What led our hotel room got cancelled prior to check-in?

Goal: Every year, people around the world is traveling around with a lot of different purposes, such as senior company employees has to meet with some of the staff member from other city, tourists visit some famous sightseeing around the world or professional athletes play an away game in different city, which they need somewhere to spend the night. Typically, most of the travelling people are living in an hotel room for nights, where they required to check-in in order to stay in the hotel. However, sometimes booking a hotel could be very frustrated that some room could got cancelled because of a lot of numerous reasons, so my goal is to see what factors that led their hotel room got cancelled even some of the guest made prior reservation to the hotel,

Description of the Data: The Data set was coming from Kaggle, The dataset can be finding from here: https://www.kaggle.com/datasets/jessemostipak/hotel-booking-demand
There are 119390 sets of observations, each observations has 32 variables: Here are the meaning for each variables:

- Hotel (Categorical): The type of Hotel that this group of guests reserved (City or Resort)
- Is_canceled (Binary): Identify the bookings was being cancelled or not (1 is canceled, 0 is not)
- Lead_time (Numerical): The days between the guest reserved the hotel to actual check-in or being cancelled (Range from 0-737)
- Arrival_date_year (Numerical): The year that the guest arrived at this hotel (2015-2017)
- Arrival_date_month (Categorical): The month that the guest arrived at this hotel (January-December)
- Arrival_date_week_number (Numerical): The week number that the guest arrived at this hotel (Range from 1-53)
- Arrival_date_day_of_month (Numerical): The day of the month that the guest arrived at this hotel (Range from 1-31)
- Stays_in_weekend_nights (Numerical): The number of weekend nights (Saturday or Sunday) that the guest stayed at this hotel (Range from 0-19)
- Stays_in_week_nights (Numerical): The number of week nights (Monday to Friday) that the guests stayed at this hotel (Range from 0-50)
- Adults (Numerical): Number of adults in this group (Range from 0-55)
- Children (Numerical): Number of children in this group (Range from 0-10)
- Babies (Numerical): Number of babies in this group (Range from 0-10)
- Meal (Categorical): Type of meals that the group selected for their hotel (Bed and Breakfast, Half Board, Full Board, Self-Catering or Undefined)
- Country (Categorical): The country that the guest originally coming from (Range from 178 countries around the globe)
- Market_segment: The methods that the hotel distribute their hotel information to other companies (Online Travel agents, Offline Tour Operators/Travel Agents, Aviation, Complementary, Corporate, Direct, Groups and Undefined

- Distribution_channel: The way that hotel distribution their Booking to those information (Corporate, Direct, Global distribution system, Travel Agents/Tour Operators, Undefined)
- Is_repeated_guest (Binary): The booking was a previously repeated guest (0 is not, 1 is yes)
- Previous_cancellations (Numerical): The Number of previous bookings that were cancelled by the customer prior to the current booking (Ranged from 0-26)
- Previous_bookings_not_canceled (Numerical): The number of previous bookings not cancelled by the customer prior to the current booking (Ranged from 0-72)
- Reserved_room_types (Categorical): The code of the room type that guest initially received (Ranged from A-P)
- Assigned_room_types (Categorical): The code of the room type that guest actually received (Ranged from A-P)
- Booking_changes (Numerical): The number of booking changes prior to this reservation (Rnage from 0-21)
- Deposit_type (Categorical): The type of deposit that guarantee to the booking (No deposit, Non refund, refundable)
- Agent (Categorical): ID of the travel agency that made the booking
- Company (Categorical): ID of the company/entity that made the booking
- Days_in_waiting_list (Numerical): Days was on the waitlist prior confirmed by the customer (Ranged from 0-391)
- Customer_type (Categorical): The type of guests booking this hotel room (Contract, Group, Transient, Transient-party)
- Adr (Numerical): Average daily rate, where defined by dividing the sum of all lodging transactions by the total number of staying nights (Ranged from -6.38 to 5400)
- Required_car_parking_spaces (Numerical): The number of parking spaces required by the customer (Ranged from 0 to 8)
- Reservation_status (Categorical): The status of this group of guests (Canceled, check-out, no-show)
- Reservation_status_date (Categorical): The date of the last status set (Range the date from 10/16/2014 to 09/13/2017

Adjustment of our dataset:
I merge adults, children and babies into people, which is still numerical that range from 0 to 55
Code: Hotel_bookings$people <-
Hotel_bookings$adults+Hotel_bookings$children+Hotel_bookings$babies

I merge the number of weekend night and week night into number of days staying, which is still numerical that range from 0
Code: Hotel_bookings$stays <-
Hotel_bookings$stays_in_weekend_nights+Hotel_bookings$stays_in_week_nights

I then use initial and assigned room type to see do they have the same room, which is a binary of True or False

Code: Hotel_bookings$matched <- ifelse(Hotel_bookings$reserved_room_type == Hotel_bookings$assigned_room_type, "1", "0")

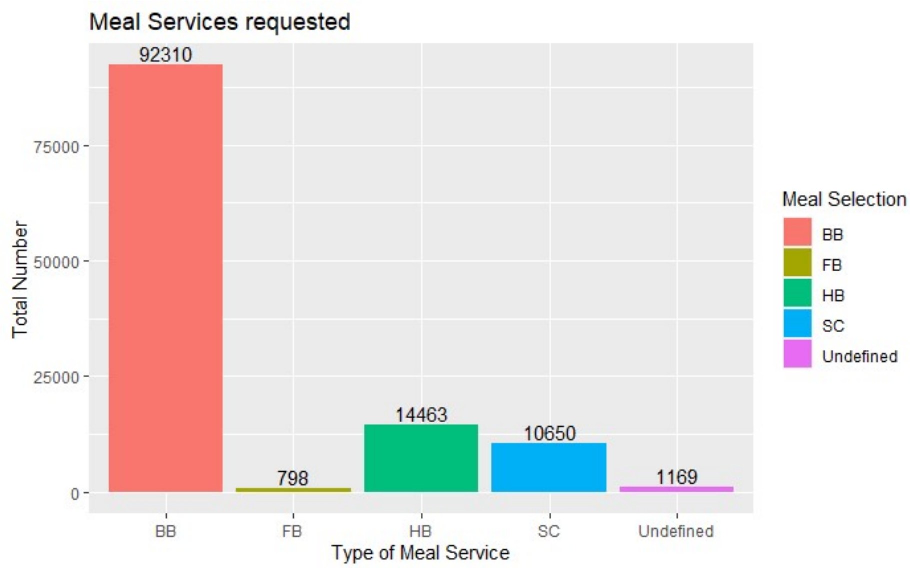
We then delete unnecessary rows of data use the following code: subset(Hotel_bookings, select = -c(arrival_date_year,arrival_date_month, arrival_date_week_number, arrival_date_day_of_month, agent, company, reservation_status_date, adults, children, babies, stays_in_weekend_nights, stays_in_week_nights, country, hotel, reservation_status, reserved_room_type, assigned_room_type))

So the initial addition from 35 has been reduced to 18

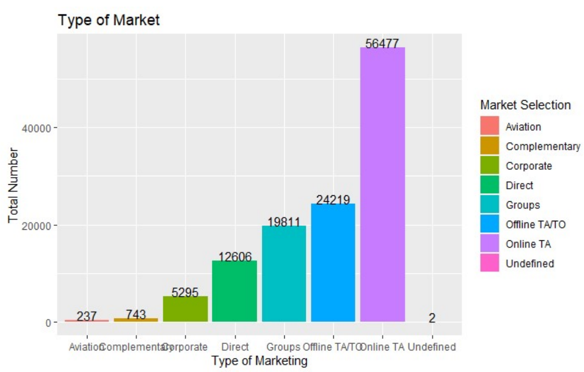
Exploratory data analysis and distributions:
Categorical:
Type of Hotel:

Is_canceled:

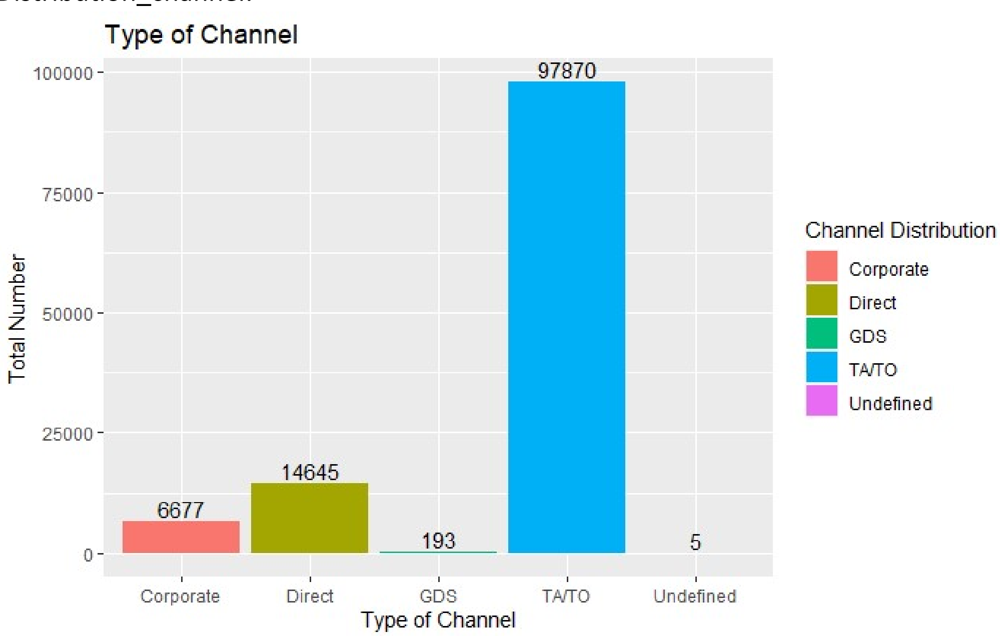
Meals:



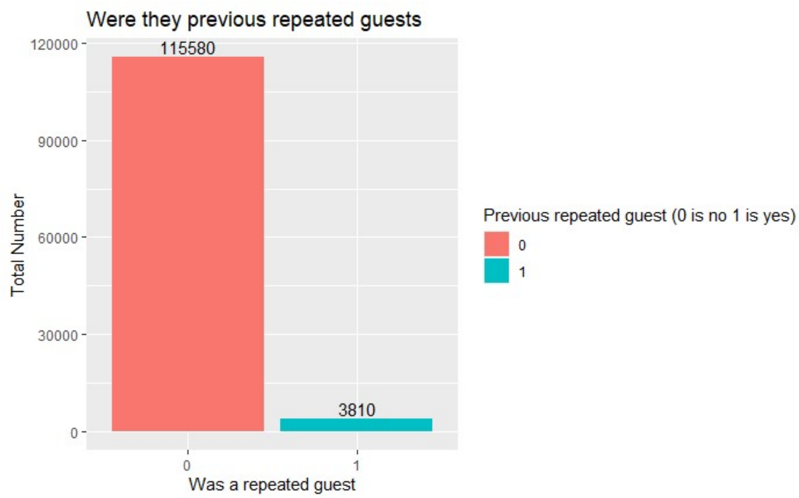
Market_segment:



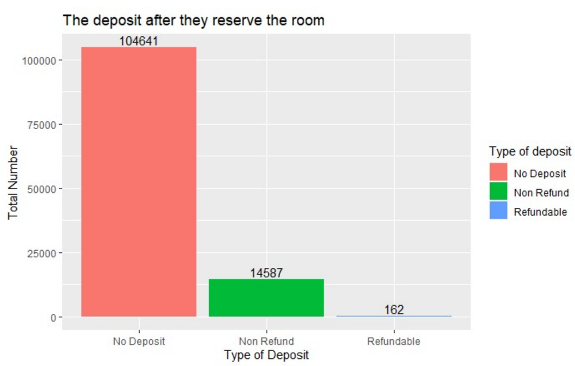
Distribution_channel:



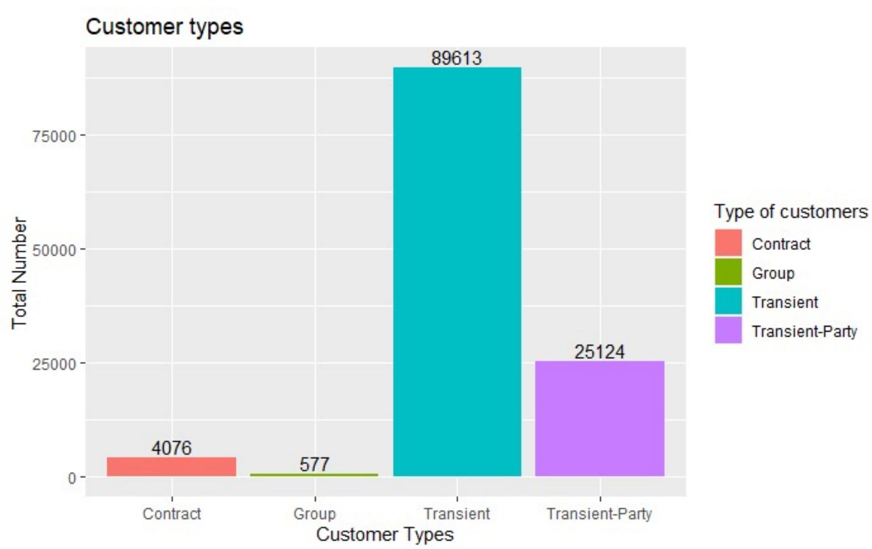
Is_repeated_guest:



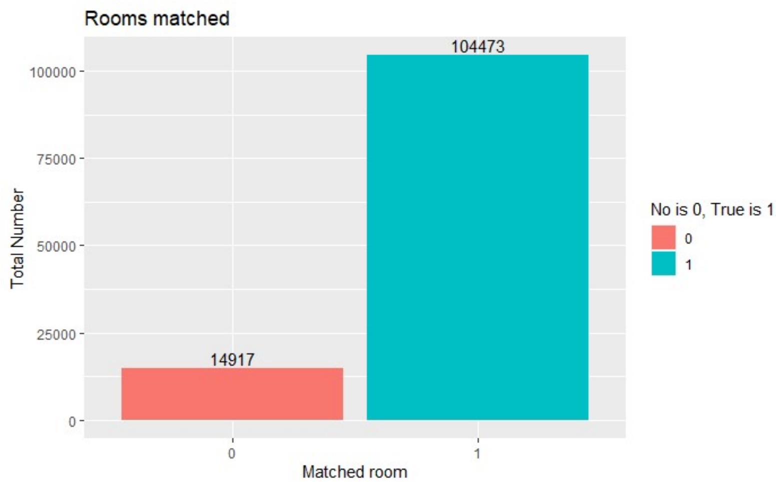
Deposit_types:



Customer_types:

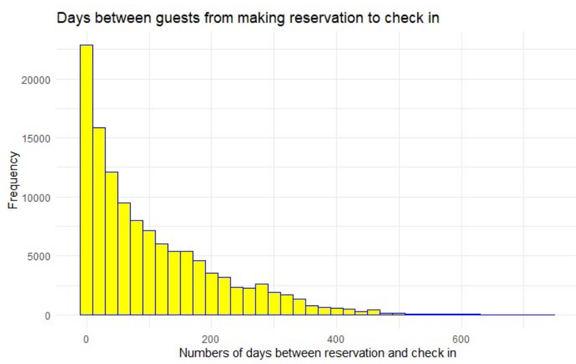


Matched room:

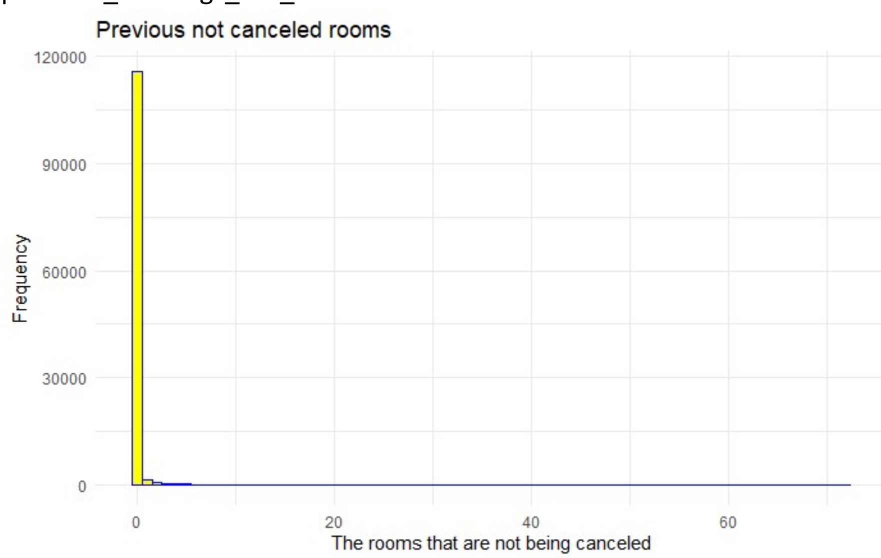


Numerical:

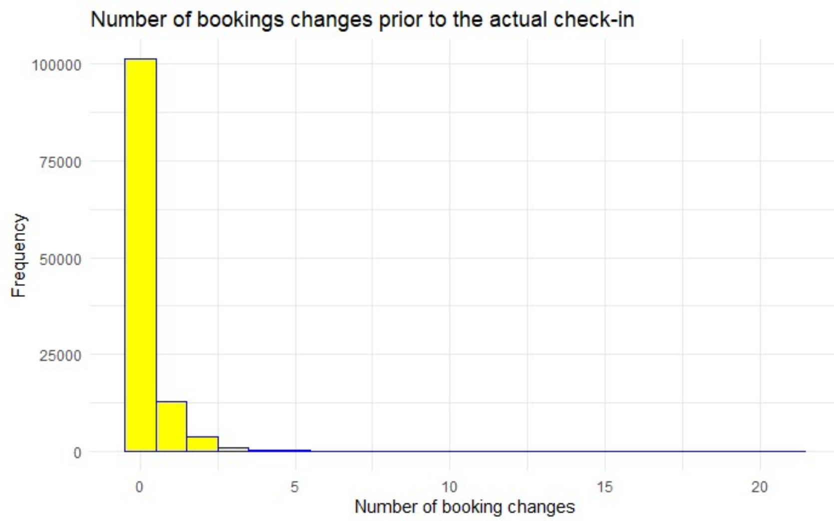
Lead_time:



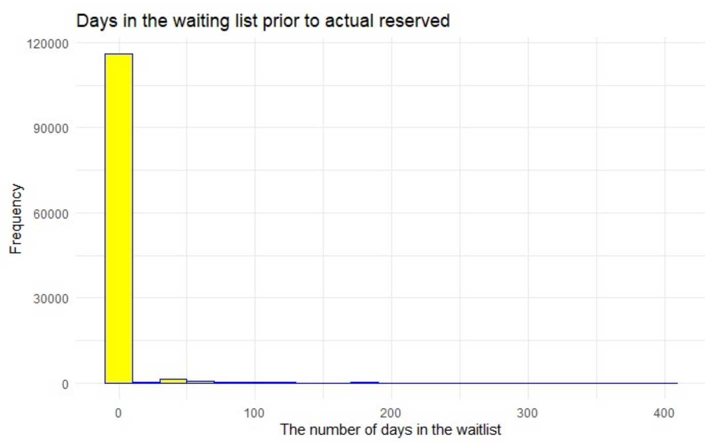
previous_bookings_not_canceled



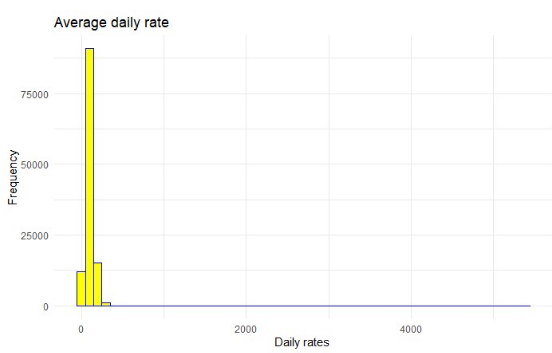
Booking changes:



