566362.58|   186777.71|
+------+-----------+---------+-------------+--------------+----------+---------+---------+----------+----------+---------+-------------+----------+------------+
only showing top 5 rows
```

Dropping Duplicate Rows

1

```
# dropping rows
testDF = [[1, "January"], [2, "February"], [1, "January"], [3, "March"], [3, "March"], [3, "March"], [4, "April"], [4, "April"], [5, "May"], [5, "May"],
          [4, "April"], [6, "June"], [5, "April"]]

# import the modules
from pyspark.sql.types import *

# define the schema
schema = StructType([StructField("ID", IntegerType()),StructField("Month", StringType())])

# create the dataframe by applying schema
df = spark.createDataFrame(testDF,schema=schema)

# display the records
df.show()
```

▸ (3) Spark Jobs

▸ df: pyspark.sql.dataframe.DataFrame = [ID: integer, Month: string]

```
+---+--------+
| ID|   Month|
+---+--------+
|  1| January|
|  2|February|
|  1| January|
|  3|   March|
|  3|   March|
|  3|   March|
|  4|   April|
|  4|   April|
|  5|     May|
|  5|     May|
|  4|   April|
|  6|    June|
|  5|   April|
+---+--------+
```

Dropping Duplicate Rows

2

```
1  # display distinct rows
2  df.distinct().show()
```

▸ (2) Spark Jobs

```
+---+--------+
| ID|   Month|
+---+--------+
|  1| January|
|  2|February|
|  3|   March|
|  4|   April|
|  5|     May|
|  5|   April|
|  6|    June|
+---+--------+
```

Dropping Duplicate Rows

3

```
# drop duplicate records based a column value
df.dropDuplicates(['Month']).show()

# drop duplicate records based multiple column values
df.dropDuplicates(['Month', 'ID']).show()
```

▸ (4) Spark Jobs

```
+---+--------+
| ID|   Month|
+---+--------+
|  1| January|
|  2|February|
|  3|   March|
|  4|   April|
|  5|     May|
|  6|    June|
+---+--------+

+---+--------+
| ID|   Month|
+---+--------+
|  1| January|
|  2|February|
|  3|   March|
|  4|   April|
|  5|     May|
|  6|    June|
|  5|   April|
+---+--------+
```

selectExpr

```
1  # rename existing columns
2  newDF = creditcardDF.withColumnRenamed("Unit Price", "UnitPrice").withColumnRenamed("Total Profit", "Total_Profit")
3
4  creditcardDF.show(3) # display records
5
6  from pyspark.sql.functions import expr # define the modules
7
8  # using select expression
9  newDF.select("Region", "Country",expr("CASE WHEN Total_Profit > 300000 THEN  'Good' ELSE 'Average' END AS value_desc")).show(3)
```

▸ (2) Spark Jobs

▸ newDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 12 more fields]

```
+------------------+-------+----------+-------------+--------------+----------+--------+----------+----------+----------+---------+-------------+----------+------------+
|            Region|Country| Item Type|Sales Channel|Order Priority|Order Date|Order ID| Ship Date|Units Sold|Unit Price|Unit Cost|Total Revenue|Total Cost|Total Profit|
+------------------+-------+----------+-------------+--------------+----------+--------+----------+----------+----------+---------+-------------+----------+------------+
|Sub-Saharan Africa|Burundi|Vegetables|       Online|             M|11/17/2010|951380240|12/20/2010|      3410|    154.06|    90.93|     525344.6|  310071.3|    215273.3|
|            Europe|Ukraine| Cosmetics|       Online|             M|11/13/2014|270001733|  1/1/2015|      8368|     437.2|   263.33|    3658489.6|2203545.44|  1454944.16|
|            Europe|Croatia| Beverages|       Online|             C| 6/16/2016|681941401| 7/28/2016|       470|     47.45|    31.79|      22301.5|   14941.3|      7360.2|
+------------------+-------+----------+-------------+--------------+----------+--------+----------+----------+----------+---------+-------------+----------+------------+
only showing top 3 rows

+------------------+-------+----------+
|            Region|Country|value_desc|
+------------------+-------+----------+
|Sub-Saharan Africa|Burundi|   Average|
|            Europe|Ukraine|      Good|
|            Europe|Croatia|   Average|
+------------------+-------+----------+
only showing top 3 rows
```

Handling null Values

1

