Airline Passenger Satisfaction Classification

Süleyman Erim, Giacomo Schiavo, Mattia Varagnolo

30.05.2023

R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com.

When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

```
# import libraries
library(tidyverse)
library(knitr)
```

```
# import datasets
data_train = read.csv("train.csv")
data_test = read.csv("test.csv")
```

```
# merge train and test data
data = rbind(data_train, data_test)
attach(data)
```

```
# dimension of data
print(dim(data))
```

```
## [1] 129880     25
```

```
##        X                id            Gender          Customer.Type
##  Min.   :     0   Min.   :     1   Length:129880      Length:129880
##  1st Qu.: 16235   1st Qu.: 32471   Class :character   Class :character
##  Median : 38964   Median : 64941   Mode  :character   Mode  :character
##  Mean   : 44159   Mean   : 64941
##  3rd Qu.: 71433   3rd Qu.: 97410
##  Max.   :103903   Max.   :129880
##
##       Age        Type.of.Travel        Class           Flight.Distance
##  Min.   : 7.00   Length:129880      Length:129880      Min.   :  31
##  1st Qu.:27.00   Class :character   Class :character   1st Qu.: 414
##  Median :40.00   Mode  :character   Mode  :character   Median : 844
##  Mean   :39.43                                         Mean   :1190
##  3rd Qu.:51.00                                         3rd Qu.:1744
##  Max.   :85.00                                         Max.   :4983
```

```
##
##  Inflight.wifi.service Departure.Arrival.time.convenient Ease.of.Online.booking
##  Min.   :0.000         Min.   :0.000                     Min.   :0.000
##  1st Qu.:2.000         1st Qu.:2.000                     1st Qu.:2.000
##  Median :3.000         Median :3.000                     Median :3.000
##  Mean   :2.729         Mean   :3.058                     Mean   :2.757
##  3rd Qu.:4.000         3rd Qu.:4.000                     3rd Qu.:4.000
##  Max.   :5.000         Max.   :5.000                     Max.   :5.000
##
##  Gate.location   Food.and.drink  Online.boarding  Seat.comfort
##  Min.   :0.000   Min.   :0.000   Min.   :0.000   Min.   :0.000
##  1st Qu.:2.000   1st Qu.:2.000   1st Qu.:2.000   1st Qu.:2.000
##  Median :3.000   Median :3.000   Median :3.000   Median :4.000
##  Mean   :2.977   Mean   :3.205   Mean   :3.253   Mean   :3.441
##  3rd Qu.:4.000   3rd Qu.:4.000   3rd Qu.:4.000   3rd Qu.:5.000
##  Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000
##
##  Inflight.entertainment On.board.service Leg.room.service Baggage.handling
##  Min.   :0.000          Min.   :0.000    Min.   :0.000    Min.   :1.000
##  1st Qu.:2.000          1st Qu.:2.000    1st Qu.:2.000    1st Qu.:3.000
##  Median :4.000          Median :4.000    Median :4.000    Median :4.000
##  Mean   :3.358          Mean   :3.383    Mean   :3.351    Mean   :3.632
##  3rd Qu.:4.000          3rd Qu.:4.000    3rd Qu.:4.000    3rd Qu.:5.000
##  Max.   :5.000          Max.   :5.000    Max.   :5.000    Max.   :5.000
##
##  Checkin.service Inflight.service  Cleanliness    Departure.Delay.in.Minutes
##  Min.   :0.000   Min.   :0.000    Min.   :0.000   Min.   :   0.00
##  1st Qu.:3.000   1st Qu.:3.000    1st Qu.:2.000   1st Qu.:   0.00
##  Median :3.000   Median :4.000    Median :3.000   Median :   0.00
##  Mean   :3.306   Mean   :3.642    Mean   :3.286   Mean   :  14.71
##  3rd Qu.:4.000   3rd Qu.:5.000    3rd Qu.:4.000   3rd Qu.:  12.00
##  Max.   :5.000   Max.   :5.000    Max.   :5.000   Max.   :1592.00
##
##  Arrival.Delay.in.Minutes satisfaction
##  Min.   :   0.00          Length:129880
##  1st Qu.:   0.00          Class :character
##  Median :   0.00          Mode  :character
##  Mean   :  15.09
##  3rd Qu.:  13.00
##  Max.   :1584.00
##  NA's   :393
```

```
# replace dots with underscores in column names
names(data) = gsub("\\.", "_", names(data))
```

```
# print column names
print(names(data))
```

```
##  [1] "X"                                "id"
##  [3] "Gender"                           "Customer_Type"
##  [5] "Age"                              "Type_of_Travel"
##  [7] "Class"                            "Flight_Distance"
##  [9] "Inflight_wifi_service"            "Departure_Arrival_time_convenient"
```

```