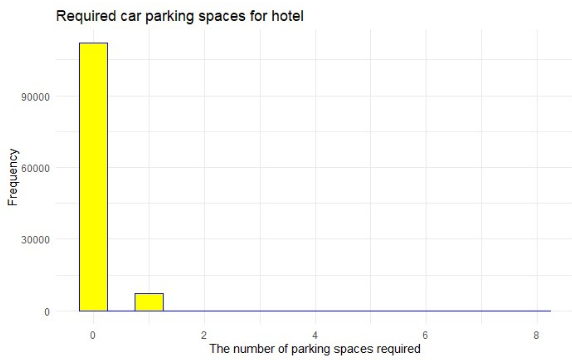
Days in the waiting list:



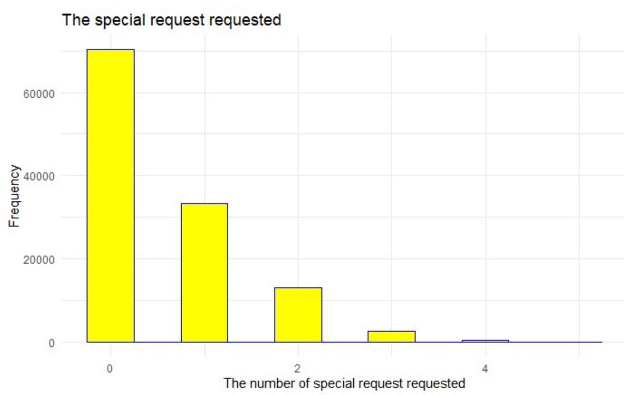
Average daily rate:



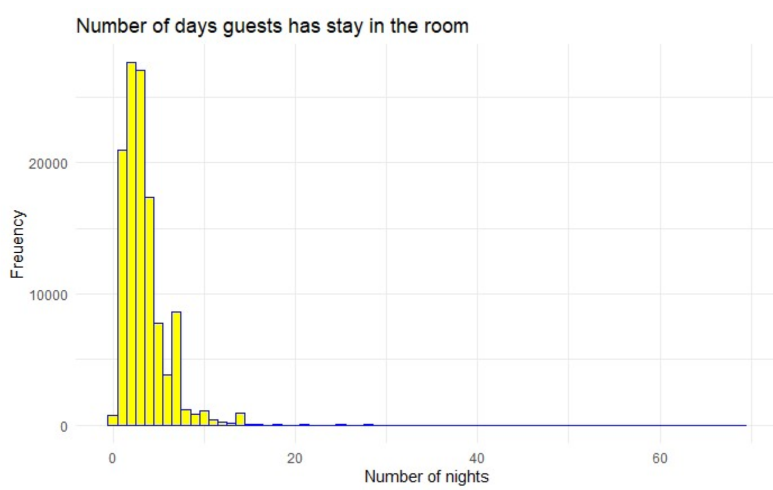
Required car parking spaces:



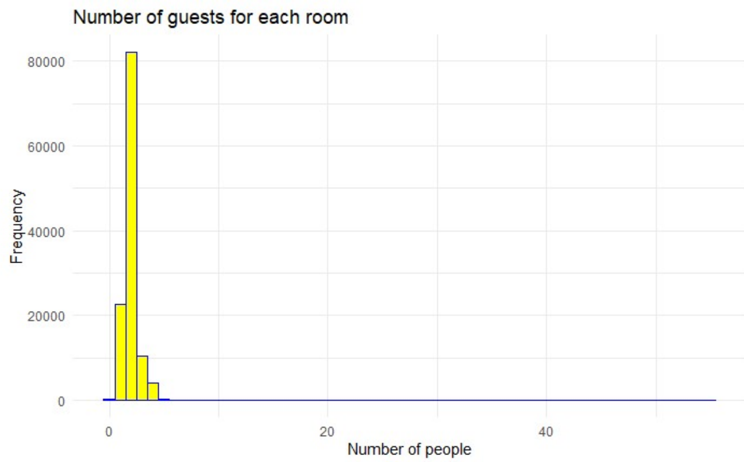
Special requests:



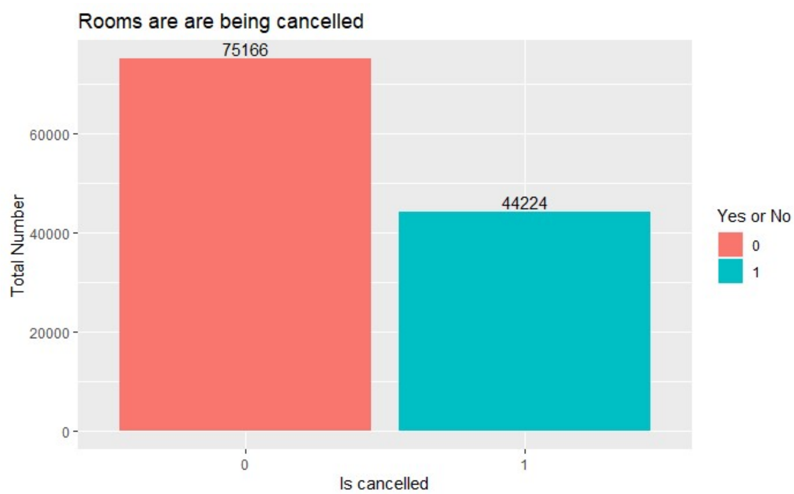
Night stay:



People:



Distribution of the response variables: Is_Canceled is our response variables



Our Rational of the fitted model:

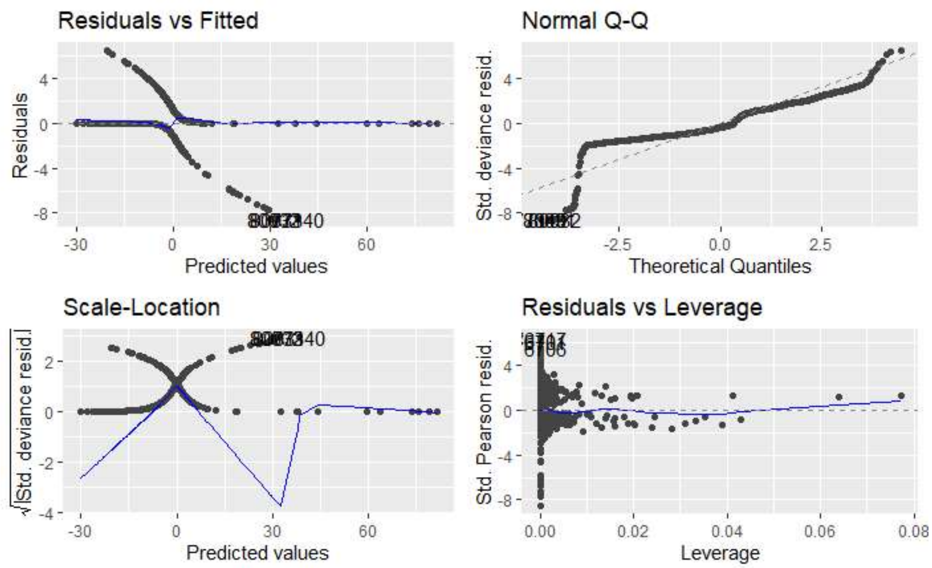
Originally, I was planned for using the lm function, which is the fitting linear models for carrying out the regression, but I have been noticed that our dataset has a lot of categorical and binary variables than the numeric variables, so it is decided to use the glm function, which is the generalized linear model to give a specific description of our best predictors. I will compare the full model and reduced model from both glm selection and then to determine, which linear regression model would be the best predictor.

Our dependent variable is Is_canceled, which the binary of 0 or 1 to determine the factors that would likely to lead the hotel room cancelled.

So for the full model: we select all the variables after some deletion of unnecessary variables and distributed into binomial distribution. We select out the significant factors inside the full model and remove the insignificant and the category that their VIF, which is the variance inflation factor that is above 5 as my reduced model. Then I use glm function again, but with those reduced categorical.

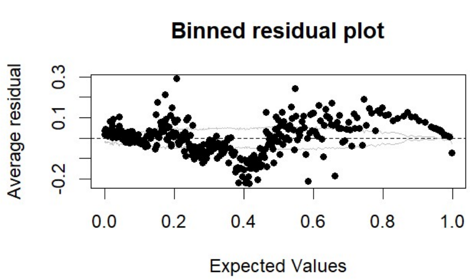
To determine which one, I decided to use anova function for both model to test their significance of which one would be the model of our selections.

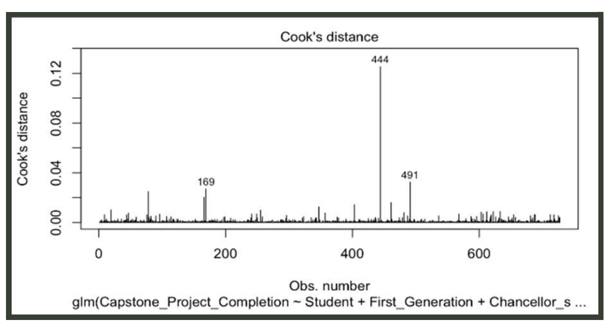
We then do some assumptions and the testing portions, where I been noticed that the accuracy of my model is around 82 percent by using the AUC plot with 30-70 test and train dataset, which is the proportion of the true results among the total number of cases examined. During the assumption testing, in the normal QQ Plot, I saw that the data at the beginning was violated the assumptions, where some of our points was off the plot line. For the residuals vs leverage plot, I noticed that most of the points are clustering at the Leverage value of 0, so it is also indicate that the assumptions are violated when using the generalized linear models.



From the binned residual plot below, I can conclude although most of our residuals follow within ±2 SE of our expected values, There are a lot of residuals that has been fallen out the expected values

In observance of these outliers, we wanted to identify the specific influential observations in our data. We conducted the Cook's distance method to identify the influential observations which could further be used in more detailed analysis.





Then we look at the Variance inflator that all the variables from my reduced model is within the value around 1, which displays that no multicollinearity exists within our model

```
                                  GVIF Df GVIF^(1/(2*Df))
lead_time                     1.172163  1        1.082665
meal                          1.180464  4        1.020955
is_repeated_guest             1.285010  1        1.133583
previous_cancellations        1.472305  1        1.213386
previous_bookings_not_canceled 1.499041  1        1.224353
booking_changes               1.020656  1        1.010275
customer_type                 1.350050  3        1.051296
adr                           1.278021  1        1.130496
total_of_special_requests     1.072047  1        1.035397
stays                         1.128518  1        1.062317
people                        1.220434  1        1.104733
matched                       1.013263  1        1.006609
```

Results of our data analysis:

Based on the comparison between the full and reduced model, I decided that to use the reduced model, where the variables are more focused on the significant factors that lead our hotel room got canceled.

Here is the table:

```
Call:
glm(formula = is_canceled ~ lead_time + meal + is_repeated_guest +
    previous_cancellations + previous_bookings_not_canceled +
    booking_changes + customer_type + adr + total_of_special_requests +
    stays + people + matched, family = binomial, data = Hotel_bookings2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-8.4904  -0.8436  -0.3956   0.8898   6.4027

Coefficients:
                                Estimate Std. Error z value Pr(>|z|)
(Intercept)                   -4.202e+00  6.808e-02 -61.715  < 2e-16 ***
lead_time                      5.956e-03  7.705e-05  77.293  < 2e-16 ***
mealFB                         8.563e-01  8.741e-02   9.796  < 2e-16 ***
mealHB                        -2.216e-01  2.330e-02  -9.510  < 2e-16 ***
mealSC                         1.022e-01  2.367e-02   4.317 1.58e-05 ***
mealUndefined                 -3.287e-01  8.238e-02  -3.990 6.60e-05 ***
is_repeated_guest             -1.182e+00  8.364e-02 -14.133  < 2e-16 ***
previous_cancellations         3.104e+00  5.690e-02  54.550  < 2e-16 ***
previous_bookings_not_canceled -6.041e-01  2.617e-02 -23.085  < 2e-16 ***
booking_changes               -5.239e-01  1.550e-02 -33.790  < 2e-16 ***
customer_typeGroup            -2.166e-02  1.640e-01  -0.132 0.894950
customer_typeTransient         1.484e+00  5.229e-02  28.372  < 2e-16 ***
customer_typeTransient-Party   2.029e-01  5.462e-02   3.714 0.000204 ***
adr                            3.569e-03  1.676e-04  21.301  < 2e-16 ***
total_of_special_requests     -7.997e-01  1.061e-02 -75.370  < 2e-16 ***
stays                         -1.142e-02  2.958e-03  -3.861 0.000113 ***
people                         4.653e-03  1.039e-02   0.448 0.654263
matched1                       2.089e+00  3.842e-02  54.363  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
```

Our equation is listed below with the reduced model below:

Is_canceled=-4.202+5.956x10^{-3}(lead_time)+0.8563(mealFB)-0.222(mealHB)+0.102(mealSC)-0.3287(mealUndefined)-1.182(is_repeated_guest)+3.104(previous_cancellations)-0.604(previous_bookings_not_canceled)-0.524(booking_changes)-0.0217(customer_typegroup)+0.1484(customer_typeTransient)+2.029(customer_typeTransient-Party)+3.569x10^{-3}(adr)-0.7997(total_of_special_requests)-0.01142(stays)+4.653x10^{-3}(people)+0.2089(matchedYes)

Where are the stars listed above the summary table can be considered as significant factors.

Conclusion and discussions:

A little bit of surprised to see there are 12 significant factors that led to their room cancelle, but at the same time, it was factual, because we will always heard a lot of reasons that they decided to cancelled their room.

I believe that I would try to work a dataset that with even numbers of hotel type between City and Resort, and at the same time, try to keep the raw data as much as possible, and considered a similar hotel booking from like two to three years ago and do a comparison to this that to discover the trend of hotel cancellation for these few years. Also, I might consider doing an extended project that compare the factors between Resort and City hotel to see are there any unique factors that led their room got cancelled or do they have some similar factors.

References:

Original Dataset: https://www.kaggle.com/datasets/jessemostipak/hotel-booking-demand

Appendix: Program Code for R:

Hotel Cancellation Study

Leo Shi

2024-05-14

```r
#packages
library(readr)
```

```
## Warning: package 'readr' was built under R version 4.1.3
```

```r
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 4.1.3
```

```
## Warning: package 'ggplot2' was built under R version 4.1.3
```

```
## Warning: package 'tibble' was built under R version 4.1.3
```

```
## Warning: package 'tidyr' was built under R version 4.1.3
```

```
## Warning: package 'purrr' was built under R version 4.1.3
```

```
## Warning: package 'dplyr' was built under R version 4.1.3
```

```
## Warning: package 'stringr' was built under R version 4.1.3
```

```
## Warning: package 'forcats' was built under R version 4.1.3
```

```
## Warning: package 'lubridate' was built under R version 4.1.3
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.2     v purrr     1.0.1
## v forcats   1.0.0     v stringr   1.5.0
## v ggplot2   3.4.2     v tibble    3.2.1
## v lubridate 1.9.2     v tidyr     1.3.0
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
e errors
```

```r
library(ggplot2)
library(gridExtra)
```

```
## Warning: package 'gridExtra' was built under R version 4.1.3
```

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

```r
library(MASS)
```

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

```r
library(dplyr)
library(car)
```

```
## Warning: package 'car' was built under R version 4.1.3
```

```
## Loading required package: carData
```

```
## Warning: package 'carData' was built under R version 4.1.3
```

```
##
## Attaching package: 'car'
##
## The following object is masked from 'package:dplyr':
##
##     recode
##
## The following object is masked from 'package:purrr':
##
##     some
```

```r
library(pROC)
```

```
## Warning: package 'pROC' was built under R version 4.1.3
```

```
## Type 'citation("pROC")' for a citation.
##
## Attaching package: 'pROC'
##
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```r
library(arm)
```

```
## Loading required package: Matrix
```

```
## Warning: package 'Matrix' was built under R version 4.1.3
```

```
##
## Attaching package: 'Matrix'
##
## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
##
## Loading required package: lme4
```

```
## Warning: package 'lme4' was built under R version 4.1.3
```

```
##
## arm (Version 1.14-4, built: 2024-4-1)
##
## Working directory is C:/Users/Leo Shi/Desktop/Homework Spring 2024
##
##
## Attaching package: 'arm'
##
## The following object is masked from 'package:car':
##
##     logit
```

```r
library(ggcorrplot)
```

```
## Warning: package 'ggcorrplot' was built under R version 4.1.3
```

```r
library(ggfortify)
```

```r
#Display the initial dataset
Hotel_bookings <- read_csv("Hotel_bookings.csv")
```

```
## Rows: 119390 Columns: 32
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (14): hotel, arrival_date_month, meal, country, market_segment, distribu...
## dbl (18): is_canceled, lead_time, arrival_date_year, arrival_date_week_numbe...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
head(Hotel_bookings)
```

```
## # A tibble: 6 x 32
##   hotel        is_canceled lead_time arrival_date_year arrival_date_month
##   <chr>              <dbl>     <dbl>             <dbl> <chr>
## 1 Resort Hotel           0       342              2015 July
## 2 Resort Hotel           0       737              2015 July
## 3 Resort Hotel           0         7              2015 July
## 4 Resort Hotel           0        13              2015 July
## 5 Resort Hotel           0        14              2015 July
## 6 Resort Hotel           0        14              2015 July
## # i 27 more variables: arrival_date_week_number <dbl>,
## #   arrival_date_day_of_month <dbl>, stays_in_weekend_nights <dbl>,
## #   stays_in_week_nights <dbl>, adults <dbl>, children <dbl>, babies <dbl>,
## #   meal <chr>, country <chr>, market_segment <chr>,
## #   distribution_channel <chr>, is_repeated_guest <dbl>,
## #   previous_cancellations <dbl>, previous_bookings_not_canceled <dbl>,
## #   reserved_room_type <chr>, assigned_room_type <chr>, ...
```

