Contents

Exercise 1: Setting up the Environment

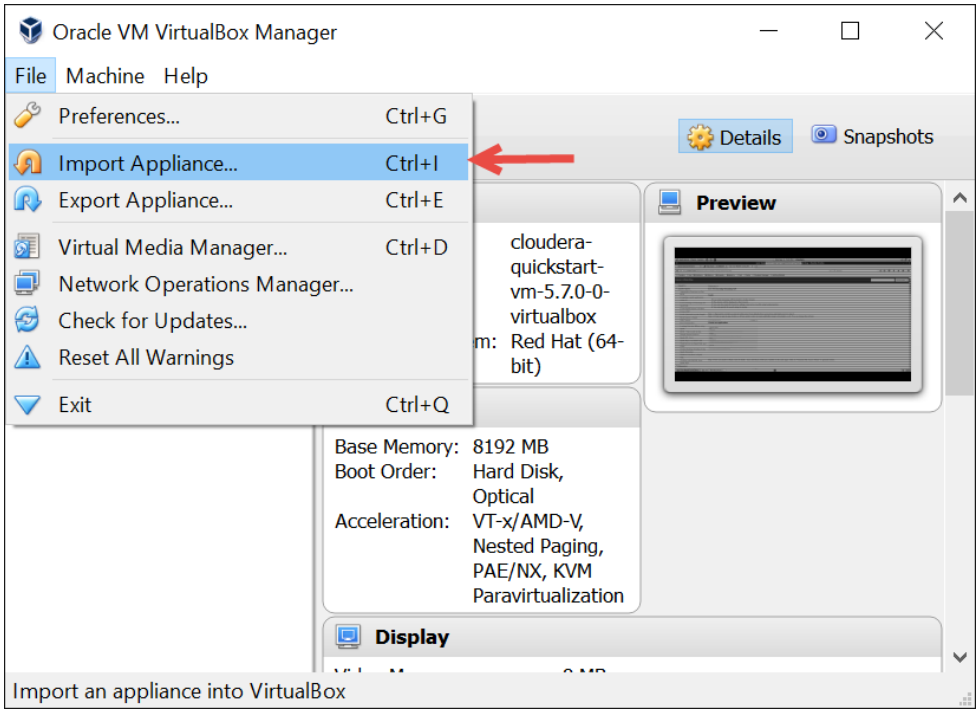
Step1: Installing Oracle VM virtual box from Training Bundle.

- Under 'Training Bundle' folder, navigate to "Software" folder.
- Find the executable file named 'VirtualBox-5.0.16-105871-Win' and complete the installation.

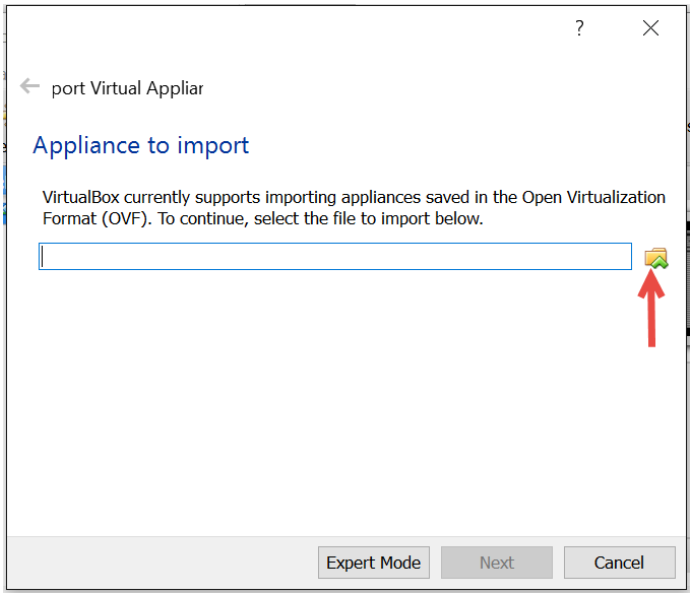
Step2: Extracting the Image

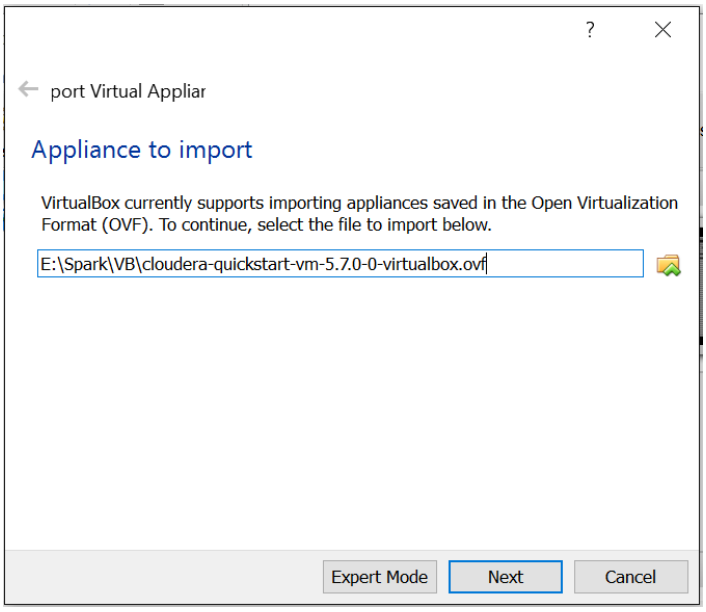
- From the same training bundle, locate the folder named VM image> 'cloudera-quickstart-vm-5.12.0-0-virtualbox'
- Load the image to get started with the machine.

Step3: Importing the file



- Browse to the location under "Training Bundle" and select the OVF file.





- This will prepare your machine.
- After import, change the number of processors to two before starting the machine.
- Verify all the running services with jps command

```
[cloudera@quickstart ~]$ sudo jps
6403 RESTServer
5709 SecondaryNameNode
5980 NodeManager
6878 RunJar
8543
10329 ZeppelinServer
9721 org.eclipse.equinox.launcher_1.3.0.v20140415-2008.jar
5841 Bootstrap
5366 DataNode
5454 JournalNode
8584
7516 HistoryServer
8518 Bootstrap
5573 NameNode
7484 Bootstrap
5303 QuorumPeerMain
6659 RunJar
5897 JobHistoryServer
18565 Jps
6184 ResourceManager
6521 ThriftServer
8191 Bootstrap
[cloudera@quickstart ~]$
```

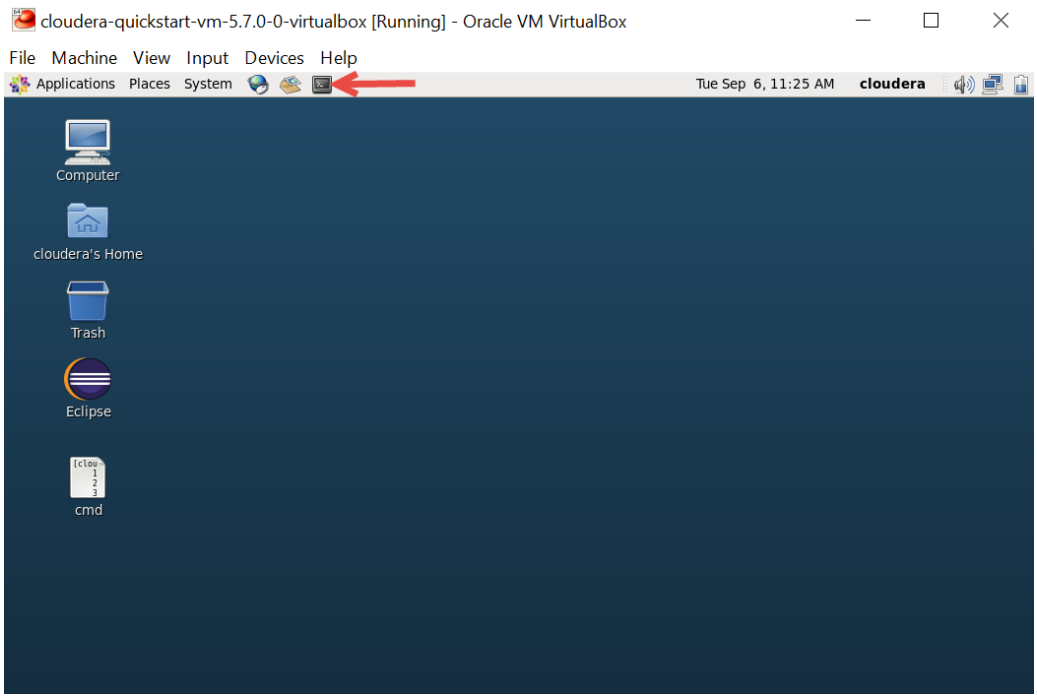
Exercise 2: Practicing HDFS Commands

Task 1: Using Hadoop Command Line Interface

Navigate to Application > System Tools > Terminal

OR

Use shortcut to open the terminal.



- Operation on Files and directories

To check the content of root directory in HDFS

```
hdfs dfs -ls /
```

```
[cloudera@quickstart ~]$ hdfs dfs -ls /
Found 5 items
drwxrwxrwx   - hdfs  supergroup          0 2016-04-05 23:56 /benchmarks
drwxr-xr-x   - hbase supergroup          0 2016-09-04 10:14 /hbase
drwxrwxrwt   - hdfs  supergroup          0 2016-08-03 01:56 /tmp
drwxr-xr-x   - hdfs  supergroup          0 2016-08-02 08:08 /user
drwxr-xr-x   - hdfs  supergroup          0 2016-04-05 23:58 /var
[cloudera@quickstart ~]$
```

View the content of /user directory

```
hdfs dfs -ls /user
```

```
[cloudera@quickstart ~]$ hdfs dfs -ls /user
Found 9 items
drwxr-xr-x   - cloudera cloudera            0 2016-08-03 01:54 /user/cloudera
drwxr-xr-x   - hdfs     supergroup          0 2016-08-02 08:08 /user/hdfs
drwxr-xr-x   - mapred   hadoop              0 2016-04-05 23:56 /user/history
drwxrwxrwx   - hive     supergroup          0 2016-04-05 23:58 /user/hive
drwxrwxrwx   - hue      supergroup          0 2016-04-05 23:57 /user/hue
drwxrwxrwx   - jenkins  supergroup          0 2016-04-05 23:56 /user/jenkins
drwxrwxrwx   - oozie    supergroup          0 2016-04-05 23:57 /user/oozie
drwxrwxrwx   - root     supergroup          0 2016-04-05 23:57 /user/root
drwxr-xr-x   - hdfs     supergroup          0 2016-04-05 23:58 /user/spark
```

For an empty directory the prompt does not show any error while querying whereas if the directory doesn't exist it will throw an error.

Example: Query a non-existing directory say /music

```
hdfs dfs -ls /music
```

```
[cloudera@quickstart ~]$ hdfs dfs -ls /music
ls: `/music': No such file or directory
[cloudera@quickstart ~]$
```

The directory structure of Hadoop filesystem is different from local filesystem i.e. Linux filesystem. To know the difference, list the files on your local filesystem.

Create a new directory named “hadoop” in HDFS

```
hdfs dfs -mkdir hadoop
```

Create a sample.txt file on local and upload the file into newly created directory

```
hdfs dfs -put sample.txt hadoop/sample.txt
```

View the content of new file

```
hdfs dfs -cat hadoop/sample.txt
```

In HDFS, any non-absolute path is considered relative to your home directory i.e. /user/cloudera. Unlike Linux filesystem concept of “current” or “present working directory”.

Download a file from HDFS to your local filesystem, specify HDFS path and local path to achieve the same.

```
hdfs dfs -get /user/cloudera/sample.text /home/cloudera
```

Remove the directory along with its content (perform this step after completing Task 2)

```
hdfs dfs -rm -r hadoop
```

List all the shell commands supported by Hadoop

```
hdfs dfs
```

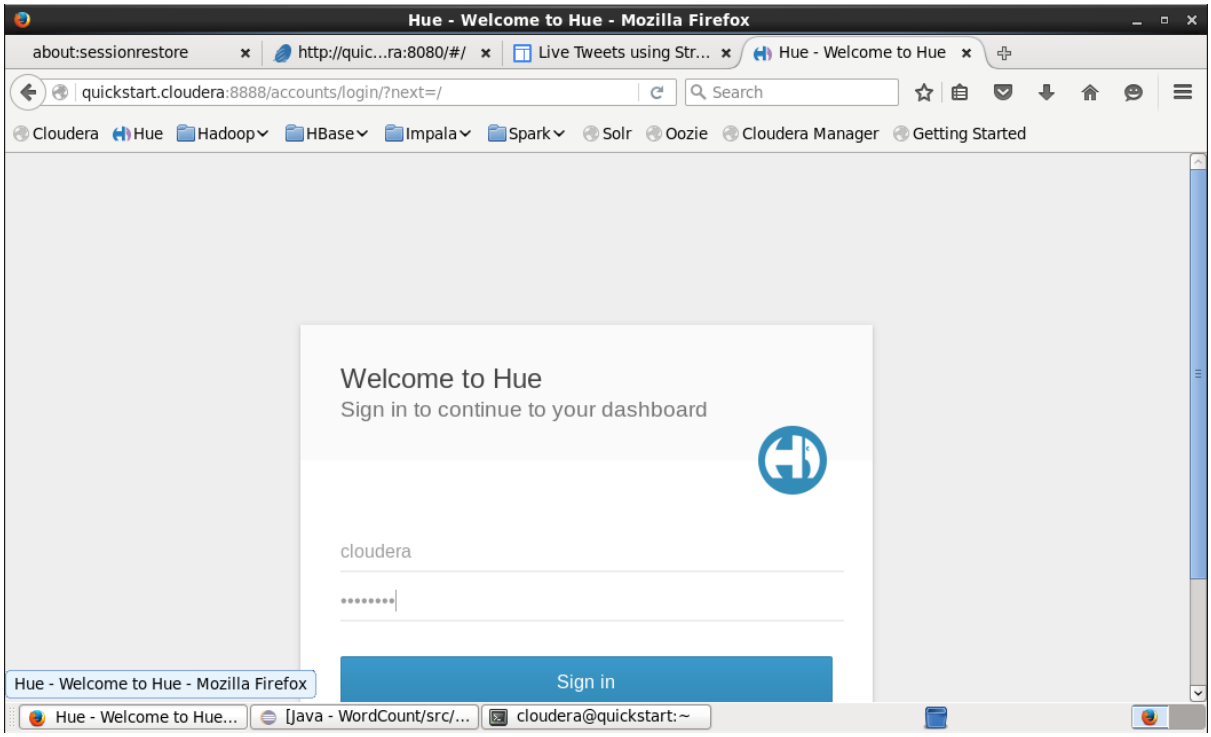
Task2: Using HUE File browser

1. Open a web browser on your VM, and navigate to bookmark tab and select HUE. This can be alternatively launched by specifying http://quickstart.cloudera:8888
2. Enter username as ‘cloudera’ and password ‘cloudera’.
3. To access HDFS, click on Manage HDFS in the HUE menu bar
4. By default, the content of home directory i.e. /user/cloudera will be visible.
5. Point out to the directory named “hadoop” created above and view the file ‘sample.txt’
6. Click on Upload button and select the appropriate format of the file to be uploaded i.e. plain file or zipped file

The zipped file will be automatically unzipped after upload.

7. Select Files> Select Files, and browser to location of data file on your local filesystem

8. Choose the file and click the Open button.
9. The selected file will be displayed in the directory /user/cloudera/
10. Click on the checkbox next to file's icon and then tab on Actions button to know the possible actions that can be performed on the file.
11. Once you have practised above steps, you can remove the files by clicking on "Move to Trash" button.

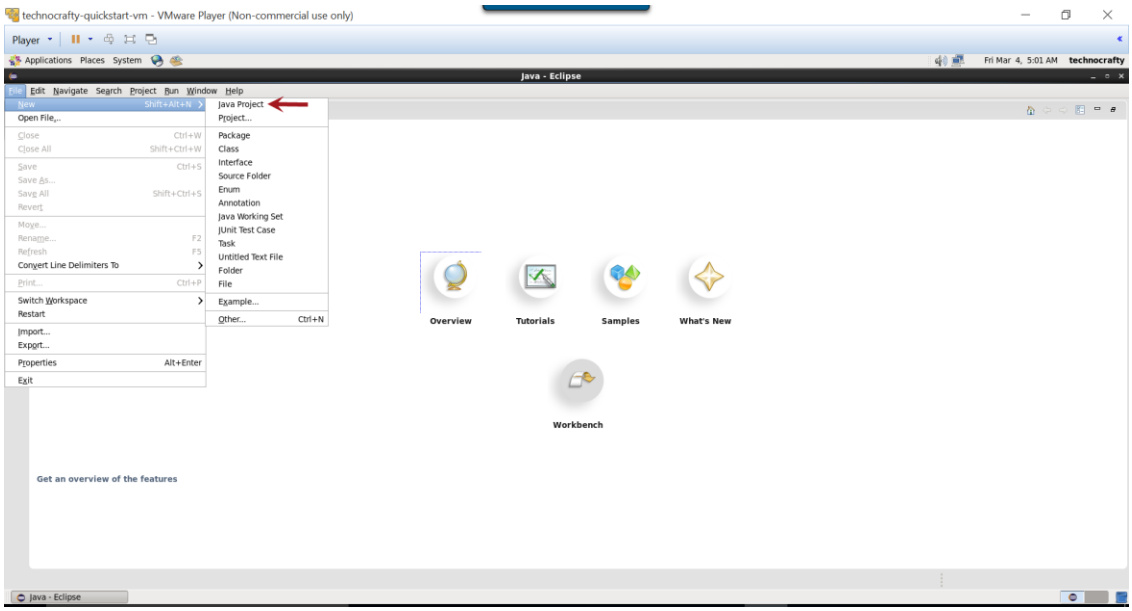


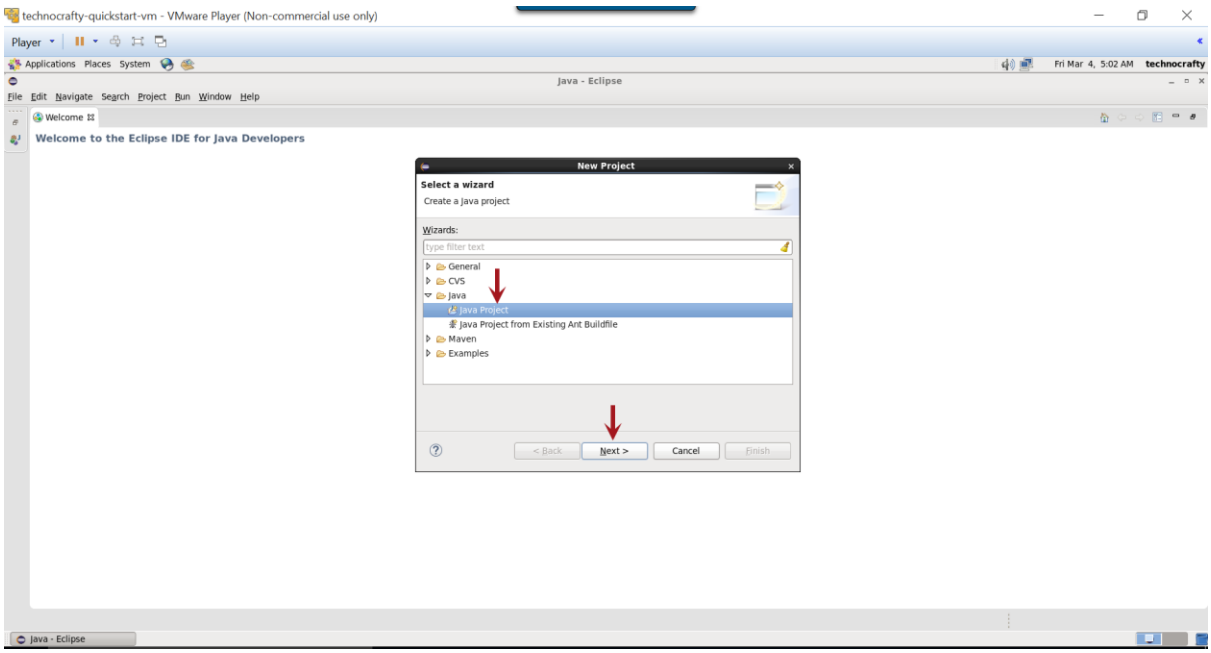
Exercise 3: Running MapReduce Job

Prerequisites: Create an Eclipse WordCount Project

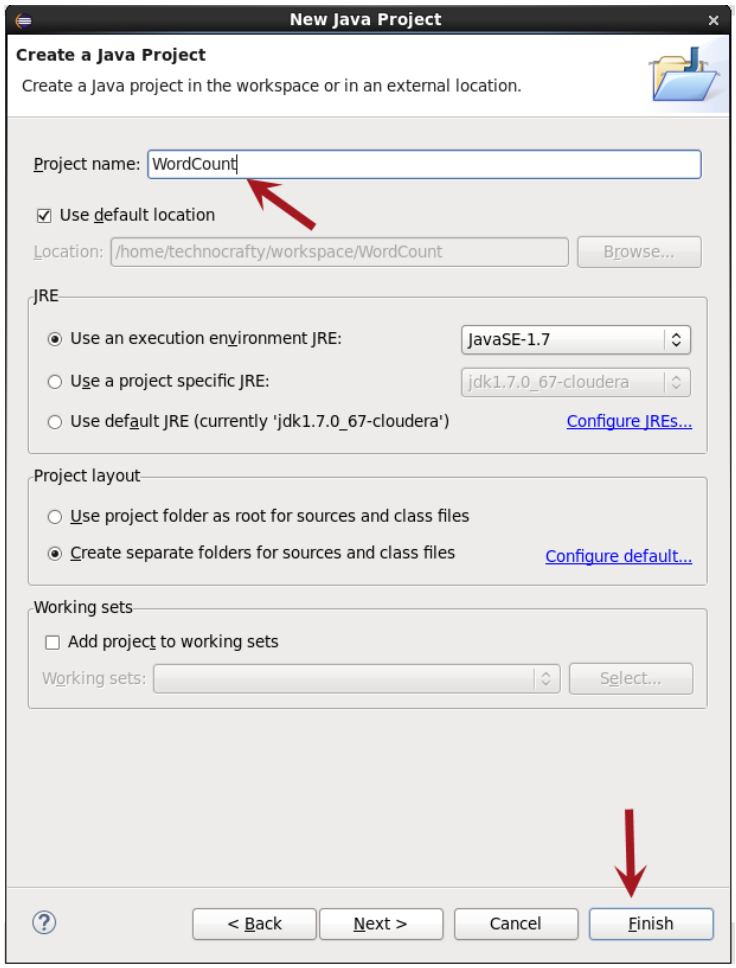
Step1: Launch Eclipse, Select the workspace location, and click on "OK".

Step2: Select File > New > Java Project > Next

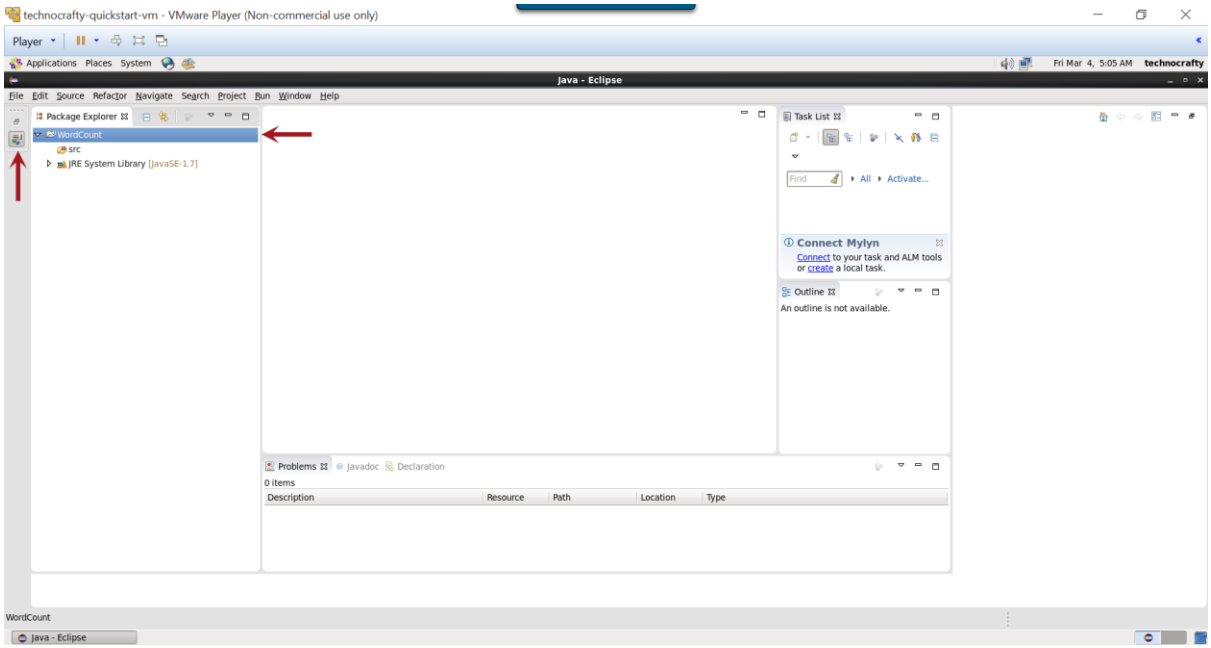




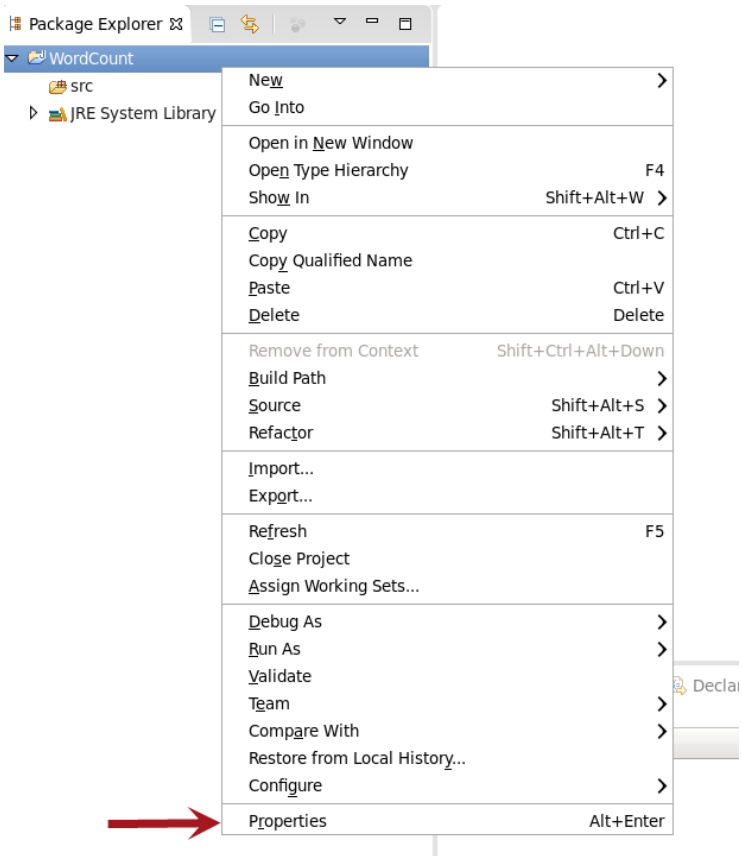
Step3: Name the project as "Wordcount" and click "Finish"



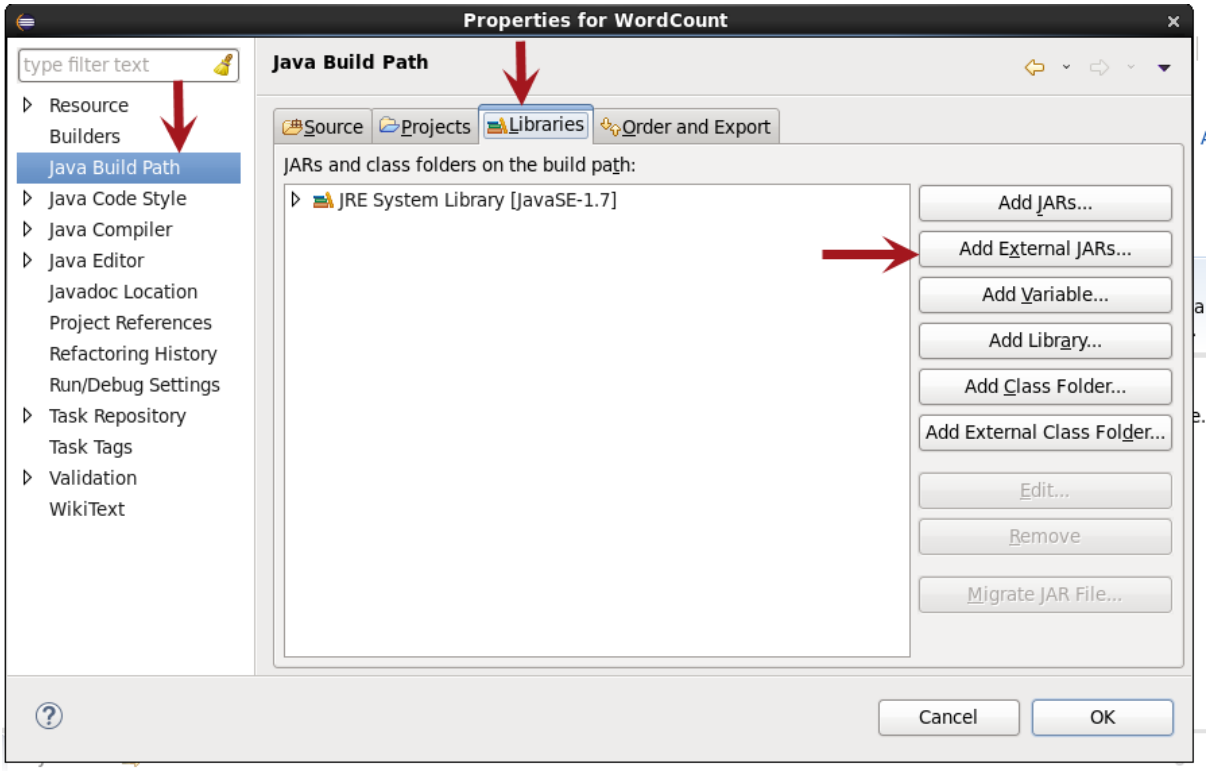
Step4: Expand the “Package Explorer” tab and locate your new project i.e. “WordCount”.



