

Apache Spark SQL

Structured Data Processing



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<https://youtu.be/53FP8BaVzks>



CN7031 – Lecture 6



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Outline

- Spark vs Hadoop (Recap)
- Spark Ecosystem
- What is Spark SQL
- What is DataFrame
- DataFrame Operations
- Spark SQL Queries
- Visualization with Matplotlib



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Learning Outcomes

- Be able to explain Spark SQL and its features
- Understand DataFrame and compare it with RDD
- Understand DataFrame operations
- Be able to write Spark SQL queries
- Use Matplotlib for visualization



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Spark vs Hadoop (Recap)

Factors	Spark	Hadoop MapReduce
Speed	100x times than MapReduce	Faster than traditional system
Written In	Scala	Java
Data Processing	Batch / real-time / iterative / interactive / graph	Batch processing
Ease of Use	Compact & easier than Hadoop	Complex & lengthy
Caching	Caches the data in-memory & enhances the system performance	Doesn't support caching of data



Spark Ecosystem

SPARK ARCHITECTURE

APIs

Scala

Python

R

Java

Libraries

Spark Streaming

Spark SQL

GraphX

MLlib

Processing engine

Spark Core



Resource management

Standalone



Data storage



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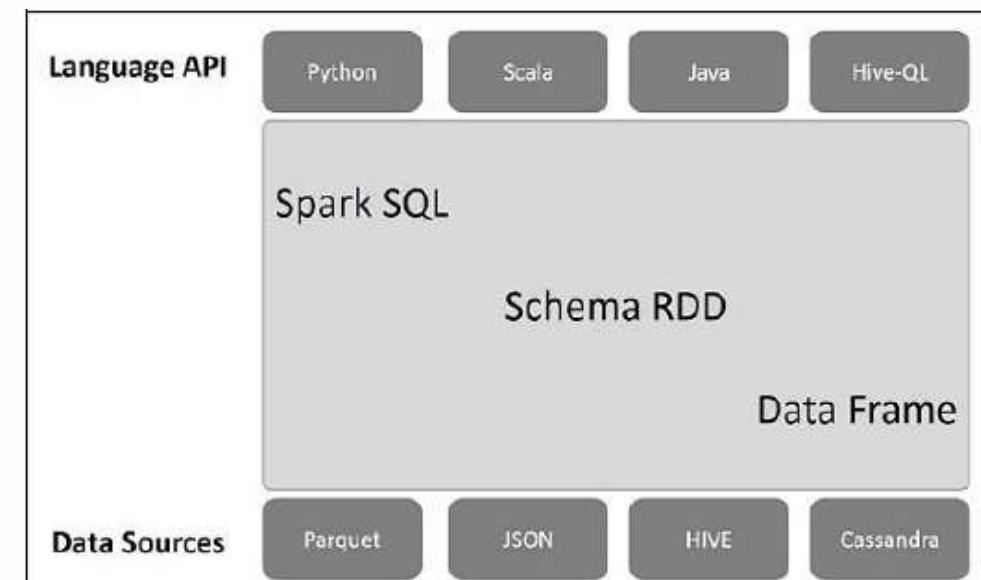
Spark Ecosystem

- **Engine — Spark Core:** It is the basic core component of Spark ecosystem on top of which the entire ecosystem is built. It performs the tasks of scheduling/monitoring and basic IO functionality
- **Management** — Spark cluster can be managed by Hadoop YARN, Mesos or Spark cluster manager.
- **Library** — Spark ecosystem comprises of Spark SQL (for running SQL like queries on RDD or data frame from external sources), Spark Mlib (for ML), Spark GraphX (for constructing graphs for better visualisation of data), Spark streaming (for batch processing and streaming of data in the same application)
- **APIs/Programming** can be done in Python, Java, Scala and R
- **Storage** — Data can be stored in HDFS, S3, local storage and it supports both SQL and NoSQL databases.



What is Spark SQL?

- Spark introduces a programming module for structured and semi-structured data processing called Spark SQL.
- Spark SQL is a component on top of Spark Core
- It introduces a new data abstraction called Schema RDD or DataFrame and can act as distributed SQL query engine.
- **Language API:** Spark is compatible with different languages- API (python, scala, java, HiveQL).
- **Schema RDD:** Spark Core is designed with RDD. Spark SQL works on Schema RDD which is called Data Frame.
- **Data Sources:** Data source for spark-core is a text file, Avro file, etc.
The Data Sources for Spark SQL are Parquet file, JSON document, HIVE tables.



