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Remove/Clean the environment

```r
rm(list=ls())
```

Set working directory

```r
setwd("C:/Monash/FIT3152")
```

Install and load the libraries used

```
## Loading required package: ggplot2

## Loading required package: lattice

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

## Loading required package: foreach

## Loading required package: doParallel

## Loading required package: iterators

## Loading required package: parallel

##
## Attaching package: 'adabag'

## The following object is masked from 'package:ipred':
##
##     bagging

##
## Attaching package: 'reshape'

## The following objects are masked from 'package:tidyr':
##
##     expand, smiths
```

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

## corrplot 0.92 loaded

## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa

## randomForest 4.7-1.1

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:dplyr':
##
##     combine

## The following object is masked from 'package:ggplot2':
##
##     margin
```

Load data in PhishingData.csv

```
rm(list = ls())
Phish <- read.csv("PhishingData.csv")
set.seed(33085625)
L <- as.data.frame(c(1:50))
L <- L[sample(nrow(L), 10, replace = FALSE),]
Phish <- Phish[(Phish$A01 %in% L),]
PD <- Phish[sample(nrow(Phish), 2000, replace = FALSE),] # sample of 2000 rows
```

Question 1

Phishing dataset dimensions after seed was set

```
dim(PD)

## [1] 2000   26
```

There is a total of 2,000 rows and 26 columns present in the dataset.

Phishing dataset column names

```
names(PD)

##  [1] "A01"   "A02"   "A03"   "A04"   "A05"   "A06"   "A07"   "A08"   "A09"
## [10] "A10"   "A11"   "A12"   "A13"   "A14"   "A15"   "A16"   "A17"   "A18"
## [19] "A19"   "A20"   "A21"   "A22"   "A23"   "A24"   "A25"   "Class"
```

The colnames are A01, A02, A03, A04, A05, A06, A07, A08 , A09, A10, A11, A12, A13, A14, A15, A16, A17, A18, A19, A20, A21, A22, A23, A24, A25 and Class.

Obtain the proportion of phishing sites to legitimate sites

```
as.data.frame(table(PD["Class"]))

##   Class Freq
## 1     0 1459
## 2     1  541
```

In binary classification, 0 is often the label for negative class and 1 for positive class. So, it can be seen from the output above that the ratio of phishing sites compared to genuine legitimate sites is observed to be 541 to 1,459 where 541 is the legitimate sites and 1,459 is the phishing sites.

Phishing dataset predictor description

```
## 'data.frame':    2000 obs. of  26 variables:
##  $ A01  : int  11 10 25 31 3 3 3 11 10 25 ...
##  $ A02  : int  0 0 0 0 0 0 1 0 0 NA ...
##  $ A03  : int  0 NA 0 0 0 0 0 0 0 0 ...
##  $ A04  : int  3 3 2 3 2 3 3 2 2 3 ...
##  $ A05  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A06  : int  1 0 1 0 0 0 0 0 0 0 ...
##  $ A07  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A08  : num  1 1 1 0.441 0.714 ...
##  $ A09  : int  1 0 0 0 0 0 0 0 0 0 ...
##  $ A10  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A11  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A12  : int  232 232 365 232 648 232 232 388 648 232 ...
##  $ A13  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A14  : int  0 0 1 0 0 0 0 0 0 0 ...
##  $ A15  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A16  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A17  : int  1 1 1 1 2 1 1 2 2 1 ...
##  $ A18  : int  96 30 89 17 42 29 39 27 46 44 ...
##  $ A19  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A20  : int  1 1 1 0 0 1 0 0 1 0 ...
##  $ A21  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A22  : num  0.0605 0.0617 0.0601 0.0633 0.0626 ...
##  $ A23  : int  15 137 107 1 110 111 116 165 107 16 ...
##  $ A24  : num  0.52291 0.52291 0.00159 0.52291 0.02856 ...
##  $ A25  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ Class: int  0 0 0 0 0 0 1 0 0 1 ...

##       A01             A02               A03                A04
##  Min.   : 3.00   Min.   : 0.0000   Min.   :0.000000   Min.   :2.000
##  1st Qu.:10.00   1st Qu.: 0.0000   1st Qu.:0.000000   1st Qu.:2.000
##  Median :15.00   Median : 0.0000   Median :0.000000   Median :3.000
##  Mean   :16.72   Mean   : 0.1602   Mean   :0.001521   Mean   :2.728
##  3rd Qu.:25.00   3rd Qu.: 0.0000   3rd Qu.:0.000000   3rd Qu.:3.000
##  Max.   :35.00   Max.   :20.0000   Max.   :1.000000   Max.   :7.000
##                  NA's   :21        NA's   :27         NA's   :27
##       A05               A06               A07                A08
##  Min.   : 0.00000   Min.   :0.0000   Min.   :0.000000   Min.   :0.1429
##  1st Qu.: 0.00000   1st Qu.:0.0000   1st Qu.:0.000000   1st Qu.:0.6774
##  Median : 0.00000   Median :0.0000   Median :0.000000   Median :1.0000
##  Mean   : 0.02375   Mean   :0.1351   Mean   :0.001515   Mean   :0.8434
##  3rd Qu.: 0.00000   3rd Qu.:0.0000   3rd Qu.:0.000000   3rd Qu.:1.0000
##  Max.   :18.00000   Max.   :1.0000   Max.   :1.000000   Max.   :1.0000
##  NA's   :21         NA's   :24       NA's   :20         NA's   :26
##       A09               A10               A11               A12
##  Min.   :0.00000   Min.   :0.00000   Min.   :0.00000   Min.   :  3.0
##  1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:232.0
##  Median :0.00000   Median :0.00000   Median :0.00000   Median :232.0
##  Mean   :0.02274   Mean   :0.04447   Mean   :0.05136   Mean   :314.3
##  3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:388.0
```

```
##  Max.   :1.00000   Max.   :1.00000   Max.   :9.00000   Max.   :692.0
##  NA's   :21        NA's   :21        NA's   :14        NA's   :21
##       A13               A14               A15            A16
##  Min.   : 0.00000   Min.   :0.0000   Min.   :0.00   Min.   :0.00000
##  1st Qu.: 0.00000   1st Qu.:0.0000   1st Qu.:0.00   1st Qu.:0.00000
##  Median : 0.00000   Median :0.0000   Median :0.00   Median :0.00000
##  Mean   : 0.01523   Mean   :0.0854   Mean   :0.15   Mean   :0.03794
##  3rd Qu.: 0.00000   3rd Qu.:0.0000   3rd Qu.:0.00   3rd Qu.:0.00000
##  Max.   :12.00000   Max.   :1.0000   Max.   :1.00   Max.   :1.00000
##  NA's   :30         NA's   :21       NA's   :20     NA's   :23
##       A17             A18                A19              A20
##  Min.   :0.000   Min.   :   4.00   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:1.000   1st Qu.:  14.00   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :1.000   Median :  33.00   Median :0.0000   Median :0.0000
##  Mean   :1.178   Mean   :  61.08   Mean   :0.1112   Mean   :0.2376
##  3rd Qu.:1.000   3rd Qu.:  89.00   3rd Qu.:0.0000   3rd Qu.:0.0000
##  Max.   :5.000   Max.   :2082.00   Max.   :1.0000   Max.   :1.0000
##  NA's   :19      NA's   :21        NA's   :22       NA's   :18
##       A21               A22                A23              A24
##  Min.   :0.00000   Min.   :0.006982   Min.   :  0.00   Min.   :0.000000
##  1st Qu.:0.00000   1st Qu.:0.050545   1st Qu.: 30.00   1st Qu.:0.007505
##  Median :0.00000   Median :0.057638   Median :100.00   Median :0.079963
##  Mean   :0.02724   Mean   :0.055725   Mean   : 83.95   Mean   :0.267362
##  3rd Qu.:0.00000   3rd Qu.:0.062879   3rd Qu.:111.00   3rd Qu.:0.522907
##  Max.   :3.00000   Max.   :0.083627   Max.   :985.00   Max.   :0.522907
##  NA's   :18        NA's   :17         NA's   :18       NA's   :19
##       A25              Class
##  Min.   :0.000000   Min.   :0.0000
##  1st Qu.:0.000000   1st Qu.:0.0000
##  Median :0.000000   Median :0.0000
##  Mean   :0.000132   Mean   :0.2705
##  3rd Qu.:0.000000   3rd Qu.:1.0000
##  Max.   :0.111000   Max.   :1.0000
##  NA's   :15

##        A01       A02        A03       A04       A05       A06        A07
## 1 10.08057 0.9944798 0.03897416 0.5313891 0.5828193 0.3419398 0.03890527
##         A08       A09       A10       A11      A12       A13       A14
## 1 0.2191602 0.1491071 0.2061821 0.4470791 141.0333 0.3939249 0.2795417
##         A15       A16       A17     A18       A19       A20       A21
## 1 0.3571616 0.1910905 0.6080678 100.063 0.3144882 0.4257441 0.1804822
##          A22      A23       A24         A25     Class
## 1 0.01073047 60.04321 0.2521005 0.003523979 0.4443292
```

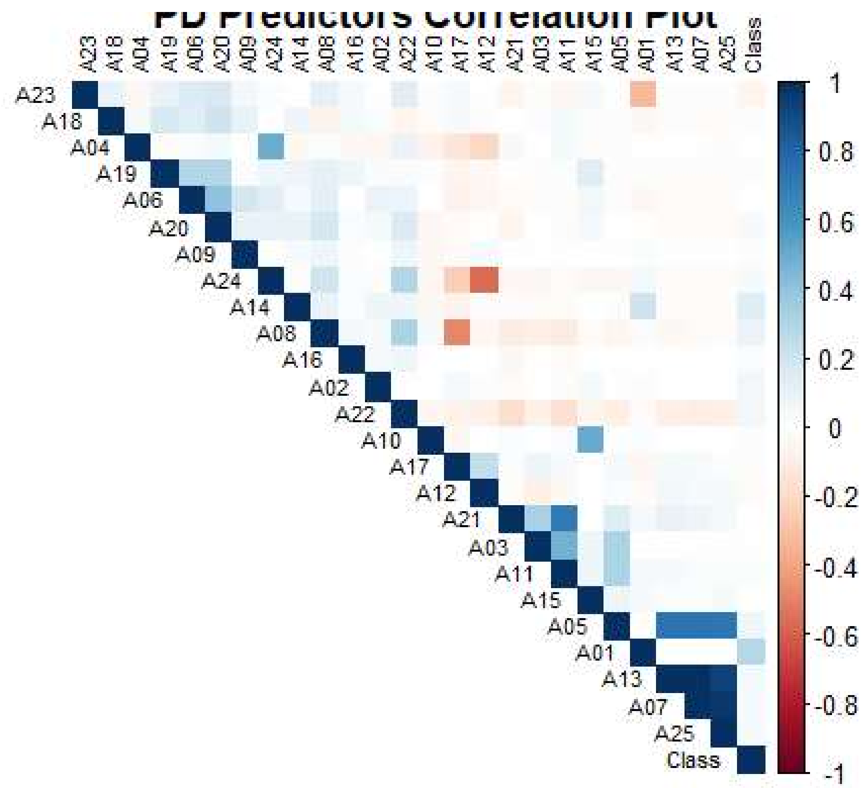
For the code chunk above, `echo = FALSE` parameter was added to prevent printing of the R code output as the output is lengthy.

`str()` method was used to obtain information on which column is to be used for `summary()` method. From `str()`, it was known that all columns datatype were either integer or number so all columns were included in the `summary()` method to obtain the **Min, Max, Median, Mean, and the Number of NAs** within the columns.

The output from the code chunk above shows that all columns have NA values between the range of **14 to 30**, other than **column A01 and Class** which have **no NA values at all**. Column **A13** contains the highest number of missing values, totaling **30**. The output also shows that column **A01, A12, A18 and A23** have standard deviation more than 1 which means that their variability is high which indicates that the data in these columns have a wider spread around the mean. This then further suggest that the values in these columns are more dispersed and less consistent compared to columns with a standard deviation less than 1. Even with these high standard deviation, column **A01, A12, A18 and A23** are not removed as any one of these column could be important predictor on whether the class is legitimate or phishing.

Phishing dataset predictor correlation

```
# Compute the correlation matrix
cor_matrix <- cor(PD, use = "complete.obs")  # Omit NA values

