# EDA

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## Introduction to data

This section introduces the purpose of the exploratory data analysis (EDA) and sets up the necessary libraries and data files.

```
# import libraries
library(tidyverse)
library(corrplot)
library(ggplot2)
library(gridExtra)
library(correlation)
library(reshape)
library(reshape2)
```

```
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)
```

## Introduction

In this project, we will predict whether a passenger will be satisfied or dissatisfied with the services offered by an airline company. The dataset comprises a survey on airline passenger satisfaction.

The main objectives of this project are to identify the factors that have a strong correlation with passenger satisfaction or dissatisfaction and to develop a predictive model for passenger satisfaction.

The dataset: https://www.kaggle.com/datasets/teejmahal20/airline-passenger-satisfaction

Here are the variables in the dataset:

- Gender: Gender of the passengers (Female, Male)
- Customer Type: The customer type (Loyal customer, disloyal customer)
- Age: The actual age of the passengers
- Type of Travel: Purpose of the flight of the passengers (Personal Travel, Business Travel)
- Class: Travel class in the plane of the passengers (Business, Eco, Eco Plus)
- Flight distance: The flight distance of this journey
- Inflight wifi service: Satisfaction level of the inflight wifi service (0: Not Applicable; 1-5)
- Departure/Arrival time convenient: Satisfaction level of Departure/Arrival time convenient
- Ease of Online booking: Satisfaction level of online booking
- Gate location: Satisfaction level of Gate location
- Food and drink: Satisfaction level of Food and drink

- Online boarding: Satisfaction level of online boarding
- Seat comfort: Satisfaction level of Seat comfort
- Inflight entertainment: Satisfaction level of inflight entertainment
- On-board service: Satisfaction level of On-board service
- Leg room service: Satisfaction level of Leg room service
- Baggage handling: Satisfaction level of baggage handling
- Check-in service: Satisfaction level of Check-in service
- Inflight service: Satisfaction level of inflight service
- Cleanliness: Satisfaction level of Cleanliness
- Departure Delay in Minutes: Minutes delayed when departure
- Arrival Delay in Minutes: Minutes delayed when Arrival
- Satisfaction: Airline satisfaction level (Satisfaction, neutral or dissatisfaction)

The objective of our report is to predict passenger satisfaction with airline services based on the provided dataset, which includes various demographic and satisfaction-related variables such as gender, age, travel type, flight class, and satisfaction levels with different aspects of the journey. The dataset represents a survey on airline passenger satisfaction and will be used to develop a predictive model to determine whether passengers will be satisfied or dissatisfied with the airline services.

Now we're going to get a summary of all the features in our dataset:

```
summary(data)
```

```
##        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
```

From the summary, it is evident that many features represent ratings on the services provided by the airline agency, and these ratings range from 0 to 5. Additionally, we noticed that the "Arrival Delay in Minutes" feature contains some missing values (NA).

Next, we will examine the distribution of all nominal features. Specifically, we have categorical data for Gender, Customer Type, Type of Travel, and Class, while all the rating features are ordinal.

```
table(data$Gender)
```

```
##
## Female   Male
##  65899  63981
```

The "Gender" feature appears to be well-balanced, meaning that it has an approximately equal number of occurrences for each category, likely male and female. This balance can be beneficial for modeling as it prevents any significant bias towards a particular gender in the analysis and predictions.

```
table(data$Customer.Type)
```

```
##
## disloyal Customer    Loyal Customer
##             23780            106100
```

The "Customer Type" feature contains only two values, "disloyal customer" and "loyal customer." The distribution of values is imbalanced, with one category potentially having significantly more occurrences than the other.

```
table(data$Type.of.Travel)
```

```
##
## Business travel Personal Travel
##           89693           40187
```

The "Type of Travel" feature consists of only two values: "personal travel" and "business travel." The distribution of values is imbalanced, with "business travel" occurring twice as much as "personal travel."

```r
table(data$Class)
```

```
##
## Business      Eco Eco Plus
##    62160    58309     9411
```

The "Class" feature contains three values: "business," "eco plus," and "eco." The distribution of values is imbalanced. "Business" and "eco" classes appear to be relatively balanced, while "eco plus" is significantly underrepresented compared to the other two classes.

```r
table(data$satisfaction)
```

```
##
## neutral or dissatisfied               satisfied
##                   73452                   56428
```

The "satisfaction" feature, which serves as our target variable, is an important aspect of the analysis. The values for this feature are not perfectly balanced, meaning that there is an unequal distribution of satisfied and dissatisfied passengers in the dataset.

## Data preprocessing

In this section of data preprocessing, several steps are performed to prepare the dataset for further analysis and modeling. The specific actions taken include:

1. Renaming columns: the names of the features (columns) are modified to improve their clarity and usability.
2. Dropping unnecessary columns: two columns, "X" and "id," are removed from the dataset. The "X" column likely represents the index of the row, which does not carry any meaningful information for analysis. The "id" column is presumed to be an unknown indexing number, which may not contribute to the predictive modeling process.
3. Converting categorical variables to factors: categorical variables, such as "Gender", "Customer Type", "Type of Travel" and "Class" are converted into factors. Converting categorical variables into factors is a common practice in R to represent these variables as distinct levels, allowing for better handling and analysis in statistical models.

By performing these data preprocessing steps, the dataset is cleaned and transformed into a more suitable format for the subsequent analysis, making it easier to build a predictive model for passenger satisfaction.

```r
# replace dots with underscores in column names
names(data) = gsub("\\.", "_", names(data))
# drop X and id column
data = data %>% select(-X, -id)
names(data)
```

```
##  [1] "Gender"                          "Customer_Type"
##  [3] "Age"                             "Type_of_Travel"
##  [5] "Class"                           "Flight_Distance"
##  [7] "Inflight_wifi_service"           "Departure_Arrival_time_convenient"
##  [9] "Ease_of_Online_booking"          "Gate_location"
## [11] "Food_and_drink"                  "Online_boarding"
## [13] "Seat_comfort"                    "Inflight_entertainment"
## [15] "On_board_service"                "Leg_room_service"
## [17] "Baggage_handling"                "Checkin_service"
## [19] "Inflight_service"                "Cleanliness"
## [21] "Departure_Delay_in_Minutes"      "Arrival_Delay_in_Minutes"
```

```
## [23] "satisfaction"
```

```
# convert categorical features to factor
data$Gender = factor(data$Gender, levels = c("Male", "Female"))
data$Customer_Type = factor(data$Customer_Type, levels = c("Loyal Customer", "disloyal Customer"))
data$Type_of_Travel = factor(data$Type_of_Travel, levels = c("Personal Travel", "Business travel"))
data$Class = factor(data$Class, levels = c("Business", "Eco Plus", "Eco"))
data$satisfaction = factor(data$satisfaction, levels = c("neutral or dissatisfied", "satisfied"))

ratings_fts_names = c("Inflight_wifi_service", "Departure_Arrival_time_convenient",
  "Ease_of_Online_booking", "Gate_location", "Food_and_drink", "Online_boarding",
  "Seat_comfort", "Inflight_entertainment", "On_board_service", "Leg_room_service",
  "Baggage_handling", "Checkin_service", "Inflight_service", "Cleanliness", "On_board_service")

for (col in ratings_fts_names) {
  data[[col]] = factor(data[[col]], levels = c(0:5))
}
```

## Handling na values

In this section, we analyze the dataset to identify variables with missing values, particularly focusing on the "Arrival_Delay_in_Minutes" variable. We calculate the proportion of missing values for the variable and subsequently remove the examples or rows with missing values from the dataset.

```
# list features with na values
prop.table(colSums(is.na(data)))
```

```
##                          Gender                   Customer_Type
##                               0                               0
##                             Age                  Type_of_Travel
##                               0                               0
##                           Class                  Flight_Distance
##                               0                               0
##            Inflight_wifi_service Departure_Arrival_time_convenient
##                               0                               0
##           Ease_of_Online_booking                     Gate_location
##                               0                               0
##                  Food_and_drink                  Online_boarding
##                               0                               0
##                     Seat_comfort           Inflight_entertainment
##                               0                               0
##                On_board_service                 Leg_room_service
##                               0                               0
##                Baggage_handling                  Checkin_service
##                               0                               0
##                Inflight_service                     Cleanliness
##                               0                               0
##       Departure_Delay_in_Minutes         Arrival_Delay_in_Minutes
##                               0                               1
##                     satisfaction
##                               0
```

To determine the proportion of missing values for the "Arrival_Delay_in_Minutes" variable, we can count the number of instances where this variable has missing values (commonly denoted as "NaN" or "NA") and divide it by the total number of examples in the dataset. This will give us the proportion of missing values

for the "Arrival_Delay_in_Minutes" variable.

```
# Arrival_Delay_in_Minutes has na values, proportion of na values
prop.table(table(is.na(data$Arrival_Delay_in_Minutes)))
```

```
##
##      FALSE       TRUE
## 0.99697413 0.00302587
```

Indeed, since the proportion of missing values for the "Arrival_Delay_in_Minutes" variable is very low (less than 3% of the entire dataset), it is reasonable to proceed with dropping these missing values from the dataset.