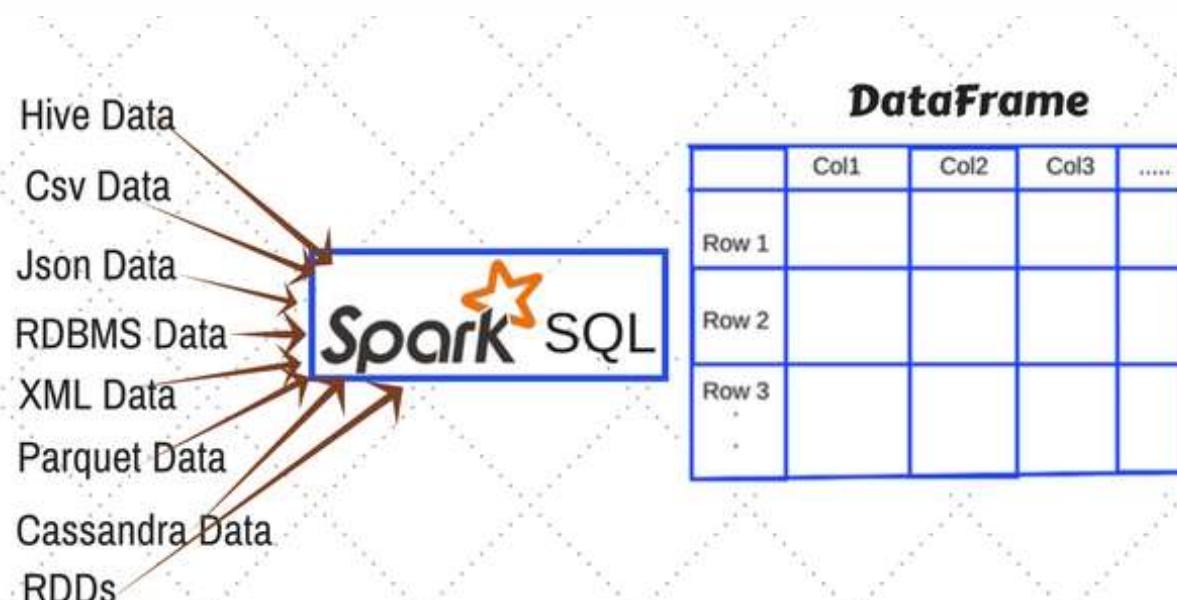
Features of Spark SQL

1. **Integrated:** Mix SQL queries with Spark programs. Spark SQL lets you query structured data as a distributed dataset (RDD) in Spark, with integrated APIs in Python, Scala and Java. This tight integration makes it easy to run SQL queries alongside complex analytic algorithms.
2. **Unified Data Access:** Load and query data from a variety of sources. SchemaRDDs provide a single interface for efficiently working with structured data, including Apache Hive tables, parquet files and JSON files.
3. **Hive Compatibility:** Run unmodified Hive queries on existing warehouses. Spark SQL reuses the Hive frontend and MetaStore, giving you full compatibility with existing Hive data, queries, and UDFs. Simply install it alongside Hive.
4. **Standard Connectivity:** Connect through JDBC or ODBC. Spark SQL includes a server mode with industry standard JDBC and ODBC connectivity.
5. **Scalability:** Use the same engine for both interactive and long queries. Spark SQL takes advantage of the RDD model to support mid-query fault tolerance, letting it scale to large jobs too. Do not worry about using a different engine for historical data.



What is DataFrame?

- A DataFrame is a distributed collection of data, which is organized into named columns. Conceptually, it is equivalent to relational tables with good optimization techniques.
- A DataFrame can be constructed from different sources such as Hive tables, Structured Data files, external databases, or existing RDDs.



Features of DataFrame

Here is a set of few characteristic features of DataFrame:

- Ability to process the data in the size of Kilobytes to Petabytes on a single node cluster to large cluster.
- Supports different data formats (Avro, csv, elastic search, and Cassandra) and storage systems (HDFS, HIVE tables, mysql, etc).
- State of art optimization and code generation through the Spark SQL Catalyst optimizer (tree transformation framework).
- Can be easily integrated with all Big Data tools and frameworks via Spark-Core.
- Provides API for Python, Java, Scala, and R Programming.



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.



RDD disadvantages

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

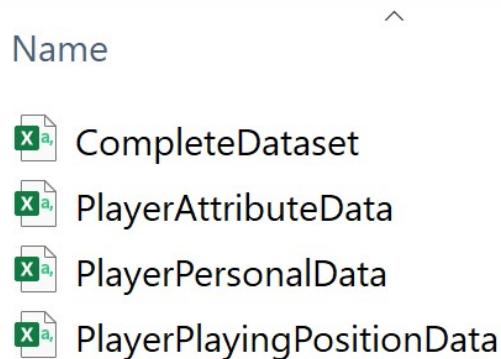


2. **Hard to Use:** RDD needs Python/Scala/Java coding, but DataFrame and Dataset need SQL-like queries, and anyone who knows SQL will understand it in one go.
3. **Slow Speed:** the main reason to not use RDD is its performance, which can be a major issue for some applications.



Example: FIFA 18

- 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>.
- This dataset contains every player featuring in the famous Soccer Video Game, FIFA 18.
- Extracting the downloaded zip file, you have four csv files.



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Example: FIFA 18

PlayerAttributeData.csv — This file contains Player performance attributes (Overall, Potential, Aggression, Agility etc.) indexed by player id.

PlayerPersonalData.csv — This file contains basic Player personal attributes (Nationality, Club, Photo, Age, Wage, Value etc.)