# Create a correlation plot
corrplot(cor_matrix, method = "color", order = "AOE", tl.cex = 0.7, tl.col = "black",
         title = "PD Predictors Correlation Plot", type = "upper")
```



Question 2

Remove rows with NA values

```
PD = data.frame(PD)
PD$Class = factor(PD$Class)
PD_na_free = PD[complete.cases(PD),]
PD_na_free = na.omit(PD)
dim(PD_na_free)

## [1] 1541   26

str(PD_na_free) # Confirm after removal of NA values, the predictor 'Class' is still a
factor

## 'data.frame':    1541 obs. of  26 variables:
##  $ A01  : int  11 25 31 3 3 3 11 10 6 13 ...
##  $ A02  : int  0 0 0 0 0 1 0 0 0 0 ...
##  $ A03  : int  0 0 0 0 0 0 0 0 0 0 ...
```

```
##  $ A04  : int  3 2 3 2 3 3 2 2 2 3 ...
##  $ A05  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A06  : int  1 1 0 0 0 0 0 0 0 0 ...
##  $ A07  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A08  : num  1 1 0.441 0.714 1 ...
##  $ A09  : int  1 0 0 0 0 0 0 0 0 0 ...
##  $ A10  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A11  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A12  : int  232 365 232 648 232 232 388 648 226 232 ...
##  $ A13  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A14  : int  0 1 0 0 0 0 0 0 0 0 ...
##  $ A15  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A16  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A17  : int  1 1 1 2 1 1 2 2 1 1 ...
##  $ A18  : int  96 89 17 42 29 39 27 46 5 97 ...
##  $ A19  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A20  : int  1 1 0 0 1 0 0 1 0 1 ...
##  $ A21  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A22  : num  0.0605 0.0601 0.0633 0.0626 0.0461 ...
##  $ A23  : int  15 107 1 110 111 116 165 107 100 124 ...
##  $ A24  : num  0.52291 0.00159 0.52291 0.02856 0.52291 ...
##  $ A25  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ Class: Factor w/ 2 levels "0","1": 1 1 1 1 1 2 1 1 1 1 ...
##  - attr(*, "na.action")= 'omit' Named int [1:459] 2 10 11 16 23 25 28 29 41 43 ...
##   ..- attr(*, "names")= chr [1:459] "69509" "65009" "61141" "91683" ...
```

Any occurrence of NA values, no matter how small, is eliminated since they can create uncertainty and lower the model's prediction accuracy, potentially resulting in biased or incorrect statistical conclusions. By making sure that the dataset is free of NA values, the algorithms can then work with fully populated data, which will lead to a more transparent understanding of the patterns and relationships within the data and its predictors.

After removing all rows that contain NA values within the Phishing dataset, there remain a total of 1541 rows within the Phishing dataset sample. `PD_na_free` contains the 1541 rows of the Phishing dataset that does not contain any NA values as shown below with `summary()` method.

In addition to that, the value in class will be changed to 1 and 2 instead of 0 and 1 as factors can't start with 0 so when class equal to 1 it is 0 which is legitimate and when class equals to 2 it is 1 which is phishing.

```
##       A01             A02                A03                A04       
##  Min.   : 3.00   Min.   : 0.0000   Min.   :0.000000   Min.   :2.000  
##  1st Qu.:10.00   1st Qu.: 0.0000   1st Qu.:0.000000   1st Qu.:2.000  
##  Median :15.00   Median : 0.0000   Median :0.000000   Median :3.000  
##  Mean   :16.48   Mean   : 0.1635   Mean   :0.001947   Mean   :2.746  
##  3rd Qu.:25.00   3rd Qu.: 0.0000   3rd Qu.:0.000000   3rd Qu.:3.000  
##  Max.   :35.00   Max.   :20.0000   Max.   :1.000000   Max.   :7.000  
##       A05                A06              A07                A08        
##  Min.   : 0.0000   Min.   :0.0000   Min.   :0.000000   Min.   :0.1429  
##  1st Qu.: 0.0000   1st Qu.:0.0000   1st Qu.:0.000000   1st Qu.:0.6818  
##  Median : 0.0000   Median :0.0000   Median :0.000000   Median :1.0000  
##  Mean   : 0.0305   Mean   :0.1369   Mean   :0.001947   Mean   :0.8429  
##  3rd Qu.: 0.0000   3rd Qu.:0.0000   3rd Qu.:0.000000   3rd Qu.:1.0000  
##  Max.   :18.0000   Max.   :1.0000   Max.   :1.000000   Max.   :1.0000  
##       A09              A10                A11                A12
```

```
##  Min.   :0.00000   Min.   :0.00000   Min.   :0.00000   Min.   :  3.0  
##  1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:232.0  
##  Median :0.00000   Median :0.00000   Median :0.00000   Median :232.0  
##  Mean   :0.02401   Mean   :0.04088   Mean   :0.04932   Mean   :314.4  
##  3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:388.0  
##  Max.   :1.00000   Max.   :1.00000   Max.   :9.00000   Max.   :692.0  
##       A13                A14               A15              A16         
##  Min.   : 0.00000   Min.   :0.00000   Min.   :0.0000   Min.   :0.00000  
##  1st Qu.: 0.00000   1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.00000  
##  Median : 0.00000   Median :0.00000   Median :0.0000   Median :0.00000  
##  Mean   : 0.01947   Mean   :0.08177   Mean   :0.1441   Mean   :0.03829  
##  3rd Qu.: 0.00000   3rd Qu.:0.00000   3rd Qu.:0.0000   3rd Qu.:0.00000  
##  Max.   :12.00000   Max.   :1.00000   Max.   :1.0000   Max.   :1.00000  
##       A17              A18               A19              A20        
##  Min.   :0.000   Min.   :   4.0   Min.   :0.0000   Min.   :0.0000  
##  1st Qu.:1.000   1st Qu.:  14.0   1st Qu.:0.0000   1st Qu.:0.0000  
##  Median :1.000   Median :  31.0   Median :0.0000   Median :0.0000  
##  Mean   :1.162   Mean   :  58.9   Mean   :0.1181   Mean   :0.2375  
##  3rd Qu.:1.000   3rd Qu.:  89.0   3rd Qu.:0.0000   3rd Qu.:0.0000  
##  Max.   :5.000   Max.   :2082.0   Max.   :1.0000   Max.   :1.0000  
##       A21                A22                A23              A24         
##  Min.   :0.00000   Min.   :0.009351   Min.   :  0.00   Min.   :0.00000  
##  1st Qu.:0.00000   1st Qu.:0.050773   1st Qu.: 28.00   1st Qu.:0.00820  
##  Median :0.00000   Median :0.057820   Median :100.00   Median :0.07996  
##  Mean   :0.02726   Mean   :0.055790   Mean   : 83.05   Mean   :0.27178  
##  3rd Qu.:0.00000   3rd Qu.:0.062943   3rd Qu.:110.00   3rd Qu.:0.52291  
##  Max.   :3.00000   Max.   :0.083627   Max.   :985.00   Max.   :0.52291  
##       A25              Class   
##  Min.   :0.0000000   0:1115  
##  1st Qu.:0.0000000   1: 426  
##  Median :0.0000000           
##  Mean   :0.0001707           
##  3rd Qu.:0.0000000           
##  Max.   :0.1110000
```

Question 3

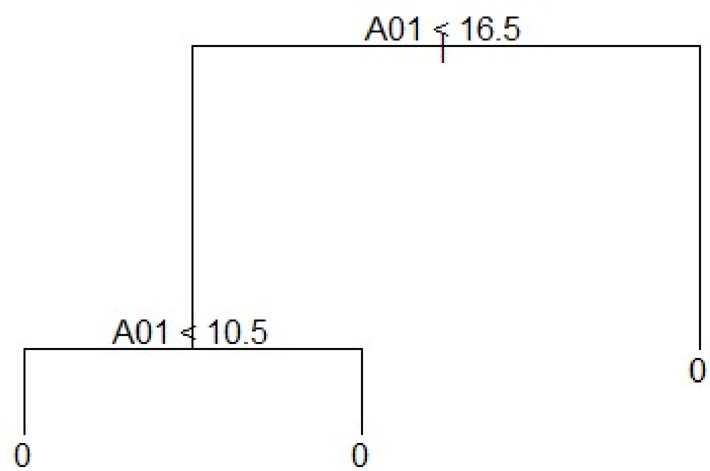
```
set.seed(33085625)
train.row = sample(1:nrow(PD_na_free), 0.7*nrow(PD_na_free))
PD_na_free.train = PD_na_free[train.row,]
PD_na_free.test = PD_na_free[-train.row,]
```

Question 4

```
decision_tree_model = tree(Class ~., data = PD_na_free.train)
summary(decision_tree_model)
```

```
## 
## Classification tree:
## tree(formula = Class ~ ., data = PD_na_free.train)
## Variables actually used in tree construction:
## [1] "A01"
## Number of terminal nodes:  3 
## Residual mean deviance:  1.099 = 1182 / 1075 
## Misclassification error rate: 0.2774 = 299 / 1078
```

```
plot(decision_tree_model, main = "Decision Tree")
text(decision_tree_model, pretty = 0)
```




```r
naive_bayes_model = naiveBayes(Class ~., data = PD_na_free.train)
summary(naive_bayes_model)
```

```
##           Length Class  Mode
## apriori    2     table  numeric
## tables    25     -none- list
## levels     2     -none- character
## isnumeric 25     -none- logical
## call       4     -none- call
```

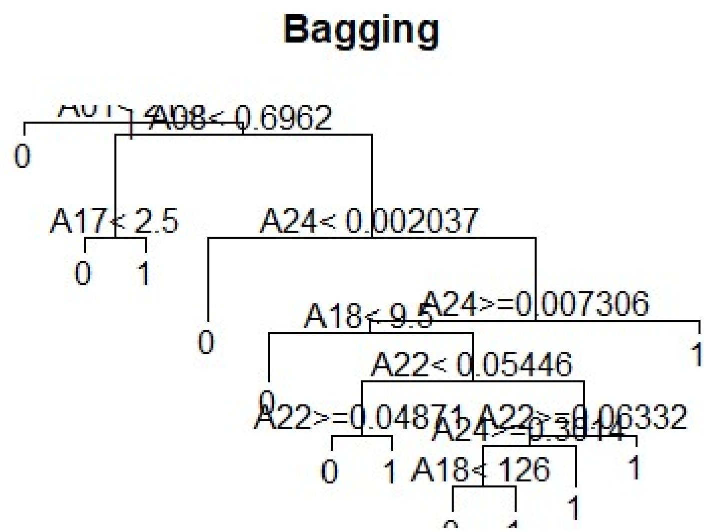
```r
# Check for NA values because Bagging algorithm cannot process NA values directly
sum(is.na(PD_na_free.train))
```

```
## [1] 0
```

```r
bagging_model <- bagging(Class ~., data = PD_na_free.train, coob = TRUE, resampling =
"bootstrap")
summary(bagging_model)
```

```
##            Length Class   Mode
## formula         3 formula call
## trees         100 -none-  list
## votes        2156 -none-  numeric
## prob         2156 -none-  numeric
## class        1078 -none-  character
## samples    107800 -none-  numeric
## importance     25 -none-  numeric
## terms           3 terms   call
## call            5 -none-  call
```

```r
plot(bagging_model$trees[[1]], main = "Bagging")
text(bagging_model$trees[[1]], pretty = 0)
```



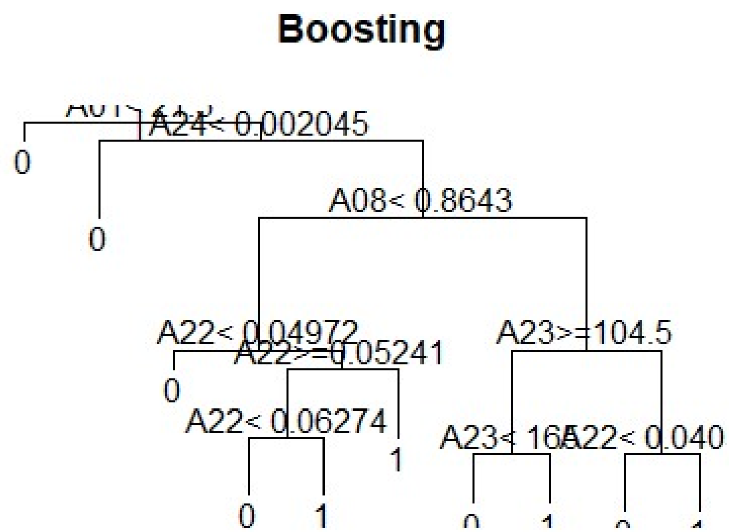

