Supervised learning: Classification

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Machine learning: Supervised learning.

Currently, lots of people talk about machine learning and its applications. People consider that the success of companies rests in the opportunity of applying ML techniques in your business. In this way, it is important having some knowledge about these techniques and more importantly how to use these techniques.

The idea of this project is to show some of the techniques available in machine learning, and we are going to start with one of the big branches: supervised learning methodologies. Supervised learning scenario occurs when "a set of variables that might be denoted as inputs have some influence on one or more outputs" (Hastie, Tibshirani, and Friedman, 2009). The purpose of supervised learning is to use the inputs to predict the values of the outputs.

On the other hand, depending on the characteristic of the output, we have different problems. If the output is a quantitative variable, we have a **regression problem**. In case that the output is qualitative, we have a **classification problem**. However, in the case of some qualitative outcomes with two classes, we can use regression techniques into classification problems.

Classification

The focus of the section is to consider the classification problem, then compare some techniques in one simple exercise and finally to use a cross-validation method for estimating the prediction error. All these steps are made in R program using the following libraries:

```r
library(tidyverse)    #ggplot
library(kknn)         #kknn
library(e1071)        #svm
library(rpart)        #tree
library(randomForest) #RF
library(ada)          #Boost
library(caret)        #CV
```

Using the "purchased bikes" file (see https://github.com/cconejov/purchased_Bike/tree/master/Data), this table contains 11 predictable variables and the binary class as output PurchasedBike. It indicates if a customer bought or not a bicycle.

