DT Scrum cycle Exercise

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Decision Tree Scrum Cycle 7

Step 1

- Load data and get summaries

```
data <-read.csv("BankLoan Dataset 2021 - Clean .csv")  #HR.csv
#str(data)
data$lead <- as.factor(data$lead)
data$won <- as.factor(data$won)
summary(data)
```

```
##       X.1              X             RefNum            agerange
##  Min.   :   1.0   Min.   :   1.0   Min.   :10023467   18-30  : 97
##  1st Qu.: 281.5   1st Qu.: 281.5   1st Qu.:10023748   31-40  :430
##  Median : 562.0   Median : 562.0   Median :10024028   41-60  :594
##  Mean   : 562.0   Mean   : 562.0   Mean   :10024028   over 60:  2
##  3rd Qu.: 842.5   3rd Qu.: 842.5   3rd Qu.:10024308
##  Max.   :1123.0   Max.   :1123.0   Max.   :10024589
##
##       age                job          marital        education
##  Min.   :22.00   blue-collar:348   divorced:165   primary  :198
##  1st Qu.:35.00   technician :167   married :709   secondary:626
##  Median :42.00   admin.     :153   single  :249   tertiary :201
##  Mean   :42.46   management :148                  unknown  : 98
##  3rd Qu.:50.00   services   :145
##  Max.   :61.00   retired    : 49
##                  (Other)    :113
##     balance        housing    loan          month           date
##  Min.   : -932.0   no :129   no :624   april    : 94   1/1/2018: 94
##  1st Qu.:   23.0   yes:994   yes:499   february: 94   2/1/2018: 94
##  Median :  167.0                       january : 94   3/1/2018: 94
##  Mean   :  567.3                       july    : 94   4/1/2018: 94
##  3rd Qu.:  446.0                       june    : 94   5/1/2018: 94
##  Max.   :58544.0                       march   : 94   6/1/2018: 94
##                                        (Other) :559   (Other) :559
##     duration         deposit       lead          product      qualified
##  Min.   :   2.0   Min.   :  1.80   0:350   auto      :217   Min.   :0.0000
##  1st Qu.: 130.0   1st Qu.: 43.75   1:773   business  : 25   1st Qu.:0.0000
##  Median : 203.0   Median : 52.94           mortgage  :312   Median :1.0000
```

```
##  Mean   : 270.5   Mean   : 84.09           no product:350   Mean   :0.6073
##  3rd Qu.: 315.5   3rd Qu.: 92.71           unsecured :219   3rd Qu.:1.0000
##  Max.   :2177.0   Max.   :388.68                            Max.   :1.0000
##
##    contacted       won       loanvalue          NPS         contacted_and_won
##  Min.   :-1.0000   0:626   Min.   : 1526   Min.   : 3.000   Min.   :0.0000
##  1st Qu.: 0.0000   1:497   1st Qu.: 3397   1st Qu.: 7.000   1st Qu.:0.0000
##  Median : 0.0000           Median : 6530   Median : 7.000   Median :0.0000
##  Mean   : 0.2787           Mean   : 5991   Mean   : 7.874   Mean   :0.4426
##  3rd Qu.: 1.0000           3rd Qu.: 7632   3rd Qu.: 9.000   3rd Qu.:1.0000
##  Max.   : 1.0000           Max.   :12353   Max.   :10.000   Max.   :1.0000
##
##  qualified_and_contacted lead_and_qualified
##  Min.   :-1.0000         Min.   :0.000
##  1st Qu.: 0.0000         1st Qu.:1.000
##  Median : 0.0000         Median :1.000
##  Mean   : 0.3419         Mean   :0.919
##  3rd Qu.: 1.0000         3rd Qu.:1.000
##  Max.   : 1.0000         Max.   :1.000
##
```

```
#str(data)
```