```
# Check for NA values because Boosting algorithm cannot process NA values directly
sum(is.na(PD_na_free.train))
```

```
## [1] 0
```

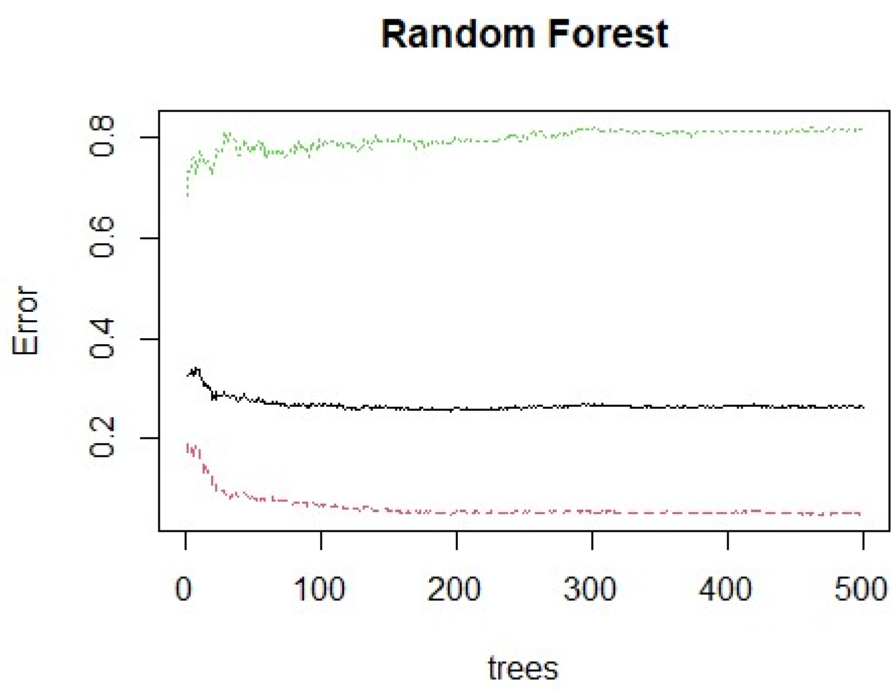
```
boosting_model = boosting(Class ~., data = PD_na_free.train)
summary(boosting_model)
```

```
##            Length Class   Mode
## formula      3    formula call
## trees      100    -none-  list
## weights    100    -none-  numeric
## votes     2156    -none-  numeric
## prob      2156    -none-  numeric
## class     1078    -none-  character
## importance  25    -none-  numeric
## terms        3    terms   call
## call         3    -none-  call
```

```
plot(boosting_model$trees[[1]], main = "Boosting")
text(boosting_model$trees[[1]], pretty = 0)
```




```
random_forest_model = randomForest(Class ~., data = PD_na_free.train)
summary(random_forest_model)

##                 Length Class  Mode
## call               3   -none- call
## type               1   -none- character
## predicted       1078   factor numeric
## err.rate        1500   -none- numeric
## confusion          6   -none- numeric
## votes           2156   matrix numeric
## oob.times       1078   -none- numeric
## classes            2   -none- character
## importance        25   -none- numeric
## importanceSD       0   -none- NULL
## localImportance    0   -none- NULL
## proximity          0   -none- NULL
## ntree              1   -none- numeric
## mtry               1   -none- numeric
## forest            14   -none- list
## y               1078   factor numeric
## test               0   -none- NULL
## inbag              0   -none- NULL
## terms              3   terms  call

plot(random_forest_model, main = "Random Forest")
```



Question 5

Phishing is labelled as 1; Legitimate is labelled as 0

In the confusion matrix obtained below, there is True Positives, True Negatives, False Positives and False Negatives given in values.

- True Positives (TP) are the cases where the model correctly predicted the positive class (phishing). In the confusion matrix, this would be in the bottom right cell.
- True Negatives (TN) are the cases where the model correctly predicted the negative class (legitimate). This is the top left cell of the confusion matrix.
- False Positives (FP) are the cases where the model incorrectly predicted the positive class. In the confusion matrix, this would be the top right cell.
- False Negatives (FN) are the cases where the model incorrectly predicted the negative class. This is the bottom left cellof the confusion matrix.

It should also be known that the accuracy of the model is calculated as: Accuracy = (TP+TN) / (FP+FN+TP+TN) where (TP+TN) / (FP+FN+TP+TN) is the formula to calculate the accuracy of the model. Other than accuracy used to evaluate the models, Precision, True Positive Ratio or also known as Sensitivity and False Positive Ratio will be used. True Positive Ratio and False Positive Ratio will be used to plot ROC where False Positive Ratio is on the x-axis and True Positive Ratio is on the y-axis.

- Precision = TP / (TP + FP)
- True Positive Ratio (TPR) = TP / (TP+FN)
- False Positive Ratio (1-Specificity) = FP / (FP+TN)

Precision is the measure of accuracy of positive predictions made while Sensitivity evaluates the model's ability to identify all relevant instances which is essentially the actual True Positive cases identified correctly by the model. In summary, Precision focus on the purity of the positive predictions when Sensitivity focus on the completeness of the positive predictions.

```r
# Predict using the testing dataset after training the model
predict_decision_tree = predict(decision_tree_model, newdata = PD_na_free.test, type =
"class")

# Evaluating the model performance
# Decision Tree Confusion Matrix
result_decision_tree = table(actual = PD_na_free.test$Class, prediction =
predict_decision_tree)
colnames(result_decision_tree) = c("legitimate", "phishing")
rownames(result_decision_tree) = c("legitimate", "phishing")
result_decision_tree

##             prediction
## actual       legitimate phishing
##   legitimate        336        0
##   phishing          127        0

# Evaluating the model accuracy
decision_tree_accuracy = (result_decision_tree[2, 2] + result_decision_tree[1, 1]) /
(result_decision_tree[2, 2] + result_decision_tree[1, 1] + result_decision_tree[2, 1] +
result_decision_tree[1, 2])
decision_tree_accuracy

## [1] 0.7257019
```

From the confusion matrix displayed above in the output, it is displayed that:

- The TP for the confusion matrix for decision tree is 0, indicating that the model did not correctly predict any phishing cases.
- The TN for the confusion matrix for decision tree is 336, indicating that the model correctly identified 336 legitimate cases.
- The FP for the confusion matrix for decision tree is 0, indicating that the model did not incorrectly predict any legitimate cases as phishing.
- The FN for the confusion matrix for decision tree is 127, indicating that the model incorrectly identified 127 phishing cases as legitimate.

Given the values from the confusion matrix above,

- The accuracy of the decision tree model is 0.7257019 which is approximately 72.57%.
- The precision of the decision tree model is not calculated as there are no instances where phishing was predicted so precision cannot be calculated as it would involve division by zero.
- The sensitivity of the decision tree model is 0 / (0+127) which is equal to 0.
- The False Positive Ratio of the decision tree model is also 0 as 0 / (0+336) equals to 0.

This indicates that the decision tree model accurately recognized around 72.57% of the instances. Nevertheless, there is a major problem with the model as it failed to accurately detect any instances of phishing, as shown by the TP cell displaying zero. Every phishing incident was labeled as legitimate, posing a significant problem for a phishing detection algorithm. This might result from a few factors like overfitting or there is a lacking representative features for the phishing class, or even an uneven distribution in the training data.

```r
# Predict using the testing dataset after training the model
predict_naive_bayes = predict(naive_bayes_model, newdata = PD_na_free.test, type =
"class")
```

```r
# Evaluating the model performance
# Naïve-Bayes Confusion Matrix
result_naive_bayes = table(actual = PD_na_free.test$Class, predicted =
predict_naive_bayes)
colnames(result_naive_bayes) = c("legitimate", "phishing")
rownames(result_naive_bayes) = c("legitimate", "phishing")
result_naive_bayes

##             predicted
## actual       legitimate phishing
##   legitimate        335        1
##   phishing          126        1

# Evaluating the model accuracy
naive_bayes_accuracy = (result_naive_bayes[2, 2] + result_naive_bayes[1, 1]) /
(result_naive_bayes[2, 2] + result_naive_bayes[1, 1] + result_naive_bayes[2, 1] +
result_naive_bayes[1, 2])
naive_bayes_accuracy

## [1] 0.7257019
```

From the confusion matrix displayed above in the output, it is shown that:

- The TP for the confusion matrix for Naïve-Bayes is 1, indicating that the model only correctly predict 1 phishing case.
- The TN for the confusion matrix for Naïve-Bayes is 335, indicating that the model correctly identified 335 legitimate cases.
- The FP for the confusion matrix for Naïve-Bayes is 1, indicating that the model did only predict 1 legitimate case as phishing.
- The FN for the confusion matrix for Naïve-Bayes is 126, indicating that the model incorrectly identified 126 phishing cases as legitimate.

Given the values from the confusion matrix above,

- The accuracy of the Naïve-Bayes model is same as the decision tree model accuracy of 0.7257019 which is approximately 72.57%.
- The precision of the Naïve-Bayes model is 0.5 as 1 / (1+1) equals to 1/2 which is 0.5
- The sensitivity of the Naïve-Bayes model is 1/127 which is roughly around 0.0079
- The False Positive Ratio of the Naïve-Bayes model is 1/336 which is roughly around 0.00289

Eventhough both decision tree model and Naïve-Bayes model have the same accuracy, the Naïve-Bayes model has managed to correctly identify 1 phishing case. Yet even with the only correct identification of the 1 phishing case, the Naïve-Bayes model still shows a significant bias towards predicting legitimate cases, with a high number of 126 false negatives which are the phishing cases misclassified as legitimate.

```r
# Predict using the testing dataset after training the model
predict_bagging = predict(bagging_model, newdata = PD_na_free.test, type = "class")

# Evaluating the model performance
# Bagging Confusion Matrix
result_bagging = predict_bagging$confusion
colnames(result_bagging) = c("legitimate", "phishing")
rownames(result_bagging) = c("legitimate", "phishing")
result_bagging
```

```
##                 Observed Class
## Predicted Class legitimate phishing
##      legitimate        315      101
##      phishing           21       26
```

```r
# Evaluating the model accuracy
bagging_accuracy = (result_bagging[2, 2] + result_bagging[1, 1]) / (result_bagging[2, 2]
+ result_bagging[1, 1] + result_bagging[2, 1] + result_bagging[1, 2])
bagging_accuracy
```

```
## [1] 0.7365011
```

From the confusion matrix displayed above in the output, it is known that:

- The TP for the confusion matrix for Bagging is 26, indicating that the model only correctly predict 26 phishing cases.
- The TN for the confusion matrix for Bagging is 315, indicating that the model correctly identified 315 legitimate cases.
- The FP for the confusion matrix for Bagging is 101, indicating that the model did only predict 101 legitimate cases as phishing.
- The FN for the confusion matrix for Bagging is 21, indicating that the model incorrectly identified 21 phishing cases as legitimate.

Given the values from the confusion matrix above,

- The accuracy of the Bagging model is 0.7365011 which is approximately 73.65%. The accuracy of the Bagging model is slightly higher than the accuracy for Naïve-Bayes and decision tree model.
- The precision of the Bagging model is 26/47 which is approximately 0.5532
- The sensitivity of the Bagging model is 26/127 which is approximately 0.2047
- The False Positive Ratio of the Bagging model is 21/336 which is approximately 0.0625

The bagging model has a better balance between predicting legitimate and phishing cases compared to the decision tree and Naïve-Bayes models as the bagging model has correctly identified more phishing cases of 26 compared to the previous models, indicating a better performance in detecting phishing attempts than the previous prediction models.

