Credit-Card_Classifier

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```
library("tidyverse")
library("skimr") # skim function
library("readxl") # used to read excel files
library("readr") # read csv
library("dplyr") # data munging
library("FNN") # knn regression (knn.reg function)
library("caret") # various predictive models
library("class") # confusion matrix function
library("rpart.plot") #plot decision tree
library("rpart")  # Regression tree
library("glmnet") # Lasso and Ridge regression
library('NeuralNetTools') # plot NN's
library("PRROC") # top plot ROC curve
library("pROC")
library("ROCR") # top plot lift curve
```

1. Project Summary

Situation: A credit card company only wants to extend credit card offers to people with an income above $50,000. Thus, the main criteria is that the person must have a projected income above $50,000 and your predictive model uses income as the target variable.

Goal: The goal is to maximize profit given the benefits of the true positives and true negatives, and the costs of the false positives and the false negatives. • The benefit of a true positive is equal to the lifetime value of a credit card customer, estimated to be $1400 • If you incorrectly give a person a credit card (false positive) and the person defaults, and it goes into collection then you can lose not only the principal but also have a cost of collection. This is estimated to be a loss of $1200 • Not issuing a card to a person who would have been a good customer (false negative) is an opportunity lost. Missing out this opportunity costs $800 • Not issuing a card to someone who did not deserve one (true negative) saves some minor processing benefit of $10.

Data: The dataset contains information on potential applicants for a credit card. There are customers with known income and those without known income (the training and test sets respectively). The data contain 48842 instances with a mix of continuous and discrete (train=32561, test=16281) in two files “train.csv” and “test.csv” respectively. The data contain following fields: • age: continuous. • workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked. • education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool. • education_years: continuous. • marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse. • occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces. • relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried. • race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black. • sex: Female, Male. • hours-per-week: continuous. • native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands. • target (income category): >50K coded as ‘1’, <=50K coded as ‘0’

2. Data Loading, Exploration, and Model Preparation

2.1 Training Data

```
# Reading Train CSV file
income_df_train <- read_csv("../Data/train-baggle.csv", col_types = "nffnfffffnff")
```

```
# Splitting the data
income_df_train_y = income_df_train %>% pull(income)
income_df_train_x = income_df_train %>% select(-income)
```

2.2 Test Data

```
# Load the test data
income_df_test <- read_csv("../Data/test-baggle.csv", col_types = "fnffnfffffnff")
```

```
# Replace missing values ('?') with 'UNK'
income_df_test <- income_df_test %>%
  mutate(
    workClassification = recode(workClassification, "?" = "UNK"),
    nativeCountry = recode(nativeCountry, "?" = "UNK"),
    occupation = recode(occupation, "?" = "UNK")
  )
```

```
# Create 'income_df_test_x' data frame without the 'income' column
income_df_test_x <- select(income_df_test, -c("income"))
```

2.3 Split Train into Training and Validation

```
# Set the seed for reproducibility
set.seed(123456)

# 75% of the data is used for training and rest for testing
smp_size <- floor(0.75 * nrow(income_df_train_x))

# randomly select row numbers for training data set
train_ind <- sample(seq_len(nrow(income_df_train_x)), size = smp_size)

# creating test and training sets for x
income_df_training_x <- income_df_train_x[train_ind, ]
income_df_validation_x <- income_df_train_x[-train_ind, ]

# creating test and training sets for y
income_df_training_y <- income_df_train_y[train_ind]
income_df_validation_y <- income_df_train_y[-train_ind]
```

2.4 Dataframe to Store Results

```
# Create an empty data frame to store results from different models
clf_results <- data.frame(matrix(ncol = 5, nrow = 0))
names(clf_results) <- c("Model", "Accuracy", "Precision", "Recall", "F1")

# Create an empty data frame to store TP, TN, FP and FN values
cost_benefit_df <- data.frame(matrix(ncol = 5, nrow = 0))
names(cost_benefit_df) <- c("Model", "TP", "FN", "FP", "TN")
```

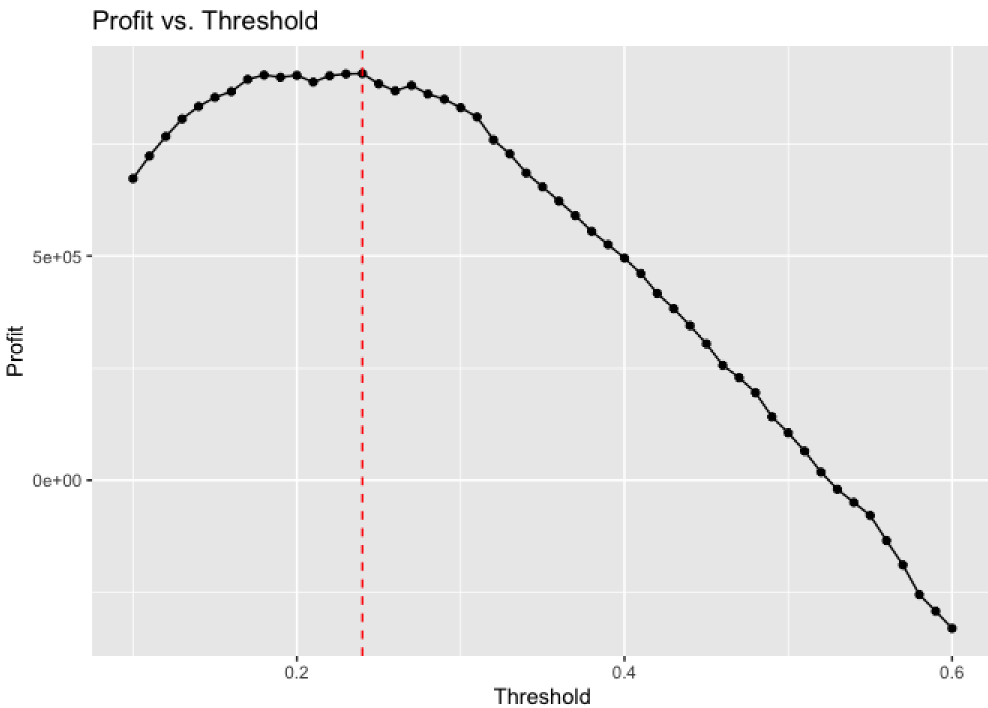
3. Model Fitting

3.1 Logistic Regression