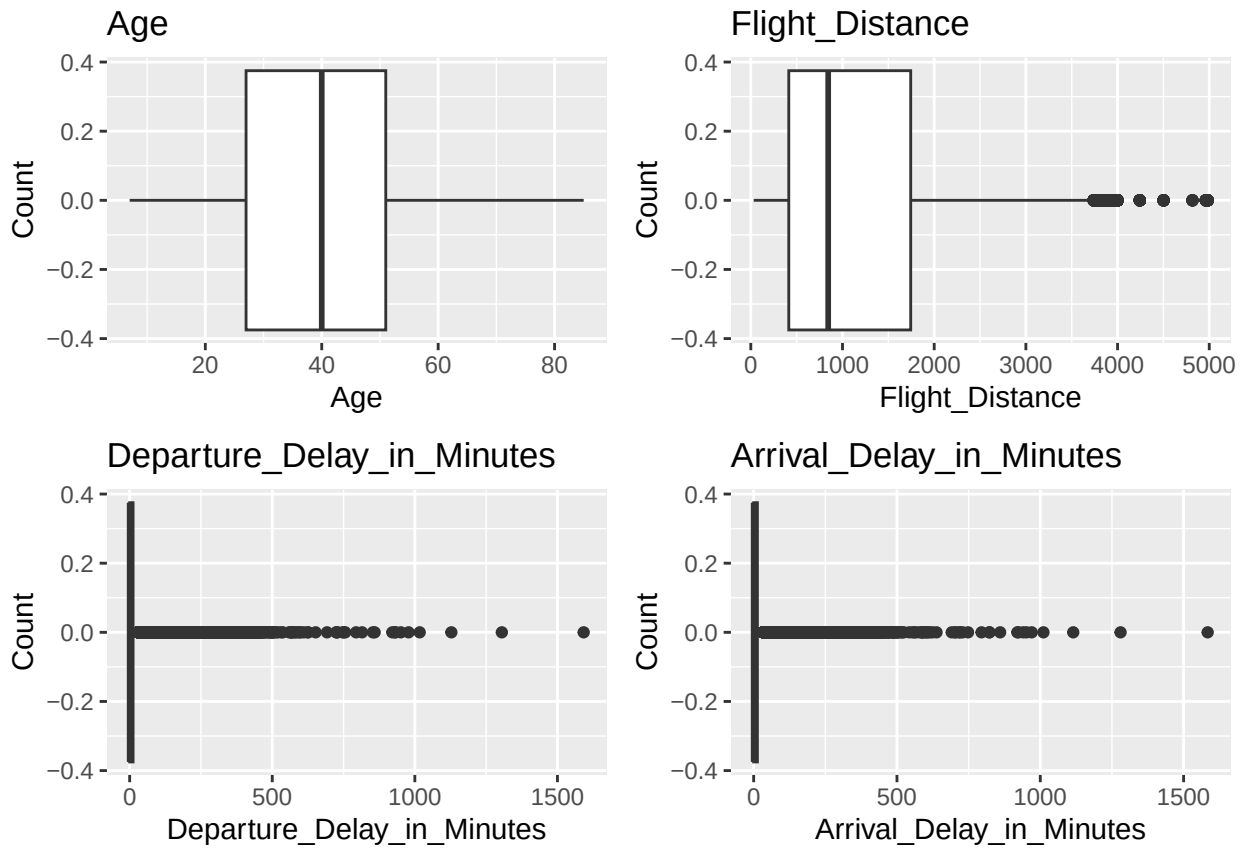
```
# na values are only 0.03% of the data -> drop na values
data = data %>% drop_na(Arrival_Delay_in_Minutes)
```

## Outliers

In this section, box plots are created for each numeric variable present in the dataset. Box plots are a powerful visualization tool used to identify the presence of outliers in the data. For each numeric variable, the box plot displays a box that represents the interquartile range (IQR), with the median indicated by a line inside the box. The "whiskers" extending from the box show the range of the data, and any data points beyond the whiskers are considered potential outliers.

By examining the box plots for each numeric variable, we can visually identify any data points that lie far outside the typical range of the data, indicating potential outliers. Outliers can significantly impact statistical analyses, so detecting and handling them appropriately is crucial for ensuring the integrity of the dataset and the accuracy of subsequent analyses and modeling.

```
# plot boxplot of each numeric variable excluding ratings features
plots = list()
for (col in names(data)[sapply(data, is.numeric)]) {
  if (col %in% ratings_fts_names) {
    next
  }
  plot = ggplot(data, aes(x = .data[[col]])) +
  geom_boxplot() +
  labs(title = col, x = col, y = "Count")
  plots[[col]] = plot
}

grid.arrange(grobs = plots, ncol = 2)
```




We can see that there are outliers in Departure_Delay_in_Minutes, Arrival_Delay_in_Minutes and Flight_Distance. Considering the presence of both near-zero and very large values in the dataset, alternative distributions like the log-normal distribution may be more appropriate for modeling the "Departure_Delay_in_Minutes" and "Arrival_Delay_in_Minutes" variables, as they can better capture the variability in delay times.

## Visualization

In this section, histograms are used to visualize the distribution of the variables in the dataset, starting with the nominal features. By creating histograms for the nominal features, we can gain insights into the distribution of categories within each feature.

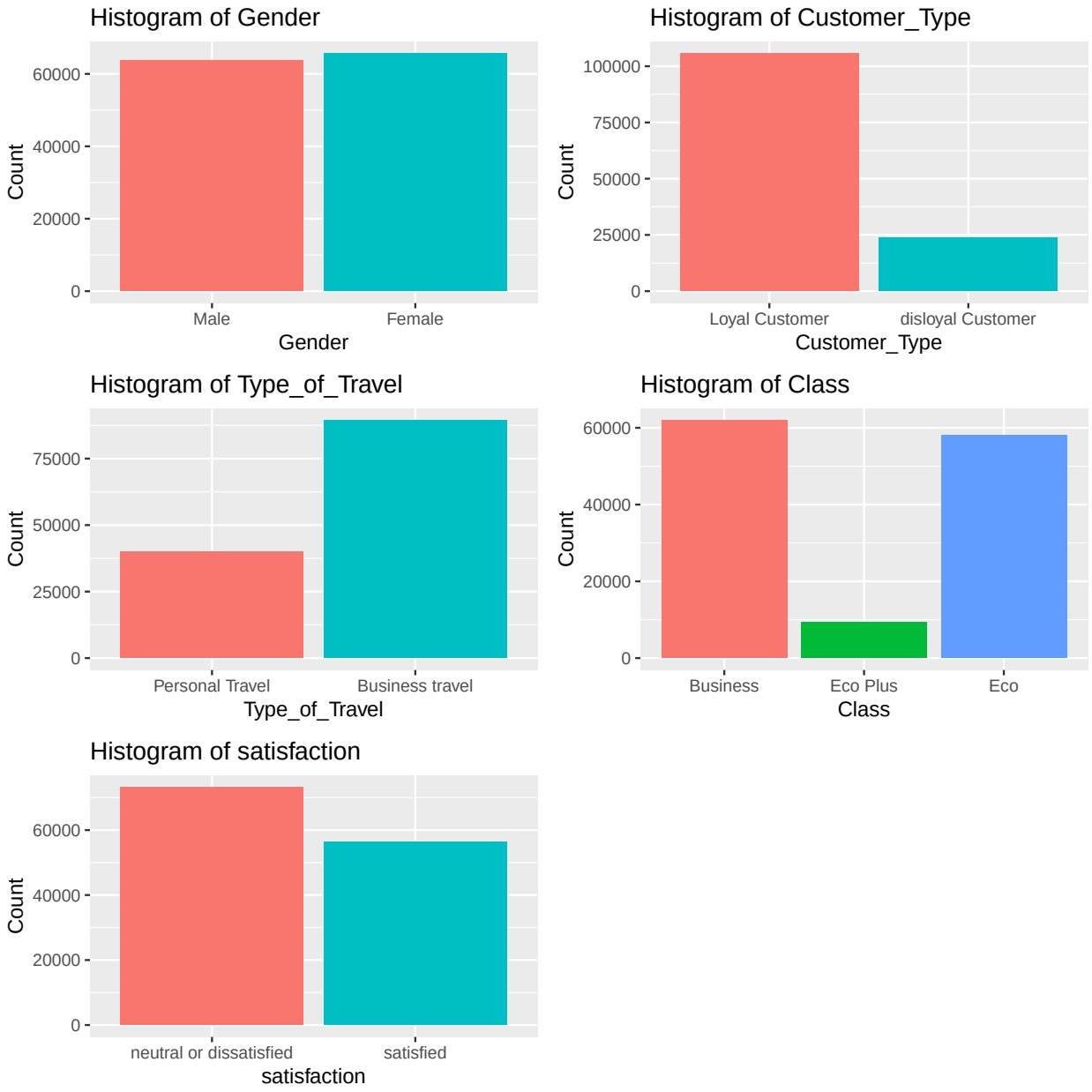
Upon visualizing the nominal features, it becomes apparent that some features exhibit heavily unbalanced distributions. This means that certain categories within these features have significantly higher frequencies compared to others. The presence of such imbalanced distributions could have implications for analysis and modeling, as it may lead to biased results or difficulties in predicting less frequent categories accurately.

```
# plot distribution of categorical variables
plots = list()
for (col in names(data)[sapply(data, is.factor)]) {
  if (col %in% ratings_fts_names) {
    next
  }
  plot = ggplot(data, aes(x = .data[[col]], fill = .data[[col]])) +
  geom_bar() +
  labs(title = paste("Histogram of", col), x = col, y = "Count") +
  guides(fill = FALSE)
```

```
  plots[[col]] = plot
}
```

```
## Warning: The `<scale>` argument of `guides()` cannot be `FALSE`. Use "none" instead as
## of ggplot2 3.3.4.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```
grid.arrange(grobs = plots, ncol = 2)
```