```r
# Predict using the testing dataset after training the model
predict_boosting = predict(boosting_model, newdata = PD_na_free.test, type = "class")

# Evaluating the model performance
# Boosting Confusion Matrix
result_boosting = predict_boosting$confusion
colnames(result_boosting) = c("legitimate", "phishing")
rownames(result_boosting) = c("legitimate", "phishing")
result_boosting
```

```
##                 Observed Class
## Predicted Class legitimate phishing
##      legitimate        281       97
##      phishing           55       30
```

```r
# Evaluating the model accuracy
boosting_accuracy = (result_boosting[2, 2] + result_boosting[1, 1]) / (result_boosting[2,
2] + result_boosting[1, 1] + result_boosting[2, 1] + result_boosting[1, 2])
boosting_accuracy
```

```
## [1] 0.6717063
```

From the confusion matrix displayed above in the output, it is presented that:

- The TP for the confusion matrix for Boosting is 30, indicating that the model only correctly predict 30 phishing cases.
- The TN for the confusion matrix for Boosting is 281, indicating that the model correctly identified 281 legitimate cases.
- The FP for the confusion matrix for Boosting is 97, indicating that the model did only predict 97 legitimate cases as phishing.
- The FN for the confusion matrix for Boosting is 55, indicating that the model incorrectly identified 55 phishing cases as legitimate.

Given the values from the confusion matrix above,

- The accuracy of the Boosting model is 0.6717063 which is approximately 67.17%. The accuracy of 67.17% is the lowest prediction model accuracy compared to the Bagging, decision tree, Naïve-Bayes model above and Random forest model below.
- The precision of the Boosting model is 30/85
- The sensitivity of the Boosting model is 30/127
- The False Positive Ratio of the Boosting model is 55/336

From the confusion matrix above, it is shown that the Boosting model has identified more phishing cases of 30 compared to the decision tree and Naïve-Bayes models but fewer than the bagging model. Other than that, the number of false positives is 97 which is high, indicating that many legitimate cases were incorrectly classified as phishing.

```
# Predict using the testing dataset after training the model
predict_random_forest = predict(random_forest_model, newdata = PD_na_free.test, type =
"class")

# Evaluating the model performance
# Random Forest Confusion Matrix
result_random_forest = table(actual = PD_na_free.test$Class, predicted =
predict_random_forest)
colnames(result_random_forest) = c("legitimate", "phishing")
rownames(result_random_forest) = c("legitimate", "phishing")
result_random_forest

##             predicted
## actual       legitimate phishing
##   legitimate        314       22
##   phishing          103       24

# Evaluating the model accuracy
random_forest_accuracy = (result_random_forest[2, 2] + result_random_forest[1, 1]) /
(result_random_forest[2, 2] + result_random_forest[1, 1] + result_random_forest[2, 1] +
result_random_forest[1, 2])
random_forest_accuracy

## [1] 0.7300216
```

From the confusion matrix displayed above in the output, it is presented that:

- The TP for the confusion matrix for Random Forest is 24, indicating that the model only correctly predict 24 phishing cases.
- The TN for the confusion matrix for Random Forest is 314, indicating that the model correctly identified 314 legitimate cases.
- The FP for the confusion matrix for Random Forest is 22, indicating that the model did only predict 22 legitimate cases as phishing.
- The FN for the confusion matrix for Random Forest is 103, indicating that the model incorrectly identified 103 phishing cases as legitimate.

Given the values from the confusion matrix above,

- The accuracy of the Random Forest model is 0.7300216 which is approximately 73.00%. This accuracy is comparable to the accuracy of the Bagging model which is approximately 73.65%.
- The precision of the Random Forest model is 24/46
- The sensitivity of the Random Forest model is 24/127
- The False Positive Ratio of the Random Forest model is 22/336

The Random Forest model has a moderate number of both false positives and false negatives, indicating that this Random Forest model has a more balanced approach to classifying legitimate and phishing cases compared to some of the other models. Nonetheless, the Bagging model has a higher accuracy than this Random Forest model by approximately 0.65%. This Random Forest model has correctly identified 24 phishing cases, which is fewer than the bagging model but more than the decision tree and Naïve-Bayes models.

Question 6

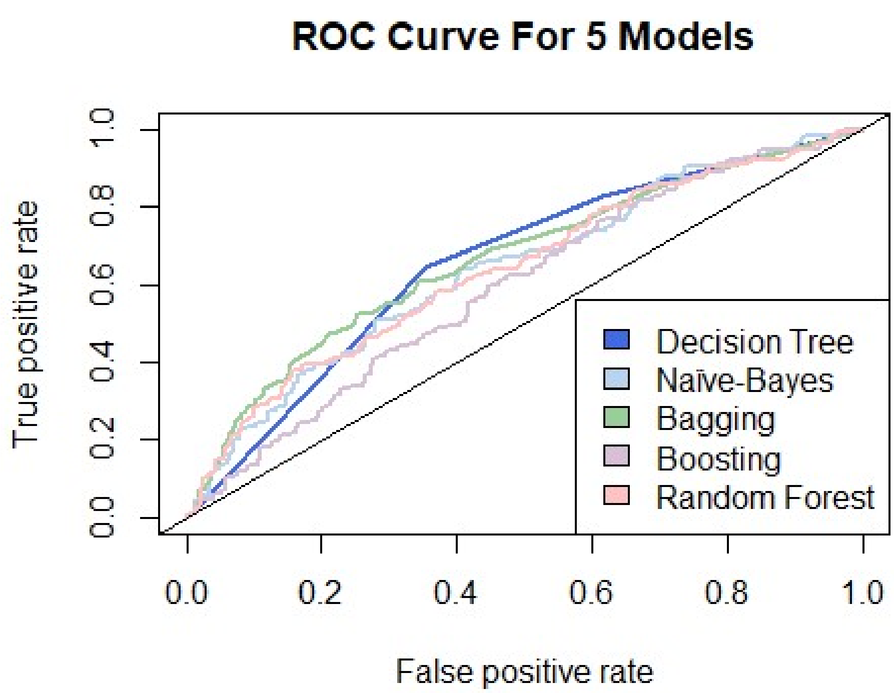
Calculate Confidence Level, Prediction and Performance of model

```
confidence_decision_tree = predict(decision_tree_model, newdata = PD_na_free.test, type =
"vector")

prediction_decision_tree = prediction(confidence_decision_tree[, 2],
PD_na_free.test$Class)
prediction_decision_tree

## A prediction instance
##   with 463 data points

performance_decision_tree = performance(prediction_decision_tree, "tpr", "fpr")
performance_decision_tree

## A performance instance
##   'False positive rate' vs. 'True positive rate' (alpha: 'Cutoff')
##   with 4 data points

confidence_naive_bayes = predict(naive_bayes_model, newdata = PD_na_free.test, type =
"raw")

prediction_naive_bayes = prediction(confidence_naive_bayes[, 2], PD_na_free.test$Class)
performance_naive_bayes = performance(prediction_naive_bayes, "tpr", "fpr")

confidence_bagging = predict(bagging_model, newdata = PD_na_free.test, type = "prob")
confidence_bagging = confidence_bagging$prob
confidence_bagging = confidence_bagging[, 1:2]
```

```
prediction_bagging = prediction(confidence_bagging[, 2], PD_na_free.test$Class)
performance_bagging = performance(prediction_bagging, "tpr", "fpr")

confidence_boosting = predict(boosting_model, newdata = PD_na_free.test, type = "prob")
confidence_boosting = confidence_boosting$prob

prediction_boosting = prediction(confidence_boosting[, 2], PD_na_free.test$Class)
performance_boosting = performance(prediction_boosting, "tpr", "fpr")

confidence_random_forest = predict(random_forest_model, newdata = PD_na_free.test, type =
"prob")

prediction_random_forest = prediction(confidence_random_forest[, 2],
PD_na_free.test$Class)
performance_random_forest = performance(prediction_random_forest,"tpr","fpr")
```

Plot ROC Curve For 5 Models

```
plot(performance_decision_tree, col = "royalblue", main = "ROC Curve For 5 Models", lwd =
2)
plot(performance_naive_bayes, col = "slategray2", add = TRUE, lwd = 2)
plot(performance_bagging, col = "darkseagreen3", add = TRUE, lwd = 2)
plot(performance_boosting, col = "thistle", add = TRUE, lwd = 2)
plot(performance_random_forest, col = "rosybrown1", add = TRUE, lwd = 2)
# lwd was used to increase the thickness of the line in the plot
abline(0, 1)

legend("bottomright", legend = c("Decision Tree", "Naïve-Bayes", "Bagging", "Boosting",
"Random Forest"), fill = c("royalblue", "slategray2", "darkseagreen3", "thistle",
"rosybrown1"))
```



The ROC Curve is a graphical method used to evaluate the performance of binary classifiers, specifically focusing on the 'Class' column in this scenario. A curve located near the upper-left corner suggests a better model. If the curve is closer to the top-left corner, it indicates a better model. By examining the curves, it is possible to assess on which model achieves optimal balance between TPR and FPR.

In the ROC Curve shown, the y-axis represents the True Positive Rate (TPR), which indicates the percentage of true positive cases correctly recognized by the model, while the x-axis represents the False Positive Rate (FPR), showing the percentage of true negative cases mistakenly classified as positive.

To identify the best model for prediction, we will use the Area Under Curve (AUC) value as the model with the greatest area under its ROC curve is typically seen as the best model.

Calculate AUC Value for each models

```
auc_decision_tree = performance(prediction_decision_tree, "auc")
auc_decision_tree_num = as.numeric(auc_decision_tree@y.values)
auc_decision_tree_num

## [1] 0.6578318

auc_naive_bayes = performance(prediction_naive_bayes, "auc")
auc_naive_bayes_num = as.numeric(auc_naive_bayes@y.values)
auc_naive_bayes_num

## [1] 0.63967

auc_bagging = performance(prediction_bagging, "auc")
auc_bagging_num = as.numeric(auc_bagging@y.values)
auc_bagging_num

## [1] 0.6660222

auc_boosting = performance(prediction_boosting, "auc")
auc_boosting_num = as.numeric(auc_boosting@y.values)
auc_boosting_num

## [1] 0.5934102

auc_random_forest = performance(prediction_random_forest, "auc")
auc_random_forest_num = as.numeric(auc_random_forest@y.values)
auc_random_forest_num

## [1] 0.6404199
```

Based on the Area Under the Curve (AUC) values calculated above, below is the ranking of these values from large to small:

1. Bagging: AUC value = 0.6660222
2. Decision Tree: AUC value = 0.6578318
3. Random Forest: AUC value = 0.6404199
4. Naïve-Bayes: AUC value = 0.63967
5. Boosting: AUC value = 0.5934102

The Bagging model stands out with the highest AUC value in the ranking, establishing itself as the top performer in ROC curve analysis among the listed models. The closer the AUC is to 1, the better the model is at distinguishing between positive and negative classes.

Question 7

```
decision_tree_accuracy_q7 = performance(prediction_decision_tree, "acc")
decision_tree_accuracy_q7_num = as.numeric(max(decision_tree_accuracy_q7@y.values[[1]]))
decision_tree_accuracy_q7_num
```

```
## [1] 0.7257019
```

```
naive_bayes_accuracy_q7 = performance(prediction_naive_bayes, "acc")
naive_bayes_accuracy_q7_num = as.numeric(max(naive_bayes_accuracy_q7@y.values[[1]]))
naive_bayes_accuracy_q7_num
```

```
## [1] 0.7321814
```

```
bagging_accuracy_q7 = performance(prediction_bagging, "acc")
bagging_accuracy_q7_num = as.numeric(max(bagging_accuracy_q7@y.values[[1]]))
bagging_accuracy_q7_num
```

```
## [1] 0.7408207
```

```
boosting_accuracy_q7 = performance(prediction_boosting, "acc")
boosting_accuracy_q7_num = as.numeric(max(boosting_accuracy_q7@y.values[[1]]))
boosting_accuracy_q7_num
```

```
## [1] 0.7300216
```

```
random_forest_accuracy_q7 = performance(prediction_random_forest, "acc")
random_forest_accuracy_q7_num = as.numeric(max(random_forest_accuracy_q7@y.values[[1]]))
random_forest_accuracy_q7_num
```

```
## [1] 0.7365011
```

```
q5_model_accuracy = c(decision_tree_accuracy, naive_bayes_accuracy, bagging_accuracy,
boosting_accuracy, random_forest_accuracy)
q6_model_accuracy = c(decision_tree_accuracy_q7_num, naive_bayes_accuracy_q7_num,
bagging_accuracy_q7_num, boosting_accuracy_q7_num, random_forest_accuracy_q7_num)

average_model_accuracy = c((decision_tree_accuracy + decision_tree_accuracy_q7_num) / 2,
(naive_bayes_accuracy + naive_bayes_accuracy_q7_num) / 2, (bagging_accuracy +
bagging_accuracy_q7_num) / 2, (boosting_accuracy + boosting_accuracy_q7_num) / 2,
(random_forest_accuracy + random_forest_accuracy_q7_num) / 2)

comparison_tbl = data.frame(q5_model_accuracy, q6_model_accuracy, average_model_accuracy)
rownames(comparison_tbl) = c("Decision Tree", "Naïve Bayes", "Bagging", "Boosting",
"Random Forest")
colnames(comparison_tbl) = c("Question 5 Model Accuracy", "Question 6 Model Accuracy",
"Average Model Accuracy")
comparison_tbl
```

```
##               Question 5 Model Accuracy Question 6 Model Accuracy
## Decision Tree                 0.7257019                 0.7257019
## Naïve Bayes                   0.7257019                 0.7321814
## Bagging                       0.7365011                 0.7408207
## Boosting                      0.6717063                 0.7300216
## Random Forest                 0.7300216                 0.7365011
##               Average Model Accuracy
## Decision Tree              0.7257019
## Naïve Bayes                0.7289417
```

```
## Bagging                     0.7386609
## Boosting                    0.7008639
## Random Forest               0.7332613
```

From looking at the AUC values alone, it is shown that the Bagging model appears to be the best classifier among all the other models listed. Even without refering to the AUC values, Bagging model still shows the highest accuracy in both Question 5 and Question 6, as well as the highest average accuracy. Therefore, based on these accuracy metrics alone, Bagging model can be seen as a single best classifier.

Question 8

```
summary(decision_tree_model)

##
## Classification tree:
## tree(formula = Class ~ ., data = PD_na_free.train)
## Variables actually used in tree construction:
## [1] "A01"
## Number of terminal nodes:  3
## Residual mean deviance:  1.099 = 1182 / 1075
## Misclassification error rate: 0.2774 = 299 / 1078
```

For the decision tree model, the most important variables in predicting whether a web site will be phishing or legitimate is A01.