```
# Fit GLM model on training set
glm_fit <- train(income_df_training_x,
                 income_df_training_y,
                 method = "glm",
                 family = "binomial",
                 preProc = c("center", "scale"))
```

```
# Predict on validation data
y_validation_pred <- predict(glm_fit, newdata = income_df_validation_x, type = "prob")

# Initialize an empty data frame to store threshold and profit values
threshold_profit_df <- data.frame(Threshold = numeric(), Profit = numeric())

# Define the range of thresholds you want to test
threshold_range <- seq(0.1, 0.6, by = 0.01)

# Initialize variables to track the maximum profit and corresponding threshold
max_profit <- -Inf
optimal_threshold <- NA

# Set costs
benefit_TP = 1400
benefit_TN = 10
cost_FN = -1200
cost_FP = -800

# Loop through each threshold value
for (threshold in threshold_range) {
  # Predict on validation data using the current threshold
  y_validation_pred_num <- ifelse(y_validation_pred[,2] > threshold, "1", "0")

  # Calculate confusion matrix
  confusion <- confusionMatrix(as.factor(y_validation_pred_num), as.factor(income_df_validation_y))

  # Calculate profit using the defined benefit and cost values
  TP <- confusion[["table"]][4]
  FN <- confusion[["table"]][3]
  FP <- confusion[["table"]][2]
  TN <- confusion[["table"]][1]
  profit <- (benefit_TP * TP) + (benefit_TN * TN) + (cost_FP * FP) + (cost_FN * FN)

  # Add threshold and profit values to the data frame
  threshold_profit_df <- rbind(threshold_profit_df, data.frame(Threshold = threshold, Profit = profit))

  # Check if the current profit is greater than the maximum profit
  if (profit > max_profit) {
```

```
    max_profit <- profit
    optimal_threshold <- threshold
  }
}

# Plot the profit vs. threshold values
library(ggplot2)
ggplot(threshold_profit_df, aes(x = Threshold, y = Profit)) +
  geom_line() +
  geom_point() +
  geom_vline(xintercept = optimal_threshold, color = "red", linetype = "dashed") +  # Add red vertical line
  ggtitle("Profit vs. Threshold") +
  xlab("Threshold") +
  ylab("Profit")
```




```
# Print the threshold that achieves maximum profit
cat("Optimal Threshold for Maximum Profit:", optimal_threshold, "\n")
```

```
## Optimal Threshold for Maximum Profit: 0.24
```

```
cat("Maximum Profit:", max_profit, "\n")
```

```
## Maximum Profit: 906830
```

```
# Choose a threshold to convert probabilities to class labels (for example 0.5)
threshold_1 <- 0.24
y_validation_pred_num <- ifelse(y_validation_pred[,2] > threshold_1, "1", "0")

# Convert both predictions and actuals into factors with the same levels
y_validation_pred_num_factor <- factor(y_validation_pred_num, levels = c("0", "1"))
income_df_validation_y_factor <- factor(income_df_validation_y, levels = c("0", "1"))
```

```
# Print Confusion matrix, Accuracy, Sensitivity etc
confusionMatrix(as.factor(y_validation_pred_num), as.factor(income_df_validation_y), positive = "1")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 4783  329
##          1 1357 1671
##
##                Accuracy : 0.7929
##                  95% CI : (0.7839, 0.8016)
##     No Information Rate : 0.7543
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5237
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.8355
##             Specificity : 0.7790
##          Pos Pred Value : 0.5518
##          Neg Pred Value : 0.9356
##              Prevalence : 0.2457
##          Detection Rate : 0.2053
##    Detection Prevalence : 0.3720
##       Balanced Accuracy : 0.8072
##
##        'Positive' Class : 1
##
```

```
# Add results into clf_results dataframe
x3 <- confusionMatrix(as.factor(y_validation_pred_num), as.factor(income_df_validation_y), positive = "1")[
y3 <- confusionMatrix(as.factor(y_validation_pred_num), as.factor(income_df_validation_y),positive = "1")[[

clf_results[nrow(clf_results) + 1,] <-  list(Model = "Logistic Regression",
                                             Accuracy = round (x3[["Accuracy"]],3),
                                            Precision = round (y3[["Precision"]],3),
                                            Recall = round (y3[["Recall"]],3),
                                            F1 = round (y3[["F1"]],3))

