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

```
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 we can see that a lot of features are ordinal because they represent ratings for different services offered during a flight. We can observe that some NA values are present in "Arrival.Delay.in.Minutes" feature, it will be dealt later. Now we will look into all the nominal features to see their primal distribution.

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

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

"Gender" feature is quite perfectly balanced.

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

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

We can see that in Customer.Type feature there are only two values, disloyal and loyal customer. The values for this feature are not balanced, we will see later if this feature is useful for our model.

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

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

Also in Type.of.Travel feature there are only two values, personal and business travel. The values for this feature are not balanced, business travel are double than personal travel.

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

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

In Class feature there are three values, business, eco plus and eco. The values for this feature are not balanced, business and eco looks quite balanced while eco plus is way more less represented.

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

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

Our target feature is satisfaction, we can see that the values are not perfectly balanced.

Data preprocessing

This section performs data preprocessing steps such as renaming columns, dropping unnecessary columns, and converting categorical variables to factors.

```
# 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"))
```

Now we can visualize how the features are distributed by satisfaction. This section provides a summary of each variable in the dataset, grouped by our target variable.

```
# Print summary for each variable grouped by satisfaction, including the name of the variable
for (col in names(data)) {
  print(col)
  print(by(data[[col]], data$satisfaction, summary))
}
```

```
## [1] "Gender"
## data$satisfaction: neutral or dissatisfied
##   Male Female
##  35822  37630
## ------------------------------------------------------------
## data$satisfaction: satisfied
##   Male Female
##  28159  28269
## [1] "Customer_Type"
## data$satisfaction: neutral or dissatisfied
##    Loyal Customer disloyal Customer
##             55372             18080
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Loyal Customer disloyal Customer
##             50728              5700
## [1] "Age"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    7.00   25.00   37.00   37.65   50.00   85.00
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    7.00   32.00   43.00   41.74   51.00   85.00
## [1] "Type_of_Travel"
## data$satisfaction: neutral or dissatisfied
## Personal Travel Business travel
##           36115           37337
## ------------------------------------------------------------
## data$satisfaction: satisfied
## Personal Travel Business travel
##            4072           52356
## [1] "Class"
## data$satisfaction: neutral or dissatisfied
## Business Eco Plus      Eco
##    18994     7092    47366
## ------------------------------------------------------------
## data$satisfaction: satisfied
```

```
## Business Eco Plus      Eco
##    43166     2319    10943
## [1] "Flight_Distance"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    31.0   372.0   674.0   929.7  1149.0  4983.0
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      31     525    1249    1530    2407    4983
## [1] "Inflight_wifi_service"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   2.000   2.398   3.000   5.000
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   4.000   3.159   5.000   5.000
## [1] "Departure_Arrival_time_convenient"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    2.00    3.00    3.13    4.00    5.00
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   3.000   2.963   4.000   5.000
## [1] "Ease_of_Online_booking"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   3.000   2.549   3.000   5.000
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   3.000   3.027   4.000   5.000
## [1] "Gate_location"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    2.00    3.00    2.98    4.00    5.00
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   3.000   2.973   4.000   5.000
## [1] "Food_and_drink"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   3.000   2.958   4.000   5.000
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   3.000   4.000   3.525   5.000   5.000
## [1] "Online_boarding"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   3.000   2.659   3.000   5.000
```

```
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   4.000   4.000   4.026   5.000   5.000
## [1] "Seat_comfort"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   3.000   3.038   4.000   5.000
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   4.000   4.000   3.966   5.000   5.000
## [1] "Inflight_entertainment"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   3.000   2.892   4.000   5.000
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   4.000   4.000   3.964   5.000   5.000
## [1] "On_board_service"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    2.00    3.00    3.02    4.00    5.00
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   3.000   4.000   3.856   5.000   5.000
## [1] "Leg_room_service"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    2.00    3.00    2.99    4.00    5.00
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    3.00    4.00    3.82    5.00    5.00
## [1] "Baggage_handling"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   3.000   4.000   3.375   4.000   5.000
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   4.000   4.000   3.967   5.000   5.000
## [1] "Checkin_service"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   3.000   3.043   4.000   5.000
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   3.000   4.000   3.649   5.000   5.000
## [1] "Inflight_service"
## data$satisfaction: neutral or dissatisfied
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    3.00    4.00    3.39    4.00    5.00
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   4.000   4.000   3.971   5.000   5.000
## [1] "Cleanliness"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   3.000   2.933   4.000   5.000
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   3.000   4.000   3.747   5.000   5.000
## [1] "Departure_Delay_in_Minutes"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    0.00    0.00   16.41   15.00 1592.00
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    0.00    0.00   12.51    9.00 1305.00
## [1] "Arrival_Delay_in_Minutes"
## data$satisfaction: neutral or dissatisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.00    0.00    0.00   17.06   16.00 1584.00     227
## ------------------------------------------------------------
## data$satisfaction: satisfied
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.00    0.00    0.00   12.53    8.00 1280.00     166
## [1] "satisfaction"
## data$satisfaction: neutral or dissatisfied
## neutral or dissatisfied               satisfied
##                   73452                       0
## ------------------------------------------------------------
## data$satisfaction: satisfied
## neutral or dissatisfied               satisfied
##                       0                   56428
```

From here we can see that: + men and women are equally satisfied and dissatisfied + dissatisfied customer are younger than satisfied customer (see 1st quartile and median) + personal travel is more likely to be dissatisfied than business travel + business travel are slightly more likely to be satisfied + business class' customers are more likely to be satisfied than eco and eco plus + longer distance flights are more likely to be satisfied + departure and arrival delays are more likely to bring dissatisfaction

Handling na values

This section identifies the variables with missing values and calculates the proportion of missing values for the "Arrival_Delay_in_Minutes" variable. It then drops the examples with missing values.

