Lab 4. Data Exploration and Visualization

The following are the topics that we will be covering in this lab:

- Sampling data
- Performing ad hoc analysis
- Finding a relationship between data elements
- Visualizing data

Sampling data

To explore large datasets, it is generally useful to work with a smaller sample of data first. For example, from a dataset consisting of 100 million records, we could take a sample of 1,000 records and start exploring some important properties of this data. Exploring the entire dataset would be ideal; however, the time required to do so would increase manifold.

Selecting the sample

Let's look at how we can make use of the Scala collection API to select sample data from a dataset:

1. Create a list of `1000` numbers using Scala's Range API. We generate a sequence of 1,000 number from `0` to `1000` (1,000 is excluded) first and turn it into a Scala `List` :

```
scala> val data = Range(0, 1000).toList
data: List[Int] = List(0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17,
18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38,
39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59,
60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80,
81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101,
102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118,
119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135,
136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150, 151, 152,
153, 154, 155, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169,
170, 171, 172, 173, 174, 175, 176,...
```

2. Use the Scala list's `take` method, select the first three elements of the aforementioned-generated `List` . This will provide another `List` with three elements:

```
scala> val first3 = data.take(3)
first3: List[Int] = List(0, 1, 2)
```

We generated a list of 1,000 integers from 0 to 999 and selected the first three integers from this. The previous steps would always produce the same result each time.

This implies that if the dataset remains constant, then the selected values would always be the same and our sample has implicit bias. Let's see how we can select random values:

1. Import the `Random` class from Scala's `util` package:

```
scala> import scala.util.Random
import scala.util.Random
```

2. Perform a random shuffle operation on the previously generated data, using Scala's random utility class's `shuffle` method. This produces another list with the same content as the original one; however, the position of the numbers in the new list is randomized and different from the original list:

```
scala> val randomizedData = Random.shuffle(data)
randomizedData: List[Int] = List(725, 225, 231, 280, 518, 818, 395, 519, 13, 648, 292,
826, 520, 885, 114, 403, 277, 218, 707, 864, 798, 575, 942, 685, 627, 95, 512, 753,
763, 923, 209, 633, 631, 743, 327, 0, 946, 147, 838, 78, 777, 473, 521, 501, 86, 590,
748, 956, 105, 963, 483, 334, 109, 5, 285, 910, 791, 102, 398, 240, 447, 493, 351,
297, 399, 365, 466, 612, 298, 529, 762, 680, 975, 253, 535, 902, 373, 36, 356, 596,
679, 717, 976, 543, 180, 894, 500, 624, 405, 754, 881, 916, 213, 768, 305, 740, 263,
422, 771, 623, 121, 989, 486, 574, 196, 987, 968, 73, 943, 662, 393, 438, 834, 714,
746, 364, 260, 139, 906, 944, 793, 485, 647, 66, 418, 909, 787, 377, 94, 25, 84, 888,
657, 23, 776, 402, 649, 472, 915, 496, 140, 155, 772, 319, 752, 964, 354, 11, 431,
413, 982, 621, 835, 468, 785, 463, ...
```

3. Select the first three elements from the randomized list, using the `take` method:

```
scala> val random3 = randomizedData.take(3)
random3: List[Int] = List(725, 225, 231)
```

4. Repeat step 2 to produce another randomized list. This randomized list is expected to be quite different compared to the original list and previously generated list:

```
scala> val randomizedDataNext = scala.util.Random.shuffle(data)
randomizedDataNext: List[Int] = List(955, 128, 857, 129, 901, 265, 535, 879, 998, 373,
601, 816, 297, 648, 624, 27, 119, 195, 868, 357, 859, 986, 569, 660, 167, 885, 416,
199, 848, 406, 751, 593, 156, 673, 333, 403, 628, 122, 775, 390, 926, 360, 513, 953,
820, 947, 867, 295, 113, 639, 897, 856, 717, 426, 865, 988, 407, 814, 110, 762, 852,
842, 940, 102, 61, 298, 815, 197, 233, 515, 318, 401, 180, 781, 262, 157, 492, 376,
747, 688, 186, 824, 961, 659, 269, 618, 819, 623, 866, 46, 557, 511, 176, 840, 800,
679, 481, 704, 551, 66, 54, 977, 732, 700, 813, 264, 625, 171, 347, 990, 290, 43, 742,
418, 836, 92, 979, 938, 369, 111, 779, 3, 613, 117, 379, 8, 764, 356, 573, 921, 893,
822, 351, 279, 164, 507, 930, 514, 805, 245, 714, 121, 694, 223, 652, 526, 755, 692,
260, 476, 105, 404, 289, 869, 5...
```

5. Select the first three elements from the new randomized `List` using the `take` method:

```
scala> val random3Next = randomizedDataNext.take(3)
random3Next: List[Int] = List(955, 128, 857)
```

In this code example, we are to able to get three random values by using the `scala.util.Random.shuffle` function. Although the preceding example illustrated the data randomization technique, it is not very efficient in terms of performance and it won't scale as the datasets get larger and larger. It does, however, illustrate a simple way to get random samples using Scala's built-in APIs. We will look at how to efficiently get random samples from large datasets in subsequent labs.

Selecting samples using Saddle

Let's look at a similar exercise using the Scala Saddle library. We will be using the CSV data from https://data.lacity.org/api/views/nxs9-385f/rows.csv?accessType=DOWNLOAD.

This dataset was introduced in earlier labs. Let's follow these steps to use Saddle:

1. First, we need to define our `build.sbt`, as follows, to include the Saddle library dependencies. Remember to save `build.sbt` as a file in your current directory:

```
scalaVersion := "2.11.12"

libraryDependencies ++= Seq(
  "org.scala-saddle" %% "saddle-core" % "1.3.4" // Saddle Dataframe like Library
)
```

2. Start SBT in your Terminal from the same directory where `build.sbt` is located and start a Scala console:

```
$ sbt
```

3. Import `BufferedReader` and `InputStreamReader` from the `java.io` package:

```
scala> import java.io.{BufferedReader, InputStreamReader}
import java.io.{BufferedReader, InputStreamReader}
```

4. Import the `saddle` package:

```
scala> import org.saddle.io._
import org.saddle.io._
```

5. Define a Scala class called `SaddleCsvSource` that takes a URL string as an input argument to the constructor and extends `CsvSource`. The constructor establishes a connection to the provided URL and creates a `BufferedReader` object that can be used to read data from the URL, line by line:

```
scala> class SaddleCsvSource(url: String) extends CsvSource {
     | val reader = new BufferedReader(new InputStreamReader(new
java.net.URL(url).openStream()))
     | override def readLine: String = {
     | reader.readLine()
     | }
     | }
defined class SaddleCsvSource
```

We have overridden the `readLine` method of the parent `CsvSource` class. The overridden method reads a line of data from the URL. This method automatically gets repeated when the parse method is invoked on `CsvSource`.

6. Create a new instance of `SaddleCsvSource` by supplying https://data.lacity.org/api/views/nxs9-385f/rows.csv?accessType=DOWNLOAD as the URL. This is our source data that is in CSV format and we want to parse this data using Saddle's CSV parser:

```
scala> val file = new SaddleCsvSource("https://data.lacity.org/api/views/nxs9-
385f/rows.csv?accessType=DOWNLOAD")
file: SaddleCsvSource = SaddleCsvSource@3f0055eb
```

7. Parse the aforementioned object using the `CsvParser` instance parse, API. This provides Saddle's `Frame` object that is used for further exploration:

```
scala> val frameOrig = CsvParser.parse(file)
frameOrig: org.saddle.Frame[Int,Int,String] =
[320 x 7]
              0 1 2 3 4 5 6
       -------- ---------------- ---------- ----------- ------------- ----------------
----------------------
  0 -> Zip Code Total Population Median Age Total Males Total Females Total Households
Average Household Size
  1 -> 91371 1 73.5 0 1 1 1
  2 -> 90001 57110 26.6 28468 28642 12971 4.4
  3 -> 90002 51223 25.5 24876 26347 11731 4.36
  4 -> 90003 66266 26.3 32631 33635 ...
scala>
```

8. Get the header:

```
scala> val head = frameOrig.rowSlice(0,1).rowAt(0)
head: org.saddle.Series[Int,String] =
[7 x 1]
0 -> Zip Code
1 -> Total Population
2 -> Median Age
3 -> Total Males
4 -> Total Females
5 -> Total Households
6 -> Average Household Size
scala>
```

