Credit Card Fradulent Detection_Final Project

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Overview: A Gentle Introduction:

This project is designed as a final project submission towards Harvardx data science learning initiative. We use the knowledge gained in the course series and its interdisciplinary area to apply data knowledge using scientific methods, techniques, models and algorithms.

Aim of the project

The aim of the project is to bild a classifer and discover the **Credit Card Fradulent transaction** which is a majour concern in most of the financial institutes. Analysing fraudelent manually is unfeasible due to huge amount of data and it's complexity.

Hence we want to make the process ease we will apply some of the modern ML Models,algorithms and techniques in this project.

In the process of finding data information, we use some of the popular Machine Learning methods and techniques, to name: data cleaning, data discovery, data visualisation and some model approaches.

this data set contains transactions made by credit card in september 2013. this dataset was orginally maintained by **www.kaggle.com/** . which it has 492 frauds and 284807 transactions.

This dataset is highly unbalanced.

It contains only numerical variables which are results for PCA transactions, and this dataset contains features from V1 to V28 are the principal component obtained with PCA. the only features which are not been transformed are "Time" and "Amount". Feature "Class" is the response variable and it takes values 1 and 0.

some of the models that we use in this project are: 1. Logistic Regression Model. 2. Decision Tree Model. 3. K-Fold Cross Validation. 4. Random Forest. 5. XGBoost.

Dataset download urls

this datasets can be obtained from the below links:

https://ln2.sync.com/dl/cc02c4800/pv3day6w-i2xn38sr-izd9apca-dsxrqhnd/view/default/9384339740003

https://www.kaggle.com/vasugv/credit-card-fraud-detection

https://www.kaggle.com/mlg-ulb/creditcardfraud

Note: This dataset was purely intended and stored in below Git hub account is for learning purpose

https://github.com/vasu0907/Datasets

Project Librarys

```
### Import Library's for the project

if(!require(dplyr))
  install.packages("dplyr", repos = "https://dplyr.tidyverse.org")
if(!require(caret))
  install.packages("caret", repos = "http://cran.us.r-project.org")
if(!require(data.table))
  install.packages("data.table", repos = "http://cran.us.r-project.org")
if(!require(ggplot2))
  install.packages("ggplot2", repos = "http://ggplot2.tidyverse.org")
if(!require(pROC))
  install.packages("pROC", repos = "https://web.expasy.org/pROC/")
if(!require(rpart))
  install.packages("rPart", repos = "https://cran.r-project.org/package=rpart")
if(!require(rpart.plot))
  install.packages("rpart.plot", repos = "http://www.milbo.org/rpart-plot")
if(!require(gbm))
  install.packages("gbm", repos = "https://github.com/gbm-developers/gbm")
if(!require(randomForest))
  install.packages("randomForest", repos = "https://www.stat.berkeley.edu/~breiman/RandomForests/")
if(!require(xgboost))
  install.packages("xgboost", repos = "https://github.com/dmlc/xgboost")
if(!require(caTools))
  install.packages("caTools", repos = "https://CRAN.R-project.org/package=caTools")
if(!require(ranger)) install.packages("ranger", repos = "https://github.com/imbs-hl/ranger")
```

Download Dataset

```
## For demonstration and better access, The dataset was download and placed in Github account.

creditcard_data <- fread("https://media.githubusercontent.com/media/vasu0907/Datasets/master/creditcard
```

Note: If you have some issues on downloading the dataset automatically, Please download the dataset from any one of the above url's into your local machine and provide the path in the below Code and follow the steps:

Step:1 Uncomment the above code step:2 provide the path in the below code creditcard_data <- fread("provide the copied local path here", header = TRUE, sep = ",")

Data Exploration:- Revising R concepts on df.

```
dim(creditcard_data)
```

```
## [1] 284807     31
```

```r
head(creditcard_data, 3)
```

```
##    Time        V1          V2        V3        V4          V5          V6
## 1:    0 -1.359807 -0.07278117 2.5363467 1.3781552 -0.33832077  0.46238778
## 2:    0  1.191857  0.26615071 0.1664801 0.4481541  0.06001765 -0.08236081
## 3:    1 -1.358354 -1.34016307 1.7732093 0.3797796 -0.50319813  1.80049938
##            V7         V8         V9         V10        V11         V12
## 1:  0.23959855 0.09869790  0.3637870  0.09079417 -0.5515995 -0.61780086
## 2: -0.07880298 0.08510165 -0.2554251 -0.16697441  1.6127267  1.06523531
## 3:  0.79146096 0.24767579 -1.5146543  0.20764287  0.6245015  0.06608369
##           V13        V14       V15        V16        V17         V18       V19
## 1: -0.9913898 -0.3111694 1.4681770 -0.4704005  0.2079712  0.02579058  0.403993
## 2:  0.4890950 -0.1437723 0.6355581  0.4639170 -0.1148047 -0.18336127 -0.145783
## 3:  0.7172927 -0.1659459 2.3458649 -2.8900832  1.1099694 -0.12135931 -2.261857
##           V20         V21        V22        V23         V24        V25
## 1:  0.25141210 -0.01830678  0.2778376 -0.1104739  0.06692807  0.1285394
## 2: -0.06908314 -0.22577525 -0.6386720  0.1012880 -0.33984648  0.1671704
## 3:  0.52497973  0.24799815  0.7716794  0.9094123 -0.68928096 -0.3276418
##           V26          V27         V28 Amount Class
## 1: -0.1891148  0.133558377 -0.02105305 149.62     0
## 2:  0.1258945 -0.008983099  0.01472417   2.69     0
## 3: -0.1390966 -0.055352794 -0.05975184 378.66     0
```

```r
tail(creditcard_data, 3)
```

```
##      Time         V1         V2         V3         V4          V5         V6
## 1: 172788  1.9195650 -0.3012538 -3.2496398 -0.5578281  2.63051512  3.0312601
## 2: 172788 -0.2404400  0.5304825  0.7025102  0.6897992 -0.37796113  0.6237077
## 3: 172792 -0.5334125 -0.1897333  0.7033374 -0.5062712 -0.01254568 -0.6496167
##            V7         V8        V9        V10        V11         V12        V13
## 1: -0.2968265  0.7084172 0.4324540 -0.4847818  0.4116137  0.06311886 -0.1836987
## 2: -0.6861800  0.6791455 0.3920867 -0.3991257 -1.9338488 -0.96288614 -1.0420817
## 3:  1.5770063 -0.4146504 0.4861795 -0.9154266 -1.0404583 -0.03151305 -0.1880929
##           V14        V15        V16        V17       V18        V19        V20
## 1: -0.51060184 1.32928351  0.1407160  0.3135018 0.3956525 -0.5772518 0.00139597
## 2:  0.44962444 1.96256312 -0.6085771  0.5099285 1.1139806  2.8978488 0.12743352
## 3: -0.08431647 0.04133346 -0.3026201 -0.6603766 0.1674299 -0.2561169 0.38294810
##          V21       V22         V23         V24        V25        V26
## 1: 0.2320450 0.5782290 -0.03750086 0.640133881  0.2657455 -0.0873706
## 2: 0.2652449 0.8000487 -0.16329794 0.123205244 -0.5691589  0.5466685
## 3: 0.2610573 0.6430784  0.37677701 0.008797379 -0.4736487 -0.8182671
##             V27         V28 Amount Class
## 1:  0.004454772 -0.02656083  67.88     0
## 2:  0.108820735  0.10453282  10.00     0
## 3: -0.002415309  0.01364891 217.00     0
```

```r
names(creditcard_data)
```

```
##  [1] "Time"   "V1"     "V2"     "V3"     "V4"     "V5"     "V6"     "V7"
##  [9] "V8"     "V9"     "V10"    "V11"    "V12"    "V13"    "V14"    "V15"
## [17] "V16"    "V17"    "V18"    "V19"    "V20"    "V21"    "V22"    "V23"
## [25] "V24"    "V25"    "V26"    "V27"    "V28"    "Amount" "Class"
```

```r
summary(creditcard_data)
```

```
##       Time              V1                    V2                   V3
##  Min.   :     0   Min.   :-56.40751   Min.   :-72.71573   Min.   :-48.3256
##  1st Qu.: 54202   1st Qu.: -0.92037   1st Qu.: -0.59855   1st Qu.: -0.8904
##  Median : 84692   Median :  0.01811   Median :  0.06549   Median :  0.1799
##  Mean   : 94814   Mean   :  0.00000   Mean   :  0.00000   Mean   :  0.0000
##  3rd Qu.:139321   3rd Qu.:  1.31564   3rd Qu.:  0.80372   3rd Qu.:  1.0272
##  Max.   :172792   Max.   :  2.45493   Max.   : 22.05773   Max.   :  9.3826
##        V4                 V5                    V6                  V7
##  Min.   :-5.68317   Min.   :-113.74331   Min.   :-26.1605   Min.   :-43.5572
##  1st Qu.:-0.84864   1st Qu.:  -0.69160   1st Qu.: -0.7683   1st Qu.: -0.5541
##  Median :-0.01985   Median :  -0.05434   Median : -0.2742   Median :  0.0401
##  Mean   : 0.00000   Mean   :   0.00000   Mean   :  0.0000   Mean   :  0.0000
##  3rd Qu.: 0.74334   3rd Qu.:   0.61193   3rd Qu.:  0.3986   3rd Qu.:  0.5704
##  Max.   :16.87534   Max.   :  34.80167   Max.   : 73.3016   Max.   :120.5895
##        V8                 V9                   V10                 V11
##  Min.   :-73.21672   Min.   :-13.43407   Min.   :-24.58826   Min.   :-4.79747
##  1st Qu.: -0.20863   1st Qu.: -0.64310   1st Qu.: -0.53543   1st Qu.:-0.76249
##  Median :  0.02236   Median : -0.05143   Median : -0.09292   Median :-0.03276
##  Mean   :  0.00000   Mean   :  0.00000   Mean   :  0.00000   Mean   : 0.00000
##  3rd Qu.:  0.32735   3rd Qu.:  0.59714   3rd Qu.:  0.45392   3rd Qu.: 0.73959
##  Max.   : 20.00721   Max.   : 15.59500   Max.   : 23.74514   Max.   :12.01891
##       V12                V13                 V14                 V15
##  Min.   :-18.6837   Min.   :-5.79188   Min.   :-19.2143   Min.   :-4.49894
##  1st Qu.: -0.4056   1st Qu.:-0.64854   1st Qu.: -0.4256   1st Qu.:-0.58288
##  Median :  0.1400   Median :-0.01357   Median :  0.0506   Median : 0.04807
##  Mean   :  0.0000   Mean   : 0.00000   Mean   :  0.0000   Mean   : 0.00000
##  3rd Qu.:  0.6182   3rd Qu.: 0.66251   3rd Qu.:  0.4931   3rd Qu.: 0.64882
##  Max.   :  7.8484   Max.   : 7.12688   Max.   : 10.5268   Max.   : 8.87774
##       V16                V17                 V18
##  Min.   :-14.12985   Min.   :-25.16280   Min.   :-9.498746
##  1st Qu.: -0.46804   1st Qu.: -0.48375   1st Qu.:-0.498850
##  Median :  0.06641   Median : -0.06568   Median :-0.003636
##  Mean   :  0.00000   Mean   :  0.00000   Mean   : 0.000000
##  3rd Qu.:  0.52330   3rd Qu.:  0.39968   3rd Qu.: 0.500807
##  Max.   : 17.31511   Max.   :  9.25353   Max.   : 5.041069
##       V19                V20                 V21
##  Min.   :-7.213527   Min.   :-54.49772   Min.   :-34.83038
##  1st Qu.:-0.456299   1st Qu.: -0.21172   1st Qu.: -0.22839
##  Median : 0.003735   Median : -0.06248   Median : -0.02945
##  Mean   : 0.000000   Mean   :  0.00000   Mean   :  0.00000
##  3rd Qu.: 0.458949   3rd Qu.:  0.13304   3rd Qu.:  0.18638
##  Max.   : 5.591971   Max.   : 39.42090   Max.   : 27.20284
##       V22                 V23                 V24
##  Min.   :-10.933144   Min.   :-44.80774   Min.   :-2.83663
##  1st Qu.: -0.542350   1st Qu.: -0.16185   1st Qu.:-0.35459
##  Median :  0.006782   Median : -0.01119   Median : 0.04098
##  Mean   :  0.000000   Mean   :  0.00000   Mean   : 0.00000
##  3rd Qu.:  0.528554   3rd Qu.:  0.14764   3rd Qu.: 0.43953
##  Max.   : 10.503090   Max.   : 22.52841   Max.   : 4.58455
##       V25                V26                 V27
##  Min.   :-10.29540   Min.   :-2.60455   Min.   :-22.565679
```

```
##  1st Qu.: -0.31715   1st Qu.:-0.32698   1st Qu.: -0.070840
##  Median :  0.01659   Median :-0.05214   Median :  0.001342
##  Mean   :  0.00000   Mean   : 0.00000   Mean   :  0.000000
##  3rd Qu.:  0.35072   3rd Qu.: 0.24095   3rd Qu.:  0.091045
##  Max.   :  7.51959   Max.   : 3.51735   Max.   : 31.612198
##       V28                 Amount              Class
##  Min.   :-15.43008   Min.   :    0.00   Min.   :0.000000
##  1st Qu.: -0.05296   1st Qu.:    5.60   1st Qu.:0.000000
##  Median :  0.01124   Median :   22.00   Median :0.000000
##  Mean   :  0.00000   Mean   :   88.35   Mean   :0.001728
##  3rd Qu.:  0.07828   3rd Qu.:   77.17   3rd Qu.:0.000000
##  Max.   : 33.84781   Max.   :25691.16   Max.   :1.000000
```

