Detect Credit Card Fraud with Machine Learning

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Library

```
knitr::opts_chunk$set(echo = TRUE)
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.0 --
```

```
## v ggplot2 3.2.1     v purrr   0.3.3
## v tibble  2.1.3     v dplyr   0.8.4
## v tidyr   1.0.2     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.4.0
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(ranger)
library(caret)
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'caret'
```

```
## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(data.table)
```

```
##
## Attaching package: 'data.table'
```

```
## The following objects are masked from 'package:dplyr':
##
##     between, first, last
```

```
## The following object is masked from 'package:purrr':
##
##     transpose
```

```
library(lattice)
setwd("/System/Volumes/Data/University of Evansville/SPRING 2020/STAT 493/Credit-card-dataset")
```

Info

To detect credit card fraud, we use the card transcations dataset that contains a mix of fraud as well as non-fraudulent transcations.

Algorithms

- Decision Trees
- Logistic Regression
- Artificial Neural Networks
- Gradient Boosting Classifier

Loading the dataset

```
creditcard_data <- read.csv("creditcard.csv")
```

Data Exploration

Display the dataset using the head() and tail() function.

```
dim(creditcard_data)
```

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

```
head(creditcard_data, 6)
```

```
##   Time         V1          V2        V3         V4          V5          V6
## 1    0 -1.3598071 -0.07278117 2.5363467  1.3781552 -0.33832077  0.46238778
## 2    0  1.1918571  0.26615071 0.1664801  0.4481541  0.06001765 -0.08236081
## 3    1 -1.3583541 -1.34016307 1.7732093  0.3797796 -0.50319813  1.80049938
## 4    1 -0.9662717 -0.18522601 1.7929933 -0.8632913 -0.01030888  1.24720317
## 5    2 -1.1582331  0.87773675 1.5487178  0.4030339 -0.40719338  0.09592146
## 6    2 -0.4259659  0.96052304 1.1411093 -0.1682521  0.42098688 -0.02972755
##            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
## 4  0.23760894  0.37743587 -1.3870241 -0.05495192 -0.2264873  0.17822823
## 5  0.59294075 -0.27053268  0.8177393  0.75307443 -0.8228429  0.53819555
## 6  0.47620095  0.26031433 -0.5686714 -0.37140720  1.3412620  0.35989384
##          V13        V14        V15        V16         V17         V18
## 1 -0.9913898 -0.3111694  1.4681770 -0.4704005  0.20797124  0.02579058
## 2  0.4890950 -0.1437723  0.6355581  0.4639170 -0.11480466 -0.18336127
## 3  0.7172927 -0.1659459  2.3458649 -2.8900832  1.10996938 -0.12135931
## 4  0.5077569 -0.2879237 -0.6314181 -1.0596472 -0.68409279  1.96577500
## 5  1.3458516 -1.1196698  0.1751211 -0.4514492 -0.23703324 -0.03819479
## 6 -0.3580907 -0.1371337  0.5176168  0.4017259 -0.05813282  0.06865315
##           V19         V20          V21          V22         V23         V24
## 1  0.40399296  0.25141210 -0.018306778  0.277837576 -0.11047391  0.06692807
## 2 -0.14578304 -0.06908314 -0.225775248 -0.638671953  0.10128802 -0.33984648
## 3 -2.26185710  0.52497973  0.247998153  0.771679402  0.90941226 -0.68928096
## 4 -1.23262197 -0.20803778 -0.108300452  0.005273597 -0.19032052 -1.17557533
## 5  0.80348692  0.40854236 -0.009430697  0.798278495 -0.13745808  0.14126698
## 6 -0.03319379  0.08496767 -0.208253515 -0.559824796 -0.02639767 -0.37142658
##          V25        V26          V27         V28 Amount Class
## 1  0.1285394 -0.1891148  0.133558377 -0.02105305 149.62     0
```

