

# Predicting Delayed Flights

```
library(readr)
library(caret)
```

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

```
## Loading required package: ggplot2
```

```
library(ISLR)
#install.packages("e1071") #install first
library(e1071)
library(cluster)
library(dplyr)
```

```
##
## 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
```

```
library(pROC)
```

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

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

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

## Read the data and Summary

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

```
## 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
```

## Clean the data

```
MyData <- MyData[,c(-3,-5,-6,-7,-9,-11,-12)]
str(MyData)
```

```
## 'data.frame': 2201 obs. of 6 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 ...
## $ DEST : Factor w/ 3 levels "EWR","JFK","LGA": 2 2 3 3 3 2 2 2 2 2 ...
## $ ORIGIN : Factor w/ 3 levels "BWI","DCA","IAD": 1 2 3 3 3 3 3 3 3 3 ...
## $ DAY_WEEK : int 4 4 4 4 4 4 4 4 4 4 ...
## $ Flight.Status: Factor w/ 2 levels "delayed","ontime": 2 2 2 2 2 2 2 2 2 2 ...
```

```
head(MyData)
```

	CRS_DEP_TIME <int>	CARRIER <fctr>	DEST <fctr>	ORIGIN <fctr>	DAY_WEEK <int>	Flight.Status <fctr>
1	1455	OH	JFK	BWI	4	ontime
2	1640	DH	JFK	DCA	4	ontime
3	1245	DH	LGA	IAD	4	ontime
4	1715	DH	LGA	IAD	4	ontime

	CRS_DEP_TIME <int>	CARRIER <fctr>	DEST <fctr>	ORIGIN <fctr>	DAY_WEEK <int>	Flight.Status <fctr>
5	1039	DH	LGA	IAD	4	ontime
6	840	DH	JFK	IAD	4	ontime

6 rows

```
set.seed(123)
```

## Week and Time Variables to be recorded as Factors

```
MyData$DAY_WEEK <- as.factor(MyData$DAY_WEEK)
levels(MyData$DAY_WEEK)
```

```
## [1] "1" "2" "3" "4" "5" "6" "7"
```

```
MyData$CRS_DEP_TIME <- as.factor(MyData$CRS_DEP_TIME)
levels(MyData$CRS_DEP_TIME)
```

```
## [1] "600" "630" "640" "645" "700" "730" "735" "759" "800" "830"
## [11] "840" "845" "850" "900" "925" "930" "1000" "1030" "1039" "1040"
## [21] "1100" "1130" "1200" "1230" "1240" "1245" "1300" "1315" "1330" "1359"
## [31] "1400" "1430" "1455" "1500" "1515" "1520" "1525" "1530" "1600" "1605"
## [41] "1610" "1630" "1640" "1645" "1700" "1710" "1715" "1720" "1725" "1730"
## [51] "1800" "1830" "1900" "1930" "2000" "2030" "2100" "2120" "2130"
```

The outcome variable is whether the flight was delayed, and thus it has two classes (1 = delayed and 0 = on time)

```
MyData$Flight.Status <- factor(MyData$Flight.Status, levels = c("delayed", "ontime"), labels = c(0, 1))
```

## Divide the data into training and Validation

```
# 60% reserved for Training
Train_Index <- createDataPartition(MyData$Flight.Status, p=0.6, list=FALSE)
Training <- MyData[Train_Index,]
# Validation is the rest 40%
Valid_Data <- MyData[-Train_Index,]
```