# Print Accuracy and F1 score
cat("Accuarcy is ", round(x3[["Accuracy"]],3), "and F1 is ", round (y3[["F1"]],3)  )
```

```
## Accuarcy is  0.793 and F1 is  0.665
```

```
# Add results into cost_benefit_df dataframe for cost benefit analysis
a3 <- confusionMatrix(as.factor(y_validation_pred_num), as.factor(income_df_validation_y))

#be careful about accurately picking up the TP, FN, FP and TN
cost_benefit_df[nrow(cost_benefit_df) + 1,] <-  list(Model = "Logistic Regression",
                                             TP = a3[["table"]][4],
                                             FN = a3[["table"]][3],
                                             FP = a3[["table"]][2],
                                             TN = a3[["table"]][1])
```

3.2 Decision Tree Classification

```r
set.seed(12345)

# Cross validation
cross_validation <- trainControl(## 10-fold CV
                                method = "repeatedcv",
                                number = 10,
                                ## repeated three times
                                repeats = 3)
# Hyperparamter tuning
Param_Grid <-  expand.grid(maxdepth = 2:10) #max depth of tree 10

# Tree fitting
dtree_fit <- train(income_df_training_x,
                   income_df_training_y,
                   method = "rpart2",
                   # split - criteria to split nodes
                   parms = list(split = "gini"),
                  tuneGrid = Param_Grid,
                   trControl = cross_validation,
                  # preProc -  perform listed pre-processing to predictor dataframe
                   preProc = c("center", "scale"))

# check the accuracy of Decision Tree
dtree_fit
```

```
## CART
##
## 24420 samples
##    11 predictor
##     2 classes: '0', '1'
##
## Pre-processing: centered (3), scaled (3), ignore (8)
## Resampling: Cross-Validated (10 fold, repeated 3 times)
## Summary of sample sizes: 21978, 21978, 21977, 21979, 21978, 21978, ...
## Resampling results across tuning parameters:
##
##   maxdepth  Accuracy   Kappa
##    2        0.8221132  0.4277376
##    3        0.8295795  0.4930633
##    4        0.8295795  0.4930633
##    5        0.8295795  0.4930633
##    6        0.8295795  0.4930633
##    7        0.8295795  0.4930633
##    8        0.8295795  0.4930633
##    9        0.8295795  0.4930633
##   10        0.8295795  0.4930633
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was maxdepth = 3.
```

```r
# Plot decision tree
prp(dtree_fit$finalModel, box.palette = "Reds", tweak = 1.2)
```


```
# Predict on validation set
dtree_predict <- predict(dtree_fit, newdata = income_df_validation_x)
```

```
# Print Confusion matrix, Accuracy, Sensitivity etc
confusionMatrix(as.factor(dtree_predict), as.factor(income_df_validation_y), positive = "1")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 5845 1220
##          1  295  780
##
##                Accuracy : 0.8139
##                  95% CI : (0.8053, 0.8223)
##     No Information Rate : 0.7543
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4051
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.39000
##             Specificity : 0.95195
##          Pos Pred Value : 0.72558
##          Neg Pred Value : 0.82732
##              Prevalence : 0.24570
##          Detection Rate : 0.09582
##    Detection Prevalence : 0.13206
##       Balanced Accuracy : 0.67098
##
##        'Positive' Class : 1
##
```

```
x2 <- confusionMatrix(as.factor(dtree_predict), as.factor(income_df_validation_y), positive = "1")[["overal
y2 <- confusionMatrix(as.factor(dtree_predict),  as.factor(income_df_validation_y),positive = "1")[["byClas

clf_results[nrow(clf_results) + 1,] <-  list(Model = "Decision Tree",
                                             Accuracy = round (x2[["Accuracy"]],3),
                                             Precision = round (y2[["Precision"]],3),
                                             Recall = round (y2[["Recall"]],3),
                                             F1 = round (y2[["F1"]],3))

# Print Accuracy and F1 score
cat("Accuarcy is ", round(x2[["Accuracy"]],3), "and F1 is ", round (y2[["F1"]],3)  )
```

```
## Accuarcy is  0.814 and F1 is  0.507
```

```
# Add results into cost_benefit_df dataframe for cost benefit analysis
a2 <- confusionMatrix(as.factor(dtree_predict), as.factor(income_df_validation_y))

cost_benefit_df[nrow(cost_benefit_df) + 1,] <-  list(Model = "Decision Tree",
                                                     TP = a2[["table"]][4],
                                                     FN = a2[["table"]][3],
                                                     FP = a2[["table"]][2],
                                                     TN = a2[["table"]][1])
```

4. Data Encoding, Preparation for XGB, NN, KNN

4.1 Filter Test and Train Sets

```
# Train: Dropping unnecessary features:
income_df_train_x <- select(income_df_train, -c("income","educationLevel", "nativeCountry"))
# Test: Dropping unnecessary features:
income_df_test_x <- select(income_df_train, -c("income","educationLevel", "nativeCountry"))
```

4.2 Encoding

```
# Define the formula for one-hot encoding
formula <- as.formula("~ .")