From the analysis of the nominal features, we can observe the following regarding their balance:

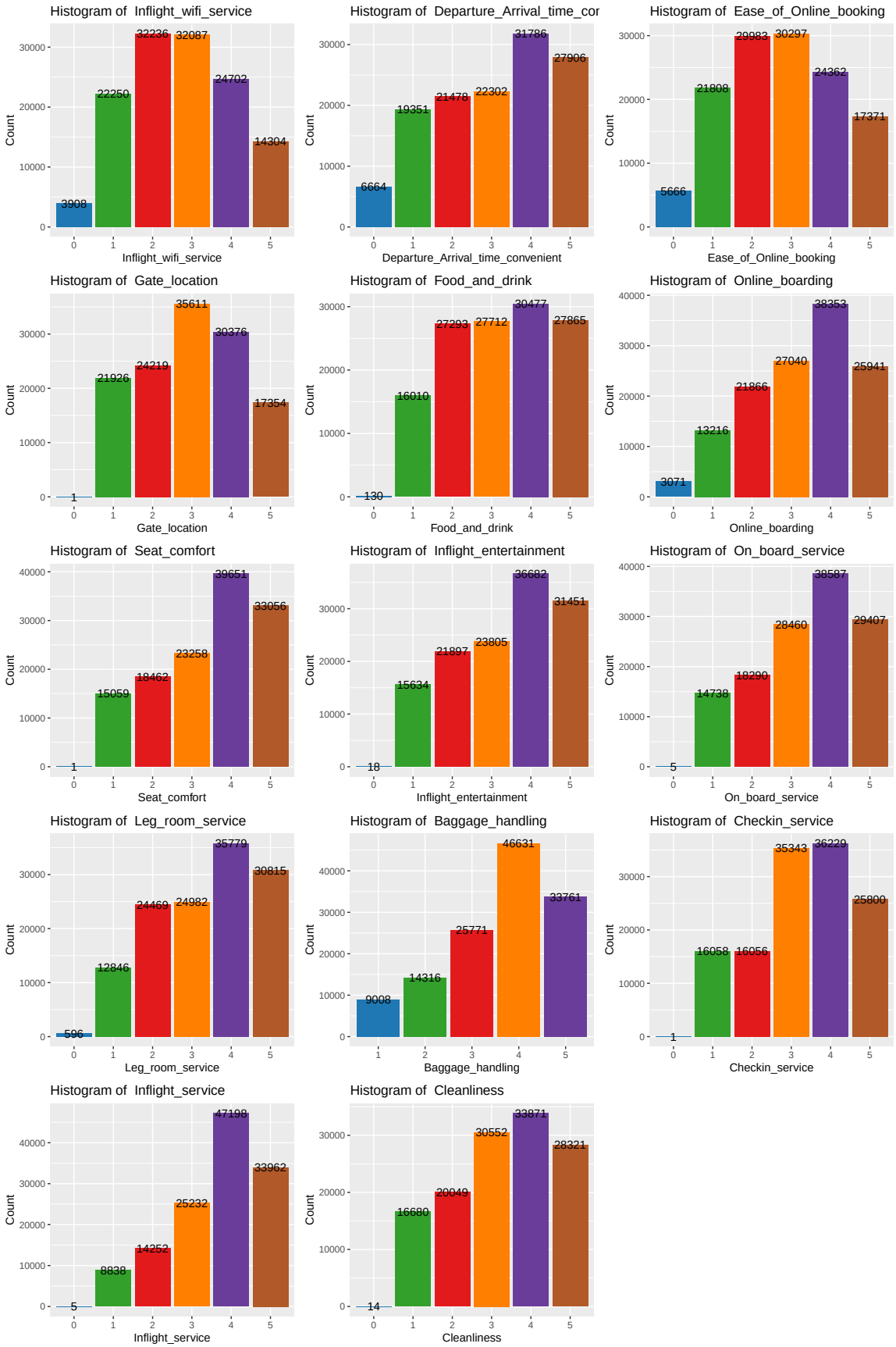
1. Gender: The "Gender" feature is almost perfectly balanced, meaning that there is a relatively equal representation of both genders in the dataset.

2. Satisfaction: The target feature appears to be imbalanced, with fewer instances of "satisfied" compared to the other class ("dissatisfied"). This imbalance could potentially impact the model's performance, and we need to handle it appropriately during the modeling process.
3. Type of Travel: The "Type of Travel" feature shows an imbalance, with more instances of "business travel" compared to "personal travel."
4. Class: The "Class" feature also exhibits imbalance, with "business" and "eco" classes having relatively balanced representations, while the "Eco Plus" class is underrepresented.
5. Customer Type: The "Customer Type" feature shows an imbalance, with a higher number of "loyal customer" instances compared to "disloyal customer."

When dealing with imbalanced data, we need to take specific measures during model training and evaluation to ensure that the model performs well and doesn't exhibit bias towards the majority class. Appropriate techniques such as resampling, using different evaluation metrics or employing specialized algorithms can help address the imbalance and lead to a more accurate and fair predictive model.

Now we plot the distribution of ratings features.

```
# plot distribution of ratings features
plots = list()
my_palette <- c("#1f78b4", "#33a02c", "#e31a1c", "#ff7f00", "#6a3d9a", "#b15928")

for (col in names(data)[sapply(data, is.factor)]) {
  if (!col %in% ratings_fts_names) {
    next
  }
  plot <- ggplot(data, aes(x = .data[[col]], fill = factor(.data[[col]]))) +
    geom_bar() +
    geom_text(stat = 'count', aes(label = after_stat(count))) +
    labs(title = paste("Histogram of ", col), x = col, y = "Count") +
    scale_fill_manual(values = my_palette) +
    guides(fill = FALSE)

  plots[[col]] <- plot
}
grid.arrange(grobs = plots, ncol = 3)
```


Histogram of Inflight_wifi_service
Count
Inflight_wifi_service
3908
22250
32236
32087
24702
14304
Histogram of Departure_Arrival_time_cor
Departure_Arrival_time_convenient
6664
19351
21478
22302
31786
27906
Histogram of Ease_of_Online_booking
Ease_of_Online_booking
5666
21808
29983
30297
24362
17371
Histogram of Gate_location
Gate_location
1
21926
24219
35611
30376
17354
Histogram of Food_and_drink
Food_and_drink
130
16010
27293
27712
30477
27865
Histogram of Online_boarding
Online_boarding
3071
13216
21866
27040
38353
25941
Histogram of Seat_comfort
Seat_comfort
1
15059
18462
23258
39651
33056
Histogram of Inflight_entertainment
Inflight_entertainment
18
15634
21897
23805
36682
31451
Histogram of On_board_service
On_board_service
5
14738
18290
28460
38587
29407
Histogram of Leg_room_service
Leg_room_service
596
12846
24469
24982
35779
30815
Histogram of Baggage_handling
Baggage_handling
9008
14316
25771
46631
33761
Histogram of Checkin_service
Checkin_service
1
16058
16056
35343
36229
25800
Histogram of Inflight_service
Inflight_service
5
8838
14252
25232
47198
33962
Histogram of Cleanliness
Cleanliness
14
16680
20049
30552
33871
28321

Based

on the graphs showing the histograms of the ratings, we can observe that the majority of them tend to fall between 3 and 4. This conclusion is drawn from the visual representation of the data, where the histogram bars are higher in the range of 3 to 4, indicating a higher frequency of ratings in that range.