```
acc = c()
for(tab in naive_bayes_model[["tables"]]) {
  acc = c(acc, ((tab[2, 2] + tab[1, 1]) / (tab[2, 2] + tab[1, 1] + tab[2, 1] + tab[1,
2])))
}

naive_bayes_model_accuracy = data.frame(Attributes = colnames(PD_na_free[, 1:25]),
Accuracy = acc)
naive_bayes_model_accuracy =
naive_bayes_model_accuracy[order(naive_bayes_model_accuracy$Accuracy, decreasing = TRUE),
]
naive_bayes_model_accuracy

##    Attributes  Accuracy
## 25        A25 0.9278274
## 13        A13 0.9249882
## 7         A07 0.9242796
## 5         A05 0.9098618
## 3         A03 0.6014463
## 11        A11 0.5558329
## 2         A02 0.5314883
## 23        A23 0.5311506
## 14        A14 0.5223521
## 21        A21 0.5056554
## 16        A16 0.5044564
## 15        A15 0.5001736
## 6         A06 0.5000609
## 17        A17 0.4996931
## 12        A12 0.4982039
## 4         A04 0.4971695
## 19        A19 0.4970307
## 20        A20 0.4962195
```

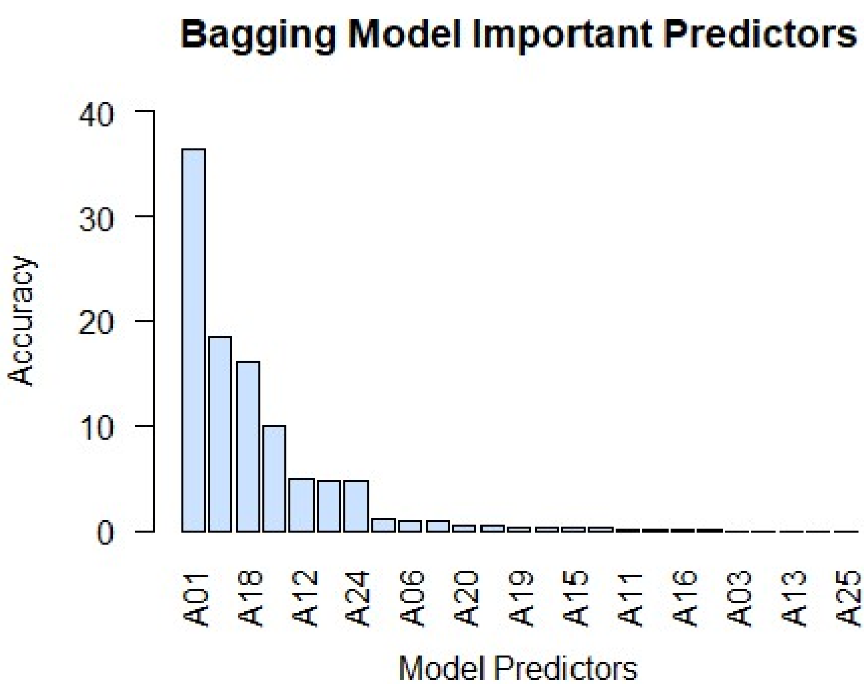
```
## 22         A22 0.4920418
## 24         A24 0.4879557
## 9          A09 0.4858980
## 8          A08 0.4847184
## 10         A10 0.4846875
## 1          A01 0.4469351
## 18         A18 0.4465845
```

For the naive bayes model, the three most important variables in predicting whether a web site will be phishing or legitimate is A25, A13 and A07 but A25 would be the most important variables in predicting whether a web site will be phishing or legitimate as it has the highest accuracy value of 0.9278274, indicating that it correctly predicts the outcome more often than the other attributes.

```
bagging_model$importance
```

```
##         A01         A02         A03         A04         A05         A06
## 36.36463533  0.41138344  0.00000000  0.27093448  0.06862954  0.85418473
##         A07         A08         A09         A10         A11         A12
##  0.00000000  4.77056071  0.03070511  0.20903342  0.16311832  4.87027002
##         A13         A14         A15         A16         A17         A18
##  0.00000000  0.81613788  0.22520005  0.05043278  1.01303572 16.05690360
##         A19         A20         A21         A22         A23         A24
##  0.37296691  0.45473774  0.00000000 18.42330859  9.89217207  4.68164955
##         A25
##  0.00000000
```

```
barplot(bagging_model$importance[order(bagging_model$importance, decreasing = TRUE)],
ylim = c(0, 40), las = 2, main = "Bagging Model Important Predictors", xlab = "Model
Predictors", ylab = "Accuracy", col = "lightsteelblue1")
```

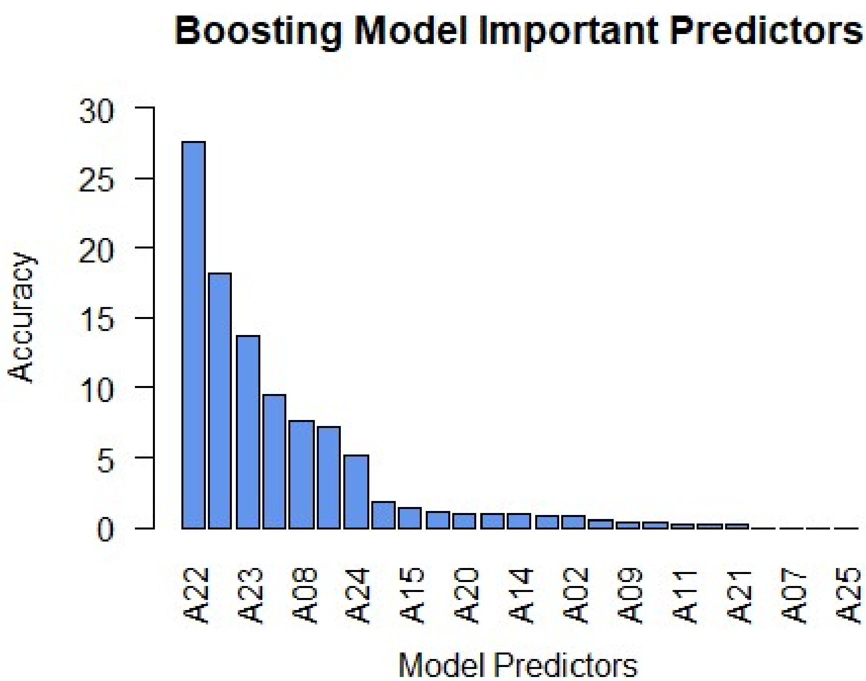


It is slightly difficult to identify which model predictor for the Bagging Model is the most important variables in predicting whether a web site will be phishing or legitimate so a bar plot is used to visualise it. From the bar plot, it is known that A01 is most important variables in predicting whether a web site will be phishing or legitimate for the Bagging Model as it has the highest accuracy of 36.36463533.

```
boosting_model$importance
```

```
##        A01        A02        A03        A04        A05        A06        A07
##  9.5373975  0.7898486  0.0000000  0.8596421  0.4837477  1.1336361  0.0000000
##        A08        A09        A10        A11        A12        A13        A14
##  7.6146331  0.4438161  0.3728328  0.2754940  7.1035051  0.0000000  0.9219427
##        A15        A16        A17        A18        A19        A20        A21
##  1.4388227  0.2437279  1.8133112 18.2057291  0.9815843  1.0184811  0.2099097
##        A22        A23        A24        A25
## 27.6298532 13.7412666  5.1808184  0.0000000
```

```
barplot(boosting_model$importance[order(boosting_model$importance, decreasing = TRUE)],
ylim = c(0, 30), las = 2, main = "Boosting Model Important Predictors", xlab = "Model
Predictors", ylab = "Accuracy", col = "cornflowerblue")
```



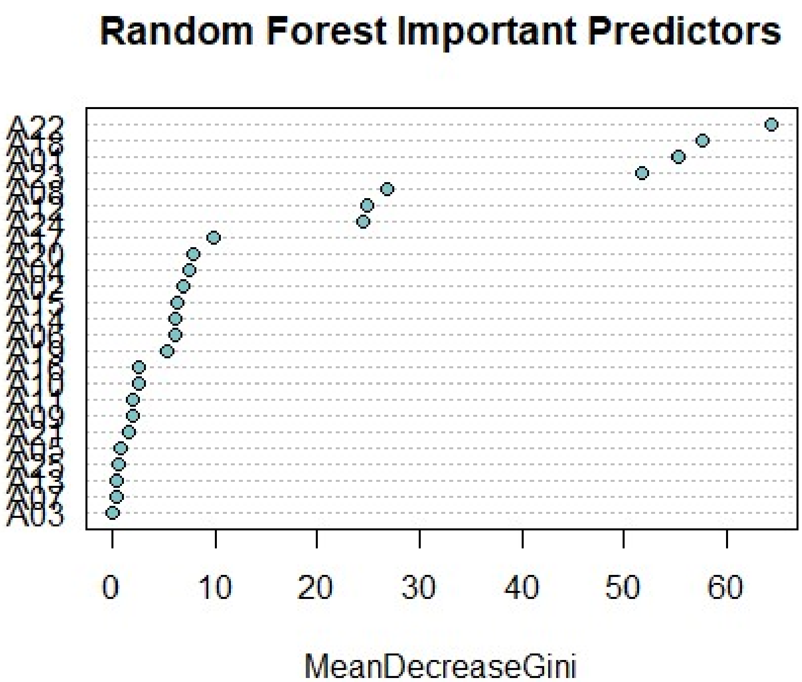
Determining the most significant predictor for the Boosting Model in distinguishing between a phishing website and a legitimate one can be somewhat challenging, hence the use of a bar plot for visualization. The bar plot reveals that A22 is the most crucial variable for determining if a website is phishing or legitimate in the Boosting Model due to its high accuracy of 27.6298532.