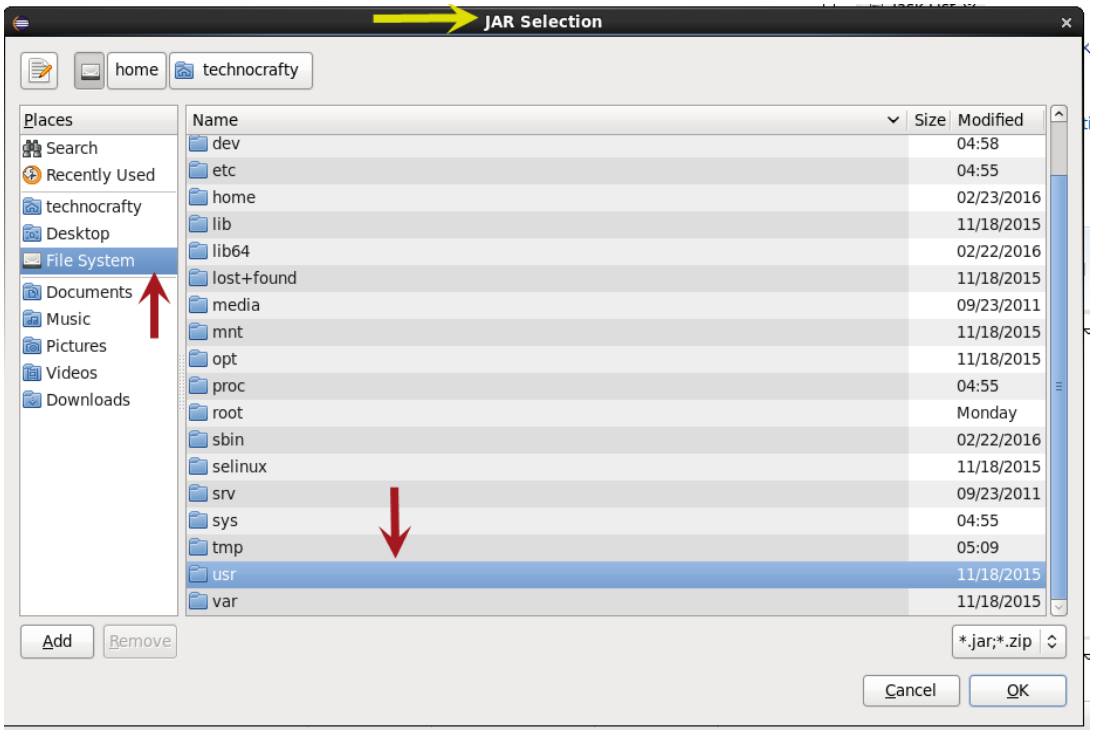
Step5: Export Hadoop Libraries by Right Click on Wordcount project and selecting Properties

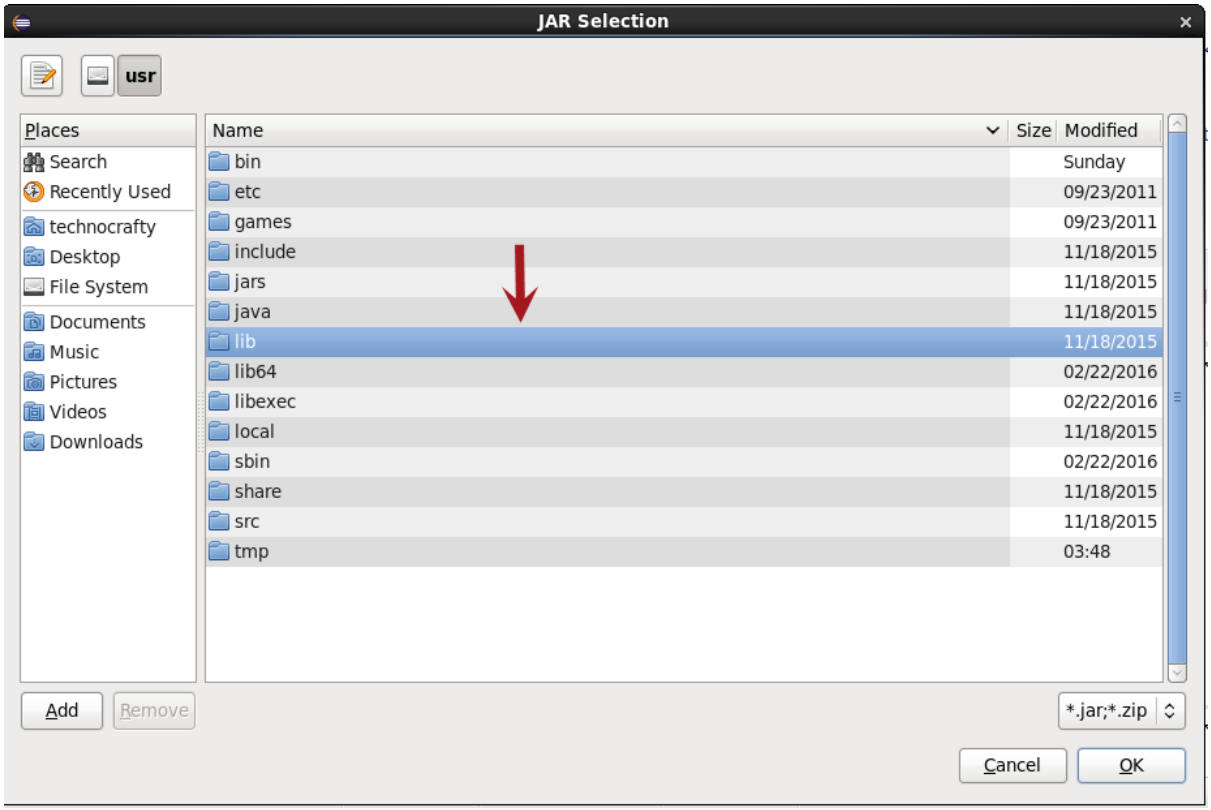


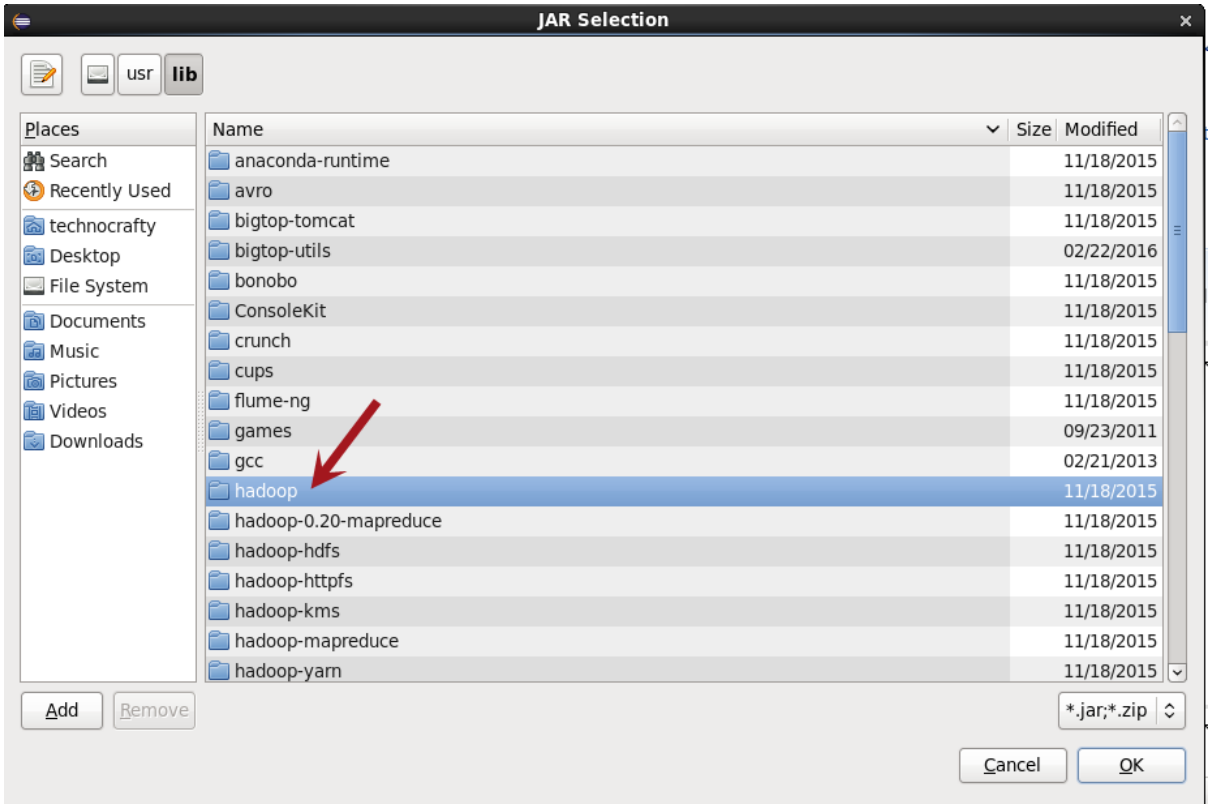
Step6: Click on Java Build Path from left panel and select “Libraries” tab from right panel view



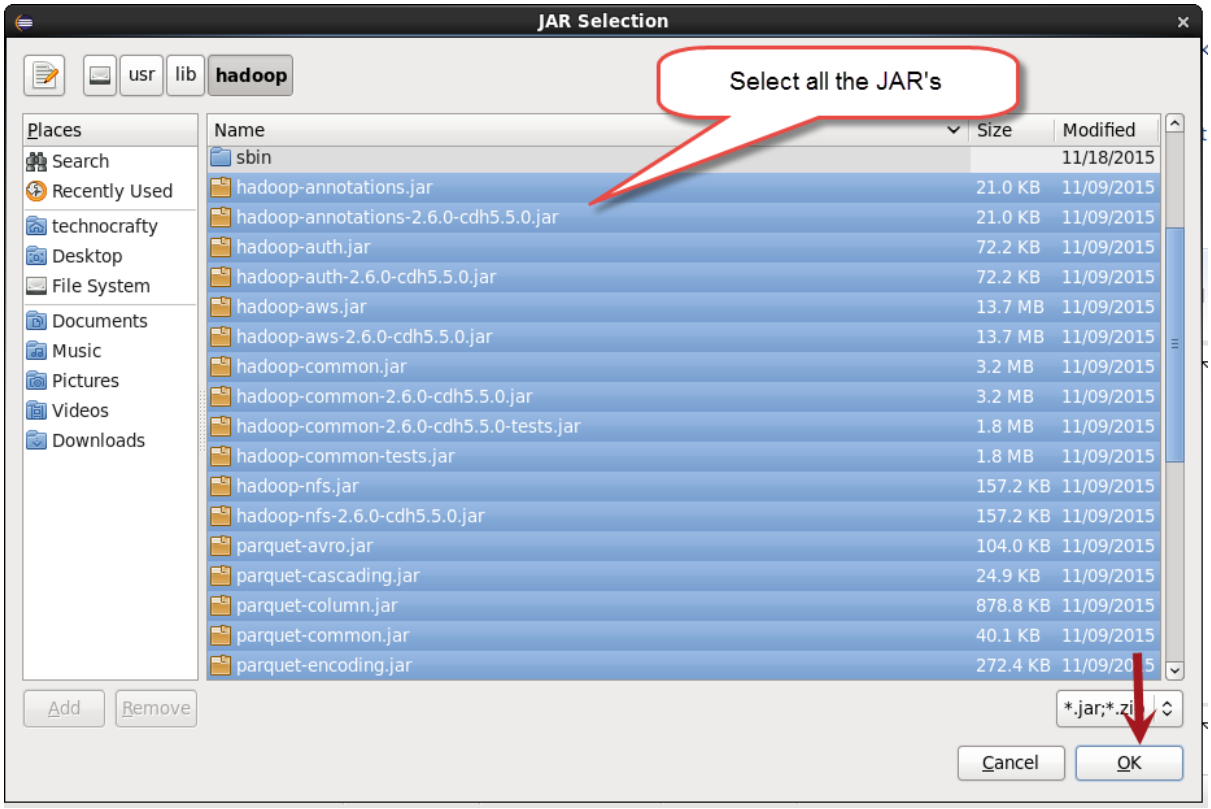
Step7: Select “Add External JAR…”, then navigate to File System > usr > lib > Hadoop



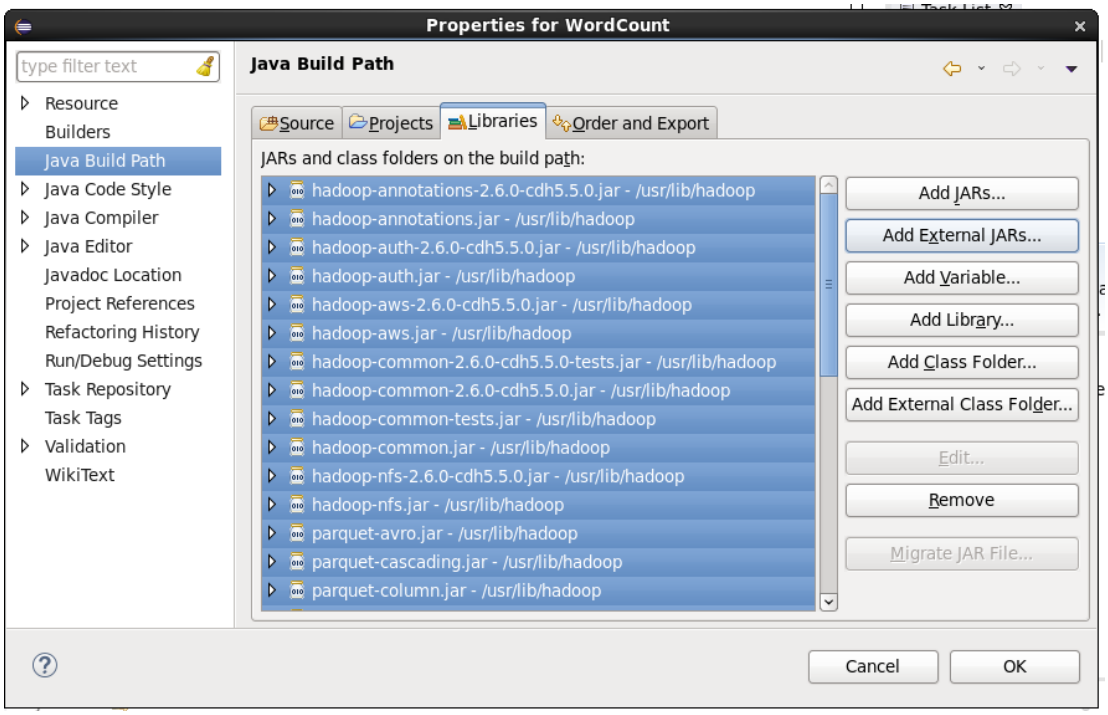




Step8: Select all the JAR available under this folder

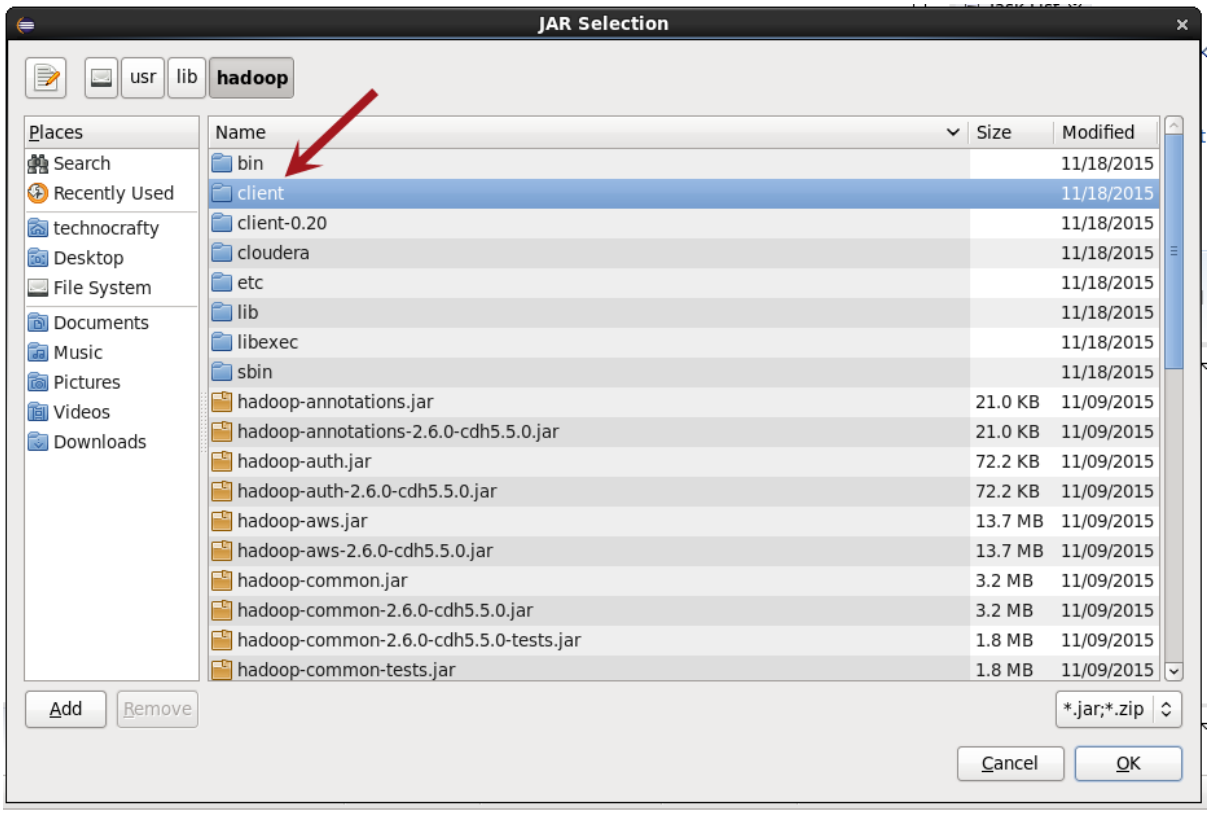


Click on "OK"

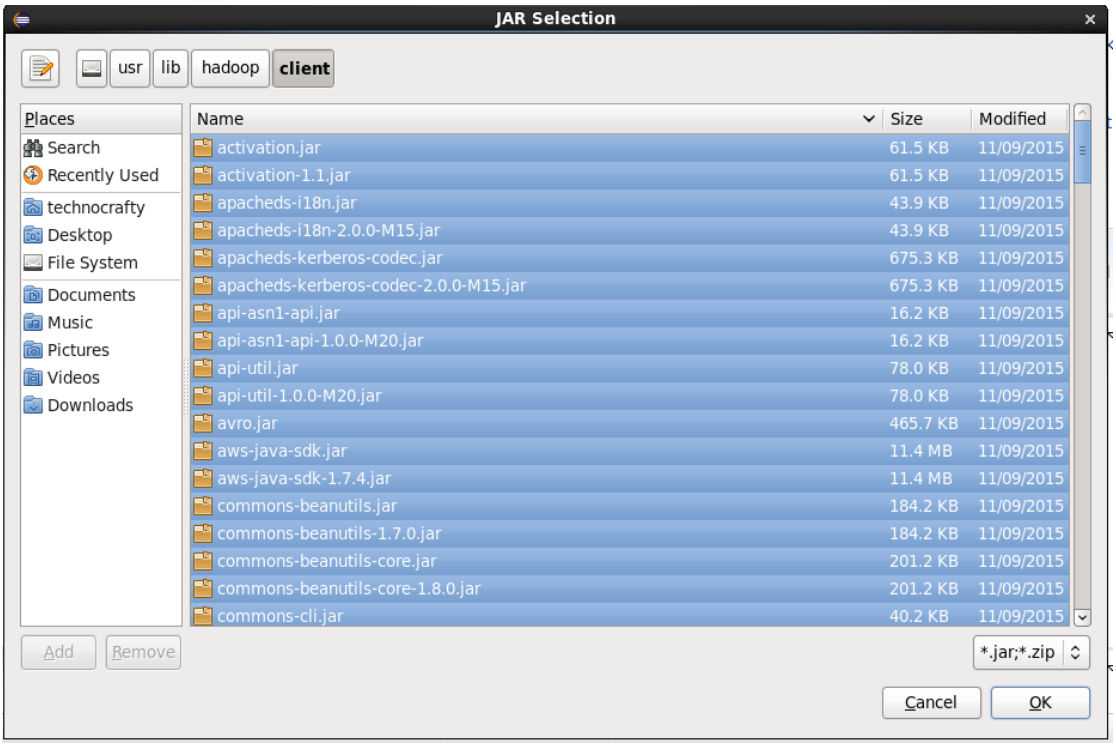


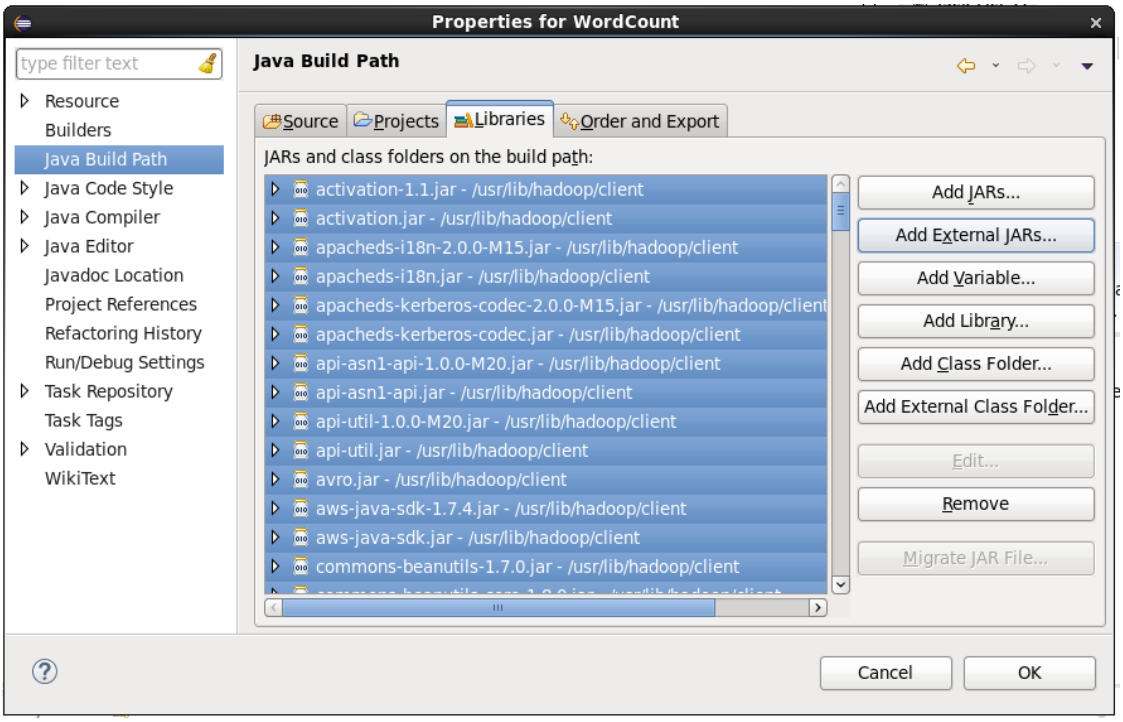
Step 9: Perform same steps for /usr/lib/hadoop-mapreduce and /usr/lib/Hadoop-yarn

Step10: Now grab all the library JAR files under "Client", by following the same method.

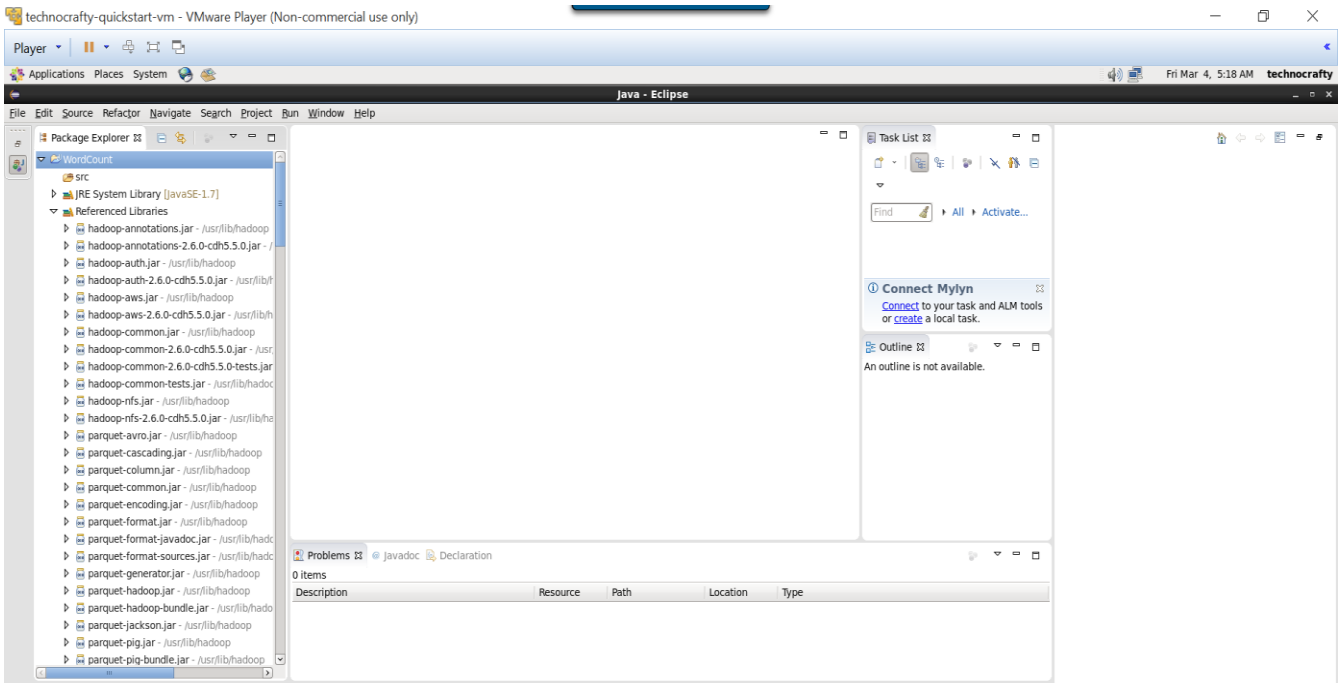


Select the files and click OK

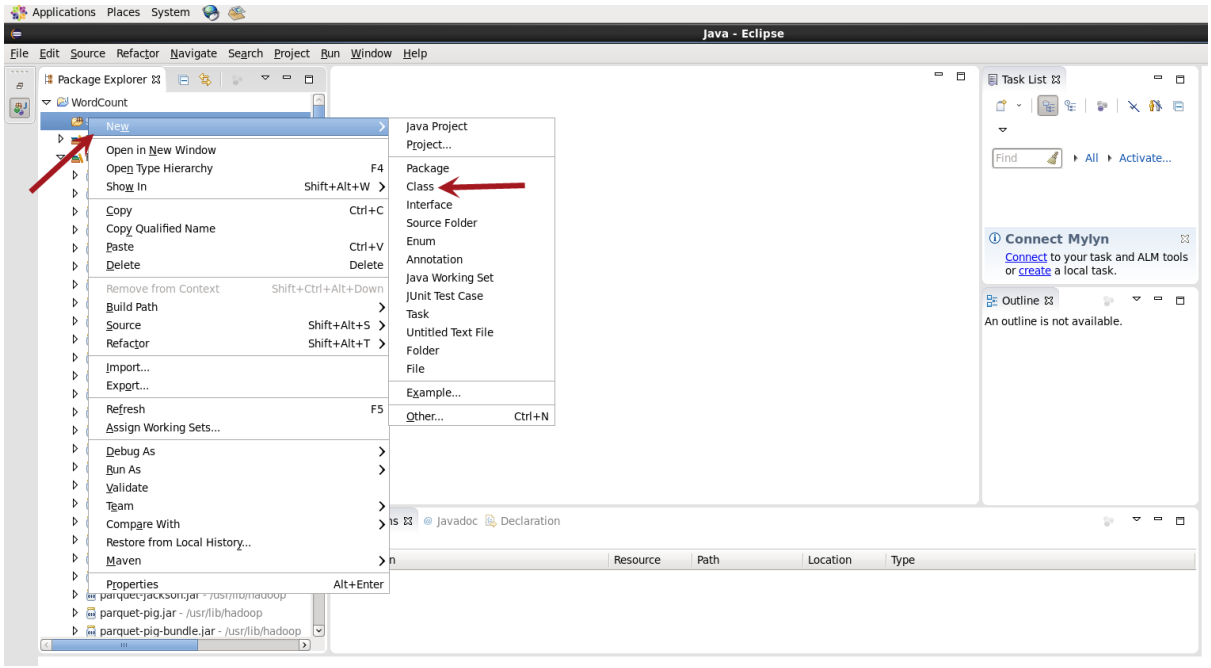




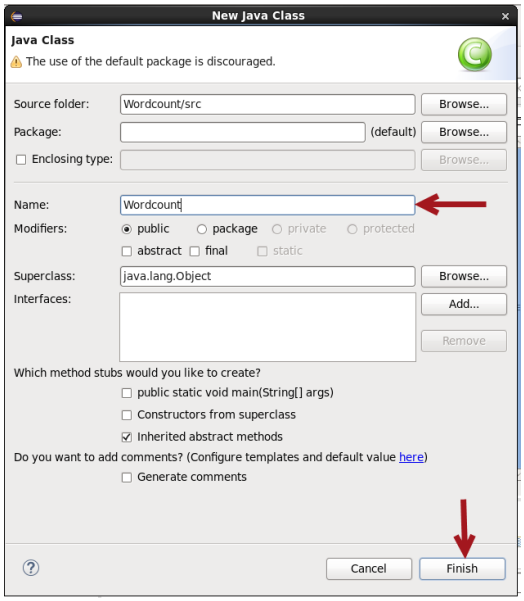
Step11: Finally, you will find all the JAR files under "Referenced Libraries"



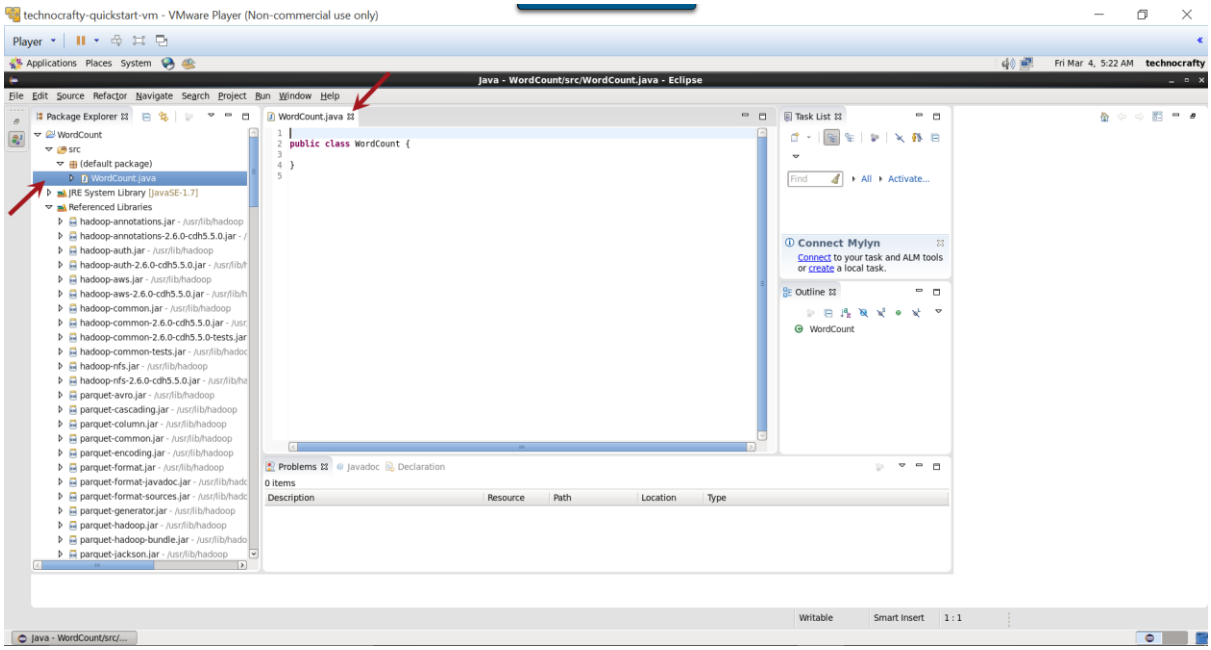
Step12: Creating the class files, Right click on src under WordCount and select New > Class



Step13: Enter the name of Java Class as "Wordcount" and click on Finish.