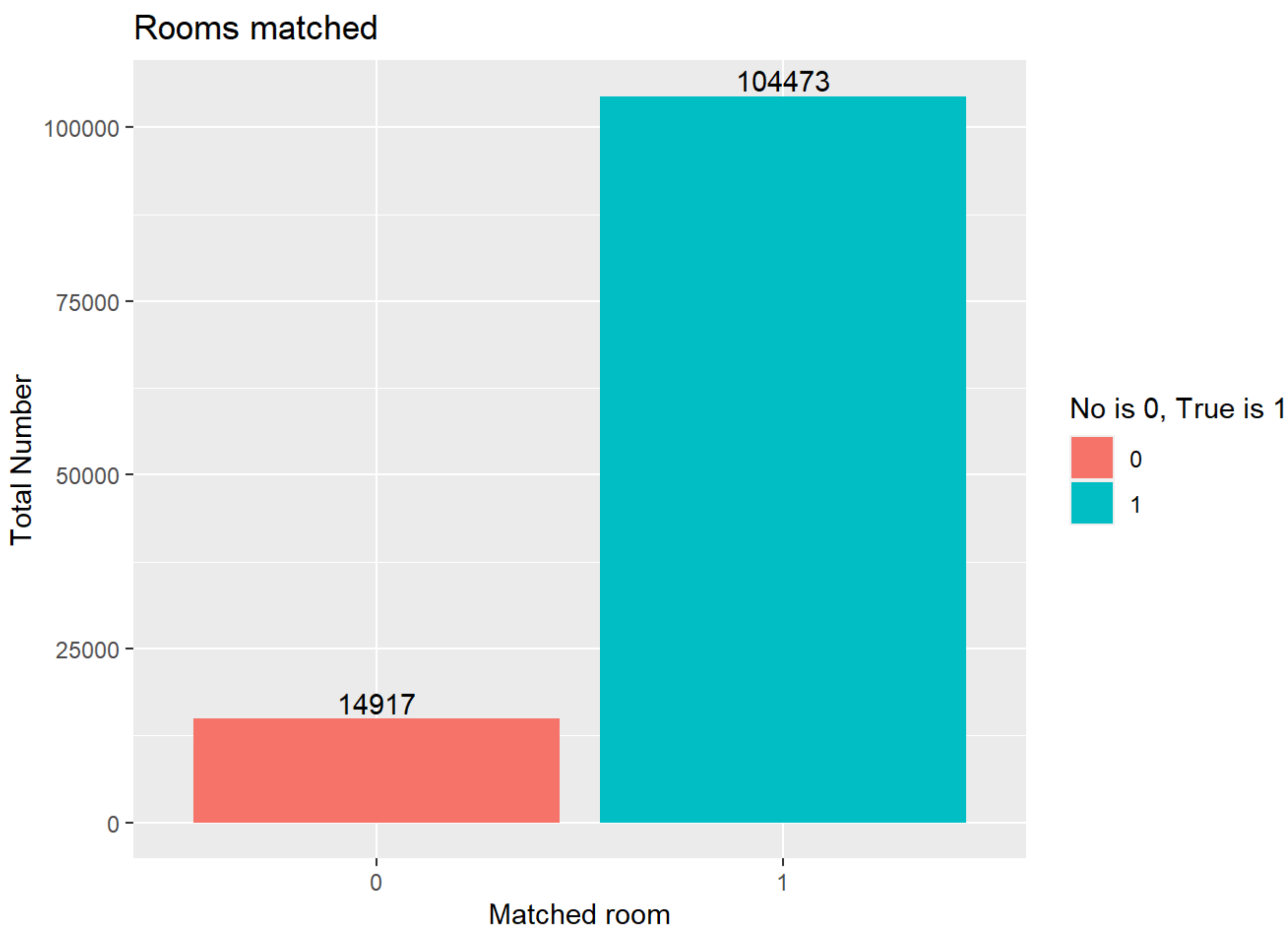
```
#EDA exploration for categorical
#Matching rooms
Hotel_bookings$matched <- ifelse(Hotel_bookings$reserved_room_type == Hotel_bookings$assigned_ro
om_type, "1", "0")
head(as.character(Hotel_bookings$matched))
```

```
## [1] "1" "1" "0" "1" "1" "1"
```

```
matched_room <- table(Hotel_bookings$matched)
matched_room_df <- as.data.frame(matched_room)
colnames(matched_room_df) <- c('Matched room', 'Total Number')
matched_room_df
```

```
##   Matched room Total Number
## 1            0        14917
## 2            1       104473
```

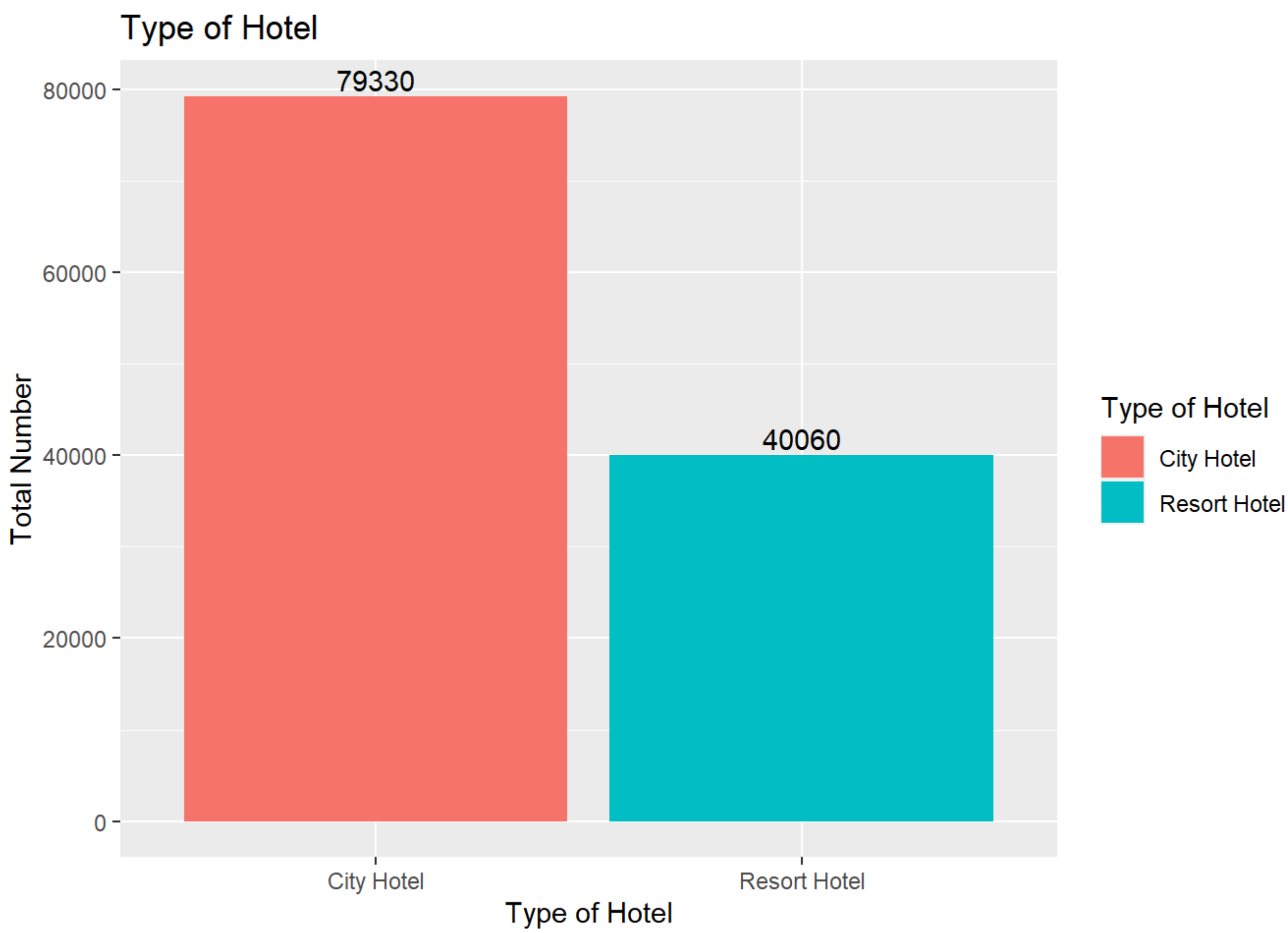
```
# Create the pie chart for market segment
matched_room_chart<- ggplot(data=matched_room_df, aes(x=`Matched room`, y=`Total Number`, fill=`
Matched room`))+
  geom_bar(stat="identity")+
    labs(title = "Rooms matched", fill = "No is 0, True is 1")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=0.9), vjust=-0.25)
matched_room_chart
```




```
hotel_types <- table(Hotel_bookings$hotel)
hotel_types_df <- as.data.frame(hotel_types)
colnames(hotel_types_df) <- c('Type of Hotel', 'Total Number')
hotel_types_df
```

```
##   Type of Hotel Total Number
## 1    City Hotel        79330
## 2  Resort Hotel        40060
```

```
# Create the pie chart for market segment
hotel_types_chart<- ggplot(data=hotel_types_df, aes(x=`Type of Hotel`, y=`Total Number`, fill=`Type of Hotel`))+
  geom_bar(stat="identity")+
    labs(title = "Type of Hotel")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=0.9), vjust=-0.25)
hotel_types_chart
```

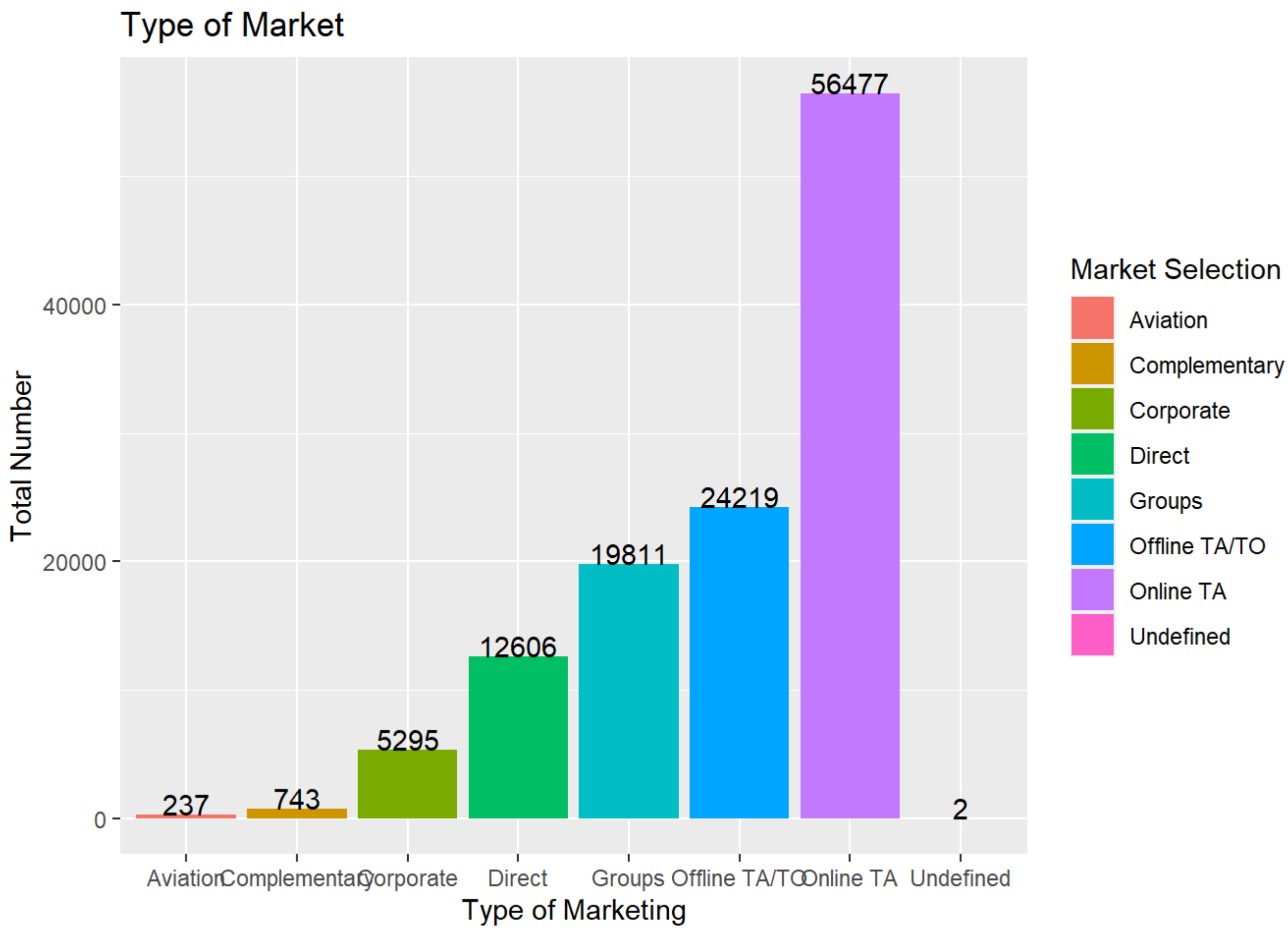



```
hotel_market <- table(Hotel_bookings$market_segment)
hotel_market_df <- as.data.frame(hotel_market)
colnames(hotel_market_df) <- c('Type of Marketing', 'Total Number')
hotel_market_df
```

```
##   Type of Marketing Total Number
## 1          Aviation          237
## 2     Complementary          743
## 3         Corporate         5295
## 4            Direct        12606
## 5            Groups        19811
## 6     Offline TA/TO        24219
## 7         Online TA        56477
## 8         Undefined            2
```

```
# Create the Bar chart for market segment

hotel_market_chart <- ggplot(data=hotel_market_df, aes(x=`Type of Marketing`, y=`Total Number`,
fill=`Type of Marketing`))+
  geom_bar(stat="identity")+
    labs(title = "Type of Market", fill = "Market Selection")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=1.2), vjust=0)
hotel_market_chart
```

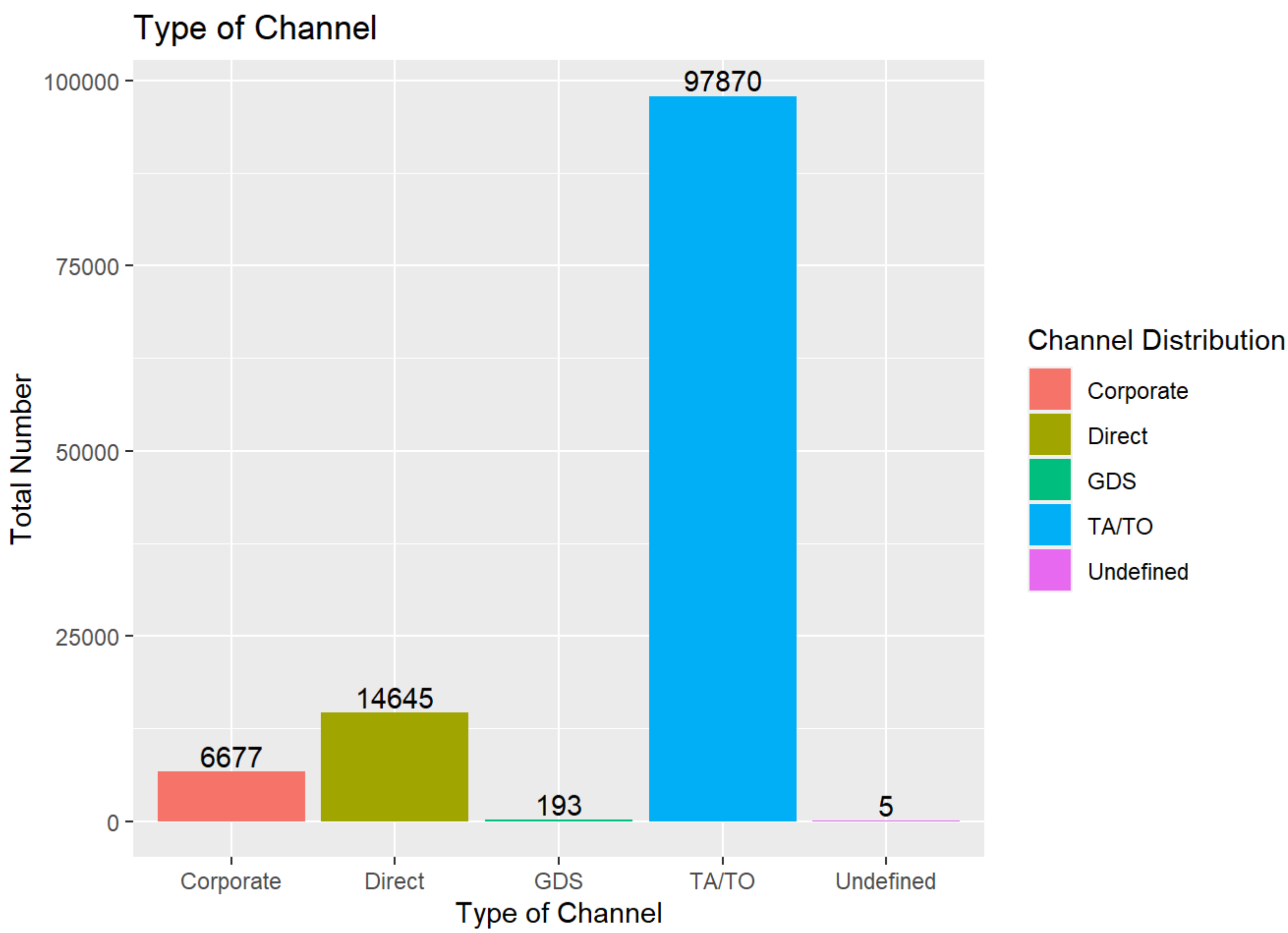
```
## Warning: `position_dodge()` requires non-overlapping x intervals
```




```
#Distribution channel
hotel_channel <- table(Hotel_bookings$distribution_channel)
hotel_channel_df <- as.data.frame(hotel_channel)
colnames(hotel_channel_df) <- c('Type of Channel', 'Total Number')
hotel_channel_df
```

```
##   Type of Channel Total Number
## 1       Corporate         6677
## 2          Direct        14645
## 3             GDS          193
## 4           TA/TO        97870
## 5       Undefined            5
```