Standard deviation for the value name "Amount"

```
sd(creditcard_data$Amount)
```

```
## [1] 250.1201
```

Data Manipulation

Check is there any NA values in the dataset

```
apply(creditcard_data,2,function(x) sum(is.na(x)))
```

```
##   Time     V1     V2     V3     V4     V5     V6     V7     V8     V9    V10
##      0      0      0      0      0      0      0      0      0      0      0
##    V11    V12    V13    V14    V15    V16    V17    V18    V19    V20    V21
##      0      0      0      0      0      0      0      0      0      0      0
##    V22    V23    V24    V25    V26    V27    V28 Amount  Class
##      0      0      0      0      0      0      0      0      0
```

```
creditcard_data %>% group_by(Class) %>% summarise(mean(Amount), median(Amount))
```

```
## # A tibble: 2 x 3
##   Class `mean(Amount)` `median(Amount)`
##   <int>          <dbl>            <dbl>
## 1     0           88.3            22
## 2     1          122.              9.25
```

We will scale our data using the scale() function. We will apply this to the amount component of our creditcard_data amount.

Scaling is also known as feature standardization. With the help of scaling, the data is structured according to a specified range.

Therefore, there are no extreme values in our dataset that might interfere with the functioning of our model.

```
creditcard_data$Amount=scale(creditcard_data$Amount)
NewData=creditcard_data[,-c(1)]
```

Data Modeling

```
## Split data set into train and test
set.seed(123)
data_sample <- sample.split(NewData$Class, SplitRatio = 0.80)
train_dataset <- subset(NewData, data_sample == TRUE)
test_dataset <- subset(NewData, data_sample == FALSE)
dim(train_dataset)
```

```
## [1] 227846     30
```

```
dim(test_dataset)
```

```
## [1] 56961    30
```

Modeling techinque for optimize & Algorithms to predict.

Fitting Logistic Regression Model:1

Logistic regression is a simple regression model whose output is a score between 0 and 1.

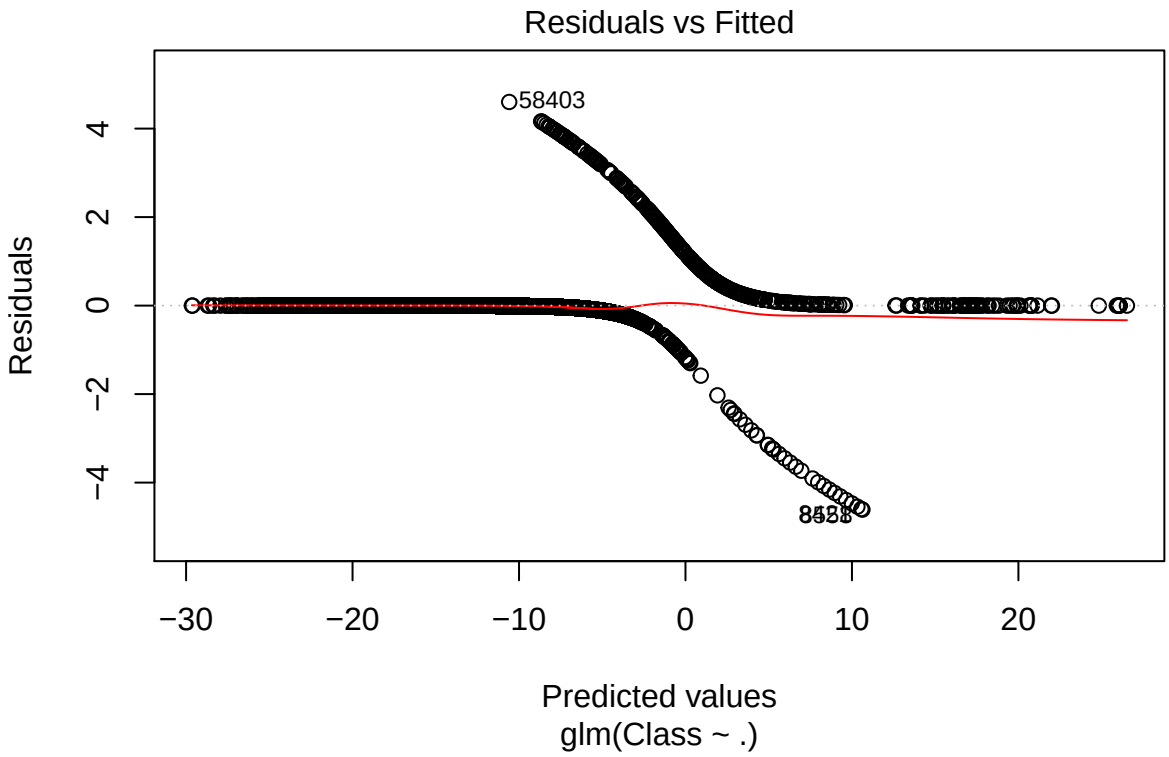
This model can be fitted using Gradient descent on the parameter vector beta. Equipped with some basic information.

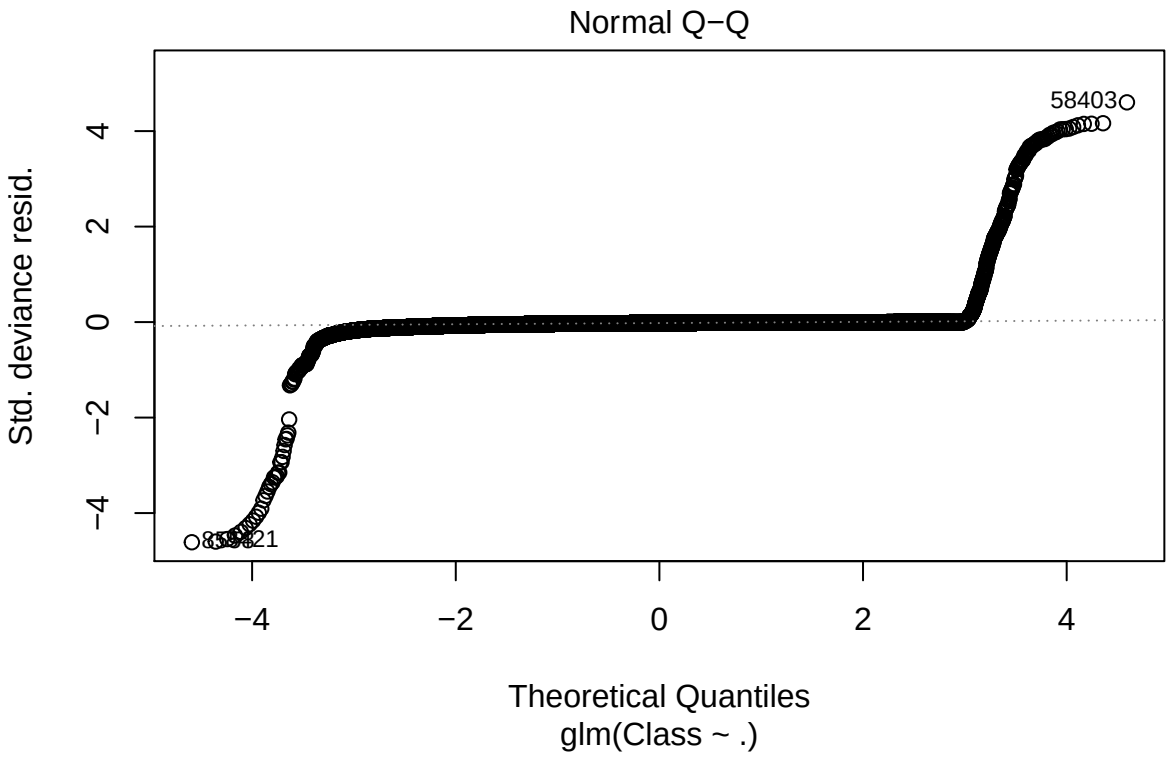
```
Logistic_Model=glm(Class~., train_dataset, family = binomial())
summary(Logistic_Model)
```

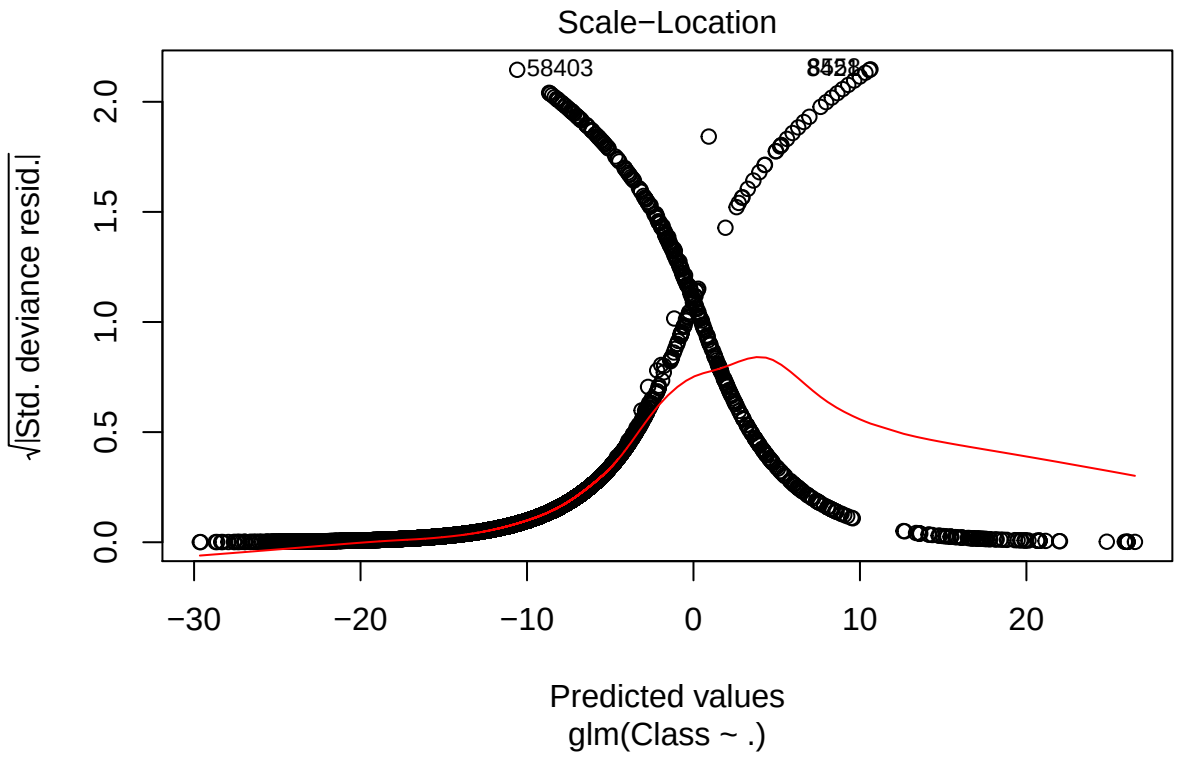
```
##
## Call:
## glm(formula = Class ~ ., family = binomial(), data = train_dataset)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.6108  -0.0292  -0.0194  -0.0125   4.6021
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -8.651305   0.160212 -53.999  < 2e-16 ***
## V1           0.072540   0.044144   1.643 0.100332
## V2           0.014818   0.059777   0.248 0.804220
## V3           0.026109   0.049776   0.525 0.599906
## V4           0.681286   0.078071   8.726  < 2e-16 ***
## V5           0.087938   0.071553   1.229 0.219079
## V6          -0.148083   0.085192  -1.738 0.082170 .
## V7          -0.117344   0.068940  -1.702 0.088731 .
## V8          -0.146045   0.035667  -4.095 4.23e-05 ***
## V9          -0.339828   0.117595  -2.890 0.003855 **
## V10         -0.785462   0.098486  -7.975 1.52e-15 ***
## V11          0.001492   0.085147   0.018 0.986018
## V12          0.087106   0.094869   0.918 0.358532
```

