Iris Dataset Simple algorithms Examples

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Iris data is loaded. We can see the summary that it has 150 observations of 5 variables of three species of the plant.

```
data(iris)
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
## 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
## 14            4.3         3.0          1.1         0.1     setosa
## 15            5.8         4.0          1.2         0.2     setosa
## 16            5.7         4.4          1.5         0.4     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
## 26            5.0         3.0          1.6         0.2     setosa
## 27            5.0         3.4          1.6         0.4     setosa
## 28            5.2         3.5          1.5         0.2     setosa
## 29            5.2         3.4          1.4         0.2     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
```

```
## 36          5.0         3.2          1.2         0.2     setosa
## 37          5.5         3.5          1.3         0.2     setosa
## 38          4.9         3.6          1.4         0.1     setosa
## 39          4.4         3.0          1.3         0.2     setosa
## 40          5.1         3.4          1.5         0.2     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
## 50          5.0         3.3          1.4         0.2     setosa
## 51          7.0         3.2          4.7         1.4 versicolor
## 52          6.4         3.2          4.5         1.5 versicolor
## 53          6.9         3.1          4.9         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
## 58          4.9         2.4          3.3         1.0 versicolor
## 59          6.6         2.9          4.6         1.3 versicolor
## 60          5.2         2.7          3.9         1.4 versicolor
## 61          5.0         2.0          3.5         1.0 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
## 66          6.7         3.1          4.4         1.4 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
## 72          6.1         2.8          4.0         1.3 versicolor
## 73          6.3         2.5          4.9         1.5 versicolor
## 74          6.1         2.8          4.7         1.2 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
## 81          5.5         2.4          3.8         1.1 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
```

```
## 86           6.0         3.4          4.5         1.6 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
## 90           5.5         2.5          4.0         1.3 versicolor
## 91           5.5         2.6          4.4         1.2 versicolor
## 92           6.1         3.0          4.6         1.4 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
## 100          5.7         2.8          4.1         1.3 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
## 111          6.5         3.2          5.1         2.0  virginica
## 112          6.4         2.7          5.3         1.9  virginica
## 113          6.8         3.0          5.5         2.1  virginica
## 114          5.7         2.5          5.0         2.0  virginica
## 115          5.8         2.8          5.1         2.4  virginica
## 116          6.4         3.2          5.3         2.3  virginica
## 117          6.5         3.0          5.5         1.8  virginica
## 118          7.7         3.8          6.7         2.2  virginica
## 119          7.7         2.6          6.9         2.3  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
## 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
## 131          7.4         2.8          6.1         1.9  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
## 135          6.1         2.6          5.6         1.4  virginica
```

```
## 136          7.7         3.0          6.1         2.3  virginica
## 137          6.3         3.4          5.6         2.4  virginica
## 138          6.4         3.1          5.5         1.8  virginica
## 139          6.0         3.0          4.8         1.8  virginica
## 140          6.9         3.1          5.4         2.1  virginica
## 141          6.7         3.1          5.6         2.4  virginica
## 142          6.9         3.1          5.1         2.3  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
## 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
```

```
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 ...
```

```
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
##
##
##
```

From the data, it can be seen that the observations are given in order of the sepcies.

To randomize the iris data set lets use the runif fucntion. It creates a uniform distribution of 150 nos. And we can use there order as a rank for our data set to mix it up.

```
set.seed(1234)

random <- runif(150)
iris_random <- iris[order(random),]
head(iris_random)
```

```
##     Sepal.Length Sepal.Width Petal.Length Petal.Width    Species
## 7            4.6         3.4          1.4         0.3     setosa
## 64           6.1         2.9          4.7         1.4 versicolor
## 73           6.3         2.5          4.9         1.5 versicolor
## 98           6.2         2.9          4.3         1.3 versicolor
## 101          6.3         3.3          6.0         2.5  virginica
## 110          7.2         3.6          6.1         2.5  virginica
```

The data set is randomized. Lets normalize the numerical variables of the data set. Normalizing the numerical values is really effective for algorithms, as it provide a measure from 0 to 1 which corresponds to min value to the max value of the data column.