PlayerPlayingPositionData.csv — This file contains Player preferred position and ratings at all positions.

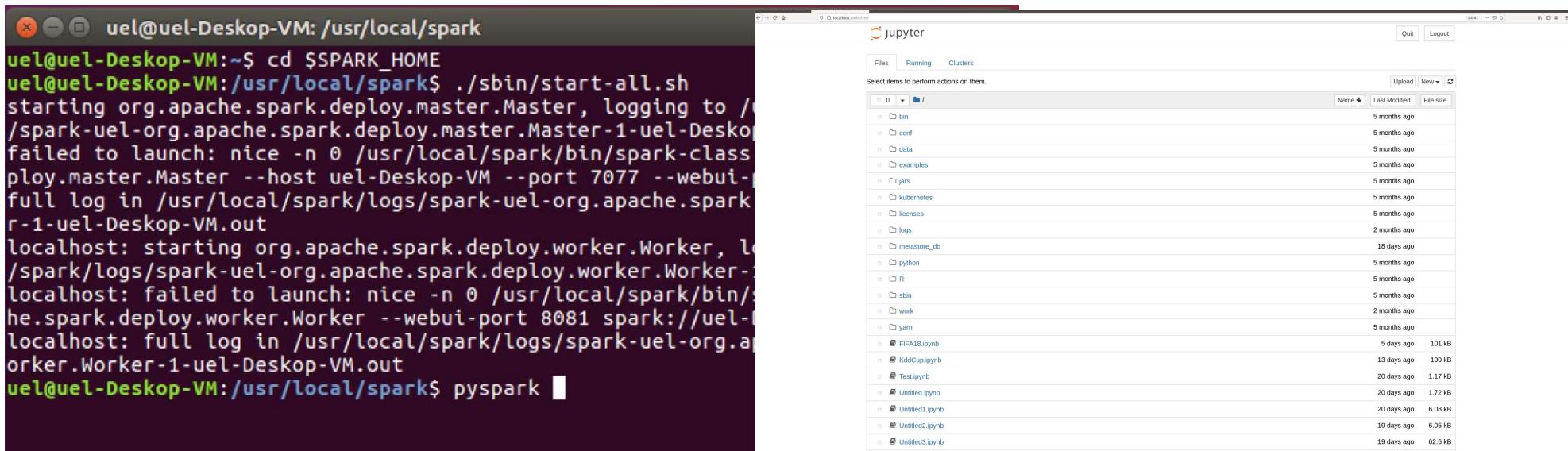
CompleteDataset.csv — This file is the complete dataset contains all information in above three dataset.



Launch PySpark in Ubuntu

You can launch PySpark in Ubuntu and execute the commands in Jupyter notebook.

- Launch VMWare
- Open and start up Ubuntu in VMWare
- Right the following commands in the terminal to launch PySpark and Jupyter
- Open a new notebook in Jupyter and type your commands.



The image shows two windows side-by-side. On the left is a terminal window titled 'uel@uel-Desktop-VM: /usr/local/spark'. It displays the following command sequence:

```
uel@uel-Desktop-VM:~$ cd $SPARK_HOME
uel@uel-Desktop-VM:/usr/local/spark$ ./sbin/start-all.sh
starting org.apache.spark.deploy.master.Master, logging to /usr/local/spark-uel-org.apache.spark.deploy.master.Master-1-uel-Desktop-VM.out
failed to launch: nice -n 0 /usr/local/spark/bin/spark-class
paly.master.Master --host uel-Desktop-VM --port 7077 --webui-p
full log in /usr/local/spark/logs/spark-uel-org.apache.spark
r-1-uel-Desktop-VM.out
localhost: starting org.apache.spark.deploy.worker.Worker, lo
/spark/logs/spark-uel-org.apache.spark.deploy.worker.Worker-1-uel-Desktop-VM.out
localhost: failed to launch: nice -n 0 /usr/local/spark/bin/s
he.spark.deploy.worker.Worker --webui-port 8081 spark://uel-Des
localhost: full log in /usr/local/spark/logs/spark-uel-org.ap
orker.Worker-1-uel-Desktop-VM.out
uel@uel-Desktop-VM:/usr/local/spark$ pyspark
```

On the right is a Jupyter notebook interface titled 'jupyter'. It shows a file list under the 'Files' tab. The table lists the following files:

Name	Last Modified	File size
bin	5 months ago	
conf	5 months ago	
data	5 months ago	
examples	5 months ago	
jars	5 months ago	
kubernetes	5 months ago	
licenses	5 months ago	
logs	2 months ago	
metastore_db	18 days ago	
python	5 months ago	
R	5 months ago	
sbin	5 months ago	
work	2 months ago	
yarn	5 months ago	
FIFA18.ipynb	5 days ago	101 kB
KidCup.ipynb	13 days ago	190 kB
Test.ipynb	20 days ago	1.17 kB
Untitled.ipynb	20 days ago	1.72 kB
Untitled1.ipynb	20 days ago	6.06 kB
Untitled2.ipynb	19 days ago	6.05 kB
Untitled3.ipynb	19 days ago	62.6 kB