```
1  from pyspark.sql.types import *   # import the libraries
2
3  # define a list
4  list_data = [["Bill Gates",23],["Henry Ford", None], ["Tim Cook", None]]
5
6  # define the schema
7  schema = StructType([StructField("Name", StringType()),StructField("Experience", IntegerType())])
8
9  # create a dataframe
10 df = spark.createDataFrame(list_data,schema=schema)
11
12 df.show() # display the dataframe
```

▸ (3) Spark Jobs

▸ df: pyspark.sql.dataframe.DataFrame = [Name: string, Experience: integer]

```
+----------+----------+
|      Name|Experience|
+----------+----------+
|Bill Gates|        23|
|Henry Ford|      null|
|  Tim Cook|      null|
+----------+----------+
```

Handling null Values


```
1  # drop null value rows
2  df.na.drop().show()
```

▸ (3) Spark Jobs

```
+----------+-----+
|        ID|Month|
+----------+-----+
|Bill Gates|   23|
+----------+-----+
```

```
1  # fill null value with a constant value
2  df.fillna(34).show()
```

▸ (3) Spark Jobs

```
+----------+----------+
|      Name|Experience|
+----------+----------+
|Bill Gates|        23|
|Henry Ford|        34|
|  Tim Cook|        34|
+----------+----------+
```

Replacing Values

```
1  # replace a single value
2  df.na.replace('Bill Gates', 'Satya Nadella').show()
```

▸ (3) Spark Jobs

```
+-------------+----------+
|         Name|Experience|
+-------------+----------+
|Satya Nadella|        23|
|   Henry Ford|      null|
|     Tim Cook|      null|
+-------------+----------+
```

```
1  # replace multiple values and also fill 'null' with a constant value
2  df.na.replace(['Bill Gates', 'Tim Cook'], ['Satya N', 'Time'], 'Name').fillna(40).show()
```

▸ (3) Spark Jobs

```
+----------+----------+
|      Name|Experience|
+----------+----------+
|   Satya N|        23|
|Henry Ford|        40|
|      Time|        40|
+----------+----------+
```

DataFrame Aggregations

1

- A set of methods for aggregations on a DataFrame:
  - agg
  - avg
  - count
  - max
  - mean
  - min
  - pivot
  - sum

DataFrame Aggregations

2

```
# rename the existing columns - "Item Type" to "ItemType" and "Total Profit" to "Total_Profit"
newDF = creditcardDF.withColumnRenamed("Item Type", "ItemType").withColumnRenamed("Total Profit", "Total_Profit")

# find maximum total_profit for each region and alias the column to "Maximum"
newDF.groupBy("Region").max("Total_Profit").alias("Maximum").show(10, False)
```

▸ (2) Spark Jobs

▸ newDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 12 more fields]

```
+---------------------------------+-----------------+
|Region                           |max(Total_Profit)|
+---------------------------------+-----------------+
|Middle East and North Africa     |1682887.73       |
|Australia and Oceania            |1631943.31       |
|Europe                           |1726181.36       |
|Sub-Saharan Africa               |1571089.32       |
|Central America and the Caribbean|1631422.21       |
|North America                    |1541620.46       |
|Asia                             |1725485.88       |
+---------------------------------+-----------------+
```

DataFrame Aggregations

3

```
1  # count of items in each region
2  newDF.groupBy("Region").agg({'ItemType':'count'}).show(10, False)
```

▸ (2) Spark Jobs

```
+---------------------------------+---------------+
|Region                           |count(ItemType)|
+---------------------------------+---------------+
|Middle East and North Africa     |132            |
|Australia and Oceania            |76             |
|Europe                           |255            |
|Sub-Saharan Africa               |247            |
|Central America and the Caribbean|93             |
|North America                    |16             |
|Asia                             |130            |
+---------------------------------+---------------+
```

DataFrame Aggregations

4

```
1  from pyspark.sql.functions import avg # include the library
2
3  # find average of column - "Total_Profit"
4  newDF.select(avg("Total_Profit").alias("Average Profit")).show()
```

▸ (2) Spark Jobs

```
+------------------+
|   Average Profit|
+------------------+
|392951.5061011591|
+------------------+
```

Ordering DataFrame Rows

```
1  # include the library
2  from pyspark.sql.functions import col
3
4  # order the records by region - ascending
5  creditcardDF.orderBy('Region', ascending=True).select("Region","Country", "Item Type", "Order ID", "Total Profit").show(3)
```

▸ (1) Spark Jobs