```
## 2  0.1671704  0.1258945 -0.008983099  0.01472417   2.69     0
## 3 -0.3276418 -0.1390966 -0.055352794 -0.05975184 378.66     0
## 4  0.6473760 -0.2219288  0.062722849  0.06145763 123.50     0
## 5 -0.2060096  0.5022922  0.219422230  0.21515315  69.99     0
## 6 -0.2327938  0.1059148  0.253844225  0.08108026   3.67     0
```

```
tail(creditcard_data, 6)
```

```
##          Time          V1          V2         V3         V4          V5
## 284802 172785   0.1203164  0.93100513 -0.5460121 -0.7450968  1.13031398
## 284803 172786 -11.8811179 10.07178497 -9.8347835 -2.0666557 -5.36447278
## 284804 172787  -0.7327887 -0.05508049  2.0350297 -0.7385886  0.86822940
## 284805 172788   1.9195650 -0.30125385 -3.2496398 -0.5578281  2.63051512
## 284806 172788  -0.2404400  0.53048251  0.7025102  0.6897992 -0.37796113
## 284807 172792  -0.5334125 -0.18973334  0.7033374 -0.5062712 -0.01254568
##                V6         V7         V8         V9        V10        V11
## 284802 -0.2359732  0.8127221  0.1150929 -0.2040635 -0.6574221  0.6448373
## 284803 -2.6068373 -4.9182154  7.3053340  1.9144283  4.3561704 -1.5931053
## 284804  1.0584153  0.0243297  0.2948687  0.5848000 -0.9759261 -0.1501888
## 284805  3.0312601 -0.2968265  0.7084172  0.4324540 -0.4847818  0.4116137
## 284806  0.6237077 -0.6861800  0.6791455  0.3920867 -0.3991257 -1.9338488
## 284807 -0.6496167  1.5770063 -0.4146504  0.4861795 -0.9154266 -1.0404583
##                V12        V13         V14         V15        V16         V17
## 284802  0.19091623 -0.5463289 -0.73170658 -0.80803553  0.5996281  0.07044075
## 284803  2.71194079 -0.6892556  4.62694203 -0.92445871  1.1076406  1.99169111
## 284804  0.91580191  1.2147558 -0.67514296  1.16493091 -0.7117573 -0.02569286
## 284805  0.06311886 -0.1836987 -0.51060184  1.32928351  0.1407160  0.31350179
## 284806 -0.96288614 -1.0420817  0.44962444  1.96256312 -0.6085771  0.50992846
## 284807 -0.03151305 -0.1880929 -0.08431647  0.04133346 -0.3026201 -0.66037665
##                V18        V19          V20        V21        V22         V23
## 284802  0.3731103  0.1289038 0.0006758329 -0.3142046 -0.8085204  0.05034266
## 284803  0.5106323 -0.6829197 1.4758291347  0.2134541  0.1118637  1.01447990
## 284804 -1.2211789 -1.5455561 0.0596158999  0.2142053  0.9243836  0.01246304
## 284805  0.3956525 -0.5772518 0.0013959703  0.2320450  0.5782290 -0.03750086
## 284806  1.1139806  2.8978488 0.1274335158  0.2652449  0.8000487 -0.16329794
## 284807  0.1674299 -0.2561169 0.3829481049  0.2610573  0.6430784  0.37677701
##                 V24        V25        V26          V27         V28 Amount Class
## 284802  0.102799590 -0.4358701  0.1240789  0.217939865  0.06880333   2.69     0
## 284803 -0.509348453  1.4368069  0.2500343  0.943651172  0.82373096   0.77     0
## 284804 -1.016225669 -0.6066240 -0.3952551  0.068472470 -0.05352739  24.79     0
## 284805  0.640133881  0.2657455 -0.0873706  0.004454772 -0.02656083  67.88     0
## 284806  0.123205244 -0.5691589  0.5466685  0.108820735  0.10453282  10.00     0
## 284807  0.008797379 -0.4736487 -0.8182671 -0.002415309  0.01364891 217.00     0
```

```
table(creditcard_data$Class)
```

```
##
##      0      1
## 284315    492
```

```
summary(creditcard_data$Amount)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##     0.00     5.60    22.00    88.35    77.17 25691.16
```

```
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"
```

```
var(creditcard_data$Amount)
```

```
## [1] 62560.07
```

