Lab 2. Data Analysis Life Cycle

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

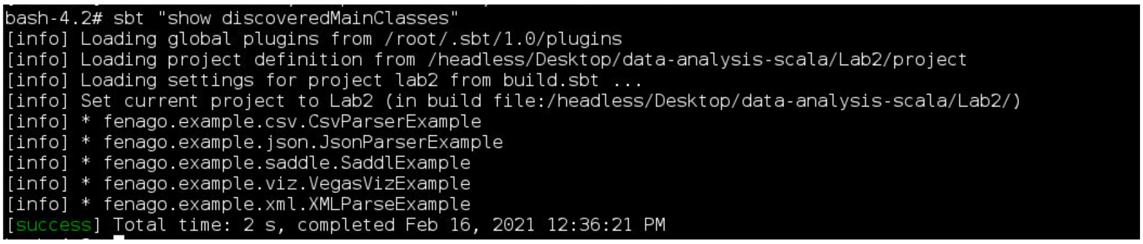
- Data journey
- Sourcing data
- Understanding data
- Using machine learning to learn from data
- Creating a data pipeline

Compile and Run

Method 1: Terminal

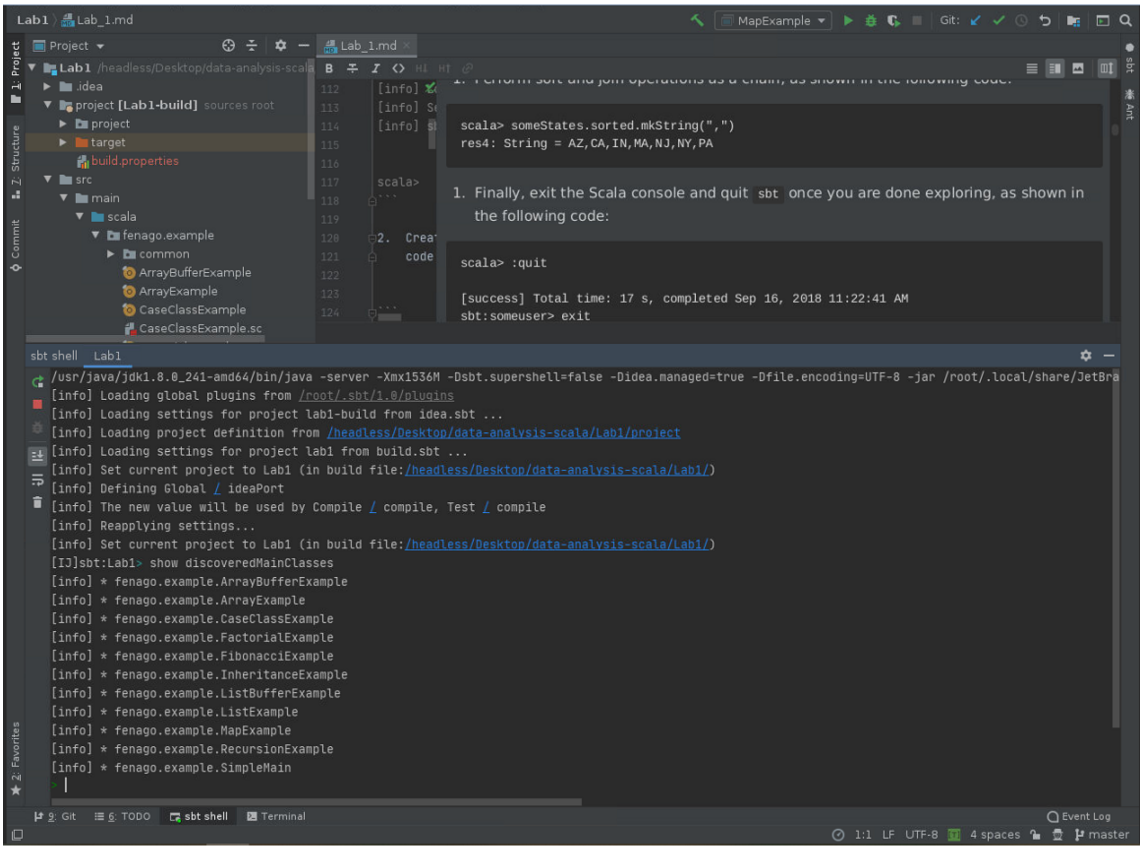
To run scala file with main function defined from the terminal, simply run the following commands. The program will the then be compiled and executed.

```
cd ~/Desktop/data-analysis-scala/Lab2

sbt "show discoveredMainClasses"

sbt "runMain fenago.example.<update>"
```