```
+------+-----------+---------------+---------+------------+
|Region|    Country|      Item Type| Order ID|Total Profit|
+------+-----------+---------------+---------+------------+
|  Asia| Uzbekistan|Office Supplies|276595246|  1203793.75|
|  Asia|South Korea|         Fruits|769205892|     9572.52|
|  Asia|   Malaysia|         Snacks|175033080|   277519.62|
+------+-----------+---------------+---------+------------+
only showing top 3 rows
```

```
1  # include the library
2  from pyspark.sql.functions import col
3
4  # order the records by region - descending
5  creditcardDF.orderBy('Region', ascending=False).select("Region","Country", "Item Type", "Order ID", "Total Profit").show(3)
```

▸ (1) Spark Jobs

```
+------------------+--------------------+---------------+---------+------------+
|            Region|             Country|      Item Type| Order ID|Total Profit|
+------------------+--------------------+---------------+---------+------------+
|Sub-Saharan Africa|            Botswana|        Clothes|680517470|   668083.68|
|Sub-Saharan Africa|Central African R...|Office Supplies|668599021|   273078.75|
|Sub-Saharan Africa|            Tanzania|  Personal Care|400304734|   198500.26|
+------------------+--------------------+---------------+---------+------------+
only showing top 3 rows
```

Cache and Persist

1

- Cache() - defaults storage level to MEMORY_ONLY
- Persist() - saves the intermediate results in 5 storage levels:
  - MEMORY_ONLY
  - MEMORY_AND_DISK
  - MEMORY_ONLY_SER
  - MEMORY_AND_DISK_SER
  - DISK_ONLY

Cache and Persist

2

```
1  # cache and persist
2  from pyspark import StorageLevel
3
4  # cache the dataframe in in-memory
5  cacheDF = creditcardDF.cache()
6
7  # read the records from cache
8  cacheDF.select("Region", "Country", "Item Type", "Sales Channel", "Order Priority", \
9                 "Order Date", "Order ID", "Ship Date").show(4, truncate=False)
```

▸ (1) Spark Jobs

▸ cacheDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 12 more fields]

```
+------------------+----------+----------+-------------+--------------+----------+---------+----------+
|Region            |Country   |Item Type |Sales Channel|Order Priority|Order Date|Order ID |Ship Date |
+------------------+----------+----------+-------------+--------------+----------+---------+----------+
|Sub-Saharan Africa|Burundi   |Vegetables|Online       |M             |11/17/2010|951380240|12/20/2010|
|Europe            |Ukraine   |Cosmetics |Online       |M             |11/13/2014|270001733|1/1/2015  |
|Europe            |Croatia   |Beverages |Online       |C             |6/16/2016 |681941401|7/28/2016 |
|Sub-Saharan Africa|Madagascar|Fruits    |Online       |L             |5/31/2016 |566935575|6/7/2016  |
+------------------+----------+----------+-------------+--------------+----------+---------+----------+
only showing top 4 rows
```

Cache and Persist

3

```
# cache and persist
from pyspark import StorageLevel

# persist the dataframe in both memo
persistDF = creditcardDF.persist(StorageLevel.MEMORY_AND_DISK)

# read the records from saved dataframe
persistDF.select("Region", "Country", "Item Type", "Sales Channel", "Order Priority", \
                 "Order Date", "Order ID").show(4, truncate=False)
```

▸ (1) Spark Jobs

▸ persistDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 12 more fields]

```
+------------------+----------+----------+-------------+--------------+----------+---------+
|Region            |Country   |Item Type |Sales Channel|Order Priority|Order Date|Order ID |
+------------------+----------+----------+-------------+--------------+----------+---------+
|Sub-Saharan Africa|Burundi   |Vegetables|Online       |M             |11/17/2010|951380240|
|Europe            |Ukraine   |Cosmetics |Online       |M             |11/13/2014|270001733|
|Europe            |Croatia   |Beverages |Online       |C             |6/16/2016 |681941401|
|Sub-Saharan Africa|Madagascar|Fruits    |Online       |L             |5/31/2016 |566935575|
+------------------+----------+----------+-------------+--------------+----------+---------+
only showing top 4 rows
```

Coalesce and Repartition

1

SNo	Coalesce	Repartition
1	Reduces the number of partitions	Can be used to either increase or decrease the number of partitions
2	Uses existing partitions to minimize the amount of data shuffling	Creates new partitions and performs full shuffling
3	Results in partitions having different sizes	Results in partitions having same size of data

Coalesce and Repartition

2

