Assignment 3 - Flight Delay Problem

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Load Data Set and Libraries

First, we will load all of the packages that will be required for this problem. Specifically, "ISLR", "caret", "dplyr", "e1071", and "pROC" will be loaded for this problem.

Next, we will import the "FlightDelays" data set into the RStudio environment.

```
# Import data set from BlackBoard into the RStudio environment

FlightDelays <- read.csv("FlightDelays.csv")
```

Data Structure

A summary of the data set will be displayed to review the data set.

```
# Investigate the structure of the data set

str(FlightDelays)

## 'data.frame':    2201 obs. of  13 variables:
##  $ CRS_DEP_TIME : int  1455 1640 1245 1715 1039 840 1240 1645 1715 2120
...
##  $ CARRIER      : Factor w/ 8 levels "CO","DH","DL",..: 5 2 2 2 2 2 2 2 2
2 ...
##  $ DEP_TIME     : int  1455 1640 1245 1709 1035 839 1243 1644 1710 2129
...
##  $ DEST         : Factor w/ 3 levels "EWR","JFK","LGA": 2 2 3 3 3 2 2 2 2
2 ...
##  $ DISTANCE     : int  184 213 229 229 229 228 228 228 228 228 ...
##  $ FL_DATE      : Factor w/ 31 levels "01/01/2004","01/02/2004",..: 1 1 1
1 1 1 1 1 1 1 ...
##  $ FL_NUM       : int  5935 6155 7208 7215 7792 7800 7806 7810 7812 7814
...
##  $ ORIGIN       : Factor w/ 3 levels "BWI","DCA","IAD": 1 2 3 3 3 3 3 3 3
3 ...
##  $ Weather      : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ DAY_WEEK     : int  4 4 4 4 4 4 4 4 4 4 ...
##  $ DAY_OF_MONTH : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ TAIL_NUM     : Factor w/ 549 levels "N10323","N10575",..: 526 263 382
350 385 374 241 227 246 372 ...
##  $ Flight.Status: Factor w/ 2 levels "delayed","ontime": 2 2 2 2 2 2 2 2 2
2 ...
```

```r
# Investigate the summary of the data set

summary(FlightDelays)
```

```
##   CRS_DEP_TIME      CARRIER        DEP_TIME      DEST        DISTANCE
##  Min.   : 600   DH     :551   Min.   :  10   EWR: 665   Min.   :169.0
##  1st Qu.:1000   RU     :408   1st Qu.:1004   JFK: 386   1st Qu.:213.0
##  Median :1455   US     :404   Median :1450   LGA:1150   Median :214.0
##  Mean   :1372   DL     :388   Mean   :1369              Mean   :211.9
##  3rd Qu.:1710   MQ     :295   3rd Qu.:1709              3rd Qu.:214.0
##  Max.   :2130   CO     : 94   Max.   :2330              Max.   :229.0
##                 (Other): 61
##        FL_DATE          FL_NUM      ORIGIN        Weather
##  1/22/2004 :  86   Min.   : 746   BWI: 145   Min.   :0.00000
##  01/06/2004:  85   1st Qu.:2156   DCA:1370   1st Qu.:0.00000
##  01/08/2004:  85   Median :2385   IAD: 686   Median :0.00000
##  1/13/2004 :  85   Mean   :3815              Mean   :0.01454
##  1/20/2004 :  85   3rd Qu.:6155              3rd Qu.:0.00000
##  1/21/2004 :  85   Max.   :7924              Max.   :1.00000
##  (Other)   :1690
##     DAY_WEEK      DAY_OF_MONTH      TAIL_NUM    Flight.Status
##  Min.   :1.000   Min.   : 1.00   N225DL :  65   delayed: 428
##  1st Qu.:2.000   1st Qu.: 8.00   N242DL :  56   ontime :1773
##  Median :4.000   Median :16.00   N223DZ :  50
##  Mean   :3.905   Mean   :16.02   N221DL :  45
##  3rd Qu.:5.000   3rd Qu.:23.00   N241DL :  36
##  Max.   :7.000   Max.   :31.00   N722UW :  36
##                                  (Other):1913
```

We can see from the data set above, it appears that 428 out of 2,201 flights (Approximately 19.5%) are delayed historically. This can be compared against the final model at the end for a reality check.