9. Remove the header row and attach the header back as column names:

```
scala> val frame = frameOrig.rowSlice(1, frameOrig.numRows).mapColIndex(i =>
head.at(i).get)
frame: org.saddle.Frame[Int,String,String] =
[319 x 7]
       Zip Code Total Population Median Age Total Males Total Females Total Households
Average Household Size
       -------- ---------------- ---------- ----------- ------------- ----------------
----------------------
  1 -> 91371 1 73.5 0 1 1 1
  2 -> 90001 57110 26.6 28468 28642 12971 4.4
  3 -> 90002 51223 25.5 24876 26347 11731 4.36
  4 -> 90003 66266 26.3 32631 33635 15642 4.22
  5 -> 90004 62180 34.8 31302 30878 2...
```

10. Get the first three records from Saddle's `Frame`:

```
scala> frame.head(3)
res1: org.saddle.Frame[Int,String,String] =
[3 x 7]
     Zip Code Total Population Median Age Total Males Total Females Total Households
Average Household Size
     -------- ---------------- ---------- ----------- ------------- ---------------- -
---------------------
1 -> 91371 1 73.5 0 1 1 1
2 -> 90001 57110 26.6 28468 28642 12971 4.4
3 -> 90002 51223 25.5 24876 26347 11731 4.36
scala>
```

11. Get a random sample of 2% of the dataset by using Frame's `rfilter` API. Note the usage of Scala's random utility's `nextDouble` method. This method provides a uniformly distributed pseudo-random double between 0.0 and 1.0. This implies that roughly only 2% of the time the following condition will hold true if called repeatedly:

    - `scala.utilRandom() < 0.02`

The `rfilter`, when combined with this mechanism, provides us with roughly 2% of the sample data:

```
scala> val sample = frame.rfilter(_ => scala.util.Random.nextDouble() < 0.02)
sample: org.saddle.Frame[Int,String,String] =
[6 x 7]
       Zip Code Total Population Median Age Total Males Total Females Total Households
Average Household Size
-------- ---------------- ---------- ----------- ------------- --------
  7 -> 90006 59185 32.4 30254 28931 18617 3.13
 80 -> 90241 42399 33.9 20466 21933 13617 3.09
126 -> 90606 32396 33.5 15936 16460 8633 3.72
156 -> 90802 39347 34.7 20387 18960 19853 1.93
259 -> 91722 34409 34 16859 17550 10...
```

We are now able to get a sample of data conveniently using the APIs provided by the Saddle library.

Please note the abstraction being used in this context is a rame that consists of rows and columns. It is to be noted that every run of a sample would produce a different result. For example:

```
scala> val sample = frame.rfilter(_ => scala.util.Random.nextDouble() < 0.02)
sample: org.saddle.Frame[Int,String,String] =
[10 x 7]
       Zip Code Total Population Median Age Total Males Total Females Total Households
Average Household Size
       -------- ---------------- ---------- ----------- ------------- ----------------
----------------------
 17 -> 90017 23768 29.4 12818 10950 9338 2.53
 18 -> 90018 49310 33.2 23770 25540 15493 3.12
 54 -> 90062 32821 31.8 15720 17101 9155 3.55
 90 -> 90262 69745 27.8 33919 35826 14669 4.57
101 -> 90290 6368 45 3180 3188 2612 2.44
131 -> 90638 49012 37.9 23520 25492 14821 3.11
188 -> 91108 13361 45.4 6410 6951 4415 3.01
273 -> 91755 27496 43.4 13271 14225 8760 3.12
```

```
281 -> 91773 33119 42.5 15737 17382 11941 2.73
311 -> 93543 13033 32.9 6695 6338 3560 3.66
```

Although the samples are small, these, however, provide an important insight into some of the properties of the data, such as typical median age and average household size. We performed the following activities in our analysis:

1. We started with a data resource on the internet, located at https://data.lacity.org/api/views/nxs9-385f/rows.csv?accessType=DOWNLOAD. This resource is in CSV format.
2. Using a combination of Java's and Saddle's APIs, we were able to read this dataset.
3. Saddle's API allowed us to parse the CSV data and convert this into a structured format of Saddle's frame.
4. Saddle's frame allowed us to see the source data in a tabular form, consisting of rows and columns.
5. We conveniently got a sample, but a randomized set of rows from the frame, by using the `rfilter` API and combining it with Scala's random utility's `nextDouble` API.

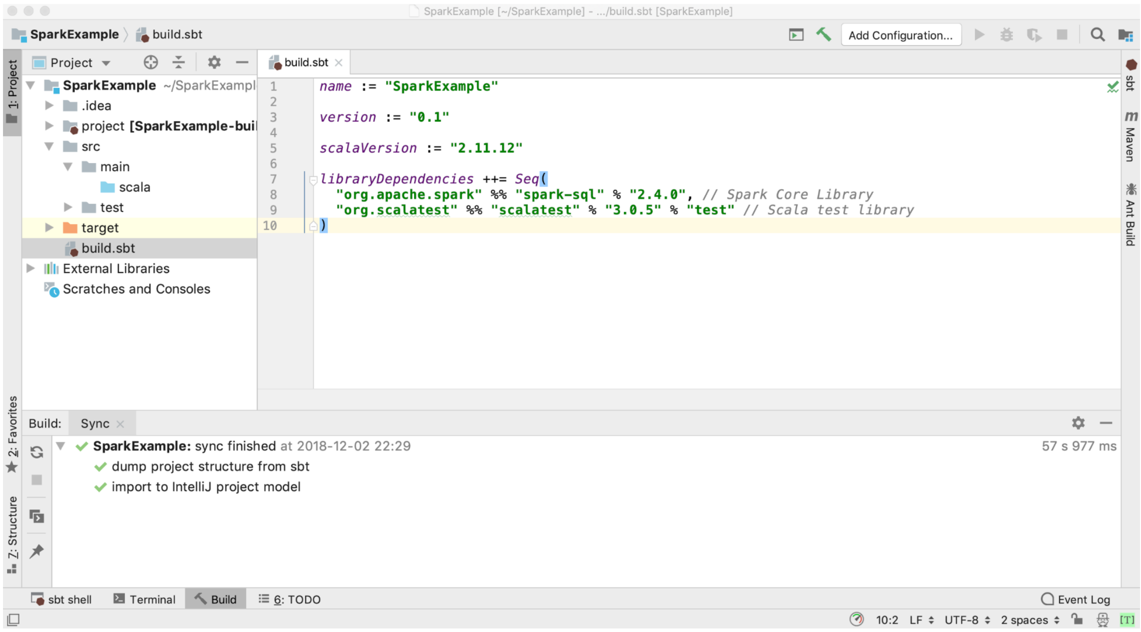
Performing ad hoc analysis

We will use Spark to perform some hands-on ad hoc analysis. Let's create an IntelliJ project with the following Spark dependencies added to `build.sbt`:

```
scalaVersion := "2.11.12"

libraryDependencies ++= Seq(
"org.apache.spark" %% "spark-sql" % "2.4.0", // Spark Core Library
"org.scalatest" %% "scalatest" % "3.0.5" % "test" // Scala test library
)
```

This is what it will look like:



Now, create a simple main Scala object to explore the same dataset that we explored in the previous section:

1. Import `SparkSession` from Spark's `sql` package. This is needed for setting up a Spark Session programmatically:

```
import org.apache.spark.sql.SparkSession
```

2. Import `SparkFiles` from Spark's `spark` package. This is needed for reading data from the internet resource located at https://data.lacity.org/api/views/nxs9-385f/rows.csv:

```
import org.apache.spark.SparkFiles
```

3. Define a Scala object called `SparkExample`, which will act an entry point into this program:

```
object SparkExample {
...
}
```

4. With the `SparkExample` object, define a method called `getSparkSession`. This creates a new Spark session running in local mode and uses the builder pattern to create or get a Spark session. The advantage of using the builder pattern is that the session being created can be customized to serve very specialized needs:

```
def getSparkSession(): SparkSession = {
val spark = SparkSession.builder().master("local").getOrCreate()
    spark.sparkContext.setLogLevel("ERROR")
    spark
  }
```

5. Finally, define the main method that facilitates the program to be executed with input arguments supplied as parameters. There are multiple actions taking place inside this method:

   a. The Spark session is established by calling

   ```
   the `getSparkSession` method of the object.
   ```

   b. The internet resource located

   ```
   at <https://data.lacity.org/api/views/nxs9-385f/rows.csv> is
   being added to the `SparkContext` object of
   `spark`, the Spark session.
   ```

   c. A new Spark DataFrame is being created by fetching the internet

   ```
   resource and treating it as CSV data with a header row. Also,
   the schema of the target DataFrame is determined  by inferring
   the contents of CSV.
   ```

   d. We print the schema of the DataFrame created. e. We show a few rows from the DataFrame. f. Stop the Spark Session on completion of the program.

```
def main(args: Array[String]): Unit = {
val spark = getSparkSession()
    spark.sparkContext.addFile("https://data.lacity.org/api/views/nxs9-385f/rows.csv")
val df = spark.read.option("header", true).option("inferSchema",
true).csv(SparkFiles.get("rows.csv"))
    df.printSchema()
```

```
    df.show()
    spark.stop()
  }
```