```r
purchased_bike <- read.table("purchasedBikes.csv",
                             header = TRUE,
                             sep = ";",
                             dec = ",",
                             row.names = 1)
```

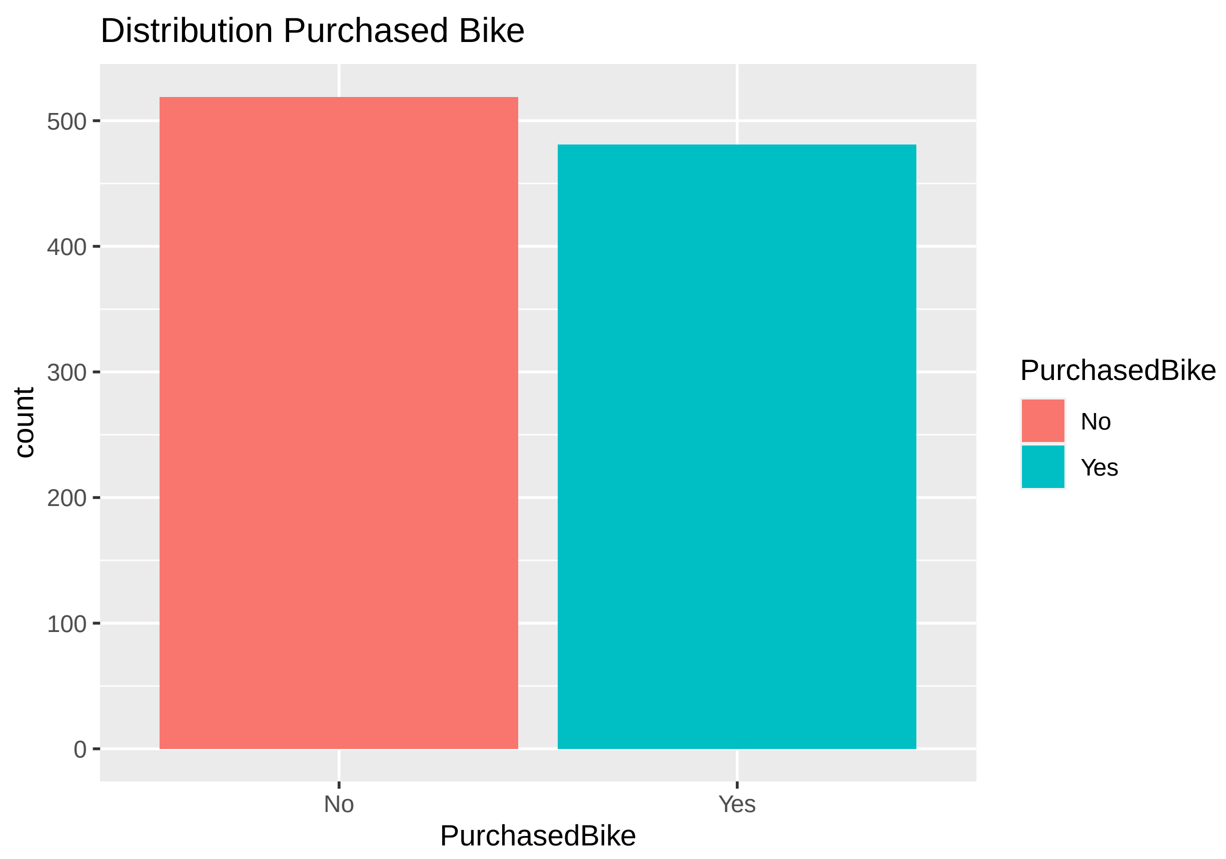
A summary of the data can be seen with this instruction:

```r
summary(purchased_bike)
```

```
##  MaritalStatus    Gender         Income          Children    
##  Married:539   Female:491   Min.   : 10000   Min.   :0.000  
##  Single :461   Male  :509   1st Qu.: 30000   1st Qu.:0.000  
##                             Median : 60000   Median :2.000  
##                             Mean   : 56140   Mean   :1.908  
##                             3rd Qu.: 70000   3rd Qu.:3.000  
##                             Max.   :170000   Max.   :5.000  
##               Education           Occupation  HomeOwner      Cars      
##  Bachelors        :306   Clerical      :177   No :315   Min.   :0.000  
##  GraduateDegree   :174   Management    :173   Yes:685   1st Qu.:1.000  
##  HighSchool       :179   Manual        :119             Median :1.000  
##  PartialCollege   :265   Professional  :276             Mean   :1.452  
##  PartialHighSchool: 76   SkilledManual:255             3rd Qu.:2.000  
##                                                         Max.   :4.000  
##   CommuteDistance          Region          Age        PurchasedBike
##  0-1Miles :366    Europe      :300   Min.   :25.00   No :519      
##  1-2Miles :169    NorthAmerica:508   1st Qu.:35.00   Yes:481      
##  10+Miles :111    Pacific     :192   Median :43.00                
##  2-5Miles :162                       Mean   :44.19                
##  5-10Miles:192                       3rd Qu.:52.00                
##                                      Max.   :89.00                
```