Given in the problem statement, we will only be using five predictors: “DAY_WEEK”, “DEP_TIME”, “ORIGIN”, “DEST”, and “CARRIER” along with the dependent variable “Flight.Status”. Therefore, we will re-write the dataframe with these 6 variables.

Additionally, we will need to convert all variables to factors for Naive Bayes model.

```r
# Isolate the 6 variables previously discussed

FlightDelays <- FlightDelays[ , c(10, 1, 8, 4, 2, 13)]

# Review the new structure of the dataset

str(FlightDelays)
```

```
## 'data.frame':    2201 obs. of  6 variables:
##  $ DAY_WEEK     : int  4 4 4 4 4 4 4 4 4 4 ...
##  $ CRS_DEP_TIME : int  1455 1640 1245 1715 1039 840 1240 1645 1715 2120
```

```
...
##  $ ORIGIN       : Factor w/ 3 levels "BWI","DCA","IAD": 1 2 3 3 3 3 3 3 3
3 ...
##  $ DEST         : Factor w/ 3 levels "EWR","JFK","LGA": 2 2 3 3 3 2 2 2 2
2 ...
##  $ CARRIER      : Factor w/ 8 levels "CO","DH","DL",..: 5 2 2 2 2 2 2 2 2
2 ...
##  $ Flight.Status: Factor w/ 2 levels "delayed","ontime": 2 2 2 2 2 2 2 2 2
2 ...
```

Now that we have the 6 varaibles in question, we must ensure all of them are converted to factors for proper use in the Naive Bayes algorithm. As shown above, “DAY_WEEK” and “CRS_DEP_TIME” are the two remaining variables that need to be converted to factors.

Additionally, “CRS_DEP_TIME” will also need to be converted to a factor with 16 time ranges (as stated in the initial problem statement). These time ranges will stretch from “6:00am to 7:00am” departure time to the final time range of “9:00pm to 10:00pm”. These will correlate to factor level 1 to 16, respectively.

```
# Convert "DAY_WEEK" to a factor for Naives Bayes

FlightDelays$DAY_WEEK <- as.factor(FlightDelays$DAY_WEEK)

# Convert "CRS_DEP_TIME" to a factor with 16 time ranges and labels

FlightDelays$CRS_DEP_TIME <- cut(FlightDelays$CRS_DEP_TIME, breaks = c(600,
700, 800, 900, 1000, 1100, 1200, 1300, 1400, 1500, 1600, 1700, 1800, 1900,
2000, 2100, 2200))

# Verify the new structure of the data set

str(FlightDelays)

## 'data.frame':    2201 obs. of  6 variables:
##  $ DAY_WEEK     : Factor w/ 7 levels "1","2","3","4",..: 4 4 4 4 4 4 4 4 4
4 ...
##  $ CRS_DEP_TIME : Factor w/ 16 levels "(600,700]","(700,800]",..: 9 11 7
12 5 3 7 11 12 16 ...
##  $ ORIGIN       : Factor w/ 3 levels "BWI","DCA","IAD": 1 2 3 3 3 3 3 3 3
3 ...
##  $ DEST         : Factor w/ 3 levels "EWR","JFK","LGA": 2 2 3 3 3 2 2 2 2
2 ...
##  $ CARRIER      : Factor w/ 8 levels "CO","DH","DL",..: 5 2 2 2 2 2 2 2 2
2 ...
##  $ Flight.Status: Factor w/ 2 levels "delayed","ontime": 2 2 2 2 2 2 2 2 2
2 ...
```