Let's put all of this together as a single program. The complete code is outlined as follows:

```
import org.apache.spark.sql.SparkSession
import org.apache.spark.SparkFiles

object SparkExample {
def getSparkSession(): SparkSession = {
val spark = SparkSession.builder().master("local").getOrCreate()
    spark.sparkContext.setLogLevel("ERROR")
    spark
  }
def main(args: Array[String]): Unit = {
val spark = getSparkSession()
    spark.sparkContext.addFile("https://data.lacity.org/api/views/nxs9-385f/rows.csv")
val df = spark.read.option("header", true).option("inferSchema",
true).csv(SparkFiles.get("rows.csv"))
    df.printSchema()
    df.show()
    spark.stop()
  }
}
```

When you run the preceding example in IntelliJ, it produces quite a bit of log information. It should output some logs like these:

- Pay attention to the schema Information. Note that the data types of the columns are inferred from the source data. Without the schema inference, the types of all the columns would have been string type:

```
root
 |-- Zip Code: integer (nullable = true)
 |-- Total Population: integer (nullable = true)
 |-- Median Age: double (nullable = true)
 |-- Total Males: integer (nullable = true)
 |-- Total Females: integer (nullable = true)
 |-- Total Households: integer (nullable = true)
 |-- Average Household Size: double (nullable = true)
```

- The output from the `show` method could look something like this. By default, the `show` method of the DataFrame display is 20 rows:

```
+--------+----------------+----------+-----------+-------------+----
|Zip Code|Total Population|Median Age|Total Males|Total Females|Total
Households|Average Household Size|
+--------+----------------+----------+-----------+-------------+----
| 91371| 1| 73.5| 0| 1| 1| 1.0|
| 90001| 57110| 26.6| 28468| 28642| 12971| 4.4|
| 90002| 51223| 25.5| 24876| 26347| 11731| 4.36|
| 90003| 66266| 26.3| 32631| 33635| 15642| 4.22|
| 90004| 62180| 34.8| 31302| 30878| 22547| 2.73|
```

```
| 90005| 37681| 33.9| 19299| 18382| 15044| 2.5|
| 90006| 59185| 32.4| 30254| 28931| 18617| 3.13|
| 90007| 40920| 24.0| 20915| 20005| 11944| 3.0|
| 90008| 32327| 39.7| 14477| 17850| 13841| 2.33|
| 90010| 3800| 37.8| 1874| 1926| 2014| 1.87|
| 90011| 103892| 26.2| 52794| 51098| 22168| 4.67|
| 90012| 31103| 36.3| 19493| 11610| 10327| 2.12|
| 90013| 11772| 44.6| 7629| 4143| 6416| 1.26|
| 90014| 7005| 44.8| 4471| 2534| 4109| 1.34|
| 90015| 18986| 31.3| 9833| 9153| 7420| 2.45|
| 90016| 47596| 33.9| 22778| 24818| 16145| 2.93|
| 90017| 23768| 29.4| 12818| 10950| 9338| 2.53|
| 90018| 49310| 33.2| 23770| 25540| 15493| 3.12|
| 90019| 64458| 35.8| 31442| 33016| 23344| 2.7|
| 90020| 38967| 34.6| 19381| 19586| 16514| 2.35|
+--------+----------------+----------+-----------+------------+----
only showing top 20 rows
```

Hence, we were able to do a quick ad hoc analysis on this information to understand some of the properties of the data and examine a few sample records. The only assumption we made about the data is that its format is CSV and the first record is a header record. Using Spark, we are also able to infer the schema of the underlying data with appropriate data types.

Spark has a comprehensive API for ad hoc analysis. For example, to get random samples, we could do the following to get a 5% sample of rows from the entire DataFrame:

```
df.sample(0.05).show() // 5% random sample

+--------+----------------+----------+-----------+------------+-------
|Zip Code|Total Population|Median Age|Total Males|Total Females|Total
Households|Average Household Size|
+--------+----------------+----------+-----------+------------+-------
| 90002| 51223| 25.5| 24876| 26347| 11731| 4.36|
| 90039| 28514| 38.8| 14383| 14131| 11436| 2.47|
| 90073| 539| 56.9| 506| 33| 4| 1.25|
| 90201| 101279| 27.8| 50658| 50621| 24104| 4.16|
| 90263| 1612| 19.7| 665| 947| 0| 0.0|
| 90703| 49399| 43.9| 23785| 25614| 15604| 3.16|
| 90822| 117| 63.9| 109| 8| 2| 4.5|
| 91042| 27585| 40.7| 13734| 13851| 9987| 2.74|
| 91214| 30356| 42.5| 14642| 15714| 10551| 2.87|
+--------+----------------+----------+-----------+------------+-------
```

We are running Spark here in local mode; however, the true power of Spark comes from its ability to run in the distributed mode and work on large-scale datasets. We will explore distributed features of Spark in the upcoming labs.

Finding a relationship between data elements

Once we have a decent understanding of the data and some of its main properties, the next step is to find a concrete relationship between data elements. We can use some of the well-established statistical techniques to understand the distribution of data.

Let's continue with our Spark example from the previous section by comparing `Total Population` to `Total Households`. We can expect the two numbers to be strongly correlated:

```
println("Covariance: " + df.stat.cov("Total Population", "Total Households"))
println("Correlation: " + df.stat.corr("Total Population", "Total Households"))
```

The output from this would be something like this:

```
Covariance: 1.2338126298368526E8
Correlation: 0.9090567549637986
```

We can also look at the data in terms of n-tiles. The following code creates 100 tiles ordered by the `Total Population` column:

1. Create a temporary view on top of the Spark DataFrame created in the preceding example. Name this temporary view `tmp_data`:

```
df.createOrReplaceTempView("tmp_data")
```

2. Run the Spark SQL on the previously created `tmp_data` view, which uses the window function, `ntile`, which does the following:
    - Orders the data by total population
    - Divides the data into 100 tiles by creating almost equally-sized tiles by starting from the top of the ordered data and going down
    - Selects all columns from the view and additionally computed tile value as the tier
3. Show the contents of the DataFrame output:

```
spark.sql("select *, ntile(100) over(order by `Total Population`) tier from
tmp_data").show()
```

Visualizing data

Graphs and charts are used to gain a better understanding of the data relationship. We will use the following to explore data visually:

- Combination of Spark and Vegas viz
- Spark Notebook

Vegas viz for data visualization

Vegas viz is a MatPlotLib-like library for Scala and Spark. The documentation for this library can be found at https://github.com/vegas-viz/Vegas. Spark does not contain any built-in support for data visualization. Vegas viz provides a convenient mechanism to add visualization to a Spark program written in Scala.

In order to use this library with Spark, let's add the following dependencies to `build.sbt`:

```
libraryDependencies ++= Seq(
"org.apache.spark" %% "spark-sql" % "2.4.0", // Spark Core Library
"org.vegas-viz" %% "vegas-spark" % "0.3.11", // Vegas Viz Library
"org.scalatest" %% "scalatest" % "3.0.5" % "test" // Scala test library
)
```

Continuing with the example from the previous section, let's say we want to see, visually, the most populated ZIP (90th percentile).

Let's create a Scala program to do so:

1. Import `SparkFiles` from the `spark` package and `SparkSession` from the `spark.sql` package. `SparkFiles` is needed for accessing the CSV file located on the internet. `SparkSession` is needed for creating a Spark session with a program:

```
import org.apache.spark.SparkFiles
import org.apache.spark.sql.SparkSession
```

2. Import Vegas viz packages needed for visualization using Spark:

```
import vegas._
import vegas.sparkExt._
```

3. Create a Scala object for an entry point into the program:

```
object SparkExample {
...
}
```

4. Define a method that creates a local Spark session:

```
def getSparkSession(): SparkSession = {
val spark = SparkSession.builder().master("local").getOrCreate()
    spark.sparkContext.setLogLevel("ERROR")
    spark
  }
```

5. Define the main method that is the entry point for this program:

```
def main(args: Array[String]): Unit = {
...
  }
```

6. Implement the main method using the following steps:

   a. Create a Spark session. b. Add the internet source file to the Spark context. c. Read the contents of the internet source CSV file as a Spark

   ```
   DataFrame, by inferring the first line as the header and
   inferring the schema from the contents of the CSV.
   ```

   d. Create a temporary view on the DataFrame. e. Run the Spark SQL on the temporary view by using the

   ```
   `ntile` window function.
   ```

   f. Filter out the tiers that are 90 or above. g. Use the `Vegas` library's API to create a plot of the

   ```
   filtered DataFrame using the `Zip Code` column as the
   [*x*] axis and the `Total Population`
   ```

```
column as the [*y*] axis. The [*x*] axis
data is a discrete number, whereas the [*y*] axis
data is quantity.  Mark the plot as a bar chart.
```

h. Show the plot on a screen. i. Stop the `SPark` session.