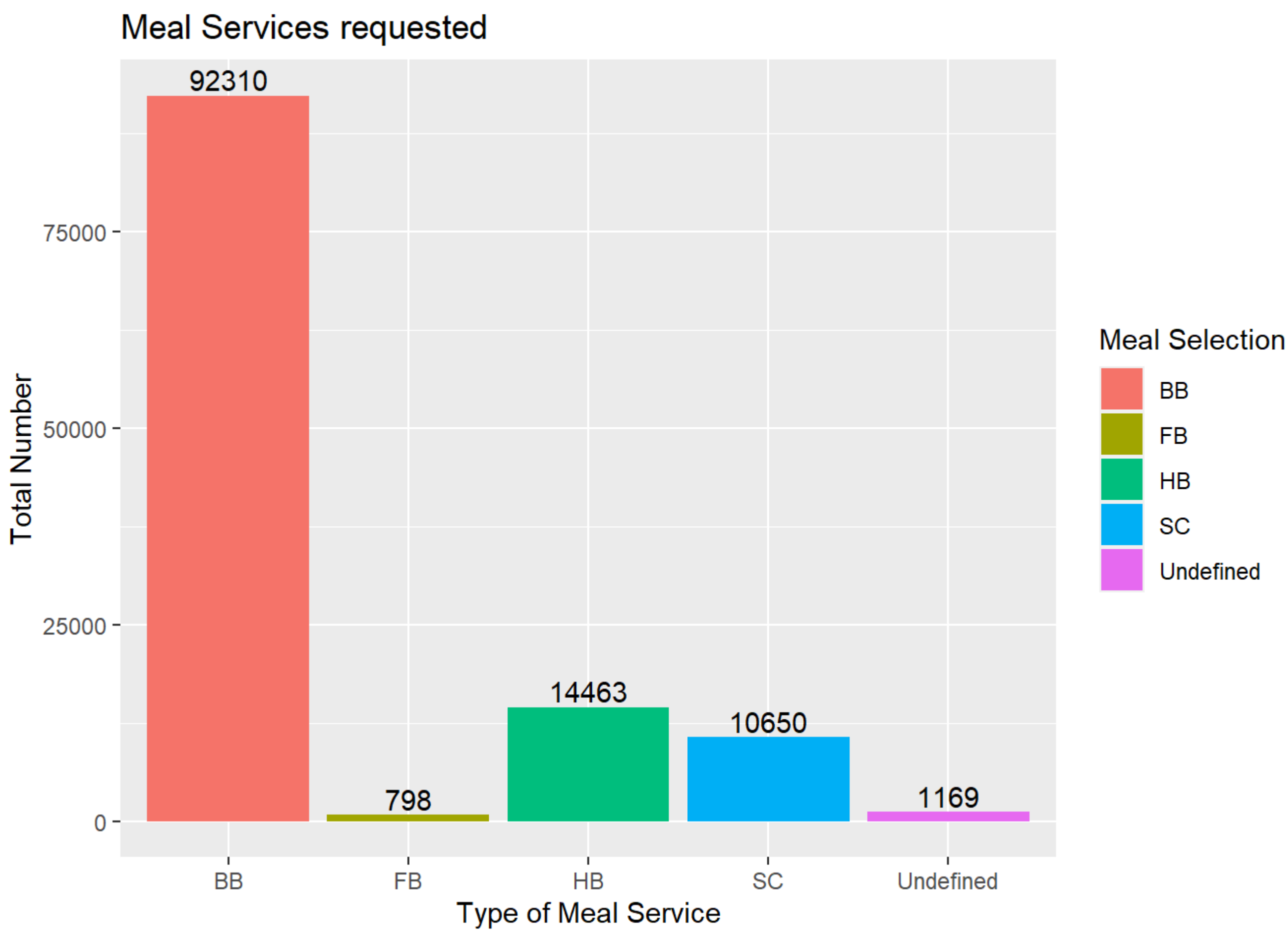
```
# Create the pie chart for channel segment
hotel_channel_chart <- ggplot(data=hotel_channel_df, aes(x=`Type of Channel`, y=`Total Number`,
fill=`Type of Channel`))+
  geom_bar(stat="identity")+
    labs(title = "Type of Channel", fill = "Channel Distribution")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=0.9), vjust=-0.25)
hotel_channel_chart
```




```
#type of meals
Meals <- table(Hotel_bookings$meal)
Meals_df <- as.data.frame(Meals)
colnames(Meals_df) <- c('Type of Meal Service', 'Total Number')
Meals_df
```

```
##   Type of Meal Service Total Number
## 1                   BB        92310
## 2                   FB          798
## 3                   HB        14463
## 4                   SC        10650
## 5            Undefined         1169
```

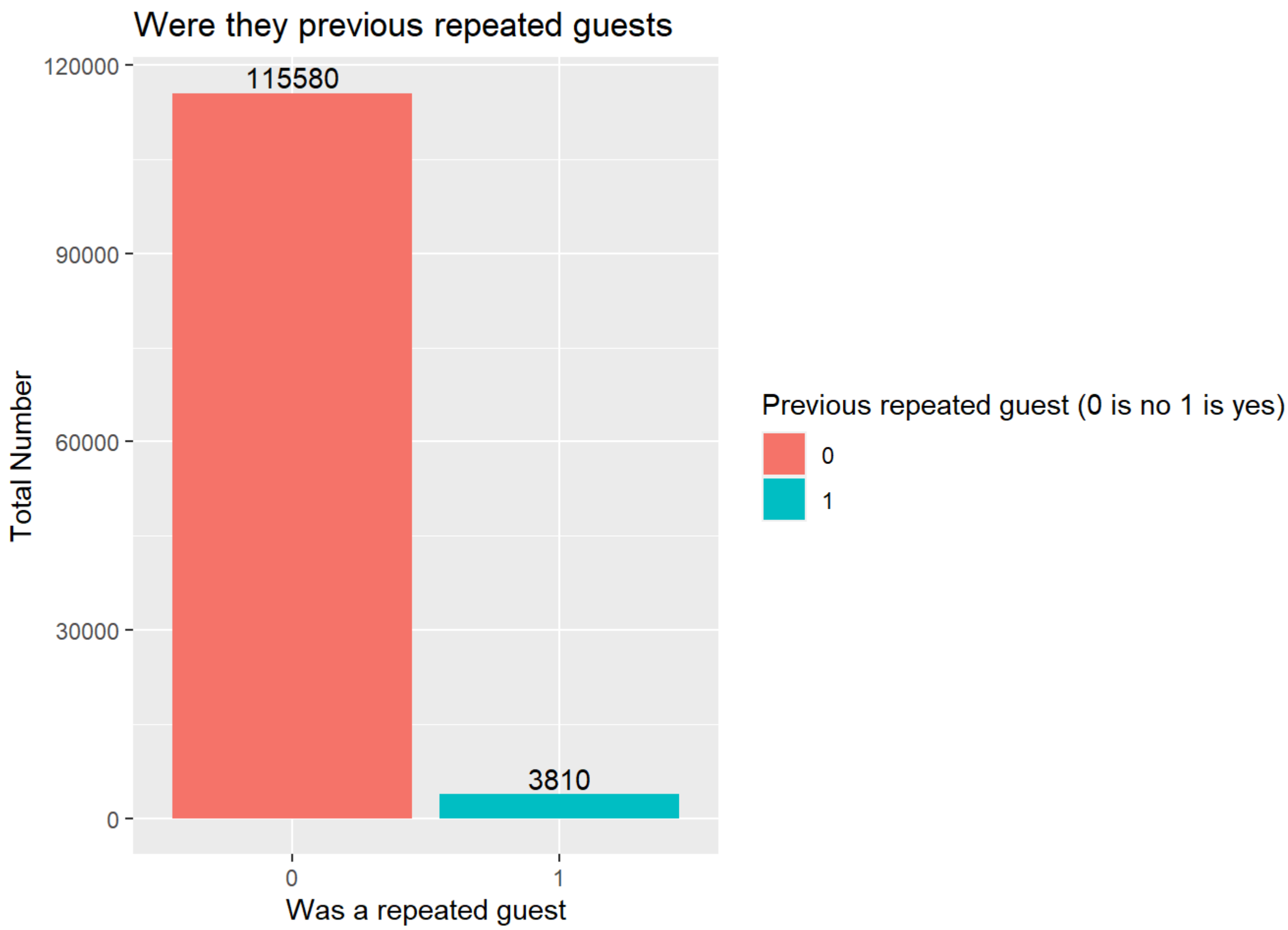
```
# Create the pie chart for Meals

Meals_chart <-ggplot(data=Meals_df, aes(x=`Type of Meal Service`, y=`Total Number`, fill=`Type o
f Meal Service`))+
  geom_bar(stat="identity")+
    labs(title = "Meal Services requested", fill = "Meal Selection")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=0.9), vjust=-0.25)
Meals_chart
```




```
#was a repeated guest
repeated_guest <- table(Hotel_bookings$is_repeated_guest)
repeated_guest_df <- as.data.frame(repeated_guest)
colnames(repeated_guest_df) <- c('Was a repeated guest', 'Total Number')
repeated_guest_df
```

```
##   Was a repeated guest Total Number
## 1                    0       115580
## 2                    1         3810
```

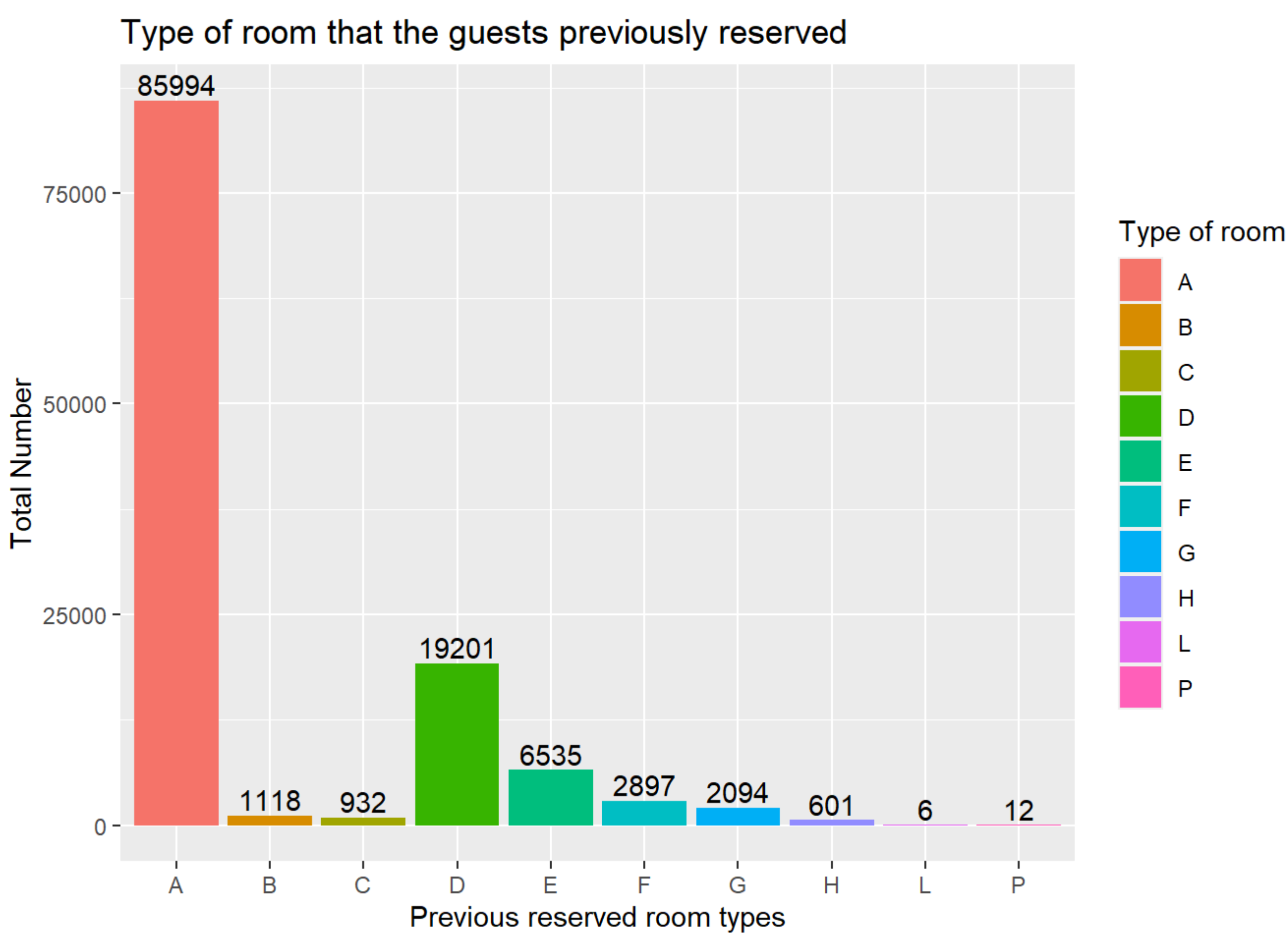
```
# Create the pie chart for market segment

repeated_guest_chart <- ggplot(data=repeated_guest_df, aes(x=`Was a repeated guest`, y=`Total Nu
mber`, fill=`Was a repeated guest`))+
  geom_bar(stat="identity")+
    labs(title = "Were they previous repeated guests", fill = "Previous repeated guest (0 is no
1 is yes)")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=0.9), vjust=-0.25)
repeated_guest_chart
```




```
#reserved_room type
reserved_room_type <- table(Hotel_bookings$reserved_room_type)
reserved_room_type_df <- as.data.frame(reserved_room_type)
colnames(reserved_room_type_df) <- c('Previous reserved room types', 'Total Number')
reserved_room_type_df
```

```
##    Previous reserved room types Total Number
## 1                             A        85994
## 2                             B         1118
## 3                             C          932
## 4                             D        19201
## 5                             E         6535
## 6                             F         2897
## 7                             G         2094
## 8                             H          601
## 9                             L            6
## 10                            P           12
```

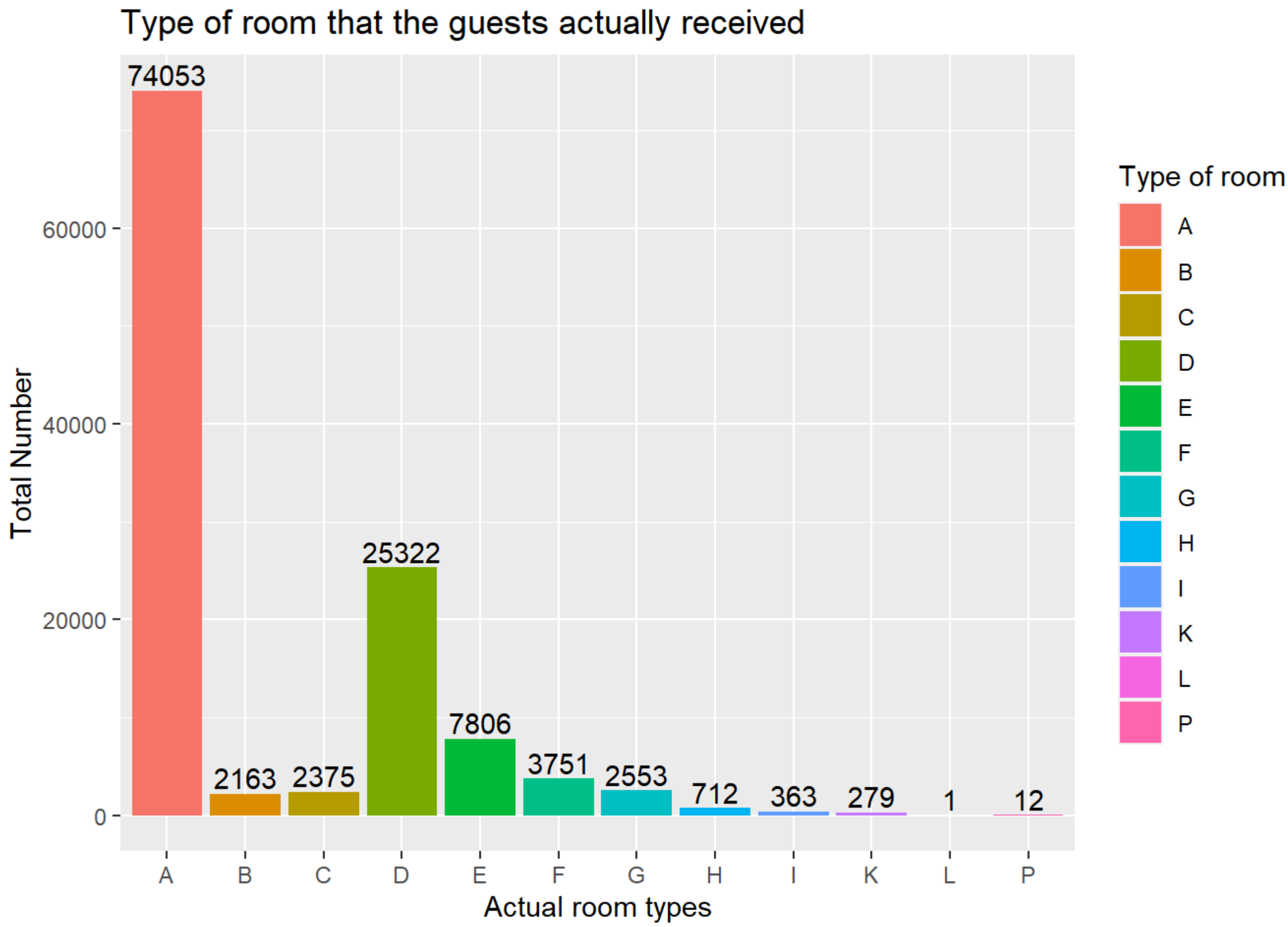
```
# Create the pie chart for market segment

reserved_room_chart <-ggplot(data=reserved_room_type_df, aes(x=`Previous reserved room types`, y
=`Total Number`, fill=`Previous reserved room types`))+
  geom_bar(stat="identity")+
    labs(title = "Type of room that the guests previously reserved", fill = "Type of room")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=0.9), vjust=-0.25)
reserved_room_chart
```



```
#actual_room type
actual_room <- table(Hotel_bookings$assigned_room_type)
actual_room_df <- as.data.frame(actual_room)
colnames(actual_room_df) <- c('Actual room types', 'Total Number')
actual_room_df
```

```
##    Actual room types Total Number
## 1                  A        74053
## 2                  B         2163
## 3                  C         2375
## 4                  D        25322
## 5                  E         7806
## 6                  F         3751
## 7                  G         2553
## 8                  H          712
## 9                  I          363
## 10                 K          279
## 11                 L            1
## 12                 P           12
```

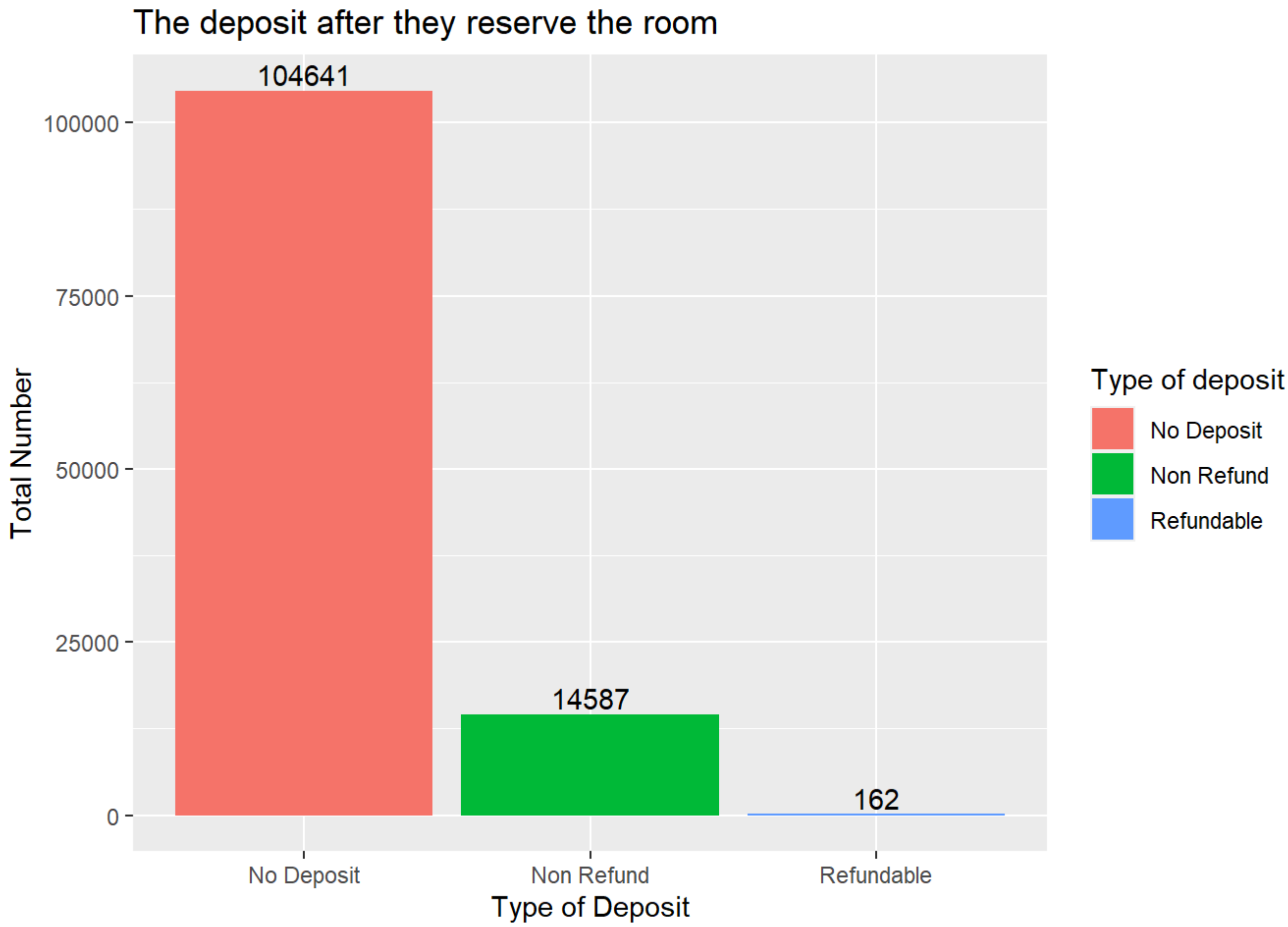
```
actual_room_chart <- ggplot(data=actual_room_df, aes(x=`Actual room types`, y=`Total Number`, fi
ll=`Actual room types`))+
  geom_bar(stat="identity")+
    labs(title = "Type of room that the guests actually received", fill = "Type of room")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=0.9), vjust=-0.25)
actual_room_chart
```




```
#deposit types
deposit <- table(Hotel_bookings$deposit_type)
deposit_df <- as.data.frame(deposit)
colnames(deposit_df) <- c('Type of Deposit', 'Total Number')
deposit_df
```

```
##   Type of Deposit Total Number
## 1      No Deposit       104641
## 2      Non Refund        14587
## 3      Refundable          162
```