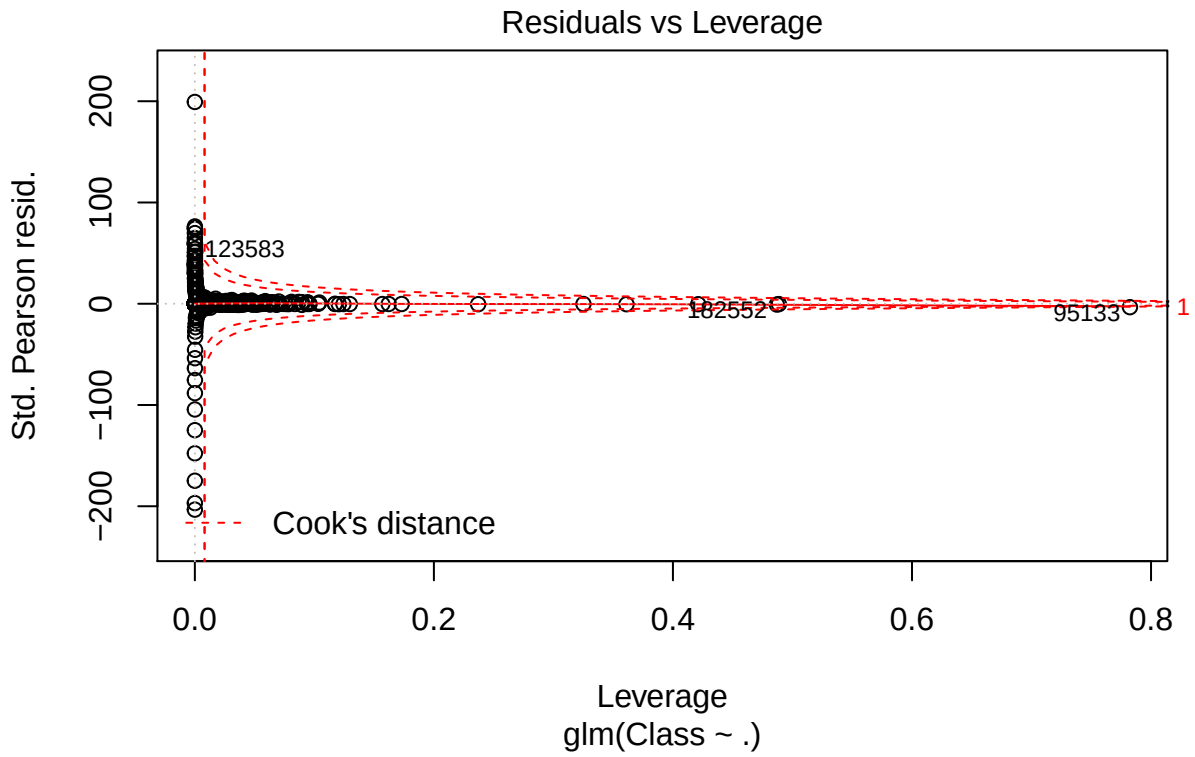
```
## V13         -0.343792   0.092381  -3.721 0.000198 ***
## V14         -0.526828   0.067084  -7.853 4.05e-15 ***
## V15         -0.095471   0.094037  -1.015 0.309991
## V16         -0.130225   0.138629  -0.939 0.347537
## V17          0.032463   0.074471   0.436 0.662900
## V18         -0.100964   0.140985  -0.716 0.473909
## V19          0.083711   0.105134   0.796 0.425897
## V20         -0.463946   0.081871  -5.667 1.46e-08 ***
## V21          0.381206   0.065880   5.786 7.19e-09 ***
## V22          0.610874   0.142086   4.299 1.71e-05 ***
## V23         -0.071406   0.058799  -1.214 0.224589
## V24          0.255791   0.170568   1.500 0.133706
## V25         -0.073955   0.142634  -0.519 0.604109
## V26          0.120841   0.202553   0.597 0.550783
## V27         -0.852018   0.118391  -7.197 6.17e-13 ***
## V28         -0.323854   0.090075  -3.595 0.000324 ***
## Amount       0.292477   0.092075   3.177 0.001491 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5799.1  on 227845  degrees of freedom
## Residual deviance: 1790.9  on 227816  degrees of freedom
## AIC: 1850.9
##
## Number of Fisher Scoring iterations: 12
```

```
plot(Logistic_Model)
```


Residuals vs Fitted
58403
Residuals
4
2
0
−2
−4
−30
−20
−10
0
10
20
Predicted values
glm(Class ~ .)


Normal Q−Q
Std. deviance resid.
Theoretical Quantiles
glm(Class ~ .)
58403
−4
−2
0
2
4


Scale−Location
58403
√|Std. deviance resid.|
0.0
0.5
1.0
1.5
2.0
−30
−20
−10
0
10
20
Predicted values
glm(Class ~ .)



Confusion Matrix

Confusion matrix is a very useful tool for calibrating the output of a model and examining all possible outcomes of your predictions (true positive, true negative, false positive, false negative). let us Use a threshold of 0.5 to transform predictions to binary and we will see how the model will fit.

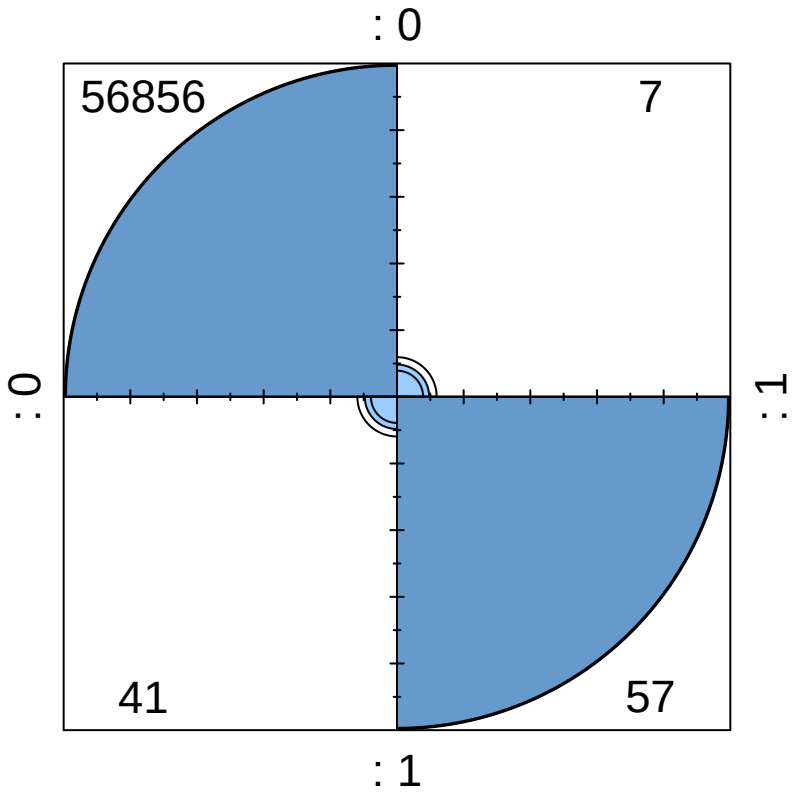
```
Confusion_matrix <- confusionMatrix(table(test_dataset$Class, as.numeric(predict(Logistic_Model, test_da
print(Confusion_matrix)
```

```
## Confusion Matrix and Statistics
##
##
##         0     1
##   0 56856     7
##   1    41    57
##
##                Accuracy : 0.9992
##                  95% CI : (0.9989, 0.9994)
##     No Information Rate : 0.9989
##     P-Value [Acc > NIR] : 0.02253
##
##                   Kappa : 0.7033
##
##  Mcnemar's Test P-Value : 1.906e-06
##
##             Sensitivity : 0.9993
```

```
##             Specificity : 0.8906
##          Pos Pred Value : 0.9999
##          Neg Pred Value : 0.5816
##              Prevalence : 0.9989
##          Detection Rate : 0.9982
##    Detection Prevalence : 0.9983
##       Balanced Accuracy : 0.9450
##
##        'Positive' Class : 0
##
```

A simple logistic regression model achieved nearly 100% accuracy, with ~99% precision (positive predictive value) and ~100% recall (sensitivity). We can see there are only 7 false negatives (transactions which were fraudulent in reality but on identified as such by the model).

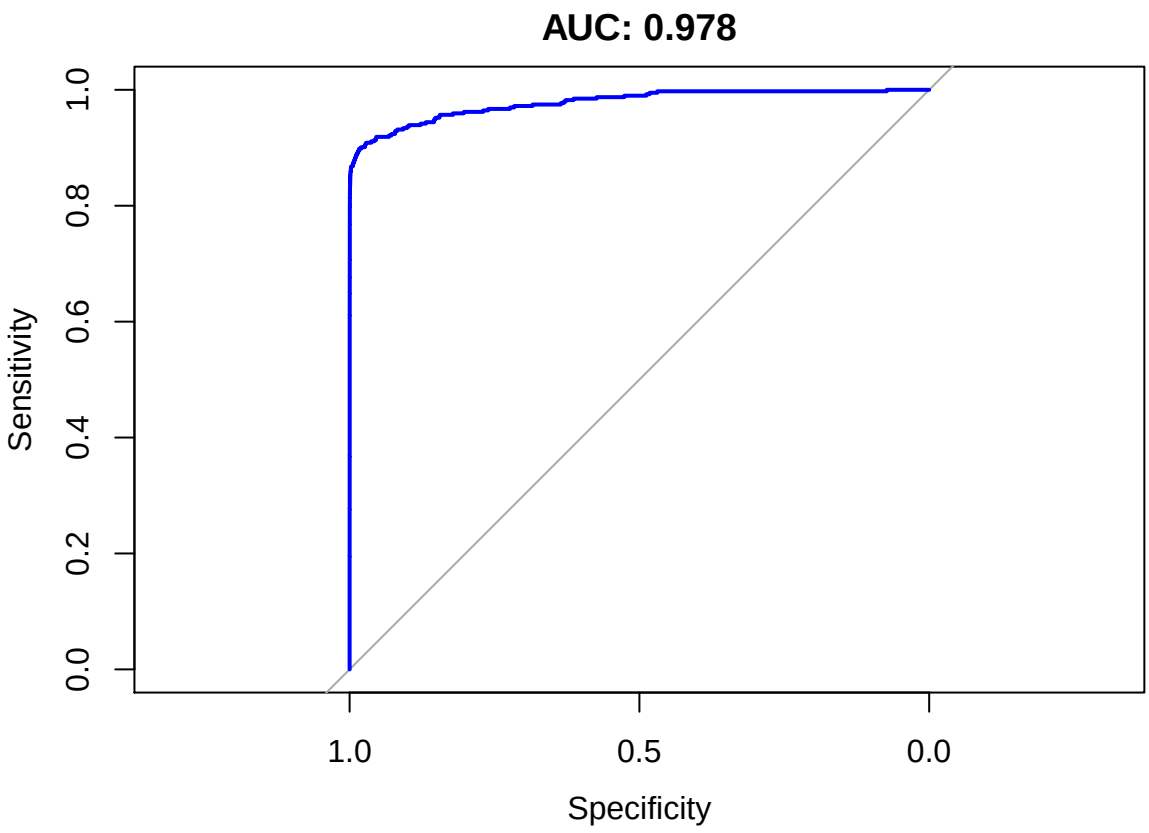
```
fourfoldplot(Confusion_matrix$table)
```



In order to assess the performance of our model, we will describe the ROC curve.