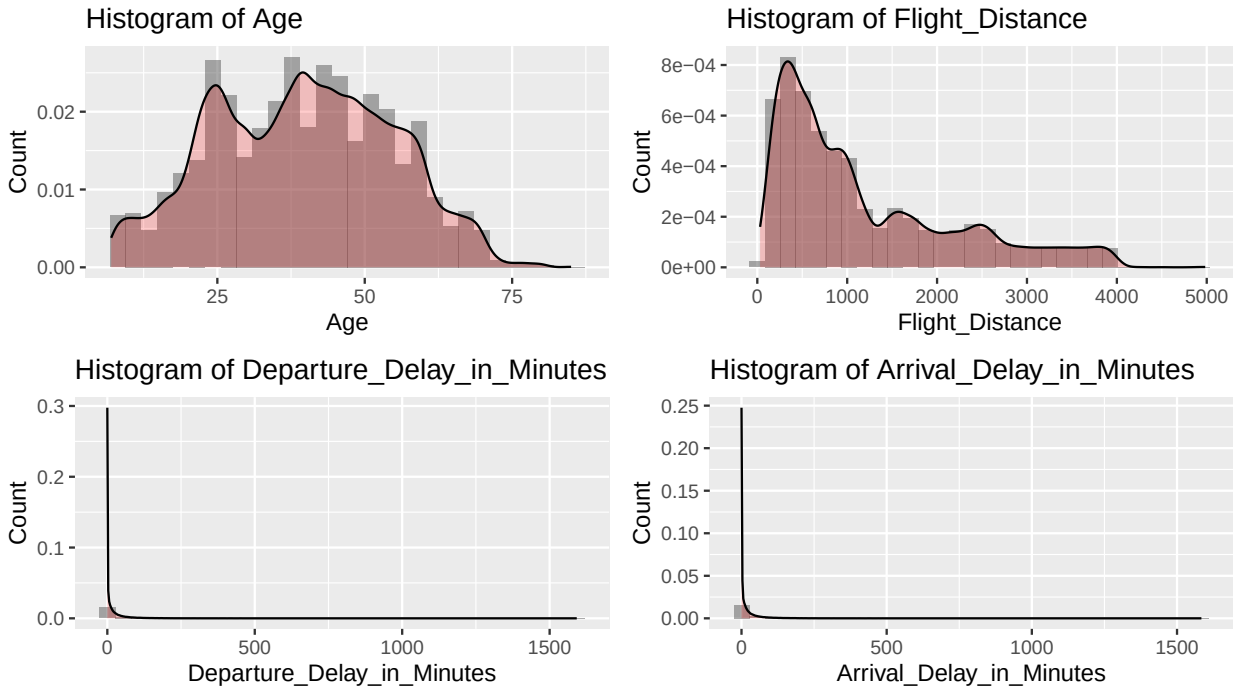
```
# compute the mean value of all the ratings
ratings_data = data[, c(ratings_fts_names)]
ratings_data <- apply(ratings_data, 2, as.numeric)
ratings_mean = colMeans(ratings_data)
ratings_mean
```

```
##             Inflight_wifi_service Departure_Arrival_time_convenient
##                          2.728544                          3.057349
##           Ease_of_Online_booking                      Gate_location
##                          2.756786                          2.976909
##                    Food_and_drink                    Online_boarding
##                          3.204685                          3.252720
##                      Seat_comfort            Inflight_entertainment
##                          3.441589                          3.358067
##                  On_board_service                  Leg_room_service
##                          3.383204                          3.351078
##                  Baggage_handling                   Checkin_service
##                          3.631886                          3.306239
##                  Inflight_service                      Cleanliness
##                          3.642373                          3.286222
##                On_board_service.1
##                          3.383204
```

This section includes histograms to visualize the distribution of numeric variables in the dataset.

**needs interpretation**

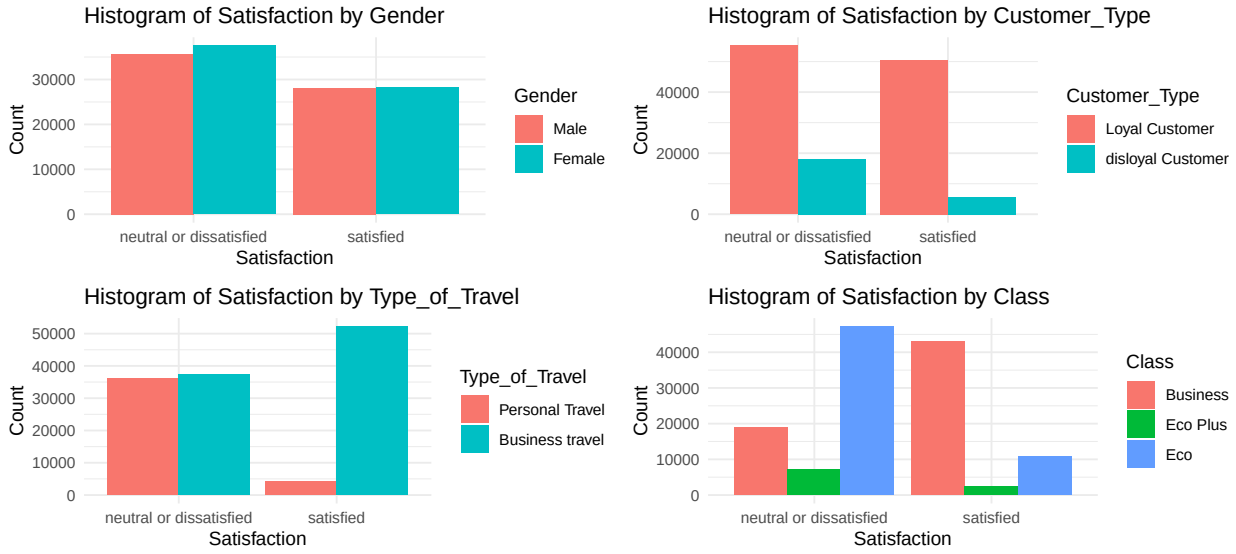
```
# plot distribution and density of numeric variables excluding ratings features
plots = list()
for (col in names(data)[sapply(data, is.numeric)]) {
  if (col %in% ratings_fts_names) {
    next
  }
  plot = ggplot(data, aes(x = .data[[col]])) +
  geom_histogram(aes(y = after_stat(density)), bins = 30, alpha = 0.5) +
  geom_density(alpha = 0.2, fill = "red") +
  labs(title = paste("Histogram of", col), x = col, y = "Count")

  plots[[col]] = plot
}

grid.arrange(grobs = plots, ncol = 2)
```




## Visualization vs satisfaction

The observations from the graph analysis provide valuable insights into how different nominal features relate to passenger satisfaction: 1. Gender: both males and females appear to have similar distributions in terms of satisfaction, indicating that gender may not be a strong predictor of passenger satisfaction. The distributions closely resemble the overall distribution of the satisfaction feature. 2. Customer type: the graph suggests that "disloyal customers" are more likely to be unsatisfied or neutral compared to "loyal customers." This indicates that customer loyalty may play a role in passenger satisfaction, with loyal customers tending to be more satisfied. 3. Type of travel: The graph indicates that "personal travelers" are more likely to be unsatisfied compared to "business travelers." Conversely, "business travelers" tend to have a higher proportion of satisfied passengers. This finding suggests that the purpose of travel may have an influence on passenger satisfaction. 4. Class: The graph shows that "business class" passengers are more satisfied than unsatisfied, whereas "eco" and "eco plus" passengers tend to have a higher proportion of unsatisfied passengers. This suggests that the class of service provided by the airline may be a significant factor affecting passenger satisfaction.

```
# plots categorical variables vs satisfaction
plots = list()
for (col in names(data)[sapply(data, is.factor)]) {
  if (col == "satisfaction" || col %in% ratings_fts_names) {
    next
  }
  plot = ggplot(data, aes(x = satisfaction, fill = .data[[col]])) +
  theme_minimal() +
  geom_bar(position = "dodge") +
  labs(title = paste("Histogram of Satisfaction by", col), x = "Satisfaction", y = "Count")

  plots[[col]] = plot

}

grid.arrange(grobs = plots, ncol = 2)
```




Based on the observed distribution of the ratings, we can draw the following conclusion: 1. For most of the ratings, the mean value for unsatisfied/neutral consumers is around 3, except for "Inflight Service" and "Baggage Handling."

```
# calculate the mean of the ratings of unsatisfied/neutral consumers
ratings_data = data[data$satisfaction == "neutral or dissatisfied", c(ratings_fts_names)]
ratings_data <- apply(ratings_data, 2, as.numeric)
ratings_mean = colMeans(ratings_data)
ratings_mean
```

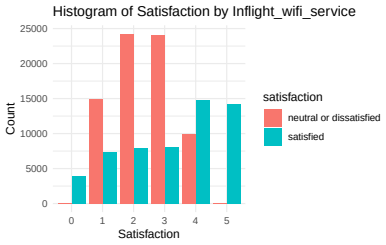
```
##             Inflight_wifi_service Departure_Arrival_time_convenient
##                          2.398470                          3.130229
##            Ease_of_Online_booking                     Gate_location
##                          2.549512                          2.980184
##                      Food_and_drink                  Online_boarding
##                          2.958525                          2.658846
##                       Seat_comfort            Inflight_entertainment
##                          3.038525                          2.892236
##                  On_board_service                 Leg_room_service
##                          3.019570                          2.990495
##                  Baggage_handling                  Checkin_service
##                          3.374681                          3.043045
##                  Inflight_service                     Cleanliness
##                          3.389662                          2.932851
##                On_board_service.1
##                          3.019570
```

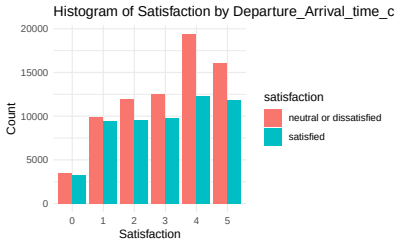
2. For most of the ratings given by satisfied consumers, the mean value is around 4. However, it's important to note that we cannot generalize from this information alone.