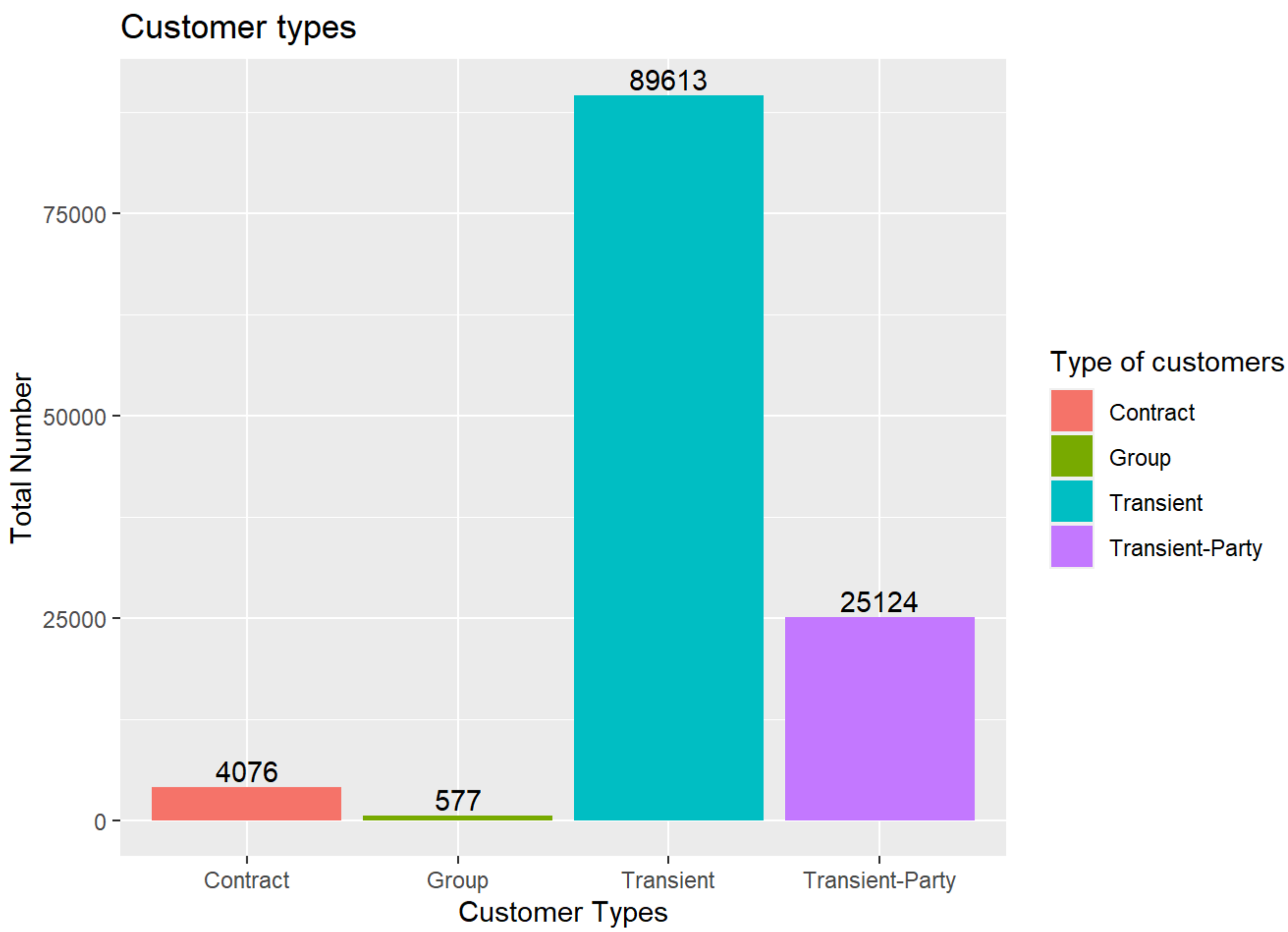
```
# Create the pie chart for market segment
deposit_chart<- ggplot(data=deposit_df, aes(x=`Type of Deposit`, y=`Total Number`, fill=`Type of
Deposit`))+
  geom_bar(stat="identity")+
    labs(title = "The deposit after they reserve the room", fill = "Type of deposit")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=0.9), vjust=-0.25)
deposit_chart
```




```
#Customer types
customer <- table(Hotel_bookings$customer_type)
customer_df <- as.data.frame(customer)
colnames(customer_df) <- c('Customer Types', 'Total Number')
customer_df
```

```
##    Customer Types Total Number
## 1        Contract         4076
## 2           Group          577
## 3       Transient        89613
## 4 Transient-Party        25124
```

```
customer_chart<- ggplot(data=customer_df, aes(x=`Customer Types`, y=`Total Number`, fill=`Custom
er Types`))+
  geom_bar(stat="identity")+
    labs(title = "Customer types", fill = "Type of customers")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=0.9), vjust=-0.25)
customer_chart
```




```
#Create the country distribution
country <- table(Hotel_bookings$country)
country_df <- as.data.frame(country)
head(country_df)
```

```
##   Var1 Freq
## 1  ABW    2
## 2  AGO  362
## 3  AIA    1
## 4  ALB   12
## 5  AND    7
## 6  ARE   51
```

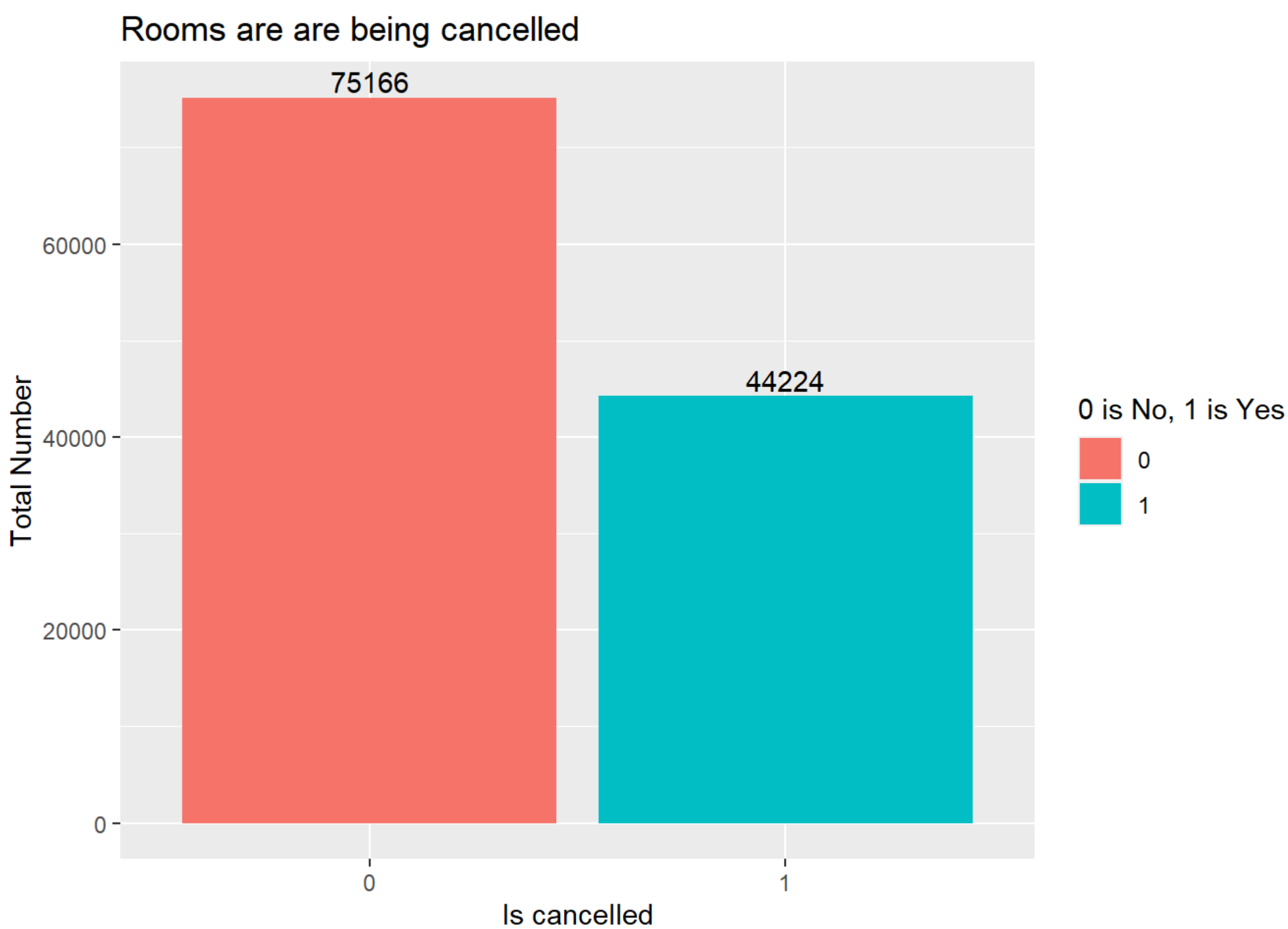
```
#Matched room
being_cancelled <- table(Hotel_bookings$is_canceled)
being_cancelled_df <- as.data.frame(being_cancelled)
colnames(being_cancelled_df) <- c('Is cancelled', 'Total Number')
being_cancelled_df
```

```
##   Is cancelled Total Number
## 1            0        75166
## 2            1        44224
```

```
head(as.character(Hotel_bookings$is_canceled))
```

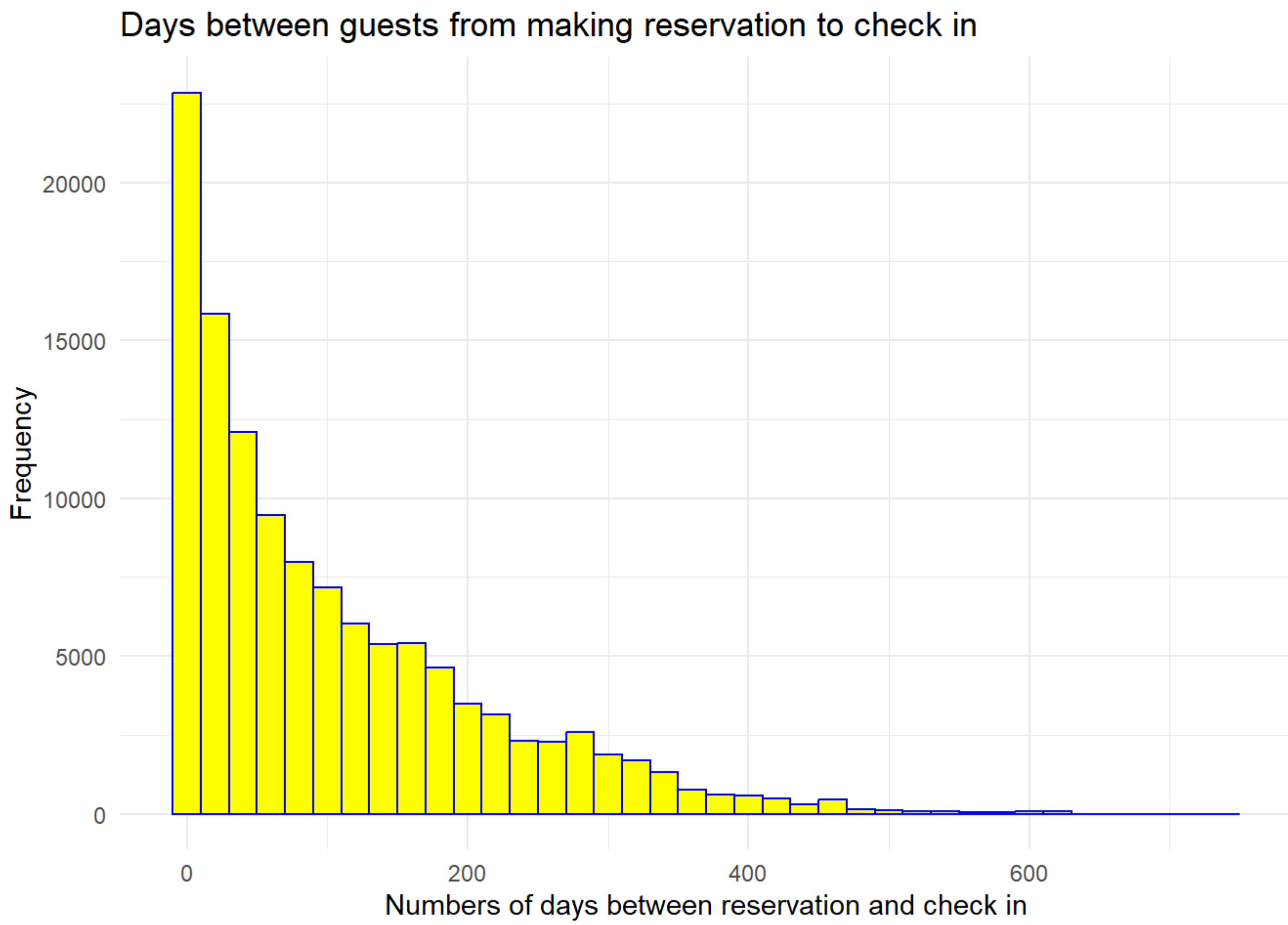
```
## [1] "0" "0" "0" "0" "0" "0"
```

```
# Create the pie chart for market segment
being_cancelled_chart<- ggplot(data=being_cancelled_df, aes(x=`Is cancelled`, y=`Total Number`,
fill=`Is cancelled`))+
  geom_bar(stat="identity")+
    labs(title = "Rooms are are being cancelled", fill = "0 is No, 1 is Yes")+
  geom_text(aes(label=`Total Number`), position=position_dodge(width=0.9), vjust=-0.25)
being_cancelled_chart
```




```
#1 is being cancelled, 0 is not cancelled
```

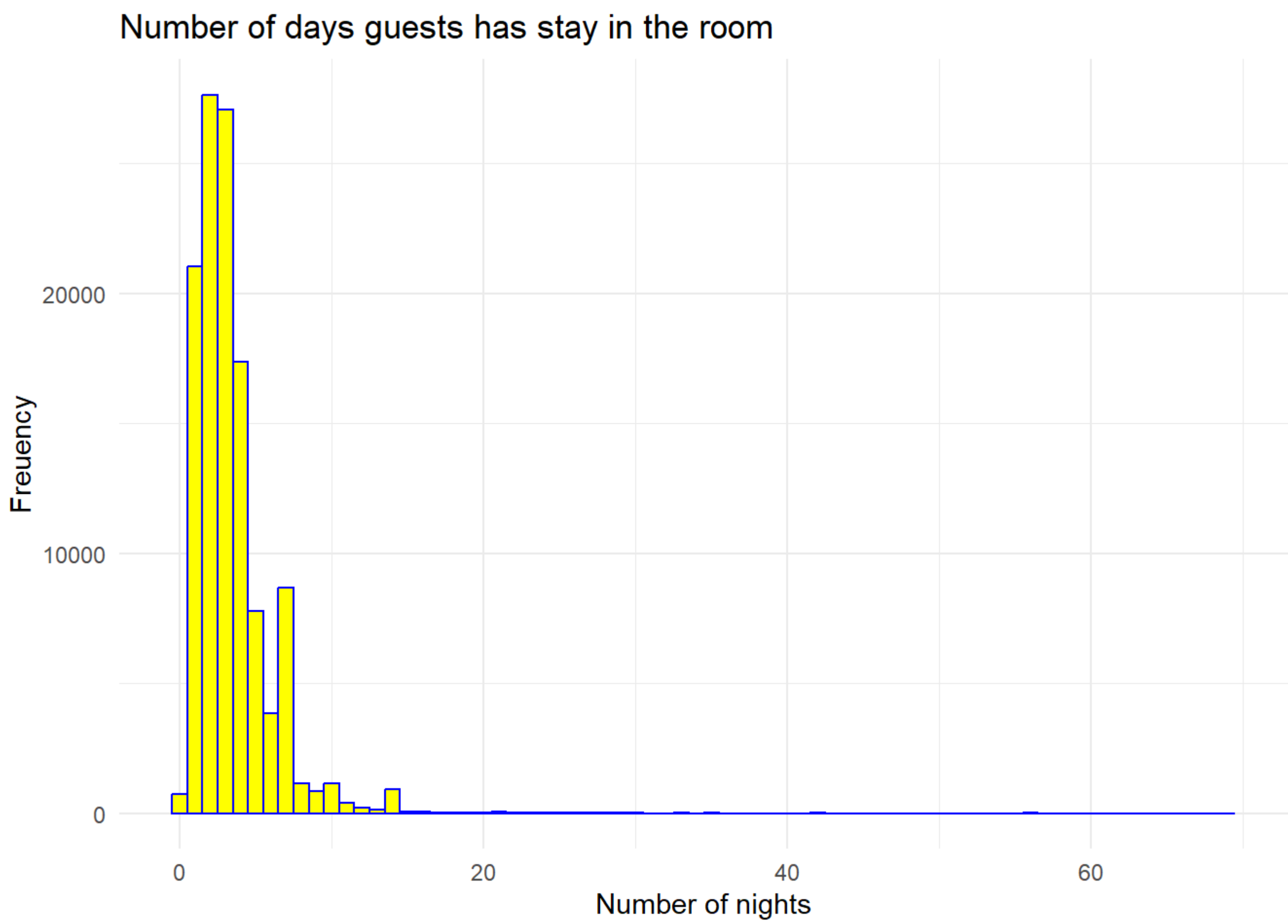
```
#EDA for numerical portion
#lead_time distribution
ggplot(Hotel_bookings, aes(x = lead_time)) +
  geom_histogram(binwidth = 20, fill = "yellow", color = "Blue") +
  labs(
    title = "Days between guests from making reservation to check in",
    x = "Numbers of days between reservation and check in",
    y= "Frequency"
  ) +
  theme_minimal()
```




```
#number of nights stayed
Hotel_bookings$stays <- Hotel_bookings$stays_in_weekend_nights+Hotel_bookings$stays_in_week_nigh
ts
head(as.numeric(Hotel_bookings$stays))
```

```
## [1] 0 0 1 1 2 2
```

```
ggplot(Hotel_bookings, aes(x = stays)) +
  geom_histogram(binwidth = 1, fill = "yellow", color = "Blue") +
  labs(
    title = "Number of days guests has stay in the room",
    x = "Number of nights",
    y = "Freuency"
  ) +
  theme_minimal()
```