```
# 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
```

From here we can see that Arrival_Delay_in_Minutes has missing values, let's the proportion of na values

```
# 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
```

We can see that the proportion of na values is very low (less than 3% of the entire dataset), we can drop the na values.

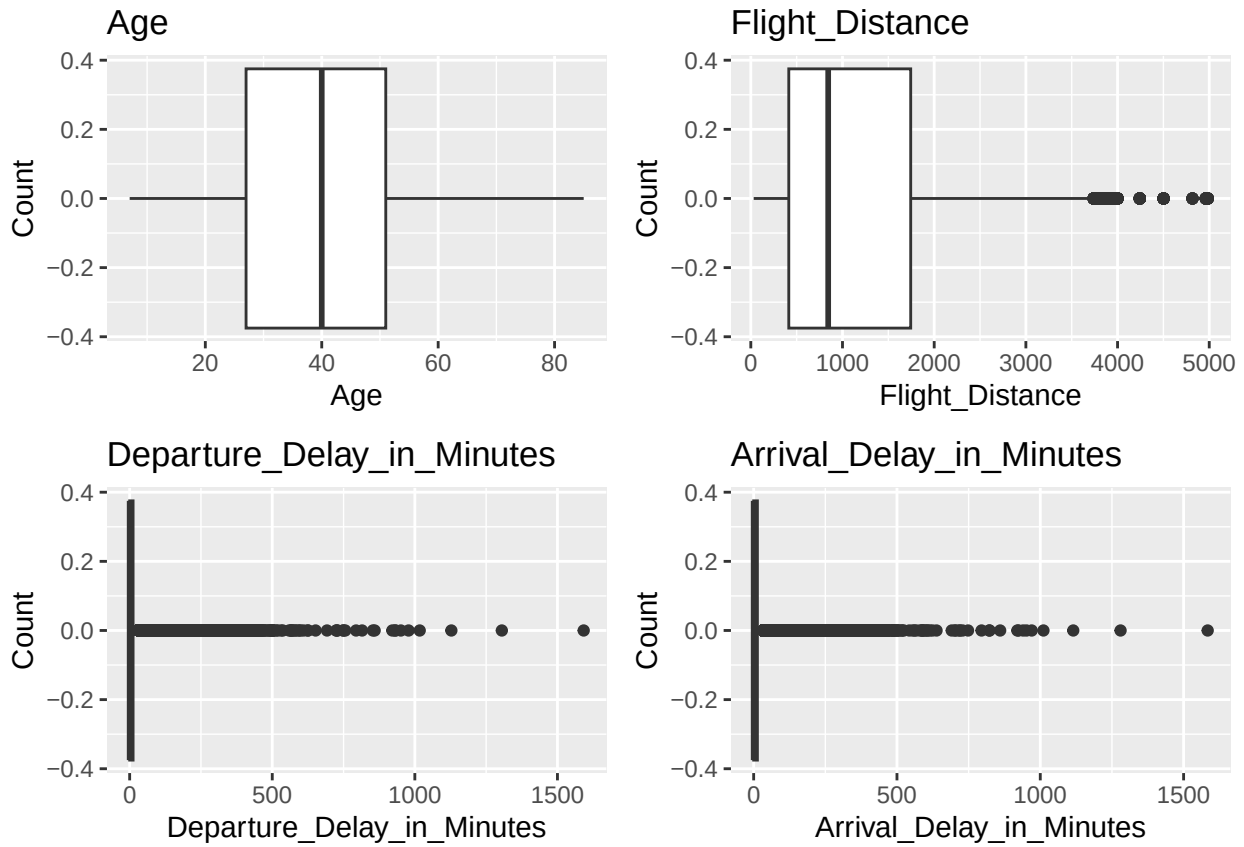
```
# na values are only 0.03% of the data -> drop na values
data = data %>% drop_na(Arrival_Delay_in_Minutes)
```

Outliers

This section creates box plots for each numeric variable in the dataset to visualize the presence of outliers. It also compares the box plots against the target variable (satisfaction).

```
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")
# 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.

Visualization

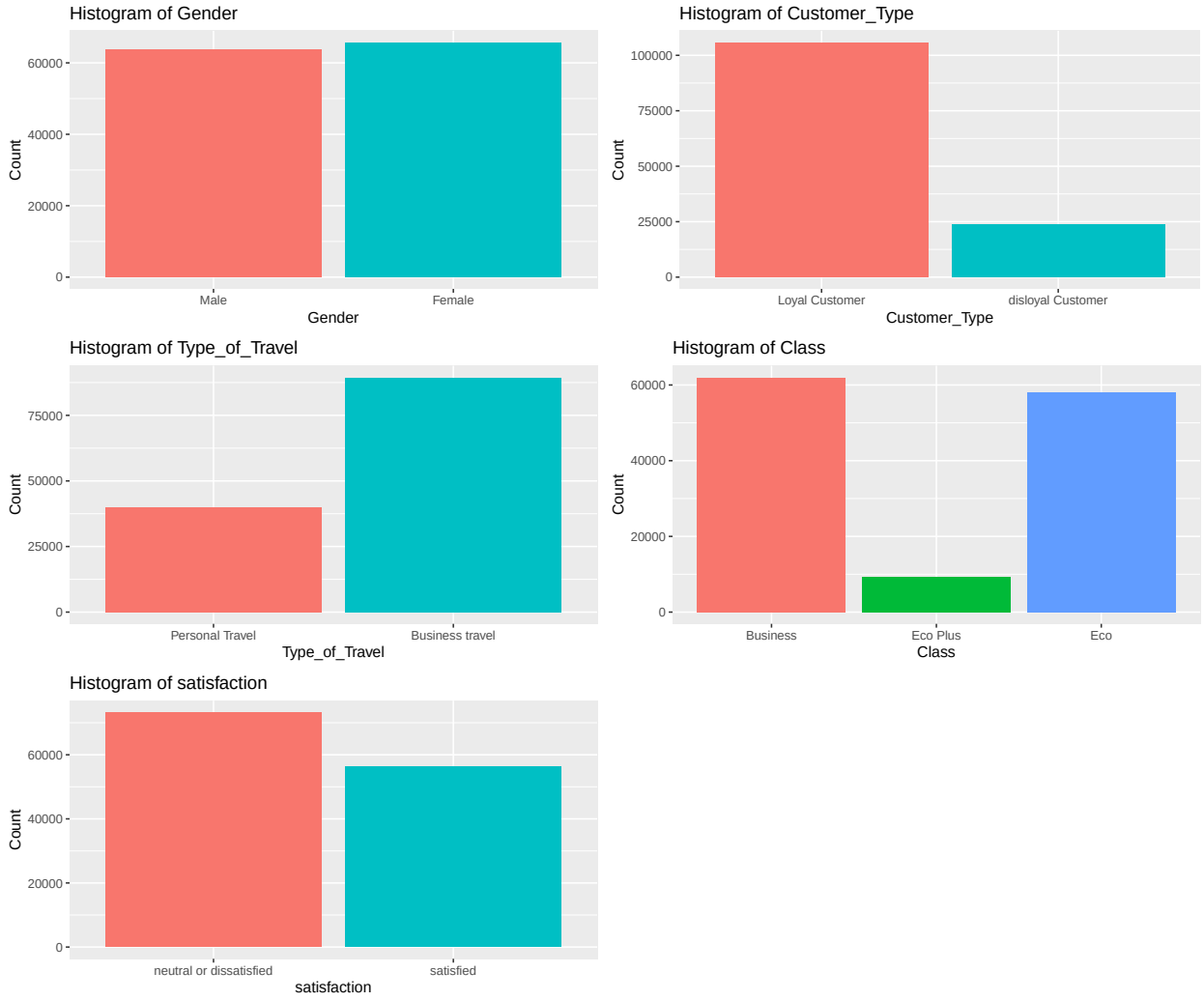
This section includes histograms to visualize the distribution of categorical variables in the dataset.

```
# plot distribution of categorical variables
plots = list()
for (col in names(data)[sapply(data, is.factor)]) {
  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)
```