We implement the preceding steps using the following code:

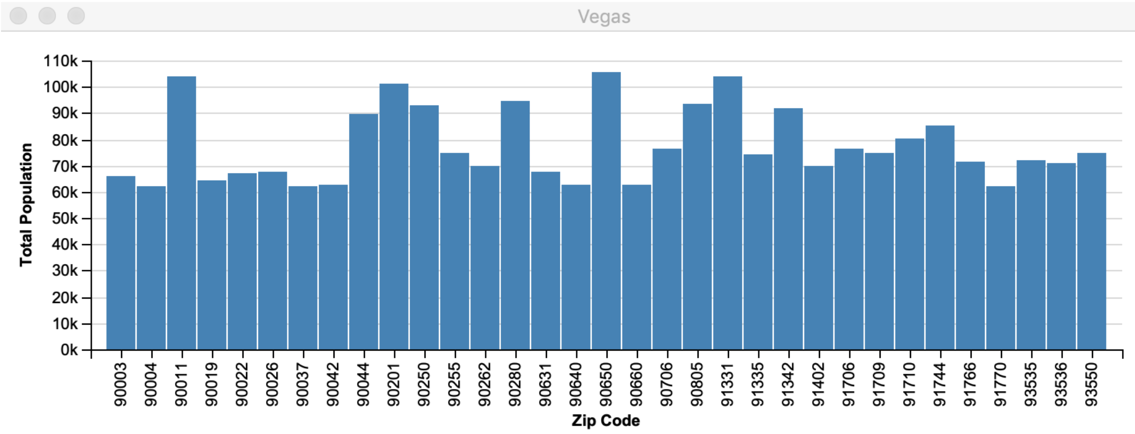
```
val spark = getSparkSession()
    spark.sparkContext.addFile("https://data.lacity.org/api/views/nxs9-385f/rows.csv")
val df = spark.read.option("header", true).option("inferSchema",
true).csv(SparkFiles.get("rows.csv"))
    df.createOrReplaceTempView("tmp_data")
val dfWithTier = spark.sql("select *, ntile(100) over(order by `Total Population`)
tier from tmp_data")
val dfTier90Plus = dfWithTier.where("tier >= 90")
val plot = Vegas().withDataFrame(dfTier90Plus).encodeX("Zip Code", Nom).
      encodeY("Total Population", Quant).
      mark(Bar)
    plot.show
    spark.stop()
```

We can put all of this together and we have a single Spark program that can be executed:

```
import org.apache.spark.SparkFiles
import org.apache.spark.sql.SparkSession
import vegas._
import vegas.sparkExt._

object SparkExample {
def getSparkSession(): SparkSession = {
val spark = SparkSession.builder().master("local").getOrCreate()
    spark.sparkContext.setLogLevel("ERROR")
    spark
  }
def main(args: Array[String]): Unit = {
val spark = getSparkSession()
    spark.sparkContext.addFile("https://data.lacity.org/api/views/nxs9-385f/rows.csv")
val df = spark.read.option("header", true).option("inferSchema",
true).csv(SparkFiles.get("rows.csv"))
    df.createOrReplaceTempView("tmp_data")
val dfWithTier = spark.sql("select *, ntile(100) over(order by `Total Population`)
tier from tmp_data")
val dfTier90Plus = dfWithTier.where("tier >= 90")
val plot = Vegas().withDataFrame(dfTier90Plus).encodeX("Zip Code", Nom).
      encodeY("Total Population", Quant).
      mark(Bar)
    plot.show
    spark.stop()
  }
}
```

Running the preceding code will produce the following screenshot:



[Export as PNGView SourceOpen in Vega Editor]()

In the aforementioned example, we visually looked at zip codes with the total population in the 90th percentile. Visual methods provide intuition about properties of the data. We can easily conclude that densely populated zip code mostly have similar total populations with an approximate population size of 80 K.

Spark Notebook for data visualization

Spark Notebook is an open source notebook that provides a web-based interface to perform interactive data analysis. Spark notebook has following features:

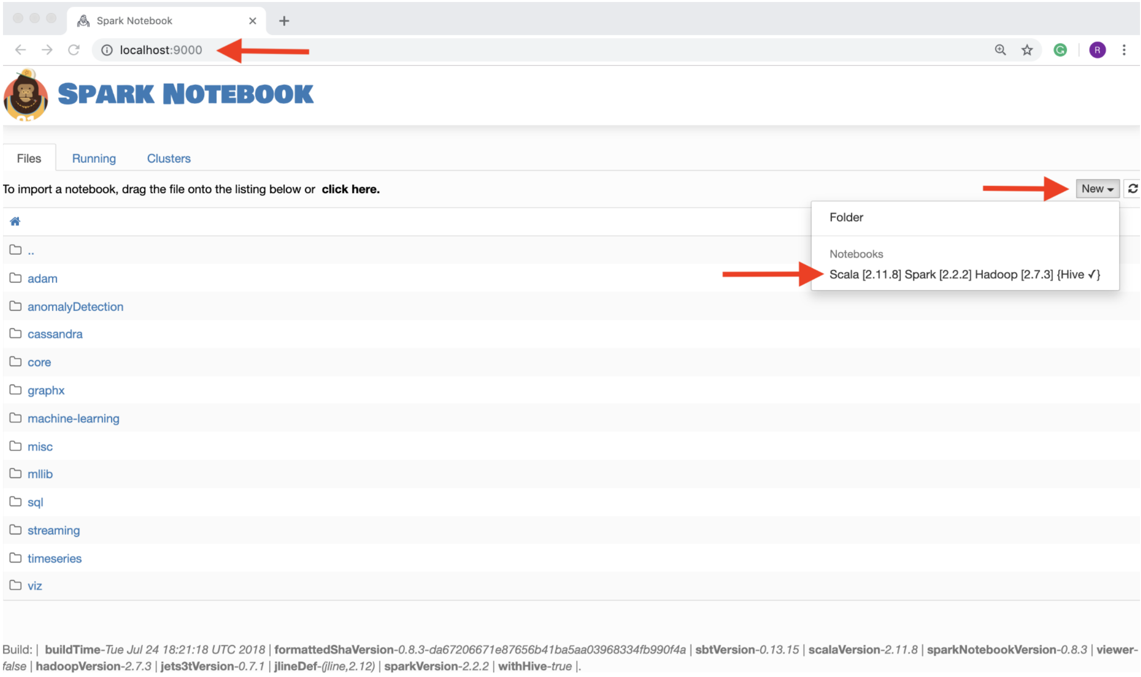
- Scala based
- Excellent integration with Spark
- Support for multiple Spark sessions that are isolated from each other
- Comprehensive support for data visualization

2. Unzip the downloaded ZIP file in a suitable location on your computer:

```
cd /headless/spark-notebook && ./run-dev.sh local
```

The final line indicates that the server can be accessed from the browser on HTTP port `9001`. Let this server keep running.