Launch Spark in Google Colab

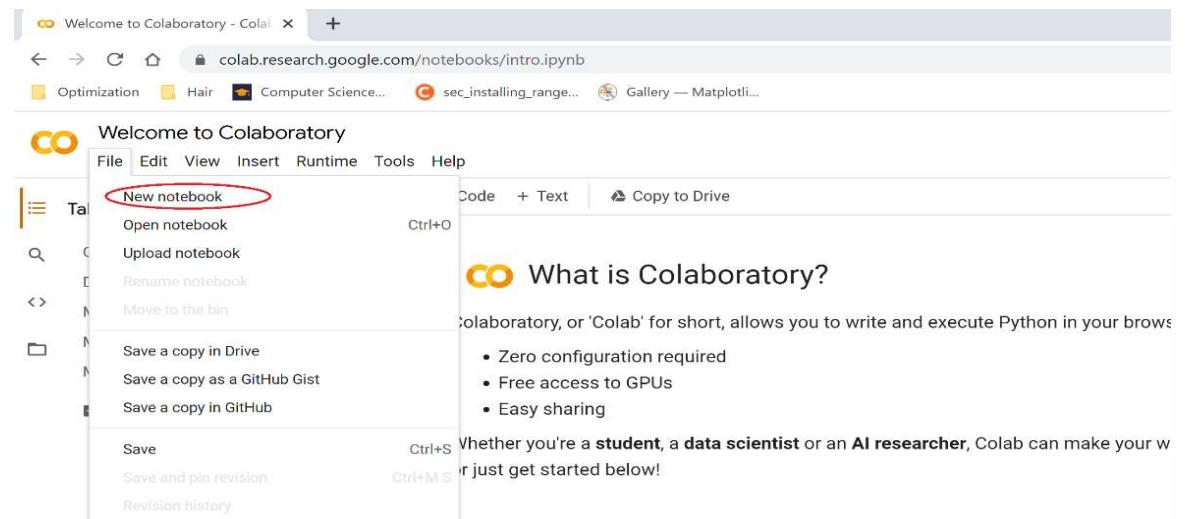
- Open the Google Colab through <https://colab.research.google.com/>
- Open a new notebook to type the commands.
- Type and run the following commands in the editor to install and launch Spark.

Old Version

```
# [1] download and install Spark in Google Colab
!sudo apt update
!apt-get install openjdk-8-jdk-headless -qq > /dev/null
!wget -q https://downloads.apache.org/spark/spark-
3.0.1/spark-3.0.1-bin-hadoop3.2.tgz
!tar xf spark-3.0.1-bin-hadoop3.2.tgz
!pip install -q findspark
```

```
# [2] Config JAVA and SPARK home
import os

os.environ["JAVA_HOME"]="/usr/lib/jvm/java-8-openjdk-amd64"
os.environ["SPARK_HOME"]="/content/spark-3.0.1-bin-hadoop3.2"
import findspark
findspark.init()
```



New Version

```
!pip3 install pyspark
```



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Starting Point: SparkSession

The entry point into all functionality in Spark is the `SparkSession` class. To create a basic `SparkSession`, just use `SparkSession.builder`:

```
from pyspark.sql import SparkSession
spark = SparkSession \
    .builder \
    .appName("Python Spark SQL basic example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

`SparkSession` in Spark 2.0 provides builtin support for Hive features including the ability to write queries using `HiveQL`, access to `Hive UDFs`, and the ability to read data from `Hive tables`. To use these features, you do not need to have an existing `Hive setup`.



Creating DataFrames (DFs)

With a SparkSession, applications can create DataFrames from an existing RDD, from a Hive table, or from Spark data sources.

- Read Data from a JSON file:
Create a DataFrame based on the content of a JSON file

```
# spark is an existing SparkSession  
df = spark.read.json("examples/src/main/resources/people.json")
```

OR

```
df = spark.read.load("examples/src/main/resources/people.json", format="json")
```



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Creating DataFrames (DFs) - continued

- Read Data from a CSV file: [FIFA Example](#)

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

OR

```
fifa_df2 = spark.read.load("/home/bigdata/Desktop/CompleteDataset.csv", format="csv", inferSchema=True, header=True)
```



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Creating DataFrames (DFs) - continued

- Read Data from Hive
 - 1) Spark SQL supports reading and writing data stored in Hive.
 - 2) Hive has a large number of dependencies, these dependencies are not included in the default Spark distribution.
 - 3) If Hive dependencies can be found on the classpath, Spark will load them automatically.

Note: Hive dependencies must be present on all of the worker nodes, as they will need access to the Hive serialization and deserialization libraries (SerDes) in order to access data stored in Hive.

Creating DataFrames (DFs) - continued

```
from os.path import join, abspath

from pyspark.sql import SparkSession
from pyspark.sql import Row

# warehouse_location points to the default location for managed databases and tables
warehouse_location = abspath('spark-warehouse')

spark = SparkSession \
    .builder \
    .appName("Python Spark SQL Hive integration example") \
    .config("spark.sql.warehouse.dir", warehouse_location) \
    .enableHiveSupport() \
    .getOrCreate()