## [11] "Ease_of_Online_booking"            "Gate_location"
## [13] "Food_and_drink"                    "Online_boarding"
## [15] "Seat_comfort"                      "Inflight_entertainment"
## [17] "On_board_service"                  "Leg_room_service"
## [19] "Baggage_handling"                  "Checkin_service"
## [21] "Inflight_service"                  "Cleanliness"
## [23] "Departure_Delay_in_Minutes"        "Arrival_Delay_in_Minutes"
## [25] "satisfaction"
```

```
# drop X and id column
#TODO: explain why
data = data %>% select(-X, -id)
```

```
# insert all categorical variables into a list
categorical_var = c(data$Cleanliness,
  data$Inflight_wifi_service,
  data$Departure_Arrival_time_convenient,
  data$Ease_of_Online_booking,
  data$Gate_location,
  data$Food_and_drink,
  data$Online_boarding,
  data$Seat_comfort,
  data$Inflight_entertainment,
  data$On_board_service,
  data$Leg_room_service,
  data$Baggage_handling,
  data$Checkin_service,
  data$Inflight_service,
  data$Cleanliness
)

# convert categorical variables to factors and then to numeric
categorical_var = as.factor(categorical_var)
categorical_var = as.numeric(categorical_var)

# convert gender to numeric and then to factor
data$Gender = as.numeric(as.factor(data$Gender))

# change type of customer to 0 and disloyal customer to 1
data$Customer_Type = as.numeric(factor(data$Customer_Type, levels = c("Loyal Customer", "disloyal Custo

# change type of tr avel to 0 and personal travel to 1
data$Type_of_Travel = as.numeric(factor(data$Type_of_Travel, levels = c("Personal Travel", "Business tr

# change class Business is 2, Eco Plus is 1 and Eco is 0
data$Class = as.numeric(factor(data$Class, levels = c("Business", "Eco Plus", "Eco"))) - 1

data$satisfaction = as.numeric(factor(data$satisfaction, levels = c("neutral or dissatisfied", "satisfi
```

```
# drop na values in Arrival Delay in Minutes
# TODO: explain why (now it's dropped to simplify the analysis)
data = data %>% drop_na(Arrival_Delay_in_Minutes)
```

```
# DATA BALANCE: quite balanced
kable(prop.table(table(data$satisfaction)),caption="dataset distribution",col.names = c("Satisfaction",
```

Table 1: dataset distribution

Satisfaction	Frequency
0	0.5655008
1	0.4344992

```
# Train-test split
set.seed(123)
train_index = sample(1:nrow(data), 0.8*nrow(data))
# 80% of data is used for training
train = data[train_index,]
# 20% of data is used for testing
test = data[-train_index,]

# print dimension of train and test data
dim(train)
```

```
## [1] 103589     23
```

```
dim(test)
```

```
## [1] 25898    23
```

```
# save true values of test satisfaction column
test_true = test$satisfaction
test_true <- as.integer(test_true)
typeof(test_true)
```

```
## [1] "integer"
```

```
# drop satisfaction column from test data
test = test %>% select(-satisfaction)
```

```
# print proportion of satisfied and dissatisfied customers in train and test data
prop.table(table(train$satisfaction))
```

```
##
##         0         1
## 0.5668845 0.4331155
```

```
prop.table(table(test_true))
```

```
## test_true
##        0        1
## 0.559966 0.440034
```

DATA ANALYSIS

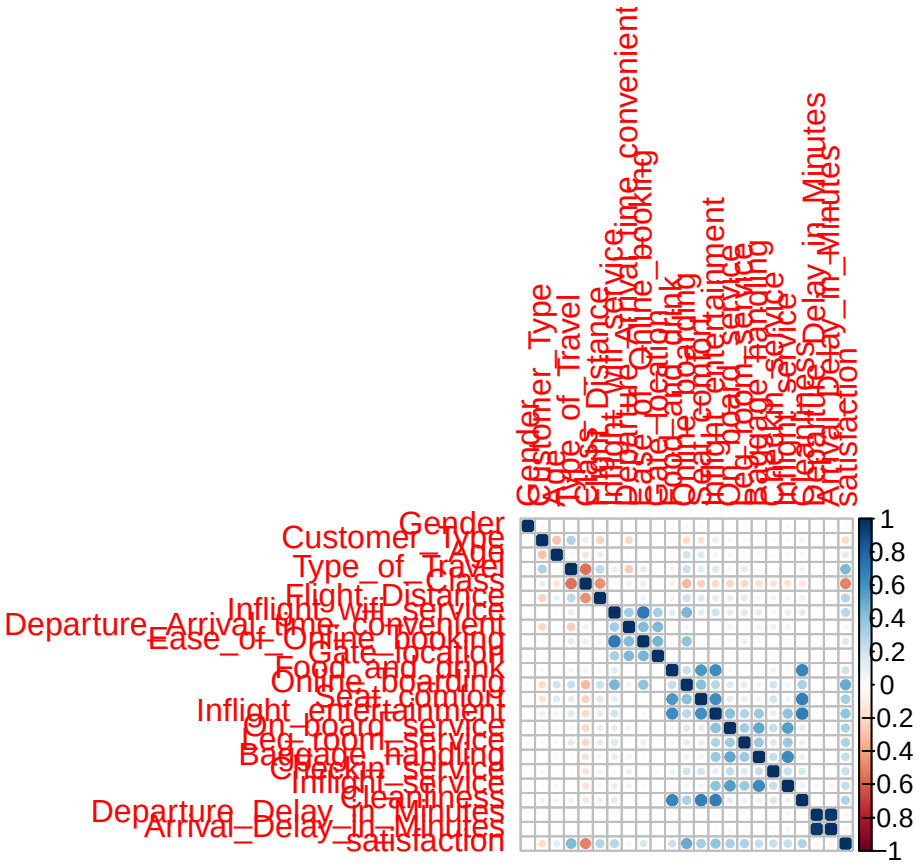
```
# save satisfaction column of train data
train_satisfaction = train$satisfaction
```

```
# correlation matrix only for numeric variables
correlation_matrix = cor(train[, sapply(train, is.numeric)])
```

```
# plot correlation matrix
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
corrplot(correlation_matrix, method = "circle")
```



train

LOGISTIC REGRESSION

```
# Model definition:
glm_compl<- glm(data = train,
                satisfaction ~ .,
```

```
                family = "binomial")
# We compute the reference level R-Squared
s<- summary(glm_compl)
r2<- 1 - (s$deviance/s$null.deviance)
1/(1-r2)
```

```
## [1] 2.045321
```

```
# VIF Iteration 1
# Using the VIF function and comparing the obtained values with the
# computed quantity:
# (The process is done iteratively where we delete one variable at time)
library(regclass)
```

```
## Loading required package: bestglm
```

```
## Loading required package: leaps
```

```
## Loading required package: VGAM
```

```
## Loading required package: stats4
```

```
## Loading required package: splines
```

```
## Loading required package: rpart
```

```
## Loading required package: randomForest
```

```
## 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
```