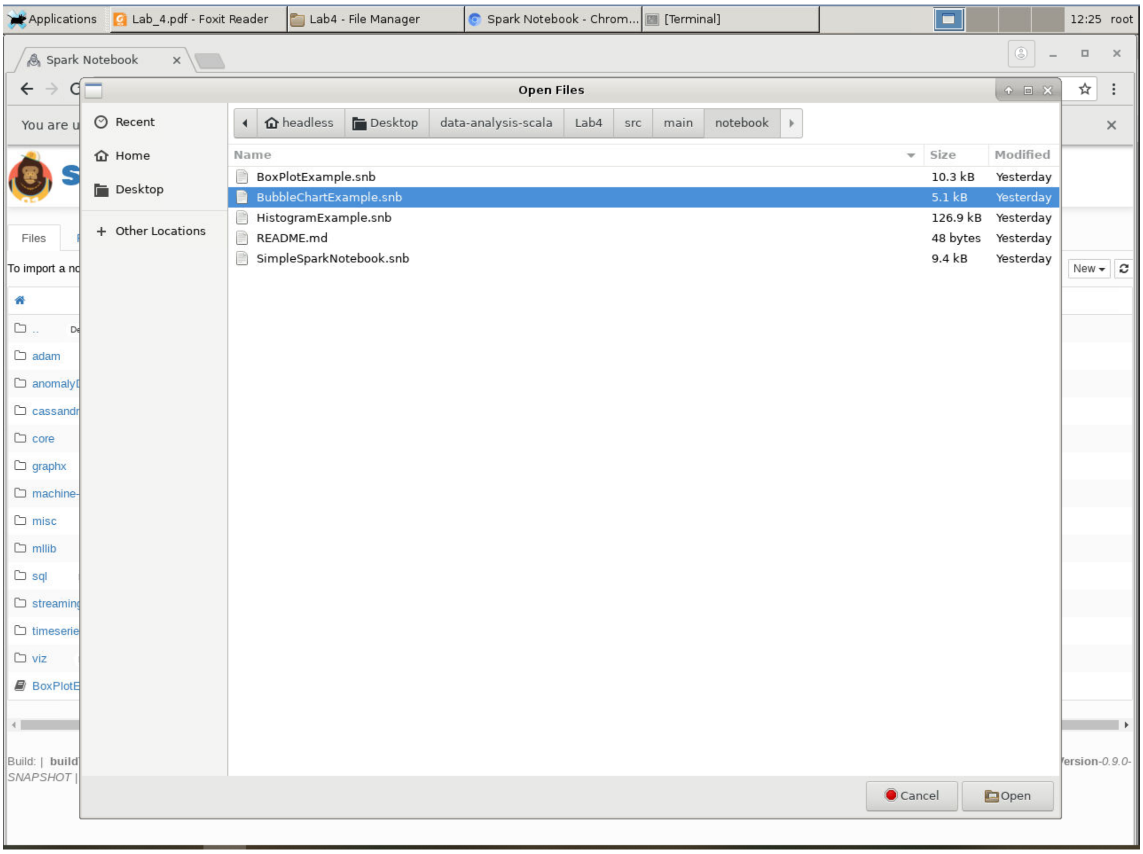
3. Verify that Spark Notebook is running correctly by visiting the landing page from your web browser by going to http://localhost:9001. You should see a screenshot similar to the one that follows:

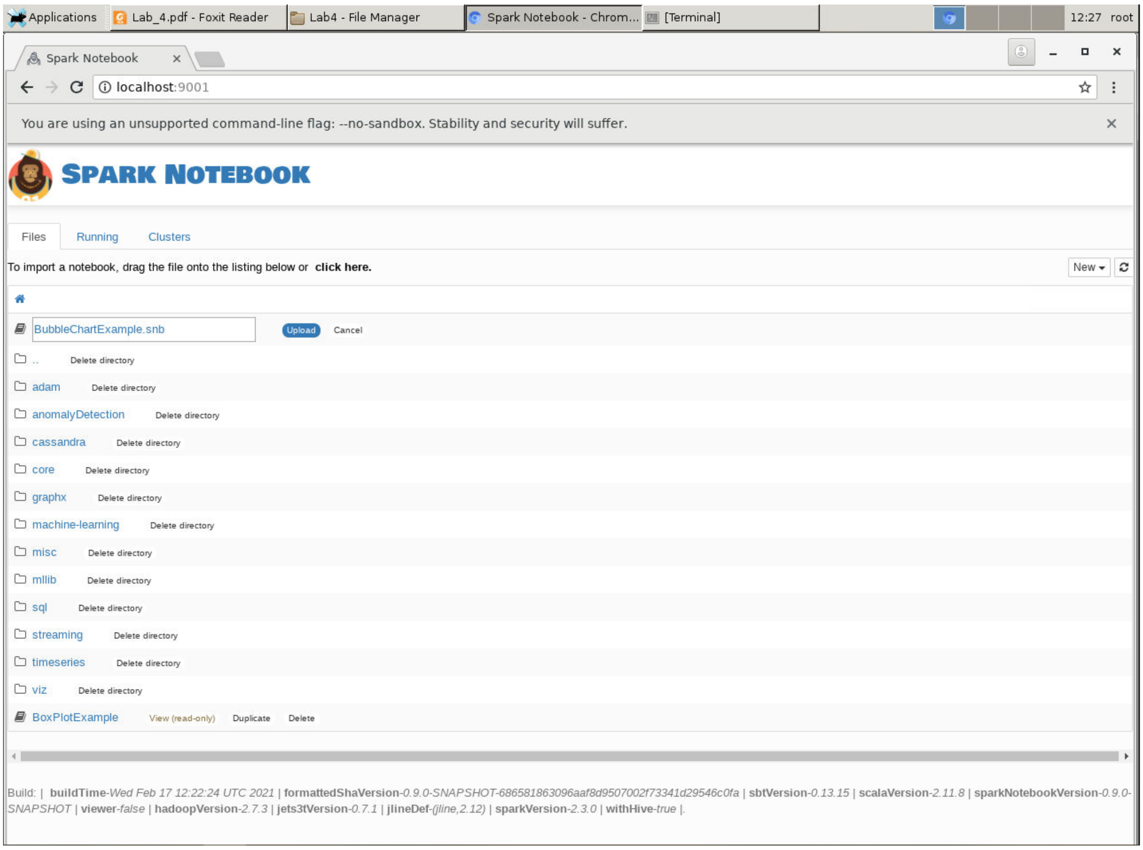


Note: It will take some time to display first time.

Import Spark Notebooks

All notebooks are present in `~/Desktop/data-analysis-scala/Lab4/src/main/notebook`. Import notebooks directly by clicking **click here** as shown in the screenshots below:

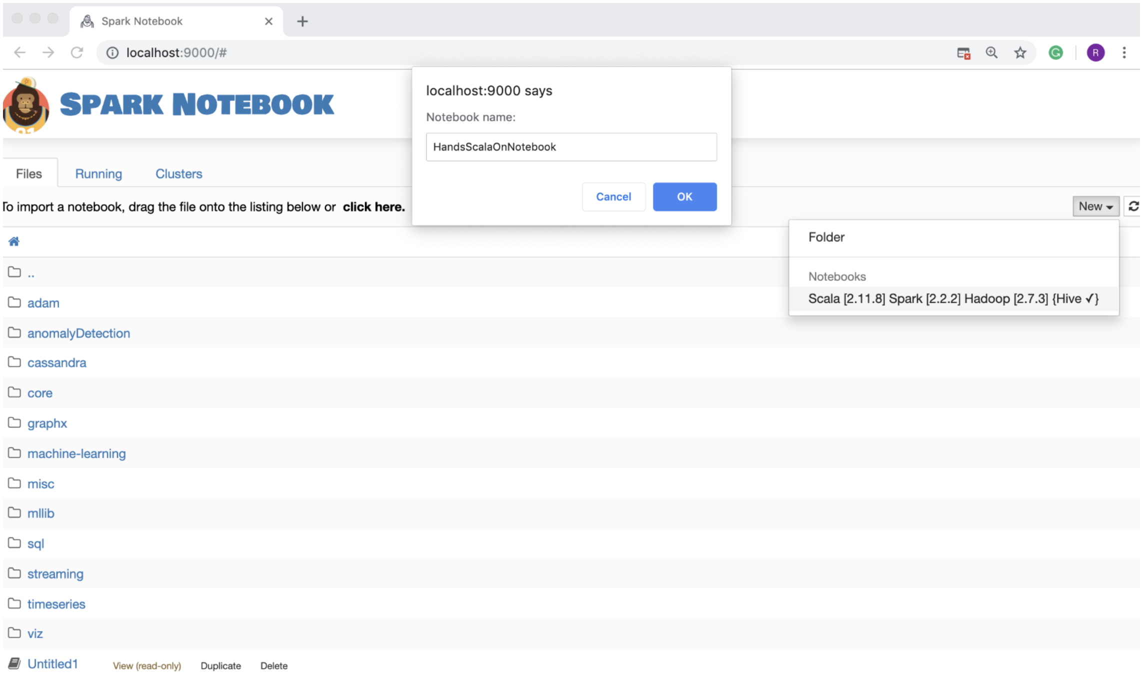

Applications
Lab_4.pdf - Foxit Reader
Lab4 - File Manager
Spark Notebook - Chrom...
[Terminal]
12:25 root
Spark Notebook
Open Files
Recent
Home
Desktop
Other Locations
headless
Desktop
data-analysis-scala
Lab4
src
main
notebook
Name
Size
Modified
BoxPlotExample.snb 10.3 kB Yesterday
BubbleChartExample.snb 5.1 kB Yesterday
HistogramExample.snb 126.9 kB Yesterday
README.md 48 bytes Yesterday
SimpleSparkNotebook.snb 9.4 kB Yesterday
Cancel
Open