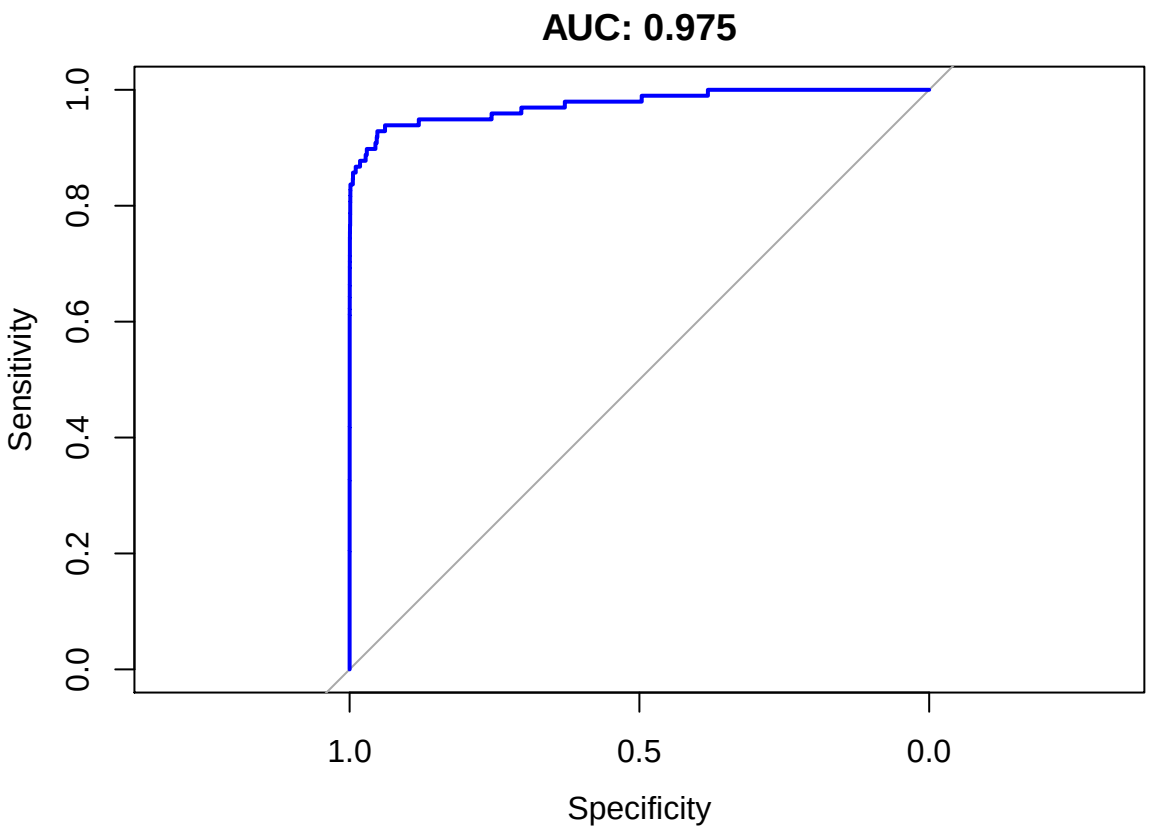
ROC is also known as Receiver Optimistic Characteristics.

```
lr.predict <- predict(Logistic_Model,train_dataset, probability = TRUE)
auc.gbm <- roc(train_dataset$Class, lr.predict)
plot(auc.gbm, main=paste0("AUC: ", round(pROC::auc(auc.gbm), 3)), col= "blue")
```



ROC on unpredicted test data

```
lr.predict_roc <- predict(Logistic_Model, test_dataset,probability= TRUE)
auc.gbm <- roc(test_dataset$Class, lr.predict_roc)
plot(auc.gbm, main=paste0("AUC: ", round(pROC::auc(auc.gbm), 3)), col = "blue")
```



Fitting a Decision Tree Models: 2

** Note: It will take a little bit time for this Decision Tree model**

We will Implement Decission Tree Algorithm and to plot the out come of decision, these outcomes are basically a consequence through which we can conclude as to what class the object belongs to. We will now implement our decision tree model and will plot it using the rpart.plot() function.

```
decissionTree_model <- rpart(Class~., creditcard_data, method = 'class')
predict_val <- predict(decissionTree_model, creditcard_data, type = 'class')
probability <- predict(decissionTree_model, creditcard_data, type = 'prob')
```

```
summary(decissionTree_model)
```

```
## Call:
## rpart(formula = Class ~ ., data = creditcard_data, method = "class")
##   n= 284807
##
##           CP nsplit rel error    xerror       xstd
## 1 0.47357724      0 1.0000000 1.0000000 0.04504452
## 2 0.05894309      1 0.5264228 0.5365854 0.03300924
## 3 0.05691057      2 0.4674797 0.4959350 0.03173538
## 4 0.02235772      3 0.4105691 0.4247967 0.02937302
## 5 0.02032520      6 0.3434959 0.4065041 0.02873408
## 6 0.01829268      9 0.2804878 0.3760163 0.02763629
```

```
## 7 0.01000000     10 0.2621951 0.3313008 0.02594206
##
## Variable importance
##  V17  V12  V16  V10  V11  V18  V14   V7  V27   V9   V6 Time   V8  V20   V3   V4
##   22   17   13   12   10    9    4    2    1    1    1    1    1    1    1    1
##  V21  V26
##    1    1
##
## Node number 1: 284807 observations,    complexity param=0.4735772
##   predicted class=0  expected loss=0.001727486  P(node) =1
##     class counts: 284315   492
##    probabilities: 0.998 0.002
##   left son=2 (284364 obs) right son=3 (443 obs)
##   Primary splits:
##       V17 < -2.75394    to the right, improve=514.2412, (0 missing)
##       V12 < -4.562479   to the right, improve=478.1819, (0 missing)
##       V14 < -5.841579   to the right, improve=403.7565, (0 missing)
##       V16 < -4.037668   to the right, improve=361.6741, (0 missing)
##       V10 < -3.833386   to the right, improve=361.0302, (0 missing)
##   Surrogate splits:
##       V12 < -4.562479   to the right, agree=0.999, adj=0.628, (0 split)
##       V16 < -4.037668   to the right, agree=0.999, adj=0.578, (0 split)
##       V10 < -5.617552   to the right, agree=0.999, adj=0.427, (0 split)
##       V18 < -3.740074   to the right, agree=0.999, adj=0.402, (0 split)
##       V11 < 4.146304    to the left,  agree=0.999, adj=0.393, (0 split)
##
## Node number 2: 284364 observations,    complexity param=0.05691057
##   predicted class=0  expected loss=0.0005415594  P(node) =0.9984446
##     class counts: 284210   154
##    probabilities: 0.999 0.001
##   left son=4 (284328 obs) right son=5 (36 obs)
##   Primary splits:
##       V14 < -8.09768    to the right, improve=56.826780, (0 missing)
##       V12 < -4.839175   to the right, improve=46.246550, (0 missing)
##       V11 < 4.372039    to the left,  improve=23.488920, (0 missing)
##       V10 < -3.84725    to the right, improve=14.658460, (0 missing)
##       V4  < 5.321513    to the left,  improve= 8.063169, (0 missing)
##   Surrogate splits:
##       V12 < -5.374364   to the right, agree=1, adj=0.444, (0 split)
##       V11 < 5.426486    to the left,  agree=1, adj=0.278, (0 split)
##
## Node number 3: 443 observations,    complexity param=0.05894309
##   predicted class=1  expected loss=0.2370203  P(node) =0.001555439
##     class counts:   105   338
##    probabilities: 0.237 0.763
##   left son=6 (33 obs) right son=7 (410 obs)
##   Primary splits:
##       V12 < -2.18088    to the right, improve=35.18035, (0 missing)
##       V10 < -1.458135   to the right, improve=33.04218, (0 missing)
##       V9  < 3.030988    to the right, improve=29.54316, (0 missing)
##       V7  < 2.484147    to the right, improve=28.99810, (0 missing)
##       V3  < 0.3881728   to the right, improve=24.38649, (0 missing)
##   Surrogate splits:
##       V10 < 1.291321    to the right, agree=0.968, adj=0.576, (0 split)
```

```
##       V9  < 3.030988    to the right, agree=0.966, adj=0.545, (0 split)
##       V7  < 3.124222    to the right, agree=0.959, adj=0.455, (0 split)
##       V3  < 0.03134823  to the right, agree=0.957, adj=0.424, (0 split)
##       V4  < -1.983926   to the left,  agree=0.955, adj=0.394, (0 split)
##
## Node number 4: 284328 observations,    complexity param=0.0203252
##   predicted class=0  expected loss=0.0004290819  P(node) =0.9983182
##     class counts: 284206   122
##    probabilities: 1.000 0.000
##   left son=8 (284081 obs) right son=9 (247 obs)
##   Primary splits:
##       V14 < -4.661454   to the right, improve=12.8981100, (0 missing)
##       V12 < -4.790606   to the right, improve= 4.5646780, (0 missing)
##       V17 < 5.534993    to the left,  improve= 3.0452870, (0 missing)
##       V10 < -3.213114   to the right, improve= 1.7679740, (0 missing)
##       V11 < 3.503332    to the left,  improve= 0.9499802, (0 missing)
##   Surrogate splits:
##       V9  < 7.906346    to the left,  agree=0.999, adj=0.113, (0 split)
##       V18 < 3.197176    to the left,  agree=0.999, adj=0.085, (0 split)
##       V10 < 12.53545    to the left,  agree=0.999, adj=0.040, (0 split)
##       V17 < -2.373553   to the right, agree=0.999, adj=0.040, (0 split)
##       V11 < 4.383243    to the left,  agree=0.999, adj=0.028, (0 split)
##
## Node number 5: 36 observations
##   predicted class=1  expected loss=0.1111111  P(node) =0.0001264014
##     class counts:     4    32
##    probabilities: 0.111 0.889
##
## Node number 6: 33 observations
##   predicted class=0  expected loss=0.06060606  P(node) =0.0001158679
##     class counts:    31     2
##    probabilities: 0.939 0.061
##
## Node number 7: 410 observations,    complexity param=0.02235772
##   predicted class=1  expected loss=0.1804878  P(node) =0.001439571
##     class counts:    74   336
##    probabilities: 0.180 0.820
##   left son=14 (45 obs) right son=15 (365 obs)
##   Primary splits:
##       V14 < -3.429828   to the right, improve=15.956910, (0 missing)
##       V26 < -0.2249219  to the left,  improve=15.134070, (0 missing)
##       V4  < 1.169294    to the left,  improve= 9.078085, (0 missing)
##       V9  < -4.031951   to the right, improve= 8.962072, (0 missing)
##       V11 < 0.5930789   to the left,  improve= 7.867805, (0 missing)
##   Surrogate splits:
##       V11 < 0.5930789   to the left,  agree=0.910, adj=0.178, (0 split)
##       V7  < 0.1852671   to the right, agree=0.900, adj=0.089, (0 split)
##       V10 < -1.617227   to the right, agree=0.900, adj=0.089, (0 split)
##       V2  < 18.05709    to the right, agree=0.898, adj=0.067, (0 split)
##       V22 < 5.743195    to the right, agree=0.898, adj=0.067, (0 split)
##
## Node number 8: 284081 observations
##   predicted class=0  expected loss=0.0002886501  P(node) =0.9974509
##     class counts: 283999    82
```