Because the purpose of this exercise is to compare the performance of some techniques, we can see that the outcome variable *PurchasedBike* is well balanced (48% of the observations in the data set corresponding to Yes value).

```r
ggplot(data = purchased_bike) +
  geom_bar(aes( x = PurchasedBike, fill = PurchasedBike)) +
    labs(title = "Distribution Purchased Bike")
```



The goal of this exercise is to compare several classification techniques with this example table. Here, the purpose is to predict Yes value in the PurchasedBike using ten cross-validations with 5 groups with the methods:

- Support Vector Machine
- KNN
- Bayes
- Decision tree
- Random Forest
- Boosting methods (AdaBoost)

Furthermore, the two metrics that we are going to use for determining how good our model is are:

- How many "yes" purchase bike variable the model detects. High values are best.
- Minimum average global error, calculated as 1 - accuracy, where accuracy is calculated as the number of correct predictions divided by the number of total predictions. Low values are best.

For determining the number of "yes" in the *PurchasedBike* and the average global error, we do the following code:

```r
#Number of observation
n <- dim(purchased_bike)[1]

#SVM
yes_detect_svm   <- rep(0,10)
error_detect_svm <- rep(0,10)

#KNN
yes_detect_knn   <- rep(0,10)
```

```r
error_detect_knn <- rep(0,10)

#Bayes
yes_detect_bayes   <- rep(0,10)
error_detect_bayes <- rep(0,10)

#trees
yes_detect_tree   <- rep(0,10)
error_detect_tree <- rep(0,10)

#RFs
yes_detect_RF   <- rep(0,10)
error_detect_RF <- rep(0,10)

#boosting
yes_detect_boosting   <- rep(0,10)
error_detect_boosting <- rep(0,10)

# cross validation 10 times
for(i in 1:10) {  #10
  groups <- createFolds(1:n,5) #5 groups

  #SVM
  yes_svm   <- 0
  error_svm <- 0

  #KNN
  yes_knn   <- 0
  error_knn <- 0

  #Bayes
  yes_bayes   <- 0
  error_bayes <- 0

  #trees
  yes_tree   <- 0
  error_tree <- 0

  #RFs
  yes_RF   <- 0
  error_RF <- 0

  #boosting
  yes_boosting   <- 0
  error_boosting <- 0

  # This for does "cross-validation"  with 5 groups (Folds)
  for(k in 1:5) {   #5

    training  <- groups[[k]]              #list
    ttesting  <- purchased_bike[training,]
    tlearning <- purchased_bike[-training,]
```

```
#SVM
model      <- svm(PurchasedBike~., data = tlearning, kernel ="radial")
prediction <- predict(model, ttesting)
Actual     <- ttesting[, 12]
MC         <- table(Actual, prediction)

# "Yes" purchase detection
yes_svm <- yes_svm + MC[2,2]
# Error detection
error_svm <- error_svm + (1 - (sum(diag(MC)))/sum(MC))*100

#KNN
model      <- train.kknn(PurchasedBike~., data = tlearning, kmax = 7)
prediction <- predict(model,ttesting[, -12])
Actual     <- ttesting[, 12]
MC         <- table(Actual, prediction)

# "Yes" purchase detection
yes_knn <- yes_knn + MC[2,2]
# Error detection
error_knn <- error_knn + (1 - (sum(diag(MC)))/sum(MC))*100

#Bayes
model      <- naiveBayes(PurchasedBike~., data = tlearning)
prediction <- predict(model, ttesting[,-12])
Actual     <- ttesting[,12]
MC         <- table(Actual, prediction)

# "Yes" purchase detection
yes_bayes <- yes_bayes + MC[2,2]
# Error detection
error_bayes <- error_bayes + (1 - (sum(diag(MC)))/sum(MC))*100

#trees
model      <- rpart(PurchasedBike~. ,data = tlearning)
prediction <- predict(model, ttesting, type='class')
Actual     <- ttesting[, 12]
MC         <- table(Actual, prediction)

# "Yes" purchase detection
yes_tree <- yes_tree + MC[2,2]
# Error detection
error_tree <- error_tree + (1 - (sum(diag(MC)))/sum(MC))*100

#RFs
model      <- randomForest(PurchasedBike~., data = tlearning, importance=TRUE)
prediction <- predict(model, ttesting[, -12])
Actual     <- ttesting[, 12]
MC         <- table(Actual, prediction)

# "Yes" purchase detection
yes_RF <- yes_RF + MC[2,2]
# Error detection
```

```
    error_RF <- error_RF + (1 - (sum(diag(MC)))/sum(MC))*100

    #boosting
    model      <- ada(PurchasedBike~., data = tlearning, iter=20, nu = 1, type = "discrete")
    prediction <- predict(model, ttesting[, -12])
    Actual     <- ttesting[, 12]
    MC         <- table(Actual, prediction)

    # "Yes" purchase detection
    yes_boosting <- yes_boosting + MC[2,2]
    # Error detection
    error_boosting <- error_boosting + (1-(sum(diag(MC)))/sum(MC))*100

  }

  #SVM
  yes_detect_svm[i]   <- yes_svm
  error_detect_svm[i] <- error_svm/5

  #KNN
  yes_detect_knn[i]   <- yes_knn
  error_detect_knn[i] <- error_knn/5

  #Bayes
  yes_detect_bayes[i]   <- yes_bayes
  error_detect_bayes[i] <- error_bayes/5

  #trees
  yes_detect_tree[i]   <- yes_tree
  error_detect_tree[i] <- error_tree/5

  #RF
  yes_detect_RF[i]   <- yes_RF
  error_detect_RF[i] <- error_RF/5

  #boosting
  yes_detect_boosting[i]   <- yes_boosting
  error_detect_boosting[i] <- error_boosting/5
}
```

Finally, we create three auxiliary tables for showing the results:

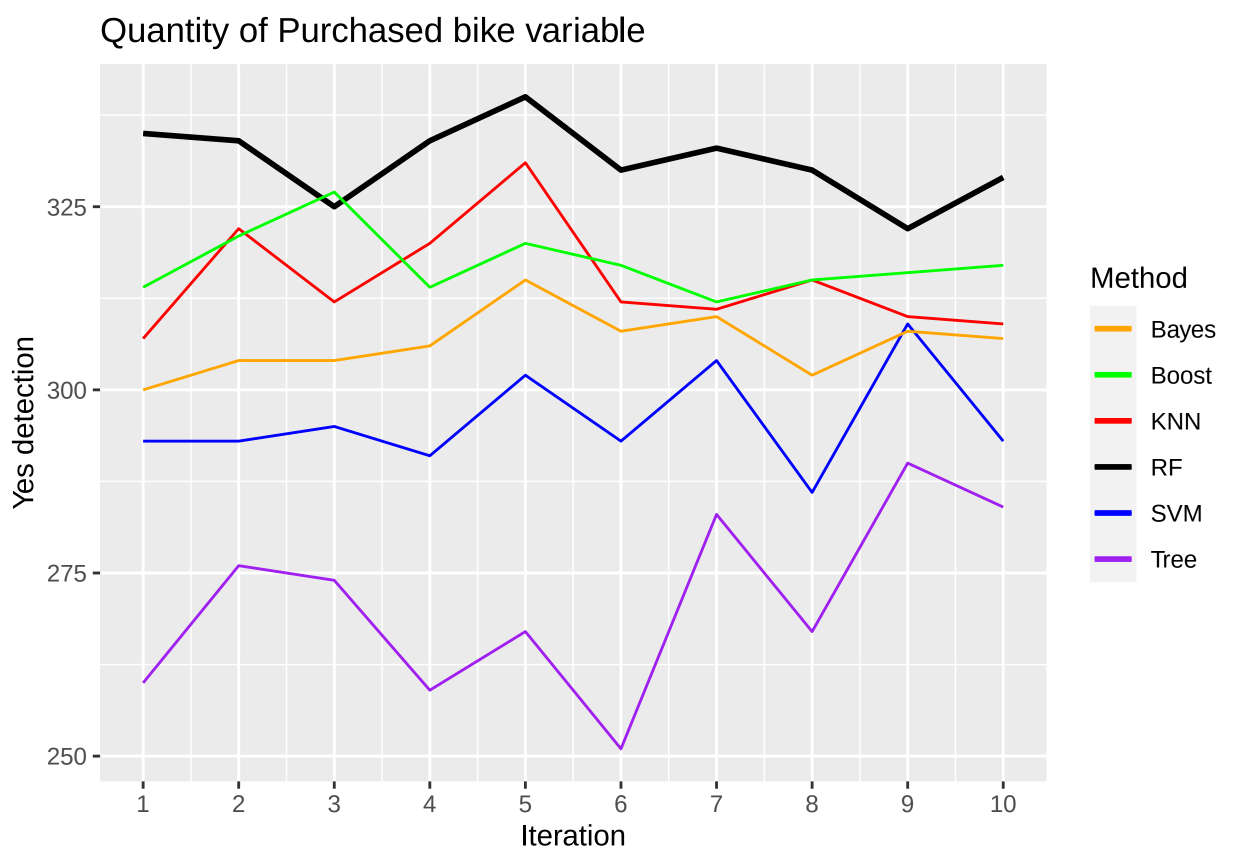
```
colors <- c("SVM"      = "blue",
            "KNN"      = "red",
            "Bayes"    =  "orange",
            "Tree"     = "purple",
            "RF"       = "black",
            "Boost" = "green"
)

detect <- tibble(Iteration = seq(1,10),
                 SVM = yes_detect_svm,
                 KNN = yes_detect_knn,
                 Bayes = yes_detect_bayes,
                 Tree = yes_detect_tree,
                 RF   = yes_detect_RF,
                 Boost = yes_detect_boosting)

global_error <- tibble(Iteration = seq(1,10),
                 SVM = error_detect_svm,
                 KNN = error_detect_knn,
                 Bayes = error_detect_bayes,
                 Tree = error_detect_tree,
                 RF   = error_detect_RF,
                 Boost = error_detect_boosting)
```