```
## Important regclass change from 1.3:
## All functions that had a . in the name now have an _
## all.correlations -> all_correlations, cor.demo -> cor_demo, etc.
```

```r
vif_values <- VIF(glm_compl)



# Create a data frame with variable names and their corresponding VIF values
vif_df <- data.frame(Variable = names(vif_values), VIF = vif_values,row.names = NULL)

# Sort the data frame in decreasing order of VIF values
sorted_df <- vif_df[order(-vif_df$VIF), ]

# Print the sorted data frame
print(sorted_df)
```

```
##                              Variable       VIF
## 22          Arrival_Delay_in_Minutes 14.214669
## 21        Departure_Delay_in_Minutes 14.179713
## 14            Inflight_entertainment  3.256814
## 9             Ease_of_Online_booking  2.605357
## 20                       Cleanliness  2.466629
## 7             Inflight_wifi_service  2.227467
## 13                      Seat_comfort  2.050528
## 11                    Food_and_drink  2.019669
## 19                  Inflight_service  2.011267
## 4                     Type_of_Travel  1.846157
## 17                  Baggage_handling  1.818810
## 8  Departure_Arrival_time_convenient  1.716303
## 15                  On_board_service  1.635092
## 2                      Customer_Type  1.593352
## 5                              Class  1.580339
## 10                    Gate_location  1.523870
## 12                   Online_boarding  1.492857
## 6                    Flight_Distance  1.321514
## 16                  Leg_room_service  1.218411
## 18                   Checkin_service  1.208941
## 3                                Age  1.180740
## 1                             Gender  1.007157
```

```r
# VIF Iteration 2
# Using the VIF function and comparing the obtained values with the
# computed quantity:
# (The process is done iteratively where we delete one variable at time)
# Model definition:
glm_compl<- glm(data = train,
                satisfaction ~ .-Arrival_Delay_in_Minutes,
                family = "binomial")
vif_values <- VIF(glm_compl)

# Create a data frame with variable names and their corresponding VIF values
vif_df <- data.frame(Variable = names(vif_values), VIF = vif_values,row.names = NULL)

# Sort the data frame in decreasing order of VIF values
sorted_df <- vif_df[order(-vif_df$VIF), ]
```

```r
# Print the sorted data frame
print(sorted_df)
```

```
##                              Variable      VIF
## 14            Inflight_entertainment 3.253083
## 9             Ease_of_Online_booking 2.604730
## 20                       Cleanliness 2.462982
## 7              Inflight_wifi_service 2.226307
## 13                      Seat_comfort 2.050264
## 11                    Food_and_drink 2.015772
## 19                  Inflight_service 2.010121
## 4                     Type_of_Travel 1.844680
## 17                  Baggage_handling 1.819082
## 8  Departure_Arrival_time_convenient 1.717985
## 15                  On_board_service 1.635354
## 2                      Customer_Type 1.591163
## 5                              Class 1.580708
## 10                    Gate_location 1.524352
## 12                   Online_boarding 1.491323
## 6                    Flight_Distance 1.321942
## 16                  Leg_room_service 1.218441
## 18                   Checkin_service 1.208792
## 3                                Age 1.180280
## 21       Departure_Delay_in_Minutes 1.019189
## 1                            Gender 1.007198
```

```r
# VIF Iteration 3
# Using the VIF function and comparing the obtained values with the
# computed quantity:
# (The process is done iteratively where we delete one variable at time)
# Model definition:
glm_compl<- glm(data = train,
                satisfaction ~ .-Arrival_Delay_in_Minutes-Inflight_entertainment,
                family = "binomial")
vif_values <- VIF(glm_compl)

# Create a data frame with variable names and their corresponding VIF values
vif_df <- data.frame(Variable = names(vif_values), VIF = vif_values,row.names = NULL)

# Sort the data frame in decreasing order of VIF values
sorted_df <- vif_df[order(-vif_df$VIF), ]

# Print the sorted data frame
print(sorted_df)
```

```
##                          Variable      VIF
## 9         Ease_of_Online_booking 2.597679
## 7          Inflight_wifi_service 2.179638
## 19                   Cleanliness 2.069021
## 13                  Seat_comfort 1.921144
## 18              Inflight_service 1.871872
## 4                 Type_of_Travel 1.808991
## 16              Baggage_handling 1.777057
```

```
## 11                     Food_and_drink 1.749368
## 8  Departure_Arrival_time_convenient 1.714919
## 5                              Class 1.568851
## 2                      Customer_Type 1.542831
## 14                  On_board_service 1.529663
## 10                     Gate_location 1.524519
## 12                   Online_boarding 1.473553
## 6                    Flight_Distance 1.321644
## 15                  Leg_room_service 1.203573
## 3                                Age 1.175796
## 17                   Checkin_service 1.168239
## 20        Departure_Delay_in_Minutes 1.017509
## 1                              Gender 1.005687
```