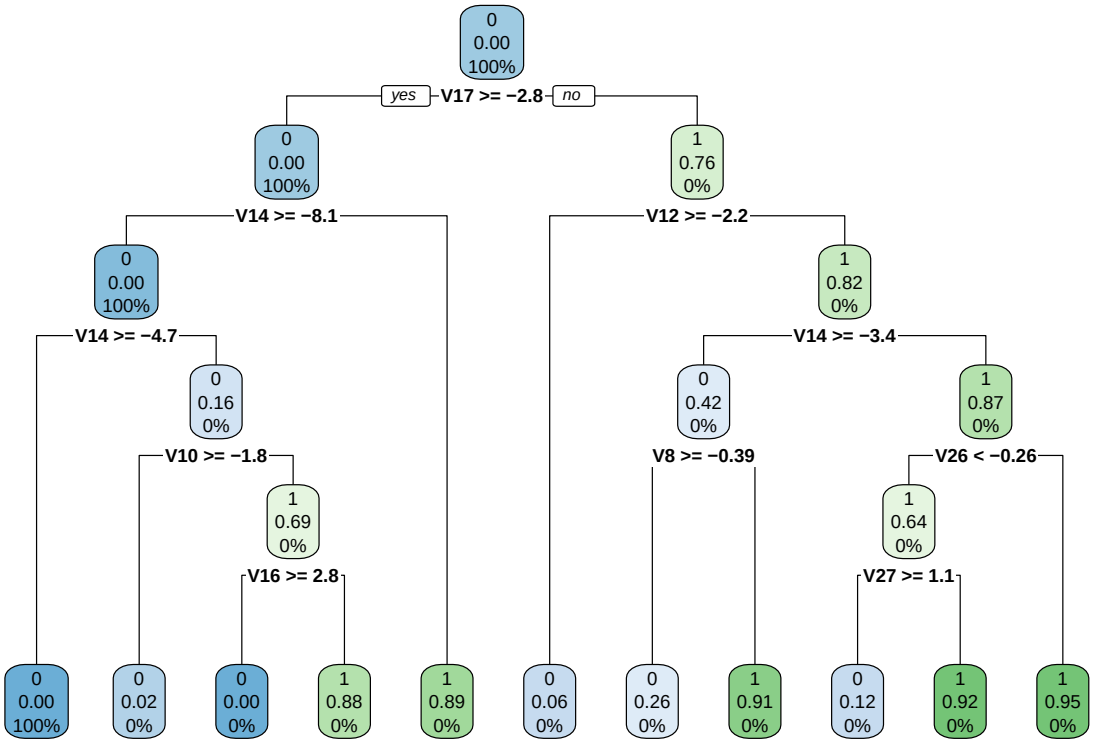
```
##    probabilities: 1.000 0.000
##
## Node number 9: 247 observations,    complexity param=0.0203252
##   predicted class=0  expected loss=0.1619433  P(node) =0.000867254
##     class counts:   207    40
##    probabilities: 0.838 0.162
##   left son=18 (195 obs) right son=19 (52 obs)
##   Primary splits:
##       V10 < -1.847304   to the right, improve=37.05479, (0 missing)
##       V7  < -0.9118796  to the right, improve=25.64453, (0 missing)
##       V12 < -2.378497   to the right, improve=21.25928, (0 missing)
##       V9  < 0.9459067   to the right, improve=19.76720, (0 missing)
##       V4  < 1.85959     to the left,  improve=18.27138, (0 missing)
##   Surrogate splits:
##       V7  < -0.9118796  to the right, agree=0.858, adj=0.327, (0 split)
##       V12 < -2.891134   to the right, agree=0.858, adj=0.327, (0 split)
##       V21 < -0.01407949 to the left,  agree=0.846, adj=0.269, (0 split)
##       V9  < -2.364669   to the right, agree=0.842, adj=0.250, (0 split)
##       V15 < -0.6340641  to the right, agree=0.838, adj=0.231, (0 split)
##
## Node number 14: 45 observations,    complexity param=0.01829268
##   predicted class=0  expected loss=0.4222222  P(node) =0.0001580017
##     class counts:    26    19
##    probabilities: 0.578 0.422
##   left son=28 (34 obs) right son=29 (11 obs)
##   Primary splits:
##       V8  < -0.3873742  to the right, improve=6.902080, (0 missing)
##       V20 < 0.3123598   to the left,  improve=5.370302, (0 missing)
##       V4  < 1.400317    to the left,  improve=5.001639, (0 missing)
##       V11 < 1.765276    to the left,  improve=4.595232, (0 missing)
##       V18 < -2.501672   to the right, improve=4.565181, (0 missing)
##   Surrogate splits:
##       V21 < -0.6257536  to the right, agree=0.911, adj=0.636, (0 split)
##       V22 < 1.495255    to the left,  agree=0.889, adj=0.545, (0 split)
##       V6  < 0.8007469   to the left,  agree=0.867, adj=0.455, (0 split)
##       V16 < -4.772197   to the right, agree=0.867, adj=0.455, (0 split)
##       V27 < -2.884922   to the right, agree=0.867, adj=0.455, (0 split)
##
## Node number 15: 365 observations,    complexity param=0.02235772
##   predicted class=1  expected loss=0.1315068  P(node) =0.00128157
##     class counts:    48   317
##    probabilities: 0.132 0.868
##   left son=30 (98 obs) right son=31 (267 obs)
##   Primary splits:
##       V26  < -0.2644702  to the left,  improve=13.641260, (0 missing)
##       V27  < 1.696946    to the right, improve=11.027410, (0 missing)
##       Time < 31379.5     to the left,  improve=10.829530, (0 missing)
##       V6   < -2.883912   to the left,  improve= 9.930779, (0 missing)
##       V20  < 0.7338922   to the right, improve= 9.524335, (0 missing)
##   Surrogate splits:
##       V9  < -0.1000254  to the right, agree=0.753, adj=0.082, (0 split)
##       V4  < 0.3721625   to the left,  agree=0.748, adj=0.061, (0 split)
##       V27 < -4.25345    to the left,  agree=0.748, adj=0.061, (0 split)
##       V7  < -28.1132    to the left,  agree=0.742, adj=0.041, (0 split)
```

```
##       V10 < -19.93122   to the left,  agree=0.742, adj=0.041, (0 split)
##
## Node number 18: 195 observations
##   predicted class=0  expected loss=0.02051282  P(node) =0.0006846742
##     class counts:   191     4
##    probabilities: 0.979 0.021
##
## Node number 19: 52 observations,    complexity param=0.0203252
##   predicted class=1  expected loss=0.3076923  P(node) =0.0001825798
##     class counts:    16    36
##    probabilities: 0.308 0.692
##   left son=38 (11 obs) right son=39 (41 obs)
##   Primary splits:
##       V16 < 2.754354    to the right, improve=13.373360, (0 missing)
##       V18 < 3.081813    to the right, improve=10.218710, (0 missing)
##       V24 < -0.662693   to the left,  improve= 9.461036, (0 missing)
##       V5  < 1.271888    to the right, improve= 7.809019, (0 missing)
##       V19 < -2.271497   to the left,  improve= 7.095023, (0 missing)
##   Surrogate splits:
##       V18  < 3.355946    to the right, agree=0.942, adj=0.727, (0 split)
##       V2   < 3.136648    to the right, agree=0.904, adj=0.545, (0 split)
##       V7   < 1.7515      to the right, agree=0.904, adj=0.545, (0 split)
##       V19  < -2.271497   to the left,  agree=0.865, adj=0.364, (0 split)
##       Time < 161088      to the right, agree=0.846, adj=0.273, (0 split)
##
## Node number 28: 34 observations
##   predicted class=0  expected loss=0.2647059  P(node) =0.0001193791
##     class counts:    25     9
##    probabilities: 0.735 0.265
##
## Node number 29: 11 observations
##   predicted class=1  expected loss=0.09090909  P(node) =3.862265e-05
##     class counts:     1    10
##    probabilities: 0.091 0.909
##
## Node number 30: 98 observations,    complexity param=0.02235772
##   predicted class=1  expected loss=0.3571429  P(node) =0.0003440927
##     class counts:    35    63
##    probabilities: 0.357 0.643
##   left son=60 (34 obs) right son=61 (64 obs)
##   Primary splits:
##       V27  < 1.077147    to the right, improve=28.72243, (0 missing)
##       Time < 33013       to the left,  improve=25.48485, (0 missing)
##       V26  < -0.3338474  to the right, improve=23.55094, (0 missing)
##       V6   < -2.446679   to the left,  improve=21.87879, (0 missing)
##       V20  < 0.7582707   to the right, improve=16.52107, (0 missing)
##   Surrogate splits:
##       V6   < -2.867273   to the left,  agree=0.939, adj=0.824, (0 split)
##       Time < 33013       to the left,  agree=0.918, adj=0.765, (0 split)
##       V8   < 1.754752    to the right, agree=0.867, adj=0.618, (0 split)
##       V11  < 7.243801    to the right, agree=0.867, adj=0.618, (0 split)
##       V20  < 0.7582707   to the right, agree=0.867, adj=0.618, (0 split)
##
## Node number 31: 267 observations
```

```
##   predicted class=1  expected loss=0.04868914  P(node) =0.000937477
##     class counts:    13   254
##    probabilities: 0.049 0.951
##
## Node number 38: 11 observations
##   predicted class=0  expected loss=0  P(node) =3.862265e-05
##     class counts:    11     0
##    probabilities: 1.000 0.000
##
## Node number 39: 41 observations
##   predicted class=1  expected loss=0.1219512  P(node) =0.0001439571
##     class counts:     5    36
##    probabilities: 0.122 0.878
##
## Node number 60: 34 observations
##   predicted class=0  expected loss=0.1176471  P(node) =0.0001193791
##     class counts:    30     4
##    probabilities: 0.882 0.118
##
## Node number 61: 64 observations
##   predicted class=1  expected loss=0.078125  P(node) =0.0002247136
##     class counts:     5    59
##    probabilities: 0.078 0.922
```

Plot

```
rpart.plot(decissionTree_model)
```



K-Fold with Cross-Validation Model:3

The K-fold cross validation is go-to-method for evaluating the performance of an algorithm on dataset. In terms of how to select k for cross validation, larger values of k are preferable but they will also take much more computational time. For this reason, the choices of k=5 and k=10 are common. we are using SMOTE resampling the data, with 5-fold cv and trains Random forest classifier with roc as a metric.

K-fold cross Validation

```
CV_control <- trainControl(method = "cv",
                           number = 5,
                           verboseIter = T,
                           classProbs = T,
                           sampling = "smote",
                           summaryFunction = twoClassSummary,
                           savePredictions = T)

train_dataset_CV <- train_dataset
train_dataset_CV$Class <- as.factor(train_dataset_CV$Class)
levels(train_dataset_CV$Class) <- make.names(c(0,1))
model_CV <- train(Class~., data = train_dataset_CV, method = "rpart", trControl = CV_control,
                  metric = 'ROC')
```

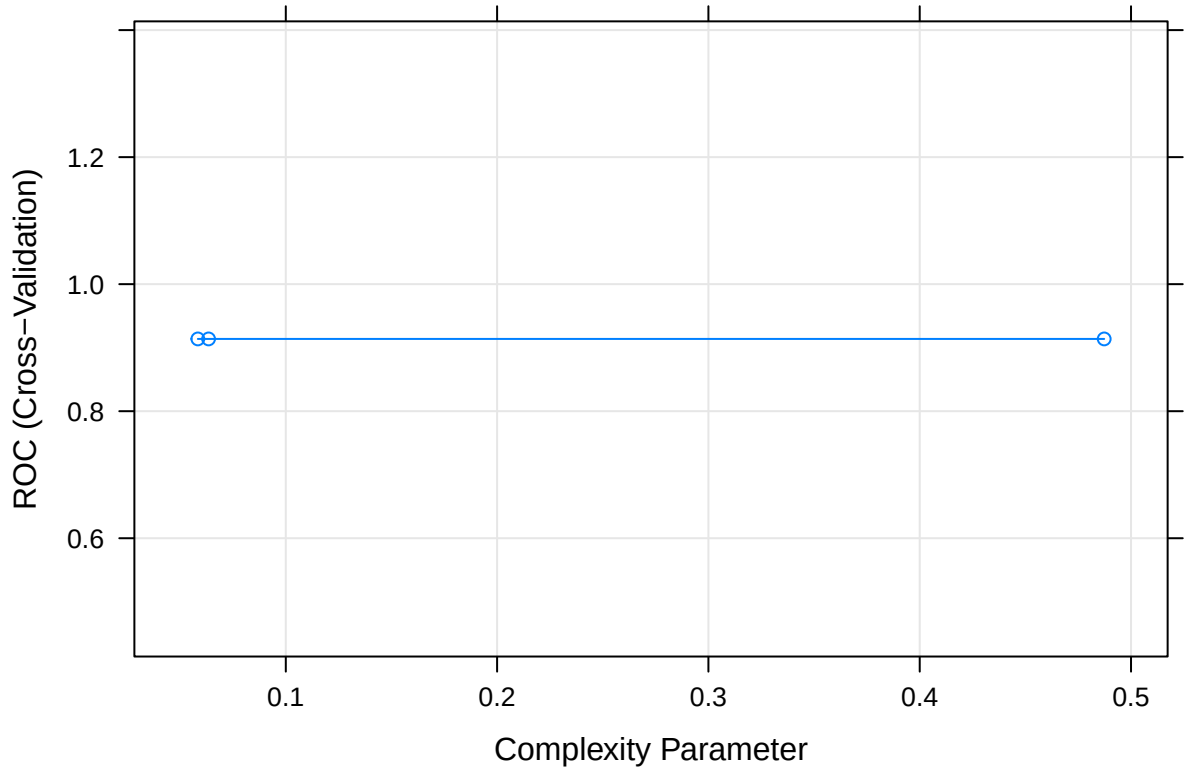
```
## + Fold1: cp=0.05838
## - Fold1: cp=0.05838
```

```
## + Fold2: cp=0.05838
## - Fold2: cp=0.05838
## + Fold3: cp=0.05838
## - Fold3: cp=0.05838
## + Fold4: cp=0.05838
## - Fold4: cp=0.05838
## + Fold5: cp=0.05838
## - Fold5: cp=0.05838
## Aggregating results
## Selecting tuning parameters
## Fitting cp = 0.487 on full training set
```

```
print(model_CV)
```

```
## CART
##
## 227846 samples
##     29 predictor
##      2 classes: 'X0', 'X1'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 182277, 182278, 182276, 182276, 182277
## Addtional sampling using SMOTE
##
## Resampling results across tuning parameters:
##
##   cp          ROC        Sens       Spec
##   0.05837563  0.9137763  0.9875006  0.8400519
##   0.06345178  0.9137763  0.9875006  0.8400519
##   0.48730964  0.9137763  0.9875006  0.8400519
##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was cp = 0.4873096.
```

```
plot(model_CV)
```



Now let see the model performing on unpredicted Test data.