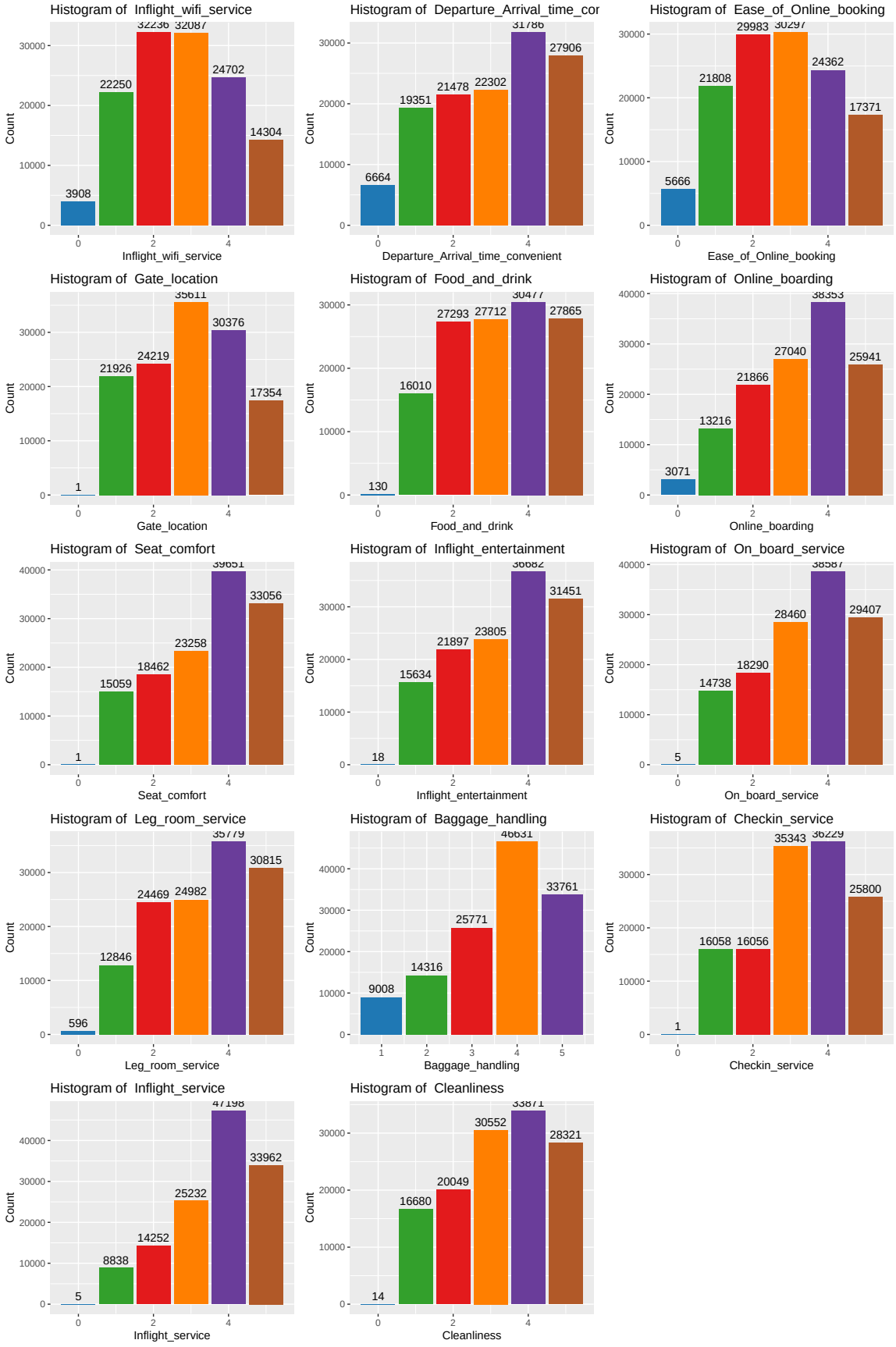


Here we plot the distribution of ratings features.