Step 2

- Split data into training and testing data

```
# separate the data for an equal split
data_lead_1 = data[data$lead == 1,]
data_lead_0 = data[data$lead == 0,]

#randomize the sampling
set.seed(15)
newDataset_lead_1 <-sample.split(Y=data_lead_1$lead, SplitRatio = 0.35)
newDataset_lead_0 <-sample.split(Y=data_lead_0$lead, SplitRatio = 0.75)

trainData <-rbind(data_lead_1[newDataset_lead_1,], data_lead_0[newDataset_lead_0,])
testData <- rbind(data_lead_1[!newDataset_lead_1,][1:100,], data_lead_0[!newDataset_lead_0,])

summary(trainData$lead)
```

```
##   0   1
## 262 270
```

```
summary(testData$lead)
```

```
##   0   1
##  88 100
```

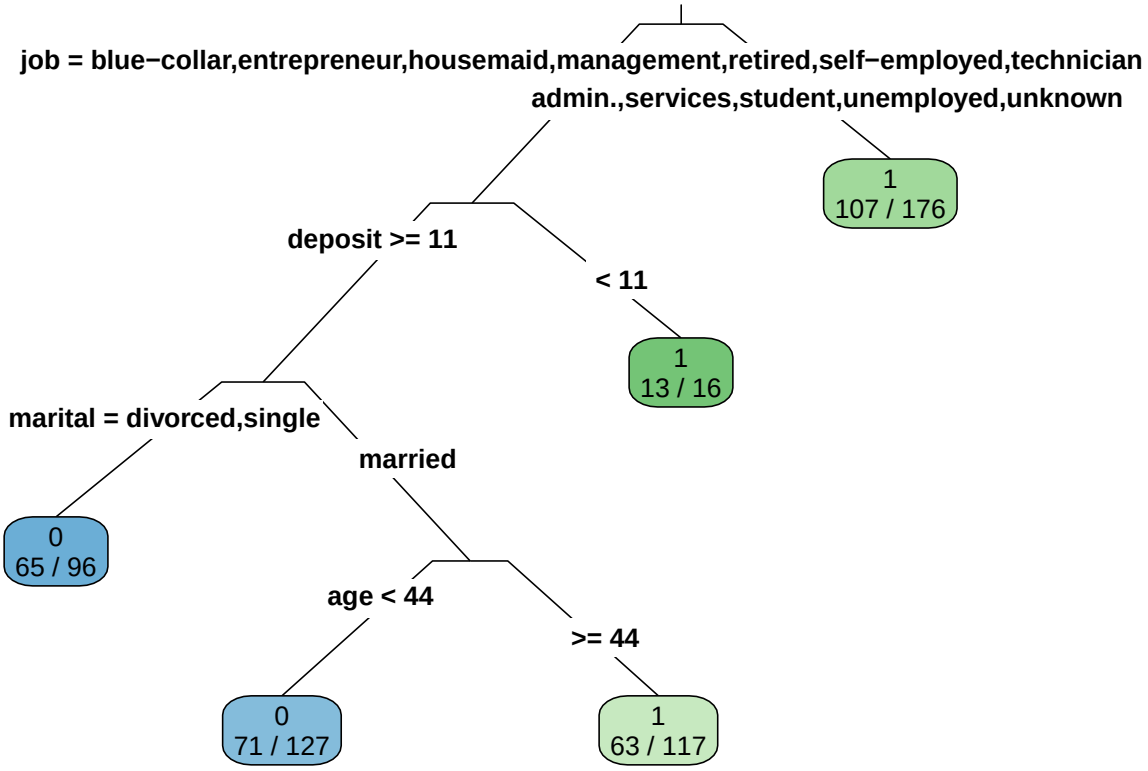
Step 3

- Fit a Decision Tree using training data

```
# The . specifies all other columns ( Class ~ . )
DTmodel <- rpart(lead ~ education + age + job + marital + deposit + balance + loan + housing, method="cl
```