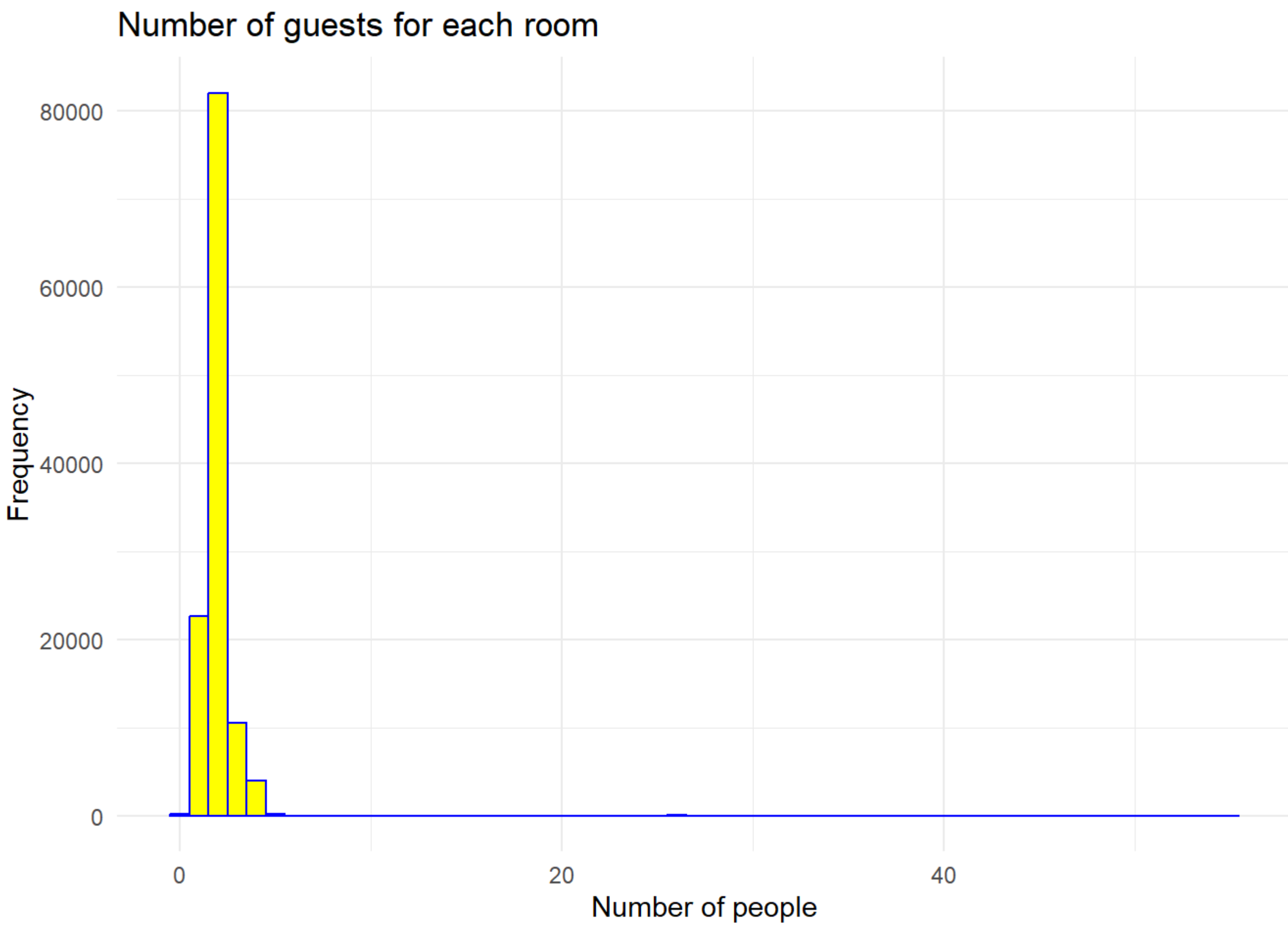



```
#number of total person

Hotel_bookings$people <- Hotel_bookings$adults+Hotel_bookings$children+Hotel_bookings$babies
head(as.numeric(Hotel_bookings$people))
```

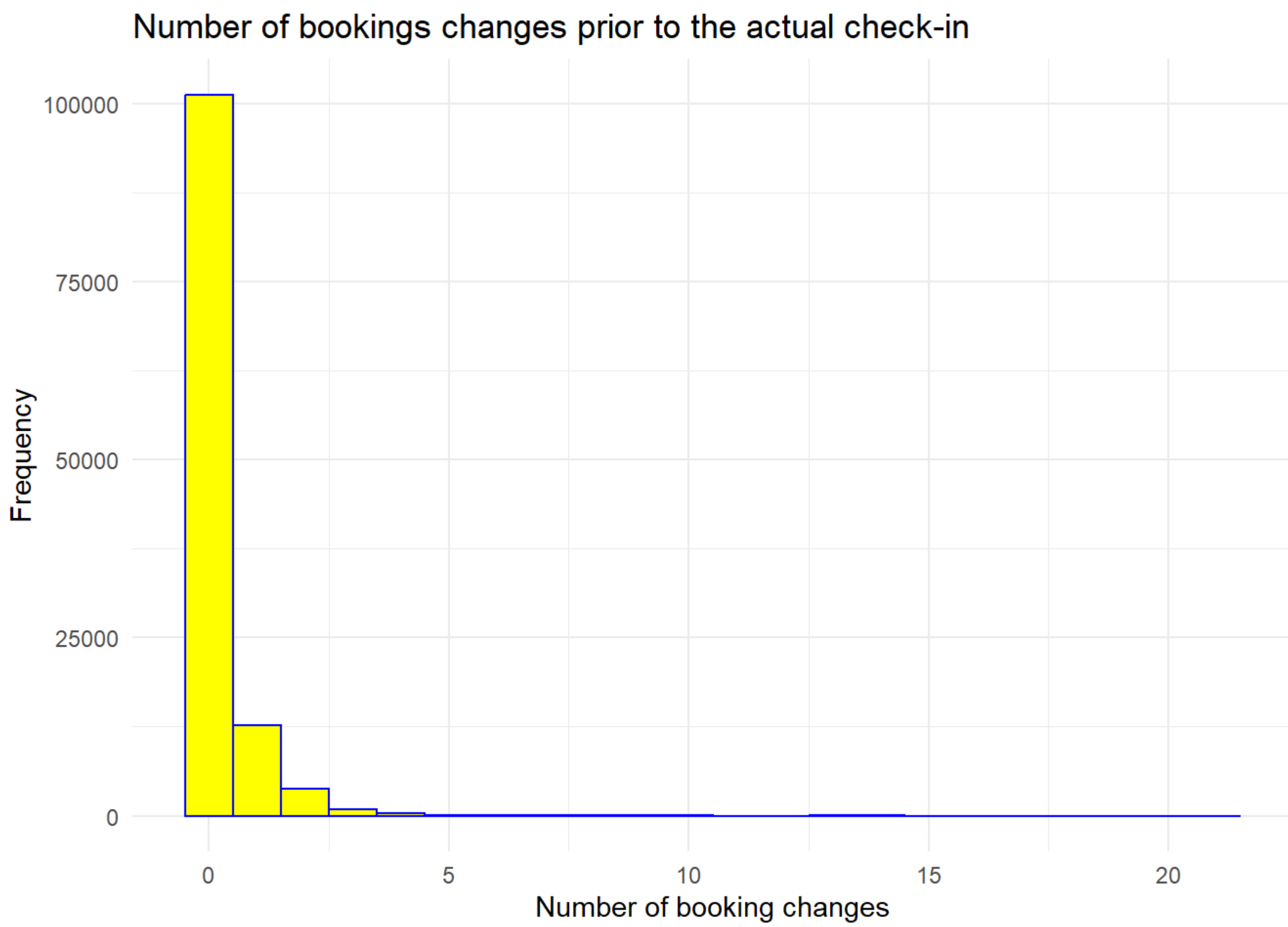
```
## [1] 2 2 1 1 2 2
```

```
ggplot(Hotel_bookings, aes(x = people)) +
  geom_histogram(binwidth = 1, fill = "yellow", color = "Blue") +
  labs(
    title = "Number of guests for each room",
    x = "Number of people",
    y = "Frequency"
  ) +
  theme_minimal()
```

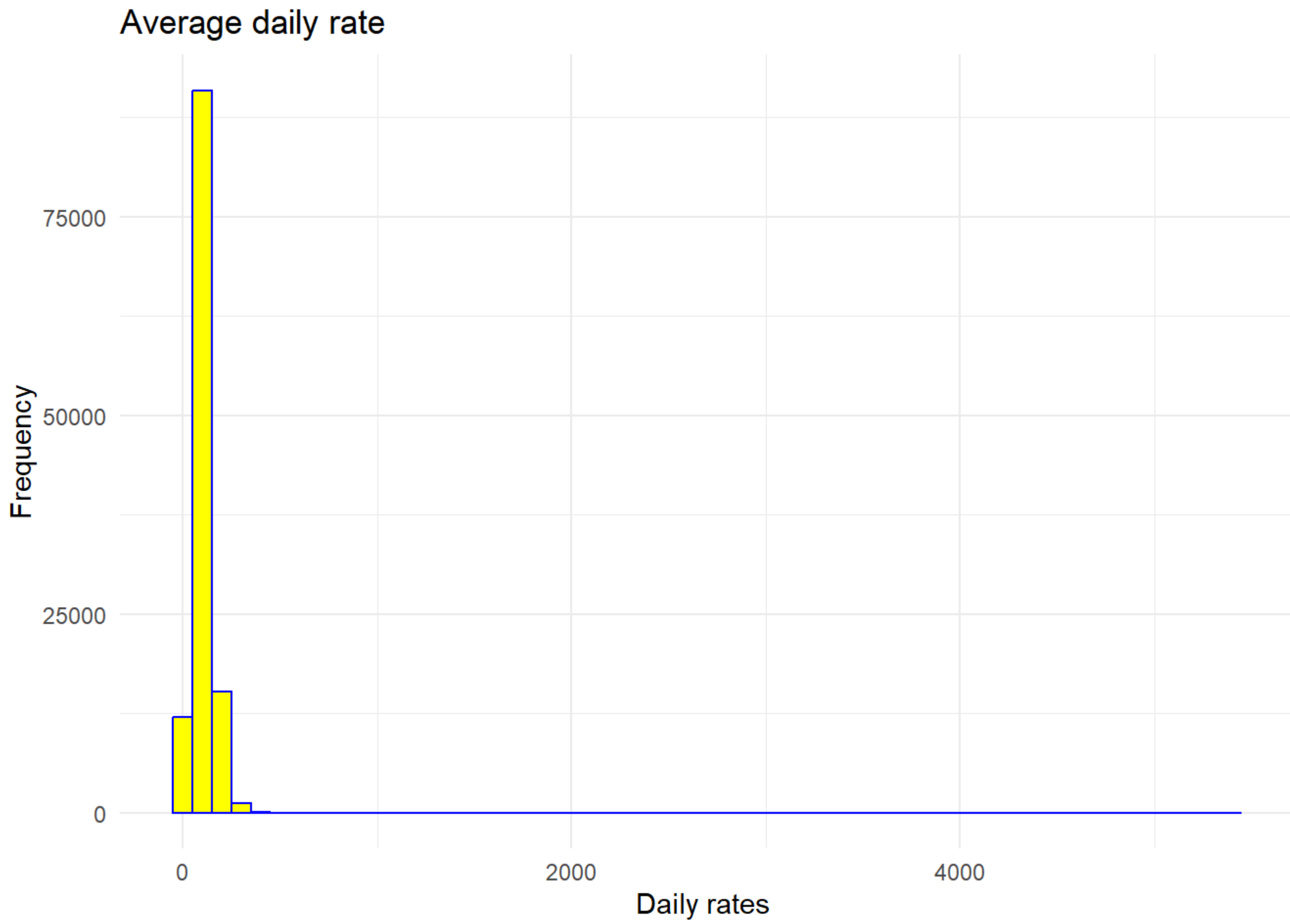
```
## Warning: Removed 4 rows containing non-finite values (`stat_bin()`).
```



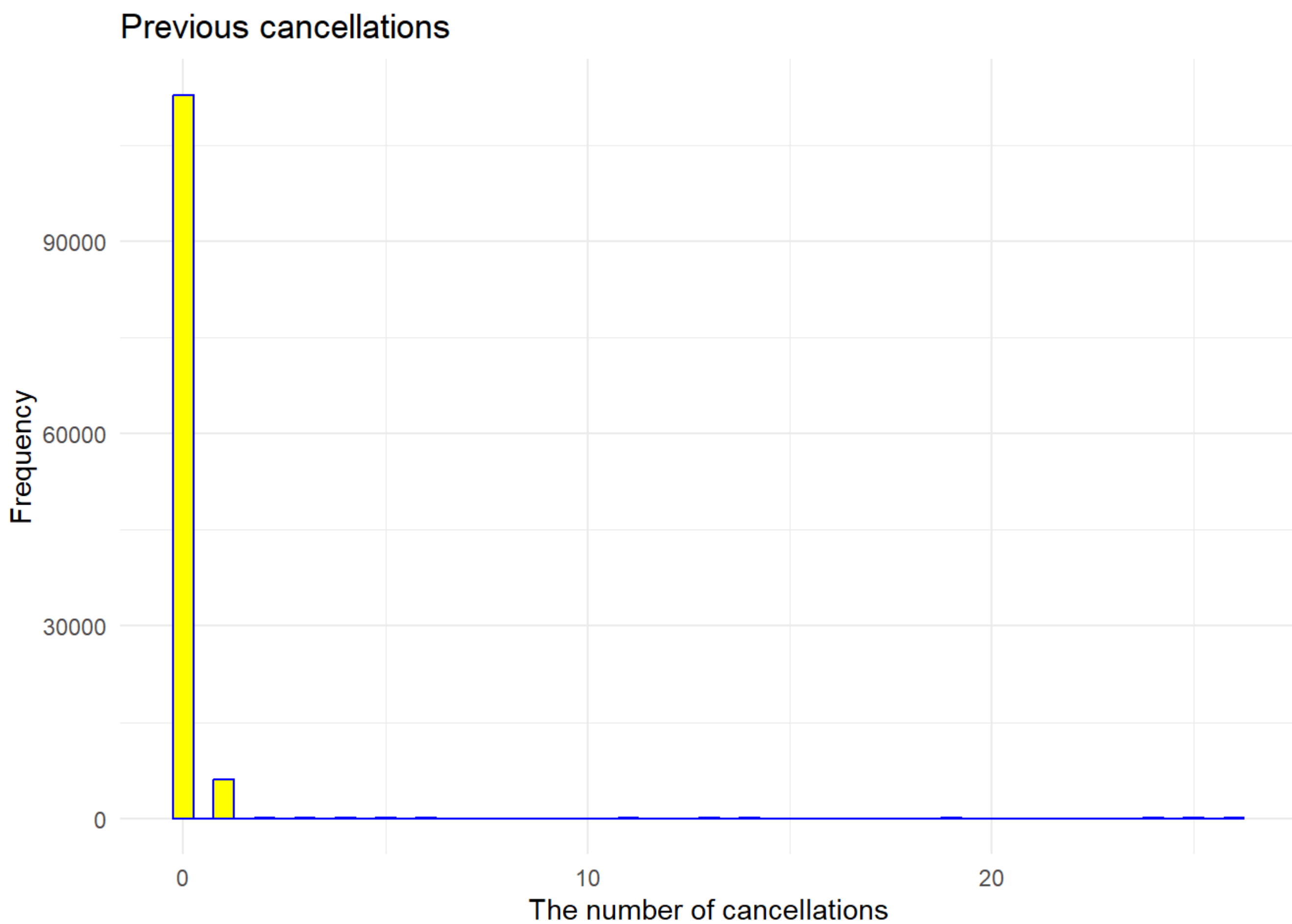

```
#booking changes
ggplot(Hotel_bookings, aes(x = booking_changes)) +
  geom_histogram(binwidth = 1, fill = "yellow", color = "Blue") +
  labs(
    title = "Number of bookings changes prior to the actual check-in",
    x = "Number of booking changes",
    y = "Frequency"
  ) +
  theme_minimal()
```




```
#adr
ggplot(Hotel_bookings, aes(x = adr)) +
  geom_histogram(binwidth = 100, fill = "yellow", color = "Blue") +
  labs(
    title = "Average daily rate",
    x = "Daily rates ",
    y = "Frequency"
  ) +
  theme_minimal()
```

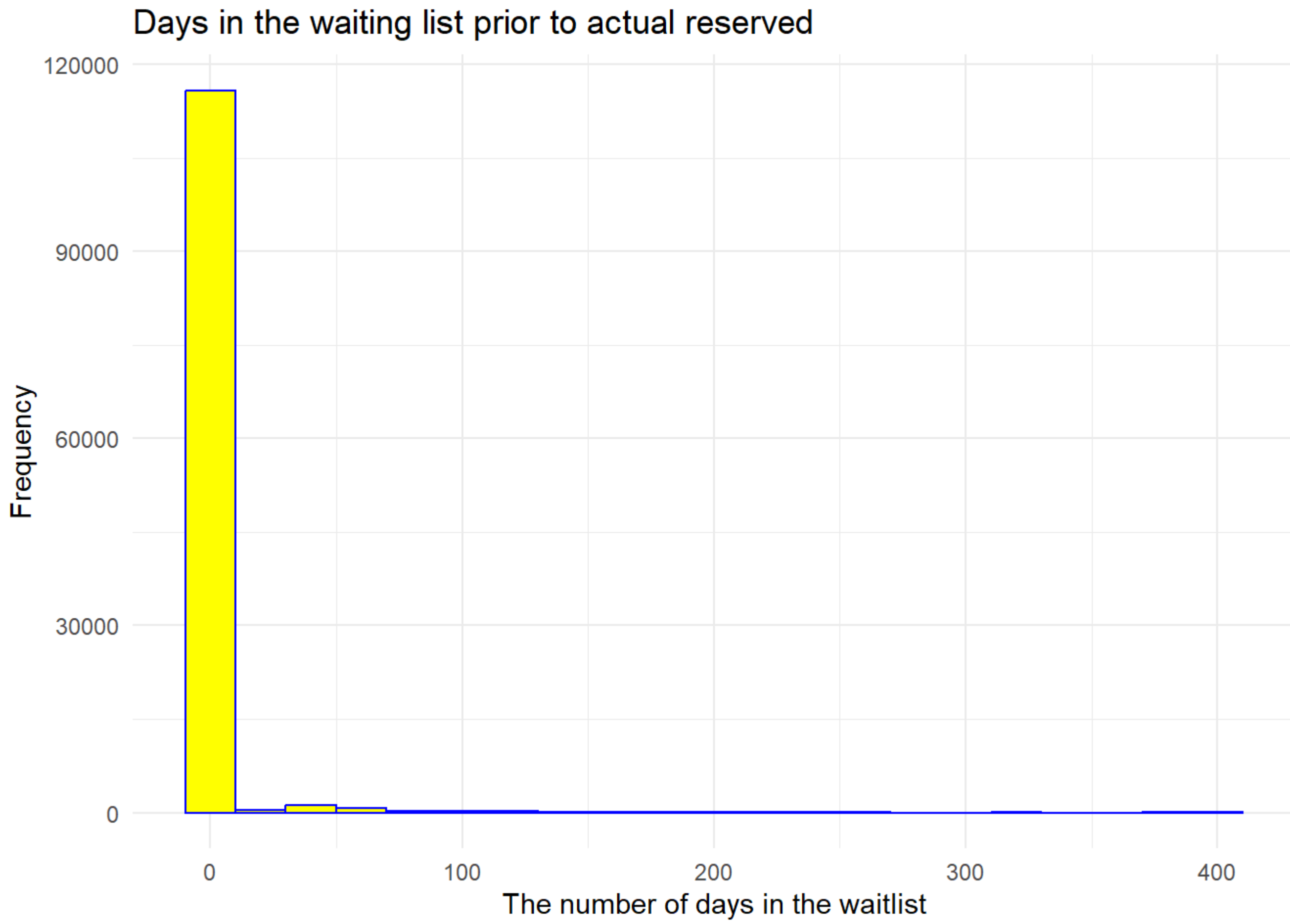



```
#previous cancellations
ggplot(Hotel_bookings, aes(x = previous_cancellations)) +
  geom_histogram(binwidth = 0.5, fill = "yellow", color = "Blue") +
  labs(
    title = "Previous cancellations",
    x = "The number of cancellations",
    y = "Frequency"
  ) +
  theme_minimal()
```