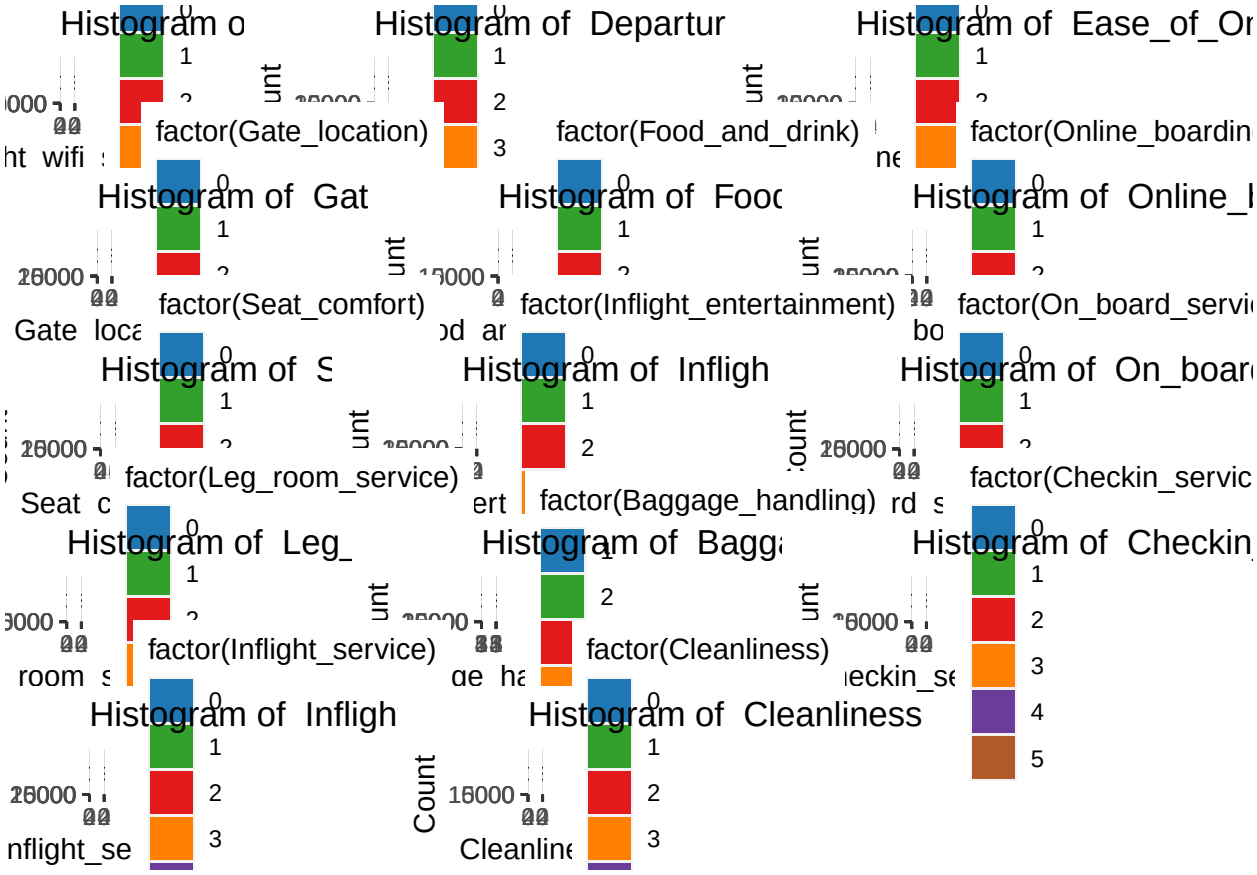
```
# plot distribution of ratings features
plots = list()
my_palette <- c("#1f78b4", "#33a02c", "#e31a1c", "#ff7f00", "#6a3d9a", "#b15928")

for (col in names(data)[sapply(data, is.numeric)]) {
  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 = ..count..), vjust = -0.5) +
    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)
```

```
## Warning: The dot-dot notation (`..count..`) was deprecated in ggplot2 3.4.0.
## i Please use `after_stat(count)` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```


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

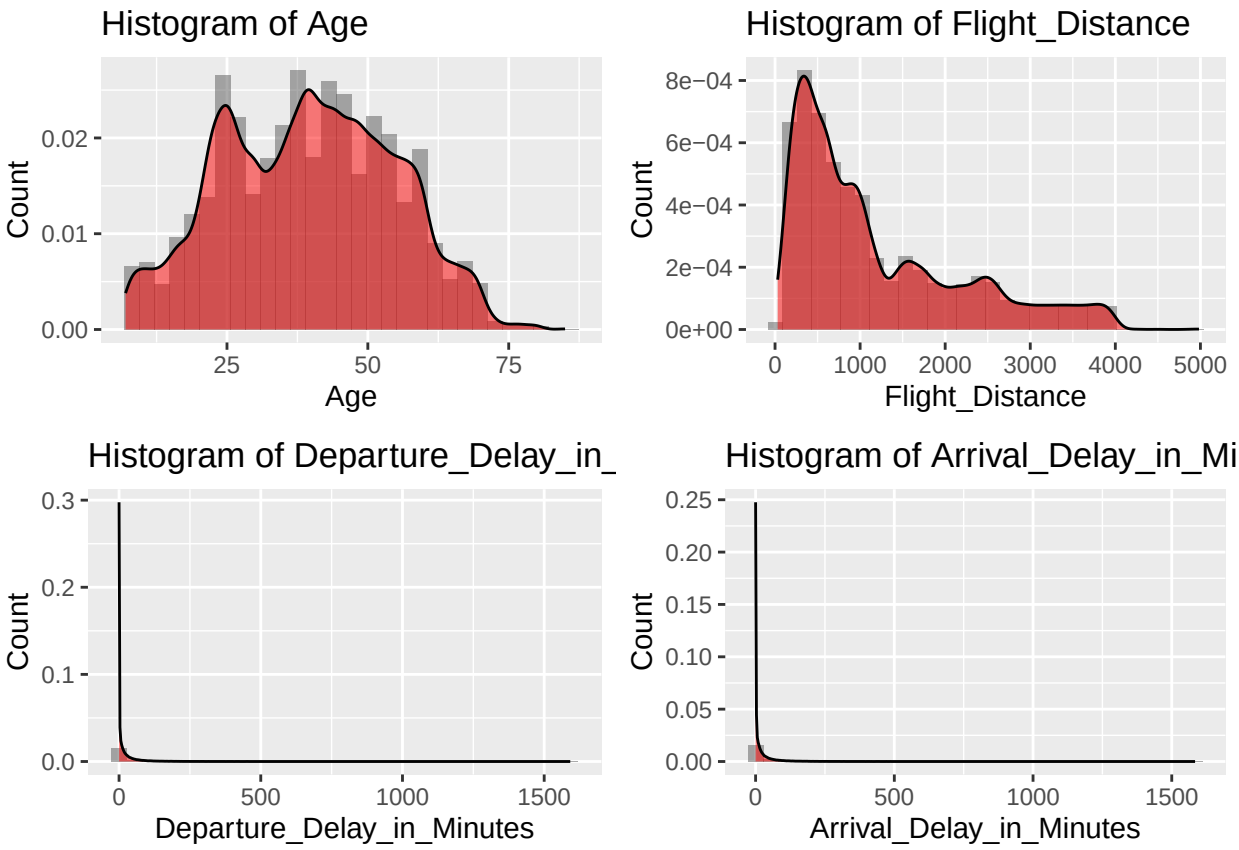
```
plots <- list()
for (col in names(data)[sapply(data, is.numeric)]) {
  if (!col %in% ratings_fts_names) {
    next
  }
  plot <- ggplot(data, aes(x = .data[[col]], fill = factor(.data[[col]]))) +
    geom_bar() +
    geom_text(stat = 'count', aes(label = ..count..), vjust = -0.5) +  # Add count labels below each ba
    labs(title = paste("Histogram of ", col), x = col, y = "Count", bins = 6) +
    scale_fill_manual(values = my_palette) +  # Adding the custom color palette
    facet_grid(. ~ satisfaction)  # Separate the plots based on 'satisfaction'