# one-hot encoding on TRAIN
dummy_trans <- dummyVars(formula, data = income_df_train_x)

# Apply the transformation to the dataset
income_df_train_x_encoded <- predict(dummy_trans, newdata = income_df_train_x)

# one-hot encoding on TEST
dummy_trans <- dummyVars(formula, data = income_df_test_x)

# Apply the transformation to the dataset
income_df_test_x_encoded <- predict(dummy_trans, newdata = income_df_test_x)
```

4.3 Split Train into Training and Validation

```
# Set the seed for reproducibility
set.seed(12345)

# 75% of the data is used for training and rest for testing
smp_size <- floor(0.75 * nrow(income_df_train_x_encoded))

# randomly select row numbers for training data set
train_ind <- sample(seq_len(nrow(income_df_train_x_encoded)), size = smp_size)

# creating test and training sets for x
income_df_training_x <- income_df_train_x_encoded[train_ind, ]
income_df_validation_x <- income_df_train_x_encoded[-train_ind, ]

# creating test and training sets for y
income_df_training_y <- income_df_train_y[train_ind]
income_df_validation_y <- income_df_train_y[-train_ind]
```

5. XG Boost Classification

```
# Create a training control object
ctrl <- trainControl(method = "cv", number = 5)  # 5 Folds

# Define the grid of hyperparameters
param_grid <- expand.grid(
  nrounds = c(100),              # boosting rounds
  max_depth = c(3, 6, 9),        # depth of trees
  eta = c(0.01, 0.1, 0.3),       # Learning rate
  gamma = c(0),                  # Regularization parameter
  colsample_bytree = c(1),       # Fraction of features used in tree building
  min_child_weight = c(1),       # Minimum sum of instance weight (Hessian) needed in a child
  subsample = c(1)               # Fraction of samples used for tree building
)

# Train the XGBoost model
xgb_fit <- train(
  x = income_df_training_x,
  y = income_df_training_y,
  method = "xgbTree",
  trControl = ctrl,
  tuneGrid = param_grid,
  preProc = c("center", "scale"),
  verbose = FALSE,               # Disable verbose output
  nthread = 2                   # Specify the number of threads
)
```

```
# Predict on validation data
XG_clf_predict <- predict(xgb_fit,income_df_validation_x)
```

```
# Print Confusion matrix, Accuracy, Sensitivity etc
confusionMatrix(as.factor(XG_clf_predict), as.factor(income_df_validation_y), positive = "1")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 5767  796
##          1  455 1122
```

```
##
##                Accuracy : 0.8463
##                  95% CI : (0.8383, 0.8541)
##     No Information Rate : 0.7644
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5454
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.5850
##             Specificity : 0.9269
##          Pos Pred Value : 0.7115
##          Neg Pred Value : 0.8787
##              Prevalence : 0.2356
##          Detection Rate : 0.1378
##    Detection Prevalence : 0.1937
##       Balanced Accuracy : 0.7559
##
##        'Positive' Class : 1
##
```

```
# Add results into clf_results dataframe
x4 <- confusionMatrix(as.factor(XG_clf_predict),  as.factor(income_df_validation_y), positive = "1" )[["ove
y4 <- confusionMatrix(as.factor(XG_clf_predict),  as.factor(income_df_validation_y), positive = "1" )[["byC

clf_results[nrow(clf_results) + 1,] <-  list(Model = "XG Boost",
                                             Accuracy = round (x4[["Accuracy"]],3),
                                            Precision = round (y4[["Precision"]],3),
                                            Recall = round (y4[["Recall"]],3),
                                            F1 = round (y4[["F1"]],3))

# Print Accuracy and F1 score
cat("Accuarcy is ", round(x4[["Accuracy"]],3), "and F1 is ", round (y4[["F1"]],3)  )
```

```
## Accuarcy is  0.846 and F1 is  0.642
```

```
# Add results into cost_benefit_df dataframe for cost benefit analysis
a4 <- confusionMatrix(as.factor(XG_clf_predict),  as.factor(income_df_validation_y) )

cost_benefit_df[nrow(cost_benefit_df) + 1,] <-  list(Model = "XG Boost",
                                             TP = a4[["table"]][4],
                                             FN = a4[["table"]][3],
                                             FP = a4[["table"]][2],
                                             TN = a4[["table"]][1])
```

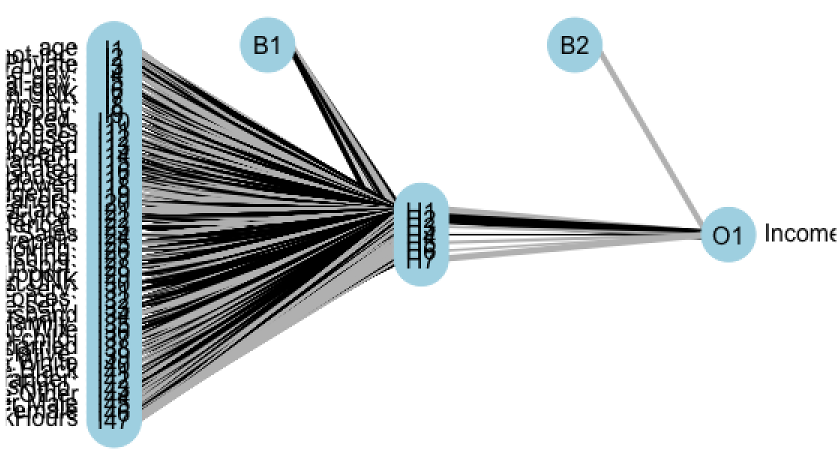
6. Neural Network classification

```
my.grid <- expand.grid(.decay = c(0.5, 0.1), .size = c(5, 7))