```
1  # coalesce vs repartition
2  print("Number of partitions : ", creditcardDF.rdd.getNumPartitions())
3
4  # increase the number of partitions
5  cDF = creditcardDF.repartition(2)
6
7  # number of partitions after repatitioning
8  print("Number of partitions : ", cDF.rdd.getNumPartitions())
9
10 # reduce the number of partitions
11 cDF = cDF.coalesce(1)
12
13 # number of partitions after coalesce
14 print("Number of partitions : ", cDF.rdd.getNumPartitions())
```

▸ (2) Spark Jobs

▸ cDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 12 more fields]

```
Number of partitions :  1
Number of partitions :  2
Number of partitions :  1
```

DataFrameWriter

1

```
1  # aggregates the Item Type count by region, brings the data to a single partition
2  writeDF = newDF.groupBy("Region").agg({'ItemType':'count'}).coalesce(1)
3
4  # write to DBFS - mode: "overwrite" replaces the existing file and "append" adds the content
5  writeDF.write.option("header","true").option("sep",",").mode("overwrite").csv("/FileStore/tables/Aggregate/")
```

▸ (2) Spark Jobs

▸ writeDF: pyspark.sql.dataframe.DataFrame = [Region: string, count(ItemType): long]

```
1  %fs ls "/FileStore/tables/Aggregate/"
```

	path	name
1	dbfs:/FileStore/tables/Aggregate/_SUCCESS	_SUCCESS
2	dbfs:/FileStore/tables/Aggregate/_committed_2341650654956389289	_committed_2341650654956389289
3	dbfs:/FileStore/tables/Aggregate/_committed_3214256169176087794	_committed_3214256169176087794
4	dbfs:/FileStore/tables/Aggregate/_committed_vacuum897728018297915484 4	_committed_vacuum897728018297915484 4
5	dbfs:/FileStore/tables/Aggregate/_started_2341650654956389289	_started_2341650654956389289
6	dbfs:/FileStore/tables/Aggregate/part-00000-tid-2341650654956389289-3daeebed-c9cf-4cf0-98bb-7a2a9f21cae7-175-1-c000.csv	part-00000-tid-2341650654956389289-3daeebed-c9cf-4cf0-98bb-7a2a9f21cae7-175-1-c000.csv

Showing all 6 rows.

%fs executes the list command (“ls”) and displays all the files in the mentioned folder

DataFrameWriter

2

```
1  # read the csv file
2  newDF = spark.read.format("csv").option("header", "true").option("inferSchema", "true") \
3     .load("/FileStore/tables/Aggregate/part-00000-tid-2341650654956389289-3daeebed-c9cf-4cf0-98bb-7a2a9f21cae7-175-1-c000.csv")
4
5  # display the records
6  newDF.show(10, False)
```

▸ (3) Spark Jobs

▸ newDF: pyspark.sql.dataframe.DataFrame = [Region: string, count(ItemType): integer]

```
+--------------------------------+---------------+
|Region                          |count(ItemType)|
+--------------------------------+---------------+
|Middle East and North Africa    |132            |
|Australia and Oceania           |76             |
|Europe                          |255            |
|Sub-Saharan Africa              |247            |
|Central America and the Caribbean|93            |
|North America                   |16             |
|Asia                            |130            |
+--------------------------------+---------------+
```

Class Exercise

- Upload a CSV file in to DBFS ("/FileStore/tables/credit.csv")
- Create a DataFrame by reading CSV file using spark.read.format("csv")
- Apply DSL methods to perform the below:
  - Select all columns, and select only a few columns
  - Rename and drop existing columns
  - Change the data type of a column from float to double
  - Replace null values
  - Apply agg functions
- Write the result DataFrame in to DBFS ("/FileStore/tables/result/")

Spark SQL

Table of Content

Spark SQL

- Spark SQL is a Spark module for structured data processing
- Provides powerful integration with the rest of the Spark ecosystem
- Spark SQL brings native support for SQL to Spark
- Provides a programming abstraction called DataFrames
- Enables working with structured data, either within Spark programs or through JDBC and ODBC connectors

Create Table from a DataFrame

1

```
# spark SQL
# create a DataFrame
from pyspark.sql.types import *   # import the library
leader_data = [["Middle East and North Africa","Mohammed Saif"],["Australia and Oceania", "George Carlin"], \
               ["Europe", "Stuart Broad"], ["Sub-Saharan Africa", "Abdalla"], ["Central America and the Caribbean", "Chris Gayle"], \
               ["North America", "George Bush"], ["Asia", "Tatyaso Martin"]]