```
random_forest_model$importance
```

```
##     MeanDecreaseGini
## A01       55.3583242
## A02        6.8675525
## A03        0.1225678
## A04        7.5604378
## A05        0.8210876
## A06        6.1359170
## A07        0.4597608
```

```
## A08       26.7886785
## A09        2.0297776
## A10        2.6695832
## A11        2.0573564
## A12       24.9033090
## A13        0.4610878
## A14        6.2308689
## A15        6.4040187
## A16        2.6742955
## A17        9.7991893
## A18       57.5730872
## A19        5.3395807
## A20        7.8959540
## A21        1.6025464
## A22       64.3995504
## A23       51.6875572
## A24       24.4078212
## A25        0.5204239
```

```r
varImpPlot(random_forest_model, main = "Random Forest Important Predictors", bg =
"cadetblue3", cex=1)
```



It is somewhat challenging to determine the most important variables in predicting if a website is phishing or legitimate using the Random Forest Model, thus the varImpPlot library is utilized to visualize the model. According to the visualization, A22 is the most crucial variable for predicting if a website is phishing or legitimate in the Random Forest Model, with the highest accuracy of 64.3995504.

Variables that could be omitted from the data with very little effect on performance are variables with the lowest importance and/or accuracy scores. First, the few lowest predictors will be evaluated from model to model before deciding on which variables are the lowest predictors for each of the models.

For the Decision Tree model, only one variable, A01, was actually used in tree construction which suggested that A01 is a significant predictor for the Decision Tree model.

For the Naïve-Bayes Model, these are the 3 predictors with the lowest score:

1. A18: 0.4465845
2. A01: 0.4469351
3. A10: 0.4846875

For the Bagging Model, these are the 3 predictors with the lowest score:

1. A03, A07, A13, A21, A25: 0.00000000
2. A09: 0.03070511
3. A16: 0.05043278

For the Boosting Model, these are the 3 predictors with the lowest score:

1. A03, A07, A13, A25: 0.0000000
2. A21: 0.2099097
3. A10: 0.3728328

For the Random Forest Model, these are the 3 predictors with the lowest score:

1. A03: 0.1225678
2. A07: 0.4597608
3. A13: 0.4610878

According to the information gain displayed above, variables that consistently exhibit minimal importance or accuracy across the 5 models could possibly be excluded from the data without significantly impacting performance. The variables include A03, A07, A10, and A13. A03 showed poor performance in the Random Forest, Boosting, and Bagging models, and did not contribute at all in the Boosting and Bagging models, resulting in its exclusion. A07 is comparable to A03, with low scores in the Random Forest model and no contribution in either the Boosting or Bagging models, hence, its excluded. A13 is of minimal significance in the Random Forest model and makes no impact in the Boosting and Bagging models, hence it is omitted. A10 scored poorly in the Naïve Bayes model and ranks near the bottom in the Boosting model, therefore it is also excluded. While A25 does not contribute to Boosting and Bagging models, it is a significant predictor in the Naïve Bayes model, so it is not excluded as it could be valuable in specific contexts or scenarios.

Hence, in conclusion, the variables that could be omitted from the data includes A03, A07, A10, and A13 as these variables does not provide any important information when classifying.

Question 9

From Question 8, it is known that the important predictors are basically A01, A18, A22, A23, and A25, hence these predictors are also chosen to be used here. Despite the low score of A01 in the Naïve Bayes model, it was the only variable used in the Decision Tree model's construction which indicates its potential significance. A25 is the best predictor in the Naïve Bayes model while A22 has the highest MeanDecreaseGini score in the Random Forest model so both A25 and A22 are chosen. Furthermore, A18 and A23 also have high MeanDecreaseGini scores in the Random Forest model which strongly suggest that they both are also important predictors.

```
new_PD = data.frame(PD)
new_PD$Class = factor(new_PD$Class)
new_PD = subset(new_PD, select = c(1, 18, 22, 23, 25, 26))
new_PD = new_PD[complete.cases(new_PD),]
new_PD = na.omit(new_PD)

str(new_PD) # Confirm after removal of NA values, the predictor 'Class' is still a factor

## 'data.frame':    1929 obs. of  6 variables:
##  $ A01  : int  11 10 25 31 3 3 3 11 10 25 ...
##  $ A18  : int  96 30 89 17 42 29 39 27 46 44 ...
##  $ A22  : num  0.0605 0.0617 0.0601 0.0633 0.0626 ...
##  $ A23  : int  15 137 107 1 110 111 116 165 107 16 ...
##  $ A25  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ Class: Factor w/ 2 levels "0","1": 1 1 1 1 1 1 2 1 1 2 ...

set.seed(33085625)
new_train.row = sample(1:nrow(new_PD), 0.7*nrow(new_PD))
new_PD.train = new_PD[new_train.row,]
new_PD.test = new_PD[-new_train.row,]
```

The simple classifier that was chosen to be used here is the decision tree. Even though the decision tree does not have the best accuracy, decision trees are simple which means that they are easy to understand and interpret. It is also important to know that decision trees are able to capture non-linear correlations between features and the target variable without any additional work.

```
simple_classifier = tree(Class ~., data = new_PD.train)
predict_simple_classifier = predict(simple_classifier, newdata = new_PD.test, type =
"class")

tbl_result = table(actual = new_PD.test$Class, predicted = predict_simple_classifier)
colnames(tbl_result) = c("legitimate", "phishing")
rownames(tbl_result) = c("legitimate", "phishing")
tbl_result

##             predicted
## actual        legitimate phishing
##   legitimate         427        0
##   phishing           152        0

simple_classifier_accuracy = (tbl_result[2, 2] + tbl_result[1, 1]) / (tbl_result[2, 2] +
tbl_result[1, 1] + tbl_result[2, 1] + tbl_result[1, 2])
simple_classifier_accuracy

## [1] 0.7374784
```

From the confusion matrix displayed above in the output, it is presented that:

- The TP for the confusion matrix for decision tree is 0, indicating that the model did not correctly predict any phishing cases.
- The TN for the confusion matrix for decision tree is 427, indicating that the model correctly identified 427 legitimate cases.

- The FP for the confusion matrix for decision tree is 0, indicating that the model did not incorrectly predict any legitimate cases as phishing.
- The FN for the confusion matrix for decision tree is 152, indicating that the model incorrectly identified 152 phishing cases as legitimate.

Given the values from the confusion matrix above, the accuracy of the decision tree model is 0.7374784 which is approximately 73.74%. Previously, the decision tree model results from Question 4 and 5 have an accuracy of 0.7257019 which is approximately 72.57% which implies that this current decision tree have a better accuracy than the decision tree before with an accuracy increase of 0.0117765 which is around 1.17% increase in accuracy.

It is also known that,

- The precision of the decision tree model is not calculated as there are no instances where phishing was predicted so precision cannot be calculated as it would involve division by zero.
- The sensitivity of the decision tree model is also not calculated.
- The False Positive Ratio of the decision tree model is also not calculated.

```
# The test data used in Question 3 is PD_na_free.test
predict_simple_classifier_q3test = predict(simple_classifier, newdata = PD_na_free.test,
type = "class")

# Confusion Matrix
tbl_result_q3test = table(actual = PD_na_free.test$Class, predicted =
predict_simple_classifier_q3test)
colnames(tbl_result_q3test) = c("legitimate", "phishing")
rownames(tbl_result_q3test) = c("legitimate", "phishing")
tbl_result_q3test

##             predicted
## actual       legitimate phishing
##   legitimate        336        0
##   phishing          127        0

simple_classifier_accuracy_q3test = (tbl_result_q3test[2, 2] + tbl_result_q3test[1, 1]) /
(tbl_result_q3test[2, 2] + tbl_result_q3test[1, 1] + tbl_result_q3test[2, 1] +
tbl_result_q3test[1, 2])
simple_classifier_accuracy_q3test

## [1] 0.7257019
```

From the confusion matrix displayed above in the output, it is presented that:

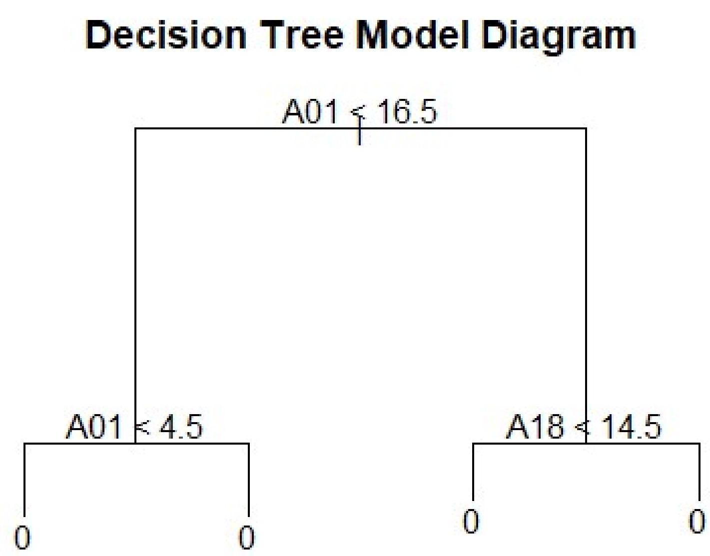
- The TP for the confusion matrix for decision tree is 0, indicating that the model did not correctly predict any phishing cases.
- The TN for the confusion matrix for decision tree is 336, indicating that the model correctly identified 336 legitimate cases.
- The FP for the confusion matrix for decision tree is 0, indicating that the model did not incorrectly predict any legitimate cases as phishing.
- The FN for the confusion matrix for decision tree is 127, indicating that the model incorrectly identified 127 phishing cases as legitimate.

Given the values from the confusion matrix above, the accuracy of the decision tree model is 0.7257019 which is approximately 72.57%.

It is also known that,

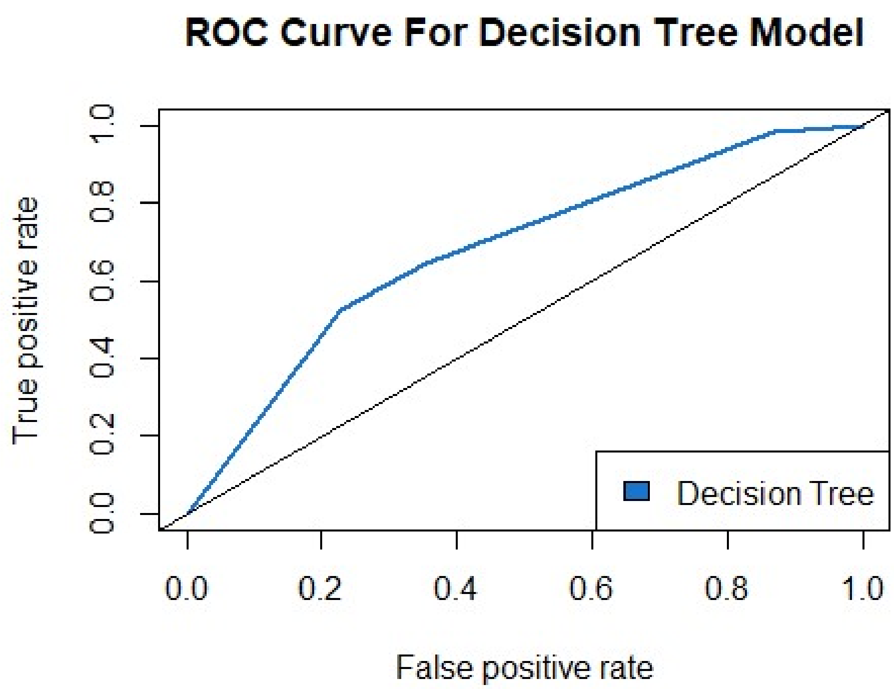
- The precision of the decision tree model is not calculated as there are no instances where phishing was predicted so precision cannot be calculated as it would involve division by zero.
- The sensitivity of the decision tree model is also not calculated.
- The False Positive Ratio of the decision tree model is also not calculated.

```
# Plot Decision tree
plot(simple_classifier)
text(simple_classifier, pretty = 0)
title(main = "Decision Tree Model Diagram")
```




```
# Confidence level on the test data used in Question 3
confidence_lvl_q3test = predict(simple_classifier, newdata = PD_na_free.test, type =
"vector")
summary(confidence_lvl_q3test)

##        0                1
##  Min.   :0.5152   Min.   :0.04861
##  1st Qu.:0.5152   1st Qu.:0.20061
##  Median :0.7994   Median :0.20061
##  Mean   :0.7156   Mean   :0.28436
##  3rd Qu.:0.7994   3rd Qu.:0.48477
##  Max.   :0.9514   Max.   :0.48477

# ROC curve
new_prediction_roc = prediction(confidence_lvl_q3test[, 2], PD_na_free.test$Class)
new_performance_roc = performance(new_prediction_roc, "tpr", "fpr")
plot(new_performance_roc, col = "dodgerblue3", main = "ROC Curve For Decision Tree
Model", lwd = 2) + abline(0, 1)

## integer(0)
```

```r
legend("bottomright", legend = c("Decision Tree"), fill = c("dodgerblue3"))
```



The root node of the decision tree tests if A01 is indeed less than 16.5 then the outcome is Class 0 but if it is not then it further tests if A18 is less than 14.5. Depending on the outcome of A18 test, if A18 is less than 14.5 then the data is Class 0 but if more than 14.5 then the data is Class 1.