- Target Variable = Class,
- Input Vaiables = All,
- split =gini or information gain
- control = rpart.control for prepruning DT minsplit- min records at node for split to occur, maxdepth - depth of the DT
- Fitting the model

```
rpart.plot(DTmodel, type=3, extra = 2, fallen.leaves = F, cex = 0.8)
```




```
#try extra with 2,8,4, 101
```

- Print out the information

```
#(DTmodel) # detailed summary of splits
DTmodel #prints the rules
```

```
## n= 532
##
## node), split, n, loss, yval, (yprob)
##       * denotes terminal node
##
##  1) root 532 262 1 (0.4924812 0.5075188)
##    2) job=blue-collar,entrepreneur,housemaid,management,retired,self-employed,technician 356 163 0 (
##      4) deposit>=11.42 340 150 0 (0.5588235 0.4411765)
##        8) marital=divorced,single 96  31 0 (0.6770833 0.3229167) *
##        9) marital=married 244 119 0 (0.5122951 0.4877049)
##         18) age< 43.5 127  56 0 (0.5590551 0.4409449) *
##         19) age>=43.5 117  54 1 (0.4615385 0.5384615) *
##      5) deposit< 11.42 16   3 1 (0.1875000 0.8125000) *
##    3) job=admin.,services,student,unemployed,unknown 176  69 1 (0.3920455 0.6079545) *
```

- Run the second model

```
#DTmodel2 <- J48(as.factor(Class) ~., trainData, control = Weka_control(R = TRUE, M = round(NROW(trainD

#DTmodel2 <- J48(as.factor(left) ~., trainData, control = Weka_control(R = TRUE, M = 50))

#IGDT5model <- J48(as.factor(eReader_Adoption)~., trainData ,control = Weka_control(R = TRUE, M = round

#IGDT10model <- J48(as.factor(eReader_Adoption)~., trainData ,control = Weka_control(R = TRUE, M = roun
```

- Plot the model

```
#plot(DTmodel)
```

Step 4

- Use the fitted model to do predictions for the test data

```
predTest <- predict(DTmodel, testData, type="class")
probTest <- predict(DTmodel, testData, type="prob")

actualTest <- testData$lead
```

Step 5

- Create Confusion Matrix and compute the misclassification error

```
t1 <- table(predictions=predTest, actual = actualTest)
t1 # Confusion matrix
```

```
##            actual
## predictions  0  1
##           0 46 33
##           1 42 67
```

```
accuracy1 <- sum(diag(t1))/sum(t1) * 100
accuracy1
```

```
## [1] 60.10638
```

```
#calculatee sensitivity
sensitivity <- t1[2,2]/sum(t1[2,]) *100
sensitivity
```