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

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

Data Manipulation

- Scale the dataset using scale() function. Apply this to the AMOUNT variable of dataset.
- Scaling is known as feature standardization. With this, the dataset is structured according to a specified range.

```
head(creditcard_data)
```

```
##   Time         V1          V2        V3         V4          V5          V6
## 1    0 -1.3598071 -0.07278117 2.5363467  1.3781552 -0.33832077  0.46238778
## 2    0  1.1918571  0.26615071 0.1664801  0.4481541  0.06001765 -0.08236081
## 3    1 -1.3583541 -1.34016307 1.7732093  0.3797796 -0.50319813  1.80049938
## 4    1 -0.9662717 -0.18522601 1.7929933 -0.8632913 -0.01030888  1.24720317
## 5    2 -1.1582331  0.87773675 1.5487178  0.4030339 -0.40719338  0.09592146
## 6    2 -0.4259659  0.96052304 1.1411093 -0.1682521  0.42098688 -0.02972755
##            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
## 4  0.23760894  0.37743587 -1.3870241 -0.05495192 -0.2264873  0.17822823
## 5  0.59294075 -0.27053268  0.8177393  0.75307443 -0.8228429  0.53819555
## 6  0.47620095  0.26031433 -0.5686714 -0.37140720  1.3412620  0.35989384
##          V13        V14        V15        V16         V17         V18
## 1 -0.9913898 -0.3111694  1.4681770 -0.4704005  0.20797124  0.02579058
## 2  0.4890950 -0.1437723  0.6355581  0.4639170 -0.11480466 -0.18336127
## 3  0.7172927 -0.1659459  2.3458649 -2.8900832  1.10996938 -0.12135931
## 4  0.5077569 -0.2879237 -0.6314181 -1.0596472 -0.68409279  1.96577500
## 5  1.3458516 -1.1196698  0.1751211 -0.4514492 -0.23703324 -0.03819479
## 6 -0.3580907 -0.1371337  0.5176168  0.4017259 -0.05813282  0.06865315
##           V19         V20          V21          V22         V23         V24
## 1  0.40399296  0.25141210 -0.018306778  0.277837576 -0.11047391  0.06692807
## 2 -0.14578304 -0.06908314 -0.225775248 -0.638671953  0.10128802 -0.33984648
## 3 -2.26185710  0.52497973  0.247998153  0.771679402  0.90941226 -0.68928096
## 4 -1.23262197 -0.20803778 -0.108300452  0.005273597 -0.19032052 -1.17557533
## 5  0.80348692  0.40854236 -0.009430697  0.798278495 -0.13745808  0.14126698
## 6 -0.03319379  0.08496767 -0.208253515 -0.559824796 -0.02639767 -0.37142658
##          V25        V26          V27         V28 Amount Class
## 1  0.1285394 -0.1891148  0.133558377 -0.02105305 149.62     0
## 2  0.1671704  0.1258945 -0.008983099  0.01472417   2.69     0
## 3 -0.3276418 -0.1390966 -0.055352794 -0.05975184 378.66     0
## 4  0.6473760 -0.2219288  0.062722849  0.06145763 123.50     0
## 5 -0.2060096  0.5022922  0.219422230  0.21515315  69.99     0
## 6 -0.2327938  0.1059148  0.253844225  0.08108026   3.67     0
```

```r
creditcard_data$Amount = scale(creditcard_data$Amount)

NewData = creditcard_data[,-c(1)]

head(NewData)
```

```
##           V1          V2        V3         V4          V5          V6
## 1 -1.3598071 -0.07278117 2.5363467  1.3781552 -0.33832077  0.46238778
## 2  1.1918571  0.26615071 0.1664801  0.4481541  0.06001765 -0.08236081
## 3 -1.3583541 -1.34016307 1.7732093  0.3797796 -0.50319813  1.80049938
## 4 -0.9662717 -0.18522601 1.7929933 -0.8632913 -0.01030888  1.24720317
## 5 -1.1582331  0.87773675 1.5487178  0.4030339 -0.40719338  0.09592146
## 6 -0.4259659  0.96052304 1.1411093 -0.1682521  0.42098688 -0.02972755
##            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
## 4  0.23760894  0.37743587 -1.3870241 -0.05495192 -0.2264873  0.17822823
## 5  0.59294075 -0.27053268  0.8177393  0.75307443 -0.8228429  0.53819555
## 6  0.47620095  0.26031433 -0.5686714 -0.37140720  1.3412620  0.35989384
##          V13        V14        V15        V16         V17         V18
## 1 -0.9913898 -0.3111694  1.4681770 -0.4704005  0.20797124  0.02579058
## 2  0.4890950 -0.1437723  0.6355581  0.4639170 -0.11480466 -0.18336127
## 3  0.7172927 -0.1659459  2.3458649 -2.8900832  1.10996938 -0.12135931
## 4  0.5077569 -0.2879237 -0.6314181 -1.0596472 -0.68409279  1.96577500
## 5  1.3458516 -1.1196698  0.1751211 -0.4514492 -0.23703324 -0.03819479
## 6 -0.3580907 -0.1371337  0.5176168  0.4017259 -0.05813282  0.06865315
##           V19         V20          V21          V22         V23         V24
## 1  0.40399296  0.25141210 -0.018306778  0.277837576 -0.11047391  0.06692807
## 2 -0.14578304 -0.06908314 -0.225775248 -0.638671953  0.10128802 -0.33984648
## 3 -2.26185710  0.52497973  0.247998153  0.771679402  0.90941226 -0.68928096
## 4 -1.23262197 -0.20803778 -0.108300452  0.005273597 -0.19032052 -1.17557533
## 5  0.80348692  0.40854236 -0.009430697  0.798278495 -0.13745808  0.14126698
## 6 -0.03319379  0.08496767 -0.208253515 -0.559824796 -0.02639767 -0.37142658
##          V25        V26          V27         V28      Amount Class
## 1  0.1285394 -0.1891148  0.133558377 -0.02105305  0.24496383     0
## 2  0.1671704  0.1258945 -0.008983099  0.01472417 -0.34247394     0
## 3 -0.3276418 -0.1390966 -0.055352794 -0.05975184  1.16068389     0
## 4  0.6473760 -0.2219288  0.062722849  0.06145763  0.14053401     0
## 5 -0.2060096  0.5022922  0.219422230  0.21515315 -0.07340321     0
## 6 -0.2327938  0.1059148  0.253844225  0.08108026 -0.33855582     0
```

Data Modeling

- Split the dataset into Training and Test set with split ratio of 0.80.
- Here, 80% of dataset will be attributed to the training data and 20% to test data.
- find the dimension using the dim() function

```r
library(caTools)
set.seed(123)

data_sample = sample.split(NewData$Class,SplitRatio = 0.80)

train_data = subset(NewData,data_sample == TRUE)
```

```
test_data = subset(NewData,data_sample == FALSE)

dim(train_data)
```

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

```
dim(test_data)
```

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

Fitting Logistic Regression Model

- Logistic Regression model is used for modeling the outcome probability of a class i.e. fraud/not fraud.
- Implement the model on test data

