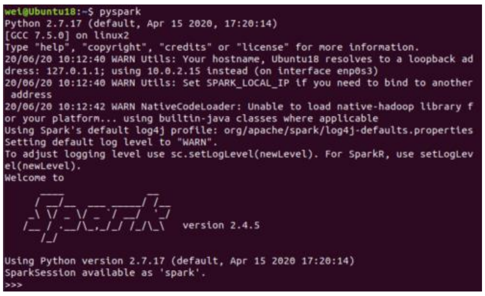
The Python code in this tutorial can be run in

1. Databricks (Cloud based)
    - Log in to your Databricks account and start a new notebook.
    - Type in and run the code in the notebook.

2. Ubuntu VM (Local setup)
    - Start PySpark shell

    $ pyspark



```
wei@Ubuntu18:~$ pyspark
Python 2.7.17 (default, Apr 15 2020, 17:20:14)
[GCC 7.5.0] on linux2
Type "help", "copyright", "credits" or "license" for more information.
20/06/20 10:12:40 WARN Utils: Your hostname, Ubuntu18 resolves to a loopback ad
dress: 127.0.1.1; using 10.0.2.15 instead (on interface enp0s3)
20/06/20 10:12:40 WARN Utils: Set SPARK_LOCAL_IP if you need to bind to another
 address
20/06/20 10:12:42 WARN NativeCodeLoader: Unable to load native-hadoop library f
or your platform... using builtin-java classes where applicable
Using Spark's default log4j profile: org/apache/spark/log4j-defaults.properties
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLev
el(newLevel).
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 2.4.5
      /_/

Using Python version 2.7.17 (default, Apr 15 2020 17:20:14)
SparkSession available as 'spark'.
>>>
```

- Type in and run the code in the PySpark shell.
- Alternatively, you may also use Jupyter Notebook to run the code if you have installed Anaconda on the Ubuntu VM.

3. PySpark SQL & DataFrames

Spark SQL is a Spark module for structured data processing. It provides a programming abstraction called DataFrames and can also act as a distributed SQL query engine.

3.1 Abstracting Data with DataFrames

A DataFrame is an immutable distributed collection of data with named columns. It is similar to a table in SQL. DataFrames are designed to process a large collection of structured data such as relational database and semi-structured data such as JSON (JavaScript Object Notation).

DataFrames in PySpark support both SQL queries (e.g. SELECT * from table) or expression methods (e.g. df.select()).

DataFrame can be created in two ways:
- From existing RDDs using SparkSession's createDataFrame() method
- Loading various data sources (CSV, JSON, TXT) into DataFrame using SparkSession's read method is the most common method to create DataFrames

```
### 1. RDD to DataFrame
# Need to pass an RDD and a schema (list of column names) into SparkSession's createDataFrame method

# Create a list of tuples
sample_list = [('Mona',20), ('Jennifer',34), ('John',20), ('Jim',26)]

# Create a RDD from the list
rdd = sc.parallelize(sample_list)

# Create a PySpark DataFrame
names_df = spark.createDataFrame(rdd, schema=['Name', 'Age'])

# Check the type of names_df
print("The type of names_df is", type(names_df))


### 2. Loading CSV into DataFrame

# Create an DataFrame from file_path
# Make you have uploaded the dataset file onto Databricks data store
# The file_path is for my Databricks account only. Yours will be different.
file_path = 'dbfs:/FileStore/shared_uploads/wei.jie@uwl.ac.uk/people.csv'
people_df = spark.read.csv(file_path, header=True, inferSchema=True)

# Check the type of people_df
print("The type of people_df is", type(people_df))
```

```
The type of names_df is <class 'pyspark.sql.dataframe.DataFrame'>
The type of people_df is <class 'pyspark.sql.dataframe.DataFrame'>
```

3.2 Operating DataFrames in PySpark

Similar to RDD operations, the DataFrame operations in PySpark (i.e. DataFrame API) can be divided into Transformation and Actions.