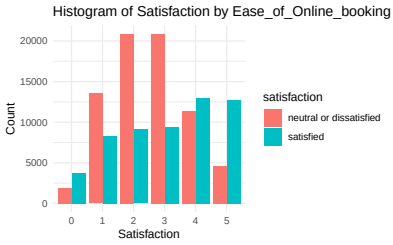
```
# calculate the mean of the ratings of unsatisfied/neutral consumers
ratings_data = data[data$satisfaction == "satisfied", c(ratings_fts_names)]
ratings_data <- apply(ratings_data, 2, as.numeric)
ratings_mean = colMeans(ratings_data)
ratings_mean
```

```
##             Inflight_wifi_service Departure_Arrival_time_convenient
##                          3.158135                          2.962497
##            Ease_of_Online_booking                     Gate_location
##                          3.026554                          2.972646
##                     Food_and_drink                  Online_boarding
##                          3.525061                          4.025648
##                       Seat_comfort            Inflight_entertainment
##                          3.966176                          3.964345
##                  On_board_service                 Leg_room_service
##                          3.856475                          3.820376
##                  Baggage_handling                  Checkin_service
##                          3.966638                          3.648786
##                  Inflight_service                     Cleanliness
##                          3.971277                          3.746134
##                On_board_service.1
##                          3.856475
```

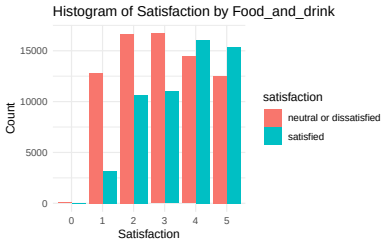
```r
# plots ratings features vs satisfaction
plots = list()
for (col in names(data)[sapply(data, is.factor)]) {
  if (!col %in% ratings_fts_names) {
    next
  }
  plot = ggplot(data, aes(x = .data[[col]], fill = satisfaction)) +
  theme_minimal() +
  geom_bar(position = "dodge") +
  labs(title = paste("Histogram of Satisfaction by", col), x = "Satisfaction", y = "Count")

  plots[[col]] = plot
}

grid.arrange(grobs = plots, ncol = 2)
```

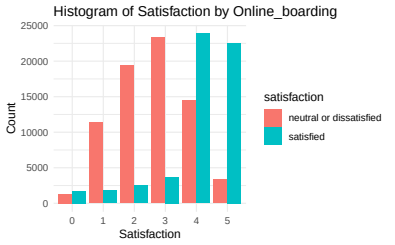

Histogram of Satisfaction by Inflight_wifi_service
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied

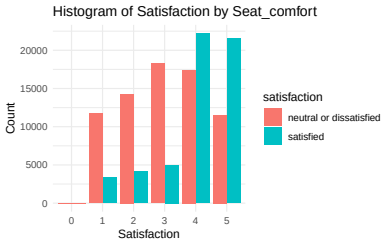

Histogram of Satisfaction by Departure_Arrival_time_c
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied

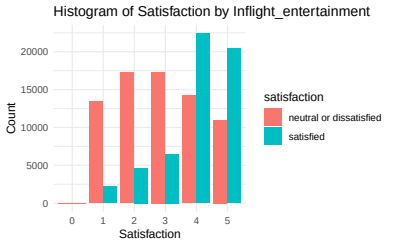

Histogram of Satisfaction by Ease_of_Online_booking
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied

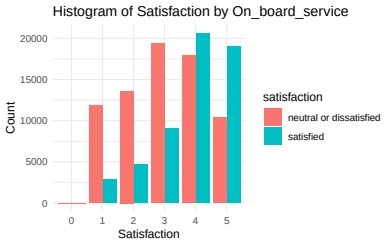

Histogram of Satisfaction by Gate_location
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied

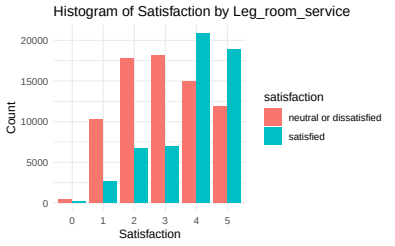

Histogram of Satisfaction by Food_and_drink
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied

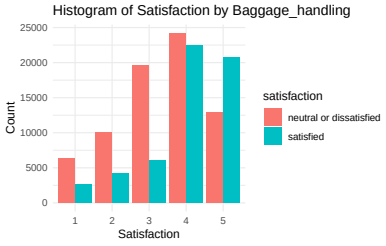

Histogram of Satisfaction by Online_boarding
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied

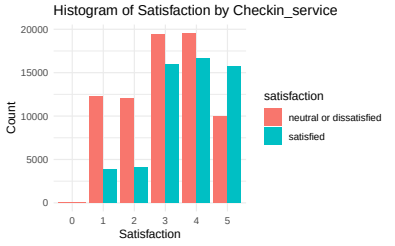

Histogram of Satisfaction by Seat_comfort
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied

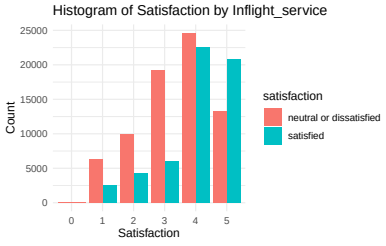

Histogram of Satisfaction by Inflight_entertainment
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied


Histogram of Satisfaction by On_board_service
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied


Histogram of Satisfaction by Leg_room_service
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied


Histogram of Satisfaction by Baggage_handling
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied


Histogram of Satisfaction by Checkin_service
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied


Histogram of Satisfaction by Inflight_service
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied

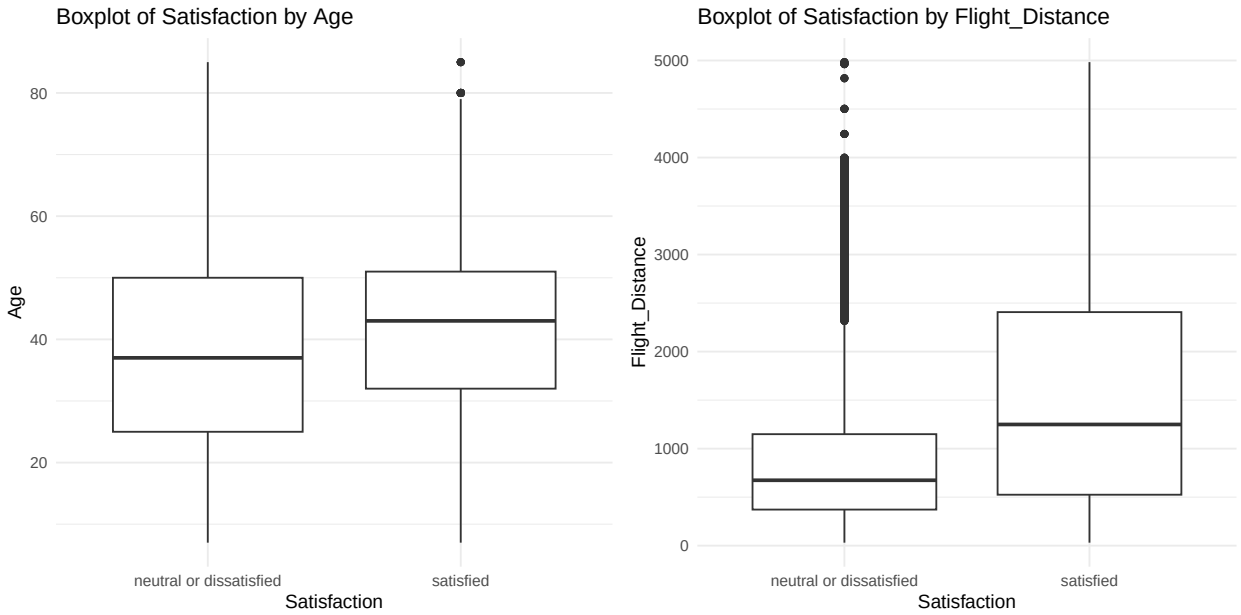

Histogram of Satisfaction by Cleanliness
Count
Satisfaction
satisfaction
neutral or dissatisfied
satisfied