Data Preprocessing

To begin preprocessing data, we must split the data set into 60% training and 40% validation, per the problem description.

```
# Set the seed for randomized functions

set.seed(102019)

# Split the data into 60% training data and 40% validation data

FlightDelaysIndex <- createDataPartition(FlightDelays$DAY_WEEK, p=0.4, list =
F)

FlightDelaysValidation <- FlightDelays[FlightDelaysIndex,]

FlightDelaysTrain <- FlightDelays[-FlightDelaysIndex,]
```

Counts and Proportion Table by Airport

Assignment calls for a table containing a count and proportion of delayed flights by airport. For this, the "dplyr" package and summarise function will be used to return these values.

```
# Summarise flight delay statisitics by airport

FlightDelays %>%
  group_by(Origin_Airport = ORIGIN, Flight_Status = Flight.Status) %>%
  summarise(Count_of_Flights = n()) %>%
  mutate(Proportion_for_Airport = 100*(Count_of_Flights /
sum(Count_of_Flights)))

## # A tibble: 6 x 4
## # Groups:   Origin_Airport [3]
##   Origin_Airport Flight_Status Count_of_Flights Proportion_for_Airport
##   <fct>          <fct>                    <int>                  <dbl>
## 1 BWI            delayed                     37                   25.5
## 2 BWI            ontime                     108                   74.5
## 3 DCA            delayed                    221                   16.1
## 4 DCA            ontime                    1149                   83.9
## 5 IAD            delayed                    170                   24.8
## 6 IAD            ontime                     516                   75.2
```

From this data table, we can see the total number of flights from each airport and the proportion of them that were delayed for each individual airport.

"BWI" had the lowest number of flights during this time period, but it also had the highest percentage of them being delayed.

Create Naive Bayes Model

Now that we have the training and validation data properly prepared, the Naive Bayes model can be created from the training data and then ran on the validation data.

```
# Create Naive Bayes model from the training data set

NB_Model <- naiveBayes(Flight.Status ~ ., data = FlightDelaysTrain)

# Use Model on the validation data set to predict if flights will be delayed

FlightDelaysValidation_Predicted <- predict(NB_Model, FlightDelaysValidation)
```

Confusion Matrix and ROC for Validation Data

A confusion matrix will be created to determine the accuracy of the model with varying statistics.

```
# Create confusion matrix for the label outputs from the Naive Bayes model

CrossTable(x = FlightDelaysValidation$Flight.Status, y =
FlightDelaysValidation_Predicted, prop.chisq = FALSE)

##
##
##    Cell Contents
## |-------------------------|
## |                       N |
## |           N / Row Total |
## |           N / Col Total |
## |         N / Table Total |
## |-------------------------|
##
##
## Total Observations in Table:  883
##
##
##                                      | FlightDelaysValidation_Predicted
## FlightDelaysValidation$Flight.Status |   delayed |    ontime | Row Total |
## -------------------------------------|-----------|-----------|-----------|
##                              delayed |        17 |       173 |       190 |
##                                      |     0.089 |     0.911 |     0.215 |
##                                      |     0.500 |     0.204 |           |
##                                      |     0.019 |     0.196 |           |
## -------------------------------------|-----------|-----------|-----------|
##                               ontime |        17 |       676 |       693 |
##                                      |     0.025 |     0.975 |     0.785 |
##                                      |     0.500 |     0.796 |           |
##                                      |     0.019 |     0.766 |           |
## -------------------------------------|-----------|-----------|-----------|
```

```
##                               Column Total |        34 |       849 |       883 |
##                                            |     0.039 |     0.961 |           |
## -------------------------------------------|-----------|-----------|-----------|
##
##
```

From this confusion matrix, we can state that:

The sensitivity (true positive rate) of the model is: 676/693 = 97.5% The specificity (true negative rate) of the model is: 17/190 = 9.0%

Next, there will be the creation of the ROC cure and return the AUC value for the validation data on this model.