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

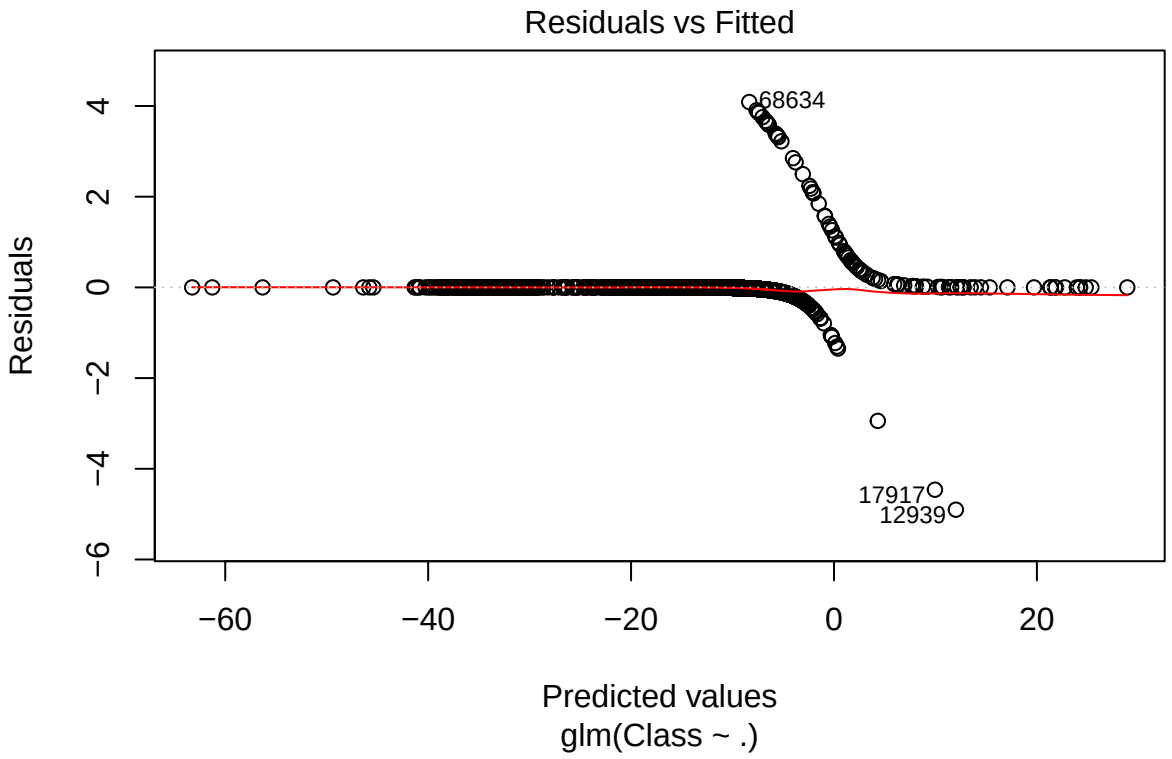
```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

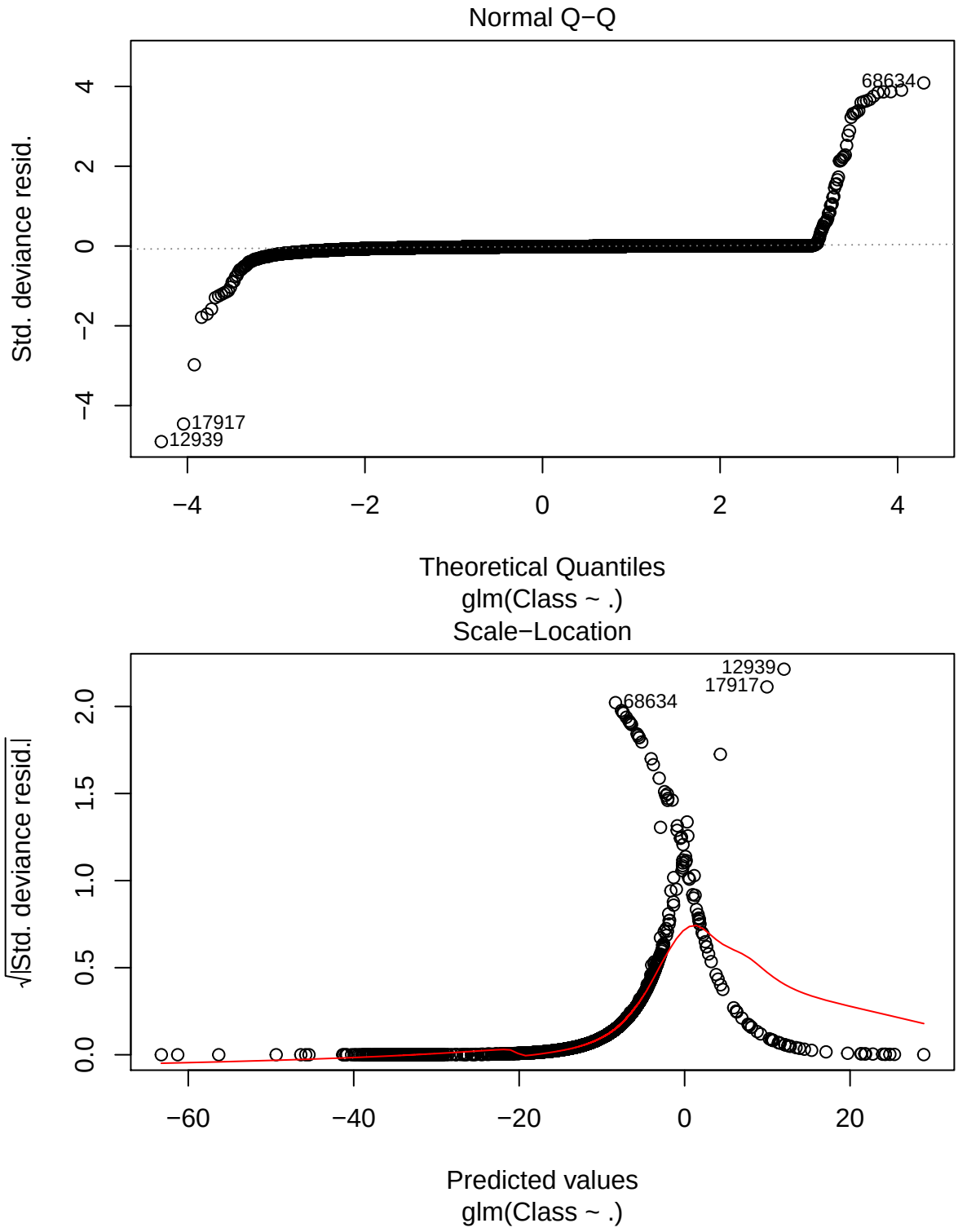
```
summary(Logistic_Model)
```