```
# VIF Iteration 4
# Using the VIF function and comparing the obtained values with the
# computed quantity:
# (The process is done iteratively where we delete one variable at time)
# Model definition:
glm_compl<- glm(data = train,
                satisfaction ~ .-Arrival_Delay_in_Minutes-Inflight_entertainment
                -Ease_of_Online_booking ,
                family = "binomial")
vif_values <- VIF(glm_compl)

# Create a data frame with variable names and their corresponding VIF values
vif_df <- data.frame(Variable = names(vif_values), VIF = vif_values,row.names = NULL)

# Sort the data frame in decreasing order of VIF values
sorted_df <- vif_df[order(-vif_df$VIF), ]

# Print the sorted data frame
print(sorted_df)
```

```
##                              Variable      VIF
## 18                       Cleanliness 2.057085
## 12                      Seat_comfort 1.907140
## 17                  Inflight_service 1.872313
## 4                     Type_of_Travel 1.786666
## 15                  Baggage_handling 1.777868
## 10                    Food_and_drink 1.747112
## 8  Departure_Arrival_time_convenient 1.583838
## 5                              Class 1.564422
## 7               Inflight_wifi_service 1.550276
## 13                  On_board_service 1.529146
## 2                      Customer_Type 1.520480
## 11                   Online_boarding 1.413533
## 9                      Gate_location 1.393553
## 6                    Flight_Distance 1.321174
## 14                  Leg_room_service 1.198613
## 3                                Age 1.168891
## 16                   Checkin_service 1.166815
## 19        Departure_Delay_in_Minutes 1.016333
## 1                              Gender 1.004951
```

```
# VIF Iteration 5
# Using the VIF function and comparing the obtained values with the
# computed quantity:
# (The process is done iteratively where we delete one variable at time)
# Model definition:
glm_compl<- glm(data = train,
                satisfaction ~ .-Arrival_Delay_in_Minutes-Inflight_entertainment
                -Ease_of_Online_booking - Cleanliness   ,
                family = "binomial")
vif_values <- VIF(glm_compl)

# Create a data frame with variable names and their corresponding VIF values
vif_df <- data.frame(Variable = names(vif_values), VIF = vif_values,row.names = NULL)

# Sort the data frame in decreasing order of VIF values
sorted_df <- vif_df[order(-vif_df$VIF), ]

# Print the sorted data frame
print(sorted_df)
```

```
##                            Variable      VIF
## 17                  Inflight_service 1.881686
## 15                  Baggage_handling 1.787458
## 4                     Type_of_Travel 1.776955
## 8  Departure_Arrival_time_convenient 1.587989
## 12                      Seat_comfort 1.585879
## 5                              Class 1.563525
## 7               Inflight_wifi_service 1.551518
## 13                   On_board_service 1.534811
## 2                       Customer_Type 1.512988
## 10                    Food_and_drink 1.431732
## 11                   Online_boarding 1.408212
## 9                      Gate_location 1.401531
## 6                    Flight_Distance 1.321957
## 14                  Leg_room_service 1.202873
## 3                                Age 1.166393
## 16                   Checkin_service 1.164245
## 18        Departure_Delay_in_Minutes 1.013281
## 1                            Gender 1.004409
```

```
glm_compl<- glm(data = train,
                satisfaction ~ .-Arrival_Delay_in_Minutes-Inflight_entertainment
                -Ease_of_Online_booking - Cleanliness   ,
                family = "binomial")
# Observation of the model summary:
summary(glm_compl)
```

```
##
## Call:
## glm(formula = satisfaction ~ . - Arrival_Delay_in_Minutes - Inflight_entertainment -
##     Ease_of_Online_booking - Cleanliness, family = "binomial",
##     data = train)
```

```
##
## Coefficients:
##                                    Estimate Std. Error  z value Pr(>|z|)
## (Intercept)                       -8.823e+00  8.653e-02 -101.973  < 2e-16 ***
## Gender                             7.017e-02  1.929e-02    3.638 0.000275 ***
## Customer_Type                     -2.047e+00  2.906e-02  -70.452  < 2e-16 ***
## Age                               -8.049e-03  7.022e-04  -11.463  < 2e-16 ***
## Type_of_Travel                     2.757e+00  3.074e-02   89.667  < 2e-16 ***
## Class                             -3.243e-01  1.264e-02  -25.653  < 2e-16 ***
## Flight_Distance                   -2.802e-06  1.103e-05   -0.254 0.799509
## Inflight_wifi_service              3.202e-01  9.479e-03   33.776  < 2e-16 ***
## Departure_Arrival_time_convenient -1.682e-01  7.817e-03  -21.520  < 2e-16 ***
## Gate_location                     -1.325e-02  8.707e-03   -1.522 0.128025
## Food_and_drink                     8.632e-02  8.915e-03    9.683  < 2e-16 ***
## Online_boarding                    