Thota, Sunil Raj - Data Mining.R

```
# Intermediate Analytics
# ALY 6015
# Module 4 - Data Mining
# 02/09/2021
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# Get and set the working directories
getwd()

## [1] "G:/NEU/Coursework/2021 Q1 Winter/ALY 6015 IA/Discussions & Assignment
s"

setwd('G:/NEU/Coursework/2021 Q1 Winter/ALY 6015 IA/Discussions & Assignments
')
getwd()

## [1] "G:/NEU/Coursework/2021 Q1 Winter/ALY 6015 IA/Discussions & Assignment
s"

# Installed the above packages into the work space
install.packages("datasets")
install.packages("plyr")
install.packages("dplyr")
install.packages("tidyr")
install.packages("factoextra")
install.packages("NbClust")
install.packages("party")
install.packages("caret")
install.packages("fpc")

# Loaded the below libraries into the work space
library(plyr)
library(dplyr)
library(tidyr)
library(factoextra)
library(NbClust)
library(party)
require(datasets)
library(caret)
library(fpc)
```

```
# Problem 1
data(iris)
View(iris)
str(iris)

## 'data.frame':    150 obs. of  5 variables:
##  $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
##  $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
##  $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
##  $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
##  $ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1
1 1 1 1 ...

head(iris)

##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa

tail(iris)

##     Sepal.Length Sepal.Width Petal.Length Petal.Width   Species
## 145          6.7         3.3          5.7         2.5 virginica
## 146          6.7         3.0          5.2         2.3 virginica
## 147          6.3         2.5          5.0         1.9 virginica
## 148          6.5         3.0          5.2         2.0 virginica
## 149          6.2         3.4          5.4         2.3 virginica
## 150          5.9         3.0          5.1         1.8 virginica

summary(iris)

##   Sepal.Length    Sepal.Width     Petal.Length    Petal.Width   
##  Min.   :4.300   Min.   :2.000   Min.   :1.000   Min.   :0.100  
##  1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300  
##  Median :5.800   Median :3.000   Median :4.350   Median :1.300  
##  Mean   :5.843   Mean   :3.057   Mean   :3.758   Mean   :1.199  
##  3rd Qu.:6.400   3rd Qu.:3.300   3rd Qu.:5.100   3rd Qu.:1.800  
##  Max.   :7.900   Max.   :4.400   Max.   :6.900   Max.   :2.500  
##        Species  
##  setosa    :50  
##  versicolor:50  
##  virginica :50  
##                 
##                 
##                 

# Let's perform some Exploratory Data Analysis and Data Mining techniques usi
ng "iris" data set. To get this data set we need to install the 'data sets' p
```

```
ackage from the packages tab which is right side to the work space in R Studi
o.

# Or we can also install the packages by using install.packages("package name
") command. Once it is loaded we can use it in the code for further analysis
and calculations. Loaded the "data sets" library into the work space. Loaded
the iris Data set into the Environment.

# I have also installed factoextra', 'party', 'caret', 'fpc', and 'NbClust' t
o perform data mining analysis in R. Let's install all the above packages

# To View the diabetes Data set we use View() command, To observe the structu
re of the Data set we use str() command, and head () and tail() shows first a
nd last few rows in the Data set. Summary() Provides the Descriptive Stats of
the iris columns. We noticed 5 variables from the statistics given in the sum
mary.

# Problem 2

# split into training and test datasets
set.seed(1234)
sampleData <- sample(2, nrow(iris), replace = T, prob = c(0.7, 0.3))
sampleData

##   [1] 1 1 1 1 2 1 1 1 1 1 1 1 1 2 1 2 1 1 1 1 1 1 1 1 1 2 1 2 2 1 1 1 1 1
1 2 1
##  [38] 1 2 2 1 1 1 1 1 1 1 1 1 2 1 1 2 1 1 1 1 2 1 2 2 1 1 1 1 2 1 1 1 1 1
2 1 2
##  [75] 1 1 1 1 1 1 2 1 1 1 1 2 1 1 1 2 1 2 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1
1 1 2
## [112] 1 2 1 1 2 2 1 1 2 2 2 2 2 1 1 1 1 1 1 2 1 1 1 2 1 2 1 1 2 1 2 1 1 1
1 2 1
## [149] 2 1

trainData <- iris[sampleData == 1, ]
trainData

##     Sepal.Length Sepal.Width Petal.Length Petal.Width    Species
## 1            5.1         3.5          1.4         0.2     setosa
## 2            4.9         3.0          1.4         0.2     setosa
## 3            4.7         3.2          1.3         0.2     setosa
## 4            4.6         3.1          1.5         0.2     setosa
## 6            5.4         3.9          1.7         0.4     setosa
## 7            4.6         3.4          1.4         0.3     setosa
## 8            5.0         3.4          1.5         0.2     setosa
## 9            4.4         2.9          1.4         0.2     setosa
## 10           4.9         3.1          1.5         0.1     setosa
## 11           5.4         3.7          1.5         0.2     setosa
## 12           4.8         3.4          1.6         0.2     setosa
## 13           4.8         3.0          1.4         0.1     setosa
```

```
## 15          5.8         4.0          1.2         0.2     setosa
## 17          5.4         3.9          1.3         0.4     setosa
## 18          5.1         3.5          1.4         0.3     setosa
## 19          5.7         3.8          1.7         0.3     setosa
## 20          5.1         3.8          1.5         0.3     setosa
## 21          5.4         3.4          1.7         0.2     setosa
## 22          5.1         3.7          1.5         0.4     setosa
## 23          4.6         3.6          1.0         0.2     setosa
## 24          5.1         3.3          1.7         0.5     setosa
## 25          4.8         3.4          1.9         0.2     setosa
## 27          5.0         3.4          1.6         0.4     setosa
## 30          4.7         3.2          1.6         0.2     setosa
## 31          4.8         3.1          1.6         0.2     setosa
## 32          5.4         3.4          1.5         0.4     setosa
## 33          5.2         4.1          1.5         0.1     setosa
## 34          5.5         4.2          1.4         0.2     setosa
## 35          4.9         3.1          1.5         0.2     setosa
## 37          5.5         3.5          1.3         0.2     setosa
## 38          4.9         3.6          1.4         0.1     setosa
## 41          5.0         3.5          1.3         0.3     setosa
## 42          4.5         2.3          1.3         0.3     setosa
## 43          4.4         3.2          1.3         0.2     setosa
## 44          5.0         3.5          1.6         0.6     setosa
## 45          5.1         3.8          1.9         0.4     setosa
## 46          4.8         3.0          1.4         0.3     setosa
## 47          5.1         3.8          1.6         0.2     setosa
## 48          4.6         3.2          1.4         0.2     setosa
## 49          5.3         3.7          1.5         0.2     setosa
## 51          7.0         3.2          4.7         1.4 versicolor
## 52          6.4         3.2          4.5         1.5 versicolor
## 54          5.5         2.3          4.0         1.3 versicolor
## 55          6.5         2.8          4.6         1.5 versicolor
## 56          5.7         2.8          4.5         1.3 versicolor
## 57          6.3         3.3          4.7         1.6 versicolor
## 59          6.6         2.9          4.6         1.3 versicolor
## 62          5.9         3.0          4.2         1.5 versicolor
## 63          6.0         2.2          4.0         1.0 versicolor
## 64          6.1         2.9          4.7         1.4 versicolor
## 65          5.6         2.9          3.6         1.3 versicolor
## 67          5.6         3.0          4.5         1.5 versicolor
## 68          5.8         2.7          4.1         1.0 versicolor
## 69          6.2         2.2          4.5         1.5 versicolor
## 70          5.6         2.5          3.9         1.1 versicolor
## 71          5.9         3.2          4.8         1.8 versicolor
## 73          6.3         2.5          4.9         1.5 versicolor
## 75          6.4         2.9          4.3         1.3 versicolor
## 76          6.6         3.0          4.4         1.4 versicolor
## 77          6.8         2.8          4.8         1.4 versicolor
## 78          6.7         3.0          5.0         1.7 versicolor
## 79          6.0         2.9          4.5         1.5 versicolor
```