```
##
## Call:
## glm(formula = Class ~ ., family = binomial(), data = test_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.9019  -0.0254  -0.0156  -0.0078   4.0877
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -12.52800   10.30537  -1.216   0.2241
## V1           -0.17299    1.27381  -0.136   0.8920
## V2            1.44512    4.23062   0.342   0.7327
## V3            0.17897    0.24058   0.744   0.4569
## V4            3.13593    7.17768   0.437   0.6622
## V5            1.49014    3.80369   0.392   0.6952
## V6           -0.12428    0.22202  -0.560   0.5756
## V7            1.40903    4.22644   0.333   0.7388
## V8           -0.35254    0.17462  -2.019   0.0435 *
## V9            3.02176    8.67262   0.348   0.7275
## V10          -2.89571    6.62383  -0.437   0.6620
## V11          -0.09769    0.28270  -0.346   0.7297
## V12           1.97992    6.56699   0.301   0.7630
## V13          -0.71674    1.25649  -0.570   0.5684
## V14           0.19316    3.28868   0.059   0.9532
## V15           1.03868    2.89256   0.359   0.7195
## V16          -2.98194    7.11391  -0.419   0.6751
## V17          -1.81809    4.99764  -0.364   0.7160
## V18           2.74772    8.13188   0.338   0.7354
## V19          -1.63246    4.77228  -0.342   0.7323
## V20          -0.69925    1.15114  -0.607   0.5436
## V21          -0.45082    1.99182  -0.226   0.8209
## V22          -1.40395    5.18980  -0.271   0.7868
## V23           0.19026    0.61195   0.311   0.7559
## V24          -0.12889    0.44701  -0.288   0.7731
```

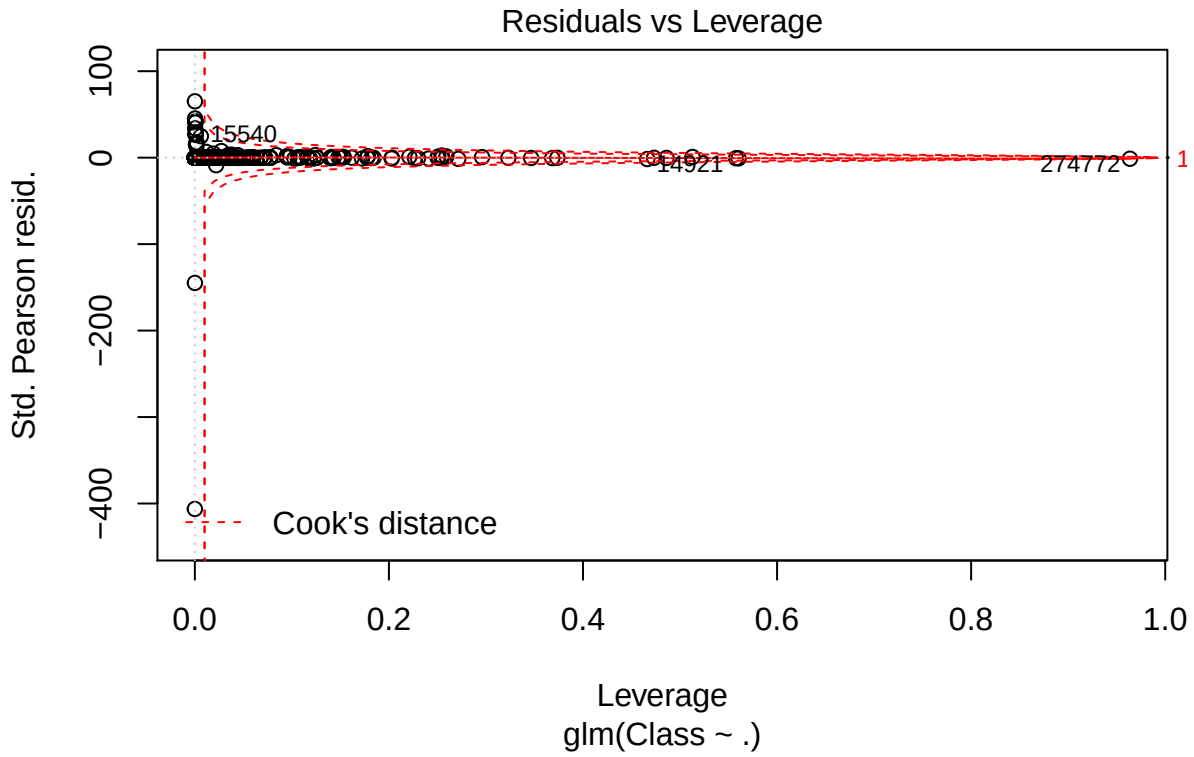
```
## V25          -0.57835    1.94988  -0.297   0.7668
## V26           2.65938    9.34957   0.284   0.7761
## V27          -0.45396    0.81502  -0.557   0.5775
## V28          -0.06639    0.35730  -0.186   0.8526
## Amount        0.22576    0.71892   0.314   0.7535
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1443.40  on 56960  degrees of freedom
## Residual deviance:  378.59  on 56931  degrees of freedom
## AIC: 438.59
##
## Number of Fisher Scoring iterations: 17
```

```
plot(Logistic_Model)
```






```
## Warning in sqrt(crit * p * (1 - hh)/hh): NaNs produced

## Warning in sqrt(crit * p * (1 - hh)/hh): NaNs produced
```



- To accesss performance of the model, we will delineate the ROC curve.
- ROC is Receiver Optimistic Characteristics