6.124e-01  9.978e-03   61.379  < 2e-16 ***
## Seat_comfort                       1.865e-01  9.774e-03   19.080  < 2e-16 ***
## On_board_service                   3.241e-01  9.740e-03   33.278  < 2e-16 ***
## Leg_room_service                   2.540e-01  8.403e-03   30.228  < 2e-16 ***
## Baggage_handling                   1.522e-01  1.116e-02   13.629  < 2e-16 ***
## Checkin_service                    3.329e-01  8.317e-03   40.023  < 2e-16 ***
## Inflight_service                   1.445e-01  1.149e-02   12.575  < 2e-16 ***
## Departure_Delay_in_Minutes        -4.336e-03  2.619e-04  -16.553  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 141746  on 103588  degrees of freedom
## Residual deviance:  70165  on 103570  degrees of freedom
## AIC: 70203
##
## Number of Fisher Scoring iterations: 5
```

```
glm_compl<- glm(data = train,
                satisfaction ~ .-Arrival_Delay_in_Minutes-Inflight_entertainment
                -Ease_of_Online_booking - Cleanliness
                -Flight_Distance -Gate_location,
                family = "binomial")
# Observation of the model summary:
summary(glm_compl)
```

```
##
## Call:
## glm(formula = satisfaction ~ . - Arrival_Delay_in_Minutes - Inflight_entertainment -
##     Ease_of_Online_booking - Cleanliness - Flight_Distance -
##     Gate_location, family = "binomial", data = train)
##
## Coefficients:
##                                    Estimate Std. Error  z value Pr(>|z|)
## (Intercept)                       -8.8521191  0.0835376 -105.966  < 2e-16 ***
## Gender                             0.0701859  0.0192865    3.639 0.000274 ***
## Customer_Type                     -2.0469787  0.0281350  -72.755  < 2e-16 ***
## Age                               -0.0080418  0.0007009  -11.474  < 2e-16 ***
## Type_of_Travel                     2.7515722  0.0303740   90.590  < 2e-16 ***
```

```
## Class                              -0.3229737  0.0119904  -26.936  < 2e-16 ***
## Inflight_wifi_service               0.3178024  0.0093146   34.119  < 2e-16 ***
## Departure_Arrival_time_convenient -0.1735864  0.0069860  -24.848  < 2e-16 ***
## Food_and_drink                      0.0866219  0.0089116    9.720  < 2e-16 ***
## Online_boarding                     0.6145055  0.0098663   62.283  < 2e-16 ***
## Seat_comfort                        0.1857609  0.0097617   19.030  < 2e-16 ***
## On_board_service                    0.3245154  0.0097307   33.350  < 2e-16 ***
## Leg_room_service                    0.2543085  0.0083920   30.304  < 2e-16 ***
## Baggage_handling                    0.1527092  0.0111576   13.687  < 2e-16 ***
## Checkin_service                     0.3332325  0.0083121   40.090  < 2e-16 ***
## Inflight_service                    0.1448930  0.0114864   12.614  < 2e-16 ***
## Departure_Delay_in_Minutes         -0.0043390  0.0002619  -16.567  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 141746  on 103588  degrees of freedom
## Residual deviance:  70167  on 103572  degrees of freedom
## AIC: 70201
##
## Number of Fisher Scoring iterations: 5
```

```
glm_compl<- glm(data = train,
                satisfaction ~ .-Arrival_Delay_in_Minutes-Inflight_entertainment
                -Ease_of_Online_booking - Cleanliness
                -Flight_Distance -Gate_location,
                family = "binomial")


# Computing the predictions with the model on the test set:
pred_glm_compl<- predict(glm_compl, test, type = "response")

# Converting the prediction in {0,1} according to the chosen threshold:

threshold4<- 0.4
threshold5<- 0.5
threshold6<- 0.6
threshold7<- 0.7


pred_glm_compl_04<- ifelse(pred_glm_compl > threshold4, 1, 0)
pred_glm_compl_05<- ifelse(pred_glm_compl > threshold5, 1, 0)
pred_glm_compl_06<- ifelse(pred_glm_compl > threshold6, 1, 0)
pred_glm_compl_07<- ifelse(pred_glm_compl > threshold7, 1, 0)
```

```
# Confusion matrix with threshold = 0.4
table(test_true, pred_glm_compl_04)
```

```
##          pred_glm_compl_04
## test_true     0     1
##         0 12382  2120
##         1  1543  9853
```

```
mean(pred_glm_compl_04==test_true)
```

```
## [1] 0.8585605
```

```
# Confusion matrix with threshold = 0.5
table(test_true, pred_glm_compl_05)
```

```
##          pred_glm_compl_05
## test_true     0     1
##         0 13057  1445
##         1  1908  9488
```

```
mean(pred_glm_compl_05==test_true)
```

```
## [1] 0.8705305
```

```
# Confusion matrix with threshold = 0.6
table(test_true, pred_glm_compl_06)
```

```
##          pred_glm_compl_06
## test_true     0     1
##         0 13574   928
##         1  2381  9015
```

```
mean(pred_glm_compl_06==test_true)
```

```
## [1] 0.8722295
```

```
# Confusion matrix with threshold = 0.7
table(test_true, pred_glm_compl_07)
```

```
##          pred_glm_compl_07
## test_true     0     1
##         0 13963   539
##         1  3015  8381
```

```
mean(pred_glm_compl_07==test_true)
```

```
## [1] 0.8627693
```

```
library(MASS)
```

```
##
## Attaching package: 'MASS'
```

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

```r
#Model definition:
# Here we don't re-apply the VIF method because we start from the
# previous result.
glm_compl<- glm(data = train,
                satisfaction ~ .-Arrival_Delay_in_Minutes-Inflight_entertainment
                -Ease_of_Online_booking - Cleanliness   ,
                family = "binomial")

# Application of the Stepwise method, specifying that we consider
# both the forward and the backward directions. We consider as
# reference metric the Akaike Information Criterion:
glm_compl_step <- stepAIC(glm_compl, direction = "both",
trace = FALSE)
# Observation of the model summary:
summary(glm_compl_step)
```

```
##
## Call:
## glm(formula = satisfaction ~ Gender + Customer_Type + Age + Type_of_Travel +
##     Class + Inflight_wifi_service + Departure_Arrival_time_convenient +
##     Gate_location + Food_and_drink + Online_boarding + Seat_comfort +
##     On_board_service + Leg_room_service + Baggage_handling +
##     Checkin_service + Inflight_service + Departure_Delay_in_Minutes,
##     family = "binomial", data = train)
##
## Coefficients:
##                                    Estimate Std. Error  z value Pr(>|z|)
## (Intercept)                      -8.8272949  0.0850834 -103.749  < 2e-16 ***
## Gender                            0.0701756  0.0192876    3.638 0.000274 ***
## Customer_Type                    -2.0454468  0.0281586  -72.640  < 2e-16 ***
## Age                              -0.0080387  0.0007009  -11.469  < 2e-16 ***
## Type_of_Travel                    2.7558641  0.0305239   90.286  < 2e-16 ***
## Class                            -0.3232424  0.0119932  -26.952  < 2e-16 ***
## Inflight_wifi_service             0.3203076  0.0094624   33.851  < 2e-16 ***
## Departure_Arrival_time_convenient -0.1682685  0.0078153  -21.531  < 2e-16 ***
## Gate_location                    -0.0132487  0.0087066   -1.522 0.128089
## Food_and_drink                    0.0863543  0.0089137    9.688  < 2e-16 ***
## Online_boarding                   0.6123211  0.0099695   61.419  < 2e-16 ***
## Seat_comfort                      0.1864373  0.0097717   19.079  < 2e-16 ***
## On_board_service                  0.3240635  0.0097375   33.280  < 2e-16 ***
## Leg_room_service                  0.2539369  0.0083974   30.240  < 2e-16 ***
## Baggage_handling                  0.1521835  0.0111626   13.633  < 2e-16 ***
## Checkin_service                   0.3328660  0.0083169   40.023  < 2e-16 ***
## Inflight_service                  0.1445549  0.0114885   12.583  < 2e-16 ***
## Departure_Delay_in_Minutes       -0.0043361  0.0002619  -16.554  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 141746  on 103588  degrees of freedom
## Residual deviance:  70165  on 103571  degrees of freedom
## AIC: 70201
```

