Machine Learning

Ravi Kumar Tiwari 14 June 2016

```
library(caret)
library(rpart.plot)
library(rattle)
library(calibrate)
library(randomForest)
library(e1071)
library(class)
library(knitr)
library(party)
```

Decision Tree Example

Problem Description

Given a data set that contains some observation and corresponding class label, can a machine learning algorithm be trained to determine the class label of any data set (not necessarily the data that was used for training) from its observation

Solution using decision tree

```
head(iris)
```

```
Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##
## 1
             5.1
                        3.5
                                     1.4
## 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
                                                0.4 setosa
             5.4
                        3.9
                                     1.7
```

Create data partition

```
set.seed(100)
inTrain <- createDataPartition(iris$Species, p = 0.6, list = FALSE)
trainData <- iris[inTrain,]
testData <- iris[-inTrain,]</pre>
```

Build a decision tree model and use it for prediction on test data set

```
treeModel <- train(Species ~ ., data = trainData, method = "rpart")
preClass <- predict(treeModel, newdata = testData)
cMatrix <- confusionMatrix(preClass, testData$Species)
cMatrix$table</pre>
```

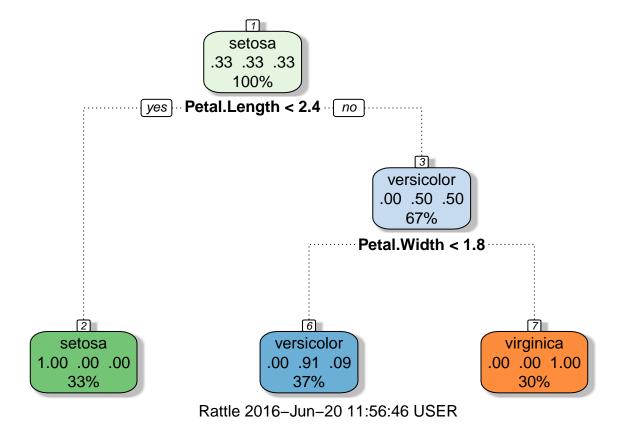
```
Reference
##
## Prediction setosa versicolor virginica
                    20
##
     setosa
                                 0
##
     versicolor
                     0
                                19
                                           2
                     0
                                 1
                                          18
##
     virginica
```

Look at what are the important variables

varImp(treeModel)

```
## rpart variable importance
##
## Overall
## Petal.Width 100.00
## Petal.Length 89.53
## Sepal.Length 18.24
## Sepal.Width 0.00
```