Applications
Lab_4.pdf - Foxit Reader
Lab4 - File Manager
Spark Notebook - Chrom...
[Terminal]
12:27 root
Spark Notebook
localhost:9001
You are using an unsupported command-line flag: --no-sandbox. Stability and security will suffer.
SPARK NOTEBOOK
Files
Running
Clusters
To import a notebook, drag the file onto the listing below or click here.
New
BubbleChartExample.snb
Upload
Cancel
.. Delete directory
adam Delete directory
anomalyDetection Delete directory
cassandra Delete directory
core Delete directory
graphx Delete directory
machine-learning Delete directory
misc Delete directory
mllib Delete directory
sql Delete directory
streaming Delete directory
timeseries Delete directory
viz Delete directory
BoxPlotExample View (read-only) Duplicate Delete
Build: | buildTime-Wed Feb 17 12:22:24 UTC 2021 | formattedShaVersion-0.9.0-SNAPSHOT-686581863096aaf8d9507002f73341d29546c0fa | sbtVersion-0.13.15 | scalaVersion-2.11.8 | sparkNotebookVersion-0.9.0-SNAPSHOT | viewer-false | hadoopVersion-2.7.3 | jets3tVersion-0.7.1 | jlineDef-(jline,2.12) | sparkVersion-2.3.0 | withHive-true |

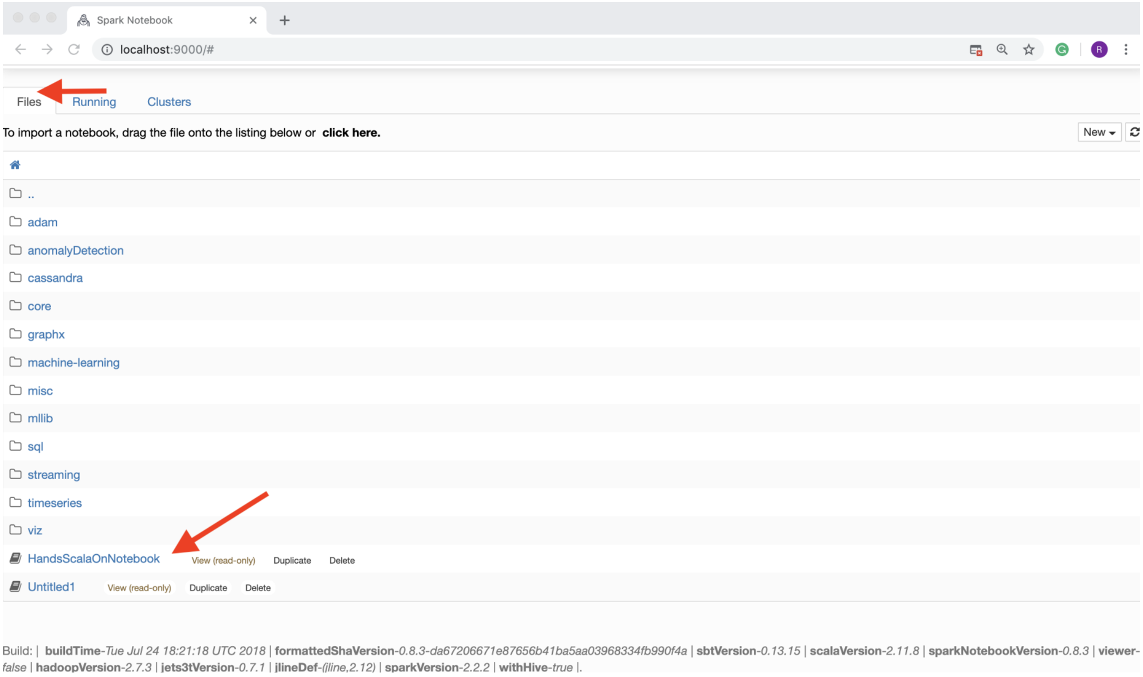
Creating a Spark Notebook with simple visuals

To begin with, we will start by creating a Spark Notebook with some simple visuals:

1. From the landing page shown previously, select **New** | **Scala [2.11.8] Spark [2.3.0] Hadoop [2.7.3] {Hive }** to create a Spark Notebook. Select an appropriate name for the notebook. The following screenshot shows the different prompts:

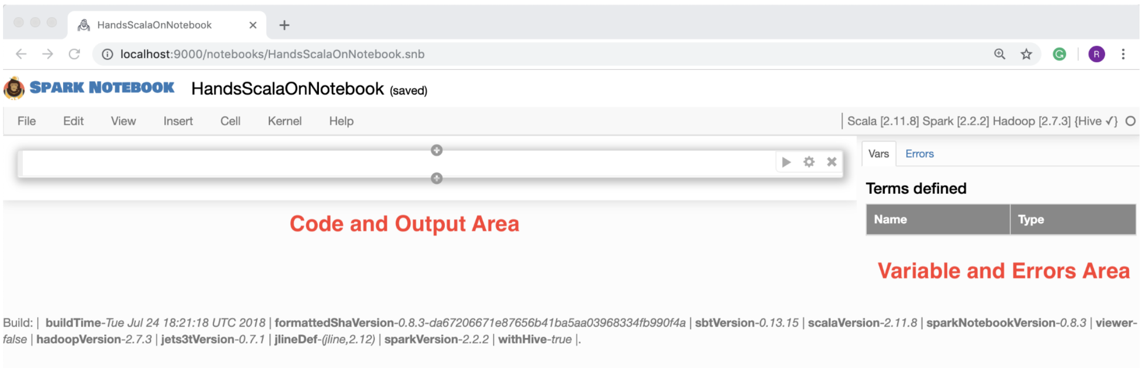


2. You should see that `HandsOnScalaNotebook` will appear on the left-hand side of the screen under the **Files** tab. Select this notebook:



3. At this point, your Spark Notebook is running. The following screenshot shows how it would look in the browser with the screen divided into two areas:

    - **Code and Output Area**
    - **Variables and Errors Area**



4. Let's create our first plot, which is a simple bar chart, by performing the following steps:

    a. Define a Scala case class as follows in this first cell on the

    ```
    notebook, and then press [*SHIFT*] +
    [*ENTER*] to execute this cell:
    ```

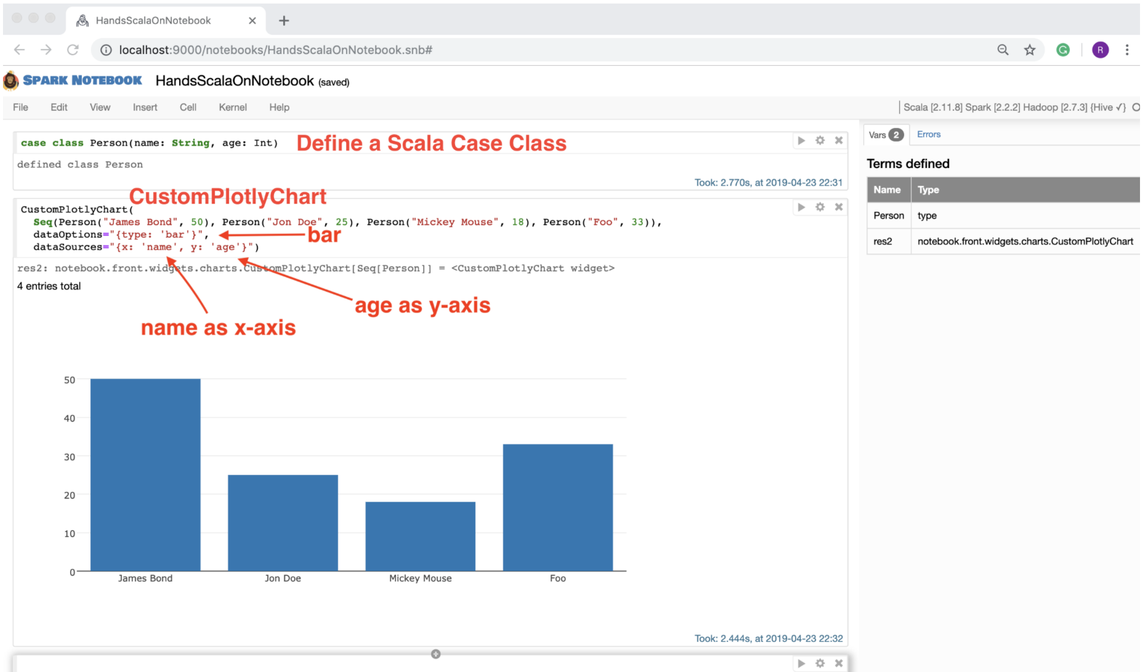
```
case class Person(name: String, age: Int)
```

2. b. Create a `CustomPlotlyChart` instance with a sequence

```
of `Person` objects as input, the type of plot as a
bar chart, the name attribute of `Person` as the
[*x*] axis, and the `age` attribute of
`Person` as the [*y*] axis. Press
[*SHIFT*] + [*ENTER*] to execute this
cell:
```

```
CustomPlotlyChart(
 Seq(Person("James Bond", 50), Person("Jon Doe", 25), Person("Mickey Mouse", 18),
Person("Foo", 33)),
 dataOptions="{type: 'bar'}",
 dataSources="{x: 'name', y: 'age'}")
```