We define a normal function which will normalize the set of values according to its minimum value and maximum value. Lets create a new data set iris_new applying the function.

```
normal <- function(x) (
  return( (x-min(x) / (max(x)-min(x))) )
)
normal(1:12)
```

```
##  [1]  0.9090909  1.9090909  2.9090909  3.9090909  4.9090909  5.9090909
##  [7]  6.9090909  7.9090909  8.9090909  9.9090909 10.9090909 11.9090909
```

```
iris_new <- as.data.frame(lapply(iris_random[,-5], normal))
summary(iris_new)
```

```
##   Sepal.Length    Sepal.Width     Petal.Length     Petal.Width
##  Min.   :3.106   Min.   :1.167   Min.   :0.8305   Min.   :0.05833
##  1st Qu.:3.906   1st Qu.:1.967   1st Qu.:1.4305   1st Qu.:0.25833
##  Median :4.606   Median :2.167   Median :4.1805   Median :1.25833
##  Mean   :4.649   Mean   :2.224   Mean   :3.5885   Mean   :1.15767
##  3rd Qu.:5.206   3rd Qu.:2.467   3rd Qu.:4.9305   3rd Qu.:1.75833
##  Max.   :6.706   Max.   :3.567   Max.   :6.7305   Max.   :2.45833
```

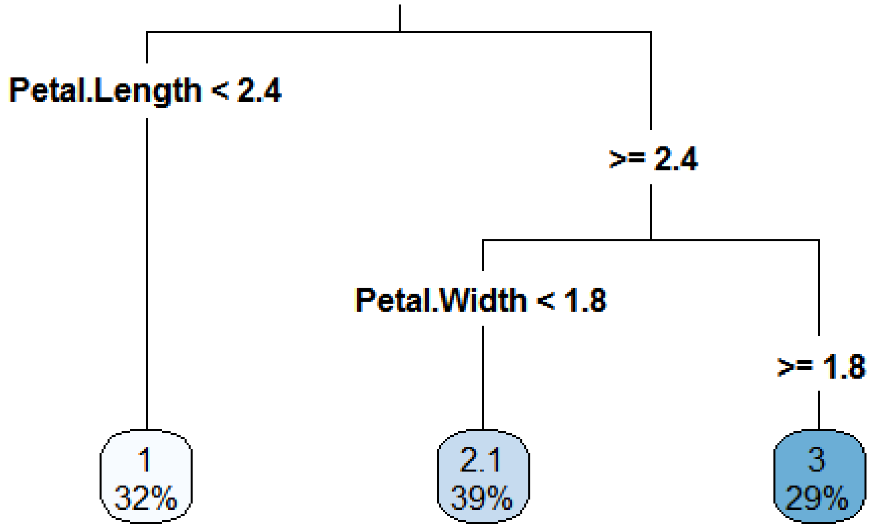
Lets create test and train data sets. Train data set is what we will build our model on. We will test our model on test data set Lets have 50 observation out of 150 for test and the rest as training data set. Lets create respective column of the observation's species to use in the model and check the accuracy of the test data.

```
train <- iris_new[1:100,]
test <- iris_new[101:150,]
train_sp <- iris_random[1:100,5]
test_sp <- iris_random[101:150,5]
```

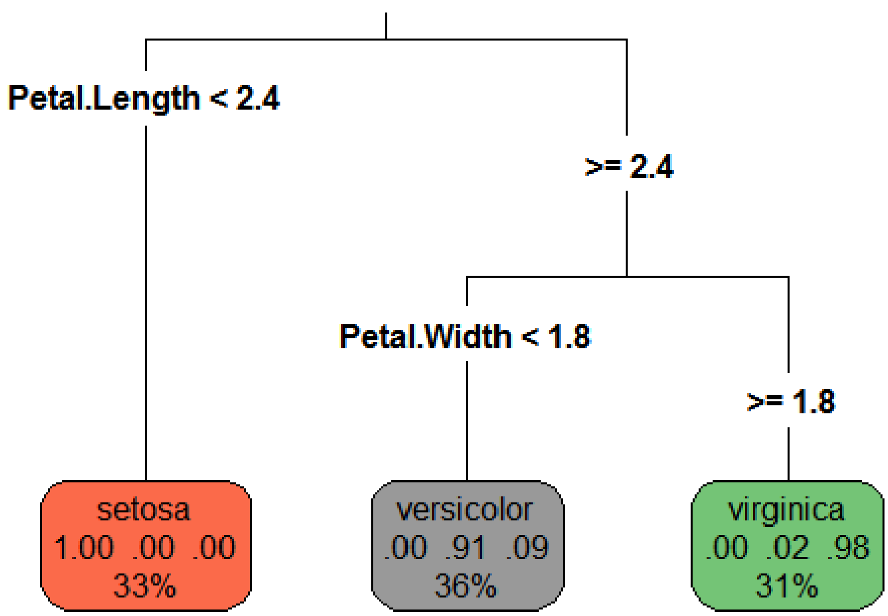
Now we can use K-NN algorithm. Lets call the "class" package which contains the K-NN algorithm. In k-NN algorithm, we have to provide 'k' value which is no of nearest neighbours(NN) to look for in order to classify it. In common we take an odd value, let's take it as square root of the observation. Lets build a model on it. cl is the class of the training data set and k is the no of neighbours to look for in order to classify it accordingly. I have included CART(from rpart library), C5.0 algorithms.

```
require(class)

## Loading required package: class

model_knn <- knn(train= train,test=test,cl= train_sp,k=13)

library(rpart)
library(rpart.plot)
model_dectree_anova <- rpart(iris_random[1:100,]$Species~ .,data =
iris_random[1:100,] ,method = "anova")
predict_anova <- predict(model_dectree_anova,test)

predict_anova[predict_anova < 1.5] <- "setosa"
predict_anova[predict_anova < 2.5 & predict_anova >=1.5] <- "versicolor"
predict_anova[predict_anova < 3.0 & predict_anova >=2.5] <- "virginica"


model_dectree_class <- rpart(iris_random$Species~ .,data = iris_random)
predict_class <- predict(model_dectree_class,test)
```