# stepmax is maximum steps for the training of the neural network
# threshold is set to 0.01, meaning that if the change in error during an iteration is
# less than 1%, then no further optimization will be carried out by the model
nn_clf_fit <- train(income_df_training_x,
                    income_df_training_y,
                    method = "nnet",
                    trace = F,
                    tuneGrid = my.grid,
```

```
                    linout = 0,
                    stepmax = 100, #max steps for training NN
                    threshold = 0.01 ) #threshold change in error 1%
print(nn_clf_fit)
```

```
## Neural Network
##
## 24420 samples
##    47 predictor
##     2 classes: '0', '1'
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 24420, 24420, 24420, 24420, 24420, 24420, ...
## Resampling results across tuning parameters:
##
##   decay  size  Accuracy   Kappa
##   0.1    5     0.8317304  0.5124989
##   0.1    7     0.8339608  0.5230628
##   0.5    5     0.8350218  0.5275197
##   0.5    7     0.8357716  0.5286403
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were size = 7 and decay = 0.5.
```

```
# Plot Neural Network
plotnet(nn_clf_fit$finalModel, y_names = "Income >50K")
```




```
# Predict on validation data
nn_clf_predict <- predict(nn_clf_fit,income_df_validation_x)
```

```
# Print Confusion matrix, Accuracy, Sensitivity etc
confusionMatrix(as.factor(nn_clf_predict), as.factor(income_df_validation_y), positive = "1")
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction    0    1
##          0 5771  808
##          1  451 1110
##                                           
##                Accuracy : 0.8453          
##                  95% CI : (0.8373, 0.8531)
##     No Information Rate : 0.7644          
##     P-Value [Acc > NIR] : < 2.2e-16       
##                                           
##                   Kappa : 0.5411          
##                                           
##  Mcnemar's Test P-Value : < 2.2e-16       
##                                           
##             Sensitivity : 0.5787          
##             Specificity : 0.9275          
##          Pos Pred Value : 0.7111          
##          Neg Pred Value : 0.8772          
##              Prevalence : 0.2356          
##          Detection Rate : 0.1364          
##    Detection Prevalence : 0.1918          
##       Balanced Accuracy : 0.7531          
##                                           
##        'Positive' Class : 1               
## 
```

```
# Add results into clf_results dataframe
x5 <- confusionMatrix(as.factor(nn_clf_predict),  as.factor(income_df_validation_y), positive = "1" )[["ove
y5 <- confusionMatrix(as.factor(nn_clf_predict),  as.factor(income_df_validation_y), positive = "1" )[["byC


clf_results[nrow(clf_results) + 1,] <-  list(Model = "Neural Network", 
                                             Accuracy = round (x5[["Accuracy"]],3), 
                                            Precision = round (y5[["Precision"]],3), 
                                            Recall = round (y5[["Recall"]],3), 
                                            F1 = round (y5[["F1"]],3))

# Print Accuracy and F1 score
cat("Accuarcy is ", round(x5[["Accuracy"]],3), "and F1 is ", round (y5[["F1"]],3)  )
```

```
## Accuarcy is  0.845 and F1 is  0.638
```

```
# Add results into cost_benefit_df dataframe for cost benefit analysis 
a5 <- confusionMatrix(as.factor(nn_clf_predict),  as.factor(income_df_validation_y) )

cost_benefit_df[nrow(cost_benefit_df) + 1,] <-  list(Model = "Neural Network", 
                                             TP = a5[["table"]][4], 
                                             FN = a5[["table"]][3], 
                                             FP = a5[["table"]][2], 
                                             TN = a5[["table"]][1])
```

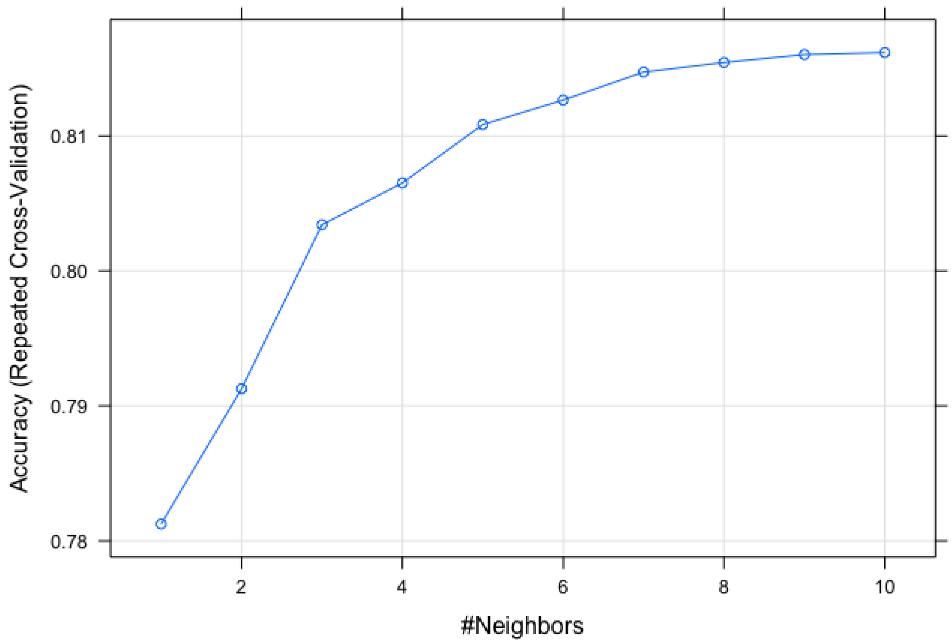
7. KNN Classification