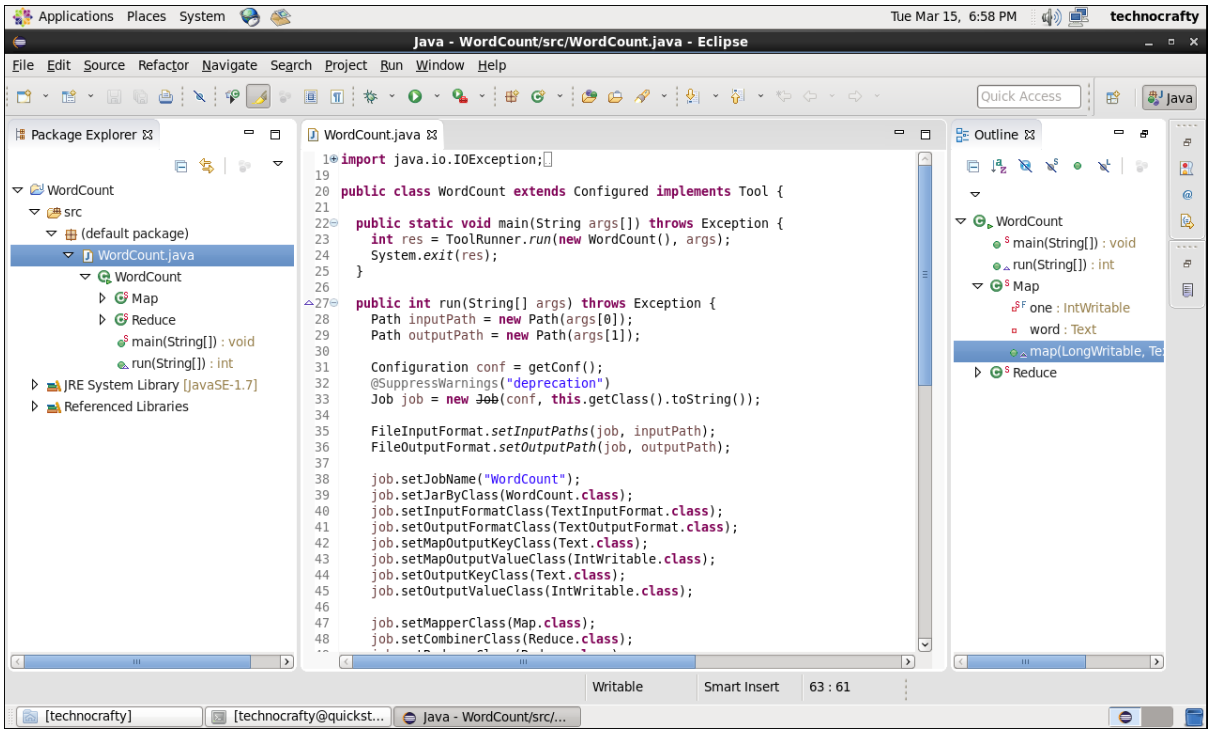
Step14: Now it's ready to take your input Mapreduce program



Step15: MapReduce Wordcount Program

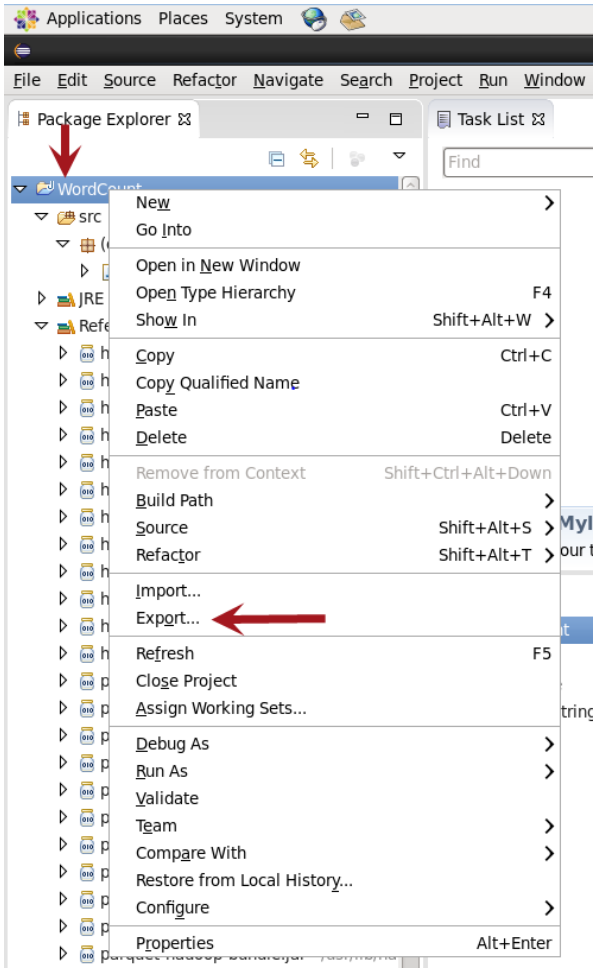
wordcount.txt

Step 16: Save the program

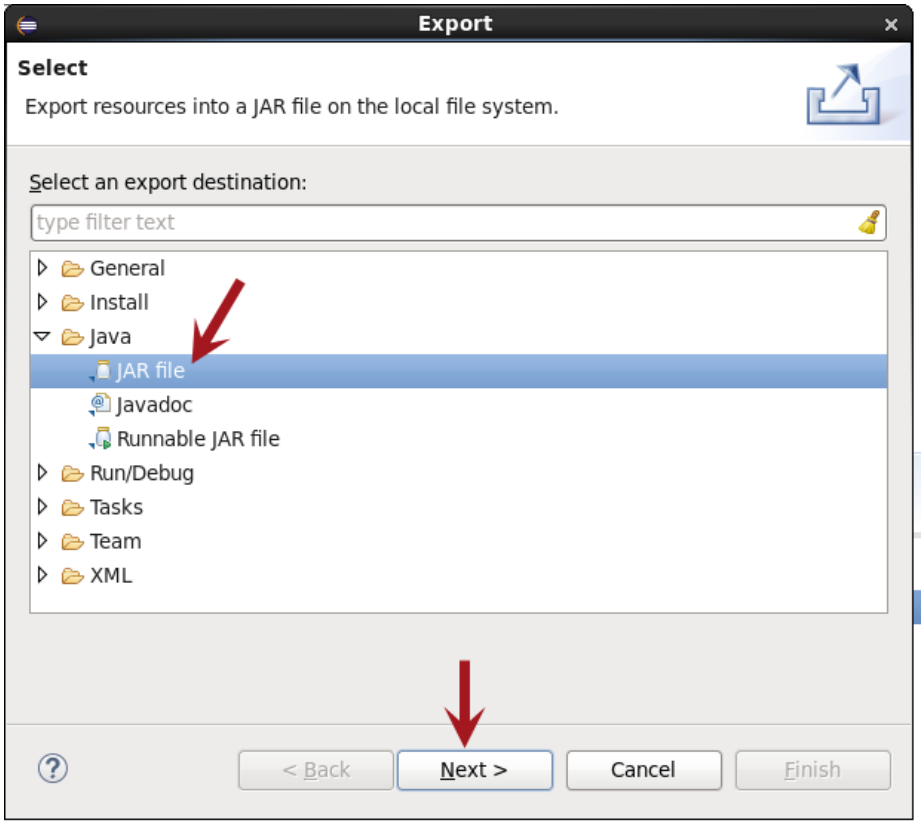


Ensure that there is no compilation error, before exporting the JAR file.

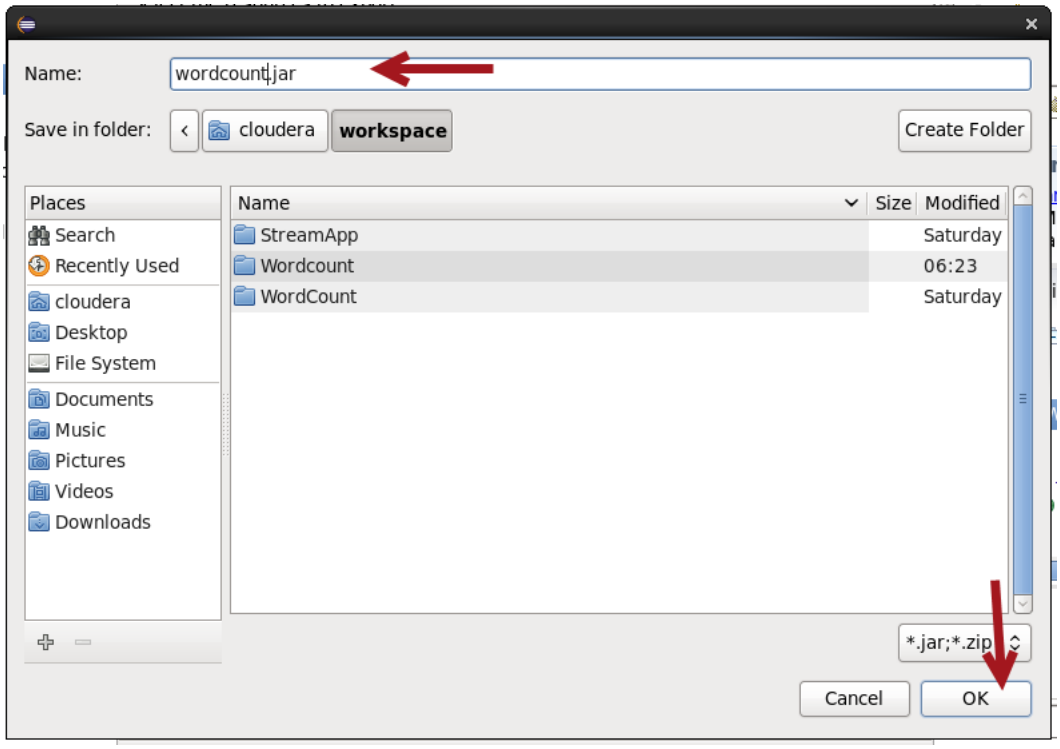
Step17: Exporting the JAR file, for that Right Click on WordCount project and select "Export"



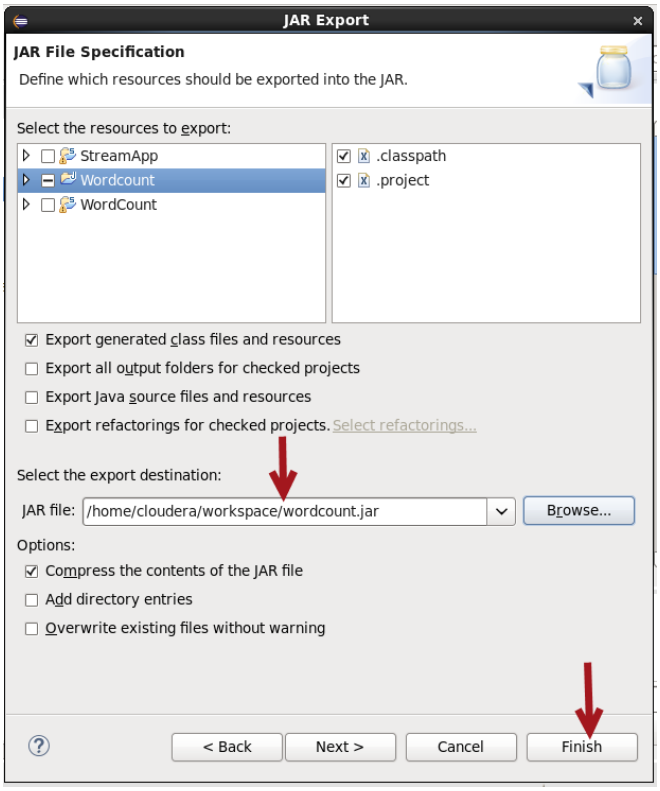
Step 18: In the next panel, expand Java and select JAR file



Step19: Name the JAR as "WordCount.jar" and select OK.



Step20: Browse to the location where you want to save the JAR and select FINISH.



Step21: Verify the file at the target location from the terminal.

```
[cloudera@quickstart workspace]$ ls -ltr
total 20
drwxrwxr-x 7 cloudera cloudera 4096 Sep 10 01:43 StreamApp
drwxrwxr-x 8 cloudera cloudera 4096 Sep 10 01:43 WordCount
drwxrwxr-x 5 cloudera cloudera 4096 Sep 13 06:23 Wordcount
-rw-rw-r-- 1 cloudera cloudera 6055 Sep 13 06:40 wordcount.jar
[cloudera@quickstart workspace]$
```

- **Let's run a simple MapReduce WordCount program.**

Step1: Import the data from local filesystem to HDFS

Under home directory of local filesystem, locate a folder named "datasets" followed by a file named story.txt

```
[cloudera@quickstart ~]$ cd datasets/
[cloudera@quickstart datasets]$ ls -ltr story.txt
-rw-rw-r-- 1 cloudera cloudera 2249 Sep  6 19:28 story.txt
[cloudera@quickstart datasets]$ pwd
/home/cloudera/datasets
[cloudera@quickstart datasets]$
```

Step2: Create a directory named "data" in the HDFS and import "story.txt" file.

```
hdfs dfs -mkdir data

hdfs dfs -put story.txt data
```

```
[cloudera@quickstart ~]$ hdfs dfs -ls data/story.txt
-rw-r--r--   1 cloudera cloudera       2249 2016-09-06 19:29 data/story.txt
[cloudera@quickstart ~]$
```

Step3: Now run the program by using the wordCount.jar created in previous steps

```
hadoop jar wordcount.jar Wordcount data/story.txt output_map
```

```
[cloudera@quickstart workspace]$ pwd
/home/cloudera/workspace
[cloudera@quickstart workspace]$ jar -tf wordcount.jar
META-INF/MANIFEST.MF
.project
Wordcount$Map.class
Wordcount$Reduce.class
Wordcount.class
.classpath
[cloudera@quickstart workspace]$ hadoop jar wordcount.jar Wordcount data/story.t
xt output_map
```

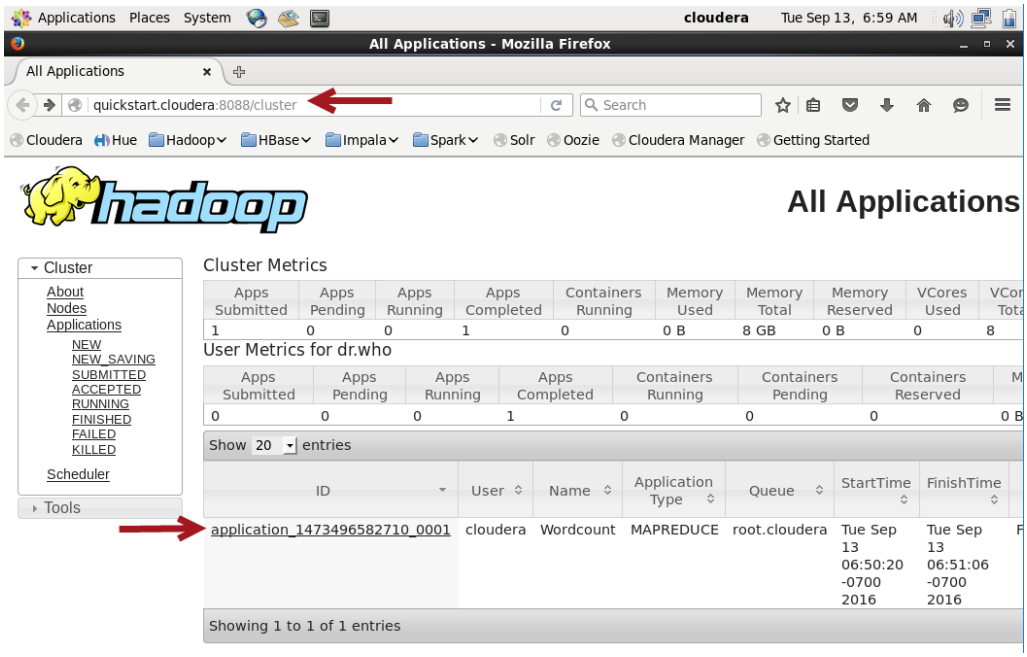

```
      16/09/13 06:51:07 INFO mapreduce.Job:  map 100% reduce 100%
16/09/13 06:51:08 INFO mapreduce.Job: Job job_1473496582710_0001 completed
successfully
16/09/13 06:51:08 INFO mapreduce.Job: Counters: 49
      File System Counters
            FILE: Number of bytes read=2906
            FILE: Number of bytes written=234627
            FILE: Number of read operations=0
            FILE: Number of large read operations=0
            FILE: Number of write operations=0
            HDFS: Number of bytes read=2374
            HDFS: Number of bytes written=2035
            HDFS: Number of read operations=6
            HDFS: Number of large read operations=0
            HDFS: Number of write operations=2
      Job Counters
            Launched map tasks=1
            Launched reduce tasks=1
            Data-local map tasks=1
            Total time spent by all maps in occupied slots (ms)=10457
            Total time spent by all reduces in occupied slots (ms)=11396
            Total time spent by all map tasks (ms)=10457
            Total time spent by all reduce tasks (ms)=11396
            Total vcore-seconds taken by all map tasks=10457
            Total vcore-seconds taken by all reduce tasks=11396
```

```
            Total megabyte-seconds taken by all map tasks=10707968
            Total megabyte-seconds taken by all reduce tasks=11669504
      Map-Reduce Framework
            Map input records=17
            Map output records=354
            Map output bytes=3656
            Map output materialized bytes=2906
            Input split bytes=125
            Combine input records=354
            Combine output records=217
            Reduce input groups=217
            Reduce shuffle bytes=2906
            Reduce input records=217
            Reduce output records=217
            Spilled Records=434
            Shuffled Maps =1
            Failed Shuffles=0
            Merged Map outputs=1
            GC time elapsed (ms)=246
            CPU time spent (ms)=1530
            Physical memory (bytes) snapshot=385163264
            Virtual memory (bytes) snapshot=3007664128
            Total committed heap usage (bytes)=354357248
      Shuffle Errors
            BAD_ID=0
            CONNECTION=0
            IO_ERROR=0
            WRONG_LENGTH=0
            WRONG_MAP=0
            WRONG_REDUCE=0
      File Input Format Counters
            Bytes Read=2249
      File Output Format Counters
            Bytes Written=2035
[cloudera@quickstart workspace]$
```

Check the output file:

```
[cloudera@quickstart workspace]$ hdfs dfs -ls output_map
Found 2 items
-rw-r--r--   1 cloudera cloudera          0 2016-09-13 06:51 output_map/_SUCCESS
-rw-r--r--   1 cloudera cloudera       2035 2016-09-13 06:51 output_map/part-r-0
0000
```

The same counters and job status can be checked from Resource Manager URL http://quickstart.cloudera:8088/cluster



Exercise 4: Launching Spark

- Spark shell can be launched in two ways i.e. Scala and Python.
- To launch Scala spark shell, follow below steps

```
$ spark-shell
```

```
[cloudera@quickstart ~]$ spark-shell
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/usr/lib/zookeeper/lib/slf4j-log4j12-1.7.5.jar!/org/
slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/jars/slf4j-log4j12-1.7.5.jar!/org/slf4j/impl/St
aticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel).
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /___/ .__/\_,_/_/ /_/\_\   version 1.6.0
      /_/

Using Scala version 2.10.5 (Java HotSpot(TM) 64-Bit Server VM, Java 1.7.0_67)
```

You will see several INFO and WARNING message on the command prompt after launching spark-shell, which can be disregarded.

Logs will appear as below and finally you will get Scala Prompt

```
SQL context available as sqlContext.

scala>
```

- Spark creates a SparkContext object called sc, verify that the object exists

```
scala> sc
res0: org.apache.spark.SparkContext = org.apache.spark.SparkContext@a23c46d
```

- To know various SparkContext methods which are available, type sc. (sc followed by dot) and then TAB key

```
scala> sc.
accumulable                   accumulableCollection
accumulator                   addFile
addJar                        addSparkListener
appName                       applicationAttemptId
applicationId                 asInstanceOf
binaryFiles                   binaryRecords
broadcast                     cancelAllJobs
cancelJobGroup                clearCallSite
clearFiles                    clearJars
clearJobGroup                 defaultMinPartitions
defaultMinSplits              defaultParallelism
emptyRDD                      externalBlockStoreFolderName
files                         getAllPools
getCheckpointDir              getConf
getExecutorMemoryStatus       getExecutorStorageStatus
getLocalProperty              getPersistentRDDs
getPoolForName                getRDDStorageInfo
getSchedulingMode             hadoopConfiguration
hadoopFile                    hadoopRDD
initLocalProperties           isInstanceOf
isLocal                       isStopped
jars                          killExecutor
killExecutors                 makeRDD
```

Spark is based on the concept of Resilient Distributed Dataset (RDD), which is fault tolerant collection of elements that can be operated in parallel.

- Invoke python spark shell by using 'pyspark'

```
[cloudera@quickstart ~]$ pyspark
Python 2.6.6 (r266:84292, Jul 23 2015, 15:22:56)
[GCC 4.4.7 20120313 (Red Hat 4.4.7-11)] on linux2
Type "help", "copyright", "credits" or "license" for more information.
```

```
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 1.6.0
      /_/

Using Python version 2.6.6 (r266:84292, Jul 23 2015 15:22:56)
SparkContext available as sc, HiveContext available as sqlContext.
>>>
```

Two ways to create RDDs:

- Parallelizing an existing collection
- Referencing a dataset from an External Storage System

Parallelized collection:

To create a parallelized collection holding numbers 1 to 6, use **sc.parallelize** method

```
data = [1, 2, 3, 4, 5, 6]

distData = sc.parallelize(data)
```

Once 'distData' RDD is created, we can perform **Action** such as:

- Finding the sum, mean & variance

```
distData.sum()

distData.mean()

distData.variance()
```

External Storage System:

Spark can create distributed datasets from any storage system supported by Hadoop, Spark supports text files, Sequence Files and any other Hadoop Input Format.

Load a file from your Local Filesystem say batting.txt using **sc.textFile** method.

```
textFile = sc.textFile("file:/home/cloudera/datasets/story.txt")
```

Operations on RDD will be discussed in next section.

Exploring Data using RDD operations:

Transformations

filter

Return a new dataset formed by selecting those elements of the source on which *func* returns true.

```
a = sc.parallelize(range(1,10))

b = a.filter(lambda x: x % 2 == 0)

b.collect
```

```
>>> a = sc.parallelize(range(1,10))
>>> b = a.filter(lambda x: x % 2 == 0)
>>> b.collect()
[2, 4, 6, 8]
>>>
```

map

Return a new distributed dataset formed by passing each element of the source through a function *func*.

```
a = sc.parallelize(["dog", "salmon", "salmon", "rat", "elephant"])

b = a.map(lambda x:len(x))

c = a.zip(b)

c.collect()
```

```
>>> c = a.zip(b)
>>> c.collect()
[('dog', 3), ('salmon', 6), ('salmon', 6), ('rat', 3), ('elephant', 8)]
```

```
nums = sc.parallelize([1, 2, 3, 4])

squared = nums.map(lambda x: x * x).collect()

for num in squared: print "%i " % (num)
```

```
>>> for num in squared: print "%i " % (num)
...
1
4
9
16
>>>
```

distinct

Return a new dataset that contains the distinct elements of the source dataset.

```
c = sc.parallelize(["Gnu", "Cat", "Rat", "Dog", "Gnu", "Rat"],2)

c.distinct().collect()
```

```
>>> c = sc.parallelize(["Gnu", "Cat", "Rat", "Dog", "Gnu", "Rat"],2)
>>> c
ParallelCollectionRDD[27] at parallelize at PythonRDD.scala:423
>>> c.distinct().collect()
['Rat', 'Gnu', 'Dog', 'Cat']
>>>
```

cartesian

When called on datasets of types T and U, returns a dataset of (T, U) pairs (all pairs of elements).

```
x = sc.parallelize([1,2,3,4,5])

y = sc.parallelize([6,7,8,9,10])

x.cartesian(y).collect()
```

```
>>> x = sc.parallelize([1,2,3,4,5])
>>> x
ParallelCollectionRDD[33] at parallelize at PythonRDD.scala:423
>>> y = sc.parallelize([6,7,8,9,10])
>>> y
ParallelCollectionRDD[34] at parallelize at PythonRDD.scala:423
>>> x.cartesian(y).collect()
[(1, 6), (1, 7), (2, 6), (2, 7), (1, 8), (1, 9), (2, 8), (2, 9), (1, 10), (2, 10), (3, 6), (3, 7), (4, 6), (4, 7), (5, 6), (5, 7), (3, 8), (3, 9), (4, 8), (4
, 9), (3, 10), (4, 10), (5, 8), (5, 9), (5, 10)]
>>>
```

coalesce

Decrease the number of partitions in the RDD to numPartitions. Useful for running operations more efficiently after filtering down a large dataset.

```
y = sc.parallelize(range(1,10), 10)

z = y.coalesce(2, False)

z.glom().collect()

z.getNumPartitions()
```

```
>>> y = sc.parallelize(range(1,10), 10)
>>> y
ParallelCollectionRDD[41] at parallelize at PythonRDD.scala:423
>>>
```

```
>>> z.glom().collect()
[[1, 2, 3, 4], [5, 6, 7, 8, 9]]
>>> z.getNumPartitions()
2
>>>
```

filterByRange

Returns an RDD containing only the items in the key range specified.

```
randRDD = sc.parallelize([ (2,"cat"), (6, "mouse"),(7, "cup"), (3, "book"),
(4, "tv"), (1, "screen"), (5, "heater")], 3)

sortedRDD = randRDD.sortByKey()

sortedRDD.filterByRange(1,3).collect()
```

```
16/08/30 07:14:40 INFO executor.Executor: Finished task 0.0 in stage 7.0 (TID 13). 1357 bytes result sent to driver
16/08/30 07:14:40 INFO scheduler.DAGScheduler: ResultStage 7 (collect at <console>:26) finished in 0.080 s
16/08/30 07:14:40 INFO scheduler.DAGScheduler: Job 5 finished: collect at <console>:26, took 0.527731 s
res5: Array[(Int, String)] = Array((1,screen), (2,cat), (3,book))
```

flatMap

Similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a Seq rather than a single item).

```
a = sc.parallelize(range(1,10), 5)

a.flatMap(lambda x: range(1, x)).collect()
```

```
>>> a = sc.parallelize(range(1,10), 5)
>>> a
ParallelCollectionRDD[52] at parallelize at PythonRDD.scala:423
>>> a.flatMap(lambda x: range(1, x)).collect()
[1, 1, 2, 1, 2, 3, 1, 2, 3, 4, 1, 2, 3, 4, 5, 1, 2, 3, 4, 5, 6, 1, 2, 3, 4, 5, 6, 7, 1, 2, 3, 4, 5, 6, 7, 8]
>>>
```

```
b = sc.parallelize([1, 2, 3], 2).flatMap(lambda x: [x, x, x])

b.collect()
```

```
>>> b = sc.parallelize([1, 2, 3], 2).flatMap(lambda x: [x, x, x])
>>> b
PythonRDD[60] at RDD at PythonRDD.scala:43
>>> b.collect()
[1, 1, 1, 2, 2, 2, 3, 3, 3]
>>>
```

```
lines = sc.parallelize(["hello world", "hi"])

words = lines.flatMap(lambda line: line.split(" "))

words.first()  // returns "hello"
```

```
>>> lines = sc.parallelize(["hello world", "hi"])
>>> words = lines.flatMap(lambda line: line.split(" "))
>>> words.first()
'hello'
>>>
```

```
odd_rdd = dist_numbers.filter(lambda x: x % 2 != 0)
```

groupBy

```
rdd = sc.parallelize([1, 1, 2, 3, 5, 8])

result = rdd.groupBy(lambda x: x % 2).collect()

sorted([(x, sorted(y)) for (x, y) in result])
```

```
>>> result = rdd.groupBy(lambda x: x % 2).collect()
>>> sorted([(x, sorted(y)) for (x, y) in result])
[(0, [2, 8]), (1, [1, 1, 3, 5])]
```

keys

Extracts the keys from all contained tuples and returns them in a new RDD.

```
a = sc.parallelize(["dog", "tiger", "lion", "cat", "panther", "eagle"], 2)

b = a.map(lambda x : (len(x), x))

b.keys().collect()
```

```
>>> b = a.map(lambda x : (len(x), x))
>>> b
PythonRDD[82] at RDD at PythonRDD.scala:43
>>> b.keys().collect()
[3, 5, 4, 3, 7, 5]
>>>
```

union

```
seta = sc.parallelize(range(1,10))

setb = sc.parallelize(range(5 ,15))

(seta.union(setb)).collect()
```

```
>>> seta = sc.parallelize(range(1,10))
>>> seta
ParallelCollectionRDD[84] at parallelize at PythonRDD.scala:423
>>> setb = sc.parallelize(range(5 ,15))
>>> (seta.union(setb)).collect()
[1, 2, 3, 4, 5, 6, 7, 8, 9, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]
>>>
```

zip

Joins two RDDs by combining the i-th of either partition with each other. The resulting RDD will consist of two-component tuples which are interpreted as key-value pairs by the methods provided by the PairRDDFunctions extension.

```
a = sc.parallelize(range(1 , 100), 3)
b = sc.parallelize(range(101 , 200), 3)
a.zip(b).collect()
```

```
>>> a = sc.parallelize(range(1 , 100), 3)
>>> a
ParallelCollectionRDD[89] at parallelize at PythonRDD.scala:423
>>> b = sc.parallelize(range(101 , 200), 3)
>>> b
ParallelCollectionRDD[90] at parallelize at PythonRDD.scala:423
>>> a.zip(b).collect()
[(1, 101), (2, 102), (3, 103), (4, 104), (5, 105), (6, 106), (7, 107), (8, 108), (9, 109), (10, 110), (11, 111), (12, 112), (13, 113), (14, 114), (15, 115),
(16, 116), (17, 117), (18, 118), (19, 119), (20, 120), (21, 121), (22, 122), (23, 123), (24, 124), (25, 125), (26, 126), (27, 127), (28, 128), (29, 129), (30
, 130), (31, 131), (32, 132), (33, 133), (34, 134), (35, 135), (36, 136), (37, 137), (38, 138), (39, 139), (40, 140), (41, 141), (42, 142), (43, 143), (44, 1
44), (45, 145), (46, 146), (47, 147), (48, 148), (49, 149), (50, 150), (51, 151), (52, 152), (53, 153), (54, 154), (55, 155), (56, 156), (57, 157), (58, 158)
, (59, 159), (60, 160), (61, 161), (62, 162), (63, 163), (64, 164), (65, 165), (66, 166), (67, 167), (68, 168), (69, 169), (70, 170), (71, 171), (72, 172), (
73, 173), (74, 174), (75, 175), (76, 176), (77, 177), (78, 178), (79, 179), (80, 180), (81, 181), (82, 182), (83, 183), (84, 184), (85, 185), (86, 186), (87,
 187), (88, 188), (89, 189), (90, 190), (91, 191), (92, 192), (93, 193), (94, 194), (95, 195), (96, 196), (97, 197), (98, 198), (99, 199)]
>>>
```
PySparkShell - Details for Job 28 - Mozilla Firefox