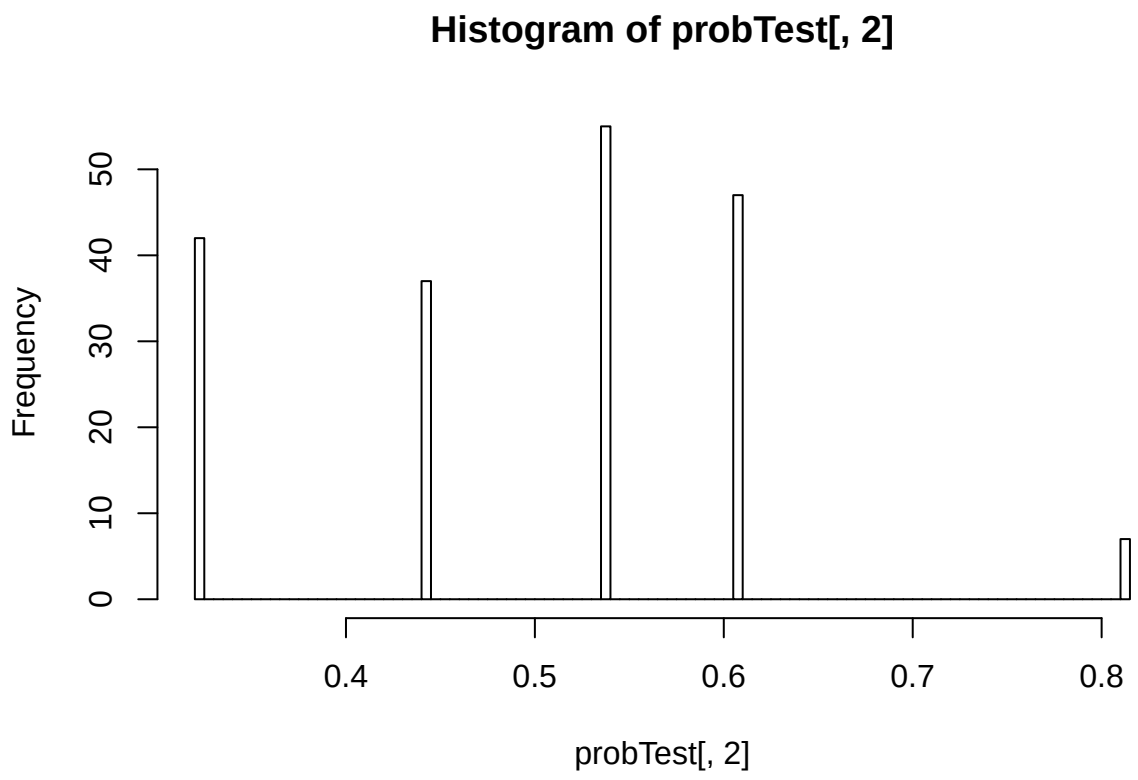
```
## [1] 61.46789
```

```
#calculate specificity
specificity <- t1[1,1]/sum(t1[1,]) *100
specificity
```

```
## [1] 58.22785
```

- Visualization of probabilities

```
hist(probTest[,2], breaks = 100)
```



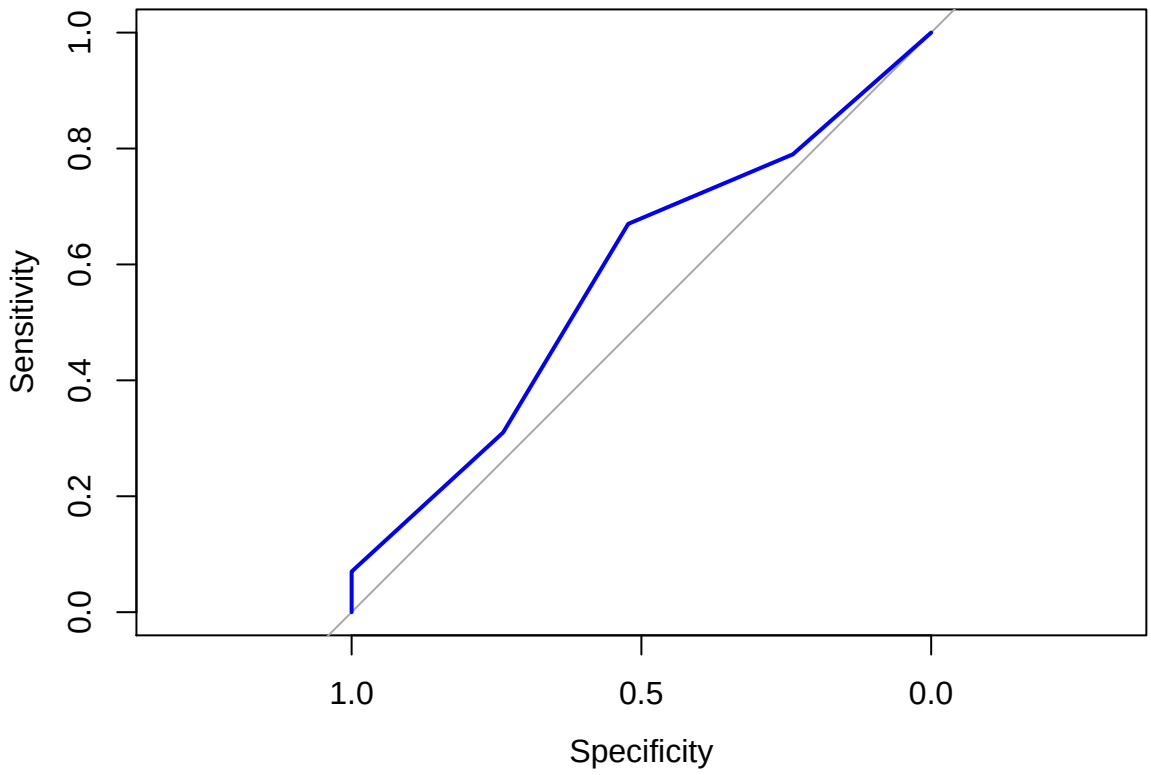
- ROC and Area Under the Curve

```
ROC <- roc(actualTest, probTest[,2])
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```
plot(ROC, col="blue")
```




```
AUC <- auc(ROC)
AUC
```