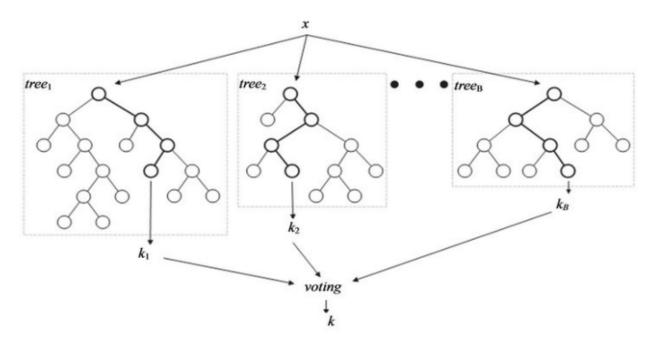
Visualization of the decision tree





random Forest

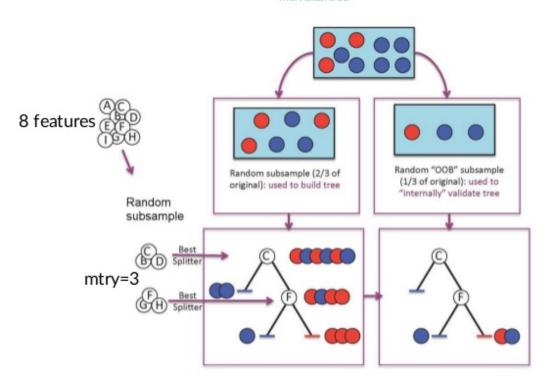
ntree



Random Forest classifier

16

Individual tree



random forest example

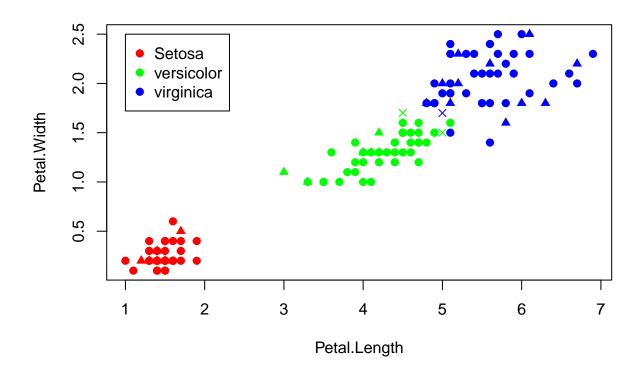
```
set.seed(100)
inTrain <- createDataPartition(iris[,5], p = 0.6, list=FALSE)
trainData <- iris[inTrain,]
testData <- iris[-inTrain, 1:4]
testClass <- iris[-inTrain, 5]

rfModel <- randomForest(Species ~ ., data=iris, mtry=3, ntree=10)
predClass <- predict(rfModel, newdata = testData)
table(predClass, testClass)</pre>
```

```
testClass
##
## predClass
                 setosa versicolor virginica
                    20
##
     setosa
                                 0
                                            0
##
     versicolor
                      0
                                20
##
     virginica
                      0
                                 0
                                           20
```

knn2

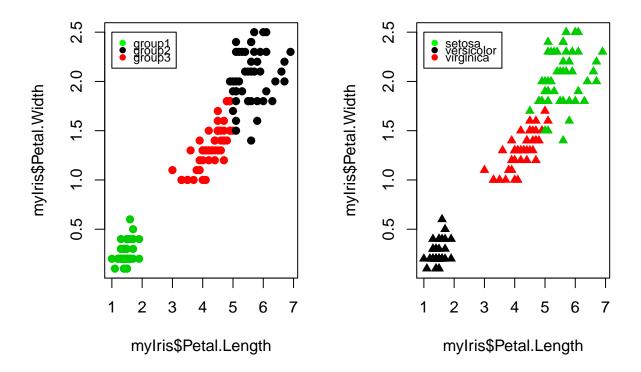
```
myIris <- iris[,3:5]</pre>
head(myIris)
     Petal.Length Petal.Width Species
##
## 1
               1.4
                           0.2 setosa
## 2
               1.4
                           0.2 setosa
## 3
               1.3
                           0.2 setosa
## 4
               1.5
                           0.2 setosa
## 5
               1.4
                           0.2 setosa
## 6
               1.7
                           0.4 setosa
nI <- nrow(myIris)</pre>
ind <- sample(1:nI, 0.8*nI)</pre>
trainData <- myIris[ind, 1:2]</pre>
trainClass <- myIris[ind, 3]</pre>
testData <- myIris[-ind, 1:2]</pre>
testClass <- myIris[-ind, 3]</pre>
preClass <- knn(trainData, testData, cl = trainClass, k = 2)</pre>
table(preClass, testClass)
##
                testClass
                 setosa versicolor virginica
## preClass
##
     setosa
                      9
                                  0
                      0
                                  7
                                            2
##
     versicolor
     virginica
                      0
                                  1
                                           11
color <- ifelse(trainClass=="setosa", "red", ifelse(trainClass=="versicolor", "green",</pre>
                 "blue"))
plot(trainData$Petal.Length, trainData$Petal.Width, pch = 19, col = color,
     xlab = "Petal.Length", ylab = "Petal.Width")
legend(x = 1, y = 2.5, legend = c("Setosa", "versicolor", "virginica"),
       col = c("red", "green", "blue"), pch = 19)
color <- ifelse(preClass=="setosa", "red", ifelse(preClass=="versicolor", "green",</pre>
                 "blue"))
pType = ifelse(preClass == testClass, 17, 4)
points(testData$Petal.Length, testData$Petal.Width, pch = pType, col = color)
```