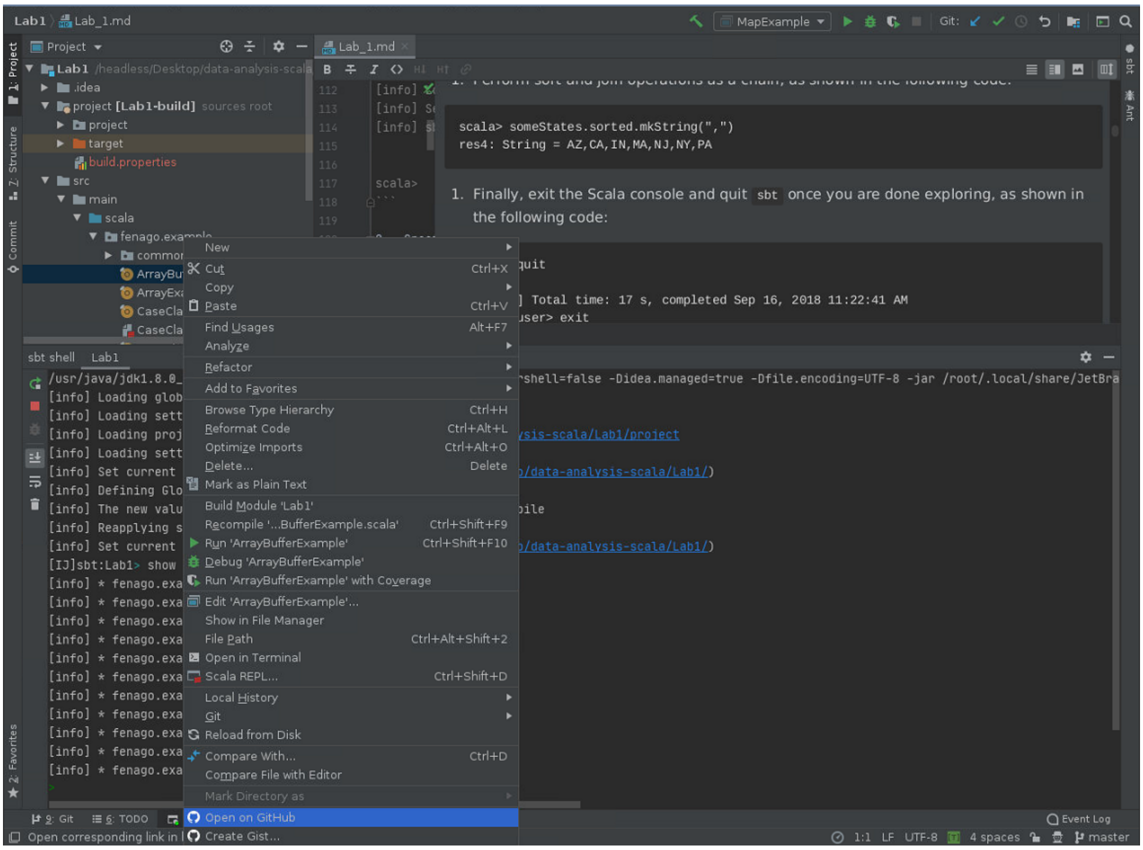


```
bash-4.2# sbt "show discoveredMainClasses"
[info] Loading global plugins from /root/.sbt/1.0/plugins
[info] Loading project definition from /headless/Desktop/data-analysis-scala/Lab2/project
[info] Loading settings for project lab2 from build.sbt ...
[info] Set current project to Lab2 (in build file:/headless/Desktop/data-analysis-scala/Lab2/)
[info] * fenago.example.csv.CsvParserExample
[info] * fenago.example.json.JsonParserExample
[info] * fenago.example.saddle.SaddlExample
[info] * fenago.example.viz.VegasVizExample
[info] * fenago.example.xml.XMLParseExample
[success] Total time: 2 s, completed Feb 16, 2021 12:36:21 PM
```

Method 2: SBT Shell in Intellij Idea



Method 3: Intellij Idea



Data formats

In this section, we will be looking at the three most prevalent data formats: XML, JSON,and CSV.

XML

Let's start by adding dependencies to the `scala-xml` library to `build.sbt`, as shown in the following code:

```
libraryDependencies ++= Seq(
"org.scala-lang.modules" %% "scala-xml" % "1.1.0"// Scala XML library
)
```

Let's explore some of the features of how this library works, as shown in the following code:

1. Import `Elem` from `scala.xml` package:

```
scala> import scala.xml.Elem
import scala.xml.Elem
```

2. Define a `Person` case class:

```
scala> case class Person(id: String, fname: String, lname: String, age: Option[Int] =
None) // class for holding Person object
defined class Person
```

3. Create an XML message:

```
scala> val personXml: Elem = <person id="123"><fname>John</fname><lname>Doe</lname>
<age>21</age></person> // sample XML data
personXml: scala.xml.Elem = <person id="123"><fname>John</fname><lname>Doe</lname>
<age>21</age></person>
```

4. Extract the `id` XML attribute from XML message:

```
scala> val id = personXml \@ "id" // extract XML attribute
id: String = 123
```

5. Extract `fname` XML element from XML message:

```
scala> val fname = personXml \ "fname" // XML element extraction
fname: scala.xml.NodeSeq = NodeSeq(<fname>John</fname>)
```

6. Extract `lname` XML element from XML message:

```
scala> val lname = personXml \ "lname"
lname: scala.xml.NodeSeq = NodeSeq(<lname>Doe</lname>)
```

7. Extract `age` XML element from XML message:

```
scala> val age = personXml \ "age"
age: scala.xml.NodeSeq = NodeSeq(<age>21</age>)
```

8. Now construct `Person` object from extracted values:

```
scala> val person = Person(id, fname.text, lname.text, Some(age.text.toInt)) // to
extract value from element, we need to use text
person: Person = Person(123,John,Doe,Some(21))
```

As you can see, the `scala-xml` library makes it really convenient to parse XML data. Creating XML is equally straightforward, as illustrated in the following code:

```
scala> import scala.xml.Elem
import scala.xml.Elem

scala> case class Person(id: String, fname: Strig, lname: String, age: Option[Int] =
None)
defined class Person

scala> def toXml(p: Person): Elem = { <person id={p.id}><fname>{p.fname}</fname>
<lname>{p.lname}</lname><age>{p.age.getOrElse(-1)}</age></person> }
toXml: (p: Person)scala.xml.Elem

scala> val person = Person("123", "John", "Doe", Some(21))
person: Person = Person(123,John,Doe,Some(21))

scala> toXml(person)
res0: scala.xml.Elem = <person id="123"><fname>John</fname><lname>Doe</lname>
<age>21</age></person>
```

JSON

We will use the Scala `json4s` (http://json4s.org/) library to work with JSON data. We will be using a native library that is the same or similar to the Scala `Lift` library.