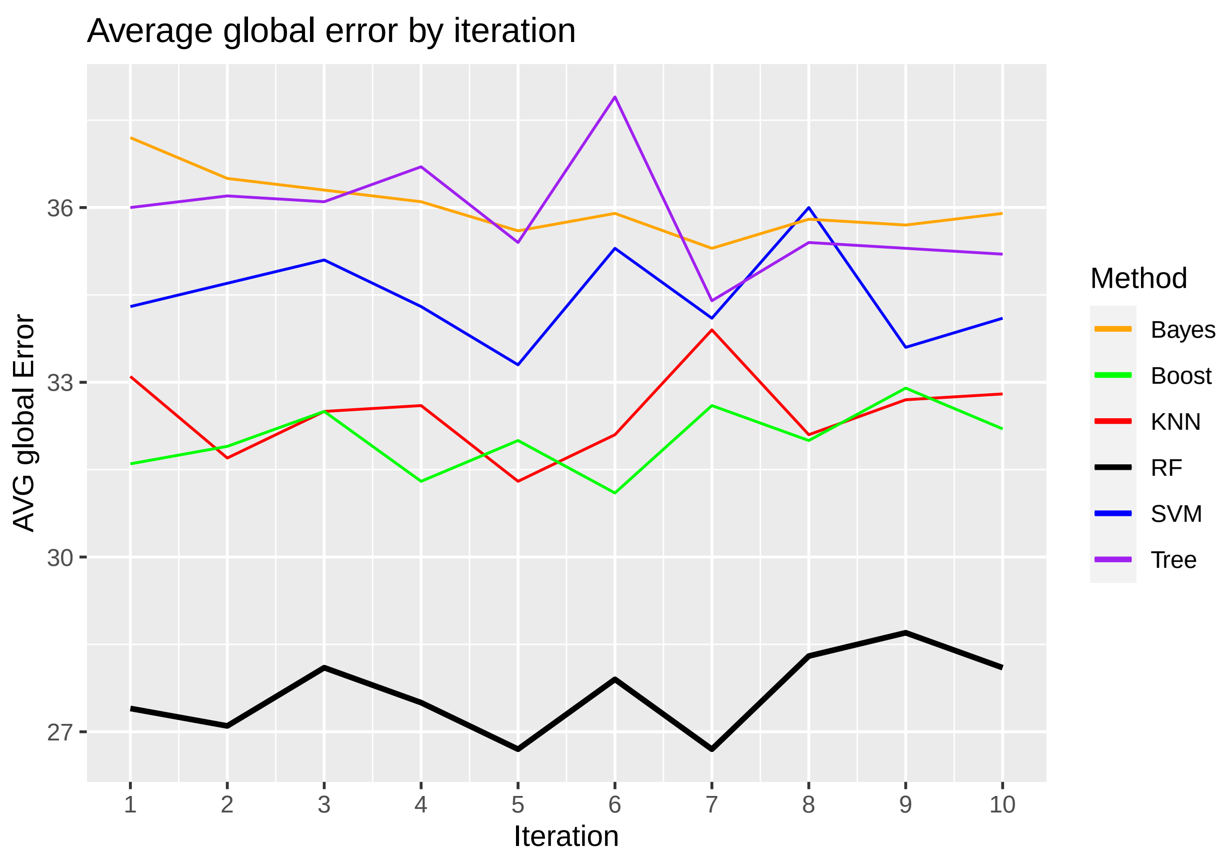
The plot with the yes value detection shows us that the metho random forest has on average the best capacity for detecting the positive cases of bikes purchased.

```
ggplot(data = detect, aes(x = Iteration) ) +
  geom_line(aes( y = SVM, color = "SVM") ) +
  geom_line(aes( y = KNN, color = "KNN")) +
  geom_line(aes( y = Bayes, color = "Bayes")) +
  geom_line(aes( y = Tree, color = "Tree")) +
  geom_line(aes( y = RF, color = "RF"), size = 1) +
  geom_line(aes( y = Boost, color = "Boost")) +
  scale_x_continuous(breaks=c(1:10), labels=c(1:10),limits=c(1,10)) +
  labs(x = "Iteration",
       y = "Yes detection",
       color = "Method",
       title = "Quantity of Purchased bike variable"
       ) +
  scale_color_manual(values = colors)
```



Besides, Random forest also has the lest average global error, so this method also classifies very well the negative case of bike did not purchase.

```r
ggplot(data = global_error, aes(x = Iteration) ) +
  geom_line(aes( y = SVM, color = "SVM") ) +
  geom_line(aes( y = KNN, color = "KNN")) +
  geom_line(aes( y = Bayes, color = "Bayes")) +
  geom_line(aes( y = Tree, color = "Tree")) +
  geom_line(aes( y = RF, color = "RF"), size = 1) +
  geom_line(aes( y = Boost, color = "Boost")) +
  scale_x_continuous(breaks=c(1:10), labels=c(1:10),limits=c(1,10)) +
  labs(x = "Iteration",
       y = "AVG global Error",
       color = "Method",
       title = "Average global error by iteration"
  ) +
  scale_color_manual(values = colors)
```



Average global error by iteration
AVG global Error
36
33
30
27
1
2
3
4
5
6
7
8
9
10
Iteration
Method
Bayes
Boost
KNN
RF
SVM
Tree