DataFrame Transformations:
- **select()** transformation is used to extract one or more columns from a DataFrame and return a new DataFrame.
- **filter()** transformation only select the rows that pass a condition specified.
- **GroupBy()** transformation groups a DataFrame using specified columns, and return a new DataFrame
- **orderBy()** transformation returns a new DataFrame sorted by the given columns.
- **dropDuplicate()** transformation returns a new DataFrame with duplicated rows removed.
- **withColumnRenamed()** transformation returns a new DataFrame by renaming an existing column

DataFrame Actions
- **printSchema()** action prints the types of columns in the DataFrame.
- **head()** action shows the first few rows in the DataFrame.
- **show()** is an action to display the rows in a DataFrame.
- **count()** is an action to show the number of rows in a DataFrame.
- **columns** operator prints the columns of a DataFrame
- **describe()** operation is used to calculate the summary statistics of the numerical columns in the DataFrame.

```
# Print the first 10 observations
people_df.show(10)

# Count the number of rows
print("There are {} rows in the people_df DataFrame.".format(people_df.count()))

# Count the number of columns and their names
print("There are {} columns in the people_df DataFrame and their names are {}".format(len(people_df.columns), people_df.columns))

# Select name, sex and date of birth columns
people_df_sub = people_df.select('name', 'sex', 'date of birth')

# Print the first 10 observations from people_df_sub
people_df_sub.show(10)

# Remove duplicate entries from people_df_sub
people_df_sub_nodup = people_df_sub.dropDuplicates()

# Count the number of rows
print("There were {} rows before removing duplicates, and {} rows after removing duplicates".format(people_df_sub.count(), people_df_sub_nodup.count()))

# Filter people_df to select females
people_df_female = people_df.filter(people_df.sex == "female")

# Filter people_df to select males
people_df_male = people_df.filter(people_df.sex == "male")

# Count the number of rows
print("There are {} rows in the people_df_female DataFrame and {} rows in the people_df_male DataFrame".format(people_df_female.count(), people_df_male.count()))
```

```
+---+---------+----------------+------+-------------+
|_c0|person_id|            name|   sex|date of birth|
+---+---------+----------------+------+-------------+
|  0|      100|  Penelope Lewis|female|   1990-08-31|
|  1|      101|   David Anthony|  male|   1971-10-14|
|  2|      102|       Ida Shipp|female|   1962-05-24|
|  3|      103|    Joanna Moore|female|   2017-03-10|
|  4|      104|  Lisandra Ortiz|female|   2020-08-05|
|  5|      105|   David Simmons|  male|   1999-12-30|
|  6|      106|   Edward Hudson|  male|   1983-05-09|
|  7|      107|    Albert Jones|  male|   1990-09-13|
|  8|      108|Leonard Cavender|  male|   1958-08-08|
|  9|      109|  Everett Vadala|  male|   2005-05-24|
+---+---------+----------------+------+-------------+
only showing top 10 rows

There are 100000 rows in the people_df DataFrame.
There are 5 columns in the people_df DataFrame and their names are ['_c0', 'person_id', 'name', 'sex', 'date of birth']
+----------------+------+-------------+
|            name|   sex|date of birth|
+----------------+------+-------------+
```

3.3 Interacting with DataFrames using PySpark SQL

In addition to the DataFrame API, PySpark SQL allows to manipulate DataFrames with SQL queries programatically. SQL queries can be more concise and easier to understand. It is portable and can be used without any modifications with every supported languages (e.g. R language).