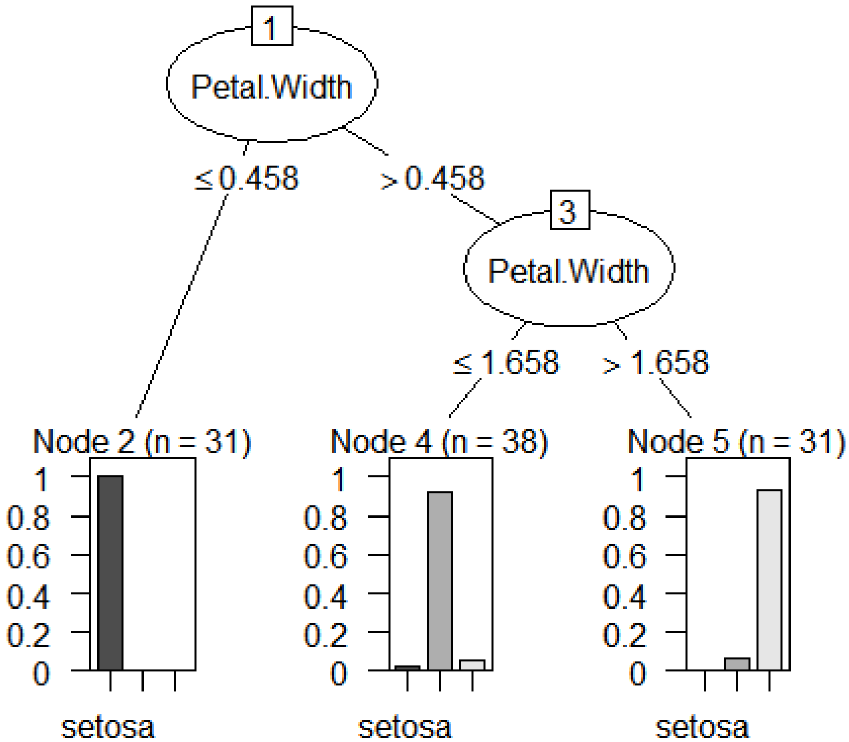
```r
rpart.plot(model_dectree_anova,type = 3)
```




```r
rpart.plot(model_dectree_class, type = 3)
```



```r
library(C50)

model_c50 <- C5.0(train,train_sp)
predict_c50 <- predict(model_c50,test)
plot(model_c50)
```