Action

collect

Return all the elements of the dataset as an array at the driver program. This is usually useful after a filter or other operation that returns a sufficiently small subset of the data.

```
c = sc.parallelize(["Gnu", "Cat", "Rat", "Dog", "Gnu", "Rat"], 2)

c.collect
```

```
>>> c = sc.parallelize(["Gnu", "Cat", "Rat", "Dog", "Gnu", "Rat"], 2)
>>> c
ParallelCollectionRDD[92] at parallelize at PythonRDD.scala:423
>>> c.collect()
['Gnu', 'Cat', 'Rat', 'Dog', 'Gnu', 'Rat']
>>>
```

collectAsMap

Similar to collect, but works on key-value RDDs and converts them into Python maps to preserve their key-value structure.

```
a = sc.parallelize([1, 2, 1, 3], 1)

b = a.zip(a)

b.collectAsMap()
```

```
>>> a = sc.parallelize([1, 2, 1, 3], 1)
>>> b = a.zip(a)
>>> b.collectAsMap()
{1: 1, 2: 2, 3: 3}
>>>
```

count

Return the number of elements in the dataset.

```
c = sc.parallelize(["Gnu", "Cat", "Rat", "Dog"], 2)

c.count()

res2: Long = 4
```

```
>>> c = sc.parallelize(["Gnu", "Cat", "Rat", "Dog"], 2)
>>> c.count()
4
>>>
```

reduce

Aggregate the elements of the dataset using a function *func* (which takes two arguments and returns one). The function should be commutative and associative so that it can be computed correctly in parallel.

```
a = sc.parallelize([1, 2, 3, 4, 5]).reduce(lambda a,b : a+b)
```

```
>>> a = sc.parallelize([1, 2, 3, 4, 5]).reduce(lambda a,b : a+b)
>>> a
15
>>>
```

take

Return an array with the first *n* elements of the dataset.

```
b = sc.parallelize(["dog", "cat", "ape", "salmon", "gnu"], 2)

b.take(2)
```

```
>>> b = sc.parallelize(["dog", "cat", "ape", "salmon", "gnu"], 2)
>>> b
ParallelCollectionRDD[103] at parallelize at PythonRDD.scala:423
>>> b.take(2)
['dog', 'cat']
>>>
```

```
b = sc.parallelize(range(1 , 100), 5)

b.take(30)
```

```
>>> b = sc.parallelize(range(1 , 100), 5)
>>> b.take(30)
[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]
>>>
```

first

Return the first element of the dataset (similar to take(1)).

```
c = sc.parallelize(["Gnu", "Cat", "Rat", "Dog"], 2)

c.first()
```

```
>>> c = sc.parallelize(["Gnu", "Cat", "Rat", "Dog"], 2)
>>> c.first()
'Gnu'
>>>
```

countByValue

Returns a map that contains all unique values of the RDD and their respective occurrence counts.

```
b = sc.parallelize([1,2,3,4,5,6,7,8,2,4,2,1,1,1,1,1])

b.countByValue()
```

```
>>> b = sc.parallelize([1,2,3,4,5,6,7,8,2,4,2,1,1,1,1,1])
>>> b.countByValue()
defaultdict(<type 'int'>, {1: 6, 2: 3, 3: 1, 4: 2, 5: 1, 6: 1, 7: 1, 8: 1})
>>>
```

lookup

Scans the RDD for all keys that match the provided value and returns their values as a Python sequence.

```
a = sc.parallelize(["dog", "tiger", "lion", "cat", "panther", "eagle"], 2)

b = a.map(lambda x : (len(x), x))

b.lookup(5)
```

```
>>> a = sc.parallelize(["dog", "tiger", "lion", "cat", "panther", "eagle"], 2)
>>> b = a.map(lambda x : (len(x), x))
>>> b.lookup(5)
['tiger', 'eagle']
>>>
>>> type(b)
<class 'pyspark.rdd.PipelinedRDD'>
>>>
```

max

Returns the largest element in the RDD

```
y = sc.parallelize(range(10, 30))

y.max()
```

```
>>> y = sc.parallelize(range(10, 30))
>>> y.max()
29
>>>
```

```
a = sc.parallelize([(10, "dog"), (3, "tiger"), (9, "lion"), (18, "cat")])

a.max()
```

```
>>> a = sc.parallelize([(10, "dog"), (3, "tiger"), (9, "lion"), (18, "cat")])
>>> a.max()
(18, 'cat')
>>>
>>> type(a)
<class 'pyspark.rdd.RDD'>
>>>
```

min

Returns the smallest element in the RDD

```
y = sc.parallelize(range(10 , 30))

y.min()
```

```
>>> y = sc.parallelize(range(10 , 30))
>>> y.min()
10
>>>
```

```
a = sc.parallelize([(10, "dog"), (3, "tiger"), (9, "lion"), (8, "cat")])
```

```
a.min()
```

```
>>> a = sc.parallelize([(10, "dog"), (3, "tiger"), (9, "lion"), (8, "cat")])
>>> a.min()
(3, 'tiger')
>>>
```

mean

Calls stats and extracts the mean component.

```
a = sc.parallelize([9.1, 1.0, 1.2, 2.1, 1.3, 5.0, 2.0, 2.1, 7.4, 7.5, 7.6,
8.8, 10.0, 8.9, 5.5], 3)

a.mean()
```

```
>>> a = sc.parallelize([9.1, 1.0, 1.2, 2.1, 1.3, 5.0, 2.0, 2.1, 7.4, 7.5, 7.6, 8.8, 10.0, 8.9, 5.5], 3)
>>> a.mean()
5.2999999999999998
>>>
```

variance

Calls stats and extracts either variance-component or corrected sampleVariance-component.

```
a = sc.parallelize([9.1, 1.0, 1.2, 2.1, 1.3, 5.0, 2.0, 2.1, 7.4, 7.5, 7.6,
8.8, 10.0, 8.9, 5.5], 3)
a.variance()
```

```
>>> a = sc.parallelize([9.1, 1.0, 1.2, 2.1, 1.3, 5.0, 2.0, 2.1, 7.4, 7.5, 7.6, 8.8, 10.0, 8.9, 5.5], 3)
>>> a
ParallelCollectionRDD[124] at parallelize at PythonRDD.scala:423
>>> a.variance()
10.605333333333332
>>>
```

PairRDD

countByKey

Only available on RDDs of type (K, V). Returns a hashmap of (K, Int) pairs with the count of each key.

```
c = sc.parallelize([(3, "Gnu"), (3, "Yak"), (5, "Mouse"), (3, "Dog")], 2)

c.countByKey()
```

```
>>> c = sc.parallelize([(3, "Gnu"), (3, "Yak"), (5, "Mouse"), (3, "Dog")], 2)
>>> c.countByKey()
defaultdict(<type 'int'>, {3: 3, 5: 1})
>>>
```

groupByKey

When called on a dataset of (K, V) pairs, returns a dataset of (K, Iterable<V>) pairs.

```
x = sc.parallelize([("a", 1), ("b", 1), ("a", 1)])

map((lambda (x,y): (x, list(y))), sorted(x.groupByKey().collect()))
```

```
>>> x = sc.parallelize([("a", 1), ("b", 1), ("a", 1)])
>>> map((lambda (x,y): (x, list(y))), sorted(x.groupByKey().collect()))
[('a', [1, 1]), ('b', [1])]
>>>
```

reduceByKey

When called on a dataset of (K, V) pairs, returns a dataset of (K, V) pairs where the values for each key are aggregated using the given reduce function *func*, which must be of type (V,V) => V

```
a = sc.parallelize(["dog", "cat", "owl", "gnu", "ant"], 2)

b = a.map(lambda x : (len(x), x))

b.reduceByKey(lambda x,y : x + y).collect()
```

```
>>> a = sc.parallelize(["dog", "cat", "owl", "gnu", "ant"], 2)
>>> b = a.map(lambda x : (len(x), x))
>>> b.reduceByKey(lambda x,y : x + y).collect()
[(3, 'dogcatowlgnuant')]
>>>
```

foldByKey

Very similar to *fold*, but performs the folding separately for each key of the RDD. This function is only available if the RDD consists of two-component tuples.

```
rdd = sc.parallelize([("a", 1), ("b", 1), ("a", 1)])

from operator import add

rdd.foldByKey(0, add).collect()
```

```
>>> rdd = sc.parallelize([("a", 1), ("b", 1), ("a", 1)])
>>> from operator import add
>>> rdd.foldByKey(0, add).collect()
[('a', 2), ('b', 1)]
>>>
```

cogroup

When called on datasets of type (K, V) and (K, W), returns a dataset of (K, (Iterable<V>, Iterable<W>)) tuples.

```
x = sc.parallelize([("a", 1), ("b", 4)])

y = sc.parallelize([("a", 2)])

map((lambda (x,y): (x, (list(y[0]), list(y[1])))),
sorted(list(x.cogroup(y).collect())))
```

```
>>> x = sc.parallelize([("a", 1), ("b", 4)])
>>> y = sc.parallelize([("a", 2)])
>>> map((lambda (x,y): (x, (list(y[0]), list(y[1])))), sorted(list(x.cogroup(y).collect())))
[('a', ([1], [2])), ('b', ([4], []))]
>>>
```

```
x = sc.parallelize([(1, "apple"), (2, "banana"), (3, "orange"), (4,
"kiwi")], 2)

y = sc.parallelize([(5, "computer"), (1, "laptop"), (1, "desktop"), (4,
"iPad")], 2)

map((lambda (x,y): (x, (list(y[0]), list(y[1])))),
sorted(list(x.cogroup(y).collect())))
```

```
>>> x = sc.parallelize([(1, "apple"), (2, "banana"), (3, "orange"), (4, "kiwi")], 2)
>>> y = sc.parallelize([(5, "computer"), (1, "laptop"), (1, "desktop"), (4, "iPad")], 2)
>>> map((lambda (x,y): (x, (list(y[0]), list(y[1])))), sorted(list(x.cogroup(y).collect())))
[(1, (['apple'], ['laptop', 'desktop'])), (2, (['banana'], [])), (3, (['orange'], [])), (4, (['kiwi'], ['iPad'])), (5, ([], ['computer']))]
>>>
```

Join

Performs an inner join using two key-value RDDs.

```
a = sc.parallelize(["dog", "salmon", "salmon", "rat", "elephant"], 3)

b = a.keyBy(lambda x:len(x))
```

```
c =
sc.parallelize(["dog","cat","gnu","salmon","rabbit","turkey","wolf","bear",
"bee"], 3)

d = c.keyBy(lambda x:len(x))

b.join(d).collect()
```

```
>>> d = c.keyBy(lambda x:len(x))
>>> b.join(d).collect()
[(6, ('salmon', 'salmon')), (6, ('salmon', 'rabbit')), (6, ('salmon', 'turkey')), (6, ('salmon', 'salmon')), (6, ('salmon', 'rabbit')), (6, ('salmon', 'turke
y')), (3, ('dog', 'dog')), (3, ('dog', 'cat')), (3, ('dog', 'gnu')), (3, ('dog', 'bee')), (3, ('rat', 'dog')), (3, ('rat', 'cat')), (3, ('rat', 'gnu')), (3,
('rat', 'bee'))]
>>>
```

leftOuterJoin

Performs an left outer join using two key-value RDDs.

```
a = sc.parallelize(["dog", "salmon", "salmon", "rat", "elephant"], 3)

b = a.keyBy(lambda x:len(x))

c =
sc.parallelize(["dog","cat","gnu","salmon","rabbit","turkey","wolf","bear",
"bee"], 3)

d = c.keyBy(lambda x:len(x))

b.leftOuterJoin(d).collect()
```

```
>>> a = sc.parallelize(["dog", "salmon", "salmon", "rat", "elephant"], 3)
>>> b = a.keyBy(lambda x:len(x))
>>> c = sc.parallelize(["dog","cat","gnu","salmon","rabbit","turkey","wolf","bear","bee"], 3)
>>> d = c.keyBy(lambda x:len(x))
>>> b.leftOuterJoin(d).collect()
[(6, ('salmon', 'salmon')), (6, ('salmon', 'rabbit')), (6, ('salmon', 'turkey')), (6, ('salmon', 'salmon')), (6, ('salmon', 'rabbit')), (6, ('salmon', 'turke
y')), (8, ('elephant', None)), (3, ('dog', 'dog')), (3, ('dog', 'cat')), (3, ('dog', 'gnu')), (3, ('dog', 'bee')), (3, ('rat', 'dog')), (3, ('rat', 'cat')),
(3, ('rat', 'gnu')), (3, ('rat', 'bee'))]
>>>
```

rightOuterJoin

Performs an right outer join using two key-value RDDs.

```
a = sc.parallelize(["dog", "salmon", "salmon", "rat", "elephant"], 3)

b = a.keyBy(lambda x:len(x))

c =
sc.parallelize(["dog","cat","gnu","salmon","rabbit","turkey","wolf","bear",
"bee"], 3)

d = c.keyBy(lambda x:len(x))

b.rightOuterJoin(d).collect()
```

```
>>> b.rightOuterJoin(d).collect()
[(6, ('salmon', 'salmon')), (6, ('salmon', 'rabbit')), (6, ('salmon', 'turkey')), (6, ('salmon', 'salmon')), (6, ('salmon', 'rabbit')), (6, ('salmon', 'turke
y')), (3, ('dog', 'dog')), (3, ('dog', 'cat')), (3, ('dog', 'gnu')), (3, ('dog', 'bee')), (3, ('rat', 'dog')), (3, ('rat', 'cat')), (3, ('rat', 'gnu')), (3,
('rat', 'bee')), (4, (None, 'wolf')), (4, (None, 'bear'))]
>>>
```

keyBy

Constructs two-component tuples (key-value pairs) by applying a function on each data item. The result of the function becomes the key and the original data item becomes the value of the newly created tuples.

```
a = sc.parallelize(["dog", "salmon", "salmon", "rat", "elephant"], 3)

b = a.keyBy(lambda x:len(x))

b.collect()
```

```
>>> a = sc.parallelize(["dog", "salmon", "salmon", "rat", "elephant"], 3)
>>> b = a.keyBy(lambda x:len(x))
>>> b.collect()
[(3, 'dog'), (6, 'salmon'), (6, 'salmon'), (3, 'rat'), (8, 'elephant')]
>>>
```

mapValues

Takes the values of a RDD that consists of two-component tuples, and applies the provided function to transform each value. Then, it forms new two-component tuples using the key and the transformed value and stores them in a new RDD.

```
a = sc.parallelize(["dog", "tiger", "lion", "cat", "panther", "eagle"], 2)

b = a.map(lambda x : (len(x), x))

b.mapValues(lambda y :"x" + y + "x").collect()
```

```
>>> a = sc.parallelize(["dog", "tiger", "lion", "cat", "panther", "eagle"], 2)
>>> b = a.map(lambda x : (len(x), x))
>>> b.mapValues(lambda y :"x" + y + "x").collect()
[(3, 'xdogx'), (5, 'xtigerx'), (4, 'xlionx'), (3, 'xcatx'), (7, 'xpantherx'), (5, 'xeaglex')]
>>>
```

cache

The cache( ) method is a shorthand for using the default storage level, which is StorageLevel.MEMORY_ONLY (store deserialized objects in memory)

```
c = sc.parallelize(["Gnu", "Cat", "Rat", "Dog", "Gnu", "Rat"], 2)

c.getStorageLevel()
```

```
>>> c = sc.parallelize(["Gnu", "Cat", "Rat", "Dog", "Gnu", "Rat"], 2)
>>> c.getStorageLevel()
StorageLevel(False, False, False, False, 1)
>>>
```

```
c.cache()

c.getStorageLevel()
```

```
>>> c.cache()
ParallelCollectionRDD[243] at parallelize at PythonRDD.scala:423
>>> c.getStorageLevel()
StorageLevel(False, True, False, False, 1)
>>>
```

repartition

Reshuffle the data in the RDD randomly to create either more or fewer partitions and balance it across them. This always shuffles all data over the network.

```
rdd = sc.parallelize([1, 2, 10, 4, 5, 2, 1, 1, 1], 3)

rdd.getNumPartitions()

rdd2 = rdd.repartition(5)

rdd2.getNumPartitions()
```

```
>>> rdd = sc.parallelize([1, 2, 10, 4, 5, 2, 1, 1, 1], 3)
>>> rdd.getNumPartitions()
3
>>> rdd2 = rdd.repartition(5)
>>> rdd2.getNumPartitions()
5
>>>
```

Developing with Spark

REPL

Example: Counting the occurrence of lines having a particular word in it

```
textFile = sc.textFile("file:/home/cloudera/datasets/Joyce.txt")
```

```
textFile.count() //Return the number of elements in the dataset
```

```
>>> textFile = sc.textFile("file:/home/cloudera/datasets/Joyce.txt")
>>> textFile.count()
32790
>>>
```

```
linesWithJoyce = textFile.filter(lambda line : "Joyce" in line)

linesWithJoyce.count() //How many lines contains "Joyce"
```

```
>>> linesWithJoyce = textFile.filter(lambda line : "Joyce" in line)
>>> linesWithJoyce.count()
6
>>>
```

Example: Add up the sizes of all the lines

```
lineLength = textFile.map(lambda s : len(s))

totalLength = lineLength.reduce(lambda a, b : a + b) //Aggregate the
elements of the dataset using a function
```

```
>>> totalLength = lineLength.reduce(lambda a, b : a + b)
>>> totalLength
1496373
```

Example: To find out the words count

```
counts=textFile.flatMap(lambda line: line.split(" ")).map(lambda word:
(word, 1))            .reduceByKey(lambda a, b: a + b)

counts.collect()
```

```
>>> counts=textFile.flatMap(lambda line: line.split(" ")).map(lambda word: (word, 1)).reduceByKey(lambda a, b: a + b).sortByKey()
>>> counts.first()
(u'', 10988)
>>> counts.take(5)
[(u'', 10988), (u'"AS-IS".', 1), (u'"COME', 1), (u'"Defects".', 1), (u'"I', 1)]
>>>
```

Additional Exercise

Analyze Movie Lens Dataset using RDD

Source: http://grouplens.org/datasets/movielens/

Objective: What are the occupations of the users who have rated the iconic movie Titanic as 5?

Information about Dataset:

RATINGS FILE DESCRIPTION

All ratings are contained in the file "**ratings.dat**" and are in the following format:

UserID::MovieID::Rating::Timestamp

- UserIDs range between 1 and 6040
- MovieIDs range between 1 and 3952
- Ratings are made on a 5-star scale (whole-star ratings only)
- Timestamp is represented in seconds since the epoch as returned by time(2)
- Each user has at least 20 ratings

USERS FILE DESCRIPTION

User information is in the file "**users.dat**" and is in the following format:

UserID::Gender::Age::Occupation::Zip-code

All demographic information is provided voluntarily by the users and is

not checked for accuracy. Only users who have provided some demographic

information are included in this data set.

Gender is denoted by a “M” for male and “F” for female

Age is chosen from the following ranges:

1: “Under 18”

18: “18-24”

25: “25-34”

35: “35-44”

45: “45-49”

50: “50-55”

56: “56+”

Occupation is chosen from the following choices:

0: “other” or not specified

1: “academic/educator”

2: “artist”

3: “clerical/admin”

4: “college/grad student”

5: “customer service”

6: “doctor/health care”

7: “executive/managerial”

8: “farmer”

9: “homemaker”

10: “K-12 student”

11: “lawyer”

12: “programmer”

13: “retired”

14: “sales/marketing”

15: “scientist”

16: “self-employed”

17: “technician/engineer”

18: “tradesman/craftsman”

19: “unemployed”

20: “writer”

MOVIES FILE DESCRIPTION

Movie information is in the file “**movies.dat**” and is in the following format:

MovieID::Title::Genres

Titles are identical to titles provided by the IMDB (including year of release)

Genres are pipe-separated and are selected from the following genres:

Action, Adventure, Animation, Children's, Comedy, Crime, Documentary, Drama, Fantasy, Film-Noir, Horror, Musical, Mystery, Romance, Sci-Fi, Thriller, War, Western

Steps:

Load the files ‘movies.dat’, ‘users.dat’ and ‘ratings.dat’ into HDFS from local filesystem

1. Create 3 RDD for movies, users and ratings respectively

```
movies = sc.textFile("/home/cloudera/datasets/movies.dat")

users = sc.textFile("/home/cloudera/datasets/users.dat")

ratings = sc.textFile("/home/cloudera/datasets/ratings.dat")
```

2. Print first 10 lines from the movies rdd

```
movies.take(10)
```

3. Find out the id of the movie Titanic

```
movies.filter(lambda x:"Titanic" in x).collect()
```

```
16/08/31 23:42:52 INFO scheduler.TaskSchedulerImpl: Removed TaskSet 1.0, whose t
asks have all completed, from pool
res1: Array[String] = Array(1721::Titanic (1997)::Drama|Romance, 2157::Chamberma
id on the Titanic, The (1998)::Romance, 3403::Raise the Titanic (1980)::Drama|Th
riller, 3404::Titanic (1953)::Action|Drama)
```

4. Print 10 lines from ratings RDD

```
ratings.take(10)
```

5. Create a filtered rdd based on the users who have rated Titanic as 1

```
titanicRating1 = ratings.map(lambda x: x.split("::")).filter(lambda
x: int(x[2]) == 5).collect()

titanicRating1.take(10)
```

```
16/08/31 23:44:48 INFO scheduler.TaskSchedulerImpl: Removed TaskSet 3.0, whose t
asks have all completed, from pool
1721    3087    5       974709030
1721    1485    5       974706178
1721    3247    5       974706026
1721    2463    5       974708897
1721    2321    5       974707939
1721    1569    5       974706315
1721    3397    5       974708938
1721    2918    5       974708773
```

6. Convert the previous RDD by assigning user id as key

```
byUser = titanicRating1.keyBy(lambda x :int(x[1]))

byUser.take(3)
```

7. Show some sample values from users rdd

```
users.take(10)
```

```
16/08/31 23:47:02 INFO scheduler.TaskSchedulerImpl: Removed TaskSet 5.0, whose t
asks have all completed, from pool
1::F::1::10::48067
2::M::56::16::70072
3::M::25::15::55117
4::M::45::7::02460
5::M::25::20::55455
6::F::50::9::55117
7::M::35::1::06810
8::M::25::12::11413
9::M::25::17::61614
10::F::35::1::95370
```

8. Create pair RDD pairRddUsers from users rdd using userid as key

```
pairRddUsers = users.keyBy(lambda x:x.split("::")[0])

pairRddUsers.take(3)
```

```
>>> users = sc.textFile("file:/home/cloudera/datasets/users.dat")
>>> pairRddUsers = users.keyBy(lambda x:x.split("::")[0])
>>> pairRddUsers.take(3)
[(u'1', u'1::F::1::10::48067'), (u'2', u'2::M::56::16::70072'), (u'3', u'3::M::25::15::55117')]
>>>
```

Assignment:

Objective: Using above transformation and action, Analyse Crime Data from San Francisco Police Department.

Steps:

1. Create an RDD with crime incident data.
2. Take first five records of RDD created and print the same.
3. Reference each field with an index map.
4. Show the first value of an RDD.
5. Check number of partition.
6. Capture the line containing header in RDD.
7. Create an RDD with only records eliminating the header.
8. Find the number of incident records?
9. List all the categories from incident data?
10. Find total number of categories?
11. What are the total number of incidents in each category?
12. Find out on which day each of incidents occurred most?

Exercise 6: Dataframe and Spark SQL

Two ways to create Spark Dataframes:

1. Create from an existing RDD
2. Create from other data sources

Creating DataFrames from Existing RDD:

1. Infer schema by Reflection
   a. Convert RDD containing case classes.
   b. Use when schema is known.

2. Construct schema programmatically
   a. Schema is dynamic
   b. Number of fields in case class is more than 22 fields.

1. Inferring the Schema Using Reflection

```
from pyspark.sql import SQLContext, Row

sqlContext = SQLContext(sc)



# Load a text file and convert each line to a Row.

lines =
sc.textFile("file:/home/cloudera/datasets/crime_incidents.csv")

parts = lines.map(lambda l: l.split(","))

crime = parts.map(lambda p: Row(IncidntNum=p[0], Category =p[1],
Descript=p[2],
day=p[3],date=p[4],time=p[5],district=p[6],resolution=p[7],address=p
[8],X=p[9],Y=p[10],location=p[11]))
```

Infer the schema, and register the DataFrame as a table.

```
schemaCrime = sqlContext.createDataFrame(crime)

schemaCrime.registerTempTable("incidents")
```

SQL can be run over DataFrames that have been registered as a table.

```
teenagers = sqlContext.sql("SELECT * from incidents")

teenagers.show()
```

Or,

The results of SQL queries are RDDs and support all the normal RDD operations.

```
teenNames = teenagers.map(lambda p: "Name: " + p.name)

for teenName in teenNames.collect():

  print(teenName)
```

2. Programmatically Specifying the Schema

A DataFrame can be created programmatically with three steps.

- Create an RDD of tuples or lists from the original RDD;
- Create the schema represented by a StructType matching the structure of tuples or lists in the RDD created in the step 1.
- Apply the schema to the RDD via createDataFrame method provided by SQLContext

Step 1. Load a text file and convert each line to a tuple.

```
lines = sc.textFile("file:/home/cloudera/datasets/people.txt")

parts = lines.map(lambda l: l.split(","))

people = parts.map(lambda p: (p[0], p[1].strip()))
```

Step 2. The schema is encoded in a string.

```
schemaString = "name age"

from pyspark.sql.types import *

fields = [StructField(field_name, StringType(), True) for field_name
in schemaString.split()]

schema = StructType(fields)
```

Step 3. Apply the schema to the RDD and dataframe is created

```
schemaPeople = sqlContext.createDataFrame(people, schema)
```

Print the schema in a tree format

```
schemaPeople.printSchema()
```

Print the rows of the dataframe

```
schemaPeople.show()
```

Let us now Register the DataFrame as a table.

```
schemaPeople.registerTempTable("people")
```

SQL can be run over DataFrames that have been registered as a table.

```
results = sqlContext.sql("SELECT name FROM people")

results.show()
```

Or,

The results of SQL queries are RDDs and support all the normal RDD operations.

```
names = results.map(lambda p: "Name: " + p.name)

for name in names.collect():  print(name)
```

Creating DataFrames with Python

```
# import pyspark class Row from module sql
from pyspark.sql import *
```

Let us Create Example Data - Departments and Employees

Create the Departments

```
department1 = Row(id='123456', name='Computer Science')

department2 = Row(id='789012', name='Mechanical Engineering')

department3 = Row(id='345678', name='Theater and Drama')

department4 = Row(id='901234', name='Indoor Recreation')
```

Create the Employees

```
Employee = Row("firstName", "lastName", "email", "salary")

employee1 = Employee('michael', 'armbrust', 'no-reply@berkeley.edu',
100000)

employee2 = Employee('xiangrui', 'meng', 'no-reply@stanford.edu',
120000)

employee3 = Employee('matei', None, 'no-reply@waterloo.edu', 140000)

employee4 = Employee(None, 'wendell', 'no-reply@berkeley.edu',
160000)
```

Create the DepartmentWithEmployees instances from Departments and Employees

```
departmentWithEmployees1 = Row(department=department1,
employees=[employee1, employee2])

departmentWithEmployees2 = Row(department=department2,
employees=[employee3, employee4])

departmentWithEmployees3 = Row(department=department3,
employees=[employee1, employee4])

departmentWithEmployees4 = Row(department=department4,
employees=[employee2, employee3])



print department1

print employee2

print departmentWithEmployees1.employees[0].email
```

Create the first DataFrame from a list of the rows.

```
departmentsWithEmployeesSeq1 = [departmentWithEmployees1,
departmentWithEmployees2]

df1 = sqlContext.createDataFrame(departmentsWithEmployeesSeq1)



display(df1)
```

Create a second DataFrame from a list of rows.

```
departmentsWithEmployeesSeq2 = [departmentWithEmployees3,
departmentWithEmployees4]

df2 = sqlContext.createDataFrame(departmentsWithEmployeesSeq2)



display(df2)
```

Working with DataFrames

Union of two DataFrames.

```
unionDF = df1.unionAll(df2)

display(unionDF)
```

Write the Unioned DataFrame to a Parquet file.

Remove the file if it exists

```
dbutils.fs.rm("file:/home/cloudera/datasets/unionParq", True)

unionDF.write.parquet("file:/home/cloudera/datasets/unionParq")
```

An example using Pandas & Matplotlib Integration

UDF in Spark Dataframe

UDF for Dataframe API

We will write an UDF for the day column and if its Sunday, that will become as weekend else weekdays for the crime_incidents.csv file from which we had created a dataframe in earlier sections.

Parse string day field into weekend/weekday

```
from pyspark.sql.types import StringType

from pyspark.sql.functions import udf


day_udf = udf(lambda day: "Weekend" if day!='Sunday' else
"Weekdays", StringType())

schemaCrime.withColumn("Calendar", day_udf(schemaCrime.day)).show()
```

Exercise 7: Produce and Consume Apache Kafka Messages

Start the Zookeeper server

1. Open a new terminal window and browse to the location "/usr/lib/zookeeper" using cd. Start the zookeeper by command

```
bin/zkServer.sh start
```

```
[cloudera@quickstart ~]$ cd /usr/lib/zookeeper
[cloudera@quickstart zookeeper]$ bin/zkServer.sh start
JMX enabled by default
Using config: /usr/lib/zookeeper/bin/../conf/zoo.cfg
Starting zookeeper ... STARTED
[cloudera@quickstart zookeeper]$
```

2. You can now validate that Zookeeper is running correctly in standalone mode by connecting to the client port and sending the four letter command "srvr".

```
telnet localhost 2181
```

```
[cloudera@quickstart zookeeper]$ telnet localhost 2181
Trying 127.0.0.1...
Connected to localhost.
Escape character is '^]'.
srvr
Zookeeper version: 3.4.5-cdh5.12.0--1, built on 06/29/2017 11:30 GMT
Latency min/avg/max: 0/0/1303
Received: 30491
Sent: 30604
Connections: 4
Outstanding: 0
Zxid: 0xe14
Mode: standalone
Node count: 737
Connection closed by foreign host.
[cloudera@quickstart zookeeper]$
```

Starting Kafka and Creating a Kafka Topic

1. Open a new terminal and start Kafka broker, Change the user to cloudera with su – and provide password as cloudera.

```
bin/kafka-server-start.sh config/server.properties
```

```
[2018-03-11 09:04:19,389] INFO starting (kafka.server.KafkaServer)
[2018-03-11 09:04:19,400] INFO Connecting to zookeeper on localhost:2181 (kafka.server.KafkaServer)
[2018-03-11 09:04:19,449] INFO Starting ZkClient event thread. (org.I0Itec.zkclient.ZkEventThread)
[2018-03-11 09:04:19,469] INFO Client environment:zookeeper.version=3.4.5-cdh5.9.0--1, built on 10/21/2016 08:05 GMT (org.apache.zookeeper.ZooKeeper)
[2018-03-11 09:04:19,469] INFO Client environment:host.name=quickstart.cloudera (org.apache.zookeeper.ZooKeeper)
[2018-03-11 09:04:19,469] INFO Client environment:java.version=1.7.0_67 (org.apache.zookeeper.ZooKeeper)
[2018-03-11 09:04:19,469] INFO Client environment:java.vendor=Oracle Corporation (org.apache.zookeeper.ZooKeeper)
[2018-03-11 09:04:19,469] INFO Client environment:java.home=/usr/java/jdk1.7.0_67-cloudera/jre (org.apache.zookeeper.ZooKeeper)
[2018-03-11 09:04:19,469] INFO Client environment:java.class.path=:/usr/lib/kafka/bin/../libs/activation-1.1.jar:/usr/lib/kafka/bin/../libs/aopalliance-1.0.jar:/usr/lib/kafka/bin
```

Kafka broker is running on port 9042.