```r
new_auc_decision_tree = performance(new_prediction_roc, "auc")
new_auc_decision_tree_num = as.numeric(new_auc_decision_tree@y.values)
new_auc_decision_tree_num

## [1] 0.6833052
```

Based on the Area Under the Curve (AUC) values calculated for the new decision tree, it is 0.6833052. The AUC value for the previous decision tree is 0.6578318. There is an increase of 0.0254734. This implies that the decision tree model have improved on distinguishing between Phishing and Legitimate classes.

Previously, the Bagging model stood out with the highest AUC value in the ranking with an AUC value of 0.6660222 now the new decision tree model have a higher auc value by 0.017283 which means that the variables selection did indeed improve the decision tree model.

Question 10

From Question 9, it is mentioned that the important predictors are basically A01, A18, A22, A23, and A25, hence these predictors are also chosen to be used here. Why A01, A18, A22, A23, and A25 are chosen as important predictors that can not be omitted is written at the start of Question 9.

In summary on why A01, A18, A22, A23, and A25 are chosen as important predictors is that although A01 didn't perform well in the Naïve Bayes model, its exclusive use in the Decision Tree model highlights its importance. A25 and A22 are key predictors in the Naïve Bayes and Random Forest models, respectively, due to their high scores. Additionally, A18 and A23 are considered important in the Random Forest model because of their significant MeanDecreaseGini scores.

```r
new_q10_PD = data.frame(PD)
new_q10_PD$Class = factor(new_q10_PD$Class)
new_q10_PD = subset(new_q10_PD, select = c(1, 18, 22, 23, 25, 26))
new_q10_PD = new_q10_PD[complete.cases(new_q10_PD),]
new_q10_PD = na.omit(new_q10_PD)

str(new_q10_PD) # Confirm after removal of NA values, the predictor 'Class' is still a
factor

## 'data.frame':    1929 obs. of  6 variables:
##  $ A01  : int  11 10 25 31 3 3 3 11 10 25 ...
##  $ A18  : int  96 30 89 17 42 29 39 27 46 44 ...
##  $ A22  : num  0.0605 0.0617 0.0601 0.0633 0.0626 ...
##  $ A23  : int  15 137 107 1 110 111 116 165 107 16 ...
##  $ A25  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ Class: Factor w/ 2 levels "0","1": 1 1 1 1 1 1 2 1 1 2 ...

set.seed(33085625)
new_q10_train.row = sample(1:nrow(new_q10_PD), 0.7*nrow(new_q10_PD))
new_q10_PD.train = new_q10_PD[new_q10_train.row,]
new_q10_PD.test = new_q10_PD[-new_q10_train.row,]
```

Since in Question 9, decision tree is used, for Question 10, the next best tree-based classifer would be random forest. Random Forest is a tree classification model that is particularly useful when there is complex relationships within the dataset and a model that can provide insights into the importance of different features is required. Random Forest is a method that combines the predictions from multiple decision trees to make more accurate and stable predictions than a single decision tree, so since the single decision tree in Question 9 has the highest model accuracy, this random forest tree-based classifer model would be an adequate choice for Question 10.

In addition to that, one more parameter was added to the random forest classifier, which is the parameter **importance**. The importance parameter refers to the feature importance and it was set to **TRUE**, which means that the importance of the predictors in the dataset should and would be assessed. This importance parameter help in understanding which features of the dataset are most important and influential in making predictions which in turn, can guide feature selection and model interpretation within the random forest.

```r
simple_tree_classifier = randomForest(Class ~., data = new_q10_PD.train, importance =
TRUE)
predict_simple_tree_classifier = predict(simple_tree_classifier, newdata =
new_q10_PD.test, type = "class")

# Confusion Matrix
tree_tbl_result = table(actual = new_q10_PD.test$Class, predicted =
predict_simple_tree_classifier)
colnames(tree_tbl_result) = c("legitimate", "phishing")
rownames(tree_tbl_result) = c("legitimate", "phishing")
tree_tbl_result

##               predicted
## actual         legitimate phishing
##   legitimate          376       51
##   phishing            113       39

simple_tree_classifier_accuracy = (tree_tbl_result[2, 2] + tree_tbl_result[1, 1]) /
(tree_tbl_result[2, 2] + tree_tbl_result[1, 1] + tree_tbl_result[2, 1] +
```

```r
tree_tbl_result[1, 2])
simple_tree_classifier_accuracy

## [1] 0.716753
```

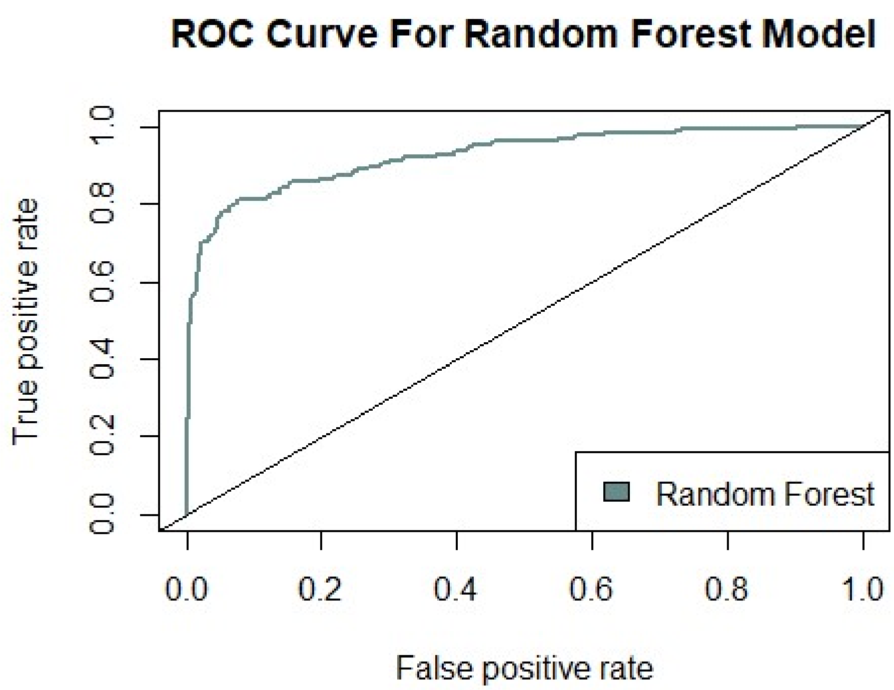
From the confusion matrix displayed above in the output, it is presented that:

- The TP for the confusion matrix for Random Forest is 39, indicating that the model did only correctly predict 39 phishing cases.
- The TN for the confusion matrix for Random Forest is 376, indicating that the model correctly identified 376 legitimate cases.
- The FP for the confusion matrix for Random Forest is 51, indicating that the model predict only 51 legitimate cases as phishing.
- The FN for the confusion matrix for Random Forest is 113, indicating that the model incorrectly identified 113 phishing cases as legitimate.

Given the values from the confusion matrix above,

- The accuracy of the Random Forest model is 0.716753 which is approximately 71.67%.
- The precision of the Random Forest = 39 / (39+51) = 39/90
- The sensitivity of the Random Forest = 39 / (39+113) = 39/152
- The False Positive Ratio of the Random Forest = 51 / (51+376) = 51/427

```r
# Confidence level on the test data used in Question 3
confidence_lvl_q3testingdataset = predict(simple_tree_classifier, newdata =
PD_na_free.test, type = "prob")
summary(confidence_lvl_q3testingdataset)

##        0                1
##  Min.   :0.0620   Min.   :0.0000
##  1st Qu.:0.5510   1st Qu.:0.0680
##  Median :0.8440   Median :0.1560
##  Mean   :0.7299   Mean   :0.2701
##  3rd Qu.:0.9320   3rd Qu.:0.4490
##  Max.   :1.0000   Max.   :0.9380

# ROC curve
tree_new_prediction_roc = prediction(confidence_lvl_q3testingdataset[, 2],
PD_na_free.test$Class)
tree_new_performance_roc = performance(tree_new_prediction_roc, "tpr", "fpr")
plot(tree_new_performance_roc, col = "paleturquoise4", main = "ROC Curve For Random
Forest Model", lwd = 2) + abline(0, 1)

## integer(0)

legend("bottomright", legend = c("Random Forest"), fill = c("paleturquoise4"))
```




```
new_auc_random_forest = performance(tree_new_prediction_roc, "auc")
new_auc_random_forest_num = as.numeric(new_auc_random_forest@y.values)
new_auc_random_forest_num

## [1] 0.9258296
```

Based on the Area Under the Curve (AUC) values calculated for the new random forest, it is 0.9258296. The AUC value for the previous random forest is 0.6404199. There is an increase of 0.2854097. This implies that the random forest model have improved on distinguishing between Phishing and Legitimate classes.

Previously, the new Decision tree model stands out with the highest AUC value in the ranking with an AUC value of 0.6833052 now the new random forest model have a higher auc value by 0.2425244 which means that the variables selection did indeed improve the random forest model significantly.

Question 11

```
# Neuralnet library is loaded here as it's functionalities clashes with “prediction” function in R while “neuralnet” library is attached
# They both seem to clash as error occurs when I tried to use “prediction” function in R while “neuralnet” library is attached when I loaded this library above
library("neuralnet") # Library for Artificial Neural Network classifier

##
## Attaching package: 'neuralnet'

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

## The following object is masked from 'package:ROCR':
##
##     prediction
```

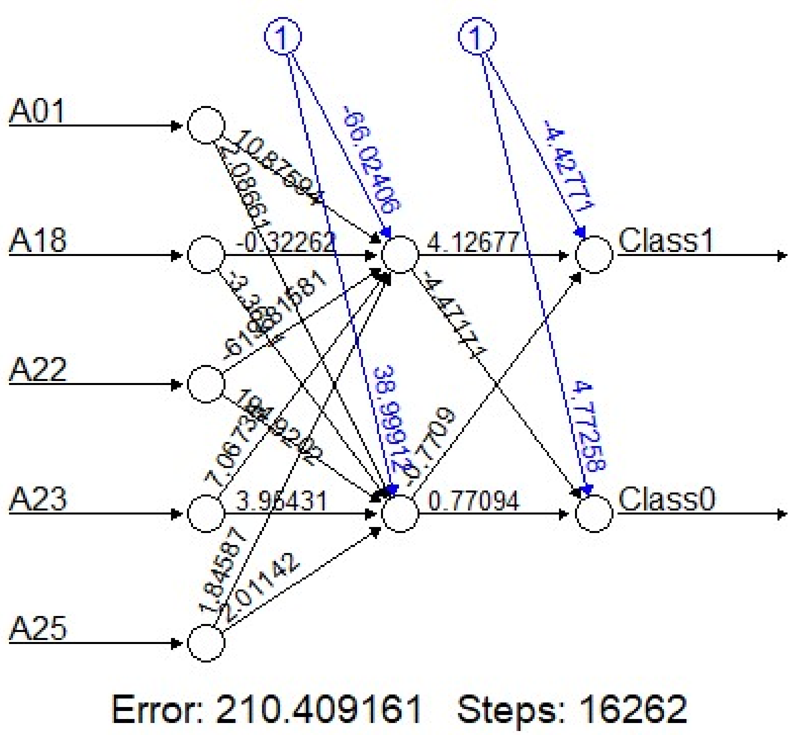
```r
# 1. Remove rows containing Missing Values (NA)
PD$Class = as.factor(PD$Class)
PD_q11 = PD[complete.cases(PD),]
PD_q11 = data.frame(PD_q11)

# 2. Recode output class as numeric
PD_q11$Class = as.numeric(PD_q11$Class)
str(PD_q11)
```

```
## 'data.frame':    1541 obs. of  26 variables:
##  $ A01  : int  11 25 31 3 3 3 11 10 6 13 ...
##  $ A02  : int  0 0 0 0 0 1 0 0 0 0 ...
##  $ A03  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A04  : int  3 2 3 2 3 3 2 2 2 3 ...
##  $ A05  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A06  : int  1 1 0 0 0 0 0 0 0 0 ...
##  $ A07  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A08  : num  1 1 0.441 0.714 1 ...
##  $ A09  : int  1 0 0 0 0 0 0 0 0 0 ...
##  $ A10  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A11  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A12  : int  232 365 232 648 232 232 388 648 226 232 ...
##  $ A13  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A14  : int  0 1 0 0 0 0 0 0 0 0 ...
##  $ A15  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A16  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A17  : int  1 1 1 2 1 1 2 2 1 1 ...
##  $ A18  : int  96 89 17 42 29 39 27 46 5 97 ...
##  $ A19  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A20  : int  1 1 0 0 1 0 0 1 0 1 ...
##  $ A21  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A22  : num  0.0605 0.0601 0.0633 0.0626 0.0461 ...
##  $ A23  : int  15 107 1 110 111 116 165 107 100 124 ...
##  $ A24  : num  0.52291 0.00159 0.52291 0.02856 0.52291 ...
##  $ A25  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ Class: num  1 1 1 1 1 2 1 1 1 1 ...
```