The SparkSession provides a method called sql which can be used to execute a SQL query. The sql() method takes a SQL statement as an argument and returns a DataFrame representing the result of the given query. Before issuing a SQL query against a DataFrame, a temporary table needs to be created (using createOrReplaceTempView() function) which is a pointer to the DataFrame.

```
# The sql() function on a SparkSession enables applications to run SQL queries programmatically
# and returns the result as another DataFrame

# Create a temporary table "people"
people_df.createOrReplaceTempView("people")

# Construct a query to select the names of the people from the temporary table "people"
query = '''SELECT name FROM people'''

# Assign the result of Spark's query to people_df_names
people_df_names = spark.sql(query)

# Print the top 10 names of the people
people_df_names.show(10)

# Filter the people table to select female sex
people_female_df = spark.sql('SELECT * FROM people WHERE sex=="female"')

# Filter the people table DataFrame to select male sex
people_male_df = spark.sql('SELECT * FROM people WHERE sex=="male"')

# Count the number of rows in both people_df_female and people_male_df DataFrames
print("There are {} rows in the people_female_df and {} rows in the people_male_df DataFrames".format(people_female_df.count(), people_male_df.count()))
```

```
+----------------+
|            name|
+----------------+
|  Penelope Lewis|
|   David Anthony|
|       Ida Shipp|
```

```
|     Joanna Moore|
|   Lisandra Ortiz|
|    David Simmons|
|    Edward Hudson|
|     Albert Jones|
|Leonard Cavender|
|   Everett Vadala|
+----------------+
only showing top 10 rows

There are 49014 rows in the people_female_df and 49066 rows in the people_male_df DataFrames
```

3.4 Data Visualization for PySpark DataFrame

Currently, there are three different methods available to create charts using PySpark DataFrames

- **pyspark_dist_explore** library: Pyspark_dist_explore is a plotting library to get quick insights on data in PySpark DataFrames
- **toPandas** method: converts the PySpark DataFrame into a Pandas DataFrame. After conversion, it's easy to create charts from pandas DataFrames using matplotlib or seaborn plotting tools.
- **HandySpark** toPandas: HandySpark is designed to improve PySpark user experience, especially when it comes to exploratory data analysis, including visualization capabilities.

Pandas DataFrame vs PySpark DataFrame

- Pandas is a single machine tool and constrained by single machine limits. So their size is limited by your server memory, and you will process them with the power of a single server. In contrast, operations on Pyspark DataFrames run parallel on different nodes in the cluster.
- In pandas DataFrames, we get the result as soon as we apply any operation Whereas operations in PySpark DataFrames are lazy in nature.
- You can change a Pandas DataFrame using methods. We can't change a PySpark DataFrame due to its immutable property.
- Finally, the Pandas API supports more operations than PySpark DataFrames.

```
# This exercise will do exploratory data analysis (EDA) on the "FIFA 2018 World Cup Player" dataset using PySpark SQL which involve DataFrame operations, SQL queries and visualization.
# Make you have uploaded the dataset file onto Databricks data store. The file_path is for my Databricks account only. Yours will be different.
file_path = 'dbfs:/FileStore/shared_uploads/wei.jie@uwl.ac.uk/Fifa2018_dataset.csv'
# Load the Dataframe
fifa_df = spark.read.csv(file_path, header=True, inferSchema=True)

# Check the schema of columns
fifa_df.printSchema()
# Show the first 10 observations
fifa_df.show(10)
# Print the total number of rows
print("There are {} rows in the fifa_df DataFrame".format(fifa_df.count()))

# Create a temporary view of fifa_df
fifa_df.createOrReplaceTempView('fifa_df_table')
# Construct the "query"
query = '''SELECT Age FROM fifa_df_table WHERE Nationality == "Germany"'''
# Apply the SQL "query"
fifa_df_germany_age = spark.sql(query)

# Generate basic statistics
fifa_df_germany_age.describe().show()
# Convert fifa_df to fifa_df_germany_age_pandas DataFrame
fifa_df_germany_age_pandas = fifa_df_germany_age.toPandas()

import matplotlib.pyplot as plt
# Plot the 'Age' density of Germany Players
fifa_df_germany_age_pandas.plot(kind='density')
plt.show()
```

```
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)
```