2. Open a new terminal window and create a Kafka topic named `weblogs` that will contain messages representing lines in `Loudacre's web server logs`.

Since your exercise environment is a single-node cluster running on a virtual machine, use a replication factor of 1 and a single partition.

Navigate to the location where Kafka is installed, which is "/usr/lib/kafka".

```
$ bin/kafka-topics.sh --create \ --zookeeper localhost:2181 \ --
replication-factor 1 \ --partitions 1 \
--topic weblogs
```

Here, Topic name

The name of the topic that you wish to create.

Replication Factor

The number of replicas of the topic to maintain within the cluster.

Partitions

The number of partitions to create for the topic.

```
[cloudera@quickstart kafka]$ bin/kafka-topics.sh --create --zookeeper localhost:2181 --replication-factor 1 --partitions 1 --topic weblogs
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.21.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.5.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
Created topic "weblogs".
```

1. Display all Kafka topics to confirm that the new topic you just created is listed:

```
$ kafka-topics --list --zookeeper localhost:2181
```

```
[cloudera@quickstart kafka]$ kafka-topics --list --zookeeper localhost:2181
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.21.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.5.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
weblogs
[cloudera@quickstart kafka]$
```

2. Describe the Kafka topic created

```
$ bin/kafka-topics.sh --describe --zookeeper localhost:2181

--topic weblogs
```

```
[cloudera@quickstart kafka]$ kafka-topics.sh --describe --zookeeper localhost:2181 --topic weblogs
bash: kafka-topics.sh: command not found
[cloudera@quickstart kafka]$ bin/kafka-topics.sh --describe --zookeeper localhost:2181 --topic weblogs
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.21.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.5.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
Topic:weblogs   PartitionCount:1        ReplicationFactor:1     Configs:
        Topic: weblogs  Partition: 0    Leader: 0       Replicas: 0     Isr: 0
```

Producing and Consuming Messages

You will now use Kafka command line utilities to start producers and consumers for the topic created earlier.

3. Start a Kafka producer for the weblogs topic:

```
$ kafka-console-producer --broker-list localhost:9092 --topic

weblogs
```

Tip : This exercise involves using multiple terminal windows. To avoid confusion, set a different title for each one by selecting Set Title... on the Terminal menu:

Set the title for this window to "Kafka Producer."

4. Publish a test message to the weblogs topic by typing the message text and then pressing Enter. For example:

```
test weblog entry 1
```

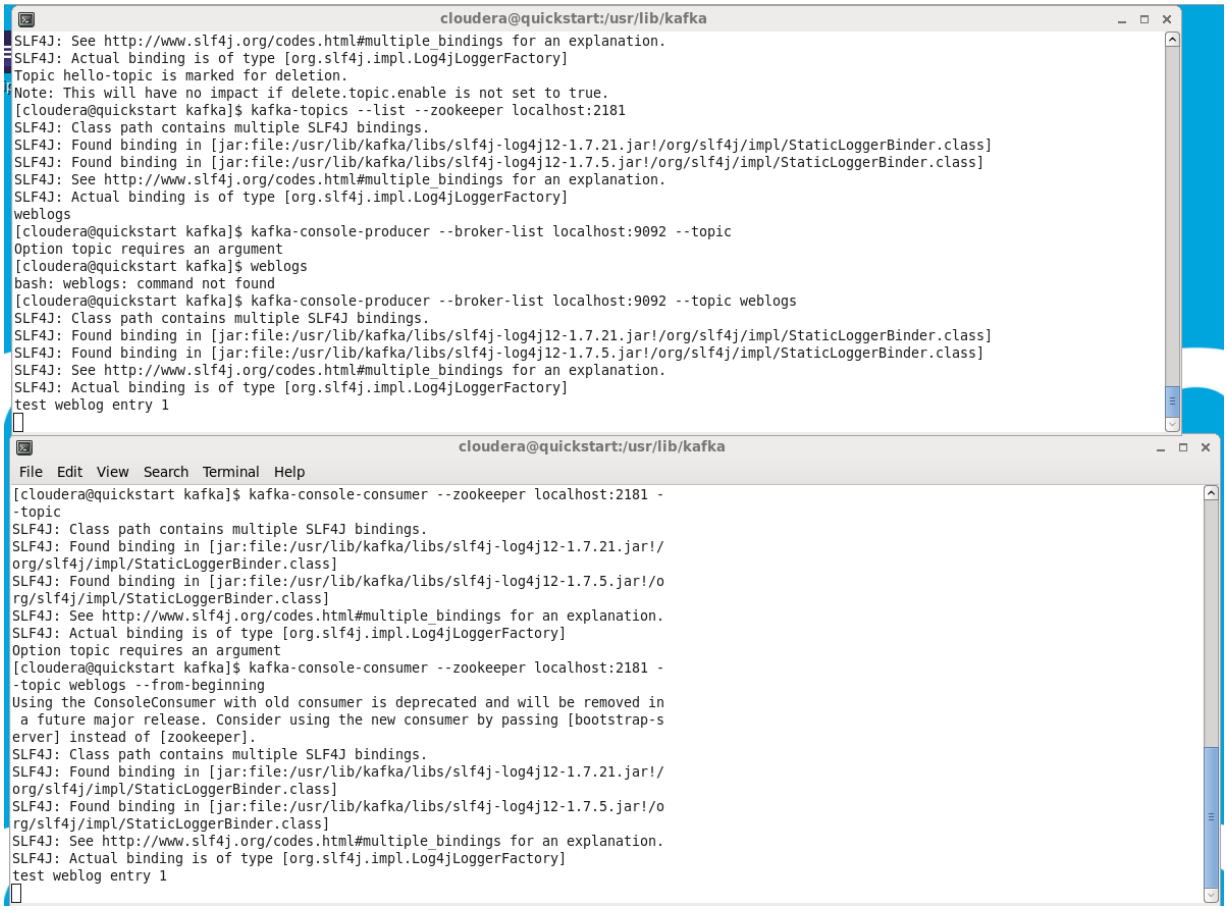
5. Open a new terminal window and adjust it to fit on the window beneath the producer window. Set the title for this window to "Kafka Consumer."

6. In the new terminal window, start a Kafka consumer that will read from the beginning of the weblogs topic:

```
$ kafka-console-consumer --zookeeper localhost:2181 --topic
weblogs --from-beginning
```

You should see the status message you sent using the producer displayed on the consumer's console, such as:

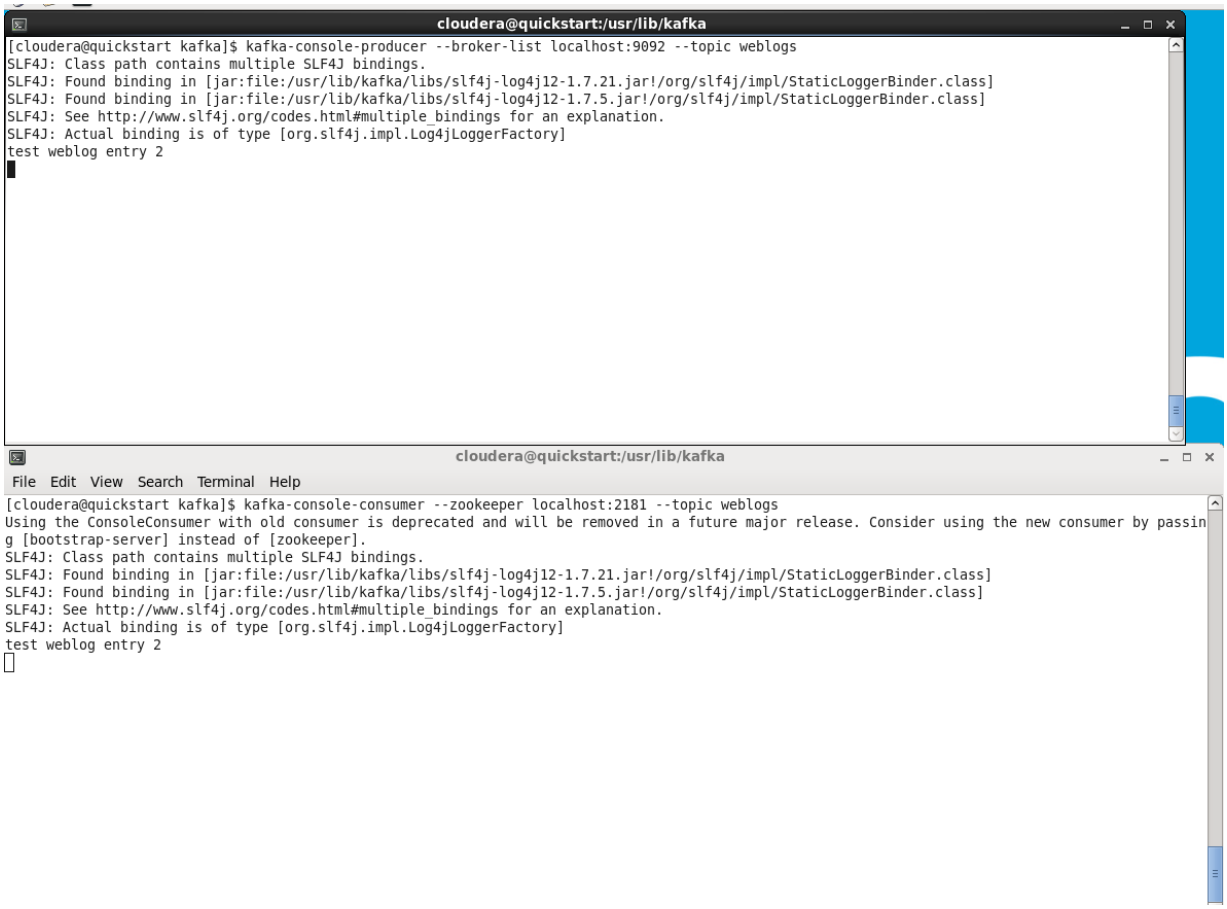
```
test weblog 1
```



7. Press Ctrl+C to stop the weblogs consumer, and restart it, but this time omit the from-beginning option to this command. You should see that no messages are displayed.

8. Switch back to the producer window and type another test message into the terminal, followed by the Enter key:

```
test weblog entry 2
```



9. Return to the consumer window and verify that it now displays the alert message you published from the producer in the previous step.

Cleaning Up

10. Press Ctrl+C in the consumer terminal window to end its process.

11. Press Ctrl+C in the producer terminal window to end its process.

Exercise 5: Alter Apache Kafka Topics

Let us try altering some parameters for the topic, but instead of using the earlier created topic <weblogs>, we will create another topic “hello-topic” to alter some parameters.

Exercise: Create a topic called hello-topic with replication factor 1 and partition 1.

1. We will add more partitions in the topic created as “hello-topic”. Below command will add 10 more partitions to the hello-topic topic. Note that before, the topic has only 1 partition.

```
bin/kafka-topics.sh --alter --zookeeper localhost:2181 --
partitions 11 --topic hello-topic
```

```
[cloudera@quickstart kafka]$ bin/kafka-topics.sh --alter --zookeeper localhost:2181 --partitions 11 --topic hello-topic
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.21.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.5.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
WARNING: If partitions are increased for a topic that has a key, the partition logic or ordering of the messages will be affected
Adding partitions succeeded!
[cloudera@quickstart kafka]$
```

Let us verify the number of partitions is being changed with the command

```
bin/kafka-topics.sh --describe --zookeeper localhost:2181 --
topic hello-topic
```

```
[cloudera@quickstart kafka]$ bin/kafka-topics.sh --describe --zookeeper localhost:2181 --topic hello-topic
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.21.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.5.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
Topic:hello-topic       PartitionCount:11       ReplicationFactor:1     Configs:
        Topic: hello-topic      Partition: 0    Leader: 0       Replicas: 0     Isr: 0
        Topic: hello-topic      Partition: 1    Leader: 0       Replicas: 0     Isr: 0
        Topic: hello-topic      Partition: 2    Leader: 0       Replicas: 0     Isr: 0
        Topic: hello-topic      Partition: 3    Leader: 0       Replicas: 0     Isr: 0
        Topic: hello-topic      Partition: 4    Leader: 0       Replicas: 0     Isr: 0
        Topic: hello-topic      Partition: 5    Leader: 0       Replicas: 0     Isr: 0
        Topic: hello-topic      Partition: 6    Leader: 0       Replicas: 0     Isr: 0
        Topic: hello-topic      Partition: 7    Leader: 0       Replicas: 0     Isr: 0
        Topic: hello-topic      Partition: 8    Leader: 0       Replicas: 0     Isr: 0
        Topic: hello-topic      Partition: 9    Leader: 0       Replicas: 0     Isr: 0
        Topic: hello-topic      Partition: 10   Leader: 0       Replicas: 0     Isr: 0
[cloudera@quickstart kafka]$
```

Tip: REDUCING PARTITION COUNTS

It is not possible to reduce the number of partitions for a topic. The reason this is not supported is because deleting a partition from a topic would cause part of the data in that topic to be deleted as well, which would be inconsistent from a client point of view. In addition, trying to redistribute the data to remaining partitions would be difficult and result in out-of-order messages. Should you need to reduce the number of partitions, you will need to delete the topic and recreate it.

2. Add configurations to the Kafka topic

   The general syntax is:

```
bin/kafka-topics.sh --alter --zookeeper localhost:2181 --topic
kafkatopic --config <key>=<value>
```

There are various configuration fields we can set for the topic, here we will set up the max.message.bytes - this is the largest size of the message the broker will allow to be appended to the topic. This size is validated pre-compression. (Defaults to broker's message.max.bytes.)

```
bin/kafka-topics.sh --zookeeper localhost:2181 --alter --topic
hello-topic --config max.message.bytes=128000
```

```
[cloudera@quickstart kafka]$ bin/kafka-topics.sh --zookeeper localhost:2181 --alter --topic hello-topic --config max.message.bytes=128000
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.21.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.5.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
WARNING: Altering topic configuration from this script has been deprecated and may be removed in future releases.
         Going forward, please use kafka-configs.sh for this functionality
Updated config for topic "hello-topic".
```

3. To remove above overridden configuration, we can use command:

```
bin/kafka-topics.sh --zookeeper localhost:2181 --alter --topic
hello-topic --delete-config max.message.bytes
```

Exercise 6: Delete a topic

If a topic is no longer needed, it can be deleted in order to free up these resources. In order to perform this action, the brokers in the cluster must have been configured with

the delete.topic.enable option set to true. If this option has been set to false, then the request to delete the topic will be ignored.

We will delete the topic created with the below command

```
bin/kafka-topics.sh --delete --zookeeper localhost:2181 --
topic hello-topic
```

```
[cloudera@quickstart kafka]$ bin/kafka-topics.sh --delete --zookeeper localhost:2181 --topic hello-topic
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.21.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.5.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
Topic hello-topic is marked for deletion.
Note: This will have no impact if delete.topic.enable is not set to true.
```

Lets verify if the topic has been deleted, with the –list command

```
[cloudera@quickstart kafka]$ bin/kafka-topics.sh --zookeeper localhost:2181 --list
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.21.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/lib/kafka/libs/slf4j-log4j12-1.7.5.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
weblogs
[cloudera@quickstart kafka]$
```

Tip: DATA LOSS AHEAD

Deleting a topic will also delete all its messages. This is not a reversible operation, so make sure it executed carefully.

Exercise 8: Spark Streaming

Let's start with simple streaming example, to count the number of words in text data received from a data server listening on a TCP socket.

Create a DStream that represents streaming data from a TCP source, specified as hostname (e.g. localhost) and port (e.g. 9999).

Create a python project with below inputs:

```
# Spark Stateful Streaming with Python
# Takes text from input network socket and prints the accumulated
count for each word


from pyspark import SparkContext
from pyspark.streaming import StreamingContext


# define the update function
def updateTotalCount(currentCount, countState):
    if countState is None:
       countState = 0
    return sum(currentCount, countState)


# create spark and streaming contexts
sc = SparkContext("local[*]", "StreamWordCounter")
ssc = StreamingContext(sc, 10)


# defining the checkpoint directory
ssc.checkpoint("/tmp")


# read text from input socket
text = ssc.socketTextStream("localhost", 9999)


# count words
countStream = text.flatMap(lambda line: line.split(" "))\
                  .map(lambda word: (word, 1))\
                  .reduceByKey(lambda a, b: a + b)


# update total count for each key
totalCounts = countStream.updateStateByKey(updateTotalCount)


# print the resulting tuples
```

```
totalCounts.pprint()


# start the streaming context

ssc.start()

ssc.awaitTermination()
```

Save the file as Streaming.py in /home/cloudera/SparkStreaming

Submit the python code in the Spark shell with the following script in the command line

```
spark-submit SparkStreaming/Streaming.py localhost 9999
```

Run the program using spark-submit

Run Netcat command and open another terminal to submit the job

```
nc -nlk 9999
```

```
[cloudera@quickstart workspace]$ nc -nlk 9999
hello world
hello hadoop
```

Any lines typed in the terminal running the netcat server will be counted and printed on screen every second. It will look something like the following

```
16/09/13 08:19:03 INFO executor.Executor: Finished task 0.0 in stage 4.0 (TID 3)
. 1312 bytes result sent to driver
16/09/13 08:19:03 INFO scheduler.TaskSetManager: Finished task 0.0 in stage 4.0
(TID 3) in 10 ms on localhost (1/1)
16/09/13 08:19:03 INFO scheduler.TaskSchedulerImpl: Removed TaskSet 4.0, whose t
asks have all completed, from pool
16/09/13 08:19:03 INFO scheduler.DAGScheduler: ResultStage 4 (print at SparkStre
amReceiver.scala:24) finished in 0.012 s
16/09/13 08:19:03 INFO scheduler.DAGScheduler: Job 2 finished: print at SparkStr
eamReceiver.scala:24, took 0.033085 s
-------------------------------------------
Time: 1473779943000 ms
-------------------------------------------
(hello,2)
(world,1)
(hadoop,1)
```

Spark Streaming with Kafka

Before we start, make sure that zookeeper is running on 2181 and Kafka broker is running on 9042 port.

Let us now create a kafka topic named as "new_topic".

```
bin/kafka-topics.sh --create --zookeeper localhost:2181 --
replication-factor 1 --partitions 1 --topic new_topic
```

Let us start Kafka Producer

```
kafka-console-producer --broker-list localhost:9092 --topic
new_topic
```

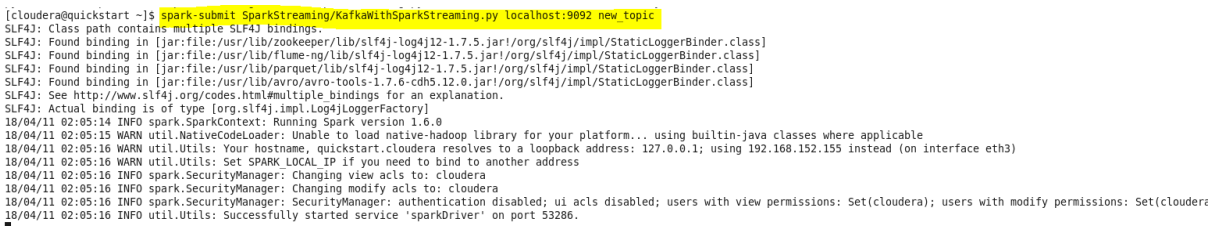
Create a python project with below inputs in home/cloudera/SparkStreaming folder and save as "KafkaWithSparkStreaming.py" :

```
import sys

from pyspark import SparkContext

from pyspark.streaming import StreamingContext

from pyspark.streaming.kafka import KafkaUtils

if __name__ == "__main__":

    sc = SparkContext(appName="PythonStreamingDirectKafkaWordCount")

    ssc = StreamingContext(sc, 2)

    brokers, topic = sys.argv[1:]

    kvs = KafkaUtils.createDirectStream(ssc,
[topic],{"metadata.broker.list": brokers})
```

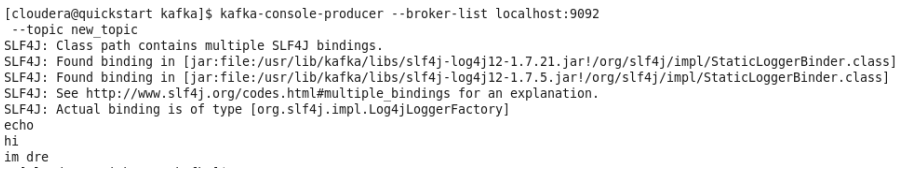
```
    lines = kvs.map(lambda x: x[1])

    counts = lines.flatMap(lambda line: line.split(" ")).map(lambda
word: (word, 1)).reduceByKey(lambda a, b: a+b)

    counts.pprint()

    ssc.start()

    ssc.awaitTermination()
```

Run the program using spark-submit

```
spark-submit /SparkStreaming/KafkaWithSparkStreaming.py
localhost:9092 new_topic
```



Now we will start sending messages from kafka producer



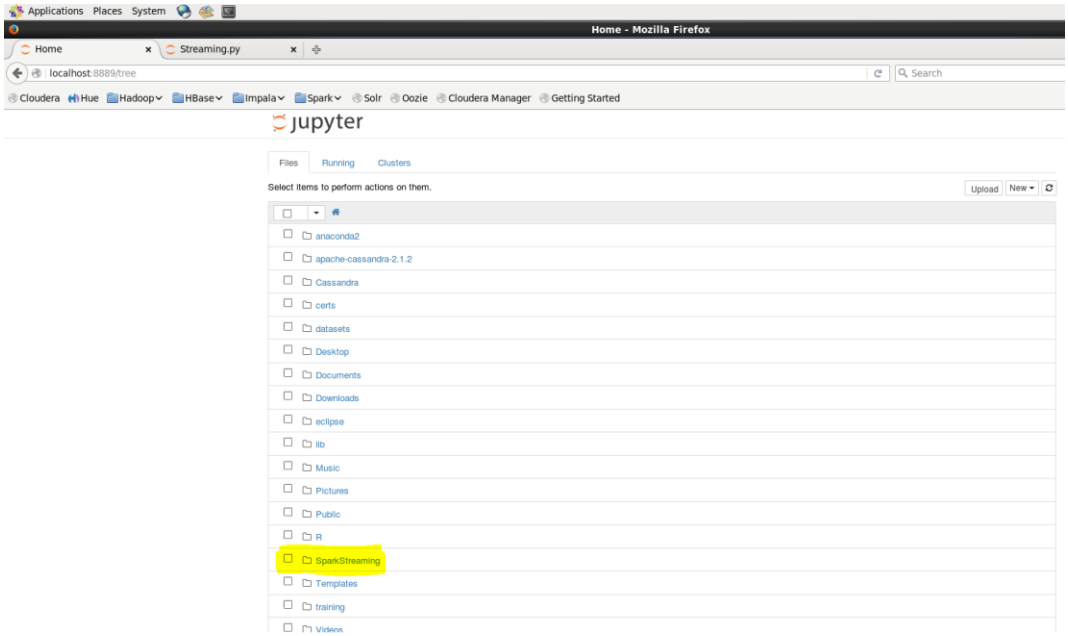
The messages will be streaming in the spark-submit screen.

To configure PySpark in Jupyter notebook

Open the new command terminal and export the below commands.

```
export PYSPARK_DRIVER_PYTHON=jupyter
export PYSPARK_DRIVER_PYTHON_OPTS='notebook'

Now type in the command terminal

pyspark
```

This will open pyspark in Jupyter notebook.



Click to go in the SparkStreaming folder already created.

Exercise 9: SparkML

Predicting power grid demand using Spark ML

Data Source: https://archive.ics.uci.edu/ml/datasets/Combined+Cycle+Power+Plant

Features consist of hourly average ambient variables

Temperature (T) in the range 1.81°C and 37.11°C,

Ambient Pressure (AP) in the range 992.89-1033.30 milibar,

Relative Humidity (RH) in the range 25.56% to 100.16%

Exhaust Vacuum (V) in the range 25.36-81.56 cm Hg

Net hourly electrical energy output (EP) 420.26-495.76 MW

The averages are taken from various sensors located around the plant that record the ambient variables every second. The variables are given without normalization.

Dataset Information:

The dataset contains 9568 data points collected from a Combined Cycle Power Plant over 6 years (2006-2011), when the power plant was set to work with full load. Features consist of hourly average ambient variables Temperature (T), Ambient Pressure (AP),

Relative Humidity (RH) and Exhaust Vacuum (V) to predict the net hourly electrical energy output (EP) of the plant.

A combined cycle power plant (CCPP) is composed of gas turbines (GT), steam turbines (ST) and heat recovery steam generators. In a CCPP, the electricity is generated by gas and steam turbines, which are combined in one cycle, and is transferred from one turbine to another. While the Vacuum is collected from and has effect on the Steam Turbine, the other three of the ambient variables effect the GT performance.

Steps:

1. Load the data

```
val df = sqlContext.read.format("csv")

.option("header","true")

.option("inferSchema","true")

.load("/data/Combined_Cycle_Power_Plant/")

df.printSchema
```

```
df: org.apache.spark.sql.DataFrame = [AT: double, V: double, AP: double, RH: double, PE: double]
root
 |-- AT: double (nullable = true)
 |-- V: double (nullable = true)
 |-- AP: double (nullable = true)
 |-- RH: double (nullable = true)
 |-- PE: double (nullable = true)
```

2. Cache the dataframe, as it will be used many time.

```
df.cache

df.count

df.show(5)
```

```
res59: df.type = [AT: double, V: double, AP: double, RH: double, PE: double]
res60: Long = 47840
+-----+-----+-------+-----+------+
|   AT|    V|     AP|   RH|    PE|
+-----+-----+-------+-----+------+
|14.96|41.76|1024.07|73.17|463.26|
|25.18|62.96|1020.04|59.08|444.37|
| 5.11| 39.4|1012.16|92.14|488.56|
|20.86|57.32|1010.24|76.64|446.48|
|10.82| 37.5|1009.23|96.62| 473.9|
+-----+-----+-------+-----+------+
only showing top 5 rows
```

3. Register the dataframe as table

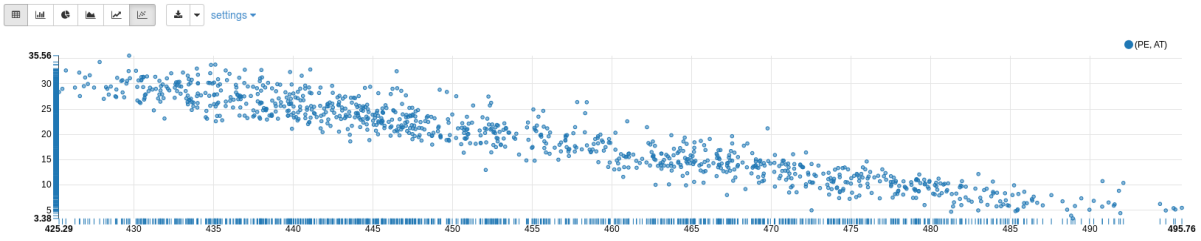
```
df.registerTempTable("pp")
```

4. Query the table using SQL interpreter from zeeplein.

```
%sql

SELECT PE,AT from pp
```

PE	AT
463.26	14.96
444.37	25.18
488.56	5.11
446.48	20.86
473.9	10.82
443.67	26.27
467.35	15.89
478.42	9.48

To view the output graphically

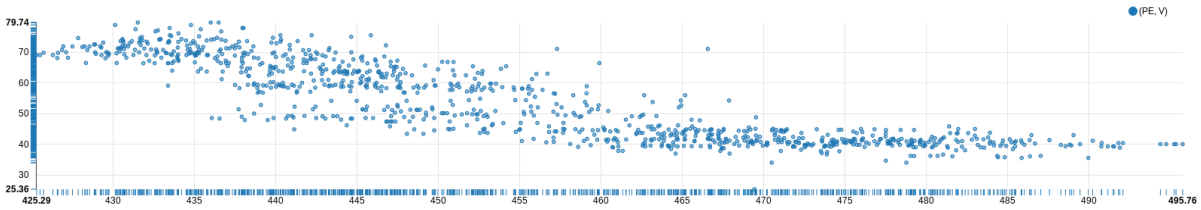


5. Query the table for analysis between PE vs V

```
%sql

SELECT PE, V FROM pp
```

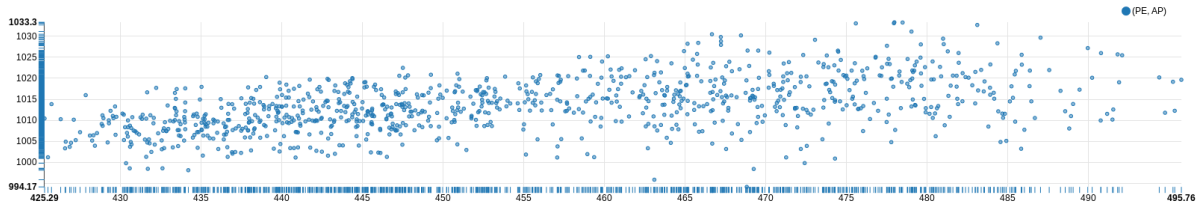
PE	V
463.26	41.76
444.37	62.96
488.56	39.4
446.48	57.32
473.9	37.5
443.67	59.44
467.35	43.96
478.42	44.71
475.98	45

Results are limited by 1000.



6. Analysis between PE and AP

```
%sql

SELECT PE, AP FROM pp
```



7. Analysis between PE and RH

```
%sql

SELECT PE, RH FROM pp
```

PE	RH
463.26	73.17
444.37	59.08
488.56	92.14
446.48	76.64
473.9	96.62
443.67	58.77
467.35	75.24

8. Data preparation

    - VectorAssembler is a transformer that combines a given list of columns into a single vector column.
    - Convert the `power_plant` SQL table into a DataFrame named `dataset`
    - Set the vectorizer's input columns to a list of the four columns of the input DataFrame: `["AT", "V", "AP", "RH"]`
    - Set the vectorizer's output column name to `"features"`

```
import org.apache.spark.ml.feature.VectorAssembler

val vectorizer = new VectorAssembler()

vectorizer.setInputCols(Array("AT", "V", "AP", "RH"))

vectorizer.setOutputCol("features")
```

```
vectorizer: org.apache.spark.ml.feature.VectorAssembler = vecAssembler_c81487e45a35
res66: vectorizer.type = vecAssembler_c81487e45a35
res67: vectorizer.type = vecAssembler_c81487e45a35
```

9. Data Modeling

    - Split the data into training and test datasets, i.e. 20% for testing and 80% for training.

Objective:

We need a way of evaluating how well our linear regression model predicts power output as a function of input parameters. We can do this by splitting up our initial data set into a _Training Set_ used to train our model and a _Test Set_ used to evaluate the model's performance in giving predictions.

```
var Array(testingSet, trainingSet) = df.randomSplit(Array(0.20,
0.80), 0L)
```

```
testingSet.count

trainingSet.count
```

```
testingSet: org.apache.spark.sql.DataFrame = [AT: double, V: double, AP: double, RH: double, PE: double]
trainingSet: org.apache.spark.sql.DataFrame = [AT: double, V: double, AP: double, RH: double, PE: double]
res69: Long = 9547
res70: Long = 38293
```

Linear Regression Model

We'll create a Linear Regression Model and use the built in help to identify how to train it.