# spark is an existing SparkSession
spark.sql("CREATE TABLE IF NOT EXISTS src (key INT, value STRING) USING hive")
spark.sql("LOAD DATA LOCAL INPATH 'examples/src/main/resources/kv1.txt' INTO TABLE src")

# Queries are expressed in HiveQL
spark.sql("SELECT * FROM src").show()
```

<https://spark.apache.org/docs/latest/sql-data-sources-hive-tables.html>



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Untyped Dataset Operations (DF Operations)

DataFrames provide a domain-specific language for structured data manipulation in Scala, Java, Python and R.

DF operations are also referred as “untyped transformations” in contrast to “typed transformations” come with strongly typed Scala/Java Datasets.

We are going to explain some basic examples of structured data processing using Datasets.

NOTE: In Python, it's possible to access a DataFrame's columns either by attribute (`df.age`) or by indexing (`df['age']`).

For a complete list of the types of operations that can be performed on a Dataset refer to the [API Documentation](#).



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DF Operations: Show ()

Show () Displays the Dataset in a tabular form.

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

```
fifa_df.show()
```

_c0	Name	Age	Photo	Nationality	Flag	Overall	Potential	C
lub	Club Logo	Value	Wage	Special	Acceleration	Aggression	Agility	Balance
ng	Dribbling	Finishing	Free kick accuracy	GK diving	GK handling	GK kicking	GK positioning	GK reflexes
Curve	Heading	Interceptions	Jumping	Long passing	Long shots	Marking	Penalties	Positioning
accuracy	Reactions	Short passing	Shot power	Sliding tackle	Sprint speed	Stamina	Standing tackle	Strength
Interceptions	Shot power	Sliding tackle	Stamina	Standing tackle	Strength	Vision	Volleys	CAM
Jumping	Sliding tackle	Stamina	Standing tackle	Strength	Vision	Volleys	CAM	CB
Long passing	Stamina	Standing tackle	Strength	Vision	Volleys	CAM	CB	CDM
Long shots	Strength	Standing tackle	Vision	Volleys	CAM	CB	CDM	CF
Marking	Vision	Volleys	Volleys	CAM	CB	CDM	CF	CM
Penalties	Volleys	CAM	CAM	CB	CDM	CF	CM	ID
Positioning	CAM	CB	CB	CDM	CF	CM	ID	L
Reactions	CB	CDM	CDM	CF	CM	ID	L	AM
Short passing	CDM	CF	CF	CM	ID	L	AM	LB
Sliding tackle	CF	CM	CM	ID	L	AM	LB	LCB
Sprint speed	CM	ID	L	AM	LB	LCB	LCM	LCM
Stamina	ID	L	AM	LB	LCB	LCM	LDM	LDM
Standing tackle	L	AM	LB	LCB	LCM	LDM	LF	LF
Strength	AM	LB	LCB	LCM	LDM	LF	LM	LM
Vision	LB	LCB	LCM	LDM	LF	LM	LS	LS
Volleys	LCB	LCM	LDM	LF	LM	LS	LW	LW
CAM	LCM	LDM	LF	LM	LS	LW	LWB	LWB
CB	LDM	LF	LM	LS	LW	LWB	Preferred Positions	Preferred Positions
CDM	LF	LM	LS	LW	LWB	Preferred Positions	RAM	RAM
CF	LM	LS	LW	LWB	Preferred Positions	RAM	RB	RB
CM	LW	LWB	Preferred Positions	RAM	RB	RB	RCB	RCB
ID	Preferred Positions	RAM	RB	RB	RCB	RCB	RCM	RCM
L	RAM	RB	RB	RCB	RCB	RCM	RDM	RDM
AM	RB	RB	RCB	RCB	RCM	RDM	RF	RF
LB	RB	RCB	RCB	RCM	RDM	RF	RM	RM
LCB	RCB	RCB	RCM	RDM	RF	RM	RS	RS
LCM	RCM	RDM	RF	RM	RS	RS	RW	RW
LDM	RDM	RF	RM	RS	RW	RW	F	ST
LF	RF	RM	RS	RW	F	ST		
LM	RM	RS	RW	F	ST			
LS	RS	RW	F	ST				
LW	RW	F	ST					
LWB	F	ST						
Preferred Positions								
RAM								
RB								
RCB								
RCM								
RDM								
RF								
RM								
RS								
RW								
F								
ST								



DF Operations: printSchema ()

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)
```



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DF Operations: Columns information

```
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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DF Operations: Select

```
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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DF Operations: Filter

This operation applies a filter on the existing DataFrame. For example, select people older than 21.

```
fifa_df.filter(fifa_df['age'] > 21).show()
```