Run the Naive Bayes model to predict whether the flight is delayed or not. Use only categorical variables for the predictor variables.

```
nb_model <- naiveBayes(Training$Flight.Status~CARRIER+DEST+ORIGIN+DAY_WEEK+CRS_DEP_TIME, data = Training)
nb_model
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##      0      1
## 0.1945496 0.8054504
##
## Conditional probabilities:
## CARRIER
## Y      CO      DH      DL      MQ      OH
## 0 0.066147860 0.322957198 0.112840467 0.178988327 0.007782101
## 1 0.037593985 0.240601504 0.186090226 0.124060150 0.013157895
## CARRIER
## Y      RU      UA      US
## 0 0.206225681 0.011673152 0.093385214
## 1 0.178571429 0.015037594 0.204887218
##
## DEST
## Y      EWR      JFK      LGA
## 0 0.3891051 0.2217899 0.3891051
## 1 0.2819549 0.1823308 0.5357143
##
## ORIGIN
## Y      BWI      DCA      IAD
## 0 0.07392996 0.51361868 0.41245136
## 1 0.06109023 0.64849624 0.29041353
##
## DAY_WEEK
## Y      1      2      3      4      5      6
## 0 0.18677043 0.15953307 0.11284047 0.15175097 0.17509728 0.05447471
## 1 0.14473684 0.12687970 0.13439850 0.18139098 0.18421053 0.12312030
## DAY_WEEK
## Y      7
## 0 0.15953307
## 1 0.10526316
##
## CRS_DEP_TIME
## Y      600      630      640      645      700
## 0 0.0000000000 0.0077821012 0.0038910506 0.0000000000 0.0466926070
## 1 0.0140977444 0.0291353383 0.0084586466 0.0112781955 0.0422932331
## CRS_DEP_TIME
## Y      730      735      759      800      830
## 0 0.0077821012 0.0077821012 0.0000000000 0.0077821012 0.0077821012
## 1 0.0103383459 0.0084586466 0.0018796992 0.0178571429 0.0140977444
## CRS_DEP_TIME
## Y      840      845      850      900      925
## 0 0.0155642023 0.0000000000 0.0116731518 0.0194552529 0.0000000000
## 1 0.0366541353 0.0018796992 0.0150375940 0.0441729323 0.0018796992
## CRS_DEP_TIME
```

```
## Y          930          1000          1030          1039          1040
## 0 0.0000000000 0.0000000000 0.0233463035 0.0038910506 0.0038910506
## 1 0.0140977444 0.0159774436 0.0281954887 0.0018796992 0.0084586466
## CRS_DEP_TIME
## Y          1100          1130          1200          1230          1240
## 0 0.0077821012 0.0000000000 0.0000000000 0.0000000000 0.0194552529
## 1 0.0263157895 0.0131578947 0.0093984962 0.0140977444 0.0150375940
## CRS_DEP_TIME
## Y          1245          1300          1315          1330          1359
## 0 0.0505836576 0.0350194553 0.0038910506 0.0000000000 0.0116731518
## 1 0.0234962406 0.0516917293 0.0000000000 0.0122180451 0.0103383459
## CRS_DEP_TIME
## Y          1400          1430          1455          1500          1515
## 0 0.0077821012 0.0272373541 0.1050583658 0.0350194553 0.0038910506
## 1 0.0234962406 0.0187969925 0.0516917293 0.0347744361 0.0018796992
## CRS_DEP_TIME
## Y          1520          1525          1530          1600          1605
## 0 0.0000000000 0.0272373541 0.0233463035 0.0350194553 0.0000000000
## 1 0.0009398496 0.0084586466 0.0225563910 0.0178571429 0.0000000000
## CRS_DEP_TIME
## Y          1610          1630          1640          1645          1700
## 0 0.0116731518 0.0155642023 0.0155642023 0.0038910506 0.0272373541
## 1 0.0103383459 0.0187969925 0.0131578947 0.0169172932 0.0291353383
## CRS_DEP_TIME
## Y          1710          1715          1720          1725          1730
## 0 0.0194552529 0.0389105058 0.0233463035 0.0000000000 0.0350194553
## 1 0.0103383459 0.0244360902 0.0093984962 0.0009398496 0.0216165414
## CRS_DEP_TIME
## Y          1800          1830          1900          1930          2000
## 0 0.0038910506 0.0389105058 0.0894941634 0.0077821012 0.0077821012
## 1 0.0122180451 0.0253759398 0.0300751880 0.0112781955 0.0112781955
## CRS_DEP_TIME
## Y          2030          2100          2120          2130
## 0 0.0116731518 0.0155642023 0.0700389105 0.0038910506
## 1 0.0140977444 0.0206766917 0.0375939850 0.0000000000
```

## Output the confusion matrix and ROC for the validation data

```
# Predicting the delayed status on Validation dataSet
Predicted_Valid_labels <- predict(nb_model, Valid_Data)
library("gmodels")
```

```
##
## Attaching package: 'gmodels'
```

```
## The following object is masked from 'package:pROC':
##
## ci
```

```
# Show the confusion matrix of the classifier
```

```
CrossTable(x=Valid_Data$Flight.Status,y=Predicted_Valid_labels, prop.chisq = FALSE)
```

```
##
##
##      Cell Contents
## |-----|
## |                N |
## |      N / Row Total |
## |      N / Col Total |
## |      N / Table Total |
## |-----|
##
##
## Total Observations in Table:  880
##
##
##               | Predicted_Valid_labels
## Valid_Data$Flight.Status |      0      |      1      | Row Total |
## -----|-----|-----|-----|
##               0 |      33      |     138      |     171 |
##               |     0.193     |     0.807     |     0.194 |
##               |     0.393     |     0.173     |           |
##               |     0.037     |     0.157     |           |
## -----|-----|-----|-----|
##               1 |      51      |     658      |     709 |
##               |     0.072     |     0.928     |     0.806 |
##               |     0.607     |     0.827     |           |
##               |     0.058     |     0.748     |           |
## -----|-----|-----|-----|
##      Column Total |      84      |     796      |     880 |
##               |     0.095     |     0.905     |           |
## -----|-----|-----|-----|
##
##
##
```

```
nb_model <- naiveBayes(Training$Flight.Status~CARRIER+DEST+ORIGIN+DAY_WEEK+CRS_DEP_TIME,data = T
raining)
```

```
#Make predictions and return probability of each class
```

```
Predicted_Valid_labels <-predict(nb_model,Valid_Data, type = "raw")
```

```
#show the first few values
```

```
head(Predicted_Valid_labels)
```

```
##           0           1
## [1,] 0.375920081 0.6240799
## [2,] 0.366764468 0.6332355
## [3,] 0.377430946 0.6225691
## [4,] 0.004975078 0.9950249
## [5,] 0.092673535 0.9073265
## [6,] 0.068785526 0.9312145
```