  plots[[col]] <- plot
}

# Adjust the heights of the plots using 'heights' argument in grid.arrange
grid.arrange(grobs = plots, ncol = 3)
```



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

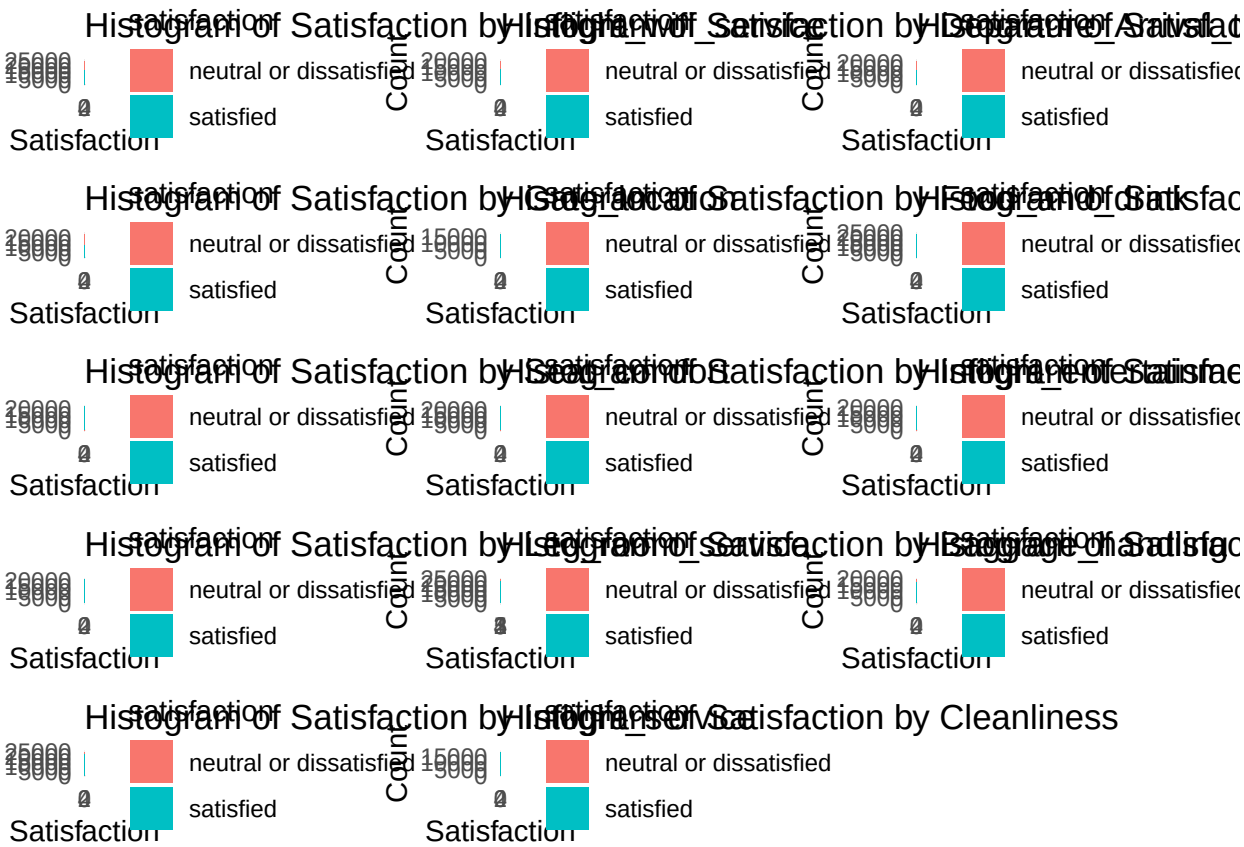
```
# plot distribution and density of numeric variables excluding ratings features
plots = list()
for (col in names(data)[sapply(data, is.numeric)]) {
  if (col %in% ratings_fts_names) {
    next
  }
```