```
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.
```

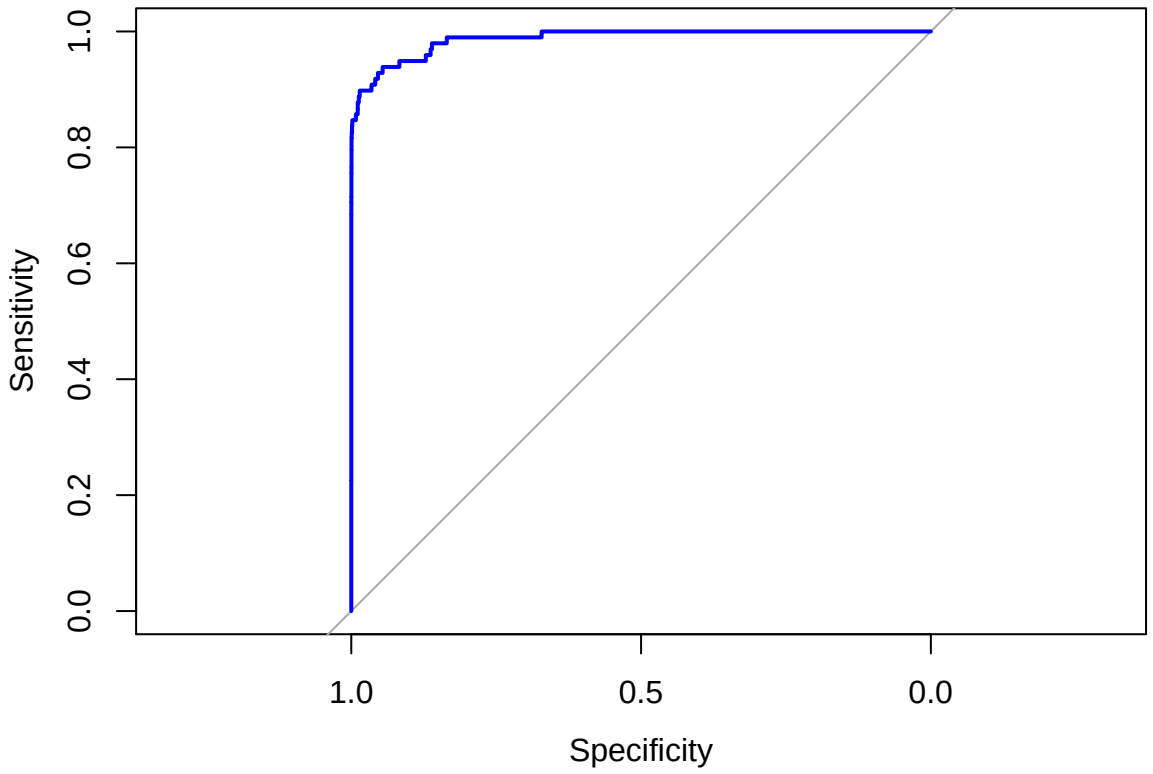
```
##
## Attaching package: 'pROC'
```

```
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```
lr.predict <- predict(Logistic_Model, test_data, probability = TRUE)

myRoc <- roc(test_data$Class, lr.predict, plot = TRUE, col = "blue")
```

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

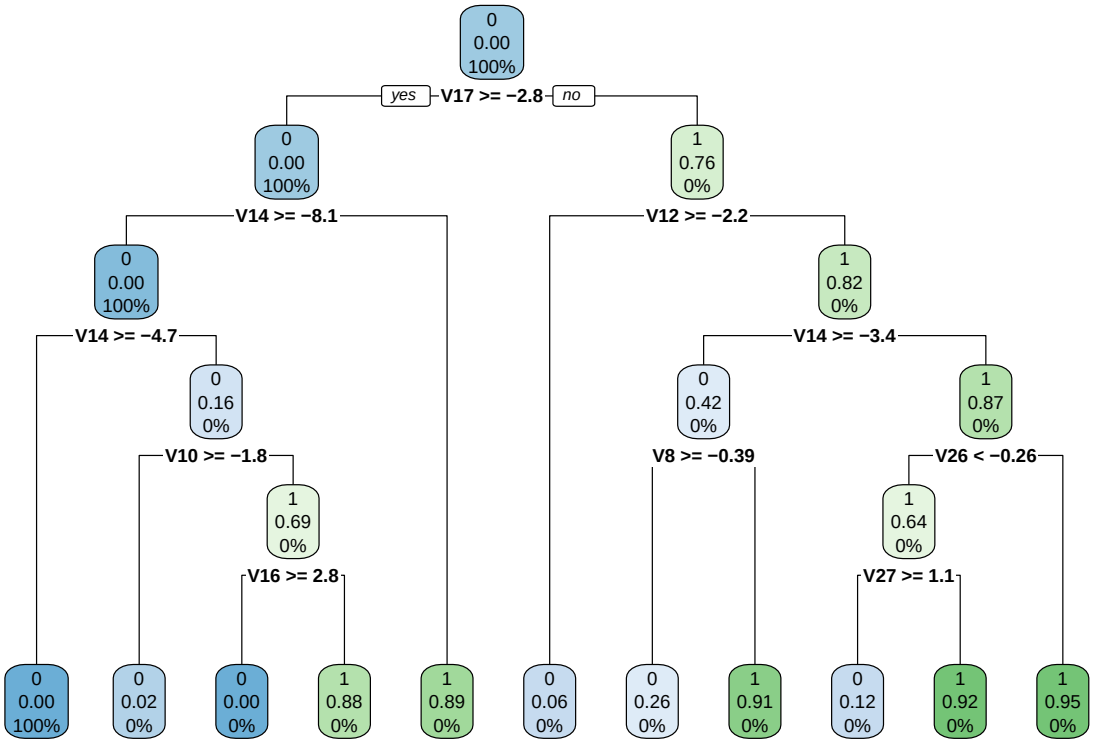
```
## Setting direction: controls < cases
```



Fitting a Decision Tree Model

- Implement a decision tree algorithm
- Decision tree to plot the outcomes of a decision. These outcomes are a consequences through which we can concludes as to what class the object belongs to.
- use the recursive parting to plot the decision tree.

