

18BCE080_PRAC9

Ishan Tewari

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Loading iris dataset

```
library(datasets)
data(iris)
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
##
##
##
```

Loading necessary libraries for decision tree classifier

```
library(rpart)
library(rpart.plot)
```

```
v = iris['Species']
```

```
table(v)
```

```
## v
##      setosa versicolor  virginica
##      50         50         50
```

```
set.seed(522)
```

```
# runif function returns a uniform distribution which can be further conditionally split into 75-25 ratio
iris[, 'train'] = ifelse(runif(nrow(iris)) < 0.75, 1, 0)
```

```
# Dividing the data into training and testing set
```

```
trainSet = iris[iris['train'] == 1,]
```

```
testSet = iris[iris['train'] == 0, ]
```

```
trainColNum = grep('train', names(trainSet))
```

```
trainSet = trainSet[, -trainColNum]
```

```
testSet = testSet[, -trainColNum]
```

```
print(trainSet)
```

```
##      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
## 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
## 9           4.4         2.9         1.4         0.2     setosa
## 10          4.9         3.1         1.5         0.1     setosa
## 12          4.8         3.4         1.6         0.2     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
```

## 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
## 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
## 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
## 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
## 36	5.0	3.2	1.2	0.2	setosa
## 38	4.9	3.6	1.4	0.1	setosa
## 39	4.4	3.0	1.3	0.2	setosa
## 42	4.5	2.3	1.3	0.3	setosa
## 43	4.4	3.2	1.3	0.2	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
## 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
## 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
## 63	6.0	2.2	4.0	1.0	versicolor
## 64	6.1	2.9	4.7	1.4	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
## 70	5.6	2.5	3.9	1.1 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
## 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
## 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
## 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
## 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
## 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
## 108	7.3	2.9	6.3	1.8 virginica
## 110	7.2	3.6	6.1	2.5 virginica
## 111	6.5	3.2	5.1	2.0 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
## 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
## 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
## 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
## 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
## 135      6.1      2.6      5.6      1.4 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
## 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
## 150      5.9      3.0      5.1      1.8 virginica
```

```
print(testSet)
```

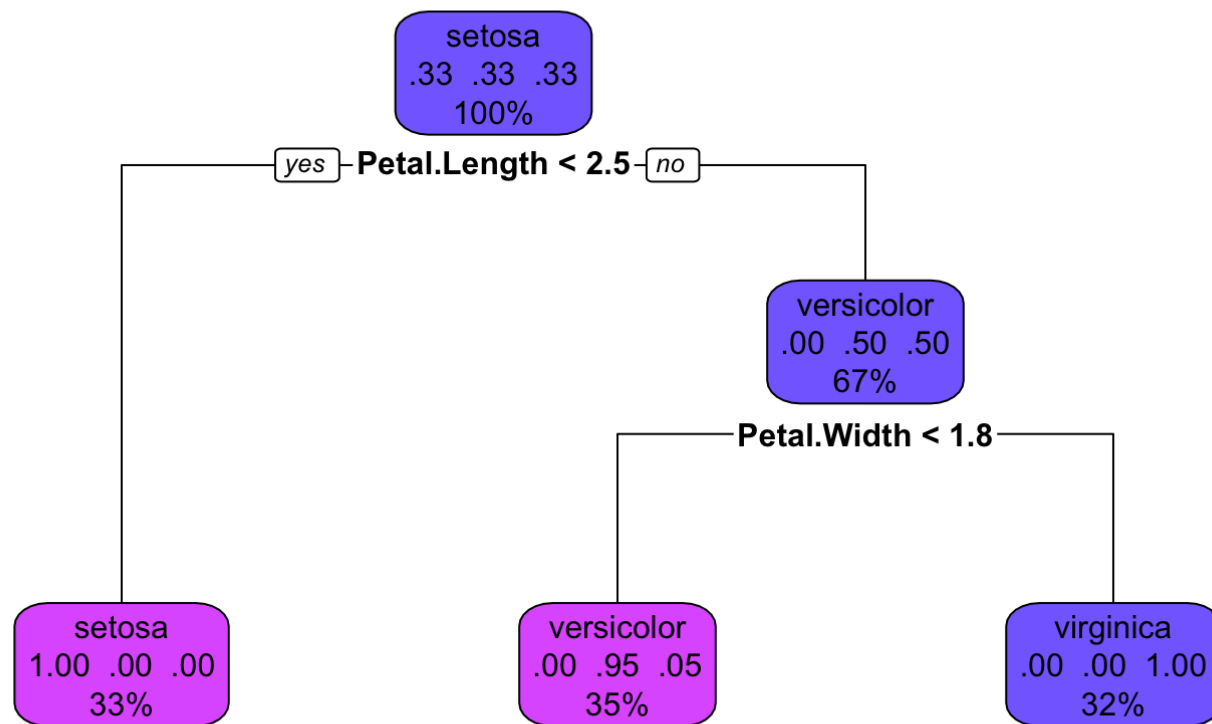
```
##      Sepal.Length Sepal.Width Petal.Length Petal.Width  Species
## 3           4.7           3.2           1.3           0.2    setosa
## 8           5.0           3.4           1.5           0.2    setosa
## 11          5.4           3.7           1.5           0.2    setosa
## 13          4.8           3.0           1.4           0.1    setosa
## 17          5.4           3.9           1.3           0.4    setosa
## 23          4.6           3.6           1.0           0.2    setosa
## 26          5.0           3.0           1.6           0.2    setosa
```

## 31	4.8	3.1	1.6	0.2	setosa
## 35	4.9	3.1	1.5	0.2	setosa
## 37	5.5	3.5	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
## 44	5.0	3.5	1.6	0.6	setosa
## 51	7.0	3.2	4.7	1.4	versicolor
## 55	6.5	2.8	4.6	1.5	versicolor
## 61	5.0	2.0	3.5	1.0	versicolor
## 62	5.9	3.0	4.2	1.5	versicolor
## 65	5.6	2.9	3.6	1.3	versicolor
## 69	6.2	2.2	4.5	1.5	versicolor
## 71	5.9	3.2	4.8	1.8	versicolor
## 75	6.4	2.9	4.3	1.3	versicolor
## 83	5.8	2.7	3.9	1.2	versicolor
## 92	6.1	3.0	4.6	1.4	versicolor
## 93	5.8	2.6	4.0	1.2	versicolor
## 97	5.7	2.9	4.2	1.3	versicolor
## 100	5.7	2.8	4.1	1.3	versicolor
## 103	7.1	3.0	5.9	2.1	virginica
## 107	4.9	2.5	4.5	1.7	virginica
## 109	6.7	2.5	5.8	1.8	virginica
## 112	6.4	2.7	5.3	1.9	virginica
## 116	6.4	3.2	5.3	2.3	virginica
## 120	6.0	2.2	5.0	1.5	virginica
## 125	6.7	3.3	5.7	2.1	virginica
## 129	6.4	2.8	5.6	2.1	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
## 145	6.7	3.3	5.7	2.5	virginica
## 149	6.2	3.4	5.4	2.3	virginica