Before the curve is plotted out, there must be another model ran with the raw probabilities listed.

```
# Re-run the model to return the raw probabilities

FlightDelaysValidation_Predicted2 <- predict(NB_Model,
FlightDelaysValidation, type = "raw")

# Return the first few values in the output table

head(FlightDelaysValidation_Predicted2)

##         delayed    ontime
## [1,] 0.13747017 0.8625298
## [2,] 0.20216762 0.7978324
## [3,] 0.36800677 0.6319932
## [4,] 0.29987116 0.7001288
## [5,] 0.03522145 0.9647786
## [6,] 0.09009041 0.9099096
```

Next, the curves can now be plotted out.

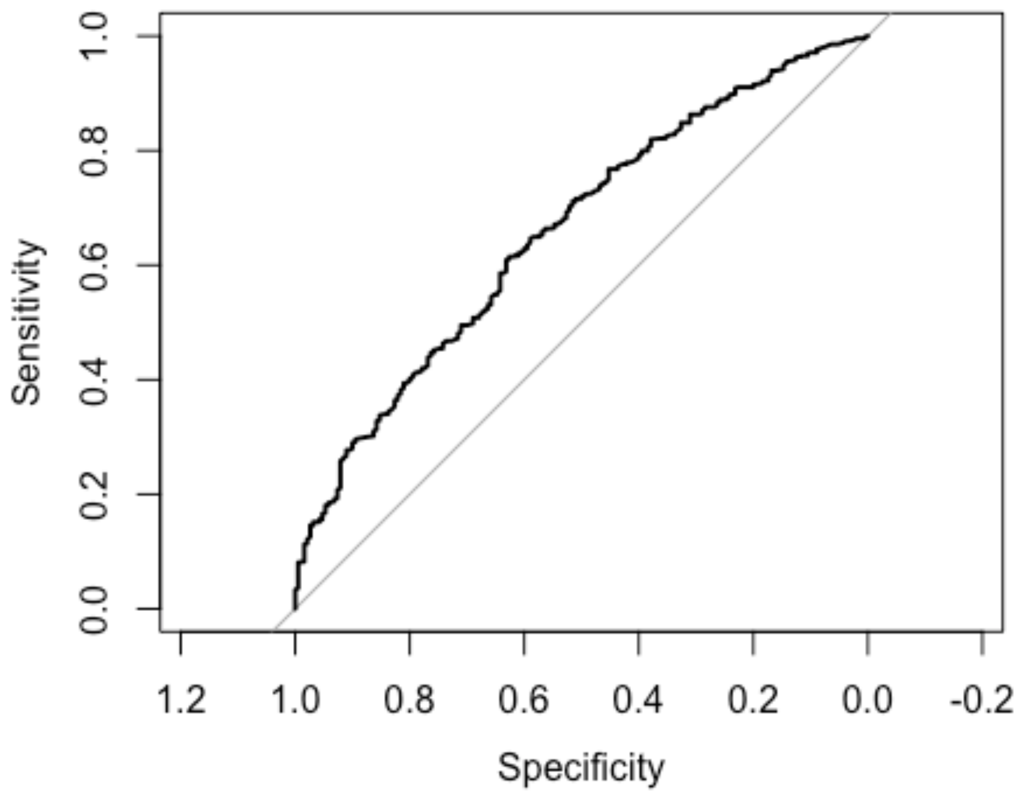
```
# Creating the ROC curve for the model

roc(FlightDelaysValidation$Flight.Status,
FlightDelaysValidation_Predicted2[,2])

##
## Call:
## roc.default(response = FlightDelaysValidation$Flight.Status,     predictor
= FlightDelaysValidation_Predicted2[, 2])
##
## Data: FlightDelaysValidation_Predicted2[, 2] in 190 controls
(FlightDelaysValidation$Flight.Status delayed) < 693 cases
(FlightDelaysValidation$Flight.Status ontime).
## Area under the curve: 0.6588
```

```r
# Plot the ROC curve

plot.roc(FlightDelaysValidation$Flight.Status,
FlightDelaysValidation_Predicted2[,2])
```



From the AUC value of 0.6588, it can be stated that the model is better than chance guessing; however, the model still has some room for improvement to increase this AUC value closer and closer to nearly 1.0.