Let's set up `build.sbt` with the following dependency and restart SBT using the following code:

```
libraryDependencies ++= Seq(
  "org.json4s" %% "json4s-native" % "3.6.1" // Scala Lift JSON Library
)
```

In the Scala REPL console, explore the library using Scala REPL, as shown in the following code:

```
scala> import org.json4s._
import org.json4s._

scala> import org.json4s.native.JsonMethods._
import org.json4s.native.JsonMethods._

scala> implicit val formats = DefaultFormats
formats: org.json4s.DefaultFormats.type = org.json4s.DefaultFormats$@59db09a7

scala> case class Person(id: String, fname: String, lname: String, age: Int)
defined class Person

scala> val personStr = """{
     | "id": "123",
     | "fname": "John",
     | "lname": "Doe",
     | "age": 21
     | }"""
personStr: String =
{
  "id": "123",
  "fname": "John",
  "lname": "Doe",
  "age": 21
}

scala> val json = parse(personStr) // parses JSON string to JValue
json: org.json4s.JValue = JObject(List((id,JString(123)), (fname,JString(John)),
(lname,JString(Doe)), (age,JInt(21))))

scala> val person = json.extract[Person] // convert to Person object
person: Person = Person(123,John,Doe,21)
```

Creating JSON is equally straightforward, as shown in the following code:

```
scala> import org.json4s.native.JsonMethods._
import org.json4s.native.JsonMethods._

scala> import org.json4s.JsonDSL._
import org.json4s.JsonDSL._
```

```
scala> val json = ("id" -> "123") ~ ("fname" -> "John") ~ ("lname" -> "Doe") ~ ("age"
-> 21) // build JSON object
json: org.json4s.JsonAST.JObject = JObject(List((id,JString(123)),
(fname,JString(John)), (lname,JString(Doe)), (age,JInt(21))))

scala> compact(render(json)) // create compact JSON string
res0: String = {"id":"123","fname":"John","lname":"Doe","age":21}
```

CSV

First, let's set up our `build.sbt` with the appropriate dependency using the following code:

```
libraryDependencies ++= Seq(
  "org.apache.commons" % "commons-csv" % "1.6" // Apache Commons CSV Java Library
)
```

Rerun SBT and explore the following code in Scala code. In this example, we are using a dataset that is available as part of the US government's Open Data initiative. This dataset is related to the 2010 census data of the City of Los Angeles in California:

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

scala> import java.util.function.Consumer
import java.util.function.Consumer

scala> import org.apache.commons.csv.{CSVFormat, CSVRecord}
import org.apache.commons.csv.{CSVFormat, CSVRecord}

scala> import scala.collection.mutable.ListBuffer
import scala.collection.mutable.ListBuffer

scala> case class CensusData(zipCode: String, totalPopulation: Int, medianAge: Double,
     | totalMales: Int, totalFemales: Int, totalHouseholds: Int, averageHouseholdSize:
Double)
defined class CensusData

scala> class DataConsumer extends Consumer[CSVRecord] {
     | val buf = ListBuffer[CensusData]()
     | override def accept(t: CSVRecord): Unit = {
     | buf += CensusData(t.get(0), t.get(1).toInt, t.get(2).toDouble,
     | t.get(3).toInt, t.get(4).toInt, t.get(5).toInt, t.get(6).toDouble)
     | }
     | }
defined class DataConsumer

scala> val reader = new BufferedReader(
     | new InputStreamReader(
     | new java.net.URL("https://data.lacity.org/api/views/nxs9-385f/rows.csv?
accessType=DOWNLOAD").openStream()
     | )
     | )
```

```
reader: java.io.BufferedReader = java.io.BufferedReader@4c83902

scala> val csvParser = CSVFormat.RFC4180.withFirstRecordAsHeader().parse(reader)
csvParser: org.apache.commons.csv.CSVParser =
org.apache.commons.csv.CSVParser@543b331c

scala> val dataConsumer = new DataConsumer
dataConsumer: DataConsumer = DataConsumer@3254eeb8

scala> csvParser.forEach(dataConsumer)

scala> val allRecords = dataConsumer.buf.toList
allRecords: List[CensusData] = List(CensusData(91371,1,73.5,0,1,1,1.0),
CensusData(90001,57110,26.6,28468,28642,12971,4.4),
CensusData(90002,51223,25.5,24876,26347,11731,4.36),
CensusData(90003,66266,26.3,32631,33635,15642,4.22),
CensusData(90004,62180,34.8,31302,30878,22547,2.73),
CensusData(90005,37681,33.9,19299,18382,15044,2.5),
CensusData(90006,59185,32.4,30254,28931,18617,3.13),
CensusData(90007,40920,24.0,20915,20005,11944,3.0),
CensusData(90008,32327,39.7,14477,17850,13841,2.33),
CensusData(90010,3800,37.8,1874,1926,2014,1.87),
CensusData(90011,103892,26.2,52794,51098,22168,4.67),
CensusData(90012,31103,36.3,19493,11610,10327,2.12),
CensusData(90013,11772,44.6,7629,4143,6416,1.26),
CensusData(90014,7005,44.8,4471,2534,4109,1.34), CensusData(90015,18986,...

scala> allRecords.take(3).foreach(println) // Output first 3 records
CensusData(91371,1,73.5,0,1,1,1.0)
CensusData(90001,57110,26.6,28468,28642,12971,4.4)
CensusData(90002,51223,25.5,24876,26347,11731,4.36)
```

As can be seen in the preceding code, we are able to get CSV data from the URL and then parse it into the Scala case class. Generating CSV data is even more straightforward.

Let's go ahead and generate some CSV data using the following code:

```
scala> import org.apache.commons.csv.{CSVFormat, CSVPrinter}
import org.apache.commons.csv.{CSVFormat, CSVPrinter}

scala> val csvPrinter = new CSVPrinter(System.out,
CSVFormat.RFC4180.withHeader("fname", "lname", "age"))
fname,lname,age
csvPrinter: org.apache.commons.csv.CSVPrinter =
org.apache.commons.csv.CSVPrinter@7ff05a74

scala> csvPrinter.printRecord("Jon", "Doe", "21")
Jon,Doe,21

scala> csvPrinter.printRecord("James", "Bond", "39")
James,Bond,39
```

```
scala> csvPrinter.flush()
```

Using statistical methods for data exploration

We will first use pure Scala code to explore and get an insight into the data. Next, we will look at some Scala libraries that simplify this task even further.

Using Scala

Let's explore the same dataset from the US government's Open Data initiative that we used for our CSV example. Let's make sure that the `sbt` dependency is defined as follows:

```
libraryDependencies ++= Seq(
  "org.apache.commons" % "commons-csv" % "1.6" // Apache Commons CSV
                                                  Java Library
)
```

Launch your SBT and start the Scala console. For the sake of clarity, all of the steps for processing the CSV have been repeated.

Import the required libraries using the following code:

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

scala> import java.util.function.Consumer
import java.util.function.Consumer

scala> import org.apache.commons.csv.{CSVFormat, CSVRecord}
import org.apache.commons.csv.{CSVFormat, CSVRecord}

scala> import scala.collection.mutable.ListBuffer
import scala.collection.mutable.ListBuffer
```