```
##
## Number of Fisher Scoring iterations: 5
```

```
# Computing the predictions with the model on the test set:
pred_glm_comp_step<- predict(glm_compl_step, test, type = "response")
# Converting the prediction in {0,1} according to the chosen threshold:
pred_glm_compl_step_04<- ifelse(pred_glm_comp_step > threshold4, 1, 0)
pred_glm_compl_step_05<- ifelse(pred_glm_comp_step > threshold5, 1, 0)
pred_glm_compl_step_06<- ifelse(pred_glm_comp_step > threshold6, 1, 0)
pred_glm_compl_step_07<- ifelse(pred_glm_comp_step > threshold7, 1, 0)


# Confusion matrix with threshold = 0.4
table(test_true, pred_glm_compl_step_04)
```

```
##          pred_glm_compl_step_04
## test_true     0     1
##         0 12385  2117
##         1  1537  9859
```

```
mean(pred_glm_compl_step_04==test_true)
```

```
## [1] 0.858908
```

```
# Confusion matrix with threshold = 0.5
table(test_true, pred_glm_compl_step_05)
```

```
##          pred_glm_compl_step_05
## test_true     0     1
##         0 13057  1445
##         1  1905  9491
```

```
mean(pred_glm_compl_step_05==test_true)
```

```
## [1] 0.8706464
```

```
# Confusion matrix with threshold = 0.6
table(test_true, pred_glm_compl_step_06)
```

```
##          pred_glm_compl_step_06
## test_true     0     1
##         0 13572   930
##         1  2366  9030
```

```
mean(pred_glm_compl_step_06==test_true)
```

```
## [1] 0.8727315
```

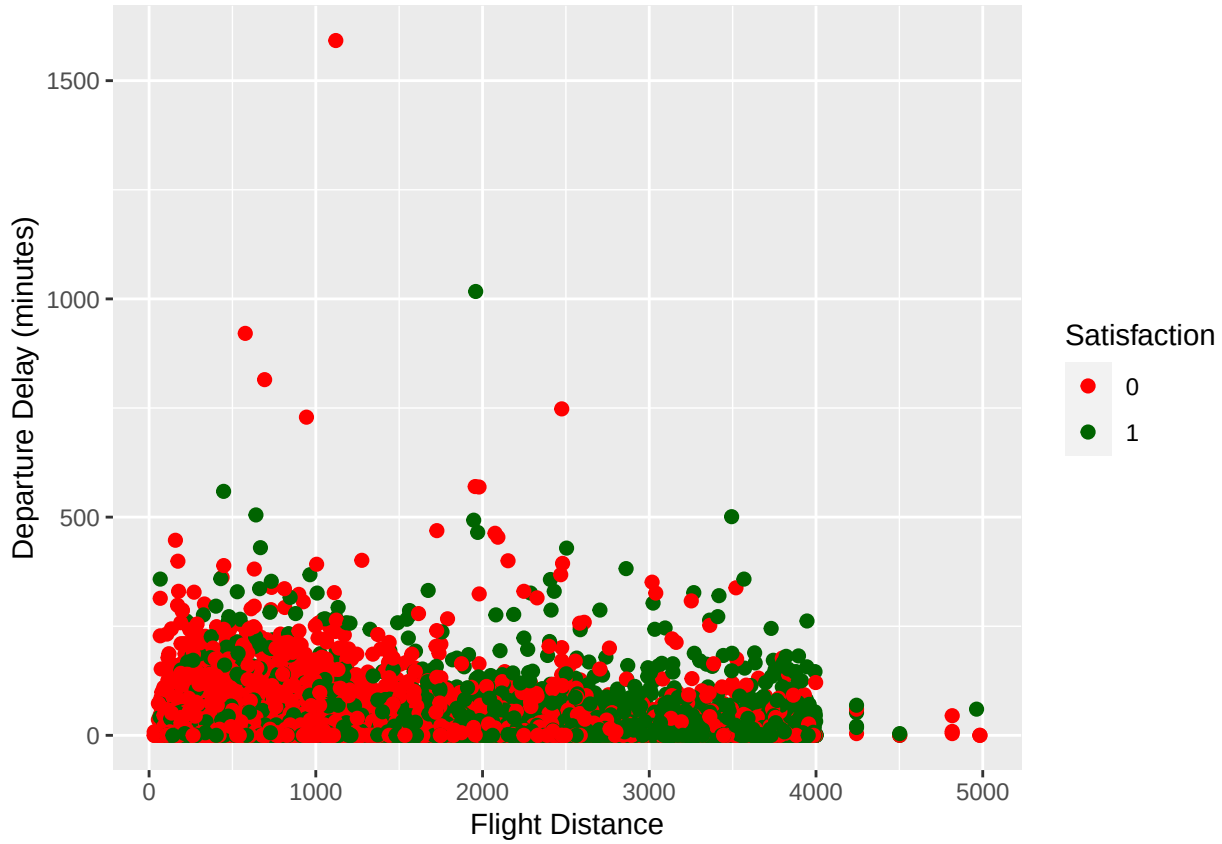
```
# Confusion matrix with threshold = 0.7
table(test_true, pred_glm_compl_step_07)
```

```
##           pred_glm_compl_step_07
## test_true     0     1
##         0 13960   542
##         1  3013  8383
```

```
mean(pred_glm_compl_step_07==test_true)
```

```
## [1] 0.8627307
```

```
library(tidyverse)
# First we present the original classification :
ggplot(test, aes(x =Flight_Distance ,
y = Departure_Delay_in_Minutes ,
color = factor(test_true))) +
  geom_point(size = 2)+
  labs(x = "Flight Distance",y = "Departure Delay (minutes)",
       color ="Satisfaction")+
  scale_color_manual(values = c("0" = "red", "1" = "darkgreen"))
```



```
  theme(legend.position = c(0.8, 0.8))
```

```
## List of 1
##  $ legend.position: num [1:2] 0.8 0.8
##  - attr(*, "class")= chr [1:2] "theme" "gg"
##  - attr(*, "complete")= logi FALSE
##  - attr(*, "validate")= logi TRUE
```

```