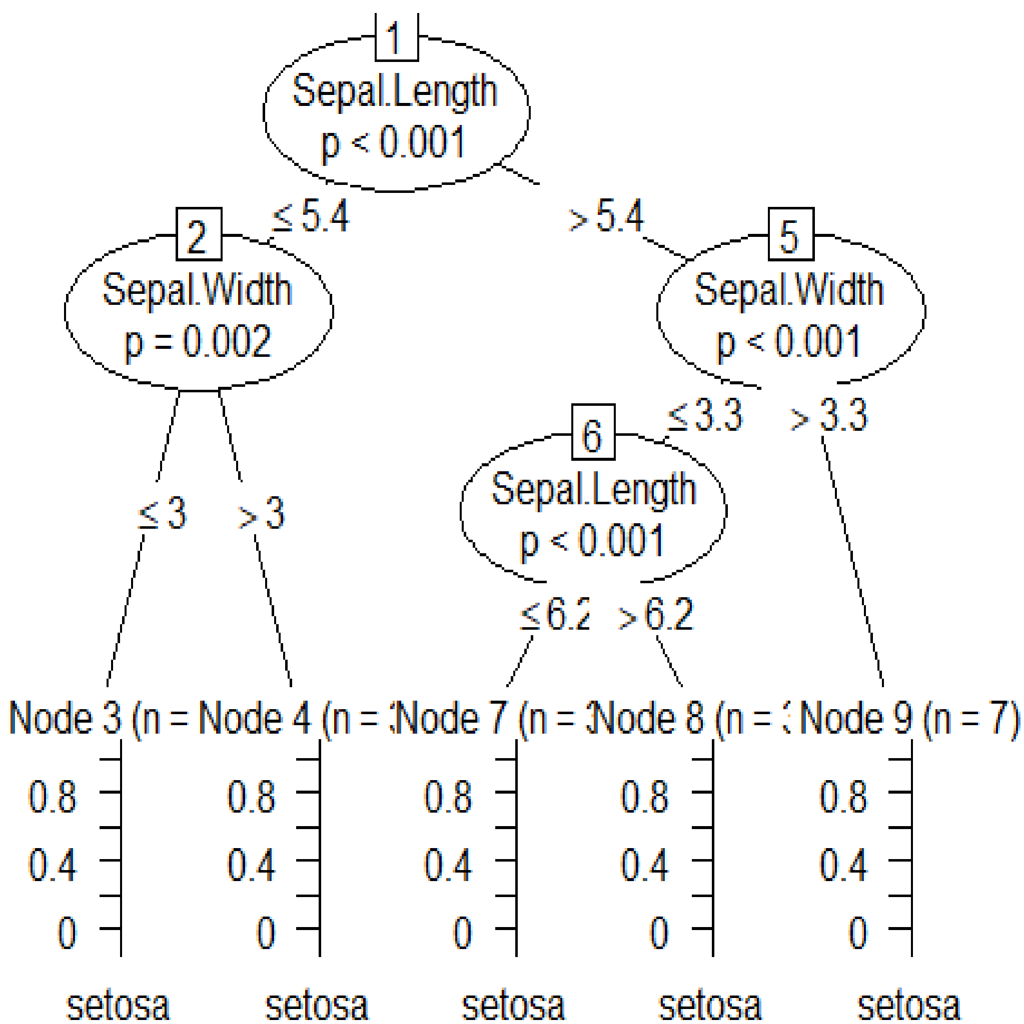
```
## 80           5.7          2.6           3.5          1.0 versicolor
## 82           5.5          2.4           3.7          1.0 versicolor
## 83           5.8          2.7           3.9          1.2 versicolor
## 84           6.0          2.7           5.1          1.6 versicolor
## 85           5.4          3.0           4.5          1.5 versicolor
## 87           6.7          3.1           4.7          1.5 versicolor
## 88           6.3          2.3           4.4          1.3 versicolor
## 89           5.6          3.0           4.1          1.3 versicolor
## 91           5.5          2.6           4.4          1.2 versicolor
## 93           5.8          2.6           4.0          1.2 versicolor
## 94           5.0          2.3           3.3          1.0 versicolor
## 95           5.6          2.7           4.2          1.3 versicolor
## 96           5.7          3.0           4.2          1.2 versicolor
## 97           5.7          2.9           4.2          1.3 versicolor
## 98           6.2          2.9           4.3          1.3 versicolor
## 99           5.1          2.5           3.0          1.1 versicolor
## 101          6.3          3.3           6.0          2.5  virginica
## 102          5.8          2.7           5.1          1.9  virginica
## 103          7.1          3.0           5.9          2.1  virginica
## 104          6.3          2.9           5.6          1.8  virginica
## 105          6.5          3.0           5.8          2.2  virginica
## 106          7.6          3.0           6.6          2.1  virginica
## 107          4.9          2.5           4.5          1.7  virginica
## 108          7.3          2.9           6.3          1.8  virginica
## 109          6.7          2.5           5.8          1.8  virginica
## 110          7.2          3.6           6.1          2.5  virginica
## 112          6.4          2.7           5.3          1.9  virginica
## 114          5.7          2.5           5.0          2.0  virginica
## 115          5.8          2.8           5.1          2.4  virginica
## 118          7.7          3.8           6.7          2.2  virginica
## 119          7.7          2.6           6.9          2.3  virginica
## 125          6.7          3.3           5.7          2.1  virginica
## 126          7.2          3.2           6.0          1.8  virginica
## 127          6.2          2.8           4.8          1.8  virginica
## 128          6.1          3.0           4.9          1.8  virginica
## 129          6.4          2.8           5.6          2.1  virginica
## 130          7.2          3.0           5.8          1.6  virginica
## 132          7.9          3.8           6.4          2.0  virginica
## 133          6.4          2.8           5.6          2.2  virginica
## 134          6.3          2.8           5.1          1.5  virginica
## 136          7.7          3.0           6.1          2.3  virginica
## 138          6.4          3.1           5.5          1.8  virginica
## 139          6.0          3.0           4.8          1.8  virginica
## 141          6.7          3.1           5.6          2.4  virginica
## 143          5.8          2.7           5.1          1.9  virginica
## 144          6.8          3.2           5.9          2.3  virginica
## 145          6.7          3.3           5.7          2.5  virginica
## 146          6.7          3.0           5.2          2.3  virginica
## 148          6.5          3.0           5.2          2.0  virginica
## 150          5.9          3.0           5.1          1.8  virginica
```

```
testData <- iris[sampleData == 2, ]
testData
```