_c0	Name	Age	Photo	Nationality	Flag	Overall	Potential
Club	Club Logo	Value	Wage	Special	Acceleration	Aggression	Agility
					Balence	Ball control	Composure
					Crossing	Curve	Dribbling
					Finishing	Free kick accuracy	GK diving
					GK handling	GK kicking	GK positioning
					GK reflexes	Heading accuracy	Interceptions
					Jumping	Long passing	Long shots
					Marking	Penalties	Positioning
					Reactions	Short passing	Shot power
					Sliding tackle	Sprint speed	Stamina
					Standing tackle	Strength	Vision
					Volleys	CAM	CB
AM	LAM	LB	LBC	LCM	LDM	LF	LM
WB	ST	LS	LW	LWB	Preferred Positions	RAM	RB
					RCB	RCM	RDM
					RF	RM	RS
					RW	F	WB



DF Operations: GroupBy

```
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
```



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Running SQL Queries (1)

We need to first register the DataFrame as a SQL temporary view and then define the queries on the view.

```
# Register the DataFrame as a SQL temporary view
fifa_df.createOrReplaceTempView("FifaView")
```

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

15	14	30	13	11	91	90	95	91	89	
25		30	78	59	16	10	47	12	85	55
11		61	44		83	70	11	null	null	167495
null	null	null	null	null	null	null	null	null	null	null
5	R. Lewandowski	28	https://cdn.sofif...		GK	null	null	null	null	FC Bayern Mur
ich	https://cdn.sofif...	€92M	€355K	2143		Poland	https://cdn.sofif...	91	91	
62	77	85	91		79	80	78	80	89	87
85		39	84	65	83	25	81	91	91	83
19		83	79		42	84	78	87	84.0	57.0
0	62.0	87.0	82.0	88.0	84.0	62.0	87.0	78.0	188545	84.0
	87.0	87.0	88.0	84.0	61.0	84.0	58.0	57.0	84.0	58.0
6	De Gea	26	https://cdn.sofif...		ST	84.0	58.0	57.0	78.0	62.0
ted	https://cdn.sofif...	€64.5M	€215K	1458		84.0	58.0	57.0	62.0	87.0
17	21	18	13		19	90	85	87		86
21		30	67	51	12	13	40	12	88	50
13		58	40		21	64	68	13	null	31
null	null	null	null	null	null	null	null	null	null	null
7	E. Hazard	26	https://cdn.sofif...		GK	null	null	null	null	Chel
sea	https://cdn.sofif...	€90.5M	€295K	2096		Belgium	https://cdn.sofif...	90	91	92
80	82	93	83		79	11	12	6		87
77	71	50	50	21	21	21	21	21	21	21



Running SQL Queries (2)

Count the number of players by age.

```
sqlDF = spark.sql("SELECT age, count(*) as count from FifaView GROUP BY age")
sqlDF.show()
```

```
+---+----+
|age|count|
+---+----+
| 31| 671|
| 34| 272|
| 28| 1051|
| 26| 1202|
| 27| 1152|
| 44| 2|
| 22| 1324|
| 47| 1|
| 16| 13|
| 20| 1245|
| 40| 8|
| 19| 1069|
| 41| 3|
| 43| 2|
| 37| 69|
| 17| 258|
| 35| 191|
| 39| 20|
| 23| 1394|
| 38| 36|
+---+----+
only showing top 20 rows
```

Running SQL Queries (3)

Count the number of players in each club.

```
sqlDF = spark.sql("SELECT club, count(*) FROM FifaView GROUP BY club")
sqlDF.show()
```

club	count(1)
Palermo	28
Yeovil Town	21
1. FC Union Berlin	27
Santiago Wanderers	20
Carpí	30
Evkur Yeni Malaty...	30
Sagan Tosu	25
FC Basel	25
Argentinos Juniors	28
Karlsruher SC	27
Lorca Deportiva CF	29
SC Paderborn 07	28
Cheltenham Town	28
San Lorenzo de Al...	28
SC Freiburg	32
SpVgg Unterhaching	28



Running SQL Queries (4)

Count the number of players in each club and displays those have more than 33 members.

```
sqlDF = spark.sql("SELECT club, count(*) FROM FifaView GROUP BY club HAVING Count(*) > 33")  
sqlDF.show()
```

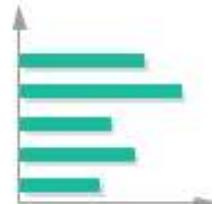
club	count(1)
Manchester United	34
UD Las Palmas	34
null	248
Olympique Lyonnais	34
VfL Wolfsburg	34
OGC Nice	34
Villarreal CF	35
FC Nantes	34
Borussia Dortmund	34

Matplotlib: Visualization with Python

Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python.