3. On the execution of the preceding code, the Spark Notebook's screen should look similar to the following screenshot, with a bar chart plotted:



As illustrated previously, using the `CustomPlotlyChart` class of the Spark Notebook library, we are able to create a bar chart with just a single line of code. Here is the complete code:

```
case class Person(name: String, age: Int)

CustomPlotlyChart(
  Seq(Person("James Bond", 50), Person("Jon Doe", 25), Person("Mickey Mouse", 18),
Person("Foo", 33)),
  dataOptions="{type: 'bar'}",
  dataSources="{x: 'name', y: 'age'}")
```

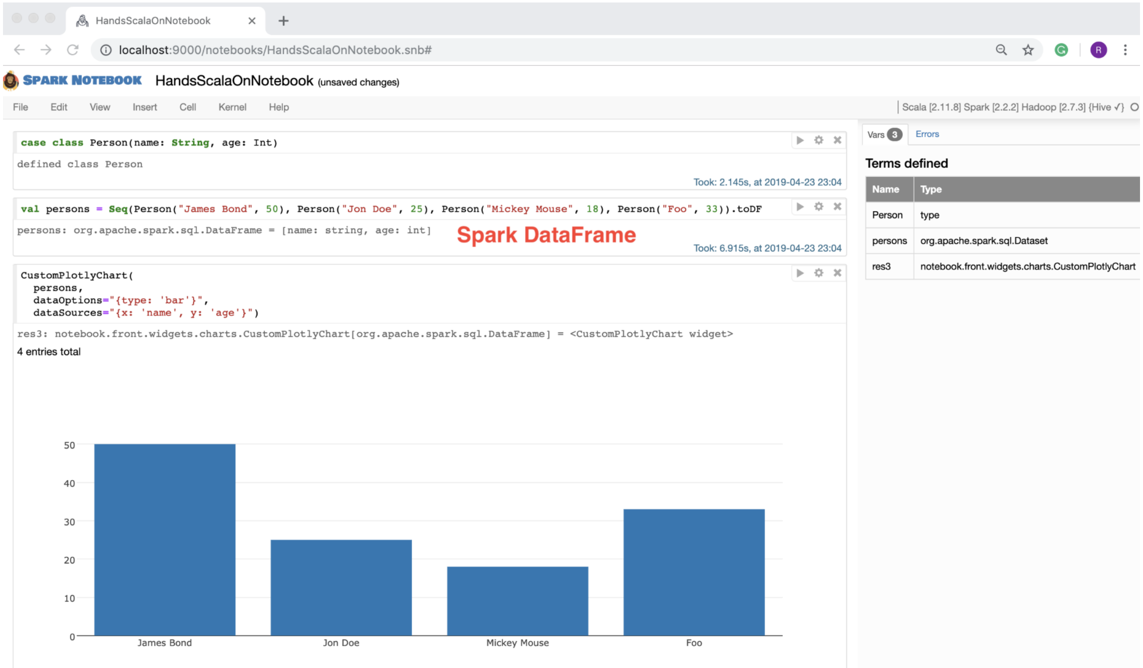
In the preceding example, we used a Scala-provided sequence of persons as the data input. We could have instead used a Spark DataFrame as the data input and would have gotten the same chart:

```
case class Person(name: String, age: Int)

val persons = Seq(Person("James Bond", 50), Person("Jon Doe", 25), Person("Mickey
Mouse", 18), Person("Foo", 33)).toDF

CustomPlotlyChart(
  persons,
  dataOptions="{type: 'bar'}",
  dataSources="{x: 'name', y: 'age'}")
```

The following is a screenshot of Spark Notebook with the aforementioned code executed:



This clearly illustrates that we can use Scala sequences and the Spark DataFrame as data input to the `CustomPlotlyChart` class of the Spark Notebook library. This offers a great deal of flexibility when using this library with data visualization.

More charts with Spark Notebook

In this section, we will look at more examples of charts using Spark Notebook. The bar chart is certainly very commonly used for data visualization but there are several other types of charts that provide different insights into the data.

Box plot

The box plot is a classic and standardized way of displaying the distribution of data based on the following properties of a dataset:

- Minimum value
- First quartile
- Median value
- Third quartile
- Maximum value

Let's explore this with an example:

1. Create three separate Spark DataFrames with 20 random numbers in the range of 0 to 100. Label each creation of the DataFrame as a unique experiment:

```
val df1 = sparkSession.range(20).map(n => (scala.util.Random.nextInt(100), "Experiment 1")).toDF("num", "experiment")

val df2 = sparkSession.range(20).map(n => (scala.util.Random.nextInt(100), "Experiment 2")).toDF("num", "experiment")

val df3 = sparkSession.range(20).map(n => (scala.util.Random.nextInt(100), "Experiment 3")).toDF("num", "experiment")
```

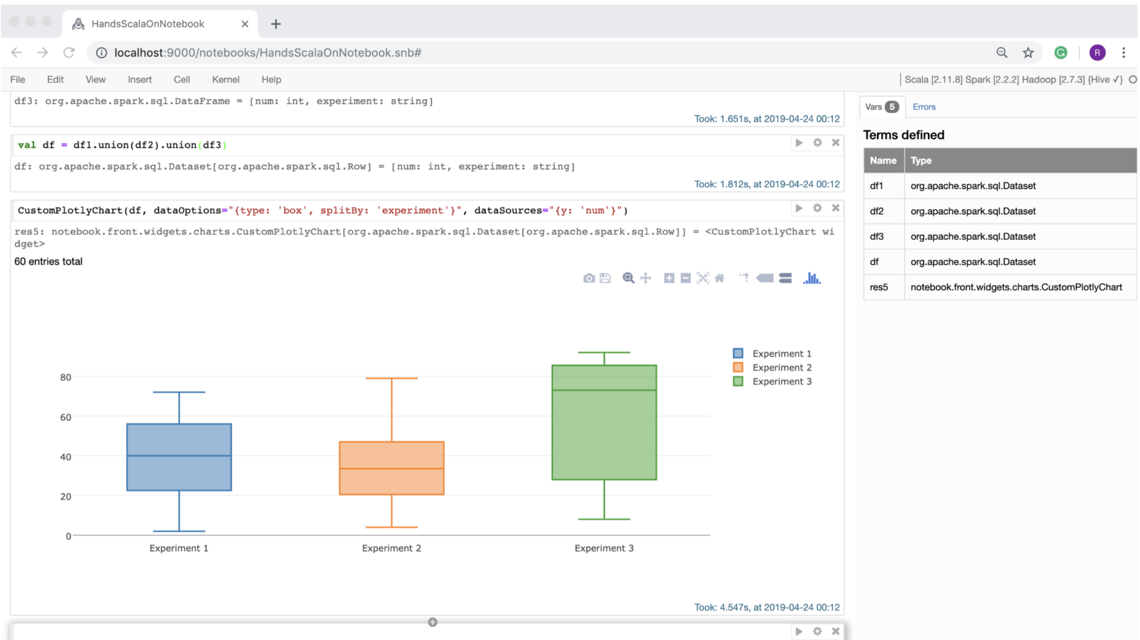
2. Create a combined DataFrame by taking the union of all three DataFrames:

```
val df = df1.union(df2).union(df3)
```

3. Use the box plot to display the properties of each of the three experiments:

```
CustomPlotlyChart(df, dataOptions="{type: 'box', splitBy: 'experiment'}", dataSources="{y: 'num'}")
```

You can run this code in Spark Notebook by executing each of the three steps as an individual cell (using the [*SHIFT]* + *[ENTER*] key combinations) and you will get an output that is similar to the following screenshot:



We can see that each of the three experiments has a slightly different distribution of data. This is expected because we are generating pseudorandom numbers with a uniform distribution property. The first experiment produced 20 random number from 0 to 100. The second experiment produced another 20 numbers from 0 to 100. Assuming uniform distribution, the second experiment's numbers would be different from the first one. Similarly, the third experiment's numbers will be different from that of the first and second, again due to the uniform distribution property.

Histogram

A histogram is a representation of the distribution of numerical data. The data is assumed to be continuous and grouped into a certain number of bins. The height of each bin determines the number of occurrences within the established range of the bin.