Cross Validation does give an unbiased estimation of the algorithms performance on unseen dataset.

```
Model_CV_predict <- predict(model_CV, test_dataset, type = "prob")
Confussion_matrix_CV <- confusionMatrix(table(as.numeric(Model_CV_predict$X1 > 0.5), test_dataset$Class
print(Confussion_matrix_CV)
```

```
## Confusion Matrix and Statistics
##
##
##         0     1
##   0 56286    17
##   1   577    81
##
##                Accuracy : 0.9896
##                  95% CI : (0.9887, 0.9904)
##     No Information Rate : 0.9983
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.2119
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9899
##             Specificity : 0.8265
```

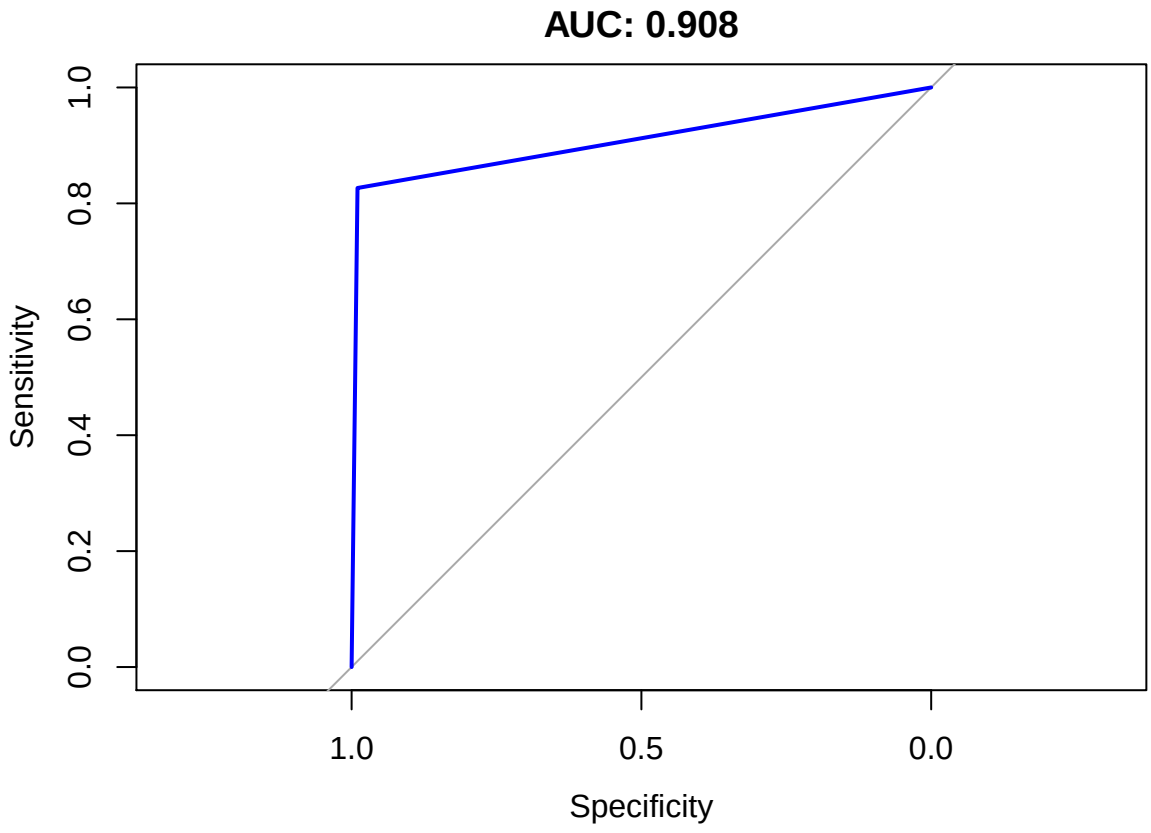
```
##          Pos Pred Value : 0.9997
##          Neg Pred Value : 0.1231
##              Prevalence : 0.9983
##          Detection Rate : 0.9881
##    Detection Prevalence : 0.9884
##       Balanced Accuracy : 0.9082
##
##        'Positive' Class : 0
##
```

** ROC on unpredicted test data**

```
model_CV_roc <- roc(test_dataset$Class, predict(model_CV,test_dataset, type = "prob")$X1)
print(model_CV_roc)
```

```
##
## Call:
## roc.default(response = test_dataset$Class, predictor = predict(model_CV,     test_dataset, type = "pr
##
## Data: predict(model_CV, test_dataset, type = "prob")$X1 in 56863 controls (test_dataset$Class 0) < 98
## Area under the curve: 0.9082
```

```
plot(model_CV_roc, main = paste0("AUC: ", round(pROC::auc(model_CV_roc), 3)), col = "blue")
```



Repeated k-fold Cross Validation Method: 2 The process of splitting the data into k-folds can be repeated a number of times, this is called Repeated k-fold Cross Validation. The final model accuracy is taken as the mean from the number of repeats.

```
CV_repeat <- trainControl(method = "repeatedcv",
                          number = 5,
                          repeats = 3,
                          verboseIter = T,
                          classProbs = T,
                          sampling = "smote",
                          summaryFunction = twoClassSummary,
                          savePredictions = T)
model_repet <- train(Class~., data = train_dataset_CV, trControl = CV_repeat, method = 'rpart2', metric
```

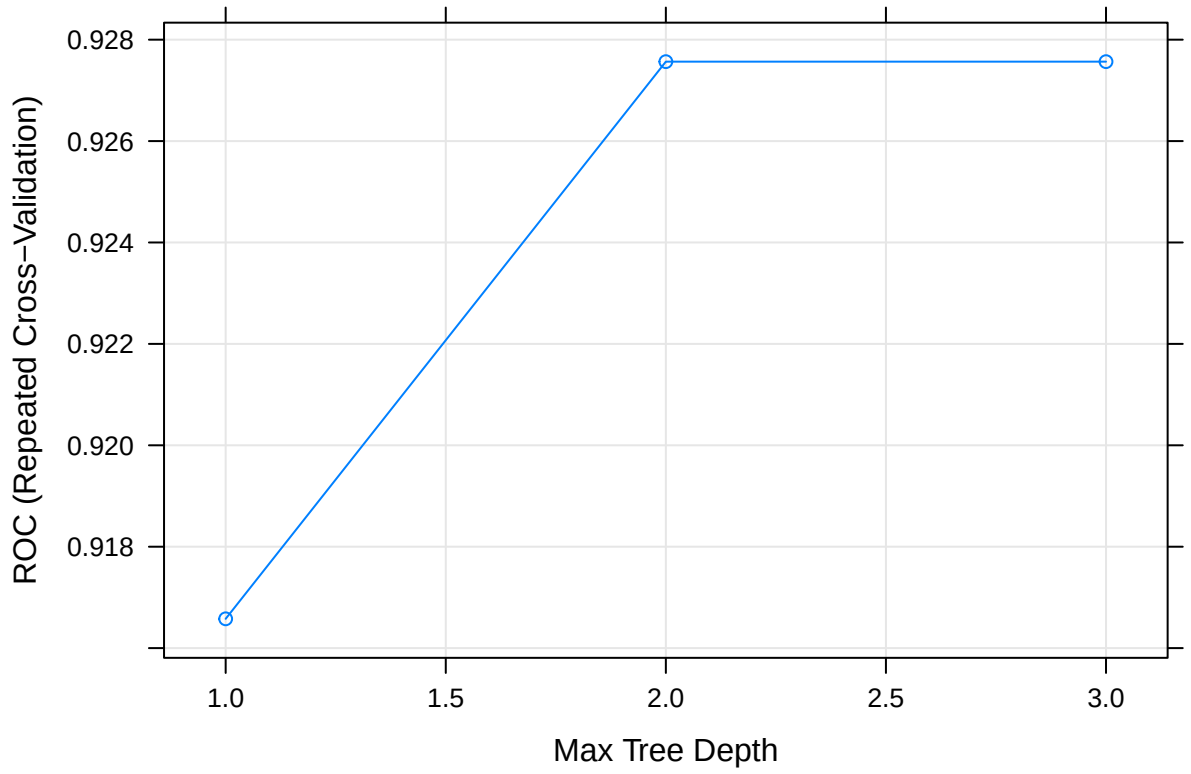
```
## + Fold1.Rep1: maxdepth=3
## - Fold1.Rep1: maxdepth=3
## + Fold2.Rep1: maxdepth=3
## - Fold2.Rep1: maxdepth=3
## + Fold3.Rep1: maxdepth=3
## - Fold3.Rep1: maxdepth=3
## + Fold4.Rep1: maxdepth=3
## - Fold4.Rep1: maxdepth=3
## + Fold5.Rep1: maxdepth=3
## - Fold5.Rep1: maxdepth=3
## + Fold1.Rep2: maxdepth=3
## - Fold1.Rep2: maxdepth=3
## + Fold2.Rep2: maxdepth=3
## - Fold2.Rep2: maxdepth=3
## + Fold3.Rep2: maxdepth=3
## - Fold3.Rep2: maxdepth=3
## + Fold4.Rep2: maxdepth=3
## - Fold4.Rep2: maxdepth=3
## + Fold5.Rep2: maxdepth=3
## - Fold5.Rep2: maxdepth=3
## + Fold1.Rep3: maxdepth=3
## - Fold1.Rep3: maxdepth=3
## + Fold2.Rep3: maxdepth=3
## - Fold2.Rep3: maxdepth=3
## + Fold3.Rep3: maxdepth=3
## - Fold3.Rep3: maxdepth=3
## + Fold4.Rep3: maxdepth=3
## - Fold4.Rep3: maxdepth=3
## + Fold5.Rep3: maxdepth=3
## - Fold5.Rep3: maxdepth=3
## Aggregating results
## Selecting tuning parameters
## Fitting maxdepth = 2 on full training set
```

```
print(model_repet)
```

```
## CART
##
## 227846 samples
```

```
##     29 predictor
##      2 classes: 'X0', 'X1'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 3 times)
## Summary of sample sizes: 182278, 182277, 182276, 182277, 182276, 182276, ...
## Addtional sampling using SMOTE
##
## Resampling results across tuning parameters:
##
##   maxdepth  ROC        Sens       Spec
##   1         0.9165777  0.9820680  0.8510873
##   2         0.9275663  0.9724294  0.8629233
##   3         0.9275663  0.9724294  0.8629233
##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was maxdepth = 2.
```

```
plot(model_repet)
```



Now let see the model performing on unpredicted Test data.

```
CV_repeat_pred <- predict(model_repet, test_dataset, type = 'prob')
confussion_Matrix_CVRepet <- confusionMatrix(table(as.numeric(CV_repeat_pred$X1 >0.5),test_dataset$Class
print(confussion_Matrix_CVRepet)
```