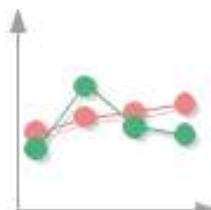
Pie



Bar



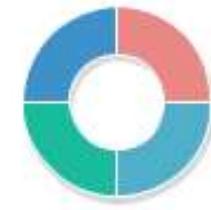
Column



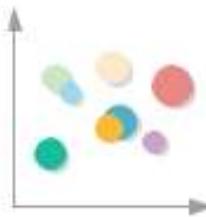
Line



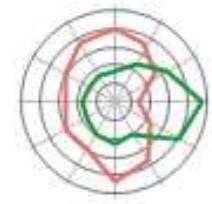
Area



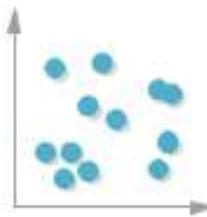
Doughnut



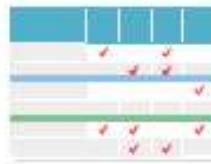
Bubble Chart



Spider and Radar



Scatter



Comparison Chart



Stacked bar chart



Gauges



Visualization with Python

Here are steps to visualize the output of Spark SQL using Matplotlib:

1. Import required libraries

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

2. Convert SQL dataframe to Pandas dataframe

```
pandas_df = sqlDF.toPandas()
```

3. Select parameters need to be visualised.
4. Decide which chart is appropriate for presenting your output.
5. Use pandas.DataFrame.plot()to define your chart.



Visualization with Python

You can also create these plots using the method `DataFrame.plot ()`

Syntax

```
DataFrame.plot (x, y, kind)
```

Each plot kind has a corresponding method on the
`DataFrame.plot` accessor:

```
df.plot(kind='line') ≈ df.plot.line()
```

x : label or position, default None
y : label, position or list of label, positions, default None
Allows plotting of one column versus another
kind : str

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot
- 'scatter' : scatter plot
- 'hexbin' : hexbin plot

Bar Chart

A bar chart is a chart that presents categorical data with rectangular bars with heights or lengths proportional to the values that they represent. The bars can be plotted vertically or horizontally.

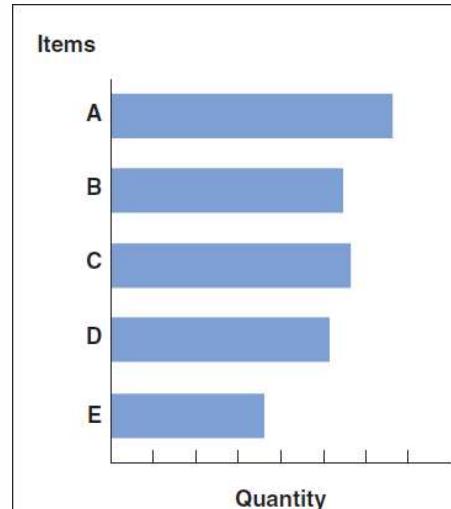


Figure 1. Horizontal graph

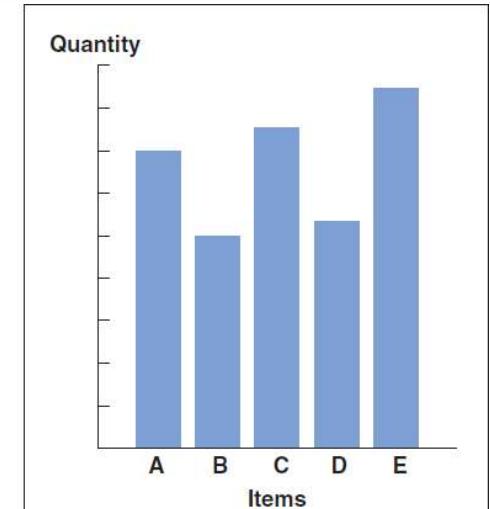


Figure 1. Vertical graph

Syntax

```
DataFrame.plot (x:str, y:str, kind='bar', logy:boolean)
```

OR

```
DataFrame.plot.bar (x:str, y:str, logy:boolean)
```



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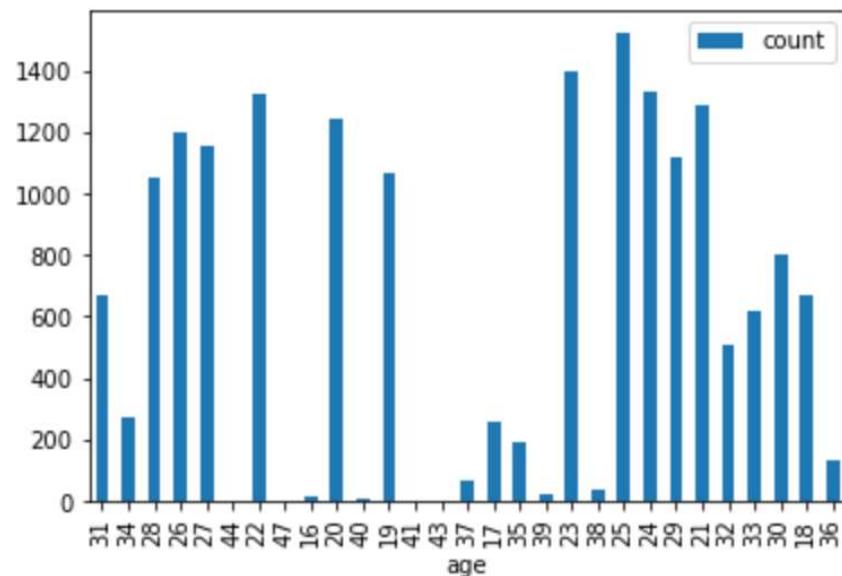
Bar Chart Example

```
sqlDF = spark.sql("SELECT age, count(*) as count from FifaView GROUP BY age")
sqlDF.show()
```

```
pandas_df = sqlDF.toPandas()
```

```
pandas_df.plot(x ='age', y='count', kind = 'bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa24f2c7580>
```