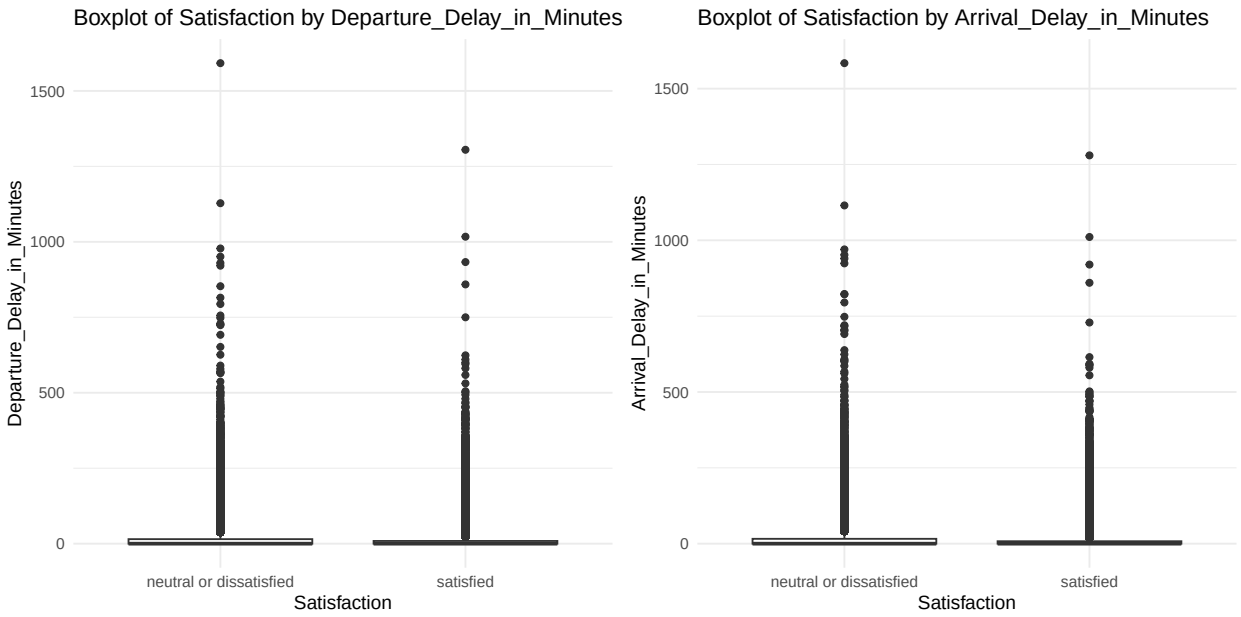
Based on the boxplots and the information provided, we can make the following observations about the distributions of the numerical features:

1. Age: the boxplot for "Age" suggests that the distribution is approximately normal. This is indicated by the symmetric shape of the box, with the median line dividing it quite evenly.
2. Flight Distance: the boxplot does not exhibit a normal distribution. Instead, it appears to have a right-skewed distribution. This is evident from the longer whisker on the right side, indicating that there are some outliers with larger flight distances.
3. Departure Delay in Minutes: the boxplot for "Departure Delay in Minutes" also shows a right-skewed distribution. The majority of the data appears to be concentrated towards the lower values, with a lot of outliers representing longer departure delays.
4. Arrival Delay in Minutes: similar to the "Departure Delay in Minutes," the boxplot for "Arrival Delay in Minutes" exhibits a right-skewed distribution. The bulk of the data is clustered towards the lower values, with a lot of outliers indicating longer arrival delays.

Based on these observations, it's essential to consider the appropriate data transformations or use different distribution models when working with "Flight Distance," "Departure Delay in Minutes," and "Arrival Delay in Minutes." For example, logarithmic transformations may be suitable to handle the skewed nature of these variables in statistical analyses and modeling tasks.

```r
# plots numeric variables vs satisfaction excluding ratings features
plots = list()

for (col in names(data)[sapply(data, is.numeric)]) {
  if (col %in% ratings_fts_names) {
    next
  }
  plot = ggplot(data, aes(x = satisfaction, y = .data[[col]])) +
  theme_minimal() +
  geom_boxplot() +
  labs(title = paste("Boxplot of Satisfaction by", col), x = "Satisfaction", y = col)

  plots[[col]] = plot
}

grid.arrange(grobs = plots, ncol = 2)
```




# Convert categorical to numerical

This section converts the categorical variables to numeric representation for further analysis.

```
gender_map = c("Male" = 0, "Female" = 1)
data$Gender = gender_map[as.numeric(data$Gender)]

customer_type_map = c("Loyal Customer" = 0, "disloyal Customer" = 1)
data$Customer_Type = customer_type_map[as.numeric(data$Customer_Type)]

type_of_travel_map = c("Personal Travel" = 0, "Business travel" = 1)
data$Type_of_Travel = type_of_travel_map[as.numeric(data$Type_of_Travel)]
```

```r
class_map = c("Business" = 0, "Eco" = 1, "Eco Plus" = 2)
data$Class = class_map[as.numeric(data$Class)]
```

```r
satisfaction_map = c("neutral or dissatisfied" = 0, "satisfied" = 1)
data$satisfaction = satisfaction_map[as.numeric(data$satisfaction)]
```

## Data balance

This section calculates the proportion of satisfied and dissatisfied customers in the dataset.

```r
prop.table(table(data$satisfaction))
```

```
##
##         0         1
## 0.5655008 0.4344992
```

## Train test split

This section splits the data into training and testing sets, prints the proportion of satisfied and dissatisfied customers in each set, and saves the true values of the target variable for the test set.

```r
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,]

# merge train and test data
data = rbind(train, test)
# save on cvs
# write.csv(data, "data.csv")

# save true values of test satisfaction column
test_true = test$satisfaction

# 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
```

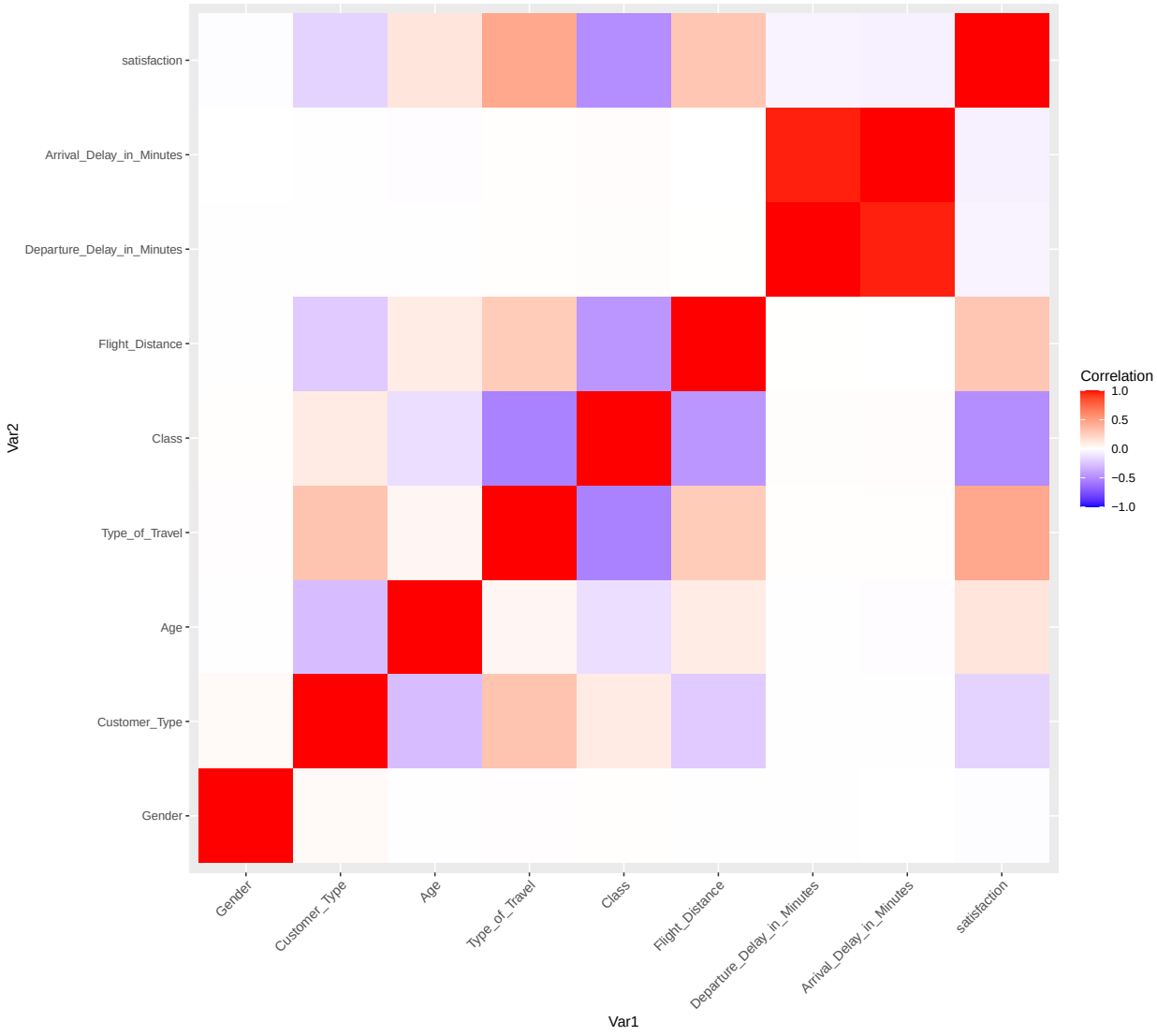
```r
prop.table(table(test_true))
```

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

## Correlation matrix

This section calculates the correlation matrix for numeric variables and plots a heatmap to visualize the correlations between variables.