clustering example

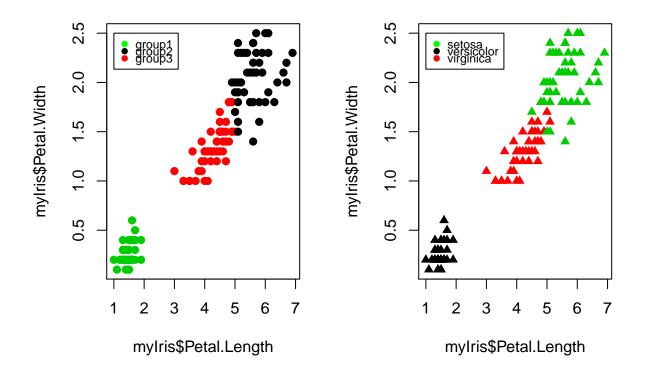
kmeans clustering

```
myIris <- iris[3:4]</pre>
group <- iris$Species</pre>
predGroup <- kmeans(myIris, centers = 3)</pre>
predGroupC <- ifelse(predGroup$cluster==2, "setosa", ifelse(predGroup$cluster==3,</pre>
                                                    "versicolor", "virginnica"))
predGroupC <- factor(predGroupC)</pre>
table(predGroupC, group)
##
               group
## predGroupC setosa versicolor virginica
##
     setosa
                   0
                               2
##
     versicolor
                     0
                               48
                                           6
                                0
##
     virginnica
                    50
par(mfrow = c(1,2))
plot(myIris$Petal.Length, myIris$Petal.Width, pch = 19, col = predGroupC)
legend(x=1,y=2.5, legend = c("group1", "group2", "group3"),
       col = c("green", "black", "red"), pch = 19, y.intersp=0.5, cex = 0.75)
plot(myIris$Petal.Length, myIris$Petal.Width, pch = 17, col = group)
legend(x=1,y=2.5, legend = c("setosa", "versicolor", "virginica"),
       col = c("green", "black", "red"), pch = 19, y.intersp=0.5, cex = 0.75)
```



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

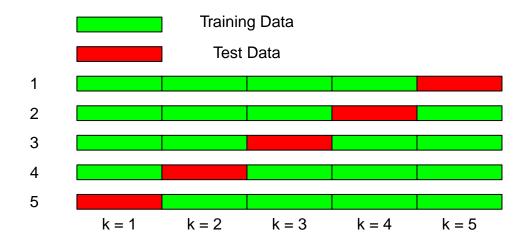
hierarchichal clustering



par(mfrow = c(1,1))

Cross-validation

5 fold cross validation illustration



```
#rfModel <- randomForest(Species ~ . , data = trainData, ntree = 3)</pre>
```

knn

```
head(trees)
    Girth Height Volume
## 1 8.3
             70 10.3
## 2 8.6
              65
                  10.3
## 3 8.8
              63 10.2
## 4 10.5
              72 16.4
## 5 10.7
              81 18.8
## 6 10.8
              83 19.7
set.seed(100)
index <- sample(nrow(iris), 0.6*nrow(iris))</pre>
p <- knn(iris[index, 1:4], iris[-index, 1:4], iris[index, 5], 1)</pre>
#data.frame(iris[-index, 5], p)
table(iris[-index, 5], p)
##
##
               setosa versicolor virginica
##
                  24
     setosa
                               0
    versicolor
                    0
                              16
                                         1
                    0
                               3
                                        16
##
     virginica
## show cross validation
## show parameter selection
## show visualization
knn2
```

```
head(trees)
    Girth Height Volume
##
## 1 8.3
           70 10.3
## 2 8.6
              65
                  10.3
## 3 8.8
              63 10.2
## 4 10.5
              72 16.4
## 5 10.7
              81 18.8
## 6 10.8
              83 19.7
set.seed(100)
index <- sample(nrow(trees), 0.6*nrow(trees))</pre>
p \leftarrow knn(trees[index, 1:2], trees[-index, 1:2], iris[index, 3], 4)
#data.frame(trees[-index, 3], p)
```

baye's theorem

#head(Titanic)

 \mathbf{svm}

#svmModel <- svm()