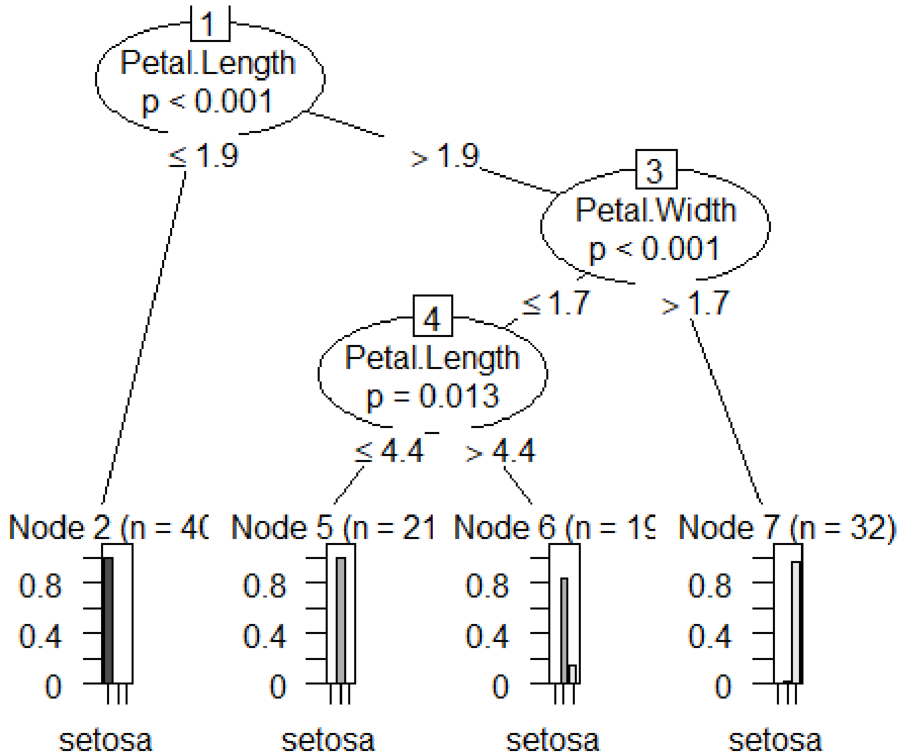
```
##     Sepal.Length Sepal.Width Petal.Length Petal.Width    Species
## 5            5.0         3.6          1.4         0.2     setosa
## 14           4.3         3.0          1.1         0.1     setosa
## 16           5.7         4.4          1.5         0.4     setosa
## 26           5.0         3.0          1.6         0.2     setosa
## 28           5.2         3.5          1.5         0.2     setosa
## 29           5.2         3.4          1.4         0.2     setosa
## 36           5.0         3.2          1.2         0.2     setosa
## 39           4.4         3.0          1.3         0.2     setosa
## 40           5.1         3.4          1.5         0.2     setosa
## 50           5.0         3.3          1.4         0.2     setosa
## 53           6.9         3.1          4.9         1.5 versicolor
## 58           4.9         2.4          3.3         1.0 versicolor
## 60           5.2         2.7          3.9         1.4 versicolor
## 61           5.0         2.0          3.5         1.0 versicolor
## 66           6.7         3.1          4.4         1.4 versicolor
## 72           6.1         2.8          4.0         1.3 versicolor
## 74           6.1         2.8          4.7         1.2 versicolor
## 81           5.5         2.4          3.8         1.1 versicolor
## 86           6.0         3.4          4.5         1.6 versicolor
## 90           5.5         2.5          4.0         1.3 versicolor
## 92           6.1         3.0          4.6         1.4 versicolor
## 100          5.7         2.8          4.1         1.3 versicolor
## 111          6.5         3.2          5.1         2.0  virginica
## 113          6.8         3.0          5.5         2.1  virginica
## 116          6.4         3.2          5.3         2.3  virginica
## 117          6.5         3.0          5.5         1.8  virginica
## 120          6.0         2.2          5.0         1.5  virginica
## 121          6.9         3.2          5.7         2.3  virginica
## 122          5.6         2.8          4.9         2.0  virginica
## 123          7.7         2.8          6.7         2.0  virginica
## 124          6.3         2.7          4.9         1.8  virginica
## 131          7.4         2.8          6.1         1.9  virginica
## 135          6.1         2.6          5.6         1.4  virginica
## 137          6.3         3.4          5.6         2.4  virginica
## 140          6.9         3.1          5.4         2.1  virginica
## 142          6.9         3.1          5.1         2.3  virginica
## 147          6.3         2.5          5.0         1.9  virginica
## 149          6.2         3.4          5.4         2.3  virginica
```

```
# To perform Data Mining, we are taking 'iris' data set which has 150 records
and 5 variables. The columns that we are working now are Sepal.Length, Sepal.
Width, Petal.Length, Petal.Width, and Species of the iris data set.

# To generate a sequence of random numbers we use set.seed() in R. With the h
elp of sample() method, we can split the data set into two parts i.e., traini
ng and testing data sets which will be splitted into 70: 30 ratio of the main
```