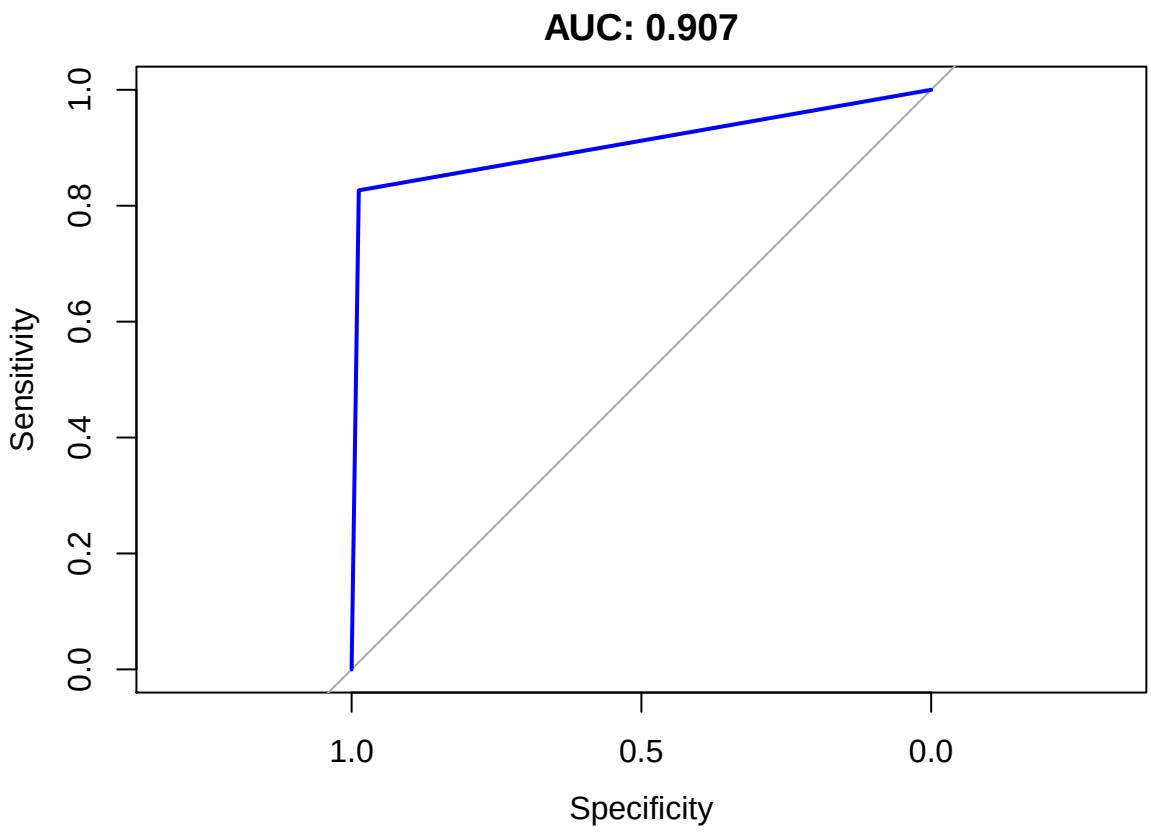
```
## Confusion Matrix and Statistics
##
##
##         0     1
##   0 56158    17
##   1   705    81
##
##                Accuracy : 0.9873
##                  95% CI : (0.9864, 0.9882)
##     No Information Rate : 0.9983
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.1808
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9876
##             Specificity : 0.8265
##          Pos Pred Value : 0.9997
##          Neg Pred Value : 0.1031
##              Prevalence : 0.9983
##          Detection Rate : 0.9859
##    Detection Prevalence : 0.9862
##       Balanced Accuracy : 0.9071
##
##        'Positive' Class : 0
##
```

** ROC on unpredicted test data **

```
CV_repet_roc <- roc(test_dataset$Class, predict(model_repet,test_dataset, type = "prob")$X1)
print(CV_repet_roc)
```

```
##
## Call:
## roc.default(response = test_dataset$Class, predictor = predict(model_repet,     test_dataset, type =
##
## Data: predict(model_repet, test_dataset, type = "prob")$X1 in 56863 controls (test_dataset$Class 0)
## Area under the curve: 0.9071
```

```
plot(CV_repet_roc, main = paste0("AUC: ", round(pROC::auc(CV_repet_roc), 3)), col ="blue")
```



Random forest Model: 4

the code below uses the SMOTE to resample the data with 5 fold cv perfomance and trains a Random Forest Classifier using ROC as a metric.

```
Model_rf <- trainControl(method = "cv",
                         number = 5,
                         verboseIter = T,
                         classProbs = T,
                         sampling = "smote",
                         summaryFunction = twoClassSummary,
                         savePredictions = T)

train_dataset_rf <- train_dataset
train_dataset_rf$Class <- as.factor(train_dataset_rf$Class)
levels(train_dataset_rf$Class) <- make.names(c(0,1))
Model_rf <- train(Class~., data = train_dataset_rf, method = 'rf', trControl = Model_rf, metric = 'ROC'
```

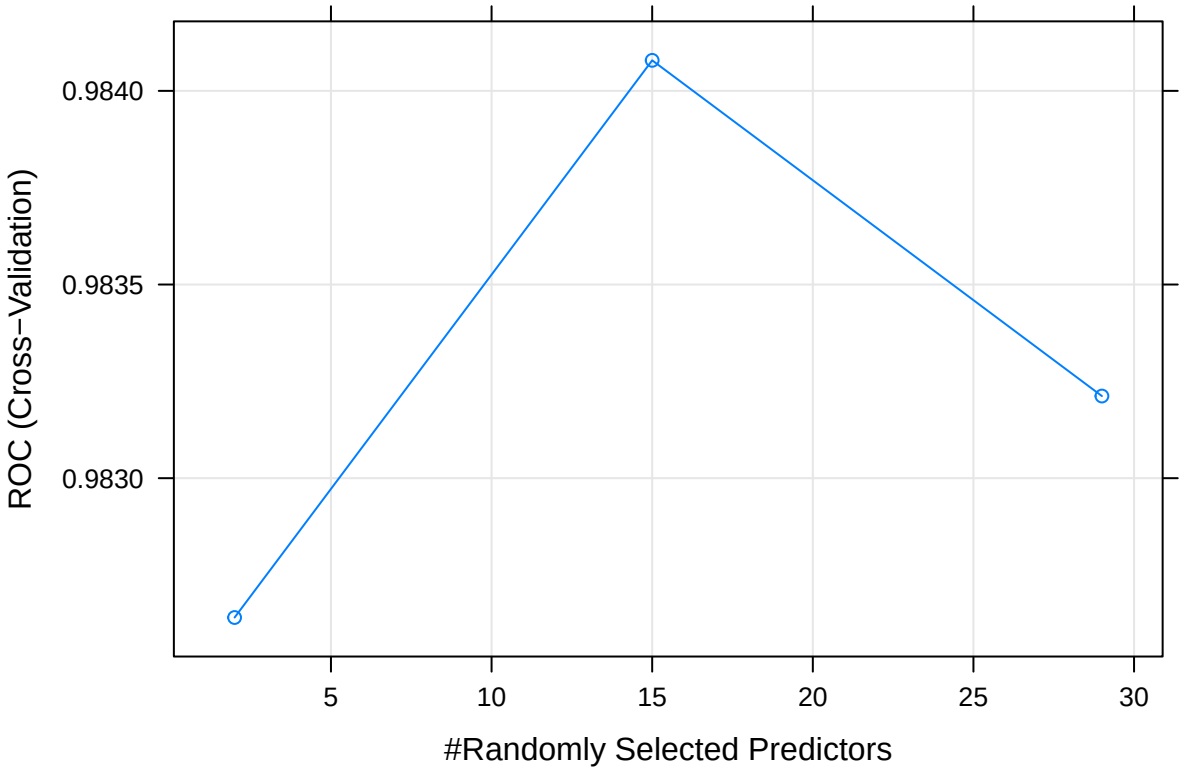
```
## + Fold1: mtry= 2
## - Fold1: mtry= 2
## + Fold1: mtry=15
## - Fold1: mtry=15
## + Fold1: mtry=29
## - Fold1: mtry=29
## + Fold2: mtry= 2
```

```
## - Fold2: mtry= 2
## + Fold2: mtry=15
## - Fold2: mtry=15
## + Fold2: mtry=29
## - Fold2: mtry=29
## + Fold3: mtry= 2
## - Fold3: mtry= 2
## + Fold3: mtry=15
## - Fold3: mtry=15
## + Fold3: mtry=29
## - Fold3: mtry=29
## + Fold4: mtry= 2
## - Fold4: mtry= 2
## + Fold4: mtry=15
## - Fold4: mtry=15
## + Fold4: mtry=29
## - Fold4: mtry=29
## + Fold5: mtry= 2
## - Fold5: mtry= 2
## + Fold5: mtry=15
## - Fold5: mtry=15
## + Fold5: mtry=29
## - Fold5: mtry=29
## Aggregating results
## Selecting tuning parameters
## Fitting mtry = 15 on full training set
```

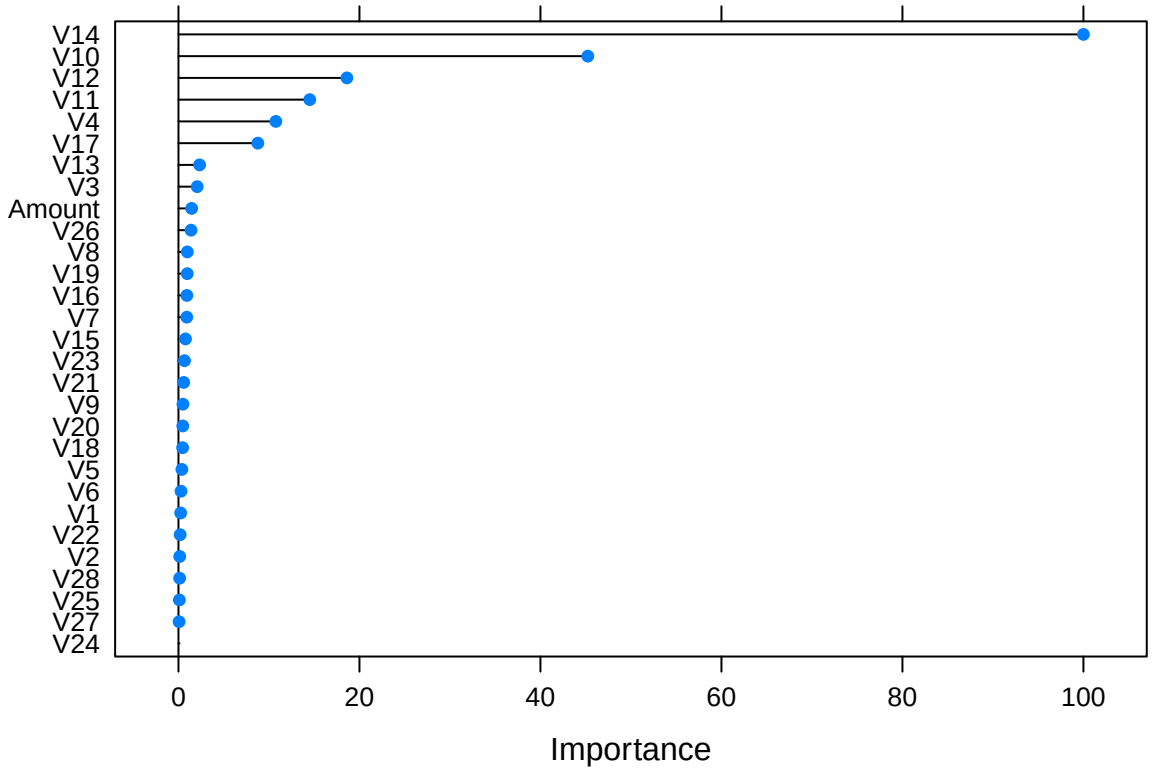
```
print(Model_rf)
```

```
## Random Forest
##
## 227846 samples
##     29 predictor
##      2 classes: 'X0', 'X1'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 182276, 182277, 182277, 182277, 182277
## Addtional sampling using SMOTE
##
## Resampling results across tuning parameters:
##
##   mtry  ROC        Sens       Spec
##    2    0.9826403  0.9950275  0.8655631
##   15    0.9840788  0.9888328  0.8858812
##   29    0.9832121  0.9831217  0.8757546
##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 15.
```

```
plot(Model_rf)
```




```
plot(varImp(Model_rf))
```



** Now let see the model performing on unpredicted Test data.**

```
rf_pred <- predict(Model_rf, test_dataset, type = "prob")
Confusion_matrix_rf <- confusionMatrix(table(as.numeric(rf_pred$X1 > 0.5), test_dataset$Class))
print(Confusion_matrix_rf)
```

```
## Confusion Matrix and Statistics
##
##
##         0     1
##   0 56504    12
##   1   359    86
##
##                Accuracy : 0.9935
##                  95% CI : (0.9928, 0.9941)
##     No Information Rate : 0.9983
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3148
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9937
##             Specificity : 0.8776
##          Pos Pred Value : 0.9998
##          Neg Pred Value : 0.1933
```