```r
# Recode the 'Class' variable
PD_q11$Class <- recode(PD_q11$Class, `1` = 0, `2` = 1)
str(PD_q11)
```

```
## 'data.frame':    1541 obs. of  26 variables:
##  $ A01  : int  11 25 31 3 3 3 11 10 6 13 ...
##  $ A02  : int  0 0 0 0 0 1 0 0 0 0 ...
##  $ A03  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A04  : int  3 2 3 2 3 3 2 2 2 3 ...
##  $ A05  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A06  : int  1 1 0 0 0 0 0 0 0 0 ...
##  $ A07  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A08  : num  1 1 0.441 0.714 1 ...
##  $ A09  : int  1 0 0 0 0 0 0 0 0 0 ...
##  $ A10  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A11  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A12  : int  232 365 232 648 232 232 388 648 226 232 ...
##  $ A13  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A14  : int  0 1 0 0 0 0 0 0 0 0 ...
```

```
##  $ A15  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A16  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A17  : int  1 1 1 2 1 1 2 2 1 1 ...
##  $ A18  : int  96 89 17 42 29 39 27 46 5 97 ...
##  $ A19  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A20  : int  1 1 0 0 1 0 0 1 0 1 ...
##  $ A21  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ A22  : num  0.0605 0.0601 0.0633 0.0626 0.0461 ...
##  $ A23  : int  15 107 1 110 111 116 165 107 100 124 ...
##  $ A24  : num  0.52291 0.00159 0.52291 0.02856 0.52291 ...
##  $ A25  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ Class: num  0 0 0 0 0 1 0 0 0 0 ...

# 3. Create training and testing dataset
new_q11_train.row = sample(1:nrow(PD_q11), 0.7*nrow(PD_q11))
PD_q11.train = PD_q11[new_q11_train.row,]
PD_q11.test = PD_q11[-new_q11_train.row,]

PD_q11.train$Class1 = PD_q11.train$Class == 1
PD_q11.train$Class0 = PD_q11.train$Class == 0

# 4. Fit neural network and test accuracy
PD_q11.nn = neuralnet(Class1 + Class0 ~ A01 + A18 + A22 + A23 + A25, PD_q11.train, hidden
= 2, linear.output = FALSE)

# Plot ANN
plot(PD_q11.nn, rep = "best")
```




```
# Plot Confusion Matrix
PD_q11.pred = compute(PD_q11.nn, PD_q11.test[c(1, 18, 22, 23, 25)])
PD_q11.pred_round = round(PD_q11.pred$net.result, 0)
df_PD_q11.pred_round = as.data.frame(as.table(PD_q11.pred_round))
```

```r
df_PD_q11.pred_round_val = df_PD_q11.pred_round[!df_PD_q11.pred_round$Freq == 0,]

df_PD_q11.pred_round_val$Freq = NULL
colnames(df_PD_q11.pred_round_val) = c("Obs", "Class")

df_PD_q11.pred_round_val = df_PD_q11.pred_round_val[order(df_PD_q11.pred_round_val$Obs),
]

table(observed = PD_q11.test$Class, predicted = df_PD_q11.pred_round_val$Class)
```

```
##          predicted
## observed   A   B
##        0   0 334
##        1   0 129
```

Firstly, I made sure that 'Class' is a factor before remove rows containing Missing Values (NA) with complete.cases so it would not affect the output of the Artificial Neural Network (ANN). Once its done, the dataset will be transformed to a dataframe just in case it wasn't beforehand.

Previously, it was noted down that all attributes are num or int datatypes before making 'Class' attribute a factor so as.numeric was used on Class attribute and the rest of the attributes within the dataset to convert them to numerical values. Beforehand, after the 'Class' attribute after convert as factor 0 became 1 and 1 became 2 so recode is used to change 1 to 0 and 2 back to 1.

Once that was done, the training and testing dataset was created and was fitted onto the ANN and the accuracy was tested. This classifier is pretty accurate compared to the other classifiers. ANNs are capable of learning and modeling complex non-linear relationships which many traditional algorithms cannot capture as effectively which made it very adaptable and hence produce high accuracy results. ANNs can do feature extraction which allows it to automatically detect the important features without any human intervention.

Methods like decreasing or increasing the hidden layers values and decreasing or increasing important predictors and/or attributes to feed into the ANN couldn't reduce the error further than the one shown above.

Referring to the confusion matrix obtain above, Observed represents the actual class labels from the datase whereas Predicted represent the class labels as predicted by the ANN. Class A and B are Class 0 and 1 which are the two classes that the ANN is trying to predict.

From the results of the confusion matrix, it implies that the ANN appears to have classified all cases as Class B and none as Class A. This might suggest issues with the model, like a lack of recognition for Class B or Class B being very challenging to predict, or could be due to an uneven distribution of data where Class A is more dominant.

Question 12

```r
# Neuralnet library is detached here as it's functionalities clashes with "prediction"
function in R while "neuralnet" library is attached
detach("package:neuralnet", unload=TRUE)

# caret library is used here for k-nearest neighbors (KNN) model
knn = knn3(Class ~., data = PD_na_free.train, k = 10)
knn_prediction = predict(knn, newdata = PD_na_free.test, type = "class")

# Confusion Matrix
knn_result = table(actual = PD_na_free.test$Class, prediction = knn_prediction)
```

```
colnames(knn_result) = c("legitimate", "phishing")
rownames(knn_result) = c("legitimate", "phishing")
knn_result

##             prediction
## actual       legitimate phishing
##   legitimate        314       22
##   phishing           98       29

# Accuracy
knn_accuracy_q5 = (knn_result[2, 2] + knn_result[1, 1]) / (knn_result[2, 2] +
knn_result[1, 1] + knn_result[2, 1] + knn_result[1, 2])
knn_accuracy_q5

## [1] 0.7408207
```

From the knn confusion matrix displayed above in the output, it is presented that:

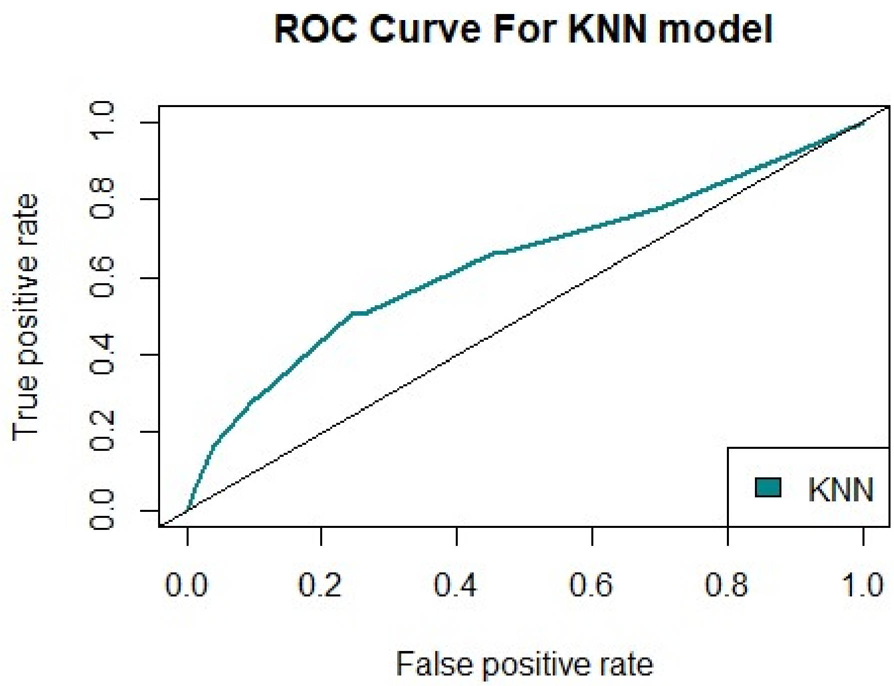
- The TP for the confusion matrix for knn is 314, indicating that the number of legitimate cases correctly predicted as legitimate, which is 314.
- The TN for the confusion matrix for knn is 29, indicating that the number of phishing cases correctly predicted as phishing is 29.
- The FP for the confusion matrix for knn is 22, indicating that the number of phishing cases incorrectly predicted as legitimate is 22.
- The FN for the confusion matrix for knn is 98, indicating that the number of legitimate cases incorrectly predicted as phishing is 98.

Given the values from the confusion matrix above, the accuracy of the decision tree model is 0.7408207 which is approximately 74.08%. This means that the KNN model correctly predicted the class is legitimate or phishing for about 74.08% of the cases in the test dataset.

The precision, sensitivity and False Positive Ratio is also calculated as listed below:

- The precision of the KNN model is 29 / (29+22) = 29/51 which is roughly around 0.569
- The sensitivity of the KNN model is 29 / (29+98) = 29/127 which is roughly around 0.228
- The False Positive Ratio of the KNN model is 22 / (22+314) = 22/336 which is roughly around 0.065

```
# Confidence level
knn_confidence = predict(knn, newdata = PD_na_free.test, type = "prob")

# ROC curve
prediction_knn_roc = prediction(knn_confidence[, 2], PD_na_free.test$Class)
performance_knn = performance(prediction_knn_roc, "tpr", "fpr")
plot(performance_knn, col = "turquoise4", main = "ROC Curve For KNN model", lwd = 2) +
abline(0, 1)

## integer(0)

legend("bottomright", legend = c("KNN"), fill = c("turquoise4"))
```



The ROC Curve above shows that the **turquoise line** starts at the origin (0,0) and curves towards the top right corner (1,1), indicating an increasing TPR as the FPR increases.

```
auc_knn = performance(prediction_knn_roc, "auc")
auc_knn_num = as.numeric(auc_knn@y.values)
auc_knn_num

## [1] 0.6367993
```

The area under the curve (AUC) calculated above represents the knn model's ability to distinguish between the legitimate or phishing classes. A larger AUC that is close to 1 indicates that the model have a better performance. The AUC value of 0.6367993 suggests that there is a 63.68% chance that the model will be able to correctly distinguish a random positive case from a negative one.

```
knn_accuracy_q6 = performance(prediction_knn_roc, "acc")
knn_accuracy_q6_num = as.numeric(max(knn_accuracy_q6@y.values[[1]]))
knn_accuracy_q6_num

## [1] 0.7429806
```

The value 0.7429806 calculated above represents the highest accuracy achieved by the KNN model.

```
comparison_with_knn = rbind(comparison_tbl, list(knn_accuracy_q5, knn_accuracy_q6_num,
(knn_accuracy_q5 + knn_accuracy_q6_num)/2))
rownames(comparison_with_knn)[rownames(comparison_with_knn) == "1"] = "KNN"
comparison_with_knn

##                 Question 5 Model Accuracy Question 6 Model Accuracy
## Decision Tree                   0.7257019                 0.7257019
## Naïve Bayes                     0.7257019                 0.7321814
## Bagging                         0.7365011                 0.7408207
## Boosting                        0.6717063                 0.7300216
## Random Forest                   0.7300216                 0.7365011
```

```
## KNN                              0.7408207                         0.7429806
##                Average Model Accuracy
## Decision Tree             0.7257019
## Naïve Bayes               0.7289417
## Bagging                   0.7386609
## Boosting                  0.7008639
## Random Forest             0.7332613
## KNN                       0.7419006
```

The KNN model shows a consistent performance with an accuracy of 0.7408207 in Question 5 and 0.7429806 in Question 6 in the table above. The average accuracy of the KNN model is 0.7419006, which is calculated by taking the average of the accuracy from Question 5 and 6. When compared to other models, the KNN model ranks among the top prediction models in average accuracy. The KNN model accuracy is equal to Bagging and have a higher accuracy than Decision Tree, Naïve Bayes, Boosting, and Random Forest models. The stability of the KNN model remains consistent from Question 5 to 6, indicating that the KNN model is reliable to perform under various data sets or conditions.