- Initialize our linear regression learner.
- Explain params to dump the parameters we can use.

```
import org.apache.spark.ml.regression.LinearRegression

import org.apache.spark.ml.regression.LinearRegressionModel

import org.apache.spark.ml.Pipeline

val lr = new LinearRegression()

lr.explainParams()
```

```
import org.apache.spark.ml.regression.LinearRegression
import org.apache.spark.ml.regression.LinearRegressionModel
import org.apache.spark.ml.Pipeline
lr: org.apache.spark.ml.regression.LinearRegression = linReg_301e5ead4215
res72: String =
elasticNetParam: the ElasticNet mixing parameter, in range [0, 1]. For alpha = 0, the penalty is an L2 penalty. For alpha = 1, it is an L1 penalty (default: 0.0)
featuresCol: features column name (default: features)
fitIntercept: whether to fit an intercept term (default: true)
labelCol: label column name (default: label)
maxIter: maximum number of iterations (>= 0) (default: 100)
predictionCol: prediction column name (default: prediction)
regParam: regularization parameter (>= 0) (default: 0.0)
solver: the solver algorithm for optimization. If this is not set or empty, default value is 'auto'. (default: auto)
standardization: whether to standardize the training features before fitting the model (default: true)
tol: the convergence tolerance for iterative algorithms (de...
```

10. Set the parameters for the method:

- Set the name of the prediction column to "Predicted_PE"
- Set the name of the label column to "PE"
- Set the maximum number of iterations to 100
- Set the regularization parameter to 0.1

```
lr.setPredictionCol("PE_Predict")

  .setLabelCol("PE")
```

```
  .setMaxIter(100)
  .setRegParam(0.1)
```

```
res74: org.apache.spark.ml.regression.LinearRegression = linReg_301e5ead4215
```

11. Create a model by training on 'trainingSet'

    - Use the new spark.ml pipeline API, Similar to python scikit-learn
    - First train on the entire dataset to see what we get

```
val lrPipeline = new Pipeline()
lrPipeline.setStages(Array(vectorizer, lr))
val lrModel = lrPipeline.fit(trainingSet)
```

```
lrPipeline: org.apache.spark.ml.Pipeline = pipeline_5a953dde602d
res76: lrPipeline.type = pipeline_5a953dde602d
lrModel: org.apache.spark.ml.PipelineModel = pipeline_5a953dde602d
```

12. Linear Regression Model

Linear Regression is simply a Line of best fit over the data that minimizes the square of the error, given multiple input dimensions we can express each predictor as a line function of the form:

[y = a + b x_1 + b x_2 + b x_i ... \\]

where \\(a\\) is the intercept and the \\(b\\) are the coefficients.

```
val model = lrModel.stages(1).asInstanceOf[LinearRegressionModel]
```

```
model: org.apache.spark.ml.regression.LinearRegressionModel = linReg_301e5ead4215
```

13. To express the coefficients of that line we can retrieve the Estimator stage from the PipelineModel and express the weights and the intercept for the function.

    - Intercepts

```
val intercept = model.intercept
```

```
intercept: Double = 437.3755581407379
```

- Weights

```
val weights = model.weights.toArray
```

```
warning: there were 1 deprecation warning(s); re-run with -deprecation for details
weights: Array[Double] = Array(-1.9184240575231875, -0.2543479937050499, 0.07825010764537191, -0.1471027706567747)
```

14. List of the column names (without PE)

```
val featuresNoLabel = df.columns.filter(col => col != "PE")
```

```
featuresNoLabel: Array[String] = Array(AT, V, AP, RH)
```

15. Merge the weights and labels

```
val coefficents =
sc.parallelize(weights).zip(sc.parallelize(featuresNoLabel))

coefficents.collect.foreach(println)
```

```
coefficents: org.apache.spark.rdd.RDD[(Double, String)] = ZippedPartitionsRDD2[116] at zip at <console>:87
(-1.9184240575231875,AT)
(-0.2543479937050499,V)
(0.07825010764537191,AP)
(-0.1471027706567747,RH)
```

16. Assigning value of intercept to equation

```
var equation = s"y = $intercept "
```

```
equation: String = "y = 437.3755581407379 "
```

17. Sort the coefficients from greatest absolute weight most to the least absolute weight

```
var variables = Array
coefficents.sortByKey().collect().foreach(x =>
  {
        val weight = Math.abs(x._1)
        val name = x._2
        val symbol = if (x._1 > 0) "+" else "-"
        equation += (s" $symbol (${weight} * ${name})")
  }
)
```

```
variables: Array.type = scala.Array$@55b81d1f
```

18. Linear Regression Equation

```
println("Linear Regression Equation: " + equation)
```

```
Linear Regression Equation: y = 437.3755581407379  - (1.9184240575231875 * AT) - (0.2543479937050499 * V) - (0.1471027706567747 * RH) + (0.07825010764537191 * AP)
```

19. Apply our LR model to the test data and predict power output

```
val predictionsAndLabels = lrModel.transform(testingSet)
predictionsAndLabels.show(5)
```

Scroll through the resulting table and notice how the values in the Power Output (PE) column compare to the corresponding values in the predicted Power Output (Predicted_PE) column.

```
predictionsAndLabels: org.apache.spark.sql.DataFrame = [AT: double, V: double, AP: double, RH: double, PE: double, features: vector, PE_Predict: double]
+----+-----+-------+-----+------+--------------------+-----------------+
|  AT|    V|     AP|   RH|    PE|            features|       PE_Predict|
+----+-----+-------+-----+------+--------------------+-----------------+
|3.38|41.31| 998.79|97.76|489.11|[3.38,41.31,998.7...| 484.1588273620686|
| 3.6|35.19|1018.73| 99.1|488.98|[3.6,35.19,1018.7...|486.65657322465705|
|3.73|39.42| 1024.4|82.42|488.58|[3.73,39.42,1024....|488.22863840871094|
|3.74|35.19|1018.58|98.84| 490.5|[3.74,35.19,1018....|486.41450306082777|
|3.95|38.44|1016.75|79.65|492.46|[3.95,38.44,1016....|487.86470750111897|
+----+-----+-------+-----+------+--------------------+-----------------+
only showing top 5 rows
```

20. Compute an evaluation metric for our test dataset

- Create an RMSE evaluator using the label and predicted columns
- Run the evaluator on the DataFrame
- Calculating R squared value.

Note: Another useful statistical evaluation metric is the coefficient of determination, denoted \\(R^2\\) or \\(r^2\\) and pronounced "R squared".

It is a number that indicates the proportion of the variance in the dependent variable that is predictable from the independent variable and it provides a measure of how well observed outcomes are replicated by the model, based on the proportion of total variation of outcomes explained by the model. The coefficient of determination ranges from 0 to 1 (closer to 1), and the higher the value, the better our model.

```
import org.apache.spark.mllib.evaluation.RegressionMetrics

val metrics = new
RegressionMetrics(predictionsAndLabels.select("PE_Predict",
"PE").rdd.map(r => (r(0).asInstanceOf[Double],
r(1).asInstanceOf[Double])))

val rmse = metrics.rootMeanSquaredError

val explainedVariance = metrics.explainedVariance

val r2 = metrics.r2

println (f"Root Mean Squared Error: $rmse")

println (f"Explained Variance: $explainedVariance")

println (f"R2: $r2")
```

```
import org.apache.spark.mllib.evaluation.RegressionMetrics
metrics: org.apache.spark.mllib.evaluation.RegressionMetrics = org.apache.spark.mllib.evaluation.RegressionMetrics@f53cfe7
rmse: Double = 4.596932972254193
explainedVariance: Double = 267.5580020580147
r2: Double = 0.9275409236725611
Root Mean Squared Error: 4.596932972254193
Explained Variance: 267.5580020580147
R2: 0.9275409236725611
```

Note: Generally, a good model will have 68% of predictions within 1 RMSE and 95% within 2 RMSE of the actual value. Let's calculate and see if a RMSE of 4.51 meets this criterion.

Tuning and Evaluation

Now that we have a model with all of the data let's try to make a better model by tuning over several parameters to see if we can get better results.

```
import org.apache.spark.ml.tuning.{ParamGridBuilder, CrossValidator}

import org.apache.spark.ml.evaluation._
```

```
import org.apache.spark.ml.tuning.{ParamGridBuilder, CrossValidator}
import org.apache.spark.ml.evaluation._
```

21. Use a cross validator to split the data into training and validation subsets

    Let's set up our evaluator class to judge the model based on the best root mean squared error

```
val regEval = new RegressionEvaluator()

regEval.setLabelCol("PE")

  .setPredictionCol("PE_Predict")

  .setMetricName("rmse")
```

```
regEval: org.apache.spark.ml.evaluation.RegressionEvaluator = regEval_6eb0d0675120
res98: regEval.type = regEval_6eb0d0675120
```

22. Create our crossvalidator with 3 fold cross validation

```
val crossval = new CrossValidator()

crossval.setEstimator(lrPipeline)

crossval.setNumFolds(5)

crossval.setEvaluator(regEval)
```

```
crossval: org.apache.spark.ml.tuning.CrossValidator = cv_a61d2e94671b
res101: crossval.type = cv_a61d2e94671b
res102: crossval.type = cv_a61d2e94671b
res103: crossval.type = cv_a61d2e94671b
```

23. Tune over our regularization parameter from 0.01 to 0.10

```
val regParam = ((1 to 10) toArray).map(x => (x /100.0))
```

```
warning: there were 1 feature warning(s); re-run with -feature for details
regParam: Array[Double] = Array(0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1)
```

24. Create a parameter grid using the ParamGridBuilder, and add the grid to the CrossValidator.

```
val paramGrid = new ParamGridBuilder()
  .addGrid(lr.regParam, regParam)
  .build()
crossval.setEstimatorParamMaps(paramGrid)
```

```
paramGrid: Array[org.apache.spark.ml.param.ParamMap] =
Array({
        linReg_301e5ead4215-regParam: 0.01
}, {
        linReg_301e5ead4215-regParam: 0.02
}, {
        linReg_301e5ead4215-regParam: 0.03
}, {
        linReg_301e5ead4215-regParam: 0.04
}, {
        linReg_301e5ead4215-regParam: 0.05
}, {
        linReg_301e5ead4215-regParam: 0.06
}, {
        linReg_301e5ead4215-regParam: 0.07
}, {
        linReg_301e5ead4215-regParam: 0.08
```

25. Let's find and return the best model

```
val cvModel = crossval.fit(trainingSet)
```

```
cvModel: org.apache.spark.ml.tuning.CrossValidatorModel = cv_a61d2e94671b
```

26. We have tuned let's see what we got for tuning parameters and what our RMSE was versus our initial model.

    - Use cvModel to compute an evaluation metric for our test dataset: testingSet

```
val predictionsAndLabels = cvModel.transform(testingSet)

val metrics = new
RegressionMetrics(predictionsAndLabels.select("PE_Predict",
"PE").rdd.map(r => (r(0).asInstanceOf[Double],
r(1).asInstanceOf[Double])))
```

```
predictionsAndLabels: org.apache.spark.sql.DataFrame = [AT: double, V: double, AP: double, RH: double, PE: double, features: vector, PE_Predict: double]
metrics: org.apache.spark.mllib.evaluation.RegressionMetrics = org.apache.spark.mllib.evaluation.RegressionMetrics@1a3b890e
```

27. Run the previously created RMSE evaluator, on the predictionsAndLabels DataFrame

    - compute the r2 evaluation metric for our test dataset

```
val rmse = metrics.rootMeanSquaredError

val explainedVariance = metrics.explainedVariance

val r2 = metrics.r2


println (f"Root Mean Squared Error: $rmse")

println (f"Explained Variance: $explainedVariance")

println (f"R2: $r2")
```

```
rmse: Double = 4.593657981825083
explainedVariance: Double = 269.9212285609958
r2: Double = 0.9276441308553334
Root Mean Squared Error: 4.593657981825083
Explained Variance: 269.9212285609958
R2: 0.9276441308553334
```

So our initial untuned and tuned linear regression models are statistically identical.

Regression Tree

Given that the only linearly correlated variable is Temperature, it makes sense try another machine learning method such a Decision Tree to handle non-linear data and see if we can improve our model

A Decision Tree creates a model based on splitting variables using a tree structure. We will first start with a single decision tree model.

1. Create a DecisionTreeRegressor

```
import org.apache.spark.ml.regression.DecisionTreeRegressor


val dt = new DecisionTreeRegressor()

dt.setLabelCol("PE")

dt.setPredictionCol("PE_Predict")

dt.setFeaturesCol("features")

dt.setMaxBins(100)
```

```
import org.apache.spark.ml.regression.DecisionTreeRegressor
dt: org.apache.spark.ml.regression.DecisionTreeRegressor = dtr_8585361dd982
res117: org.apache.spark.ml.regression.DecisionTreeRegressor = dtr_8585361dd982
res118: org.apache.spark.ml.regression.DecisionTreeRegressor = dtr_8585361dd982
res119: org.apache.spark.ml.regression.DecisionTreeRegressor = dtr_8585361dd982
res120: dt.type = dtr_8585361dd982
```

2. Create a Pipeline and set the stages of the pipeline

```
val dtPipeline = new Pipeline()

dtPipeline.setStages(Array(vectorizer, dt))
```

3. Let's reuse our CrossValidator

    - Use [ParamGridBuilder to build a parameter grid with the parameter `dt.maxDepth` and a list of the values 2 and 3, and add the grid to the [CrossValidator].

- Run the [CrossValidator] to find the parameters that yield the best model (i.e. lowest RMSE) and return the best model.

```
crossval.setEstimator(dtPipeline)


val paramGrid = new ParamGridBuilder()
  .addGrid(dt.maxDepth, Array(2, 3))
  .build()
crossval.setEstimatorParamMaps(paramGrid)


val dtModel = crossval.fit(trainingSet)
```

```
dtPipeline: org.apache.spark.ml.Pipeline = pipeline_78ed1072fa9d
res122: dtPipeline.type = pipeline_78ed1072fa9d
res123: crossval.type = cv_a61d2e94671b
paramGrid: Array[org.apache.spark.ml.param.ParamMap] =
Array({
        dtr_8585361dd982-maxDepth: 2
}, {
        dtr_8585361dd982-maxDepth: 3
})
res124: crossval.type = cv_a61d2e94671b
dtModel: org.apache.spark.ml.tuning.CrossValidatorModel = cv_a61d2e94671b
```

Let's see how our tuned DecisionTreeRegressor model's RMSE and \\(r^2\\) values compare to our tuned LinearRegression model.

```
import org.apache.spark.ml.regression.DecisionTreeRegressionModel
import org.apache.spark.ml.PipelineModel


val predictionsAndLabels = dtModel.bestModel.transform(testingSet)
val metrics = new
RegressionMetrics(predictionsAndLabels.select("PE_Predict",
"PE").map(r => (r(0).asInstanceOf[Double],
r(1).asInstanceOf[Double])))


val rmse = metrics.rootMeanSquaredError
```

```
val explainedVariance = metrics.explainedVariance

val r2 = metrics.r2


println (f"Root Mean Squared Error: $rmse")

println (f"Explained Variance: $explainedVariance")

println (f"R2: $r2")
```

```
import org.apache.spark.ml.regression.DecisionTreeRegressionModel
import org.apache.spark.ml.PipelineModel
predictionsAndLabels: org.apache.spark.sql.DataFrame = [AT: double, V: double, AP: double, RH: double, PE: double, features: vector, PE_Predict: double]
metrics: org.apache.spark.mllib.evaluation.RegressionMetrics = org.apache.spark.mllib.evaluation.RegressionMetrics@54e2ea3
rmse: Double = 5.169951561569703
explainedVariance: Double = 264.7744220845704
r2: Double = 0.9083506479156687
Root Mean Squared Error: 5.169951561569703
Explained Variance: 264.7744220845704
R2: 0.9083506479156687
```

This line will pull the Decision Tree model from the Pipeline as display it as an if-then-else string

```
dtModel.bestModel.asInstanceOf[PipelineModel].stages.last.asInstanceOf[DecisionTreeRegressionModel].toDebugString
```

```
res132: String =
"DecisionTreeRegressionModel (uid=dtr_8585361dd982) of depth 3 with 15 nodes
  If (feature 0 <= 17.85)
   If (feature 0 <= 11.67)
    If (feature 0 <= 8.63)
     Predict: 483.79243774574053
    Else (feature 0 > 8.63)
     Predict: 476.3108737113401
   Else (feature 0 > 11.67)
    If (feature 0 <= 14.35)
     Predict: 469.0458953626635
    Else (feature 0 > 14.35)
     Predict: 462.1050880962613
  Else (feature 0 > 17.85)
   If (feature 0 <= 22.99)
    If (feature 1 <= 45.87)
     Predict: 458.12494773519165
```

So our DecisionTree has slightly worse RMSE than our LinearRegression model (LR: 4.59 vs DT: 5.19).

Exercise10: Machine Learning

To configure PySpark in Jupyter notebook

Open the new command terminal and export the below commands.

```
export PYSPARK_DRIVER_PYTHON=jupyter
export PYSPARK_DRIVER_PYTHON_OPTS='notebook'

Now type in the command terminal

pyspark --packages com.databricks:spark-csv_2.10:1.0.3
```

This will open pyspark in Jupyter notebook.

Start explorining as per the instructions.

To perform below exercise, install R-studio from 'software' folder or open R console and run below commands from command line.

Alternatively, while dealing with huge datasets we will use 'Zeepelin' with R interpreter pre-installed on the machine.

Statistical analysis in R is performed by using many in-built functions.

Functions are part of the R base package. These functions take R vector as an input along with the arguments and give the result.

1. Mean

From R console, use function mean( ) to calculate mean.

```
# Create a vector.

x <- c(12,7,3,4.2,18,2,54,-21,8,-5)

# Find Mean.

result.mean <- mean(x)

print(result.mean)
```

```
> x <- c(12,7,3,4.2,18,2,54,-21,8,-5)
> result.mean <- mean(x)
> print(result.mean)
[1] 8.22
```

2. Median

Similarly, to calculate median

```
# Create the vector.

x <- c(12,7,3,4.2,18,2,54,-21,8,-5)

# Find the median.

median.result <- median(x)

print(median.result)
```

```
> median.result <- median(x)
> print(median.result)
[1] 5.6
>
```

Linear Regression

Exercise9.1- Using R-studio/ R-console

Example: Predicting the weight of a person when his height is known.

Steps:

1. Gather the sample of observed values of height and corresponding weight.

Input:

```
# Values of height

151, 174, 138, 186, 128, 136, 179, 163, 152, 131

# Values of weight.

63, 81, 56, 91, 47, 57, 76, 72, 62, 48
```

2. Create relationship model using **lm()** function.
   Find the coefficients from the model and create the equation.

```
x <- c(151, 174, 138, 186, 128, 136, 179, 163, 152, 131)

y <- c(63, 81, 56, 91, 47, 57, 76, 72, 62, 48)

# Apply the lm() function.

relation <- lm(y~x)

print(relation)
```

```
> x <- c(151, 174, 138, 186, 128, 136, 179, 163, 152, 131)
> y <- c(63, 81, 56, 91, 47, 57, 76, 72, 62, 48)
> relation <- lm(y~x)
> print(relation)

Call:
lm(formula = y ~ x)

Coefficients:
(Intercept)            x
   -38.4551       0.6746
```

3. Get summary of the model to know average error i.e. **residuals.**

```
x <- c(151, 174, 138, 186, 128, 136, 179, 163, 152, 131)

y <- c(63, 81, 56, 91, 47, 57, 76, 72, 62, 48)

# Apply the lm() function.

relation <- lm(y~x)

print(summary(relation))
```

```
> relation <- lm(y~x)
> print(summary(relation))

Call:
lm(formula = y ~ x)

Residuals:
    Min      1Q  Median      3Q     Max
-6.3002 -1.6629  0.0412  1.8944  3.9775

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -38.45509    8.04901  -4.778  0.00139 **
x             0.67461    0.05191  12.997 1.16e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.253 on 8 degrees of freedom
Multiple R-squared:  0.9548,    Adjusted R-squared:  0.9491
F-statistic: 168.9 on 1 and 8 DF,  p-value: 1.164e-06
```

4. To predict the weight of new person use **predict( )** function.

```
# The predictor vector.

x <- c(151, 174, 138, 186, 128, 136, 179, 163, 152, 131)

# The response vector.
```

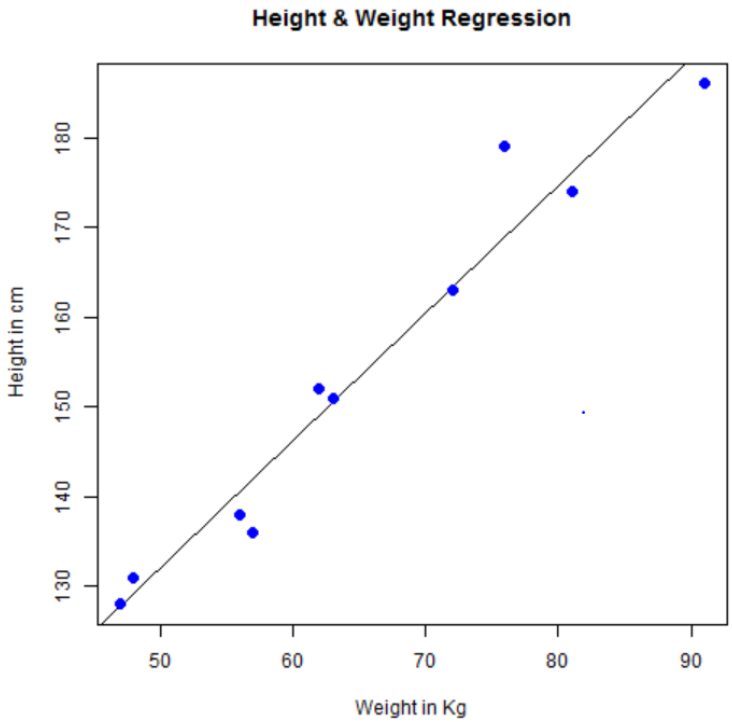
```
y <- c(63, 81, 56, 91, 47, 57, 76, 72, 62, 48)

# Apply the lm() function.

relation <- lm(y~x)

# Find weight of a person with height 170.

a <- data.frame(x = 170)

result <-  predict(relation,a)

print(result)
```

```
> relation <- lm(y~x)
> a <- data.frame(x = 170)
> result <-  predict(relation,a)
> print(result)
       1
76.22869
>
```

5. Visualize the regression graphically

```
# Create the predictor and response variable.

x <- c(151, 174, 138, 186, 128, 136, 179, 163, 152, 131)

y <- c(63, 81, 56, 91, 47, 57, 76, 72, 62, 48)

relation <- lm(y~x)

# Give the chart file a name.

png(file = "linearregression.png")

# Plot the chart.

plot(y,x,col = "blue",main = "Height & Weight Regression",

abline(lm(x~y)),cex = 1.3,pch = 16,xlab = "Weight in Kg",ylab =
"Height in cm")

# Save the file.

dev.off()
```

```
> relation <- lm(y~x)
> png(file = "linearregression.png")
> plot(y,x,col = "blue",main = "Height & Weight Regression",abline(lm(x~y)),cex = 1.3,pch = 16,xlab
 = "Weight in Kg",ylab = "Height in cm")
> dev.off()
null device
          1
>
```



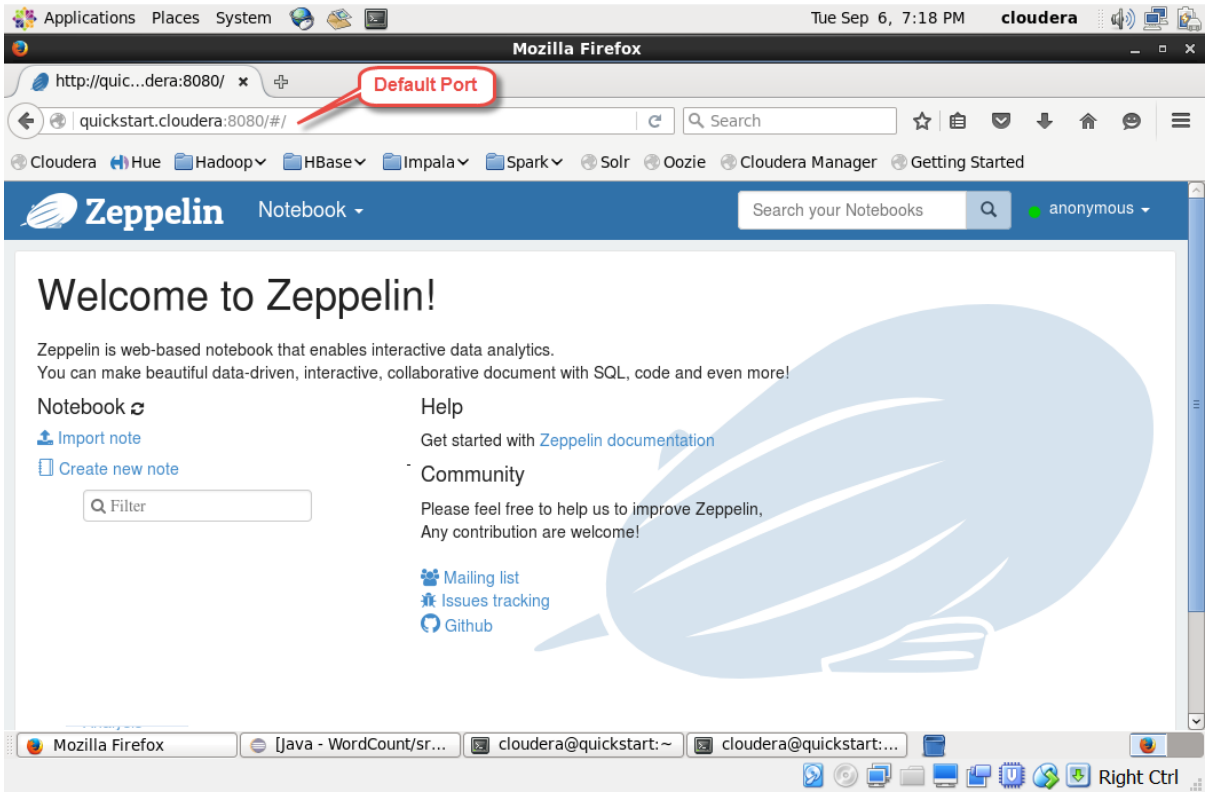
Exercise9.2 Perform below exercise using zeppelin notebook

```
To start Zeepelin service

cd /usr/lib/zeppelin-0.6.0-bin-all

sudo bin/zeppelin-daemon.sh start
```

```
[cloudera@quickstart ~]$ cd /usr/lib/zeppelin-0.6.0-bin-all/
[cloudera@quickstart zeppelin-0.6.0-bin-all]$ ls bin
common.cmd     functions.sh            interpreter.sh      zeppelin.sh
common.sh      install-interpreter.sh  zeppelin.cmd
functions.cmd  interpreter.cmd         zeppelin-daemon.sh
[cloudera@quickstart zeppelin-0.6.0-bin-all]$ bin/zeppelin-daemon.sh start
Zeppelin start                                             [  OK  ]
[cloudera@quickstart zeppelin-0.6.0-bin-all]$
```

Accessing Zeppelin UI

Open browser and use port 8080 to access Zeepelin notebook <quickstart.cloudera:8080>



Goal:

1. Start with importing the required package for R

```
%r require(ggplot2)
```

2. Load the data and list the features

```
%r

power_plant = read.table("/data/CCPP/Folds5x2_pp_1.csv", header =
TRUE, sep = ",")

str(power_plant)


# Features consist of hourly average ambient variables

# Temperature (T) in the range 1.81°C and 37.11°C,

# Ambient Pressure (AP) in the range 992.89-1033.30 milibar,

# Relative Humidity (RH) in the range 25.56% to 100.16%
```

```
# Exhaust Vacuum (V) in teh range 25.36-81.56 cm Hg

# Net hourly electrical energy output (EP) 420.26-495.76 MW
```

```
'data.frame':   9568 obs. of  5 variables:
 $ AT: num  14.96 25.18 5.11 20.86 10.82 …
 $ V : num  41.8 63 39.4 57.3 37.5 …
 $ AP: num  1024 1020 1012 1010 1009 …
 $ RH: num  73.2 59.1 92.1 76.6 96.6 …
 $ PE: num  463 444 489 446 474 …
```

3. To check first few entries

```
%r head(power_plant)
```

```
1 14.96 41.76 1024.07 73.17 463.26
2 25.18 62.96 1020.04 59.08 444.37
3  5.11 39.40 1012.16 92.14 488.56
4 20.86 57.32 1010.24 76.64 446.48
5 10.82 37.50 1009.23 96.62 473.90
6 26.27 59.44 1012.23 58.77 443.67
```

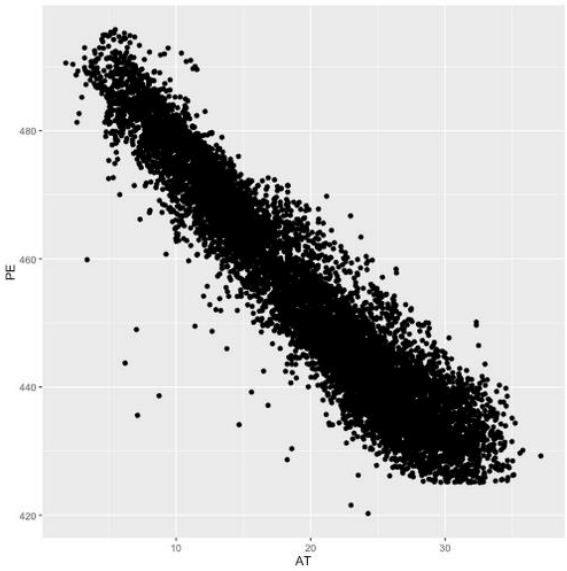
4. To check the summary of the dataset

```
%r summary(power_plant)
```

```
Min.   : 1.81   Min.   :25.36   Min.   : 992.9   Min.   : 25.56<br />
 1st Qu.:13.51   1st Qu.:41.74   1st Qu.:1009.1   1st Qu.: 63.33<br />
 Median :20.34   Median :52.08   Median :1012.9   Median : 74.97<br />
 Mean   :19.65   Mean   :54.31   Mean   :1013.3   Mean   : 73.31<br />
 3rd Qu.:25.72   3rd Qu.:66.54   3rd Qu.:1017.3   3rd Qu.: 84.83<br />
 Max.   :37.11   Max.   :81.56   Max.   :1033.3   Max.   :100.16<br />
       PE<br />
 Min.   :420.3<br />
 1st Qu.:439.8<br />
 Median :451.6<br />
 Mean   :454.4<br />
 3rd Qu.:468.4<br />
 Max.   :495.8
```

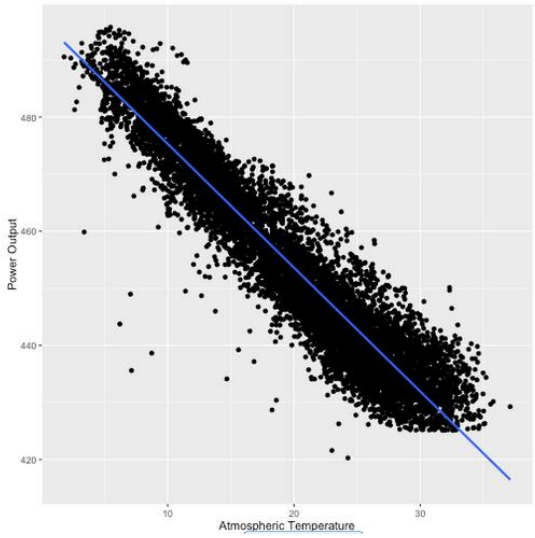
5. Plot between AT and PE

```
%r
ggplot(power_plant, aes(x = AT, y = PE)) +
geom_point()
```



6. Another way of representation

```
%r
ggplot(power_plant, aes(x = AT, y = PE)) +
geom_point() +
geom_smooth(method = "lm") +
labs(x = "Atmospheric Temperature", y = "Power Output")
```



Linear Regression Model

```
%r

lm.fit = lm(PE ~ AT, data = power_plant)

#Statistical Significance of the Model

capture.output(summary(lm.fit))
```

```
 [2] "Call:"<br />
 [3] "lm(formula = PE ~ AT, data = power_plant)"<br />
 [4] ""<br />
 [5] "Residuals:"<br />
 [6] "    Min      1Q  Median      3Q     Max "<br />
 [7] "-45.951  -3.644   0.101   3.696  23.251 "<br />
 [8] ""<br />
 [9] "Coefficients:"<br />
[10] "             Estimate Std. Error t value Pr(&gt;|t|)    "<br />
[11] "(Intercept) 497.034120   0.156434  3177.3   &lt;2e-16 <em>**"<br />
[12] "AT           -2.171320   0.007443  -291.7   &lt;2e-16 *</em><em>"<br />
[13] "—"<br />
[14] "Signif. codes:  0 '</em><strong>' 0.001 '</strong>' 0.01 '*' 0.05 '.' 0.1 ' ' 1"
[15] ""<br />
[16] "Residual standard error: 5.426 on 9566 degrees of freedom"<br />
[17] "Multiple R-squared:  0.8989,\tAdjusted R-squared:  0.8989 "<br />
[18] "F-statistic: 8.51e+04 on 1 and 9566 DF,  p-value: &lt; 2.2e-16"<br />
```

Interpretation

Residuals:

The residuals are the difference between the actual values of the variable you're predicting and predicted values from your regression–y - ŷ. For most regressions

you want your residuals to look like a normal distribution when plotted. If our residuals are normally distributed, this indicates the mean of the difference between our predictions and the actual values is close to 0 (good) and that when we miss, we're missing both short and long of the actual value, and the likelihood of a miss being far from the actual value gets smaller as the distance from the actual value gets larger.