Let's explore the histogram plot with an example:

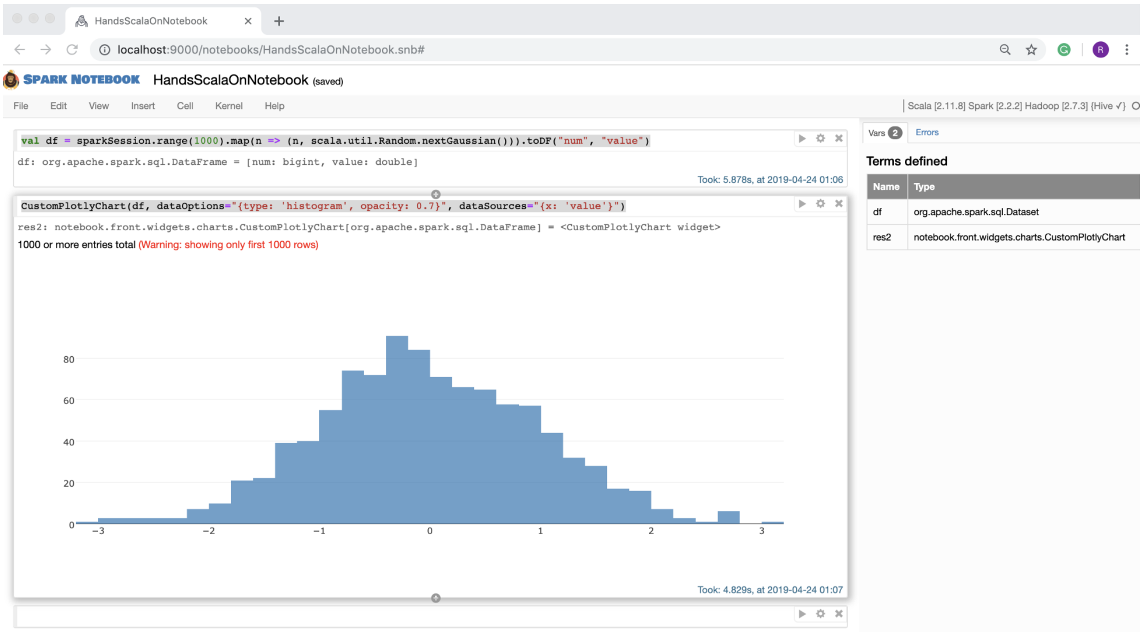
1. Create a Spark DataFrame consisting of 1,000 random numbers with Gaussian distribution properties:

```
val df = sparkSession.range(1000).map(n => (n,
scala.util.Random.nextGaussian())).toDF("num", "value")
```

2. Plot histogram of random values with Gaussian distribution properties:

```
CustomPlotlyChart(df, dataOptions="{type: 'histogram', opacity: 0.7}", dataSources="
{x: 'value'}")
```

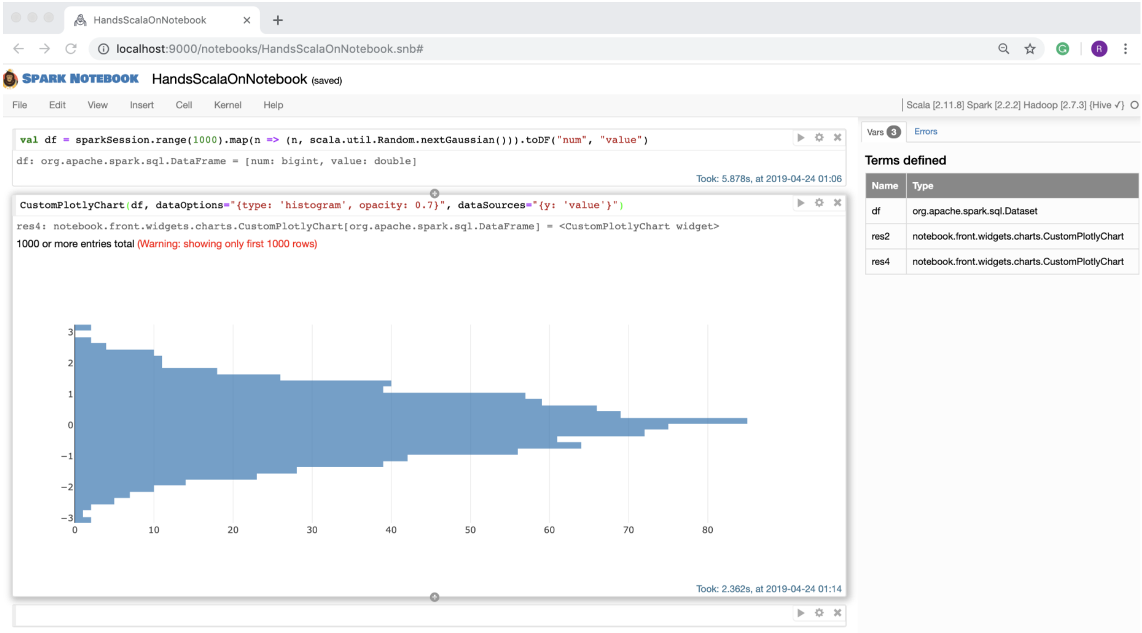
Running the aforementioned code in Spark Notebook results in the following screenshot:



We can easily change the axis from the [*x*] axis to the [*y*] axis by doing the following:

```
CustomPlotlyChart(df, dataOptions="{type: 'histogram', opacity: 0.7}", dataSources="
{y: 'value'}")
```

On running this code, the histogram would look like the following screenshot:



This is the same data, now with the inverted axis. Depending upon the use case, either one can be used. However, the first representation that uses the [*x*] axis is more common in practice.

Bubble chart

Bubble charts are generally used to represent the impacts of outcomes by representing them as different sized bubbles. The bigger the size of the bubble, the greater the impact.

Let's explore this kind of chart with a simple example:

1. Create a Spark DataFrame consisting of three records with different impacts:

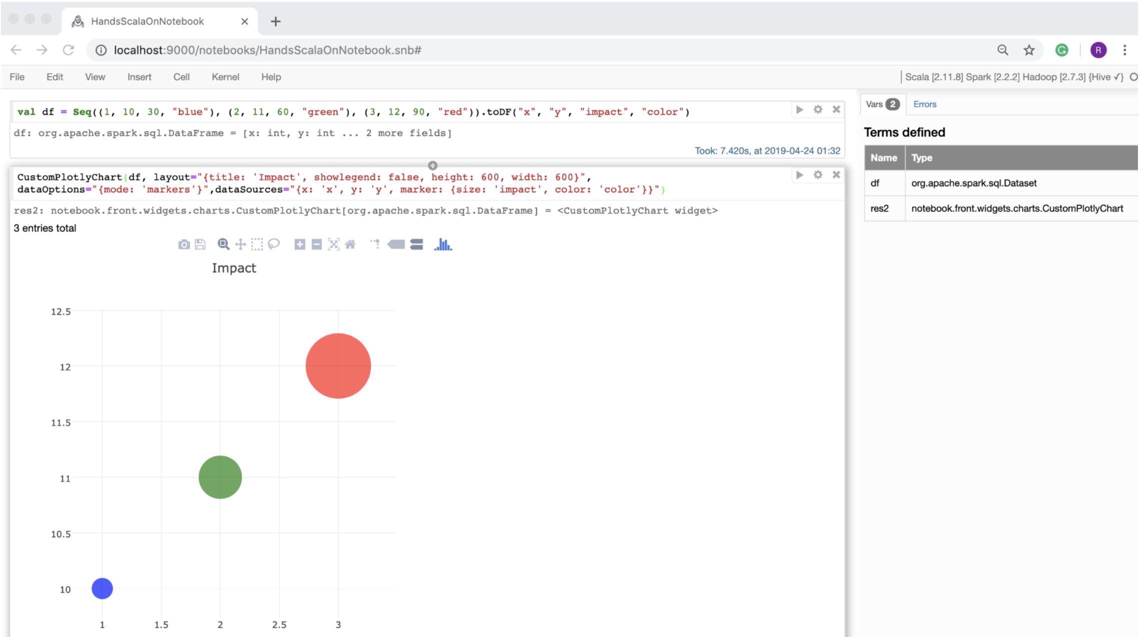
```
val df = Seq((1, 10, 30, "blue"), (2, 11, 60, "green"), (3, 12, 90, "red")).toDF("x",
"y", "impact", "color")
```

2. Create a bubble chart:

```
CustomPlotlyChart(df, layout="{title: 'Impact', showlegend: false, height: 600, width:
600}",

dataOptions="{mode: 'markers'}",dataSources="{x: 'x', y: 'y', marker: {size: 'impact',
color: 'color'}}")
```

When this code is run in Spark Notebook, we will see an output similar to the following screenshot:



Bubble charts find a significant usage when we use data to communicate a story and want to make it interesting for the target audience who might not be familiar with in-depth details of the underlying data.

Summary

This lab primarily focused on data exploration and visualization techniques to understand and establish a relationship between data elements. We also learned how to work with samples of data and apply randomness appropriately to select unbiased samples. Understanding properties and the relationship of data are very important because it helps in streamlining the data processing and simplifies the subsequent life cycles of the data.

In the next lab, we will deep dive into statistical techniques and hypothesis testing.