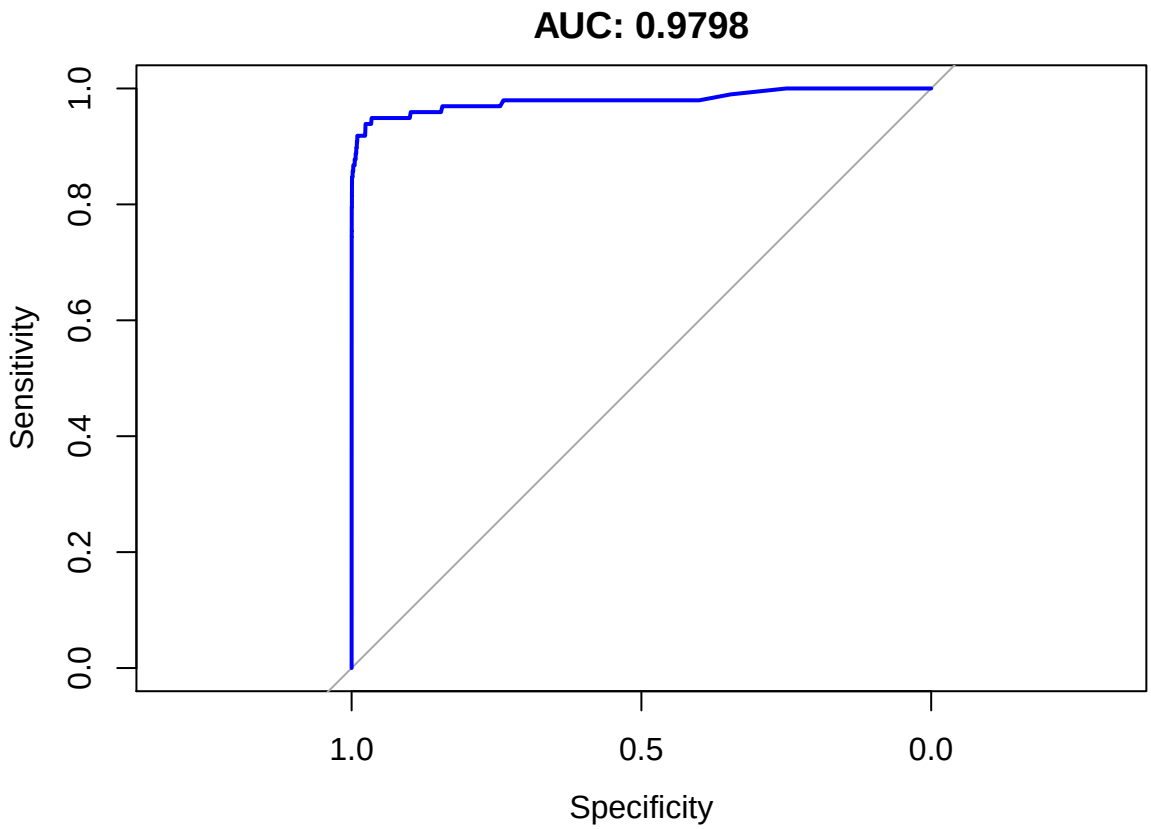
```
##              Prevalence : 0.9983
##          Detection Rate : 0.9920
##    Detection Prevalence : 0.9922
##       Balanced Accuracy : 0.9356
##
##        'Positive' Class : 0
##
```

** Now we will look ROC on unpredicted test data.**

```
rf_roc <- roc(test_dataset$Class, predict(Model_rf, test_dataset, type = "prob")$X1)
print(rf_roc)
```

```
##
## Call:
## roc.default(response = test_dataset$Class, predictor = predict(Model_rf,     test_dataset, type = "p
##
## Data: predict(Model_rf, test_dataset, type = "prob")$X1 in 56863 controls (test_dataset$Class 0) < 9
## Area under the curve: 0.9798
```

```
plot(rf_roc, main = paste0("AUC: ", round(pROC::auc(rf_roc), 4)), col ="blue")
```



Model XG Boost: Gradient Boosted Tress: 5

Finally we will use XGboost which is based on Gradient Boosted Tress, which is a most powerful model when compared to the other models discussed above.

```r
train_XGB <- xgb.DMatrix(data = as.matrix(train_dataset[, -c("Class")]), label = as.numeric(train_datas
Model_xgb <- xgboost(data = train_XGB, nrounds = 100, gamma = 0.1, max_depth = 10, objective = "binary:
```

```
## [1]  train-error:0.000391
## [2]  train-error:0.000356
## [3]  train-error:0.000342
## [4]  train-error:0.000320
## [5]  train-error:0.000285
## [6]  train-error:0.000281
## [7]  train-error:0.000281
## [8]  train-error:0.000272
## [9]  train-error:0.000263
## [10] train-error:0.000263
## [11] train-error:0.000263
## [12] train-error:0.000259
## [13] train-error:0.000259
## [14] train-error:0.000259
## [15] train-error:0.000259
## [16] train-error:0.000250
## [17] train-error:0.000250
## [18] train-error:0.000246
## [19] train-error:0.000233
## [20] train-error:0.000228
## [21] train-error:0.000224
## [22] train-error:0.000202
## [23] train-error:0.000189
## [24] train-error:0.000180
## [25] train-error:0.000162
## [26] train-error:0.000158
## [27] train-error:0.000140
## [28] train-error:0.000132
## [29] train-error:0.000127
## [30] train-error:0.000114
## [31] train-error:0.000105
## [32] train-error:0.000097
## [33] train-error:0.000088
## [34] train-error:0.000075
## [35] train-error:0.000057
## [36] train-error:0.000044
## [37] train-error:0.000040
## [38] train-error:0.000026
## [39] train-error:0.000022
## [40] train-error:0.000022
## [41] train-error:0.000018
## [42] train-error:0.000013
## [43] train-error:0.000004
## [44] train-error:0.000004
## [45] train-error:0.000000
## [46] train-error:0.000000
## [47] train-error:0.000000
## [48] train-error:0.000000
## [49] train-error:0.000000
## [50] train-error:0.000000
```

```
## [51] train-error:0.000000
## [52] train-error:0.000000
## [53] train-error:0.000000
## [54] train-error:0.000000
## [55] train-error:0.000000
## [56] train-error:0.000000
## [57] train-error:0.000000
## [58] train-error:0.000000
## [59] train-error:0.000000
## [60] train-error:0.000000
## [61] train-error:0.000000
## [62] train-error:0.000000
## [63] train-error:0.000000
## [64] train-error:0.000000
## [65] train-error:0.000000
## [66] train-error:0.000000
## [67] train-error:0.000000
## [68] train-error:0.000000
## [69] train-error:0.000000
## [70] train-error:0.000000
## [71] train-error:0.000000
## [72] train-error:0.000000
## [73] train-error:0.000000
## [74] train-error:0.000000
## [75] train-error:0.000000
## [76] train-error:0.000000
## [77] train-error:0.000000
## [78] train-error:0.000000
## [79] train-error:0.000000
## [80] train-error:0.000000
## [81] train-error:0.000000
## [82] train-error:0.000000
## [83] train-error:0.000000
## [84] train-error:0.000000
## [85] train-error:0.000000
## [86] train-error:0.000000
## [87] train-error:0.000000
## [88] train-error:0.000000
## [89] train-error:0.000000
## [90] train-error:0.000000
## [91] train-error:0.000000
## [92] train-error:0.000000
## [93] train-error:0.000000
## [94] train-error:0.000000
## [95] train-error:0.000000
## [96] train-error:0.000000
## [97] train-error:0.000000
## [98] train-error:0.000000
## [99] train-error:0.000000
## [100]    train-error:0.000000
```

** Let's see into unseen test test**

```
test_XBG <- xgb.DMatrix(data = as.matrix(test_dataset[, -c("Class")]), label = as.numeric(test_dataset$
predit_xgb <- predict(Model_xgb,test_XBG)
confusionMatrix(table(as.numeric(predit_xgb > 0.5), test_dataset$Class))
```

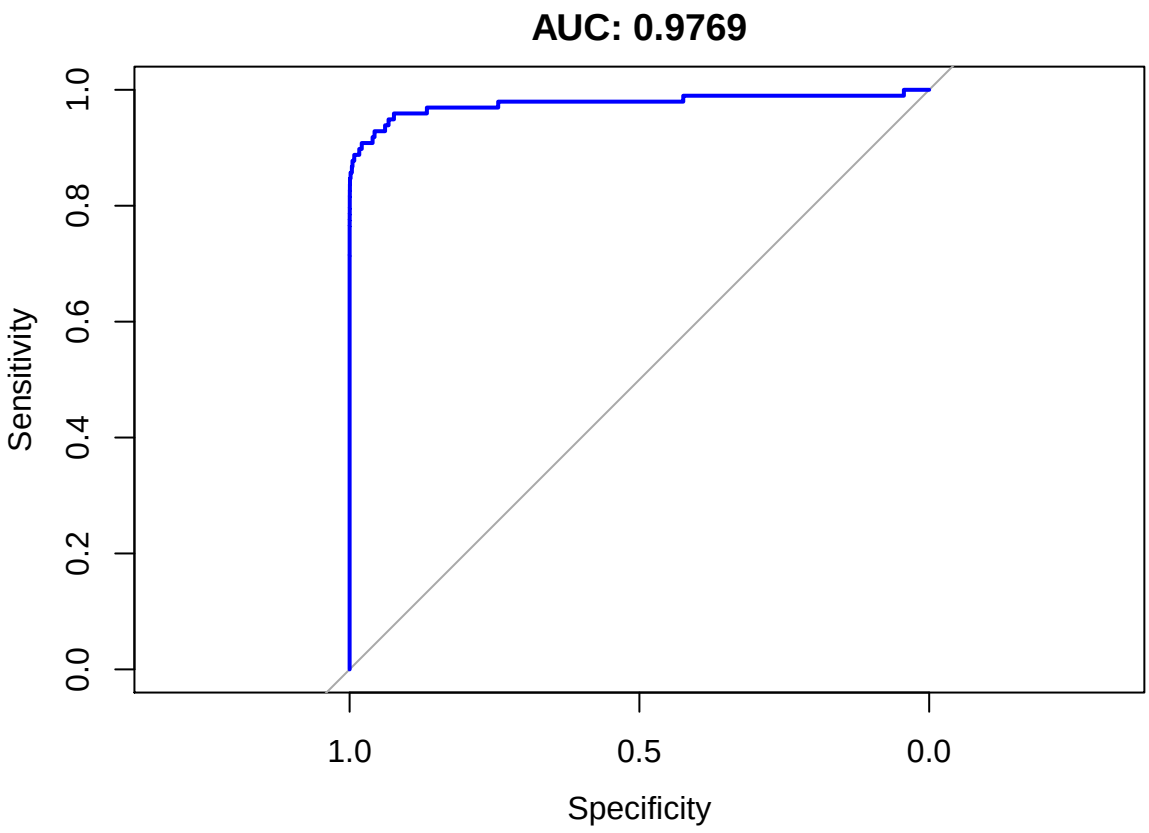
```
## Confusion Matrix and Statistics
##
##
##         0     1
##   0 56857    22
##   1     6    76
##
##                Accuracy : 0.9995
##                  95% CI : (0.9993, 0.9997)
##     No Information Rate : 0.9983
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8442
##
##  Mcnemar's Test P-Value : 0.004586
##
##             Sensitivity : 0.9999
##             Specificity : 0.7755
##          Pos Pred Value : 0.9996
##          Neg Pred Value : 0.9268
##              Prevalence : 0.9983
##          Detection Rate : 0.9982
##    Detection Prevalence : 0.9986
##       Balanced Accuracy : 0.8877
##
##        'Positive' Class : 0
##
```

** Let's see ROC for XGBoost**

```
roc_xgb <- roc(test_dataset$Class, predit_xgb)
print(roc_xgb)
```

```
##
## Call:
## roc.default(response = test_dataset$Class, predictor = predit_xgb)
##
## Data: predit_xgb in 56863 controls (test_dataset$Class 0) < 98 cases (test_dataset$Class 1).
## Area under the curve: 0.9769
```

```
plot(roc_xgb, main = paste0("AUC: ", round(pROC::auc(roc_xgb), 4)), col = "blue")
```



Summary:

In the credit Card Fraudulent detection project we have a applied some of common and popular Machine Learning Models / algorithms to detect fraudulent.

Based on over exploration it has shown that even a very simple logistic regression model can achieved good recall. while the other models improve in term of Logistic Regression in terms of AUC.

As we see the best model: XGBoost (0.9769), Random Forest (0.9798) with a very marginal difference when comparative with Logistic Regression in terms of AUC.

Appendix - Enviroment

```
version
```

```
##                _
## platform       x86_64-w64-mingw32
## arch           x86_64
## os             mingw32
## system         x86_64, mingw32
## status
## major          3
```

```
## minor          6.3
## year           2020
## month          02
## day            29
## svn rev        77875
## language       R
## version.string R version 3.6.3 (2020-02-29)
## nickname       Holding the Windsock
```