Significance Stars

The stars are shorthand for significance levels, with the number of asterisks displayed according to the p-value computed. for high significance and * for low significance.

Estimated Coefficient

The estimated coefficient is the value of slope calculated by the regression. It might seem a little confusing that the Intercept also has a value, but just think of it as a slope that is always multiplied by 1.

Standard Error of the Coefficient Estimate

Measure of the variability in the estimate for the coefficient. Lower means better but this number is relative to the value of the coefficient. As a rule of thumb, you'd like this value to be at least an order of magnitude less than the coefficient estimate.

t-value or t-statistics

Score that measures whether or not the coefficient for this variable is meaningful for the model. You probably won't use this value itself, but know that it is used to calculate the p-value and the significance levels.

Significance Legend

The more punctuation there is next to your variables, the better.

Blank=bad,

Dots=pretty good

Stars=good

More Stars=very good

Residual Std Error / Degrees of Freedom

The Residual Std Error is just the standard deviation of your residuals. You'd like this number to be proportional to the quantiles of the residuals in #1. For a normal distribution, the 1st and 3rd quantiles should be 1.5 +/- the std error.

The Degrees of Freedom is the difference between the number of observations included in your training sample and the number of variables used in your model (intercept counts as a variable).

Variable p-value

Probability the variable is NOT relevant. You want this number to be as small as possible. If the number is really small, R will display it in scientific notation.

R-squared

Metric for evaluating the goodness of fit of your model. Higher is better with 1 being the best. An R2 value close to 1 indicates that the model explains a large portion of the variance in the response variable.

WARNING: While a high R-squared indicates good correlation, correlation does not always imply causation.

R-square adjusted

R-square adjusted is penalized for having a large number of parameters in the model

R2_adjusted = 1 - (1 - R2)(n - 1) / (n - p)

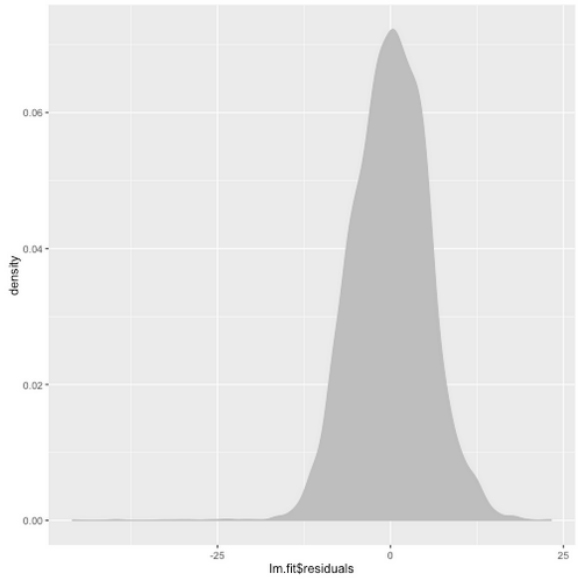
F-statistic & resulting p-value

F = (explained variance) / (unexplained variance)

Performs an F-test on the model. This takes the parameters of our model (in our case we only have 1) and compares it to a model that has fewer parameters. In theory the model with more parameters should fit better. If the model with more parameters (your model) doesn't perform better than the model with fewer parameters, the F-test will have a high p-value (probability NOT significant boost). If the model with more parameters is better than the model with fewer parameters, you will have a lower p-value.

When there is no relationship between the response and predictors, one would expect the F-statistic to take on a value close to 1. Large F-statistic suggests that at least some predicators are related to the response variable.

```
%r ggplot() + geom_density(aes(xlm.fit$residuals), fill = "grey", color =
"grey")
```




```
%r #Residual standard error:

sd(lm.fit$residuals)
```

```
[1] 5.425383
```

```
%r #R2:
```

```
R2 = sum((lm.fit$fitted.values - mean(power_plant$PE)) ^ 2) /
sum((power_plant$PE - mean(power_plant$PE)) ^ 2)

R2
```

```
[1] 0.8989476
```

```
%r #F-statistics


# F = ((TSS - RSS) / p) / (RSS / (n - p - 1))

# TSS = Total sum of suare = sum((y - mean(y)) ^ 2)

# RSS = Residual Sum of Square = sum((y_predicted - y) ^ 2)

# p = no of predicators

# n = number of observations


p = 1

TSS = sum((power_plant$PE - mean(power_plant$PE)) ^ 2)

RSS = sum((lm.fit$fitted.values - power_plant$PE) ^ 2)


n = 9568

F =  ((TSS - RSS) / p) / (RSS / (n - p - 1))

F
```

```
[1] 85097.76
```

```
%r #R-squared Adjusted


R2.adjusted = 1 - (1 - R2)*(n - 1) / (n - p)

R2.adjusted
```

```
[1] 0.8989476
```

```
%r names(lm.fit)
```

```
[1] “coefficients”  “residuals”     “effects”       “rank”<br />
 [5] “fitted.values” “assign”        “qr”            “df.residual”<br />
 [9] “xlevels”       “call”          “terms”         “model”
```

```
%r coef(lm.fit)
```

```
(Intercept)          AT
  497.03412    -2.17132
```

```
%r confint(lm.fit)
```

```
(Intercept) 496.72748 497.34076
AT           -2.18591  -2.15673
```

Logistic Regression

The Logistic Regression is a regression model in which the response variable (dependent variable) has categorical values such as True/False or 0/1.

Example:

In "mtcars" data set, the transmission mode (automatic or manual) is described by the column am which is a binary value (0 or 1). We can create a logistic regression model between the columns "am" and 3 other columns - hp, wt and cyl.

```
# Select some columns form mtcars.

input <- mtcars[,c("am","cyl","hp","wt")]


print(head(input))
```

```
> input <- mtcars[,c("am","cyl","hp","wt")]
> print(head(input))
                  am cyl  hp    wt
Mazda RX4          1   6 110 2.620
Mazda RX4 Wag      1   6 110 2.875
Datsun 710         1   4  93 2.320
Hornet 4 Drive     0   6 110 3.215
Hornet Sportabout  0   8 175 3.440
Valiant            0   6 105 3.460
```

Create Regression Model:

```
input <- mtcars[,c("am","cyl","hp","wt")]


am.data = glm(formula = am ~ cyl + hp + wt, data = input, family =
binomial)


print(summary(am.data))
```

```
> input <- mtcars[,c("am","cyl","hp","wt")]
> am.data = glm(formula = am ~ cyl + hp + wt, data = input, family = binomial)
> print(summary(am.data))

Call:
glm(formula = am ~ cyl + hp + wt, family = binomial, data = input)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.17272  -0.14907  -0.01464   0.14116   1.27641

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 19.70288    8.11637   2.428   0.0152 *
cyl          0.48760    1.07162   0.455   0.6491
hp           0.03259    0.01886   1.728   0.0840 .
wt          -9.14947    4.15332  -2.203   0.0276 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 43.2297  on 31  degrees of freedom
Residual deviance:  9.8415  on 28  degrees of freedom
AIC: 17.841

Number of Fisher Scoring iterations: 8
```

Conclusion:

As the p-value in the last column is more than 0.05 for the variables "cyl" and "hp", we consider them to be insignificant in contributing to the value of the variable "am". Only weight (wt) impacts the "am" value in this regression model.

Decision Tree

Decision tree is a graph to represent choices and their results in form of a tree. The nodes in the graph represent an event or choice and the edges of the graph represent the decision rules or conditions.

The R package **"party"** is used to create decision trees.

```
install.packages("party")
```

Input Data

We will use the R in-built data set named **readingSkills** to create a decision tree. It describes the score of someone's readingSkills if we know the variables "age", "shoe size", "score" and whether the person is a native speaker or not.

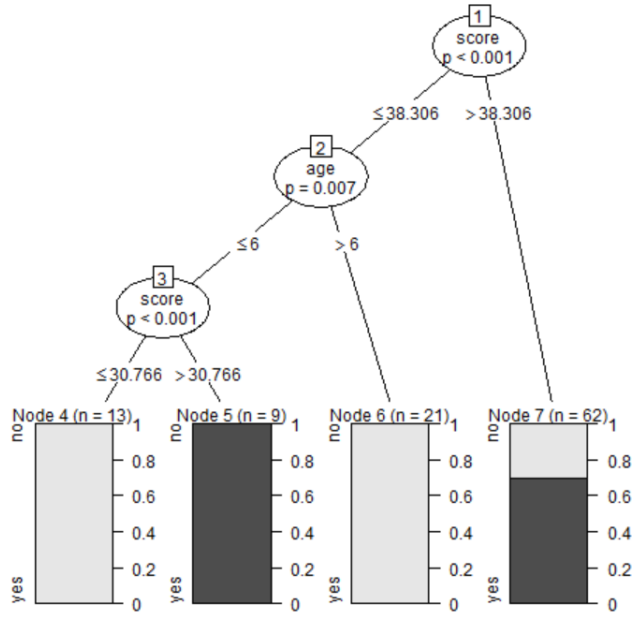
```
# Load the party package. It will automatically load other dependent
packages.

library(party)



# Print some records from data set readingSkills.

print(head(readingSkills))
```

```
> library(party)
Loading required package: grid
Loading required package: mvtnorm
Loading required package: modeltools
Loading required package: stats4
Loading required package: strucchange
Loading required package: zoo

Attaching package: 'zoo'

The following objects are masked from 'package:base':

    as.Date, as.Date.numeric

Loading required package: sandwich
> print(head(readingSkills))
  nativeSpeaker age shoeSize    score
1           yes   5 24.83189 32.29385
2           yes   6 25.95238 36.63105
3            no  11 30.42170 49.60593
4           yes   7 28.66450 40.28456
5           yes  11 31.88207 55.46085
6           yes  10 30.07843 52.83124
> 
```

We will use the **ctree()** function to create the decision tree and see its graph.

```
# Load the party package. It will automatically load other dependent
packages.

library(party)


# Create the input data frame.

input.dat <- readingSkills[c(1:105),]


# Give the chart file a name.

png(file = "decision_tree.png")


# Create the tree.

  output.tree <- ctree(

  nativeSpeaker ~ age + shoeSize + score,

  data = input.dat)


# Plot the tree.

plot(output.tree)
```

```
# Save the file.

dev.off()
```



Conclusion

From the decision tree shown above we can conclude that anyone whose readingSkills score is less than 38.3 and age is more than 6 is not a native Speaker.

Random Forest

In the random forest approach, a large number of decision trees are created. Every observation is fed into every decision tree. The most common outcome for each observation is used as the final output. A new observation is fed into all the trees and taking a majority vote for each classification model.

An error estimate is made for the cases which were not used while building the tree. That is called an **OOB (Out-of-bag)** error estimate which is mentioned as a percentage.

The R package **"randomForest"** is used to create random forests.

```
install.packages("randomForest")
```

```
> install.packages("randomForest")
trying URL 'https://cran.rstudio.com/bin/windows/contrib/3.3/randomForest_4.6-12.zip'
Content type 'application/zip' length 177129 bytes (172 KB)
downloaded 172 KB

package 'randomForest' successfully unpacked and MD5 sums checked

The downloaded binary packages are in
        C:\Users\technocrafty\AppData\Local\Temp\RtmpcJlGBQ\downloaded_packages
```

Input Data

We will use the R in-built data set named readingSkills to create a decision tree. It describes the score of someone's readingSkills if we know the variables "age","shoesize","score" and whether the person is a native speaker.

```
# Load the party package. It will automatically load other required
packages.

library(party)


# Print some records from data set readingSkills.

print(head(readingSkills))
```

We will use the **randomForest()** function to create the decision tree and see it's graph.

```
# Load the party package. It will automatically load other required
packages.

library(party)

library(randomForest)


# Create the forest.

output.forest <- randomForest(nativeSpeaker ~ age + shoeSize + score,

            data = readingSkills)


# View the forest results.
```

```
print(output.forest)


# Importance of each predictor.

print(importance(fit,type = 2))
```

```
> print(output.forest)

Call:
 randomForest(formula = nativeSpeaker ~ age + shoeSize + score,      data = readingSkills)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 1

        OOB estimate of  error rate: 1%
Confusion matrix:
    no yes class.error
no  99   1        0.01
yes  1  99        0.01
> |
```

Conclusion

From the random forest shown above we can conclude that the shoesize and score are the important factors deciding if someone is a native speaker or not. Also the model has only 1% error which means we can predict with 99% accuracy.

Classification

About Dataset: D2hawkEye

D2Hawkeye, Inc. develops data service solutions for the healthcare industry.

D2ReportManager that helps to design, distribute, and archive financial and clinical reports; D2BenefitAdvisor and D2Analyzer, on-line analytical processing tools that enable users to build data sets for data mining and ad hoc query analysis; D2Consulting, a medical and clinical advisory service; and D2Connect that provides e-business services, custom software development, and technology outsourcing. It also provides medical advisory, medical analytics, benchmarking, and other business services on an outsourced basis. The company serves health plans, third party administrators, case management and disease management industry, benefit consultants, physician groups, employers, and pharmaceutical industry, as well as re-insurers, MGUs, and stop-loss groups.

Mission

D2Hawkeye tries to improve healthcare case management

• Identifyhigh-riskpatients

• Work with patients to manage treatment and associated costs

• Arrange specialist care

• Medical costs often relate to severity of health problems, and are an issue for both patient and provider

Goal: Improve the quality of cost predictions

1. Load the data from local filesystem.

```
%r Claims = read.csv("data/ClaimsData.csv")
```

2. List the variables

```
%r str(Claims)
```

```
'data.frame':   458005 obs. of  16 variables:
 $ age              : int  85 59 67 52 67 68 75 70 67 67 …
 $ alzheimers       : int  0 0 0 0 0 0 0 0 0 0 …
 $ arthritis        : int  0 0 0 0 0 0 0 0 0 0 …
 $ cancer           : int  0 0 0 0 0 0 0 0 0 0 …
 $ copd             : int  0 0 0 0 0 0 0 0 0 0 …
 $ depression       : int  0 0 0 0 0 0 0 0 0 0 …
 $ diabetes         : int  0 0 0 0 0 0 0 0 0 0 …
 $ heart.failure    : int  0 0 0 0 0 0 0 0 0 0 …
 $ ihd              : int  0 0 0 0 0 0 0 0 0 0 …
 $ kidney           : int  0 0 0 0 0 0 0 0 0 0 …
 $ osteoporosis     : int  0 0 0 0 0 0 0 0 0 0 …
 $ stroke           : int  0 0 0 0 0 0 0 0 0 0 …
 $ reimbursement2008: int  0 0 0 0 0 0 0 0 0 0 …
 $ bucket2008       : int  1 1 1 1 1 1 1 1 1 1 …
 $ reimbursement2009: int  0 0 0 0 0 0 0 0 0 0 …
 $ bucket2009       : int  1 1 1 1 1 1 1 1 1 1 …
```

3. List the output of $bucket2009

```
%r capture.output(base::table(Claims$bucket2009))
```

```
[1] ""<br />
[2] "     1      2      3      4      5 "
[3] "307444  87099  40976  19843   2643 "
```

Took a few seconds. Last updated by anonymous at September 06 2016, 10:32:33 PM.

4. View the summary of claims dataset

```
%r summary(Claims)
```

```
Min.   : 26.00   Min.   :0.0000   Min.   :0.0000   Min.   :0.00000<br />
 1st Qu.: 67.00   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.00000<br />
 Median : 73.00   Median :0.0000   Median :0.0000   Median :0.00000<br />
 Mean   : 72.63   Mean   :0.1922   Mean   :0.1543   Mean   :0.06411<br />
 3rd Qu.: 81.00   3rd Qu.:0.0000   3rd Qu.:0.0000   3rd Qu.:0.00000<br />
 Max.   :100.00   Max.   :1.0000   Max.   :1.0000   Max.   :1.00000<br />
      copd          depression       diabetes      heart.failure<br />
 Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000<br />
 1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000<br />
 Median :0.0000   Median :0.0000   Median :0.0000   Median :0.0000<br />
 Mean   :0.1361   Mean   :0.2131   Mean   :0.3805   Mean   :0.2847<br />
 3rd Qu.:0.0000   3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:1.0000<br />
 Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000<br />
      ihd             kidney        osteoporosis       stroke<br />
 Min.   :0.0000   Min.   :0.0000   Min.   :0.000   Min.   :0.00000<br />
 1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:0.00000<br />
 Median :0.0000   Median :0.0000   Median :0.000   Median :0.00000<br />
```

5. Percentage of patients in each cost bucket

```
%r base::table(Claims$bucket2009)/nrow(Claims)
```

```
0.671267781 0.190170413 0.089466272 0.043324855 0.005770679
```

6. Model for healthcare cost prediction

Goal: To predict the cost bucket the patient fell into in 2009 using the CART model.

```
%r require(caTools) #For splitting data into training and test sets
```

7. Split the entire data into training and test sets, with 70/30 split.

```
%r

set.seed(88)

split = sample.split(Claims$bucket2009, SplitRatio = 0.7)

ClaimsTrain = subset(Claims, split == TRUE)

ClaimsTest = subset(Claims, split == FALSE)

Summary(ClaimsTrain)
```

What is the average age of patients in the training set, ClaimsTrain?

```
mean(ClaimsTrain$age)
```

Baseline Method and Penalty Matrix

The baseline method would predict that the cost bucket for a patient in 2009 will be the same as it was in 2008.
So let's create a classification matrix to compute the accuracy for the baseline method on the test set.

The accuracy is the sum of the diagonal, the observations that were classified correctly, divided by the total number of observations in our test set.

```
%r

confMatrix = base::table(ClaimsTest$bucket2009, ClaimsTest$bucket2008)

confMatrix
```

```
  1 110138   7787   3427   1452    174
    2  16000  10721   4629   2931    559
    3   7006   4629   2774   1621    360
    4   2688   1943   1415   1539    352
    5    293    191    160    309    104
```

```
%r diag(confMatrix)
```

```
110138  10721   2774   1539    104
```

8. Baseline accuracy on test set

```
%r

sum(diag(confMatrix)) / nrow(ClaimsTest)
```

```
[1] 0.6838135
```

9. Define a “penaltymatrix” as the cost of being wrong

```
%r

PenaltyMatrix =
matrix(c(0,1,2,3,4,2,0,1,2,3,4,2,0,1,2,6,4,2,0,1,8,6,4,2,0), byrow = TRUE,
nrow = 5)

PenaltyMatrix

# X axis corresponds to the predictions and Y axis to the actuals
```

```
[1,]    0    1    2    3    4
[2,]    2    0    1    2    3
[3,]    4    2    0    1    2
[4,]    6    4    2    0    1
[5,]    8    6    4    2    0
```

10. Penalty error of Baseline Method

```
%r

penaltyErrors = as.matrix(base::table(ClaimsTest$bucket2009,
ClaimsTest$bucket2008)) * PenaltyMatrix

penaltyErrors
```

```
     1     2     3     4     5
1    0  7787  6854  4356   696
2 32000     0  4629  5862  1677
3 28024  9258     0  1621   720
4 16128  7772  2830     0   352
5  2344  1146   640   618     0
```

```
%r #Penalty Error Rate based on baseline data

sum(penaltyErrors) / nrow(ClaimsTest)
```

```
[1] 0.7386055
```

Our Goals:

Now our goal is to create a CART model that will give better accuracy higher than 68.38% and a penalty error lower than 0.739

```
%r

# Load necessary libraries

library(rpart) #For building cart model

library(rpart.plot) #For plotting cart model
```

Complexity Parameter using Cross Validation

The complexity parameter (cp) is used to control the size of the decision tree and to select the optimal tree size.

```
%r

library(e1071)

library(caret)
```

```
%r

numFolds = trainControl( method = "cv", number = 10 )
```

```
cpGrid = expand.grid( .cp = seq(0.0,0.03,0.001))
```

11. Perform the cross validation

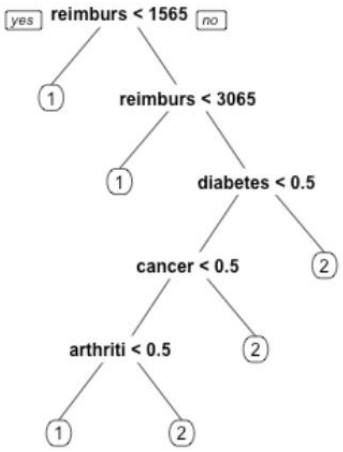
```
cv = train(bucket2009 ~ age + alzheimers + arthritis + cancer + copd +
depression + diabetes + heart.failure + ihd + kidney + osteoporosis +
stroke + bucket2008 + reimbursement2008, data = ClaimsTrain, method =
"rpart", trControl = numFolds, tuneGrid = cpGrid )
```

```
%r

capture.output(cv)
```

```
[1] "CART "<br />
 [2] ""<br />
 [3] "274803 samples"<br />
 [4] "    15 predictor"<br />
 [5] ""<br />
 [6] "No pre-processing"<br />
 [7] "Resampling: Cross-Validated (10 fold) "<br />
 [8] "Summary of sample sizes: 247322, 247322, 247323, 247322, 247322, 247323, … "
 [9] "Resampling results across tuning parameters:"<br />
[10] ""<br />
[11] "  cp     RMSE       Rsquared "<br />
[12] "  0.000  0.7938988  0.2168627"<br />
[13] "  0.001  0.7276304  0.3012112"<br />
[14] "  0.002  0.7295325  0.2975572"<br />
[15] "  0.003  0.7347164  0.2875466"<br />
[16] "  0.004  0.7364503  0.2841780"<br />
[17] "  0.005  0.7388593  0.2794822"<br />
```

```
%r

ClaimsTree = rpart(bucket2009 ~ age + alzheimers + arthritis + cancer +
copd + depression + diabetes + heart.failure + ihd + kidney + osteoporosis
+ stroke + bucket2008 + reimbursement2008, data=ClaimsTrain,
method="class", cp=0.001)
```

```
%r {"imageWidth": "700px"}

prp(ClaimsTree)

# The size of the tree depends on the volume of training data and number of
classifications
```



12. Make predictions

```
%r

PredictTest = predict(ClaimsTree, newdata = ClaimsTest, type =
"class")
```

13. Confusion Matrix

```
%r

confusionMatrixTest = base::table(ClaimsTest$bucket2009,
PredictTest)
```

14. Prediction Accuracy

```
%r

sum(diag(confusionMatrixTest)) / nrow(ClaimsTest)

#Remember baseline accuracy was 0.6838135
```

```
[1] 0.7105545
```

The accuracy of CART model is 71.05%

15. Penalty Error

```
%r

as.matrix(base::table(ClaimsTest$bucket2009, PredictTest)) *
PenaltyMatrix
```

```
PredictTest
       1     2    3    4    5
  1    0  9274    0    0    0
  2 36738     0    0    0    0
  3 31648 16956    0    0    0
  4 18456 19444    0    0    0
  5  2752  4278    0    0    0
```

16. Penalty Error Rate on Test Data based on the prediction result

```
%r

sum(as.matrix(base::table(ClaimsTest$bucket2009, PredictTest)) *
PenaltyMatrix) / nrow(ClaimsTest)

# Remember penalty error rate based on baseline data was 0.7386055
```

```
[1] 0.7617057
```

The penalty error of the baseline method is 0.758

While we increased the accuracy, the penalty error also went up. Why?

By default, rpart will try to maximize the overall accuracy, and every type of error is seen as having a penalty of one.

Our CART model predicts 3, 4, and 5 so rarely because there are very few observations in these classes. Therefore, we do not really expect this model to do better on the penalty error than the baseline method.

To fix this, rpart function allows us to specify a parameter called loss.

17. New CART model with loss matrix

```
%r

ClaimsTree = rpart(bucket2009 ~ age + alzheimers + arthritis +
cancer + copd + depression + diabetes + heart.failure + ihd + kidney
+ osteoporosis + stroke + bucket2008 + reimbursement2008,
data=ClaimsTrain, method="class", cp=0.00005, parms = list(loss =
PenaltyMatrix))
```

18. Redo predictions and penalty error

```
%r

PredictTest = predict(ClaimsTree, newdata = ClaimsTest, type =
"class")

base::table(ClaimsTest$bucket2009, PredictTest)
```

```
PredictTest
       1     2     3     4     5
  1 94310 25295  3087   286     0
  2  7176 18942  8079   643     0
  3  3590  7706  4692   401     1
  4  1304  3193  2803   636     1
  5   135   356   408   156     2
```

19. Baseline Accuracy for each bucket

```
%r

base::table(ClaimsTest$bucket2009) / nrow(ClaimsTest)
```

```
0.671269964 0.190172596 0.089464089 0.043323763 0.005769588
```

20. Prediction Accuracy for each bucket

```
%r

buckets = base::table(ClaimsTest$bucket2009)

accuracy_buckets = diag(base::table(ClaimsTest$bucket2009,
PredictTest)) / buckets

accuracy_buckets
```

```
0.766885134 0.543685419 0.286272117 0.080131032 0.001892148
```

21. Penalty Error Rate

```
%r

sum(as.matrix(base::table(ClaimsTest$bucket2009, PredictTest)) *
PenaltyMatrix) / nrow(ClaimsTest)


#Remember baseline accuracy was 0.6838135 and accuracy based on
previous model was 0.7578902
```

```
[1] 0.6418161
```

The accuracy of this CART model is the 64.73%.

22. Penalty Error Rate based on model with penalty condition

```
%r

sum(as.matrix(base::table(ClaimsTest$bucket2009, PredictTest)) *
PenaltyMatrix) / nrow(ClaimsTest)

# Remember penalty error rate based on baseline data was 0.7386055

# And model without penalty condition was 0.7578902
```

```
[1] 0.6418161
```

The penalty error of the CART model with loss is 0.642.

Our accuracy is now lower than the baseline method, but our penalty error is also much lower.

Observations:

Model accuracy of each bucket improved substantially

Penalty Error Rate has gone down

Sacrificed model accuracy to reduce penalty error rate

Clustering

It is an unsupervised algorithm help segment data into groups

Two popular clustering algorithms –

1. Hierarchical and
2. k-means (works best with large dataset)

Similarity is calculated as distance between two points based on feature values

```
%r #Eucleadian distance between 2 movies


God_Father = c(0,1,0,0,0,0,1,0,1,0,0,0,0,0,0,0,0,0,0)
```

```
Titanic = c(0,1,0,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0)


#Distance between these two data points in feature space

sqrt(sum((God_Father - Titanic) ^ 2))


#God_Father - Titanic
```

```
[1] 1.414214
```

Hierarchical Clustering

- Start each point with its own cluster.
- Find two nearest clusters based on the Euclidean distance between two centroids and merge into a single cluster.
- Eventually all points will belong to a single cluster.
- The clustering data is visualized using a dendrogram.
- Height presents the distance before the 2 clusters were combined.
- Dendrogram can help us decide how many clustering do we want.