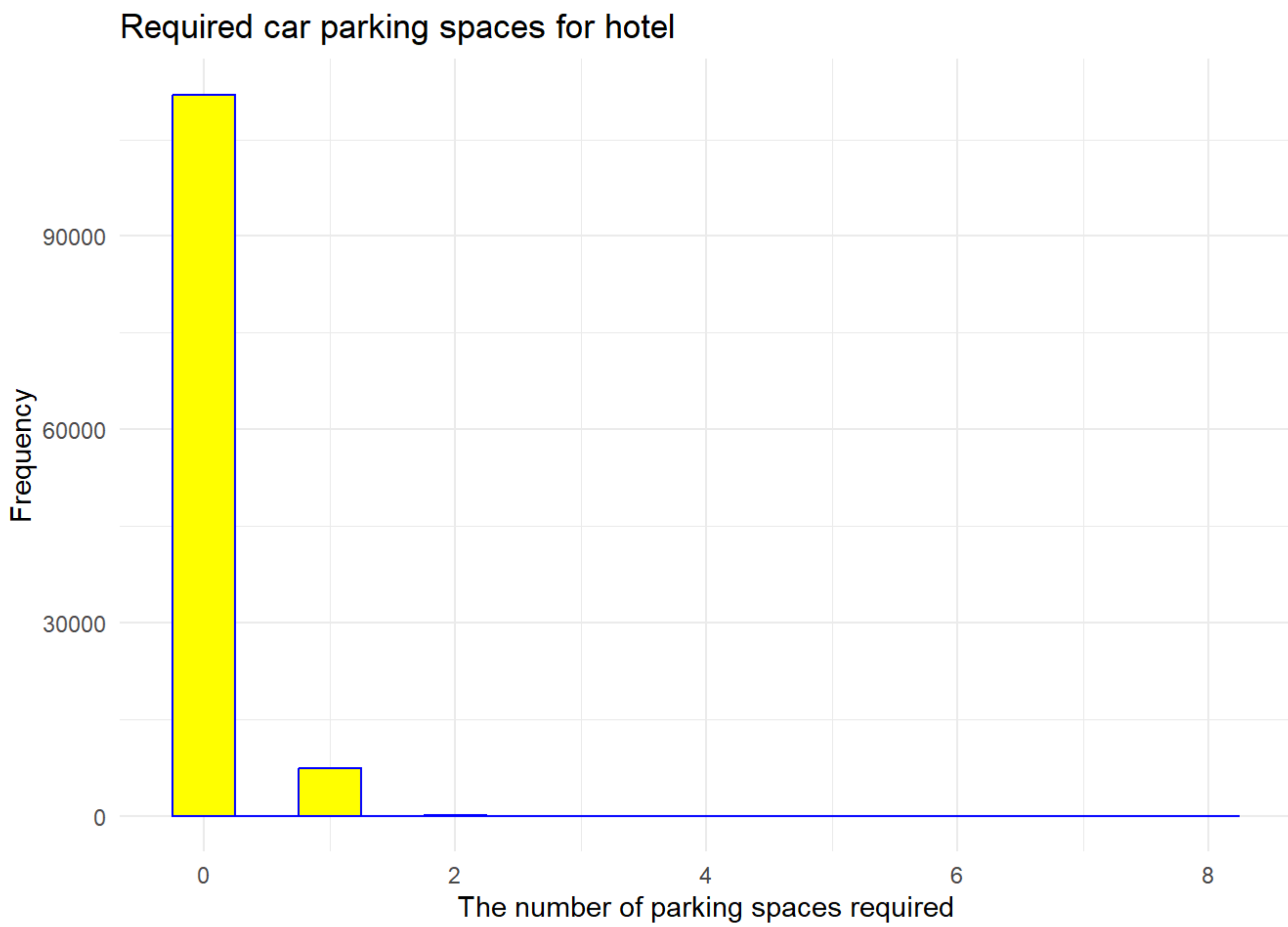



```
#previous not canceled room
ggplot(Hotel_bookings, aes(x = previous_bookings_not_canceled)) +
  geom_histogram(binwidth = 1, fill = "yellow", color = "Blue") +
  labs(
    title = "Previous not canceled rooms",
    x = "The rooms that are not being canceled",
    y = "Frequency"
  ) +
  theme_minimal()
```

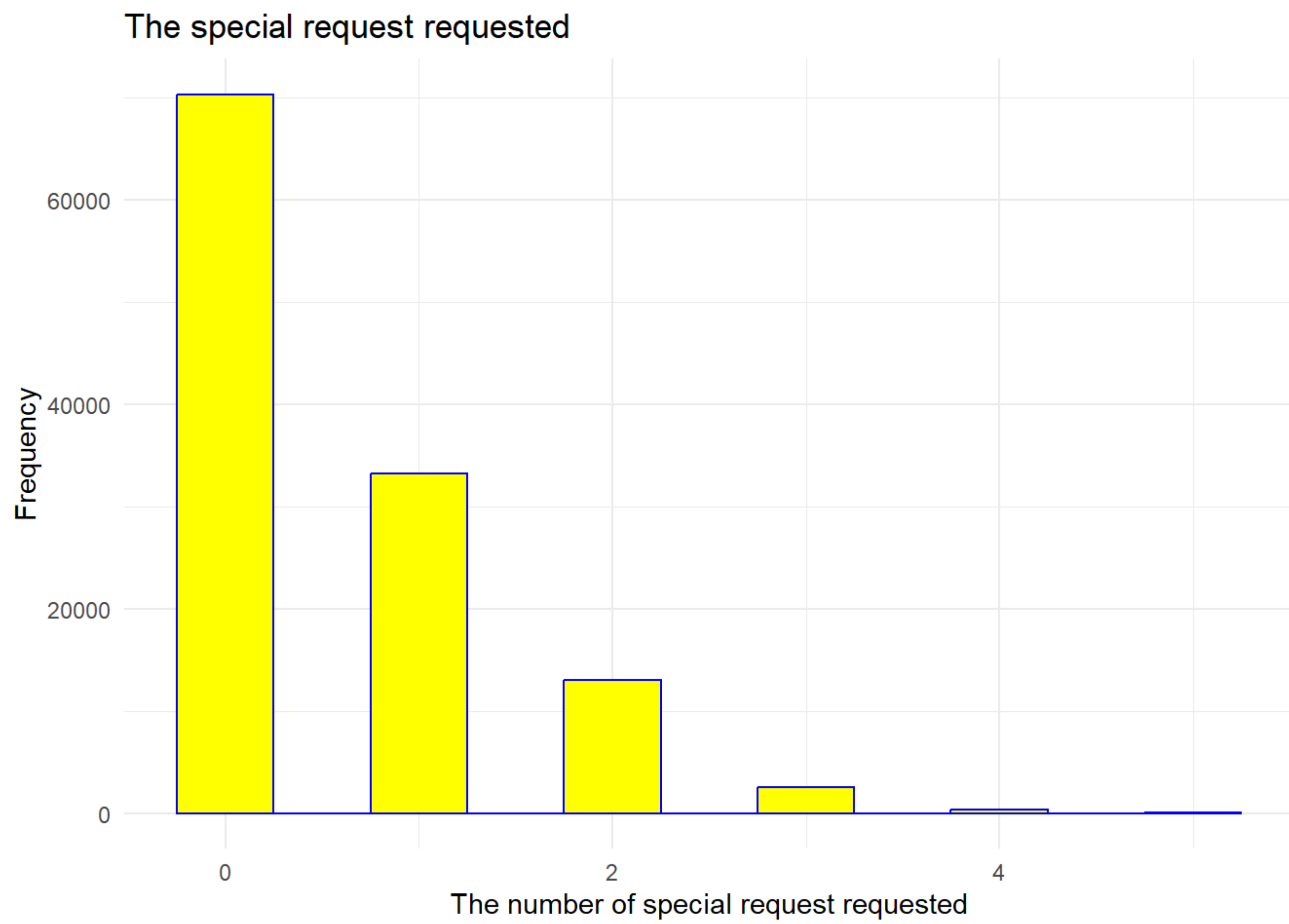

```r
#Waiting list
ggplot(Hotel_bookings, aes(x = days_in_waiting_list)) +
  geom_histogram(binwidth = 20, fill = "yellow", color = "Blue") +
  labs(
    title = "Days in the waiting list prior to actual reserved",
    x = "The number of days in the waitlist",
    y = "Frequency"
  ) +
  theme_minimal()
```




```
#require spaces
ggplot(Hotel_bookings, aes(x = required_car_parking_spaces)) +
  geom_histogram(binwidth = 0.5, fill = "yellow", color = "Blue") +
  labs(
    title = "Required car parking spaces for hotel",
    x = "The number of parking spaces required",
    y = "Frequency"
  ) +
  theme_minimal()
```



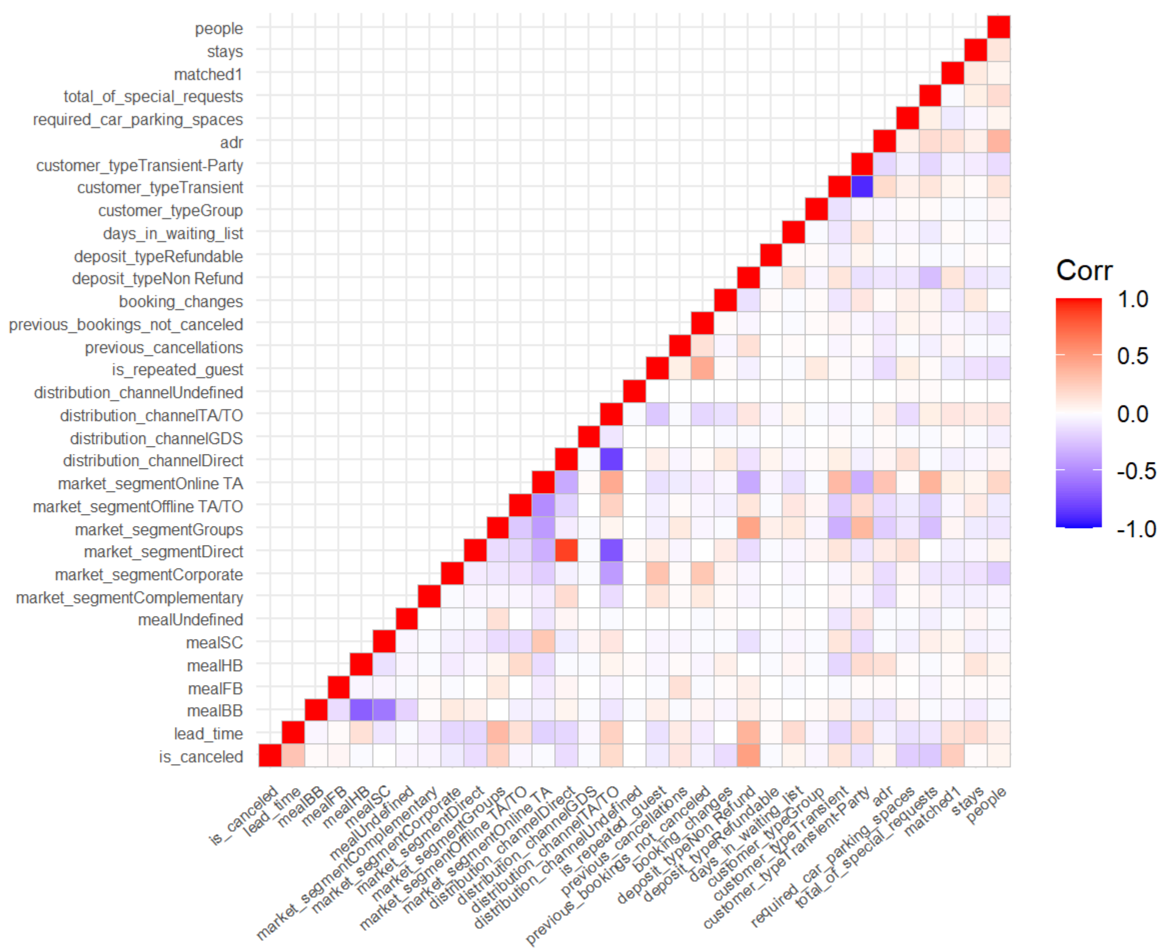

```
#special requests
ggplot(Hotel_bookings, aes(x = total_of_special_requests)) +
  geom_histogram(binwidth = 0.5, fill = "yellow", color = "Blue") +
  labs(
    title = "The special request requested",
    x = "The number of special request requested",
    y = "Frequency"
  ) +
  theme_minimal()
```




```
#delete unnecessary columns
Hotel_bookings2 <- subset(Hotel_bookings, select = -c(arrival_date_year,arrival_date_month, arri
val_date_week_number, arrival_date_day_of_month, agent, company, reservation_status_date, adult
s, children, babies, stays_in_weekend_nights, stays_in_week_nights, country, hotel, reservation_
status, reserved_room_type, assigned_room_type))
head(Hotel_bookings2)
```

```
## # A tibble: 6 x 18
##   is_canceled lead_time meal  market_segment distribution_channel
##         <dbl>     <dbl> <chr> <chr>          <chr>
## 1           0       342 BB    Direct         Direct
## 2           0       737 BB    Direct         Direct
## 3           0         7 BB    Direct         Direct
## 4           0        13 BB    Corporate      Corporate
## 5           0        14 BB    Online TA      TA/TO
## 6           0        14 BB    Online TA      TA/TO
## # i 13 more variables: is_repeated_guest <dbl>, previous_cancellations <dbl>,
## #   previous_bookings_not_canceled <dbl>, booking_changes <dbl>,
## #   deposit_type <chr>, days_in_waiting_list <dbl>, customer_type <chr>,
## #   adr <dbl>, required_car_parking_spaces <dbl>,
## #   total_of_special_requests <dbl>, matched <chr>, stays <dbl>, people <dbl>
```

```
#correlation matrix:

matrix<- model.matrix(~0+., data=Hotel_bookings2) %>%
  cor(use="pairwise.complete.obs") %>%
  ggcorrplot(show.diag=TRUE, type="lower", lab=FALSE, lab_size=1, tl.cex=6, tl.srt=40)

matrix
```




```
#Build out regression models: Full models
full_model <- glm(is_canceled ~., data=Hotel_bookings2, family=binomial)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(full_model)
```

```
## 
## Call:
## glm(formula = is_canceled ~ ., family = binomial, data = Hotel_bookings2)
## 
## Deviance Residuals: 
##     Min       1Q   Median       3Q      Max  
## -8.4904  -0.7444  -0.3047   0.2046   5.9435  
## 
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)    
## (Intercept)                    -4.129e+00  1.838e-01 -22.465  < 2e-16 ***
## lead_time                       3.579e-03  9.309e-05  38.445  < 2e-16 ***
## mealFB                          7.938e-01  1.083e-01   7.331 2.28e-13 ***
## mealHB                         -8.222e-02  2.647e-02  -3.106 0.001894 ** 
## mealSC                          5.882e-02  2.459e-02   2.392 0.016745 *  
## mealUndefined                  -4.678e-01  9.857e-02  -4.746 2.07e-06 ***
## market_segmentComplementary     7.987e-01  2.254e-01   3.544 0.000395 ***
## market_segmentCorporate         9.784e-03  1.765e-01   0.055 0.955789    
## market_segmentDirect            2.113e-01  1.960e-01   1.078 0.281083    
## market_segmentGroups            2.444e-01  1.847e-01   1.324 0.185599    
## market_segmentOffline TA/TO    -3.656e-01  1.852e-01  -1.975 0.048306 *  
## market_segmentOnline TA         9.168e-01  1.845e-01   4.968 6.76e-07 ***
## distribution_channelDirect     -5.964e-01  9.542e-02  -6.251 4.09e-10 ***
## distribution_channelGDS        -1.161e+00  2.018e-01  -5.755 8.67e-09 ***
## distribution_channelTA/TO      -1.870e-01  7.108e-02  -2.631 0.008516 ** 
## distribution_channelUndefined   1.941e+03  7.673e+05   0.003 0.997981    
## is_repeated_guest              -6.213e-01  8.553e-02  -7.264 3.75e-13 ***
## previous_cancellations          2.724e+00  6.051e-02  45.019  < 2e-16 ***
## previous_bookings_not_canceled -4.914e-01  2.526e-02 -19.452  < 2e-16 ***
## booking_changes                -3.421e-01  1.524e-02 -22.456  < 2e-16 ***
## deposit_typeNon Refund          5.429e+00  1.127e-01  48.151  < 2e-16 ***
## deposit_typeRefundable          1.457e-01  2.149e-01   0.678 0.497738    
## days_in_waiting_list           -1.653e-04  4.812e-04  -0.344 0.731189    
## customer_typeGroup             -1.212e-01  1.713e-01  -0.707 0.479324    
## customer_typeTransient          8.585e-01  5.356e-02  16.031  < 2e-16 ***
## customer_typeTransient-Party    3.931e-01  5.699e-02   6.897 5.30e-12 ***
## adr                             3.230e-03  1.959e-04  16.486  < 2e-16 ***
## required_car_parking_spaces    -1.953e+03  7.673e+05  -0.003 0.997969    
## total_of_special_requests      -7.086e-01  1.152e-02 -61.488  < 2e-16 ***
## matched1                        1.778e+00  4.031e-02  44.101  < 2e-16 ***
## stays                           4.009e-02  3.128e-03  12.817  < 2e-16 ***
## people                          1.237e-01  1.281e-02   9.655  < 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: 157390  on 119385  degrees of freedom
## Residual deviance:  99685  on 119354  degrees of freedom
##   (4 observations deleted due to missingness)
## AIC: 99749
```

```
##
## Number of Fisher Scoring iterations: 12
```

```
anova(full_model)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: is_canceled
##
## Terms added sequentially (first to last)
##
##
##                              Df Deviance Resid. Df Resid. Dev
## NULL                                       119385     157390
## lead_time                     1  10244.0    119384     147146
## meal                          4    768.2    119380     146378
## market_segment                6   4145.3    119374     142233
## distribution_channel          4    471.7    119370     141761
## is_repeated_guest             1    191.2    119369     141570
## previous_cancellations        1   4419.8    119368     137150
## previous_bookings_not_canceled 1   1677.3    119367     135473
## booking_changes               1   2471.7    119366     133001
## deposit_type                  2  19646.4    119364     113355
## days_in_waiting_list          1      0.7    119363     113354
## customer_type                 3    713.0    119360     112641
## adr                           1    525.5    119359     112115
## required_car_parking_spaces   1   4598.4    119358     107517
## total_of_special_requests     1   4529.0    119357     102988
## matched                       1   3022.4    119356      99966
## stays                         1    176.1    119355      99789
## people                        1    104.8    119354      99685
```

```
vif(full_model)
```

```
##                                        GVIF Df GVIF^(1/(2*Df))
## lead_time                      1.298135e+00  1        1.139357
## meal                           1.377405e+00  4        1.040837
## market_segment                 6.903104e+01  6        1.423160
## distribution_channel           5.170651e+07  4        9.208590
## is_repeated_guest              1.325286e+00  1        1.151211
## previous_cancellations         1.545963e+00  1        1.243367
## previous_bookings_not_canceled 1.624514e+00  1        1.274564
## booking_changes                1.034910e+00  1        1.017305
## deposit_type                   1.082540e+00  2        1.020025
## days_in_waiting_list           1.072591e+00  1        1.035660
## customer_type                  2.209880e+00  3        1.141287
## adr                            1.475681e+00  1        1.214776
## required_car_parking_spaces    2.053906e+06  1     1433.145343
## total_of_special_requests      1.184319e+00  1        1.088264
## matched                        1.016251e+00  1        1.008093
## stays                          1.158580e+00  1        1.076374
## people                         1.314950e+00  1        1.146713
```

```
#reduced model, after displayed the full model, key factors exposed to hotel cancellation

reduced_model <- glm(is_canceled ~ lead_time + meal +
    is_repeated_guest + previous_cancellations + previous_bookings_not_canceled +
    booking_changes + customer_type +
    adr + total_of_special_requests +
    stays + people + matched, data=Hotel_bookings2, family=binomial)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(reduced_model)
```

```
##
## Call:
## glm(formula = is_canceled ~ lead_time + meal + is_repeated_guest +
##     previous_cancellations + previous_bookings_not_canceled +
##     booking_changes + customer_type + adr + total_of_special_requests +
##     stays + people + matched, family = binomial, data = Hotel_bookings2)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -8.4904  -0.8436  -0.3956   0.8898   6.4027
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    -4.202e+00  6.808e-02 -61.715  < 2e-16 ***
## lead_time                       5.956e-03  7.705e-05  77.293  < 2e-16 ***
## mealFB                          8.563e-01  8.741e-02   9.796  < 2e-16 ***
## mealHB                         -2.216e-01  2.330e-02  -9.510  < 2e-16 ***
## mealSC                          1.022e-01  2.367e-02   4.317 1.58e-05 ***
## mealUndefined                  -3.287e-01  8.238e-02  -3.990 6.60e-05 ***
## is_repeated_guest              -1.182e+00  8.364e-02 -14.133  < 2e-16 ***
## previous_cancellations          3.104e+00  5.690e-02  54.550  < 2e-16 ***
## previous_bookings_not_canceled -6.041e-01  2.617e-02 -23.085  < 2e-16 ***
## booking_changes                -5.239e-01  1.550e-02 -33.790  < 2e-16 ***
## customer_typeGroup             -2.166e-02  1.640e-01  -0.132 0.894950
## customer_typeTransient          1.484e+00  5.229e-02  28.372  < 2e-16 ***
## customer_typeTransient-Party    2.029e-01  5.462e-02   3.714 0.000204 ***
## adr                             3.569e-03  1.676e-04  21.301  < 2e-16 ***
## total_of_special_requests      -7.997e-01  1.061e-02 -75.370  < 2e-16 ***
## stays                          -1.142e-02  2.958e-03  -3.861 0.000113 ***
## people                          4.653e-03  1.039e-02   0.448 0.654263
## matched1                        2.089e+00  3.842e-02  54.363  < 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: 157390  on 119385  degrees of freedom
## Residual deviance: 118986  on 119368  degrees of freedom
##   (4 observations deleted due to missingness)
## AIC: 119022
##
## Number of Fisher Scoring iterations: 8
```

```
anova(reduced_model)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: algorithm did not converge
```