```
set.seed(12345)
# Cross validation
```

```
cross_validation <- trainControl(## 10-fold CV
                                 method = "repeatedcv",
                                 number = 10,
                                 ## repeated three times
                                 repeats = 3)
# Hyperparamter tuning
Param_Grid <-  expand.grid( k = 1:10)

# fit the model to training data
knn_clf_fit <- train(income_df_training_x,
                     income_df_training_y,
                     method = "knn",
                     tuneGrid = Param_Grid,
                     trControl = cross_validation )

# check the accuracy for different models
knn_clf_fit
```

```
## k-Nearest Neighbors
##
## 24420 samples
##    47 predictor
##     2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 3 times)
## Summary of sample sizes: 21977, 21978, 21978, 21979, 21978, 21978, ...
## Resampling results across tuning parameters:
##
##   k   Accuracy   Kappa
##    1  0.7812586  0.4080040
##    2  0.7912778  0.4302529
##    3  0.8034259  0.4554872
##    4  0.8065248  0.4627983
##    5  0.8108520  0.4717769
##    6  0.8126670  0.4757714
##    7  0.8147422  0.4783944
##    8  0.8154520  0.4800451
##    9  0.8160388  0.4796862
##   10  0.8161891  0.4791266
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was k = 10.
```

```
# Plot accuracies for different k values
plot(knn_clf_fit)
```




```
# print the best model
print(knn_clf_fit$finalModel)
```

```
## 10-nearest neighbor model
## Training set outcome distribution:
##
##     0     1
## 18497  5923
```

```
# Predict on validation data
knnPredict <- predict(knn_clf_fit, newdata = income_df_validation_x)
```

```
# Print Confusion matrix, Accuracy, Sensitivity etc
confusionMatrix(as.factor(knnPredict), as.factor(income_df_validation_y), positive = "1")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 5603  853
##          1  619 1065
##
##                Accuracy : 0.8192
##                  95% CI : (0.8106, 0.8275)
##     No Information Rate : 0.7644
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4759
##
##  Mcnemar's Test P-Value : 1.256e-09
##
##             Sensitivity : 0.5553
##             Specificity : 0.9005
##          Pos Pred Value : 0.6324
```

```
##          Neg Pred Value : 0.8679
##              Prevalence : 0.2356
##          Detection Rate : 0.1308
##    Detection Prevalence : 0.2069
##       Balanced Accuracy : 0.7279
##
##        'Positive' Class : 1
##
```

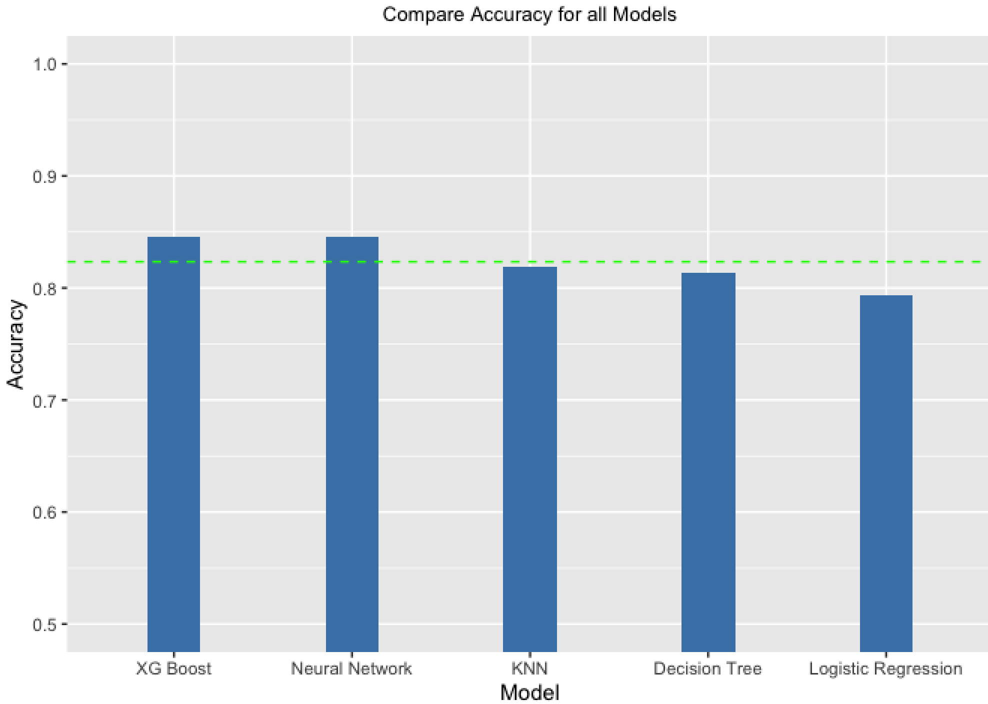
```
# Add results into clf_results dataframe
x1 <- confusionMatrix(as.factor(knnPredict),  as.factor(income_df_validation_y), positive = "1" )[["overall
y1 <- confusionMatrix(as.factor(knnPredict),  as.factor(income_df_validation_y), positive = "1" )[["byClass

clf_results[nrow(clf_results) + 1,] <-  list(Model = "KNN",
                                             Accuracy = round (x1[["Accuracy"]],3),
                                            Precision = round (y1[["Precision"]],3),
                                            Recall = round (y1[["Recall"]],3),
                                            F1 = round (y1[["F1"]],3))
# Print Accuracy and F1 score

cat("Accuarcy is ", round(x1[["Accuracy"]],3), "and F1 is ", round (y1[["F1"]],3)  )
```