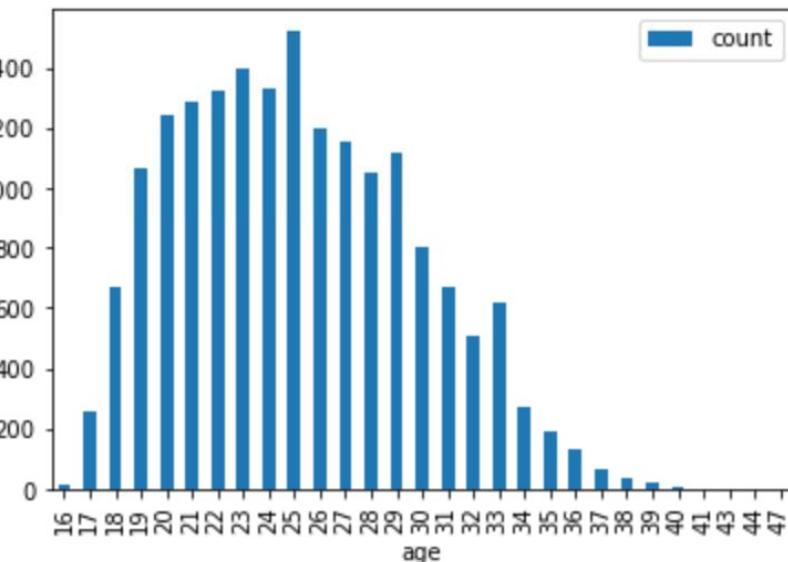
Bar Chart – Sorting Values

Syntax

```
DataFrame.sort_values (by:str, ascending:boolean)
```

Example

```
pandas_df.sort_values(by='age', ascending=True).plot(x ='age', y='count', kind = 'bar')  
<matplotlib.axes._subplots.AxesSubplot at 0x7f7303ebb6a0>
```



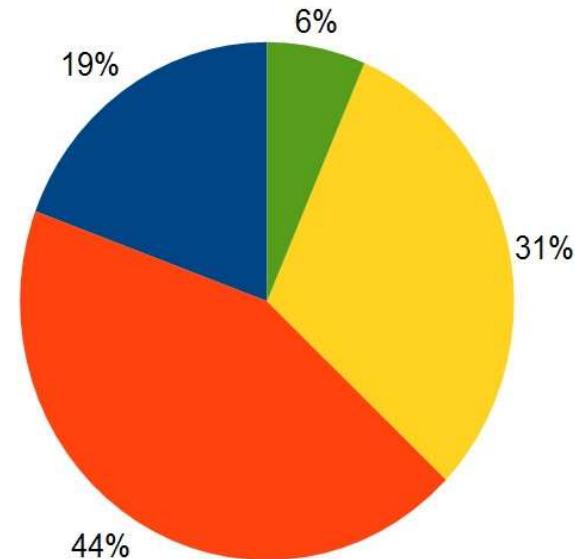
https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.sort_values.html



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Pie Chart

A pie chart is a circular statistical graphic, which is divided into slices to illustrate numerical proportion. In a pie chart, the arc length of each slice, is proportional to the quantity it represents.



Syntax

```
DataFrame.plot (x, y, kind='pie')
```

OR

```
DataFrame.plot.pie (x, y)
```



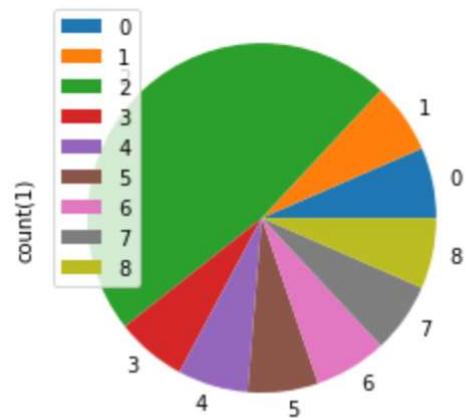
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Pie Chart Example

```
sqlDF = spark.sql("SELECT club, count(*) FROM FifaView GROUP BY club HAVING Count(*) > 33")
sqlDF.show()
```

```
pandas_df = sqlDF.toPandas()
```

```
pandas_df.plot(x ='club', y='count(1)', kind = 'pie')
<matplotlib.axes._subplots.AxesSubplot at 0x7f2ace8480d0>
```



Summary

- Introduced DataFrame
- Compared RDD vs DataFrame
- DataFrame Operations
- Learned SparkSQL
- Practiced SparkSQL Queries
- Learned Visualization with Matplotlib in Python



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