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

# Plot a heatmap of the correlation matrix
ggplot(data = reshape2::melt(correlation_matrix)) +
  geom_tile(aes(x = Var1, y = Var2, fill = value)) +
  scale_fill_gradient2(low = "blue", mid = "white", high = "red",
                       midpoint = 0, limit = c(-1,1), space = "Lab",
                       name="Correlation") +
  theme(axis.text.x = element_text(angle = 45, vjust = 1,
                                   size = 10, hjust = 1)) +
  coord_fixed()
```




```r
par(mfrow = c(1, 1))
```

```r
# Find high correlated features with satisfaction
# TODO: do the same with different threshold to find differences
# NOTE: i decided to use 0.3 as threshold
satisfaction_corr <- correlation_matrix['satisfaction',]
high_corr_satis <- names(satisfaction_corr[abs(satisfaction_corr) > 0.3 | abs(satisfaction_corr) < -0.3])
high_corr_satis <- high_corr_satis[high_corr_satis != "satisfaction"]
high_corr_satis
```

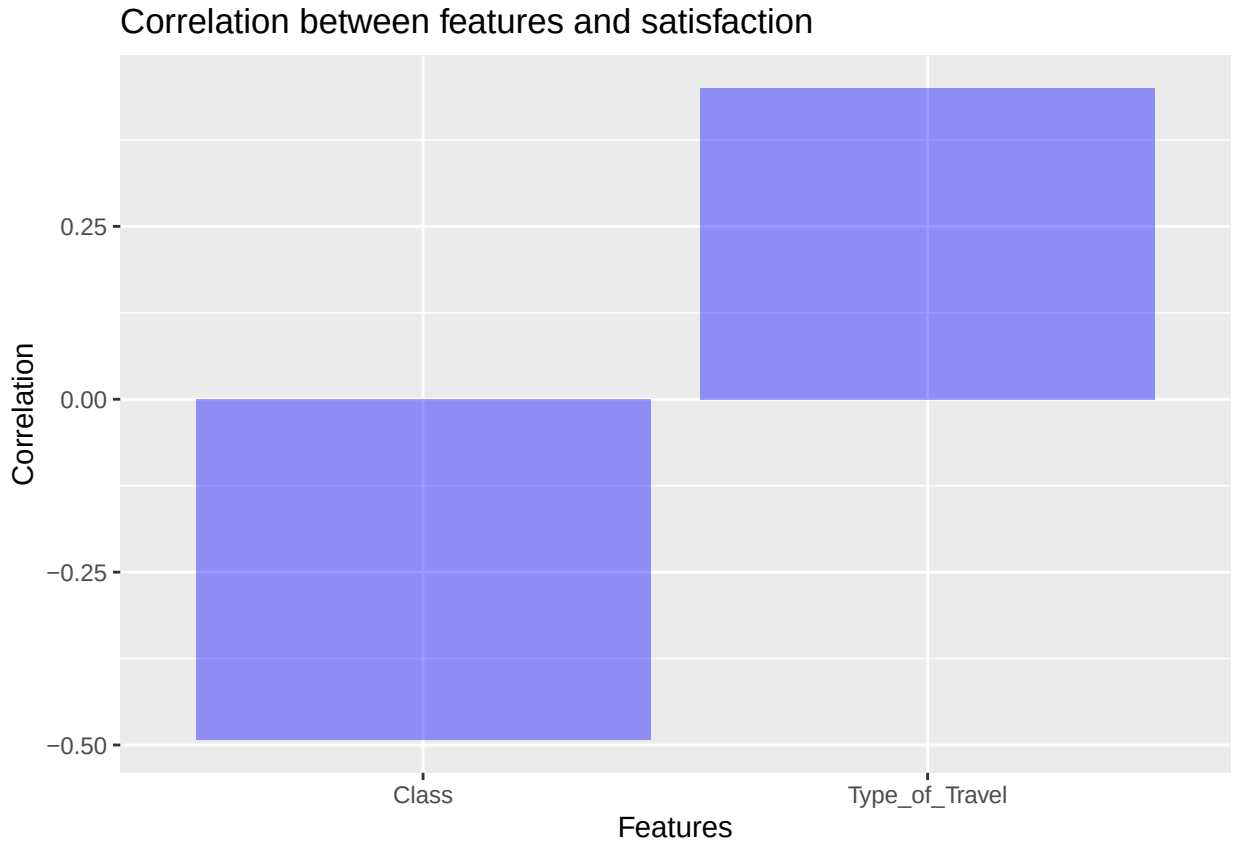
```
## [1] "Type_of_Travel" "Class"
```

```r
# Compute the correlations between the high correlation features and satisfaction
correlations <- data.frame(
  feature = high_corr_satis,
```

```
  correlation = sapply(high_corr_satis, function(x) cor(data[,x], data$satisfaction))
)
correlations
```

```
##                        feature correlation
## Type_of_Travel Type_of_Travel   0.4497939
## Class                  Class  -0.4930659
```

```
# plot the correlations
ggplot(correlations, aes(x = reorder(feature, correlation), y = correlation)) +
  geom_bar(stat = "identity", fill = "blue", alpha = 0.4) +
  ggtitle("Correlation between features and satisfaction") +
  xlab('Features') +
  ylab('Correlation')
```



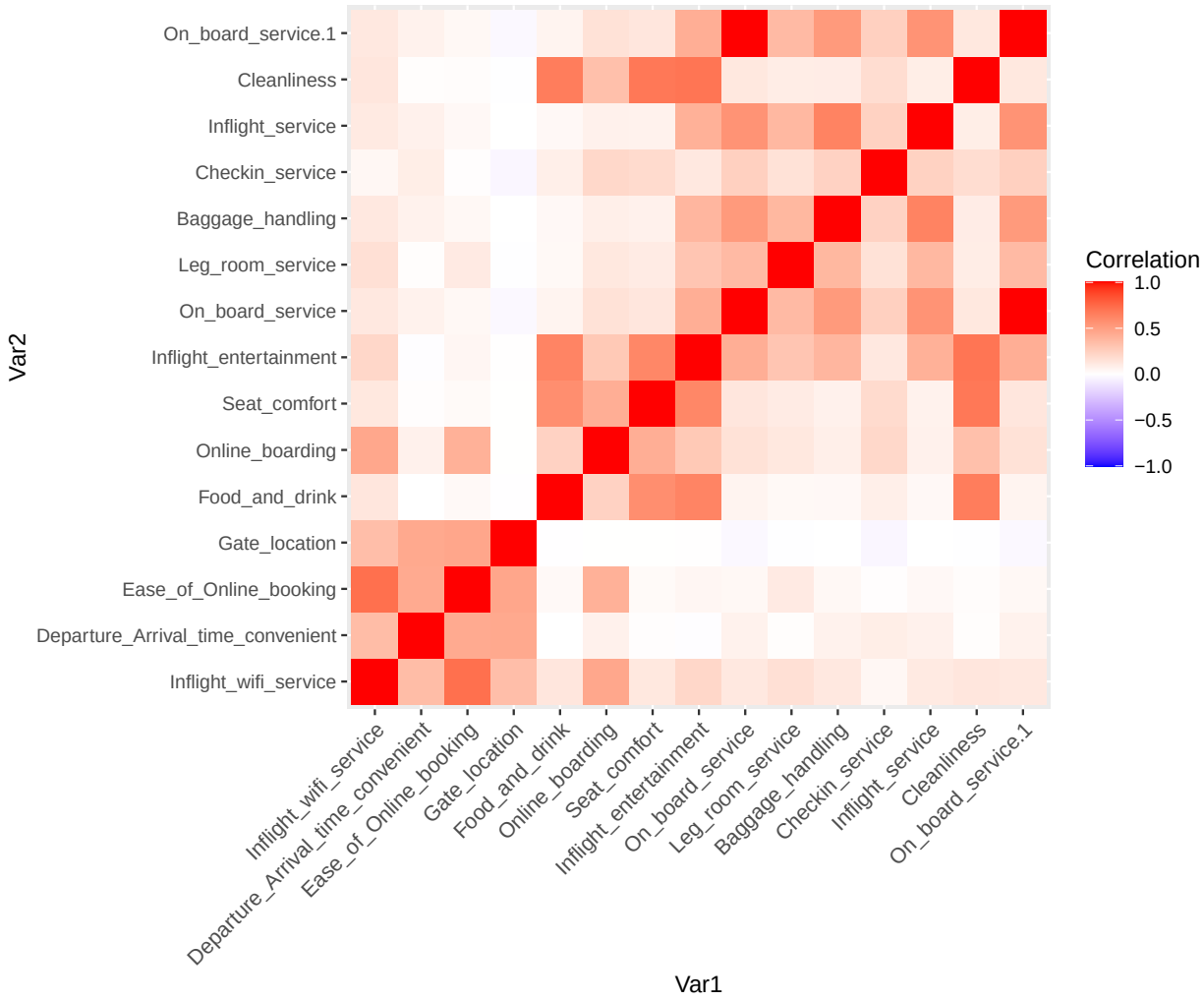

```
par(mfrow = c(1, 1))
```

```
#save on cvs
# write.csv(correlations, file = "correlations.csv")
```

## Correlation with different ratings

```
# compute correlation matrix with only ratings features
ratings_data = data[, c(ratings_fts_names)]
ratings_data <- apply(ratings_data, 2, as.numeric)
```

```r
# correlation matrix only for ratings features
ratings_correlation_matrix = cor(ratings_data)

# Plot a heatmap of the correlation matrix
ggplot(data = reshape2::melt(ratings_correlation_matrix)) +
  geom_tile(aes(x = Var1, y = Var2, fill = value)) +
  scale_fill_gradient2(low = "blue", mid = "white", high = "red",
                       midpoint = 0, limit = c(-1,1), space = "Lab",
                       name="Correlation") +
  theme(axis.text.x = element_text(angle = 45, vjust = 1,
                                   size = 10, hjust = 1)) +
  coord_fixed()
```



```r
par(mfrow = c(1, 1))
```

```r
# Assuming you have already calculated the 'ratings_correlation_matrix' using the code you provided.