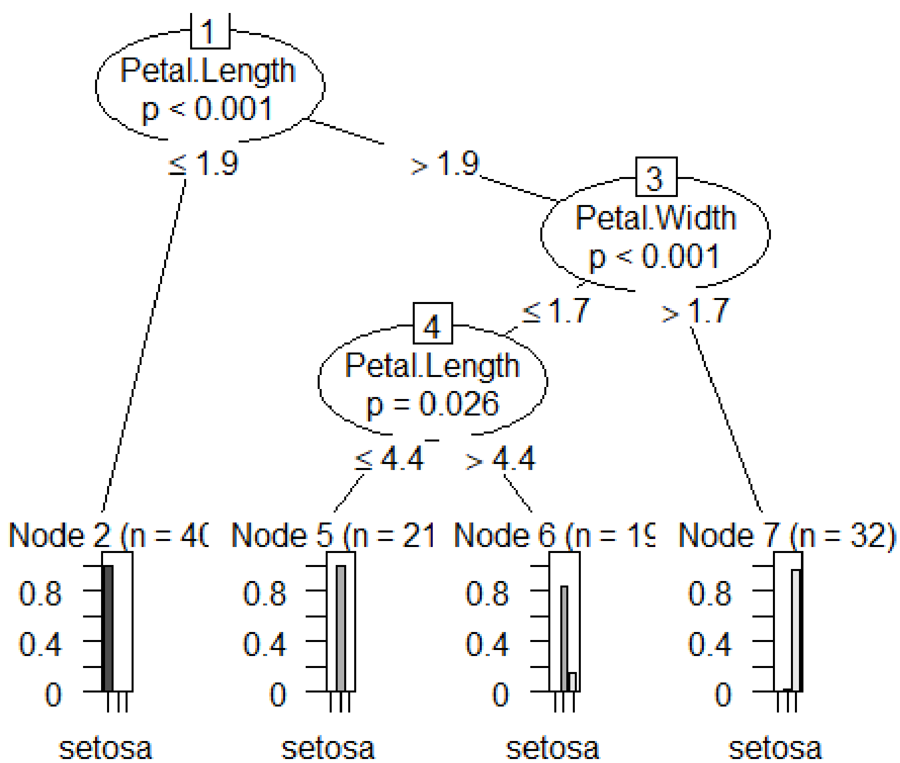
```
data set ('iris').

# To store these splitted data sets we require two different variables that n
eeds to be assigned as 'trainData' and 'testdata'.

# Problem 3
irisSepal <- Species ~ Sepal.Length + Sepal.Width
irisPetal <- Species ~ Petal.Length + Petal.Width
irisAll <-
  Species ~ Sepal.Length + Sepal.Width + Petal.Length + Petal.Width

irisTree1 <- ctree(irisSepal, data = trainData)
irisTree2 <- ctree(irisPetal, data = trainData)
irisTree3 <- ctree(irisAll, data = trainData)

plot(irisTree1)
```