# The we try to reproduce the same plot as above, considering the
# classifications obtained with the models
library(gridExtra)
```

```
##
## Attaching package: 'gridExtra'
```

```
## The following object is masked from 'package:randomForest':
##
##     combine
```

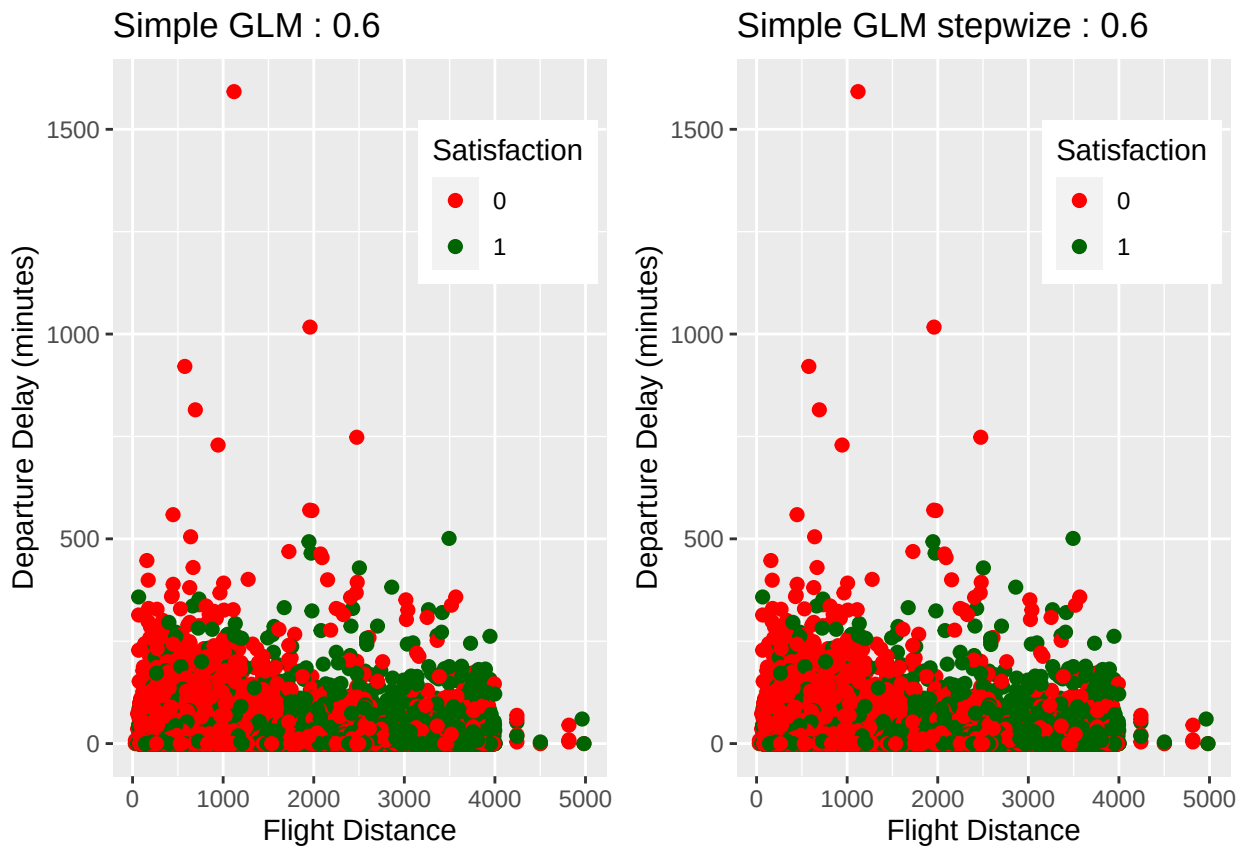
```
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
a <- ggplot(test,
            aes(
              x = Flight_Distance ,
              y = Departure_Delay_in_Minutes ,
              color = factor(pred_glm_compl_06)
            )) +
  geom_point(size = 2) +
  labs(
    x = "Flight Distance",
    y = "Departure Delay (minutes)",
    color = "Satisfaction",
    title = "Simple GLM : 0.6"
  ) +
  scale_color_manual(values = c("0" = "red", "1" = "darkgreen")) +
  theme(legend.position = c(0.8, 0.8))

b <- ggplot(test,
            aes(
              x = Flight_Distance ,
              y = Departure_Delay_in_Minutes ,
              color = factor(pred_glm_compl_step_06)
            )) +
  geom_point(size = 2) +
  labs(
    x = "Flight Distance",
    y = "Departure Delay (minutes)",
    color = "Satisfaction",
    title = "Simple GLM stepwize : 0.6"
```

```
  ) +
  scale_color_manual(values = c("0" = "red", "1" = "darkgreen")) +
theme(legend.position = c(0.8, 0.8))

grid.arrange(a, b,ncol = 2)
```




```
# We compare the results obtained with the two different models, plotting
# now an estimation of the logistic curve using the predictions given by
# the models:
predicted_data <-
  data.frame(prob.of.Satisfaction = pred_glm_compl, Satisfaction = test_true)
predicted_data <-
  predicted_data[order(predicted_data$prob.of.Satisfaction, decreasing = FALSE), ]
predicted_data$rank <- 1:nrow(predicted_data)
a <- ggplot(data = predicted_data, aes(x = rank, y = prob.of.Satisfaction)) +
  geom_point(
    aes(color = as.factor(Satisfaction)),
    alpha = 1,
    shape = 1,
    stroke = 1
  ) +
  xlab("Index") +
  ylab("Predicted probability") +
  ggtitle("Estimated Logistic Curve - Simple GLM")
```

```
predicted_data <-
  data.frame(prob.of.Satisfaction = pred_glm_comp_step, Satisfaction = test_true)
predicted_data <-
  predicted_data[order(predicted_data$prob.of.Satisfaction, decreasing = FALSE), ]
predicted_data$rank <- 1:nrow(predicted_data)
b <- ggplot(data = predicted_data, aes(x = rank, y = prob.of.Satisfaction)) +
  geom_point(
    aes(color = as.factor(Satisfaction)),
    alpha = 1,
    shape = 1,
    stroke = 1
  ) +
  xlab("Index") +
  ylab("Predicted probability") +
  ggtitle("Estimated Logistic Curve - GLM with Stepwise")

grid.arrange(a, b, nrow = 2)
```