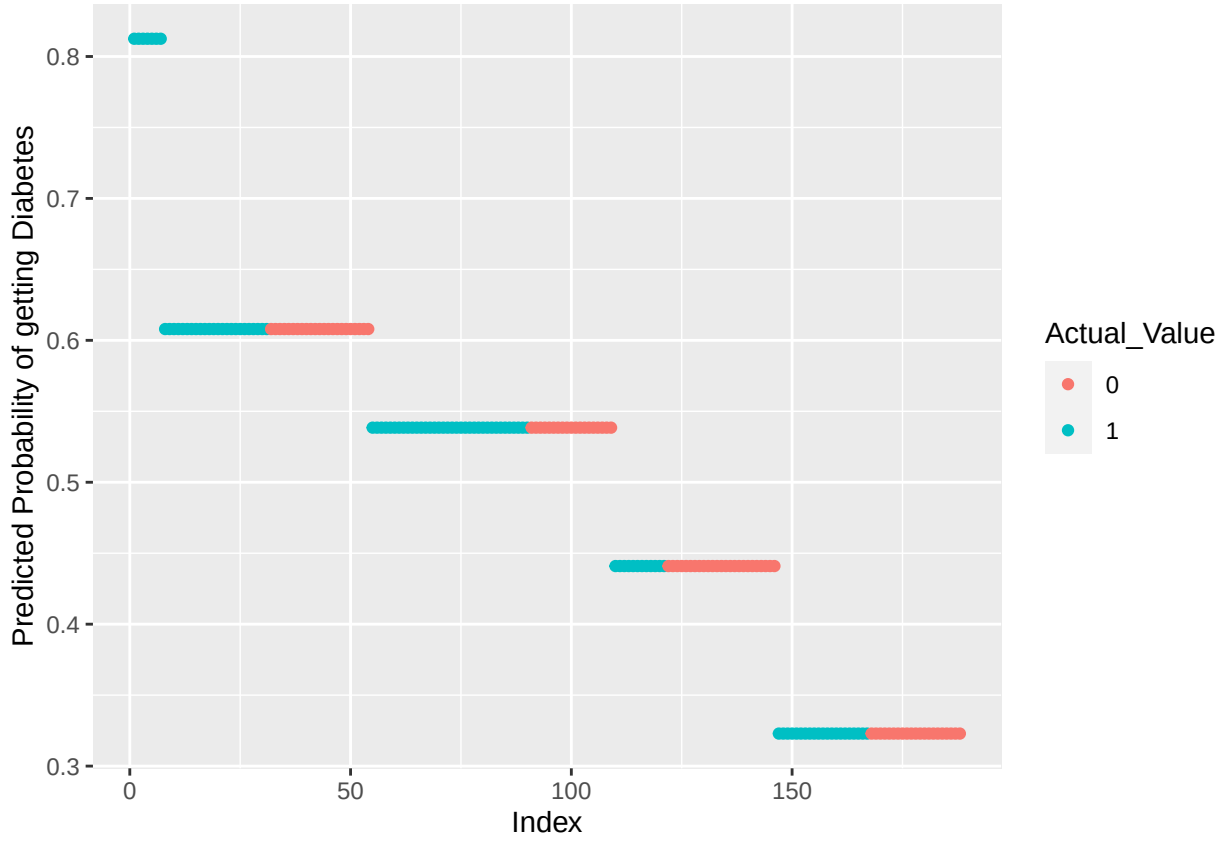
```
## Area under the curve: 0.5764
```

- A new dataframe with Predicted Prob, Actual Value and Predicted Value

```
predicted_data <- data.frame(Probs = probTest, Actual_Value= actualTest ,Predicted_Value = predTest )
  #predicted_data$Probs.0 <- Class 0 Probability
  #predicted_data$Probs.1 <-  Class 1 Probability
predicted_data <- predicted_data[order(predicted_data$Probs.1, decreasing=TRUE),] # Sort on Probabiliti
predicted_data$Rank <- 1:nrow(predicted_data) # Add a new variable rank
```

- plot the graph

```
ggplot(data=predicted_data, aes(x=Rank, y=Probs.1)) +
  geom_point(aes(color = Actual_Value)) + xlab("Index") + ylab("Predicted Probability of getting Diabet
```



Step 6

- Use model to make predictions on newdata. Note we can specify the newData as data.frame with one or many records

```
#newData <- data.frame(Nbr_Preg = 4 , Glucose_test = 100, Triceps_SF=40,BP =95, S_insulin = 150, BMI= 3

#predProbability <-predict(DTmodel, newData, type='prob')
#predProbability

## Performnce measures -
#setseed(1), gini
# Simplicity = 15 leaves
# Accuracy = 0.734
# AUC = 0.7627

#setseed(1), information
# Simplicity = 10 leaves
# Accuracy = 0.71
# AUC = 0.7834
```