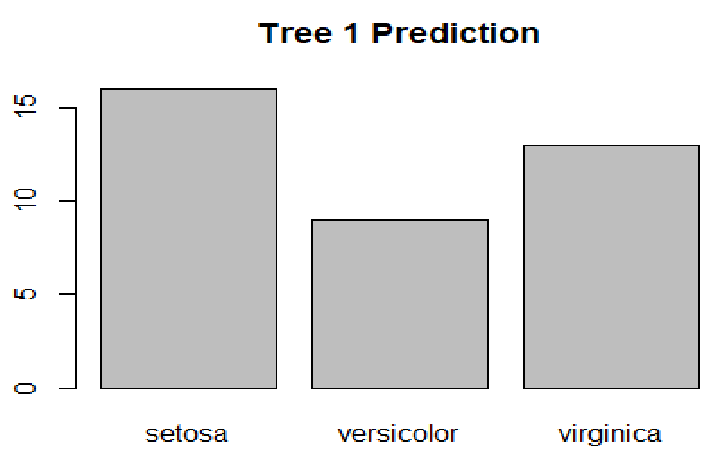

```
plot(irisTree2)
```




```
plot(irisTree3)
```



```r
# To apply Decision Tree Model to our data set, we have to use "ctree()" meth
od and include our Training Data set. Here we are performing by taking variou
s independent variables and named as irisSepal, irisPetal, and irisAll. Let u
s also delve into the analysis by plotting these Decision Trees models to com
pare and observe the differences in each plot.

# From the plots, we can depict that there is a change in the root nodes and
leaves. Primary node is called as the root and the bottom nodes are known as
leaves. In this model, the decision makers are leaves. The final result is va
lidated by a leaf node where the model terminates and has a value on the leaf

# Problem 4
pred1 <- predict(irisTree1, testData)
pred1

##  [1] setosa     setosa     setosa     setosa     setosa     setosa
##  [7] setosa     setosa     setosa     setosa     virginica  setosa
## [13] setosa     setosa     virginica  versicolor versicolor versicolor
## [19] setosa     versicolor versicolor versicolor virginica  virginica
## [25] virginica  virginica  versicolor virginica  versicolor virginica
## [31] virginica  virginica  versicolor setosa     virginica  virginica
## [37] virginica  setosa
## Levels: setosa versicolor virginica

table(pred1, testData$Species)

##
## pred1        setosa versicolor virginica
##   setosa         10          4         2
##   versicolor      0          6         3
##   virginica       0          2        11

plot(pred1, main = "Tree 1 Prediction")
```



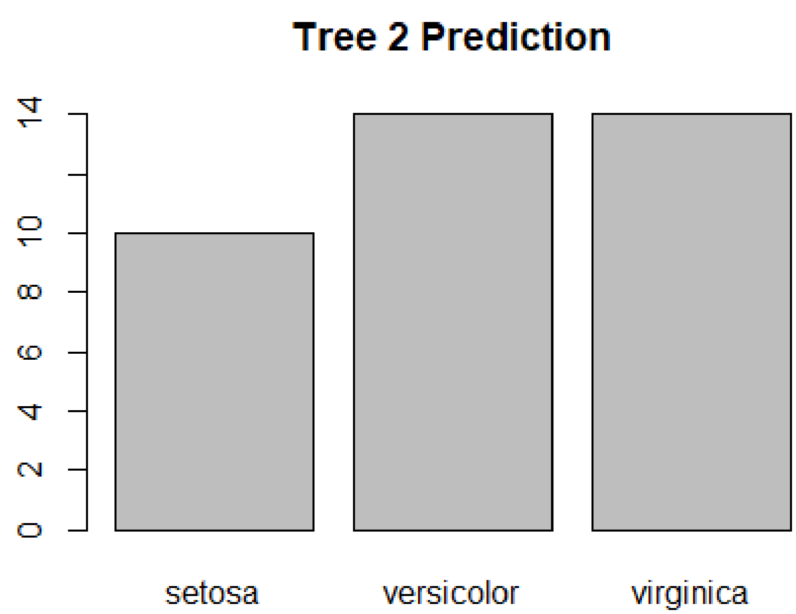
```
pred2 <- predict(irisTree2, testData)
pred2
```

```
##  [1] setosa     setosa     setosa     setosa     setosa     setosa
##  [7] setosa     setosa     setosa     setosa     versicolor versicolor
## [13] versicolor versicolor versicolor versicolor versicolor versicolor
## [19] versicolor versicolor versicolor versicolor virginica  virginica
## [25] virginica  virginica  versicolor virginica  virginica  virginica
## [31] virginica  virginica  versicolor virginica  virginica  virginica
## [37] virginica  virginica
## Levels: setosa versicolor virginica
```

```
table(pred2, testData$Species)
```

```
##
## pred2        setosa versicolor virginica
##   setosa         10          0         0
##   versicolor      0         12         2
##   virginica       0          0        14
```

```
plot(pred2, main = "Tree 2 Prediction")
```




```
pred3 <- predict(irisTree3, testData)
pred3
```

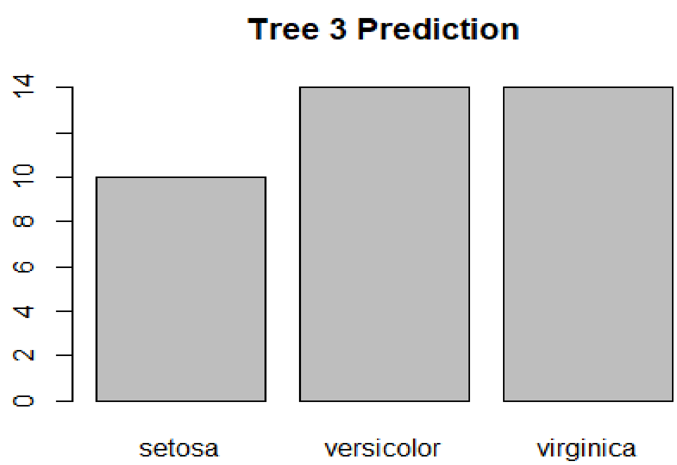
```
##  [1] setosa     setosa     setosa     setosa     setosa     setosa
##  [7] setosa     setosa     setosa     setosa     versicolor versicolor
## [13] versicolor versicolor versicolor versicolor versicolor versicolor
```

```
## [19] versicolor versicolor versicolor versicolor virginica  virginica
## [25] virginica  virginica  versicolor virginica  virginica  virginica
## [31] virginica  virginica  versicolor virginica  virginica  virginica
## [37] virginica  virginica
## Levels: setosa versicolor virginica
```

```
table(pred3, testData$Species)
```

```
##
## pred3        setosa versicolor virginica
##   setosa         10          0         0
##   versicolor      0         12         2
##   virginica       0          0        14
```

```
plot(pred3, main = "Tree 3 Prediction")
```




```
# Let's predict our model with the help of testing data set which was initial
ly splitted as testData with 305 of main data set. For this, we have to use p
redict() method on the testing data set. In this, lets mix and match various
columns to implement several various decision tree models and compare the pre
diction results of each.

# From the plots, we can depict that there is change in each prediction with
respect to the columns. If the independent variable is tweaked then the final
result will also get altered with respect to the columns

# Problem 5

set.seed(9000)
irisData2 <- iris
irisData2
```

```
irisData2$Species <- NULL
irisData2$species
```

```
## NULL
```