```
treeFit = rpart(Species~.,data=trainSet,method = 'class')
print(treeFit)
```

```
## n= 111
##
## node), split, n, loss, yval, (yprob)
##      * denotes terminal node
##
## 1) root 111 74 setosa (0.33333333 0.33333333 0.33333333)
##   2) Petal.Length< 2.45 37  0 setosa (1.00000000 0.00000000 0.00000000) *
##   3) Petal.Length>=2.45 74 37 versicolor (0.00000000 0.50000000 0.50000000)
##     6) Petal.Width< 1.75 39  2 versicolor (0.00000000 0.94871795 0.05128205) *
##     7) Petal.Width>=1.75 35  0 virginica (0.00000000 0.00000000 1.00000000) *
```

```
rpart.plot(treeFit, box.col=c("lightslateblue", "mediumorchid1"))
```



```
Prediction1 = predict(treeFit,newdata=testSet[-5],type = 'class')
```

```
print(Prediction1)
```

```
##      3      8      11      13      17      23      26
##   setosa  setosa  setosa  setosa  setosa  setosa  setosa
##    31    35    37    40    41    44    51
##   setosa  setosa  setosa  setosa  setosa  setosa  versicolor
```



```
##          55          61          62          65          69          71          75
## versicolor versicolor versicolor versicolor versicolor virginica versicolor
##          83          92          93          97          100          103          107
## versicolor versicolor versicolor versicolor versicolor virginica versicolor
##          109          112          116          120          125          129          133
## virginica virginica virginica versicolor virginica virginica virginica
##          134          136          145          149
## versicolor virginica virginica virginica
## Levels: setosa versicolor virginica
```

```
library(caret)
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
confusionMatrix(Prediction1,testSet$Species)
```

```
## Confusion Matrix and Statistics
##
##              Reference
## Prediction  setosa versicolor virginica
## setosa      13          0          0
## versicolor   0          12         3
## virginica    0           1        10
##
## Overall Statistics
##
##              Accuracy : 0.8974
##              95% CI : (0.7578, 0.9713)
## No Information Rate : 0.3333
## P-Value [Acc > NIR] : 3.435e-13
##
##              Kappa : 0.8462
```

```
##
## McNemar's Test P-Value : NA
##
## Statistics by Class:
##
##          Class: setosa Class: versicolor Class: virginica
## Sensitivity          1.0000          0.9231          0.7692
## Specificity          1.0000          0.8846          0.9615
## Pos Pred Value       1.0000          0.8000          0.9091
## Neg Pred Value       1.0000          0.9583          0.8929
## Prevalence           0.3333          0.3333          0.3333
## Detection Rate       0.3333          0.3077          0.2564
## Detection Prevalence 0.3333          0.3846          0.2821
## Balanced Accuracy     1.0000          0.9038          0.8654
```