```
library(rpart)
library(rpart.plot)

decisionTree_model <- rpart(Class ~ . , creditcard_data, method = 'class')

predicted_val <- predict(decisionTree_model, creditcard_data, type = 'class')

probability <- predict(decisionTree_model, creditcard_data, type = 'prob')

rpart.plot(decisionTree_model)
```



Artifical Neural Network (ANN)

- It is a type of machine learning algorithm that are modeled after the human nervous system.
- ANN model are able to learn the pattern using the historical data and are able to perform classification on the input data.
- Import the neuralnet package to implement ANNs.
- In case of ANN, there is a range of values that between 0 and 1.
- Set threshold as 0.5 i.e. values above 0.5 will correspond to 1, and rest will be 0.

```
library(neuralnet)
```

```
##
## Attaching package: 'neuralnet'
```

```
## The following object is masked from 'package:dplyr':
##
##     compute
```

```
ANN_model = neuralnet(Class~., train_data, linear.output=FALSE)

plot(ANN_model)

predANN = compute(ANN_model,test_data)

resultANN = predANN$net.result
resultANN = ifelse(resultANN > 0.5,1,0)
```

Gradient Boosting (GBM)

- It is a popular machine learning algorithm that is used to classification adn regression tasks.
- This model comprises of several underlying ensemble models like weak decision trees.
- This decision trees combine together to form a strong model of gradient boosting.

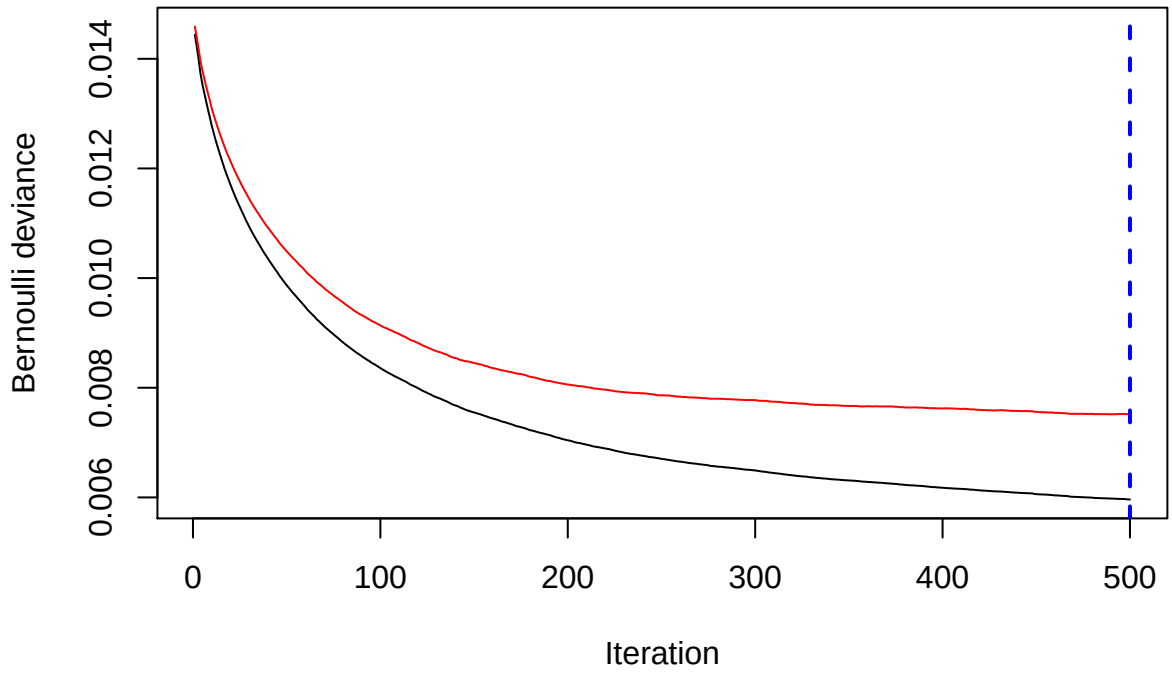
```r
library(gbm, quietly=TRUE)
```

```
## Loaded gbm 2.1.5
```

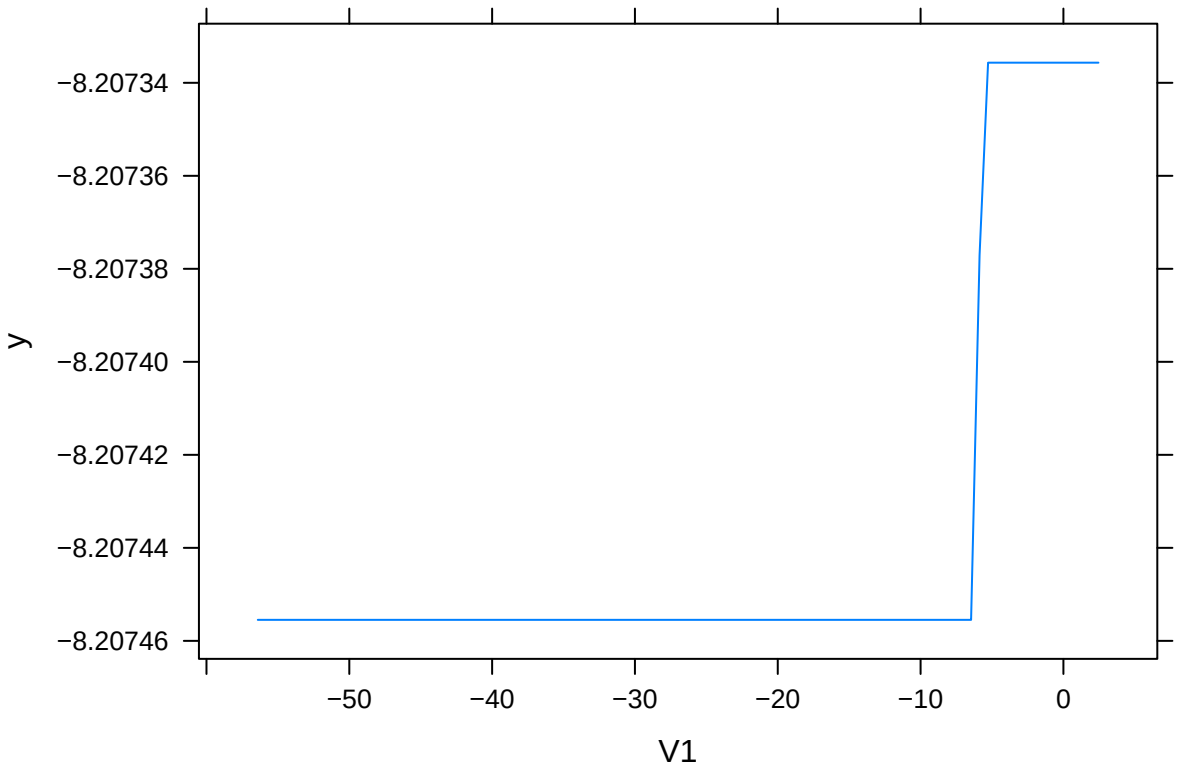
```r
# Get the time to train the GBM model
system.time(model_gbm <- gbm(Class ~ . , distribution = "bernoulli"
                             , data = rbind(train_data, test_data)
                             , n.trees = 500
                             , interaction.depth = 3
                             , n.minobsinnode = 100
                             , shrinkage = 0.01
                             , bag.fraction = 0.5
                             , train.fraction = nrow(train_data) / (nrow(train_data) + nrow(test_data))))
```