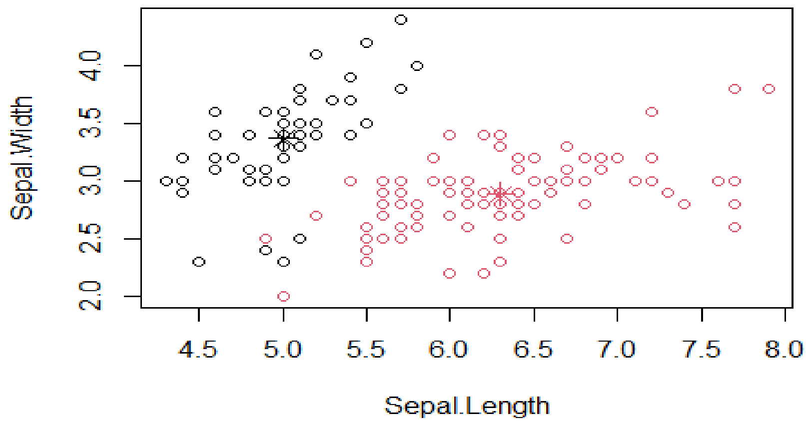
```
irisKMeansClustering2 <- kmeans(irisData2, 2)
irisKMeansClustering2
```

```
## K-means clustering with 2 clusters of sizes 53, 97
##
## Cluster means:
##   Sepal.Length Sepal.Width Petal.Length Petal.Width
## 1     5.005660    3.369811     1.560377    0.290566
## 2     6.301031    2.886598     4.958763    1.695876
##
## Clustering vector:
##   [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
##  [38] 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2
2 2 2
##  [75] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2
2 2 2
## [112] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
2 2 2
## [149] 2 2
##
## Within cluster sum of squares by cluster:
## [1]  28.55208 123.79588
##  (between_SS / total_SS =  77.6 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withi
nss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

```
table(irisKMeansClustering2$cluster, iris$Species)
```

```
##
##     setosa versicolor virginica
##   1     50          3         0
##   2      0         47        50
```

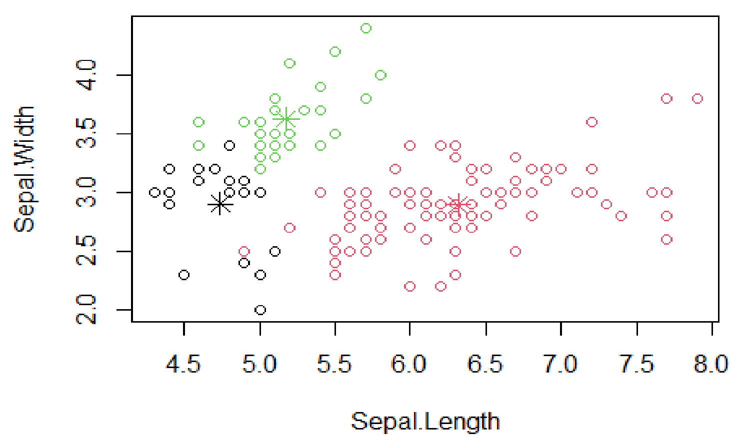
```
plot(iris[c("Sepal.Length", "Sepal.Width")], col = irisKMeansClustering2$clus
ter)
points(
  irisKMeansClustering2$centers[, c("Sepal.Length", "Sepal.Width")],
  col = 1:3,
  pch = 8,
  cex = 1.5
)
```




```
irisKMeansClustering3 <- kmeans(irisData2, 3)
irisKMeansClustering3

## K-means clustering with 3 clusters of sizes 21, 96, 33
##
## Cluster means:
##   Sepal.Length Sepal.Width Petal.Length Petal.Width
## 1     4.738095    2.904762     1.790476   0.3523810
## 2     6.314583    2.895833     4.973958   1.7031250
## 3     5.175758    3.624242     1.472727   0.2727273
##
## Clustering vector:
##   [1] 3 1 1 1 3 3 3 3 1 1 3 3 1 1 3 3 3 3 3 3 3 3 3 3 1 1 3 3 3 1 1 3 3 3
1 3 3
##  [38] 3 1 3 3 1 1 3 3 1 3 1 3 3 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2
2 2 2
##  [75] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
2 2 2
## [112] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
2 2 2
## [149] 2 2
##
## Within cluster sum of squares by cluster:
## [1]  17.669524 118.651875   6.432121
##  (between_SS / total_SS =  79.0 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withi
nss"
## [6] "betweenss"    "size"         "iter"         "ifault"

table(irisKMeansClustering3$cluster, iris$Species)
```

```
##
##      setosa versicolor virginica
##    1     17          4         0
##    2      0         46        50
##    3     33          0         0
```

```
plot(iris[c("Sepal.Length", "Sepal.Width")], col = irisKMeansClustering3$clus
ter)
points(
  irisKMeansClustering3$centers[, c("Sepal.Length", "Sepal.Width")],
  col = 1:3,
  pch = 8,
  cex = 1.5
)
```