# Convert the correlation matrix to a data frame to work with it easily
ratings_correlation_df <- as.data.frame(as.table(ratings_correlation_matrix))

# Rename the columns in the data frame
colnames(ratings_correlation_df) <- c("Var1", "Var2", "Correlation")

# Sort the data frame by the absolute correlation values in descending order
sorted_correlation_df <- ratings_correlation_df[order(-abs(ratings_correlation_df$Correlation)), ]

# Filter out the self-correlations (correlation of a variable with itself)
sorted_correlation_df <- sorted_correlation_df[sorted_correlation_df$Var1 != sorted_correlation_df$Var2

# Print the top N most correlated features
N <- 15  # Change N to get more or fewer correlated features
top_correlated_features <- head(sorted_correlation_df, N)

print(top_correlated_features)
```

```
##                         Var1                  Var2 Correlation
## 135     On_board_service.1       On_board_service   1.0000000
## 219       On_board_service     On_board_service.1   1.0000000
## 3   Ease_of_Online_booking  Inflight_wifi_service   0.7148885
## 31   Inflight_wifi_service Ease_of_Online_booking   0.7148885
## 119            Cleanliness Inflight_entertainment   0.6924911
## 203 Inflight_entertainment            Cleanliness   0.6924911
## 104            Cleanliness           Seat_comfort   0.6796570
## 202           Seat_comfort            Cleanliness   0.6796570
## 74             Cleanliness         Food_and_drink   0.6580260
## 200         Food_and_drink            Cleanliness   0.6580260
## 163       Inflight_service       Baggage_handling   0.6294924
## 191       Baggage_handling       Inflight_service   0.6294924
## 68  Inflight_entertainment         Food_and_drink   0.6233659
## 110         Food_and_drink Inflight_entertainment   0.6233659
## 98  Inflight_entertainment           Seat_comfort   0.6119491
```

## Relation between Arrival_Delay_in_Minutes and Departure_Delay_in_Minutes (linear)

This section explores the partial correlation matrix and identifies variables with high correlations with the target variable (satisfaction). It also creates a bar plot to show the correlations.

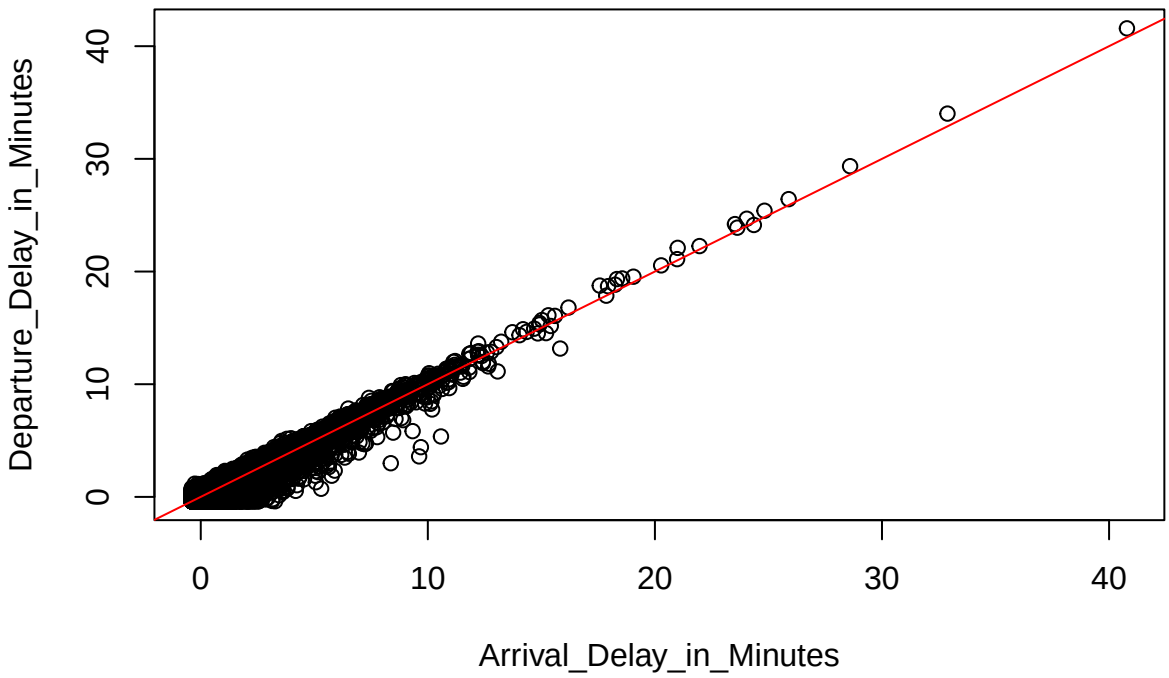
```r
#CORRELATION MATRIX again but now we are interested in partial correlation
#So we look for all the correlations between variables
#We pick the highest, setting a treshold of our choice

#build a dataframe where for each variable we look the partial correlation with all the others
#we pick the highest and we save it in a dataframe
#we set a treshold of 0
```

```r
#correlation(train, partial=TRUE, method='pearson')
#save the partial correlation matrix result in a dataframe and output a file for further analysis


#partial_corr <- correlation(train, partial=TRUE, method='pearson')
#write.csv(partial_corr, file = "partial_corr.csv")

partial_correlations = read.csv("partial_corr.csv", header = TRUE, sep = ",")

#make the first column the row names
rownames(partial_correlations) = partial_correlations[,1]

#drop the first  (X) column
partial_correlations = partial_correlations[,-1]

# Create a new matrix with rounded partial correlations
partial_correlations_rounded <- round(partial_correlations, digits = 3)


# Initialize empty data frame with 0 rows
# We need it to create a data frame with the results and
# so to show better the correlations.
df <- data.frame(variable1 = character(),
                 variable2 = character(),
                 value = numeric(),
                 stringsAsFactors = FALSE)

# Loop over rows and columns of matrix
for (i in 1:nrow(partial_correlations_rounded)) {
  for (j in 1:ncol(partial_correlations_rounded)) {
    # Check if value meets criterion
    if ((partial_correlations_rounded[i,j] > 0.300 | partial_correlations_rounded[i,j] < -0.300)& i != j
      # Add row to data frame
      df <- rbind(df, data.frame(variable1 = rownames(partial_correlations_rounded)[i],
                                 variable2 = colnames(partial_correlations_rounded)[j],
                                 value = partial_correlations_rounded[i,j],
                                 stringsAsFactors = FALSE))
    }
  }
}


# Group the data frame by variable1 and extract top 3 values for each group
df_top3 <- df %>% group_by(variable1) %>% top_n(4, value) %>% ungroup()

#order by variable1
df_top3 <- df_top3[order(df_top3$variable1),]


#delete duplicates in the dataframe if variable1 is equal to variable2
df_top3 <- df_top3[!(df_top3$variable1 == df_top3$variable2),]

print(df_top3, n = nrow(df_top3))
```

```
## # A tibble: 16 x 3
##    variable1                  variable2                  value
##    <chr>                      <chr>                      <dbl>
##  1 Arrival_Delay_in_Minutes   Departure_Delay_in_Minutes  0.964
##  2 Baggage_handling           Inflight_service            0.366
##  3 Class                      Type_of_Travel             -0.423
##  4 Cleanliness                Inflight_entertainment      0.411
##  5 Customer_Type              Type_of_Travel              0.497
##  6 Departure_Delay_in_Minutes Arrival_Delay_in_Minutes    0.964
##  7 Ease_of_Online_booking     Inflight_wifi_service       0.539
##  8 Food_and_drink             Inflight_entertainment      0.353
##  9 Inflight_entertainment     Food_and_drink              0.353
## 10 Inflight_entertainment     Cleanliness                 0.411
## 11 Inflight_service           Baggage_handling            0.366
## 12 Inflight_wifi_service      Ease_of_Online_booking      0.539
## 13 satisfaction               Type_of_Travel              0.351
## 14 Type_of_Travel             Customer_Type               0.497
## 15 Type_of_Travel             Class                      -0.423
## 16 Type_of_Travel             satisfaction                0.351
```

```r
#save on cvs
# write.csv(df_top3, file = "df_top3.csv")
```

```r
# standardize Arrival_Delay_in_Minutes and Departure_Delay_in_Minutes
arrival_std = scale(data$Arrival_Delay_in_Minutes)
departure_std = scale(data$Departure_Delay_in_Minutes)
# scatter plot of Arrival_Delay_in_Minutes and Departure_Delay_in_Minutes
plot(arrival_std, departure_std, xlab = "Arrival_Delay_in_Minutes", ylab = "Departure_Delay_in_Minutes")
# plot line y = x
abline(0, 1, col = "red")
```


Departure_Delay_in_Minutes
0
10
20
30
40
Arrival_Delay_in_Minutes
0
10
20
30
40