```
  plot = ggplot(data, aes(x = .data[[col]])) +
  geom_histogram(aes(y = after_stat(density)), bins = 30, alpha = 0.5) +
  geom_density(alpha = 0.5, fill = "red") +
  labs(title = paste("Histogram of", col), x = col, y = "Count")

  plots[[col]] = plot
}

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

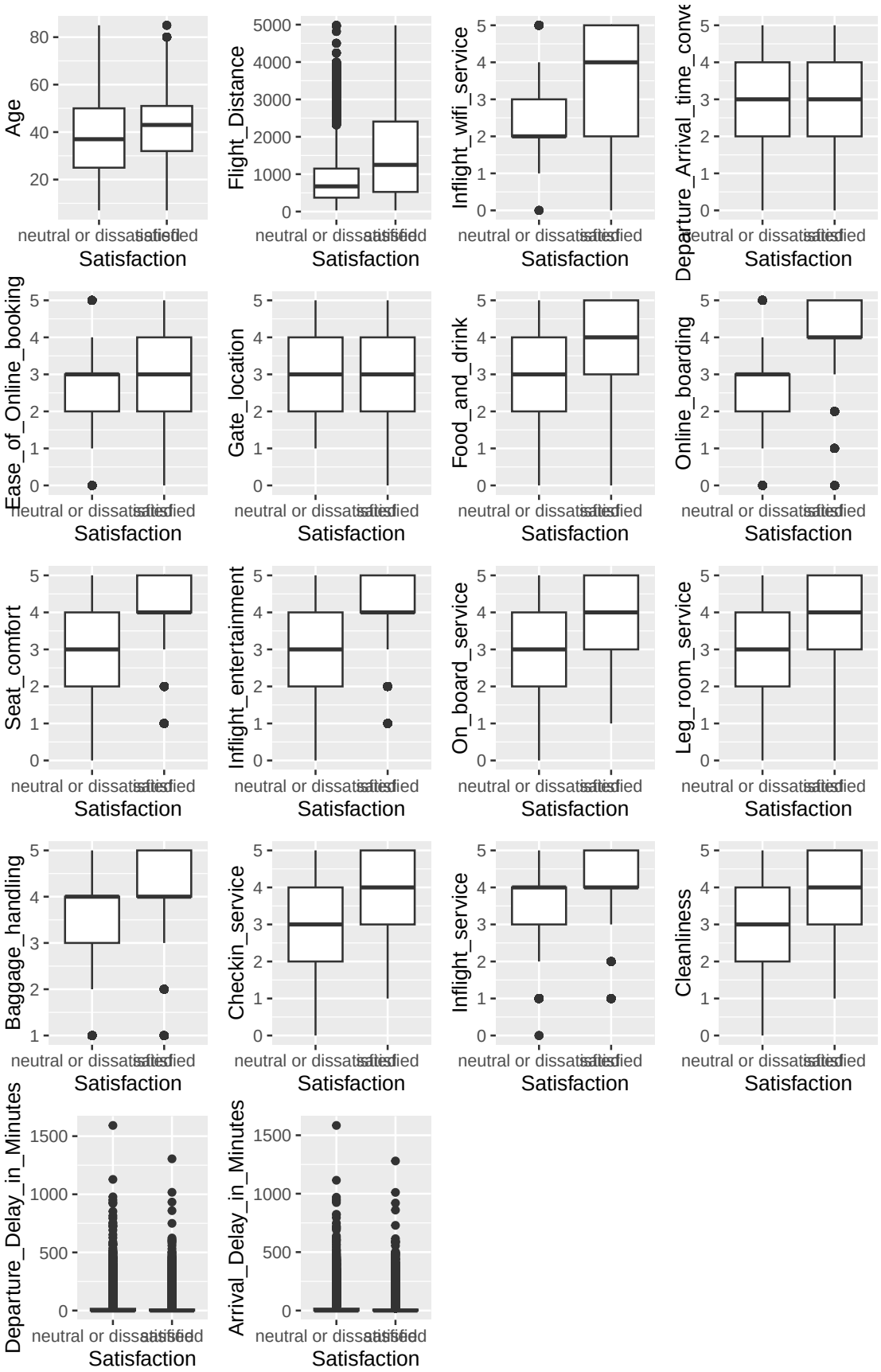



```
# plots categorical variables vs satisfaction
plots = list()
for (col in names(data)[sapply(data, is.factor)]) {
  if (col == "satisfaction") {
    next
  }
  plot = ggplot(data, aes(x = satisfaction, fill = .data[[col]])) +
  theme_minimal() +
  geom_bar(position = "dodge") +
  labs(title = paste("Histogram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

  plots[[col]] = plot

}

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


```r
# plots ratings features vs satisfaction
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]], 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 = 3)
```




```
# plots numeric variables vs satisfaction
plots = list()
for (col in names(data)[sapply(data, is.numeric)]) {
  if (col == "satisfaction") {
    next
  }
  plot = ggplot(data, aes(x = satisfaction, y = .data[[col]])) +
  geom_boxplot() +
  labs(x = "Satisfaction", y = col)

  plots[[col]] = plot

}

grid.arrange(grobs = plots, ncol = 4)
```


Age
Flight_Distance
Inflight_wifi_service
Departure_Arrival_time_conve
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
Departure_Delay_in_Minutes
Arrival_Delay_in_Minutes
neutral or dissatisfied
satisfied
Satisfaction

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)]

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

```
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.

```
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.