```
irisKMeansClustering4 <- kmeans(irisData2, 4)
irisKMeansClustering4
```

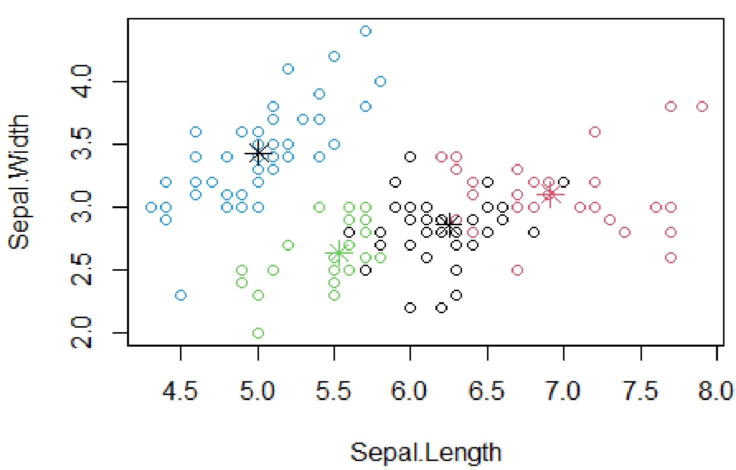
```
## K-means clustering with 4 clusters of sizes 40, 32, 28, 50
##
## Cluster means:
##   Sepal.Length Sepal.Width Petal.Length Petal.Width
## 1     6.252500    2.855000     4.815000    1.625000
## 2     6.912500    3.100000     5.846875    2.131250
## 3     5.532143    2.635714     3.960714    1.228571
## 4     5.006000    3.428000     1.462000    0.246000
##
## Clustering vector:
##   [1] 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4
4 4 4
##  [38] 4 4 4 4 4 4 4 4 4 4 4 4 4 1 1 1 3 1 3 1 3 1 3 3 3 3 1 3 1 3 3 1 3 1
3 1 1
##  [75] 1 1 1 1 1 3 3 3 3 1 3 1 1 1 3 3 3 1 3 3 3 3 3 1 3 3 2 1 2 2 2 2 3 2
```

```
2 2 1
## [112] 1 2 1 1 2 2 2 2 1 2 1 2 1 2 2 1 1 2 2 2 2 2 1 1 2 2 2 1 2 2 2 1 2 2
2 1 1
## [149] 2 1
##
## Within cluster sum of squares by cluster:
## [1] 13.624750 18.703437  9.749286 15.151000
##  (between_SS / total_SS =  91.6 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withi
nss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

```
table(irisKMeansClustering4$cluster, iris$Species)
```

```
##
##     setosa versicolor virginica
##   1      0         23        17
##   2      0          0        32
##   3      0         27         1
##   4     50          0         0
```

```
plot(iris[c("Sepal.Length", "Sepal.Width")], col = irisKMeansClustering4$clus
ter)
points(
  irisKMeansClustering4$centers[, c("Sepal.Length", "Sepal.Width")],
  col = 1:3,
  pch = 8,
  cex = 1.5
)
```



```r
irisKMeansClustering5 <- kmeans(irisData2, 5)
irisKMeansClustering5
```

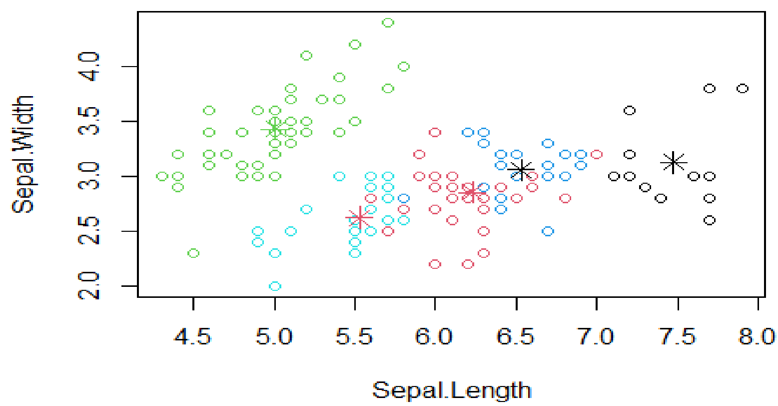
```
## K-means clustering with 5 clusters of sizes 12, 37, 50, 24, 27
##
## Cluster means:
##   Sepal.Length Sepal.Width Petal.Length Petal.Width
## 1     7.475000    3.125000     6.300000    2.050000
## 2     6.229730    2.851351     4.767568    1.572973
## 3     5.006000    3.428000     1.462000    0.246000
## 4     6.529167    3.058333     5.508333    2.162500
## 5     5.529630    2.622222     3.940741    1.218519
##
## Clustering vector:
##   [1] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
3 3 3
##  [38] 3 3 3 3 3 3 3 3 3 3 3 3 3 2 2 2 5 2 5 2 5 2 5 5 5 5 2 5 2 2 5 2 5 2
5 2 2
##  [75] 2 2 2 2 2 5 5 5 5 2 5 2 2 2 5 5 5 2 5 5 5 5 5 2 5 5 4 2 1 4 4 1 5 1
4 1 4
## [112] 4 4 2 4 4 4 1 1 2 4 2 1 2 4 1 2 2 4 1 1 1 4 2 2 1 4 4 2 4 4 4 2 4 4
4 2 4
## [149] 4 2
##
## Within cluster sum of squares by cluster:
## [1]  4.655000 11.963784 15.151000  5.462500  9.228889
##  (between_SS / total_SS =  93.2 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withi
nss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