Let's move ahead and write our main code, as follows:

```
scala> case class CensusData(zipCode: String, totalPopulation: Int, medianAge: Double,
     | totalMales: Int, totalFemales: Int, totalHouseholds: Int, averageHouseholdSize:
Double)
defined class CensusData

scala> class DataConsumer extends Consumer[CSVRecord] {
     | val buf = ListBuffer[CensusData]()
     | override def accept(t: CSVRecord): Unit = {
     | buf += CensusData(t.get(0), t.get(1).toInt, t.get(2).toDouble,
     | t.get(3).toInt, t.get(4).toInt, t.get(5).toInt, t.get(6).toDouble)
     | }
     | }
defined class DataConsumer

scala> val reader = new BufferedReader(
     | new InputStreamReader(
     | new java.net.URL("https://data.lacity.org/api/views/nxs9-385f/rows.csv?
```

```
accessType=DOWNLOAD").openStream()
     | )
     | )
reader: java.io.BufferedReader = java.io.BufferedReader@572caa8b

scala> val csvParser = CSVFormat.RFC4180.withFirstRecordAsHeader().parse(reader)
csvParser: org.apache.commons.csv.CSVParser =
org.apache.commons.csv.CSVParser@19405f70

scala> val dataConsumer = new DataConsumer
dataConsumer: DataConsumer = DataConsumer@20d9ee6f

scala> csvParser.forEach(dataConsumer)

scala> val allRecords = dataConsumer.buf.toList
allRecords: List[CensusData] = List(CensusData(91371,1,73.5,0,1,1,1.0),
CensusData(90001,57110,26.6,28468,28642,12971,4.4),
CensusData(90002,51223,25.5,24876,26347,11731,4.36),
CensusData(90003,66266,26.3,32631,33635,15642,4.22),
CensusData(90004,62180,34.8,31302,30878,22547,2.73),
CensusData(90005,37681,33.9,19299,18382,15044,2.5),
CensusData(90006,59185,32.4,30254,28931,18617,3.13),
CensusData(90007,40920,24.0,20915,20005,11944,3.0),
CensusData(90008,32327,39.7,14477,17850,13841,2.33),
CensusData(90010,3800,37.8,1874,1926,2014,1.87),
CensusData(90011,103892,26.2,52794,51098,22168,4.67),
CensusData(90012,31103,36.3,19493,11610,10327,2.12),
CensusData(90013,11772,44.6,7629,4143,6416,1.26),
CensusData(90014,7005,44.8,4471,2534,4109,1.34), CensusData(90015,18986,...
```

Record the analysis using the following code:

```
scala> // Records Analysis

scala> allRecords.size // total records
res1: Int = 319

scala> allRecords.distinct.size // distinct records
res2: Int = 319

scala> allRecords.take(3) // 3 records from dataset
res3: List[CensusData] = List(CensusData(91371,1,73.5,0,1,1,1.0),
CensusData(90001,57110,26.6,28468,28642,12971,4.4),
CensusData(90002,51223,25.5,24876,26347,11731,4.36))

scala> // Zip Code Analysis

scala> allRecords.map(_.zipCode).distinct.size // distinct zipCode
res4: Int = 319

scala> allRecords.map(_.zipCode).min // minimum zipCode
res5: String = 90001
```

```
scala> allRecords.map(_.zipCode).max
res6: String = 93591

scala> val averageZip = allRecords.map(_.zipCode).aggregate(0)((a, b) => a + b.toInt,
(x, y) => x + y) / allRecords.size
averageZip: Int = 91000

scala> allRecords.map(_.zipCode.toInt).sum /allRecords.size // another way to compute
the same
res7: Int = 91000
```

Perform the total population analysis using the following code:

```
scala> // Total Population Analysis

scala> allRecords.map(_.totalPopulation).sum
res8: Int = 10603988

scala> val averagePop = allRecords.map(_.totalPopulation).sum / allRecords.size
averagePop: Int = 33241

scala> allRecords.sortBy(_.totalPopulation).head // record with lowest Population
res9: CensusData = CensusData(90079,0,0.0,0,0,0,0.0)

scala> allRecords.sortBy(-_.totalPopulation).head // record with highest Population
res10: CensusData = CensusData(90650,105549,32.5,52364,53185,27130,3.83)

scala> // Aggregate total numbers using a single aggregate method

scala> val (totalPopulation, totalMales, totalFemales, totalHouseholds) =
allRecords.aggregate((0, 0, 0, 0))((a, b) => (a._1 + b.totalPopulation, a._2 +
b.totalMales, a._3 + b.totalFemales, a._4 + b.totalHouseholds), (x,y) => (x._1 + y._1,
x._2 + y._2, x._3 + y._3, x._4 + y._4))
totalPopulation: Int = 10603988
totalMales: Int = 5228909
totalFemales: Int = 5375079
totalHouseholds: Int = 3497698
```

As can be seen in the preceding code, the Scala collection API comes in handy when performing data analysis. Also, note the `aggregate` method of the API; it is a generalized way to create an aggregated value over a collection. Let's look at some more ways to create aggregate values in Scala, as shown in the following code:

```
scala> // Aggregate using foldLeft

scala> allRecords.map(_.totalPopulation).foldLeft(0)(_+_)
res11: Int = 10603988

scala> allRecords.map(_.totalMales).foldLeft(0)(_+_)
res12: Int = 5228909

scala> allRecords.map(_.totalFemales).foldLeft(0)(_+_)
res13: Int = 5375079
```

```
scala> allRecords.map(_.totalHouseholds).foldLeft(0)(_+_)
res14: Int = 3497698

scala> // Aggregate using foldRight

scala> allRecords.map(_.totalPopulation).foldRight(0)(_+_)
res15: Int = 10603988

scala> allRecords.map(_.totalMales).foldRight(0)(_+_)
res16: Int = 5228909

scala> allRecords.map(_.totalFemales).foldRight(0)(_+_)
res17: Int = 5375079

scala> allRecords.map(_.totalHouseholds).foldRight(0)(_+_)
res18: Int = 3497698

scala> // Aggregate using reduce

scala> allRecords.map(_.totalPopulation).reduce(_+_)
res19: Int = 10603988

scala> allRecords.map(_.totalMales).reduce(_+_)
res20: Int = 5228909

scala> allRecords.map(_.totalFemales).reduce(_+_)
res21: Int = 5375079

scala> allRecords.map(_.totalHouseholds).reduce(_+_)
res22: Int = 3497698
```

Note

Note that we are getting the same results using the `foldLeft`, `foldRight`, and `reduce` methods.