# ROC Curve for Validation Data Set

```
roc(Valid_Data$Flight.Status, Predicted_Valid_labels[,2])
```

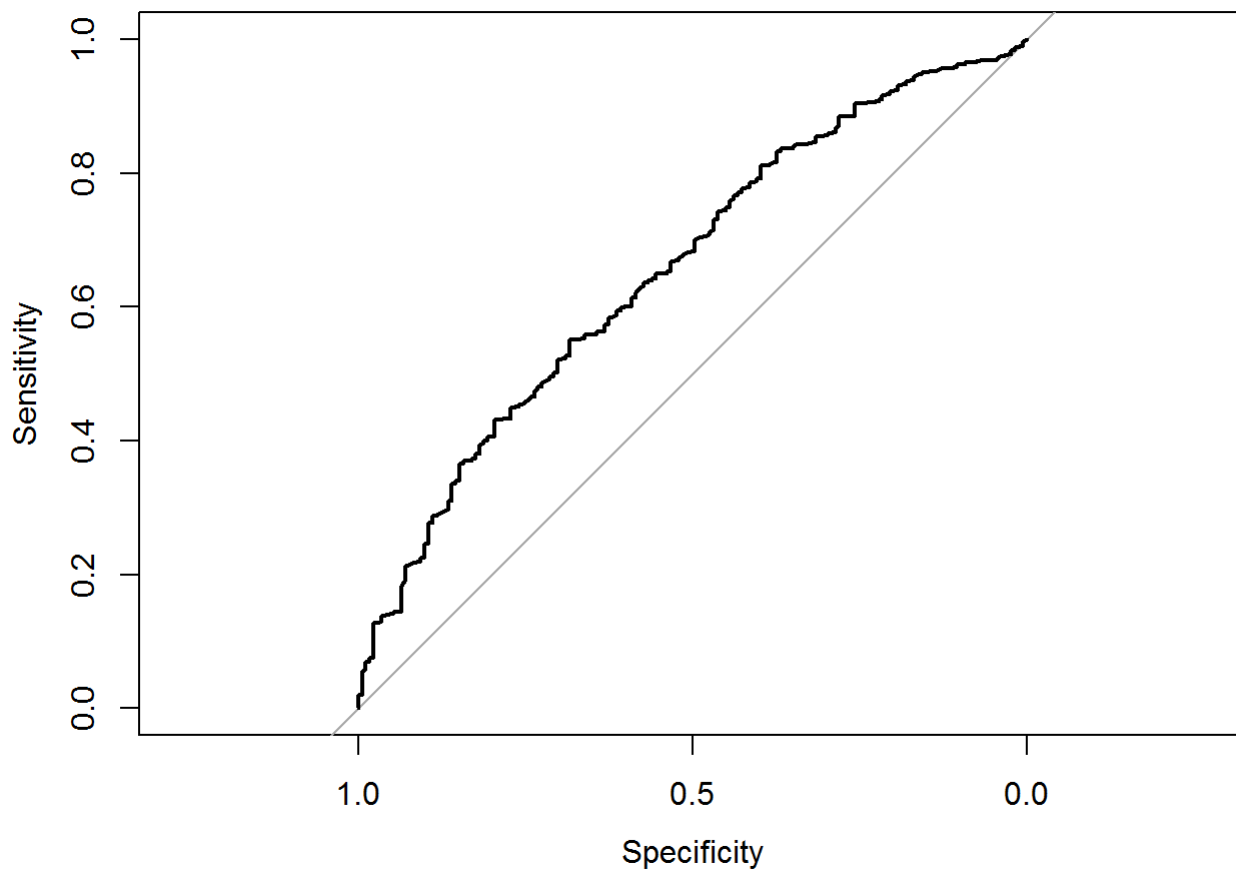
```
## Setting levels: control = 0, case = 1
```

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

```
##  
## Call:  
## roc.default(response = Valid_Data$Flight.Status, predictor = Predicted_Valid_labels[, 2])  
##  
## Data: Predicted_Valid_labels[, 2] in 171 controls (Valid_Data$Flight.Status 0) < 709 cases (Valid_Data$Flight.Status 1).  
## Area under the curve: 0.6553
```

```
plot.roc(Valid_Data$Flight.Status, Predicted_Valid_labels[,2])
```

```
## Setting levels: control = 0, case = 1  
## Setting direction: controls < cases
```





Output both a counts table and a proportion table outlining how many and what proportion of flights were delayed and on-time at each of the three airports.

```
# Counts Table  
table(MyData$Flight.Status, MyData$DEST)
```

```
##  
##      EWR  JFK  LGA  
##  0 161   84 183  
##  1 504  302 967
```

```
# Proportion Table  
prop.table(table(MyData$Flight.Status , MyData$DEST))
```

```
##  
##           EWR           JFK           LGA  
##  0 0.07314857 0.03816447 0.08314403  
##  1 0.22898682 0.13721036 0.43934575
```