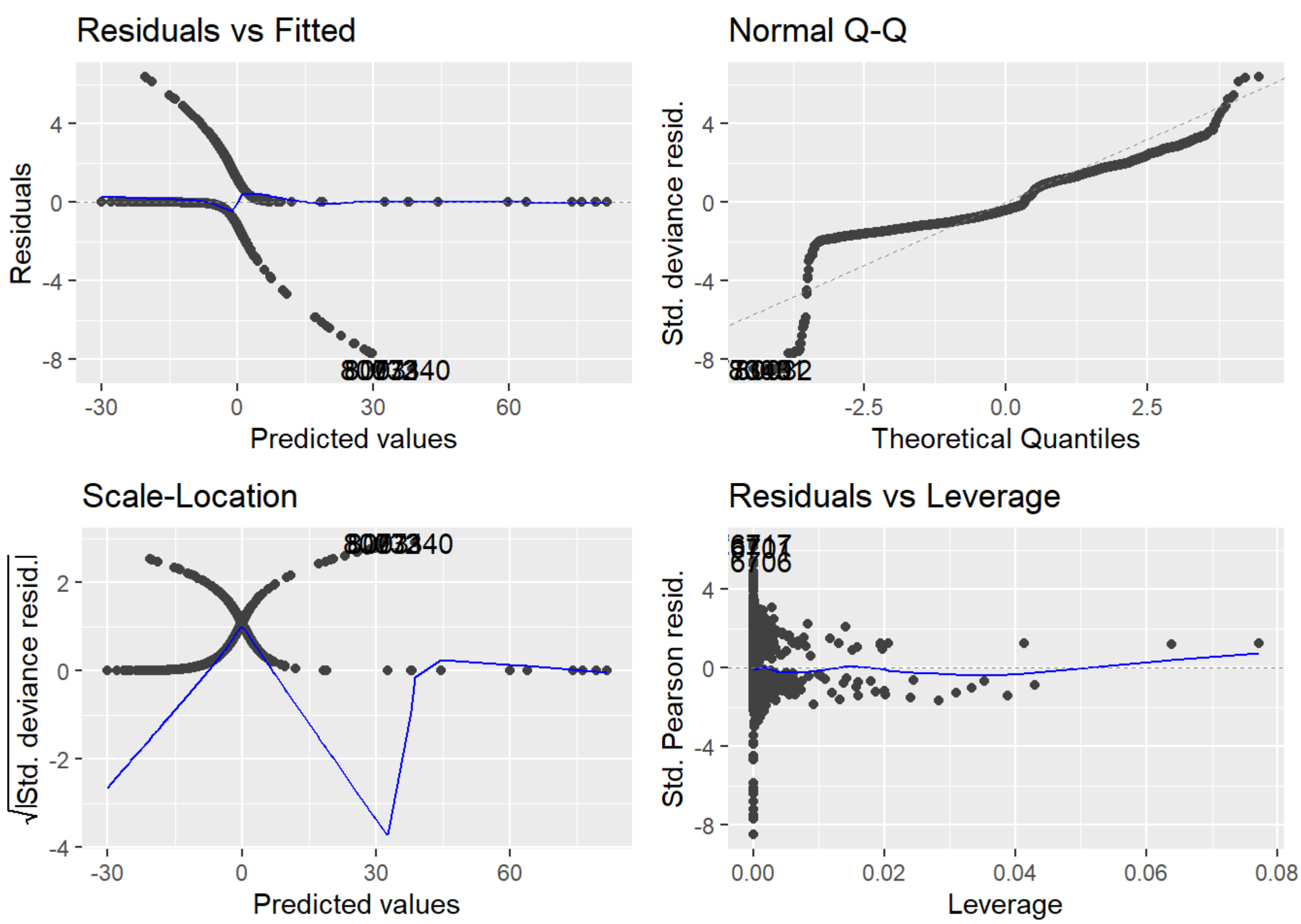
```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: is_canceled
##
## Terms added sequentially (first to last)
##
##
##                                Df Deviance Resid. Df Resid. Dev
## NULL                                          119385     157390
## lead_time                       1  10244.0    119384     147146
## meal                            4    768.2    119380     146378
## is_repeated_guest               1    410.9    119379     145967
## previous_cancellations          1   4946.4    119378     141021
## previous_bookings_not_canceled  1   2020.3    119377     139001
## booking_changes                 1   2738.8    119376     136262
## customer_type                   3   5041.3    119373     131220
## adr                             1    408.9    119372     130812
## total_of_special_requests       1   7022.6    119371     123789
## stays                           1      2.2    119370     123787
## people                          1      1.2    119369     123785
## matched                         1   4799.4    119368     118986
```

```
#Determine which one
anova(full_model, reduced_model)
```

```
## Analysis of Deviance Table
##
## Model 1: is_canceled ~ lead_time + meal + market_segment + distribution_channel +
##     is_repeated_guest + previous_cancellations + previous_bookings_not_canceled +
##     booking_changes + deposit_type + days_in_waiting_list + customer_type +
##     adr + required_car_parking_spaces + total_of_special_requests +
##     matched + stays + people
## Model 2: is_canceled ~ lead_time + meal + is_repeated_guest + previous_cancellations +
##     previous_bookings_not_canceled + booking_changes + customer_type +
##     adr + total_of_special_requests + stays + people + matched
##   Resid. Df Resid. Dev  Df Deviance
## 1    119354      99685
## 2    119368     118986 -14   -19301
```

```
#assumptions for the selection ones
autoplot(reduced_model)
```




```
#VIF for selected model
vif(reduced_model)
```

```
##                                    GVIF Df GVIF^(1/(2*Df))
## lead_time                      1.172163  1        1.082665
## meal                           1.180464  4        1.020955
## is_repeated_guest              1.285010  1        1.133583
## previous_cancellations         1.472305  1        1.213386
## previous_bookings_not_canceled 1.499041  1        1.224353
## booking_changes                1.020656  1        1.010275
## customer_type                  1.350050  3        1.051296
## adr                            1.278021  1        1.130496
## total_of_special_requests      1.072047  1        1.035397
## stays                          1.128518  1        1.062317
## people                         1.220434  1        1.104733
## matched                        1.013263  1        1.006609
```

```
durbinWatsonTest(reduced_model)
```

```
##  lag Autocorrelation D-W Statistic p-value
##    1       0.7600409     0.4799015       0
##  Alternative hypothesis: rho != 0
```

```
set.seed(1)
sample <- sample(c(TRUE, FALSE), nrow(Hotel_bookings2), replace=TRUE, prob=c(0.7,0.3))
train <- Hotel_bookings2[sample, ]
test <- Hotel_bookings2[!sample, ]

#AUC
prediction <- predict(reduced_model, test, type="response")
roc_object <- roc(test$is_canceled, prediction)
```

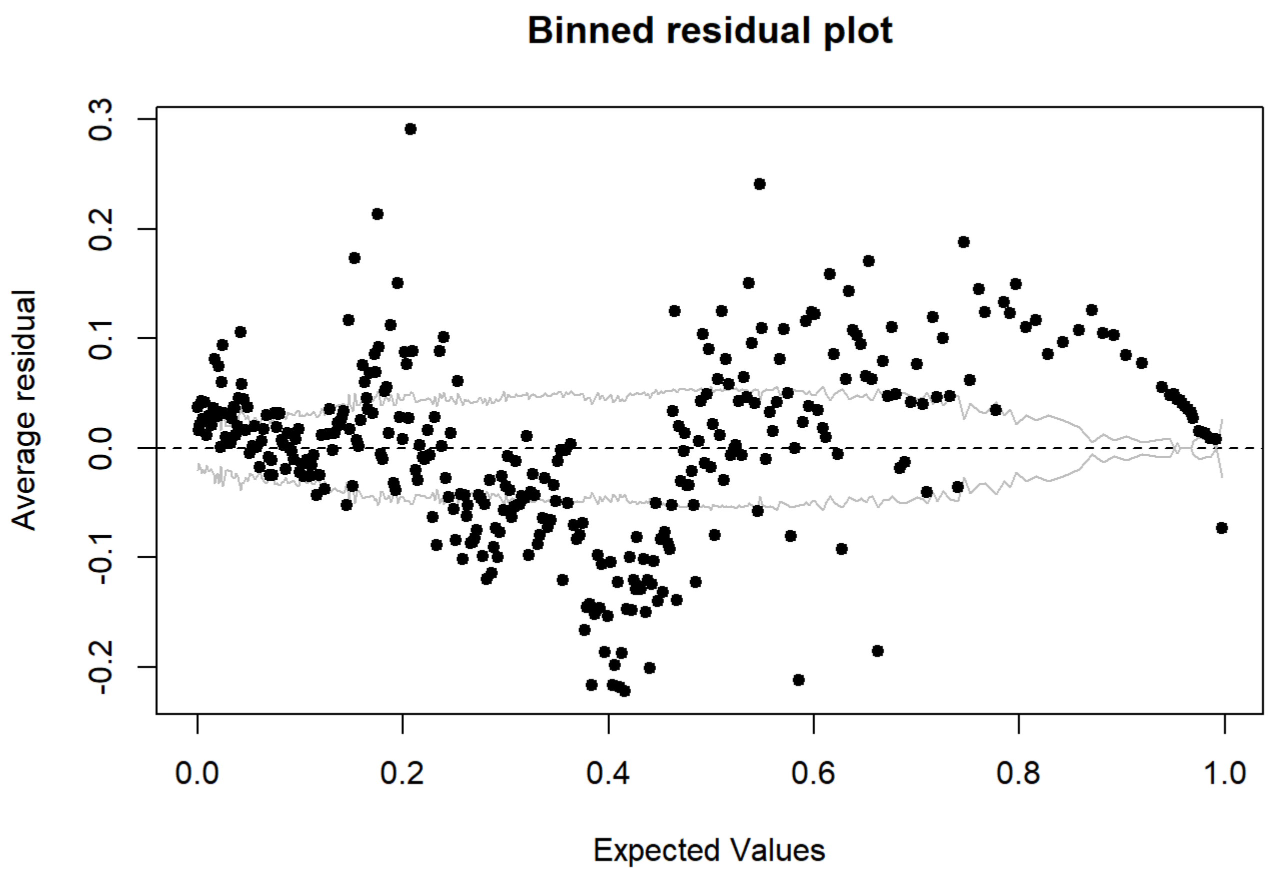
```
## Setting levels: control = 0, case = 1
```

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

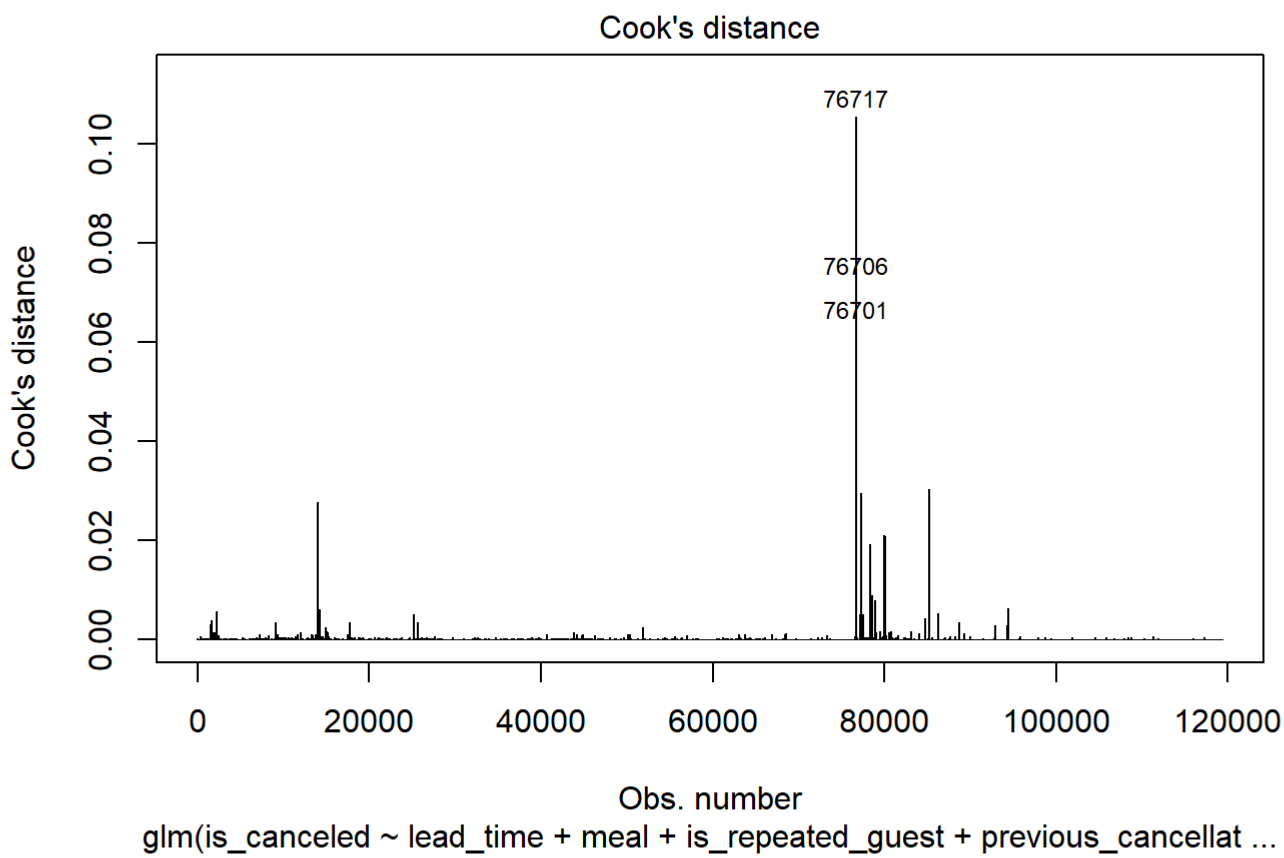
```
auc(roc_object)
```

```
## Area under the curve: 0.817
```

```
binnedplot(fitted(reduced_model),
           residuals(reduced_model, type="response"),
           nclass=NULL,
           xlab="Expected Values",
           ylab="Average residual",
           main="Binned residual plot",
           cex.pts=0.8,
           col.pts=1,
           col.int="gray")
```




```
plot(reduced_model, which = 4, id.n = 3)
```




```
anov <- aov(reduced_model)
anov
```

```
## Call:
##    aov(formula = reduced_model)
##
## Terms:
##                 lead_time      meal is_repeated_guest previous_cancellations
## Sum of Squares   2393.028   165.065            66.059                209.853
## Deg. of Freedom         1         4                 1                      1
##                 previous_bookings_not_canceled booking_changes customer_type
## Sum of Squares                          24.735         523.532       793.919
## Deg. of Freedom                              1               1             3
##                       adr total_of_special_requests     stays    people
## Sum of Squares     48.376                  1465.415     2.695     0.470
## Deg. of Freedom         1                         1         1         1
##                   matched Residuals
## Sum of Squares    774.652 21373.327
## Deg. of Freedom         1    119368
##
## Residual standard error: 0.4231478
## Estimated effects may be unbalanced
## 4 observations deleted due to missingness
```