# define the schema
schema = StructType([StructField("Region", StringType()), StructField("SalesPerson", StringType())])

# create a dataframe and display the records
df = spark.createDataFrame(leader_data,schema=schema)
df.show(10, False)
```

▸ (3) Spark Jobs

▸ df: pyspark.sql.dataframe.DataFrame = [Region: string, SalesPerson: string]

```
+-------------------------------+--------------+
|Region                         |SalesPerson   |
+-------------------------------+--------------+
|Middle East and North Africa   |Mohammed Saif |
|Australia and Oceania          |George Carlin |
|Europe                         |Stuart Broad  |
|Sub-Saharan Africa             |Abdalla       |
|Central America and the Caribbean|Chris Gayle   |
|North America                  |George Bush   |
|Asia                           |Tatyaso Martin|
+-------------------------------+--------------+
```

Create Table from a DataFrame

2

```
1  df.createOrReplaceTempView("sales_table")  # convert dataframe to view
2
3  # write sql queries using sql()
4  sql("select * from sales_table").show(10, False)
```

▸ (3) Spark Jobs

```
+--------------------------------+--------------+
|Region                          |SalesPerson   |
+--------------------------------+--------------+
|Middle East and North Africa    |Mohammed Saif |
|Australia and Oceania           |George Carlin |
|Europe                          |Stuart Broad  |
|Sub-Saharan Africa              |Abdalla       |
|Central America and the Caribbean|Chris Gayle   |
|North America                   |George Bush   |
|Asia                            |Tatyaso Martin|
+--------------------------------+--------------+
```

Querying the Table

```
1  sql("select * from sales_table where Region = 'Asia'").show(10, False)
```

▸ (3) Spark Jobs

```
+------+--------------+
|Region|SalesPerson   |
+------+--------------+
|Asia  |Tatyaso Martin|
+------+--------------+
```

```
1  sql("select * from sales_table where SalesPerson like '%George%'").show(10, False)
```

▸ (3) Spark Jobs

```
+---------------------+-------------+
|Region               |SalesPerson  |
+---------------------+-------------+
|Australia and Oceania|George Carlin|
|North America        |George Bush  |
+---------------------+-------------+
```

```
1  sql("select count(*) from sales_table").show()
```

▸ (2) Spark Jobs

```
+--------+
|count(1)|
+--------+
|       7|
+--------+
```

Aggregations

```
1  # renaming a column using DSL
2  newDF = creditcardDF.withColumnRenamed("Total Revenue", "TotalRevenue")
3
4  # create a temp view
5
6  newDF.createOrReplaceTempView("creditcard")
7
8  # apply aggregations on the table data
9  sql("select Region, max(TotalRevenue) from creditcard group by Region").show(truncate=False)
```

▸ (2) Spark Jobs

▸ newDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 12 more fields]

```
+---------------------------------+-----------------+
|Region                           |max(TotalRevenue)|
+---------------------------------+-----------------+
|Middle East and North Africa     |6160781.13       |
|Australia and Oceania            |6580454.69       |
|Europe                           |6617209.54       |
|Sub-Saharan Africa               |6263026.44       |
|Central America and the Caribbean|6354579.43       |
|North America                    |6216247.54       |
|Asia                             |6557065.24       |
+---------------------------------+-----------------+
```

Ordering the Records (Asc, Desc)

```
1  sql("select Region, max(TotalRevenue) from creditcard group by Region order by Region").show(truncate=False)
```

▸ (2) Spark Jobs

```
+---------------------------------+-----------------+
|Region                           |max(TotalRevenue)|
+---------------------------------+-----------------+
|Asia                             |6557065.24       |
|Australia and Oceania            |6580454.69       |
|Central America and the Caribbean|6354579.43       |
|Europe                           |6617209.54       |
|Middle East and North Africa     |6160781.13       |
|North America                    |6216247.54       |
|Sub-Saharan Africa               |6263026.44       |
+---------------------------------+-----------------+
```

```
1  sql("select Region, max(TotalRevenue) from creditcard group by Region order by Region desc").show(truncate=False)
```

▸ (2) Spark Jobs

```
+---------------------------------+-----------------+
|Region                           |max(TotalRevenue)|
+---------------------------------+-----------------+
|Sub-Saharan Africa               |6263026.44       |
|North America                    |6216247.54       |
|Middle East and North Africa     |6160781.13       |
|Europe                           |6617209.54       |
|Central America and the Caribbean|6354579.43       |
|Australia and Oceania            |6580454.69       |
|Asia                             |6557065.24       |
+---------------------------------+-----------------+
```

Joining the Tables

1