```
## Accuarcy is  0.819 and F1 is  0.591
```

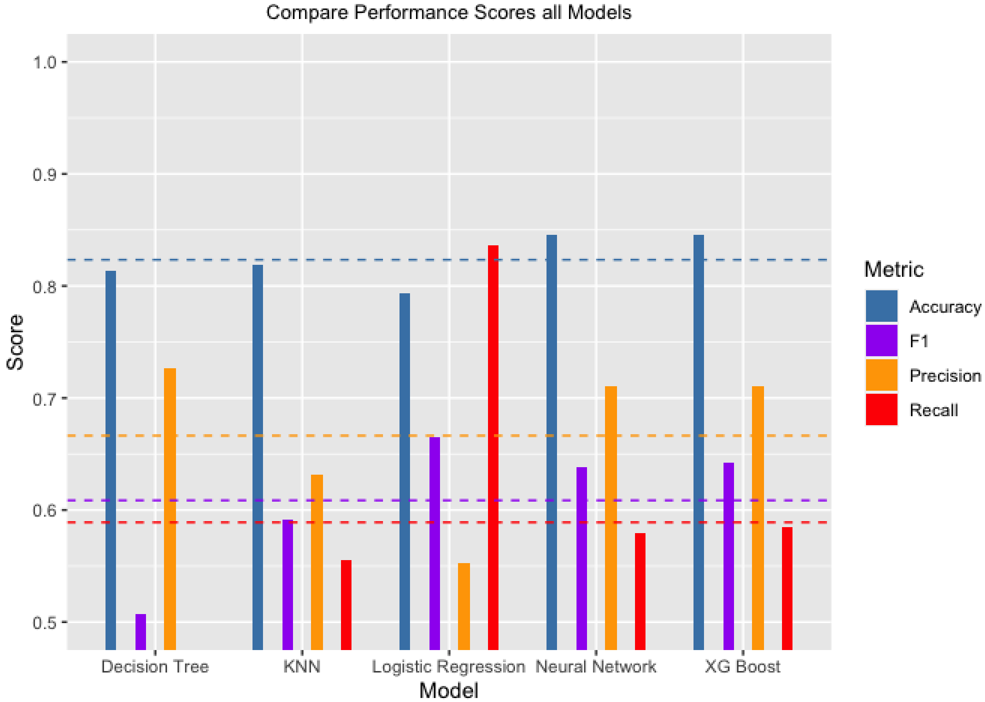
```
# Add results into cost_benefit_df dataframe for cost benefit analysis
a1 <- confusionMatrix(as.factor(knnPredict),  as.factor(income_df_validation_y) )

cost_benefit_df[nrow(cost_benefit_df) + 1,] <-  list(Model = "KNN",
                                             TP = a1[["table"]][4],
                                             FN = a1[["table"]][3],
                                             FP = a1[["table"]][2],
                                             TN = a1[["table"]][1])
```

8. Compare Accuracy for all Classification models

```
print(clf_results)

# Plot accuracy for all the Classification Models

ggplot(clf_results %>% arrange(desc(Accuracy)) %>%
       mutate(Model=factor(Model, levels=Model) ),
       aes(x = Model, y = Accuracy)) +
  geom_bar(stat = "identity" , width=0.3, fill="steelblue") +
  coord_cartesian(ylim = c(0.50, 1)) +
  geom_hline(aes(yintercept = mean(Accuracy)),
             colour = "green",linetype="dashed") +
  ggtitle("Compare Accuracy for all Models") +
  theme(plot.title = element_text(color="black", size=10, hjust = 0.5))
```




```
# Arrange in long format
clf_results_long <- clf_results %>%
  gather(Metric, Score, -Model)

# Calculate mean values for geom_hline
mean_accuracy <- mean(clf_results_long$Score[clf_results_long$Metric == "Accuracy"])
mean_precision <- mean(clf_results_long$Score[clf_results_long$Metric == "Precision"])
mean_recall <- mean(clf_results_long$Score[clf_results_long$Metric == "Recall"])
mean_f1 <- mean(clf_results_long$Score[clf_results_long$Metric == "F1"])