```
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
```

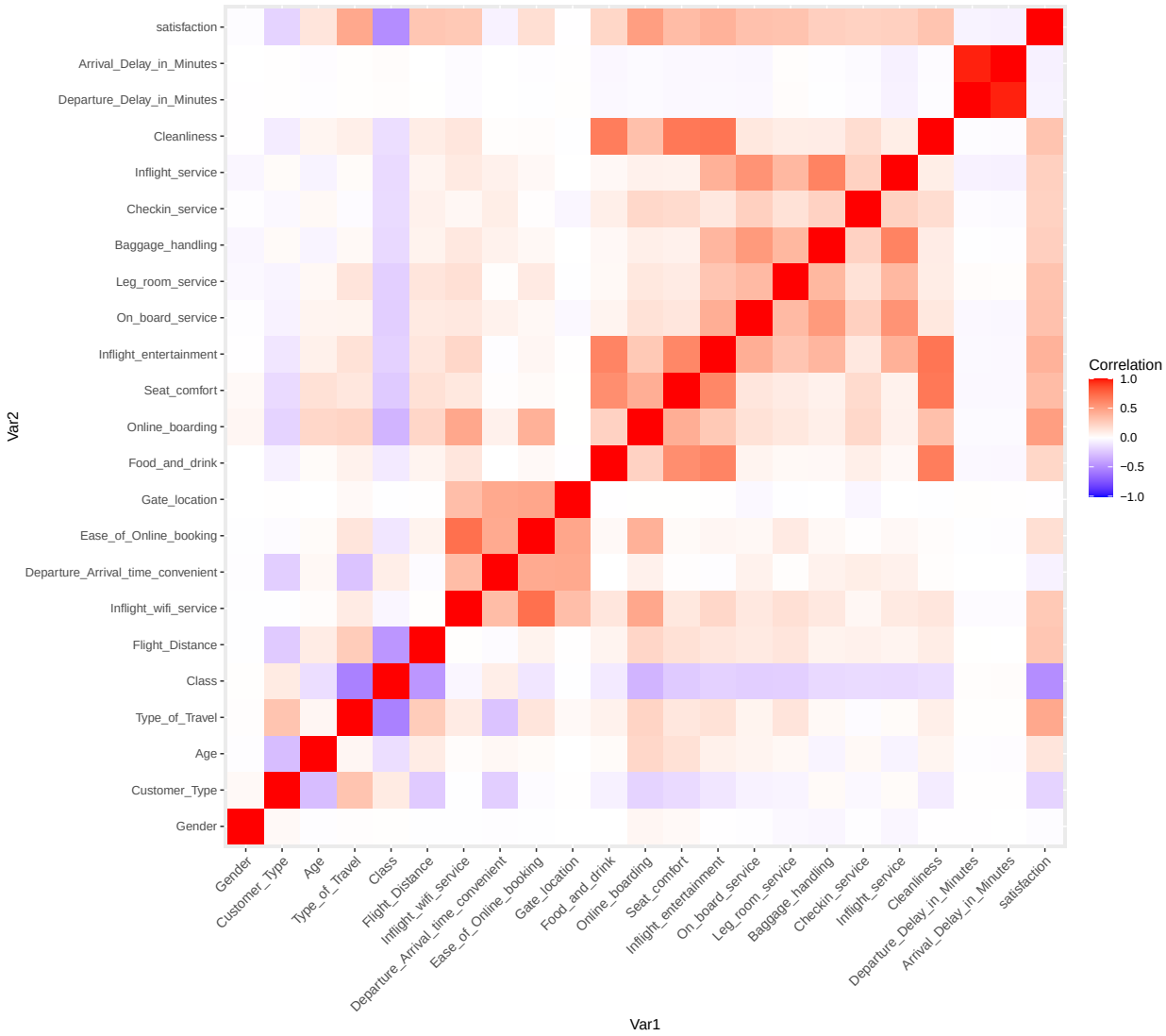
```r
prop.table(table(test_true))
```

```
## 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.

```r
# 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()
```




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

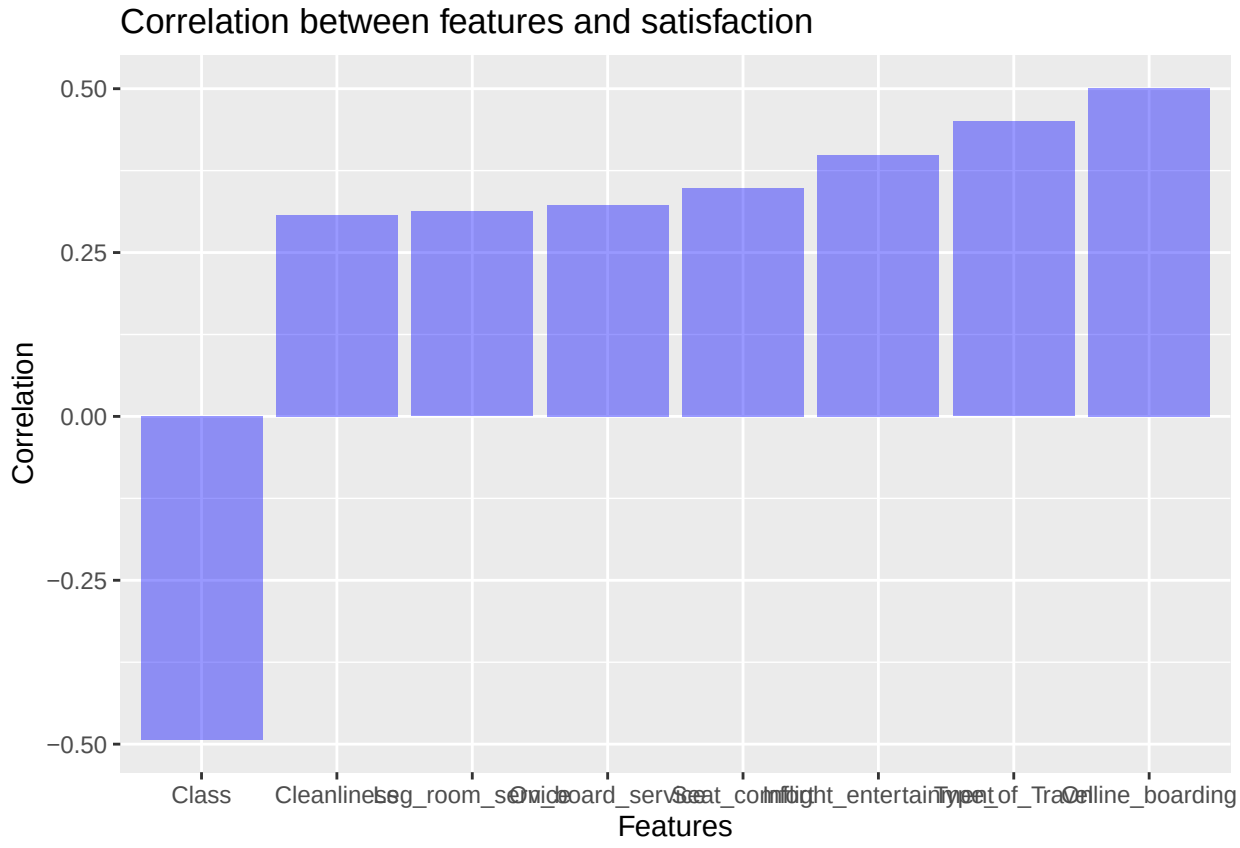
```
# Find high correlated features with satisfaction
# TODO: do the same with different threshold to find differences
# NOTE: i decided to use 0.3 as threshold
satisfaction_corr <- correlation_matrix['satisfaction',]
high_corr_satis <- names(satisfaction_corr[abs(satisfaction_corr) > 0.3 | abs(satisfaction_corr)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