Step 7

- EXAMINING STABILITY - Creating Decile Plots for Class 1 or 0 Sort

```
#-----Create empty df-------
#decileDF<- data.frame(matrix(ncol=3,nrow = 0))
#colnames(decileDF)<- c("Decile","per_correct_preds","No_correct_Preds","cum_preds")
#-----Initialize varables
#num_of_deciles=10
#Obs_per_decile<-nrow(predicted_data)/num_of_deciles
#decile_count=1
#start=1
#stop=(start-1) + Obs_per_decile
#prev_cum_pred<-0
#x=0
#-----Loop through DF and create deciles
#while (x < nrow(predicted_data)) {
#  subset<-predicted_data[c(start:stop),]
#  correct_count<- ifelse(subset$Actual_Value==subset$Predicted_Value,1,0)
#  no_correct_Preds<-sum(correct_count,na.rm = TRUE)
#  per_correct_Preds<-(no_correct_Preds/Obs_per_decile)*100
#  cum_preds<-no_correct_Preds+prev_cum_pred
#  addRow<-data.frame("Decile"=decile_count,"per_correct_preds"=per_correct_Preds,"No_correct_Preds"=no
#  decileDF<-rbind(decileDF,addRow)
#  prev_cum_pred<-prev_cum_pred+no_correct_Preds
#  start<-stop+1
#  stop=(start-1) + Obs_per_decile
#  x<-x+Obs_per_decile
#  decile_count<-decile_count+1
#}
#------Stability plot (correct preds per decile)
#plot(decileDF$Decile,decileDF$per_correct_preds,type = "l",xlab = "Decile",ylab = "Percentage of corre
```