# Plot Scores
ggplot(clf_results_long %>% arrange(Model, desc(Score)),
       aes(x = Model, y = Score, fill = Metric)) +
  geom_bar(stat = "identity", position = position_dodge(width = 0.8), width = 0.3) +
  coord_cartesian(ylim = c(0.50, 1)) +
  geom_hline(aes(yintercept = mean_accuracy),
             colour = "steelblue", linetype = "dashed") +
  geom_hline(aes(yintercept = mean_precision),
             colour = "orange", linetype = "dashed") +
  geom_hline(aes(yintercept = mean_recall),
             colour = "red", linetype = "dashed") +
  geom_hline(aes(yintercept = mean_f1),
             colour = "purple", linetype = "dashed") +
  ggtitle("Compare Performance Scores all Models") +
  theme(plot.title = element_text(color = "black", size = 10, hjust = 0.5)) +
  labs(x = "Model", y = "Score") +
  scale_fill_manual(values = c("Accuracy" = "steelblue", "Precision" = "orange", "Recall" = "red", "F1" = "
```



9. Cost Benefit analysis

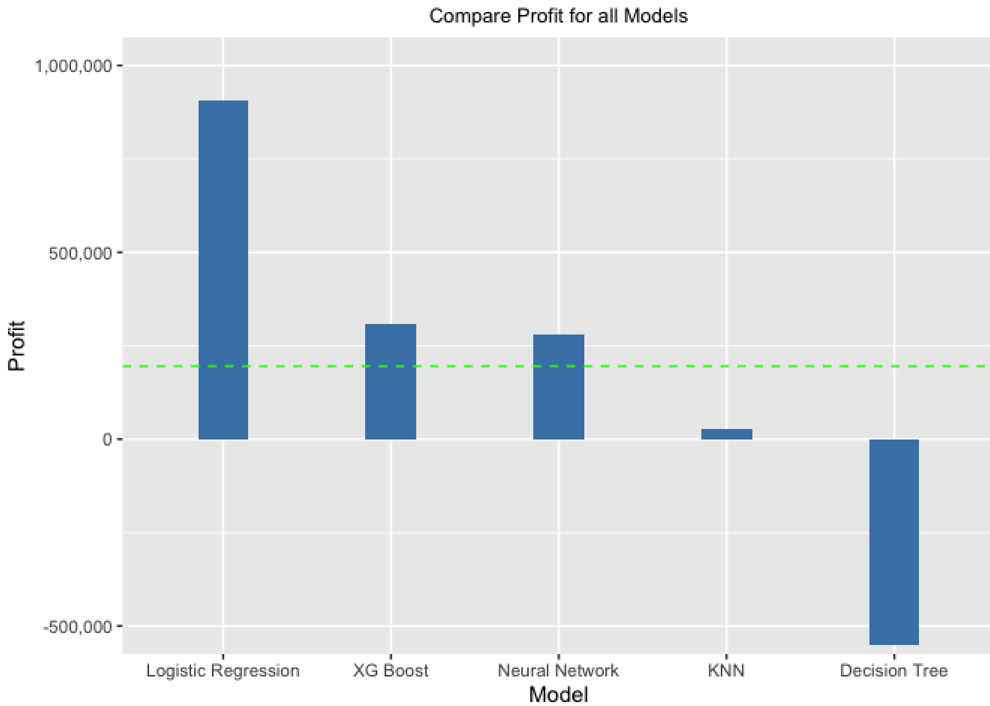
• benefit_TP: The benefit of a true positive is equal to the lifetime value of a credit card customer, estimated to be $1400 • cost_FP: If you incorrectly give a person a credit card (false positive) and the person defaults, and it goes into collection then you can lose not only the principal but also have a cost of collection. This is estimated to be a loss of $1200 • cost_FN: Not issuing a card to a person who would have been a good customer (false negative) is an opportunity lost. Missing out this opportunity costs $800 • benefit_TN: Not issuing a card to someone who did not deserve one (true negative) saves some minor processing benefit of $10.

```
benefit_TP = 1400
benefit_TN = 10
cost_FN = -1200
cost_FP = -800

cost_benefit_df <- cost_benefit_df %>%
                    mutate(Profit = (benefit_TP * TP) + (benefit_TN * TN) +
                                    (cost_FP * FP) + (cost_FN * FN))
```

9.1 Compare Profit for all Classification models

```
print(cost_benefit_df)

# Plot Profit for all the Classification Models

ggplot(cost_benefit_df %>% arrange(desc(Profit)) %>%
       mutate(Model=factor(Model, levels=Model) ),
       aes(x = Model, y = Profit)) +
  geom_bar(stat = "identity" , width=0.3, fill="steelblue") +
  coord_cartesian(ylim = c(-500000, 1000000)) +
  geom_hline(aes(yintercept = mean(Profit)),
             colour = "green",linetype="dashed") +
  ggtitle("Compare Profit for all Models") +
```

```
  scale_y_continuous(breaks = c(-500000, 0, 500000, 1000000),
                     labels = scales::comma) +
  theme(plot.title = element_text(color="black", size=10, hjust = 0.5))
```



10. Choose Model - Predict on Test

Although Logistic Regression Model had the lowest Accuracy score, the high Recall results in the highest profit.

```
#
# # Predict on probabilities of Test data
# y_predict_prob <- predict(glm_fit, newdata = income_df_test_x, type = "prob")
#
# # Set Threshold that Maximizes Profit
# threshold_2 <- 0.24
# y_pred_num <- ifelse(y_predict_prob[,2] > threshold_2, 1, 0)
#
# y_pred_factor <- as.factor(ifelse(y_predict_prob[,2] > threshold_2, "1", "0"))
```

11. Submit Scores for Contest

```
#filename <- "Chargers"

#scoreAllOne <- y_pred_factor
#Id <- seq(1,nrow(income_df_test),1)

#tempScoreFrame <- data.frame(Id, scoreAllOne) #new dataframe for submission
#names(tempScoreFrame) <- c("Id", "income") #naming 2 columns

# Download results to csv file.

#write.csv(tempScoreFrame, paste(trimws(filename), ".csv"), row.names=FALSE)
```