Other Scala tools

Spark is a very popular distributed data-processing engine. It has built-in support for exploring data in many different formats. We will look at Spark functionality in subsequent labs. Let's look at another Scala library called **Saddle** (http://saddle.github.io/) and see how we can leverage this library to work with data.

This library is not yet available for Scala 2.12, so we will be using Scala 2.11.12 to explore this library. Configure your `sbt build.sbt` file as follows:

```
scalaVersion := "2.11.12"

libraryDependencies ++= Seq(
  "org.scala-saddle" %% "saddle-core" % "1.3.4"
)
```

For this exploration using Saddle, we will continue to use the dataset that we used in our earlier exercise. In your `sbt` console, try the following:

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

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

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

scala> val file = new SaddleCsvSource("https://data.lacity.org/api/views/nxs9-
385f/rows.csv?accessType=DOWNLOAD")
file: SaddleCsvSource = SaddleCsvSource@6437b766

scala> val frame = CsvParser.parse(file)
frame: 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 1564...
scala> frame.print() // prints 10 records from the frame
[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 15642 4.22
...
315 -> 93552 38158 28.4 18711 19447 9690 3.93
316 -> 93553 2138 43.3 1121 1017 816 2.62
317 -> 93560 18910 32.4 9491 9419 6469 2.92
318 -> 93563 388 44.5 263 125 103 2.53
319 -> 93591 7285 30.9 3653 3632 1982 3.67
```

If you are familiar with R or Python's pandas library, you will find a great deal of similarity between Saddle's API and these APIs. The `frame` object that we constructed previously lets us work with the data at a higher level of abstraction using Saddle's API. Let's further explore Saddle's frame API, as shown in the following code:

```
scala> val df = frame.withColIndex(0) // first row is the CSV header
df: 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 2254...
scala> df.col("Zip Code") // we can access each column by name
res1: org.saddle.Frame[Int,String,String] =
[319 x 1]
       Zip Code
       --------
  1 -> 91371
  2 -> 90001
  3 -> 90002
  4 -> 90003
  5 -> 90004
...
315 -> 93552
316 -> 93553
317 -> 93560
318 -> 93563
319 -> 93591

scala> df.col("Zip Code").min // should fail
<console>:17: error: No implicit view available from org.saddle.Series[_, String] =>
org.saddle.stats.VecStats[String].
       df.col("Zip Code").min // should fail
                          ^

scala> df.col("Zip Code").mapValues(CsvParser.parseInt).min // convert from string to
integer
res3: org.saddle.Series[String,Int] =
[1 x 1]
Zip Code -> 90001
```

The preceding example demonstrates how to work with a frame that consists of rows and columns. It also shows you how to extract a specific column using the qualified name and compute some simple stats, such as `min`.

Next, let's look at how to get the same information using Saddle. Here, we'll try obtaining the ZIP codes using the following code:

```
scala> df.col("Zip Code").mapValues(CsvParser.parseInt).min
res4: org.saddle.Series[String,Int] =
[1 x 1]
Zip Code -> 90001

scala> df.col("Zip Code").mapValues(CsvParser.parseInt).max
res5: org.saddle.Series[String,Int] =
```

```
[1 x 1]
Zip Code -> 93591

scala> df.col("Zip Code").mapValues(CsvParser.parseInt).mean
res6: org.saddle.Series[String,Double] =
[1 x 1]
Zip Code -> 91000.6740
```

Next, let's obtain the total population using the following code:

```
scala> df.col("Total Population").mapValues(CsvParser.parseInt).min
res7: org.saddle.Series[String,Int] =
[1 x 1]
Total Population -> 0

scala> df.col("Total Population").mapValues(CsvParser.parseInt).max
res8: org.saddle.Series[String,Int] =
[1 x 1]
Total Population -> 105549

scala> df.col("Total Population").mapValues(CsvParser.parseInt).sum
res9: org.saddle.Series[String,Int] =
[1 x 1]
Total Population -> 10603988
```

Next, let's find the total number of males using the following code:

```
scala> df.col("Total Males").mapValues(CsvParser.parseInt).min
res10: org.saddle.Series[String,Int] =
[1 x 1]
Total Males -> 0

scala> df.col("Total Males").mapValues(CsvParser.parseInt).max
res11: org.saddle.Series[String,Int] =
[1 x 1]
Total Males -> 52794

scala> df.col("Total Males").mapValues(CsvParser.parseInt).sum
res12: org.saddle.Series[String,Int] =
[1 x 1]
Total Males -> 5228909
```

Next, let's find the total number of females using the following code:

```
scala> df.col("Total Females").mapValues(CsvParser.parseInt).min
res13: org.saddle.Series[String,Int] =
[1 x 1]
Total Females -> 0

scala> df.col("Total Females").mapValues(CsvParser.parseInt).max
res14: org.saddle.Series[String,Int] =
[1 x 1]
Total Females -> 53185
```

```
scala> df.col("Total Females").mapValues(CsvParser.parseInt).sum
res15: org.saddle.Series[String,Int] =
[1 x 1]
Total Females -> 5375079
```

Now let's find the total number of households using the following code:

```
scala> df.col("Total Households").mapValues(CsvParser.parseInt).min
res16: org.saddle.Series[String,Int] =
[1 x 1]
Total Households -> 0

scala> df.col("Total Households").mapValues(CsvParser.parseInt).max
res17: org.saddle.Series[String,Int] =
[1 x 1]
Total Households -> 31087

scala> df.col("Total Households").mapValues(CsvParser.parseInt).sum
res18: org.saddle.Series[String,Int] =
[1 x 1]
Total Households -> 3497698
```

Saddle's Scala library has a lot more to offer in terms of computing useful statistical information and working with data. Let's implement some other methods supported by Saddle using the following code:

```
scala> df.numRows
res19: Int = 319

scala> df.numCols
res20: Int = 7

scala> df.col("Total Households").mapValues(CsvParser.parseInt).mean
res21: org.saddle.Series[String,Double] =
[1 x 1]
Total Households -> 10964.5705

scala> df.col("Total Households").mapValues(CsvParser.parseInt).median
res22: org.saddle.Series[String,Double] =
[1 x 1]
Total Households -> 10968.0000

scala> df.col("Total Households").mapValues(CsvParser.parseInt).stdev
res23: org.saddle.Series[String,Double] =
[1 x 1]
Total Households -> 6270.6464
```

Let's see a list of the total number of households, as shown in the following code:

```
// convert to Scala List
scala> df.col("Total
      Households").mapValues(CsvParser.parseInt).toSeq.map(_._3).toList
```

```
res24: List[Int] = List(1, 12971, 11731, 15642, 22547, 15044, 18617, 11944, 13841,
2014, 22168, 10327, 6416, 4109, 7420, 16145, 9338, 15493, 23344, 16514, 1561, 17023,
10727, 17903, 21228, 24956, 21929, 14964, 13883, 11156, 12765, 12924, 25592, 12814,
18646, 15869, 11928, 11436, 3317, 9513, 19892, 16075, 25144, 15224, 28534, 16168,
11821, 16657, 3371, 15658, 892, 9596, 6892, 9155, 13260, 10968, 14476, 23985, 1510,
12326, 13364, 0, 4, 3615, 0, 31, 0, 2949, 2, 24104, 8669, 3706, 5567, 12741, 11630,
7520, 12883, 6605, 7632, 13617, 12687, 7085, 15830, 3427, 8880, 31087, 9550, 18419,
10429, 14669, 0, 7174, 14038, 6554, 9212, 9479, 15618, 16910, 16009, 23278, 2612,
14261, 12654, 6575, 11895, 10684, 7290, 6634, 5933, 4188, 5301, 13970, 10089, 14376,
14610, 5717, 17183, 11580, 14244, 0, 11027, ...
```

As we can see from the preceding examples, Saddle's API has a lot to offer in terms of conveniently exploring and working with data.

Using the vegas-viz library for data visualization

We will explore some sample dates using the `vegas-viz` (https://www.vegas-viz.org/) Scala library for data visualization. This is a powerful Scala library that integrates very well with Spark. We will work with Spark in subsequent labs.

To explore this library in `sbt`, we will first set up the `build.sbt` file using the following code. At the time of writing, `vegas-viz` and Spark are only supported for Scala 2.11.x, so we will use Scala version 2.11.12 for our exploration:

```
// We will use Scala 2.11.x because many of Scala libraries such as
// Spark, vegas-viz are not yet supported for Scala 2.12.x
scalaVersion := "2.11.12"

libraryDependencies ++= Seq(
  "org.vegas-viz" %% "vegas" % "0.3.11" // Vegas Visualization Library
)
```

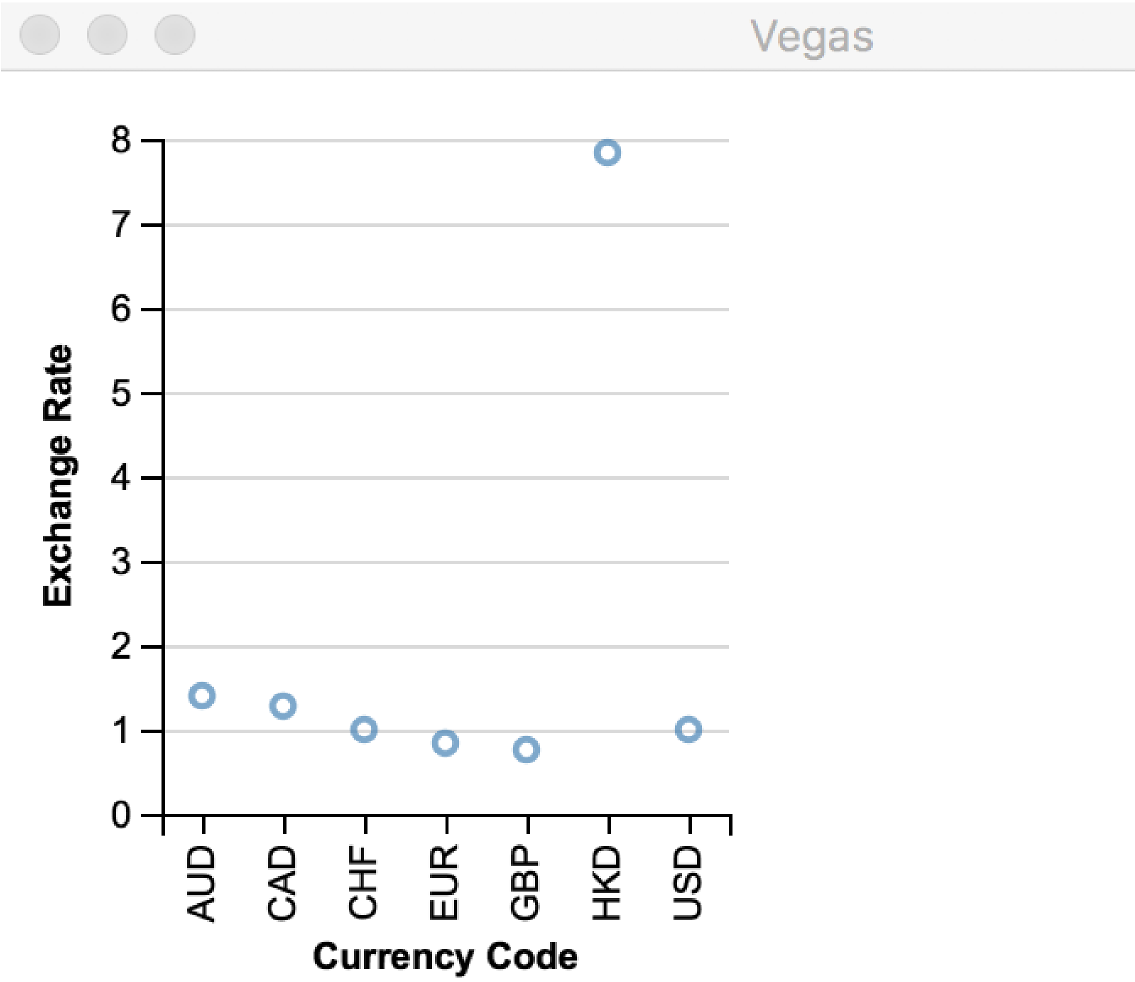
After creating the aforementioned `build.sbt`, run SBT. Once inside SBT, run the following console command to start Scala REPL:

```
scala> val plot = Vegas("Currency Exchange Rates").
     | withData(
     | Seq(
     | Map("Currency Code" -> "USD", "Exchange Rate" -> 1.00),
     | Map("Currency Code" -> "EUR", "Exchange Rate" -> 0.86),
     | Map("Currency Code" -> "GBP", "Exchange Rate" -> 0.76),
     | Map("Currency Code" -> "CHF", "Exchange Rate" -> 0.99),
     | Map("Currency Code" -> "CAD", "Exchange Rate" -> 1.29),
     | Map("Currency Code" -> "AUD", "Exchange Rate" -> 1.41),
     | Map("Currency Code" -> "HKD", "Exchange Rate" -> 7.83)
     | )
     | ).
     | encodeX("Currency Code", Nom).
     | encodeY("Exchange Rate", Quant).
     | mark(Point)
```

Done. Now, let's plot the following:

```
scala> plot.show
```

This will produce the following scatter plot of `Currency Code` versus `Exchange Rate` (USD):

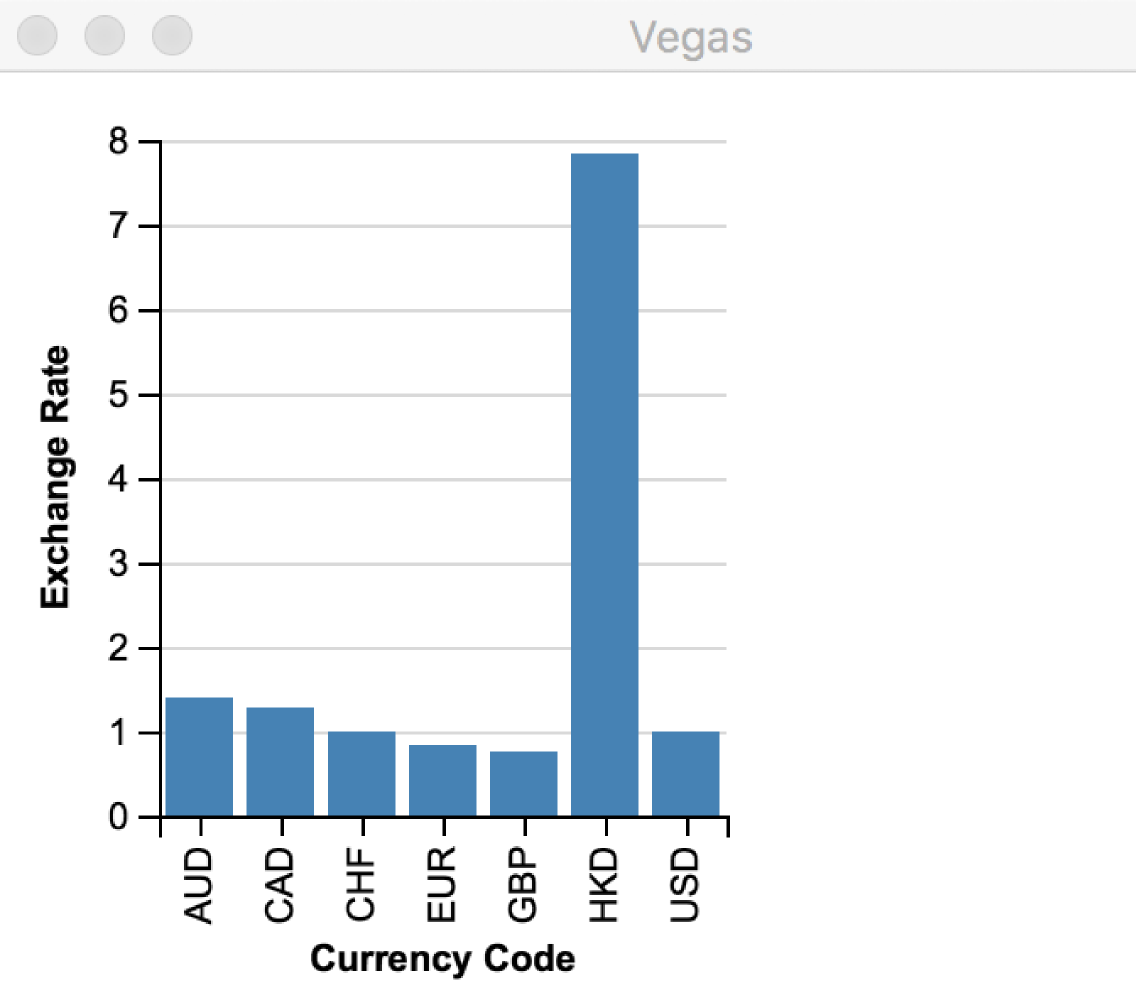


[Export as PNG](#)[View Source](#)[Open in Vega Editor](#)

Change the plot mark to `Bar` to output the bar chart using the following code:

```
val plot = Vegas("Currency Exchange Rates").
...
  mark(Bar) // for bar chart
```

This produces the following bar chart:



[Export as PNG](#)[View Source](#)[Open in Vega Editor](#)

As we can see, by using the `vegas-viz` Scala library, we can easily perform data visualization using a simple set of APIs.

Setting up Smile

There are multiple ways to set up Smile on your machine. Refer to Smile Quick Start at https://haifengl.github.io . The easiest and fastest way to get started is to download the binaries from https://github.com/haifengl/smile/releases.

The following is a set of commands that are used to perform the Smile setup:

```
$ curl -L -o smile-1.5.1.zip
https://github.com/haifengl/smile/releases/download/v1.5.1/smile-1.5.1.zip # download
and save in zip file
  % Total % Received % Xferd Average Speed Time Time Time Current
                                 Dload Upload Total Spent Left Speed
100 605 0 605 0 0 1729 0 --:--:-- --:--:-- --:--:-- 1733
100 165M 100 165M 0 0 11.2M 0 0:00:14 0:00:14 --:--:-- 12.2M

$ unzip smile-1.5.1.zip # unzip file
```

```
Archive: smile-1.5.1.zip
  inflating: smile-1.5.1/smile_config.txt
  inflating: smile-1.5.1/bin/init.scala
  inflating: smile-1.5.1/bin/libblas3.dll
...
  inflating: smile-1.5.1/lib/com.github.javaparser.javaparser-core-3.2.5.jar
  inflating: smile-1.5.1/lib/com.github.scopt.scopt_2.12-3.5.0.jar
  inflating: smile-1.5.1/bin/smile
  inflating: smile-1.5.1/bin/smile.bat

$ cd smile-1.5.1 # Smile is setup in this directory

$ ls -1 # List the contents
bin
conf
data
doc
examples
lib
smile_config.txt

$ ls -l bin/smile # This is the Smile start up script
-rwxr-xr-x 1 uid gid 12980 Feb 25 2018 bin/smile
```

Once the setup is complete, let's confirm that it is working properly using the following code. Note that there is a JVM memory parameter that might have to be adjusted depending upon the size of the dataset that is being worked on:

```
$ ./bin/smile -J-Xmx2048M # 2048M (2 GB) of memory to JVM
Compiling (synthetic)/ammonite/predef/interpBridge.sc
Compiling (synthetic)/ammonite/predef/replBridge.sc
Compiling (synthetic)/ammonite/predef/DefaultPredef.sc
Compiling (synthetic)/ammonite/predef/CodePredef.sc

                                                       ..::''''::..
                                                     .;''  ``;.
     .... :: :: :: ::
   ,;' .;: () ..: :: :: :: ::
   ::. ..:,:;.,:;. . :: .:. :: .:' :: :: `:. ::
    '''::, :: :: :: `:: :: ;: .:: :: : : ::
  ,:'; ::; :: :: :: :: :: ::,::''. :: `:. .:' ::
  `:,,,,;;' ,;; ,;;, ;;, ,;;, ,;;, `:,,,,:' `;..``:''..;'
                                                       ``::,,,,::''

  Welcome to Smile Shell; enter 'help<RETURN>' for the list of commands.
  Type "exit<RETURN>" to leave the Smile Shell
  Version 1.5.1, Scala 2.12.4, SBT 1.1.0, Built at 2018-02-26
                                          02:31:25.456
=======================================================================
```

Let's see what things can be done using the Smile shell, as shown in the following code:

```
smile> help

 General:
   help -- print this summary
   :help -- print Scala shell command summary
   :quit -- exit the shell
   demo -- show demo window
   benchmark -- benchmark tests

 I/O:
   read -- Reads an object/model back from a file created by write command.
...
 Classification:
   knn -- K-nearest neighbor classifier.
   logit -- Logistic regression.
...
 Regression:
   ols -- Ordinary least square.
   ridge -- Ridge regression.
   lasso -- Least absolute shrinkage and selection operator.
...
 Graphics:
   plot -- Scatter plot.
   line -- Scatter plot which connects points by straight lines.
   boxplot -- Boxplots can be useful to display differences between populations.
...
```

As can be seen from the `help` message, Smile supports a wide range of classification and regression ML algorithms. Another nice feature of Smile is that it also has support for data visualization.

Running Smile

To explore Smile, we will run some of the examples that are included with the Smile code base.

The following is an example of applying a random forest algorithm to the data:

```
smile> val data = read.arff("data/weka/iris.arff", 4)
data: AttributeDataset = iris
  class sepallength sepalwidth petallength petalwidth
[1] Iris-setosa 5.1000 3.5000 1.4000 0.2000
[2] Iris-setosa 4.9000 3.0000 1.4000 0.2000
[3] Iris-setosa 4.7000 3.2000 1.3000 0.2000
[4] Iris-setosa 4.6000 3.1000 1.5000 0.2000
[5] Iris-setosa 5.0000 3.6000 1.4000 0.2000
[6] Iris-setosa 5.4000 3.9000 1.7000 0.4000
[7] Iris-setosa 4.6000 3.4000 1.4000 0.3000
[8] Iris-setosa 5.0000 3.4000 1.5000 0.2000
[9] Iris-setosa 4.4000 2.9000 1.4000 0.2000
[10] Iris-setosa 4.9000 3.1000 1.5000 0.1000
140 more rows...

smile> val (x, y) = data.unzipInt
x: Array[Array[Double]] = Array(
```

```
  Array(5.1, 3.5, 1.4, 0.2),
  Array(4.9, 3.0, 1.4, 0.2),
  Array(4.7, 3.2, 1.3, 0.2),
  Array(4.6, 3.1, 1.5, 0.2),
...
smile> val rf = randomForest(x, y)
[Thread-209] INFO smile.classification.RandomForest - Random forest tree OOB size: 59,
accuracy: 89.83%
[Thread-210] INFO smile.classification.RandomForest - Random forest tree OOB size: 52,
accuracy: 88.46%
[Thread-213] INFO smile.classification.RandomForest - Random forest tree OOB size: 50,
accuracy: 100.00%
...
[Thread-210] INFO smile.classification.RandomForest - Random forest tree OOB size: 56,
accuracy: 100.00%
[main] INFO smile.util.package$ - runtime: 97.07988 ms
rf: RandomForest = smile.classification.RandomForest@a4df251

smile> println(s"OOB error = ${rf.error}")
OOB error = 0.04666666666666667



smile> rf.predict(x(0))
res4: Int = 0
```

Summary

In this lab, we looked at the journey of data and the data analysis life cycle at a broad level. Using hands-on examples, we looked at how to perform some of the tasks using mainly Scala and some Java libraries.

In the next lab, we will look at data ingestion and associated tasks.