```
##    user  system elapsed
## 450.555   1.798 455.988
```

```r
# Determine best iteration based on test data
gbm.iter = gbm.perf(model_gbm, method = "test")
```



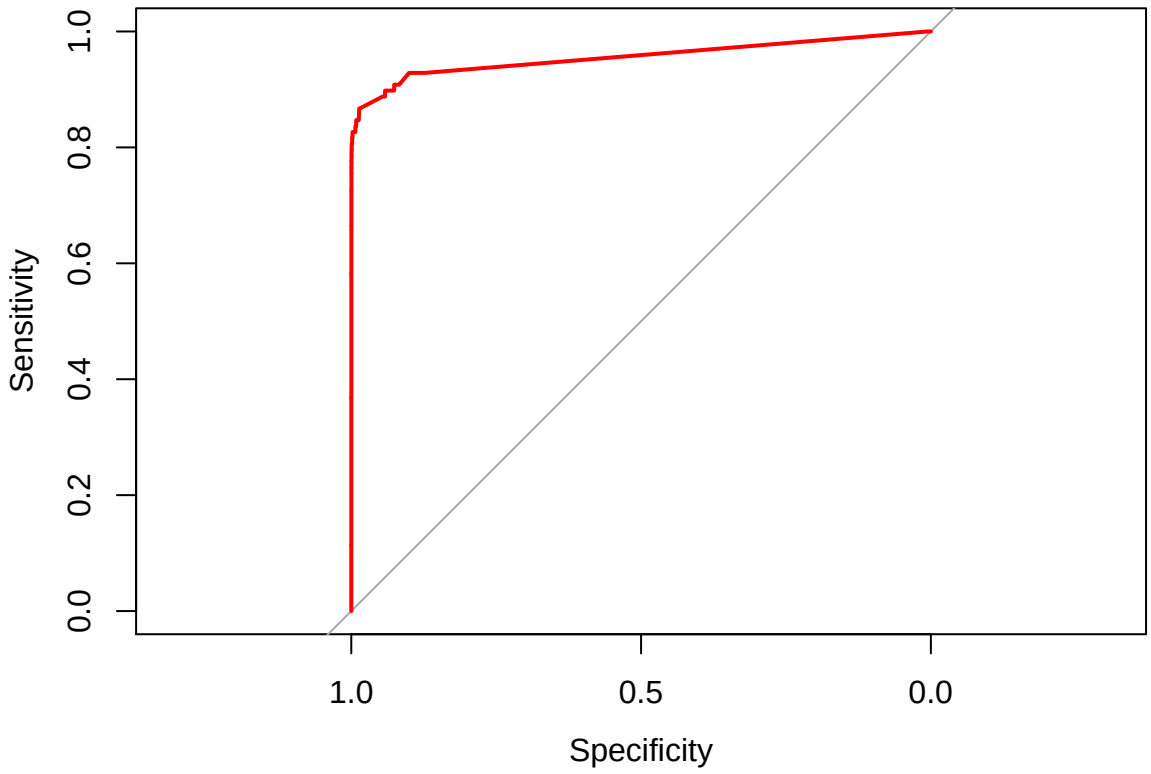

```r
model.influence = relative.influence(model_gbm, n.trees = gbm.iter, sort. = TRUE)

# Plot the gbm model
plot(model_gbm)
```




```
# Plot and calculate AUC on test data
gbm_test = predict(model_gbm, newdata = test_data, n.trees = gbm.iter)
gbm_auc = roc(test_data$Class, gbm_test, plot = TRUE, col = "red")
```

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

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




```
print(gbm_auc)
```

```
##
## Call:
## roc.default(response = test_data$Class, predictor = gbm_test,     plot = TRUE, col = "red")
##
## Data: gbm_test in 56863 controls (test_data$Class 0) < 98 cases (test_data$Class 1).
## Area under the curve: 0.9555
```

Summary

- Used a variety of Machine Learning alogrithms to implement this model
- Plotted the respective perfomance curves for the models
- Analyzed and visualized to discern fraudulent transcations from other types of data