```
1  # join (inner) creditcard and sales_table, display the results
2  sql("""select a.Region, a.Country, b.SalesPerson
3         from creditcard a
4         join sales_table b
5         on trim(a.Region) = trim(b.Region)""").show(5, False)
```

▸ (2) Spark Jobs

```
+----------------------------+--------------------+-------------+
|Region                      |Country             |SalesPerson  |
+----------------------------+--------------------+-------------+
|Middle East and North Africa|United Arab Emirates|Mohammed Saif|
|Middle East and North Africa|Azerbaijan          |Mohammed Saif|
|Middle East and North Africa|Yemen               |Mohammed Saif|
|Middle East and North Africa|Bahrain             |Mohammed Saif|
|Middle East and North Africa|Jordan              |Mohammed Saif|
+----------------------------+--------------------+-------------+
only showing top 5 rows
```

Joining the Tables

2

```
# join (inner) creditcard and sales_table, apply a where condition, display the results
df = sql("""select a.Region, a.Country, b.SalesPerson
       from creditcard a
       join sales_table b
       on trim(a.Region) = trim(b.Region)
       where trim(a.Region) = "Asia"
       """).show(5, False)
```

▸ (3) Spark Jobs

```
+------+--------+--------------+
|Region|Country |SalesPerson   |
+------+--------+--------------+
|Asia  |Nepal   |Tatyaso Martin|
|Asia  |Mongolia|Tatyaso Martin|
|Asia  |Brunei  |Tatyaso Martin|
|Asia  |Laos    |Tatyaso Martin|
|Asia  |Mongolia|Tatyaso Martin|
+------+--------+--------------+
only showing top 5 rows
```

Saving the Results in to DBFS

1

```
# write the results in to DBFS
df = sql("""select a.Region, a.Country, b.SalesPerson
       from creditcard a
       join sales_table b
       on trim(a.Region) = trim(b.Region)
       where trim(a.Region) = "Asia"
       """)


df.coalesce(1).write.option("header","true").mode("overwrite").csv("/FileStore/tables/spark/")
```

▸ (1) Spark Jobs

▸ df: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 1 more fields]

Saving the Results in to DBFS

2

```
%fs ls "/FileStore/tables/spark/"
```

	path	name
1	dbfs:/FileStore/tables/spark/_SUCCESS	_SUCCESS
2	dbfs:/FileStore/tables/spark/_committed_6906066050643623387	_committed_6906066050643623387
3	dbfs:/FileStore/tables/spark/_started_6906066050643623387	_started_6906066050643623387
4	dbfs:/FileStore/tables/spark/part-00000-tid-6906066050643623387-cf95ee82-b0a3-45fe-8105-779871192a2c-479-1-c000.csv	part-00000-tid-6906066050643623387-cf95ee82-b0a3-45fe-8105-779871192a2c-479-1-c000.csv

Showing all 4 rows.

```
# read the csv file from stored location
newDF = spark.read.format("csv").option("header", "true").option("inferSchema", "true") \
.load("/FileStore/tables/spark/part-00000-tid-7896517250555459845-acebf487-b3db-448d-ab44-06942b9588b2-254-1-c000.csv")

newDF.show(10, False)
```

▸ (3) Spark Jobs

▸ newDF: pyspark.sql.dataframe.DataFrame = [Region: string, Country: string ... 1 more fields]

```
+------+----------+--------------+
|Region|Country   |SalesPerson   |
+------+----------+--------------+
|Asia  |Nepal     |Tatyaso Martin|
|Asia  |Mongolia  |Tatyaso Martin|
|Asia  |Brunei    |Tatyaso Martin|
|Asia  |Laos      |Tatyaso Martin|
|Asia  |Mongolia  |Tatyaso Martin|
|Asia  |Indonesia |Tatyaso Martin|
|Asia  |Bhutan    |Tatyaso Martin|
|Asia  |Tajikistan|Tatyaso Martin|
|Asia  |India     |Tatyaso Martin|
|Asia  |Maldives  |Tatyaso Martin|
+------+----------+--------------+
only showing top 10 rows
```

Summary

- Apache Spark is a open Source from Apache Software Foundation
- It is 100 times faster than Hadoop MapReduce
- Resilient Distributed Dataset (RDD) and Direct Acyclic Graph (DAG) are the two important abstractions of Spark
- There are two types of RDD Operations: Transformation and Actions
- Spark SQL API provides structured data processing

Thank You