```r
table(irisKMeansClustering5$cluster, iris$Species)
```

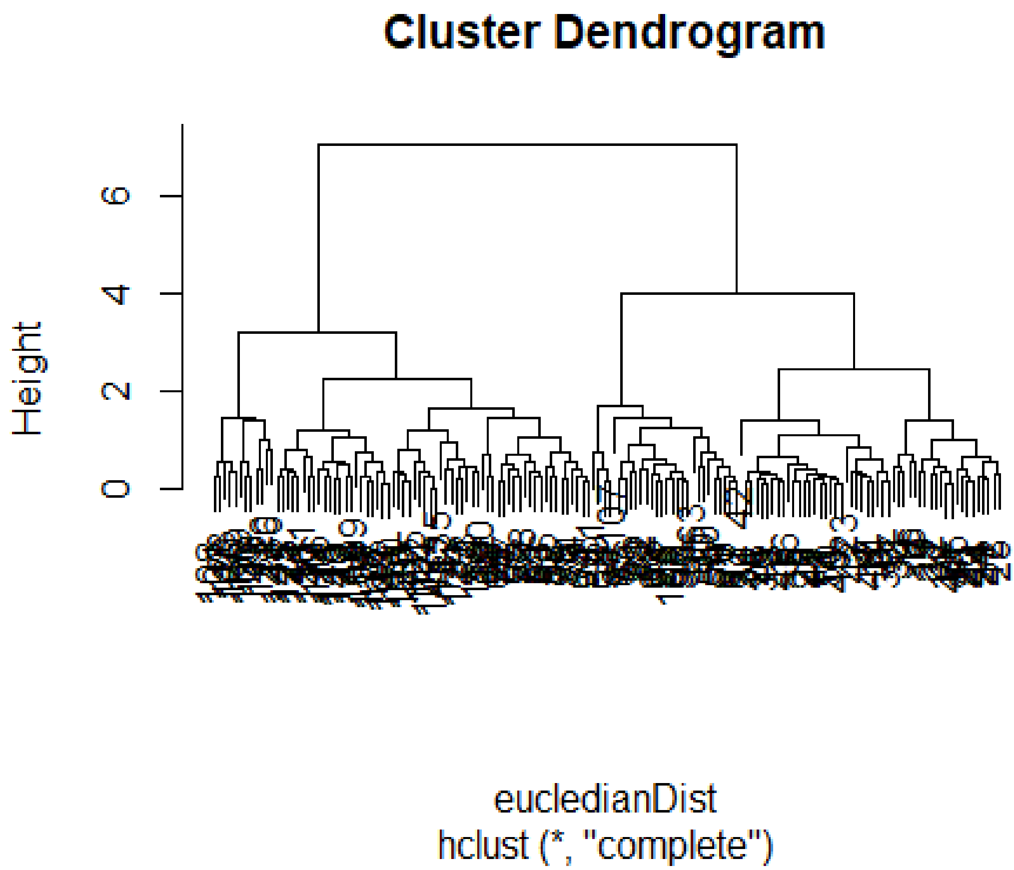
```
##
##     setosa versicolor virginica
##   1      0          0        12
##   2      0         24        13
##   3     50          0         0
##   4      0          0        24
##   5      0         26         1
```

```r
plot(iris[c("Sepal.Length", "Sepal.Width")], col = irisKMeansClustering5$clus
ter)
points(
  irisKMeansClustering5$centers[, c("Sepal.Length", "Sepal.Width")],
  col = 1:3,
  pch = 8,
```

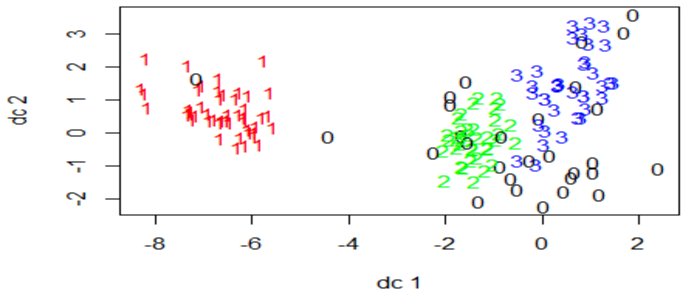
```
  cex = 1.5
)
```




```
# We have set the seed to 9000 and duplicated the data set with irisData2. Th
en removed the Species column by assigning it to the NULL. Let's perform some
K-Means Clustering model also known as K-Means/ K Nearest Neighbors which seg
regates the the whole data set into various clusters/ groups/ partitions. Aft
er this, it further splits the data into alike clusters. groups/ partitions a
s nearer as available and cluster as apart as possible.

# We don't know the data sets features and parameters they show. And , also t
he clustering technique will use numerical data and drop non-numeric columns.
After that, we will perform clustering by using the kmeans() method with 2 cl
usters with our normalized data set. Once it is performed, we again feed with
3 clusters, and then 4, and then 5.

# By doing like so, we can observe the change in the distances between them.
The Euclidean Distances becomes lesser with increase in the clusters. Here, w
e can plot to see the clusters.

# Problem 6

eucledianDist <- dist(irisData2)
hieraracyCluster <- hclust(eucledianDist)
plot(hieraracyCluster)
```




```
# In this, we perform Hierarchical Clustering and it is not necessary to spec
ify the number of clusters required to get the best result. This is known as
a Dendogram and it looks like an inverted tree structure.

# Problem 7

densityCluster <- dbscan(irisData2, eps = 0.42, MinPts = 5)
table(densityCluster$cluster, iris$Species)

##
##     setosa versicolor virginica
##   0      2         10        17
##   1     48          0         0
##   2      0         37         0
##   3      0          3        33

plotcluster(irisData2, densityCluster$cluster)
```




```
# In this, let us remove the Species ID's and use dbscan() method for cluster
ing with the irisData2 data set. After that, let us compare with the original
Species ID's in a table and plot the clusters. We can see few 0's in the grap
hs which are looked as outliers.
```