```
## [1] "Type_of_Travel"         "Class"                  "Online_boarding"
## [4] "Seat_comfort"           "Inflight_entertainment" "On_board_service"
## [7] "Leg_room_service"       "Cleanliness"
```

```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
## Online_boarding              Online_boarding   0.5016203
## Seat_comfort                    Seat_comfort   0.3485759
## Inflight_entertainment Inflight_entertainment   0.3983339
## On_board_service             On_board_service   0.3223292
## Leg_room_service             Leg_room_service   0.3125570
## Cleanliness                       Cleanliness   0.3068906
```

```r
# 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')
```

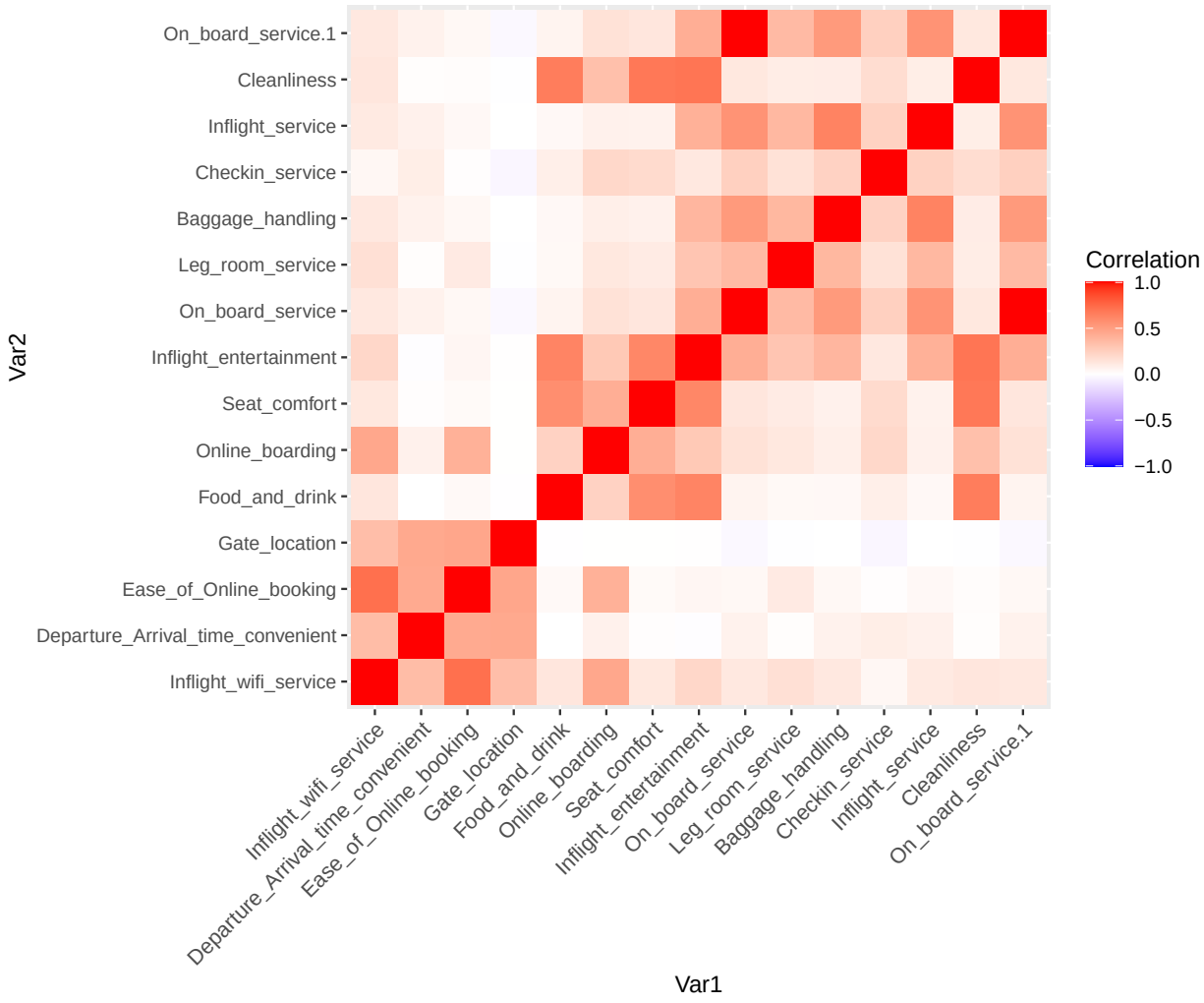



```r
par(mfrow = c(1, 1))
```

```
#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)]

# 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))

# 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)
```

```r
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


#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
```

```r
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")
```