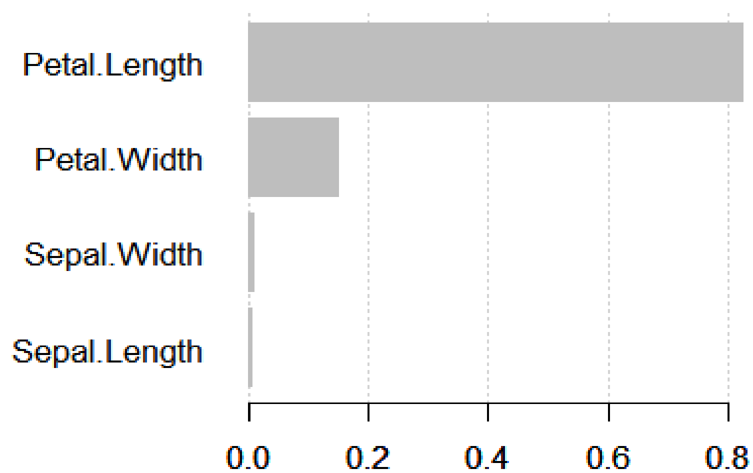


I know I should not use it at this scale. But then again!

```r
library(xgboost)
model_xgboost <- xgboost(
  data= data.matrix(train),
  label = as.factor(train_sp),
  nrounds = 15,
  objective= "reg:linear"
)



## [1]  train-rmse:1.204551
## [2]  train-rmse:0.862699
## [3]  train-rmse:0.622392
## [4]  train-rmse:0.454554
## [5]  train-rmse:0.340005
## [6]  train-rmse:0.256243
## [7]  train-rmse:0.194087
## [8]  train-rmse:0.148642
## [9]  train-rmse:0.122280
## [10] train-rmse:0.097089
```

```
## [11] train-rmse:0.078371
## [12] train-rmse:0.064456
## [13] train-rmse:0.053747
## [14] train-rmse:0.043997
## [15] train-rmse:0.036353
```

```
names <- dimnames(data.matrix(train))[[2]]
importance_matrix <- xgb.importance(names, model = model_xgboost)
xgb.plot.importance(importance_matrix[1:4,])
```




```
pred_test <- predict(model_xgboost,data.matrix(test))

predict_xgb <- NULL
predict_xgb[pred_test <=1.5] <- "setosa"
predict_xgb[pred_test > 1.5 & pred_test < 2.5 ] <- "versicolor"
predict_xgb[pred_test > 2.5] <- "virginica"
```

Lets have a look at the confusion matrix from each model. Although we have very small no of observations. Powerful algorithms like xgboost work really well for very large dataset and so are the other algorithms.

```
table(model_knn,test_sp)

##             test_sp
## model_knn    setosa versicolor virginica
##   setosa         18          0         0
##   versicolor      0         13         2
##   virginica       0          0        17
```

```r
table(predict_anova,test_sp)
```

```
##                test_sp
## predict_anova setosa versicolor virginica
##    setosa         18          0         0
##    versicolor      0         13         2
##    virginica       0          0        17
```

```r
table(predict_c50,test_sp)
```

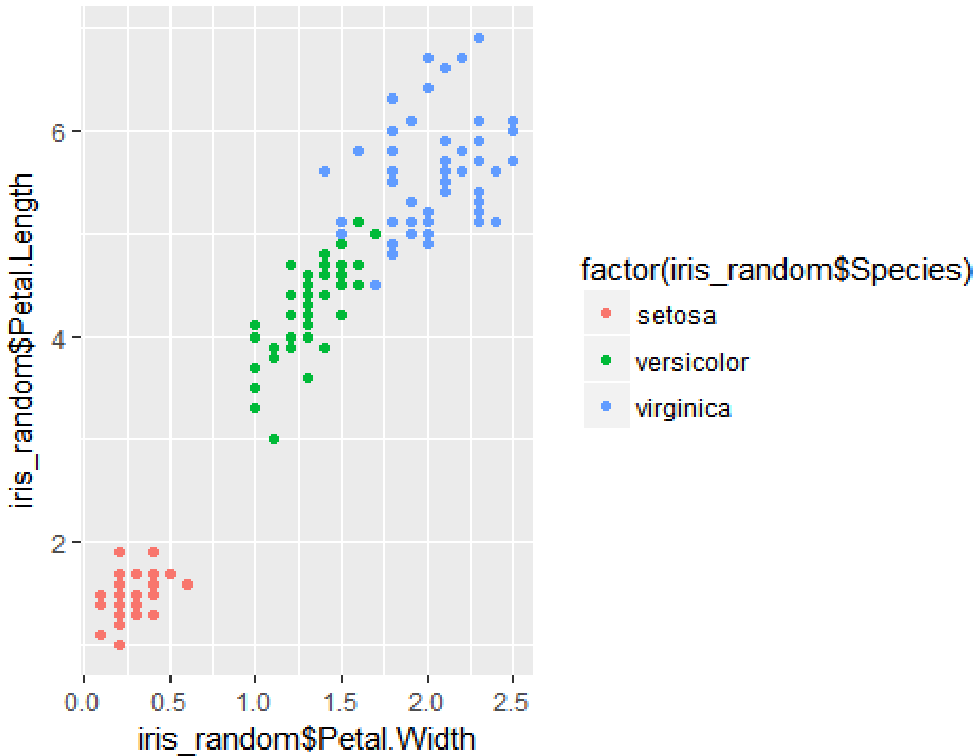
```
##               test_sp
## predict_c50  setosa versicolor virginica
##   setosa         17          0         0
##   versicolor      1         13         2
##   virginica       0          0        17
```

```r
table(predict_xgb,test_sp)
```

```
##               test_sp
## predict_xgb  setosa versicolor virginica
##   setosa         18          0         0
##   versicolor      0         13         2
##   virginica       0          0        17
```

The table(test_sp, model) matrix is also called confusion matrix. It has test_sp on one axis and model prediction on the other. The diagonal elements are the no of correctly predicted observations for that species. We can see how the model performed. It predicted all the species correctly.

```r
library(ggplot2)
ggplot(aes(iris_random$Petal.Width,iris_random$Petal.Length), data =
iris_random)+ geom_point(aes(color= factor(iris_random$Species)))
```



From the above graph and the decision trees, we can see that how model considered petal width and petal length as most important factor to classify the species. 3 virginica samples are lying in versicolor samples. And that is where the algorithms are most probably making wrong choices.