Example1:

1. Load the movie_lens.txt file and list the variables.

```
%r

movies = read.table("/data/movie_lens.txt", header=FALSE,
sep="|",quote="\"")

str(movies)
```

```
'data.frame':   1682 obs. of  24 variables:
 $ V1 : int  1 2 3 4 5 6 7 8 9 10 …
 $ V2 : Factor w/ 1664 levels "'Til There Was You (1997)",..: 1525 618 555 594 344 1318 1545 111 391 1240 …
 $ V3 : Factor w/ 241 levels "","01-Aug-1997",..: 71 71 71 71 71 71 71 71 71 182 …
 $ V4 : logi  NA NA NA NA NA NA …
 $ V5 : Factor w/ 1661 levels "","<a href="http://us.imdb.com/M/title-exact?%22Langoliers,%20The%22%20(1995)%20(mini)%22,..:">http://us.
imdb.com/M/title-exact?%22Langoliers,%20The%22%20(1995)%20(mini)",..:</a> 1430 564 504 542 309 1661 1452 102 356 1182 …
 $ V6 : int  0 0 0 0 0 0 0 0 0 0 …
 $ V7 : int  0 1 0 1 0 0 0 0 0 0 …
 $ V8 : int  0 1 0 0 0 0 0 0 0 0 …
 $ V9 : int  1 0 0 0 0 0 0 0 0 0 …
 $ V10: int  1 0 0 0 0 0 0 1 0 0 …
 $ V11: int  1 0 0 1 0 0 0 1 0 0 …
 $ V12: int  0 0 0 0 1 0 0 0 0 0 …
 $ V13: int  0 0 0 0 0 0 0 0 0 0 …
 $ V14: int  0 0 0 1 1 1 1 1 1 1 …
 $ V15: int  0 0 0 0 0 0 0 0 0 0 …
```

2. Add names to the column

```
%r

colnames(movies) = c("ID", "Title", "ReleaseDate",
"VideoReleaseDate", "IMDB", "Unknown", "Action", "Adventure",
"Animation", "Childrens", "Comedy", "Crime", "Documentary", "Drama",
"Fantasy", "FilmNoir", "Horror", "Musical", "Mystery", "Romance",
"SciFi", "Thriller", "War", "Western")
```

3. List the variables again

```
%r str(movies)
```

```
'data.frame':   1682 obs. of  24 variables:
 $ ID              : int  1 2 3 4 5 6 7 8 9 10 …
 $ Title           : Factor w/ 1664 levels "'Til There Was You (1997)",..: 1525 618 555 594 344 1318 1545 111 391 1240 …
 $ ReleaseDate     : Factor w/ 241 levels "","01-Aug-1997",..: 71 71 71 71 71 71 71 71 71 182 …
 $ VideoReleaseDate: logi  NA NA NA NA NA NA …
 $ IMDB            : Factor w/ 1661 levels "","<a href="http://us.imdb.com/M/title-exact?%22Langoliers,%20The%22%20(1995)%20(mini)%22,..
:">http://us.imdb.com/M/title-exact?%22Langoliers,%20The%22%20(1995)%20(mini)",..:</a> 1430 564 504 542 309 1661 1452 102 356 1182 …
 $ Unknown         : int  0 0 0 0 0 0 0 0 0 0 …
 $ Action          : int  0 1 0 1 0 0 0 0 0 0 …
 $ Adventure       : int  0 1 0 0 0 0 0 0 0 0 …
 $ Animation       : int  1 0 0 0 0 0 0 0 0 0 …
 $ Childrens       : int  1 0 0 0 0 0 0 1 0 0 …
 $ Comedy          : int  1 0 0 1 0 0 0 1 0 0 …
 $ Crime           : int  0 0 0 0 1 0 0 0 0 0 …
 $ Documentary     : int  0 0 0 0 0 0 0 0 0 0 …
 $ Drama           : int  0 0 0 1 1 1 1 1 1 1 …
 $ Fantasy         : int  0 0 0 0 0 0 0 0 0 0 …
```

4. Remove unnecessary variables

```
%r

movies$ID = NULL

movies$ReleaseDate = NULL

movies$VideoReleaseDate = NULL

movies$IMDB = NULL


str(movies)
```

```
'data.frame':   1682 obs. of  20 variables:
 $ Title      : Factor w/ 1664 levels "'Til There Was You (1997)",..: 1525 618 555 594 344 1318 1545 111 391 1240 …
 $ Unknown    : int  0 0 0 0 0 0 0 0 0 0 …
 $ Action     : int  0 1 0 1 0 0 0 0 0 0 …
 $ Adventure  : int  0 1 0 0 0 0 0 0 0 0 …
 $ Animation  : int  1 0 0 0 0 0 0 0 0 0 …
 $ Childrens  : int  1 0 0 0 0 0 0 1 0 0 …
 $ Comedy     : int  1 0 0 1 0 0 0 1 0 0 …
 $ Crime      : int  0 0 0 0 1 0 0 0 0 0 …
 $ Documentary: int  0 0 0 0 0 0 0 0 0 0 …
 $ Drama      : int  0 0 0 1 1 1 1 1 1 1 …
 $ Fantasy    : int  0 0 0 0 0 0 0 0 0 0 …
 $ FilmNoir   : int  0 0 0 0 0 0 0 0 0 0 …
 $ Horror     : int  0 0 0 0 0 0 0 0 0 0 …
 $ Musical    : int  0 0 0 0 0 0 0 0 0 0 …
 $ Mystery    : int  0 0 0 0 0 0 0 0 0 0 …
 $ Romance    : int  0 0 0 0 0 0 0 0 0 0 …
```

5. Remove duplicate entries from the dataset

```
%r # Remove duplicates

movies = unique(movies)

str(movies)
```

```
'data.frame':   1664 obs. of  20 variables:
 $ Title      : Factor w/ 1664 levels "'Til There Was You (1997)",..: 1525 618 555 594 344 1318 1545 111 391 1240 …
 $ Unknown    : int  0 0 0 0 0 0 0 0 0 0 …
 $ Action     : int  0 1 0 1 0 0 0 0 0 0 …
 $ Adventure  : int  0 1 0 0 0 0 0 0 0 0 …
 $ Animation  : int  1 0 0 0 0 0 0 0 0 0 …
 $ Childrens  : int  1 0 0 0 0 0 0 1 0 0 …
 $ Comedy     : int  1 0 0 1 0 0 0 1 0 0 …
 $ Crime      : int  0 0 0 0 1 0 0 0 0 0 …
 $ Documentary: int  0 0 0 0 0 0 0 0 0 0 …
 $ Drama      : int  0 0 0 1 1 1 1 1 1 1 …
 $ Fantasy    : int  0 0 0 0 0 0 0 0 0 0 …
 $ FilmNoir   : int  0 0 0 0 0 0 0 0 0 0 …
 $ Horror     : int  0 0 0 0 0 0 0 0 0 0 …
 $ Musical    : int  0 0 0 0 0 0 0 0 0 0 …
 $ Mystery    : int  0 0 0 0 0 0 0 0 0 0 …
 $ Romance    : int  0 0 0 0 0 0 0 0 0 0 …
```

6. Compute the euclidean distance

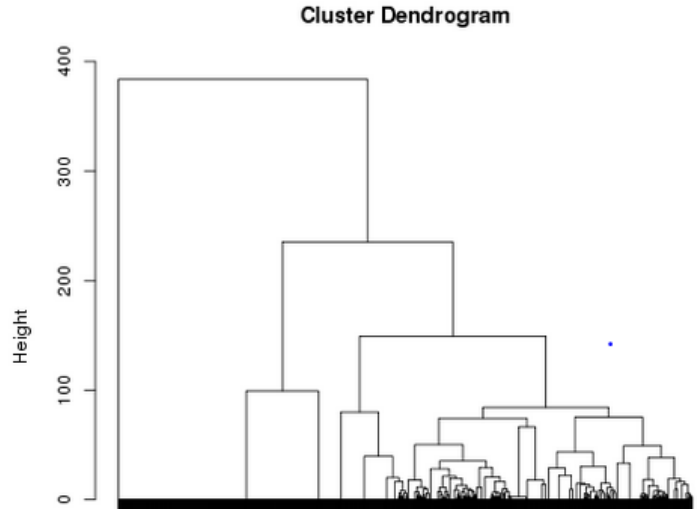
```
%r

distances = dist(movies[2:20], method = "euclidean")

#Clustering is based on column 2 through 20.
```

7. Calculates distance using centroid and variance within a cluster.

```
%r

# Hierarchical clustering

clusterMovies = hclust(distances, method = "ward.D")

#ward.D
```

8. Plot the Dendrogram

```
%r

plot(clusterMovies)
```



9. Assign points to cluster

```
%r

clusterGroups = cutree(clusterMovies, k = 10)
```

```
%r clusterGroups
```

```
  1   2   3   4   5   6   7   8   9  10  11  12  13  14  15
  1   2   3   1   3   4   1   1   4   1   3   3   5   6   4
 16  17  18  19  20  21  22  23  24  25  26  27  28  29  30
  7   3   4   4   6   1   1   3   3   5   5   2   2   3   4
 31  32  33  34  35  36  37  38  39  40  41  42  43  44  45
  1   8   6   9   1   6   4   2   3   5   5   5   3   3   9
 46  47  48  49  50  51  52  53  54  55  56  57  58  59  60
  4   9   8   7   1   1   4   2   2   6   3   4   4   4   4
 61  62  63  64  65  66  67  68  69  70  71  72  73  74  75
  4   2   1   4   9   7   5   6   1   7   1   1   1   1   8
 76  77  78  79  80  81  82  83  84  85  86  87  88  89  90
  3   3   1   2   1   7   2   7   2   5   4   4   7   3   6
 91  92  93  94  95  96  97  98  99 100 101 102 103 104 105
  1   6   9   1   1   2   1   3   1   3   2   1   1   5   5
106 107 108 109 110 111 112 113 114 115 116 117 118 119 120
  3   4   5   2   1   7   1   4   1   8   5   2   2   8   1
121 122 123 124 125 126 127 128 129 130 131 132 133 134 135
```

10. Let's use the tapply function to compute the percentage of movies in each genre and cluster

```
%r

# Now let's figure out what the clusters are like.

tapply(movies$Action, clusterGroups, mean) #This will calculate mean of Action variable for each of 10 clusters
```

```
0.1784512 0.7839196 0.1238532 0.0000000 0.0000000 0.1015625 0.0000000
        8         9        10
0.0000000 0.0000000 0.0000000
```

```
%r tapply(movies$Romance, clusterGroups, mean)
```

```
0.10437710 0.04522613 0.03669725 0.00000000 0.00000000 1.00000000
         7          8          9         10
1.00000000 0.00000000 0.00000000 0.00000000
```

```
%r

clusters = data.frame()

for(i in 1:10){

    clusters = rbind(clusters, colMeans(subset(movies[2:20], clusterGroups == i)))

}

clusters = t(clusters)

rownames(clusters) = colnames(movies[2:20])

clusters
```

```
Unknown     0.006734007 0.000000000 0.000000000 0 0 0.0000000 0 0.0000000
Action      0.178451178 0.783919598 0.123853211 0 0 0.1015625 0 0.0000000
Adventure   0.185185185 0.351758794 0.036697248 0 0 0.0000000 0 0.0000000
Animation   0.134680135 0.010050251 0.000000000 0 0 0.0000000 0 0.0000000
Childrens   0.393939394 0.005025126 0.009174312 0 0 0.0000000 0 0.0000000
Comedy      0.363636364 0.065326633 0.064220183 0 1 0.1093750 1 0.0212766
Crime       0.033670034 0.005025126 0.412844037 0 0 0.0468750 0 0.0000000
Documentary 0.010101010 0.000000000 0.000000000 0 0 0.0000000 0 1.0000000
Drama       0.306397306 0.110552764 0.380733945 1 0 0.6640625 0 0.0000000
Fantasy     0.070707071 0.000000000 0.004587156 0 0 0.0000000 0 0.0000000
FilmNoir    0.000000000 0.000000000 0.105504587 0 0 0.0078125 0 0.0000000
Horror      0.016835017 0.080402010 0.018348624 0 0 0.0156250 0 0.0000000
Musical     0.188552189 0.000000000 0.000000000 0 0 0.0000000 0 0.0000000
Mystery     0.000000000 0.000000000 0.275229358 0 0 0.0000000 0 0.0000000
Romance     0.104377104 0.045226131 0.036697248 0 0 1.0000000 1 0.0000000
SciFi       0.074074074 0.346733668 0.041284404 0 0 0.0000000 0 0.0000000
Thriller    0.040404040 0.376884422 0.610091743 0 0 0.1406250 0 0.0000000
```

11. Find which cluster 'Men in Black' is in.

```
%r

subset(movies, Title=="Men in Black (1997)")
```

```
257 Men in Black (1997)      0     1        1        0        0
    Comedy Crime Documentary Drama Fantasy FilmNoir Horror Musical Mystery
257      1     0           0     0       0       0      0       0       0
    Romance SciFi Thriller War Western
257       0     1        0   0       0
```

```
%r

clusterGroups[which(movies$Title=="Men in Black (1997)")]
```

```
257
  2
```

12. Create a new data set with just the movies from cluster 2

```
%r

cluster2 = subset(movies, clusterGroups==2)
```

13. Look at the first 10 titles in this cluster

```
%r

cluster2$Title[1:10]
```

```
[1] GoldenEye (1995)<br />
 [2] Bad Boys (1995)<br />
 [3] Apollo 13 (1995)<br />
 [4] Net, The (1995)<br />
 [5] Natural Born Killers (1994)<br />
 [6] Outbreak (1995)<br />
 [7] Stargate (1994)<br />
 [8] Fugitive, The (1993)<br />
 [9] Jurassic Park (1993)<br />
[10] Robert A. Heinlein's The Puppet Masters (1994)
1664 Levels: 'Til There Was You (1997) …
```

Example2:

1. Load the flower.csv file and list the variables

```
%r

flower = read.csv("/data/flower.csv", header=FALSE)

str(flower)
```

```
'data.frame':   50 obs. of  50 variables:
 $ V1 : num  0.0991 0.0991 0.1034 0.1034 0.1034 …
 $ V2 : num  0.112 0.108 0.112 0.116 0.108 …
 $ V3 : num  0.134 0.116 0.121 0.116 0.112 …
 $ V4 : num  0.138 0.138 0.121 0.121 0.112 …
 $ V5 : num  0.138 0.134 0.125 0.116 0.112 …
 $ V6 : num  0.138 0.129 0.121 0.108 0.112 …
 $ V7 : num  0.129 0.116 0.103 0.108 0.112 …
 $ V8 : num  0.116 0.103 0.103 0.103 0.116 …
 $ V9 : num  0.1121 0.0991 0.1078 0.1121 0.1164 …
 $ V10: num  0.121 0.108 0.112 0.116 0.125 …
 $ V11: num  0.134 0.125 0.129 0.134 0.129 …
 $ V12: num  0.147 0.134 0.138 0.129 0.138 …
 $ V13: num  0.000862 0.146552 0.142241 0.142241 0.133621 …
 $ V14: num  0.000862 0.000862 0.142241 0.133621 0.12931 …
 $ V15: num  0.142 0.142 0.134 0.121 0.116 …
 $ V16: num  0.125 0.125 0.116 0.108 0.108 …
```

2. Change the data type to matrix

```
%r

flowerMatrix = as.matrix(flower)

str(flowerMatrix)
```

```
num [1:50, 1:50] 0.0991 0.0991 0.1034 0.1034 0.1034 …
```

3. Turn matrix into a vector

```
%r

flowerVector = as.vector(flowerMatrix)

str(flowerVector)
```

```
 num [1:2500] 0.0991 0.0991 0.1034 0.1034 0.1034 …
```

4. Compute the euclidean distance

```
%r

distance = dist(flowerVector, method = "euclidean")
```

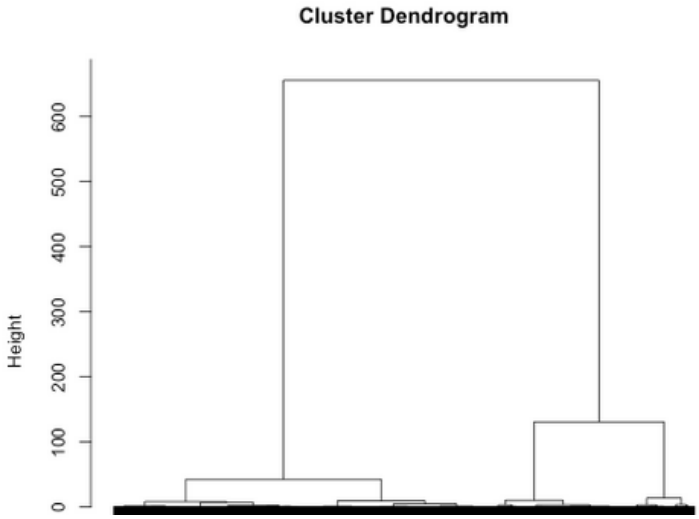
5. Prepare the data for clustering

```
%r

# Hierarchical clustering

clusterIntensity = hclust(distance, method="ward.D")
```

6. Plot the dendrogram

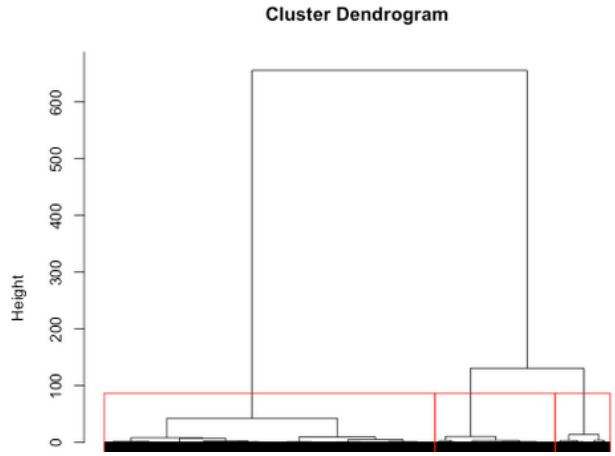
```
%r
```

```
plot(clusterIntensity)
```



7. Select 3 cluster and plot the dendrogram

```
%r

plot(clusterIntensity)

rect.hclust(clusterIntensity, k = 3, border = "red")
```




```
%r

flowerClusters = cutree(clusterIntensity, k = 3)

flowerClusters
```

```
 [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  [35] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  [69] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [103] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [137] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [171] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [205] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [239] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [273] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [307] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [341] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 3 3
 [375] 2 2 3 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [409] 1 1 1 1 1 1 1 1 1 2 2 1 1 1 3 3 3 3 3 2 1 2 3 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [443] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 3 3 1 1 1 3 3 3 3
 [477] 3 2 2 3 3 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 [511] 1 1 1 1 1 1 1 2 3 3 2 1 1 3 3 3 3 3 2 3 3 3 1 2 3 3 1 1 1 1 1 1 1 1 1 1 1 1 1
 [545] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 3 2 1 2 3 3 3 1 1 3 3 3 3 3 2
```

8. Find the mean intensity values using tapply function

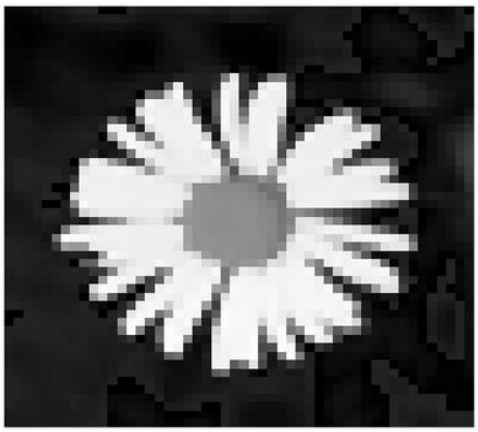
```
%r

tapply(flowerVector, flowerClusters, mean)
```

```
0.08574315 0.50826255 0.93147713
```

9. Plot the image and the clusters

```
%r

dim(flowerClusters) = c(50,50)

image(flowerClusters, axes = FALSE)
```

```
%r

# Original image

image(flowerMatrix,axes=FALSE, col=grey(seq(0,1,length=256)))
```



k-means Clustering

Algorithm in nutshell

Step 1: Specify a desired number of clusters k based on previous knowledge or experimenting

Step 2: Randomly assign each data to a cluster

Step 3: Compute cluster centroids

Step 4: Reassign each point to the closest cluster centroid

Step 5: Repeat 4 and 5 until no improvement is made

MRI Image Clustering using K-means

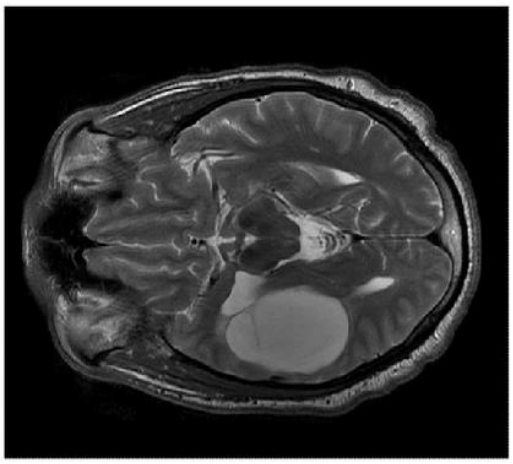
1. Load the tumor.csv file and list the variables

```
%r

healthy = read.csv("/data/tumor.csv", header=FALSE)

healthyMatrix = as.matrix(healthy)

str(healthyMatrix)
```

```
num [1:571, 1:512] 0 0 0 0 0 0 0 0 0 0 …
```

2. Plot the image

```
%r

image(healthyMatrix,axes=FALSE,col=grey(seq(0,1,length=256)))
```



3. Run k-means algorithm with number of clusters as 5

```
%r

# Run k-means

set.seed(1)

healthyVector = as.vector(healthyMatrix)

KMC = kmeans(healthyVector, centers = k, iter.max = 1000)

str(KMC)
```

```
List of 9
 $ cluster     : int [1:292352] 5 5 5 5 5 5 5 5 5 5 …
 $ centers     : num [1:5, 1] 0.43396 0.61961 0.28868 0.18492 0.00708
  ..- attr(*, "dimnames")=List of 2
  .. ..$ : chr [1:5] "1" "2" "3" "4" …
  .. ..$ : NULL
 $ totss       : num 8600
 $ withinss    : num [1:5] 54.3 50.6 69 76.8 43.8
 $ tot.withinss: num 294
 $ betweenss   : num 8305
 $ size        : int [1:5] 29811 8366 60806 53943 139426
 $ iter        : int 5
 $ ifault      : int 0
```

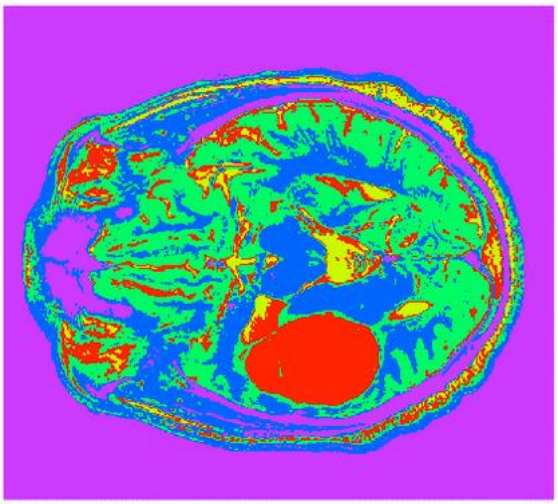
4. Extract clusters

```
%r

healthyClusters = KMC$cluster

KMC$centers[2]
```

```
[1] 0.6196116
```

5. Plot the image of clusters

```
%r

dim(healthyClusters) = c(nrow(healthyMatrix), ncol(healthyMatrix))

image(healthyClusters, axes = FALSE, col=rainbow(k))
```



PCA (Principle Component Analysis)

```
%r

library(ISLR)

nci.labs=NCI60$labs

nci.data=NCI60$data

dim(nci.data)
```

```
[1]   64 6830
```

```
%r pr.out=prcomp(nci.data, scale=TRUE) #Performs a principal
components analysis on the given data matrix and returns the results
as an object of class prcomp.

pr.out
```

```
Standard deviations:
 [1] 2.785347e+01 2.148136e+01 1.982046e+01 1.703256e+01 1.597181e+01
 [6] 1.572108e+01 1.447145e+01 1.354427e+01 1.314400e+01 1.273860e+01
[11] 1.268672e+01 1.215769e+01 1.183019e+01 1.162554e+01 1.143779e+01
[16] 1.100051e+01 1.065666e+01 1.048880e+01 1.043518e+01 1.032194e+01
[21] 1.014608e+01 1.005439e+01 9.902655e+00 9.647656e+00 9.507638e+00
[26] 9.332529e+00 9.273200e+00 9.090046e+00 8.981173e+00 8.750031e+00
[31] 8.599622e+00 8.447375e+00 8.373048e+00 8.215787e+00 8.157313e+00
[36] 7.974655e+00 7.904462e+00 7.821271e+00 7.721562e+00 7.586035e+00
[41] 7.456193e+00 7.344380e+00 7.104489e+00 7.013055e+00 6.958385e+00
[46] 6.866265e+00 6.807439e+00 6.647630e+00 6.616068e+00 6.407926e+00
[51] 6.219838e+00 6.203258e+00 6.067065e+00 5.918049e+00 5.912333e+00
[56] 5.735386e+00 5.472610e+00 5.292148e+00 5.021174e+00 4.683979e+00
[61] 4.175673e+00 4.082121e+00 4.041243e+00 2.148247e-14
```

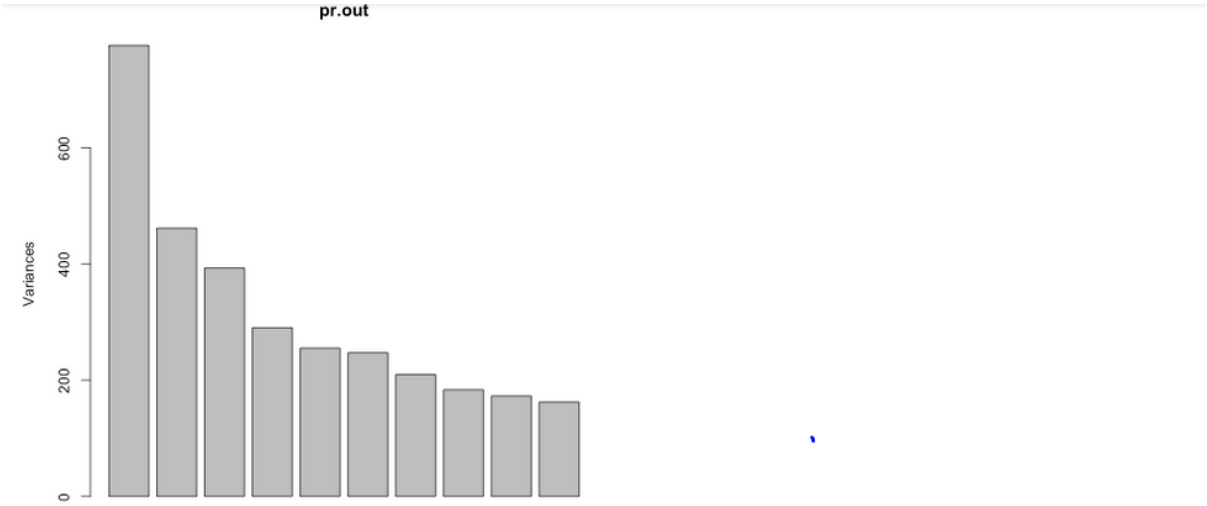
```
%r str(pr.out$x)
```

```
num [1:64, 1:64] -19.7 -22.9 -27.2 -42.5 -55 …
```

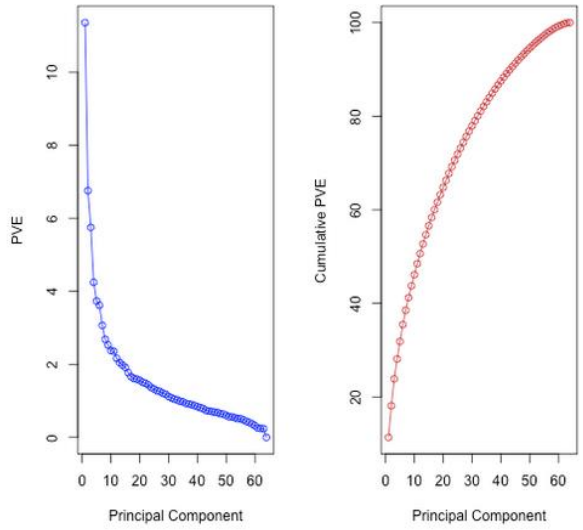
```
%r capture.output(summary(pr.out))
```

```
[1] “Importance of components:”<br />
 [2] “                           PC1      PC2      PC3      PC4      PC5”<br />
 [3] “Standard deviation     27.8535 21.48136 19.82046 17.03256 15.97181”<br />
 [4] “Proportion of Variance  0.1136  0.06756  0.05752  0.04248  0.03735”<br />
 [5] “Cumulative Proportion   0.1136  0.18115  0.23867  0.28115  0.31850”<br />
 [6] “                           PC6      PC7      PC8      PC9     PC10”<br />
 [7] “Standard deviation     15.72108 14.47145 13.54427 13.14400 12.73860”<br />
 [8] “Proportion of Variance  0.03619  0.03066  0.02686  0.02529  0.02376”<br />
 [9] “Cumulative Proportion   0.35468  0.38534  0.41220  0.43750  0.46126”<br />
[10] “                          PC11     PC12     PC13     PC14     PC15”<br />
[11] “Standard deviation     12.68672 12.15769 11.83019 11.62554 11.43779”<br />
[12] “Proportion of Variance  0.02357  0.02164  0.02049  0.01979  0.01915”<br />
[13] “Cumulative Proportion   0.48482  0.50646  0.52695  0.54674  0.56590”<br />
[14] “                          PC16     PC17     PC18     PC19    PC20”<br />
[15] “Standard deviation     11.00051 10.65666 10.48880 10.43518 10.3219”<br />
[16] “Proportion of Variance  0.01772  0.01663  0.01611  0.01594  0.0156”<br />
[17] “Cumulative Proportion   0.58361  0.60024  0.61635  0.63229  0.6479”<br />
```

```
%r plot(pr.out)
```




```
%r

pve=100*pr.out$sdev^2/sum(pr.out$sdev^2)

par(mfrow=c(1,2))

plot(pve, type="o", ylab="PVE", xlab="Principal Component",
col="blue")

plot(cumsum(pve), type="o", ylab="Cumulative PVE", xlab="Principal
Component", col="brown3")
```

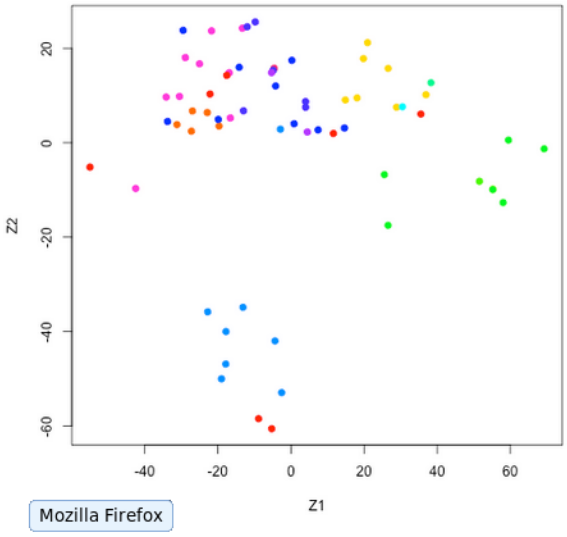



```
%r base::table(nci.labs)
```

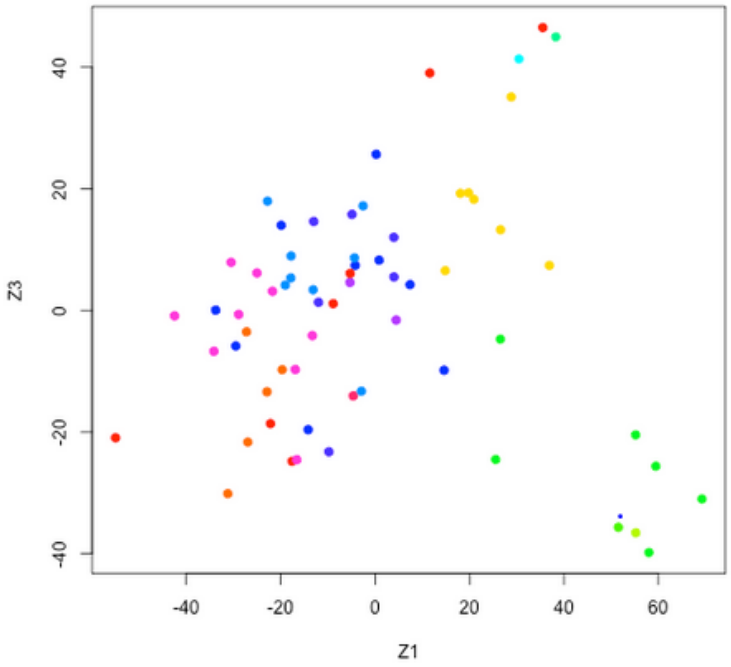
```
nci.labs
     BREAST         CNS       COLON K562A-repro K562B-repro    LEUKEMIA
          7           5           7           1           1           6
MCF7A-repro MCF7D-repro    MELANOMA       NSCLC     OVARIAN    PROSTATE
          1           1           8           9           6           2
      RENAL     UNKNOWN
          9           1
```

```
%r

Cols=function(vec){

    cols=rainbow(length(unique(vec))) #rainbow: Create a vector of n
contiguous colors.

    return(cols[as.numeric(as.factor(vec))])

}

par(mfrow=c(1,2))
```

```
%r plot(pr.out$x[,1:2], col=Cols(nci.labs),
pch=19,xlab="Z1",ylab="Z2")
```




```
%r plot(pr.out$x[,c(1,3)], col=Cols(nci.labs),
pch=19,xlab="Z1",ylab="Z3")
```


Z3
40
20
0
-20
-40
-40
-20
0
20
40
60
Z1